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NetworkX is a Python language software package for the creation, manipulation, and study of the structure, dynamics, and function of complex networks.

With NetworkX you can load and store networks in standard and nonstandard data formats, generate many types of random and classic networks, analyze network structure, build network models, design new network algorithms, draw networks, and much more.

1.1 Who uses NetworkX?

The potential audience for NetworkX includes mathematicians, physicists, biologists, computer scientists, and social scientists. Good reviews of the state-of-the-art in the science of complex networks are presented in Albert and Barabási [BA02], Newman [Newman03], and Dorogovtsev and Mendes [DM03]. See also the classic texts [Bollobas01], [Diestel97] and [West01] for graph theoretic results and terminology. For basic graph algorithms, we recommend the texts of Sedgewick, e.g. [Sedgewick01] and [Sedgewick02] and the survey of Brandes and Erlebach [BE05].

1.2 Goals

NetworkX is intended to provide

- tools for the study the structure and dynamics of social, biological, and infrastructure networks,
- a standard programming interface and graph implementation that is suitable for many applications,
- a rapid development environment for collaborative, multidisciplinary projects,
- an interface to existing numerical algorithms and code written in C, C++, and FORTRAN,
- the ability to painlessly slurp in large nonstandard data sets.

1.3 The Python programming language

Python is a powerful programming language that allows simple and flexible representations of networks, and clear and concise expressions of network algorithms (and other algorithms too). Python has a vibrant and growing ecosystem of packages that NetworkX uses to provide more features such as numerical linear algebra and drawing. In addition Python is also an excellent “glue” language for putting together pieces of software from other languages which allows reuse of legacy code and engineering of high-performance algorithms [Langtangen04].

Equally important, Python is free, well-supported, and a joy to use.
In order to make the most out of NetworkX you will want to know how to write basic programs in Python. Among
the many guides to Python, we recommend the documentation at http://www.python.org and the text by Alex Martelli
[Martelli03].

1.4 Free software

NetworkX is free software; you can redistribute it and/or modify it under the terms of the BSD License. We welcome
contributions from the community. Information on NetworkX development is found at the NetworkX Developer Zone
at Github https://github.com/networkx/networkx

1.5 History

NetworkX was born in May 2002. The original version was designed and written by Aric Hagberg, Dan Schult, and
Pieter Swart in 2002 and 2003. The first public release was in April 2005.

Many people have contributed to the success of NetworkX. Some of the contributors are listed in the credits.

1.5.1 What Next

• A Brief Tour
• Installing
• Reference
• Examples
The structure of NetworkX can be seen by the organization of its source code. The package provides classes for graph objects, generators to create standard graphs, IO routines for reading in existing datasets, algorithms to analyse the resulting networks and some basic drawing tools.

Most of the NetworkX API is provided by functions which take a graph object as an argument. Methods of the graph object are limited to basic manipulation and reporting. This provides modularity of code and documentation. It also makes it easier for newcomers to learn about the package in stages. The source code for each module is meant to be easy to read and reading this Python code is actually a good way to learn more about network algorithms, but we have put a lot of effort into making the documentation sufficient and friendly. If you have suggestions or questions please contact us by joining the NetworkX Google group.

Classes are named using CamelCase (capital letters at the start of each word). functions, methods and variable names are lower_case_underscore (lowercase with an underscore representing a space between words).

## 2.1 NetworkX Basics

After starting Python, import the networkx module with (the recommended way)

```python
>>> import networkx as nx
```

To save repetition, in the documentation we assume that NetworkX has been imported this way.

If importing networkx fails, it means that Python cannot find the installed module. Check your installation and your PYTHONPATH.

The following basic graph types are provided as Python classes:

- **Graph** This class implements an undirected graph. It ignores multiple edges between two nodes. It does allow self-loop edges between a node and itself.
- **DiGraph** Directed graphs, that is, graphs with directed edges. Operations common to directed graphs, (a subclass of Graph).
- **MultiGraph** A flexible graph class that allows multiple undirected edges between pairs of nodes. The additional flexibility leads to some degradation in performance, though usually not significant.
- **MultiDiGraph** A directed version of a MultiGraph.

Empty graph-like objects are created with

```python
>>> G=nx.Graph()
>>> G=nx.DiGraph()
>>> G=nx.MultiGraph()
>>> G=nx.MultiDiGraph()
```
All graph classes allow any *hashable* object as a node. Hashable objects include strings, tuples, integers, and more. Arbitrary edge attributes such as weights and labels can be associated with an edge.

The graph internal data structures are based on an adjacency list representation and implemented using Python *dictionary* datastructures. The graph adjacency structure is implemented as a Python dictionary of dictionaries; the outer dictionary is keyed by nodes to values that are themselves dictionaries keyed by neighboring node to the edge attributes associated with that edge. This “dict-of-dicts” structure allows fast addition, deletion, and lookup of nodes and neighbors in large graphs. The underlying datastructure is accessed directly by methods (the programming interface “API”) in the class definitions. All functions, on the other hand, manipulate graph-like objects solely via those API methods and not by acting directly on the datastructure. This design allows for possible replacement of the ‘dicts-of-dicts’-based datastructure with an alternative datastructure that implements the same methods.

### 2.1.1 Graphs

The first choice to be made when using NetworkX is what type of graph object to use. A graph (network) is a collection of nodes together with a collection of edges that are pairs of nodes. Attributes are often associated with nodes and/or edges. NetworkX graph objects come in different flavors depending on two main properties of the network:

- **Directed**: Are the edges *directed*? Does the order of the edge pairs \((u, v)\) matter? A directed graph is specified by the “Di” prefix in the class name, e.g. `DiGraph()`. We make this distinction because many classical graph properties are defined differently for directed graphs.

- **Multi-edges**: Are multiple edges allowed between each pair of nodes? As you might imagine, multiple edges requires a different data structure, though tricky users could design edge data objects to support this functionality. We provide a standard data structure and interface for this type of graph using the prefix “Multi”, e.g. `MultiGraph()`.

The basic graph classes are named: `Graph`, `DiGraph`, `MultiGraph`, and `MultiDiGraph`.

### 2.2 Nodes and Edges

The next choice you have to make when specifying a graph is what kinds of nodes and edges to use.

If the topology of the network is all you care about then using integers or strings as the nodes makes sense and you need not worry about edge data. If you have a data structure already in place to describe nodes you can simply use that structure as your nodes provided it is *hashable*. If it is not hashable you can use a unique identifier to represent the node and assign the data as a *node attribute*.

Edges often have data associated with them. Arbitrary data can associated with edges as an *edge attribute*. If the data is numeric and the intent is to represent a *weighted* graph then use the ‘weight’ keyword for the attribute. Some of the graph algorithms, such as Dijkstra’s shortest path algorithm, use this attribute name to get the weight for each edge.

Other attributes can be assigned to an edge by using keyword/value pairs when adding edges. You can use any keyword except ‘weight’ to name your attribute and can then easily query the edge data by that attribute keyword.

Once you’ve decided how to encode the nodes and edges, and whether you have an undirected/directed graph with or without multiedges you are ready to build your network.

### 2.2.1 Graph Creation

NetworkX graph objects can be created in one of three ways:

- **Graph generators** – standard algorithms to create network topologies.
- **Importing data** from pre-existing (usually file) sources.
Explicit addition and removal of nodes/edges is the easiest to describe. Each graph object supplies methods to manipulate the graph. For example,

```python
>>> import networkx as nx
>>> G=nx.Graph()
>>> G.add_edge(1,2)  # default edge data=1
>>> G.add_edge(2,3,weight=0.9)  # specify edge data
```

Edge attributes can be anything:

```python
>>> import math
>>> G.add_edge('y','x',function=math.cos)
>>> G.add_node(math.cos)  # any hashable can be a node
```

You can add many edges at one time:

```python
>>> elist=[('a','b',5.0),('b','c',3.0),('a','c',1.0),('c','d',7.3)]
>>> G.add_weighted_edges_from(elist)
```

See the /tutorial/index for more examples.

Some basic graph operations such as union and intersection are described in the `Operators module` documentation. Graph generators such as `binomial_graph` and `powerlaw_graph` are provided in the `Graph generators` subpackage.

For importing network data from formats such as GML, GraphML, edge list text files see the `Reading and writing graphs` subpackage.

### 2.2.2 Graph Reporting

Class methods are used for the basic reporting functions neighbors, edges and degree. Reporting of lists is often needed only to iterate through that list so we supply iterator versions of many property reporting methods. For example `edges()` and `nodes()` have corresponding methods `edges_iter()` and `nodes_iter()`. Using these methods when you can will save memory and often time as well.

The basic graph relationship of an edge can be obtained in two basic ways. One can look for neighbors of a node or one can look for edges incident to a node. We jokingly refer to people who focus on nodes/neighbors as node-centric and people who focus on edges as edge-centric. The designers of NetworkX tend to be node-centric and view edges as a relationship between nodes. You can see this by our avoidance of notation like `G[u,v]` in favor of `G[u][v]`. Most data structures for sparse graphs are essentially adjacency lists and so fit this perspective. In the end, of course, it doesn’t really matter which way you examine the graph. `G.edges()` removes duplicate representations of each edge while `G.neighbors(n)` or `G[n]` is slightly faster but doesn’t remove duplicates.

Any properties that are more complicated than edges, neighbors and degree are provided by functions. For example `nx.triangles(G,n)` gives the number of triangles which include node n as a vertex. These functions are grouped in the code and documentation under the term `algorithms`.

### 2.2.3 Algorithms

A number of graph algorithms are provided with NetworkX. These include shortest path, and breadth first search (see `traversal`), clustering and isomorphism algorithms and others. There are many that we have not developed yet too. If you implement a graph algorithm that might be useful for others please let us know through the NetworkX Google group or the Github Developer Zone.

As an example here is code to use Dijkstra’s algorithm to find the shortest weighted path:
>>> G=nx.Graph()
>>> e=[('a','b',0.3),('b','c',0.9),('a','c',0.5),('c','d',1.2)]
>>> G.add_weighted_edges_from(e)
>>> print(nx.dijkstra_path(G,'a','d'))
['a', 'c', 'd']

2.2.4 Drawing

While NetworkX is not designed as a network layout tool, we provide a simple interface to drawing packages and some simple layout algorithms. We interface to the excellent Graphviz layout tools like dot and neato with the (suggested) pygraphviz package or the pydot interface. Drawing can be done using external programs or the Matplotlib Python package. Interactive GUI interfaces are possible though not provided. The drawing tools are provided in the module drawing.

The basic drawing functions essentially place the nodes on a scatterplot using the positions in a dictionary or computed with a layout function. The edges are then lines between those dots.

>>> G=nx.cubical_graph()
>>> nx.draw(G)
# default spring_layout
>>> nx.draw(G,pos=nx.spectral_layout(G), nodecolor='r',edge_color='b')

See the examples for more ideas.

2.2.5 Data Structure

NetworkX uses a “dictionary of dictionaries of dictionaries” as the basic network data structure. This allows fast lookup with reasonable storage for large sparse networks. The keys are nodes so G[u] returns an adjacency dictionary keyed by neighbor to the edge attribute dictionary. The expression G[u][v] returns the edge attribute dictionary itself. A dictionary of lists would have also been possible, but not allowed fast edge detection nor convenient storage of edge data.

Advantages of dict-of-dicts-of-dicts data structure:

- Find edges and remove edges with two dictionary look-ups.
- Prefer to “lists” because of fast lookup with sparse storage.
- Prefer to “sets” since data can be attached to edge.
- G[u][v] returns the edge attribute dictionary.
- n in G tests if node n is in graph G.
- for n in G: iterates through the graph.
- for nbr in G[n]: iterates through neighbors.

As an example, here is a representation of an undirected graph with the edges (‘A’,’B’), (’B’,’C’)

>>> G=nx.Graph()
>>> G.add_edge('A','B')
>>> G.add_edge('B','C')
>>> print(G.adj)
{'A': {'B': {}}, 'C': {'B': {}}, 'B': {'A': {}, 'C': {}}}

The data structure gets morphed slightly for each base graph class. For DiGraph two dict-of-dicts-of-dicts structures are provided, one for successors and one for predecessors. For MultiGraph/MultiDiGraph we use a dict-of-dicts-of-
dicts-of-dicts \(^1\) where the third dictionary is keyed by an edge key identifier to the fourth dictionary which contains the edge attributes for that edge between the two nodes.

Graphs use a dictionary of attributes for each edge. We use a dict-of-dicts-of-dicts data structure with the inner dictionary storing “name-value” relationships for that edge.

```python
>>> G=nx.Graph()
>>> G.add_edge(1,2,color='red',weight=0.84,size=300)
>>> print(G[1][2]['size'])
300
```

\(^1\) “It’s dictionaries all the way down.”
NetworkX provides data structures and methods for storing graphs.

All NetworkX graph classes allow (hashable) Python objects as nodes, and any Python object can be assigned as an edge attribute.

The choice of graph class depends on the structure of the graph you want to represent.

### 3.1 Which graph class should I use?

<table>
<thead>
<tr>
<th>Graph Type</th>
<th>NetworkX Class</th>
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<td>Undirected Simple</td>
<td>Graph</td>
</tr>
<tr>
<td>Directed Simple</td>
<td>DiGraph</td>
</tr>
<tr>
<td>With Self-loops</td>
<td>Graph, DiGraph</td>
</tr>
<tr>
<td>With Parallel edges</td>
<td>MultiGraph, MultiDiGraph</td>
</tr>
</tbody>
</table>

### 3.2 Basic graph types

#### 3.2.1 Graph – Undirected graphs with self loops

**Overview**

**Graph** \((data=None, **attr\))
- Base class for undirected graphs.
- A Graph stores nodes and edges with optional data, or attributes.
- Graphs hold undirected edges. Self loops are allowed but multiple (parallel) edges are not.
- Nodes can be arbitrary (hashable) Python objects with optional key/value attributes.
- Edges are represented as links between nodes with optional key/value attributes.

**Parameters**

- **data** : input graph
  - Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.

- **attr** : keyword arguments, optional (default= no attributes)
  - Attributes to add to graph as key=value pairs.
See also:
- `DiGraph`
- `MultiGraph`
- `MultiDiGraph`

Examples

Create an empty graph structure (a “null graph”) with no nodes and no edges.

```python
>>> G = nx.Graph()
```

G can be grown in several ways.

**Nodes:**

Add one node at a time:

```python
>>> G.add_node(1)
```

Add the nodes from any container (a list, dict, set or even the lines from a file or the nodes from another graph).

```python
>>> G.add_nodes_from([2, 3])
>>> G.add_nodes_from(range(100, 110))
>>> H = nx.Graph()
>>> H.add_path([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> G.add_nodes_from(H)
```

In addition to strings and integers any hashable Python object (except `None`) can represent a node, e.g. a customized node object, or even another `Graph`.

```python
>>> G.add_node(H)
```

**Edges:**

G can also be grown by adding edges.

Add one edge,

```python
>>> G.add_edge(1, 2)
```

a list of edges,

```python
>>> G.add_edges_from([(1, 2), (1, 3)])
```

or a collection of edges,

```python
>>> G.add_edges_from(H.edges())
```

If some edges connect nodes not yet in the graph, the nodes are added automatically. There are no errors when adding nodes or edges that already exist.

**Attributes:**

Each graph, node, and edge can hold key/value attribute pairs in an associated attribute dictionary (the keys must be hashable). By default these are empty, but can be added or changed using `add_edge`, `add_node` or direct manipulation of the attribute dictionaries named `graph`, `node` and `edge` respectively.

```python
>>> G = nx.Graph(day="Friday")
>>> G.graph
{'day': 'Friday'}
```

Add node attributes using `add_node()`, `add_nodes_from()` or `G.node`
>>> G.add_node(1, time='5pm')
>>> G.add_nodes_from([3], time='2pm')
>>> G.node[1]
{'time': '5pm'}
>>> del G.node[1]['room'] # remove attribute
>>> G.nodes(data=True)
[(1, {'time': '5pm'}), (3, {'time': '2pm'})]

Warning: adding a node to G.node does not add it to the graph.

Add edge attributes using add_edge(), add_edges_from(), subscript notation, or G.edge.

>>> G.add_edge(1, 2, weight=4.7 )
>>> G.add_edges_from(((3,4),(4,5)), color='red')
>>> G.add_edges_from(((1,2),{'color':'blue'}), (2,3,{'weight':8}))
>>> G[1][2]['weight'] = 4.7
>>> G.edge[1][2]['weight'] = 4

Shortcuts:

Many common graph features allow python syntax to speed reporting.

>>> 1 in G # check if node in graph
True
>>> [n for n in G if n<3] # iterate through nodes
[1, 2]
>>> len(G) # number of nodes in graph
5

The fastest way to traverse all edges of a graph is via adjacency_iter(), but the edges() method is often more convenient.

>>> for n,nbrsdict in G.adjacency_iter():
...     for nbr,eattr in nbrsdict.items():
...         if 'weight' in eattr:
...             (n,nbr,eattr['weight'])
(1, 2, 4)
(2, 1, 4)
(2, 3, 8)
(3, 2, 8)

Reporting:

Simple graph information is obtained using methods. Iterator versions of many reporting methods exist for efficiency. Methods exist for reporting nodes(), edges(), neighbors() and degree() as well as the number of nodes and edges.

For details on these and other miscellaneous methods, see below.

### Adding and removing nodes and edges

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graph.<strong>init</strong>((data))</td>
<td>Initialize a graph with edges, name, graph attributes.</td>
</tr>
<tr>
<td>Graph.add_node(n[, attr_dict])</td>
<td>Add a single node n and update node attributes.</td>
</tr>
<tr>
<td>Graph.add_nodes_from(nodes, **attr)</td>
<td>Add multiple nodes.</td>
</tr>
</tbody>
</table>

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<tr>
<th>Method</th>
<th>Description</th>
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</thead>
<tbody>
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<td><code>Graph.remove_node(n)</code></td>
<td>Remove node n.</td>
</tr>
<tr>
<td><code>Graph.remove_nodes_from(nodes)</code></td>
<td>Remove multiple nodes.</td>
</tr>
<tr>
<td><code>Graph.add_edge(u, v[, attr_dict])</code></td>
<td>Add an edge between u and v.</td>
</tr>
<tr>
<td><code>Graph.add_edges_from(ebunch[, attr_dict])</code></td>
<td>Add all the edges in ebunch.</td>
</tr>
<tr>
<td><code>Graph.add_weighted_edges_from(ebunch[, weight])</code></td>
<td>Add all the edges in ebunch as weighted edges with specified weights.</td>
</tr>
<tr>
<td><code>Graph.remove_edge(u, v)</code></td>
<td>Remove the edge between u and v.</td>
</tr>
<tr>
<td><code>Graph.remove_edges_from(ebunch)</code></td>
<td>Remove all edges specified in ebunch.</td>
</tr>
<tr>
<td><code>Graph.add_star(nodes, **attr)</code></td>
<td>Add a star.</td>
</tr>
<tr>
<td><code>Graph.add_path(nodes, **attr)</code></td>
<td>Add a path.</td>
</tr>
<tr>
<td><code>Graph.add_cycle(nodes, **attr)</code></td>
<td>Add a cycle.</td>
</tr>
<tr>
<td><code>Graph.clear()</code></td>
<td>Remove all nodes and edges from the graph.</td>
</tr>
</tbody>
</table>

---

**__init__**

`Graph.__init__(data=None, **attr)`

Initialize a graph with edges, name, graph attributes.

**Parameters**

- **data** : input graph
  
  Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.

- **name** : string, optional (default="")
  
  An optional name for the graph.

- **attr** : keyword arguments, optional (default= no attributes)
  
  Attributes to add to graph as key=value pairs.

**See also:**

convert

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G = nx.Graph(name='my graph')
>>> e = [(1,2),(2,3),(3,4)]  # list of edges
>>> G = nx.Graph(e)
```

Arbitrary graph attribute pairs (key=value) may be assigned

```python
>>> G=nx.Graph(e, day="Friday")
>>> G.graph
{'day': 'Friday'}
```

**add_node**

`Graph.add_node(n, attr_dict=None, **attr)`

Add a single node n and update node attributes.

**Parameters**

- **n** : node
A node can be any hashable Python object except None.

**attr_dict** : dictionary, optional (default= no attributes)

Dictionary of node attributes. Key/value pairs will update existing data associated with the node.

**attr** : keyword arguments, optional

Set or change attributes using key=value.

**See also:**

* add_nodes_from

**Notes**

A hashable object is one that can be used as a key in a Python dictionary. This includes strings, numbers, tuples of strings and numbers, etc.

On many platforms hashable items also include mutables such as NetworkX Graphs, though one should be careful that the hash doesn’t change on mutables.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_node(1)
>>> G.add_node('Hello')
>>> K3 = nx.Graph([(0,1),(1,2),(2,0)])
>>> G.add_node(K3)
>>> G.number_of_nodes()
3
```

Use keywords set/change node attributes:

```python
>>> G.add_node(1,size=10)
>>> G.add_node(3,weight=0.4,UTM=('13S',382871,3972649))
```

**add_nodes_from**

```
Graph.add_nodes_from(nodes, **attr)
```

Add multiple nodes.

**Parameters**

- **nodes** : iterable container
  
  A container of nodes (list, dict, set, etc.). OR A container of (node, attribute dict) tuples. Node attributes are updated using the attribute dict.

- **attr** : keyword arguments, optional (default= no attributes)

  Update attributes for all nodes in nodes. Node attributes specified in nodes as a tuple take precedence over attributes specified generally.

**See also:**

* add_node
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> K3 = nx.Graph([(0,1), (1,2), (2,0)])
>>> G.add_nodes_from(K3)
>>> sorted(G.nodes(), key=str)
[0, 1, 2, 'H', 'e', 'l', 'o']
```

Use keywords to update specific node attributes for every node.

```python
>>> G.add_nodes_from([1,2], size=10)
>>> G.add_nodes_from([3,4], weight=0.4)
```

Use (node, attrdict) tuples to update attributes for specific nodes.

```python
>>> G.add_nodes_from([(1,dict(size=11)), (2,{'color':'blue'})])
```

```python
>>> G.node[1]['size']
11
```

```python
>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))
```

```python
>>> H.node[1]['size']
11
```

`remove_node`

Graph.remove_node(n)

Remove node n.

Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.

Parameters

- **n**: node

A node in the graph

Raises

- NetworkXError:

  If n is not in the graph.

See also:

remove_nodes_from

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.edges()
[(0, 1), (1, 2)]
>>> G.remove_node(1)
>>> G.edges()
[]
```

`remove_nodes_from`

Graph.remove_nodes_from(nodes)

Remove multiple nodes.
**Parameters**  

`nodes` : iterable container  

A container of nodes (list, dict, set, etc.). If a node in the container is not in the graph it is silently ignored.

**See also:**

`remove_node`

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> e = G.nodes()
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> G.nodes()
[]
```

**add_edge**

`Graph.add_edge(u, v, attr_dict=None, **attr)`  

Add an edge between u and v.  

The nodes u and v will be automatically added if they are not already in the graph.  

Edge attributes can be specified with keywords or by providing a dictionary with key/value pairs. See examples below.

**Parameters**  

`u, v` : nodes  

Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.

`attr_dict` : dictionary, optional (default= no attributes)  

Dictionary of edge attributes. Key/value pairs will update existing data associated with the edge.

`attr` : keyword arguments, optional  

Edge data (or labels or objects) can be assigned using keyword arguments.

**See also:**

`add_edges_from` add a collection of edges

**Notes**

Adding an edge that already exists updates the edge data.

Many NetworkX algorithms designed for weighted graphs use as the edge weight a numerical value assigned to a keyword which by default is ‘weight’.
Examples

The following all add the edge e=(1,2) to graph G:

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = (1,2)
>>> G.add_edge(1, 2)  # explicit two-node form
>>> G.add_edge(*e)  # single edge as tuple of two nodes
>>> G.add_edges_from([(1,2)])  # add edges from iterable container

Associate data to edges using keywords:

```python
>>> G.add_edge(1, 2, weight=3)
```  
```python
>>> G.add_edge(1, 3, weight=7, capacity=15, length=342.7)
```

add_edges_from

```python
Graph.add_edges_from(ebunch, attr_dict=None, **attr)
```
Add all the edges in ebunch.

**Parameters**

- **ebunch**: container of edges
  
  Each edge given in the container will be added to the graph. The edges must be given as 2-tuples (u,v) or 3-tuples (u,v,d) where d is a dictionary containing edge data.

- **attr_dict**: dictionary, optional (default= None attributes)
  
  Dictionary of edge attributes. Key/value pairs will update existing data associated with each edge.

- **attr**: keyword arguments, optional
  
  Edge data (or labels or objects) can be assigned using keyword arguments.

**See also**

- **add_edge** add a single edge
- **add_weighted_edges_from** convenient way to add weighted edges

**Notes**

Adding the same edge twice has no effect but any edge data will be updated when each duplicate edge is added.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edges_from([(0,1),(1,2)])  # using a list of edge tuples
>>> e = zip(range(0,3),range(1,4))
>>> G.add_edges_from(e)  # Add the path graph 0-1-2-3

Associate data to edges

```python
>>> G.add_edges_from([(1,2),(2,3)], weight=3)
```  
```python
>>> G.add_edges_from([(3,4),(1,4)], label='WN2898')
```
add_weighted_edges_from

```python
add_weighted_edges_from(ebunch, weight='weight', **attr)
```

Add all the edges in ebunch as weighted edges with specified weights.

**Parameters**

- **ebunch**: container of edges
  
  Each edge given in the list or container will be added to the graph. The edges must be given as 3-tuples (u,v,w) where w is a number.
  
  - **weight**: string, optional (default= ‘weight’) The attribute name for the edge weights to be added.
  - **attr**: keyword arguments, optional (default= no attributes) Edge attributes to add/update for all edges.

**See also:**

- `add_edge` add a single edge
- `add_edges_from` add multiple edges

**Notes**

Adding the same edge twice for Graph/DiGraph simply updates the edge data. For MultiGraph/MultiDiGraph, duplicate edges are stored.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0,1,3.0),(1,2,7.5)])
```

remove_edge

```python
remove_edge(u, v)
```

Remove the edge between u and v.

**Parameters**

- **u,v**: nodes
  
  Remove the edge between nodes u and v.

**Raises**

- **NetworkXError**: If there is not an edge between u and v.

**See also:**

- `remove_edges_from` remove a collection of edges

**Examples**
```python
>>> G = nx.Graph()  # or DiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.remove_edge(0,1)
>>> e = (1,2)
>>> G.remove_edge(e)  # unpacks e from an edge tuple
>>> e = (2,3,{'weight':7})  # an edge with attribute data
>>> G.remove_edge(e[:2])  # select first part of edge tuple
```

### remove_edges_from

**Graph.remove_edges_from(ebunch)**

Remove all edges specified in ebunch.

**Parameters**

- **ebunch**: list or container of edge tuples

  Each edge given in the list or container will be removed from the graph. The edges can be:
  - 2-tuples (u,v) edge between u and v.
  - 3-tuples (u,v,k) where k is ignored.

**See also:**

- **remove_edge**: remove a single edge

**Notes**

Will fail silently if an edge in ebunch is not in the graph.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> ebunch=[(1,2),(2,3)]
>>> G.remove_edges_from(ebunch)
```

### add_star

**Graph.add_star(nodes, **attr)**

Add a star.

The first node in nodes is the middle of the star. It is connected to all other nodes.

**Parameters**

- **nodes**: iterable container

  A container of nodes.

  **attr**: keyword arguments, optional (default= no attributes)

  Attributes to add to every edge in star.

**See also:**

- **add_path, add_cycle**
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_star([0,1,2,3])
>>> G.add_star([10,11,12], weight=2)
```

add_path

```python
add_path(nodes, **attr)
```

Add a path.

Parameters:
- `nodes` : iterable container
  
  A container of nodes. A path will be constructed from the nodes (in order) and added to the graph.

- `attr` : keyword arguments, optional (default= no attributes)
  
  Attributes to add to every edge in path.

See also:
- `add_star`, `add_cycle`

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.add_path([10,11,12], weight=7)
```

add_cycle

```python
add_cycle(nodes, **attr)
```

Add a cycle.

Parameters:
- `nodes` : iterable container
  
  A container of nodes. A cycle will be constructed from the nodes (in order) and added to the graph.

- `attr` : keyword arguments, optional (default= no attributes)
  
  Attributes to add to every edge in cycle.

See also:
- `add_path`, `add_star`

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_cycle([0,1,2,3])
>>> G.add_cycle([10,11,12], weight=7)
```
clear

Graph.clear()

Remove all nodes and edges from the graph.
This also removes the name, and all graph, node, and edge attributes.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.clear()
>>> G.nodes()
[]
>>> G.edges()
[]
```

Iterating over nodes and edges

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</table>

nodes

Graph.nodes(data=False)
Return a list of the nodes in the graph.

Parameters data : boolean, optional (default=False)
If False return a list of nodes. If True return a two-tuple of node and node data dictionary

Returns nlist : list
A list of nodes. If data=True a list of two-tuples containing (node, node data dictionary).

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.nodes()
[0, 1, 2]
>>> G.add_node(1, time='5pm')
```
>>> G.nodes(data=True)
[(0, {}), (1, {'time': '5pm'}), (2, {})]

**nodes_iter**

*Graph.nodes_iter(data=False)*

Return an iterator over the nodes.

**Parameters data**: boolean, optional (default=False)

If False the iterator returns nodes. If True return a two-tuple of node and node data dictionary

**Returns niter**: iterator

An iterator over nodes. If data=True the iterator gives two-tuples containing (node, node data, dictionary)

**Notes**

If the node data is not required it is simpler and equivalent to use the expression ‘for n in G’.

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
```

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])

>>> [d for n,d in G.nodes_iter(data=True)]
[[], [], []]
```

**__iter__**

*Graph.__iter__()*

Iterate over the nodes. Use the expression ‘for n in G’.

**Returns niter**: iterator

An iterator over all nodes in the graph.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
```
edges

NetworkX Reference, Release 1.8

edges

Graph.edges(nbunch=None, data=False)

Return a list of edges.

Edges are returned as tuples with optional data in the order (node, neighbor, data).

Parameters nbunch: iterable container, optional (default= all nodes)

A container of nodes. The container will be iterated through once.

data: bool, optional (default=False)

Return two tuples (u,v) (False) or three-tuples (u,v,data) (True).

Returns edge_list: list of edge tuples:

Edges that are adjacent to any node in nbunch, or a list of all edges if nbunch is not specified.

See also:

edges_iter return an iterator over the edges

Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.edges()
[(0, 1), (1, 2), (2, 3)]
>>> G.edges(data=True)  # default edge data is {} (empty dictionary)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> G.edges([0,3])
[(0, 1), (3, 2)]
>>> G.edges(0)
[(0, 1)]

dates_iter

Graph.edges_iter(nbunch=None, data=False)

Return an iterator over the edges.

Edges are returned as tuples with optional data in the order (node, neighbor, data).

Parameters nbunch: iterable container, optional (default= all nodes)

A container of nodes. The container will be iterated through once.

data: bool, optional (default=False)

If True, return edge attribute dict in 3-tuple (u,v,data).

Returns edge_iter: iterator

An iterator of (u,v) or (u,v,d) tuples of edges.
See also:

**edges** return a list of edges

Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [e for e in G.edges_iter()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges_iter(data=True))  # default data is {} (empty dict)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> list(G.edges_iter([0,3]))
[(0, 1), (3, 2)]
>>> list(G.edges_iter(0))
[(0, 1)]
```

**get_edge_data**

NetworkX Reference, Release 1.8

```
Graph.get_edge_data(u, v, default=None)
Return the attribute dictionary associated with edge (u,v).

Parameters  u,v : nodes

    default: any Python object (default=None) :

        Value to return if the edge (u,v) is not found.

Returns  edge_dict : dictionary

    The edge attribute dictionary.
```

Notes

It is faster to use G[u][v].

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G[0][1]
{}
```

Warning: Assigning G[u][v] corrupts the graph data structure. But it is safe to assign attributes to that dictionary.

```python
>>> G[0][1]['weight'] = 7
>>> G[0][1]['weight']
7
>>> G[1][0]['weight']
7
```
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.get_edge_data(0,1)  # default edge data is {}
{}
>>> e = (0,1)
>>> G.get_edge_data(*e)  # tuple form
{}
>>> G.get_edge_data('a','b',default=0)  # edge not in graph, return 0
0
```
Notes

It is faster to use the idiom “in G[0]”, e.g.

```python
>>> G = nx.path_graph(4)
>>> [n for n in G[0]]
[1]
```

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [n for n in G.neighbors_iter(0)]
[1]
```

__getitem__

Graph.__getitem__(n)

Return a dict of neighbors of node n. Use the expression ‘G[n]’.

Parameters

n : node

A node in the graph.

Returns

adj_dict : dictionary

The adjacency dictionary for nodes connected to n.

Notes

G[n] is similar to G.neighbors(n) but the internal data dictionary is returned instead of a list. Assigning G[n] will corrupt the internal graph data structure. Use G[n] for reading data only.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G[0]
{1: {}}
```

adjacency_list

Graph.adjacency_list()

Return an adjacency list representation of the graph.

The output adjacency list is in the order of G.nodes(). For directed graphs, only outgoing adjacencies are included.

Returns

adj_list : lists of lists

The adjacency structure of the graph as a list of lists.

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See also:

adjacency_iter

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.adjacency_list()  # in order given by G.nodes()
[[1], [0, 2], [1, 3], [2]]
```

**adjacency_iter**

Graph.**adjacency_iter**()

Return an iterator of (node, adjacency dict) tuples for all nodes.

This is the fastest way to look at every edge. For directed graphs, only outgoing adjacencies are included.

**Returns**  
adj_iter : iterator

An iterator of (node, adjacency dictionary) for all nodes in the graph.

See also:

adjacency_list

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [(n,nbrdict) for n,nbrdict in G.adjacency_iter()]
[(0, {1: {}}), (1, {0: {}, 2: {}}), (2, {1: {}, 3: {}}), (3, {2: {}})]
```

**nbunch_iter**

Graph.**nbunch_iter**(nbunch=None)

Return an iterator of nodes contained in nbunch that are also in the graph.

The nodes in nbunch are checked for membership in the graph and if not are silently ignored.

**Parameters**  
nbunch : iterable container, optional (default=all nodes)

A container of nodes. The container will be iterated through once.

**Returns**  
niter : iterator

An iterator over nodes in nbunch that are also in the graph. If nbunch is None, iterate over all nodes in the graph.

**Raises**  
NetworkXError :

If nbunch is not a node or or sequence of nodes. If a node in nbunch is not hashable.

See also:

Graph.__iter__
Notes

When nbunch is an iterator, the returned iterator yields values directly from nbunch, becoming exhausted when nbunch is exhausted.

To test whether nbunch is a single node, one can use “if nbunch in self.”, even after processing with this routine. If nbunch is not a node or a (possibly empty) sequence/iterator or None, a NetworkXError is raised. Also, if any object in nbunch is not hashable, a NetworkXError is raised.

Information about graph structure

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<td>Return True if the graph contains the node n.</td>
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<td><code>Graph.__contains__(n)</code></td>
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<tr>
<td><code>Graph.number_of_selfloops()</code></td>
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has_node

Graph.has_node(n)
Return True if the graph contains the node n.

**Parameters**

- `n`: node

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.has_node(0)
True

It is more readable and simpler to use

```python
>>> 0 in G
True
```

__contains__

Graph.__contains__(n)
Return True if n is a node, False otherwise. Use the expression ‘n in G’.
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> 1 in G
True
```

**has_edge**

Graph has_edge(u, v)

Return True if the edge (u,v) is in the graph.

**Parameters**

- **u,v**: nodes
  
  Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.

**Returns**

- **edge_ind**: bool
  
  True if edge is in the graph, False otherwise.

**Examples**

Can be called either using two nodes u,v or edge tuple (u,v)

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.has_edge(0,1)  # using two nodes
True
>>> e = (0,1)
>>> G.has_edge(*e)  # e is a 2-tuple (u,v)
True
>>> e = (0,1,{'weight':7})
>>> G.has_edge(*e[:2])  # e is a 3-tuple (u,v,data_dictionary)
True
```

The following syntax are all equivalent:

```python
>>> G.has_edge(0,1)
True
>>> 1 in G[0]  # though this gives KeyError if 0 not in G
True
```

**order**

Graph order()

Return the number of nodes in the graph.

**Returns**

- **nnodes**: int
  
  The number of nodes in the graph.

**See also:**

- number_of_nodes.__len__
number_of_nodes

Graph.number_of_nodes()  
Return the number of nodes in the graph.

Returns nnodes : int  
The number of nodes in the graph.

See also:
order, __len__

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> len(G)
3

__len__

Graph.__len__()  
Return the number of nodes. Use the expression ‘len(G)’.

Returns nnodes : int  
The number of nodes in the graph.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> len(G)
4

degree

Graph.degree(nbunch=None, weight=None)  
Return the degree of a node or nodes.

The node degree is the number of edges adjacent to that node.

Parameters nbunch : iterable container, optional (default=all nodes)  
A container of nodes. The container will be iterated through once.

weight : string or None, optional (default=None)  
The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns nd : dictionary, or number  
A dictionary with nodes as keys and degree as values or a number if a single node is specified.
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.degree(0)
1
>>> G.degree([0,1])
{0: 1, 1: 2}
>>> list(G.degree([0,1]).values())
[1, 2]
```

degree_iter

Graph.degree_iter(nbunch=None, weight=None)

Return an iterator for (node, degree).

The node degree is the number of edges adjacent to the node.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)
  
  A container of nodes. The container will be iterated through once.

- **weight**: string or None, optional (default=None)
  
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**Returns**

- **nd_iter**: an iterator
  
  The iterator returns two-tuples of (node, degree).

See also:

degree

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> list(G.degree_iter(0))
# node 0 with degree 1
[(0, 1)]
>>> list(G.degree_iter([0,1]))
[(0, 1), (1, 2)]
```

size

Graph.size(weight=None)

Return the number of edges.

**Parameters**

- **weight**: string or None, optional (default=None)
  
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**

- **nedges**: int
  
  The number of edges of sum of edge weights in the graph.
See also:

number_of_edges

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.size()
3

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a','b',weight=2)
>>> G.add_edge('b','c',weight=4)
>>> G.size()
2
>>> G.size(weight='weight')
6.0
```

number_of_edges

Graph.number_of_edges(u=None, v=None)

Return the number of edges between two nodes.

Parameters u, v : nodes, optional (default=all edges)

If u and v are specified, return the number of edges between u and v. Otherwise return the total number of all edges.

Returns nedges : int

The number of edges in the graph. If nodes u and v are specified return the number of edges between those nodes.

See also:

size

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.number_of_edges()
3
>>> G.number_of_edges(0,1)
1
>>> e = (0,1)
>>> G.number_of_edges(*e)
1
```

nodes_with_selfloops

Graph.nodes_with_selfloops()

Return a list of nodes with self loops.

A node with a self loop has an edge with both ends adjacent to that node.
Returns nodelist : list
A list of nodes with self loops.

See also:
selfloop_edges, number_of_selfloops

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.nodes_with_selfloops()
[1]
```

selfloop_edges

Graph.selfloop_edges(data=False)
Return a list of selfloop edges.
A selfloop edge has the same node at both ends.

Parameters data : bool, optional (default=False)
Return selfloop edges as two tuples (u,v) (data=False) or three-tuples (u,v,data) (data=True)

Returns edgelist : list of edge tuples
A list of all selfloop edges.

See also:
nodes_with_selfloops, number_of_selfloops

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.selfloop_edges()
[(1, 1)]
>>> G.selfloop_edges(data=True)
[(1, 1, {})]
```

number_of_selfloops

Graph.number_of_selfloops()
Return the number of selfloop edges.
A selfloop edge has the same node at both ends.

Returns nloops : int
The number of selfloops.
See also:

*nodes_with_selfloops, selfloop_edges*

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> G.number_of_selfloops()
1
```

Making copies and subgraphs

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<td>Return a copy of the graph.</td>
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<td>Return an undirected copy of the graph.</td>
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<td>Return a directed representation of the graph.</td>
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<td><code>Graph.subgraph(nbunch)</code></td>
<td>Return the subgraph induced on nodes in <code>nbunch</code>.</td>
</tr>
</tbody>
</table>

**copy**

`Graph.copy()`

Return a copy of the graph.

**Returns**

- `G : Graph`
  
  A copy of the graph.

**See also:**

`to_directed` return a directed copy of the graph.

**Notes**

This makes a complete copy of the graph including all of the node or edge attributes.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> H = G.copy()
```

**to_undirected**

`Graph.to_undirected()`

Return an undirected copy of the graph.

**Returns**

- `G : Graph/MultiGraph`
  
  A deepcopy of the graph.
See also:

`copy`, `add_edge`, `add_edges_from`

Notes

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar `G=DiGraph(D)` which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Examples

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1), (1, 0)]
>>> G2 = H.to_undirected()
>>> G2.edges()
[(0, 1)]
```

```python
to_directed()
Graph.to_directed()
Return a directed representation of the graph.

Returns

G : DiGraph
A directed graph with the same name, same nodes, and with each edge `(u,v,data)` replaced by two directed edges `(u,v,data)` and `(v,u,data)`.

Notes

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar `D=DiGraph(G)` which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Examples

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1), (1, 0)]
```
If already directed, return a (deep) copy

```python
>>> G = nx.DiGraph()     # or MultiDiGraph, etc
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1)]
```

**subgraph**

`Graph.subgraph(nbunch)`

Return the subgraph induced on nodes in `nbunch`.

The induced subgraph of the graph contains the nodes in `nbunch` and the edges between those nodes.

**Parameters**

- `nbunch` : list, iterable
  - A container of nodes which will be iterated through once.

**Returns**

- `G` : Graph
  - A subgraph of the graph with the same edge attributes.

**Notes**

The graph, edge or node attributes just point to the original graph. So changes to the node or edge structure will not be reflected in the original graph while changes to the attributes will.

To create a subgraph with its own copy of the edge/node attributes use: `nx.Graph(G.subgraph(nbunch))`

If edge attributes are containers, a deep copy can be obtained using: `G.subgraph(nbunch).copy()`

For an inplace reduction of a graph to a subgraph you can remove nodes: `G.remove_nodes_from([ n in G if n not in set(nbunch)])`

**Examples**

```python
>>> G = nx.Graph()    # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> H = G.subgraph([0,1,2])
>>> H.edges()
[(0, 1), (1, 2)]
```

### 3.2.2 DiGraph - Directed graphs with self loops

**Overview**

**DiGraph**

- `data=None, **attr`
  - Base class for directed graphs.

  A DiGraph stores nodes and edges with optional data, or attributes.

  DiGraphs hold directed edges. Self loops are allowed but multiple (parallel) edges are not.

  Nodes can be arbitrary (hashable) Python objects with optional key/value attributes.

  Edges are represented as links between nodes with optional key/value attributes.
Parameters  

**data** : input graph

Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.

**attr** : keyword arguments, optional (default= no attributes)

Attributes to add to graph as key=value pairs.

See also:

*Graph, MultiGraph, MultiDiGraph*

Examples

Create an empty graph structure (a “null graph”) with no nodes and no edges.

```python
>>> G = nx.DiGraph()
```

G can be grown in several ways.

**Nodes:**

Add one node at a time:

```python
>>> G.add_node(1)
```

Add the nodes from any container (a list, dict, set or even the lines from a file or the nodes from another graph).

```python
>>> G.add_nodes_from([2, 3])
>>> G.add_nodes_from(range(100, 110))
>>> H = nx.Graph()
>>> H.add_path([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> G.add_nodes_from(H)
```

In addition to strings and integers any hashable Python object (except None) can represent a node, e.g. a customized node object, or even another Graph.

```python
>>> G.add_node(H)
```

**Edges:**

G can also be grown by adding edges.

Add one edge,

```python
>>> G.add_edge(1, 2)
```

a list of edges,

```python
>>> G.add_edges_from([(1, 2), (1, 3)])
```

or a collection of edges,

```python
>>> G.add_edges_from(H.edges())
```

If some edges connect nodes not yet in the graph, the nodes are added automatically. There are no errors when adding nodes or edges that already exist.

**Attributes:**
Each graph, node, and edge can hold key/value attribute pairs in an associated attribute dictionary (the keys must be hashable). By default these are empty, but can be added or changed using add_edge, add_node or direct manipulation of the attribute dictionaries named graph, node and edge respectively.

```python
>>> G = nx.DiGraph(day="Friday")
>>> G.graph
{'day': 'Friday'}
```

Add node attributes using add_node(), add_nodes_from() or G.node

```python
>>> G.add_node(1, time='5pm')
>>> G.add_nodes_from([3], time='2pm')
>>> G.node[1]
{'time': '5pm'}
>>> G.node[1]['room'] = 714
>>> del G.node[1]['room']  # remove attribute
>>> G.nodes(data=True)
[(1, {'time': '5pm'}), (3, {'time': '2pm'})]
```

Warning: adding a node to G.node does not add it to the graph.

Add edge attributes using add_edge(), add_edges_from(), subscript notation, or G.edge.

```python
>>> G.add_edge(1, 2, weight=4.7)
>>> G.add_edges_from([(3,4),(4,5)], color='red')
>>> G.add_edges_from([(1,2,{'color':'blue'}), (2,3,{'weight':8})])
>>> G[1][2]['weight'] = 4.7
>>> G.edge[1][2]['weight'] = 4
```

Shortcuts:

Many common graph features allow python syntax to speed reporting.

```python
>>> 1 in G  # check if node in graph
True
>>> [n for n in G if n<3]  # iterate through nodes
[1, 2]
>>> len(G)  # number of nodes in graph
5
```

The fastest way to traverse all edges of a graph is via adjacency_iter(), but the edges() method is often more convenient.

```python
>>> for n,nbrsdct in G.adjacency_iter():
...     for nbr,eattr in nbrsdct.items():
...         if 'weight' in eattr:
...             (n,nbr,eattr['weight'])
(1, 2, 4)
(2, 3, 8)
```

```python
>>> [ (u,v,edata['weight']) for u,v,edata in G.edges(data=True) if 'weight' in edata ]
[(1, 2, 4), (2, 3, 8)]
```

Reporting:

Simple graph information is obtained using methods. Iterator versions of many reporting methods exist for efficiency. Methods exist for reporting nodes(), edges(), neighbors() and degree() as well as the number of nodes and edges.

For details on these and other miscellaneous methods, see below.
Adding and removing nodes and edges

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
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<td>DiGraph.<strong>init</strong>((data)]</td>
<td>Initialize a graph with edges, name, graph attributes.</td>
</tr>
<tr>
<td>DiGraph.add_node[n[, attr_dict]]</td>
<td>Add a single node n and update node attributes.</td>
</tr>
<tr>
<td>DiGraph.add_nodes_from(nodes, **attr)</td>
<td>Add multiple nodes.</td>
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<td>DiGraph.remove_node(n)</td>
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<td>DiGraph.remove_nodes_from(nbunch)</td>
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<tr>
<td>DiGraph.add_edge(u, v[, attr_dict])</td>
<td>Add an edge between u and v.</td>
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<td>Add all the edges in ebunch.</td>
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<td>DiGraph.add_weighted_edges_from(ebunch[, weight])</td>
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<td>DiGraph.remove_edges_from(ebunch)</td>
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</tr>
<tr>
<td>DiGraph.add_star(nodes, **attr)</td>
<td>Add a star.</td>
</tr>
<tr>
<td>DiGraph.add_path(nodes, **attr)</td>
<td>Add a path.</td>
</tr>
<tr>
<td>DiGraph.add_cycle(nodes, **attr)</td>
<td>Add a cycle.</td>
</tr>
<tr>
<td>DiGraph.clear()</td>
<td>Remove all nodes and edges from the graph.</td>
</tr>
</tbody>
</table>

__init__

DiGraph.__init__(data=None, **attr)
Initialize a graph with edges, name, graph attributes.

Parameters

data : input graph
Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.

name : string, optional (default='')
An optional name for the graph.

attr : keyword arguments, optional (default= no attributes)
Attributes to add to graph as key=value pairs.

See also:

convert

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G = nx.Graph(name='my graph')
>>> e = [(1,2), (2,3), (3,4)] # list of edges
>>> G = nx.Graph(e)

Arbitrary graph attribute pairs (key=value) may be assigned

>>> G=nx.Graph(e, day="Friday")
>>> G.graph
{'day': 'Friday'}
**add_node**

```
DiGraph.add_node(n, attr_dict=None, **attr)
```

Add a single node n and update node attributes.

**Parameters**

- `n`: node
  
  A node can be any hashable Python object except None.

- `attr_dict`: dictionary, optional (default= no attributes)
  
  Dictionary of node attributes. Key/value pairs will update existing data associated with the node.

- `attr`: keyword arguments, optional
  
  Set or change attributes using key=value.

**See also:**

`add_nodes_from`

**Notes**

A hashable object is one that can be used as a key in a Python dictionary. This includes strings, numbers, tuples of strings and numbers, etc.

On many platforms hashable items also include mutables such as NetworkX Graphs, though one should be careful that the hash doesn’t change on mutables.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_node(1)
>>> G.add_node('Hello')
>>> K3 = nx.Graph([(0,1),(1,2),(2,0)])
>>> G.add_node(K3)
>>> G.number_of_nodes()
3
```

Use keywords set/change node attributes:

```python
>>> G.add_node(1, size=10)
>>> G.add_node(3, weight=0.4, UTM=('13S', 382871, 3972649))
```

**add_nodes_from**

```
DiGraph.add_nodes_from(nodes, **attr)
```

Add multiple nodes.

**Parameters**

- `nodes`: iterable container
  
  A container of nodes (list, dict, set, etc.). OR A container of (node, attribute dict) tuples.

- `attr`: keyword arguments, optional (default= no attributes)
Update attributes for all nodes in nodes. Node attributes specified in nodes as a tuple take precedence over attributes specified generally.

See also:
add_node

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_nodes_from('Hello')
>>> K3 = nx.Graph(((0,1),(1,2),(2,0))
>>> G.add_nodes_from(K3)
>>> sorted(G.nodes(),key=str)
[0, 1, 2, 'H', 'e', 'l', 'o']
Use keywords to update specific node attributes for every node.
>>> G.add_nodes_from([1,2], size=10)
>>> G.add_nodes_from([3,4], weight=0.4)
Use (node, attrdict) tuples to update attributes for specific nodes.
>>> G.add_nodes_from([(1,dict(size=11)), (2,{'color':'blue'})])
>>> G.node[1]['size']
11
>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))
>>> H.node[1]['size']
11
```

remove_node

DiGraph.remove_node(n)
Remove node n.

Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.

Parameters n : node
A node in the graph

Raises NetworkXError :
If n is not in the graph.

See also:
remove_nodes_from

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.edges()
[(0, 1), (1, 2)]
>>> G.remove_node(1)
```
>>> G.edges()
[]

remove_nodes_from

DiGraph.remove_nodes_from(nbunch)
Remove multiple nodes.

Parameters

nodes : iterable container
A container of nodes (list, dict, set, etc.). If a node in the container is not in the graph it is silently ignored.

See also:
remove_node

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> e = G.nodes()
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> G.nodes()
[]

add_edge

DiGraph.add_edge(u, v, attr_dict=None, **attr)
Add an edge between u and v.

The nodes u and v will be automatically added if they are not already in the graph.

Edge attributes can be specified with keywords or by providing a dictionary with key/value pairs. See examples below.

Parameters

u,v : nodes
Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.

attr_dict : dictionary, optional (default= no attributes)
Dictionary of edge attributes. Key/value pairs will update existing data associated with the edge.

attr : keyword arguments, optional
Edge data (or labels or objects) can be assigned using keyword arguments.

See also:

add_edges_from add a collection of edges

3.2. Basic graph types
Notes

Adding an edge that already exists updates the edge data.

Many NetworkX algorithms designed for weighted graphs use as the edge weight a numerical value assigned to
a keyword which by default is ‘weight’.

Examples

The following all add the edge e=(1,2) to graph G:

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = (1,2)
>>> G.add_edge(1, 2)  # explicit two-node form
>>> G.add_edge(*e)   # single edge as tuple of two nodes
>>> G.add_edges_from( [(1,2)] )  # add edges from iterable container
```

Associate data to edges using keywords:

```python
>>> G.add_edge(1, 2, weight=3)
>>> G.add_edge(1, 3, weight=7, capacity=15, length=342.7)
```

add_edges_from

DiGraph.add_edges_from(ebunch, attr_dict=None, **attr)
Add all the edges in ebunch.

Parameters
ebunch : container of edges
    Each edge given in the container will be added to the graph. The edges must be given
    as as 2-tuples (u,v) or 3-tuples (u,v,d) where d is a dictionary containing edge data.

attr_dict : dictionary, optional (default= no attributes)
    Dictionary of edge attributes. Key/value pairs will update existing data associated with
    each edge.

attr : keyword arguments, optional
    Edge data (or labels or objects) can be assigned using keyword arguments.

See also:

add_edge  add a single edge
add_weighted_edges_from  convenient way to add weighted edges

Notes

Adding the same edge twice has no effect but any edge data will be updated when each duplicate edge is added.

Examples
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edges_from([(0,1),(1,2)]) # using a list of edge tuples
>>> e = zip(range(0,3),range(1,4))
>>> G.add_edges_from(e) # Add the path graph 0-1-2-3

Associate data to edges
>>> G.add_edges_from([(1,2),(2,3)], weight=3)
>>> G.add_edges_from([(3,4),(1,4)], label='WN2898')

add_weighted_edges_from

DiGraph.add_weighted_edges_from(ebunch, weight='weight', **attr)
Add all the edges in ebunch as weighted edges with specified weights.

Parameters  
ebunch : container of edges
Each edge given in the list or container will be added to the graph. The edges must be
given as 3-tuples (u,v,w) where w is a number.
weight : string, optional (default= 'weight')
The attribute name for the edge weights to be added.
attr : keyword arguments, optional (default= no attributes)
Edge attributes to add/update for all edges.

See also:
add_edge add a single edge
add_edges_from add multiple edges

Notes
Adding the same edge twice for Graph/DiGraph simply updates the edge data. For MultiGraph/MultiDiGraph,
duplicate edges are stored.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0,1,3.0),(1,2,7.5)])

remove_edge

DiGraph.remove_edge(u, v)
Remove the edge between u and v.

Parameters  
u,v: nodes :
Remove the edge between nodes u and v.

Raises  
NetworkXError :
If there is not an edge between u and v.

3.2. Basic graph types
See also:

remove_edges_from  remove a collection of edges

Examples

>>> G = nx.Graph()  # or DiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.remove_edge(0,1)
>>> e = (1,2)
>>> G.remove_edge(*e)  # unpacks e from an edge tuple
>>> e = (2,3,{'weight':7})  # an edge with attribute data
>>> G.remove_edge(*e[:2])  # select first part of edge tuple

remove_edges_from

DiGraph.remove_edges_from(ebunch)
Remove all edges specified in ebunch.

Parameters   ebunch: list or container of edge tuples :

   Each edge given in the list or container will be removed from the graph. The edges can be:
   • 2-tuples (u,v) edge between u and v.
   • 3-tuples (u,v,k) where k is ignored.

See also:

remove_edge  remove a single edge

Notes

Will fail silently if an edge in ebunch is not in the graph.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> ebunch=[(1,2),(2,3)]
>>> G.remove_edges_from(ebunch)

add_star

DiGraph.add_star(nodes, **attr)
Add a star.

The first node in nodes is the middle of the star. It is connected to all other nodes.

Parameters   nodes : iterable container

   A container of nodes.
**add_star**

Add a star.

**Parameters**

- attr : keyword arguments, optional (default= no attributes)
  Attributes to add to every edge in star.

**See also:**

add_path, add_cycle

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_star([0,1,2,3])
>>> G.add_star([10,11,12], weight=2)
```

**add_path**

DiGraph.add_path(nodes, **attr)

Add a path.

**Parameters**

- nodes : iterable container
  A container of nodes. A path will be constructed from the nodes (in order) and added to the graph.

- attr : keyword arguments, optional (default= no attributes)
  Attributes to add to every edge in path.

**See also:**

add_star, add_cycle

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.add_path([10,11,12], weight=7)
```

**add_cycle**

DiGraph.add_cycle(nodes, **attr)

Add a cycle.

**Parameters**

- nodes : iterable container
  A container of nodes. A cycle will be constructed from the nodes (in order) and added to the graph.

- attr : keyword arguments, optional (default= no attributes)
  Attributes to add to every edge in cycle.

**See also:**

add_path, add_star
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_cycle([0, 1, 2, 3])
>>> G.add_cycle([10, 11, 12], weight=7)
```

clear

```
DiGraph.clear()
```

Remove all nodes and edges from the graph.

This also removes the name, and all graph, node, and edge attributes.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> G.clear()
>>> G.nodes()
[]
>>> G.edges()
[]
```

Iterating over nodes and edges

```
DiGraph.nodes([data]) Return a list of the nodes in the graph.
DiGraph.nodes_iter([data]) Return an iterator over the nodes.
DiGraph.__iter__() Iterate over the nodes.
DiGraph.edges((nbunch, data)) Return a list of edges.
DiGraph.edges_iter((nbunch, data)) Return an iterator over the edges.
DiGraph.out_edges((nbunch, data)) Return a list of edges.
DiGraph.out_edges_iter((nbunch, data)) Return an iterator over the edges.
DiGraph.in_edges((nbunch, data)) Return a list of edges.
DiGraph.in_edges_iter((nbunch, data)) Return an iterator over the incoming edges.
DiGraph.get_edge_data(u, v[, default]) Return the attribute dictionary associated with edge (u,v).
DiGraph.neighbors(n) Return a list of successor nodes of n.
DiGraph.neighbors_iter(n) Return an iterator over successor nodes of n.
DiGraph.__getitem__(n) Return a dict of neighbors of node n.
DiGraph.successors(n) Return a list of successor nodes of n.
DiGraph.successors_iter(n) Return an iterator over successor nodes of n.
DiGraph.predecessors(n) Return a list of predecessor nodes of n.
DiGraph.predecessors_iter(n) Return an iterator over predecessor nodes of n.
DiGraph.adjacency_list() Return an adjacency list representation of the graph.
DiGraph.adjacency_iter() Return an iterator of (node, adjacency dict) tuples for all nodes.
DiGraph.nbunch_iter((nbunch)) Return an iterator of nodes contained in nbunch that are also in the graph.
```
nodes

DiGraph.nodes(data=False)

Return a list of the nodes in the graph.

Parameters data : boolean, optional (default=False)

If False return a list of nodes. If True return a two-tuple of node and node data dictionary

Returns nlist : list

A list of nodes. If data=True a list of two-tuples containing (node, node data dictionary).

Examples

>>> G = nx.Graph()    # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.nodes()
[0, 1, 2]
>>> G.add_node(1, time='5pm')
>>> G.nodes(data=True)
[(0, {}), (1, {'time': '5pm'}), (2, {})]

nodes_iter

DiGraph.nodes_iter(data=False)

Return an iterator over the nodes.

Parameters data : boolean, optional (default=False)

If False the iterator returns nodes. If True return a two-tuple of node and node data dictionary

Returns niter : iterator

An iterator over nodes. If data=True the iterator gives two-tuples containing (node, node data, dictionary)

Notes

If the node data is not required it is simpler and equivalent to use the expression ‘for n in G’.

Examples

>>> G = nx.Graph()    # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])

>>> [d for n,d in G.nodes_iter(data=True)]
[{}, {}, {}]
__iter__

DiGraph.__iter__()  
Iterate over the nodes. Use the expression ‘for n in G’.

Returns niter: iterator  
An iterator over all nodes in the graph.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
```

edges

DiGraph.edges(nbunch=None, data=False)  
Return a list of edges.

Edges are returned as tuples with optional data in the order (node, neighbor, data).

Parameters nbunch: iterable container, optional (default=all nodes)  
A container of nodes. The container will be iterated through once.

data: bool, optional (default=False)  
Return two tuples (u,v) (False) or three-tuples (u,v,data) (True).

Returns edge_list: list of edge tuples:  
Edges that are adjacent to any node in nbunch, or a list of all edges if nbunch is not specified.

See also:
edges_iter  return an iterator over the edges

Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.edges()
[(0, 1), (1, 2), (2, 3)]
>>> G.edges(data=True)  # default edge data is {} (empty dictionary)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> G.edges([0,3])
[(0, 1), (3, 2)]
>>> G.edges(0)
[(0, 1)]
```
**edges_iter**

DiGraph.edges_iter(nbunch=None, data=False)

Return an iterator over the edges.

Edges are returned as tuples with optional data in the order (node, neighbor, data).

**Parameters**

- **nbunch**: iterable container, optional (default= all nodes)
  
  A container of nodes. The container will be iterated through once.

- **data**: bool, optional (default=False)
  
  If True, return edge attribute dict in 3-tuple (u,v,data).

**Returns**

- **edge_iter**: iterator
  
  An iterator of (u,v) or (u,v,d) tuples of edges.

**See also:**

- edges return a list of edges

**Notes**

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

**Examples**

```python
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [e for e in G.edges_iter()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges_iter(data=True))  # default data is {} (empty dict)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> list(G.edges_iter([0,2]))
[(0, 1), (2, 3)]
>>> list(G.edges_iter(0))
[(0, 1)]
```

**out_edges**

DiGraph.out_edges(nbunch=None, data=False)

Return a list of edges.

Edges are returned as tuples with optional data in the order (node, neighbor, data).

**Parameters**

- **nbunch**: iterable container, optional (default= all nodes)
  
  A container of nodes. The container will be iterated through once.

- **data**: bool, optional (default=False)
  
  Return two tuples (u,v) (False) or three-tuples (u,v,data) (True).

**Returns**

- **edge_list**: list of edge tuples
  
  Edges that are adjacent to any node in nbunch, or a list of all edges if nbunch is not specified.

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See also:

`edges_iter` return an iterator over the edges

Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.edges()
[(0, 1), (1, 2), (2, 3)]
>>> G.edges(data=True)  # default edge data is {} (empty dictionary)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> G.edges([0,3])
[(0, 1), (3, 2)]
>>> G.edges(0)
[(0, 1)]
```

`out_edges_iter`

DiGraph.out_edges_iter (nbunch=None, data=False)

Return an iterator over the edges.

Edges are returned as tuples with optional data in the order (node, neighbor, data).

Parameters

`nbunch` : iterable container, optional (default= all nodes)

A container of nodes. The container will be iterated through once.

`data` : bool, optional (default=False)

If True, return edge attribute dict in 3-tuple (u,v,data).

Returns

`edge_iter` : iterator

An iterator of (u,v) or (u,v,d) tuples of edges.

See also:

`edges` return a list of edges

Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [e for e in G.edges_iter()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges_iter(data=True))  # default data is {} (empty dict)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> list(G.edges_iter([0,2]))
[(0, 1), (2, 3)]
>>> list(G.edges_iter(0))
[(0, 1)]

in_edges

DiGraph.in_edges(nbunch=None, data=False)
Return a list of the incoming edges.

See also:

edges return a list of edges

in_edges_iter

DiGraph.in_edges_iter(nbunch=None, data=False)
Return an iterator over the incoming edges.

Parameters

nbunch : iterable container, optional (default= all nodes)
A container of nodes. The container will be iterated through once.

data : bool, optional (default=False)
If True, return edge attribute dict in 3-tuple (u,v,data).

Returns

in_edge_iter : iterator
An iterator of (u,v) or (u,v,d) tuples of incoming edges.

See also:

edges_iter return an iterator of edges

get_edge_data

DiGraph.get_edge_data(u, v, default=None)
Return the attribute dictionary associated with edge (u,v).

Parameters

u,v : nodes

default: any Python object (default=None) :
Value to return if the edge (u,v) is not found.

Returns

edge_dict : dictionary
The edge attribute dictionary.
Notes

It is faster to use G[u][v].

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G[0][1]
{}

Warning: Assigning G[u][v] corrupts the graph data structure. But it is safe to assign attributes to that dictionary,

>>> G[0][1][‘weight’] = 7
>>> G[0][1][‘weight’]
7
>>> G[1][0][‘weight’]
7

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.get_edge_data(0,1)  # default edge data is {}
{}
>>> e = (0,1)
>>> G.get_edge_data(*e)  # tuple form
{}
>>> G.get_edge_data(‘a’,’b’,default=0) # edge not in graph, return 0
0

neighbors

DiGraph.neighbors(n)

Return a list of successor nodes of n.

neighbors() and successors() are the same function.

neighbors_iter

DiGraph.neighbors_iter(n)

Return an iterator over successor nodes of n.

neighbors_iter() and successors_iter() are the same.

__getitem__

DiGraph.__getitem__(n)

Return a dict of neighbors of node n. Use the expression ‘G[n]’.

Parameters n : node

A node in the graph.

Returns adj_dict : dictionary

The adjacency dictionary for nodes connected to n.
Notes

G[n] is similar to G.neighbors(n) but the internal data dictionary is returned instead of a list. Assigning G[n] will corrupt the internal graph data structure. Use G[n] for reading data only.

Examples

```python
>>> G = nx.Graph()   # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G[0]
{1: {}}
```

successors

DiGraph.successors(n)
Return a list of successor nodes of n.
neighbors() and successors() are the same function.

successors_iter

DiGraph.successors_iter(n)
Return an iterator over successor nodes of n.
neighbors_iter() and successors_iter() are the same.

predecessors

DiGraph.predecessors(n)
Return a list of predecessor nodes of n.

predecessors_iter

DiGraph.predecessors_iter(n)
Return an iterator over predecessor nodes of n.

adjacency_list

DiGraph.adjacency_list()
Return an adjacency list representation of the graph.
The output adjacency list is in the order of G.nodes(). For directed graphs, only outgoing adjacencies are included.

Returns adj_list : lists of lists
The adjacency structure of the graph as a list of lists.

See also:
adjacency_iter
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.adjacency_list()  # in order given by G.nodes()
[[1], [0, 2], [1, 3], [2]]
```

**adjacency_iter**

DiGraph.adjacency_iter()

Return an iterator of (node, adjacency dict) tuples for all nodes.

This is the fastest way to look at every edge. For directed graphs, only outgoing adjacencies are included.

Returns  
adj_iter : iterator

An iterator of (node, adjacency dictionary) for all nodes in the graph.

See also:

adjacency_list

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [(n,nbrdict) for n,nbrdict in G.adjacency_iter()]
[(0, {1: {}}), (1, {0: {}, 2: {}}), (2, {1: {}, 3: {}}), (3, {2: {}})]
```

**nbunch_iter**

DiGraph.nbunch_iter(nbunch=None)

Return an iterator of nodes contained in nbunch that are also in the graph.

The nodes in nbunch are checked for membership in the graph and if not are silently ignored.

Parameters  
nbunch : iterable container, optional (default=all nodes)

A container of nodes. The container will be iterated through once.

Returns  
niter : iterator

An iterator over nodes in nbunch that are also in the graph. If nbunch is None, iterate over all nodes in the graph.

Raises  
NetworkXError :

If nbunch is not a node or or sequence of nodes. If a node in nbunch is not hashable.

See also:

Graph.__iter__
Notes

When nbunch is an iterator, the returned iterator yields values directly from nbunch, becoming exhausted when nbunch is exhausted.

To test whether nbunch is a single node, one can use “if nbunch in self;”, even after processing with this routine.

If nbunch is not a node or a (possibly empty) sequence/iterator or None, a NetworkXError is raised. Also, if any object in nbunch is not hashable, a NetworkXError is raised.

Information about graph structure

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has_node

DiGraph.has_node(n)

Return True if the graph contains the node n.

Parameters n : node

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.has_node(0)
True

It is more readable and simpler to use

>>> 0 in G
True
__contains__

DiGraph.__contains__(n)

Return True if n is a node, False otherwise. Use the expression ‘n in G’.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> 1 in G
True

has_edge

DiGraph.has_edge(u, v)

Return True if the edge (u,v) is in the graph.

Parameters  u, v : nodes

Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None)
Python objects.

Returns  edge_ind : bool

True if edge is in the graph, False otherwise.

Examples

Can be called either using two nodes u,v or edge tuple (u,v)

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.has_edge(0,1)  # using two nodes
True
>>> e = (0,1)
>>> G.has_edge(*e)  # e is a 2-tuple (u,v)
True
>>> e = (0,1,{'weight':7})
>>> G.has_edge(*e[:2])  # e is a 3-tuple (u,v,data_dictionary)
True

The following syntax are all equivalent:

>>> G.has_edge(0,1)
True
>>> 1 in G[0]  # though this gives KeyError if 0 not in G
True

order

DiGraph.order()

Return the number of nodes in the graph.

Returns  nnodes : int
The number of nodes in the graph.

See also:

number_of_nodes, __len__

number_of_nodes

DiGraph.number_of_nodes()

Return the number of nodes in the graph.

Returns nnodes : int

The number of nodes in the graph.

See also:

order, __len__

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> len(G)
3
```

__len__

DiGraph.__len__()

Return the number of nodes. Use the expression ‘len(G)’.

Returns nnodes : int

The number of nodes in the graph.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> len(G)
4
```

degree

diGraph.degree (nbunch=None, weight=None)

Return the degree of a node or nodes.

The node degree is the number of edges adjacent to that node.

Parameters nbunch : iterable container, optional (default=all nodes)

A container of nodes. The container will be iterated through once.

weight : string or None, optional (default=None)
The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns nd : dictionary, or number

A dictionary with nodes as keys and degree as values or a number if a single node is specified.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.degree(0)
1
>>> G.degree([0,1])
{0: 1, 1: 2}
>>> list(G.degree([0,1]).values())
[1, 2]
```

degree_iter

DiGraph.degrees_iter (nbunch=None, weight=None)

Return an iterator for (node, degree).

The node degree is the number of edges adjacent to the node.

Parameters nbunch : iterable container, optional (default=all nodes)

A container of nodes. The container will be iterated through once.

weight : string or None, optional (default=None)

The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns nd_iter : an iterator

The iterator returns two-tuples of (node, degree).

See also:

degree, in_degree, out_degree, in_degree_iter, out_degree_iter

Examples

```python
>>> G = nx.DiGraph()  # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> list(G.degree_iter(0))  # node 0 with degree 1
[(0, 1)]
>>> list(G.degree_iter([0,1]))
[(0, 1), (1, 2)]
```

in_degree

DiGraph.in_degree (nbunch=None, weight=None)

Return the in-degree of a node or nodes.
The node in-degree is the number of edges pointing in to the node.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)
  
  A container of nodes. The container will be iterated through once.

- **weight**: string or None, optional (default=None)
  
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**Returns**

- **nd**: dictionary, or number
  
  A dictionary with nodes as keys and in-degree as values or a number if a single node is specified.

**See also:**

degree, out_degree, in_degree_iter

**Examples**

```python
>>> G = nx.DiGraph()  # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> G.in_degree(0)
0
>>> G.in_degree([0,1])
{0: 0, 1: 1}
>>> list(G.in_degree([0,1]).values())
[0, 1]
```

**in_degree_iter**

DiGraph.in_degree_iter(nbunch=None, weight=None)

Return an iterator for (node, in-degree).

The node in-degree is the number of edges pointing in to the node.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)
  
  A container of nodes. The container will be iterated through once.

- **weight**: string or None, optional (default=None)
  
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**Returns**

- **nd_iter**: an iterator
  
  The iterator returns two-tuples of (node, in-degree).

**See also:**

degree, in_degree, out_degree, out_degree_iter

**Examples**
```python
>>> G = nx.DiGraph()
>>> G.add_path([0,1,2,3])
>>> list(G.in_degree_iter(0))  # node 0 with degree 0
[(0, 0)]
>>> list(G.in_degree_iter([0,1]))
[(0, 0), (1, 1)]
```

### out_degree

**DiGraph.out_degree**(nbunch=None, weight=None)

Return the out-degree of a node or nodes.

The node out-degree is the number of edges pointing out of the node.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)
  - A container of nodes. The container will be iterated through once.

- **weight**: string or None, optional (default=None)
  - The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**Returns**

- **nd**: dictionary, or number
  - A dictionary with nodes as keys and out-degree as values or a number if a single node is specified.

**Examples**

```python
>>> G = nx.DiGraph()  # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> G.out_degree(0)
1
>>> G.out_degree([0,1])
{0: 1, 1: 1}
>>> list(G.out_degree([0,1]).values())
[1, 1]
```

### out_degree_iter

**DiGraph.out_degree_iter**(nbunch=None, weight=None)

Return an iterator for (node, out-degree).

The node out-degree is the number of edges pointing out of the node.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)
  - A container of nodes. The container will be iterated through once.

- **weight**: string or None, optional (default=None)
  - The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**Returns**

- **nd_iter**: an iterator
  - The iterator returns two-tuples of (node, out-degree).
See also:

degree, in_degree, out_degree, in_degree_iter

Examples

```python
g = nx.DiGraph()
g.add_path([0,1,2,3])
list(g.out_degree_iter(0))  # node 0 with degree 1
[(0, 1)]
list(g.out_degree_iter([0,1]))
[(0, 1), (1, 1)]
```

di_graph.size(weight=None)

Return the number of edges.

**Parameters**

- **weight** : string or None, optional (default=None)
  
The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**

- **nedges** : int
  
The number of edges of sum of edge weights in the graph.

See also:

count_of_edges

Examples

```python
g = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
g.add_path([0,1,2,3])
g.size()
3

g = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
g.add_edge('a','b',weight=2)
g.add_edge('b','c',weight=4)
g.size()
2
```

count_of_edges

di_graph.count_of_edges(u=None, v=None)

Return the number of edges between two nodes.

**Parameters**

- **u**, **v** : nodes, optional (default=all edges)
  
  If u and v are specified, return the number of edges between u and v. Otherwise return the total number of all edges.
Returns nedges : int

The number of edges in the graph. If nodes u and v are specified return the number of
edges between those nodes.

See also:
size

Examples

>>> G = nx.Graph()    # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.number_of_edges()
3
>>> G.number_of_edges(0,1)
1
>>> e = (0,1)
>>> G.number_of_edges(*e)
1

nodes_with_selfloops

DiGraph.nodes_with_selfloops()
Return a list of nodes with self loops.

A node with a self loop has an edge with both ends adjacent to that node.

Returns nodelist : list
A list of nodes with self loops.

See also:
selfloop_edges,number_of_selfloops

Examples

>>> G = nx.Graph()    # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.nodes_with_selfloops()
[1]

selfloop_edges

DiGraph.selfloop_edges(data=False)
Return a list of selfloop edges.

A selfloop edge has the same node at both ends.

Parameters data : bool, optional (default=False)

Return selfloop edges as two tuples (u,v) (data=False) or three-tuples (u,v,data)
(data=True)

Returns edgelist : list of edge tuples
A list of all selfloop edges.

See also:

nodes_with_selfloops, number_of_selfloops

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.selfloop_edges()
[(1, 1)]
>>> G.selfloop_edges(data=True)
[(1, 1, {})]
```

number_of_selfloops

DiGraph.number_of_selfloops()
Return the number of selfloop edges.
A selfloop edge has the same node at both ends.

