# NetworkX Reference 

Release 1.3

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## CONTENTS

1 Introduction ..... 1
1.1 Who uses NetworkX? ..... I
1.2 The Python programming language ..... 1
1.3 Free software ..... 1
1.4 Goals ..... 1
1.5 History ..... 2
2 Overview ..... 3
2.1 NetworkX Basics ..... 3
2.2 Nodes and Edges ..... 4
3 Graph types ..... 9
3.1 Which graph class should I use? ..... 9
3.2 Basic graph types ..... 9
4 Algorithms ..... 133
4.1 Bipartite ..... 133
4.2 Blockmodeling ..... 135
4.3 Boundary ..... 136
4.4 Centrality ..... 137
4.5 Clique ..... 145
4.6 Clustering ..... 148
4.7 Components ..... 150
4.8 Cores ..... 158
4.9 Cycles ..... 159
4.10 Directed Acyclic Graphs ..... 159
4.11 Distance Measures ..... 161
4.12 Eulerian ..... 163
4.13 Flows ..... 164
4.14 Isolates ..... 175
4.15 Isomorphism ..... 176
4.16 Link Analysis ..... 188
4.17 Matching ..... 194
4.18 Mixing Patterns ..... 195
4.19 Minimum Spanning Tree ..... 200
4.20 Operators ..... 201
4.21 Shortest Paths ..... 205
4.22 Traversal ..... 220
4.23 Vitality ..... 221
5 Functions ..... 223
5.1 Graph functions ..... 223
6 Graph generators ..... 227
6.1 Atlas ..... 227
6.2 Classic ..... 227
6.3 Small ..... 232
6.4 Random Graphs ..... 236
6.5 Degree Sequence ..... 246
6.6 Directed ..... 253
6.7 Geometric ..... 257
6.8 Hybrid ..... 257
6.9 Bipartite ..... 257
6.10 Line Graph ..... 261
6.11 Ego Graph ..... 262
6.12 Stochastic ..... 262
7 Linear algebra ..... 263
7.1 Spectrum ..... 263
7.2 Attribute Matrices ..... 265
8 Converting to and from other data formats ..... 269
8.1 To NetworkX Graph ..... 269
8.2 Relabeling ..... 270
8.3 Dictionaries ..... 271
8.4 Lists ..... 272
8.5 Numpy ..... 274
8.6 Scipy ..... 275
9 Reading and writing graphs ..... 279
9.1 Adjacency List ..... 279
9.2 Edge List ..... 283
9.3 GML ..... 289
9.4 Pickle ..... 291
9.5 GraphML ..... 293
9.6 LEDA ..... 294
9.7 YAML ..... 295
9.8 SparseGraph6 ..... 297
9.9 Pajek ..... 298
10 Drawing ..... 301
10.1 Matplotlib ..... 301
10.2 Graphviz AGraph (dot) ..... 309
10.3 Graphviz with pydot ..... 312
10.4 Graph Layout ..... 315
11 Exceptions ..... 319
12 Utilities ..... 321
12.1 Helper functions ..... 321
12.2 Data structures and Algorithms ..... 322
12.3 Random sequence generators ..... 322
12.4 SciPy random sequence generators ..... 323
13 License ..... 325
14 Citing ..... 327
15 Credits ..... 329
16 Glossary ..... 331
Bibliography ..... 333
Module Index ..... 337
Index ..... 339

## INTRODUCTION

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

The structure of a graph or network is encoded in the edges (connections, links, ties, arcs, bonds) between nodes (vertices, sites, actors). If unqualified, by graph we mean an undirected graph, i.e. no multiple edges are allowed. By a network we usually mean a graph with weights (fields, properties) on nodes and/or edges.