Returns nloops : int
The number of selfloops.

See also:

nodes_with_selfloops, selfloop_edges

Examples

```python
>>> G=nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.number_of_selfloops()
1
```

Making copies and subgraphs

<table>
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<th>Description</th>
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<td>DiGraph.copy()</td>
<td>Return a copy of the graph.</td>
</tr>
<tr>
<td>DiGraph.to_undirected()</td>
<td>Return an undirected representation of the digraph.</td>
</tr>
<tr>
<td>DiGraph.to_directed()</td>
<td>Return a directed copy of the graph.</td>
</tr>
<tr>
<td>DiGraph.subgraph(nbunch)</td>
<td>Return the subgraph induced on nodes in nbunch.</td>
</tr>
<tr>
<td>DiGraph.reverse([copy])</td>
<td>Return the reverse of the graph.</td>
</tr>
</tbody>
</table>

copy

DiGraph.copy()
Return a copy of the graph.

Returns G : Graph
A copy of the graph.

See also:

to_directed  return a directed copy of the graph.

Notes

This makes a complete copy of the graph including all of the node or edge attributes.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> H = G.copy()

to_undirected

DiGraph.to_undirected(reciprocal=False)

Return an undirected representation of the digraph.

Parameters reciprocal : bool (optional)

If True only keep edges that appear in both directions in the original digraph.

Returns G : Graph

An undirected graph with the same name and nodes and with edge (u,v,data) if either
(u,v,data) or (v,u,data) is in the digraph. If both edges exist in digraph and their edge
data is different, only one edge is created with an arbitrary choice of which edge data to
use. You must check and correct for this manually if desired.

Notes

If edges in both directions (u,v) and (v,u) exist in the graph, attributes for the new undirected edge will be a
combination of the attributes of the directed edges. The edge data is updated in the (arbitrary) order that the
edges are encountered. For more customized control of the edge attributes use add_edge().

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the
data and references.

This is in contrast to the similar G=DiGraph(D) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies,

to_directed

DiGraph.to_directed()

Return a directed copy of the graph.

Returns G : DiGraph

A deepcopy of the graph.
Notes

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar D=DiGraph(G) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Examples

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1), (1, 0)]
```

If already directed, return a (deep) copy

```python
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1)]
```

subgraph

DiGraph.subgraph(nbunch)

Return the subgraph induced on nodes in nbunch.

The induced subgraph of the graph contains the nodes in nbunch and the edges between those nodes.

Parameters nbunch : list, iterable

A container of nodes which will be iterated through once.

Returns G : Graph

A subgraph of the graph with the same edge attributes.

Notes

The graph, edge or node attributes just point to the original graph. So changes to the node or edge structure will not be reflected in the original graph while changes to the attributes will.

To create a subgraph with its own copy of the edge/node attributes use: nx.Graph(G.subgraph(nbunch))

If edge attributes are containers, a deep copy can be obtained using: G.subgraph(nbunch).copy()

For an inplace reduction of a graph to a subgraph you can remove nodes: G.remove_nodes_from([ n in G if n not in set(nbunch)])
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> H = G.subgraph([0, 1, 2])
>>> H.edges()
[(0, 1), (1, 2)]
```

reverse

DiGraph.reverse(copy=True)

Return the reverse of the graph.

The reverse is a graph with the same nodes and edges but with the directions of the edges reversed.

Parameters

- `copy`: bool, optional (default=True)
  If True, return a new DiGraph holding the reversed edges. If False, reverse the reverse graph is created using the original graph (this changes the original graph).

3.2.3 MultiGraph - Undirected graphs with self loops and parallel edges

Overview

MultiGraph(data=None, **attr)

An undirected graph class that can store multiedges.

Multiedges are multiple edges between two nodes. Each edge can hold optional data or attributes.

A MultiGraph holds undirected edges. Self loops are allowed.

Nodes can be arbitrary (hashable) Python objects with optional key/value attributes.

Edges are represented as links between nodes with optional key/value attributes.

Parameters

- `data`: input graph
  Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.

- `attr`: keyword arguments, optional (default= no attributes)
  Attributes to add to graph as key=value pairs.

See also:

Graph, DiGraph, MultiDiGraph

Examples

Create an empty graph structure (a “null graph”) with no nodes and no edges.

```python
>>> G = nx.MultiGraph()
```
G can be grown in several ways.

**Nodes:**
Add one node at a time:
```python
>>> G.add_node(1)
```
Add the nodes from any container (a list, dict, set or even the lines from a file or the nodes from another graph).
```python
>>> G.add_nodes_from([2, 3])
>>> G.add_nodes_from(range(100, 110))
>>> H = nx.Graph()
>>> H.add_path([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> G.add_nodes_from(H)
```
In addition to strings and integers any hashable Python object (except None) can represent a node, e.g. a customized node object, or even another Graph.
```python
>>> G.add_node(H)
```

**Edges:**
G can also be grown by adding edges.
Add one edge,
```python
>>> G.add_edge(1, 2)
```
a list of edges,
```python
>>> G.add_edges_from([(1, 2), (1, 3)])
```
or a collection of edges,
```python
>>> G.add_edges_from(H.edges())
```
If some edges connect nodes not yet in the graph, the nodes are added automatically. If an edge already exists, an additional edge is created and stored using a key to identify the edge. By default the key is the lowest unused integer.
```python
>>> G.add_edges_from([(4, 5, dict(route=282)), (4, 5, dict(route=37))])
>>> G[4]
{3: {0: {}}, 5: {0: {}, 1: {'route': 282}, 2: {'route': 37}}}
```

**Attributes:**
Each graph, node, and edge can hold key/value attribute pairs in an associated attribute dictionary (the keys must be hashable). By default these are empty, but can be added or changed using add_edge, add_node or direct manipulation of the attribute dictionaries named graph, node and edge respectively.
```python
>>> G = nx.MultiGraph(day="Friday")
>>> G.graph
{'day': 'Friday'}
```
Add node attributes using add_node(), add_nodes_from() or G.node
```python
>>> G.add_node(1, time='5pm')
>>> G.add_nodes_from([3], time='2pm')
>>> G.node[1]
{'time': '5pm'}
>>> G.node[1]['room'] = 714
>>> del G.node[1]['room']  # remove attribute
```
>>> G.nodes(data=True)
[(1, {'time': '5pm'}), (3, {'time': '2pm'})]

Warning: adding a node to G.node does not add it to the graph.

Add edge attributes using add_edge(), add_edges_from(), subscript notation, or G.edge.

>>> G.add_edge(1, 2, weight=4.7)
>>> G.add_edges_from([(3, 4), (4, 5)], color='red')
>>> G.add_edges_from([(1, 2, {'color': 'blue'}), (2, 3, {'weight': 8})])
>>> G[1][2][0]['weight'] = 4.7
>>> G.edge[1][2][0]['weight'] = 4

Shortcuts:

Many common graph features allow python syntax to speed reporting.

>>> 1 in G  # check if node in graph
True
>>> [n for n in G if n<3]  # iterate through nodes
[1, 2]
>>> len(G)  # number of nodes in graph
5
>>> G[1]  # adjacency dict keyed by neighbor to edge attributes
...  # Note: you should not change this dict manually!
{2: {0: {'weight': 4}, 1: {'color': 'blue'}}}

The fastest way to traverse all edges of a graph is via adjacency_iter(), but the edges() method is often more convenient.

>>> for n, nbrsdict in G.adjacency_iter():
...     for nbr, keydict in nbrsdict.items():
...         for key, eattr in keydict.items():
...             if 'weight' in eattr:
...                 (n, nbr, eattr['weight'])

(1, 2, 4)
(2, 1, 4)
(2, 3, 8)
(3, 2, 8)

>>> [(u, v, edata['weight']) for u, v, edata in G.edges(data=True) if 'weight' in edata]
[(1, 2, 4), (2, 3, 8)]

Reporting:

Simple graph information is obtained using methods. Iterator versions of many reporting methods exist for efficiency. Methods exist for reporting nodes(), edges(), neighbors() and degree() as well as the number of nodes and edges.

For details on these and other miscellaneous methods, see below.

Adding and removing nodes and edges

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
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<tbody>
<tr>
<td>MultiGraph.<strong>init</strong>(data)</td>
<td>Initialize a graph with edges, name, graph attributes.</td>
</tr>
<tr>
<td>MultiGraph.add_node(n[, attr_dict])</td>
<td>Add a single node n and update node attributes.</td>
</tr>
<tr>
<td>MultiGraph.add_nodes_from(nodes, **attr)</td>
<td>Add multiple nodes.</td>
</tr>
<tr>
<td>MultiGraph.remove_node(n)</td>
<td>Remove node n.</td>
</tr>
<tr>
<td>MultiGraph.remove_nodes_from(nodes)</td>
<td>Remove multiple nodes.</td>
</tr>
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<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MultiGraph.add_edge(u, v[, key, attr_dict])</td>
<td>Add an edge between u and v.</td>
</tr>
<tr>
<td>MultiGraph.add_edges_from(ebunch[, attr_dict])</td>
<td>Add all the edges in ebunch.</td>
</tr>
<tr>
<td>MultiGraph.add_weighted_edges_from(ebunch[, ...])</td>
<td>Add all the edges in ebunch as weighted edges with specified weights.</td>
</tr>
<tr>
<td>MultiGraph.remove_edge(u, v[, key])</td>
<td>Remove an edge between u and v.</td>
</tr>
<tr>
<td>MultiGraph.remove_edges_from(ebunch)</td>
<td>Remove all edges specified in ebunch.</td>
</tr>
<tr>
<td>MultiGraph.add_star(nodes, **attr)</td>
<td>Add a star.</td>
</tr>
<tr>
<td>MultiGraph.add_path(nodes, **attr)</td>
<td>Add a path.</td>
</tr>
<tr>
<td>MultiGraph.add_cycle(nodes, **attr)</td>
<td>Add a cycle.</td>
</tr>
<tr>
<td>MultiGraph.clear()</td>
<td>Remove all nodes and edges from the graph.</td>
</tr>
</tbody>
</table>

**__init__**

MultiGraph.__init__(data=None, **attr)

Initialize a graph with edges, name, graph attributes.

**Parameters**

- **data**: input graph
  Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.

- **name**: string, optional (default='')
  An optional name for the graph.

- **attr**: keyword arguments, optional (default= no attributes)
  Attributes to add to graph as key=value pairs.

**See also:**

convert

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G = nx.Graph(name='my graph')
>>> e = [(1,2), (2,3), (3,4)]  # list of edges
>>> G = nx.Graph(e)

Arbitrary graph attribute pairs (key=value) may be assigned

```python
>>> G=nx.Graph(e, day="Friday")
>>> G.graph
{'day': 'Friday'}
```

**add_node**

MultiGraph.add_node(n, attr_dict=None, **attr)

Add a single node n and update node attributes.

**Parameters**

- **n**: node
  A node can be any hashable Python object except None.

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**attr_dict** : dictionary, optional (default= no attributes)

  Dictionary of node attributes. Key/value pairs will update existing data associated with the node.

**attr** : keyword arguments, optional

  Set or change attributes using key=value.

See also:

add_nodes_from

Notes

A hashable object is one that can be used as a key in a Python dictionary. This includes strings, numbers, tuples of strings and numbers, etc.

On many platforms hashable items also include mutables such as NetworkX Graphs, though one should be careful that the hash doesn’t change on mutables.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_node(1)
>>> G.add_node('Hello')
>>> K3 = nx.Graph([(0,1),(1,2),(2,0)])
>>> G.add_node(K3)
>>> G.number_of_nodes()
3

Use keywords set/change node attributes:

```python
>>> G.add_node(1,size=10)
>>> G.add_node(3,weight=0.4,UTM=('13S',382871,3972649))
```

add_nodes_from

```
MultiGraph.add_nodes_from(nodes, **attr)
```

  Add multiple nodes.

  **Parameters**  
  
  nodes : iterable container

  A container of nodes (list, dict, set, etc.). OR A container of (node, attribute dict) tuples.  
  Node attributes are updated using the attribute dict.

  attr : keyword arguments, optional (default= no attributes)

  Update attributes for all nodes in nodes. Node attributes specified in nodes as a tuple take precedence over attributes specified generally.

  See also:

  add_node
Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_nodes_from('Hello')
>>> K3 = nx.Graph([(0,1),(1,2),(2,0)])
>>> G.add_nodes_from(K3)
>>> sorted(G.nodes(), key=str)
[0, 1, 2, 'H', 'e', 'l', 'o']

Use keywords to update specific node attributes for every node.

>>> G.add_nodes_from([1,2], size=10)
>>> G.add_nodes_from([3,4], weight=0.4)

Use (node, attrdict) tuples to update attributes for specific nodes.

>>> G.add_nodes_from([(1,dict(size=11)), (2,{'color':'blue'})])

>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))

remove_node

MultiGraph.remove_node(n)
Remove node n.
Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.

Parameters n : node
A node in the graph

Raises NetworkXError:
If n is not in the graph.

See also:
remove_nodes_from

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.edges()
[(0, 1), (1, 2)]
>>> G.remove_node(1)
>>> G.edges()
[]

remove_nodes_from

MultiGraph.remove_nodes_from(nodes)
Remove multiple nodes.
Parameters  nodes : iterable container

A container of nodes (list, dict, set, etc.). If a node in the container is not in the graph it
is silently ignored.

See also:
remove_node

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> e = G.nodes()
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> G.nodes()
[]

add_edge

MultiGraph.add_edge(u, v, key=None, attr_dict=None, **attr)

Add an edge between u and v.

The nodes u and v will be automatically added if they are not already in the graph.

Edge attributes can be specified with keywords or by providing a dictionary with key/value pairs. See examples
below.

Parameters  u,v : nodes

Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None)
Python objects.

key : hashable identifier, optional (default=lowest unused integer)

Used to distinguish multiedges between a pair of nodes.

attr_dict : dictionary, optional (default= no attributes)

Dictionary of edge attributes. Key/value pairs will update existing data associated with
the edge.

attr : keyword arguments, optional

Edge data (or labels or objects) can be assigned using keyword arguments.

See also:
add_edges_from add a collection of edges

Notes

To replace/update edge data, use the optional key argument to identify a unique edge. Otherwise a new edge
will be created.
NetworkX algorithms designed for weighted graphs cannot use multigraphs directly because it is not clear how to handle multiedge weights. Convert to Graph using edge attribute ‘weight’ to enable weighted graph algorithms.

**Examples**

The following all add the edge e=(1,2) to graph G:

```python
>>> G = nx.Graph()   # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = (1,2)
>>> G.add_edge(1, 2)  # explicit two-node form
>>> G.add_edge(*e)    # single edge as tuple of two nodes
>>> G.add_edges_from( [(1,2)] )  # add edges from iterable container
```

Add data to edges using keywords:

```python
>>> G.add_edge(1, 2, weight=3)
>>> G.add_edge(1, 2, key=0, weight=4)  # update data for key=0
>>> G.add_edge(1, 3, weight=7, capacity=15, length=342.7)
```

**add_edges_from**

MultiGraph.add_edges_from(ebunch, attr_dict=None, **attr)

Add all the edges in ebunch.

**Parameters**

- **ebunch**: container of edges

  Each edge given in the container will be added to the graph. The edges can be:
  
  - 2-tuples (u,v) or
  
  - 3-tuples (u,v,d) for an edge attribute dict d, or
  
  - 4-tuples (u,v,k,d) for an edge identified by key k

- **attr_dict**: dictionary, optional (default= no attributes)

  Dictionary of edge attributes. Key/value pairs will update existing data associated with each edge.

- **attr**: keyword arguments, optional

  Edge data (or labels or objects) can be assigned using keyword arguments.

**See also**

- **add_edge** add a single edge
- **add_weighted_edges_from** convenient way to add weighted edges

**Notes**

Adding the same edge twice has no effect but any edge data will be updated when each duplicate edge is added.
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edges_from([(0, 1), (1, 2)])  # using a list of edge tuples
>>> e = zip(range(0, 3), range(1, 4))
>>> G.add_edges_from(e)  # Add the path graph 0-1-2-3

Associate data to edges

>>> G.add_edges_from([(1, 2), (2, 3)], weight=3)
>>> G.add_edges_from([(3, 4), (1, 4)], label='WN2898')
```

add_weighted_edges_from

```python
MultiGraph.add_weighted_edges_from(ebunch, weight='weight', **attr)
```

Add all the edges in `ebunch` as weighted edges with specified weights.

**Parameters**

- `ebunch`: container of edges
  
  Each edge given in the list or container will be added to the graph. The edges must be given as 3-tuples (u,v,w) where w is a number.

- `weight`: string, optional (default='weight')
  
  The attribute name for the edge weights to be added.

- `attr`: keyword arguments, optional (default= no attributes)
  
  Edge attributes to add/update for all edges.

**See also:**

- `add_edge` add a single edge
- `add_edges_from` add multiple edges

**Notes**

Adding the same edge twice for Graph/DiGraph simply updates the edge data. For MultiGraph/MultiDiGraph, duplicate edges are stored.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0, 1, 3.0), (1, 2, 7.5)])
```

remove_edge

```python
MultiGraph.remove_edge(u, v, key=None)
```

Remove an edge between u and v.

**Parameters**

- `u,v`: nodes
  
  Remove an edge between nodes u and v.

- `key`: hashable identifier, optional (default=None)
Used to distinguish multiple edges between a pair of nodes. If None remove a single (arbitrary) edge between u and v.

Raises NetworkXError:

If there is not an edge between u and v, or if there is no edge with the specified key.

See also:

remove_edges_from  remove a collection of edges

Examples

```
>>> G = nx.MultiGraph()
>>> G.add_path([0,1,2,3])
>>> G.remove_edge(0,1)
>>> e = (1,2)
>>> G.remove_edge(*e)  # unpacks e from an edge tuple
```

For multiple edges

```
>>> G = nx.MultiGraph()  # or MultiDiGraph, etc
>>> G.add_edges_from([(1,2),(1,2),(1,2)])
>>> G.remove_edge(1,2)  # remove a single (arbitrary) edge
```

For edges with keys

```
>>> G = nx.MultiGraph()  # or MultiDiGraph, etc
>>> G.add_edge(1,2,key='first')
>>> G.add_edge(1,2,key='second')
>>> G.remove_edge(1,2,key='second')
```

remove_edges_from

```
MultiGraph.remove_edges_from(ebunch)
Remove all edges specified in ebunch.

Parameters  

- ebunch: list or container of edge tuples :

  Each edge given in the list or container will be removed from the graph. The edges can be:
  - 2-tuples (u,v) All edges between u and v are removed.
  - 3-tuples (u,v,key) The edge identified by key is removed.
  - 4-tuples (u,v,key,data) where data is ignored.

See also:

remove_edge  remove a single edge

Notes

Will fail silently if an edge in ebunch is not in the graph.

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Examples

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_path([0, 1, 2, 3])
>>> ebunch=[(1,2), (2,3)]
>>> G.remove_edges_from(ebunch)
```

Removing multiple copies of edges

```python
>>> G = nx.MultiGraph()
>>> G.add_edges_from([(1, 2), (1, 2), (1, 2)])
>>> G.remove_edges_from([(1, 2), (1, 2)])
>>> G.edges()
[(1, 2)]
>>> G.remove_edges_from([(1, 2), (1, 2)])  # silently ignore extra copy
>>> G.edges()  # now empty graph
[]
```

add_star

```python
MultiGraph.add_star(nodes, **attr)
```

Add a star.

The first node in nodes is the middle of the star. It is connected to all other nodes.

**Parameters**

- nodes : iterable container
  A container of nodes.

- attr : keyword arguments, optional (default= no attributes)
  Attributes to add to every edge in star.

**See also:**

add_path, add_cycle

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_star([0, 1, 2, 3])
>>> G.add_star([10, 11, 12], weight=2)
```

add_path

```python
MultiGraph.add_path(nodes, **attr)
```

Add a path.

**Parameters**

- nodes : iterable container
  A container of nodes. A path will be constructed from the nodes (in order) and added to the graph.

- attr : keyword arguments, optional (default= no attributes)
  Attributes to add to every edge in path.
See also:

add_star, add_cycle

Examples

>>> G = nx.Graph() # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.add_path([10,11,12], weight=7)

add_cycle

MultiGraph.add_cycle(nodes, **attr)
Add a cycle.

Parameters

nodes: iterable container
A container of nodes. A cycle will be constructed from the nodes (in order) and added
to the graph.

attr: keyword arguments, optional (default= no attributes)
Attributes to add to every edge in cycle.

See also:

add_path, add_star

Examples

>>> G = nx.Graph() # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_cycle([0,1,2,3])
>>> G.add_cycle([10,11,12], weight=7)

clear

MultiGraph.clear()
Remove all nodes and edges from the graph.
This also removes the name, and all graph, node, and edge attributes.

Examples

>>> G = nx.Graph() # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.clear()
>>> G.nodes()
[]
>>> G.edges()
[]
Iterating over nodes and edges
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### nodes

**MultiGraph.nodes(data=False)**

Return a list of the nodes in the graph.

**Parameters**

- **data**: boolean, optional (default=False)

  If False return a list of nodes. If True return a two-tuple of node and node data dictionary

**Returns**

- **nlist**: list

  A list of nodes. If data=True a list of two-tuples containing (node, node data dictionary).

#### Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.nodes()
[0, 1, 2]
>>> G.add_node(1, time='5pm')
>>> G.nodes(data=True)
[(0, {}), (1, {'time': '5pm'}), (2, {})]
```

### nodes_iter

**MultiGraph.nodes_iter(data=False)**

Return an iterator over the nodes.

**Parameters**

- **data**: boolean, optional (default=False)

  If False the iterator returns nodes. If True return a two-tuple of node and node data dictionary

**Returns**

- **niter**: iterator

  An iterator over nodes. If data=True the iterator gives two-tuples containing (node, node data dictionary)
Notes

If the node data is not required it is simpler and equivalent to use the expression ‘for n in G’.

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
```

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])

>>> [d for n,d in G.nodes_iter(data=True)]
[{}, {}, {}]
```

__iter__

MultiGraph.__iter__() Iterate over the nodes. Use the expression ‘for n in G’.

Returns niter : iterator
An iterator over all nodes in the graph.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
```

edges

MultiGraph.edges(nbunch=None, data=False, keys=False)
Return a list of edges.

Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).

Parameters nbunch : iterable container, optional (default= all nodes)
A container of nodes. The container will be iterated through once.

data : bool, optional (default=False)
Return two tuples (u,v) (False) or three-tuples (u,v,data) (True).

keys : bool, optional (default=False)
Return two tuples (u,v) (False) or three-tuples (u,v,key) (True).

Returns edge_list : list of edge tuples
Edges that are adjacent to any node in nbunch, or a list of all edges if nbunch is not specified.

See also:

edges_iter return an iterator over the edges
Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> G.edges()
[(0, 1), (1, 2), (2, 3)]
>>> G.edges(data=True)  # default edge data is {} (empty dictionary)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> G.edges(keys=True)  # default keys are integers
[(0, 1, 0), (1, 2, 0), (2, 3, 0)]
>>> G.edges(data=True,keys=True)  # default keys are integers
[(0, 1, 0, {}), (1, 2, 0, {}), (2, 3, 0, {})]
>>> G.edges([0,3])
[(0, 1), (3, 2)]
>>> G.edges(0)
[(0, 1)]
```

**edges_iter**

`MultiGraph.edges_iter(nbunch=None, data=False, keys=False)`

Return an iterator over the edges.

Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).

**Parameters**

- **nbunch** : iterable container, optional (default= all nodes)
  
  A container of nodes. The container will be iterated through once.

- **data** : bool, optional (default=False)

  If True, return edge attribute dict with each edge.

- **keys** : bool, optional (default=False)

  If True, return edge keys with each edge.

**Returns**

- **edge_iter** : iterator

  An iterator of (u,v), (u,v,d) or (u,v,key,d) tuples of edges.

**See also:**

- **edges** return a list of edges

**Notes**

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.
Examples

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_path([0, 1, 2, 3])
>>> [e for e in G.edges_iter()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges_iter(data=True))
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> list(G.edges_iter(keys=True))
[(0, 1, 0), (1, 2, 0), (2, 3, 0)]
>>> list(G.edges_iter(data=True, keys=True))
[(0, 1, 0, {}), (1, 2, 0, {}), (2, 3, 0, {})]
>>> list(G.edges_iter([0, 3]))
[(0, 1), (3, 2)]
>>> list(G.edges_iter(0))
[(0, 1)]
```

get_edge_data

`MultiGraph.get_edge_data(u, v, key=None, default=None)`

Return the attribute dictionary associated with edge (u,v).

Parameters  
- `u,v`: nodes  
- `default`: any Python object (default=None)
  Value to return if the edge (u,v) is not found.
- `key`: hashable identifier, optional (default=None)
  Return data only for the edge with specified key.

Returns  
- `edge_dict`: dictionary
  The edge attribute dictionary.

Notes

It is faster to use `G[u][v][key].`

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_edge(0, 1, key='a', weight=7)
>>> G[0][1]['a']  # key='a'
{'weight': 7}
```

Warning: Assigning `G[u][v][key]` corrupts the graph data structure. But it is safe to assign attributes to that dictionary.

```python
>>> G[0][1]['a']['weight'] = 10
>>> G[0][1]['a']['weight']
10
>>> G[1][0]['a']['weight']
10
```
Examples

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> G.get_edge_data(0,1)
{0: {}}
>>> e = (0,1)
>>> G.get_edge_data(*e)  # tuple form
{0: {}}
>>> G.get_edge_data('a','b',default=0)  # edge not in graph, return 0
0
```

neighbors

**MultiGraph.neighbors(n)**
Return a list of the nodes connected to the node n.

**Parameters**
- **n**: node
  A node in the graph

**Returns**
- **nlist**: list
  A list of nodes that are adjacent to n.

**Raises**
- **NetworkXError**
  If the node n is not in the graph.

Notes

It is usually more convenient (and faster) to access the adjacency dictionary as G[n]:

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a','b',weight=7)
>>> G['a']
{'b': {'weight': 7}}
```

Examples

```
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.neighbors(0)
[1]
```

neighbors_iter

**MultiGraph.neighbors_iter(n)**
Return an iterator over all neighbors of node n.
Notes

It is faster to use the idiom “in G[0]”, e.g.

```python
>>> G = nx.path_graph(4)
>>> [n for n in G[0]]
[1]
```

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [n for n in G.neighbors_iter(0)]
[1]
```

__getitem__

MultiGraph.__getitem__(n)
Return a dict of neighbors of node n. Use the expression ‘G[n]’.

Parameters  n : node
A node in the graph.

Returns  adj_dict : dictionary
The adjacency dictionary for nodes connected to n.

Notes

G[n] is similar to G.neighbors(n) but the internal data dictionary is returned instead of a list.
Assigning G[n] will corrupt the internal graph data structure. Use G[n] for reading data only.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G[0]
{1: {}}
```

adjacency_list

MultiGraph.adjacency_list()
Return an adjacency list representation of the graph.

The output adjacency list is in the order of G.nodes(). For directed graphs, only outgoing adjacencies are included.

Returns  adj_list : lists of lists
The adjacency structure of the graph as a list of lists.
adjacency_iter

MultiGraph.adjacency_iter()
Return an iterator of (node, adjacency dict) tuples for all nodes.

This is the fastest way to look at every edge. For directed graphs, only outgoing adjacencies are included.

Returns adj_iter : iterator
An iterator of (node, adjacency dictionary) for all nodes in the graph.

See also:
adjacency_list

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.adjacency_list()  # in order given by G.nodes()
[[1], [0, 2], [1, 3], [2]]

nbunch_iter

MultiGraph.nbunch_iter(nbunch=None)
Return an iterator of nodes contained in nbunch that are also in the graph.

The nodes in nbunch are checked for membership in the graph and if not are silently ignored.

Parameters nbunch : iterable container, optional (default=all nodes)
A container of nodes. The container will be iterated through once.

Returns niter : iterator
An iterator over nodes in nbunch that are also in the graph. If nbunch is None, iterate over all nodes in the graph.

Raises NetworkXError :
If nbunch is not a node or or sequence of nodes. If a node in nbunch is not hashable.

See also:
Graph.__iter__

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Notes

When nbunch is an iterator, the returned iterator yields values directly from nbunch, becoming exhausted when nbunch is exhausted.

To test whether nbunch is a single node, one can use “if nbunch in self:”, even after processing with this routine.

If nbunch is not a node or a (possibly empty) sequence/iterator or None, a NetworkXError is raised. Also, if any object in nbunch is not hashable, a NetworkXError is raised.

Information about graph structure

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<td>MultiGraph.number_of_selfloops()</td>
<td>Return the number of selfloop edges.</td>
</tr>
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</table>

has_node

MultiGraph.has_node(n)

Return True if the graph contains the node n.

Parameters

- n : node

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.has_node(0)
True

It is more readable and simpler to use

```python
>>> 0 in G
True
```

__contains__

MultiGraph.__contains__(n)

Return True if n is a node, False otherwise. Use the expression ‘n in G’.
Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> 1 in G
True

has_edge

MultiGraph.has_edge(u, v, key=None)

Return True if the graph has an edge between nodes u and v.

Parameters u,v : nodes

Nodes can be, for example, strings or numbers.

key : hashable identifier, optional (default=None)

If specified return True only if the edge with key is found.

Returns edge_ind : bool

True if edge is in the graph, False otherwise.

Examples

Can be called either using two nodes u,v, an edge tuple (u,v), or an edge tuple (u,v,key).

>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> G.has_edge(0,1)  # using two nodes
True
>>> e = (0,1)
>>> G.has_edge(*e)  # e is a 2-tuple (u,v)
True
>>> G.add_edge(0,1,key='a')
>>> G.has_edge(0,1,key='a')  # specify key
True
>>> e=(0,1,'a')
>>> G.has_edge(*e)  # e is a 3-tuple (u,v,'a')
True

The following syntax are equivalent:

>>> G.has_edge(0,1)
True
>>> 1 in G[0]  # though this gives KeyError if 0 not in G
True

order

MultiGraph.order()

Return the number of nodes in the graph.

Returns nnodes : int

The number of nodes in the graph.
See also:

number_of_nodes, __len__

number_of_nodes

MultiGraph.number_of_nodes()
Return the number of nodes in the graph.

    Returns nnodes : int
                  The number of nodes in the graph.

See also:

order, __len__

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> len(G)
3

__len__

MultiGraph.__len__()
Return the number of nodes. Use the expression ‘len(G)’.

    Returns nnodes : int
                  The number of nodes in the graph.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> len(G)
4

degree

MultiGraph.degree(nbunch=None, weight=None)
Return the degree of a node or nodes.

The node degree is the number of edges adjacent to that node.

    Parameters nbunch : iterable container, optional (default=all nodes)
                        A container of nodes. The container will be iterated through once.

                         weight : string or None, optional (default=None)
                              The edge attribute that holds the numerical value used as a weight. If None, then each
                              edge has weight 1. The degree is the sum of the edge weights adjacent to the node.
Returns  **nd**: dictionary, or number

A dictionary with nodes as keys and degree as values or a number if a single node is specified.

**Examples**

```python
g = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
g.add_path([0,1,2,3])
g.degree(0)
1
>>> g.degree([0,1])
{0: 1, 1: 2}
>>> list(g.degree([0,1]).values())
[1, 2]
```

**degree_iter**

```
MultiGraph.degree_iter(nbunch=None, weight=None)
Return an iterator for (node, degree).
The node degree is the number of edges adjacent to the node.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)
  A container of nodes. The container will be iterated through once.
- **weight**: string or None, optional (default=None)
  The edge attribute that holds the numerical value used as a weight. If None, then each
  edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**Returns**  **nd_iter**: an iterator

The iterator returns two-tuples of (node, degree).

**See also:**

*degree*

**Examples**

```python
g = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
g.add_path([0,1,2,3])
list(g.degree_iter(0))  # node 0 with degree 1
[(0, 1)]
list(g.degree_iter([0,1]))
[(0, 1), (1, 2)]
```

**size**

```
MultiGraph.size(weight=None)
Return the number of edges.

**Parameters**

- **weight**: string or None, optional (default=None)
```

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The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

Returns nedges : int

The number of edges of sum of edge weights in the graph.

See also:

number_of_edges

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.size()
3

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a','b',weight=2)
>>> G.add_edge('b','c',weight=4)
>>> G.size()
2
>>> G.size(weight='weight')
6.0
```

number_of_edges

MultiGraph.number_of_edges (u=None, v=None)

Return the number of edges between two nodes.

Parameters u,v : nodes, optional (default=all edges)

If u and v are specified, return the number of edges between u and v. Otherwise return the total number of all edges.

Returns nedges : int

The number of edges in the graph. If nodes u and v are specified return the number of edges between those nodes.

See also:

size

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.number_of_edges()
3
>>> G.number_of_edges(0,1)
1
>>> e = (0,1)
>>> G.number_of_edges(*e)
1
```
nodes_with_selfloops

MultiGraph.nodes_with_selfloops()
Return a list of nodes with self loops.
A node with a self loop has an edge with both ends adjacent to that node.

Returns nodelist : list
A list of nodes with self loops.

See also:
selfloop_edges, number_of_selfloops

Examples

>>> G = nx.Graph()    # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.nodes_with_selfloops()
[1]

selfloop_edges

MultiGraph.selfloop_edges(data=False, keys=False)
Return a list of selfloop edges.
A selfloop edge has the same node at both ends.

Parameters data : bool, optional (default=False)
Return selfloop edges as two tuples (u,v) (data=False) or three-tuples (u,v,data) (data=True)

keys : bool, optional (default=False)
If True, return edge keys with each edge.

Returns edgelist : list of edge tuples
A list of all selfloop edges.

See also:
nodes_with_selfloops, number_of_selfloops

Examples

>>> G = nx.MultiGraph()    # or MultiDiGraph
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.selfloop_edges()
[(1, 1)]
>>> G.selfloop_edges(data=True)
[(1, 1, {})]
>>> G.selfloop_edges(keys=True)
[(1, 1, 0)]
>>> G.selfloop_edges(keys=True, data=True)
[(1, 1, 0, {})]

number_of_selfloops

MultiGraph.number_of_selfloops()
Return the number of selfloop edges.
A selfloop edge has the same node at both ends.

Returns nloops : int
The number of selfloops.

See also:
nodes_with_selfloops, selfloop_edges

Examples

```python
>>> G=nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.number_of_selfloops()
1
```

Making copies and subgraphs

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<tr>
<td>MultiGraph.subgraph(nbunch)</td>
<td>Return the subgraph induced on nodes in nbunch.</td>
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copy

MultiGraph.copy()
Return a copy of the graph.

Returns G : Graph
A copy of the graph.

See also:
to_directed return a directed copy of the graph.

Notes

This makes a complete copy of the graph including all of the node or edge attributes.
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> H = G.copy()
```

**to_undirected**

`MultiGraph.to_undirected()`  
Return an undirected copy of the graph.

**Returns**  
`G : Graph/MultiGraph`

A deepcopy of the graph.

**See also:**  
copy, add_edge, add_edges_from

**Notes**

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar `G=DiGraph(D)` which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, [http://docs.python.org/library/copy.html](http://docs.python.org/library/copy.html).

**Examples**

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_path([0, 1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1), (1, 0)]
>>> G2 = H.to_undirected()
>>> G2.edges()
[(0, 1)]
```

**to_directed**

`MultiGraph.to_directed()`  
Return a directed representation of the graph.

**Returns**  
`G : MultiDiGraph`

A directed graph with the same name, same nodes, and with each edge `(u,v,data)` replaced by two directed edges `(u,v,data)` and `(v,u,data).`
Notes

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar D=DiGraph(G) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Examples

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1), (1, 0)]
```

If already directed, return a (deep) copy

```python
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1)]
```

subgraph

MultiGraph.subgraph(nbunch)

Return the subgraph induced on nodes in nbunch.

The induced subgraph of the graph contains the nodes in nbunch and the edges between those nodes.

Parameters

nbunch : list, iterable

A container of nodes which will be iterated through once.

Returns

G : Graph

A subgraph of the graph with the same edge attributes.

Notes

The graph, edge or node attributes just point to the original graph. So changes to the node or edge structure will not be reflected in the original graph while changes to the attributes will.

To create a subgraph with its own copy of the edge/node attributes use: nx.Graph(G.subgraph(nbunch))

If edge attributes are containers, a deep copy can be obtained using: G.subgraph(nbunch).copy()

For an inplace reduction of a graph to a subgraph you can remove nodes: G.remove_nodes_from([ n in G if n not in set(nbunch)])
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> H = G.subgraph([0,1,2])
>>> H.edges()
[(0, 1), (1, 2)]
```

3.2.4 MultiDiGraph - Directed graphs with self loops and parallel edges

Overview

**MultiDiGraph** (*data=None, **attr*)

A directed graph class that can store multiedges.

Multiedges are multiple edges between two nodes. Each edge can hold optional data or attributes.

A MultiDiGraph holds directed edges. Self loops are allowed.

Nodes can be arbitrary (hashable) Python objects with optional key/value attributes.

Edges are represented as links between nodes with optional key/value attributes.

**Parameters**

- **data**: input graph
  - Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.

- **attr**: keyword arguments, optional (default= no attributes)
  - Attributes to add to graph as key=value pairs.

**See also:**

Graph, DiGraph, MultiGraph

Examples

Create an empty graph structure (a “null graph”) with no nodes and no edges.

```python
>>> G = nx.MultiDiGraph()
```

G can be grown in several ways.

**Nodes:**

Add one node at a time:

```python
>>> G.add_node(1)
```

Add the nodes from any container (a list, dict, set or even the lines from a file or the nodes from another graph).

```python
>>> G.add_nodes_from([2,3])
>>> G.add_nodes_from(range(100,110))
>>> H=nx.Graph()
>>> H.add_path([0,1,2,3,4,5,6,7,8,9])
>>> G.add_nodes_from(H)
```
In addition to strings and integers any hashable Python object (except None) can represent a node, e.g. a customization node object, or even another Graph.

```python
>>> G.add_node(H)
```

**Edges:**

G can also be grown by adding edges.

Add one edge,

```python
>>> G.add_edge(1, 2)
```

a list of edges,

```python
>>> G.add_edges_from([(1,2),(1,3)])
```

or a collection of edges,

```python
>>> G.add_edges_from(H.edges())
```

If some edges connect nodes not yet in the graph, the nodes are added automatically. If an edge already exists, an additional edge is created and stored using a key to identify the edge. By default the key is the lowest unused integer.

```python
>>> G.add_edges_from([(4,5,dict(route=282)), (4,5,dict(route=37))])
```

```python
>>> G[4]  
{5: {0: {}, 1: {'route': 282}, 2: {'route': 37}}}
```

**Attributes:**

Each graph, node, and edge can hold key/value attribute pairs in an associated attribute dictionary (the keys must be hashable). By default these are empty, but can be added or changed using add_edge, add_node or direct manipulation of the attribute dictionaries named graph, node and edge respectively.

```python
>>> G = nx.MultiDiGraph(day="Friday")
```

```python
>>> G.graph
{'day': 'Friday'}
```

Add node attributes using add_node(), add_nodes_from() or G.node

```python
>>> G.add_node(1, time='5pm')
```

```python
>>> G.add_nodes_from([3], time='2pm')
```

```python
>>> G.node[1]  
{'time': '5pm'}
```

```python
>>> del G.node[1]['room']
# remove attribute
```

```python
>>> G.nodes(data=True)
[(1, {'time': '5pm'}), (3, {'time': '2pm'})]
```

Warning: adding a node to G.node does not add it to the graph.

Add edge attributes using add_edge(), add_edges_from(), subscript notation, or G.edge.

```python
>>> G.add_edge(1, 2, weight=4.7 )
```

```python
>>> G.add_edges_from([(3,4),(4,5)], color='red')
```

```python
>>> G.add_edges_from([(1,2,{'color':'blue'}), (2,3,{'weight':8})])
```

```python
>>> G[1][2][0]['weight'] = 4.7
```

```python
>>> G.edge[1][2][0]['weight'] = 4
```

**Shortcuts:**

Many common graph features allow python syntax to speed reporting.
>>> 1 in G  # check if node in graph
True
>>> [n for n in G if n<3]  # iterate through nodes
[1, 2]
>>> len(G)  # number of nodes in graph
5
>>> G[1]  # adjacency dict keyed by neighbor to edge attributes
...  # Note: you should not change this dict manually!
{2: {0: {'weight': 4}, 1: {'color': 'blue'}}}

The fastest way to traverse all edges of a graph is via adjacency_iter(), but the edges() method is often more convenient.

```python
>>> for n,nbrsdict in G.adjacency_iter():
...     for nbr,keydict in nbrsdict.items():
...         for key,eattr in keydict.items():
...             if 'weight' in eattr:
...                 (n,nbr,eattr['weight'])
(1, 2, 4)
(2, 3, 8)
```

Reporting:

Simple graph information is obtained using methods. Iterator versions of many reporting methods exist for efficiency. Methods exist for reporting nodes(), edges(), neighbors() and degree() as well as the number of nodes and edges.

For details on these and other miscellaneous methods, see below.

## Adding and Removing Nodes and Edges

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<th>Description</th>
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<td>Initialize a graph with edges, name, graph attributes.</td>
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<td>MultiDiGraph.add_node(n[, attr_dict])</td>
<td>Add a single node n and update node attributes.</td>
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<td>MultiDiGraph.add_nodes_from(nodes, **attr)</td>
<td>Add multiple nodes.</td>
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<td>Remove node n.</td>
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<tr>
<td>MultiDiGraph.add_edge(u, v[, key, attr_dict])</td>
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<td>Add a cycle.</td>
</tr>
<tr>
<td>MultiDiGraph.clear()</td>
<td>Remove all nodes and edges from the graph.</td>
</tr>
</tbody>
</table>

__init__

MultiDiGraph.__init__(data=None, **attr)
Initialize a graph with edges, name, graph attributes.

Parameters  data : input graph

3.2. Basic graph types
Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.

**name**: string, optional (default='')

An optional name for the graph.

**attr**: keyword arguments, optional (default= no attributes)

Attributes to add to graph as key=value pairs.

### See also:

convert

### Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G = nx.Graph(name='my graph')
>>> e = [(1,2),(2,3),(3,4)]  # list of edges
>>> G = nx.Graph(e)
```

Arbitrary graph attribute pairs (key=value) may be assigned

```python
>>> G=nx.Graph(e, day="Friday")
>>> G.graph
{'day': 'Friday'}
```

### add_node

*MultiDiGraph*.add_node(n, attr_dict=None, **attr)*

Add a single node n and update node attributes.

**Parameters**

- **n**: node

  A node can be any hashable Python object except None.

- **attr_dict**: dictionary, optional (default= no attributes)

  Dictionary of node attributes. Key/value pairs will update existing data associated with the node.

- **attr**: keyword arguments, optional

  Set or change attributes using key=value.

### See also:

add_nodes_from

### Notes

A hashable object is one that can be used as a key in a Python dictionary. This includes strings, numbers, tuples of strings and numbers, etc.

On many platforms hashable items also include mutables such as NetworkX Graphs, though one should be careful that the hash doesn’t change on mutables.
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_node(1)
>>> G.add_node('Hello')
>>> K3 = nx.Graph([(0,1),(1,2),(2,0)])
>>> G.add_node(K3)
>>> G.number_of_nodes()
3

Use keywords set/change node attributes:

```python
>>> G.add_node(1, size=10)
>>> G.add_node(3, weight=0.4, UTM=('13S', 382871, 3972649))
```

add_nodes_from

```python
MultiDiGraph.add_nodes_from(nodes, **attr)
Add multiple nodes.

Parameters

- nodes : iterable container
  A container of nodes (list, dict, set, etc.). OR A container of (node, attribute dict) tuples. Node attributes are updated using the attribute dict.

- attr : keyword arguments, optional (default= no attributes)
  Update attributes for all nodes in nodes. Node attributes specified in nodes as a tuple take precedence over attributes specified generally.

See also:
add_node
```

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_nodes_from('Hello')
>>> K3 = nx.Graph([(0,1),(1,2),(2,0)])
>>> G.add_nodes_from(K3)
>>> sorted(G.nodes(), key=str)
[0, 1, 2, 'H', 'e', 'l', 'o']

Use keywords to update specific node attributes for every node.

```python
>>> G.add_nodes_from([[1,2], size=10])
>>> G.add_nodes_from([3,4], weight=0.4)
```

Use (node, attrdict) tuples to update attributes for specific nodes.

```python
>>> G.add_nodes_from([[(1,dict(size=11)), (2,{'color':'blue'})]])
>>> G.node[1]['size']
11
>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))
>>> H.node[1]['size']
11
```
remove_node

MultiDiGraph.remove_node(n)
Remove node n.

Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.

Parameters n : node
A node in the graph

Raises NetworkXError :
If n is not in the graph.

See also:
remove_nodes_from

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2])
>>> G.edges()
[(0, 1), (1, 2)]
>>> G.remove_node(1)
>>> G.edges()
[]

remove_nodes_from

MultiDiGraph.remove_nodes_from(nbunch)
Remove multiple nodes.

Parameters nodes : iterable container
A container of nodes (list, dict, set, etc.). If a node in the container is not in the graph it is silently ignored.

See also:
remove_node

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2])
>>> e = G.nodes()
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> G.nodes()
[]
add_edge

`MultiDiGraph.add_edge(u, v, key=None, attr_dict=None, **attr)`

Add an edge between u and v. The nodes u and v will be automatically added if they are not already in the graph.

Edge attributes can be specified with keywords or by providing a dictionary with key/value pairs. See examples below.

**Parameters**

u,v : nodes

Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.

key : hashable identifier, optional (default=lowest unused integer)

Used to distinguish multiedges between a pair of nodes.

attr_dict : dictionary, optional (default= no attributes)

Dictionary of edge attributes. Key/value pairs will update existing data associated with the edge.

attr : keyword arguments, optional

Edge data (or labels or objects) can be assigned using keyword arguments.

**See also:**

`add_edges_from` add a collection of edges

**Notes**

To replace/update edge data, use the optional key argument to identify a unique edge. Otherwise a new edge will be created.

NetworkX algorithms designed for weighted graphs cannot use multigraphs directly because it is not clear how to handle multiedge weights. Convert to Graph using edge attribute ‘weight’ to enable weighted graph algorithms.

**Examples**

The following all add the edge e=(1,2) to graph G:

```python
>>> G = nx.MultiDiGraph()
>>> e = (1,2)
>>> G.add_edge(1, 2)  # explicit two-node form
>>> G.add_edge(*e)   # single edge as tuple of two nodes
>>> G.add_edges_from( [(1,2)] )  # add edges from iterable container
```

Associate data to edges using keywords:

```python
>>> G.add_edge(1, 2, weight=3)
>>> G.add_edge(1, 2, key=0, weight=4)  # update data for key=0
>>> G.add_edge(1, 3, weight=7, capacity=15, length=342.7)
```
add_edges_from

MultiDiGraph.add_edges_from(ebunch, attr_dict=None, **attr)
Add all the edges in ebunch.

Parameters

- **ebunch** : container of edges
  
  Each edge given in the container will be added to the graph. The edges can be:
  
  - 2-tuples (u,v) or
  - 3-tuples (u,v,d) for an edge attribute dict d, or
  - 4-tuples (u,v,k,d) for an edge identified by key k

- **attr_dict** : dictionary, optional (default= no attributes)
  
  Dictionary of edge attributes. Key/value pairs will update existing data associated with each edge.

- **attr** : keyword arguments, optional
  
  Edge data (or labels or objects) can be assigned using keyword arguments.

See also:

- add_edge add a single edge
- add_weighted_edges_from convenient way to add weighted edges

Notes

Adding the same edge twice has no effect but any edge data will be updated when each duplicate edge is added.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edges_from([(0, 1), (1, 2)])  # using a list of edge tuples
>>> e = zip(range(0, 3), range(1, 4))
>>> G.add_edges_from(e)  # Add the path graph 0-1-2-3

Associate data to edges

>>> G.add_edges_from([[(1, 2), (2, 3)], weight=3]
>>> G.add_edges_from([[(3, 4), (1, 4)], label='WN2898'])
```

add_weighted_edges_from

MultiDiGraph.add_weighted_edges_from(ebunch, weight='weight', **attr)
Add all the edges in ebunch as weighted edges with specified weights.

Parameters

- **ebunch** : container of edges
  
  Each edge given in the list or container will be added to the graph. The edges must be given as 3-tuples (u,v,w) where w is a number.

- **weight** : string, optional (default= ‘weight’)
  
  The attribute name for the edge weights to be added.
attr : keyword arguments, optional (default= no attributes)
    Edge attributes to add/update for all edges.

See also:

add_edge  add a single edge
add_edges_from  add multiple edges

Notes

Adding the same edge twice for Graph/DiGraph simply updates the edge data. For MultiGraph/MultiDiGraph, duplicate edges are stored.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0,1,3.0),(1,2,7.5)])

remove_edge

MultiDiGraph.remove_edge(u, v, key=None)
    Remove an edge between u and v.

Parameters  u,v: nodes :
    Remove an edge between nodes u and v.

key : hashable identifier, optional (default=None)
    Used to distinguish multiple edges between a pair of nodes. If None remove a single
    (arbitrary) edge between u and v.

Raises  NetworkXError :
    If there is not an edge between u and v, or if there is no edge with the specified key.

See also:

remove_edges_from  remove a collection of edges

Examples

>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1,2,3])
>>> G.remove_edge(0,1)
>>> e = (1,2)
>>> G.remove_edge(*e)  # unpacks e from an edge tuple

For multiple edges

>>> G = nx.MultiDiGraph()
>>> G.add_edges_from([(1,2),(1,2),(1,2)])
>>> G.remove_edge(1,2)  # remove a single (arbitrary) edge
For edges with keys

```python
>>> G = nx.MultiDiGraph()
>>> G.add_edge(1, 2, key='first')
>>> G.add_edge(1, 2, key='second')
>>> G.remove_edge(1, 2, key='second')
```

remove_edges_from

`MultiDiGraph.remove_edges_from(ebunch)`

Remove all edges specified in ebunch.

**Parameters**

- **ebunch**: list or container of edge tuples

  Each edge given in the list or container will be removed from the graph. The edges can be:
  - 2-tuples `(u,v)` All edges between `u` and `v` are removed.
  - 3-tuples `(u,v,key)` The edge identified by `key` is removed.
  - 4-tuples `(u,v,key,data)` where data is ignored.

**See also:**

- `remove_edge` remove a single edge

**Notes**

Will fail silently if an edge in `ebunch` is not in the graph.

**Examples**

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_path([0, 1, 2, 3])
>>> ebunch = [(1, 2), (2, 3)]
>>> G.remove_edges_from(ebunch)
```

Removing multiple copies of edges

```python
>>> G = nx.MultiGraph()
>>> G.add_edges_from([(1, 2), (1, 2), (1, 2)])
>>> G.remove_edges_from([(1, 2), (1, 2)])
>>> G.edges()
[(1, 2)]
>>> G.remove_edges_from([(1, 2), (1, 2)])  # silently ignore extra copy
>>> G.edges()  # now empty graph
[]
```

**add_star**

`MultiDiGraph.add_star(nodes, **attr)`

Add a star.

The first node in `nodes` is the middle of the star. It is connected to all other nodes.
Parameters nodes : iterable container

A container of nodes.

attr : keyword arguments, optional (default= no attributes)

Attributes to add to every edge in star.

See also:

add_path, add_cycle

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_star([0,1,2,3])
>>> G.add_star([10,11,12], weight=2)

add_path

MultiDiGraph.add_path(nodes, **attr)

Add a path.

Parameters nodes : iterable container

A container of nodes. A path will be constructed from the nodes (in order) and added to the graph.

attr : keyword arguments, optional (default= no attributes)

Attributes to add to every edge in path.

See also:

add_star, add_cycle

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.add_path([10,11,12], weight=7)

add_cycle

MultiDiGraph.add_cycle(nodes, **attr)

Add a cycle.

Parameters nodes : iterable container

A container of nodes. A cycle will be constructed from the nodes (in order) and added to the graph.

attr : keyword arguments, optional (default= no attributes)

Attributes to add to every edge in cycle.

See also:

add_path, add_star

3.2. Basic graph types
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_cycle([0, 1, 2, 3])
>>> G.add_cycle([10, 11, 12], weight=7)
```

clear

`MultiDiGraph.clear()`

Remove all nodes and edges from the graph.
This also removes the name, and all graph, node, and edge attributes.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> G.clear()
>>> G.nodes()
[]
>>> G.edges()
[]
```

Iterating over nodes and edges

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<th>Description</th>
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<td>Return a list of the nodes in the graph.</td>
</tr>
<tr>
<td><code>MultiDiGraph.nodes_iter(data)</code></td>
<td>Return an iterator over the nodes.</td>
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<tr>
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<td>Iterate over the nodes.</td>
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</tr>
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<td>Return an iterator over the outgoing edges.</td>
</tr>
<tr>
<td><code>MultiDiGraph.in_edges(nbunch, keys, data)</code></td>
<td>Return a list of the incoming edges.</td>
</tr>
<tr>
<td><code>MultiDiGraph.in_edges_iter(nbunch, data, keys)</code></td>
<td>Return an iterator over the incoming edges.</td>
</tr>
<tr>
<td><code>MultiDiGraph.get_edge_data(u, v[, key, default])</code></td>
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</tr>
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<td><code>MultiDiGraph.neighbors(n)</code></td>
<td>Return a list of successor nodes of n.</td>
</tr>
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<td>Return an iterator over successor nodes of n.</td>
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<td><code>MultiDiGraph.__getitem__(n)</code></td>
<td>Return a dict of neighbors of node n.</td>
</tr>
<tr>
<td><code>MultiDiGraph.successors(n)</code></td>
<td>Return a list of successor nodes of n.</td>
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<td><code>MultiDiGraph.successors_iter(n)</code></td>
<td>Return an iterator over successor nodes of n.</td>
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<td><code>MultiDiGraph.predecessors(n)</code></td>
<td>Return a list of predecessor nodes of n.</td>
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<tr>
<td><code>MultiDiGraph.adjacency_list()</code></td>
<td>Return an adjacency list representation of the graph.</td>
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<td>Return an iterator of (node, adjacency dict) tuples for all nodes.</td>
</tr>
<tr>
<td><code>MultiDiGraph.nbunch_iter(nbunch)</code></td>
<td>Return an iterator of nodes contained in nbunch that are also in the graph.</td>
</tr>
</tbody>
</table>
nodes

MultiDiGraph.nodes (data=False)
Return a list of the nodes in the graph.

Parameters  data : boolean, optional (default=False)
If False return a list of nodes. If True return a two-tuple of node and node data dictionary

Returns  nlist : list
A list of nodes. If data=True a list of two-tuples containing (node, node data dictionary).

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.nodes()
[0, 1, 2]
>>> G.add_node(1, time='5pm')
>>> G.nodes(data=True)
[(0, {}), (1, {'time': '5pm'}), (2, {})]
```

nodes_iter

MultiDiGraph.nodes_iter (data=False)
Return an iterator over the nodes.

Parameters  data : boolean, optional (default=False)
If False the iterator returns nodes. If True return a two-tuple of node and node data dictionary

Returns  niter : iterator
An iterator over nodes. If data=True the iterator gives two-tuples containing (node, node data, dictionary)

Notes

If the node data is not required it is simpler and equivalent to use the expression ‘for n in G’.

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
```

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
```
__iter__

MultiDiGraph.__iter__()  
Iterate over the nodes. Use the expression ‘for n in G’.

Returns niter : iterator  
An iterator over all nodes in the graph.

Examples

>>> G = nx.Graph()       # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])

dep

MultiDiGraph.edges(nbunch=None, data=False, keys=False)  
Return a list of edges.

Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).

Parameters nbunch : iterable container, optional (default= all nodes)  
A container of nodes. The container will be iterated through once.

data : bool, optional (default=False)  
Return two tuples (u,v) (False) or three-tuples (u,v,data) (True).

keys : bool, optional (default=False)  
Return two tuples (u,v) (False) or three-tuples (u,v,key) (True).

Returns edge_list : list of edge tuples :  
Edges that are adjacent to any node in nbunch, or a list of all edges if nbunch is not specified.

See also:

dep

dep

dep
>>> G.edges(data=True, keys=True) # default keys are integers
[(0, 1, 0, {}), (1, 2, 0, {}), (2, 3, 0, {})]

MultDiGraph.edges_iter (nbunch=None, data=False, keys=False)
Return an iterator over the edges.

Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).

**Parameters**

nbunch : iterable container, optional (default= all nodes)
A container of nodes. The container will be iterated through once.

data : bool, optional (default=False)
If True, return edge attribute dict with each edge.

keys : bool, optional (default=False)
If True, return edge keys with each edge.

**Returns**

edge_iter : iterator
An iterator of (u,v), (u,v,d) or (u,v,key,d) tuples of edges.

**Notes**

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

**Examples**

```python
>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1,2,3])
>>> [e for e in G.edges_iter()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges_iter(data=True)) # default data is {} (empty dict)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> list(G.edges_iter([0,2]))
[(0, 1), (2, 3)]
>>> list(G.edges_iter(0))
[(0, 1)]
```

MultDiGraph.out_edges (nbunch=None, keys=False, data=False)
Return a list of the outgoing edges.
Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).

**Parameters** nbunch : iterable container, optional (default=all nodes)

A container of nodes. The container will be iterated through once.

data : bool, optional (default=False)

If True, return edge attribute dict with each edge.

keys : bool, optional (default=False)

If True, return edge keys with each edge.

**Returns** out_edges : list

An list of (u,v), (u,v,d) or (u,v,key,d) tuples of edges.

**See also:**

* in_edges return a list of incoming edges

**Notes**

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs edges() is the same as out_edges().

**out_edges_iter**

MultiDiGraph.**out_edges_iter** (nbunch=None, data=False, keys=False)  
Return an iterator over the edges.

Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).

**Parameters** nbunch : iterable container, optional (default=all nodes)

A container of nodes. The container will be iterated through once.

data : bool, optional (default=False)

If True, return edge attribute dict with each edge.

keys : bool, optional (default=False)

If True, return edge keys with each edge.

**Returns** edge_iter : iterator

An iterator of (u,v), (u,v,d) or (u,v,key,d) tuples of edges.

**See also:**

* edges return a list of edges

**Notes**

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.
Examples

```python
>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1,2,3])
>>> [e for e in G.edges_iter()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges_iter(data=True))  # default data is {} (empty dict)
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
>>> list(G.edges_iter([0,2]))
[(0, 1), (2, 3)]
>>> list(G.edges_iter(0))
[(0, 1)]
```

in_edges

```python
MultiDiGraph.in_edges(nbunch=None, keys=False, data=False)
```

Return a list of the incoming edges.

**Parameters**

- **nbunch**: iterable container, optional (default= all nodes)
  - A container of nodes. The container will be iterated through once.

- **data**: bool, optional (default=False)
  - If True, return edge attribute dict with each edge.

- **keys**: bool, optional (default=False)
  - If True, return edge keys with each edge.

**Returns**

- **in_edges**: list
  - A list of (u,v), (u,v,d) or (u,v,key,d) tuples of edges.

**See also**:

- `out_edges` return a list of outgoing edges

in_edges_iter

```python
MultiDiGraph.in_edges_iter(nbunch=None, data=False, keys=False)
```

Return an iterator over the incoming edges.

**Parameters**

- **nbunch**: iterable container, optional (default= all nodes)
  - A container of nodes. The container will be iterated through once.

- **data**: bool, optional (default=False)
  - If True, return edge attribute dict with each edge.

- **keys**: bool, optional (default=False)
  - If True, return edge keys with each edge.

**Returns**

- **in_edge_iter**: iterator
  - An iterator of (u,v), (u,v,d) or (u,v,key,d) tuples of edges.

**See also**:

3.2. Basic graph types
edges_iter return an iterator of edges

get_edge_data

MultiDiGraph.get_edge_data (u, v, key=None, default=None)
Return the attribute dictionary associated with edge (u,v).

Parameters u,v : nodes
    default: any Python object (default=None):
        Value to return if the edge (u,v) is not found.
    key : hashable identifier, optional (default=None)
        Return data only for the edge with specified key.

Returns edge_dict : dictionary
    The edge attribute dictionary.

Notes

It is faster to use G[u][v][key].

>>> G = nx.MultiGraph() # or MultiDiGraph
>>> G.add_edge(0,1,key='a',weight=7)
>>> G[0][1][‘a’] # key=’a’
{‘weight’: 7}

Warning: Assigning G[u][v][key] corrupts the graph data structure. But it is safe to assign attributes to that
dictionary,

>>> G[0][1][‘a’][‘weight’] = 10
>>> G[0][1][‘a’][‘weight’]
10
>>> G[1][0][‘a’][‘weight’]
10

Examples

>>> G = nx.MultiGraph() # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> G.get_edge_data(0,1)
{0: {}}
>>> e = (0,1)
>>> G.get_edge_data(*e) # tuple form
{0: {}}
>>> G.get_edge_data(‘a’,’b’,default=0) # edge not in graph, return 0
0

neighbors

MultiDiGraph.neighbors (n)
Return a list of successor nodes of n.
neighbors() and successors() are the same function.

**neighbors_iter**

MultiDiGraph.neighbors_iter(n)
Return an iterator over successor nodes of n.
neighbors_iter() and successors_iter() are the same.

**__getitem__**

MultiDiGraph.__getitem__(n)
Return a dict of neighbors of node n. Use the expression ‘G[n]’.

Parameters
- n : node
  A node in the graph.

Returns
- adj_dict : dictionary
  The adjacency dictionary for nodes connected to n.

Notes

G[n] is similar to G.neighbors(n) but the internal data dictionary is returned instead of a list.
Assigning G[n] will corrupt the internal graph data structure. Use G[n] for reading data only.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G[0]
{1: {}}

**successors**

MultiDiGraph.successors(n)
Return a list of successor nodes of n.
neighbors() and successors() are the same function.

**successors_iter**

MultiDiGraph.successors_iter(n)
Return an iterator over successor nodes of n.
neighbors_iter() and successors_iter() are the same.
predecessors

MultiDiGraph.predecessors(n)
Return a list of predecessor nodes of n.

predecessors_iter

MultiDiGraph.predecessors_iter(n)
Return an iterator over predecessor nodes of n.

adjacency_list

MultiDiGraph.adjacency_list()
Return an adjacency list representation of the graph.
The output adjacency list is in the order of G.nodes(). For directed graphs, only outgoing adjacencies are included.

Returns  adj_list : lists of lists
The adjacency structure of the graph as a list of lists.

See also:
adjacency_iter

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> G.adjacency_list()  # in order given by G.nodes()
[[1], [0, 2], [1, 3], [2]]

adjacency_iter

MultiDiGraph.adjacency_iter()
Return an iterator of (node, adjacency dict) tuples for all nodes.
This is the fastest way to look at every edge. For directed graphs, only outgoing adjacencies are included.

Returns  adj_iter : iterator
An iterator of (node, adjacency dictionary) for all nodes in the graph.

See also:
adjacency_list

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [(n,nbrdict) for n,nbrdict in G.adjacency_iter()]
[[(0, {1: {}}), (1, {0: {}, 2: {}}), (2, {1: {}, 3: {}}), (3, {2: {}})]]
**nbunch_iter**

**MultiDiGraph.nbunch_iter** *(nbunch=None)*

Return an iterator of nodes contained in nbunch that are also in the graph.

The nodes in nbunch are checked for membership in the graph and if not are silently ignored.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)

A container of nodes. The container will be iterated through once.

**Returns**

- **niter**: iterator

An iterator over nodes in nbunch that are also in the graph. If nbunch is None, iterate over all nodes in the graph.

**Raises**

- **NetworkXError**:

If nbunch is not a node or or sequence of nodes. If a node in nbunch is not hashable.

**See also**:

- Graph.__iter__

**Notes**

When nbunch is an iterator, the returned iterator yields values directly from nbunch, becoming exhausted when nbunch is exhausted.

To test whether nbunch is a single node, one can use “if nbunch in self.”, even after processing with this routine.

If nbunch is not a node or a (possibly empty) sequence/iterator or None, a NetworkXError is raised. Also, if any object in nbunch is not hashable, a NetworkXError is raised.

**Information about graph structure**

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<td>Return the degree of a node or nodes.</td>
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<td>Return the in-degree of a node or nodes.</td>
</tr>
<tr>
<td>MultiDiGraph.in_degree_iter([nbunch, weight])</td>
<td>Return an iterator for (node, in-degree).</td>
</tr>
<tr>
<td>MultiDiGraph.out_degree([nbunch, weight])</td>
<td>Return the out-degree of a node or nodes.</td>
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<tr>
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</tr>
</tbody>
</table>
has_node

MultiDiGraph.has_node(n)
  Return True if the graph contains the node n.

Parameters
  node

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> G.has_node(0)
True

It is more readable and simpler to use

>>> 0 in G
True

__contains__

MultiDiGraph.__contains__(n)
  Return True if n is a node, False otherwise. Use the expression ‘n in G’.

Examples

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> 1 in G
True

has_edge

MultiDiGraph.has_edge(u, v, key=None)
  Return True if the graph has an edge between nodes u and v.

Parameters
  u, v : nodes
    Nodes can be, for example, strings or numbers.

  key : hashable identifier, optional (default=None)
    If specified return True only if the edge with key is found.

Returns
  edge_ind : bool
    True if edge is in the graph, False otherwise.

Examples

Can be called either using two nodes u,v, an edge tuple (u,v), or an edge tuple (u,v,key).
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> G.has_edge(0,1)    # using two nodes
True
>>> e = (0,1)
>>> G.has_edge(*e)    # e is a 2-tuple (u,v)
True
>>> G.add_edge(0,1,key='a')
>>> G.has_edge(0,1,key='a')    # specify key
True
>>> e=(0,1,'a')
>>> G.has_edge(*e)    # e is a 3-tuple (u,v,'a')
True

The following syntax are equivalent:

>>> G.has_edge(0,1)
True
>>> 1 in G[0]    # though this gives KeyError if 0 not in G
True

order

MultiDiGraph.order()
Return the number of nodes in the graph.

Returns nnodes: int
The number of nodes in the graph.

See also:
number_of_nodes, __len__

number_of_nodes

MultiDiGraph.number_of_nodes()
Return the number of nodes in the graph.

Returns nnodes: int
The number of nodes in the graph.

See also:
order, __len__

Examples

>>> G = nx.Graph()    # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> len(G)
3

3.2. Basic graph types
__len__

MultiDiGraph.__len__()

Return the number of nodes. Use the expression ‘len(G)’.

Returns nnodes : int

The number of nodes in the graph.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> len(G)
4
```

degree

MultiDiGraph.degree (nbunch=None, weight=None)

Return the degree of a node or nodes.

The node degree is the number of edges adjacent to that node.

Parameters nbunch : iterable container, optional (default=all nodes)

A container of nodes. The container will be iterated through once.

weight : string or None, optional (default=None)

The edge attribute that holds the numerical value used as a weight. If None, then each
edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns nd : dictionary, or number

A dictionary with nodes as keys and degree as values or a number if a single node is
specified.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> G.degree(0)
1
>>> G.degree([0, 1])
{0: 1, 1: 2}
>>> list(G.degree([0, 1]).values())
[1, 2]
```

degree_iter

MultiDiGraph.degree_iter (nbunch=None, weight=None)

Return an iterator for (node, degree).

The node degree is the number of edges adjacent to the node.

Parameters nbunch : iterable container, optional (default=all nodes)
A container of nodes. The container will be iterated through once.

weight : string or None, optional (default=None)
The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights.

Returns nd_iter : an iterator
The iterator returns two-tuples of (node, degree).

See also:
degree

Examples

```python
g = nx.MultiDiGraph()
g.add_path([0,1,2,3])
list(g.degree_iter(0)) # node 0 with degree 1
[(0, 1)]
list(g.degree_iter([0,1]))
[(0, 1), (1, 2)]
```

in_degree

MultiDiGraph.in_degree(nbunch=None, weight=None)
Return the in-degree of a node or nodes.
The node in-degree is the number of edges pointing in to the node.

Parameters nbunch : iterable container, optional (default=all nodes)
A container of nodes. The container will be iterated through once.
weight : string or None, optional (default=None)
The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns nd : dictionary, or number
A dictionary with nodes as keys and in-degree as values or a number if a single node is specified.

See also:
degree, out_degree, in_degree_iter

Examples

```python
g = nx.DiGraph() # or MultiDiGraph
g.add_path([0,1,2,3])
g.in_degree(0) 0
g.in_degree([0,1])
0: 0, 1: 1
list(g.in_degree([0,1]).values())
[0, 1]
```
in_degree_iter

```
MultiDiGraph.in_degree_iter(nbunch=None, weight=None)
```

Return an iterator for (node, in-degree).

The node in-degree is the number of edges pointing in to the node.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)
  A container of nodes. The container will be iterated through once.

- **weight**: string or None, optional (default=None)
  The edge attribute that holds the numerical value used as a weight. If None, then each
  edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**Returns**

- **nd_iter**: an iterator
  The iterator returns two-tuples of (node, in-degree).

**See also:**

degree, in_degree, out_degree, out_degree_iter

**Examples**

```python
>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1,2,3])
>>> list(G.in_degree_iter(0))  # node 0 with degree 0
[(0, 0)]
>>> list(G.in_degree_iter([0,1]))
[(0, 0), (1, 1)]
```

out_degree

```
MultiDiGraph.out_degree(nbunch=None, weight=None)
```

Return the out-degree of a node or nodes.

The node out-degree is the number of edges pointing out of the node.

**Parameters**

- **nbunch**: iterable container, optional (default=all nodes)
  A container of nodes. The container will be iterated through once.

- **weight**: string or None, optional (default=None)
  The edge attribute that holds the numerical value used as a weight. If None, then each
  edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**Returns**

- **nd**: dictionary, or number
  A dictionary with nodes as keys and out-degree as values or a number if a single node
  is specified.

**Examples**

```python
>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1,2,3])
>>> list(G.out_degree(0))  # node 0 with degree 0
[(0, 0)]
>>> list(G.out_degree([0,1]))
[(0, 0), (1, 1)]
```
```python
>>> G = nx.DiGraph()  # or MultiDiGraph
>>> G.add_path([0,1,2,3])
>>> G.out_degree(0)
1
>>> G.out_degree([0,1])
{0: 1, 1: 1}
>>> list(G.out_degree([0,1]).values())
[1, 1]
```

**out_degree_iter**

`MultiDiGraph.out_degree_iter(nbunch=None, weight=None)`

Return an iterator for (node, out-degree).

The node out-degree is the number of edges pointing out of the node.

Parameters:

- **nbunch**: iterable container, optional (default=all nodes)
  A container of nodes. The container will be iterated through once.
- **weight**: string or None, optional (default=None)
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights.

Returns:

- **nd_iter**: an iterator
  The iterator returns two-tuples of (node, out-degree).

See also:

- `degree`
- `in_degree`
- `out_degree`
- `in_degree_iter`

**Examples**

```python
>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1,2,3])
>>> list(G.out_degree_iter(0))  # node 0 with degree 1
[(0, 1)]
>>> list(G.out_degree_iter([0,1]))
[(0, 1), (1, 1)]
```

**size**

`MultiDiGraph.size(weight=None)`

Return the number of edges.

Parameters:

- **weight**: string or None, optional (default=None)
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

Returns:

- **nedges**: int
  The number of edges of sum of edge weights in the graph.

See also:

- `number_of_edges`
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> G.size()
3

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=2)
>>> G.add_edge('b', 'c', weight=4)
>>> G.size()
2
>>> G.size(weight='weight')
6.0
```

**number_of_edges**

`MultiDiGraph.number_of_edges(u=None, v=None)`

Return the number of edges between two nodes.

**Parameters**

- `u,v`: nodes, optional (default=all edges)

  If `u` and `v` are specified, return the number of edges between `u` and `v`. Otherwise return the total number of all edges.

**Returns**

- `nedges`: int

  The number of edges in the graph. If nodes `u` and `v` are specified return the number of edges between those nodes.

**See also:**

- `size`

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0, 1, 2, 3])
>>> G.number_of_edges()
3
>>> G.number_of_edges(0, 1)
1
>>> e = (0, 1)
>>> G.number_of_edges(*e)
1
```

**nodes_with_selfloops**

`MultiDiGraph.nodes_with_selfloops()`

Return a list of nodes with self loops.

A node with a self loop has an edge with both ends adjacent to that node.

**Returns**

- `nodelist`: list

  A list of nodes with self loops.
See also:

selfloop_edges, number_of_selfloops

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.nodes_with_selfloops()
[1]
```

**selfloop_edges**

`MultiDiGraph.selfloop_edges(data=False, keys=False)`

Return a list of selfloop edges.

A selfloop edge has the same node at both ends.

**Parameters**

- `data`: bool, optional (default=False)
  
  Return selfloop edges as two tuples (u,v) (data=False) or three-tuples (u,v,data) (data=True)
  
- `keys`: bool, optional (default=False)
  
  If True, return edge keys with each edge.

**Returns**

- `edgelist`: list of edge tuples
  
  A list of all selfloop edges.

See also:

nodes_with_selfloops, number_of_selfloops

Examples

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.selfloop_edges()
[(1, 1)]
>>> G.selfloop_edges(data=True)
[(1, 1, {})]
>>> G.selfloop_edges(keys=True)
[(1, 1, 0)]
>>> G.selfloop_edges(keys=True, data=True)
[(1, 1, 0, {})]
```

**number_of_selfloops**

`MultiDiGraph.number_of_selfloops()`

Return the number of selfloop edges.

A selfloop edge has the same node at both ends.

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Returns nloops : int

The number of selfloops.

See also:
nodes_with_selfloops, selfloop_edges

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1,1)
>>> G.add_edge(1,2)
>>> G.number_of_selfloops()
1
```

Making copies and subgraphs

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copy

MultiDiGraph.copy()

Return a copy of the graph.

Returns G : Graph

A copy of the graph.

See also:

to_directed return a directed copy of the graph.

Notes

This makes a complete copy of the graph including all of the node or edge attributes.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> H = G.copy()
```

to_undirected

MultiDiGraph.to_undirected(reciprocal=False)

Return an undirected representation of the digraph.
Parameters **reciprocal** : bool (optional)

If True only keep edges that appear in both directions in the original digraph.

Returns **G** : MultiGraph

An undirected graph with the same name and nodes and with edge (u,v,data) if either (u,v,data) or (v,u,data) is in the digraph. If both edges exist in digraph and their edge data is different, only one edge is created with an arbitrary choice of which edge data to use. You must check and correct for this manually if desired.

Notes

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar D=DiGraph(G) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, [http://docs.python.org/library/copy.html](http://docs.python.org/library/copy.html).

**to_directed**

```
MultiDiGraph.to_directed()
```

Return a directed copy of the graph.

Returns **G** : MultiDiGraph

A deepcopy of the graph.

Notes

If edges in both directions (u,v) and (v,u) exist in the graph, attributes for the new undirected edge will be a combination of the attributes of the directed edges. The edge data is updated in the (arbitrary) order that the edges are encountered. For more customized control of the edge attributes use add_edge().

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar G=DiGraph(D) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, [http://docs.python.org/library/copy.html](http://docs.python.org/library/copy.html).

Examples

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1), (1, 0)]
```

If already directed, return a (deep) copy

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```python
>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
[(0, 1)]
```

**subgraph**

`MultiDiGraph.subgraph(nbunch)`

Return the subgraph induced on nodes in `nbunch`.

The induced subgraph of the graph contains the nodes in `nbunch` and the edges between those nodes.

**Parameters**

- `nbunch`: list, iterable
  
  A container of nodes which will be iterated through once.

**Returns**

- `G`: Graph
  
  A subgraph of the graph with the same edge attributes.

**Notes**

The graph, edge or node attributes just point to the original graph. So changes to the node or edge structure will not be reflected in the original graph while changes to the attributes will.

To create a subgraph with its own copy of the edge/node attributes use: `nx.Graph(G.subgraph(nbunch))`

If edge attributes are containers, a deep copy can be obtained using: `G.subgraph(nbunch).copy()`

For an inplace reduction of a graph to a subgraph you can remove nodes: `G.remove_nodes_from([ n in G if n not in set(nbunch)])`

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> H = G.subgraph([0,1,2])
>>> H.edges()
[(0, 1), (1, 2)]
```

**reverse**

`MultiDiGraph.reverse(copy=True)`

Return the reverse of the graph.

The reverse is a graph with the same nodes and edges but with the directions of the edges reversed.

**Parameters**

- `copy`: bool optional (default=True)
  
  If True, return a new DiGraph holding the reversed edges. If False, reverse the reverse graph is created using the original graph (this changes the original graph).
4.1 Approximation

4.1.1 Clique

Clique.

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<td>Find the Maximum Clique</td>
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<td>Repeatedly remove cliques from the graph.</td>
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**max_clique**

**max_clique** \((G)\)

Find the Maximum Clique

Finds the \(O(|V|/(\log|V|)^2)\) apx of maximum clique/independent set in the worst case.

**Parameters**

- \(G\) : NetworkX graph
  - Undirected graph

**Returns**

- **clique** : set
  - The apx-maximum clique of the graph

**Notes**

A clique in an undirected graph \(G = (V, E)\) is a subset of the vertex set \(C \subseteq V\), such that for every two vertices in \(C\), there exists an edge connecting the two. This is equivalent to saying that the subgraph induced by \(C\) is complete (in some cases, the term clique may also refer to the subgraph).

A maximum clique is a clique of the largest possible size in a given graph. The clique number \(\omega(G)\) of a graph \(G\) is the number of vertices in a maximum clique in \(G\). The intersection number of \(G\) is the smallest number of cliques that together cover all edges of \(G\).


**References**

[R126]
clique_removal

`clique_removal(G)`
Repeatedly remove cliques from the graph.

Results in a $O(|V|/\log |V|)^2$ approximation of maximum clique & independent set. Returns the largest independent set found, along with a list of maximal cliques.

**Parameters**  
$G$: NetworkX graph  
Undirected graph

**Returns**  
`max_ind_cliques`: (set, list) tuple  
Maximal independent set and list of maximal cliques (sets) in the graph.

**References**

[R125]

### 4.1.2 Dominating Set

A dominating set for a graph $G = (V, E)$ is a subset $D$ of $V$ such that every vertex not in $D$ is joined to at least one member of $D$ by some edge. The domination number $\gamma(G)$ is the number of vertices in a smallest dominating set for $G$. Given a graph $G = (V, E)$ find a minimum weight dominating set $V'$.


An edge dominating set for a graph $G = (V, E)$ is a subset $D$ of $E$ such that every edge not in $D$ is adjacent to at least one edge in $D$.


**min_weighted_dominating_set**

`min_weighted_dominating_set(G[, weight])`  
Return minimum weight vertex dominating set.

**min_edge_dominating_set**

`min_edge_dominating_set(G)`  
Return minimum cardinality edge dominating set.

**min_weighted_dominating_set**

`min_weighted_dominating_set(G, weight=None)`  
Return minimum weight vertex dominating set.

**Parameters**  
$G$: NetworkX graph  
Undirected graph

`weight`: None or string, optional (default = None)  
If None, every edge has weight/distance/weight 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

**Returns**  
`min_weight_dominating_set`: set  
Returns a set of vertices whose weight sum is no more than $\log w(V) \times OPT$
Notes

This algorithm computes an approximate minimum weighted dominating set for the graph G. The upper-bound on the size of the solution is \( \log w(V) \times \text{OPT} \). Runtime of the algorithm is \( O(|E|) \).

References

[R127]

\texttt{min\_edge\_dominating\_set}

\texttt{min\_edge\_dominating\_set}(G)

Return minimum cardinality edge dominating set.

Parameters

\texttt{G} : NetworkX graph

Undirected graph

Returns \texttt{min\_edge\_dominating\_set} : set

Returns a set of dominating edges whose size is no more than \( 2 \times \text{OPT} \).

Notes

The algorithm computes an approximate solution to the edge dominating set problem. The result is no more than \( 2 \times \text{OPT} \) in terms of size of the set. Runtime of the algorithm is \( O(|E|) \).

4.1.3 Independent Set

Independent Set

Independent set or stable set is a set of vertices in a graph, no two of which are adjacent. That is, it is a set I of vertices such that for every two vertices in I, there is no edge connecting the two. Equivalently, each edge in the graph has at most one endpoint in I. The size of an independent set is the number of vertices it contains.

A maximum independent set is a largest independent set for a given graph G and its size is denoted \( \alpha(G) \). The problem of finding such a set is called the maximum independent set problem and is an NP-hard optimization problem. As such, it is unlikely that there exists an efficient algorithm for finding a maximum independent set of a graph.

\texttt{http://en.wikipedia.org/wiki/Independent_set\_(graph\_theory)}

Independent set algorithm is based on the following paper:

\( O(|V|/(\log|V|)^2) \) apx of maximum clique/independent set.


\texttt{maximum\_independent\_set}(G) \hspace{0.5cm} \text{Return an approximate maximum independent set.}

\texttt{maximum\_independent\_set}(G) \hspace{0.5cm} \text{Return an approximate maximum independent set.}
Parameters  
\( G \) : NetworkX graph
Undirected graph

Returns  
\( \text{iset} \) : Set
The apx-maximum independent set

Notes
Finds the \( O(|V|/(\log|V|)^2) \) apx of independent set in the worst case.

References
[R128]

4.1.4 Matching

Given a graph \( G = (V,E) \), a matching \( M \) in \( G \) is a set of pairwise non-adjacent edges; that is, no two edges share a common vertex.

http://en.wikipedia.org/wiki/Matching_(graph_theory)

\[
\text{min\_maximal\_matching}(G) \quad \text{Returns the minimum maximal matching of } G. \text{ That is, out of all maximal}
\]

\text{min\_maximal\_matching}

\( \text{min\_maximal\_matching}(G) \)  Returns the minimum maximal matching of \( G \). That is, out of all maximal matchings of the graph \( G \), the smallest is returned.

Parameters  
\( G \) : NetworkX graph
Undirected graph

Returns  
\( \text{min\_maximal\_matching} \) : set
Returns a set of edges such that no two edges share a common endpoint and every edge not in the set shares some common endpoint in the set. Cardinality will be \( 2 \* \text{OPT} \) in the worst case.

Notes
The algorithm computes an approximate solution fo the minimum maximal cardinality matching problem. The solution is no more than \( 2 \* \text{OPT} \) in size. Runtime is \( O(|E|) \).

References
[R129]
4.1.5 Ramsey

Ramsey numbers.

\texttt{ramsey\_R2}(G) \quad \text{Approximately computes the Ramsey number } R(2; s, t) \text{ for graph.}

\texttt{ramsey\_R2}

\texttt{ramsey\_R2}(G)

Approximately computes the Ramsey number \( R(2; s, t) \) for graph.

\textbf{Parameters} \quad G : \text{NetworkX graph}

Undirected graph

\textbf{Returns} \quad \texttt{max\_pair} : \text{(set, set) tuple}

Maximum clique, Maximum independent set.

4.1.6 Vertex Cover

Given an undirected graph \( G = (V, E) \) and a function \( w \) assigning nonnegative weights to its vertices, find a minimum weight subset of \( V \) such that each edge in \( E \) is incident to at least one vertex in the subset.

\url{http://en.wikipedia.org/wiki/Vertex_cover}

\texttt{min\_weighted\_vertex\_cover}(G[, weight]) \quad \text{2-OPT Local Ratio for Minimum Weighted Vertex Cover}

\texttt{min\_weighted\_vertex\_cover}

\texttt{min\_weighted\_vertex\_cover}(G, weight=None)

2-OPT Local Ratio for Minimum Weighted Vertex Cover

Find an approximate minimum weighted vertex cover of a graph.

\textbf{Parameters} \quad G : \text{NetworkX graph}

Undirected graph

\textbf{weight} : \text{None or string, optional (default = None)}

If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

\textbf{Returns} \quad \texttt{min\_weighted\_cover} : \text{set}

Returns a set of vertices whose weight sum is no more than 2 * OPT.

\textbf{Notes}

Local-Ratio algorithm for computing an approximate vertex cover. Algorithm greedily reduces the costs over edges and iteratively builds a cover. Worst-case runtime is \( O(|E|) \).
4.2 Assortativity

4.2.1 Assortativity

degree_assortativity_coefficient(G[, x, y,...]) Compute degree assortativity of graph.

attribute_assortativity_coefficient(G, attribute) Compute assortativity for node attributes.

numeric_assortativity_coefficient(G, attribute) Compute assortativity for numerical node attributes.

degree_pearson_correlation_coefficient(G[, ...]) Compute degree assortativity of graph.

degree_assortativity_coefficient

degree_assortativity_coefficient (G, x='out', y='in', weight=None, nodes=None)
Compute degree assortativity of graph.

Assortativity measures the similarity of connections in the graph with respect to the node degree.

Parameters

- G : NetworkX graph
- x: string ('in','out'):
  The degree type for source node (directed graphs only).
- y: string ('in','out'):
  The degree type for target node (directed graphs only).
- weight : string or None, optional (default=None) :
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.
- nodes: list or iterable (optional) :
  Compute degree assortativity only for nodes in container. The default is all nodes.

Returns

- r : float
  Assortativity of graph by degree.

See also:

attribute_assortativity_coefficient, numeric_assortativity_coefficient, neighbor_connectivity, degree_mixing_dict, degree_mixing_matrix

Notes

This computes Eq. (21) in Ref. [R134], where e is the joint probability distribution (mixing matrix) of the degrees. If G is directed than the matrix e is the joint probability of the user-specified degree type for the source and target.
## References

[R134], [R135]

## Examples

```python
>>> G=nx.path_graph(4)
>>> r=nx.degree_assortativity_coefficient(G)
>>> print("%3.1f"%r)
-0.5
```

### attribute_assortativity_coefficient

**attribute_assortativity_coefficient** *(G, attribute, nodes=None)*

Compute assortativity for node attributes.

Assortativity measures the similarity of connections in the graph with respect to the given attribute.

### Parameters

- **G** : NetworkX graph
- **attribute** : string
- **nodes** : list or iterable (optional)
  - Compute attribute assortativity for nodes in container. The default is all nodes.

### Returns

- **r** : float
  - Assortativity of graph for given attribute

### Notes

This computes Eq. (2) in Ref. [R131], trace(M)-sum(M)/(1-sum(M), where M is the joint probability distribution (mixing matrix) of the specified attribute.

### References

[R131]

### Examples

```python
>>> G=nx.Graph()
>>> G.add_nodes_from([0,1],color='red')
>>> G.add_nodes_from([2,3],color='blue')
>>> G.add_edges_from([(0,1),(2,3)])
>>> print(nx.attribute_assortativity_coefficient(G,'color'))
1.0
```
numeric_assortativity_coefficient

**numeric_assortativity_coefficient** (*G, attribute, nodes=None*)

Compute assortativity for numerical node attributes.

Assortativity measures the similarity of connections in the graph with respect to the given numeric attribute.

**Parameters**

- **G**: NetworkX graph
- **attribute**: string
  Node attribute key
- **nodes**: list or iterable (optional)
  Compute numeric assortativity only for attributes of nodes in container. The default is all nodes.

**Returns**

- **r**: float
  Assortativity of graph for given attribute

**Notes**

This computes Eq. (21) in Ref. [R139], for the mixing matrix of of the specified attribute.

**References**

[R139]

**Examples**

```python
>>> G = nx.Graph()
>>> G.add_nodes_from([(0, 1), size=2])
>>> G.add_nodes_from([(2, 3), size=3])
>>> G.add_edges_from([(0, 1), (2, 3)])
>>> print(nx.numeric_assortativity_coefficient(G, 'size'))
1.0
```

degree_pearson_correlation_coefficient

degree_pearson_correlation_coefficient (*G, x='out', y='in', weight=None, nodes=None*)

Compute degree assortativity of graph.

Assortativity measures the similarity of connections in the graph with respect to the node degree.

This is the same as degree_assortativity_coefficient but uses the potentially faster scipy.stats.pearsonr function.

**Parameters**

- **G**: NetworkX graph
- **x**: string (‘in’,’out’) :
  The degree type for source node (directed graphs only).
- **y**: string (‘in’,’out’) :
  The degree type for target node (directed graphs only).
- **weight**: string or None, optional (default=None) :
The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

**nodes**: list or iterable (optional):
Compute pearson correlation of degrees only for specified nodes. The default is all nodes.

**Returns**  
*r*: float
Assortativity of graph by degree.

**Notes**
This calls scipy.stats.pearsonr.

**References**
[R136], [R137]

**Examples**
```python
g = nx.path_graph(4)
r = nx.degree_pearson_correlation_coefficient(g)
r
-0.5
```

### 4.2.2 Average neighbor degree

**average_neighbor_degree** *(G[, source, target,...])*  
Returns the average degree of the neighborhood of each node.

**average_neighbor_degree**  
**average_neighbor_degree** *(G, source='out', target='out', nodes=None, weight=None)*
Returns the average degree of the neighborhood of each node.

The average degree of a node *i* is

\[
k_{nn,i} = \frac{1}{|N(i)|} \sum_{j \in N(i)} k_j
\]

where *N*(i) are the neighbors of node *i* and *k*<sub>j</sub> is the degree of node *j* which belongs to *N*(i). For weighted graphs, an analogous measure can be defined [R133],

\[
k_{nn,i}^w = \frac{1}{s_i} \sum_{j \in N(i)} w_{ij}k_j
\]

where *s*<sub>i</sub> is the weighted degree of node *i*, *w*<sub>ij</sub> is the weight of the edge that links *i* and *j* and *N*(i) are the neighbors of node *i*.

**Parameters**
- **G**: NetworkX graph
- **source**: string (“in”|”out”)

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Directed graphs only. Use “in”- or “out”-degree for source node.

**target** : string (“in”|”out”)

Directed graphs only. Use “in”- or “out”-degree for target node.

**nodes** : list or iterable, optional

Compute neighbor degree for specified nodes. The default is all nodes in the graph.

**weight** : string or None, optional (default=None)

The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**

**d** : dict

A dictionary keyed by node with average neighbors degree value.

**See also**

*average_degree_connectivity*

**Notes**

For directed graphs you can also specify in-degree or out-degree by passing keyword arguments.

**References**

[R133]

**Examples**

```python
>>> G=nx.path_graph(4)
>>> G.edge[0][1][‘weight’] = 5
>>> G.edge[2][3][‘weight’] = 3

>>> nx.average_neighbor_degree(G)
{0: 2.0, 1: 1.5, 2: 1.5, 3: 2.0}
>>> nx.average_neighbor_degree(G, weight=’weight’)
{0: 2.0, 1: 1.1666666666666667, 2: 1.25, 3: 2.0}

>>> G=nx.DiGraph()
>>> G.add_path([0,1,2,3])
>>> nx.average_neighbor_degree(G, source=’in’, target=’in’)
{0: 1.0, 1: 1.0, 2: 1.0, 3: 0.0}

>>> nx.average_neighbor_degree(G, source=’out’, target=’out’)
{0: 1.0, 1: 1.0, 2: 0.0, 3: 0.0}
```

### 4.2.3 Average degree connectivity

- **average_degree_connectivity**(G[, source, ...])  Compute the average degree connectivity of graph.
- **k_nearest_neighbors**(G[, source, target, ...])  Compute the average degree connectivity of graph.
**average_degree_connectivity**

**average_degree_connectivity** \((G, \text{source}='in+out', \text{target}='in+out', \text{nodes}=\text{None}, \text{weight}=\text{None})\)

Compute the average degree connectivity of graph.

The average degree connectivity is the average nearest neighbor degree of nodes with degree \(k\). For weighted graphs, an analogous measure can be computed using the weighted average neighbors degree defined in [R132], for a node \(i\), as:

\[
k_{nn,i}^w = \frac{1}{s_i} \sum_{j \in N(i)} w_{ij} k_j
\]

where \(s_i\) is the weighted degree of node \(i\), \(w_{ij}\) is the weight of the edge that links \(i\) and \(j\), and \(N(i)\) are the neighbors of node \(i\).

**Parameters**

- **G** : NetworkX graph
- **source** : “in”|”out”|”in+out” (default:”in+out”)  
  Directed graphs only. Use “in”- or “out”-degree for source node.
- **target** : “in”|”out”|”in+out” (default:”in+out”)  
  Directed graphs only. Use “in”- or “out”-degree for target node.
- **nodes** : list or iterable (optional) :  
  Compute neighbor connectivity for these nodes. The default is all nodes.
- **weight** : string or None, optional (default=None)  
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**

- **d** : dict :  
  A dictionary keyed by degree \(k\) with the value of average connectivity.

**See also:**

neighbors_average_degree

**Notes**

This algorithm is sometimes called ‘k nearest neighbors’.

**References**

[R132]

**Examples**

```python
>>> G=nx.path_graph(4)
>>> G.edge[1][2][‘weight’] = 3
>>> nx.k_nearest_neighbors(G)
{1: 2.0, 2: 1.5}
>>> nx.k_nearest_neighbors(G, weight=’weight’)
{1: 2.0, 2: 1.75}
```

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k_nearest_neighbors

k_nearest_neighbors \((G, \text{source} = \text{'in+out'}, \text{target} = \text{'in+out'}, \text{nodes} = \text{None}, \text{weight} = \text{None})\)  
Compute the average degree connectivity of graph.

The average degree connectivity is the average nearest neighbor degree of nodes with degree \(k\). For weighted graphs, an analogous measure can be computed using the weighted average neighbors degree defined in [R138], for a node \(i\), as:

\[
k_{nw, i} = \frac{1}{s_i} \sum_{j \in N(i)} w_{ij} k_j
\]

where \(s_i\) is the weighted degree of node \(i\), \(w_{ij}\) is the weight of the edge that links \(i\) and \(j\), and \(N(i)\) are the neighbors of node \(i\).

**Parameters**  
\(G\) : NetworkX graph  
\text{source} : “in”|“out”|“in+out” (default:“in+out”)  
Directed graphs only. Use “in”- or “out”-degree for source node.  
\text{target} : “in”|“out”|“in+out” (default:”in+out”)  
Directed graphs only. Use “in”- or “out”-degree for target node.  
\text{nodes} : list or iterable (optional) :  
Compute neighbor connectivity for these nodes. The default is all nodes.  
\text{weight} : string or None, optional (default=None)  
The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**  
d : dict :  
A dictionary keyed by degree \(k\) with the value of average connectivity.

**See also:**  
neighbors_average_degree

**Notes**

This algorithm is sometimes called “k nearest neighbors”.

**References**

[R138]

**Examples**

```python
>>> G=nx.path_graph(4)
>>> G.edge[1][2][\text{’weight’}] = 3
>>> nx.k_nearest_neighbors(G)
{1: 2.0, 2: 1.5}
>>> nx.k_nearest_neighbors(G, weight=\text{’weight’})
{1: 2.0, 2: 1.75}
```
4.2.4 Mixing

**attribute_mixing_matrix**

```python
attribute_mixing_matrix(G, attribute[, ...])
```
Return mixing matrix for attribute.

**Parameters**

- **G**: graph
  NetworkX graph object.
- **attribute**: string
  Node attribute key.
- **nodes**: list or iterable (optional)
  Use only nodes in container to build the matrix. The default is all nodes.
- **mapping**: dictionary, optional
  Mapping from node attribute to integer index in matrix. If not specified, an arbitrary ordering will be used.
- **normalized**: bool (default=False)
  Return counts if False or probabilities if True.

**Returns**

- **m**: numpy array
  Counts or joint probability of occurrence of attribute pairs.

**degree_mixing_matrix**

```python
degree_mixing_matrix(G[, x, y, weight, ...])
```
Return mixing matrix for attribute.

**Parameters**

- **G**: graph
  NetworkX graph object.
- **x**: string (‘in’,’out’)
  The degree type for source node (directed graphs only).
- **y**: string (‘in’,’out’)
  The degree type for target node (directed graphs only).
- **nodes**: list or iterable (optional)
  Build the matrix using only nodes in container. The default is all nodes.
- **weight**: string or None, optional (default=None)
  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.
normalized : bool (default=False)

Return counts if False or probabilities if True.

Returns m: numpy array :

Counts, or joint probability, of occurrence of node degree.

degree_mixing_dict

degree_mixing_dict (G, x='out', y='in', weight=None, nodes=None, normalized=False)

Return dictionary representation of mixing matrix for degree.

Parameters G : graph

NetworkX graph object.

x: string ('in','out') :

The degree type for source node (directed graphs only).

y: string ('in','out') :

The degree type for target node (directed graphs only).

weight: string or None, optional (default=None) :

The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

normalized : bool (default=False)

Return counts if False or probabilities if True.

Returns d: dictionary :

Counts or joint probability of occurrence of degree pairs.

attribute_mixing_dict

attribute_mixing_dict (G, attribute, nodes=None, normalized=False)

Return dictionary representation of mixing matrix for attribute.

Parameters G : graph

NetworkX graph object.

attribute : string

Node attribute key.

nodes: list or iterable (optional) :

Unse nodes in container to build the dict. The default is all nodes.

normalized : bool (default=False)

Return counts if False or probabilities if True.

Returns d : dictionary

Counts or joint probability of occurrence of attribute pairs.
4.3 Bipartite

This module provides functions and operations for bipartite graphs. Bipartite graphs \( B = (U, V, E) \) have two node sets \( U, V \) and edges in \( E \) that only connect nodes from opposite sets. It is common in the literature to use a spatial analogy referring to the two node sets as top and bottom nodes.

The bipartite algorithms are not imported into the networkx namespace at the top level so the easiest way to use them is with:

```python
>>> import networkx as nx
>>> from networkx.algorithms import bipartite
```

NetworkX does not have a custom bipartite graph class but the Graph() or DiGraph() classes can be used to represent bipartite graphs. However, you have to keep track of which set each node belongs to, and make sure that there is no edge between nodes of the same set. The convention used in NetworkX is to use a node attribute named “bipartite” with values 0 or 1 to identify the sets each node belongs to.

For example:

```python
>>> B = nx.Graph()
>>> B.add_nodes_from([1, 2, 3, 4], bipartite=0)  # Add the node attribute "bipartite"
>>> B.add_nodes_from(['a', 'b', 'c'], bipartite=1)
>>> B.add_edges_from([(1, 'a'), (1, 'b'), (2, 'b'), (2, 'c'), (3, 'c'), (4, 'a')])
```

Many algorithms of the bipartite module of NetworkX require, as an argument, a container with all the nodes that belong to one set, in addition to the bipartite graph \( B \). If \( B \) is connected, you can find the node sets using a two-coloring algorithm:

```python
>>> nx.is_connected(B)
True
>>> bottom_nodes, top_nodes = bipartite.sets(B)
```

list(top_nodes) [1, 2, 3, 4] list(bottom_nodes) ['a', 'c', 'b']

However, if the input graph is not connected, there are more than one possible colorations. Thus, the following result is correct:

```python
>>> B.remove_edge(2, 'c')
>>> nx.is_connected(B)
False
>>> bottom_nodes, top_nodes = bipartite.sets(B)
```

list(top_nodes) [1, 2, 4, 'c'] list(bottom_nodes) ['a', 3, 'b']

Using the “bipartite” node attribute, you can easily get the two node sets:
NetworkX Reference, Release 1.8

```python
top_nodes = set(n for n,d in B.nodes(data=True) if d['bipartite']==0)
bottom_nodes = set(B) - top_nodes
```

list(top_nodes) [1, 2, 3, 4] list(bottom_nodes) ['a', 'c', 'b']

So you can easily use the bipartite algorithms that require, as an argument, a container with all nodes that belong to one node set:

```python
print(round(bipartite.density(B, bottom_nodes),2))
0.42
G = bipartite.projected_graph(B, top_nodes)
G.edges()
[(1, 2), (1, 4)]
```

All bipartite graph generators in NetworkX build bipartite graphs with the “bipartite” node attribute. Thus, you can use the same approach:

```python
RB = nx.bipartite_random_graph(5, 7, 0.2)
RB_top = set(n for n,d in RB.nodes(data=True) if d['bipartite']==0)
RB_bottom = set(RB) - RB_top
list(RB_top)
[0, 1, 2, 3, 4]
list(RB_bottom)
[5, 6, 7, 8, 9, 10, 11]
```

For other bipartite graph generators see the bipartite section of Graph generators.

### 4.3.1 Basic functions

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<th>Function</th>
<th>Description</th>
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<td>is_bipartite(G)</td>
<td>Returns True if graph G is bipartite, False if not.</td>
</tr>
<tr>
<td>is_bipartite_node_set(G, nodes)</td>
<td>Returns True if nodes and G/nodes are a bipartition of G.</td>
</tr>
<tr>
<td>sets(G)</td>
<td>Returns bipartite node sets of graph G.</td>
</tr>
<tr>
<td>color(G)</td>
<td>Returns a two-coloring of the graph.</td>
</tr>
<tr>
<td>degrees(B, nodes[, weight])</td>
<td>Return the degrees of the two node sets in the bipartite graph B.</td>
</tr>
<tr>
<td>biadjacency_matrix(G, row_order[, ...])</td>
<td>Return the biadjacency matrix of the bipartite graph G.</td>
</tr>
</tbody>
</table>

#### is_bipartite

**is_bipartite**(G)

Returns True if graph G is bipartite, False if not.

**Parameters**

- G : NetworkX graph

**See also:**

color, is_bipartite_node_set

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> print(bipartite.is_bipartite(G))
True
```
is_bipartite_node_set

is_bipartite_node_set\((G, \text{nodes})\)
Returns True if nodes and G/nodes are a bipartition of G.

**Parameters**

- **G**: NetworkX graph
- **nodes**: list or container

  Check if nodes are a one of a bipartite set.

**Notes**
For connected graphs the bipartite sets are unique. This function handles disconnected graphs.

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> X = set([1,3])
>>> bipartite.is_bipartite_node_set(G,X)
True
```

sets

**sets\((G)\)**
Returns bipartite node sets of graph G.
Raises an exception if the graph is not bipartite.

**Parameters**

- **G**: NetworkX graph

**Returns**

- \((X,Y)\): two-tuple of sets

  One set of nodes for each part of the bipartite graph.

**See also:**

color

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> X, Y = bipartite.sets(G)
>>> list(X)
[0, 2]
>>> list(Y)
[1, 3]
```

color

color\((G)\)
Returns a two-coloring of the graph.
Raises an exception if the graph is not bipartite.

**Parameters**

- **G**: NetworkX graph

**Returns**

- **color**: dictionary
  A dictionary keyed by node with a 1 or 0 as data for each node color.

Raises NetworkXError if the graph is not two-colorable.

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> c = bipartite.color(G)
>>> print(c)
{0: 1, 1: 0, 2: 1, 3: 0}
```

You can use this to set a node attribute indicating the bipartite set:

```python
>>> nx.set_node_attributes(G, 'bipartite', c)
>>> print(G.node[0]['bipartite'])
1
>>> print(G.node[1]['bipartite'])
0
```

**density**

**density** *(B, nodes)*

Return density of bipartite graph B.

**Parameters**

- **G**: NetworkX graph

- **nodes**: list or container
  Nodes in one set of the bipartite graph.

**Returns**

- **d**: float
  The bipartite density

**See also:**

- **color**

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.complete_bipartite_graph(3,2)
>>> X=set([0,1,2])
>>> bipartite.density(G,X)
1.0
>>> Y=set([3,4])
>>> bipartite.density(G,Y)
1.0
```
degrees

degrees \((B, \text{nodes}, \text{weight}=\text{None})\)
Return the degrees of the two node sets in the bipartite graph \(B\).

Parameters

- **G**: NetworkX graph
- **nodes**: list or container
  - Nodes in one set of the bipartite graph.
- **weight**: string or None, optional (default=None)
  - The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns

- (degX,degY): tuple of dictionaries
  - The degrees of the two bipartite sets as dictionaries keyed by node.

See also:

color, density

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.complete_bipartite_graph(3,2)
>>> Y=set([3,4])
>>> degX,degY=bipartite.degrees(G,Y)
>>> degX
{0: 2, 1: 2, 2: 2}
```

biadjacency_matrix

biadjacency_matrix \((G, \text{row_order}, \text{column_order}=\text{None}, \text{weight}=\text{’weight’}, \text{dtype}=\text{None})\)
Return the biadjacency matrix of the bipartite graph \(G\).

Let \(G = (U, V, E)\) be a bipartite graph with node sets \(U = u_1, \ldots, u_r\) and \(V = v_1, \ldots, v_s\). The biadjacency matrix [1] is the \(r \times s\) matrix \(B\) in which \(b_{i,j} = 1\) if, and only if, \((u_i, v_j) \in E\). If the parameter \text{weight} is not \text{None} and matches the name of an edge attribute, its value is used instead of 1.

Parameters

- **G**: graph
  - A NetworkX graph
- **row_order**: list of nodes
  - The rows of the matrix are ordered according to the list of nodes.
- **column_order**: list, optional
  - The columns of the matrix are ordered according to the list of nodes. If \text{column_order} is \text{None}, then the ordering of columns is arbitrary.
- **weight**: string or None, optional (default=’weight’)
  - The edge data key used to provide each value in the matrix. If \text{None}, then each edge has weight 1.
- **dtype**: NumPy data type, optional

4.3. Bipartite
A valid single NumPy data type used to initialize the array. This must be a simple type such as int or numpy.float64 and not a compound data type (see to_numpy_recarray) If None, then the NumPy default is used.

**Returns**  

B : numpy matrix

Biadjacency matrix representation of the bipartite graph G.

**See also:**

to_numpy_matrix, adjacency_matrix

**Notes**

No attempt is made to check that the input graph is bipartite.

For directed bipartite graphs only successors are considered as neighbors. To obtain an adjacency matrix with ones (or weight values) for both predecessors and successors you have to generate two biadjacency matrices where the rows of one of them are the columns of the other, and then add one to the transpose of the other.

**References**


### 4.3.2 Projections

One-mode (unipartite) projections of bipartite graphs.

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<td>Returns the projection of B onto one of its node sets.</td>
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<td>Returns a weighted projection of B onto one of its node sets.</td>
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<td>generic_weighted_projected_graph</td>
<td>Weighted projection of B with a user-specified weight function.</td>
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**projected_graph**

projected_graph (B, nodes[, multigraph])

Returns the projection of B onto one of its node sets.

Returns the graph G that is the projection of the bipartite graph B onto the specified nodes. They retain their attributes and are connected in G if they have a common neighbor in B.

**Parameters**

B : NetworkX graph

The input graph should be bipartite.

nodes : list or iterable

Nodes to project onto (the “bottom” nodes).

multigraph : bool (default=False)

If True return a multigraph where the multiple edges represent multiple shared neighbors. They edge key in the multigraph is assigned to the label of the neighbor.

**Returns**

Graph : NetworkX graph or multigraph
A graph that is the projection onto the given nodes.

See also:

is_bipartite, is_bipartite_node_set, sets, weighted_projected_graph, collaboration_weighted_projected_graph, overlap_weighted_projected_graph, generic_weighted_projected_graph

Notes

No attempt is made to verify that the input graph B is bipartite. Returns a simple graph that is the projection of the bipartite graph B onto the set of nodes given in list nodes. If multigraph=True then a multigraph is returned with an edge for every shared neighbor.

Directed graphs are allowed as input. The output will also then be a directed graph with edges if there is a directed path between the nodes.

The graph and node properties are (shallow) copied to the projected graph.

Examples

```python
>>> from networkx.algorithms import bipartite
>>> B = nx.path_graph(4)
>>> G = bipartite.projected_graph(B, [1,3])
>>> print(G.nodes())
[1, 3]
>>> print(G.edges())
[(1, 3)]
```

If nodes a, and b are connected through both nodes 1 and 2 then building a multigraph results in two edges in the projection onto [a,’b’]:

```python
>>> B = nx.Graph()
>>> B.add_edges_from([('a', 1), ('b', 1), ('a', 2), ('b', 2)])
>>> G = bipartite.projected_graph(B, ['a', 'b'], multigraph=True)
>>> print({sorted((u,v)) for u,v in G.edges()})
[('a', 'b'), ('a', 'b')]```

weighted_projected_graph

```python
weighted_projected_graph (B, nodes, ratio=False)
```

Returns a weighted projection of B onto one of its node sets.

The weighted projected graph is the projection of the bipartite network B onto the specified nodes with weights representing the number of shared neighbors or the ratio between actual shared neighbors and possible shared neighbors if ratio=True [R149]. The nodes retain their attributes and are connected in the resulting graph if they have an edge to a common node in the original graph.

Parameters B : NetworkX graph

The input graph should be bipartite.

nodes : list or iterable

Nodes to project onto (the “bottom” nodes).

ratio : Bool (default=False) :
If True, edge weight is the ratio between actual shared neighbors and possible shared neighbors. If False, edges weight is the number of shared neighbors.

**Returns**  
**Graph** : NetworkX graph  
A graph that is the projection onto the given nodes.

**See also:**  
is_bipartite, is_bipartite_node_set, sets, collaboration_weighted_projected_graph, overlap_weighted_projected_graph, generic_weighted_projected_graph, projected_graph

**Notes**

No attempt is made to verify that the input graph B is bipartite. The graph and node properties are (shallow) copied to the projected graph.

**References**

[R149]

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> B = nx.path_graph(4)
>>> G = bipartite.weighted_projected_graph(B, [1, 3])
>>> print(G.nodes())
[1, 3]
>>> print(G.edges(data=True))
[(1, 3, {'weight': 1})]
>>> G = bipartite.weighted_projected_graph(B, [1, 3], ratio=True)
>>> print(G.edges(data=True))
[(1, 3, {'weight': 0.5})]
```

**collaboration_weighted_projected_graph**

The collaboration weighted projection is the projection of the bipartite network B onto the specified nodes with weights assigned using Newman’s collaboration model [R147]:

$$w_{v,u} = \sum_k \frac{\delta^w \delta^k}{k_w - 1}$$

where \(v\) and \(u\) are nodes from the same bipartite node set, and \(w\) is a node of the opposite node set. The value \(k_w\) is the degree of node \(w\) in the bipartite network and \(\delta^w\) is 1 if node \(v\) is linked to node \(w\) in the original bipartite graph or 0 otherwise.

The nodes retain their attributes and are connected in the resulting graph if have an edge to a common node in the original bipartite graph.

**Parameters**  
**B** : NetworkX graph
The input graph should be bipartite.

**nodes** : list or iterable

Nodes to project onto (the “bottom” nodes).

**Returns**  Graph : NetworkX graph

A graph that is the projection onto the given nodes.

**See also:**

is_bipartite, is_bipartite_node_set, sets, weighted_projected_graph, overlap_weighted_projected_graph, generic_weighted_projected_graph, projected_graph

**Notes**

No attempt is made to verify that the input graph B is bipartite. The graph and node properties are (shallow) copied to the projected graph.

**References**

[R147]

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> B = nx.path_graph(5)
>>> B.add_edge(1,5)
>>> G = bipartite.collaboration_weighted_projected_graph(B, [0, 2, 4, 5])
>>> print(G.nodes())
[0, 2, 4, 5]
>>> for edge in G.edges(data=True): print(edge)
...  (0, 2, {'weight': 0.5})
  (0, 5, {'weight': 0.5})
  (2, 4, {'weight': 1.0})
  (2, 5, {'weight': 0.5})
```

**overlap_weighted_projected_graph**

**overlap_weighted_projected_graph** *(B, nodes, jaccard=True)*

Overlap weighted projection of B onto one of its node sets.

The overlap weighted projection is the projection of the bipartite network B onto the specified nodes with weights representing the Jaccard index between the neighborhoods of the two nodes in the original bipartite network [R148]:

\[
w_{v,u} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|}
\]
or if the parameter ‘jaccard’ is False, the fraction of common neighbors by minimum of both nodes degree in
the original bipartite graph [R148]:

\[
\begin{align*}
    w_{v,u} &= \frac{|N(u) \cap N(v)|}{\min(|N(u)|, |N(v)|)}
\end{align*}
\]

The nodes retain their attributes and are connected in the resulting graph if have an edge to a common node in
the original bipartite graph.

**Parameters**

- **B**: NetworkX graph
  
  The input graph should be bipartite.

- **nodes**: list or iterable
  
  Nodes to project onto (the “bottom” nodes).

- **jaccard**: Bool (default=True):
  
  Returns **Graph**: NetworkX graph
  
  A graph that is the projection onto the given nodes.

**See also:**

- is_bipartite
- is_bipartite_node_set
- sets
- weighted_projected_graph
- collaboration_weighted_projected_graph
- generic_weighted_projected_graph
- projected_graph

**Notes**

No attempt is made to verify that the input graph B is bipartite. The graph and node properties are (shallow)
copied to the projected graph.

**References**

[R148]

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> B = nx.path_graph(5)
>>> G = bipartite.overlap_weighted_projected_graph(B, [0, 2, 4])
>>> print(G.nodes())
[0, 2, 4]
>>> print(G.edges(data=True))
[(0, 2, {'weight': 0.5}), (2, 4, {'weight': 0.5})]
>>> G = bipartite.overlap_weighted_projected_graph(B, [0, 2, 4], jaccard=False)
>>> print(G.edges(data=True))
[(0, 2, {'weight': 1.0}), (2, 4, {'weight': 1.0})]
```

generic_weighted_projected_graph

**generic_weighted_projected_graph**

\((B, \text{nodes}, \text{weight\_function=None})\)

Weighted projection of B with a user-specified weight function.
The bipartite network B is projected on to the specified nodes with weights computed by a user-specified function. This function must accept as a parameter the neighborhood sets of two nodes and return an integer or a float.

The nodes retain their attributes and are connected in the resulting graph if they have an edge to a common node in the original graph.

**Parameters**

- **B**: NetworkX graph
  
  The input graph should be bipartite.

- **nodes**: list or iterable
  
  Nodes to project onto (the “bottom” nodes).

- **weight_function**: function
  
  This function must accept as parameters the same input graph that this function, and two nodes; and return an integer or a float. The default function computes the number of shared neighbors.

**Returns**

- **Graph**: NetworkX graph
  
  A graph that is the projection onto the given nodes.

**See also:**

- `is_bipartite`
- `is_bipartite_node_set`
- `sets`
- `weighted_projected_graph`
- `collaboration_weighted_projected_graph`
- `overlap_weighted_projected_graph`
- `projected_graph`

**Notes**

No attempt is made to verify that the input graph B is bipartite. The graph and node properties are (shallow) copied to the projected graph.

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> # Define some custom weight functions
>>> def jaccard(G, u, v):
...    unbrs = set(G[u])
...    vnbrs = set(G[v])
...    return float(len(unbrs & vnbrs)) / len(unbrs | vnbrs)
...    
>>> def my_weight(G, u, v, weight='weight'):
...    w = 0
...    for nbr in set(G[u]) & set(G[v]):
...        w += G.edge[u][nbr].get(weight, 1) + G.edge[v][nbr].get(weight, 1)
...    return w
...    
>>> # A complete bipartite graph with 4 nodes and 4 edges
>>> B = nx.complete_bipartite_graph(2,2)
>>> # Add some arbitrary weight to the edges
>>> for i, (u,v) in enumerate(B.edges()):
...        B.edge[u][v][‘weight’] = i + 1
...        
>>> for edge in B.edges(data=True):
...            print(edge)
```
NetworkX Reference, Release 1.8

>>> (0, 2, {'weight': 1})
>>> (0, 3, {'weight': 2})
>>> (1, 2, {'weight': 3})
>>> (1, 3, {'weight': 4})

>>> # Without specifying a function, the weight is equal to # shared partners
>>> G = bipartite.generic_weighted_projected_graph(B, [0, 1])
>>> print(G.edges(data=True))
[(0, 1, {'weight': 2})]

>>> # To specify a custom weight function use the weight_function parameter
>>> G = bipartite.generic_weighted_projected_graph(B, [0, 1], weight_function=jaccard)
>>> print(G.edges(data=True))
[(0, 1, {'weight': 1.0})]

4.3.3 Spectral

Spectral bipartivity measure.

spectral_bipartivity

spectral_bipartivity(G[, nodes, weight]) Returns the spectral bipartivity.

Parameters

- **G**: NetworkX graph
- **nodes**: list or container optional (default is all nodes)
- **weight**: string or None optional (default = 'weight')

Returns

- **sb**: float or dict
  - A single number if the keyword nodes is not specified, or a dictionary keyed by node with the spectral bipartivity contribution of that node as the value.

See also:

color

Notes

This implementation uses Numpy (dense) matrices which are not efficient for storing large sparse graphs.

References

[R151]
Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> bipartite.spectral_bipartivity(G)
1.0
```

4.3.4 Clustering

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<td>Compute a bipartite clustering coefficient for nodes.</td>
</tr>
<tr>
<td><code>average_clustering(G[, nodes, mode])</code></td>
<td>Compute the average bipartite clustering coefficient.</td>
</tr>
<tr>
<td><code>latapy_clustering(G[, nodes, mode])</code></td>
<td>Compute a bipartite clustering coefficient for nodes.</td>
</tr>
<tr>
<td><code>robins_alexander_clustering(G)</code></td>
<td>Compute the bipartite clustering of G.</td>
</tr>
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</table>

**clustering**

**clustering** *(G, nodes=None, mode=’dot’)*

Compute a bipartite clustering coefficient for nodes.

The bipartite clustering coefficient is a measure of local density of connections defined as [R144]:

\[ c_u = \frac{\sum_{v \in N(N(u))} c_{uv}}{|N(N(u))|} \]

where \( N(N(u)) \) are the second order neighbors of \( u \) in \( G \) excluding \( u \), and \( c_{uv} \) is the pairwise clustering coefficient between nodes \( u \) and \( v \).

The mode selects the function for \( c_{uv} \) which can be:

- **dot**:

\[ c_{uv} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|} \]

- **min**:

\[ c_{uv} = \frac{|N(u) \cap N(v)|}{\min(|N(u)|, |N(v)|)} \]

- **max**:

\[ c_{uv} = \frac{|N(u) \cap N(v)|}{\max(|N(u)|, |N(v)|)} \]

**Parameters**

\[ G : \text{graph} \]

A bipartite graph

\[ \text{nodes} : \text{list or iterable (optional)} \]

Compute bipartite clustering for these nodes. The default is all nodes in \( G \).

\[ \text{mode} : \text{string} \]

The pairwise bipartite clustering method to be used in the computation. It must be “dot”, “max”, or “min”.

**Returns**

clustering : dictionary

4.3. Bipartite
A dictionary keyed by node with the clustering coefficient value.

See also:

robins_alexander_clustering, square_clustering, average_clustering

References

[R144]

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)  # path graphs are bipartite
>>> c = bipartite.clustering(G)
>>> c[0]
0.5
>>> c = bipartite.clustering(G, mode='min')
>>> c[0]
1.0
```

average_clustering

```python
average_clustering(G, nodes=None, mode='dot')
```

Compute the average bipartite clustering coefficient.

A clustering coefficient for the whole graph is the average,

\[
C = \frac{1}{n} \sum_{v \in G} c_v,
\]

where \( n \) is the number of nodes in \( G \).

Similar measures for the two bipartite sets can be defined [R143]

\[
C_X = \frac{1}{|X|} \sum_{v \in X} c_v,
\]

where \( X \) is a bipartite set of \( G \).

Parameters

- **G**: graph
  - a bipartite graph
- **nodes**: list or iterable, optional
  - A container of nodes to use in computing the average. The nodes should be either the entire graph (the default) or one of the bipartite sets.
- **mode**: string
  - The pairwise bipartite clustering method. It must be “dot”, “max”, or “min”

Returns

- **clustering**: float
  - The average bipartite clustering for the given set of nodes or the entire graph if no nodes are specified.

See also:

clustering
Notes

The container of nodes passed to this function must contain all of the nodes in one of the bipartite sets (“top” or “bottom”) in order to compute the correct average bipartite clustering coefficients.

References

[R143]

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G=nx.star_graph(3)  # star graphs are bipartite
>>> bipartite.average_clustering(G)
0.75
>>> X,Y=bipartite.sets(G)
>>> bipartite.average_clustering(G,X)
0.0
>>> bipartite.average_clustering(G,Y)
1.0
```

latex_clustering

latex_clustering (G, nodes=None, mode='dot')

Compute a bipartite clustering coefficient for nodes.

The bipartite clustering coefficient is a measure of local density of connections defined as [R145]:

\[ c_u = \frac{\sum_{v \in N(N(u))} c_{uv}}{|N(N(u))|} \]

where \( N(N(u)) \) are the second order neighbors of \( u \) in \( G \) excluding \( u \), and \( c_{uv} \) is the pairwise clustering coefficient between nodes \( u \) and \( v \).

The mode selects the function for \( c_{uv} \) which can be:

**dot**:

\[ c_{uv} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|} \]

**min**:

\[ c_{uv} = \frac{|N(u) \cap N(v)|}{\min(|N(u)|, |N(v)|)} \]

**max**:

\[ c_{uv} = \frac{|N(u) \cap N(v)|}{\max(|N(u)|, |N(v)|)} \]

Parameters

- **G** : graph
  A bipartite graph
- **nodes** : list or iterable (optional)
Compute bipartite clustering for these nodes. The default is all nodes in G.

**mode**: string

The pairwise bipartite clustering method to be used in the computation. It must be “dot”, “max”, or “min”.

**Returns clustering**: dictionary

A dictionary keyed by node with the clustering coefficient value.

**See also:**

robins_alexander_clustering, square_clustering, average_clustering

**References**

[R145]

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)  # path graphs are bipartite
>>> c = bipartite.clustering(G)
>>> c[0]
0.5
>>> c = bipartite.clustering(G, mode='min')
>>> c[0]
1.0
```

**robins_alexander_clustering**

**robins_alexander_clustering** *(G)*

Compute the bipartite clustering of G.

Robins and Alexander [R146] defined bipartite clustering coefficient as four times the number of four cycles \( C_4 \) divided by the number of three paths \( L_3 \) in a bipartite graph:

\[
CC_4 = \frac{4 \times C_4}{L_3}
\]

**Parameters**

\( G \) : graph

A bipartite graph

**Returns clustering** : float

The Robins and Alexander bipartite clustering for the input graph.

**See also:**

latapy_clustering, square_clustering

**References**

[R146]
Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.davis_southern_women_graph()
>>> print(round(bipartite.robins_alexander_clustering(G), 3))
0.468
```

4.3.5 Redundancy

Node redundancy for bipartite graphs.

```
node_redundancy(G[, nodes])  Compute bipartite node redundancy coefficient.
```

```
node_redundancy (G, nodes=None)
  Compute bipartite node redundancy coefficient.

  The redundancy coefficient of a node \(v\) is the fraction of pairs of neighbors of \(v\) that are both linked to other nodes. In a one-mode projection these nodes would be linked together even if \(v\) were not there.

  \[
  rc(v) = \frac{|\{\{u, w\} \subseteq N(v), \exists v' \neq v, (v', u) \in E \text{ and } (v', w) \in E\}|}{|N(v)||N(v)| - 1}
  \]

  where \(N(v)\) are the neighbors of \(v\) in \(G\).

  Parameters
  
  * G : graph
    A bipartite graph
  
  * nodes : list or iterable (optional)
    Compute redundancy for these nodes. The default is all nodes in \(G\).

  Returns
  
  * redundancy : dictionary
    A dictionary keyed by node with the node redundancy value.

  References

  [R150]
```

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.cycle_graph(4)
>>> rc = bipartite.node_redundancy(G)
>>> rc[0]
1.0
```

Compute the average redundancy for the graph:

```python
>>> sum(rc.values()) / len(G)
1.0
```
Compute the average redundancy for a set of nodes:

```python
>>> nodes = [0, 2]
>>> sum(rc[n] for n in nodes)/len(nodes)
1.0
```

### 4.3.6 Centrality

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<td>Compute the closeness centrality for nodes in a bipartite network.</td>
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<td><code>degree_centrality(G, nodes)</code></td>
<td>Compute the degree centrality for nodes in a bipartite network.</td>
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<td><code>betweenness_centrality(G, nodes)</code></td>
<td>Compute betweenness centrality for nodes in a bipartite network.</td>
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#### closeness_centrality

**closeness_centrality** *(G, nodes, normalized=True)*

Compute the closeness centrality for nodes in a bipartite network.

The closeness of a node is the distance to all other nodes in the graph or in the case that the graph is not connected to all other nodes in the connected component containing that node.

**Parameters**

- **G**: graph
  - A bipartite network
- **nodes**: list or container
  - Container with all nodes in one bipartite node set.
- **normalized**: bool, optional
  - If True (default) normalize by connected component size.

**Returns**

- **closeness**: dictionary
  - Dictionary keyed by node with bipartite closeness centrality as the value.

**See also:**

- `betweenness_centrality`, `degree_centrality`, `sets`, `is_bipartite`

**Notes**

The nodes input parameter must contain all nodes in one bipartite node set, but the dictionary returned contains all nodes from both node sets.

Closeness centrality is normalized by the minimum distance possible. In the bipartite case the minimum distance for a node in one bipartite node set is 1 from all nodes in the other node set and 2 from all other nodes in its own set [R141]. Thus the closeness centrality for node *v* in the two bipartite sets *U* with *n* nodes and *V* with *m* nodes is

\[
c_v = \frac{m + 2(n - 1)}{d}, \text{for } v \in U,
\]

\[
c_v = \frac{n + 2(m - 1)}{d}, \text{for } v \in V,
\]

where *d* is the sum of the distances from *v* to all other nodes.

Higher values of closeness indicate higher centrality.
As in the unipartite case, setting normalized=True causes the values to normalized further to n-1 / size(G)-1
where n is the number of nodes in the connected part of graph containing the node. If the graph is not completely
connected, this algorithm computes the closeness centrality for each connected part separately.

References

[R141]
degree_centrality
degree_centrality (G, nodes)
Compute the degree centrality for nodes in a bipartite network.
The degree centrality for a node v is the fraction of nodes connected to it.

Parameters  G : graph
A bipartite network
nodes : list or container
Container with all nodes in one bipartite node set.

Returns  centrality : dictionary
Dictionary keyed by node with bipartite degree centrality as the value.

See also:
betweenness_centrality, closeness_centrality, sets, is_bipartite

Notes

The nodes input parameter must contain all nodes in one bipartite node set, but the dictionary returned contains
all nodes from both bipartite node sets.

For unipartite networks, the degree centrality values are normalized by dividing by the maximum possible degree
(which is n – 1 where n is the number of nodes in G).

In the bipartite case, the maximum possible degree of a node in a bipartite node set is the number of nodes in
the opposite node set [R142]. The degree centrality for a node v in the bipartite sets U with n nodes and V with
m nodes is

\[ d_v = \frac{\text{deg}(v)}{m}, \text{for } v \in U, \]

\[ d_v = \frac{\text{deg}(v)}{n}, \text{for } v \in V, \]

where \( \text{deg}(v) \) is the degree of node v.

References

[R142]
betweenness_centrality

betweenness_centrality \( (G, \text{nodes}) \)
Compute betweenness centrality for nodes in a bipartite network.

Betweenness centrality of a node \( v \) is the sum of the fraction of all-pairs shortest paths that pass through \( v \).

Values of betweenness are normalized by the maximum possible value which for bipartite graphs is limited by the relative size of the two node sets \([R140]\).

Let \( n \) be the number of nodes in the node set \( U \) and \( m \) be the number of nodes in the node set \( V \), then nodes in \( U \) are normalized by dividing by

\[
\frac{1}{2}[m^2(s+1)^2 + m(s+1)(2t - s - 1) - t(2s - t + 3)],
\]

where

\[
s = (n - 1) \div m, \quad t = (n - 1) \mod m,
\]

and nodes in \( V \) are normalized by dividing by

\[
\frac{1}{2}[n^2(p+1)^2 + n(p+1)(2r - p - 1) - r(2p - r + 3)],
\]

where,

\[
p = (m - 1) \div n, \quad r = (m - 1) \mod n.
\]

**Parameters**

- \( G \) : graph
  A bipartite graph

- \( \text{nodes} \) : list or container
  Container with all nodes in one bipartite node set.

**Returns**

- betweenness : dictionary
  Dictionary keyed by node with bipartite betweenness centrality as the value.

**See also:**

degree_centrality, closeness_centrality, sets, is_bipartite

**Notes**

The nodes input parameter must contain all nodes in one bipartite node set, but the dictionary returned contains all nodes from both node sets.

**References**

[R140]

### 4.4 Blockmodeling

Functions for creating network blockmodels from node partitions.

Created by Drew Conway <drew.conway@nyu.edu> Copyright (c) 2010. All rights reserved.
blockmodel(G, partitions[, multigraph]) Returns a reduced graph constructed using the generalized block modeling technique.

4.4.1 blockmodel

blockmodel (G, partitions, multigraph=False)
Returns a reduced graph constructed using the generalized block modeling technique.

The blockmodel technique collapses nodes into blocks based on a given partitioning of the node set. Each partition of nodes (block) is represented as a single node in the reduced graph.

Edges between nodes in the block graph are added according to the edges in the original graph. If the parameter multigraph is False (the default) a single edge is added with a weight equal to the sum of the edge weights between nodes in the original graph. The default is a weight of 1 if weights are not specified. If the parameter multigraph is True then multiple edges are added each with the edge data from the original graph.

Parameters
G : graph
A networkx Graph or DiGraph
partitions : list of lists, or list of sets
The partition of the nodes. Must be non-overlapping.
multigraph : bool, optional
If True return a MultiGraph with the edge data of the original graph applied to each corresponding edge in the new graph. If False return a Graph with the sum of the edge weights, or a count of the edges if the original graph is unweighted.

Returns blockmodel : a Networkx graph object

References
[R152]

Examples
>>> G=nx.path_graph(6)
>>> partition=[[0,1],[2,3],[4,5]]
>>> M=nx.blockmodel(G,partition)

4.5 Boundary

Routines to find the boundary of a set of nodes.

Edge boundaries are edges that have only one end in the set of nodes.

Node boundaries are nodes outside the set of nodes that have an edge to a node in the set.

edge_boundary(G, nbunch1[, nbunch2]) Return the edge boundary.
node_boundary(G, nbunch1[, nbunch2]) Return the node boundary.
4.5.1 edge_boundary

**edge_boundary** *(G, nbunch1, nbunch2=None)*

Return the edge boundary.

Edge boundaries are edges that have only one end in the given set of nodes.

**Parameters**

- **G** : graph
  A networkx graph
- **nbunch1** : list, container
  Interior node set
- **nbunch2** : list, container
  Exterior node set. If None then it is set to all of the nodes in G not in nbunch1.

**Returns**

- **elist** : list
  List of edges

**Notes**

Nodes in nbunch1 and nbunch2 that are not in G are ignored.

nbunch1 and nbunch2 are usually meant to be disjoint, but in the interest of speed and generality, that is not required here.

4.5.2 node_boundary

**node_boundary** *(G, nbunch1, nbunch2=None)*

Return the node boundary.

The node boundary is all nodes in the edge boundary of a given set of nodes that are in the set.

**Parameters**

- **G** : graph
  A networkx graph
- **nbunch1** : list, container
  Interior node set
- **nbunch2** : list, container
  Exterior node set. If None then it is set to all of the nodes in G not in nbunch1.

**Returns**

- **nlist** : list
  List of nodes.

**Notes**

Nodes in nbunch1 and nbunch2 that are not in G are ignored.

nbunch1 and nbunch2 are usually meant to be disjoint, but in the interest of speed and generality, that is not required here.
4.6 Centrality

4.6.1 Degree

degree_centrality

degree_centrality \( (G) \)
Compute the degree centrality for nodes.

The degree centrality for a node \( v \) is the fraction of nodes it is connected to.

Parameters:
- \( G \) : graph
  A networkx graph

Returns:
- \( \text{nodes} \) : dictionary
  Dictionary of nodes with degree centrality as the value.

See also:
- betweenness_centrality, load_centrality, eigenvector_centrality

Notes

The degree centrality values are normalized by dividing by the maximum possible degree in a simple graph \( n-1 \) where \( n \) is the number of nodes in \( G \).

For multigraphs or graphs with self loops the maximum degree might be higher than \( n-1 \) and values of degree centrality greater than 1 are possible.

in_degree_centrality

in_degree_centrality \( (G) \)
Compute the in-degree centrality for nodes.

The in-degree centrality for a node \( v \) is the fraction of nodes its incoming edges are connected to.

Parameters:
- \( G \) : graph
  A NetworkX graph

Returns:
- \( \text{nodes} \) : dictionary
  Dictionary of nodes with in-degree centrality as values.

See also:
- degree_centrality, out_degree_centrality
Notes

The degree centrality values are normalized by dividing by the maximum possible degree in a simple graph \(n-1\) where \(n\) is the number of nodes in \(G\).

For multigraphs or graphs with self loops the maximum degree might be higher than \(n-1\) and values of degree centrality greater than 1 are possible.

**out_degree_centrality**

**out_degree_centrality**\((G)\)

Compute the out-degree centrality for nodes.

The out-degree centrality for a node \(v\) is the fraction of nodes its outgoing edges are connected to.

**Parameters**

- \(G\) : graph
  A NetworkX graph

**Returns**

- nodes : dictionary
  Dictionary of nodes with out-degree centrality as values.

**See also:**

degree_centrality, in_degree_centrality

Notes

The degree centrality values are normalized by dividing by the maximum possible degree in a simple graph \(n-1\) where \(n\) is the number of nodes in \(G\).

For multigraphs or graphs with self loops the maximum degree might be higher than \(n-1\) and values of degree centrality greater than 1 are possible.

### 4.6.2 Closeness

**closeness_centrality**\((G[, u, distance, ...])\)

Compute closeness centrality for nodes.

Closeness centrality [R157] of a node \(u\) is the reciprocal of the sum of the shortest path distances from \(u\) to all \(n - 1\) other nodes. Since the sum of distances depends on the number of nodes in the graph, closeness is normalized by the sum of minimum possible distances \(n - 1\).

\[
C(u) = \frac{n - 1}{\sum_{v=1}^{n} d(v, u)},
\]

where \(d(v, u)\) is the shortest-path distance between \(v\) and \(u\), and \(n\) is the number of nodes in the graph.

Notice that higher values of closeness indicate higher centrality.

**Parameters**

- \(G\) : graph
A NetworkX graph

\[ u : \text{node, optional} \]

Return only the value for node \( u \)

\[ \text{distance} : \text{edge attribute key, optional (default=None)} \]

Use the specified edge attribute as the edge distance in shortest path calculations

\[ \text{normalized} : \text{bool, optional} \]

If True (default) normalize by the number of nodes in the connected part of the graph.

**Returns**

\[ \text{nodes} : \text{dictionary} \]

Dictionary of nodes with closeness centrality as the value.

**See also:**

\[ \text{betweenness_centrality, load_centrality, eigenvector_centrality, degree_centrality} \]

**Notes**

The closeness centrality is normalized to \((n - 1)/(|G| - 1)\) where \( n \) is the number of nodes in the connected part of graph containing the node. If the graph is not completely connected, this algorithm computes the closeness centrality for each connected part separately.

If the ‘distance’ keyword is set to an edge attribute key then the shortest-path length will be computed using Dijkstra’s algorithm with that edge attribute as the edge weight.

**References**

[R157]

### 4.6.3 Betweenness

**betweenness_centrality**

\[ \text{betweenness_centrality}(G[\, \text{k=None, normalized, ...}]) \]

Compute the shortest-path betweenness centrality for nodes.

**edge_betweenness_centrality**

\[ \text{edge_betweenness_centrality}(G[\, \text{normalized, ...}]) \]

Compute betweenness centrality for edges.

**betweenness_centrality**

\[ \text{betweenness_centrality}(G, \text{k=None, normalized=True, weight=None, endpoints=False, seed=None}) \]

Compute the shortest-path betweenness centrality for nodes.

Betweenness centrality of a node \( v \) is the sum of the fraction of all-pairs shortest paths that pass through \( v \):

\[ c_B(v) = \sum_{s,t \in V} \frac{\sigma(s, t \mid v)}{\sigma(s, t)} \]

where \( V \) is the set of nodes, \( \sigma(s, t) \) is the number of shortest \((s, t)\)-paths, and \( \sigma(s, t \mid v) \) is the number of those paths passing through some node \( v \) other than \( s, t \). If \( s = t \), \( \sigma(s, t) = 1 \), and if \( v \in s, t \), \( \sigma(s, t \mid v) = 0 \) [R155].

**Parameters**

\[ G : \text{graph} \]

A NetworkX graph
k : int, optional (default=None)
    If k is not None use k node samples to estimate betweenness. The value of k <= n where n is the number of nodes in the graph. Higher values give better approximation.

normalized : bool, optional
    If True the betweenness values are normalized by \(2/((n-1)(n-2))\) for graphs, and \(1/((n-1)(n-2))\) for directed graphs where n is the number of nodes in G.

weight : None or string, optional
    If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

equivalents : bool, optional
    If True include the endpoints in the shortest path counts.

Returns nodes : dictionary
    Dictionary of nodes with betweenness centrality as the value.

See also:
    edge_betweenness_centrality, load_centrality

Notes

The algorithm is from Ulrik Brandes [R154]. See [R155] for details on algorithms for variations and related metrics.

For approximate betweenness calculations set k=#samples to use k nodes ("pivots") to estimate the betweenness values. For an estimate of the number of pivots needed see [R156].

For weighted graphs the edge weights must be greater than zero. Zero edge weights can produce an infinite number of equal length paths between pairs of nodes.

References

[R154], [R155], [R156]

edge_betweenness_centrality

equivalents (G, normalized=True, weight=0)
    Compute betweenness centrality for edges.

    Betweenness centrality of an edge e is the sum of the fraction of all-pairs shortest paths that pass through e:

\[
c_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|e)}{\sigma(s,t)}
\]

where V is the set of nodes, \(\sigma(s,t)\) is the number of shortest \((s,t)\)-paths, and \(\sigma(s,t|e)\) is the number of those paths passing through edge e [R171].

Parameters G : graph
    A NetworkX graph

    normalized : bool, optional
If True the betweenness values are normalized by $2/(n(n-1))$ for graphs, and $1/(n(n-1))$ for directed graphs where $n$ is the number of nodes in $G$.

**weight**: None or string, optional

If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

**Returns**

**edges**: dictionary

Dictionary of edges with betweenness centrality as the value.

**See also**:

`betweenness_centrality`, `edge_load`

**Notes**

The algorithm is from Ulrik Brandes [R170].

For weighted graphs the edge weights must be greater than zero. Zero edge weights can produce an infinite number of equal length paths between pairs of nodes.

**References**

[R170], [R171]

### 4.6.4 Current Flow Closeness

`current_flow_closeness_centrality(G, ...)` Compute current-flow closeness centrality for nodes.

**current_flow_closeness_centrality**

`current_flow_closeness_centrality(G, normalized=True, weight='weight', dtype=<type 'float'>, solver='lu')`

Compute current-flow closeness centrality for nodes.

A variant of closeness centrality based on effective resistance between nodes in a network. This metric is also known as information centrality.

**Parameters**

**G**: graph

A NetworkX graph

**normalized**: bool, optional

If True the values are normalized by $1/(n-1)$ where $n$ is the number of nodes in $G$.

**dtype**: data type (float)

Default data type for internal matrices. Set to np.float32 for lower memory consumption.

**solver**: string (default='lu')

Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).
Returns `nodes`: dictionary

Dictionary of nodes with current flow closeness centrality as the value.

See also:

closeness_centrality

Notes

The algorithm is from Brandes [R168].

See also [R169] for the original definition of information centrality.

References

[R168], [R169]

4.6.5 Current-Flow Betweenness

current_flow_betweenness_centrality(G[, ...]) Compute current-flow betweenness centrality for nodes.

dict = current_flow_betweenness_centrality(G)

edge_current_flow_betweenness_centrality(G) Compute current-flow betweenness centrality for edges.

approximate_current_flow_betweenness_centrality(G) Compute the approximate current-flow betweenness centrality for nodes.

current_flow_betweenness_centrality

current_flow_betweenness_centrality(G, normalized=True, weight='weight', dtype=<type 'float'>, solver='full') Compute current-flow betweenness centrality for nodes.

Current-flow betweenness centrality uses an electrical current model for information spreading in contrast to betweenness centrality which uses shortest paths.

Current-flow betweenness centrality is also known as random-walk betweenness centrality [R167].

Parameters

`G`: graph

A NetworkX graph

`normalized`: bool, optional (default=True)

If True the betweenness values are normalized by \( 2/[(n-1)(n-2)] \) where \( n \) is the number of nodes in \( G \).

`weight`: string or None, optional (default='weight')

Key for edge data used as the edge weight. If None, then use 1 as each edge weight.

`dtype`: data type (float)

Default data type for internal matrices. Set to np.float32 for lower memory consumption.

`solver`: string (default='lu')

Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).
Returns  nodes : dictionary

Dictionary of nodes with betweenness centrality as the value.

See also:
approximate_current_flow_betweenness_centrality,  betweenness_centrality,
edge_betweenness_centrality,edge_current_flow_betweenness_centrality

Notes

Current-flow betweenness can be computed in \( O(I(n - 1) + mn \log n) \) time [R166], where \( I(n - 1) \) is the time needed to compute the inverse Laplacian. For a full matrix this is \( O(n^3) \) but using sparse methods you can achieve \( O(nm\sqrt{k}) \) where \( k \) is the Laplacian matrix condition number.

The space required is \( O(nw) \) where \( w \) is the width of the sparse Laplacian matrix. Worse case is \( w = n \) for \( O(n^2) \).

If the edges have a ‘weight’ attribute they will be used as weights in this algorithm. Unspecified weights are set to 1.

References

[R166], [R167]

edge_current_flow_betweenness_centrality

edge_current_flow_betweenness_centrality \((G, \ normalized=True, \ weight='weight', \ dtype=<type 'float'>, \ solver='full')\)

Compute current-flow betweenness centrality for edges.

Current-flow betweenness centrality uses an electrical current model for information spreading in contrast to betweenness centrality which uses shortest paths.

Current-flow betweenness centrality is also known as random-walk betweenness centrality [R173].

Parameters  G : graph

A NetworkX graph

normalized : bool, optional (default=True)

If True the betweenness values are normalized by \( 2/((n-1)(n-2)) \) where \( n \) is the number of nodes in \( G \).

weight : string or None, optional (default='weight')

Key for edge data used as the edge weight. If None, then use 1 as each edge weight.

dtype: data type (float) :

Default data type for internal matrices. Set to np.float32 for lower memory consumption.

solver: string (default='lu') :

Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses less memory).

Returns  nodes : dictionary
Dictionary of edge tuples with betweenness centrality as the value.

See also:

betweenness_centrality, edge_betweenness_centrality, current_flow_betweenness_centrality

Notes

Current-flow betweenness can be computed in $O\left(I(n - 1) + mn \log n\right)$ time [R172], where $I(n - 1)$ is the time needed to compute the inverse Laplacian. For a full matrix this is $O(n^3)$ but using sparse methods you can achieve $O\left(mn \sqrt{k}\right)$ where $k$ is the Laplacian matrix condition number.

The space required is $O(nw)$ where $w$ is the width of the sparse Laplacian matrix. Worse case is $w = n$ for $O(n^2)$.

If the edges have a ‘weight’ attribute they will be used as weights in this algorithm. Unspecified weights are set to 1.

References

[R172], [R173]

approximate_current_flow_betweenness_centrality

approximate_current_flow_betweenness_centrality(G, normalized=True, weight='weight', dtype=<type 'float'>, solver='full', epsilon=0.5, kmax=10000)

Compute the approximate current-flow betweenness centrality for nodes.

Approximates the current-flow betweenness centrality within absolute error of epsilon with high probability [R153].

Parameters

G : graph
  A NetworkX graph
normalized : bool, optional (default=True)
  If True the betweenness values are normalized by $2/(n-1)(n-2)$ where $n$ is the number of nodes in $G$.
weight : string or None, optional (default='weight')
  Key for edge data used as the edge weight. If None, then use 1 as each edge weight.
dtype : data type (float)
  Default data type for internal matrices. Set to np.float32 for lower memory consumption.
solver : string (default='lu')
  Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).
epsilon : float
  Absolute error tolerance.
kmax : int
Maximum number of sample node pairs to use for approximation.

**Returns** nodes : dictionary

Dictionary of nodes with betweenness centrality as the value.

**See also:**

*current_flow_betweenness_centrality*

**Notes**

The running time is $O((1/\epsilon^2)m\sqrt{k}\log n)$ and the space required is $O(m)$ for $n$ nodes and $m$ edges.

If the edges have a 'weight' attribute they will be used as weights in this algorithm. Unspecified weights are set to 1.

**References**

[R153]

### 4.6.6 Eigenvector

**eigenvector_centrality**($G$, max_iter, tol, ...)

Compute the eigenvector centrality for the graph $G$.

**eigenvector_centrality_numpy**($G$)

Compute the eigenvector centrality for the graph $G$.

**katz_centrality**($G$, alpha, beta, max_iter, ...)

Compute the Katz centrality for the nodes of the graph $G$.

**katz_centrality_numpy**($G$, alpha, beta, ...)

Compute the Katz centrality for the graph $G$.

**eigenvector_centrality**

**eigenvector_centrality** ($G$, max_iter=100, tol=1e-06, nstart=None)

Compute the eigenvector centrality for the graph $G$.

Uses the power method to find the eigenvector for the largest eigenvalue of the adjacency matrix of $G$.

**Parameters**

- $G$ : graph
  - A networkx graph
- max_iter : integer, optional
  - Maximum number of iterations in power method.
- tol : float, optional
  - Error tolerance used to check convergence in power method iteration.
- nstart : dictionary, optional
  - Starting value of eigenvector iteration for each node.

**Returns**

- nodes : dictionary
  - Dictionary of nodes with eigenvector centrality as the value.

**See also:**

*eigenvector_centrality_numpy*, pagerank, hits
Notes

The eigenvector calculation is done by the power iteration method and has no guarantee of convergence. The iteration will stop after max_iter iterations or an error tolerance of number_of_nodes(G)*tol has been reached. For directed graphs this is “right” eigenvector centrality. For “left” eigenvector centrality, first reverse the graph with G.reverse().

Examples

```python
>>> G=nx.path_graph(4)
>>> centrality=nx.eigenvector_centrality(G)
>>> print(['%s %0.2f' % (node,centrality[node]) for node in centrality])
['0 0.37', '1 0.60', '2 0.60', '3 0.37']
```

eigenvector_centrality_numpy

**eigenvector_centrality_numpy** *(G)*

Compute the eigenvector centrality for the graph G.

**Parameters**

- `G` : graph
  A networkx graph

**Returns**

- `nodes` : dictionary
  Dictionary of nodes with eigenvector centrality as the value.

**See also:**

eigenvector_centrality, pagerank, hits

Notes

This algorithm uses the NumPy eigenvalue solver. For directed graphs this is “right” eigenvector centrality. For “left” eigenvector centrality, first reverse the graph with G.reverse().

Examples

```python
>>> G=nx.path_graph(4)
>>> centrality=nx.eigenvector_centrality_numpy(G)
>>> print(['%s %0.2f' % (node,centrality[node]) for node in centrality])
['0 0.37', '1 0.60', '2 0.60', '3 0.37']
```

katz_centrality

**katz_centrality** *(G, alpha=0.1, beta=1.0, max_iter=1000, tol=1e-06, nstart=None, normalized=True)*

Compute the Katz centrality for the nodes of the graph G.
Katz centrality is related to eigenvalue centrality and PageRank. The Katz centrality for node \( i \) is

\[
x_i = \alpha \sum_j A_{ij} x_j + \beta,
\]

where \( A \) is the adjacency matrix of the graph \( G \) with eigenvalues \( \lambda \).

The parameter \( \beta \) controls the initial centrality and

\[
\alpha < \frac{1}{\lambda_{max}}.
\]

Katz centrality computes the relative influence of a node within a network by measuring the number of the immediate neighbors (first degree nodes) and also all other nodes in the network that connect to the node under consideration through these immediate neighbors.

Extra weight can be provided to immediate neighbors through the parameter \( \beta \). Connections made with distant neighbors are, however, penalized by an attenuation factor \( \alpha \) which should be strictly less than the inverse largest eigenvalue of the adjacency matrix in order for the Katz centrality to be computed correctly. More information is provided in [R175].

**Parameters**

\( G \) : graph
- A NetworkX graph

\( \alpha \) : float
- Attenuation factor

\( \beta \) : scalar or dictionary, optional (default=1.0)
- Weight attributed to the immediate neighborhood. If not a scalar the dictionary must have an value for every node.

\( \text{max}_\text{iter} \) : integer, optional (default=1000)
- Maximum number of iterations in power method.

\( \text{tol} \) : float, optional (default=1.0e-6)
- Error tolerance used to check convergence in power method iteration.

\( \text{nstart} \) : dictionary, optional
- Starting value of Katz iteration for each node.

\( \text{normalized} \) : bool, optional (default=True)
- If True normalize the resulting values.

**Returns**

\( \text{nodes} \) : dictionary
- Dictionary of nodes with Katz centrality as the value.

**See also:**
- \text{katz centrality numpy, eigenvector centrality, eigenvector centrality numpy, pagerank, hits}

**Notes**

This algorithm it uses the power method to find the eigenvector corresponding to the largest eigenvalue of the adjacency matrix of \( G \). The constant alpha should be strictly less than the inverse of largest eigenvalue of the adjacency matrix for the algorithm to converge. The iteration will stop after \( \text{max}_\text{iter} \) iterations or an error tolerance of \( \text{number_of_nodes}(G)^*\text{tol} \) has been reached.
When $\alpha = 1/\lambda_{\text{max}}$ and $\beta = 1$ Katz centrality is the same as eigenvector centrality.

References

[R175]

Examples