### 1.1 Who uses NetworkX?

The potential audience for NetworkX includes mathematicians, physicists, biologists, computer scientists, and social scientists. The current state of the art of the science of complex networks is 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 The Python programming language

Why Python? Past experience showed this approach to maximize productivity, power, multi-disciplinary scope (applications include large communication, social, data and biological networks), and platform independence. This philosophy does not exclude using whatever other language is appropriate for a specific subtask, since Python is also an excellent "glue" language [Langtangen04]. Equally important, Python is free, well-supported and a joy to use. Among the many guides to Python, we recommend the documentation at http://www.python.org and the text by Alex Martelli [Martelli03].

### 1.3 Free software

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

### 1.4 Goals

NetworkX is intended to:

- Be a tool to study the structure and dynamics of social, biological, and infrastructure networks
- Provide ease-of-use and rapid development in a collaborative, multidisciplinary environment
- Be an Open-source software package that can provide functionality to a diverse community of active and easily participating users and developers.
- Provide an easy interface to existing code bases written in C, C++, and FORTRAN
- Painlessly slurp in large nonstandard data sets
- Provide a standard API and/or graph implementation that is suitable for many applications.


### 1.5 History

- NetworkX was inspired by Guido van Rossum's 1998 Python graph representation essay [vanRossum98].
- First public release in April 2005. Version 1.0 released in 2009.


### 1.5.1 What Next

- A Brief Tour
- Installing
- Reference
- Examples


## OVERVIEW

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)

```
>>> 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

```
>>> 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 adjaceny 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.
- Adding edges and nodes explicitly.

Explicit addition and removal of nodes/edges is the easiest to describe. Each graph object supplies methods to manipulate the graph. For example,

```
>>> 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:

```
>>> 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:

```
>>> 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 $\mathrm{G}[\mathrm{u}, \mathrm{v}]$ in favor of $\mathrm{G}[\mathrm{u}][\mathrm{v}]$. 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 $\mathrm{G}[\mathrm{n}]$ 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 $n x . t r i a n g l e s(G, n)$ 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 Developer Zone.
As an example here is code to use Dijkstra's algorithm to find the shortest weighted path:

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



```
>>> G.add_weighted_edges_from(e)
>>> print(nx.dijkstra_path(G,' '',' 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 $\mathrm{G}[\mathrm{u}]$ 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.
- $\mathrm{G}[\mathrm{u}][\mathrm{v}]$ 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.

```
>>> G=nx.Graph()
>>> G.add_edge(1,2,color='red', weight=0. 84, size=300)
>>> print(G[1][2]['size'])
300
```

[^0]
## GRAPH TYPES

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?

| Graph Type | NetworkX Class |
| :--- | :--- |
| Undirected Simple | Graph |
| Directed Simple | DiGraph |
| With Self-loops | Graph, DiGraph |
| With Parallel edges | MultiGraph, MultiDiGraph |

### 3.2 Basic graph types

### 3.2.1 Graph - Undirected graphs with self loops

## Overview

Graph (data=None, name=", **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.
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:

DiGraph, MultiGraph, MultiDiGraph

## Examples

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

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

G can be grown in several ways.

## Nodes:

Add one node at a time:

```
>>> 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).

```
>>> 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.

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


## Edges:

G can also be grown by adding edges.
Add one edge,
>>> G.add_edge (1, 2)
a list of edges,
>>> G.add_edges_from $([(1,2),(1,3)])$
or a collection of edges,
>>> 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.

```
>>> 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' }
>>> G.node[1]['room'] = 714
>>> G.nodes(data=True)
[(1, {'room' : 714, '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
>>> G[1] # adjacency dict keyed by neighbor to edge attributes
... # Note: you should not change this dict manually!
{2: {'color': 'blue', 'weight': 4} }
```