```python
>>> import math
>>> G = nx.path_graph(4)
>>> phi = (1+math.sqrt(5))/2.0  # largest eigenvalue of adj matrix
>>> centrality = nx.katz_centrality(G,1/phi-0.01)
>>> for n,c in sorted(centrality.items()):
...     print("%d %0.2f"%(n,c))
0 0.37
1 0.60
2 0.60
3 0.37
```

**katz_centrality_numpy**

**katz_centrality_numpy** (*G, alpha=0.1, beta=1.0, normalized=True*)

Compute the Katz centrality for the graph *G*.

Katz centrality is related to eigenvalue centrality and PageRank. The Katz centrality for node *i* is

$$x_i = \alpha \sum_j A_{ij} x_j + \beta,$$

where $A$ is the adjacency matrix of the graph *G* with eigenvalues $\lambda$.

The parameter $\beta$ controls the initial centrality and

$$\alpha < \frac{1}{\lambda_{\text{max}}}.$$

Katz centrality computes the relative influence of a node within a network by measuring the number of the immediate neighbors (first degree nodes) and also all other nodes in the network that connect to the node under consideration through these immediate neighbors.

Extra weight can be provided to immediate neighbors through the parameter $\beta$. Connections made with distant neighbors are, however, penalized by an attenuation factor $\alpha$ which should be strictly less than the inverse largest eigenvalue of the adjacency matrix in order for the Katz centrality to be computed correctly. More information is provided in [R176].

**Parameters**

- **G** : graph
  A NetworkX graph

- **alpha** : float
  Attenuation factor

- **beta** : scalar or dictionary, optional (default=1.0)
  Weight attributed to the immediate neighborhood. If not a scalar the dictionary must have an value for every node.
normalized : bool
    If True normalize the resulting values.

Returns nodes : dictionary
    Dictionary of nodes with Katz centrality as the value.

See also:
    katz_centrality, eigenvector_centrality_numpy, eigenvector_centrality,
pagerank, hits

Notes
    This algorithm uses a direct linear solver to solve the above equation. The constant alpha should be strictly less
    than the inverse of largest eigenvalue of the adjacency matrix for there to be a solution. When $\alpha = 1/\lambda_{\text{max}}$ and
    $\beta = 1$ Katz centrality is the same as eigenvector centrality.

References

[R176]

Examples

    >>> import math
    >>> G = nx.path_graph(4)
    >>> phi = (1+math.sqrt(5))/2.0 # largest eigenvalue of adj matrix
    >>> centrality = nx.katz_centrality_numpy(G,1/phi)
    >>> for n,c in sorted(centrality.items()):
    ...     print("%d %0.2f"%(n,c))
    0 0.37
    1 0.60
    2 0.60
    3 0.37

4.6.7 Communicability

communicability(G)  Return communicability between all pairs of nodes in G.
communicability_exp(G)  Return communicability between all pairs of nodes in G.
communicability_centrality(G)  Return communicability centrality for each node in G.
communicability_centrality_exp(G)  Return the communicability centrality for each node of G
communicability_betweenness_centrality(G[, ...])  Return communicability betweenness for all pairs of nodes in G.
estrada_index(G)  Return the Estrada index of a the graph G.

communicability

    communicability(G)  Return communicability between all pairs of nodes in G.

    The communicability between pairs of nodes in G is the sum of closed walks of different lengths starting at node
    u and ending at node v.
Parameters  G: graph:

Returns  comm: dictionary of dictionaries:

Dictionary of dictionaries keyed by nodes with communicability as the value.

Raises  NetworkXError:

If the graph is not undirected and simple.

See also:

communicability_centrality_exp  Communicability centrality for each node of G using matrix exponential.

communicability_centrality  Communicability centrality for each node in G using spectral decomposition.

communicability  Communicability between pairs of nodes in G.

Notes

This algorithm uses a spectral decomposition of the adjacency matrix. Let G=(V,E) be a simple undirected graph. Using the connection between the powers of the adjacency matrix and the number of walks in the graph, the communicability between nodes $u$ and $v$ based on the graph spectrum is [R158]

$$C(u, v) = \sum_{j=1}^{n} \phi_j(u)\phi_j(v)e^{\lambda_j},$$

where $\phi_j(u)$ is the $u$th element of the $j$th orthonormal eigenvector of the adjacency matrix associated with the eigenvalue $\lambda_j$.

References

[R158]

Examples

```python
>>> G = nx.Graph([(0,1),(1,2),(1,5),(5,4),(2,4),(2,3),(4,3),(3,6)])
>>> c = nx.communicability(G)
```

communicability_exp

**communicability_exp**(*G*)

Return communicability between all pairs of nodes in G.

Communicability between pair of node $(u,v)$ of node in G is the sum of closed walks of different lengths starting at node $u$ and ending at node $v$.

Parameters  G: graph:

Returns  comm: dictionary of dictionaries:

Dictionary of dictionaries keyed by nodes with communicability as the value.
Raises *NetworkXError*:
If the graph is not undirected and simple.

See also:

- `communicability_centrality_exp` Communicability centrality for each node of G using matrix exponential.
- `communicability_centrality` Communicability centrality for each node in G using spectral decomposition.
- `communicability_exp` Communicability between all pairs of nodes in G using spectral decomposition.

Notes

This algorithm uses matrix exponentiation of the adjacency matrix.

Let $G=(V,E)$ be a simple undirected graph. Using the connection between the powers of the adjacency matrix and the number of walks in the graph, the communicability between nodes $u$ and $v$ is \([R165]\),

$$ C(u, v) = (e^A)_{uv}, $$

where $A$ is the adjacency matrix of $G$.

References

[R165]

Examples

```python
>>> G = nx.Graph([(0,1),(1,2),(1,5),(5,4),(2,4),(2,3),(4,3),(3,6)])
>>> c = nx.communicability_exp(G)
```

`communicability_centrality`

`communicability_centrality(G)`

Return communicability centrality for each node in G.

Communicability centrality, also called subgraph centrality, of a node $n$ is the sum of closed walks of all lengths starting and ending at node $n$.

Parameters  

- `G`: graph

Returns  

- `nodes`: dictionary

Dictionary of nodes with communicability centrality as the value.

Raises *NetworkXError*:
If the graph is not undirected and simple.

See also:

- `communicability` Communicability between all pairs of nodes in G.
- `communicability_centrality` Communicability centrality for each node of G.
Notes

This version of the algorithm computes eigenvalues and eigenvectors of the adjacency matrix.

Communicability centrality of a node $u$ in $G$ can be found using a spectral decomposition of the adjacency matrix [R161] [R162],

$$SC(u) = \sum_{j=1}^{N} (v_j^u)^2 e^{\lambda_j},$$

where $v_j$ is an eigenvector of the adjacency matrix $A$ of $G$ corresponding corresponding to the eigenvalue $\lambda_j$.

References

[R161], [R162]

Examples

```python
>>> G = nx.Graph([(0,1),(1,2),(1,5),(5,4),(2,4),(2,3),(4,3),(3,6)])
>>> sc = nx.communicability_centrality(G)
```

communicability_centrality_exp

**communicability_centrality_exp**($G$)

Return the communicability centrality for each node of $G$

Communicability centrality, also called subgraph centrality, of a node $n$ is the sum of closed walks of all lengths starting and ending at node $n$.

**Parameters**

- **G**: graph

**Returns**

- **nodes**:dictionary

  Dictionary of nodes with communicability centrality as the value.

**Raises**

- **NetworkXError**

  If the graph is not undirected and simple.

See also:

communicability Communicability between all pairs of nodes in $G$.

communicability_centrality Communicability centrality for each node of $G$.

Notes

This version of the algorithm exponentiates the adjacency matrix. The communicability centrality of a node $u$ in $G$ can be found using the matrix exponential of the adjacency matrix of $G$ [R163] [R164],

$$SC(u) = (e^A)_{uu}.$$
References

[R163], [R164]

Examples

```python
>>> G = nx.Graph([(0, 1), (1, 2), (1, 5), (5, 4), (2, 4), (2, 3), (4, 3), (3, 6)])
>>> sc = nx.communicability_centrality_exp(G)
```

communicability_betweenness_centrality

`communicability_betweenness_centrality(G, normalized=True)`

Return communicability betweenness for all pairs of nodes in G.

Communicability betweenness measure makes use of the number of walks connecting every pair of nodes as the basis of a betweenness centrality measure.

**Parameters**

- `G`: graph

**Returns**

- `nodes`: dictionary
  - Dictionary of nodes with communicability betweenness as the value.

**Raises**

- `NetworkXError`
  - If the graph is not undirected and simple.

**See also**:

- `communicability`
  - Communicability between all pairs of nodes in G.

- `communicability_centrality`
  - Communicability centrality for each node of G using matrix exponential.

- `communicability_centrality_exp`
  - Communicability centrality for each node in G using spectral decomposition.

**Notes**

Let $G = (V, E)$ be a simple undirected graph with $n$ nodes and $m$ edges, and $A$ denote the adjacency matrix of $G$.

Let $G(r) = (V, E(r))$ be the graph resulting from removing all edges connected to node $r$ but not the node itself.

The adjacency matrix for $G(r)$ is $A + E(r)$, where $E(r)$ has nonzeros only in row and column $r$.

The communicability betweenness of a node $r$ is [R160]

$$
\omega_r = \frac{1}{C} \sum_p \sum_q G_{pq} \frac{G_{prq}}{G_{pq}}, p \neq q, q \neq r,
$$

where $G_{pq} = (e^A - (e^A + E(r))_{pq}$ is the number of walks involving node $r$, $G_{pq} = (e^A)_{pq}$ is the number of closed walks starting at node $p$ and ending at node $q$, and $C = (n - 1)^2 - (n - 1)$ is a normalization factor equal to the number of terms in the sum.
The resulting $\omega_r$ takes values between zero and one. The lower bound cannot be attained for a connected graph, and the upper bound is attained in the star graph.

References

[R160]

Examples

```python
>>> G = nx.Graph([(0,1), (1,2), (1,5), (5,4), (2,4), (2,3), (4,3), (3,6)])
>>> cbc = nx.communicability_betweenness_centrality(G)
```

### estrada_index

**estrada_index**\( (G) \)

Return the Estrada index of a the graph \( G \).

**Parameters**

- \( G \): graph

**Returns**

- estrada index: float

**Raises**

- NetworkXError

  If the graph is not undirected and simple.

**See also:**

estrada_index_exp

**Notes**

Let \( G = (V, E) \) be a simple undirected graph with \( n \) nodes and let \( \lambda_1 \leq \lambda_2 \leq \cdots \lambda_n \) be a non-increasing ordering of the eigenvalues of its adjacency matrix \( A \). The Estrada index is

\[
EE(G) = \sum_{j=1}^{n} e^{\lambda_j}.
\]

References

[R174]

Examples

```python
>>> G=nx.Graph([(0,1), (1,2), (1,5), (5,4), (2,4), (2,3), (4,3), (3,6)])
>>> ei=nx.estrada_index(G)
```

4.6.8 Load
load_centrality(G[, v, cutoff, normalized, ...])  Compute load centrality for nodes.

edge_load(G[, nodes, cutoff])  Compute edge load.

load_centrality

load_centrality(G, v=None, cutoff=None, normalized=True, weight=None)  Compute load centrality for nodes.

The load centrality of a node is the fraction of all shortest paths that pass through that node.

Parameters

G : graph
    A networkx graph

normalized : bool, optional
    If True the betweenness values are normalized by \( b = \frac{b}{(n-1)(n-2)} \) where \( n \) is the number
    of nodes in \( G \).

weight : None or string, optional
    If None, edge weights are ignored. Otherwise holds the name of the edge attribute used
    as weight.

cutoff : bool, optional
    If specified, only consider paths of length \( \leq \) cutoff.

Returns

nodes : dictionary
    Dictionary of nodes with centrality as the value.

See also:

betweenness_centrality

Notes


edge_load

eedge_load(G, nodes=None, cutoff=False)  Compute edge load.

WARNING:

This module is for demonstration and testing purposes.

4.7 Chordal

Algorithms for chordal graphs.

A graph is chordal if every cycle of length at least 4 has a chord (an edge joining two nodes not adjacent in the cycle).

http://en.wikipedia.org/wiki/Chordal_graph

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is_chordal(G) Checks whether G is a chordal graph.

chordal_graph_cliques(G) Returns the set of maximal cliques of a chordal graph.

chordal_graph_treewidth(G) Returns the treewidth of the chordal graph G.

find_induced_nodes(G, s, t[, treewidth_bound]) Returns the set of induced nodes in the path from s to t.

4.7.1 is_chordal

is_chordal(G)

Checks whether G is a chordal graph.

A graph is chordal if every cycle of length at least 4 has a chord (an edge joining two nodes not adjacent in the cycle).

Parameters G : graph

A NetworkX graph.

Returns chordal : bool

True if G is a chordal graph and False otherwise.

Raises NetworkXError :

The algorithm does not support DiGraph, MultiGraph and MultiDiGraph. If the input graph is an instance of one of these classes, a NetworkXError is raised.

Notes

The routine tries to go through every node following maximum cardinality search. It returns False when it finds that the separator for any node is not a clique. Based on the algorithms in [R179].

References

[R179]

Examples

>>> import networkx as nx
>>> e=[(1,2),(1,3),(2,3),(2,4),(3,4),(3,5),(3,6),(4,5),(4,6),(5,6)]
>>> G=nx.Graph(e)
>>> nx.is_chordal(G)
True

4.7.2 chordal_graph_cliques

chordal_graph_cliques(G)

Returns the set of maximal cliques of a chordal graph.

The algorithm breaks the graph in connected components and performs a maximum cardinality search in each component to get the cliques.

Parameters G : graph
A NetworkX graph

**Returns**  **cliques** : A set containing the maximal cliques in G.

**Raises**  **NetworkXError** :

The algorithm does not support DiGraph, MultiGraph and MultiDiGraph. If the input graph is an instance of one of these classes, a NetworkXError is raised. The algorithm can only be applied to chordal graphs. If the input graph is found to be non-chordal, a NetworkXError is raised.

### 4.7.3 chordal_graph_treewidth

**chordal_graph_treewidth** *(G)*

Returns the treewidth of the chordal graph G.

**Parameters**  **G** : graph

A NetworkX graph

**Returns**  **treewidth** : int

The size of the largest clique in the graph minus one.

**Raises**  **NetworkXError** :

The algorithm does not support DiGraph, MultiGraph and MultiDiGraph. If the input graph is an instance of one of these classes, a NetworkXError is raised. The algorithm can only be applied to chordal graphs. If the input graph is found to be non-chordal, a NetworkXError is raised.

### References

[R177]

### Examples

```python
>>> import networkx as nx
>>> e = [(1,2), (1,3), (2,3), (2,4), (3,4), (3,5), (3,6), (4,5), (4,6), (5,6), (7,8)]
>>> G = nx.Graph(e)
>>> G.add_node(9)
>>> setlist = nx.chordal_graph_cliques(G)
```

```python
>>> import networkx as nx
>>> e = [(1,2), (1,3), (2,3), (2,4), (3,4), (3,5), (3,6), (4,5), (4,6), (5,6), (7,8)]
>>> G = nx.Graph(e)
>>> G.add_node(9)
>>> nx.chordal_graph_treewidth(G)
3
```
4.7.4 find_induced_nodes

**find_induced_nodes** *(G, s, t, treewidth_bound=922372036854775807)*

Returns the set of induced nodes in the path from s to t.

**Parameters**

- **G**: graph
  A chordal NetworkX graph
- **s**: node
  Source node to look for induced nodes
- **t**: node
  Destination node to look for induced nodes
- **treewidth_bound**: float
  Maximum treewidth acceptable for the graph H. The search for induced nodes will end as soon as the treewidth_bound is exceeded.

**Returns**

- **I**: Set of nodes
  The set of induced nodes in the path from s to t in G

**Raises** **NetworkXError**

The algorithm does not support DiGraph, MultiGraph and MultiDiGraph. If the input graph is an instance of one of these classes, a NetworkXError is raised. The algorithm can only be applied to chordal graphs. If the input graph is found to be non-chordal, a NetworkXError is raised.

**Notes**

G must be a chordal graph and (s,t) an edge that is not in G.

If a treewidth_bound is provided, the search for induced nodes will end as soon as the treewidth_bound is exceeded.

The algorithm is inspired by Algorithm 4 in [R178]. A formal definition of induced node can also be found on that reference.

**References**

[R178]

**Examples**

```python
>>> import networkx as nx
>>> G=nx.Graph()
>>> G = nx.generators.classic.path_graph(10)
>>> I = nx.find_induced_nodes(G,1,9,2)
>>> list(I)
[1, 2, 3, 4, 5, 6, 7, 8, 9]
```
4.8 Clique

Find and manipulate cliques of graphs.

Note that finding the largest clique of a graph has been shown to be an NP-complete problem; the algorithms here could take a long time to run.


## find_cliques(G)
Search for all maximal cliques in a graph.

Maximal cliques are the largest complete subgraph containing a given node. The largest maximal clique is sometimes called the maximum clique.

Returns generator of lists: genetor of member list for each maximal clique:

See also:

find_cliques_recursive, A

Notes

To obtain a list of cliques, use list(find_cliques(G)).

Based on the algorithm published by Bron & Kerbosch (1973) [R180] as adapted by Tomita, Tanaka and Takahashi (2006) [R181] and discussed in Cazals and Karande (2008) [R182]. The method essentially unrolls the recursion used in the references to avoid issues of recursion stack depth.

This algorithm is not suitable for directed graphs.

This algorithm ignores self-loops and parallel edges as clique is not conventionally defined with such edges.

There are often many cliques in graphs. This algorithm can run out of memory for large graphs.

References

[R180], [R181], [R182]

## make_max_clique_graph(G, create_using=None, name=None)
Create the maximal clique graph of a graph.
Finds the maximal cliques and treats these as nodes. The nodes are connected if they have common members in the original graph. Theory has done a lot with clique graphs, but I haven’t seen much on maximal clique graphs.

**Notes**

This should be the same as `make_clique_bipartite` followed by `project_up`, but it saves all the intermediate steps.

### 4.8.3 `make_clique_bipartite`

`make_clique_bipartite`: `(G, fpos=None, create_using=None, name=None)`
Create a bipartite clique graph from a graph `G`.

Nodes of `G` are retained as the “bottom nodes” of `B` and cliques of `G` become “top nodes” of `B`. Edges are present if a bottom node belongs to the clique represented by the top node.

Returns a Graph with additional attribute dict `B.node_type` which is keyed by nodes to “Bottom” or “Top” appropriately.

if `fpos` is not None, a second additional attribute dict `B.pos` is created to hold the position tuple of each node for viewing the bipartite graph.

### 4.8.4 `graph_clique_number`

`graph_clique_number`: `(G, cliques=None)`
Return the clique number (size of the largest clique) for `G`.

An optional list of cliques can be input if already computed.

### 4.8.5 `graph_number_of_cliques`

`graph_number_of_cliques`: `(G, cliques=None)`
Returns the number of maximal cliques in `G`.

An optional list of cliques can be input if already computed.

### 4.8.6 `node_clique_number`

`node_clique_number`: `(G, nodes=None, cliques=None)`
Returns the size of the largest maximal clique containing each given node.

Returns a single or list depending on input nodes. Optional list of cliques can be input if already computed.

### 4.8.7 `number_of_cliques`

`number_of_cliques`: `(G, nodes=None, cliques=None)`
Returns the number of maximal cliques for each node.

Returns a single or list depending on input nodes. Optional list of cliques can be input if already computed.
4.8.8 cliques_containing_node

cliques_containing_node \((G, \text{nodes}=\text{None}, \text{cliques}=\text{None})\)

Returns a list of cliques containing the given node.

Returns a single list or list of lists depending on input nodes. Optional list of cliques can be input if already computed.

4.9 Clustering

Algorithms to characterize the number of triangles in a graph.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>triangles ((G, \text{nodes}=\text{None}))</td>
<td>Compute the number of triangles. Find the number of triangles that include a node as one vertex.</td>
</tr>
<tr>
<td>transitivity ((G))</td>
<td>Compute graph transitivity, the fraction of all possible triangles</td>
</tr>
<tr>
<td>clustering ((G, \text{nodes}, \text{weight}))</td>
<td>Compute the clustering coefficient for nodes.</td>
</tr>
<tr>
<td>average_clustering ((G, \text{nodes}, \text{weight}, ...))</td>
<td>Compute the average clustering coefficient for the graph (G).</td>
</tr>
<tr>
<td>square_clustering ((G, \text{nodes}))</td>
<td>Compute the squares clustering coefficient for nodes.</td>
</tr>
</tbody>
</table>

4.9.1 triangles

triangles \((G, \text{nodes}=\text{None})\)

Compute the number of triangles.

Find the number of triangles that include a node as one vertex.

**Parameters**

- **G**: graph
- A networkx graph
- **nodes**: container of nodes, optional (default=all nodes in \(G\))
- Compute triangles for nodes in this container.

**Returns**

- **out**: dictionary
  - Number of triangles keyed by node label.

**Notes**

When computing triangles for the entire graph each triangle is counted three times, once at each node. Self loops are ignored.

**Examples**

```python
>>> G=nx.complete_graph(5)
>>> print(nx.triangles(G,0))
6
>>> print(nx.triangles(G))
{0: 6, 1: 6, 2: 6, 3: 6, 4: 6}
>>> print(list(nx.triangles(G,(0,1)).values()))
[6, 6]
```
4.9.2 transitivity

\texttt{transitivity}(G)

Compute graph transitivity, the fraction of all possible triangles present in G.

Possible triangles are identified by the number of “triads” (two edges with a shared vertex).

The transitivity is

\[ T = \frac{3 \times \text{#triangles}}{\text{#triads}}. \]

**Parameters**

- **G** : graph

**Returns**

- **out** : float

**Transitivity**

**Examples**

```python
>>> G = nx.complete_graph(5)
>>> print(nx.transitivity(G))
1.0
```

4.9.3 clustering

\texttt{clustering}(G, nodes=None, weight=None)

Compute the clustering coefficient for nodes.

For unweighted graphs, the clustering of a node \( u \) is the fraction of possible triangles through that node that exist,

\[ c_u = \frac{2T(u)}{\text{deg}(u)(\text{deg}(u) - 1)}, \]

where \( T(u) \) is the number of triangles through node \( u \) and \( \text{deg}(u) \) is the degree of \( u \).

For weighted graphs, the clustering is defined as the geometric average of the subgraph edge weights [R185],

\[ c_u = \frac{1}{\text{deg}(u)(\text{deg}(u) - 1)} \sum_{uv} (\tilde{w}_{uv}\tilde{w}_{uw}\tilde{w}_{vw})^{1/3}. \]

The edge weights \( \tilde{w}_{uv} \) are normalized by the maximum weight in the network \( \tilde{w}_{uv} = w_{uv} / \max(w) \).

The value of \( c_u \) is assigned to 0 if \( \text{deg}(u) < 2 \).

**Parameters**

- **G** : graph

- **nodes** : container of nodes, optional (default=all nodes in G)

  Compute clustering for nodes in this container.

- **weight** : string or None, optional (default=None)

  The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**

- **out** : float, or dictionary

  Clustering coefficient at specified nodes
Notes

Self loops are ignored.

References

[R185]

Examples

```python
>>> G=nx.complete_graph(5)
>>> print(nx.clustering(G,0))
1.0
>>> print(nx.clustering(G))
{0: 1.0, 1: 1.0, 2: 1.0, 3: 1.0, 4: 1.0}
```

4.9.4 average_clustering

`average_clustering(G, nodes=None, weight=None, count_zeros=True)`

Compute the average clustering coefficient for the graph G.

The clustering coefficient for the graph is the average,

\[ C = \frac{1}{n} \sum_{v \in G} c_v, \]

where \( n \) is the number of nodes in \( G \).

**Parameters**

- **G** : graph
  - nodes : container of nodes, optional (default=all nodes in G)
    - Compute average clustering for nodes in this container.
  - weight : string or None, optional (default=None)
    - The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.
  - count_zeros : bool (default=False)
    - If False include only the nodes with nonzero clustering in the average.

**Returns**

- **avg** : float
  - Average clustering

**Notes**

This is a space saving routine; it might be faster to use the clustering function to get a list and then take the average.

Self loops are ignored.
4.9.5 square_clustering

square_clustering \( G, \text{nodes}=\text{None} \)

Compute the squares clustering coefficient for nodes.

For each node return the fraction of possible squares that exist at the node \[R186\]

\[
C_4(v) = \frac{\sum_{u=1}^{k_v} \sum_{w=u+1}^{k_v} q_v(u, w)}{\sum_{u=1}^{k_v} \sum_{w=1}^{k_v} [a_v(u, w) + q_v(u, w)]},
\]

where \( q_v(u, w) \) are the number of common neighbors of \( u \) and \( w \) other than \( v \) (i.e., squares), and \( a_v(u, w) = (k_u - 1 + q_v(u, w) + \theta_{uw}) (k_w - 1 + q_v(u, w) + \theta_{uw}) \), where \( \theta_{uw} = 1 \) if \( u \) and \( w \) are connected and 0 otherwise.

Parameters
- \( G \) : graph
  - nodes : container of nodes, optional (default=all nodes in \( G \))
    - Compute clustering for nodes in this container.

Returns
- \( c4 \) : dictionary
  - A dictionary keyed by node with the square clustering coefficient value.

Notes

While \( C_3(v) \) (triangle clustering) gives the probability that two neighbors of node \( v \) are connected with each other, \( C_4(v) \) is the probability that two neighbors of node \( v \) share a common neighbor different from \( v \). This algorithm can be applied to both bipartite and unipartite networks.

References

[\( R186 \)]

Examples

\[
\begin{align*}
G & = \text{nx.complete_graph}(5) \\
\text{print}(\text{nx.average_clustering}(G)) & = 1.0 \\
\text{print}(\text{nx.square_clustering}(G, 0)) & = 1.0 \\
\text{print}(\text{nx.square_clustering}(G)) & = \{0: 1.0, 1: 1.0, 2: 1.0, 3: 1.0, 4: 1.0\}
\end{align*}
\]
4.10 Communities

4.10.1 K-Clique

```python
k_clique_communities(G, k[, cliques]) Find k-clique communities in graph using the percolation method.
```

**k_clique_communities**

**k_clique_communities** *(G, k, cliques=*)

Find k-clique communities in graph using the percolation method.

A k-clique community is the union of all cliques of size k that can be reached through adjacent (sharing k-1 nodes) k-cliques.

**Parameters**

- **G**: NetworkX graph
- **k**: int
  - Size of smallest clique
- **cliques**: list or generator
  - Precomputed cliques (use networkx.find_cliques(G))

**Returns**

Yields sets of nodes, one for each k-clique community.

**References**

[R187]

**Examples**

```python
>>> G = nx.complete_graph(5)
>>> K5 = nx.convert_node_labels_to_integers(G, first_label=2)
>>> G.add_edges_from(K5.edges())
>>> c = list(nx.k_clique_communities(G, 4))
>>> list(c[0])
[0, 1, 2, 3, 4, 5, 6]
>>> list(nx.k_clique_communities(G, 6))
[]
```

4.11 Components

4.11.1 Connectivity

Connected components.

```python
is_connected(G) Test graph connectivity.
number_connected_components(G) Return number of connected components in graph.
connected_components(G) Return nodes in connected components of graph.
```

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Table 4.32 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>connected_component_subgraphs(G)</code></td>
<td>Return connected components as subgraphs.</td>
</tr>
<tr>
<td><code>node_connected_component(G, n)</code></td>
<td>Return nodes in connected components of graph containing node n.</td>
</tr>
</tbody>
</table>

**is_connected**

**is_connected** \((G)\)

Test graph connectivity.

**Parameters**

- `G` : NetworkX Graph
  
  An undirected graph.

**Returns**

- `connected` : bool
  
  True if the graph is connected, false otherwise.

**See also:**

- `connected_components`

**Notes**

For undirected graphs only.

**Examples**

```python
>>> G=nx.path_graph(4)
>>> print(nx.is_connected(G))
True
```

**number_connected_components**

**number_connected_components** \((G)\)

Return number of connected components in graph.

**Parameters**

- `G` : NetworkX Graph
  
  An undirected graph.

**Returns**

- `n` : integer
  
  Number of connected components

**See also:**

- `connected_components`

**Notes**

For undirected graphs only.
**connected_components**

`connected_components(G)`

Return nodes in connected components of graph.

**Parameters**

- `G` : NetworkX Graph
  An undirected graph.

**Returns**

- `comp` : list of lists
  A list of nodes for each component of G.

**See also:**

- `strongly_connected_components`

**Notes**

The list is ordered from largest connected component to smallest. For undirected graphs only.

**connected_component_subgraphs**

`connected_component_subgraphs(G)`

Return connected components as subgraphs.

**Parameters**

- `G` : NetworkX Graph
  An undirected graph.

**Returns**

- `glist` : list
  A list of graphs, one for each connected component of G.

**See also:**

- `connected_components`

**Notes**

The list is ordered from largest connected component to smallest. For undirected graphs only. Graph, node, and edge attributes are copied to the subgraphs.

**Examples**

Get largest connected component as subgraph

```python
>>> G=nx.path_graph(4)
>>> G.add_edge(5,6)
>>> H=nx.connected_component_subgraphs(G)[0]
```
node_connected_component

node_connected_component \((G, n)\)
Return nodes in connected components of graph containing node \(n\).

Parameters

\[G\] : NetworkX Graph
An undirected graph.

\[n\] : node label
A node in \(G\)

Returns

\[\text{comp}\] : lists
A list of nodes in component of \(G\) containing node \(n\).

See also:

connected_components

Notes

For undirected graphs only.

4.11.2 Strong connectivity

Strongly connected components.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>\text{is_strongly_connected}(G)</td>
<td>Test directed graph for strong connectivity.</td>
</tr>
<tr>
<td>\text{number_strongly_connected_components}(G)</td>
<td>Return number of strongly connected components in graph.</td>
</tr>
<tr>
<td>\text{strongly_connected_components}(G)</td>
<td>Return nodes in strongly connected components of graph.</td>
</tr>
<tr>
<td>\text{strongly_connected_component_subgraphs}(G)</td>
<td>Return strongly connected components as subgraphs.</td>
</tr>
<tr>
<td>\text{kosaraju_strongly_connected_components}(G[,...])</td>
<td>Return nodes in strongly connected components of graph.</td>
</tr>
<tr>
<td>\text{condensation}(G[, scc])</td>
<td>Returns the condensation of (G).</td>
</tr>
</tbody>
</table>

is_strongly_connected

is_strongly_connected \((G)\)
Test directed graph for strong connectivity.

Parameters

\[G\] : NetworkX Graph
A directed graph.

Returns

\[\text{connected}\] : bool
True if the graph is strongly connected, False otherwise.

See also:

strongly_connected_components

Notes

For directed graphs only.
**number_strongly_connected_components**

**number_strongly_connected_components** \((G)\)

Return number of strongly connected components in graph.

**Parameters**

- **G** : NetworkX graph
  
  A directed graph.

**Returns**

- **n** : integer
  
  Number of strongly connected components

**See also:**

- `connected_components`

**Notes**

For directed graphs only.

**strongly_connected_components**

**strongly_connected_components** \((G)\)

Return nodes in strongly connected components of graph.

**Parameters**

- **G** : NetworkX Graph
  
  An directed graph.

**Returns**

- **comp** : list of lists
  
  A list of nodes for each component of G. The list is ordered from largest connected component to smallest.

**Raises**

- `NetworkXError`: If G is undirected.

**See also:**

- `connected_components`, `weakly_connected_components`

**Notes**

Uses Tarjan’s algorithm with Nuutila’s modifications. Nonrecursive version of algorithm.

**References**

[R193], [R194]

**strongly_connected_component_subgraphs**

**strongly_connected_component_subgraphs** \((G)\)

Return strongly connected components as subgraphs.

**Parameters**

- **G** : NetworkX Graph
  
  A graph.
Returns  

\textbf{glist} : list

A list of graphs, one for each strongly connected component of \( G \).

See also:

\texttt{connected_component_subgraphs}

Notes

The list is ordered from largest strongly connected component to smallest.

Graph, node, and edge attributes are copied to the subgraphs.

\texttt{strongly_connected_components_recursive}

\texttt{strongly_connected_components_recursive}(G)

Return nodes in strongly connected components of graph.

Recursive version of algorithm.

Parameters  

\textbf{G} : NetworkX Graph

An directed graph.

Returns  

\textbf{comp} : list of lists

A list of nodes for each component of \( G \). The list is ordered from largest connected component to smallest.

Raises  

\texttt{NetworkXError} : If \( G \) is undirected

See also:

\texttt{connected_components}

Notes

Uses Tarjan’s algorithm with Nuutila’s modifications.

References

[R195], [R196]

\texttt{kosaraju_strongly_connected_components}

\texttt{kosaraju_strongly_connected_components}(G, source=None)

Return nodes in strongly connected components of graph.

Parameters  

\textbf{G} : NetworkX Graph

An directed graph.

Returns  

\textbf{comp} : list of lists

A list of nodes for each component of \( G \). The list is ordered from largest connected component to smallest.
Raises NetworkXError: If G is undirected:

See also:

calendar

Notes

Uses Kosaraju’s algorithm.

condensation

calendar\((G, \text{scc}=\text{None})\)

Returns the condensation of G.

The condensation of G is the graph with each of the strongly connected components contracted into a single node.

Parameters

\(G\) : NetworkX DiGraph

A directed graph.

scc: list (optional, default=None):

A list of strongly connected components. If provided, the elements in \(scc\) must partition the nodes in \(G\). If not provided, it will be calculated as \(scc=nx.\text{strongly}\_\text{connected}\_\text{components}(G)\).

Returns

\(C\) : NetworkX DiGraph

The condensation of G. The node labels are integers corresponding to the index of the component in the list of strongly connected components.

Raises NetworkXError: If G is not directed:

Notes

After contracting all strongly connected components to a single node, the resulting graph is a directed acyclic graph.

4.11.3 Weak connectivity

Weakly connected components.

\(\text{is}\_\text{weakly}\_\text{connected}(G)\)

Test directed graph for weak connectivity.

\(\text{number}\_\text{weakly}\_\text{connected}\_\text{components}(G)\)

Return the number of connected components in G.

\(\text{weakly}\_\text{connected}\_\text{components}(G)\)

Return weakly connected components of G.

\(\text{weakly}\_\text{connected}\_\text{component}\_\text{subgraphs}(G)\)

Return weakly connected components as subgraphs.

\(\text{is}\_\text{weakly}\_\text{connected}\)
A directed graph.

Returns connected : bool

True if the graph is weakly connected, False otherwise.

See also:
strongly_connected_components

Notes

For directed graphs only.

number_weakly_connected_components

number_weakly_connected_components(G)

Return the number of connected components in G. For directed graphs only.

weakly_connected_components

weakly_connected_components(G)

Return weakly connected components of G.

weakly_connected_component_subgraphs

weakly_connected_component_subgraphs(G)

Return weakly connected components as subgraphs.

Graph, node, and edge attributes are copied to the subgraphs.

4.11.4 Attracting components

Attracting components.

<table>
<thead>
<tr>
<th>is_attracting_component(G)</th>
<th>Returns True if G consists of a single attracting component.</th>
</tr>
</thead>
<tbody>
<tr>
<td>number_attracting_components(G)</td>
<td>Returns the number of attracting components in G.</td>
</tr>
<tr>
<td>attracting_components(G)</td>
<td>Returns a list of attracting components in G.</td>
</tr>
<tr>
<td>attracting_component_subgraphs(G)</td>
<td>Returns a list of attracting component subgraphs from G.</td>
</tr>
</tbody>
</table>

is_attracting_component

is_attracting_component(G)

Returns True if G consists of a single attracting component.

Parameters G : DiGraph, MultiDiGraph

The graph to be analyzed.

Returns attracting : bool

True if G has a single attracting component. Otherwise, False.

See also:
number_attracting_components

number_attracting_components(G)
Returns the number of attracting components in G.

Parameters  G : DiGraph, MultiDiGraph
            The graph to be analyzed.

Returns  n : int
            The number of attracting components in G.

See also:
attracting_components, is_attracting_component, attracting_component_subgraphs

attracting_components

attracting_components(G)
Returns a list of attracting components in G.

An attracting component in a directed graph G is a strongly connected component with the property that a
random walker on the graph will never leave the component, once it enters the component.

The nodes in attracting components can also be thought of as recurrent nodes. If a random walker enters the
attractor containing the node, then the node will be visited infinitely often.

Parameters  G : DiGraph, MultiDiGraph
            The graph to be analyzed.

Returns  attractors : list
            The list of attracting components, sorted from largest attracting component to smallest
            attracting component.

See also:
number_attracting_components, is_attracting_component, attracting_component_subgraphs

attracting_component_subgraphs

attracting_component_subgraphs(G)
Returns a list of attracting component subgraphs from G.

Parameters  G : DiGraph, MultiDiGraph
            The graph to be analyzed.

Returns  subgraphs : list
            A list of node-induced subgraphs of the attracting components of G.

See also:
attracting_components, number_attracting_components, is_attracting_component

4.11. Components
Notes

Graph, node, and edge attributes are copied to the subgraphs.

4.11.5 Biconnected components

Biconnected components and articulation points.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_biconnected(G)</code></td>
<td>Return True if the graph is biconnected, False otherwise.</td>
</tr>
<tr>
<td><code>biconnected_components(G)</code></td>
<td>Return a generator of sets of nodes, one set for each biconnected component of the input graph.</td>
</tr>
<tr>
<td><code>biconnected_component_edges(G)</code></td>
<td>Return a generator of lists of edges, one list for each biconnected component of the input graph.</td>
</tr>
<tr>
<td><code>articulation_points_subgraphs(G)</code></td>
<td>Return a generator of graphs, one graph for each biconnected component of the input graph.</td>
</tr>
</tbody>
</table>

**is_biconnected**

**is_biconnected** *(G)*

Return True if the graph is biconnected, False otherwise.

A graph is biconnected if, and only if, it cannot be disconnected by removing only one node (and all edges incident on that node). If removing a node increases the number of disconnected components in the graph, that node is called an articulation point, or cut vertex. A biconnected graph has no articulation points.

**Parameters**

- **G**: NetworkX Graph
  - An undirected graph.

**Returns**

- **bicnected**: bool
  - True if the graph is biconnected, False otherwise.

**Raises**

- **NetworkXError**
  - If the input graph is not undirected.

**See also**

- `biconnected_components`, `articulation_points`, `biconnected_component_edges`, `articulation_points_subgraphs`

**Notes**

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node is an articulation point if, and only if, there exists a subtree rooted at that node such that there is no back edge from any successor of that node that links to a predecessor of in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

**References**

[R192]
Examples

```python
g = nx.path_graph(4)
print(nx.is_biconnected(g))
False
g.add_edge(0, 3)
print(nx.is_biconnected(g))
True
```

**biconnected_components**

*biconnected_components*(G)  
Return a generator of sets of nodes, one set for each biconnected component of the graph

Biconnected components are maximal subgraphs such that the removal of a node (and all edges incident on that node) will not disconnect the subgraph. Note that nodes may be part of more than one biconnected component. Those nodes are articulation points, or cut vertices. The removal of articulation points will increase the number of connected components of the graph.

Notice that by convention a dyad is considered a biconnected component.

**Parameters**  
G : NetworkX Graph  
An undirected graph.

**Returns**  
nodes : generator  
Generator of sets of nodes, one set for each biconnected component.

**Raises**  
NetworkXError :  
If the input graph is not undirected.

**See also:**  
is_biconnected, articulation_points, biconnected_component_edges, biconnected_component_subgraphs

**Notes**

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node \( n \) is an articulation point if, and only if, there exists a subtree rooted at \( n \) such that there is no back edge from any successor of \( n \) that links to a predecessor of \( n \) in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

**References**

[RJ91]

**Examples**
>>> G = nx.barbell_graph(4, 2)
>>> print(nx.is_biconnected(G))
False
>>> components = nx.biconnected_components(G)
>>> G.add_edge(2, 8)
>>> print(nx.is_biconnected(G))
True
>>> components = nx.biconnected_components(G)

biconnected_component_edges

biconnected_component_edges(G)

Return a generator of lists of edges, one list for each biconnected component of the input graph.

Biconnected components are maximal subgraphs such that the removal of a node (and all edges incident on that node) will not disconnect the subgraph. Note that nodes may be part of more than one biconnected component. Those nodes are articulation points, or cut vertices. However, each edge belongs to one, and only one, biconnected component.

Notice that by convention a dyad is considered a biconnected component.

**Parameters**

- **G : NetworkX Graph**
  
  An undirected graph.

**Returns**

- **edges : generator**
  
  Generator of lists of edges, one list for each bicomponent.

**Raises**

- **NetworkXError**
  
  If the input graph is not undirected.

**See also:**

- `is_biconnected`
- `biconnected_components`
- `articulation_points`
- `biconnected_component_subgraphs`

**Notes**

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node \( n \) is an articulation point if, and only if, there exists a subtree rooted at \( n \) such that there is no back edge from any successor of \( n \) that links to a predecessor of \( n \) in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

**References**

- [R189]

**Examples**
>>> G = nx.barbell_graph(4,2)
>>> print(nx.is_biconnected(G))
False
>>> components = nx.biconnected_component_edges(G)
>>> G.add_edge(2,8)
>>> print(nx.is_biconnected(G))
True
>>> components = nx.biconnected_component_edges(G)

**biconnected_component_subgraphs**

*biconnected_component_subgraphs*(*G*)

Return a generator of graphs, one graph for each biconnected component of the input graph.

Biconnected components are maximal subgraphs such that the removal of a node (and all edges incident on that node) will not disconnect the subgraph. Note that nodes may be part of more than one biconnected component. Those nodes are articulation points, or cut vertices. The removal of articulation points will increase the number of connected components of the graph.

Notice that by convention a dyad is considered a biconnected component.

**Parameters**

*G* : NetworkX Graph

An undirected graph.

**Returns**

generators : generator

Generator of graphs, one graph for each biconnected component.

**Raises**

NetworkXError

If the input graph is not undirected.

See also:

is_biconnected, articulation_points, biconnected_component_edges, biconnected_components

**Notes**

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node *n* is an articulation point if, and only if, there exists a subtree rooted at *n* such that there is no back edge from any successor of *n* that links to a predecessor of *n* in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

Graph, node, and edge attributes are copied to the subgraphs.

**References**

[R190]
articulation_points

articulation_points(G)

Return a generator of articulation points, or cut vertices, of a graph.

An articulation point or cut vertex is any node whose removal (along with all its incident edges) increases the number of connected components of a graph. An undirected connected graph without articulation points is biconnected. Articulation points belong to more than one biconnected component of a graph.

Notice that by convention a dyad is considered a biconnected component.

Parameters

G : NetworkX Graph
    An undirected graph.

Returns

articulation_points : generator
generator of nodes

Raises

NetworkXError :
    If the input graph is not undirected.

See also:

is_biconnected, biconnected_components, biconnected_component_edges, biconnected_component_subgraphs

Notes

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node \( n \) is an articulation point if, and only if, there exists a subtree rooted at \( n \) such that there is no back edge from any successor of \( n \) that links to a predecessor of \( n \) in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

References

[R188]

Examples

```python
>>> G = nx.barbell_graph(4,2)
>>> print(nx.is_biconnected(G))
False
>>> subgraphs = nx.biconnected_component_subgraphs(G)
```

```python
>>> G = nx.barbell_graph(4,2)
>>> print(nx.is_biconnected(G))
False
>>> list(nx.articulation_points(G))
[6, 5, 4, 3]
```
>>> G.add_edge(2,8)
>>> print(nx.is_biconnected(G))
True
>>> list(nx.articulation_points(G))
[]

4.12 Connectivity

Flow based connectivity and cut algorithms

4.12.1 Connectivity functions

Flow based connectivity algorithms

<table>
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<tr>
<th>Function</th>
<th>Description</th>
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<td><code>average_node_connectivity(G)</code></td>
<td>Returns the average connectivity of a graph G.</td>
</tr>
<tr>
<td><code>local_node_connectivity(G, s, t[, ...])</code></td>
<td>Computes local node connectivity for nodes s and t.</td>
</tr>
<tr>
<td><code>node_connectivity(G[, s, t])</code></td>
<td>Returns node connectivity for a graph or digraph G.</td>
</tr>
<tr>
<td><code>local_edge_connectivity(G, u, v[, aux_digraph])</code></td>
<td>Returns local edge connectivity for nodes s and t in G.</td>
</tr>
<tr>
<td><code>edge_connectivity(G[, s, t])</code></td>
<td>Returns the edge connectivity of the graph or digraph G.</td>
</tr>
<tr>
<td><code>all_pairs_node_connectivity_matrix(G)</code></td>
<td>Return a numpy 2d ndarray with node connectivity between all pairs of nodes.</td>
</tr>
</tbody>
</table>

**average_node_connectivity**

The average connectivity $\bar{\kappa}$ of a graph G is the average of local node connectivity over all pairs of nodes of G [R197].

$$\bar{\kappa}(G) = \frac{\sum_{u,v} \kappa_G(u,v)}{\binom{n}{2}}$$

**Parameters**

- **G**: NetworkX graph
  - Undirected graph

**Returns**

- **K**: float
  - Average node connectivity

**See also:**

- `local_node_connectivity`, `node_connectivity`, `local_edge_connectivity`, `edge_connectivity`, `max_flow`, `ford_fulkerson`

**References**

[R197]
local_node_connectivity

local_node_connectivity \((G, s, t, aux\_digraph=None, mapping=None)\)
Computes local node connectivity for nodes \(s\) and \(t\).

Local node connectivity for two non adjacent nodes \(s\) and \(t\) is the minimum number of nodes that must be removed (along with their incident edges) to disconnect them.

This is a flow based implementation of node connectivity. We compute the maximum flow on an auxiliary digraph build from the original input graph (see below for details). This is equal to the local node connectivity because the value of a maximum \(s-t\)-flow is equal to the capacity of a minimum \(s-t\)-cut (Ford and Fulkerson theorem) \([R201]\).

Parameters

\(G\) : NetworkX graph
Undirected graph

\(s\) : node
Source node

\(t\) : node
Target node

\(aux\_digraph\) : NetworkX DiGraph (default=None)
Auxiliary digraph to compute flow based node connectivity. If None the auxiliary digraph is build.

\(mapping\) : dict (default=None)
Dictionary with a mapping of node names in \(G\) and in the auxiliary digraph.

Returns

\(K\) : integer
local node connectivity for nodes \(s\) and \(t\)

See also:
node_connectivity, local_edge_connectivity, edge_connectivity, max_flow, ford_fulkerson

Notes

This is a flow based implementation of node connectivity. We compute the maximum flow using the Ford and Fulkerson algorithm on an auxiliary digraph build from the original input graph:

For an undirected graph \(G\) having \(n\) nodes and \(m\) edges we derive a directed graph \(D\) with \(2n\) nodes and \(2m+n\) arcs by replacing each original node \(v\) with two nodes \(v_A, v_B\) linked by an (internal) arc in \(D\). Then for each edge \((u, v)\) in \(G\) we add two arcs \((u_B, v_A)\) and \((v_B, u_A)\) in \(D\). Finally we set the attribute capacity = 1 for each arc in \(D\) \([R201]\).

For a directed graph \(G\) having \(n\) nodes and \(m\) arcs we derive a directed graph \(D\) with \(2n\) nodes and \(m + n\) arcs by replacing each original node \(v\) with two nodes \(v_A, v_B\) linked by an (internal) arc \((v_A, v_B)\) in \(D\). Then for each arc \((u, v)\) in \(G\) we add one arc \((u_B, v_A)\) in \(D\). Finally we set the attribute capacity = 1 for each arc in \(D\).

This is equal to the local node connectivity because the value of a maximum \(s-t\)-flow is equal to the capacity of a minimum \(s-t\)-cut (Ford and Fulkerson theorem).
References

[R201]

Examples

>>> # Platonic icosahedral graph has node connectivity 5
>>> # for each non adjacent node pair
>>> G = nx.icosahedral_graph()
>>> nx.local_node_connectivity(G,0,6)
5

node_connectivity

node_connectivity \((G, s=None, t=None)\)

Returns node connectivity for a graph or digraph \(G\).

Node connectivity is equal to the minimum number of nodes that must be removed to disconnect \(G\) or render it trivial. If source and target nodes are provided, this function returns the local node connectivity: the minimum number of nodes that must be removed to break all paths from source to target in \(G\).

This is a flow based implementation. The algorithm is based in solving a number of max-flow problems (ie local st-node connectivity, see local_node_connectivity) to determine the capacity of the minimum cut on an auxiliary directed network that corresponds to the minimum node cut of \(G\). It handles both directed and undirected graphs.

Parameters

- **G**: NetworkX graph
  - Undirected graph
- **s**: node
  - Source node. Optional (default=None)
- **t**: node
  - Target node. Optional (default=None)

Returns **K**: integer

Node connectivity of \(G\), or local node connectivity if source and target were provided

See also:

- local_node_connectivity, all_pairs_node_connectivity_matrix, local_edge_connectivity, edge_connectivity, max_flow, ford_fulkerson

Notes

This is a flow based implementation of node connectivity. The algorithm works by solving \(O((n - \delta - 1 + \delta(\delta - 1)/2)\) max-flow problems on an auxiliary digraph. Where \(\delta\) is the minimum degree of \(G\). For details about the auxiliary digraph and the computation of local node connectivity see local_node_connectivity.

This implementation is based on algorithm 11 in [R202]. We use the Ford and Fulkerson algorithm to compute max flow (see ford_fulkerson).
References

[R202]

Examples

```python
>>> # Platonic icosahedral graph is 5-node-connected
>>> G = nx.icosahedral_graph()
>>> nx.node_connectivity(G)
5
>>> nx.node_connectivity(G, 3, 7)
5
```

local_edge_connectivity

`local_edge_connectivity(G, u, v, aux_digraph=None)`

Returns local edge connectivity for nodes $s$ and $t$ in $G$.

Local edge connectivity for two nodes $s$ and $t$ is the minimum number of edges that must be removed to disconnect them.

This is a flow based implementation of edge connectivity. We compute the maximum flow on an auxiliary digraph build from the original network (see below for details). This is equal to the local edge connectivity because the value of a maximum $s$-$t$-flow is equal to the capacity of a minimum $s$-$t$-cut (Ford and Fulkerson theorem) [R199].

**Parameters**

- $G$ : NetworkX graph
  - Undirected or directed graph
- $s$ : node
  - Source node
- $t$ : node
  - Target node
- `aux_digraph` : NetworkX DiGraph (default=None)
  - Auxiliary digraph to compute flow based edge connectivity. If None the auxiliary di-graph is build.

**Returns**

- $K$ : integer
  - local edge connectivity for nodes $s$ and $t$

See also:

- `local_node_connectivity`, `node_connectivity`, `edge_connectivity`, `max_flow`, `ford_fulkerson`

Notes

This is a flow based implementation of edge connectivity. We compute the maximum flow using the Ford and Fulkerson algorithm on an auxiliary digraph build from the original graph:
If the input graph is undirected, we replace each edge \((u,v)\) with two reciprocal arcs \((u, v)\) and \((v, u)\) and then we set the attribute ‘capacity’ for each arc to 1. If the input graph is directed we simply add the ‘capacity’ attribute. This is an implementation of algorithm 1 in [R199].

The maximum flow in the auxiliary network is equal to the local edge connectivity because the value of a maximum s-t-flow is equal to the capacity of a minimum s-t-cut (Ford and Fulkerson theorem).

**References**

[R199]

**Examples**

```python
>>> # Platonic icosahedral graph has edge connectivity 5
>>> # for each non adjacent node pair
>>> G = nx.icosahedral_graph()
>>> nx.local_edge_connectivity(G,0,6)
5
```

**edge_connectivity**

**edge_connectivity** \((G, s=None, t=None)\)

Returns the edge connectivity of the graph or digraph G.

The edge connectivity is equal to the minimum number of edges that must be removed to disconnect G or render it trivial. If source and target nodes are provided, this function returns the local edge connectivity: the minimum number of edges that must be removed to break all paths from source to target in G.

This is a flow based implementation. The algorithm is based in solving a number of max-flow problems (ie local st-edge connectivity, see local_edge_connectivity) to determine the capacity of the minimum cut on an auxiliary directed network that corresponds to the minimum edge cut of G. It handles both directed and undirected graphs.

**Parameters**

\( G \) : NetworkX graph

Undirected or directed graph

\( s \) : node

Source node. Optional (default=None)

\( t \) : node

Target node. Optional (default=None)

**Returns**

\( K \) : integer

Edge connectivity for G, or local edge connectivity if source and target were provided

**See also:**

local_node_connectivity, node_connectivity, local_edge_connectivity, max_flow, ford_fulkerson

**Notes**

This is a flow based implementation of global edge connectivity. For undirected graphs the algorithm works by finding a ‘small’ dominating set of nodes of G (see algorithm 7 in [R198]) and computing local max flow (see
local_edge_connectivity) between an arbitrary node in the dominating set and the rest of nodes in it. This is an implementation of algorithm 6 in [R198].

For directed graphs, the algorithm does \( n \) calls to the max flow function. This is an implementation of algorithm 8 in [R198]. We use the Ford and Fulkerson algorithm to compute max flow (see ford_fulkerson).

References

[R198]

Examples

```python
>>> # Platonic icosahedral graph is 5-edge-connected
>>> G = nx.icosahedral_graph()
>>> nx.edge_connectivity(G)
5
```

**all_pairs_node_connectivity_matrix**

**all_pairs_node_connectivity_matrix**

Return a numpy 2d ndarray with node connectivity between all pairs of nodes.

**Parameters**

- **G**: NetworkX graph
  - Undirected graph

**Returns**

- **K**: 2d numpy ndarray
  - node connectivity between all pairs of nodes.

**See also:**

- local_node_connectivity, node_connectivity, local_edge_connectivity, edge_connectivity, max_flow, ford_fulkerson

### 4.12.2 Cut functions

Flow based cut algorithms

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>minimum_st_node_cut(G, s, t[, aux_digraph, ...])</td>
<td>Returns a set of nodes of minimum cardinality that disconnect source</td>
</tr>
<tr>
<td>minimum_node_cut(G[, s, t])</td>
<td>Returns a set of nodes of minimum cardinality that disconnects G.</td>
</tr>
<tr>
<td>minimum_st_edge_cut(G, s, t[, capacity])</td>
<td>Returns the edges of the cut-set of a minimum (s, t)-cut.</td>
</tr>
<tr>
<td>minimum_edge_cut(G[, s, t])</td>
<td>Returns a set of edges of minimum cardinality that disconnects G.</td>
</tr>
</tbody>
</table>

**minimum_st_node_cut**

**minimum_st_node_cut**

Returns a set of nodes of minimum cardinality that disconnect source from target in G.

This function returns the set of nodes of minimum cardinality that, if removed, would destroy all paths among source and target in G.

**Parameters**

- **G**: NetworkX graph
minimum_node_cut

minimum_node_cut(G, s=None, t=None)

Returns a set of nodes of minimum cardinality that disconnects G.

If source and target nodes are provided, this function returns the set of nodes of minimum cardinality that, if removed, would destroy all paths among source and target in G. If not, it returns a set of nodes of minimum cardinality that disconnects G.

Parameters  

G : NetworkX graph

s : node

Source node. Optional (default=None)

t : node

Target node. Optional (default=None)

Returns  

cutset : set

Set of nodes that, if removed, would destroy all paths between source and target in G.

Notes

This is a flow based implementation of minimum node cut. The algorithm is based in solving a number of max-flow problems (ie local st-node connectivity, see local_node_connectivity) to determine the capacity of the minimum cut on an auxiliary directed network that corresponds to the minimum node cut of G. It handles both directed and undirected graphs.

This implementation is based on algorithm 11 in [R205]. We use the Ford and Fulkerson algorithm to compute max flow (see ford_fulkerson).

Examples

<<< # Platonic icosahedral graph has node connectivity 5 >>> G = nx.icosahedral_graph() >>> len(nx.minimum_node_cut(G, 0, 6)) 5
Set of nodes that, if removed, would disconnect G. If source and target nodes are provided, the set contains the nodes that if removed, would destroy all paths between source and target.

See also:
node_connectivity, edge_connectivity, minimum_edge_cut, max_flow, ford_fulkerson

Notes
This is a flow based implementation of minimum node cut. The algorithm is based in solving a number of max-flow problems (ie local st-node connectivity, see local_node_connectivity) to determine the capacity of the minimum cut on an auxiliary directed network that corresponds to the minimum node cut of G. It handles both directed and undirected graphs.

This implementation is based on algorithm 11 in [R204]. We use the Ford and Fulkerson algorithm to compute max flow (see ford_fulkerson).

References

[R204]

Examples

>>> # Platonic icosahedral graph has node connectivity 5
>>> G = nx.icosahedral_graph()
>>> len(nx.minimum_node_cut(G))
5
>>> # this is the minimum over any pair of non adjacent nodes
>>> from itertools import combinations
>>> for u,v in combinations(G, 2):
...     if v not in G[u]:
...         assert(len(nx.minimum_node_cut(G,u,v)) == 5)
...

minimum_st_edge_cut

minimum_st_edge_cut (G, s, t, capacity='capacity')

Returns the edges of the cut-set of a minimum (s, t)-cut.

We use the max-flow min-cut theorem, i.e., the capacity of a minimum capacity cut is equal to the flow value of a maximum flow.

Parameters

G : NetworkX graph

Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.

s : node
Source node for the flow.

t : node
Sink node for the flow.
capacity: string :

Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.

Returns cutset : set

Set of edges that, if removed from the graph, will disconnect it

Raises NetworkXUnbounded :

If the graph has a path of infinite capacity, all cuts have infinite capacity and the function raises a NetworkXError.

Examples

```python
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity = 3.0)
>>> G.add_edge('x','b', capacity = 1.0)
>>> G.add_edge('a','c', capacity = 3.0)
>>> G.add_edge('b','c', capacity = 5.0)
>>> G.add_edge('b','d', capacity = 4.0)
>>> G.add_edge('d','e', capacity = 2.0)
>>> G.add_edge('c','y', capacity = 2.0)
>>> G.add_edge('e','y', capacity = 3.0)
>>> sorted(nx.minimum_edge_cut(G, 'x', 'y'))
[('c', 'y'), ('x', 'b')]
>>> nx.min_cut(G, 'x', 'y')
3.0
```

minimum_edge_cut

minimum_edge_cut (G, s=None, t=None)

Returns a set of edges of minimum cardinality that disconnects G.

If source and target nodes are provided, this function returns the set of edges of minimum cardinality that, if removed, would break all paths among source and target in G. If not, it returns a set of edges of minimum cardinality that disconnects G.

Parameters G : NetworkX graph

s : node

Source node. Optional (default=None)

t : node

Target node. Optional (default=None)

Returns cutset : set

Set of edges that, if removed, would disconnect G. If source and target nodes are provided, the set contains the edges that if removed, would destroy all paths between source and target.

See also:

node_connectivity, edge_connectivity, minimum_node_cut, max_flow, ford_fulkerson
Notes

This is a flow based implementation of minimum edge cut. For undirected graphs the algorithm works by finding a ‘small’ dominating set of nodes of G (see algorithm 7 in [R203]) and computing the maximum flow between an arbitrary node in the dominating set and the rest of nodes in it. This is an implementation of algorithm 6 in [R203].

For directed graphs, the algorithm does n calls to the max flow function. This is an implementation of algorithm 8 in [R203]. We use the Ford and Fulkerson algorithm to compute max flow (see ford_fulkerson).

References

[R203]

Examples

```python
>>> # Platonic icosahedral graph has edge connectivity 5
>>> G = nx.icosahedral_graph()
>>> len(nx.minimum_edge_cut(G))
5
>>> # this is the minimum over any pair of nodes
>>> from itertools import combinations
>>> for u, v in combinations(G, 2):
...    assert (len(nx.minimum_edge_cut(G, u, v)) == 5)
...```

4.13 Cores

Find the k-cores of a graph.

The k-core is found by recursively pruning nodes with degrees less than k.

See the following reference for details:


<table>
<thead>
<tr>
<th>core_number(G)</th>
<th>Return the core number for each vertex.</th>
</tr>
</thead>
<tbody>
<tr>
<td>k_core(G, k, core_number)</td>
<td>Return the k-core of G.</td>
</tr>
<tr>
<td>k_shell(G, k, core_number)</td>
<td>Return the k-shell of G.</td>
</tr>
<tr>
<td>k_crust(G, k, core_number)</td>
<td>Return the k-crust of G.</td>
</tr>
<tr>
<td>k_corona(G, k, core_number)</td>
<td>Return the k-crust of G.</td>
</tr>
</tbody>
</table>

4.13.1 core_number

core_number(G)

Return the core number for each vertex.

A k-core is a maximal subgraph that contains nodes of degree k or more.

The core number of a node is the largest value k of a k-core containing that node.
Parameters  

G : NetworkX graph  
A graph or directed graph

Returns  

core_number : dictionary  
A dictionary keyed by node to the core number.

Raises  

NetworkXError :  
The k-core is not defined for graphs with self loops or parallel edges.

Notes  

Not implemented for graphs with parallel edges or self loops.  
For directed graphs the node degree is defined to be the in-degree + out-degree.

References  

[R206]

4.13.2 k_core

k_core  

(G, k=None, core_number=None)  
Return the k-core of G.

A k-core is a maximal subgraph that contains nodes of degree k or more.

Parameters  

G : NetworkX graph  
A graph or directed graph

k : int, optional  
The order of the core. If not specified return the main core.

core_number : dictionary, optional  
Precomputed core numbers for the graph G.

Returns  

G : NetworkX graph  
The k-core subgraph

Raises  

NetworkXError :  
The k-core is not defined for graphs with self loops or parallel edges.

See also:  

core_number

Notes  

The main core is the core with the largest degree.  
Not implemented for graphs with parallel edges or self loops.  
For directed graphs the node degree is defined to be the in-degree + out-degree.  
Graph, node, and edge attributes are copied to the subgraph.

4.13. Cores
References

[R207]

4.13.3 k_shell

k_shell (G, k=None, core_number=None)
Return the k-shell of G.

The k-shell is the subgraph of nodes in the k-core containing nodes of exactly degree k.

Parameters

- **G**: NetworkX graph
  - A graph or directed graph.
- **k**: int, optional
  - The order of the shell. If not specified return the main shell.
- **core_number**: dictionary, optional
  - Precomputed core numbers for the graph G.

Returns

- **G**: NetworkX graph
  - The k-shell subgraph

Raises

- **NetworkXError**
  - The k-shell is not defined for graphs with self loops or parallel edges.

See also:

core_number, k_corona, -------

Shai Carmi, Shlomo Havlin, Scott Kirkpatrick, Yuval Shavitt, and Eran Shir, PNAS July 3, 2007 vol. 104 no. 27 11150-11154

http //www.pnas.org/content/104/27/11150.full

Notes

This is similar to k_corona but in that case only neighbors in the k-core are considered.
Not implemented for graphs with parallel edges or self loops.
For directed graphs the node degree is defined to be the in-degree + out-degree.
Graph, node, and edge attributes are copied to the subgraph.

4.13.4 k_crust

k_crust (G, k=None, core_number=None)
Return the k-crust of G.

The k-crust is the graph G with the k-core removed.

Parameters

- **G**: NetworkX graph
  - A graph or directed graph.
- **k**: int, optional
The order of the shell. If not specified return the main crust.

**core_number** : dictionary, optional

Precomputed core numbers for the graph G.

**Returns**

G : NetworkX graph

The k-crust subgraph

**Raises**

NetworkXError :

The k-crust is not defined for graphs with self loops or parallel edges.

**See also:**

core_number

**Notes**

This definition of k-crust is different than the definition in [R209]. The k-crust in [R209] is equivalent to the k+1 crust of this algorithm.

Not implemented for graphs with parallel edges or self loops.

For directed graphs the node degree is defined to be the in-degree + out-degree.

Graph, node, and edge attributes are copied to the subgraph.

**References**

[R209]

### 4.13.5 k_corona

**k_corona** *(G, k, core_number=None)*

Return the k-crust of G.

The k-corona is the subset of vertices in the k-core which have exactly k neighbours in the k-core.

**Parameters**

G : NetworkX graph

A graph or directed graph

k : int

The order of the corona.

core_number : dictionary, optional

Precomputed core numbers for the graph G.

**Returns**

G : NetworkX graph

The k-corona subgraph

**Raises**

NetworkXError :

The k-corona is not defined for graphs with self loops or parallel edges.

**See also:**

core_number
Notes

Not implemented for graphs with parallel edges or self loops.
For directed graphs the node degree is defined to be the in-degree + out-degree.
Graph, node, and edge attributes are copied to the subgraph.

References

[R208]

4.14 Cycles

\[ \text{cycle\_basis}\ (G[, \ root]) \quad \text{Returns a list of cycles which form a basis for cycles of } G. \]
\[ \text{simple\_cycles}\ (G) \quad \text{Find simple cycles (elementary circuits) of a directed graph.} \]

4.14.1 cycle\_basis

cycle\_basis\ (G, \ root=None)  
Returns a list of cycles which form a basis for cycles of G.

A basis for cycles of a network is a minimal collection of cycles such that any cycle in the network can be written as a sum of cycles in the basis. Here summation of cycles is defined as “exclusive or” of the edges. Cycle bases are useful, e.g. when deriving equations for electric circuits using Kirchhoff’s Laws.

Parameters

- G : NetworkX Graph
- root : node, optional
  Specify starting node for basis.

Returns

A list of cycle lists. Each cycle list is a list of nodes:
which forms a cycle (loop) in G.

See also:

simple\_cycles

Notes

This is adapted from algorithm CACM 491 [R210].

References

[R210]
>>> G=nx.Graph()
>>> G.add_cycle([0,1,2,3])
>>> G.add_cycle([0,3,4,5])
>>> print(nx.cycle_basis(G,0))
[[3, 4, 5, 0], [1, 2, 3, 0]]

4.14.2 simple_cycles

simple_cycles(G)

Find simple cycles (elementary circuits) of a directed graph.

An simple cycle, or elementary circuit, is a closed path where no node appears twice, except that the first and last node are the same. Two elementary circuits are distinct if they are not cyclic permutations of each other.

This is a nonrecursive, iterator/generator version of Johnson’s algorithm [R211]. There may be better algorithms for some cases [R212][R213].

Parameters  G : NetworkX DiGraph

A directed graph

Returns  cycle_generator: generator :

A generator that produces elementary cycles of the graph. Each cycle is a list of nodes with the first and last nodes being the same.

See also:
cycle_basis

Notes

The implementation follows pp. 79-80 in [R211].
The time complexity is O((n+e)(c+1)) for n nodes, e edges and c elementary circuits.

To filter the cycles so that they don’t include certain nodes or edges, copy your graph and eliminate those nodes or edges before calling. >>> copyG = G.copy() >>> copyG.remove_nodes_from([1]) >>> copyG.remove_edges_from([(0,1)]) >>> list(nx.simple_cycles(copyG)) [[2], [2, 0], [0]]

References

[R211], [R212], [R213]

Examples

>>> G = nx.DiGraph([(0, 0), (0, 1), (0, 2), (1, 2), (2, 0), (2, 1), (2, 2)])
>>> list(nx.simple_cycles(G))
[[2], [2, 1], [2, 0], [2, 0, 1], [0]]

4.15 Directed Acyclic Graphs
4.15.1 ancestors

ancestors(G, source)

Return all nodes having a path to source in G.

Parameters

- G : NetworkX DiGraph
- source : node in G

Returns

ancestors : set()

The ancestors of source in G

4.15.2 descendants

descendants(G, source)

Return all nodes reachable from source in G.

Parameters

- G : NetworkX DiGraph
- source : node in G

Returns

des : set()

The descendants of source in G

4.15.3 topological_sort

topological_sort(G, nbunch=None)

Return a list of nodes in topological sort order.

A topological sort is a nonunique permutation of the nodes such that an edge from u to v implies that u appears before v in the topological sort order.

Parameters

- G : NetworkX digraph
  - A directed graph
- nbunch : container of nodes (optional)
  - Explore graph in specified order given in nbunch

Raises

- NetworkXError : Topological sort is defined for directed graphs only. If the graph G is undirected, a NetworkXError is raised.
- NetworkXUnfeasible : If G is not a directed acyclic graph (DAG) no topological sort exists and a NetworkX- Unfeasible exception is raised.
See also:

is_directed_acyclic_graph

Notes

This algorithm is based on a description and proof in The Algorithm Design Manual [R215].

References

[R215]

4.15.4 topological_sort_recursive

topological_sort_recursive(G, nbunch=None)

Return a list of nodes in topological sort order.

A topological sort is a nonunique permutation of the nodes such that an edge from u to v implies that u appears before v in the topological sort order.

Parameters

G : NetworkX digraph

nbunch : container of nodes (optional)

Explore graph in specified order given in nbunch

Raises

NetworkXError :

Topological sort is defined for directed graphs only. If the graph G is undirected, a NetworkXError is raised.

NetworkXUnfeasible :

If G is not a directed acyclic graph (DAG) no topological sort exists and a NetworkXUnfeasible exception is raised.

See also:

topological_sort, is_directed_acyclic_graph

Notes

This is a recursive version of topological sort.

4.15.5 is_directed_acyclic_graph

is_directed_acyclic_graph(G)

Return True if the graph G is a directed acyclic graph (DAG) or False if not.

Parameters

G : NetworkX graph

A graph

Returns

is_dag : bool

True if G is a DAG, false otherwise
4.15.6 is_aperiodic

is_aperiodic(G)

Return True if G is aperiodic.

A directed graph is aperiodic if there is no integer k > 1 that divides the length of every cycle in the graph.

Parameters  
G : NetworkX DiGraph

Graph

Returns  
aperiodic : boolean

True if the graph is aperiodic False otherwise

Notes

This uses the method outlined in [R214], which runs in O(m) time given m edges in G. Note that a graph is not aperiodic if it is acyclic as every integer trivial divides length 0 cycles.

References

[R214]

4.16 Distance Measures

Graph diameter, radius, eccentricity and other properties.

center(G[, e]) Return the center of the graph G.

diameter(G[, e]) Return the diameter of the graph G.

eccentricity(G[, v, sp]) Return the eccentricity of nodes in G.

periphery(G[, e]) Return the periphery of the graph G.

radius(G[, e]) Return the radius of the graph G.

4.16.1 center

center(G, e=None)

Return the center of the graph G.

The center is the set of nodes with eccentricity equal to radius.

Parameters  
G : NetworkX graph

A graph

e : eccentricity dictionary, optional

A precomputed dictionary of eccentricities.

Returns  
c : list

List of nodes in center
4.16.2 diameter

diameter\( (G, e=None) \)
Return the diameter of the graph \( G \).

The diameter is the maximum eccentricity.

**Parameters**

- **\( G \) :** NetworkX graph
  - A graph
- **\( e \) :** eccentricity dictionary, optional
  - A precomputed dictionary of eccentricities.

**Returns**

- **\( d \) :** integer
  - Diameter of graph

**See also:**

eccentricity

4.16.3 eccentricity

eccentricity\( (G, v=None, sp=None) \)
Return the eccentricity of nodes in \( G \).

The eccentricity of a node \( v \) is the maximum distance from \( v \) to all other nodes in \( G \).

**Parameters**

- **\( G \) :** NetworkX graph
  - A graph
- **\( v \) :** node, optional
  - Return value of specified node
- **\( sp \) :** dict of dicts, optional
  - All pairs shortest path lengths as a dictionary of dictionaries

**Returns**

- **\( ecc \) :** dictionary
  - A dictionary of eccentricity values keyed by node.

4.16.4 periphery

periphery\( (G, e=None) \)
Return the periphery of the graph \( G \).

The periphery is the set of nodes with eccentricity equal to the diameter.

**Parameters**

- **\( G \) :** NetworkX graph
  - A graph
- **\( e \) :** eccentricity dictionary, optional
  - A precomputed dictionary of eccentricities.

**Returns**

- **\( p \) :** list
  - List of nodes in periphery
4.16.5 radius

radius \((G, e=None)\)

Return the radius of the graph \(G\).

The radius is the minimum eccentricity.

**Parameters**

\(G\) : NetworkX graph

A graph

\(e\) : eccentricity dictionary, optional

A precomputed dictionary of eccentricities.

**Returns**

\(r\) : integer

Radius of graph

4.17 Distance-Regular Graphs

**is_distance_regular** \((G)\)

Returns True if the graph is distance regular, False otherwise.

**intersection_array** \((G)\)

Returns the intersection array of a distance-regular graph.

**global_parameters** \((b, c)\)

Return global parameters for a given intersection array.

4.17.1 is_distance_regular

**is_distance_regular** \((G)\)

Returns True if the graph is distance regular, False otherwise.

A connected graph \(G\) is distance-regular if for any nodes \(x, y\) and any integers \(i, j=0, 1, ..., d\) (where \(d\) is the graph diameter), the number of vertices at distance \(i\) from \(x\) and distance \(j\) from \(y\) depends only on \(i, j\) and the graph distance between \(x\) and \(y\), independently of the choice of \(x\) and \(y\).

**Parameters**

\(G\) : Networkx graph (undirected)

**Returns**

\(bool\) : 

True if the graph is Distance Regular, False otherwise

**See also:**

intersection_array, global_parameters

**Notes**

For undirected and simple graphs only

**References**

[R218], [R219]
4.17.2 intersection_array

intersection_array \( G \)

Returns the intersection array of a distance-regular graph.

Given a distance-regular graph \( G \) with integers \( b_i, c_i, i = 0, \ldots, d \) such that for any 2 vertices \( x, y \) in \( G \) at a distance \( i=d(x,y) \), there are exactly \( c_i \) neighbors of \( y \) at a distance of \( i-1 \) from \( x \) and \( b_i \) neighbors of \( y \) at a distance of \( i+1 \) from \( x \).

A distance regular graph’s intersection array is given by, \([b_0,b_1,\ldots,b_{d-1};c_1,c_2,\ldots,c_d]\)

Parameters  
\( G \): Networkx graph (undirected)

Returns  
\( b,c \): tuple of lists

See also:  
global_parameters

References

[R217]

Examples

```python
>>> G=nx.hypercube_graph(6)
>>> nx.is_distance_regular(G)
True
```

4.17.3 global_parameters

global_parameters \( (b, c) \)

Return global parameters for a given intersection array.

Given a distance-regular graph \( G \) with integers \( b_i, c_i, i = 0, \ldots, d \) such that for any 2 vertices \( x, y \) in \( G \) at a distance \( i=d(x,y) \), there are exactly \( c_i \) neighbors of \( y \) at a distance of \( i-1 \) from \( x \) and \( b_i \) neighbors of \( y \) at a distance of \( i+1 \) from \( x \).

Thus, a distance regular graph has the global parameters, \([[c_0,a_0,b_0],[c_1,a_1,b_1],\ldots,[c_d,a_d,b_d]]\) for the intersection array \([b_0,b_1,\ldots,b_{d-1};c_1,c_2,\ldots,c_d]\) where \( a_i+b_i+c_i=k \), \( k= \) degree of every vertex.

Parameters  
\( b,c \): tuple of lists

Returns  
\( p \): list of three-tuples

See also:  
intersection_array
References

[R216]

Examples

```python
>>> G=nx.dodecahedral_graph()
>>> b,c=nx.intersection_array(G)
>>> list(nx.global_parameters(b,c))
[(0, 0, 3), (1, 0, 2), (1, 1, 1), (1, 1, 1), (2, 0, 1), (3, 0, 0)]
```

4.18 Eulerian

Eulerian circuits and graphs.

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<th>is_eulerian(G)</th>
<th>Return True if G is an Eulerian graph, False otherwise.</th>
</tr>
</thead>
<tbody>
<tr>
<td>eulerian_circuit(G[, source])</td>
<td>Return the edges of an Eulerian circuit in G.</td>
</tr>
</tbody>
</table>

4.18.1 is_eulerian

**is_eulerian** *(G)*

Return True if G is an Eulerian graph, False otherwise.

An Eulerian graph is a graph with an Eulerian circuit.

**Parameters**

- **G** : graph
  A NetworkX Graph

**Notes**

This implementation requires the graph to be connected (or strongly connected for directed graphs).

**Examples**

```python
>>> nx.is_eulerian(nx.DiGraph({0:[3], 1:[2], 2:[3], 3:[0, 1]}))
True
>>> nx.is_eulerian(nx.complete_graph(5))
True
>>> nx.is_eulerian(nx.petersen_graph())
False
```

4.18.2 eulerian_circuit

**eulerian_circuit** *(G, source=None)*

Return the edges of an Eulerian circuit in G.

An Eulerian circuit is a path that crosses every edge in G exactly once and finishes at the starting node.

**Parameters**

- **G** : graph
A NetworkX Graph

**source** : node, optional
Starting node for circuit.

**Returns** **edges** : generator
A generator that produces edges in the Eulerian circuit.

**Raises** **NetworkXError** :
If the graph is not Eulerian.

**See also:**
`is_eulerian`

**Notes**
Uses Fleury’s algorithm [R220],[R221].

**References**
[R220], [R221]

**Examples**

```python
>>> G=nx.complete_graph(3)
>>> list(nx.eulerian_circuit(G))
[(0, 1), (1, 2), (2, 0)]
>>> list(nx.eulerian_circuit(G,source=1))
[(1, 0), (0, 2), (2, 1)]
>>> [u for u,v in nx.eulerian_circuit(G)] # nodes in circuit
[0, 1, 2]
```

### 4.19 Flows

#### 4.19.1 Ford-Fulkerson

<table>
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<th>Function</th>
<th>Description</th>
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<td><code>max_flow(G, s, t[, capacity])</code></td>
<td>Find the value of a maximum single-commodity flow.</td>
</tr>
<tr>
<td><code>min_cut(G, s, t[, capacity])</code></td>
<td>Compute the value of a minimum (s, t)-cut.</td>
</tr>
<tr>
<td><code>ford_fulkerson(G, s, t[, capacity])</code></td>
<td>Find a maximum single-commodity flow using the Ford-Fulkerson</td>
</tr>
<tr>
<td><code>ford_fulkerson_flow(G, s, t[, capacity])</code></td>
<td>Return a maximum flow for a single-commodity flow problem.</td>
</tr>
<tr>
<td><code>ford_fulkerson_flow_and_auxiliary(G, s, t[, ...])</code></td>
<td>Find a maximum single-commodity flow using the Ford-Fulkerson</td>
</tr>
</tbody>
</table>

**max_flow**

`max_flow(G, s, t[, capacity])`
Find the value of a maximum single-commodity flow.

**Parameters** **G** : NetworkX graph
Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.

**s**: node
Source node for the flow.

**t**: node
Sink node for the flow.

**capacity**: string:
Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.

Returns **flow_value**: integer, float
Value of the maximum flow, i.e., net outflow from the source.

Raises **NetworkXError**:
The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.

**NetworkXUnbounded**:
If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('d','e', capacity=2.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
>>> flow = nx.max_flow(G, 'x', 'y')
>>> flow
3.0
```

**min_cut**

**min_cut** *(G, s, t, capacity=’capacity’)*
Compute the value of a minimum (s, t)-cut.
Use the max-flow min-cut theorem, i.e., the capacity of a minimum capacity cut is equal to the flow value of a maximum flow.

Parameters **G** : NetworkX graph
Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.

**s** : node
Source node for the flow.

\( t \) : node

Sink node for the flow.

capacity: string :

Edges of the graph \( G \) are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.

Returns cutValue : integer, float

Value of the minimum cut.

Raises NetworkXUnbounded :

If the graph has a path of infinite capacity, all cuts have infinite capacity and the function raises a NetworkXError.

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity = 3.0)
>>> G.add_edge('x','b', capacity = 1.0)
>>> G.add_edge('a','c', capacity = 3.0)
>>> G.add_edge('b','c', capacity = 5.0)
>>> G.add_edge('b','d', capacity = 4.0)
>>> G.add_edge('d','e', capacity = 2.0)
>>> G.add_edge('c','y', capacity = 2.0)
>>> G.add_edge('e','y', capacity = 3.0)
>>> nx.min_cut(G, 'x', 'y')
3.0
```

ford_fulkerson

ford_fulkerson \((G, s, t, capacity=’capacity’)\)

Find a maximum single-commodity flow using the Ford-Fulkerson algorithm.

This algorithm uses Edmonds-Karp-Dinitz path selection rule which guarantees a running time of \( O(nm^2) \) for \( n \) nodes and \( m \) edges.

Parameters

\( G \) : NetworkX graph

Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.

\( s \) : node

Source node for the flow.

\( t \) : node

Sink node for the flow.

capacity: string :

Edges of the graph \( G \) are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
Returns  

flow_value : integer, float

Value of the maximum flow, i.e., net outflow from the source.

flow_dict : dictionary

Dictionary of dictionaries keyed by nodes such that flow_dict[u][v] is the flow edge (u, v).

Raises  

NetworkXError :

The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.

NetworkXUnbounded :

If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('d','e', capacity=4.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
>>> flow, F = nx.ford_fulkerson(G, 'x', 'y')
>>> flow
3.0
```

ford_fulkerson_flow

```
ford_fulkerson_flow (G, s, t, capacity='capacity')
```

Return a maximum flow for a single-commodity flow problem.

Parameters  

G : NetworkX graph

Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.

s : node

Source node for the flow.

t : node

Sink node for the flow.

capacity: string :

Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.

Returns  

flow_dict : dictionary
Dictionary of dictionaries keyed by nodes such that \(\text{flow_dict}[u][v]\) is the flow edge \((u, v)\).

**Raises** NetworkXError:

The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.

**NetworkXUnbounded**:

If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

**Examples**

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('d','e', capacity=2.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
>>> F = nx.ford_fulkerson_flow(G, 'x', 'y')
```

```python
>>> for u, v in sorted(G.edges_iter()):
...    print('(' + u + ', ' + v + ') %.2f' % (F[u][v]))
...    
...    (a, c) 2.00
(b, c) 0.00
(b, d) 1.00
(c, y) 2.00
(d, e) 1.00
(e, y) 1.00
(x, a) 2.00
(x, b) 1.00
```

**ford_fulkerson_flow_and_auxiliary**

```python
ford_fulkerson_flow_and_auxiliary(G, s, t, capacity='capacity')
```

Find a maximum single-commodity flow using the Ford-Fulkerson algorithm. This function returns both the value of the maximum flow and the auxiliary network resulting after finding the maximum flow, which is also named residual network in the literature. The auxiliary network has edges with capacity equal to the capacity of the edge in the original network minus the flow that went through that edge. Notice that it can happen that a flow from \(v\) to \(u\) is allowed in the auxiliary network, though disallowed in the original network. A dictionary with infinite capacity edges can be found as an attribute of the auxiliary network.

**Parameters**

- **G** : NetworkX graph
  
  Edges of the graph are expected to have an attribute called `capacity`. If this attribute is not present, the edge is considered to have infinite capacity.

- **s** : node
  
  Source node for the flow.

- **t** : node
  
  Sink node for the flow.
Sink node for the flow.

**capacity**: string

Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.

**Returns**  **flow_value**: integer, float

Value of the maximum flow, i.e., net outflow from the source.

**auxiliary**: DiGraph

Residual/auxiliary network after finding the maximum flow. A dictionary with infinite capacity edges can be found as an attribute of this network: auxiliary.graph[‘inf_capacity_flows’]

**Raises**  **NetworkXError**: The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.

**NetworkXUnbounded**: If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

**Notes**

This algorithm uses Edmonds-Karp-Dinitz path selection rule which guarantees a running time of $O(nm^2)$ for $n$ nodes and $m$ edges.

**Examples**

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('c','e', capacity=2.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
>>> flow, auxiliary = nx.ford_fulkerson_flow_and_auxiliary(G, 'x', 'y')
>>> flow
3.0
>>> # A dictionary with infinite capacity flows can be found as an
>>> # attribute of the auxiliary network
>>> inf_capacity_flows = auxiliary.graph[‘inf_capacity_flows’]
```

### 4.19.2 Network Simplex

```python
network_simplex(G[, demand, capacity, weight]) Find a minimum cost flow satisfying all demands in digraph G.
```

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Table 4.46 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>min_cost_flow_cost(G, demand, capacity, weight)</code></td>
<td>Find the cost of a minimum cost flow satisfying all demands in digraph G.</td>
</tr>
<tr>
<td><code>min_cost_flow(G, demand, capacity, weight)</code></td>
<td>Return a minimum cost flow satisfying all demands in digraph G.</td>
</tr>
<tr>
<td><code>cost_of_flow(G, flowDict[, weight])</code></td>
<td>Compute the cost of the flow given by flowDict on graph G.</td>
</tr>
<tr>
<td><code>max_flow_min_cost(G, s, t[, capacity, weight])</code></td>
<td>Return a maximum (s, t)-flow of minimum cost.</td>
</tr>
</tbody>
</table>

---

**network_simplex**

`network_simplex(G, demand='demand', capacity='capacity', weight='weight')`

Find a minimum cost flow satisfying all demands in digraph G.

This is a primal network simplex algorithm that uses the leaving arc rule to prevent cycling.

G is a digraph with edge costs and capacities and in which nodes have demand, i.e., they want to send or receive some amount of flow. A negative demand means that the node wants to send flow, a positive demand means that the node want to receive flow. A flow on the digraph G satisfies all demand if the net flow into each node is equal to the demand of that node.

**Parameters**

- `G` : NetworkX graph
  DiGraph on which a minimum cost flow satisfying all demands is to be found.
- `demand` : string :
  Nodes of the graph G are expected to have an attribute demand that indicates how much flow a node wants to send (negative demand) or receive (positive demand). Note that the sum of the demands should be 0 otherwise the problem in not feasible. If this attribute is not present, a node is considered to have 0 demand. Default value: ‘demand’.
- `capacity` : string :
  Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- `weight` : string :
  Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.

**Returns**

- `flowCost` : integer, float :
  Cost of a minimum cost flow satisfying all demands.
- `flowDict` : dictionary :
  Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge (u, v).

**Raises**

- `NetworkXError` :
  This exception is raised if the input graph is not directed, not connected or is a multigraph.
- `NetworkXUnfeasible` :
  This exception is raised in the following situations:
  - The sum of the demands is not zero. Then, there is no flow satisfying all demands.
  - There is no flow satisfying all demand.

---

4.19. Flows
This exception is raised if the digraph G has a cycle of negative cost and infinite capacity. Then, the cost of a flow satisfying all demands is unbounded below.

See also:

cost_of_flow, max_flow_min_cost, min_cost_flow, min_cost_flow_cost

Notes

This algorithm is not guaranteed to work if edge weights are floating point numbers (overflows and roundoff errors can cause problems).

References


Examples

A simple example of a min cost flow problem.

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_node('a', demand = -5)
>>> G.add_node('d', demand = 5)
>>> G.add_edge('a', 'b', weight = 3, capacity = 4)
>>> G.add_edge('a', 'c', weight = 6, capacity = 10)
>>> G.add_edge('b', 'd', weight = 1, capacity = 9)
>>> G.add_edge('c', 'd', weight = 2, capacity = 5)
>>> flowCost, flowDict = nx.network_simplex(G)
>>> flowCost
24
>>> flowDict
{'a': {'c': 1, 'b': 4}, 'c': {'d': 1}, 'b': {'d': 4}, 'd': {}}
```

The mincost flow algorithm can also be used to solve shortest path problems. To find the shortest path between two nodes u and v, give all edges an infinite capacity, give node u a demand of -1 and node v a demand a 1. Then run the network simplex. The value of a min cost flow will be the distance between u and v and edges carrying positive flow will indicate the path.

```python
>>> G=nx.DiGraph()
>>> G.add_weighted_edges_from([('s','u',10), ('s','x',5),
... ('u','v',1), ('u','x',2),
... ('v','y',1), ('x','u',3),
... ('x','v',5), ('x','y',2),
... ('y','s',7), ('y','v',6)])
>>> G.add_node('s', demand = -1)
>>> G.add_node('v', demand = 1)
>>> flowCost, flowDict = nx.network_simplex(G)
>>> flowCost == nx.shortest_path_length(G, 's', 'v', weight = 'weight')
True
>>> sorted([u, v] for u in flowDict for v in flowDict[u] if flowDict[u][v] > 0)
[('s', 'x'), ('u', 'v'), ('x', 'u')]
>>> nx.shortest_path(G, 's', 'v', weight = 'weight')
['s', 'x', 'u', 'v']
```
It is possible to change the name of the attributes used for the algorithm.

```python
>>> G = nx.DiGraph()
>>> G.add_node('p', spam = -4)
>>> G.add_node('q', spam = 2)
>>> G.add_node('a', spam = -2)
>>> G.add_node('d', spam = -1)
>>> G.add_node('t', spam = 2)
>>> G.add_node('w', spam = 3)
>>> G.add_edge('p', 'q', cost = 7, vacancies = 5)
>>> G.add_edge('p', 'a', cost = 1, vacancies = 4)
>>> G.add_edge('q', 'd', cost = 2, vacancies = 3)
>>> G.add_edge('t', 'q', cost = 1, vacancies = 2)
>>> G.add_edge('a', 't', cost = 2, vacancies = 4)
>>> G.add_edge('d', 'w', cost = 3, vacancies = 4)
>>> G.add_edge('t', 'w', cost = 4, vacancies = 1)
>>> flowCost, flowDict = nx.network_simplex(G, demand = 'spam',
...                                       capacity = 'vacancies',
...                                       weight = 'cost')
>>> flowCost
37
>>> flowDict
{'a': {'t': 4}, 'd': {'w': 2}, 'q': {'d': 1}, 'p': {'q': 2, 'a': 2}, 't': {'q': 1, 'w': 1}, 'w':

```

**min_cost_flow_cost**

`min_cost_flow_cost(G, demand=’demand’, capacity=’capacity’, weight=’weight’)`

Find the cost of a minimum cost flow satisfying all demands in digraph `G`.

`G` is a digraph with edge costs and capacities and in which nodes have demand, i.e., they want to send or receive some amount of flow. A negative demand means that the node wants to send flow, a positive demand means that the node want to receive flow. A flow on the digraph `G` satisfies all demand if the net flow into each node is equal to the demand of that node.

**Parameters**

- **G**: NetworkX graph
  DiGraph on which a minimum cost flow satisfying all demands is to be found.

- **demand**: string
  Nodes of the graph `G` are expected to have an attribute demand that indicates how much flow a node wants to send (negative demand) or receive (positive demand). Note that the sum of the demands should be 0 otherwise the problem in not feasible. If this attribute is not present, a node is considered to have 0 demand. Default value: ‘demand’.

- **capacity**: string
  Edges of the graph `G` are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.

- **weight**: string
  Edges of the graph `G` are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.

**Returns**

- **flowCost**: integer, float
  Cost of a minimum cost flow satisfying all demands.
Raises NetworkXError:

This exception is raised if the input graph is not directed or not connected.

NetworkXUnfeasible:

This exception is raised in the following situations:

- The sum of the demands is not zero. Then, there is no flow satisfying all demands.
- There is no flow satisfying all demand.

NetworkXUnbounded:

This exception is raised if the digraph G has a cycle of negative cost and infinite capacity. Then, the cost of a flow satisfying all demands is unbounded below.

See also:

cost_of_flow, max_flow_min_cost, min_cost_flow, network_simplex

Examples

A simple example of a min cost flow problem.

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_node('a', demand = -5)
>>> G.add_node('d', demand = 5)
>>> G.add_edge('a', 'b', weight = 3, capacity = 4)
>>> G.add_edge('a', 'c', weight = 6, capacity = 10)
>>> G.add_edge('b', 'd', weight = 1, capacity = 9)
>>> G.add_edge('c', 'd', weight = 2, capacity = 5)
>>> flowCost = nx.min_cost_flow_cost(G)
>>> flowCost
24
```

min_cost_flow

`min_cost_flow(G, demand='demand', capacity='capacity', weight='weight')`

Return a minimum cost flow satisfying all demands in digraph G.

G is a digraph with edge costs and capacities and in which nodes have demand, i.e., they want to send or receive some amount of flow. A negative demand means that the node wants to send flow, a positive demand means that the node want to receive flow. A flow on the digraph G satisfies all demand if the net flow into each node is equal to the demand of that node.

Parameters G : NetworkX graph

DiGraph on which a minimum cost flow satisfying all demands is to be found.

demand: string

Nodes of the graph G are expected to have an attribute demand that indicates how much flow a node wants to send (negative demand) or receive (positive demand). Note that the sum of the demands should be 0 otherwise the problem in not feasible. If this attribute is not present, a node is considered to have 0 demand. Default value: ‘demand’.

capacity: string
Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.

weight: string:
Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.

Returns flowDict: dictionary:
Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge (u, v).

Raises NetworkXError:
This exception is raised if the input graph is not directed or not connected.

NetworkXUnfeasible:

This exception is raised in the following situations:

• The sum of the demands is not zero. Then, there is no flow satisfying all demands.
• There is no flow satisfying all demand.

NetworkXUnbounded:

This exception is raised if the digraph G has a cycle of negative cost and infinite capacity. Then, the cost of a flow satisfying all demands is unbounded below.

See also:
cost_of_flow, max_flow_min_cost, min_cost_flow_cost, network_simplex

Examples

A simple example of a min cost flow problem.

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_node('a', demand = -5)
>>> G.add_node('d', demand = 5)
>>> G.add_edge('a', 'b', weight = 3, capacity = 4)
>>> G.add_edge('a', 'c', weight = 6, capacity = 10)
>>> G.add_edge('b', 'd', weight = 1, capacity = 9)
>>> G.add_edge('c', 'd', weight = 2, capacity = 5)
>>> flowDict = nx.min_cost_flow(G)
```

**cost_of_flow**

`cost_of_flow(G, flowDict, weight='weight')`

Compute the cost of the flow given by flowDict on graph G.

Note that this function does not check for the validity of the flow flowDict. This function will fail if the graph G and the flow don’t have the same edge set.

Parameters G : NetworkX graph

DiGraph on which a minimum cost flow satisfying all demands is to be found.
weight: string :
   Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.

flowDict: dictionary :
   Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge (u, v).

Returns cost: Integer, float :
   The total cost of the flow. This is given by the sum over all edges of the product of the edge’s flow and the edge’s weight.

See also:
   max_flow_min_cost, min_cost_flow, min_cost_flow_cost, network_simplex

max_flow_min_cost

max_flow_min_cost (G, s, t, capacity='capacity', weight='weight')
   Return a maximum (s, t)-flow of minimum cost.
   G is a digraph with edge costs and capacities. There is a source node s and a sink node t. This function finds a maximum flow from s to t whose total cost is minimized.

Parameters  
   G : NetworkX graph
      DiGraph on which a minimum cost flow satisfying all demands is to be found.
   s: node label :
      Source of the flow.
   t: node label :
      Destination of the flow.
   capacity: string :
      Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
   weight: string :
      Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.

Returns flowDict: dictionary :
   Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge (u, v).

Raises NetworkXError :
   This exception is raised if the input graph is not directed or not connected.

NetworkXUnbounded :
This exception is raised if there is an infinite capacity path from s to t in G. In this case there is no maximum flow. This exception is also raised if the digraph G has a cycle of negative cost and infinite capacity. Then, the cost of a flow is unbounded below.

See also:

- cost_of_flow
- ford_fulkerson
- min_cost_flow
- min_cost_flow_cost
- network_simplex

Examples

```python
>>> G = nx.DiGraph()
>>> G.add_edges_from([((1, 2, {'capacity': 12, 'weight': 4}),
... (1, 3, {'capacity': 20, 'weight': 6}),
... (2, 3, {'capacity': 6, 'weight': -3}),
... (2, 6, {'capacity': 14, 'weight': 1}),
... (3, 4, {'weight': 9}),
... (3, 5, {'capacity': 10, 'weight': 5}),
... (4, 2, {'capacity': 19, 'weight': 13}),
... (4, 5, {'capacity': 4, 'weight': 0}),
... (5, 7, {'capacity': 28, 'weight': 2}),
... (6, 5, {'capacity': 11, 'weight': 1}),
... (6, 7, {'weight': 8}),
... (7, 4, {'capacity': 6, 'weight': 6})])
>>> mincostFlow = nx.max_flow_min_cost(G, 1, 7)
>>> nx.cost_of_flow(G, mincostFlow)
373
>>> maxFlow = nx.ford_fulkerson_flow(G, 1, 7)
>>> nx.cost_of_flow(G, maxFlow)
428
>>> mincostFlowValue = (sum((mincostFlow[u][7] for u in G.predecessors(7)))
... - sum((mincostFlow[7][v] for v in G.successors(7))))
>>> mincostFlowValue == nx.max_flow(G, 1, 7)
True
```

4.20 Graphical degree sequence

Test sequences for graphiness.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>is_graphical(sequence[, method])</td>
<td>Returns True if sequence is a valid degree sequence.</td>
</tr>
<tr>
<td>is_digraphical(in_sequence, out_sequence)</td>
<td>Returns True if some directed graph can realize the in- and out-degree.</td>
</tr>
<tr>
<td>is_multigraphical(sequence)</td>
<td>Returns True if some multigraph can realize the sequence.</td>
</tr>
<tr>
<td>is_pseudographical(sequence)</td>
<td>Returns True if some pseudograph can realize the sequence.</td>
</tr>
<tr>
<td>is_valid_degree_sequence_havel_hakimi(...)</td>
<td>Returns True if deg_sequence can be realized by a simple graph.</td>
</tr>
<tr>
<td>is_valid_degree_sequence_erdos_gallai(...)</td>
<td>Returns True if deg_sequence can be realized by a simple graph.</td>
</tr>
</tbody>
</table>

4.20.1 is_graphical

is_graphical (sequence, method=‘eg’)

Returns True if sequence is a valid degree sequence.

A degree sequence is valid if some graph can realize it.
**Parameters**  
*sequence*: list or iterable container  
A sequence of integer node degrees  

*method*: “eg” | “hh”  
The method used to validate the degree sequence. “eg” corresponds to the Erdős-Gallai algorithm, and “hh” to the Havel-Hakimi algorithm.

**Returns**  
*valid*: bool  
True if the sequence is a valid degree sequence and False if not.

**References**

Erdős-Gallai [EG1960], [choudum1986]  
Havel-Hakimi [havel1955], [hakimi1962], [CL1996]

**Examples**

```python
g = nx.path_graph(4)
sequence = g.degree().values()
nx.is_valid_degree_sequence(sequence)
```

True

### 4.20.2 is_digraphical

**is_digraphical**(in_sequence, out_sequence)  
Returns True if some directed graph can realize the in- and out-degree sequences.

**Parameters**

*in_sequence*: list or iterable container  
A sequence of integer node in-degrees  

*out_sequence*: list or iterable container  
A sequence of integer node out-degrees  

**Returns**  
*valid*: bool  
True if in and out-sequences are digraphic False if not.

**Notes**

This algorithm is from Kleitman and Wang [R222]. The worst case runtime is \( O(s \times \log n) \) where \( s \) and \( n \) are the sum and length of the sequences respectively.

**References**

[R222]
### 4.20.3 is_multigraphical

**is_multigraphical** *(sequence)*

Returns True if some multigraph can realize the sequence.

- **Parameters**
  - **deg_sequence** : list
    - A list of integers

- **Returns**
  - **valid** : bool
    - True if deg_sequence is a multigraphic degree sequence and False if not.

**Notes**

The worst-case run time is $O(n)$ where $n$ is the length of the sequence.

**References**

[R223]

### 4.20.4 is_pseudographical

**is_pseudographical** *(sequence)*

Returns True if some pseudograph can realize the sequence.

Every nonnegative integer sequence with an even sum is pseudographical (see [R224]).

- **Parameters**
  - **sequence** : list or iterable container
    - A sequence of integer node degrees

- **Returns**
  - **valid** : bool
    - True if the sequence is a pseudographic degree sequence and False if not.

**Notes**

The worst-case run time is $O(n)$ where $n$ is the length of the sequence.

**References**

[R224]

### 4.20.5 is_valid_degree_sequence_havel_hakimi

**is_valid_degree_sequence_havel_hakimi** *(deg_sequence)*

Returns True if deg_sequence can be realized by a simple graph.

The validation proceeds using the Havel-Hakimi theorem. Worst-case run time is: $O(s)$ where $s$ is the sum of the sequence.

- **Parameters**
  - **deg_sequence** : list
    - A list of integers where each element specifies the degree of a node in a graph.
Returns valid : bool

True if deg_sequence is graphical and False if not.

Notes

The ZZ condition says that for the sequence d if

$$|d| > \frac{(\max(d) + \min(d) + 1)^2}{4 \times \min(d)}$$

then d is graphical. This was shown in Theorem 6 in [R227].

References

[havel1955], [hakimi1962], [CL1996]

[R227]

4.20.6 is_valid_degree_sequence_erdos_gallai

is_valid_degree_sequence_erdos_gallai (deg_sequence)

Returns True if deg_sequence can be realized by a simple graph.

The validation is done using the Erdős-Gallai theorem [EG1960].

Parameters deg_sequence : list

A list of integers

Returns valid : bool

True if deg_sequence is graphical and False if not.

Notes

This implementation uses an equivalent form of the Erdős-Gallai criterion. Worst-case run time is: O(n) where n is the length of the sequence.

Specifically, a sequence d is graphical if and only if the sum of the sequence is even and for all strong indices k in the sequence,

$$\sum_{i=1}^{k} d_i \leq k(k - 1) + \sum_{j=k+1}^{n} \min(d_i, k) = k(n - 1) - (k \sum_{j=0}^{k-1} j) - (k \sum_{j=0}^{k-1} jn_j)$$

A strong index k is any index where $d_k \geq k$ and the value $n_j$ is the number of occurrences of j in d. The maximal strong index is called the Durfee index.

This particular rearrangement comes from the proof of Theorem 3 in [R226].
The ZZ condition says that for the sequence \(d\) if

\[
|d| \geq \frac{(\max(d) + \min(d) + 1)^2}{4 \times \min(d)}
\]

then \(d\) is graphical. This was shown in Theorem 6 in [R226].

References

[EG1960], [choudum1986]
[R225], [R226]

### 4.21 Hierarchy

Flow Hierarchy.

\[
\text{flow}_\text{hierarchy}(G[, \text{weight}]) \quad \text{Returns the flow hierarchy of a directed network.}
\]

#### 4.21.1 flow\_hierarchy

\texttt{flow\_hierarchy}(G, weight=None)

Returns the flow hierarchy of a directed network.

Flow hierarchy is defined as the fraction of edges not participating in cycles in a directed graph [R228].

**Parameters**

- \(G\) : DiGraph or MultiDiGraph
  - A directed graph
- \texttt{weight} : key, optional (default=None)
  - Attribute to use for node weights. If None the weight defaults to 1.

**Returns**

- \(h\) : float
  - Flow hierarchy value

**Notes**

The algorithm described in [R228] computes the flow hierarchy through exponentiation of the adjacency matrix. This function implements an alternative approach that finds strongly connected components. An edge is in a cycle if and only if it is in a strongly connected component, which can be found in \(O(m)\) time using Tarjan’s algorithm.

**References**

[R228]
4.22 Isolates

Functions for identifying isolate (degree zero) nodes.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_isolate(G, n)</code></td>
<td>Determine if node n is an isolate (degree zero).</td>
</tr>
<tr>
<td><code>isolates(G)</code></td>
<td>Return list of isolates in the graph.</td>
</tr>
</tbody>
</table>

4.22.1 is_isolate

`is_isolate(G, n)`
Determine if node n is an isolate (degree zero).

**Parameters**
- `G`: graph
  A NetworkX graph
- `n`: node
  A node in G

**Returns**
- `isolate`: bool
  True if n has no neighbors, False otherwise.

**Examples**

```python
>>> G = nx.Graph()
>>> G.add_edge(1,2)
>>> G.add_node(3)
>>> nx.is_isolate(G, 2)
False
>>> nx.is_isolate(G, 3)
True
```

4.22.2 isolates

`isolates(G)`
Return list of isolates in the graph.

Isolates are nodes with no neighbors (degree zero).

**Parameters**
- `G`: graph
  A NetworkX graph

**Returns**
- `isolates`: list
  List of isolate nodes.

**Examples**

```python
>>> G = nx.Graph()
>>> G.add_edge(1,2)
>>> G.add_node(3)
```
>>> nx.isolates(G)
[3]

To remove all isolates in the graph use >>> G.remove_nodes_from(nx.isolates(G)) >>> G.nodes() [1, 2]

For digraphs isolates have zero in-degree and zero out_degree >>> G = nx.DiGraph([(0,1),(1,2)])

>>> G.add_node(3) >>> nx.isolates(G) [3]

4.23 Isomorphism

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>is_isomorphic(G1, G2[, node_match, edge_match])</td>
<td>Returns True if the graphs G1 and G2 are isomorphic and False otherwise.</td>
</tr>
<tr>
<td>could_be_isomorphic(G1, G2)</td>
<td>Returns False if graphs are definitely not isomorphic.</td>
</tr>
<tr>
<td>fast_could_be_isomorphic(G1, G2)</td>
<td>Returns False if graphs are definitely not isomorphic.</td>
</tr>
<tr>
<td>faster_could_be_isomorphic(G1, G2)</td>
<td>Returns False if graphs are definitely not isomorphic.</td>
</tr>
</tbody>
</table>

4.23.1 is_isomorphic

**is_isomorphic**(G1, G2, node_match=None, edge_match=None)

Returns True if the graphs G1 and G2 are isomorphic and False otherwise.

**Parameters**

G1, G2: graphs :

The two graphs G1 and G2 must be the same type.

node_match : callable

A function that returns True if node n1 in G1 and n2 in G2 should be considered equal during the isomorphism test. If node_match is not specified then node attributes are not considered.

The function will be called like

node_match(G1.node[n1], G2.node[n2]).

That is, the function will receive the node attribute dictionaries for n1 and n2 as inputs.

edge_match : callable

A function that returns True if the edge attribute dictionary for the pair of nodes (u1, v1) in G1 and (u2, v2) in G2 should be considered equal during the isomorphism test. If edge_match is not specified then edge attributes are not considered.

The function will be called like

eedge_match(G1[u1][v1], G2[u2][v2]).

That is, the function will receive the edge attribute dictionaries of the edges under consideration.

**See also:**

numerical_node_match, numerical_edge_match, numerical_multiedge_match, categorical_node_match, categorical_edge_match, categorical_multiedge_match

**Notes**

Uses the vf2 algorithm [R229].

4.23. Isomorphism 245
References

[R229]

Examples

```python
>>> import networkx.algorithms.isomorphism as iso

For digraphs G1 and G2, using ‘weight’ edge attribute (default: 1)
```  >>> G1 = nx.DiGraph()
>>> G2 = nx.DiGraph()
```  >>> G1.add_path([1,2,3,4],weight=1)
>>> G2.add_path([10,20,30,40],weight=2)
```  >>> em = iso.numerical_edge_match('weight', 1)
```  >>> nx.is_isomorphic(G1, G2)  # no weights considered
True
```  >>> nx.is_isomorphic(G1, G2, edge_match=em)  # match weights
False
```

For multidigraphs G1 and G2, using ‘fill’ node attribute (default: ‘’)
```  >>> G1 = nx.MultiDiGraph()
>>> G2 = nx.MultiDiGraph()
```  >>> G1.add_nodes_from([1,2,3],fill='red')
```  >>> G2.add_nodes_from([10,20,30,40],fill='red')
```  >>> G1.add_path([1,2,3,4],weight=3, linewidth=2.5)
```  >>> G2.add_path([10,20,30,40],weight=3)
```  >>> nm = iso.categorical_node_match('fill', 'red')
```  >>> nx.is_isomorphic(G1, G2, node_match=nm)
True
```

For multigraphs G1 and G2, using ‘weight’ edge attribute (default: 7)
```  >>> G1.add_edge(1,2, weight=7)
>>> G2.add_edge(10,20)
```  >>> em = iso.numerical_multiedge_match('weight', 7, rtol=1e-6)
```  >>> nx.is_isomorphic(G1, G2, edge_match=em)
True
```

For multigraphs G1 and G2, using ‘weight’ and ‘linewidth’ edge attributes with default values 7 and 2.5. Also using ‘fill’ node attribute with default value ‘red’.
```  >>> em = iso.numerical_multiedge_match(['weight', 'linewidth'], [7, 2.5])
>>> nm = iso.categorical_node_match('fill', 'red')
```  >>> nx.is_isomorphic(G1, G2, edge_match=em, node_match=nm)
True
```

4.23.2 could_be_isomorphic

`could_be_isomorphic(G1, G2)`

Returns False if graphs are definitely not isomorphic. True does NOT guarantee isomorphism.

Parameters

- `G1, G2`: graphs

The two graphs G1 and G2 must be the same type.
Notes

Checks for matching degree, triangle, and number of cliques sequences.

4.23.3 fast_could_be_isomorphic

fast_could_be_isomorphic\((G_1, G_2)\)
Returns False if graphs are definitely not isomorphic.
True does NOT guarantee isomorphism.

Parameters  
G1, G2 : graphs

The two graphs G1 and G2 must be the same type.

Notes

Checks for matching degree and triangle sequences.

4.23.4 faster_could_be_isomorphic

faster_could_be_isomorphic\((G_1, G_2)\)
Returns False if graphs are definitely not isomorphic.
True does NOT guarantee isomorphism.

Parameters  
G1, G2 : graphs

The two graphs G1 and G2 must be the same type.

Notes

Checks for matching degree sequences.

4.23.5 Advanced Interface to VF2 Algorithm

VF2 Algorithm

An implementation of VF2 algorithm for graph isomorphism testing.
The simplest interface to use this module is to call networkx.is_isomorphic().

Introduction

The GraphMatcher and DiGraphMatcher are responsible for matching graphs or directed graphs in a predetermined manner. This usually means a check for an isomorphism, though other checks are also possible. For example, a subgraph of one graph can be checked for isomorphism to a second graph.

Matching is done via syntactic feasibility. It is also possible to check for semantic feasibility. Feasibility, then, is defined as the logical AND of the two functions.
To include a semantic check, the (Di)GraphMatcher class should be subclassed, and the semantic_feasibility() function should be redefined. By default, the semantic feasibility function always returns True. The effect of this is that semantics are not considered in the matching of G1 and G2.

Examples

Suppose G1 and G2 are isomorphic graphs. Verification is as follows:

```python
>>> from networkx.algorithms import isomorphism
>>> G1 = nx.path_graph(4)
>>> G2 = nx.path_graph(4)
>>> GM = isomorphism.GraphMatcher(G1,G2)
>>> GM.is_isomorphic()
True
```

GM.mapping stores the isomorphism mapping from G1 to G2.

```python
>>> GM.mapping
{0: 0, 1: 1, 2: 2, 3: 3}
```

Suppose G1 and G2 are isomorphic directed graphs.

```python
>>> G1 = nx.path_graph(4, create_using=nx.DiGraph())
>>> G2 = nx.path_graph(4, create_using=nx.DiGraph())
>>> DiGM = isomorphism.DiGraphMatcher(G1,G2)
>>> DiGM.is_isomorphic()
True
```

DiGM.mapping stores the isomorphism mapping from G1 to G2.

```python
>>> DiGM.mapping
{0: 0, 1: 1, 2: 2, 3: 3}
```

Subgraph Isomorphism

Graph theory literature can be ambiguous about the meaning of the above statement, and we seek to clarify it now.

In the VF2 literature, a mapping M is said to be a graph-subgraph isomorphism iff M is an isomorphism between G2 and a subgraph of G1. Thus, to say that G1 and G2 are graph-subgraph isomorphic is to say that a subgraph of G1 is isomorphic to G2.

Other literature uses the phrase ‘subgraph isomorphic’ as in ‘G1 does not have a subgraph isomorphic to G2’. Another use is as an in adverb for isomorphic. Thus, to say that G1 and G2 are subgraph isomorphic is to say that a subgraph of G1 is isomorphic to G2.

Finally, the term ‘subgraph’ can have multiple meanings. In this context, ‘subgraph’ always means a ‘node-induced subgraph’. Edge-induced subgraph isomorphisms are not directly supported, but one should be able to perform the check by making use of nx.line_graph(). For subgraphs which are not induced, the term ‘monomorphism’ is preferred over ‘isomorphism’. Currently, it is not possible to check for monomorphisms.

Let G=(N,E) be a graph with a set of nodes N and set of edges E.

- **If G’=(N’,E’) is a subgraph, then:** N’ is a subset of N E’ is a subset of E
- **If G’=(N’,E’) is a node-induced subgraph, then:** N’ is a subset of N E’ is the subset of edges in E relating nodes in N’
- **If G’=(N’,E’) is an edge-induced subgraph, then:** N’ is the subset of nodes in N related by edges in E’ E’ is a subset of E

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References


See Also

syntactic_feasibility(), semantic_feasibility()

Notes

Modified to handle undirected graphs. Modified to handle multiple edges.

In general, this problem is NP-Complete.

Graph Matcher

GraphMatcher.__init__(G1, G2[, node_match, ...]) Initialize graph matcher.

Parameters G1, G2: graph :

The graphs to be tested.

node_match: callable :

A function that returns True iff node n1 in G1 and n2 in G2 should be considered equal during the isomorphism test. The function will be called like:

node_match(G1.node[n1], G2.node[n2])

That is, the function will receive the node attribute dictionaries of the nodes under consideration. If None, then no attributes are considered when testing for an isomorphism.

edge_match: callable :

__init__

GraphMatcher.__init__(G1, G2, node_match=None, edge_match=None) Initialize graph matcher.

Parameters G1, G2: graph :

The graphs to be tested.

node_match: callable :

A function that returns True iff node n1 in G1 and n2 in G2 should be considered equal during the isomorphism test. The function will be called like:

node_match(G1.node[n1], G2.node[n2])

That is, the function will receive the node attribute dictionaries of the nodes under consideration. If None, then no attributes are considered when testing for an isomorphism.

edge_match: callable :

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A function that returns True iff the edge attribute dictionary for the pair of nodes \((u_1, v_1)\) in \(G_1\) and \((u_2, v_2)\) in \(G_2\) should be considered equal during the isomorphism test. The function will be called like:

```python
def edge_match(G1[u1][v1], G2[u2][v2])
```

That is, the function will receive the edge attribute dictionaries of the edges under consideration. If None, then no attributes are considered when testing for an isomorphism.

**initialize**

```python
GraphMatcher.initialize()
```

Reinitializes the state of the algorithm.

This method should be redefined if using something other than GMState. If only subclassing GraphMatcher, a redefinition is not necessary.

**is_isomorphic**

```python
GraphMatcher.is_isomorphic()
```

Returns True if \(G_1\) and \(G_2\) are isomorphic graphs.

**subgraph_is_isomorphic**

```python
GraphMatcher.subgraph_is_isomorphic()
```

Returns True if a subgraph of \(G_1\) is isomorphic to \(G_2\).

**isomorphisms_iter**

```python
GraphMatcher.isomorphisms_iter()
```

Generator over isomorphisms between \(G_1\) and \(G_2\).

**subgraph_isomorphisms_iter**

```python
GraphMatcher.subgraph_isomorphisms_iter()
```

Generator over isomorphisms between a subgraph of \(G_1\) and \(G_2\).

**candidate_pairs_iter**

```python
GraphMatcher.candidate_pairs_iter()
```

Iterator over candidate pairs of nodes in \(G_1\) and \(G_2\).

**match**

```python
GraphMatcher.match()
```

Extends the isomorphism mapping.

This function is called recursively to determine if a complete isomorphism can be found between \(G_1\) and \(G_2\). It cleans up the class variables after each recursive call. If an isomorphism is found, we yield the mapping.

**semantic_feasibility**

```python
GraphMatcher.semantic_feasibility(G1_node, G2_node)
```

Returns True if mapping \(G_1\_node\) to \(G_2\_node\) is semantically feasible.
syntactic_feasibility

GraphMatcher.syntactic_feasibility(G1_node, G2_node)

Returns True if adding (G1_node, G2_node) is syntactically feasible.

This function returns True if it is adding the candidate pair to the current partial isomorphism mapping is allowable. The addition is allowable if the inclusion of the candidate pair does not make it impossible for an isomorphism to be found.

DiGraph Matcher

DiGraphMatcher.__init__(G1, G2[, ...])
Initialize graph matcher.

Parameters G1, G2 : graph
The graphs to be tested.

node_match : callable
A function that returns True iff node n1 in G1 and n2 in G2 should be considered equal during the isomorphism test. The function will be called like:
	node_match(G1.node[n1], G2.node[n2])

That is, the function will receive the node attribute dictionaries of the nodes under consideration. If None, then no attributes are considered when testing for an isomorphism.

di_graph_matcher : callable
A function that returns True iff the edge attribute dictionary for the pair of nodes (u1, v1) in G1 and (u2, v2) in G2 should be considered equal during the isomorphism test. The function will be called like:

di_graph_matcher(G1[u1][v1], G2[u2][v2])

That is, the function will receive the edge attribute dictionaries of the edges under consideration. If None, then no attributes are considered when testing for an isomorphism.

initialize

DiGraphMatcher.initialize()
Reinitializes the state of the algorithm.

4.23. Isomorphism
This method should be redefined if using something other than DiGMState. If only subclassing GraphMatcher, a redefinition is not necessary.

**is_isomorphic**

DiGraphMatcher.is_isomorphic()
Returns True if G1 and G2 are isomorphic graphs.

**subgraph_is_isomorphic**

DiGraphMatcher.subgraph_is_isomorphic()
Returns True if a subgraph of G1 is isomorphic to G2.

**isomorphisms_iter**

DiGraphMatcher.isomorphisms_iter()
Generator over isomorphisms between G1 and G2.

**subgraph_isomorphisms_iter**

DiGraphMatcher.subgraph_isomorphisms_iter()
Generator over isomorphisms between a subgraph of G1 and G2.

**candidate_pairs_iter**

DiGraphMatcher.candidate_pairs_iter()
Iterator over candidate pairs of nodes in G1 and G2.

**match**

DiGraphMatcher.match()
Extends the isomorphism mapping.

This function is called recursively to determine if a complete isomorphism can be found between G1 and G2. It cleans up the class variables after each recursive call. If an isomorphism is found, we yield the mapping.

**semantic_feasibility**

DiGraphMatcher.semantic_feasibility(G1_node, G2_node)
Returns True if mapping G1_node to G2_node is semantically feasible.

**syntactic_feasibility**

DiGraphMatcher.syntactic_feasibility(G1_node, G2_node)
Returns True if adding (G1_node, G2_node) is syntactically feasible.

This function returns True if it is adding the candidate pair to the current partial isomorphism mapping is allowable. The addition is allowable if the inclusion of the candidate pair does not make it impossible for an isomorphism to be found.

**Match helpers**

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<th>Description</th>
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<td>categorical_node_match(attr, default)</td>
<td>Returns a comparison function for a categorical node attribute.</td>
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<td><code>numerical_node_match(attr, default[, rtol, atol])</code></td>
<td>Returns a comparison function for a numerical node attribute.</td>
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<td><code>generic_node_match(attr, default, op)</code></td>
<td>Returns a comparison function for a generic attribute.</td>
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<td>Returns a comparison function for a generic attribute.</td>
</tr>
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</table>

**categorical_node_match**

categorical_node_match *(attr, default)*  
Returns a comparison function for a categorical node attribute.

The value(s) of the attr(s) must be hashable and comparable via the `==` operator since they are placed into a `set([])` object. If the sets from G1 and G2 are the same, then the constructed function returns True.

**Parameters**

- **attr**: string | list  
The categorical node attribute to compare, or a list of categorical node attributes to compare.

- **default**: value | list  
The default value for the categorical node attribute, or a list of default values for the categorical node attributes.

**Returns**

- **match**: function  
The customized, categorical node_match function.

**Examples**

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.categorical_node_match('size', 1)
>>> nm = iso.categorical_node_match(['color', 'size'], ['red', 2])
```

**categorical_edge_match**

categorical_edge_match *(attr, default)*  
Returns a comparison function for a categorical edge attribute.

The value(s) of the attr(s) must be hashable and comparable via the `==` operator since they are placed into a `set([])` object. If the sets from G1 and G2 are the same, then the constructed function returns True.

**Parameters**

- **attr**: string | list  
The categorical edge attribute to compare, or a list of categorical edge attributes to compare.

- **default**: value | list  
The default value for the categorical edge attribute, or a list of default values for the categorical edge attributes.

**Returns**

- **match**: function  
The customized, categorical edge_match function.
Examples

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.categorical_edge_match('size', 1)
>>> nm = iso.categorical_edge_match(['color', 'size'], ['red', 2])
```

categorical_multiedge_match

categorical_multiedge_match(attr, default)

Returns a comparison function for a categorical edge attribute.

The value(s) of the attr(s) must be hashable and comparable via the == operator since they are placed into a set([]) object. If the sets from G1 and G2 are the same, then the constructed function returns True.

Parameters

- **attr**: string | list
  The categorical edge attribute to compare, or a list of categorical edge attributes to compare.

- **default**: value | list
  The default value for the categorical edge attribute, or a list of default values for the categorical edge attributes.

Returns

- **match**: function
  The customized, categorical edge_match function.

Examples

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.categorical_multiedge_match('size', 1)
>>> nm = iso.categorical_multiedge_match(['color', 'size'], ['red', 2])
```

numerical_node_match

numerical_node_match(attr, default, rtol=1e-05, atol=1e-08)

Returns a comparison function for a numerical node attribute.

The value(s) of the attr(s) must be numerical and sortable. If the sorted list of values from G1 and G2 are the same within some tolerance, then the constructed function returns True.

Parameters

- **attr**: string | list
  The numerical node attribute to compare, or a list of numerical node attributes to compare.

- **default**: value | list
  The default value for the numerical node attribute, or a list of default values for the numerical node attributes.

- **rtol**: float
  The relative error tolerance.

- **atol**: float
  The absolute error tolerance.

Returns

- **match**: function
The customized, numerical node\textit{match} function.

**Examples**

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.numerical_node_match('weight', 1.0)
>>> nm = iso.numerical_node_match(['weight', 'linewidth'], [.25, .5])
```

**numerical_edge_match**

\texttt{numerical\_edge\_match}(\textit{attr}, \textit{default}, \textit{rtol}=1e-05, \textit{atol}=1e-08)

Returns a comparison function for a numerical edge attribute.

The value(s) of the attr(s) must be numerical and sortable. If the sorted list of values from G1 and G2 are the same within some tolerance, then the constructed function returns True.

**Parameters**

\textit{attr} : string | list

The numerical edge attribute to compare, or a list of numerical edge attributes to compare.

\textit{default} : value | list

The default value for the numerical edge attribute, or a list of default values for the numerical edge attributes.

\textit{rtol} : float

The relative error tolerance.

\textit{atol} : float

The absolute error tolerance.

**Returns**

\textit{match} : function

The customized, numerical edge\textit{match} function.

**Examples**

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.numerical_edge_match('weight', 1.0)
>>> nm = iso.numerical_edge_match(['weight', 'linewidth'], [.25, .5])
```

**numerical_multiedge_match**

\texttt{numerical\_multiedge\_match}(\textit{attr}, \textit{default}, \textit{rtol}=1e-05, \textit{atol}=1e-08)

Returns a comparison function for a numerical edge attribute.

The value(s) of the attr(s) must be numerical and sortable. If the sorted list of values from G1 and G2 are the same within some tolerance, then the constructed function returns True.

**Parameters**

\textit{attr} : string | list

The numerical edge attribute to compare, or a list of numerical edge attributes to compare.

\textit{default} : value | list

The default value for the numerical edge attribute, or a list of default values for the numerical edge attributes.
The default value for the numerical edge attribute, or a list of default values for the numerical edge attributes.

```
rtol : float
    The relative error tolerance.

atol : float
    The absolute error tolerance.
```

Returns match : function
The customized, numerical `edge_match` function.

Examples

```
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.numerical_multiedge_match('weight', 1.0)
>>> nm = iso.numerical_multiedge_match(['weight', 'linewidth'], [.25, .5])
```

generic_node_match
generic_node_match (attr, default, op)
Returns a comparison function for a generic attribute.

The value(s) of the attr(s) are compared using the specified operators. If all the attributes are equal, then the constructed function returns True.

Parameters attr : string | list
    The node attribute to compare, or a list of node attributes to compare.

default : value | list
    The default value for the node attribute, or a list of default values for the node attributes.

op : callable | list
    The operator to use when comparing attribute values, or a list of operators to use when comparing values for each attribute.

Returns match : function
The customized, generic `node_match` function.

Examples

```
>>> from operator import eq
>>> from networkx.algorithms.isomorphism.matchhelpers import close
>>> from networkx.algorithms.isomorphism import generic_node_match
>>> nm = generic_node_match('weight', 1.0, close)
>>> nm = generic_node_match('color', 'red', eq)
>>> nm = generic_node_match(['weight', 'color'], [1.0, 'red'], [close, eq])
```

generic_edge_match
**generic_edge_match** *(attr, default, op)*  
Returns a comparison function for a generic attribute.

The value(s) of the attr(s) are compared using the specified operators. If all the attributes are equal, then the constructed function returns True.

**Parameters**  
```
attr : string | list
```

The edge attribute to compare, or a list of edge attributes to compare.

```
default : value | list
```

The default value for the edge attribute, or a list of default values for the edge attributes.

```
op : callable | list
```

The operator to use when comparing attribute values, or a list of operators to use when comparing values for each attribute.

**Returns**  
```
match : function
```

The customized, generic `edge_match` function.

**Examples**

```python
>>> from operator import eq
>>> from networkx.algorithms.isomorphism.matchhelpers import close
>>> from networkx.algorithms.isomorphism import generic_edge_match

>>> nm = generic_edge_match('weight', 1.0, close)
>>> nm = generic_edge_match('color', 'red', eq)
>>> nm = generic_edge_match(['weight', 'color'], [1.0, 'red'], [close, eq])
```
Examples

```python
>>> from operator import eq
>>> from networkx.algorithms.isomorphism.matchhelpers import close
>>> from networkx.algorithms.isomorphism import generic_node_match

>>> nm = generic_node_match('weight', 1.0, close)

>>> nm = generic_node_match('color', 'red', eq)

>>> nm = generic_node_match([['weight', 'color'], [1.0, 'red'], [close, eq]])
```

4.24 Link Analysis

4.24.1 PageRank

PageRank analysis of graph structure.

```python
pagerank(G[, alpha, personalization, ...]) Return the PageRank of the nodes in the graph.
pagerank_numpy(G[, alpha, personalization, ...]) Return the PageRank of the nodes in the graph.
pagerank_scipy(G[, alpha, personalization, ...]) Return the PageRank of the nodes in the graph.
google_matrix(G[, alpha, personalization, ...]) Return the Google matrix of the graph.
```

```python
pagerank(G, alpha=0.85, personalization=None, max_iter=100, tol=1e-08, nstart=None, weight='weight')
```

Return the PageRank of the nodes in the graph.

PageRank computes a ranking of the nodes in the graph G based on the structure of the incoming links. It was originally designed as an algorithm to rank web pages.

**Parameters**

- **G**: graph
  
  A NetworkX graph

- **alpha**: float, optional
  
  Damping parameter for PageRank, default=0.85

- **personalization**: dict, optional
  
  The “personalization vector” consisting of a dictionary with a key for every graph node and nonzero personalization value for each node.

- **max_iter**: integer, optional
  
  Maximum number of iterations in power method eigenvalue solver.

- **tol**: float, optional
  
  Error tolerance used to check convergence in power method solver.

- **nstart**: dictionary, optional
  
  Starting value of PageRank iteration for each node.

- **weight**: key, optional
  
  The edge data key used for weight.  A None (default) indicates there is no weight.
```
Edge data key to use as weight. If None weights are set to 1.

Returns pagerank : dictionary

Dictionary of nodes with PageRank as value

See also:
pagerank_numpy, pagerank_scipy, google_matrix

Notes

The eigenvector calculation is done by the power iteration method and has no guarantee of convergence. The iteration will stop after max_iter iterations or an error tolerance of number_of_nodes(G)*tol has been reached.

The PageRank algorithm was designed for directed graphs but this algorithm does not check if the input graph is directed and will execute on undirected graphs by converting each oriented edge in the directed graph to two edges.

References

[R236], [R237]

Examples

>>> G=nx.DiGraph(nx.path_graph(4))

>>> pr=nx.pagerank(G, alpha=0.9)

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NetworkX Reference, Release 1.8
See also:

```python
pagerank, pagerank_scipy, google_matrix
```

Notes

The eigenvector calculation uses NumPy’s interface to the LAPACK eigenvalue solvers. This will be the fastest and most accurate for small graphs.

This implementation works with Multi(Di)Graphs.

References

[R238], [R239]

Examples

```python
>>> G=nx.DiGraph(nx.path_graph(4))
>>> pr=nx.pagerank_numpy(G,alpha=0.9)
```

**pagerank_scipy**

```python
 pagerank_scipy (G, alpha=0.85, personalization=None, max_iter=100, tol=1e-06, weight='weight')
```

Return the PageRank of the nodes in the graph.

PageRank computes a ranking of the nodes in the graph G based on the structure of the incoming links. It was originally designed as an algorithm to rank web pages.

**Parameters**

- `G` : graph
  A NetworkX graph
- `alpha` : float, optional
  Damping parameter for PageRank, default=0.85
- `personalization` : dict, optional
  The “personalization vector” consisting of a dictionary with a key for every graph node and nonzero personalization value for each node.
- `max_iter` : integer, optional
  Maximum number of iterations in power method eigenvalue solver.
- `tol` : float, optional
  Error tolerance used to check convergence in power method solver.
- `weight` : key, optional
  Edge data key to use as weight. If None weights are set to 1.

**Returns**

`pagerank` : dictionary

Dictionary of nodes with PageRank as value

See also:

```python
pagerank, pagerank_numpy, google_matrix
```
Notes

The eigenvector calculation uses power iteration with a SciPy sparse matrix representation.

References

[R240], [R241]

Examples

>>> G=nx.DiGraph(nx.path_graph(4))
>>> pr=nx.pagerank_scipy(G, alpha=0.9)

google_matrix

google_matrix(G, alpha=0.85, personalization=None, nodelist=None, weight='weight')

Return the Google matrix of the graph.

Parameters

G : graph

A NetworkX graph

alpha : float

The damping factor

personalization : dict, optional

The “personalization vector” consisting of a dictionary with a key for every graph node and nonzero personalization value for each node.

nodelist : list, optional

The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().

weight : key, optional

Edge data key to use as weight. If None weights are set to 1.

Returns

A : NumPy matrix

Google matrix of the graph

See also:

pagerank, pagerank_numpy, pagerank_scipy

4.24.2 Hits

Hubs and authorities analysis of graph structure.

| hits(G[, max_iter, tol, nstart, normalized]) | Return HITS hubs and authorities values for nodes. |
| hits_numpy(G[, normalized]) | Return HITS hubs and authorities values for nodes. |
| hits_scipy(G[, max_iter, tol, normalized]) | Return HITS hubs and authorities values for nodes. |
| hub_matrix(G[, nodelist]) | Return the HITS hub matrix. |

Continued on next page
hits

**hits** *(G, max_iter=100, tol=1e-08, nstart=None, normalized=True)*

Return HITS hubs and authorities values for nodes.

The HITS algorithm computes two numbers for a node. Authorities estimates the node value based on the incoming links. Hubs estimates the node value based on outgoing links.

**Parameters**

- **G** : graph
  A NetworkX graph
- **max_iter** : integer, optional
  Maximum number of iterations in power method.
- **tol** : float, optional
  Error tolerance used to check convergence in power method iteration.
- **nstart** : dictionary, optional
  Starting value of each node for power method iteration.
- **normalized** : bool (default=True)
  Normalize results by the sum of all of the values.

**Returns** *(hubs,authorities)* : two-tuple of dictionaries

Two dictionaries keyed by node containing the hub and authority values.

**Notes**

The eigenvector calculation is done by the power iteration method and has no guarantee of convergence. The iteration will stop after max_iter iterations or an error tolerance of number_of_nodes(G)*tol has been reached.

The HITS algorithm was designed for directed graphs but this algorithm does not check if the input graph is directed and will execute on undirected graphs.

**References**

[R230], [R231]

**Examples**

```python
>>> G=nx.path_graph(4)
>>> h,a=nx.hits(G)
```
hits_numpy

**hits_numpy** *(G, normalized=True)*

Return HITS hubs and authorities values for nodes.

The HITS algorithm computes two numbers for a node. Authorities estimates the node value based on the incoming links. Hubs estimates the node value based on outgoing links.

**Parameters**

*G*: graph

A NetworkX graph

**normalized**: bool (default=True)

Normalize results by the sum of all of the values.

**Returns** *(hubs,authorities)* : two-tuple of dictionaries

Two dictionaries keyed by node containing the hub and authority values.

**Notes**

The eigenvector calculation uses NumPy’s interface to LAPACK.

The HITS algorithm was designed for directed graphs but this algorithm does not check if the input graph is directed and will execute on undirected graphs.

**References**

[R232], [R233]

**Examples**

```python
>>> G=nx.path_graph(4)
>>> h,a=nx.hits(G)
```

hits_scipy

**hits_scipy** *(G, max_iter=100, tol=1e-06, normalized=True)*

Return HITS hubs and authorities values for nodes.

The HITS algorithm computes two numbers for a node. Authorities estimates the node value based on the incoming links. Hubs estimates the node value based on outgoing links.

**Parameters**

*G*: graph

A NetworkX graph

**max_iter**: integer, optional

Maximum number of iterations in power method.

**tol**: float, optional

Error tolerance used to check convergence in power method iteration.

**nstart**: dictionary, optional

Starting value of each node for power method iteration.
**networkx**: bool (default=True)

Normalize results by the sum of all of the values.

**Returns**  (hubs,authorities) : two-tuple of dictionaries

Two dictionaries keyed by node containing the hub and authority values.

**Notes**

This implementation uses SciPy sparse matrices.

The eigenvector calculation is done by the power iteration method and has no guarantee of convergence. The
iteration will stop after max_iter iterations or an error tolerance of number_of_nodes(G)*tol has been reached.

The HITS algorithm was designed for directed graphs but this algorithm does not check if the input graph is
directed and will execute on undirected graphs.

**References**

[R234], [R235]

**Examples**

```python
>>> G=nx.path_graph(4)
>>> h,a=nx.hits(G)
```

**hub_matrix**

**hub_matrix** (G, nodelist=None)

Return the HITS hub matrix.

**authority_matrix**

**authority_matrix** (G, nodelist=None)

Return the HITS authority matrix.

### 4.25 Matching

**maximal_matching** (G)

Find a maximal cardinality matching in the graph.

**max_weight_matching** (G, maxcardinality)

Compute a maximum-weighted matching of G.

### 4.25.1 maximal_matching

**maximal_matching** (G)

Find a maximal cardinality matching in the graph.

A matching is a subset of edges in which no node occurs more than once. The cardinality of a matching is the
number of matched edges.
Parameters G : NetworkX graph
   Undirected graph

Returns matching : set
   A maximal matching of the graph.

Notes

The algorithm greedily selects a maximal matching M of the graph G (i.e. no superset of M exists). It runs in \(O(|E|)\) time.

4.25.2 max_weight_matching

max_weight_matching \(G, \text{maxcardinality=False}\)
Compute a maximum-weighted matching of G.

A matching is a subset of edges in which no node occurs more than once. The cardinality of a matching is the number of matched edges. The weight of a matching is the sum of the weights of its edges.

Parameters G : NetworkX graph
   Undirected graph

   maxcardinality: bool, optional :

   If maxcardinality is True, compute the maximum-cardinality matching with maximum weight among all maximum-cardinality matchings.

Returns mate : dictionary
   The matching is returned as a dictionary, mate, such that mate[v] == w if node v is matched to node w. Unmatched nodes do not occur as a key in mate.

Notes

If G has edges with ‘weight’ attribute the edge data are used as weight values else the weights are assumed to be 1.

This function takes time \(O(\text{number_of_nodes}^3)\).

If all edge weights are integers, the algorithm uses only integer computations. If floating point weights are used, the algorithm could return a slightly suboptimal matching due to numeric precision errors.

This method is based on the “blossom” method for finding augmenting paths and the “primal-dual” method for finding a matching of maximum weight, both methods invented by Jack Edmonds [R242].

References

[R242]

4.26 Maximal independent set

Algorithm to find a maximal (not maximum) independent set.
4.26.1 maximal_independent_set

**maximal_independent_set** \((G, \text{nodes}=\text{None})\)

Return a random maximal independent set guaranteed to contain a given set of nodes.

An independent set is a set of nodes such that the subgraph of \(G\) induced by these nodes contains no edges. A maximal independent set is an independent set such that it is not possible to add a new node and still get an independent set.

**Parameters**

- \(G:\) NetworkX graph
- \(\text{nodes}::\) list or iterable

Nodes that must be part of the independent set. This set of nodes must be independent.

**Returns**

- \(\text{indep_nodes}::\) list

List of nodes that are part of a maximal independent set.

**Raises**

- NetworkXUnfeasible:

  If the nodes in the provided list are not part of the graph or do not form an independent set, an exception is raised.

**Notes**

This algorithm does not solve the maximum independent set problem.

**Examples**

```python
>>> G = nx.path_graph(5)
>>> nx.maximal_independent_set(G)
[4, 0, 2]
>>> nx.maximal_independent_set(G, [1])
[1, 3]
```

4.27 Minimum Spanning Tree

Computes minimum spanning tree of a weighted graph.

**minimum_spanning_tree** \((G, \text{weight})\)  
Return a minimum spanning tree or forest of an undirected weighted graph.

**minimum_spanning_edges** \((G, \text{weight}, \text{data})\)  
Generate edges in a minimum spanning forest of an undirected weighted graph.

4.27.1 minimum_spanning_tree

**minimum_spanning_tree** \((G, \text{weight}=\text{‘weight’})\)

Return a minimum spanning tree or forest of an undirected weighted graph.

A minimum spanning tree is a subgraph of the graph (a tree) with the minimum sum of edge weights.
If the graph is not connected a spanning forest is constructed. A spanning forest is a union of the spanning trees for each connected component of the graph.

**Parameters**
- `G` : NetworkX Graph
- `weight` : string
  Edge data key to use for weight (default `weight`).

**Returns**
- `G` : NetworkX Graph
  A minimum spanning tree or forest.

**Notes**
Uses Kruskal’s algorithm.

If the graph edges do not have a weight attribute a default weight of 1 will be used.

**Examples**

```python
>>> G=nx.cycle_graph(4)
>>> G.add_edge(0,3,weight=2)  # assign weight 2 to edge 0-3
>>> T=nx.minimum_spanning_tree(G)
>>> print(sorted(T.edges(data=True))
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
```

### 4.27.2 minimum_spanning_edges

**minimum_spanning_edges** *(G, weight='weight', data=True)*

Generate edges in a minimum spanning forest of an undirected weighted graph.

A minimum spanning tree is a subgraph of the graph (a tree) with the minimum sum of edge weights. A spanning forest is a union of the spanning trees for each connected component of the graph.

**Parameters**
- `G` : NetworkX Graph
- `weight` : string
  Edge data key to use for weight (default `weight`).
- `data` : bool, optional
  If True yield the edge data along with the edge.

**Returns**
- `edges` : iterator
  A generator that produces edges in the minimum spanning tree. The edges are three-tuples (u,v,w) where w is the weight.

**Notes**
Uses Kruskal’s algorithm.

If the graph edges do not have a weight attribute a default weight of 1 will be used.

Examples

```python
>>> G = nx.cycle_graph(4)
>>> G.add_edge(0, 3, weight=2)  # assign weight 2 to edge 0-3
>>> mst = nx.minimum_spanning_edges(G, data=False)  # a generator of MST edges
>>> edgelist = list(mst)  # make a list of the edges
>>> print(sorted(edgelist))
[(0, 1), (1, 2), (2, 3)]
```

### 4.28 Operators

Unary operations on graphs

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<th>Description</th>
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<td><code>complement(G[, name])</code></td>
<td>Return the graph complement of G.</td>
</tr>
<tr>
<td><code>reverse(G[, copy])</code></td>
<td>Return the reverse directed graph of G.</td>
</tr>
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</table>

#### 4.28.1 complement

**complement** *(G, name=None)*

Return the graph complement of G.

**Parameters**

- **G**: graph
  
  A NetworkX graph

- **name**: string
  
  Specify name for new graph

**Returns**

- **GC**: A new graph.

**Notes**

Note that complement() does not create self-loops and also does not produce parallel edges for MultiGraphs. Graph, node, and edge data are not propagated to the new graph.

#### 4.28.2 reverse

**reverse** *(G, copy=True)*

Return the reverse directed graph of G.

**Parameters**

- **G**: directed graph

  A NetworkX directed graph

- **copy**: bool

  If True, then a new graph is returned. If False, then the graph is reversed in place.

**Returns**

- **H**: directed graph

  The reversed G.

Operations on graphs including union, intersection, difference.
## 4.28.3 compose

compose \((G, H[, \text{name}])\)  
Return a new graph of \(G\) composed with \(H\).

Composition is the simple union of the node sets and edge sets. The node sets of \(G\) and \(H\) need not be disjoint.

**Parameters**  
\(G, H\) : graph  
A NetworkX graph  
\text{name} : string  
Specify name for new graph

**Returns**  
\(C\) : A new graph with the same type as \(G\):

**Notes**

It is recommended that \(G\) and \(H\) be either both directed or both undirected. Attributes from \(H\) take precedent over attributes from \(G\).

## 4.28.4 union

union \((G, H[, \text{rename}, \text{name}])\)  
Return the union of graphs \(G\) and \(H\).

Graphs \(G\) and \(H\) must be disjoint, otherwise an exception is raised.

**Parameters**  
\(G, H\) : graph  
A NetworkX graph  
\text{create_using} : NetworkX graph  
Use specified graph for result. Otherwise  
\text{rename} : bool , default=(None, None)  
Node names of \(G\) and \(H\) can be changed by specifying the tuple \text{rename}=\('G-','H-'\) (for example). Node “\(u\)” in \(G\) is then renamed “\(G-u\)” and “\(v\)” in \(H\) is renamed “\(H-v\)”.

\text{name} : string  
Specify the name for the union graph

**Returns**  
\(U\) : A union graph with the same type as \(G\).

See also:  
disjoint_union
Notes

To force a disjoint union with node relabeling, use disjoint_union(G,H) or convert_node_labels_to_integers().

Graph, edge, and node attributes are propagated from G and H to the union graph. If a graph attribute is present
in both G and H the value from H is used.

4.28.5 disjoint_union

disjoint_union(G, H)

Return the disjoint union of graphs G and H.

This algorithm forces distinct integer node labels.

Parameters  G,H : graph

A NetworkX graph

Returns  U : A union graph with the same type as G.

Notes

A new graph is created, of the same class as G. It is recommended that G and H be either both directed or both
undirected.

The nodes of G are relabeled 0 to len(G)-1, and the nodes of H are relabeled len(G) to len(G)+len(H)-1.

Graph, edge, and node attributes are propagated from G and H to the union graph. If a graph attribute is present
in both G and H the value from H is used.

4.28.6 intersection

intersection(G, H)

Return a new graph that contains only the edges that exist in both G and H.

The node sets of H and G must be the same.

Parameters  G,H : graph

A NetworkX graph. G and H must have the same node sets.

Returns  GH : A new graph with the same type as G.

Notes

Attributes from the graph, nodes, and edges are not copied to the new graph. If you want a new graph of the
intersection of G and H with the attributes (including edge data) from G use remove_nodes_from() as follows

```python
>>> G=nx.path_graph(3)
>>> H=nx.path_graph(5)
>>> R=G.copy()
>>> R.remove_nodes_from(n for n in G if n not in H)
```
4.28.7 difference

difference $(G, H)$  
Return a new graph that contains the edges that exist in $G$ but not in $H$.  
The node sets of $H$ and $G$ must be the same.

**Parameters**  
$G, H$ : graph  
A NetworkX graph. $G$ and $H$ must have the same node sets.

**Returns**  
$D$ : A new graph with the same type as $G$.

**Notes**
Attributes from the graph, nodes, and edges are not copied to the new graph. If you want a new graph of 
the difference of $G$ and $H$ with with the attributes (including edge data) from $G$ use remove_nodes_from() as 
follows:

```python  
>>> G=nx.path_graph(3)  
>>> H=nx.path_graph(5)  
>>> R=G.copy()  
>>> R.remove_nodes_from(n for n in G if n in H)  
```

4.28.8 symmetric_difference

symmetric_difference $(G, H)$  
Return new graph with edges that exist in either $G$ or $H$ but not both.  
The node sets of $H$ and $G$ must be the same.

**Parameters**  
$G, H$ : graph  
A NetworkX graph. $G$ and $H$ must have the same node sets.

**Returns**  
$D$ : A new graph with the same type as $G$.

**Notes**
Attributes from the graph, nodes, and edges are not copied to the new graph.

Operations on many graphs.

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<th>Function</th>
<th>Description</th>
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<td>compose_all $(graphs[, name])$</td>
<td>Return the composition of all graphs.</td>
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<td>disjoint_union_all $(graphs)$</td>
<td>Return the disjoint union of all graphs.</td>
</tr>
<tr>
<td>intersection_all $(graphs)$</td>
<td>Return a new graph that contains only the edges that exist in all graphs.</td>
</tr>
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4.28.9 compose_all

compose_all $(graphs, name=None)$  
Return the composition of all graphs.
Composition is the simple union of the node sets and edge sets. The node sets of the supplied graphs need not be disjoint.
Parameters graphs : list
    List of NetworkX graphs

name : string
    Specify name for new graph

Returns C : A graph with the same type as the first graph in list

Notes

It is recommended that the supplied graphs be either all directed or all undirected.
Graph, edge, and node attributes are propagated to the union graph. If a graph attribute is present in multiple
graphs, then the value from the last graph in the list with that attribute is used.

4.28.10 union_all

union_all (graphs, rename=(None, ), name=None)
    Return the union of all graphs.
    The graphs must be disjoint, otherwise an exception is raised.

Parameters graphs : list of graphs
    List of NetworkX graphs

rename : bool, default=(None, None)
    Node names of G and H can be changed by specifying the tuple rename=(‘G-‘,’H-‘) (for example). Node “u” in G is then renamed “G-u” and “v” in H is renamed “H-v”.

name : string
    Specify the name for the union graph

Returns U : a graph with the same type as the first graph in list

See also:
    union, disjoint_union_all

Notes

To force a disjoint union with node relabeling, use disjoint_union_all(G,H) or convert_node_labels_to_integers().
Graph, edge, and node attributes are propagated to the union graph. If a graph attribute is present in multiple
graphs, then the value from the last graph in the list with that attribute is used.

4.28.11 disjoint_union_all

disjoint_union_all (graphs)
    Return the disjoint union of all graphs.
    This operation forces distinct integer node labels starting with 0 for the first graph in the list and numbering
    consecutively.

Parameters graphs : list
List of NetworkX graphs

Returns U : A graph with the same type as the first graph in list

Notes

It is recommended that the graphs be either all directed or all undirected.

Graph, edge, and node attributes are propagated to the union graph. If a graph attribute is present in multiple graphs, then the value from the last graph in the list with that attribute is used.

4.28.12 intersection_all

.intersection_all (graphs)

Return a new graph that contains only the edges that exist in all graphs.

All supplied graphs must have the same node set.

Parameters graphs_list : list

List of NetworkX graphs

Returns R : A new graph with the same type as the first graph in list

Notes

Attributes from the graph, nodes, and edges are not copied to the new graph.

Graph products.

<table>
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<th>Return the Cartesian product of G and H.</th>
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<td>lexicographic_product(G, H)</td>
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<tr>
<td>tensor_product(G, H)</td>
<td>Return the tensor product of G and H.</td>
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4.28.13 cartesian_product

cartesian_product (G, H)

Return the Cartesian product of G and H.

The tensor product P of the graphs G and H has a node set that is the Cartesian product of the node sets, \(V(P)=V(G) \times V(H)\). P has an edge \((u,v),(x,y)\) if and only if \((u,v)\) is an edge in G and \(x=y\) or and \((x,y)\) is an edge in H and \(u=v\). and \((x,y)\) is an edge in H.

Parameters G, H: graphs

Networkx graphs.

Returns P: NetworkX graph

The Cartesian product of G and H. P will be a multi-graph if either G or H is a multigraph. Will be a directed if G and H are directed, and undirected if G and H are undirected.

Raises NetworkXError

If G and H are not both directed or both undirected.
Notes

Node attributes in P are two-tuple of the G and H node attributes. Missing attributes are assigned None.

For example >>> G = nx.Graph() >>> H = nx.Graph() >>> G.add_node(0,a1=True) >>>
H.add_node('a',a2='Spam') >>> P = nx.cartesian_product(G,H) >>> P.nodes() [(0, 'a')]

Edge attributes and edge keys (for multigraphs) are also copied to the new product graph

4.28.14 lexicographic_product

_lexicographic_product(G, H)_

Return the lexicographic product of G and H.

The lexicographical product P of the graphs G and H has a node set that is the Cartesian product of the node sets, \(V(P)=V(G) \times V(H)\). P has an edge ((u,v),(x,y)) if and only if (u,v) is an edge in G or u==v and (x,y) is an edge in H.