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)
>>> [ (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

```
Graph.__init__(**attr[, data, name]) Initialize a graph with edges, name, graph attributes.
Graph.add_node(n, **attr[, attr_dict]) Add a single node n and update node attributes.
Graph.add_nodes_from(nodes, **attr) Add multiple nodes.
Graph.remove_node(n) Remove node n.
Graph.remove_nodes_from(nodes) Remove multiple nodes.
Graph.add_edge(u, v, **attr[, attr_dict]) Add an edge between u and v.
Graph.add_edges_from(ebunch, **attr[, Add all the edges in ebunch.
attr_dict])
Graph.add_weighted_edges_from(ebunch, Add all the edges in ebunch as weighted edges with
**attr)
Graph.remove_edge(u,v) Remove the edge between u and v.
Graph.remove_edges_from(ebunch) Remove all edges specified in ebunch.
Graph.add_star(nlist, **attr) Add a star.
Graph.add_path(nlist, **attr) Add a path.
Graph.add_cycle(nlist, **attr) Add a cycle.
Graph.clear() Remove all nodes and edges from the graph.
```

networkx.Graph.__init__
init__(data=None, name=", **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' }
```


## networkx.Graph.add_node

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

```
>>> G n 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:

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


## networkx.Graph.add_nodes_from

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')
$\ggg K 3=n x \cdot \operatorname{Graph}([(0,1),(1,2),(2,0)])$
$\ggg$ G.add_nodes_from (K3)
$\ggg$ sorted (G.nodes(),key=str)
$\left[0,1,2, \quad H^{\prime}, ~ ' e^{\prime}, ~ ' l^{\prime}, ~ ' o '\right]$

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
```


## networkx.Graph.remove_node

## 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()
[]
```


## networkx.Graph.remove_nodes_from

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])
$\ggg$ e $=$ G.nodes()
>>> e
$[0,1,2]$
>>> G.remove_nodes_from(e)
>>> G.nodes()
[]
networkx.Graph.add_edge
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.
NetworkX algorithms designed for weighted graphs use as the edge weight a numerical value assigned to the keyword 'weight'.

## Examples

The following all add the edge $\mathrm{e}=(1,2)$ to graph G :

```
>>> 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:

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


## networkx.Graph.add_edges_from

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 ( $\mathrm{u}, \mathrm{v}$ ) or 3-tuples ( $\mathrm{u}, \mathrm{v}, \mathrm{d}$ ) 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')
```


## networkx.Graph.add_weighted_edges_from

## add_weighted_edges_from (ebunch, **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 ( $\mathrm{u}, \mathrm{v}, \mathrm{w}$ ) where w is a number.
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 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_weighted_edges_from([(0,1,3.0),(1,2,7.5)])
```

networkx.Graph.remove_edge
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
>>> 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
networkx.Graph.remove_edges_from
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 $(\mathrm{u}, \mathrm{v}, \mathrm{k})$ 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)
```


## networkx.Graph.add_star

```
add_star (nlist, **attr)
```

Add a star.
The first node in nlist is the middle of the star. It is connected to all other nodes in nlist.
Parameters nlist : list
A list of nodes.
attr : keyword arguments, optional (default= no attributes)
Attributes to add to every edge in star.

## See Also:

```
add_path,add_cycle
```


## Examples

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

## networkx.Graph.add_path

```
add_path (nlist, **attr)
```

Add a path.
Parameters nlist : list
A list 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)
```


## networkx.Graph.add_cycle

add_cycle (nlist, **attr)
Add a cycle.

## Parameters nlist : list

A list 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
$\ggg$ G.add_cycle([0,1,2,3])
>>> G.add_cycle([10,11,12], weight=7)

## networkx.Graph.clear

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
$\ggg$ G.add_path $([0,1,2,3])$
>>> G.clear()
$\ggg$ G.nodes()
[]
>>> G.edges()
[]

## Iterating over nodes and edges

| Graph.nodes([data]) | Return a list of the nodes in the graph. |
| :--- | :--- |
| Graph.nodes_iter([data]) | Return an iterator over the nodes. |
| Graph.__iter_() | Iterate over the nodes. |
| Graph.edges([nbunch, data]) | Return a list of edges. |
| Graph.edges_iter([nbunch, data]) | Return an iterator over the edges. |
| Graph.get_edge_data(u, v[, default]) | Return the attribute dictionary associated with edge (u,v). |
| Graph. neighbors(n) | Return a list of the nodes connected to the node n. |
| Graph. neighbors_iter(n) | Return an iterator over all neighbors of node n. |
| Graph.__getitem_(n) | Return a dict of neighbors of node n. |
| Graph.adjacency_list $)$ | Return an adjacency list representation of the graph. |
| Graph.adjacency_iter() | Return an iterator of (node, adjacency dict) tuples for all nodes. |
| Graph.nbunch_iter([nbunch]) | Return an iterator of nodes contained in nbunch that are also in the graph. |

## networkx.Graph.nodes

## 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=' 5 pm')
>>> G.nodes (data=True)
[(0, \{\}), (1, \{'time': '5pm'\}), (2, \{\})]

## networkx.Graph.nodes_iter

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 '.

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


## 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)]
[{}, {}, {}]
```