Parameters **G, H**: graphs :

- Networkx graphs.

Returns **P**: NetworkX graph :

- The Cartesian product of G and H. P will be a multi-graph if either G or H is a multi-graph. Will be a directed if G and H are directed, and undirected if G and H are undirected.

Raises **NetworkXError** :

- If G and H are not both directed or both undirected.

Notes

Node attributes in P are two-tuple of the G and H node attributes. Missing attributes are assigned None.

For example >>> G = nx.Graph() >>> H = nx.Graph() >>> G.add_node(0,a1=True) >>>
H.add_node('a',a2='Spam') >>> P = nx.lexicographic_product(G,H) >>> P.nodes() [(0, 'a')]

Edge attributes and edge keys (for multigraphs) are also copied to the new product graph

4.28.15 strong_product

_strong_product(G, H)_

Return the strong product of G and H.

The strong product P of the graphs G and H has a node set that is the Cartesian product of the node sets, \(V(P)=V(G) \times V(H)\). P has an edge ((u,v),(x,y)) if and only if u==v and (x,y) is an edge in H, or x==y and (u,v) is an edge in G, or (u,v) is an edge in G and (x,y) is an edge in H.

Parameters **G, H**: graphs :

- Networkx graphs.

Returns **P**: NetworkX graph :

- The Cartesian product of G and H. P will be a multi-graph if either G or H is a multi-graph. Will be a directed if G and H are directed, and undirected if G and H are undirected.
Raises NetworkXError:

If G and H are not both directed or both undirected.

Notes

Node attributes in P are two-tuple of the G and H node attributes. Missing attributes are assigned None.

For example >>> G = nx.Graph() >>> H = nx.Graph() >>> G.add_node(0,a1=True) >>> H.add_node('a',a2='Spam') >>> P = nx.strong_product(G,H) >>> P.nodes() [(0, 'a')]

Edge attributes and edge keys (for multigraphs) are also copied to the new product graph

4.28.16 tensor_product

tensor_product (G, H)

Return the tensor product of G and H.

The tensor product P of the graphs G and H has a node set that is the Cartesian product of the node sets, $V(P) = V(G) \times V(H)$. P has an edge ((u,v),(x,y)) if and only if (u,v) is an edge in G and (x,y) is an edge in H.

Sometimes referred to as the categorical product.

Parameters  G, H: graphs:

Networkx graphs.

Returns  P: NetworkX graph:

The tensor product of G and H. P will be a multi-graph if either G or H is a multi-graph.
Will be a directed if G and H are directed, and undirected if G and H are undirected.

Raises NetworkXError:

If G and H are not both directed or both undirected.

Notes

Node attributes in P are two-tuple of the G and H node attributes. Missing attributes are assigned None.

For example >>> G = nx.Graph() >>> H = nx.Graph() >>> G.add_node(0,a1=True) >>> H.add_node('a',a2='Spam') >>> P = nx.tensor_product(G,H) >>> P.nodes() [(0, 'a')]

Edge attributes and edge keys (for multigraphs) are also copied to the new product graph

4.29 Rich Club

rich_club_coefficient(G[, normalized, Q]) Return the rich-club coefficient of the graph G.

4.29.1 rich_club_coefficient

rich_club_coefficient (G, normalized=True, Q=100)

Return the rich-club coefficient of the graph G.
The rich-club coefficient is the ratio, for every degree $k$, of the number of actual to the number of potential edges for nodes with degree greater than $k$:

$$\phi(k) = \frac{2E_k}{N_k(N_k - 1)}$$

where $N_k$ is the number of nodes with degree larger than $k$, and $E_k$ be the number of edges among those nodes.

Parameters  
- `G` : NetworkX graph
- `normalized` : bool (optional)  
  Normalize using randomized network (see [R243])
- `Q` : float (optional, default=100)  
  If normalized=True build a random network by performing $Q*M$ double-edge swaps, where $M$ is the number of edges in $G$, to use as a null-model for normalization.

Returns  
- `rc` : dictionary  
  A dictionary, keyed by degree, with rich club coefficient values.

Notes

The rich club definition and algorithm are found in [R243]. This algorithm ignores any edge weights and is not defined for directed graphs or graphs with parallel edges or self loops.

Estimates for appropriate values of $Q$ are found in [R244].

References

[R243], [R244]

Examples

```python
>>> G = nx.Graph([(0,1), (0,2), (1,2), (1,3), (1,4), (4,5)])
>>> rc = nx.rich_club_coefficient(G, normalized=False)
>>> rc[0]
0.4
```

## 4.30 Shortest Paths

Compute the shortest paths and path lengths between nodes in the graph.

These algorithms work with undirected and directed graphs.

For directed graphs the paths can be computed in the reverse order by first flipping the edge orientation using $R=G.reverse(copy=False)$.

| short_path(G, source, target, weight) | Compute shortest paths in the graph. |
| all_shortest_paths(G, source, target[, weight]) | Compute all shortest paths in the graph. |
| shortest_path_length(G, source, target, weight) | Compute shortest path lengths in the graph. |
| average_shortest_path_length(G[, weight]) | Return the average shortest path length. |
| has_path(G, source, target) | Return True if G has a path from source to target, False otherwise. |
4.30.1 shortest_path

shortest_path \((G, source=None, target=None, weight=None)\)
Compute shortest paths in the graph.

Parameters

- **G**: NetworkX graph
- **source**: node, optional
  Starting node for path. If not specified, compute shortest paths using all nodes as source nodes.
- **target**: node, optional
  Ending node for path. If not specified, compute shortest paths using all nodes as target nodes.
- **weight**: None or string, optional (default = None)
  If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

Returns

- **path**: list or dictionary
  All returned paths include both the source and target in the path.
  If the source and target are both specified, return a single list of nodes in a shortest path from the source to the target.
  If only the source is specified, return a dictionary keyed by targets with a list of nodes in a shortest path from the source to one of the targets.
  If only the target is specified, return a dictionary keyed by sources with a list of nodes in a shortest path from one of the sources to the target.
  If neither the source nor target are specified return a dictionary of dictionaries with path[source][target]=[list of nodes in path].

See also:

all_pairs_shortest_path, all_pairs_dijkstra_path, single_source_shortest_path, single_source_dijkstra_path

Notes

There may be more than one shortest path between a source and target. This returns only one of them.
For digraphs this returns a shortest directed path. To find paths in the reverse direction first use G.reverse(copy=False) to flip the edge orientation.

Examples

```python
>>> G=nx.path_graph(5)
>>> print(nx.shortest_path(G,source=0,target=4))
[0, 1, 2, 3, 4]
>>> p=nx.shortest_path(G,source=0) # target not specified
>>> p[4]
[0, 1, 2, 3, 4]
>>> p=nx.shortest_path(G,target=4) # source not specified
>>> p[0]
```
4.30.2 \texttt{all\_shortest\_paths}

\texttt{all\_shortest\_paths}(G, \texttt{source}, \texttt{target}, \texttt{weight}={\tt None})

Compute all shortest paths in the graph.

- **Parameters**
  - \texttt{G} : NetworkX graph
  - \texttt{source} : node
    
    Starting node for path.
  - \texttt{target} : node
    
    Ending node for path.
  - \texttt{weight} : None or string, optional (default = \tt None)
    
    If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

- **Returns**
  - \texttt{paths} : generator of lists
    
    A generator of all paths between source and target.

- **See also**
  
  \texttt{shortest\_path} , \texttt{single\_source\_shortest\_path} , \texttt{all\_pairs\_shortest\_path}

- **Notes**

  There may be many shortest paths between the source and target.

- **Examples**

  ```python
  >>> G=nx.Graph()
  >>> G.add_path([0,1,2])
  >>> G.add_path([0,10,2])
  >>> print([p for p in nx.all_shortest_paths(G,source=0,target=2)])
  [[0, 1, 2], [0, 10, 2]]
  ```

4.30.3 \texttt{shortest\_path\_length}

\texttt{shortest\_path\_length}(G, \texttt{source}=\tt None, \texttt{target}=\tt None, \texttt{weight}=\tt None)

Compute shortest path lengths in the graph.

- **Parameters**
  - \texttt{G} : NetworkX graph
    
    Starting node for path. If not specified, compute shortest path lengths using all nodes as source nodes.
**target**: node, optional

Ending node for path. If not specified, compute shortest path lengths using all nodes as target nodes.

**weight**: None or string, optional (default = None)

If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

**Returns**

**length**: int or dictionary

If the source and target are both specified, return the length of the shortest path from the source to the target.

If only the source is specified, return a dictionary keyed by targets whose values are the lengths of the shortest path from the source to one of the targets.

If only the target is specified, return a dictionary keyed by sources whose values are the lengths of the shortest path from one of the sources to the target.

If neither the source nor target are specified return a dictionary of dictionaries with path[source][target]=L, where L is the length of the shortest path from source to target.

**Raises**

NetworkXNoPath: If no path exists between source and target.

**See also**:

all_pairs_shortest_path_length, all_pairs_dijkstra_path_length, single_source_shortest_path_length, single_source_dijkstra_path_length

**Notes**

The length of the path is always 1 less than the number of nodes involved in the path since the length measures the number of edges followed.

For digraphs this returns the shortest directed path length. To find path lengths in the reverse direction use G.reverse(copy=False) first to flip the edge orientation.

**Examples**

```python
>>> G=nx.path_graph(5)
>>> print(nx.shortest_path_length(G,source=0,target=4))
4
>>> p=nx.shortest_path_length(G,source=0) # target not specified
>>> p[4]
4
>>> p=nx.shortest_path_length(G,target=4) # source not specified
>>> p[0]
4
>>> p=nx.shortest_path_length(G) # source,target not specified
>>> p[0][4]
4
```

4.30. Shortest Paths
### 4.30.4 average_shortest_path_length

**average_shortest_path_length** *(G, weight=\text{None})*

Return the average shortest path length.

The average shortest path length is

\[
\alpha = \frac{\sum_{s,t \in V} d(s, t)}{n(n - 1)}
\]

where \(V\) is the set of nodes in \(G\), \(d(s, t)\) is the shortest path from \(s\) to \(t\), and \(n\) is the number of nodes in \(G\).

**Parameters**

- **G**: NetworkX graph
- **weight**: None or string, optional (default = None)
  
  If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

**Raises**

NetworkXError:

if the graph is not connected.

**Examples**

```python
g = nx.path_graph(5)
p = nx.average_shortest_path_length(g)
p
```

2.0

For disconnected graphs you can compute the average shortest path length for each component:

```python
g = nx.Graph([(1,2),(3,4)])
g average_shortest_path_length(g)
g average_shortest_path_length(g)
```

1.0 1.0

### 4.30.5 has_path

**has_path** *(G, source, target)*

Return True if \(G\) has a path from source to target, False otherwise.

**Parameters**

- **G**: NetworkX graph
- **source**: node
  
  Starting node for path
- **target**: node
  
  Ending node for path

### 4.30.6 Advanced Interface

Shortest path algorithms for unweighted graphs.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>single_source_shortest_path(G, source[, cutoff])</td>
<td>Compute shortest path between source and all other nodes reachable</td>
</tr>
<tr>
<td>single_source_shortest_path_length(G, source)</td>
<td>Compute the shortest path lengths from source to all reachable nodes</td>
</tr>
<tr>
<td>all_pairs_shortest_path(G[, cutoff])</td>
<td>Compute shortest paths between all nodes.</td>
</tr>
<tr>
<td>all_pairs_shortest_path_length(G[, cutoff])</td>
<td>Compute the shortest path lengths between all nodes in (G).</td>
</tr>
<tr>
<td>predecessor(G, source[, target, cutoff, ...])</td>
<td>Returns dictionary of predecessors for the path from source to all nodes.</td>
</tr>
</tbody>
</table>
single_source_shortest_path

single_source_shortest_path \((G, source, cutoff=None)\)
Compute shortest path between source and all other nodes reachable from source.

Parameters
- \(G\) : NetworkX graph
- \(source\) : node label
  Starting node for path
- \(cutoff\) : integer, optional
  Depth to stop the search. Only paths of length \(\leq\) cutoff are returned.

Returns
- \(lengths\) : dictionary
  Dictionary, keyed by target, of shortest paths.

See also:
- shortest_path

Notes
The shortest path is not necessarily unique. So there can be multiple paths between the source and each target node, all of which have the same ‘shortest’ length. For each target node, this function returns only one of those paths.

Examples

```python
>>> G=nx.path_graph(5)
>>> path=nx.single_source_shortest_path(G,0)
>>> path[4]
[0, 1, 2, 3, 4]
```

single_source_shortest_path_length

single_source_shortest_path_length \((G, source, cutoff=None)\)
Compute the shortest path lengths from source to all reachable nodes.

Parameters
- \(G\) : NetworkX graph
- \(source\) : node
  Starting node for path
- \(cutoff\) : integer, optional
  Depth to stop the search. Only paths of length \(\leq\) cutoff are returned.

Returns
- \(lengths\) : dictionary
  Dictionary of shortest path lengths keyed by target.

See also:
- shortest_path_length
Examples

```python
>>> G=nx.path_graph(5)
>>> length=nx.single_source_shortest_path_length(G,0)
>>> length[4]
4
>>> print(length)
{0: 0, 1: 1, 2: 2, 3: 3, 4: 4}
```

**all_pairs_shortest_path**

`all_pairs_shortest_path(G, cutoff=None)`

Compute shortest paths between all nodes.

Parameters

- **G**: NetworkX graph
- **cutoff**: integer, optional
  
Depth to stop the search. Only paths of length <= cutoff are returned.

Returns

- **lengths**: dictionary
  
Dictionary, keyed by source and target, of shortest paths.

See also:

floyd_warshall

Examples

```python
>>> G=nx.path_graph(5)
>>> path=nx.all_pairs_shortest_path(G)
>>> print(path[0][4])
[0, 1, 2, 3, 4]
```

**all_pairs_shortest_path_length**

`all_pairs_shortest_path_length(G, cutoff=None)`

Compute the shortest path lengths between all nodes in G.

Parameters

- **G**: NetworkX graph
- **cutoff**: integer, optional
  
Depth to stop the search. Only paths of length <= cutoff are returned.

Returns

- **lengths**: dictionary
  
Dictionary of shortest path lengths keyed by source and target.

Notes

The dictionary returned only has keys for reachable node pairs.
Examples

>>> G=nx.path_graph(5)
>>> length=nx.all_pairs_shortest_path_length(G)
>>> print(length[1][4])
3
>>> length[1]
{0: 1, 1: 0, 2: 1, 3: 2, 4: 3}

predecessor

predecessor (G, source, target=None, cutoff=None, return_seen=None)  
Returns dictionary of predecessors for the path from source to all nodes in G.

Parameters  
G : NetworkX graph
    Starting node for path

source : node label
            Ending node for path. If provided only predecessors between source and target are returned

target : node label, optional

    Depth to stop the search. Only paths of length <= cutoff are returned.

cutoff : integer, optional

Returns  
pred : dictionary
    Dictionary, keyed by node, of predecessors in the shortest path.

Examples

>>> G=nx.path_graph(4)
>>> print(G.nodes())
[0, 1, 2, 3]
>>> nx.predecessor(G,0)
{0: [], 1: [0], 2: [1], 3: [2]}

4.30. Shortest Paths

---

**Dijkstra's Shortest Path Algorithms**

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>dijkstra_path(G, source[, target, weight])</code></td>
<td>Returns the shortest path from source to target in a weighted graph G.</td>
</tr>
<tr>
<td><code>dijkstra_path_length(G, source[, target, weight])</code></td>
<td>Returns the shortest path length from source to target in a weighted graph G.</td>
</tr>
<tr>
<td><code>single_source_dijkstra_path(G, source[, ...])</code></td>
<td>Compute shortest path between source and all other reachable nodes.</td>
</tr>
<tr>
<td><code>single_source_dijkstra_path_length(G, source)</code></td>
<td>Compute the shortest path length between source and all other reachable nodes.</td>
</tr>
<tr>
<td><code>all_pairs_dijkstra_path(G[, cutoff, weight])</code></td>
<td>Compute shortest paths between all nodes in a weighted graph.</td>
</tr>
<tr>
<td><code>all_pairs_dijkstra_path_length(G[, cutoff, ...])</code></td>
<td>Compute shortest path lengths between all nodes in a weighted graph.</td>
</tr>
<tr>
<td><code>single_source_dijkstra(G, source[, target, ...])</code></td>
<td>Compute shortest paths and lengths in a weighted graph G.</td>
</tr>
<tr>
<td><code>bidirectional_dijkstra(G, source[, target, ...])</code></td>
<td>Dijkstra's algorithm for shortest paths using bidirectional search.</td>
</tr>
<tr>
<td><code>dijkstra_predecessor_and_distance(G[, source])</code></td>
<td>Compute shortest path length and predecessors on shortest paths in a weighted graph.</td>
</tr>
<tr>
<td><code>bellman_ford(G[, source, weight])</code></td>
<td>Compute shortest path lengths and predecessors on shortest paths in a weighted graph.</td>
</tr>
<tr>
<td><code>negative_edge_cycle(G[, weight])</code></td>
<td>Return True if there exists a negative edge cycle anywhere in G.</td>
</tr>
</tbody>
</table>
**dijkstra_path**

**dijkstra_path** *(G, source, target, weight='weight')*

Returns the shortest path from source to target in a weighted graph G.

- **Parameters**
  - G : NetworkX graph
  - source : node
    Starting node
  - target : node
    Ending node
  - weight : string, optional (default='weight') :
    Edge data key corresponding to the edge weight

- **Returns**
  - path : list
    List of nodes in a shortest path.

- **Raises**
  - NetworkXNoPath :
    If no path exists between source and target.

**See also:**

bidirectional_dijkstra

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

**Examples**

```python
>>> G=nx.path_graph(5)
>>> print(nx.dijkstra_path(G,0,4))
[0, 1, 2, 3, 4]
```

**dijkstra_path_length**

**dijkstra_path_length** *(G, source, target, weight='weight')*

Returns the shortest path length from source to target in a weighted graph.

- **Parameters**
  - G : NetworkX graph
  - source : node label
    Starting node for path
  - target : node label
    Ending node for path
  - weight : string, optional (default='weight') :
    Edge data key corresponding to the edge weight

- **Returns**
  - length : number
Shortest path length.

**Raises** NetworkXNoPath:

If no path exists between source and target.

**See also:**

bidirectional_dijkstra

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

**Examples**

```python
g = nx.path_graph(5)
print(nx.dijkstra_path_length(g, 0, 4))
```

4

---

**single_source_dijkstra_path**

`single_source_dijkstra_path(G, source, cutoff=None, weight='weight')`

Compute shortest path between source and all other reachable nodes for a weighted graph.

**Parameters**

- `G` : NetworkX graph
- `source` : node
- `weight` : string, optional (default='weight')
- `cutoff` : integer or float, optional

**Returns**

- `paths` : dictionary

Dictionary of shortest path lengths keyed by target.

**See also:**

single_source_dijkstra

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

**Examples**

```python
g = nx.path_graph(5)
path = nx.single_source_dijkstra_path(g, 0)
path[4]
```

[0, 1, 2, 3, 4]
**single_source_dijkstra_path_length**

**single_source_dijkstra_path_length** \((G, \text{source}, \text{cutoff}=\text{None}, \text{weight}=\text{'weight'})\)

Compute the shortest path length between source and all other reachable nodes for a weighted graph.

**Parameters**

- **G**: NetworkX graph
- **source**: node label
  
  Starting node for path
- **weight**: string, optional (default=\text{'weight'})
  
  Edge data key corresponding to the edge weight.
- **cutoff**: integer or float, optional
  
  Depth to stop the search. Only paths of length \(\leq\) cutoff are returned.

**Returns**

- **length**: dictionary
  
  Dictionary of shortest lengths keyed by target.

**See also:**

- **single_source_dijkstra**

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

**Examples**

```python
>>> G=nx.path_graph(5)
>>> length=nx.single_source_dijkstra_path_length(G,0)
>>> length[4]
4
>>> print(length)
{0: 0, 1: 1, 2: 2, 3: 3, 4: 4}
```

**all_pairs_dijkstra_path**

**all_pairs_dijkstra_path** \((G, \text{cutoff}=\text{None}, \text{weight}=\text{'weight'})\)

Compute shortest paths between all nodes in a weighted graph.

**Parameters**

- **G**: NetworkX graph
- **weight**: string, optional (default=\text{'weight'})
  
  Edge data key corresponding to the edge weight
- **cutoff**: integer or float, optional
  
  Depth to stop the search. Only paths of length \(\leq\) cutoff are returned.

**Returns**

- **distance**: dictionary
  
  Dictionary, keyed by source and target, of shortest paths.

**See also:**

- **floyd_warshall**
Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

Examples

```python
>>> G=nx.path_graph(5)
>>> path=nx.all_pairs_dijkstra_path(G)
>>> print(path[0][4])
[0, 1, 2, 3, 4]
```

**all_pairs_dijkstra_path_length**

`all_pairs_dijkstra_path_length(G, cutoff=None, weight='weight')`

Compute shortest path lengths between all nodes in a weighted graph.

- **Parameters**
  - `G` : NetworkX graph
  - `weight` : string, optional (default='weight')
    - Edge data key corresponding to the edge weight
  - `cutoff` : integer or float, optional
    - Depth to stop the search. Only paths of length <= cutoff are returned.

- **Returns**
  - `distance` : dictionary
    - Dictionary, keyed by source and target, of shortest path lengths.

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.
The dictionary returned only has keys for reachable node pairs.

Examples

```python
>>> G=nx.path_graph(5)
>>> length=nx.all_pairs_dijkstra_path_length(G)
>>> print(length[1][4])
3
>>> length[1]
{0: 1, 1: 0, 2: 1, 3: 2, 4: 3}
```

**single_source_dijkstra**

`single_source_dijkstra(G, source=None, cutoff=None, weight='weight')`

Compute shortest paths and lengths in a weighted graph `G`.

- **Parameters**
  - `G` : NetworkX graph
  - `source` : node label

4.30. Shortest Paths
Starting node for path

**target** : node label, optional

Ending node for path

**cutoff** : integer or float, optional

Depth to stop the search. Only paths of length $\leq$ cutoff are returned.

**Returns**  **distance, path** : dictionaries

Returns a tuple of two dictionaries keyed by node. The first dictionary stores distance from the source. The second stores the path from the source to that node.

**See also:**

`single_source_dijkstra_path`, `single_source_dijkstra_path_length`

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

Based on the Python cookbook recipe (119466) at [http://aspn.activestate.com/ASPN/Cookbook/Python/Recipe/119466](http://aspn.activestate.com/ASPN/Cookbook/Python/Recipe/119466)

This algorithm is not guaranteed to work if edge weights are negative or are floating point numbers (overflows and roundoff errors can cause problems).

**Examples**

```python
>>> G=nx.path_graph(5)
>>> length,path=nx.single_source_dijkstra(G,0)
>>> print(length[4])
4
>>> print(length)
{0: 0, 1: 1, 2: 2, 3: 3, 4: 4}
>>> path[4]
[0, 1, 2, 3, 4]
```

**bidirectional_dijkstra**

`bidirectional_dijkstra (G, source, target, weight='weight')`

Dijkstra’s algorithm for shortest paths using bidirectional search.

**Parameters**  **G** : NetworkX graph

**source** : node

Starting node.

**target** : node

Ending node.

**weight** : string, optional (default='weight') :

Edge data key corresponding to the edge weight

**Returns**  **length** : number

Shortest path length.
Returns a tuple of two dictionaries keyed by node:

The first dictionary stores distance from the source:

The second stores the path from the source to that node.

Raises NetworkXNoPath:
If no path exists between source and target.

See also:
shortest_path, shortest_path_length

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

In practice bidirectional Dijkstra is much more than twice as fast as ordinary Dijkstra.

Ordinary Dijkstra expands nodes in a sphere-like manner from the source. The radius of this sphere will eventually be the length of the shortest path. Bidirectional Dijkstra will expand nodes from both the source and the target, making two spheres of half this radius. Volume of the first sphere is $\pi r^2 r$ while the others are $2\pi r^2 r/2$, making up half the volume.

This algorithm is not guaranteed to work if edge weights are negative or are floating point numbers (overflows and roundoff errors can cause problems).

Examples

```python
>>> G=nx.path_graph(5)
>>> length,path=nx.bidirectional_dijkstra(G,0,4)
>>> print(length)
4
>>> print(path)
[0, 1, 2, 3, 4]
```

dijkstra_predecessor_and_distance

dijkstra_predecessor_and_distance(G, source, cutoff=None, weight='weight')

Compute shortest path length and predecessors on shortest paths in weighted graphs.

Parameters

- **G**: NetworkX graph
- **source**: node label
  - Starting node for path
- **weight**: string, optional (default='weight'):
  - Edge data key corresponding to the edge weight
- **cutoff** : integer or float, optional
  - Depth to stop the search. Only paths of length <= cutoff are returned.

Returns

- **pred, distance** : dictionaries
  - Returns two dictionaries representing a list of predecessors of a node and the distance to each node.
Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.
The list of predecessors contains more than one element only when there are more than one shortest paths to the key node.

bellman_ford

bellman_ford(G, source, weight='weight')

Compute shortest path lengths and predecessors on shortest paths in weighted graphs.

The algorithm has a running time of O(mn) where n is the number of nodes and m is the number of edges. It is slower than Dijkstra but can handle negative edge weights.

Parameters

- G : NetworkX graph
  The algorithm works for all types of graphs, including directed graphs and multigraphs.
- source: node label:
  Starting node for path
- weight: string, optional (default='weight'):
  Edge data key corresponding to the edge weight

Returns

- pred, dist : dictionaries
  Returns two dictionaries keyed by node to predecessor in the path and to the distance from the source respectively.

Raises

- NetworkXUnbounded:
  If the (di)graph contains a negative cost (di)cycle, the algorithm raises an exception to indicate the presence of the negative cost (di)cycle. Note: any negative weight edge in an undirected graph is a negative cost cycle.

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.
The dictionaries returned only have keys for nodes reachable from the source.

In the case where the (di)graph is not connected, if a component not containing the source contains a negative cost (di)cycle, it will not be detected.

Examples

```python
>>> import networkx as nx
>>> G = nx.path_graph(5, create_using = nx.DiGraph())
>>> pred, dist = nx.bellman_ford(G, 0)
>>> pred
{0: None, 1: 0, 2: 1, 3: 2, 4: 3}
>>> dist
{0: 0, 1: 1, 2: 2, 3: 3, 4: 4}
```
>>> from nose.tools import assert_raises
>>> G = nx.cycle_graph(5, create_using = nx.DiGraph())
>>> G[1][2][‘weight’] = -7
>>> assert_raises(nx.NetworkXUnbounded, nx.bellman_ford, G, 0)

negative_edge_cycle

negative_edge_cycle(G, weight=’weight’)  
Return True if there exists a negative edge cycle anywhere in G.

Parameters  
G : NetworkX graph
    weight : string, optional (default=’weight’) :  
    Edge data key corresponding to the edge weight

Returns  
negative_cycle : bool  
    True if a negative edge cycle exists, otherwise False.

Notes  
Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.
This algorithm uses bellman_ford() but finds negative cycles on any component by first adding a new node connected to every node, and starting bellman_ford on that node. It then removes that extra node.

Examples

>>> import networkx as nx
>>> G = nx.cycle_graph(5, create_using = nx.DiGraph())
>>> print(nx.negative_edge_cycle(G))
False
>>> G[1][2][‘weight’] = -7
>>> print(nx.negative_edge_cycle(G))
True

4.30.7 Dense Graphs

Floyd-Warshall algorithm for shortest paths.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>floyd_warshall(G[, weight])</td>
<td>Find all-pairs shortest path lengths using Floyd’s algorithm.</td>
</tr>
<tr>
<td>floyd_warshall_predecessor_and_distance(G[,...])</td>
<td>Find all-pairs shortest path lengths using Floyd’s algorithm.</td>
</tr>
<tr>
<td>floyd_warshall_numpy(G[, nodelist, weight])</td>
<td>Find all-pairs shortest path lengths using Floyd’s algorithm.</td>
</tr>
</tbody>
</table>

floyd_warshall

floyd_warshall(G, weight=’weight’)  
Find all-pairs shortest path lengths using Floyd’s algorithm.

Parameters  
G : NetworkX graph
    weight : string, optional (default= ‘weight’) :
Edge data key corresponding to the edge weight.

**Returns**

**distance**: dict

A dictionary, keyed by source and target, of shortest paths distances between nodes.

**See also:**

- `floyd_warshall_predecessor_and_distance`
- `floyd_warshall_numpy`
- `all_pairs_shortest_path`
- `all_pairs_shortest_path_length`

**Notes**

Floyd’s algorithm is appropriate for finding shortest paths in dense graphs or graphs with negative weights when Dijkstra’s algorithm fails. This algorithm can still fail if there are negative cycles. It has running time $O(n^3)$ with running space of $O(n^2)$.

### floyd_warshall_predecessor_and_distance

#### floyd_warshall_predecessor_and_distance

$(G, \text{weight}=\text{'weight'})$

Find all-pairs shortest path lengths using Floyd’s algorithm.

**Parameters**

- $G$: NetworkX graph
- **weight**: string, optional (default= ‘weight’) :
  
  Edge data key corresponding to the edge weight.

**Returns**

- **predecessor**: dictionary
  
  Dictionaries, keyed by source and target, of predecessors and distances in the shortest path.

**See also:**

- `floyd_warshall`
- `floyd_warshall_numpy`
- `all_pairs_shortest_path`
- `all_pairs_shortest_path_length`

**Notes**

Floyd’s algorithm is appropriate for finding shortest paths in dense graphs or graphs with negative weights when Dijkstra’s algorithm fails. This algorithm can still fail if there are negative cycles. It has running time $O(n^3)$ with running space of $O(n^2)$.

### floyd_warshall_numpy

#### floyd_warshall_numpy

$(G, \text{nodelist}=\text{None}, \text{weight}=\text{'weight'})$

Find all-pairs shortest path lengths using Floyd’s algorithm.

**Parameters**

- $G$: NetworkX graph
- **nodelist**: list, optional
  
  The rows and columns are ordered by the nodes in nodelist. If nodelist is None then the ordering is produced by G.nodes().

- **weight**: string, optional (default= ‘weight’) :
  
  Edge data key corresponding to the edge weight.
Returns distance : NumPy matrix

A matrix of shortest path distances between nodes. If there is no path between to nodes
the corresponding matrix entry will be Inf.

Notes

Floyd’s algorithm is appropriate for finding shortest paths in dense graphs or graphs with negative weights when
Dijkstra’s algorithm fails. This algorithm can still fail if there are negative cycles. It has running time O(n^3)
with running space of O(n^2).

4.30.8 A* Algorithm

Shortest paths and path lengths using A* (“A star”) algorithm.

astar_path(G, source, target[, heuristic, ...]) Return a list of nodes in a shortest path between source and target

astar_path_length(G, source, target[, ...]) Return the length of the shortest path between source and target using

astar_path

astar_path (G, source, target, heuristic=None, weight='weight')

Return a list of nodes in a shortest path between source and target using the A* (“A-star”) algorithm.

There may be more than one shortest path. This returns only one.

Parameters

G : NetworkX graph

source : node

Starting node for path

target : node

Ending node for path

heuristic : function

A function to evaluate the estimate of the distance from the a node to the target. The
function takes two nodes arguments and must return a number.

weight: string, optional (default='weight') :

Edge data key corresponding to the edge weight.

Raises

NetworkXNoPath :

If no path exists between source and target.

See also:

shortest_path, dijkstra_path

Examples

>>> G=nx.path_graph(5)
>>> print(nx.astar_path(G,0,4))
[0, 1, 2, 3, 4]
>>> G=nx.grid_graph(dim=[3,3])  # nodes are two-tuples (x,y)
>>> def dist(a, b):
...     (x1, y1) = a
...     (x2, y2) = b
...     return ((x1 - x2) ** 2 + (y1 - y2) ** 2) ** 0.5

>>> print(nx.astar_path_length(G,(0,0),(2,2),dist))
[(0, 0), (0, 1), (1, 1), (1, 2), (2, 2)]

astar_path_length

**astar_path_length** *(G, source, target, heuristic=None, weight=’weight’)*

Return the length of the shortest path between source and target using the A* ("A-star") algorithm.

**Parameters**

- **G**: NetworkX graph
- **source**: node
  - Starting node for path
- **target**: node
  - Ending node for path
- **heuristic**: function
  - A function to evaluate the estimate of the distance from the a node to the target. The function takes two nodes arguments and must return a number.

**Raises**

- **NetworkXNoPath**
  - If no path exists between source and target.

**See also**

- astar_path

### 4.31 Simple Paths

**all_simple_paths** *(G, source, target[, cutoff]*)

Generate all simple paths in the graph G from source to target.

### 4.31.1 all_simple_paths

**all_simple_paths** *(G, source, target, cutoff=’None’)*

Generate all simple paths in the graph G from source to target.

A simple path is a path with no repeated nodes.

**Parameters**

- **G**: NetworkX graph
  - source : node
    - Starting node for path
  - **target**: node
    - Ending node for path
  - **cutoff**: integer, optional
    - Depth to stop the search. Only paths of length <= cutoff are returned.
Returns  path_generator: generator:

A generator that produces lists of simple paths. If there are no paths between the source and target within the given cutoff the generator produces no output.

See also:
all_shortest_paths, shortest_path

Notes

This algorithm uses a modified depth-first search to generate the paths [R245]. A single path can be found in \(O(V + E)\) time but the number of simple paths in a graph can be very large, e.g. \(O(n!)\) in the complete graph of order \(n\).

References

[R245]

Examples

```python
>>> G = nx.complete_graph(4)
>>> for path in nx.all_simple_paths(G, source=0, target=3):
...     print(path)
...[0, 1, 2, 3]
[0, 1, 3]
[0, 2, 1, 3]
[0, 2, 3]
[0, 3]

>>> paths = nx.all_simple_paths(G, source=0, target=3, cutoff=2)
>>> print(list(paths))
[[0, 1, 3], [0, 2, 3], [0, 3]]
```

### 4.32 Swap

Swap edges in a graph.

| double_edge_swap\( (G, nswap, max\_tries) \) | Swap two edges in the graph while keeping the node degrees fixed. |
| connected_double_edge_swap\( (G, nswap) \) | Attempt nswap double-edge swaps in the graph G. |

#### 4.32.1 double_edge_swap

**double_edge_swap\( (G, nswap=1, max\_tries=100) \)**

Swap two edges in the graph while keeping the node degrees fixed.

A double-edge swap removes two randomly chosen edges \(u-v\) and \(x-y\) and creates the new edges \(u-x\) and \(v-y\):

\[
\begin{array}{ccc}
\text{u--v} & \quad & \text{u v} \\
\text{x--y} & \quad & \text{x y}
\end{array}
\]

```
```
If either the edge u-x or v-y already exist no swap is performed and another attempt is made to find a suitable edge pair.

**Parameters**

- **G** : graph
  - An undirected graph
- **nswap** : integer (optional, default=1)
  - Number of double-edge swaps to perform
- **max_tries** : integer (optional)
  - Maximum number of attempts to swap edges

**Returns**

- **G** : graph
  - The graph after double edge swaps.

**Notes**

Does not enforce any connectivity constraints.
The graph G is modified in place.

### 4.32.2 connected_double_edge_swap

**connected_double_edge_swap**(G, nswap=1)

Attempt nswap double-edge swaps in the graph G.

A double-edge swap removes two randomly chosen edges u-v and x-y and creates the new edges u-x and v-y:

\[
\begin{align*}
\text{u--v} & \quad \text{becomes} \quad | \quad | \\
\text{x--y} & \quad \text{becomes} \quad | \quad |
\end{align*}
\]

If either the edge u-x or v-y already exist no swap is performed so the actual count of swapped edges is always \(\leq nswap\)

**Parameters**

- **G** : graph
  - An undirected graph
- **nswap** : integer (optional, default=1)
  - Number of double-edge swaps to perform

**Returns**

- **G** : int
  - The number of successful swaps

**Notes**

The initial graph G must be connected, and the resulting graph is connected. The graph G is modified in place.

**References**

[R246]
### 4.33 Traversal

#### 4.33.1 Depth First Search

Basic algorithms for depth-first searching.


<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>dfs_edges(G[, source])</code></td>
<td>Produce edges in a depth-first-search starting at source.</td>
</tr>
<tr>
<td><code>dfs_tree(G, source)</code></td>
<td>Return directed tree of depth-first-search from source.</td>
</tr>
<tr>
<td><code>dfs_predecessors(G[, source])</code></td>
<td>Return dictionary of predecessors in depth-first-search from source.</td>
</tr>
<tr>
<td><code>dfs_successors(G[, source])</code></td>
<td>Return dictionary of successors in depth-first-search from source.</td>
</tr>
<tr>
<td><code>dfs_preorder_nodes(G[, source])</code></td>
<td>Produce nodes in a depth-first-search pre-ordering starting at source.</td>
</tr>
<tr>
<td><code>dfs_postorder_nodes(G[, source])</code></td>
<td>Produce nodes in a depth-first-search post-ordering starting</td>
</tr>
<tr>
<td><code>dfs_labeled_edges(G[, source])</code></td>
<td>Produce edges in a depth-first-search starting at source and</td>
</tr>
</tbody>
</table>

**dfs_edges**

`dfs_edges (G, source=None)`

Produce edges in a depth-first-search starting at source.

**dfs_tree**

`dfs_tree (G, source)`

Return directed tree of depth-first-search from source.

**dfs_predecessors**

`dfs_predecessors (G, source=None)`

Return dictionary of predecessors in depth-first-search from source.

**dfs_successors**

`dfs_successors (G, source=None)`

Return dictionary of successors in depth-first-search from source.

**dfs_preorder_nodes**

`dfs_preorder_nodes (G, source=None)`

Produce nodes in a depth-first-search pre-ordering starting at source.

**dfs_postorder_nodes**

`dfs_postorder_nodes (G, source=None)`

Produce nodes in a depth-first-search post-ordering starting from source.
**dfs_labeled_edges**

**dfs_labeled_edges** \((G, \text{source}=\text{None})\)

Produce edges in a depth-first-search starting at source and labeled by direction type (forward, reverse, nontree).

### 4.33.2 Breadth First Search

Basic algorithms for breadth-first searching.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>bfs_edges</strong> ((G, \text{source}, \text{reverse}=\text{False}))</td>
<td>Produce edges in a breadth-first-search starting at source.</td>
</tr>
<tr>
<td><strong>bfs_tree</strong> ((G, \text{source}, \text{reverse}=\text{False}))</td>
<td>Return directed tree of breadth-first-search from source.</td>
</tr>
<tr>
<td><strong>bfs_predecessors</strong> ((G, \text{source}))</td>
<td>Return dictionary of predecessors in breadth-first-search from source.</td>
</tr>
<tr>
<td><strong>bfs_successors</strong> ((G, \text{source}))</td>
<td>Return dictionary of successors in breadth-first-search from source.</td>
</tr>
</tbody>
</table>

**bfs_edges**

**bfs_edges** \((G, \text{source}, \text{reverse}=\text{False})\)

Produce edges in a breadth-first-search starting at source.

**bfs_tree**

**bfs_tree** \((G, \text{source}, \text{reverse}=\text{False})\)

Return directed tree of breadth-first-search from source.

**bfs_predecessors**

**bfs_predecessors** \((G, \text{source})\)

Return dictionary of predecessors in breadth-first-search from source.

**bfs_successors**

**bfs_successors** \((G, \text{source})\)

Return dictionary of successors in breadth-first-search from source.

### 4.34 Vitality

Vitality measures.

**closeness_vitality** \((G[, \text{weight}])\)

Compute closeness vitality for nodes.

#### 4.34.1 closeness_vitality

**closeness_vitality** \((G, \text{weight}=\text{None})\)

Compute closeness vitality for nodes.

Closeness vitality of a node is the change in the sum of distances between all node pairs when excluding that node.
**Parameters**  
\[ G : \text{graph} \]

- **weight** : None or string (optional)  
  The name of the edge attribute used as weight. If None the edge weights are ignored.

**Returns**  
\[ \text{nodes} : \text{dictionary} \]

Dictionary with nodes as keys and closeness vitality as the value.

**See also:**

closeness_centrality

**References**

[R247]

**Examples**

```python
>>> G=nx.cycle_graph(3)
>>> nx.closeness_vitality(G)
{0: 4.0, 1: 4.0, 2: 4.0}
```
CHAPTER
FIVE

FUNCTIONS

Functional interface to graph methods and assorted utilities.

5.1 Graph

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>degree(G[, nbunch, weight])</code></td>
<td>Return degree of single node or of nbunch of nodes.</td>
</tr>
<tr>
<td><code>degree_histogram(G)</code></td>
<td>Return a list of the frequency of each degree value.</td>
</tr>
<tr>
<td><code>density(G)</code></td>
<td>Return the density of a graph.</td>
</tr>
<tr>
<td><code>info(G[, n])</code></td>
<td>Print short summary of information for the graph G or the node n.</td>
</tr>
<tr>
<td><code>create_empty_copy(G[, with_nodes])</code></td>
<td>Return a copy of the graph G with all of the edges removed.</td>
</tr>
<tr>
<td><code>is_directed(G)</code></td>
<td>Return True if graph is directed.</td>
</tr>
</tbody>
</table>

5.1.1 degree

degree(G, nbunch=None, weight=None)

Return degree of single node or of nbunch of nodes. If nbunch is omitted, then return degrees of all nodes.

5.1.2 degree_histogram

degree_histogram(G)

Return a list of the frequency of each degree value.

Parameters

- `G` : Networkx graph
  - A graph

Returns

- `hist` : list
  - A list of frequencies of degrees. The degree values are the index in the list.

Notes

Note: the bins are width one, hence len(list) can be large (Order(number_of_edges))

5.1.3 density

density(G)

Return the density of a graph.
The density for undirected graphs is

\[ d = \frac{2m}{n(n - 1)} \]

and for directed graphs is

\[ d = \frac{m}{n(n - 1)} \]

where \( n \) is the number of nodes and \( m \) is the number of edges in \( G \).

**Notes**

The density is 0 for a graph without edges and 1 for a complete graph. The density of multigraphs can be higher than 1.

Self loops are counted in the total number of edges so graphs with self loops can have density higher than 1.

### 5.1.4 info

**info** \((G, n=None)\)

Print short summary of information for the graph \( G \) or the node \( n \).

**Parameters**

- \( G \) : Networkx graph
  - A graph
- \( n \) : node (any hashable)
  - A node in the graph \( G \)

### 5.1.5 create_empty_copy

**create_empty_copy** \((G, with_nodes=True)\)

Return a copy of the graph \( G \) with all of the edges removed.

**Parameters**

- \( G \) : graph
  - A NetworkX graph
- \( with_nodes \) : bool (default=True)
  - Include nodes.

**Notes**

Graph, node, and edge data is not propagated to the new graph.

### 5.1.6 is_directed

**is_directed** \((G)\)

Return True if graph is directed.
5.2 Nodes
5.2.1 nodes

nodes(G)
Return a copy of the graph nodes in a list.

5.2.2 number_of_nodes

number_of_nodes(G)
Return the number of nodes in the graph.

5.2.3 nodes_iter

nodes_iter(G)
Return an iterator over the graph nodes.

5.2.4 all_neighbors

all_neighbors(graph, node)
Returns all of the neighbors of a node in the graph.
If the graph is directed returns predecessors as well as successors.

Parameters  graph : NetworkX graph
   Graph to find neighbors.

       node : node
   The node whose neighbors will be returned.

Returns  neighbors : iterator
   Iterator of neighbors

5.2.5 non_neighbors

non_neighbors(graph, node)
Returns the non-neighbors of the node in the graph.

Parameters  graph : NetworkX graph
   Graph to find neighbors.

       node : node
   The node whose neighbors will be returned.

Returns  non_neighbors : iterator
5.3 Edges

**edges** *(G[, nbunch]*)
Return list of edges adjacent to nodes in nbunch.
Return all edges if nbunch is unspecified or nbunch=None.
For digraphs, edges=out_edges

**number_of_edges** *(G)*
Return the number of edges in the graph.

**edges_iter** *(G[, nbunch]*)
Return iterator over edges adjacent to nodes in nbunch.
Return all edges if nbunch is unspecified or nbunch=None.
For digraphs, edges=out_edges

5.4 Attributes

**set_node_attributes** *(G, name, attributes)*
Set node attributes from dictionary of nodes and values

**get_node_attributes** *(G, name)*
Get node attributes from graph

**set_edge_attributes** *(G, name, attributes)*
Set edge attributes from dictionary of edge tuples and values

**get_edge_attributes** *(G, name)*
Get edge attributes from graph

5.4.1 set_node_attributes

**set_node_attributes** *(G, name, attributes)*
Set node attributes from dictionary of nodes and values

Parameters

- **G**: NetworkX Graph
- **name**: string
  Attribute name
- **attributes**: dict

Dictionary of attributes keyed by node.

Examples

```python
>>> G = nx.path_graph(3)
>>> bb = nx.betweenness_centrality(G)
>>> nx.set_node_attributes(G, ’betweenness’, bb)
>>> G.node[1][’betweenness’]
1.0
```

5.4.2 get_node_attributes

**get_node_attributes** (*G, name*)

Get node attributes from graph

Parameters

<table>
<thead>
<tr>
<th>G</th>
<th>NetworkX Graph</th>
</tr>
</thead>
<tbody>
<tr>
<td>name</td>
<td>string</td>
</tr>
</tbody>
</table>

Returns

Dictionary of attributes keyed by node.

Examples

```python
>>> G = nx.Graph()
>>> G.add_nodes_from([1, 2, 3], color=’red’)
>>> color = nx.get_node_attributes(G, ’color’)
>>> color[1]
’red’
```

5.4.3 set_edge_attributes

**set_edge_attributes** (*G, name, attributes*)

Set edge attributes from dictionary of edge tuples and values

Parameters

<table>
<thead>
<tr>
<th>G</th>
<th>NetworkX Graph</th>
</tr>
</thead>
<tbody>
<tr>
<td>name</td>
<td>string</td>
</tr>
<tr>
<td>attributes: dict:</td>
<td></td>
</tr>
</tbody>
</table>

Dictionary of attributes keyed by edge (tuple).

Examples

```python
>>> G = nx.path_graph(3)
>>> bb = nx.edge_betweenness_centrality(G, normalized=False)
>>> nx.set_edge_attributes(G, ’betweenness’, bb)
>>> G[1][2][’betweenness’]
2.0
```
5.4.4 get_edge_attributes

`get_edge_attributes(G, name)`
Get edge attributes from graph

**Parameters**
- `G`: NetworkX Graph
- `name`: string

**Returns**
Dictionary of attributes keyed by node.

**Examples**

```python
>>> G = nx.Graph()
>>> G.add_path([1, 2, 3], color='red')
>>> color = nx.get_edge_attributes(G, 'color')
>>> color[(1, 2)]
'red'
```

5.5 Freezing graph structure

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>freeze(G)</code></td>
<td>Modify graph to prevent further change by adding or removing nodes or edges.</td>
</tr>
<tr>
<td><code>is_frozen(G)</code></td>
<td>Return True if graph is frozen.</td>
</tr>
</tbody>
</table>

5.5.1 freeze

`freeze(G)`
Modify graph to prevent further change by adding or removing nodes or edges.

Node and edge data can still be modified.

**Parameters**
- `G`: graph
  A NetworkX graph

**See also:**
- `is_frozen`

**Notes**

To “unfreeze” a graph you must make a copy by creating a new graph object:

```python
>>> graph = nx.path_graph(4)
>>> frozen_graph = nx.freeze(graph)
>>> unfrozen_graph = nx.Graph(frozen_graph)
>>> nx.is_frozen(unfrozen_graph)
False
```
Examples

```python
>>> G=nx.Graph()
>>> G.add_path([0,1,2,3])
>>> G=nx.freeze(G)
>>> try:
...    G.add_edge(4,5)
... except nx.NetworkXError as e:
...    print(str(e))
Frozen graph can't be modified
```

5.5.2 is_frozen

`is_frozen(G)`
Return True if graph is frozen.

Parameters

- `G : graph`
  A NetworkX graph

See also:

- `freeze`
6.1 Atlas

Generators for the small graph atlas.


Because of its size, this module is not imported by default.

```
graph_atlas_g() Return the list [G0,G1,...,G1252] of graphs as named in the Graph Atlas.
```

6.1.1 graph_atlas_g

```
graph_atlas_g()
Return the list [G0,G1,...,G1252] of graphs as named in the Graph Atlas. G0,G1,...,G1252 are all graphs with
up to 7 nodes.

The graphs are listed:

1. in increasing order of number of nodes;
2. for a fixed number of nodes, in increasing order of the number of edges;
3. for fixed numbers of nodes and edges, in increasing order of the degree sequence, for example 111223
   < 112222;
4. for fixed degree sequence, in increasing number of automorphisms.

Note that indexing is set up so that for GAG=graph_atlas_g(), then G123=GAG[123] and G[0]=empty_graph(0)
```

6.2 Classic

Generators for some classic graphs.

The typical graph generator is called as follows:

```
>>> G=nx.complete_graph(100)
```

returning the complete graph on n nodes labeled 0,...,99 as a simple graph. Except for empty_graph, all the generators
in this module return a Graph class (i.e. a simple, undirected graph).

```
balanced_tree(r, h[, create_using]) Return the perfectly balanced r-tree of height h.
```
Table 6.2 – continued from previous page

<table>
<thead>
<tr>
<th>Function Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>barbell_graph(m1, m2[, create_using])</code></td>
<td>Return the Barbell Graph: two complete graphs connected by a path.</td>
</tr>
<tr>
<td><code>complete_graph(n[, create_using])</code></td>
<td>Return the complete graph ( K_n ) with ( n ) nodes.</td>
</tr>
<tr>
<td><code>complete_bipartite_graph(n1, n2[, create_using])</code></td>
<td>Return the complete bipartite graph ( K_{n1 _n2} ).</td>
</tr>
<tr>
<td><code>circular_ladder_graph(n[, create_using])</code></td>
<td>Return the circular ladder graph ( CL_n ) of length ( n ).</td>
</tr>
<tr>
<td><code>cycle_graph(n[, create_using])</code></td>
<td>Return the cycle graph ( C_n ) over ( n ) nodes.</td>
</tr>
<tr>
<td><code>dorogovtsev_goltsev_mendes_graph(n[, ...])</code></td>
<td>Return the hierarchically constructed Dorogovtsev-Goltsev-Mendes graph.</td>
</tr>
<tr>
<td><code>empty_graph([n, create_using])</code></td>
<td>Return the empty graph with ( n ) nodes and zero edges.</td>
</tr>
<tr>
<td><code>grid_2d_graph(m, n[, periodic, create_using])</code></td>
<td>Return the 2d grid graph of ( mxn ) nodes, each connected to its nearest neighbors.</td>
</tr>
<tr>
<td><code>grid_graph(dim[, periodic])</code></td>
<td>Return the ( n )-dimensional grid graph.</td>
</tr>
<tr>
<td><code>hypercube_graph(n)</code></td>
<td>Return the ( n )-dimensional hypercube.</td>
</tr>
<tr>
<td><code>ladder_graph(n[, create_using])</code></td>
<td>Return the Ladder graph of length ( n ).</td>
</tr>
<tr>
<td><code>lollipop_graph(m, n[, create_using])</code></td>
<td>Return the Lollipop Graph; ( K_m ) connected to ( P_n ).</td>
</tr>
<tr>
<td><code>null_graph([create_using])</code></td>
<td>Return the Null graph with no nodes or edges.</td>
</tr>
<tr>
<td><code>path_graph(n[, create_using])</code></td>
<td>Return the Path graph ( P_n ) of ( n ) nodes linearly connected by ( n-1 ) edges.</td>
</tr>
<tr>
<td><code>star_graph(n[, create_using])</code></td>
<td>Return the Star graph with ( n+1 ) nodes: one center node, connected to ( n ) nodes.</td>
</tr>
<tr>
<td><code>trivial_graph([create_using])</code></td>
<td>Return the Trivial graph with one node (with integer label 0) and no edges.</td>
</tr>
<tr>
<td><code>wheel_graph(n[, create_using])</code></td>
<td>Return the wheel graph: a single hub node connected to each node of the ( P_n ).</td>
</tr>
</tbody>
</table>

### 6.2.1 balanced_tree

**balanced_tree** \((r, h, create_using=None)\)

Return the perfectly balanced \( r \)-tree of height \( h \).

**Parameters**

- **\( r \)**: int
  - Branching factor of the tree
- **\( h \)**: int
  - Height of the tree

**create_using**: NetworkX graph type, optional

Use specified type to construct graph (default = networkx.Graph)

**Returns**

- **\( G \)**: networkx Graph
  - A tree with \( n \) nodes

**Notes**

This is the rooted tree where all leaves are at distance \( h \) from the root. The root has degree \( r \) and all other internal nodes have degree \( r+1 \).

Node labels are the integers 0 (the root) up to number_of_nodes - 1.

Also referred to as a complete \( r \)-ary tree.

### 6.2.2 barbell_graph

**barbell_graph** \((m1, m2, create_using=None)\)

Return the Barbell Graph: two complete graphs connected by a path.

For \( m1 > 1 \) and \( m2 \geq 0 \).

Two identical complete graphs \( K_{\_m1} \) form the left and right bells, and are connected by a path \( P_{\_m2} \).
The $2m_1+m_2$ nodes are numbered $0,...,m_1-1$ for the left barbell, $m_1,...,m_1+m_2-1$ for the path, and $m_1+m_2,...,2m_1+m_2-1$ for the right barbell.

The 3 subgraphs are joined via the edges $(m_1-1,m_1)$ and $(m_1+m_2-1,m_1+m_2)$. If $m_2=0$, this is merely two complete graphs joined together.

This graph is an extremal example in David Aldous and Jim Fill’s etext on Random Walks on Graphs.

### 6.2.3 complete_graph

**complete_graph**($n$, *create_using=None*)

Return the complete graph $K_n$ with $n$ nodes.

Node labels are the integers $0$ to $n-1$.

### 6.2.4 complete_bipartite_graph

**complete_bipartite_graph**($n_1$, $n_2$, *create_using=None*)

Return the complete bipartite graph $K_{n_1,n_2}$.

Composed of two partitions with $n_1$ nodes in the first and $n_2$ nodes in the second. Each node in the first is connected to each node in the second.

Node labels are the integers $0$ to $n_1+n_2-1$.

### 6.2.5 circular_ladder_graph

**circular_ladder_graph**($n$, *create_using=None*)

Return the circular ladder graph $CL_n$ of length $n$.

$CL_n$ consists of two concentric $n$-cycles in which each of the $n$ pairs of concentric nodes are joined by an edge.

Node labels are the integers $0$ to $n-1$.

### 6.2.6 cycle_graph

**cycle_graph**($n$, *create_using=None*)

Return the cycle graph $C_n$ over $n$ nodes.

$C_n$ is the $n$-path with two end-nodes connected.

Node labels are the integers $0$ to $n-1$ If *create_using* is a DiGraph, the direction is in increasing order.

### 6.2.7 dorogovtsev_goltsev_mendes_graph

**dorogovtsev_goltsev_mendes_graph**($n$, *create_using=None*)

Return the hierarchically constructed Dorogovtsev-Goltsev-Mendes graph.

$n$ is the generation. See: arXiv:cond-mat/0112143 by Dorogovtsev, Goltsev and Mendes.
6.2.8 empty_graph

empty_graph \( (n=0, \text{create}_\text{using}=\text{None}) \)
Return the empty graph with \( n \) nodes and zero edges.

Node labels are the integers 0 to \( n-1 \)

For example: >>> G=nx.empty_graph(10) >>> G.number_of_nodes() 10 >>> G.number_of_edges() 0
The variable create_using should point to a “graph”-like object that will be cleaned (nodes and edges will be removed) and refitted as an empty “graph” with \( n \) nodes with integer labels. This capability is useful for specifying the class-nature of the resulting empty “graph” (i.e. Graph, DiGraph, MyWeirdGraphClass, etc.).

The variable create_using has two main uses: Firstly, the variable create_using can be used to create an empty digraph, network, etc. For example,

```plaintext
>>> n=10
>>> G=nx.empty_graph(n,create_using=nx.DiGraph())
```
will create an empty digraph on \( n \) nodes.

Secondly, one can pass an existing graph (digraph, pseudograph, etc.) via create_using. For example, if \( G \) is an existing graph (resp. digraph, pseudograph, etc.), then empty_graph(n,create_using=G) will empty \( G \) (i.e. delete all nodes and edges using \( G\.clear() \) in base) and then add \( n \) nodes and zero edges, and return the modified graph (resp. digraph, pseudograph, etc.).

See also create_empty_copy(G).

6.2.9 grid_2d_graph

grid_2d_graph \( (m, n, \text{periodic}=\text{False}, \text{create}_\text{using}=\text{None}) \)
Return the 2d grid graph of \( mn \) nodes, each connected to its nearest neighbors. Optional argument periodic=True will connect boundary nodes via periodic boundary conditions.

6.2.10 grid_graph

grid_graph \( (\text{dim}, \text{periodic}=\text{False}) \)
Return the n-dimensional grid graph.

The dimension is the length of the list ‘dim’ and the size in each dimension is the value of the list element.

E.g. \( G=\text{grid}\_\text{graph}(\text{dim}=[2,3]) \) produces a 2x3 grid graph.

If periodic=True then join grid edges with periodic boundary conditions.

6.2.11 hypercube_graph

hypercube_graph \( (n) \)
Return the n-dimensional hypercube.

Node labels are the integers 0 to \( 2^{**n} - 1 \).
### 6.2.12 ladder_graph

`ladder_graph(n, create_using=None)`

Return the Ladder graph of length n.

This is two rows of n nodes, with each pair connected by a single edge.

Node labels are the integers 0 to 2*n - 1.

### 6.2.13 lollipop_graph

`lollipop_graph(m, n, create_using=None)`

Return the Lollipop Graph; K_m connected to P_n.

This is the Barbell Graph without the right barbell.

For m>1 and n>=0, the complete graph K_m is connected to the path P_n. The resulting m+n nodes are labelled 0,...,m-1 for the complete graph and m,...,m+n-1 for the path. The 2 subgraphs are joined via the edge (m-1,m).

If n=0, this is merely a complete graph.

Node labels are the integers 0 to number_of_nodes - 1.

(This graph is an extremal example in David Aldous and Jim Fill’s etext on Random Walks on Graphs.)

### 6.2.14 null_graph

`null_graph(create_using=None)`

Return the Null graph with no nodes or edges.

See empty_graph for the use of create_using.

### 6.2.15 path_graph

`path_graph(n, create_using=None)`

Return the Path graph P_n of n nodes linearly connected by n-1 edges.

Node labels are the integers 0 to n - 1. If create_using is a DiGraph then the edges are directed in increasing order.

### 6.2.16 star_graph

`star_graph(n, create_using=None)`

Return the Star graph with n+1 nodes: one center node, connected to n outer nodes.

Node labels are the integers 0 to n.

### 6.2.17 trivial_graph

`trivial_graph(create_using=None)`

Return the Trivial graph with one node (with integer label 0) and no edges.
6.2.18 wheel_graph

wheel_graph \((n, \text{create\_using}=\text{None})\)

Return the wheel graph: a single hub node connected to each node of the \((n-1)\)-node cycle graph.

Node labels are the integers 0 to \(n - 1\).

6.3 Small

Various small and named graphs, together with some compact generators.

- make_small_graph(graph_description[, ...])
  Return the small graph described by graph_description.
  graph_description is a list of the form \([\text{ltype}, \text{name}, n, xlist]\)
  Here ltype is one of “adjacencylist” or “edgelist”, name is the name of the graph and \(n\) the number of nodes.
  This constructs a graph of \(n\) nodes with integer labels 0,...,\(n-1\).

- LCF_graph(n, shift_list, repeats[, \text{create\_using}])
  Return the cubic graph specified in LCF notation.

- bull_graph([\text{create\_using}])
  Return the Bull graph.

- chvatal_graph([\text{create\_using}])
  Return the Chvátal graph.

- cubical_graph([\text{create\_using}])
  Return the 3-regular Platonic Cubical graph.

- desargues_graph([\text{create\_using}])
  Return the Desargues graph.

- diamond_graph([\text{create\_using}])
  Return the Diamond graph.

- dodecahedral_graph([\text{create\_using}])
  Return the Platonic Dodecahedral graph.

- frucht_graph([\text{create\_using}])
  Return the Frucht Graph.

- heawood_graph([\text{create\_using}])
  Return the Heawood graph, a \((3,6)\) cage.

- house_graph([\text{create\_using}])
  Return the House graph (square with triangle on top).

- house_x_graph([\text{create\_using}])
  Return the House graph with a cross inside the house square.

- icosahedral_graph([\text{create\_using}])
  Return the Platonic Icosahedral graph.

- krackhardt_kite_graph([\text{create\_using}])
  Return the Krackhardt Kite Social Network.

- moebius_kantor_graph([\text{create\_using}])
  Return the Moebius-Kantor graph.

- octahedral_graph([\text{create\_using}])
  Return the Platonic Octahedral graph.

- pappus_graph()
  Return the Pappus graph.

- petersen_graph([\text{create\_using}])
  Return the Petersen graph.

- sedgewick_maze_graph([\text{create\_using}])
  Return a small maze with a cycle.

- tetrahedral_graph([\text{create\_using}])
  Return the 3-regular Platonic Tetrahedral graph.

- truncated_cube_graph([\text{create\_using}])
  Return the skeleton of the truncated cube.

- truncated_tetrahedron_graph([\text{create\_using}])
  Return the skeleton of the truncated Platonic tetrahedron.

- tutte_graph([\text{create\_using}])
  Return the Tutte graph.

6.3.1 make_small_graph

make_small_graph(graph_description, create_using=\text{None})

Return the small graph described by graph_description.

graph_description is a list of the form \([\text{ltype}, \text{name}, n, xlist]\)

Here ltype is one of “adjacencylist” or “edgelist”, name is the name of the graph and \(n\) the number of nodes.
This constructs a graph of \(n\) nodes with integer labels 0,...,\(n-1\).

If ltype=“adjacencylist” then xlist is an adjacency list with exactly \(n\) entries, in with the \(j\)’th entry (which can be empty) specifies the nodes connected to vertex \(j\). e.g. the “square” graph \(C_4\) can be obtained by

```python
>>> G=nx.make_small_graph(["adjacencylist","C_4",4,[[2,4],[1,3],[2,4],[1,3]]])
```

or, since we do not need to add edges twice,
>>> G=nx.make_small_graph(("adjacencylist","C_4","4",[[2,4],[3],[4],[]]))

If ltype="edgelist" then xlist is an edge list written as [[v1,w2],[v2,w2],...,[vk,wk]], where vj and wj integers in the range 1...n e.g. the “square” graph C_4 can be obtained by

>>> G=nx.make_small_graph(("edgelist","C_4","4",[[1,2],[3,4],[2,3],[4,1]]))

Use the create_using argument to choose the graph class/type.

6.3.2 LCF_graph

LCF_graph (n, shift_list, repeats, create_using=None)
Return the cubic graph specified in LCF notation.

LCF notation (LCF=Lederberg-Coxeter-Fruchte) is a compressed notation used in the generation of various cubic Hamiltonian graphs of high symmetry. See, for example, dodecahedral_graph, desargues_graph, heawood_graph and pappus_graph below.

n (number of nodes)  The starting graph is the n-cycle with nodes 0,...,n-1. (The null graph is returned if n < 0.)
shift_list = [s1,s2,...,sk], a list of integer shifts mod n,
repeats  integer specifying the number of times that shifts in shift_list are successively applied to each v_current in the n-cycle to generate an edge between v_current and v_current+shift mod n.

For v1 cycling through the n-cycle a total of k*repeats with shift cycling through shiftlist repeats times connect v1 with v1+shift mod n.

The utility graph K_{3,3}

>>> G=nx.LCF_graph(6,[3,-3],3)

The Heawood graph

>>> G=nx.LCF_graph(14,[5,-5],7)

See http://mathworld.wolfram.com/LCFNotation.html for a description and references.

6.3.3 bull_graph

bull_graph (create_using=None)
Return the Bull graph.

6.3.4 chvatal_graph

chvatal_graph (create_using=None)
Return the Chvátal graph.

6.3.5 cubical_graph

cubical_graph (create_using=None)
Return the 3-regular Platonic Cubical graph.
6.3.6 desargues_graph

desargues_graph(create_using=None)
    Return the Desargues graph.

6.3.7 diamond_graph

diamond_graph(create_using=None)
    Return the Diamond graph.

6.3.8 dodecahedral_graph

dodecahedral_graph(create_using=None)
    Return the Platonic Dodecahedral graph.

6.3.9 frucht_graph

frucht_graph(create_using=None)
    Return the Frucht Graph.
    The Frucht Graph is the smallest cubical graph whose automorphism group consists only of the identity element.

6.3.10 heawood_graph

heawood_graph(create_using=None)
    Return the Heawood graph, a (3,6) cage.

6.3.11 house_graph

house_graph(create_using=None)
    Return the House graph (square with triangle on top).

6.3.12 house_x_graph

house_x_graph(create_using=None)
    Return the House graph with a cross inside the house square.

6.3.13 icosahedral_graph

icosahedral_graph(create_using=None)
    Return the Platonic Icosahedral graph.
6.3.14 krackhardt_kite_graph

krackhardt_kite_graph (create_using=None)
Return the Krackhardt Kite Social Network.

A 10 actor social network introduced by David Krackhardt to illustrate: degree, betweenness, centrality, closeness, etc. The traditional labeling is: Andre=1, Beverley=2, Carol=3, Diane=4, Ed=5, Fernando=6, Garth=7, Heather=8, Ike=9, Jane=10.

6.3.15 moebius_kantor_graph

moebius_kantor_graph (create_using=None)
Return the Moebius-Kantor graph.

6.3.16 octahedral_graph

octahedral_graph (create_using=None)
Return the Platonic Octahedral graph.

6.3.17 pappus_graph

pappus_graph ()
Return the Pappus graph.

6.3.18 petersen_graph

petersen_graph (create_using=None)
Return the Petersen graph.

6.3.19 sedgewick_maze_graph

sedgewick_maze_graph (create_using=None)
Return a small maze with a cycle.

This is the maze used in Sedgewick, 3rd Edition, Part 5, Graph Algorithms, Chapter 18, e.g. Figure 18.2 and following. Nodes are numbered 0,...,7

6.3.20 tetrahedral_graph

tetrahedral_graph (create_using=None)
Return the 3-regular Platonic Tetrahedral graph.

6.3.21 truncated_cube_graph

truncated_cube_graph (create_using=None)
Return the skeleton of the truncated cube.
6.3.22 truncated_tetrahedron_graph

truncated_tetrahedron_graph (create_using=None)

Return the skeleton of the truncated Platonic tetrahedron.

6.3.23 tutte_graph

tutte_graph (create_using=None)

Return the Tutte graph.

6.4 Random Graphs

Generators for random graphs.

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<th>Function</th>
<th>Description</th>
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<td>fast_gnp_random_graph(n, p[, seed, directed])</td>
<td>Return a random graph $G_{n,p}$ (Erdős-Rényi graph, binomial graph).</td>
</tr>
<tr>
<td>gnp_random_graph(n, p[, seed, directed])</td>
<td>Return a random graph $G_{n,p}$ (Erdős-Rényi graph, binomial graph).</td>
</tr>
<tr>
<td>dense_gnm_random_graph(n, m[, seed])</td>
<td>Return the random graph $G_{n,m}$.</td>
</tr>
<tr>
<td>gnm_random_graph(n, m[, seed, directed])</td>
<td>Return the random graph $G_{n,m}$.</td>
</tr>
<tr>
<td>erdos_renyi_graph(n, p[, seed, directed])</td>
<td>Return a random graph $G_{n,p}$ (Erdős-Rényi graph, binomial graph).</td>
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<tr>
<td>binomial_graph(n, p[, seed, directed])</td>
<td>Return a random graph $G_{n,p}$ (Erdős-Rényi graph, binomial graph).</td>
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<tr>
<td>newman_watts_strogatz_graph(n, k, p[, seed])</td>
<td>Return a Newman-Watts-Strogatz small world graph.</td>
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<td>Return a Watts-Strogatz small-world graph.</td>
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<td>random_regular_graph(d, n[, seed])</td>
<td>Return a random regular graph of $n$ nodes each with degree $d$.</td>
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<td>powerlaw_cluster_graph(n, m, p[, seed])</td>
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<td>random_lobster(n, p1, p2[, seed])</td>
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<tr>
<td>random_powerlaw_tree(n[, gamma, seed, tries])</td>
<td>Return a tree with a powerlaw degree distribution.</td>
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<td>random_powerlaw_tree_sequence(n[, gamma, ...])</td>
<td>Return a degree sequence for a tree with a powerlaw distribution.</td>
</tr>
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</table>

6.4.1 fast_gnp_random_graph

fast_gnp_random_graph (n, p, seed=None, directed=False)

Return a random graph $G_{n,p}$ (Erdős-Rényi graph, binomial graph).

Parameters

- **n**: int
  
The number of nodes.

- **p**: float
  
  Probability for edge creation.

- **seed**: int, optional
  
  Seed for random number generator (default=None).

- **directed**: bool, optional (default=False)
  
  If True return a directed graph

See also:

- gnp_random_graph
Notes

The $G_{n,p}$ graph algorithm chooses each of the $\frac{n(n-1)}{2}$ (undirected) or $n(n-1)$ (directed) possible edges with probability $p$.
This algorithm is $O(n+m)$ where $m$ is the expected number of edges $m=p*n*(n-1)/2$.
It should be faster than gnp_random_graph when $p$ is small and the expected number of edges is small (sparse graph).

References

[R280]

6.4.2 gnp_random_graph

gnp_random_graph $(n, p, seed=None, directed=False)$
Return a random graph $G_{n,p}$ (Erdős-Rényi graph, binomial graph).
Chooses each of the possible edges with probability $p$.
This is also called binomial_graph and erdos_renyi_graph.

Parameters

$n$ : int
The number of nodes.
$p$ : float
Probability for edge creation.
$seed$ : int, optional
Seed for random number generator (default=None).
$directed$ : bool, optional (default=False)
If True return a directed graph

See also:

fast_gnp_random_graph

Notes

This is an $O(n^2)$ algorithm. For sparse graphs (small $p$) see fast_gnp_random_graph for a faster algorithm.

References

[R281], [R282]

6.4. Random Graphs
6.4.3 dense_gnm_random_graph

dense_gnm_random_graph(n, m, seed=None)
    Return the random graph \( G_{n,m} \).

    Gives a graph picked randomly out of the set of all graphs with \( n \) nodes and \( m \) edges. This algorithm should be faster than gnm_random_graph for dense graphs.

    Parameters
        \( n \) : int
            The number of nodes.
        \( m \) : int
            The number of edges.
        seed : int, optional
            Seed for random number generator (default=None).

    See also:

gnm_random_graph

Notes

Algorithm by Keith M. Briggs Mar 31, 2006. Inspired by Knuth’s Algorithm S (Selection sampling technique), in section 3.4.2 of [R277].

References

[R277]

6.4.4 gnm_random_graph

gnm_random_graph(n, m, seed=None, directed=False)
    Return the random graph \( G_{n,m} \).

    Produces a graph picked randomly out of the set of all graphs with \( n \) nodes and \( m \) edges.

    Parameters
        \( n \) : int
            The number of nodes.
        \( m \) : int
            The number of edges.
        seed : int, optional
            Seed for random number generator (default=None).
        directed : bool, optional (default=False)
            If True return a directed graph
6.4.5 erdos_renyi_graph

erdos_renyi_graph\((n, p, \text{seed}=None, \text{directed}=False)\)

Return a random graph \(G_{n,p}\) (Erdős-Rényi graph, binomial graph).

Chooses each of the possible edges with probability \(p\).

This is also called binomial_graph and erdos_renyi_graph.

Parameters

\(n\) : int

The number of nodes.

\(p\) : float

Probability for edge creation.

\(\text{seed}\) : int, optional

Seed for random number generator (default=None).

\(\text{directed}\) : bool, optional (default=False)

If True return a directed graph

See also:

fast_gnp_random_graph

Notes

This is an \(O(n^2)\) algorithm. For sparse graphs (small \(p\)) see fast_gnp_random_graph for a faster algorithm.

References

[R278], [R279]

6.4.6 binomial_graph

binomial_graph\((n, p, \text{seed}=None, \text{directed}=False)\)

Return a random graph \(G_{n,p}\) (Erdős-Rényi graph, binomial graph).

Chooses each of the possible edges with probability \(p\).

This is also called binomial_graph and erdos_renyi_graph.

Parameters

\(n\) : int

The number of nodes.

\(p\) : float

Probability for edge creation.

\(\text{seed}\) : int, optional

Seed for random number generator (default=None).

\(\text{directed}\) : bool, optional (default=False)

If True return a directed graph
6.4.7 newman_watts_strogatz_graph

`newman_watts_strogatz_graph(n, k, p, seed=None)`
Return a Newman-Watts-Strogatz small world graph.

**Parameters**
- `n`: int
  The number of nodes
- `k`: int
  Each node is connected to k nearest neighbors in ring topology
- `p`: float
  The probability of adding a new edge for each edge
- `seed`: int, optional
  seed for random number generator (default=None)

**See also:**
`watts_strogatz_graph`

**Notes**
First create a ring over n nodes. Then each node in the ring is connected with its k nearest neighbors (k-1 neighbors if k is odd). Then shortcuts are created by adding new edges as follows: for each edge u-v in the underlying “n-ring with k nearest neighbors” with probability p add a new edge u-w with randomly-chosen existing node w. In contrast with `watts_strogatz_graph()`, no edges are removed.

**References**
[R283]
The number of nodes

\( \kappa \): int

Each node is connected to \( \kappa \) nearest neighbors in ring topology

\( p \): float

The probability of rewiring each edge

\( \text{seed} \): int, optional

Seed for random number generator (default=None)

See also:

newman_watts_strogatz_graph, connected_watts_strogatz_graph

Notes

First create a ring over \( n \) nodes. Then each node in the ring is connected with its \( \kappa \) nearest neighbors (\( \kappa-1 \) neighbors if \( \kappa \) is odd). Then shortcuts are created by replacing some edges as follows: for each edge \( u-v \) in the underlying “\( n \)-ring with \( \kappa \) nearest neighbors” with probability \( p \) replace it with a new edge \( u-w \) with uniformly random choice of existing node \( w \).

In contrast with newman_watts_strogatz_graph(), the random rewiring does not increase the number of edges. The rewired graph is not guaranteed to be connected as in connected_watts_strogatz_graph().