networkx.Graph.__iter $\qquad$
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 $\ggg$ G.add_path ( $[0,1,2,3])$

## networkx.Graph.edges

## 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.

## 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)]
```

networkx.Graph.edges_iter
edges_iter ( $n b u n c h=$ 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.

## Examples

```
>>> 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))
$[(0,1)]$

## networkx.Graph.get_edge_data

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 $\mathrm{G}[\mathrm{u}][\mathrm{v}]$ 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
```


## networkx.Graph.neighbors

```
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 $G[n]$ :

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


## Examples

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


## networkx.Graph.neighbors_iter

```
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. >>> [n for $n$ in G[0]] [1]

## Examples

>>> G $=$ nx.Graph() \# or DiGraph, MultiGraph, MuItiDiGraph, etc
$\ggg$ G.add_path ([0, 1, 2, 3])
>>> [n for $n$ in G.neighbors_iter (0)]
[1]
networkx.Graph.__getitem_

Return a dict of neighbors of node $n$. Use the expression ' $\mathrm{G}[\mathrm{n}]$ '.

Parameters n: node
A node in the graph.
Returns adj_dict : dictionary
The adjacency dictionary for nodes connected to n .

## Notes

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

## Examples

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


## networkx.Graph.adjacency_list

```
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]]

## networkx.Graph.adjacency_iter

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()]
$[(0,\{1:\{ \}\}),(1,\{0:\{ \}, 2:\{ \}\}),(2,\{1:\{ \}, 3:\{ \}\}),(3,\{2:\{ \}\})]$

## networkx.Graph.nbunch_iter

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:

$\qquad$

## 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

| Graph.has_node(n) | Return True if the graph contains the node n . |
| :---: | :---: |
| Graph.__contains__(n) | Return True if n is a node, False otherwise. Use the expression |
| Graph.has_edge(u, v) | Return True if the edge ( $u, v$ ) is in the graph. |
| Graph.order() | Return the number of nodes in the graph. |
| Graph. number_of_nodes() | Return the number of nodes in the graph. |
| Graph.__len__() | Return the number of nodes. |
| Graph. degree([nbunch, weighted]) | Return the degree of a node or nodes. |
| Graph.degree_iter([nbunch, weighted]) | Return an iterator for (node, degree). |
| Graph.size([weighted]) | Return the number of edges. |
| Graph. number_of_edges([u, v]) | Return the number of edges between two nodes. |
| Graph. nodes_with_selfloops() | Return a list of nodes with self loops. |
| Graph.selfloop_edges([data]) | Return a list of selfloop edges. |
| Graph. number_of_selfloops() | Return the number of selfloop edges. |

## networkx.Graph.has_node

has_node ( $n$ )
Return True if the graph contains the node $n$.
Parameters n: node

## Examples

>>> G $=$ nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
$\ggg$ G.add_path $([0,1,2])$
>>> G.has_node (0)
True
It is more readable and simpler to use

```
>>>0 in G
```