References

[R287]

6.4.9 connected_watts_strogatz_graph

`connected_watts_strogatz_graph(n, k, p, tries=100, seed=None)`

Return a connected Watts-Strogatz small-world graph.

Attempt to generate a connected realization by repeated generation of Watts-Strogatz small-world graphs. An exception is raised if the maximum number of tries is exceeded.

Parameters

\( n \): int

The number of nodes

\( \kappa \): int

Each node is connected to \( \kappa \) nearest neighbors in ring topology

\( p \): float

The probability of rewiring each edge

\( \text{tries} \): int

Number of attempts to generate a connected graph.

\( \text{seed} \): int, optional

The seed for random number generator.
See also:
newman_watts_strogatz_graph, watts_strogatz_graph

6.4.10 random_regular_graph

random_regular_graph(d, n, seed=None)
Return a random regular graph of n nodes each with degree d.
The resulting graph G has no self-loops or parallel edges.

Parameters  
  d : int
    Degree
  n : integer
    Number of nodes. The value of n*d must be even.
  seed : hashable object
    The seed for random number generator.

Notes
The nodes are numbered form 0 to n-1.
Kim and Vu’s paper [R286] shows that this algorithm samples in an asymptotically uniform way from the space of random graphs when d = O(n**(1/3-epsilon)).

References
[R285], [R286]

6.4.11 barabasi_albert_graph

barabasi_albert_graph(n, m, seed=None)
Return random graph using Barabási-Albert preferential attachment model.
A graph of n nodes is grown by attaching new nodes each with m edges that are preferentially attached to existing nodes with high degree.

Parameters  
  n : int
    Number of nodes
  m : int
    Number of edges to attach from a new node to existing nodes
  seed : int, optional
    Seed for random number generator (default=None).

Returns  
  G : Graph
Notes
The initialization is a graph with with m nodes and no edges.

References
[R274]

6.4.12 powerlaw_cluster_graph

`powerlaw_cluster_graph(n, m, p, seed=None)`
Holme and Kim algorithm for growing graphs with powerlaw degree distribution and approximate average clustering.

Parameters
- `n`: int
  the number of nodes
- `m`: int
  the number of random edges to add for each new node
- `p`: float,
  Probability of adding a triangle after adding a random edge
- `seed`: int, optional
  Seed for random number generator (default=None).

Notes
The average clustering has a hard time getting above a certain cutoff that depends on m. This cutoff is often quite low. Note that the transitivity (fraction of triangles to possible triangles) seems to go down with network size.

It is essentially the Barabási-Albert (B-A) growth model with an extra step that each random edge is followed by a chance of making an edge to one of its neighbors too (and thus a triangle).

This algorithm improves on B-A in the sense that it enables a higher average clustering to be attained if desired.

It seems possible to have a disconnected graph with this algorithm since the initial m nodes may not be all linked to a new node on the first iteration like the B-A model.

References
[R284]

6.4.13 random_lobster

`random_lobster(n, p1, p2, seed=None)`
Return a random lobster.

A lobster is a tree that reduces to a caterpillar when pruning all leaf nodes.

A caterpillar is a tree that reduces to a path graph when pruning all leaf nodes (p2=0).
Parameters  
n : int
The expected number of nodes in the backbone

p1 : float
Probability of adding an edge to the backbone

p2 : float
Probability of adding an edge one level beyond backbone

seed : int, optional
Seed for random number generator (default=None).

6.4.14 random_shell_graph
random_shell_graph(constructor, seed=None)
Return a random shell graph for the constructor given.

Parameters  constructor: a list of three-tuples :
(n,m,d) for each shell starting at the center shell.

n : int
The number of nodes in the shell

m : int
The number or edges in the shell

d : float
The ratio of inter-shell (next) edges to intra-shell edges. d=0 means no intra shell edges,
d=1 for the last shell

seed : int, optional
Seed for random number generator (default=None).

Examples
>>> constructor=[(10,20,0.8),(20,40,0.8)]
>>> G=nx.random_shell_graph(constructor)

6.4.15 random_powerlaw_tree
random_powerlaw_tree(n, gamma=3, seed=None, tries=100)
Return a tree with a powerlaw degree distribution.

Parameters  n : int,
The number of nodes

gamma : float
Exponent of the power-law

seed : int, optional
Seed for random number generator (default=None).

tries : int

Number of attempts to adjust sequence to make a tree

Notes

A trial powerlaw degree sequence is chosen and then elements are swapped with new elements from a powerlaw distribution until the sequence makes a tree (#edges=#nodes-1).

### 6.4.16 random_powerlaw_tree_sequence

**random_powerlaw_tree_sequence**(n, gamma=3, seed=None, tries=100)

Return a degree sequence for a tree with a powerlaw distribution.

**Parameters**

- **n**: int,
  The number of nodes
- **gamma**: float
  Exponent of the power-law
- **seed**: int, optional
  Seed for random number generator (default=None).
- **tries**: int
  Number of attempts to adjust sequence to make a tree

**Notes**

A trial powerlaw degree sequence is chosen and then elements are swapped with new elements from a powerlaw distribution until the sequence makes a tree (#edges=#nodes-1).

### 6.5 Degree Sequence

Generate graphs with a given degree sequence or expected degree sequence.

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<td>directed_configuration_model(deg_sequence[, ...])</td>
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### 6.5.1 configuration_model

**configuration_model**(deg_sequence, create_using=None, seed=None)

Return a random graph with the given degree sequence.
The configuration model generates a random pseudograph (graph with parallel edges and self loops) by randomly assigning edges to match the given degree sequence.

**Parameters**  
**deg_sequence**: list of integers  
Each list entry corresponds to the degree of a node.

**create_using**: graph, optional (default MultiGraph)  
Return graph of this type. The instance will be cleared.

**seed**: hashable object, optional  
Seed for random number generator.

**Returns**  
**G**: MultiGraph  
A graph with the specified degree sequence. Nodes are labeled starting at 0 with an index corresponding to the position in deg_sequence.

**Raises**  
**NetworkXError**:  
If the degree sequence does not have an even sum.

**See also:**  
`is_valid_degree_sequence`

**Notes**

As described by Newman [R251].

A non-graphical degree sequence (not realizable by some simple graph) is allowed since this function returns graphs with self loops and parallel edges. An exception is raised if the degree sequence does not have an even sum.

This configuration model construction process can lead to duplicate edges and loops. You can remove the self-loops and parallel edges (see below) which will likely result in a graph that doesn’t have the exact degree sequence specified. This “finite-size effect” decreases as the size of the graph increases.

**References**

[R251]

**Examples**

```python
>>> from networkx.utils import powerlaw_sequence
>>> z=nx.utils.create_degree_sequence(100,powerlaw_sequence)
>>> G=nx.configuration_model(z)
```

To remove parallel edges:

```python
>>> G=nx.Graph(G)
```

To remove self loops:

```python
>>> G.remove_edges_from(G.selfloop_edges())
```
6.5.2 directed_configuration_model

`directed_configuration_model` *(in_degree_sequence, out_degree_sequence, create_using=None, seed=None)*

Return a directed random graph with the given degree sequences.

The configuration model generates a random directed pseudograph (graph with parallel edges and self loops) by randomly assigning edges to match the given degree sequences.

**Parameters**

- **in_degree_sequence**: list of integers
  - Each list entry corresponds to the in-degree of a node.

- **out_degree_sequence**: list of integers
  - Each list entry corresponds to the out-degree of a node.

- **create_using**: graph, optional (default MultiDiGraph)
  - Return graph of this type. The instance will be cleared.

- **seed**: hashable object, optional
  - Seed for random number generator.

**Returns**

- **G**: MultiDiGraph
  - A graph with the specified degree sequences. Nodes are labeled starting at 0 with an index corresponding to the position in deg_sequence.

**Raises**

- **NetworkXError**: If the degree sequences do not have the same sum.

**See also:**

configuration_model

**Notes**

Algorithm as described by Newman [R252].

A non-graphical degree sequence (not realizable by some simple graph) is allowed since this function returns graphs with self loops and parallel edges. An exception is raised if the degree sequences does not have the same sum.

This configuration model construction process can lead to duplicate edges and loops. You can remove the self-loops and parallel edges (see below) which will likely result in a graph that doesn’t have the exact degree sequence specified. This “finite-size effect” decreases as the size of the graph increases.

**References**

[R252]

**Examples**

```python
>>> D=nx.DiGraph([(0,1),(1,2),(2,3)]) # directed path graph
>>> din=list(D.in_degree().values())
>>> dout=list(D.out_degree().values())
>>> din.append(1)
```
>>> dout[0]=2
>>> D=nx.directed_configuration_model(din,dout)

To remove parallel edges:
>>> D=nx.DiGraph(D)

To remove self loops:
>>> D.remove_edges_from(D.selfloop_edges())

### 6.5.3 expected_degree_graph

**expected_degree_graph** *(w, seed=None, selfloops=True)*

Return a random graph with given expected degrees.

Given a sequence of expected degrees \( W = (w_0, w_1, \ldots, w_{n-1}) \) of length \( n \) this algorithm assigns an edge between node \( u \) and node \( v \) with probability

\[
p_{uv} = \frac{w_u w_v}{\sum_k w_k}.
\]

**Parameters**

- **w** : list
  - The list of expected degrees.

- **selfloops** : bool (default=True)
  - Set to False to remove the possibility of self-loop edges.

- **seed** : hashable object, optional
  - The seed for the random number generator.

**Returns** **Graph** :

**Notes**

The nodes have integer labels corresponding to index of expected degrees input sequence.

The complexity of this algorithm is \( \mathcal{O}(n + m) \) where \( n \) is the number of nodes and \( m \) is the expected number of edges.

The model in [R254] includes the possibility of self-loop edges. Set selfloops=False to produce a graph without self loops.

For finite graphs this model doesn’t produce exactly the given expected degree sequence. Instead the expected degrees are as follows.

For the case without self loops (selfloops=False),

\[
E[\text{deg}(u)] = \sum_{v \neq u} p_{uv} = w_u \left( 1 - \frac{w_u}{\sum_k w_k} \right).
\]

NetworkX uses the standard convention that a self-loop edge counts 2 in the degree of a node, so with self loops (selfloops=True),

\[
E[\text{deg}(u)] = \sum_{v \neq u} p_{uv} + 2p_{uu} = w_u \left( 1 + \frac{w_u}{\sum_k w_k} \right).
\]
References

[R254], [R255]

Examples

```python
>>> z=[10 for i in range(100)]
>>> G=nx.expected_degree_graph(z)
```

6.5.4 havel_hakimi_graph

**havel_hakimi_graph**(deg_sequence, create_using=None)

Return a simple graph with given degree sequence constructed using the Havel-Hakimi algorithm.

**Parameters**
- deg_sequence: list of integers
  - Each integer corresponds to the degree of a node (need not be sorted).
- create_using : graph, optional (default Graph)
  - Return graph of this type. The instance will be cleared. Directed graphs are not allowed.

**Raises**
- NetworkXException
  - For a non-graphical degree sequence (i.e. one not realizable by some simple graph).

**Notes**

The Havel-Hakimi algorithm constructs a simple graph by successively connecting the node of highest degree to other nodes of highest degree, resorting remaining nodes by degree, and repeating the process. The resulting graph has a high degree-associativity. Nodes are labeled 1,.., len(deg_sequence), corresponding to their position in deg_sequence.

The basic algorithm is from Hakimi [R256] and was generalized by Kleitman and Wang [R257].

**References**

[R256], [R257]

6.5.5 directed_havel_hakimi_graph

directed_havel_hakimi_graph**(in_deg_sequence, out_deg_sequence, create_using=None)

Return a directed graph with the given degree sequences.

**Parameters**
- in_deg_sequence : list of integers
  - Each list entry corresponds to the in-degree of a node.
- out_deg_sequence : list of integers
  - Each list entry corresponds to the out-degree of a node.
- create_using : graph, optional (default DiGraph)
  - Return graph of this type. The instance will be cleared.
Returns  G : DiGraph
   A graph with the specified degree sequences. Nodes are labeled starting at 0 with an
   index corresponding to the position in deg_sequence
Raises  NetworkXError :
   If the degree sequences are not digraphical.

See also:
configuration_model

Notes
Algorithm as described by Kleitman and Wang [R253].

References

[R253]

6.5.6 degree_sequence_tree

degree_sequence_tree (deg_sequence, create_using=None)
   Make a tree for the given degree sequence.
   A tree has #nodes-#edges=1 so the degree sequence must have len(deg_sequence)-sum(deg_sequence)/2=1

6.5.7 random_degree_sequence_graph

random_degree_sequence_graph (sequence, seed=None, tries=10)
   Return a simple random graph with the given degree sequence.
   If the maximum degree $d_m$ in the sequence is $O(m^{1/4})$ then the algorithm produces almost uniform random
   graphs in $O(md_m)$ time where $m$ is the number of edges.

   Parameters  sequence : list of integers
                 Sequence of degrees
   seed : hashable object, optional
          Seed for random number generator
   tries : int, optional
          Maximum number of tries to create a graph

Returns  G : Graph
   A graph with the specified degree sequence. Nodes are labeled starting at 0 with an
   index corresponding to the position in the sequence.
Raises  NetworkXUnfeasible :
   If the degree sequence is not graphical.

NetworkXError :
   If a graph is not produced in specified number of tries
See also:

is_valid_degree_sequence, configuration_model

Notes

The generator algorithm [R258] is not guaranteed to produce a graph.

References

[R258]

Examples

```python
>>> sequence = [1, 2, 2, 3]
>>> G = nx.random_degree_sequence_graph(sequence)
>>> sorted(G.degree().values())
[1, 2, 2, 3]
```

6.6 Random Clustered

Generate graphs with given degree and triangle sequence.

random_clustered_graph(joint_degree_sequence)  Generate a random graph with the given joint degree and triangle degree sequence.

6.6.1 random_clustered_graph

random_clustered_graph(joint_degree_sequence, create_using=None, seed=None)  Generate a random graph with the given joint degree and triangle degree sequence.

This uses a configuration model-like approach to generate a random pseudograph (graph with parallel edges and self loops) by randomly assigning edges to match the given independent edge and triangle degree sequence.

Parameters

joint_degree_sequence : list of integer pairs

Each list entry corresponds to the independent edge degree and triangle degree of a node.

create_using : graph, optional (default MultiGraph)

Return graph of this type. The instance will be cleared.

seed : hashable object, optional

The seed for the random number generator.

Returns

G : MultiGraph

A graph with the specified degree sequence. Nodes are labeled starting at 0 with an index corresponding to the position in deg_sequence.

Raises

NetworkXError :
If the independent edge degree sequence sum is not even or the triangle degree sequence sum is not divisible by 3.

Notes

As described by Miller [R272] (see also Newman [R273] for an equivalent description).

A non-graphical degree sequence (not realizable by some simple graph) is allowed since this function returns graphs with self loops and parallel edges. An exception is raised if the independent degree sequence does not have an even sum or the triangle degree sequence sum is not divisible by 3.

This configuration model-like construction process can lead to duplicate edges and loops. You can remove the self-loops and parallel edges (see below) which will likely result in a graph that doesn’t have the exact degree sequence specified. This “finite-size effect” decreases as the size of the graph increases.

References

[R272], [R273]

Examples

```python
>>> deg_tri=[[1,0],[1,0],[1,0],[2,0],[1,0],[2,1],[0,1],[0,1]]
>>> G = nx.random_clustered_graph(deg_tri)

To remove parallel edges:

```python
g=nx.Graph(G)
```

To remove self loops:

```python
G.remove_edges_from(G.selfloop_edges())
```

6.7 Directed

Generators for some directed graphs.

**gn_graph**: growing network **gnc_graph**: growing network with copying **gnr_graph**: growing network with redirection **scale_free_graph**: scale free graph

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<th>Description</th>
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<td><code>gn_graph</code></td>
<td>Return the GN digraph with n nodes.</td>
</tr>
<tr>
<td><code>gnr_graph</code></td>
<td>Return the GNR digraph with n nodes and redirection probability p.</td>
</tr>
<tr>
<td><code>gnc_graph</code></td>
<td>Return the GNC digraph with n nodes.</td>
</tr>
<tr>
<td><code>scale_free_graph</code></td>
<td>Return a scale free directed graph.</td>
</tr>
</tbody>
</table>

6.7.1 gn_graph

```python
gn_graph(n[, kernel=None, create_using=None, seed=None])
```

Return the GN digraph with n nodes.

The GN (growing network) graph is built by adding nodes one at a time with a link to one previously added node. The target node for the link is chosen with probability based on degree. The default attachment kernel is
a linear function of degree.
The graph is always a (directed) tree.

Parameters

- **n**: int
  The number of nodes for the generated graph.

- **kernel**: function
  The attachment kernel.

- **create_using**: graph, optional (default DiGraph)
  Return graph of this type. The instance will be cleared.

- **seed**: hashable object, optional
  The seed for the random number generator.

References

[R259]

Examples

```python
>>> D = nx.gn_graph(10)  # the GN graph
>>> G = D.to_undirected()  # the undirected version
```

To specify an attachment kernel use the kernel keyword

```python
>>> D = nx.gn_graph(10, kernel=lambda x: x**1.5)  # A_k=k^1.5
```

6.7.2 gnr_graph

gnr_graph (n, p, create_using=None, seed=None)

Return the GNR digraph with n nodes and redirection probability p.

The GNR (growing network with redirection) graph is built by adding nodes one at a time with a link to one previously added node. The previous target node is chosen uniformly at random. With probability p the link is instead “redirected” to the successor node of the target. The graph is always a (directed) tree.

Parameters

- **n**: int
  The number of nodes for the generated graph.

- **p**: float
  The redirection probability.

- **create_using**: graph, optional (default DiGraph)
  Return graph of this type. The instance will be cleared.

- **seed**: hashable object, optional
  The seed for the random number generator.
References

[R261]

Examples

```python
>>> D=nx.gnr_graph(10,0.5)  # the GNR graph
>>> G=D.to_undirected()  # the undirected version
```

6.7.3 gnc_graph

The GNC (growing network with copying) graph is built by adding nodes one at a time with a links to one previously added node (chosen uniformly at random) and to all of that node’s successors.

**Parameters**

- `n` : int
  The number of nodes for the generated graph.

- `create_using` : graph, optional (default DiGraph)
  Return graph of this type. The instance will be cleared.

- `seed` : hashable object, optional
  The seed for the random number generator.

**References**

[R260]

6.7.4 scale_free_graph

The scale-free graph is a model for generating networks where a small number of nodes have a large number of connections, while the majority of the nodes have only a few connections.

**Parameters**

- `n` : integer
  Number of nodes in graph

- `alpha` : float
  Probability for adding a new node connected to an existing node chosen randomly according to the in-degree distribution.

- `beta` : float
  Probability for adding an edge between two existing nodes. One existing node is chosen randomly according to the in-degree distribution and the other chosen randomly according to the out-degree distribution.

- `gamma` : float

Probability for adding a new node connected to an existing node chosen randomly according to the out-degree distribution.

\[ \text{delta_in : float} \]
Bias for choosing nodes from in-degree distribution.

\[ \text{delta_out : float} \]
Bias for choosing nodes from out-degree distribution.

\[ \text{create_using : graph, optional (default MultiDiGraph)} \]
Use this graph instance to start the process (default=3-cycle).

\[ \text{seed : integer, optional} \]
Seed for random number generator

Notes

The sum of alpha, beta, and gamma must be 1.

References

[R262]

Examples

\[
>>> G=nx.scale_free_graph(100)
\]

6.8 Geometric

Generators for geometric graphs.

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<td>Return the random geometric graph in the unit cube.</td>
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<tr>
<td>geographical_threshold_graph</td>
<td>Return a geographical threshold graph.</td>
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<tr>
<td>waxman_graph</td>
<td>Return a Waxman random graph.</td>
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<tr>
<td>navigable_small_world_graph</td>
<td>Return a navigable small-world graph.</td>
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6.8.1 random_geometric_graph

random_geometric_graph \((n, radius[, dim, pos])\)  
Return the random geometric graph in the unit cube.

The random geometric graph model places \(n\) nodes uniformly at random in the unit cube. Two nodes \(u, v\) are connected with an edge if \(d(u, v) \leq r\) where \(d\) is the Euclidean distance and \(r\) is a radius threshold.

Parameters

\[ \text{n : int} \]
Number of nodes

\[ \text{radius : float} \]
Distance threshold value

**dim**: int, optional
Dimension of graph

**pos**: dict, optional
A dictionary keyed by node with node positions as values.

Returns **Graph**:

**Notes**

This uses an \( n^2 \) algorithm to build the graph. A faster algorithm is possible using k-d trees.

The pos keyword can be used to specify node positions so you can create an arbitrary distribution and domain for positions. If you need a distance function other than Euclidean you'll have to hack the algorithm.

E.g to use a 2d Gaussian distribution of node positions with mean (0,0) and std. dev. 2

```python
>>> import random

>>> n=20

>>> p=dict((i,(random.gauss(0,2),random.gauss(0,2))) for i in range(n))

>>> G = nx.random_geometric_graph(n,0.2,pos=p)
```

**References**

[R266]

**Examples**

```python
>>> G = nx.random_geometric_graph(20,0.1)
```

### 6.8.2 geographical_threshold_graph

geographical_threshold_graph \((n, \theta, \alpha=2, \text{dim}=2, \text{pos}=\text{None}, \text{weight}=\text{None})\)

Return a geographical threshold graph.

The geographical threshold graph model places \( n \) nodes uniformly at random in a rectangular domain. Each node \( u \) is assigned a weight \( w_u \). Two nodes \( u, v \) are connected with an edge if

\[
w_u + w_v \geq \theta r^\alpha
\]

where \( r \) is the Euclidean distance between \( u \) and \( v \), and \( \theta, \alpha \) are parameters.

**Parameters**

**n**: int
Number of nodes

**theta**: float
Threshold value

**alpha**: float, optional
Exponent of distance function
**dim**: int, optional
Dimension of graph

**pos**: dict
Node positions as a dictionary of tuples keyed by node.

**weight**: dict
Node weights as a dictionary of numbers keyed by node.

Returns: Graph

Notes
If weights are not specified they are assigned to nodes by drawing randomly from an exponential distribution with rate parameter $\lambda = 1$. To specify a weights from a different distribution assign them to a dictionary and pass it as the weight= keyword

```python
>>> import random
>>> n = 20
>>> w=dict((i,random.expovariate(5.0)) for i in range(n))
>>> G = nx.geographical_threshold_graph(20,50,weight=w)
```

If node positions are not specified they are randomly assigned from the uniform distribution.

References

[R263], [R264]

Examples

```python
>>> G = nx.geographical_threshold_graph(20,50)
```

### 6.8.3 waxman_graph

**waxman_graph** ($n$, $alpha=0.4$, $beta=0.1$, $L=None$, $domain=(0, 0, 1, 1)$)
Return a Waxman random graph.

The Waxman random graph models place $n$ nodes uniformly at random in a rectangular domain. Two nodes $u,v$ are connected with an edge with probability

$$p = \alpha \cdot exp(-d/(\beta \cdot L)).$$

This function implements both Waxman models.

**Waxman-1**: $L$ not specified
The distance $d$ is the Euclidean distance between the nodes $u$ and $v$. $L$ is the maximum distance between all nodes in the graph.

**Waxman-2**: $L$ specified
The distance $d$ is chosen randomly in $[0, L]$.

Parameters

**n**: int
Number of nodes
alpha: float:
    Model parameter
beta: float:
    Model parameter
L : float, optional
    Maximum distance between nodes. If not specified the actual distance is calculated.
domain : tuple of numbers, optional
    Domain size (xmin, ymin, xmax, ymax)

Returns G: Graph:

References

[R267]

6.8.4 navigable_small_world_graph

navigable_small_world_graph (n, p=1, q=1, r=2, dim=2, seed=None)
    Return a navigable small-world graph.
    A navigable small-world graph is a directed grid with additional long-range connections that are chosen randomly. From [R265]:
    Begin with a set of nodes that are identified with the set of lattice points in an \(n \times n\) square, \((i, j) : i \in 1, 2, \ldots, n, j \in 1, 2, \ldots, n\) and define the lattice distance between two nodes \((i, j)\) and \((k, l)\) to be the number of “lattice steps” separating them: \(d((i, j), (k, l)) = |k - i| + |l - j|\).
    For a universal constant \(p\), the node \(u\) has a directed edge to every other node within lattice distance \(p\) (local contacts).
    For universal constants \(q \geq 0\) and \(r \geq 0\) construct directed edges from \(u\) to \(q\) other nodes (long-range contacts) using independent random trials; the \(i\)’th directed edge from \(u\) has endpoint \(v\) with probability proportional to \(d((u, v))^{-r}\).

Parameters n : int
    The number of nodes.
p : int
    The diameter of short range connections. Each node is connected to every other node within lattice distance \(p\).
q : int
    The number of long-range connections for each node.
r : float
    Exponent for decaying probability of connections. The probability of connecting to a node at lattice distance \(d\) is \(1/d^r\).
dim : int
    Dimension of grid
seed : int, optional
Seed for random number generator (default=None).

References

[R265]

6.9 Hybrid

Hybrid

kl_connected_subgraph(G, k, l[, low_memory, ...]) Returns the maximum locally (k,l) connected subgraph of G.
is_kl_connected(G, k, l[, low_memory]) Returns True if G is kl connected.

6.9.1 kl_connected_subgraph

kl_connected_subgraph (G, k, l, low_memory=False, same_as_graph=False) Returns the maximum locally (k,l) connected subgraph of G.

(k,l)-connected subgraphs are presented by Fan Chung and Li in “The Small World Phenomenon in hybrid power law graphs” to appear in “Complex Networks” (Ed. E. Ben-Naim) Lecture Notes in Physics, Springer (2004)

low_memory=True then use a slightly slower, but lower memory version same_as_graph=True then return a tuple with subgraph and pflag for if G is kl-connected

6.9.2 is_kl_connected

is_kl_connected (G, k, l, low_memory=False) Returns True if G is kl connected.

6.10 Bipartite

Generators and functions for bipartite graphs.

bipartite_configuration_model(aseq, bseq[, ...]) Return a random bipartite graph from two given degree sequences
bipartite_havel_hakimi_graph(aseq, bseq[, ...]) Return a bipartite graph from two given degree sequences using a
bipartite_reverse_havel_hakimi_graph(aseq, bseq) Return a bipartite graph from two given degree sequences using
bipartite_alternating_havel_hakimi_graph(...) Return a bipartite graph from two given degree sequences using
bipartite_preferential_attachment_graph(aseq, p) Create a bipartite graph with a preferential attachment model from
bipartite_random_graph(n, m, p[, seed, directed]) Return a bipartite random graph.
bipartite_gnmk_random_graph(n, m, k[, seed, ...]) Return a random bipartite graph G_{n,m,k}.

6.10.1 bipartite_configuration_model

bipartite_configuration_model (aseq, bseq, create_using=None, seed=None) Return a random bipartite graph from two given degree sequences.

Parameters aseq : list or iterator
Degree sequence for node set A.

**bseq** : list or iterator

Degree sequence for node set B.

**create_using** : NetworkX graph instance, optional

Return graph of this type.

**seed** : integer, optional

Seed for random number generator.

**Notes**

The sum of the two sequences must be equal: \( \text{sum(aseq)=sum(bseq)} \) If no graph type is specified use MultiGraph with parallel edges. If you want a graph with no parallel edges use create_using=Graph() but then the resulting degree sequences might not be exact.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

### 6.10.2 bipartite_havel_hakimi_graph

**bipartite_havel_hakimi_graph** *(aseq, bseq, create_using=None)*

Return a bipartite graph from two given degree sequences using a Havel-Hakimi style construction.

Nodes from the set A are connected to nodes in the set B by connecting the highest degree nodes in set A to the highest degree nodes in set B until all stubs are connected.

**Parameters**

- **aseq** : list or iterator
  
  Degree sequence for node set A.

- **bseq** : list or iterator
  
  Degree sequence for node set B.

- **create_using** : NetworkX graph instance, optional
  
  Return graph of this type.

**Notes**

The sum of the two sequences must be equal: \( \text{sum(aseq)=sum(bseq)} \) If no graph type is specified use MultiGraph with parallel edges. If you want a graph with no parallel edges use create_using=Graph() but then the resulting degree sequences might not be exact.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.
6.10.3 bipartite_reverse_havel_hakimi_graph

*bipartite_reverse_havel_hakimi_graph* *(aseq, bseq, create_using=None)*

Return a bipartite graph from two given degree sequences using a Havel-Hakimi style construction.

Nodes from set A are connected to nodes in the set B by connecting the highest degree nodes in set A to the lowest degree nodes in set B until all stubs are connected.

**Parameters**

- **aseq**: list or iterator
  
  Degree sequence for node set A.

- **bseq**: list or iterator
  
  Degree sequence for node set B.

- **create_using**: NetworkX graph instance, optional

  Return graph of this type.

**Notes**

The sum of the two sequences must be equal: \( \text{sum}(aseq) = \text{sum}(bseq) \) If no graph type is specified use MultiGraph with parallel edges. If you want a graph with no parallel edges use create_using=Graph() but then the resulting degree sequences might not be exact.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

6.10.4 bipartite_alternating_havel_hakimi_graph

*bipartite_alternating_havel_hakimi_graph* *(aseq, bseq, create_using=None)*

Return a bipartite graph from two given degree sequences using an alternating Havel-Hakimi style construction.

Nodes from the set A are connected to nodes in the set B by connecting the highest degree nodes in set A to alternatively the highest and the lowest degree nodes in set B until all stubs are connected.

**Parameters**

- **aseq**: list or iterator

  Degree sequence for node set A.

- **bseq**: list or iterator

  Degree sequence for node set B.

- **create_using**: NetworkX graph instance, optional

  Return graph of this type.

**Notes**

The sum of the two sequences must be equal: \( \text{sum}(aseq) = \text{sum}(bseq) \) If no graph type is specified use MultiGraph with parallel edges. If you want a graph with no parallel edges use create_using=Graph() but then the resulting degree sequences might not be exact.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.
6.10.5 bipartite_preferential_attachment_graph

bipartite_preferential_attachment_graph (aseq, p, create_using=None, seed=None)
Create a bipartite graph with a preferential attachment model from a given single degree sequence.

Parameters
aseq : list or iterator
Degree sequence for node set A.
p : float
Probability that a new bottom node is added.
create_using : NetworkX graph instance, optional
Return graph of this type.
seed : integer, optional
Seed for random number generator.

References

[R249]

6.10.6 bipartite_random_graph

bipartite_random_graph (n, m, p, seed=None, directed=False)
Return a bipartite random graph.
This is a bipartite version of the binomial (Erdős-Rényi) graph.

Parameters
n : int
The number of nodes in the first bipartite set.
m : int
The number of nodes in the second bipartite set.
p : float
Probability for edge creation.
seed : int, optional
Seed for random number generator (default=None).
directed : bool, optional (default=False)
If True return a directed graph

See also:
gnp_random_graph, bipartite_configuration_model

Notes
The bipartite random graph algorithm chooses each of the n*m (undirected) or 2*nm (directed) possible edges with probability p.
This algorithm is O(n+m) where m is the expected number of edges.
The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

**References**

[R250]

### 6.10.7 bipartite_gnmk_random_graph

**bipartite_gnmk_random_graph** \((n, m, k, \text{seed}\text{=}None, \text{directed}\text{=}False)\)

Return a random bipartite graph \(G_{n,m,k}\).

Produces a bipartite graph chosen randomly out of the set of all graphs with \(n\) top nodes, \(m\) bottom nodes, and \(k\) edges.

**Parameters**

- **\(n\)**: int
  - The number of nodes in the first bipartite set.
- **\(m\)**: int
  - The number of nodes in the second bipartite set.
- **\(k\)**: int
  - The number of edges
- **\(\text{seed}\)**: int, optional
  - Seed for random number generator (default=None).
- **\(\text{directed}\)**: bool, optional (default=False)
  - If True return a directed graph

**See also:**

gnm_random_graph

**Notes**

If \(k > m \times n\) then a complete bipartite graph is returned.

This graph is a bipartite version of the \(G_{nm}\) random graph model.

**Examples**

\[G = \text{nx.bipartite_gnmk_random_graph}(10,20,50)\]

### 6.11 Line Graph

Line graphs.

**line_graph(G)**  Return the line graph of the graph or digraph \(G\).
6.11.1 line_graph

line_graph(G)

Return the line graph of the graph or digraph G.

The line graph of a graph G has a node for each edge in G and an edge between those nodes if the two edges in G share a common node.

For DiGraphs an edge an edge represents a directed path of length 2.

The original node labels are kept as two-tuple node labels in the line graph.

Parameters  
G : graph
    A NetworkX Graph or DiGraph

Notes

Not implemented for MultiGraph or MultiDiGraph classes.

Graph, node, and edge data are not propagated to the new graph.

Examples

```python
>>> G=nx.star_graph(3)
>>> L=nx.line_graph(G)
>>> print(sorted(L.edges()))  # makes a clique, K3
[((0, 1), (0, 2)), ((0, 1), (0, 3)), ((0, 3), (0, 2))]
```

6.12 Ego Graph

Ego graph.

ego_graph(G, n[, radius, center, ...])  Returns induced subgraph of neighbors centered at node n within a given radius.

6.12.1 ego_graph

go_graph(G, n, radius=1, center=True, undirected=False, distance=None)

Returns induced subgraph of neighbors centered at node n within a given radius.

Parameters  
G : graph
    A NetworkX Graph or DiGraph
n : node
    A single node
radius : number, optional
    Include all neighbors of distance<=radius from n.
center : bool, optional
    If False, do not include center node in graph
**undirected** : bool, optional

If True use both in- and out-neighbors of directed graphs.

**distance** : key, optional

Use specified edge data key as distance. For example, setting distance='weight' will use the edge weight to measure the distance from the node n.

**Notes**

For directed graphs D this produces the “out” neighborhood or successors. If you want the neighborhood of predecessors first reverse the graph with D.reverse(). If you want both directions use the keyword argument undirected=True.

Node, edge, and graph attributes are copied to the returned subgraph.

## 6.13 Stochastic

Stochastic graph.

```python
stochastic_graph(G[, copy, weight])  # Return a right-stochastic representation of G.
```

### 6.13.1 stochastic_graph

**stochastic_graph** *(G, copy=True, weight='weight')*

Return a right-stochastic representation of G.

A right-stochastic graph is a weighted digraph in which all of the node (out) neighbors edge weights sum to 1.

**Parameters**

- **G** : graph
  - A NetworkX graph
- **copy** : boolean, optional
  - If True make a copy of the graph, otherwise modify the original graph
- **weight** : edge attribute key (optional, default='weight')
  - Edge data key used for weight. If no attribute is found for an edge the edge weight is set to 1.

## 6.14 Intersection

Generators for random intersection graphs.

```python
uniform_random_intersection_graph(n, m, p[, ...])  # Return a uniform random intersection graph.
k_random_intersection_graph(n, m, k)  # Return a intersection graph with randomly chosen attribute sets for each node.
general_random_intersection_graph(n, m, p)  # Return a random intersection graph with independent probabilities for each attribute.
```
6.14.1 uniform_random_intersection_graph

uniform_random_intersection_graph \((n, m, p, seed=None)\)

Return a uniform random intersection graph.

Parameters:
- \(n\) : int
  The number of nodes in the first bipartite set (nodes)
- \(m\) : int
  The number of nodes in the second bipartite set (attributes)
- \(p\) : float
  Probability of connecting nodes between bipartite sets
- \(seed\) : int, optional
  Seed for random number generator (default=None).

See also:
- gnp_random_graph

References:
- [R270], [R271]  

6.14.2 k_random_intersection_graph

k_random_intersection_graph \((n, m, k)\)

Return a intersection graph with randomly chosen attribute sets for each node that are of equal size \((k)\).

Parameters:
- \(n\) : int
  The number of nodes in the first bipartite set (nodes)
- \(m\) : int
  The number of nodes in the second bipartite set (attributes)
- \(k\) : float
  Size of attribute set to assign to each node
- \(seed\) : int, optional
  Seed for random number generator (default=None).

See also:
- gnp_random_graph, uniform_random_intersection_graph

References:
- [R269]
6.14.3 general_random_intersection_graph

general_random_intersection_graph \((n, m, p)\)
Return a random intersection graph with independent probabilities for connections between node and attribute sets.

Parameters
\(n\) : int
The number of nodes in the first bipartite set (nodes)
\(m\) : int
The number of nodes in the second bipartite set (attributes)
\(p\) : list of floats of length \(m\)
Probabilities for connecting nodes to each attribute
\(seed\) : int, optional
Seed for random number generator (default=None).

See also:
gnp_random_graph, uniform_random_intersection_graph

References

[R268]

6.15 Social Networks

Famous social networks.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>karate_club_graph()</td>
<td>Return Zachary’s Karate club graph.</td>
</tr>
<tr>
<td>davis_southern_women_graph()</td>
<td>Return Davis Southern women social network.</td>
</tr>
<tr>
<td>florentine_families_graph()</td>
<td>Return Florentine families graph.</td>
</tr>
</tbody>
</table>

6.15.1 karate_club_graph

karate_club_graph()
Return Zachary’s Karate club graph.

References

[R290], [R291]

6.15.2 davis_southern_women_graph

davis_southern_women_graph()
Return Davis Southern women social network.

This is a bipartite graph.
References

[R288]

6.15.3 florentine_families_graph

florentine_families_graph()

Return Florentine families graph.

References

[R289]
7.1 Graph Matrix

Adjacency matrix and incidence matrix of graphs.

**adjacency_matrix**

```
adjacency_matrix(G[, nodelist, weight])
```

Return adjacency matrix of G.

**incidence_matrix**

```
incidence_matrix(G[, nodelist, edgelist, ...])
```

Return incidence matrix of G.

### 7.1.1 adjacency_matrix

**adjacency_matrix** *(G, nodelist=None, weight='weight')*  
Return adjacency matrix of G.

**Parameters**

- **G**: graph  
  A NetworkX graph

- **nodelist**: list, optional  
  The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().

- **weight**: string or None, optional (default='weight')  
  The edge data key used to provide each value in the matrix. If None, then each edge has weight 1.

**Returns**

- **A**: numpy matrix  
  Adjacency matrix representation of G.

**See also:**

- to_numpy_matrix, to_dict_of_dicts

**Notes**

If you want a pure Python adjacency matrix representation try networkx.convert.to_dict_of_dicts which will return a dictionary-of-dictionaries format that can be addressed as a sparse matrix.

For MultiGraph/MultiDiGraph, the edges weights are summed. See to_numpy_matrix for other options.
### 7.1.2 incidence_matrix

The incidence matrix assigns each row to a node and each column to an edge. For a standard incidence matrix a 1 appears wherever a row’s node is incident on the column’s edge. For an oriented incidence matrix each edge is assigned an orientation (arbitrarily for undirected and aligning to direction for directed). A -1 appears for the tail of an edge and 1 for the head of the edge. The elements are zero otherwise.

**Parameters**

- **G**: graph
  A NetworkX graph
- **nodelist**: list, optional (default= all nodes in G)
  The rows are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().
- **edgelist**: list, optional (default= all edges in G)
  The columns are ordered according to the edges in edgelist. If edgelist is None, then the ordering is produced by G.edges().
- **oriented**: bool, optional (default=False)
  If True, matrix elements are +1 or -1 for the head or tail node respectively of each edge. If False, +1 occurs at both nodes.
- **weight**: string or None, optional (default=None)
  The edge data key used to provide each value in the matrix. If None, then each edge has weight 1. Edge weights, if used, should be positive so that the orientation can provide the sign.

**Returns**

- **A**: NumPy matrix
  The incidence matrix of G.

**Notes**

For MultiGraph/MultiDiGraph, the edges in edgelist should be (u,v,key) 3-tuples.

“Networks are the best discrete model for so many problems in applied mathematics” [R292].

**References**

[R292]

### 7.2 Laplacian Matrix

Laplacian matrix of graphs.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>laplacian_matrix(G[, nodelist, weight])</td>
<td>Return the Laplacian matrix of G.</td>
</tr>
<tr>
<td>normalized_laplacian_matrix(G[, nodelist, ...])</td>
<td>Return the normalized Laplacian matrix of G.</td>
</tr>
<tr>
<td>directed_laplacian_matrix(G[, nodelist, ...])</td>
<td>Return the directed Laplacian matrix of G.</td>
</tr>
</tbody>
</table>
7.2.1 laplacian_matrix

```python
laplacian_matrix(G, nodelist=None, weight='weight')
```

Return the Laplacian matrix of G.

The graph Laplacian is the matrix $L = D - A$, where $A$ is the adjacency matrix and $D$ is the diagonal matrix of node degrees.

**Parameters**

- **G**: graph
  - A NetworkX graph
- **nodelist**: list, optional
  - The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, the ordering is produced by G.nodes().
- **weight**: string or None, optional (default='weight')
  - The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.

**Returns**

- **L**: NumPy matrix
  - The Laplacian matrix of G.

**See also:**

- to_numpy_matrix
- normalized_laplacian_matrix

**Notes**

For MultiGraph/MultiDiGraph, the edges weights are summed. See to_numpy_matrix for other options.

7.2.2 normalized_laplacian_matrix

```python
normalized_laplacian_matrix(G, nodelist=None, weight='weight')
```

Return the normalized Laplacian matrix of G.

The normalized graph Laplacian is the matrix

$$NL = D^{-1/2}LD^{-1/2}$$

where $L$ is the graph Laplacian and $D$ is the diagonal matrix of node degrees.

**Parameters**

- **G**: graph
  - A NetworkX graph
- **nodelist**: list, optional
  - The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, the ordering is produced by G.nodes().
- **weight**: string or None, optional (default='weight')
  - The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.

**Returns**

- **L**: NumPy matrix
  - The normalized Laplacian matrix of G.
See also:

laplacian_matrix

Notes

For MultiGraph/MultiDiGraph, the edges weights are summed. See to_numpy_matrix for other options. If the Graph contains selfloops, D is defined as diag(sum(A,1)), where A is the adjacency matrix [R295].

References

[R294], [R295]

7.2.3 directed_laplacian_matrix

directed_laplacian_matrix (G, nodelist=None, weight='weight', walk_type=None, alpha=0.95)

Return the directed Laplacian matrix of G.

The graph directed Laplacian is the matrix

\[
L = I - (\Phi^{1/2} P \Phi^{-1/2} + \Phi^{-1/2} P^T \Phi^{1/2})/2
\]

where \(I\) is the identity matrix, \(P\) is the transition matrix of the graph, and \(\Phi\) a matrix with the Perron vector of \(P\) in the diagonal and zeros elsewhere.

Depending on the value of walk_type, \(P\) can be the transition matrix induced by a random walk, a lazy random walk, or a random walk with teleportation (PageRank).

Parameters

- **G**: DiGraph
- **nodelist**: list, optional
  - The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().
- **weight**: string or None, optional (default='weight')
  - The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.
- **walk_type**: string or None, optional (default=None)
  - If None, \(P\) is selected depending on the properties of the graph. Otherwise is one of ‘random’, ‘lazy’, or ‘pagerank’
- **alpha**: real
  - \((1 - \alpha)\) is the teleportation probability used with pagerank

Returns

- **L**: NumPy array
  - Normalized Laplacian of G.

Raises

- **NetworkXError**
  - If NumPy cannot be imported
- **NetworkXNotImplemented**
If G is not a DiGraph

See also:

laplacian_matrix

Notes

Only implemented for DiGraphs

References

[R293]

7.3 Spectrum

Eigenvalue spectrum of graphs.

<table>
<thead>
<tr>
<th>function</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>laplacian_spectrum(G[, weight])</td>
<td>Return eigenvalues of the Laplacian of G</td>
</tr>
<tr>
<td>adjacency_spectrum(G[, weight])</td>
<td>Return eigenvalues of the adjacency matrix of G.</td>
</tr>
</tbody>
</table>

7.3.1 laplacian_spectrum

laplacian_spectrum(G, weight='weight')
Return eigenvalues of the Laplacian of G

Parameters

- G (graph)
  A NetworkX graph
- weight (string or None, optional (default='weight'))
  The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.

Returns

- evals (NumPy array)
  Eigenvalues

See also:

laplacian_matrix

Notes

For MultiGraph/MultiDiGraph, the edges weights are summed. See to_numpy_matrix for other options.

7.3.2 adjacency_spectrum

adjacency_spectrum(G, weight='weight')
Return eigenvalues of the adjacency matrix of G.

Parameters

- G (graph)
A NetworkX graph

**weight** : string or None, optional (default='weight')

The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.

**Returns**  
**evals** : NumPy array

Eigenvalues

**See also:**  
adjacency_matrix

**Notes**

For MultiGraph/MultiDiGraph, the edges weights are summed. See to_numpy_matrix for other options.

### 7.4 Attribute Matrices

Functions for constructing matrix-like objects from graph attributes.

```python
attr_matrix(G[, edge_attr, node_attr, ...])  Returns a NumPy matrix using attributes from G.
```

```python
attr_sparse_matrix(G[, edge_attr, ...])  Returns a SciPy sparse matrix using attributes from G.
```

#### 7.4.1 attr_matrix

**attr_matrix** *(G, edge_attr=None, node_attr=None, normalized=False, rc_order=None, dtype=None, order=None)*

Returns a NumPy matrix using attributes from G.

If only *G* is passed in, then the adjacency matrix is constructed.

Let *A* be a discrete set of values for the node attribute *node_attr*. Then the elements of *A* represent the rows and columns of the constructed matrix. Now, iterate through every edge *e*=(*u*,*v*) in *G* and consider the value of the edge attribute *edge_attr*. If *ua* and *va* are the values of the node attribute *node_attr* for *u* and *v*, respectively, then the value of the edge attribute is added to the matrix element at (*ua*, *va*).

**Parameters**

*G* : graph

The NetworkX graph used to construct the NumPy matrix.

**edge_attr** : str, optional

Each element of the matrix represents a running total of the specified edge attribute for edges whose node attributes correspond to the rows/cols of the matrix. The attribute must be present for all edges in the graph. If no attribute is specified, then we just count the number of edges whose node attributes correspond to the matrix element.

**node_attr** : str, optional

Each row and column in the matrix represents a particular value of the node attribute. The attribute must be present for all nodes in the graph. Note, the values of this attribute should be reliably hashable. So, float values are not recommended. If no attribute is specified, then the rows and columns will be the nodes of the graph.

**normalized** : bool, optional
If True, then each row is normalized by the summation of its values.

**rc_order** : list, optional

A list of the node attribute values. This list specifies the ordering of rows and columns of the array. If no ordering is provided, then the ordering will be random (and also, a return value).

**Returns**

- **M** : NumPy matrix

  The attribute matrix.

- **ordering** : list

  If *rc_order* was specified, then only the matrix is returned. However, if *rc_order* was None, then the ordering used to construct the matrix is returned as well.

**Other Parameters**

- **dtype** : NumPy data-type, optional

  A valid NumPy dtype used to initialize the array. Keep in mind certain dtypes can yield unexpected results if the array is to be normalized. The parameter is passed to numpy.zeros(). If unspecified, the NumPy default is used.

- **order** : {'C', 'F'}, optional

  Whether to store multidimensional data in C- or Fortran-contiguous (row- or column-wise) order in memory. This parameter is passed to numpy.zeros(). If unspecified, the NumPy default is used.

**Examples**

Construct an adjacency matrix:

```
>>> G = nx.Graph()
>>> G.add_edge(0,1,thickness=1,weight=3)
>>> G.add_edge(0,2,thickness=2)
>>> G.add_edge(1,2,thickness=3)
>>> nx.attr_matrix(G, rc_order=[0,1,2])
matrix([[ 0., 1., 1.],
        [ 1., 0., 1.],
        [ 1., 1., 0.]])
```

Alternatively, we can obtain the matrix describing edge thickness.

```
>>> nx.attr_matrix(G, edge_attr='thickness', rc_order=[0,1,2])
matrix([[ 0., 1., 2.],
        [ 1., 0., 3.],
        [ 2., 3., 0.]])
```

We can also color the nodes and ask for the probability distribution over all edges (u,v) describing:

Pr(v has color Y | u has color X)

```
>>> G.node[0]['color'] = 'red'
>>> G.node[1]['color'] = 'red'
>>> G.node[2]['color'] = 'blue'
>>> rc = ['red', 'blue']
>>> nx.attr_matrix(G, node_attr='color', normalized=True, rc_order=rc)
matrix([[ 0.33333333, 0.66666667],
        [ 1., 0.]])
```

For example, the above tells us that for all edges (u,v):
\[
\begin{align*}
\Pr(v \text{ is red} | u \text{ is red}) &= \frac{1}{3} \\
\Pr(v \text{ is blue} | u \text{ is red}) &= \frac{2}{3} \\
\Pr(v \text{ is red} | u \text{ is blue}) &= 1 \\
\Pr(v \text{ is blue} | u \text{ is blue}) &= 0
\end{align*}
\]
Finally, we can obtain the total weights listed by the node colors.

```python
>>> nx.attr_matrix(G, edge_attr='weight', node_attr='color', rc_order=rc)
matrix([[ 3.,  2.],
        [ 2.,  0.]])
```
Thus, the total weight over all edges \((u,v)\) with \(u\) and \(v\) having colors:

- (red, red) is 3 # the sole contribution is from edge (0,1)
- (red, blue) is 2 # contributions from edges (0,2) and (1,2)
- (blue, red) is 2 # same as (red, blue) since graph is undirected
- (blue, blue) is 0 # there are no edges with blue endpoints

### 7.4.2 attr_sparse_matrix

`attr_sparse_matrix` function is defined as:

```python
attr_sparse_matrix(G, edge_attr=None, node_attr=None, normalized=False, rc_order=None, dtype=None)
```

Returns a SciPy sparse matrix using attributes from \(G\).

If only \(G\) is passed in, then the adjacency matrix is constructed.

Let \(A\) be a discrete set of values for the node attribute \(node_a ttr\). Then the elements of \(A\) represent the rows and columns of the constructed matrix. Now, iterate through every edge \(e=(u,v)\) in \(G\) and consider the value of the edge attribute \(edge_a ttr\). If \(ua\) and \(va\) are the values of the node attribute \(node_a ttr\) for \(u\) and \(v\), respectively, then the value of the edge attribute is added to the matrix element at \((ua, va)\).

**Parameters**

- \(G\) : graph
  - The NetworkX graph used to construct the NumPy matrix.
- \(edge\_attr\) : str, optional
  - Each element of the matrix represents a running total of the specified edge attribute for edges whose node attributes correspond to the rows/cols of the matrix. The attribute must be present for all edges in the graph. If no attribute is specified, then we just count the number of edges whose node attributes correspond to the matrix element.
- \(node\_attr\) : str, optional
  - Each row and column in the matrix represents a particular value of the node attribute. The attribute must be present for all nodes in the graph. Note, the values of this attribute should be reliably hashable. So, float values are not recommended. If no attribute is specified, then the rows and columns will be the nodes of the graph.
- \(normalized\) : bool, optional
  - If True, then each row is normalized by the summation of its values.
- \(rc\_order\) : list, optional
  - A list of the node attribute values. This list specifies the ordering of rows and columns of the array. If no ordering is provided, then the ordering will be random (and also, a return value).

**Returns**

- \(M\) : SciPy sparse matrix
  - The attribute matrix.
- \(ordering\) : list
If $rc\_order$ was specified, then only the matrix is returned. However, if $rc\_order$ was None, then the ordering used to construct the matrix is returned as well.

**Other Parameters**  
**dtype**: NumPy data-type, optional

A valid NumPy dtype used to initialize the array. Keep in mind certain dtypes can yield unexpected results if the array is to be normalized. The parameter is passed to numpy.zeros(). If unspecified, the NumPy default is used.

**Examples**

Construct an adjacency matrix:

```python
>>> G = nx.Graph()
>>> G.add_edge(0,1,thickness=1,weight=3)
>>> G.add_edge(0,2,thickness=2)
>>> G.add_edge(1,2,thickness=3)
>>> M = nx.attr_sparse_matrix(G, rc_order=[0,1,2])
>>> M.todense()
matrix([[ 0., 1., 1.],
        [ 1., 0., 1.],
        [ 1., 1., 0.]])
```

Alternatively, we can obtain the matrix describing edge thickness.

```python
>>> M = nx.attr_sparse_matrix(G, edge_attr='thickness', rc_order=[0,1,2])
>>> M.todense()
matrix([[ 0., 1., 2.],
        [ 1., 0., 3.],
        [ 2., 3., 0.]])
```

We can also color the nodes and ask for the probability distribution over all edges $(u,v)$ describing:

$Pr(v \text{ has color } Y | u \text{ has color } X)$

```python
>>> G.node[0]['color'] = 'red'
>>> G.node[1]['color'] = 'red'
>>> G.node[2]['color'] = 'blue'
>>> rc = ['red', 'blue']
>>> M = nx.attr_sparse_matrix(G, node_attr='color', rc_order=rc)
>>> M.todense()
matrix([[ 0.33333333, 0.66666667],
        [ 1. , 0. ]])
```

For example, the above tells us that for all edges $(u,v)$:

$Pr( v \text{ is red } | u \text{ is red}) = 1/3$  
$Pr( v \text{ is blue } | u \text{ is red}) = 2/3$

$Pr( v \text{ is red } | u \text{ is blue}) = 1$  
$Pr( v \text{ is blue } | u \text{ is blue}) = 0$

Finally, we can obtain the total weights listed by the node colors.

```python
>>> M = nx.attr_sparse_matrix(G, edge_attr='weight', node_attr='color', rc_order=rc)
>>> M.todense()
matrix([[ 3., 2.],
        [ 2., 0.]])
```

Thus, the total weight over all edges $(u,v)$ with $u$ and $v$ having colors:
(red, red) is 3 # the sole contribution is from edge (0,1) (red, blue) is 2 # contributions from edges (0,2) and (1,2) (blue, red) is 2 # same as (red, blue) since graph is undirected (blue, blue) is 0 # there are no edges with blue endpoints
CHAPTER EIGHT

CONVERTING TO AND FROM OTHER DATA FORMATS

8.1 To NetworkX Graph

This module provides functions to convert NetworkX graphs to and from other formats.

The preferred way of converting data to a NetworkX graph is through the graph constuctor. The constructor calls the `to_networkx_graph()` function which attempts to guess the input type and convert it automatically.

8.1.1 Examples

Create a 10 node random graph from a numpy matrix

```python
>>> import numpy

>>> a=numpy.reshape(numpy.random.random_integers(0,1,size=100),(10,10))

>>> D=nx.DiGraph(a)
```

or equivalently

```python
>>> D=nx.to_networkx_graph(a,create_using=nx.DiGraph())
```

Create a graph with a single edge from a dictionary of dictionaries

```python
>>> d={0: {1: {'weight':1}}} # dict-of-dicts single edge (0,1)

>>> G=nx.Graph(d)
```

8.1.2 See Also

`nx_pygraphviz, nx_pydot`

`to_networkx_graph(data[, create_using, ...])` Make a NetworkX graph from a known data structure.

8.1.3 `to_networkx_graph`

`to_networkx_graph(data, create_using=None, multigraph_input=False)`

Make a NetworkX graph from a known data structure.

The preferred way to call this is automatically from the class constructor

```python
>>> d={0: {1: {'weight':1}}) # dict-of-dicts single edge (0,1)

>>> G=nx.Graph(d)
```
instead of the equivalent

```python
>>> G=nx.from_dict_of_dicts(d)
```

**Parameters**
- **data**: a object to be converted

**Current known types** are:
- any NetworkX graph dict-of-dicts dist-of-lists list of edges
- numpy matrix numpy ndarray scipy sparse matrix pygraphviz agraph

- **create_using**: NetworkX graph
  - Use specified graph for result. Otherwise a new graph is created.

- **multigraph_input**: bool (default False)
  - If True and data is a dict_of_dicts, try to create a multigraph assuming
dict_of_dict_of_lists. If data and create_using are both multigraphs then create a multi-
graph from a multigraph.

### 8.2 Dictionaries

#### to_dict_of_dicts

```python
to_dict_of_dicts(G[, nodelist, edge_data])
```

Return adjacency representation of graph as a dictionary of dictionaries.

**Parameters**
- **G**: graph
  - A NetworkX graph

- **nodelist**: list
  - Use only nodes specified in nodelist

- **edge_data**: list, optional
  - If provided, the value of the dictionary will be set to edge_data for all edges. This
is useful to make an adjacency matrix type representation with 1 as the edge data. If
edgedata is None, the edgedata in G is used to fill the values. If G is a multigraph, the
edgedata is a dict for each pair (u,v).

#### from_dict_of_dicts

```python
from_dict_of_dicts(d[, create_using, ...])
```

Return a graph from a dictionary of dictionaries.

**Parameters**
- **d**: dictionary of dictionaries
  - A dictionary of dictionaries adjacency representation.

- **create_using**: NetworkX graph
  - Use specified graph for result. Otherwise a new graph is created.

- **multigraph_input**: bool (default False)
When True, the values of the inner dict are assumed to be containers of edge data for multiple edges. Otherwise this routine assumes the edge data are singletons.

Examples

```python
>>> dod = {0: {1:{'weight':1}}}  # single edge (0,1)
>>> G=nx.from_dict_of_dicts(dod)

or >>> G=nx.Graph(dod)  # use Graph constructor
```

### 8.3 Lists

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#### 8.3.1 to_dict_of_lists

**to_dict_of_lists** *(G[, nodelist])*

Return adjacency representation of graph as a dictionary of lists.

**Parameters**

- **G**: graph
  A NetworkX graph

- **nodelist**: list
  Use only nodes specified in nodelist

**Notes**

Completely ignores edge data for MultiGraph and MultiDiGraph.

#### 8.3.2 from_dict_of_lists

**from_dict_of_lists** *(d[, create_using])*

Return a graph from a dictionary of lists.

**Parameters**

- **d**: dictionary of lists
  A dictionary of lists adjacency representation.

- **create_using**: NetworkX graph
  Use specified graph for result. Otherwise a new graph is created.

**Examples**

```python
>>> dol = {0:[1]}  # single edge (0,1)
>>> G=nx.from_dict_of_lists(dol)
```
8.3.3 to_edgelist

to_edgelist \((G, \text{nodelist}=\text{None})\)

Return a list of edges in the graph.

Parameters

\(G\) : graph

A NetworkX graph

\text{nodelist} : list

Use only nodes specified in nodelist

8.3.4 from_edgelist

from_edgelist \((\text{edgelist}, \text{create_using}=\text{None})\)

Return a graph from a list of edges.

Parameters

\text{edgelist} : list or iterator

Edge tuples

\text{create_using} : NetworkX graph

Use specified graph for result. Otherwise a new graph is created.

Examples

>>> edgelist= [(0,1)] # single edge (0,1)
>>> G=nx.from_edgelist(edgelist)

or >>> G=nx.Graph(edgelist) # use Graph constructor

8.4 Numpy

<table>
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8.4.1 to_numpy_matrix

to_numpy_matrix \((G, \text{nodelist}=\text{None}, \text{dtype}=\text{None}, \text{order}=\text{None}, \text{multigraph_weight}=<\text{built-in function \text{sum}>}, \text{weight}='weight')\)

Return the graph adjacency matrix as a NumPy matrix.

Parameters

\(G\) : graph

The NetworkX graph used to construct the NumPy matrix.

\text{nodelist} : list, optional

The rows and columns are ordered according to the nodes in \text{nodelist}. If \text{nodelist} is
None, then the ordering is produced by G.nodes().

**dtype**: NumPy data type, optional

A valid single NumPy data type used to initialize the array. This must be a simple type such as int or numpy.float64 and not a compound data type (see to_numpy_recarray) If None, then the NumPy default is used.

**order**: {‘C’, ‘F’}, optional

Whether to store multidimensional data in C- or Fortran-contiguous (row- or column-wise) order in memory. If None, then the NumPy default is used.

**multigraph_weight**: {sum, min, max}, optional

An operator that determines how weights in multigraphs are handled. The default is to sum the weights of the multiple edges.

**weight**: string or None optional (default='weight')

The edge attribute that holds the numerical value used for the edge weight. If None then all edge weights are 1.

**Returns** M : NumPy matrix

Graph adjacency matrix.

See also:

*to_numpy_recarray*, *from_numpy_matrix*

Notes

The matrix entries are assigned with weight edge attribute. When an edge does not have the weight attribute, the value of the entry is 1. For multiple edges, the values of the entries are the sums of the edge attributes for each edge.

When *nodelist* does not contain every node in *G*, the matrix is built from the subgraph of *G* that is induced by the nodes in *nodelist*.

Examples

```python
>>> G = nx.MultiDiGraph()
>>> G.add_edge(0,1,weight=2)
>>> G.add_edge(1,0)
>>> G.add_edge(2,2,weight=3)
>>> G.add_edge(2,2)
>>> nx.to_numpy_matrix(G, nodelist=[0,1,2])
matrix([[ 0., 2., 0.],
        [ 1., 0., 0.],
        [ 0., 0., 4.]])
```

### 8.4.2 to_numpy_recarray

**to_numpy_recarray** *(G, nodelist=None, dtype=[('weight', <type 'float'>)], order=None)*

Return the graph adjacency matrix as a NumPy recarray.

**Parameters**

* G : graph
The NetworkX graph used to construct the NumPy matrix.

**nodelist** : list, optional
The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().

**dtype** : NumPy data-type, optional
A valid NumPy named dtype used to initialize the NumPy recarray. The data type names are assumed to be keys in the graph edge attribute dictionary.

**order** : {'C', 'F'}, optional
Whether to store multidimensional data in C- or Fortran-contiguous (row- or column-wise) order in memory. If None, then the NumPy default is used.

Returns
**M** : NumPy recarray
The graph with specified edge data as a Numpy recarray

Notes
When nodelist does not contain every node in G, the matrix is built from the subgraph of G that is induced by the nodes in nodelist.

Examples
>>> G = nx.Graph()
>>> G.add_edge(1,2,weight=7.0,cost=5)
>>> A=nx.to_numpy_recarray(G,dtype=[('weight',float),('cost',int)])
>>> print(A.weight)
[[ 0.  7.]
 [ 7.  0.]]
>>> print(A.cost)
[[0 5]
 [5 0]]

8.4.3 from_numpy_matrix

**from_numpy_matrix** (A, create_using=None)
Return a graph from numpy matrix.

The numpy matrix is interpreted as an adjacency matrix for the graph.

Parameters
**A** : numpy matrix
An adjacency matrix representation of a graph

**create_using** : NetworkX graph
Use specified graph for result. The default is Graph()

See also:

to_numpy_matrix, to_numpy_recarray
Notes

If the numpy matrix has a single data type for each matrix entry it will be converted to an appropriate Python
data type.

If the numpy matrix has a user-specified compound data type the names of the data fields will be used as attribute
keys in the resulting NetworkX graph.

Examples

Simple integer weights on edges:

```python
>>> import numpy
>>> A=numpy.matrix([[1,1],[2,1]])
>>> G=nx.from_numpy_matrix(A)
```

User defined compound data type on edges:

```python
>>> import numpy
>>> dt=[('weight',float),('cost',int)]
>>> A=numpy.matrix([[1.0,2]],dtype=dt)
>>> G=nx.from_numpy_matrix(A)
>>> G.edges(data=True)
[(0, 0, {'cost': 2, 'weight': 1.0})]
```

8.5 Scipy

```python
to_scipy_sparse_matrix(G[, nodelist, dtype, ...]) Return the graph adjacency matrix as a SciPy sparse matrix.
from_scipy_sparse_matrix(A[, create_using]) Return a graph from scipy sparse matrix adjacency list.
```

8.5.1 to_scipy_sparse_matrix

```python
to_scipy_sparse_matrix(G, nodelist=None, dtype=None, weight='weight', format='csr')
Return the graph adjacency matrix as a SciPy sparse matrix.

Parameters G : graph
The NetworkX graph used to construct the NumPy matrix.

nodelist : list, optional
The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().

dtype : NumPy data-type, optional
A valid NumPy dtype used to initialize the array. If None, then the NumPy default is used.

weight : string or None optional (default='weight')
The edge attribute that holds the numerical value used for the edge weight. If None then all edge weights are 1.

format : str in {'bsr', 'csr', 'csc', 'coo', 'lil', 'dia', 'dok'}
```
The type of the matrix to be returned (default ‘csr’). For some algorithms different implementations of sparse matrices can perform better. See [R248] for details.

**Returns**  
\( M \) : SciPy sparse matrix  
Graph adjacency matrix.

**Notes**

The matrix entries are populated using the edge attribute held in parameter weight. When an edge does not have that attribute, the value of the entry is 1.

For multiple edges the matrix values are the sums of the edge weights.

When nodelist does not contain every node in \( G \), the matrix is built from the subgraph of \( G \) that is induced by the nodes in nodelist.

Uses coo_matrix format. To convert to other formats specify the format= keyword.

**References**

[R248]

**Examples**

```python
g = nx.MultiDiGraph()
g.add_edge(0,1,weight=2)
g.add_edge(1,0)
g.add_edge(2,2,weight=3)
g.add_edge(2,2)
s = nx.to_scipy_sparse_matrix(g, nodelist=[0,1,2])
```

```python
print(s.toarray())
```

```
[[0 2 0]
 [1 0 0]
 [0 0 4]]
```

### 8.5.2 from_scipy_sparse_matrix

**from_scipy_sparse_matrix \((A, create_using=None)\)**  
Return a graph from scipy sparse matrix adjacency list.

**Parameters**  
\( A \) : scipy sparse matrix  
An adjacency matrix representation of a graph

\( create\_using \) : NetworkX graph  
Use specified graph for result. The default is Graph()

**Examples**

```python
import scipy.sparse
A=scipy.sparse.eye(2,2,1)
G=nx.from_scipy_sparse_matrix(A)
```
9.1 Adjacency List

Read and write NetworkX graphs as adjacency lists.

Adjacency list format is useful for graphs without data associated with nodes or edges and for nodes that can be meaningfully represented as strings.

9.1.1 Format

The adjacency list format consists of lines with node labels. The first label in a line is the source node. Further labels in the line are considered target nodes and are added to the graph along with an edge between the source node and target node.

The graph with edges a-b, a-c, d-e can be represented as the following adjacency list (anything following the # in a line is a comment):

```
a b c # source target target
d e
```

---

### read_adjlist(path[, comments, delimiter, ...])
Read graph in adjacency list format from path.

- **parameters**
  - path: string or file
    - Filename or file handle to read. Filenames ending in .gz or .bz2 will be uncompressed.
  - create_using: NetworkX graph container
    - Use given NetworkX graph for holding nodes or edges.
  - nodetype: Python type, optional
    - Convert nodes to this type.
  - comments: string, optional
Marker for comment lines

**delimiter** : string, optional

Separator for node labels. The default is whitespace.

**create_using**: NetworkX graph container :

Use given NetworkX graph for holding nodes or edges.

**Returns**  
**G**: NetworkX graph :

The graph corresponding to the lines in adjacency list format.

**See also**:

write_adjlist

**Notes**

This format does not store graph or node data.

**Examples**

```python
>>> G=nx.path_graph(4)
>>> nx.write_adjlist(G, "test.adjlist")
>>> G=nx.read_adjlist("test.adjlist")
```

The path can be a filehandle or a string with the name of the file. If a filehandle is provided, it has to be opened in ‘rb’ mode.

```python
>>> fh=open("test.adjlist", ‘rb’)
>>> G=nx.read_adjlist(fh)
```

Filenames ending in .gz or .bz2 will be compressed.

```python
>>> nx.write_adjlist(G,"test.adjlist.gz")
>>> G=nx.read_adjlist("test.adjlist.gz")
```

The optional nodetype is a function to convert node strings to nodetype.

For example

```python
>>> G=nx.read_adjlist("test.adjlist", nodetype=int)
```

will attempt to convert all nodes to integer type.

Since nodes must be hashable, the function nodetype must return hashable types (e.g. int, float, str, frozenset - or tuples of those, etc.)

The optional create_using parameter is a NetworkX graph container. The default is Graph(), an undirected graph. To read the data as a directed graph use

```python
>>> G=nx.read_adjlist("test.adjlist", create_using=nx.DiGraph())
```

### 9.1.3 write_adjlist

**write_adjlist** *(G, path, comments='#', delimiter=' ', encoding='utf-8')*

Write graph G in single-line adjacency-list format to path.
Parameters  

\textbf{G} : NetworkX graph

\textbf{path} : string or file

Filename or file handle for data output. Filenames ending in .gz or .bz2 will be compressed.

\textbf{comments} : string, optional

Marker for comment lines

\textbf{delimiter} : string, optional

Separator for node labels

\textbf{encoding} : string, optional

Text encoding.

\textbf{See also:}

\texttt{read_adjlist, generate_adjlist}

\textbf{Notes}

This format does not store graph, node, or edge data.

\textbf{Examples}

```python
>>> G=nx.path_graph(4)
>>> nx.write_adjlist(G,"test.adjlist")
```

The path can be a filehandle or a string with the name of the file. If a filehandle is provided, it has to be opened in ‘wb’ mode.

```python
>>> fh=open("test.adjlist","wb")
>>> nx.write_adjlist(G, fh)
```

\textbf{9.1.4 parse_adjlist}

\texttt{parse_adjlist (lines, comments='#', delimiter=None, create_using=None, nodetype=None)}

Parse lines of a graph adjacency list representation.

\textbf{Parameters}  

\textbf{lines} : list or iterator of strings

Input data in adjlist format

\textbf{create_using} : NetworkX graph container :

Use given NetworkX graph for holding nodes or edges.

\textbf{nodetype} : Python type, optional

Convert nodes to this type.

\textbf{comments} : string, optional

Marker for comment lines

\textbf{delimiter} : string, optional

Separator for node labels. The default is whitespace.
create_using: NetworkX graph container:
Use given NetworkX graph for holding nodes or edges.

Returns G: NetworkX graph:
The graph corresponding to the lines in adjacency list format.

See also:
read_adjlist

Examples

>>> lines = ['1 2 5',
... '2 3 4',
... '3 5',
... '4',
... '5']
>>> G = nx.parse_adjlist(lines, nodetype = int)
>>> G.nodes()
[1, 2, 3, 4, 5]
>>> G.edges()
[(1, 2), (1, 5), (2, 3), (2, 4), (3, 5)]

9.1.5 generate_adjlist

generate_adjlist(G, delimiter=' ')
Generate a single line of the graph G in adjacency list format.

Parameters G : NetworkX graph
delimiter : string, optional
    Separator for node labels

Returns lines : string
    Lines of data in adjlist format.

See also:
write_adjlist, read_adjlist

Examples

>>> G = nx.lollipop_graph(4, 3)
>>> for line in nx.generate_adjlist(G):
...     print(line)
0 1 2 3
1 2 3
2 3
3 4
4 5
5 6
6
9.2 Multiline Adjacency List

Read and write NetworkX graphs as multi-line adjacency lists.

The multi-line adjacency list format is useful for graphs with nodes that can be meaningfully represented as strings. With this format simple edge data can be stored but node or graph data is not.

9.2.1 Format

The first label in a line is the source node label followed by the node degree d. The next d lines are target node labels and optional edge data. That pattern repeats for all nodes in the graph.

The graph with edges a-b, a-c, d-e can be represented as the following adjacency list (anything following the # in a line is a comment):

```
# example.multiline-adjlist
a 2
b
c
d 1
e
```

```
read_multiline_adjlist(path[, comments, ...])  Read graph in multi-line adjacency list format from path.
write_multiline_adjlist(G, path[, ...])        Write the graph G in multiline adjacency list format to path
parse_multiline_adjlist(lines[, comments, ...]) Parse lines of a multiline adjacency list representation of a graph.
generate_multiline_adjlist(G[, delimiter])     Generate a single line of the graph G in multiline adjacency list format.
```

9.2.2 read_multiline_adjlist

```
read_multiline_adjlist(path[, comments='#', delimiter=None, create_using=None, nodetype=None, edgetype=None, encoding='utf-8')]  Read graph in multi-line adjacency list format from path.
```

Parameters  **path**: string or file

Filename or file handle to read. Filenames ending in .gz or .bz2 will be uncompressed.

**create_using**: NetworkX graph container

Use given NetworkX graph for holding nodes or edges.

**nodetype**: Python type, optional

Convert nodes to this type.

**edgetype**: Python type, optional

Convert edge data to this type.

**comments**: string, optional

Marker for comment lines

**delimiter**: string, optional

Separator for node labels. The default is whitespace.

**create_using**: NetworkX graph container

Use given NetworkX graph for holding nodes or edges.
Returns  G: NetworkX graph :

See also:
write_multiline_adjlist

Notes

This format does not store graph, node, or edge data.

Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_multiline_adjlist(G,"test.adjlist")
>>> G=nx.read_multiline_adjlist("test.adjlist")
```

The path can be a file or a string with the name of the file. If a file is provided, it has to be opened in ‘rb’ mode.

```python
>>> fh=open("test.adjlist", ’rb’)
>>> G=nx.read_multiline_adjlist(fh)
```

Filenames ending in .gz or .bz2 will be compressed.

```python
>>> nx.write_multiline_adjlist(G,"test.adjlist.gz")
>>> G=nx.read_multiline_adjlist("test.adjlist.gz")
```

The optional nodetype is a function to convert node strings to nodetype.

For example

```python
>>> G=nx.read_multiline_adjlist("test.adjlist", nodetype=int)
```

will attempt to convert all nodes to integer type.

The optional edgetype is a function to convert edge data strings to edgetype.

```python
>>> G=nx.read_multiline_adjlist("test.adjlist")
```

The optional create_using parameter is a NetworkX graph container. The default is Graph(), an undirected graph. To read the data as a directed graph use

```python
>>> G=nx.read_multiline_adjlist("test.adjlist", create_using=nx.DiGraph())
```

### 9.2.3 write_multiline_adjlist

**write_multiline_adjlist** *(G, path, delimiter=' ', comments='#', encoding='utf-8')*

Write the graph G in multiline adjacency list format to path

**Parameters**  

- **G**: NetworkX graph
- **comments**: string, optional
  - Marker for comment lines
- **delimiter**: string, optional
  - Separator for node labels
- **encoding**: string, optional
  - Character encoding for file"
Text encoding.

See also:

read_multiline_adjlist

Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_multiline_adjlist(G,"test.adjlist")
```

The path can be a file handle or a string with the name of the file. If a file handle is provided, it has to be opened in 'wb' mode.

```python
>>> fh=open("test.adjlist","wb")
>>> nx.write_multiline_adjlist(G,fh)
```

Filenames ending in .gz or .bz2 will be compressed.