True
networkx.Graph._contains

```
contains___(n)
```

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

## Examples

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

## networkx.Graph.has_edge

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 O not in G
True
```

networkx.Graph.order
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__
```

networkx.Graph.number_of_nodes
number_of_nodes ()
Return the number of nodes in the graph.
Returns nnodes : int

The number of nodes in the graph.
See Also:

```
order,
``` \(\qquad\)
``` en
``` \(\qquad\)

\section*{Examples}
\(\ggg G=n x . G r a p h() \quad\) \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2])\)
>>> len (G)
3
networkx.Graph. Ien \(\qquad\)
len ()

Return the number of nodes. Use the expression 'len(G)'.
Returns nnodes : int
The number of nodes in the graph.

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc \(\ggg\) G.add_path ([0, 1, 2, 3])
>>> len (G)
4

\section*{networkx.Graph.degree}
degree (nbunch=None, weighted=False)
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.
weighted : bool, optional (default=False)
If True return the sum of 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.

\section*{Examples}
```

>>> 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]

```

\section*{networkx.Graph.degree_iter}
```

degree_iter(nbunch=None, weighted=False)

```

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.
weighted : bool, optional (default=False)
If True return the sum of edge weights adjacent to the node.
Returns nd_iter : an iterator
The iterator returns two-tuples of (node, degree).

\section*{See Also:}
```

degree

```

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.Graph.size}
size (weighted=False)
Return the number of edges.
Parameters weighted : boolean, optional (default=False)
If True return the sum of the edge weights.
Returns nedges : int
The number of edges in the graph.

See Also:
```

number_of__edges

```

\section*{Examples}
```

>>> 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(weighted=True)
6.0

```

\section*{networkx.Graph.number_of_edges}
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.

\section*{See Also:}
size

\section*{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
\(\ggg e=(0,1)\)
\(\ggg\) G.number_of_edges (*e)
1

\section*{networkx.Graph.nodes_with_selfloops}

\section*{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

```

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_edge \((1,1)\)
>>> G.add_edge \((1,2)\)
>>> G.nodes_with_selfloops()
[1]

\section*{networkx.Graph.selfloop_edges}

\section*{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.

\section*{See Also:}
```

selfloop_nodes, number_of_selfloops

```

\section*{Examples}
>>> 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)
\([(1,1,\{ \})]\)

\section*{networkx.Graph.number_of_selfloops}
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:
```

selfloop_nodes,selfloop__edges

```

\section*{Examples}
>>> G=nx.Graph() \# or DiGraph, MuItiGraph, MuItiDiGraph, etc
\(\ggg\) G.add_edge \((1,1)\)
\(\ggg\) G.add_edge \((1,2)\)
>>> G.number_of_selfloops()
1

\section*{Making copies and subgraphs}
\begin{tabular}{ll}
\hline Graph. copy() & Return a copy of the graph. \\
Graph.to_undirected() & Return an undirected copy of the graph. \\
Graph.to_directed() & Return a directed representation of the graph. \\
Graph.subgraph(nbunch) & Return the subgraph induced on nodes in nbunch. \\
\hline
\end{tabular}

\section*{networkx.Graph.copy}

\section*{copy ()}

Return a copy of the graph.
Returns G: Graph
A copy of the graph.

\section*{See Also:}
to_directed return a directed copy of the graph.

\section*{Notes}

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

\section*{Examples}
```

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

```

\section*{networkx.Graph.to_undirected}
to_undirected()
Return an undirected copy of the graph.
Returns G: Graph/MultiGraph
A deepcopy of the graph.

\section*{See Also:}
copy, add_edge, add_edges_from

\section*{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 \(\mathrm{G}=\mathrm{DiGraph}(\mathrm{D})\) 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.

\section*{Examples}
>>> G \(=\) nx.Graph() \# or MultiGraph, etc
\(\ggg\) G.add_path ([0,1])
\(\ggg H=\) G.to_directed()
>>> H.edges()
\([(0,1),(1,0)]\)
>>> G2 = H.to_undirected()
>>> G2.edges ()
\([(0,1)]\)

\section*{networkx.Graph.to_directed}

\section*{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).

\section*{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 \(\mathrm{D}=\mathrm{DiGraph}(\mathrm{G})\) 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.

\section*{Examples}
```

>>> 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
```

>>> G = nx.DiGraph() \# or MultiDiGraph, etc

```
\(\ggg\) G.add_path ([0,1])
>>> H = G.to_directed()
>>> H.edges()
\([(0,1)]\)

\section*{networkx.Graph.subgraph}

\section*{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.