```python
>>> nx.write_multiline_adjlist(G,"test.adjlist.gz")
```

9.2.4 parse_multiline_adjlist

**parse_multiline_adjlist** *(lines, comments='#', delimiter=None, create_using=None, nodetype=None, edgetype=None)*

Parse lines of a multiline adjacency list representation of a graph.

**Parameters**

- **lines**: list or iterator of strings
  Input data in multiline adjlist format

- **create_using**: NetworkX graph container
  Use given NetworkX graph for holding nodes or edges.

- **nodetype**: Python type, optional
  Convert nodes to this type.

- **comments**: string, optional
  Marker for comment lines

- **delimiter**: string, optional
  Separator for node labels. The default is whitespace.

**Returns**

- **G**: NetworkX graph
  The graph corresponding to the lines in multiline adjacency list format.

Examples
>>> lines = ['1 2',
... "2 {'weight':3, 'name': 'Frodo'}",
... "3 {}",
... "2 1",
... "5 {'weight':6, 'name': 'Saruman'}"]
>>> G = nx.parse_multiline_adjlist(iter(lines), nodetype = int)
>>> G.nodes()
[1, 2, 3, 5]

9.2.5 generate_multiline_adjlist

generate_multiline_adjlist (G, delimiter=' ')
Generate a single line of the graph G in multiline adjacency list format.

Parameters
G : NetworkX graph
delimiter : string, optional
Separator for node labels

Returns
lines : string
Lines of data in multiline adjlist format.

See also:
write_multiline_adjlist, read_multiline_adjlist

Examples

>>> G = nx.lollipop_graph(4, 3)
>>> for line in nx.generate_multiline_adjlist(G):
... print(line)
0 3
1 {}
2 {}
3 {}
1 2
2 {}
3 {}
2 1
3 {}
3 1
4 {}
4 1
5 {}
5 1
6 {}
6 0

9.3 Edge List

Read and write NetworkX graphs as edge lists.
The multi-line adjacency list format is useful for graphs with nodes that can be meaningfully represented as strings. With the edgelist format simple edge data can be stored but node or graph data is not. There is no way of representing isolated nodes unless the node has a self-loop edge.

9.3.1 Format

You can read or write three formats of edge lists with these functions.

Node pairs with no data:

1 2

Python dictionary as data:

1 2 {'weight':7, 'color':'green'}

Arbitrary data:

1 2 7 green

9.3.2 read_edgelist

read_edgelist (path[, comments, delimiter, ...]) Read a graph from a list of edges.

Parameters

path : file or string
File or filename to write. If a file is provided, it must be opened in ‘rb’ mode. Filenames ending in .gz or .bz2 will be uncompressed.

comments : string, optional
The character used to indicate the start of a comment.

delimiter : string, optional
The string used to separate values. The default is whitespace.

create_using : Graph container, optional,
Use specified container to build graph. The default is networkx.Graph, an undirected graph.

nodetype : int, float, str, Python type, optional
Convert node data from strings to specified type

data : bool or list of (label,type) tuples
Tuples specifying dictionary key names and types for edge data

edgetype : int, float, str, Python type, optional OBSOLETE
Convert edge data from strings to specified type and use as ‘weight’

**encoding:** string, optional :

Specify which encoding to use when reading file.

**Returns**  \( G \) : graph

A networkx Graph or other type specified with create_using

See also:

parse_edgelist

**Notes**

Since nodes must be hashable, the function nodetype must return hashable types (e.g. int, float, str, frozenset - or tuples of those, etc.)

**Examples**

```python
>>> nx.write_edgelist(nx.path_graph(4), "test.edgelist")
>>> G=nx.read_edgelist("test.edgelist")

>>> fh=open("test.edgelist", 'rb')
>>> G=nx.read_edgelist(fh)
>>> fh.close()

>>> G=nx.read_edgelist("test.edgelist", nodetype=int)
>>> G=nx.read_edgelist("test.edgelist",create_using=nx.DiGraph())

Edgelist with data in a list:
```n
```python
textline = '1 2 3'
fh = open('test.edgelist','w')
d = fh.write(textline)
fh.close()
G = nx.read_edgelist('test.edgelist', nodetype=int, data=(("weight",float),))
G.nodes()
[1, 2]
G.edges(data = True)
[(1, 2, {'weight': 3.0})]
```

See parse_edgelist() for more examples of formatting.

**9.3.3 write_edgelist**

**write_edgelist** \((G, path, comments=\#’, delimiter=‘’, data=True, encoding=‘utf-8’))

Write graph as a list of edges.

**Parameters**  \( G \) : graph

A NetworkX graph

\( path \) : file or string

File or filename to write. If a file is provided, it must be opened in ‘wb’ mode. Filenames ending in .gz or .bz2 will be compressed.
**comments** : string, optional

The character used to indicate the start of a comment

**delimiter** : string, optional

The string used to separate values. The default is whitespace.

**data** : bool or list, optional

If False write no edge data. If True write a string representation of the edge data dictionary. If a list (or other iterable) is provided, write the keys specified in the list.

**encoding** : string, optional

Specify which encoding to use when writing file.

See also:

`write_edgelist`, `write_weighted_edgelist`

### Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_edgelist(G, "test.edgelist")
>>> G=nx.path_graph(4)
>>> fh=open("test.edgelist",'wb')
>>> nx.write_edgelist(G, fh)
>>> nx.write_edgelist(G, "test.edgelist.gz")
>>> nx.write_edgelist(G, "test.edgelist.gz", data=False)

>>> G=nx.Graph()
>>> G.add_edge(1,2,weight=7,color='red')
>>> nx.write_edgelist(G,"test.edgelist",data=False)
>>> nx.write_edgelist(G,"test.edgelist",data=['color'])
>>> nx.write_edgelist(G,"test.edgelist",data=['color','weight'])
```

### 9.3.4 read_weighted_edgelist

**read_weighted_edgelist**(path, comments='#', delimiter=None, create_using=None, nodetype=None, encoding='utf-8')

Read a graph as list of edges with numeric weights.

**Parameters**

- **path** : file or string
  
  File or filename to write. If a file is provided, it must be opened in ‘rb’ mode. Filenames ending in .gz or .bz2 will be uncompressed.

- **comments** : string, optional
  
  The character used to indicate the start of a comment.

- **delimiter** : string, optional
  
  The string used to separate values. The default is whitespace.

- **create_using** : Graph container, optional,
  
  Use specified container to build graph. The default is networkx.Graph, an undirected graph.

- **nodetype** : int, float, str, Python type, optional

9.3. Edge List 379
Convert node data from strings to specified type

**encoding**: string, optional :
Specify which encoding to use when reading file.

**Returns**  
G : graph
A networkx Graph or other type specified with create_using

**Notes**

Since nodes must be hashable, the function nodetype must return hashable types (e.g. int, float, str, frozenset - or tuples of those, etc.)

Example edgelist file format.

With numeric edge data:

```python
# read with
# >>> G=nx.read_weighted_edgelist(fh)
# source target data
a b 1
a c 3.14159
d e 42
```

### 9.3.5 write_weighted_edgelist

**write_weighted_edgelist** *(G, path, comments='#', delimiter=' ', encoding='utf-8')*

Write graph G as a list of edges with numeric weights.

**Parameters**

- **G** : graph
  A NetworkX graph
- **path** : file or string
  File or filename to write. If a file is provided, it must be opened in ‘wb’ mode. Filenames ending in .gz or .bz2 will be compressed.
- **comments** : string, optional
  The character used to indicate the start of a comment
- **delimiter** : string, optional
  The string used to separate values. The default is whitespace.
- **encoding** : string, optional :
  Specify which encoding to use when writing file.

**See also:**
read_edgelist, write_edgelist, write_weighted_edgelist

**Examples**

```python
>>> G=nx.Graph()
>>> G.add_edge(1,2,weight=7)
>>> nx.write_weighted_edgelist(G, 'test.weighted.edgelist')
```
9.3.6 generate_edgelist

generate_edgelist \texttt{(G, \text{delimiter}='\ ', \text{data}=True)}
Generate a single line of the graph G in edge list format.

\textbf{Parameters} \hspace{1em} \text{G} \hspace{0.5em} : \hspace{0.5em} \text{NetworkX graph}

\hspace{2em} \text{delimiter} \hspace{0.5em} : \hspace{0.5em} \text{string, optional}
\hspace{3em} \text{Separator for node labels}

\hspace{2em} \text{data} \hspace{0.5em} : \hspace{0.5em} \text{bool or list of keys}
\hspace{3em} \text{If False generate no edge data. If True use a dictionary representation of edge data. If a}
\hspace{3em} \text{list of keys use a list of data values corresponding to the keys.}

\textbf{Returns} \hspace{1em} \text{lines} \hspace{0.5em} : \hspace{0.5em} \text{string}
\hspace{2em} \text{Lines of data in adjlist format.}

\textbf{See also:}
write_adjlist, read_adjlist

\textbf{Examples}

\begin{verbatim}
>>> G = nx.lollipop_graph(4, 3)
>>> G[1][2]['weight'] = 3
>>> G[3][4]['capacity'] = 12
>>> for line in nx.generate_edgelist(G, data=False):
...     print(line)
 0 1
 0 2
 0 3
 1 2
 1 3
 2 3
 3 4
 4 5
 5 6

>>> for line in nx.generate_edgelist(G):
...     print(line)
 0 1 {'weight': 3}
 0 2 {}
 0 3 {}
 1 2 {'weight': 3}
 1 3 {}
 2 3 {}
 3 4 {'capacity': 12}
 4 5 {}
 5 6 {}

>>> for line in nx.generate_edgelist(G, data=['weight']):
...     print(line)
 0 1
 0 2
 0 3
 1 2 3
 1 3
\end{verbatim}
Parse lines of an edge list representation of a graph.

Returns  

G: NetworkX Graph:

The graph corresponding to lines

data: bool or list of (label,type) tuples

If False generate no edge data or if True use a dictionary representation of edge data or
a list tuples specifying dictionary key names and types for edge data.

create_using: NetworkX graph container, optional:

Use given NetworkX graph for holding nodes or edges.

nodetype: Python type, optional

Convert nodes to this type.

comments: string, optional

Marker for comment lines
delimiter: string, optional

Separator for node labels

create_using: NetworkX graph container:

Use given NetworkX graph for holding nodes or edges.

See also:
read_weighted_edgelist

Examples

Edgelist with no data:

```python
g = nx.parse_edgelist(lines, nodetype = int)
g.nodes()
g.edges()
```

Edgelist with data in Python dictionary representation:
```python
>>> lines = [
    "1 2 {'weight':3}",
    "2 3 {'weight':27}",
    "3 4 {'weight':3.0}"
]
>>> G = nx.parse_edgelist(lines, nodetype = int)
>>> G.nodes()
[1, 2, 3, 4]
>>> G.edges(data = True)
[(1, 2, {'weight': 3}), (2, 3, {'weight': 27}), (3, 4, {'weight': 3.0})]
```

Edgelist with data in a list:
```python
>>> lines = [
    "1 2 3",
    "2 3 27",
    "3 4 3.0"
]
>>> G = nx.parse_edgelist(lines, nodetype = int, data=(('weight',float),))
>>> G.nodes()
[1, 2, 3, 4]
>>> G.edges(data = True)
[(1, 2, {'weight': 3.0}), (2, 3, {'weight': 27.0}), (3, 4, {'weight': 3.0})]
```

## 9.4 GEXF

Read and write graphs in GEXF format.

GEXF (Graph Exchange XML Format) is a language for describing complex network structures, their associated data and dynamics.

This implementation does not support mixed graphs (directed and undirected edges together).

### 9.4.1 Format

GEXF is an XML format. See [http://gexf.net/format/schema.html](http://gexf.net/format/schema.html) for the specification and [http://gexf.net/format/basic.html](http://gexf.net/format/basic.html) for examples.

```
read_gexf(path[, node_type, relabel, version])  Read graph in GEXF format from path.
write_gexf(G, path[, encoding, prettyprint, ...]) Write G in GEXF format to path.
relabel_gexf_graph(G)  Relabel graph using “label” node keyword for node label.
```

### 9.4.2 read_gexf

```
read_gexf(path, node_type=None, relabel=False, version='1.1draft')  Read graph in GEXF format from path.
```

“GEXF (Graph Exchange XML Format) is a language for describing complex networks structures, their associated data and dynamics” [R296].

**Parameters**
- **path**: file or string
  - File or file name to write. File names ending in .gz or .bz2 will be compressed.
- **node_type**: Python type (default: None)
  - Convert node ids to this type if not None.
- **relabel**: bool (default: False)
If True relabel the nodes to use the GEXF node “label” attribute instead of the node “id” attribute as the NetworkX node label.

Returns graph: NetworkX graph:
If no parallel edges are found a Graph or DiGraph is returned. Otherwise a MultiGraph or MultiDiGraph is returned.

Notes
This implementation does not support mixed graphs (directed and undirected edges together).

References
[R296]

9.4.3 write_gexf

write_gexf (G, path, encoding='utf-8', prettyprint=True, version='1.1draft')
Write G in GEXF format to path.

“GEXF (Graph Exchange XML Format) is a language for describing complex networks structures, their associated data and dynamics” [R297].

Parameters
G : graph
A NetworkX graph

path : file or string
File or file name to write. File names ending in .gz or .bz2 will be compressed.

encoding : string (optional)
Encoding for text data.

prettyprint : bool (optional)
If True use line breaks and indenting in output XML.

Notes
This implementation does not support mixed graphs (directed and undirected edges together).

The node id attribute is set to be the string of the node label. If you want to specify an id use set it as node data, e.g. node[‘a’][‘id’]=1 to set the id of node ‘a’ to 1.

References
[R297]
Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_gexf(G, "test.gexf")
```

### 9.4.4 relabel_gexf_graph

relabel_gexf_graph(G)

Relabel graph using “label” node keyword for node label.

**Parameters**

- G : graph
  
  A NetworkX graph read from GEXF data

**Returns**

- H : graph
  
  A NetworkX graph with relabeled nodes

**Notes**

This function relabels the nodes in a NetworkX graph with the “label” attribute. It also handles relabeling the specific GEXF node attributes “parents”, and “pid”.

### 9.5 GML

Read graphs in GML format.

“GML, the G>raph Modelling Language, is our proposal for a portable file format for graphs. GML’s key features are portability, simple syntax, extensibility and flexibility. A GML file consists of a hierarchical key-value lists. Graphs can be annotated with arbitrary data structures. The idea for a common file format was born at the GD’95; this proposal is the outcome of many discussions. GML is the standard file format in the Graphlet graph editor system. It has been overtaken and adapted by several other systems for drawing graphs.”

See [http://www.infosun.fim.uni-passau.de/Graphlet/GML/gml-tr.html](http://www.infosun.fim.uni-passau.de/Graphlet/GML/gml-tr.html)

Requires pyParsing: [http://pyparsing.wikispaces.com/](http://pyparsing.wikispaces.com/)

#### 9.5.1 Format

See [http://www.infosun.fim.uni-passau.de/Graphlet/GML/gml-tr.html](http://www.infosun.fim.uni-passau.de/Graphlet/GML/gml-tr.html) for format specification.

**Example graphs in GML format:** [http://www-personal.umich.edu/~mejn/netdata/](http://www-personal.umich.edu/~mejn/netdata/)

<table>
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<tr>
<th>Function</th>
<th>Description</th>
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<td>Read graph in GML format from path.</td>
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</tr>
<tr>
<td>parse_gml</td>
<td>Parse GML graph from a string or iterable.</td>
</tr>
<tr>
<td>generate_gml</td>
<td>Generate a single entry of the graph G in GML format.</td>
</tr>
</tbody>
</table>

#### 9.5.2 read_gml

read_gml(path[, encoding, relabel])

Read graph in GML format from path.
Parameters  path  : filename or filehandle
The filename or filehandle to read from.

encoding  : string, optional
Text encoding.

relabel  : bool, optional
If True use the GML node label attribute for node names otherwise use the node id.

Returns  G  : MultiGraph or MultiDiGraph

Raises  ImportError  :
If the pyparsing module is not available.

See also:
write_gml, parse_gml

Notes

Requires pyparsing: http://pyparsing.wikispaces.com/

References

GML specification: http://www.infosun.fim.uni-passau.de/Graphlet/GML/gml-tr.html

Examples

>>> G=nx.path_graph(4)
>>> nx.write_gml(G,'test.gml')
>>> H=nx.read_gml('test.gml')

9.5.3  write_gml

write_gml (G, path)
Write the graph G in GML format to the file or file handle path.

Parameters  path  : filename or filehandle
The filename or filehandle to write. Filenames ending in .gz or.gz2 will be compressed.

See also:
read_gml, parse_gml

Notes

GML specifications indicate that the file should only use 7bit ASCII text encoding.iso8859-1 (latin-1).
This implementation does not support all Python data types as GML data. Nodes, node attributes, edge attributes,
and graph attributes must be either dictionaries or single stings or numbers. If they are not an attempt is made
to represent them as strings. For example, a list as edge data G[1][2][‘somedata’]=[1,2,3], will be represented
in the GML file as:
edge [ 
    source 1 
    target 2 
    somedata "[1, 2, 3]"
]

Examples

>>> G=nx.path_graph(4)
>>> nx.write_gml(G,"test.gml")

Filenames ending in .gz or .b2 will be compressed.
>>> nx.write_gml(G,"test.gml.gz")

9.5.4 parse_gml

parse_gml (lines, relabel=True)
Parse GML graph from a string or iterable.

Parameters
lines : string or iterable
Data in GML format.

relabel : bool, optional
If True use the GML node label attribute for node names otherwise use the node id.

Returns
G : MultiGraph or MultiDiGraph

Raises
ImportError :
If the pyparsing module is not available.

See also:
write_gml, read_gml

Notes
This stores nested GML attributes as dictionaries in the NetworkX graph, node, and edge attribute structures.

Requires pyparsing: http://pyparsing.wikispaces.com/

References
GML specification: http://www.infosun.fim.uni-passau.de/Graphlet/GML/gml-tr.html

9.5.5 generate_gml

generate_gml (G)
Generate a single entry of the graph G in GML format.

Parameters
G : NetworkX graph
Returns  lines: string :
    Lines in GML format.

Notes

This implementation does not support all Python data types as GML data. Nodes, node attributes, edge attributes, and graph attributes must be either dictionaries or single strings or numbers. If they are not an attempt is made to represent them as strings. For example, a list as edge data G[1][2]['somedata']=[1,2,3], will be represented in the GML file as:

data [  
    source 1  
    target 2  
    somedata "[1, 2, 3]"
]  

9.6 Pickle

Read and write NetworkX graphs as Python pickles.

“The pickle module implements a fundamental, but powerful algorithm for serializing and de-serializing a Python object structure. “Pickling” is the process whereby a Python object hierarchy is converted into a byte stream, and “unpickling” is the inverse operation, whereby a byte stream is converted back into an object hierarchy.”

Note that NetworkX graphs can contain any hashable Python object as node (not just integers and strings). For arbitrary data types it may be difficult to represent the data as text. In that case using Python pickles to store the graph data can be used.

9.6.1 Format

See http://docs.python.org/library/pickle.html

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<tr>
<th>read_gpickle(path)</th>
<th>Read graph object in Python pickle format.</th>
</tr>
</thead>
<tbody>
<tr>
<td>write_gpickle(G, path)</td>
<td>Write graph in Python pickle format.</td>
</tr>
</tbody>
</table>

9.6.2 read_gpickle

read_gpickle (path)
    Read graph object in Python pickle format.

Pickles are a serialized byte stream of a Python object [R298]. This format will preserve Python objects used as nodes or edges.

Parameters  path : file or string
    File or filename to write. Filenames ending in .gz or .bz2 will be uncompressed.

Returns  G : graph
    A NetworkX graph
Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_gpickle(G,"test.gpickle")
>>> G=nx.read_gpickle("test.gpickle")
```

9.6.3 write_gpickle

write_gpickle(\(G, path\))
Write graph in Python pickle format.

Pickles are a serialized byte stream of a Python object [R299]. This format will preserve Python objects used as nodes or edges.

Parameters

- **G**: graph
  A NetworkX graph
- **path**: file or string
  File or filename to write. Filenames ending in .gz or .bz2 will be compressed.

References

[R299]

Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_gpickle(G,"test.gpickle")
```

9.7 GraphML

Read and write graphs in GraphML format.

This implementation does not support mixed graphs (directed and undirected edges together), hyperedges, nested graphs, or ports.

“GraphML is a comprehensive and easy-to-use file format for graphs. It consists of a language core to describe the structural properties of a graph and a flexible extension mechanism to add application-specific data. Its main features include support of

- directed, undirected, and mixed graphs,
- hypergraphs,
- hierarchical graphs,
- graphical representations,
• references to external data,
• application-specific attribute data, and
• light-weight parsers.

Unlike many other file formats for graphs, GraphML does not use a custom syntax. Instead, it is based on XML and hence ideally suited as a common denominator for all kinds of services generating, archiving, or processing graphs.”

http://graphml.graphdrawing.org/

9.7.1 Format

GraphML is an XML format. See http://graphml.graphdrawing.org/specification.html for the specification and http://graphml.graphdrawing.org/primer/graphml-primer.html for examples.

| read_graphml(path[, node_type]) | Read graph in GraphML format from path. |
| write_graphml(G, path[, encoding, prettyprint]) | Write G in GraphML XML format to path |

9.7.2 read_graphml

read_graphml(path, node_type=<type 'str'>)
Read graph in GraphML format from path.

Parameters path : file or string
File or filename to write. Filenames ending in .gz or .bz2 will be compressed.

node_type: Python type (default: str) :
Convert node ids to this type

Returns graph: NetworkX graph :
If no parallel edges are found a Graph or DiGraph is returned. Otherwise a MultiGraph or MultiDiGraph is returned.

Notes

This implementation does not support mixed graphs (directed and undirected edges together), hypergraphs, nested graphs, or ports.

For multigraphs the GraphML edge “id” will be used as the edge key. If not specified then they “key” attribute will be used. If there is no “key” attribute a default NetworkX multigraph edge key will be provided.

Files with the yEd “yfiles” extension will can be read but the graphics information is discarded.

yEd compressed files (“file.graphmlz” extension) can be read by renaming the file to “file.graphml.gz”.

9.7.3 write_graphml

write_graphml(G, path, encoding='utf-8', prettyprint=True)
Write G in GraphML XML format to path.

Parameters G : graph
A networkx graph
**path**: file or string

File or filename to write. Filenames ending in .gz or .bz2 will be compressed.

**encoding**: string (optional)

Encoding for text data.

**prettyprint**: bool (optional)

If True use line breaks and indenting in output XML.

**Notes**

This implementation does not support mixed graphs (directed and undirected edges together) hyperedges, nested graphs, or ports.

**Examples**

```python
>>> G = nx.path_graph(4)
>>> nx.write_graphml(G, "test.graphml")
```

## 9.8 JSON

Generate and parse JSON serializable data for NetworkX graphs.

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<td>Return data in node-link format that is suitable for JSON serialization</td>
</tr>
<tr>
<td><code>node_link_graph(data[, directed, multigraph])</code></td>
<td>Return graph from node-link data format.</td>
</tr>
<tr>
<td><code>adjacency_data(G)</code></td>
<td>Return data in adjacency format that is suitable for JSON serialization</td>
</tr>
<tr>
<td><code>adjacency_graph(data[, directed, multigraph])</code></td>
<td>Return graph from adjacency data format.</td>
</tr>
<tr>
<td><code>tree_data(G, root)</code></td>
<td>Return data in tree format that is suitable for JSON serialization</td>
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<tr>
<td><code>dumps</code></td>
<td>Serialize obj to a JSON formatted str.</td>
</tr>
<tr>
<td><code>loads</code></td>
<td>Deserialize s (a str or unicode instance containing a JSON)</td>
</tr>
<tr>
<td><code>dump</code></td>
<td>Serialize obj as a JSON formatted stream to fp (a</td>
</tr>
<tr>
<td><code>load</code></td>
<td>Deserialize fp(a .read()-supporting file-like object containing)</td>
</tr>
</tbody>
</table>

### 9.8.1 node_link_data

**node_link_data**(G)

Return data in node-link format that is suitable for JSON serialization and use in Javascript documents.

**Parameters**  

- **G**: NetworkX graph

**Returns**  

- **data**: dict

A dictionary with node-link formatted data.

**See also:**

node_link_graph, adjacency_data, tree_data

---

9.8. JSON 391
Notes

Graph, node, and link attributes are stored in this format but keys for attributes must be strings if you want to serialize with JSON.

Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.Graph([(1,2)])
>>> data = json_graph.node_link_data(G)

To serialize with json
```nn
```python
>>> import json
>>> s = json.dumps(data)
```

9.8.2 node_link_graph

**node_link_graph** (*data, directed=False, multigraph=True*)

Return graph from node-link data format.

**Parameters**

- **data**: dict
  - node-link formatted graph data
- **directed**: bool
  - If True, and direction not specified in data, return a directed graph.
- **multigraph**: bool
  - If True, and multigraph not specified in data, return a multigraph.

**Returns**

- **G**: NetworkX graph
  - A NetworkX graph object

**See also:**

- node_link_data, adjacency_data, tree_data

Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.Graph([(1,2)])
>>> data = json_graph.node_link_data(G)
>>> H = json_graph.node_link_graph(data)
```

9.8.3 adjacency_data

**adjacency_data** (*G*)

Return data in adjacency format that is suitable for JSON serialization and use in Javascript documents.

**Parameters**

- **G**: NetworkX graph

**Returns**

- **data**: dict
A dictionary with node-link formatted data.

See also:

adjacency_graph, node_link_data, tree_data

Notes

Graph, node, and link attributes will be written when using this format but attribute keys must be strings if you want to serialize the resulting data with JSON.

Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.Graph([(1,2)])
>>> data = json_graph.adjacency_data(G)
```

To serialize with json

```python
>>> import json
>>> s = json.dumps(data)
```

9.8.4 adjacency_graph

`adjacency_graph (data, directed=False, multigraph=True)`

Return graph from adjacency data format.

Parameters

- `data` : dict
  
  Adjacency list formatted graph data

Returns

- `G` : NetworkX graph
  
  A NetworkX graph object

- `directed` : bool
  
  If True, and direction not specified in data, return a directed graph.

- `multigraph` : bool
  
  If True, and multigraph not specified in data, return a multigraph.

See also:

adjacency_graph, node_link_data, tree_data

Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.Graph([(1,2)])
>>> data = json_graph.adjacency_data(G)
>>> H = json_graph.adjacency_graph(data)
```
9.8.5 tree_data

tree_data (G, root)
Return data in tree format that is suitable for JSON serialization and use in Javascript documents.

Parameters  G : NetworkX graph
            G must be an oriented tree
            root : node
            The root of the tree

Returns  data : dict
            A dictionary with node-link formatted data.

See also:
    tree_graph, node_link_data, node_link_data

Notes

Node attributes are stored in this format but keys for attributes must be strings if you want to serialize with
JSON.

Graph and edge attributes are not stored.

Examples

>>> from networkx.readwrite import json_graph
>>> G = nx.DiGraph([(1,2)])
>>> data = json_graph.tree_data(G, root=1)

To serialize with json

>>> import json
>>> s = json.dumps(data)

9.8.6 tree_graph

tree_graph (data)
Return graph from tree data format.

Parameters  data : dict
            Tree formatted graph data

Returns  G : NetworkX DiGraph

See also:
    tree_graph, node_link_data, adjacency_data

Examples
>>> from networkx.readwrite import json_graph
>>> G = nx.DiGraph([(1,2)])
>>> data = json_graph.tree_data(G, root=1)
>>> H = json_graph.tree_graph(data)

9.8.7 dumps

dumps = <functools.partial object at 0x3739680>
Serialize obj to a JSON formatted str.

If skipkeys is false then dict keys that are not basic types (str, unicode, int, long, float, bool, None) will be skipped instead of raising a TypeError.

If ensure_ascii is false, then the return value will be a unicode instance subject to normal Python str to unicode coercion rules instead of being escaped to an ASCII str.

If check_circular is false, then the circular reference check for container types will be skipped and a circular reference will result in an OverflowError (or worse).

If allow_nan is false, then it will be a ValueError to serialize out of range float values (nan, inf, -inf) in strict compliance of the JSON specification, instead of using the JavaScript equivalents (NaN, Infinity, -Infinity).

If indent is a non-negative integer, then JSON array elements and object members will be pretty-printed with that indent level. An indent level of 0 will only insert newlines. None is the most compact representation.

If separators is an (item_separator, dict_separator) tuple then it will be used instead of the default (', ', ': ') separators. ('',', ':') is the most compact JSON representation.

encoding is the character encoding for str instances, default is UTF-8.

default(obj) is a function that should return a serializable version of obj or raise TypeError. The default simply raises TypeError.

To use a custom JSONEncoder subclass (e.g. one that overrides the .default() method to serialize additional types), specify it with the cls kwarg; otherwise JSONEncoder is used.

9.8.8 loads

loads = <functools.partial object at 0x37396d8>
Deserialize s (a str or unicode instance containing a JSON document) to a Python object.

If s is a str instance and is encoded with an ASCII based encoding other than utf-8 (e.g. latin-1) then an appropriate encoding name must be specified. Encodings that are not ASCII based (such as UCS-2) are not allowed and should be decoded to unicode first.

object_hook is an optional function that will be called with the result of any object literal decode (a dict). The return value of object_hook will be used instead of the dict. This feature can be used to implement custom decoders (e.g. JSON-RPC class hinting).

object_pairs_hook is an optional function that will be called with the result of any object literal decoded with an ordered list of pairs. The return value of object_pairs_hook will be used instead of the dict. This feature can be used to implement custom decoders that rely on the order that the key and value pairs are decoded (for example, collections.OrderedDict will remember the order of insertion). If object_hook is also defined, the object_pairs_hook takes priority.
parse_float, if specified, will be called with the string of every JSON float to be decoded. By default this is equivalent to float(num_str). This can be used to use another datatype or parser for JSON floats (e.g. decimal.Decimal).

parse_int, if specified, will be called with the string of every JSON int to be decoded. By default this is equivalent to int(num_str). This can be used to use another datatype or parser for JSON integers (e.g. float).

parse_constant, if specified, will be called with one of the following strings: -Infinity, Infinity, NaN, null, true, false. This can be used to raise an exception if invalid JSON numbers are encountered.

To use a custom JSONDecoder subclass, specify it with the cls kwarg; otherwise JSONDecoder is used.

9.8.9 dump

dump = <functools.partial object at 0x3739e10>
Serialize obj as a JSON formatted stream to fp (a .write()-supporting file-like object).

If skipkeys is true then dict keys that are not basic types (str, unicode, int, long, float, bool, None) will be skipped instead of raising a TypeError.

If ensure_ascii is false, then the some chunks written to fp may be unicode instances, subject to normal Python str to unicode coercion rules. Unless fp.write() explicitly understands unicode (as in codecs.getwriter()) this is likely to cause an error.

If check_circular is false, then the circular reference check for container types will be skipped and a circular reference will result in an OverflowError (or worse).

If allow_nan is false, then it will be a ValueError to serialize out of range float values (nan, inf, -inf) in strict compliance of the JSON specification, instead of using the JavaScript equivalents (NaN, Infinity, -Infinity).

If indent is a non-negative integer, then JSON array elements and object members will be pretty-printed with that indent level. An indent level of 0 will only insert newlines. None is the most compact representation.

If separators is an (item_separator, dict_separator) tuple then it will be used instead of the default (', ', ': ') separators. ('', '', '') is the most compact JSON representation.

encoding is the character encoding for str instances, default is UTF-8.

default(obj) is a function that should return a serializable version of obj or raise TypeError. The default simply raises TypeError.

To use a custom JSONEncoder subclass (e.g. one that overrides the .default() method to serialize additional types), specify it with the cls kwarg; otherwise JSONEncoder is used.

9.8.10 load

load = <functools.partial object at 0x3739e68>
Deserialize fp (a .read()-supporting file-like object containing a JSON document) to a Python object.

If the contents of fp is encoded with an ASCII based encoding other than utf-8 (e.g. latin-1), then an appropriate encoding name must be specified. Encodings that are not ASCII based (such as UCS-2) are not allowed, and should be wrapped with codecs.getreader(fp) (encoding), or simply decoded to a unicode object and passed to loads()

object_hook is an optional function that will be called with the result of any object literal decode (a dict). The return value of object_hook will be used instead of the dict. This feature can be used to implement custom decoders (e.g. JSON-RPC class hinting).
object_pairs_hook is an optional function that will be called with the result of any object literal decoded with an ordered list of pairs. The return value of object_pairs_hook will be used instead of the dict. This feature can be used to implement custom decoders that rely on the order that the key and value pairs are decoded (for example, collections.OrderedDict will remember the order of insertion). If object_hook is also defined, the object_pairs_hook takes priority.

To use a custom JSONDecoder subclass, specify it with the cls kwarg; otherwise JSONDecoder is used.

## 9.9 LEDA

Read graphs in LEDA format.

LEDA is a C++ class library for efficient data types and algorithms.

### 9.9.1 Format

See [http://www.algorithmic-solutions.info/leda_guide/graphs/leda_native_graph_fileformat.html](http://www.algorithmic-solutions.info/leda_guide/graphs/leda_native_graph_fileformat.html)

| read_lleda(path[, encoding]) | Read graph in LEDA format from path. |
| parse_lleda(lines)           | Read graph in LEDA format from string or iterable. |

### 9.9.2 read_lleda

read_lleda(path, encoding='UTF-8')

Read graph in LEDA format from path.

**Parameters**

- path : file or string
  
  File or filename to read. Filenames ending in .gz or .bz2 will be uncompressed.

**Returns**

G : NetworkX graph

**References**

[R301]

**Examples**

G=nx.read_lleda(‘file.leda’)

### 9.9.3 parse_lleda

parse_lleda(lines)

Read graph in LEDA format from string or iterable.

**Parameters**

- lines : string or iterable

  Data in LEDA format.

**Returns**

G : NetworkX graph
References

[R300]

Examples

G=nx.parse_leda(string)

9.10 YAML

Read and write NetworkX graphs in YAML format.

“YAML is a data serialization format designed for human readability and interaction with scripting languages.” See http://www.yaml.org for documentation.

9.10.1 Format

http://pyyaml.org/wiki/PyYAML

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<td>Write graph G in YAML format to path.</td>
</tr>
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9.10.2 read_yaml

read_yaml(path)

Read graph in YAML format from path.

YAML is a data serialization format designed for human readability and interaction with scripting languages [R304].

Parameters path : file or string

File or filename to read. Filenames ending in .gz or .bz2 will be uncompressed.

Returns G : NetworkX graph

References

[R304]

Examples

>>> G=nx.path_graph(4)
>>> nx.write_yaml(G,‘test.yaml’)   
>>> G=nx.read_yaml(‘test.yaml’)
9.10.3 **write_yaml**

**write_yaml** *(G, path, encoding='UTF-8', **kwds)*

Write graph G in YAML format to path.

YAML is a data serialization format designed for human readability and interaction with scripting languages [R305].

**Parameters**

- **G**: graph
  A NetworkX graph
- **path**: file or string
  File or filename to write. Filenames ending in .gz or .bz2 will be compressed.
- **encoding**: string, optional
  Specify which encoding to use when writing file.

**References**

[R305]

**Examples**

```python
>>> G=nx.path_graph(4)
>>> nx.write_yaml(G,'test.yaml')
```

## 9.11 SparseGraph6

Read graphs in graph6 and sparse6 format.

### 9.11.1 Format

“graph6 and sparse6 are formats for storing undirected graphs in a compact manner, using only printable ASCII characters. Files in these formats have text type and contain one line per graph.” [http://cs.anu.edu.au/~bdm/data/formats.html](http://cs.anu.edu.au/~bdm/data/formats.html)


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### 9.11.2 **read_graph6**

**read_graph6**(path)

Read simple undirected graphs in graph6 format from path.
Returns a single Graph.

9.11.3 parse_graph6

parse_graph6 (str)
Read a simple undirected graph in graph6 format from string.
Returns a single Graph.

9.11.4 read_graph6_list

read_graph6_list (path)
Read simple undirected graphs in graph6 format from path.
Returns a list of Graphs, one for each line in file.

9.11.5 read_sparse6

read_sparse6 (path)
Read simple undirected graphs in sparse6 format from path.
Returns a single MultiGraph.

9.11.6 parse_sparse6

parse_sparse6 (string)
Read undirected graph in sparse6 format from string.
Returns a MultiGraph.

9.11.7 read_sparse6_list

read_sparse6_list (path)
Read undirected graphs in sparse6 format from path.
Returns a list of MultiGraphs, one for each line in file.

9.12 Pajek

Read graphs in Pajek format.
This implementation handles directed and undirected graphs including those with self loops and parallel edges.

9.12.1 Format


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9.12.2 read_pajek

**read_pajek**(path, encoding='UTF-8')
Read graph in Pajek format from path.

Parameters  
**path** : file or string
File or filename to write. Filenames ending in .gz or .bz2 will be uncompressed.

Returns  
**G** : NetworkX MultiGraph or MultiDiGraph.

References


Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_pajek(G, "test.net")
>>> G=nx.read_pajek("test.net")
```

To create a Graph instead of a MultiGraph use

```python
>>> G1=nx.Graph(G)
```

9.12.3 write_pajek

**write_pajek**(G, path, encoding='UTF-8')
Write graph in Pajek format to path.

Parameters  
**G** : graph
A Networkx graph
**path** : file or string
File or filename to write. Filenames ending in .gz or .bz2 will be compressed.

References


Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_pajek(G, "test.net")
```
9.12.4 parse_pajek

parse_pajek (lines)
Parse Pajek format graph from string or iterable.

Parameters  lines : string or iterable
   Data in Pajek format.

Returns  G : NetworkX graph

See also:
    read_pajek

9.13 GIS Shapefile

Generates a networkx.DiGraph from point and line shapefiles.

“The Esri Shapefile or simply a shapefile is a popular geospatial vector data format for geographic information systems software. It is developed and regulated by Esri as a (mostly) open specification for data interoperability among Esri and other software products.” See http://en.wikipedia.org/wiki/Shapefile for additional information.

    read_shp(path)  Generates a networkx.DiGraph from shapefiles. Point geometries are
    write_shp(G, outdir)  Writes a networkx.DiGraph to two shapefiles, edges and nodes.

9.13.1 read_shp

read_shp (path)
Generates a networkx.DiGraph from shapefiles. Point geometries are translated into nodes, lines into edges. Coordinate tuples are used as keys. Attributes are preserved, line geometries are simplified into start and end coordinates. Accepts a single shapefile or directory of many shapefiles.

“The Esri Shapefile or simply a shapefile is a popular geospatial vector data format for geographic information systems software [R302].”

Parameters  path : file or string
       File, directory, or filename to read.

Returns  G : NetworkX graph

References

[R302]

Examples

    >>> G=nx.read_shp('test.shp')
9.13.2 write_shp

**write_shp**(*G*, *outdir*)

Writes a networkx.DiGraph to two shapefiles, edges and nodes. Nodes and edges are expected to have a Well Known Binary (Wkb) or Well Known Text (Wkt) key in order to generate geometries. Also acceptable are nodes with a numeric tuple key (x,y).

“The Esri Shapefile or simply a shapefile is a popular geospatial vector data format for geographic information systems software [R303].”

**Parameters**

- **outdir** : directory path
  
  Output directory for the two shapefiles.

**Returns** None :

**References**

[R303]

**Examples**

```python
nx.write_shp(digraph, '/shapefiles')  # doctest +SKIP
```
10.1 Matplotlib

Draw networks with matplotlib.

10.1.1 See Also

matplotlib: http://matplotlib.sourceforge.net/
pygraphviz: http://networkx.lanl.gov/pygraphviz/

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10.1.2 draw

**draw** *(G, pos=None, ax=None, hold=None, **kwds)*

Draw the graph G with Matplotlib.

Draw the graph as a simple representation with no node labels or edge labels and using the full Matplotlib figure area and no axis labels by default. See draw_networkx() for more full-featured drawing that allows title, axis labels etc.

**Parameters**

- **G**: graph
  - A networkx graph
- **pos**: dictionary, optional
  - A dictionary with nodes as keys and positions as values. If not specified a spring layout positioning will be computed. See networkx.layout for functions that compute node positions.
ax : Matplotlib Axes object, optional

Draw the graph in specified Matplotlib axes.

hold : bool, optional

Set the Matplotlib hold state. If True subsequent draw commands will be added to the current axes.

**kwds : optional keywords

See networkx.draw_networkx() for a description of optional keywords.

See also:
draw_networkx, draw_networkx_nodes, draw_networkx_edges, draw_networkx_labels, draw_networkx_edge_labels

Notes

This function has the same name as pylab.draw and pyplot.draw so beware when using

```python
>>> from networkx import *
```

since you might overwrite the pylab.draw function.

With pyplot use

```python
>>> import matplotlib.pyplot as plt
>>> import networkx as nx

>>> G=nx.dodecahedral_graph()

>>> nx.draw(G)  # networkx draw()
>>> plt.draw()  # pyplot draw()
```

Also see the NetworkX drawing examples at http://networkx.lanl.gov/gallery.html

Examples

```python
>>> G=nx.dodecahedral_graph()
>>> nx.draw(G)
>>> nx.draw(G,pos=nx.spring_layout(G))  # use spring layout
```

10.1.3 draw_networkx

draw_networkx(G, pos=None, with_labels=True, **kwds)

Draw the graph G using Matplotlib.

Draw the graph with Matplotlib with options for node positions, labeling, titles, and many other drawing features. See draw() for simple drawing without labels or axes.

Parameters

- G : graph

  A networkx graph

- pos : dictionary, optional

  A dictionary with nodes as keys and positions as values. If not specified a spring layout positioning will be computed. See networkx.layout for functions that compute node positions.
with_labels: bool, optional (default=True)
    Set to True to draw labels on the nodes.

ax: Matplotlib Axes object, optional
    Draw the graph in the specified Matplotlib axes.

nodelist: list, optional (default G.nodes())
    Draw only specified nodes

edgelist: list, optional (default=G.edges())
    Draw only specified edges

node_size: scalar or array, optional (default=300)
    Size of nodes. If an array is specified it must be the same length as nodelist.

node_color: color string, or array of floats, (default=’r’)
    Node color. Can be a single color format string, or a sequence of colors with the same
    length as nodelist. If numeric values are specified they will be mapped to colors using
    the cmap and vmin,vmax parameters. See matplotlib.scatter for more details.

node_shape: string, optional (default=’o’)
    The shape of the node. Specification is as matplotlib.scatter marker, one of
    ‘so^>v<dph8’.

alpha: float, optional (default=1.0)
    The node transparency

cmap: Matplotlib colormap, optional (default=None)
    Colormap for mapping intensities of nodes

vmin,vmax: float, optional (default=None)
    Minimum and maximum for node colormap scaling

linewidths: [None | scalar | sequence]
    Line width of symbol border (default =1.0)

width: float, optional (default=1.0)
    Line width of edges

edge_color: color string, or array of floats (default=’r’)
    Edge color. Can be a single color format string, or a sequence of colors with the same
    length as edgelist. If numeric values are specified they will be mapped to colors using
    the edge_cmap and edge_vmin,edge_vmax parameters.

edge_cmap: Matplotlib colormap, optional (default=None)
    Colormap for mapping intensities of edges

edge_vmin,edge_vmax: floats, optional (default=None)
    Minimum and maximum for edge colormap scaling

style: string, optional (default=’solid’)
    Edge line style (solid|dashed|dotted,dashdot)

labels: dictionary, optional (default=None)
Node labels in a dictionary keyed by node of text labels

**font_size**: int, optional (default=12)
Font size for text labels

**font_color**: string, optional (default='k' black)
Font color string

**font_weight**: string, optional (default='normal')
Font weight

**font_family**: string, optional (default='sans-serif')
Font family

**label**: string, optional
Label for graph legend

See also:
draw, draw_networkx_nodes, draw_networkx_edges, draw_networkx_labels, draw_networkx_edge_labels

Examples

```python
g=nx.dodecahedral_graph()
>>> nx.draw(G)
>>> nx.draw(G,pos=nx.spring_layout(G))  # use spring layout

>>> import matplotlib.pyplot as plt
>>> limits=plt.axis('off')  # turn of axis
```

Also see the NetworkX drawing examples at http://networkx.lanl.gov/gallery.html

### 10.1.4 draw_networkx_nodes

draw_networkx_nodes (G, pos, nodelist=None, node_size=300, node_color='r', node_shape='o', alpha=1.0, cmap=None, vmin=None, vmax=None, ax=None, linewidths=None, label=None, **kwds)

draw the nodes of the graph G.

This draws only the nodes of the graph G.

**Parameters**

- **G**: graph
  - A networkx graph
- **pos**: dictionary
  - A dictionary with nodes as keys and positions as values. If not specified a spring layout positioning will be computed. See networkx.layout for functions that compute node positions.
- **ax**: Matplotlib Axes object, optional
  - Draw the graph in the specified Matplotlib axes.
- **nodelist**: list, optional

Draw only specified nodes (default G.nodes())

**node_size**: scalar or array

Size of nodes (default=300). If an array is specified it must be the same length as nodelist.

**node_color**: color string, or array of floats

Node color. Can be a single color format string (default='r'), or a sequence of colors with the same length as nodelist. If numeric values are specified they will be mapped to colors using the cmap and vmin,vmax parameters. See matplotlib.scatter for more details.

**node_shape**: string

The shape of the node. Specification is as matplotlib.scatter marker, one of 'so^>v<dph8' (default='o').

**alpha**: float

The node transparency (default=1.0)

**cmap**: Matplotlib colormap

Colormap for mapping intensities of nodes (default=None)

**vmin,vmax**: floats

Minimum and maximum for node colormap scaling (default=None)

**linewidths**: [None | scalar | sequence]

Line width of symbol border (default =1.0)

**label**: [None| string]

Label for legend

See also:
draw, draw_networkx, draw_networkx_edges, draw_networkx_labels, draw_networkx_edge_labels

Examples

```python
>>> G=nx.dodecahedral_graph()
```

Also see the NetworkX drawing examples at [http://networkx.lanl.gov/gallery.html](http://networkx.lanl.gov/gallery.html)

### 10.1.5 draw_networkx_edges

**draw_networkx_edges** *(G, pos, edgelist=None, width=1.0, edge_color='k', style='solid', alpha=None, edge_cmap=None, edge_vmin=None, edge_vmax=None, ax=None, arrows=True, label=None, **kwds)*

Draw the edges of the graph G.

This draws only the edges of the graph G.

**Parameters**

G : graph

A networkx graph
pos : dictionary
A dictionary with nodes as keys and positions as values. If not specified a spring layout positioning will be computed. See networkx.layout for functions that compute node positions.
edgelist : collection of edge tuples
Draw only specified edges (default=G.edges())
width : float
Line width of edges (default=1.0)
edge_color : color string, or array of floats
Edge color. Can be a single color format string (default='r'), or a sequence of colors with the same length as edgelist. If numeric values are specified they will be mapped to colors using the edge_cmap and edge_vmin,edge_vmax parameters.
style : string
Edge line style (default='solid') (solid|dashed|dotted,dashdot)
alpha : float
The edge transparency (default=1.0)
edge_cmap : Matplotlib colormap
Colormap for mapping intensities of edges (default=None)
edge_vmin,edge_vmax : floats
Minimum and maximum for edge colormap scaling (default=None)
ax : Matplotlib Axes object, optional
Draw the graph in the specified Matplotlib axes.
arrows : bool, optional (default=True)
For directed graphs, if True draw arrowheads.
label : [None| string]
Label for legend

See also:
draw, draw_networkx, draw_networkx_nodes, draw_networkx_labels, draw_networkx_edge_labels

Notes
For directed graphs, “arrows” (actually just thicker stubs) are drawn at the head end. Arrows can be turned off with keyword arrows=False. Yes, it is ugly but drawing proper arrows with Matplotlib this way is tricky.

Examples
>>> G=nx.dodecahedral_graph()
>>> edges=nx.draw_networkx_edges(G,pos=nx.spring_layout(G))

Also see the NetworkX drawing examples at http://networkx.lanl.gov/gallery.html
10.1.6 draw_networkx_labels

**draw_networkx_labels** *(G, pos, labels=None, font_size=12, font_color='k', font_family='sans-serif', font_weight='normal', alpha=1.0, ax=None, **kwds)*

Draw node labels on the graph G.

**Parameters**

- **G**: graph
  - A networkx graph
- **pos**: dictionary, optional
  - A dictionary with nodes as keys and positions as values. If not specified a spring layout positioning will be computed. See networkx.layout for functions that compute node positions.
- **labels**: dictionary, optional (default=None)
  - Node labels in a dictionary keyed by node of text labels
- **font_size**: int
  - Font size for text labels (default=12)
- **font_color**: string
  - Font color string (default='k' black)
- **font_family**: string
  - Font family (default='sans-serif')
- **font_weight**: string
  - Font weight (default='normal')
- **alpha**: float
  - The text transparency (default=1.0)
- **ax**: Matplotlib Axes object, optional
  - Draw the graph in the specified Matplotlib axes.

**See also:**

draw, draw_networkx, draw_networkx_nodes, draw_networkx_edges, draw_networkx_edge_labels

**Examples**

```python
>>> G=nx.dodecahedral_graph()
>>> labels=nx.draw_networkx_labels(G,pos=nx.spring_layout(G))
```

Also see the NetworkX drawing examples at http://networkx.lanl.gov/gallery.html

10.1.7 draw_networkx_edge_labels

**draw_networkx_edge_labels** *(G, pos, edge_labels=None, label_pos=0.5, font_size=10, font_color='k', font_family='sans-serif', font_weight='normal', alpha=1.0, bbox=None, ax=None, rotate=True, **kwds)*

Draw edge labels.
Parameters

**G** : graph
A networkx graph

**pos** : dictionary, optional
A dictionary with nodes as keys and positions as values. If not specified a spring layout positioning will be computed. See networkx.layout for functions that compute node positions.

**ax** : Matplotlib Axes object, optional
Draw the graph in the specified Matplotlib axes.

**alpha** : float
The text transparency (default=1.0)

**edge_labels** : dictionary
Edge labels in a dictionary keyed by edge two-tuple of text labels (default=None). Only labels for the keys in the dictionary are drawn.

**label_pos** : float
Position of edge label along edge (0=head, 0.5=center, 1=tail)

**font_size** : int
Font size for text labels (default=12)

**font_color** : string
Font color string (default='k' black)

**font_weight** : string
Font weight (default='normal')

**font_family** : string
Font family (default='sans-serif')

**bbox** : Matplotlib bbox
Specify text box shape and colors.

**clip_on** : bool
Turn on clipping at axis boundaries (default=True)

See also:
draw, draw_networkx, draw_networkx_nodes, draw_networkx_edges, draw_networkx_labels

Examples

>>> G=nx.dodecahedral_graph()

>>> edge_labels=nx.draw_networkx_edge_labels(G,pos=nx.spring_layout(G))

Also see the NetworkX drawing examples at http://networkx.lanl.gov/gallery.html
## 10.1.8 draw_circular

draw_circular\( (G, **kwargs) \)
Draw the graph G with a circular layout.

## 10.1.9 draw_random

draw_random\( (G, **kwargs) \)
Draw the graph G with a random layout.

## 10.1.10 draw_spectral

draw_spectral\( (G, **kwargs) \)
Draw the graph G with a spectral layout.

## 10.1.11 draw_spring

draw_spring\( (G, **kwargs) \)
Draw the graph G with a spring layout.

## 10.1.12 draw_shell

draw_shell\( (G, **kwargs) \)
Draw networkx graph with shell layout.

## 10.1.13 draw_graphviz

draw_graphviz\( (G, \text{prog}='neato', **kwargs) \)
Draw networkx graph with graphviz layout.

### 10.2 Graphviz AGraph (dot)

Interface to pygraphviz AGraph class.

#### 10.2.1 Examples

```python
>>> G=nx.complete_graph(5)
>>> A=nx.to_agraph(G)
>>> H=nx.from_agraph(A)
```

#### 10.2.2 See Also

Pygraphviz: [http://networkx.lanl.gov/pygraphviz](http://networkx.lanl.gov/pygraphviz)

#### from_agraph\( (A[, \text{create_using}]) \)
Return a NetworkX Graph or DiGraph from a PyGraphviz graph.
Table 10.2 – continued from previous page

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<th>Function</th>
<th>Description</th>
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<td>Return a pygraphviz graph from a NetworkX graph N.</td>
</tr>
<tr>
<td><code>write_dot(G, path)</code></td>
<td>Write NetworkX graph G to Graphviz dot format on path.</td>
</tr>
<tr>
<td><code>read_dot(path)</code></td>
<td>Return a NetworkX graph from a dot file on path.</td>
</tr>
<tr>
<td><code>graphviz_layout(G[, prog, root, args])</code></td>
<td>Create node positions for G using Graphviz.</td>
</tr>
<tr>
<td><code>pygraphviz_layout(G[, prog, root, args])</code></td>
<td>Create node positions for G using Graphviz.</td>
</tr>
</tbody>
</table>

### 10.2.3 from_agraph

**from_agraph** *(A, create_using=None)*

Return a NetworkX Graph or DiGraph from a PyGraphviz graph.

**Parameters**

- **A**: PyGraphviz AGraph
  - A graph created with PyGraphviz
- **create_using**: NetworkX graph class instance
  - The output is created using the given graph class instance

**Notes**

The Graph G will have a dictionary `G.graph_attr` containing the default graphviz attributes for graphs, nodes and edges.

Default node attributes will be in the dictionary `G.node_attr` which is keyed by node.

Edge attributes will be returned as edge data in G. With `edge_attr=False` the edge data will be the Graphviz edge weight attribute or the value 1 if no edge weight attribute is found.

**Examples**

```python
>>> K5=nx.complete_graph(5)
>>> A=nx.to_agraph(K5)
>>> G=nx.from_agraph(A)
>>> G=nx.from_agraph(A)
```

### 10.2.4 to_agraph

**to_agraph** *(N)*

Return a pygraphviz graph from a NetworkX graph N.

**Parameters**

- **N**: NetworkX graph
  - A graph created with NetworkX

**Notes**

If N has a dict `N.graph_attr` an attempt will be made first to copy properties attached to the graph (see from_agraph) and then updated with the calling arguments if any.
Examples

```python
>>> K5=nx.complete_graph(5)
```
```python
>>> A=nx.to_agraph(K5)
```

### 10.2.5 write_dot

**write_dot** *(G, path)*
Write NetworkX graph G to Graphviz dot format on path.

**Parameters**
- **G**: graph
  A networkx graph
- **path**: filename
  Filename or file handle to write

### 10.2.6 read_dot

**read_dot** *(path)*
Return a NetworkX graph from a dot file on path.

**Parameters**
- **path**: file or string
  File name or file handle to read.

### 10.2.7 graphviz_layout

**graphviz_layout** *(G, prog='neato', root=None, args='')*
Create node positions for G using Graphviz.

**Parameters**
- **G**: NetworkX graph
  A graph created with NetworkX
- **prog**: string
  Name of Graphviz layout program
- **root**: string, optional
  Root node for twopi layout
- **args**: string, optional
  Extra arguments to Graphviz layout program

**Returns**
- dictionary
  Dictionary of x,y, positions keyed by node.

**Notes**
This is a wrapper for pygraphviz_layout.
Examples

>>> G=nx.petersen_graph()
>>> pos=nx.graphviz_layout(G)
>>> pos=nx.graphviz_layout(G,prog='dot')

10.2.8 pygraphviz_layout

pygraphviz_layout(G, prog='neato', root=None, args='')
Create node positions for G using Graphviz.

Parameters

- **G**: NetworkX graph
  - A graph created with NetworkX
- **prog**: string
  - Name of Graphviz layout program
- **root**: string, optional
  - Root node for twopi layout
- **args**: string, optional
  - Extra arguments to Graphviz layout program

Returns

- dictionary
  - Dictionary of x,y, positions keyed by node.

Examples

>>> G=nx.petersen_graph()
>>> pos=nx.graphviz_layout(G)
>>> pos=nx.graphviz_layout(G,prog='dot')

10.3 Graphviz with pydot

Import and export NetworkX graphs in Graphviz dot format using pydot.
Either this module or nx_pygraphviz can be used to interface with graphviz.

10.3.1 See Also


<table>
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<tr>
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<tbody>
<tr>
<td>from_pydot(P)</td>
<td>Return a NetworkX graph from a Pydot graph.</td>
</tr>
<tr>
<td>to_pydot(N[, strict])</td>
<td>Return a pydot graph from a NetworkX graph N.</td>
</tr>
<tr>
<td>write_dot(G, path)</td>
<td>Write NetworkX graph G to Graphviz dot format on path.</td>
</tr>
<tr>
<td>read_dot(path)</td>
<td>Return a NetworkX MultiGraph or MultiDiGraph from a dot file on path.</td>
</tr>
<tr>
<td>graphviz_layout(G[, prog, root])</td>
<td>Create node positions using Pydot and Graphviz.</td>
</tr>
<tr>
<td>pydot_layout(G[, prog, root])</td>
<td>Create node positions using Pydot and Graphviz.</td>
</tr>
</tbody>
</table>
10.3.2 from_pydot

from_pydot(P)
Return a NetworkX graph from a Pydot graph.

Parameters P : Pydot graph
A graph created with Pydot

Returns G : NetworkX multigraph
A MultiGraph or MultiDiGraph.

Examples

>>> K5=nx.complete_graph(5)
>>> A=nx.to_pydot(K5)
>>> G=nx.from_pydot(A)  # return MultiGraph
>>> G=nx.Graph(nx.from_pydot(A))  # make a Graph instead of MultiGraph

10.3.3 to_pydot

to_pydot(N, strict=True)
Return a pydot graph from a NetworkX graph N.

Parameters N : NetworkX graph
A graph created with NetworkX

Examples

>>> K5=nx.complete_graph(5)
>>> P=nx.to_pydot(K5)

10.3.4 write_dot

write_dot(G, path)
Write NetworkX graph G to Graphviz dot format on path.

Path can be a string or a file handle.

10.3.5 read_dot

read_dot(path)
Return a NetworkX MultiGraph or MultiDiGraph from a dot file on path.

Parameters path : filename or file handle

Returns G : NetworkX multigraph
A MultiGraph or MultiDiGraph.
Notes

Use G=nx.Graph(nx.read_dot(path)) to return a Graph instead of a MultiGraph.

10.3.6 graphviz_layout

graphviz_layout(G, prog='neato', root=None, **kwds)
Create node positions using Pydot and Graphviz.
Returns a dictionary of positions keyed by node.

Notes

This is a wrapper for pydot_layout.

Examples

```python
>>> G=nx.complete_graph(4)
>>> pos=nx.graphviz_layout(G)
>>> pos=nx.graphviz_layout(G,prog='dot')
```

10.3.7 pydot_layout

pydot_layout(G, prog='neato', root=None, **kwds)
Create node positions using Pydot and Graphviz.
Returns a dictionary of positions keyed by node.

Examples

```python
>>> G=nx.complete_graph(4)
>>> pos=nx.pydot_layout(G)
>>> pos=nx.pydot_layout(G,prog='dot')
```

10.4 Graph Layout

Node positioning algorithms for graph drawing.

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<tr>
<th>Function</th>
<th>Description</th>
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<tbody>
<tr>
<td>circular_layout(G[, dim, scale])</td>
<td>Position nodes on a circle.</td>
</tr>
<tr>
<td>random_layout(G[, dim])</td>
<td>Position nodes uniformly at random in the unit square.</td>
</tr>
<tr>
<td>shell_layout(G[, nlist, dim, scale])</td>
<td>Position nodes in concentric circles.</td>
</tr>
<tr>
<td>spring_layout(G[, dim, k, pos, fixed, ...])</td>
<td>Position nodes using Fruchterman-Reingold force-directed algorithm.</td>
</tr>
<tr>
<td>spectral_layout(G[, dim, weight, scale])</td>
<td>Position nodes using the eigenvectors of the graph Laplacian.</td>
</tr>
</tbody>
</table>
10.4.1 circular_layout

circular_layout(G, dim=2, scale=1)

Position nodes on a circle.

Parameters

G : NetworkX graph

dim : int
    Dimension of layout, currently only dim=2 is supported

scale : float
    Scale factor for positions

Returns

dict :
    A dictionary of positions keyed by node

Notes

This algorithm currently only works in two dimensions and does not try to minimize edge crossings.

Examples

>>> G=nx.path_graph(4)
>>> pos=nx.circular_layout(G)

10.4.2 random_layout

random_layout(G, dim=2)

Position nodes uniformly at random in the unit square.

For every node, a position is generated by choosing each of dim coordinates uniformly at random on the interval [0.0, 1.0).

NumPy (http://scipy.org) is required for this function.

Parameters

G : NetworkX graph
    A position will be assigned to every node in G.

dim : int
    Dimension of layout.

Returns

dict :
    A dictionary of positions keyed by node

Examples

>>> G = nx.lollipop_graph(4, 3)
>>> pos = nx.random_layout(G)
10.4.3 shell_layout

**shell_layout** *(G, nlist=None, dim=2, scale=1)*

Position nodes in concentric circles.

**Parameters**

- **G**: NetworkX graph
  - **nlist**: list of lists
    - List of node lists for each shell.
  - **dim**: int
    - Dimension of layout, currently only dim=2 is supported
  - **scale**: float
    - Scale factor for positions

**Returns**

A dictionary of positions keyed by node

**Notes**

This algorithm currently only works in two dimensions and does not try to minimize edge crossings.

**Examples**

```python
>>> G=nx.path_graph(4)
>>> shells=[[0],[1,2,3]]
>>> pos=nx.shell_layout(G,shells)
```

10.4.4 spring_layout

**spring_layout** *(G, dim=2, k=None, pos=None, fixed=None, iterations=50, weight='weight', scale=1.0)*

Position nodes using Fruchterman-Reingold force-directed algorithm.

**Parameters**

- **G**: NetworkX graph
  - **dim**: int
    - Dimension of layout
  - **k**: float (default=None)
    - Optimal distance between nodes. If None the distance is set to 1/sqrt(n) where n is the number of nodes. Increase this value to move nodes farther apart.
  - **pos**: dict or None optional (default=None)
    - Initial positions for nodes as a dictionary with node as keys and values as a list or tuple. If None, then nuse random initial positions.
  - **fixed**: list or None optional (default=None)
    - Nodes to keep fixed at initial position.
  - **iterations**: int optional (default=50)
    - Number of iterations of spring-force relaxation
weight : string or None optional (default='weight')

The edge attribute that holds the numerical value used for the edge weight. If None, then all edge weights are 1.

scale : float (default=1.0)

Scale factor for positions. The nodes are positioned in a box of size [0,scale] x [0,scale].

Returns dict :

A dictionary of positions keyed by node

Examples

```python
>>> G=nx.path_graph(4)
>>> pos=nx.spring_layout(G)
```

# The same using longer function name >>> pos=nx.fruchterman_reingold_layout(G)

10.4.5 spectral_layout

spectral_layout (G, dim=2, weight='weight', scale=1)

Position nodes using the eigenvectors of the graph Laplacian.

Parameters G : NetworkX graph
dim : int

Dimension of layout

weight : string or None optional (default='weight')

The edge attribute that holds the numerical value used for the edge weight. If None, then all edge weights are 1.
scale : float

Scale factor for positions

Returns dict :

A dictionary of positions keyed by node

Notes

Directed graphs will be considered as undirected graphs when positioning the nodes.

For larger graphs (>500 nodes) this will use the SciPy sparse eigenvalue solver (ARPACK).

Examples

```python
>>> G=nx.path_graph(4)
>>> pos=nx.spectral_layout(G)
```
Base exceptions and errors for NetworkX.

**class NetworkXException**
Base class for exceptions in NetworkX.

**class NetworkXError**
Exception for a serious error in NetworkX

**class NetworkXPointlessConcept**

**class NetworkXAlgorithmError**
Exception for unexpected termination of algorithms.

**class NetworkXUnfeasible**
Exception raised by algorithms trying to solve a problem instance that has no feasible solution.

**class NetworkXNoPath**
Exception for algorithms that should return a path when running on graphs where such a path does not exist.

**class NetworkXUnbounded**
Exception raised by algorithms trying to solve a maximization or a minimization problem instance that is unbounded.
12.1 Helper functions

Miscellaneous Helpers for NetworkX.

These are not imported into the base networkx namespace but can be accessed, for example, as

```python
>>> import networkx
```

```python
>>> networkx.utils.is_string_like('spam')
True
```

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
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<tr>
<td><code>is_string_like(obj)</code></td>
<td>Check if obj is string.</td>
</tr>
<tr>
<td><code>flatten(obj, result=None)</code></td>
<td>Return flattened version of (possibly nested) iterable object.</td>
</tr>
<tr>
<td><code>iterable(obj)</code></td>
<td>Return True if obj is iterable with a well-defined len().</td>
</tr>
<tr>
<td><code>is_list_of_ints(intlist)</code></td>
<td>Return True if list is a list of ints.</td>
</tr>
<tr>
<td><code>make_str(t)</code></td>
<td>Return the string representation of t.</td>
</tr>
<tr>
<td><code>cumulative_sum(numbers)</code></td>
<td>Yield cumulative sum of numbers.</td>
</tr>
<tr>
<td><code>generate_unique_node()</code></td>
<td>Generate a unique node label.</td>
</tr>
<tr>
<td><code>default_opener(filename)</code></td>
<td>Opens <code>filename</code> using system’s default program.</td>
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</table>

12.1.1 is_string_like

`is_string_like(obj)`
Check if obj is string.

12.1.2 flatten

`flatten(obj, result=None)`
Return flattened version of (possibly nested) iterable object.

12.1.3 iterable

`iterable(obj)`
Return True if obj is iterable with a well-defined len().
12.1.4 is_list_of_ints

is_list_of_ints(intlist)
    Return True if list is a list of ints.

12.1.5 make_str

make_str(t)
    Return the string representation of t.

12.1.6 cumulative_sum

cumulative_sum(numbers)
    Yield cumulative sum of numbers.

>>> import networkx.utils as utils
>>> list(utils.cumulative_sum([1,2,3,4]))
[1, 3, 6, 10]

12.1.7 generate_unique_node

generate_unique_node()
    Generate a unique node label.

12.1.8 default_opener

default_opener(filename)
    Opens filename using system’s default program.
    Parameters filename : str
        The path of the file to be opened.

12.2 Data structures and Algorithms

Union-find data structure.

    UnionFind.union(*objects)  Find the sets containing the objects and merge them all.

12.2.1 union

UnionFind.union(*objects)
    Find the sets containing the objects and merge them all.

12.3 Random sequence generators

Utilities for generating random numbers, random sequences, and random selections.
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<th>Function</th>
<th>Description</th>
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<td><code>create_degree_sequence</code></td>
<td>Attempt to create a valid degree sequence of length n using specified function</td>
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<tr>
<td><code>pareto_sequence</code></td>
<td>Return sample sequence of length n from a Pareto distribution.</td>
</tr>
<tr>
<td><code>powerlaw_sequence</code></td>
<td>Return sample sequence of length n from a power law distribution.</td>
</tr>
<tr>
<td><code>uniform_sequence</code></td>
<td>Return sample sequence of length n from a uniform distribution.</td>
</tr>
<tr>
<td><code>cumulative_distribution</code></td>
<td>Return normalized cumulative distribution from discrete distribution.</td>
</tr>
<tr>
<td><code>discrete_sequence</code></td>
<td>Return sample sequence of length n from a given discrete distribution or</td>
</tr>
<tr>
<td><code>zipf_sequence</code></td>
<td>Return a sample sequence of length n from a Zipf distribution with</td>
</tr>
<tr>
<td><code>zipf_rv</code></td>
<td>Return a random value chosen from the Zipf distribution.</td>
</tr>
<tr>
<td><code>random_weighted_sample</code></td>
<td>Return k items without replacement from a weighted sample.</td>
</tr>
<tr>
<td><code>weighted_choice</code></td>
<td>Return a single element from a weighted sample.</td>
</tr>
</tbody>
</table>

### 12.3.1 `create_degree_sequence`

**Function**

`create_degree_sequence(n[, sfunction, max_tries])`

Attempt to create a valid degree sequence of length n using specified function sfunction(n,**kwds).

**Parameters**

- **n**: int
  
  Length of degree sequence = number of nodes

- **sfunction**: function
  
  Function which returns a list of n real or integer values. Called as “sfunction(n,**kwds)”.

- **max_tries**: int
  
  Max number of attempts at creating valid degree sequence.

**Notes**

Repeatedly create a degree sequence by calling sfunction(n,**kwds) until achieving a valid degree sequence. If unsuccessful after max_tries attempts, raise an exception.

For examples of sfunctions that return sequences of random numbers, see networkx.Utils.

**Examples**

```python
>>> from networkx.utils import uniform_sequence, create_degree_sequence
>>> seq=create_degree_sequence(10,uniform_sequence)
```

### 12.3.2 `pareto_sequence`

**Function**

`pareto_sequence(n[, exponent=1.0])`

Return sample sequence of length n from a Pareto distribution.

### 12.3.3 `powerlaw_sequence`

**Function**

`powerlaw_sequence(n[, exponent=2.0])`

Return sample sequence of length n from a power law distribution.
12.3.4 uniform_sequence

uniform_sequence(n)
   Return sample sequence of length n from a uniform distribution.

12.3.5 cumulative_distribution

cumulative_distribution(distribution)
   Return normalized cumulative distribution from discrete distribution.

12.3.6 discrete_sequence

discrete_sequence(n, distribution=None, cdistribution=None)
   Return sample sequence of length n from a given discrete distribution or discrete cumulative distribution.
   One of the following must be specified.
   distribution = histogram of values, will be normalized
   cdistribution = normalized discrete cumulative distribution

12.3.7 zipf_sequence

zipf_sequence(n, alpha=2.0, xmin=1)
   Return a sample sequence of length n from a Zipf distribution with exponent parameter alpha and minimum value xmin.
   See also:
   zipf_rv

12.3.8 zipf_rv

zipf_rv(alpha, xmin=1, seed=None)
   Return a random value chosen from the Zipf distribution.
   The return value is an integer drawn from the probability distribution ::math:
   \[ p(x) = \frac{x^{-\alpha}}{\zeta(\alpha, x_{\text{min}})} \],
   where \( \zeta(\alpha, x_{\text{min}}) \) is the Hurwitz zeta function.

   Parameters
   alpha : float
      Exponent value of the distribution
   xmin : int
      Minimum value
   seed : int
      Seed value for random number generator

   Returns
   x : int
      Random value from Zipf distribution

   Raises
   ValueError:
If xmin < 1 or If alpha <= 1

Notes

The rejection algorithm generates random values for a the power-law distribution in uniformly bounded expected time dependent on parameters. See [1] for details on its operation.

References


Examples

```python
>>> nx.zipf_rv(alpha=2, xmin=3, seed=42)
```

12.3.9 random_weighted_sample

random_weighted_sample(mapping, k)

Return k items without replacement from a weighted sample.

The input is a dictionary of items with weights as values.

12.3.10 weighted_choice

weighted_choice(mapping)

Return a single element from a weighted sample.

The input is a dictionary of items with weights as values.

12.4 Decorators

<table>
<thead>
<tr>
<th>Decorator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>open_file(path_arg[, mode])</td>
<td>Decorator to ensure clean opening and closing of files.</td>
</tr>
<tr>
<td>require(*packages)</td>
<td>Decorator to check whether specific packages can be imported.</td>
</tr>
</tbody>
</table>

12.4.1 open_file

open_file(path_arg, mode='r')

Decorator to ensure clean opening and closing of files.

Parameters

- `path_arg`: int
  
  Location of the path argument in args. Even if the argument is a named positional argument (with a default value), you must specify its index as a positional argument.

- `mode`: str
  
  String for opening mode.

Returns

- `_open_file`: function
Function which cleanly executes the io.

**Examples**

Decorate functions like this:

```python
@open_file(0,'r')
def read_function(pathname):
    pass

@open_file(1,'w')
def write_function(G,pathname):
    pass

@open_file(1,'w')
def write_function(G, pathname='graph.dot'):
    pass

@open_file('path', 'w+')
def another_function(arg, **kwargs):
    path = kwargs['path']
    pass
```

### 12.4.2 require

`require(*packages)`

Decorator to check whether specific packages can be imported.

If a package cannot be imported, then NetworkXError is raised. If all packages can be imported, then the original function is called.

- **Parameters**
  - `packages`: container of strings
    - Container of module names that will be imported.

- **Returns**
  - `_require`: function
    - The decorated function.

- **Raises**
  - `NetworkXError`
    - If any of the packages cannot be imported

**Examples**

Decorate functions like this:

```python
@require('scipy')
def sp_function():
    import scipy
    pass

@require('numpy','scipy')
def sp_np_function():
    import numpy
    import scipy
    pass
```
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Aric Hagberg <hagberg@lanl.gov>
Dan Schult <dschult@colgate.edu>
Pieter Swart <swart@lanl.gov>
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Thanks to David Eppstein for the idea of representing a graph $G$ so that “for $n$ in $G$” loops over the nodes in $G$ and $G[n]$ are node $n$’s neighbors.

Thanks to everyone who has improved NetworkX by contributing code, bug reports (and fixes), documentation, and input on design, features, and the future of NetworkX.

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Dustin Smith wrote the dictionary to numpy array function

Mathieu Larose sped up the topological sort code

Vincent Gauthier contributed the Katz centrality algorithm

Sérgio Nery Simões developed the code for finding all simple paths
**dictionary**  A Python dictionary maps keys to values. Also known as “hashes”, or “associative arrays”. See [http://docs.python.org/tutorial/datastructures.html#dictionaries](http://docs.python.org/tutorial/datastructures.html#dictionaries)

**ebunch**  An iterable container of edge tuples like a list, iterator, or file.

**edge**  Edges are either two-tuples of nodes (u,v) or three tuples of nodes with an edge attribute dictionary (u,v,dict).

**edge attribute**  Edges can have arbitrary Python objects assigned as attributes by using keyword/value pairs when adding an edge assigning to the G.edge[u][v] attribute dictionary for the specified edge u-v.

**hashable**  An object is hashable if it has a hash value which never changes during its lifetime (it needs a \_\_hash\_(\) method), and can be compared to other objects (it needs an \_\_eq\_(\) or \_\_cmp\_(\) method). Hashable objects which compare equal must have the same hash value.

Hashability makes an object usable as a dictionary key and a set member, because these data structures use the hash value internally.

All of Python’s immutable built-in objects are hashable, while no mutable containers (such as lists or dictionaries) are. Objects which are instances of user-defined classes are hashable by default; they all compare unequal, and their hash value is their id().

Definition from [http://docs.python.org/glossary.html](http://docs.python.org/glossary.html)

**nbunch**  An nbunch is any iterable container of nodes that is not itself a node in the graph. It can be an iterable or an iterator, e.g. a list, set, graph, file, etc..

**node**  A node can be any hashable Python object except None.

**node attribute**  Nodes can have arbitrary Python objects assigned as attributes by using keyword/value pairs when adding a node or assigning to the G.node[n] attribute dictionary for the specified node n.


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