\section*{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)])

\section*{Examples}
```

>>> 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)]

```

\subsection*{3.2.2 DiGraph - Directed graphs with self loops}

\section*{Overview}

DiGraph (data=None, name=", **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.
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:
Graph, MultiGraph, MultiDiGraph

\section*{Examples}

Create an empty graph structure (a "null graph") with no nodes and no edges.
>>> G = nx.DiGraph()
G can be grown in several ways.

\section*{Nodes:}

Add one node at a time:
>>> 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).
```

>>> 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.
>>> G.add_node (H)

\section*{Edges:}

G can also be grown by adding edges.
Add one edge,
>>> G.add_edge (1, 2)
a list of edges,
```

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

```
or a collection of edges,
>>> 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.

\section*{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.
```

>>> G = nx.DiGraph(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' }
>>> G.node[1]['room'] = 714
>>> G.nodes(data=True)
[(1, {'room' : 714, '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

```

\section*{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: {'color': 'blue', 'weight': 4 }}

```

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

```

\section*{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.

\section*{Adding and removing nodes and edges}
```

DiGraph.__init__(**attr[, data, name]) Initialize a graph with edges, name, graph attributes.
DiGraph.add_node(n, **attr[, attr_dict]) Add a single node n and update node attributes.
DiGraph.add_nodes_from(nodes, **attr) Add multiple nodes.
DiGraph.remove_node(n) Remove node n.
DiGraph.remove_nodes_from(nbunch) Remove multiple nodes.
DiGraph.add_edge(u,v,**attr[, attr_dict]) Add an edge between u and v.
DiGraph.add_edges_from(ebunch, **attr[, Add all the edges in ebunch.
...])
DiGraph.add_weighted_edges_from(ebunch, Add all the edges in ebunch as weighted edges with
**attr) specified weights.
DiGraph.remove_edge(u,v) Remove the edge between u and v.
DiGraph.remove_edges_from(ebunch) Remove all edges specified in ebunch.
DiGraph.add_star(nlist, **attr) Add a star.
DiGraph.add_path(nlist, **attr) Add a path.
DiGraph.add_cycle(nlist, **attr) Add a cycle.
DiGraph.clear() Remove all nodes and edges from the graph.

```

\section*{networkx.DiGraph.__init_}
```

init___(data=None, name=", **attr)

```

Initialize a graph with edges, name, graph attributes.

\section*{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.

\section*{See Also:}
convert

\section*{Examples}
\(\ggg G=n x . G r a p h() \quad\) \# or DiGraph, MultiGraph, MuItiDiGraph, etc
\(\ggg G=n x . G r a p h\left(n a m e={ }^{\prime} m y\right.\) graph')
\(\ggg e=[(1,2),(2,3),(3,4)]\) \# list of edges
\(\ggg G=n x . G r a p h(e)\)
Arbitrary graph attribute pairs (key=value) may be assigned
```

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

```

\section*{networkx.DiGraph.add_node}
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.

\section*{See Also:}
```

add_nodes_from

```

\section*{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.

\section*{Examples}
```

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

\section*{networkx.DiGraph.add_nodes_from}
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.

\section*{See Also:}

\section*{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'})])
>>> G.node[1]['size']
11
>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))
>>> H.node[1]['size']
11

```

\section*{networkx.DiGraph.remove_node}

\section*{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 \(\mathbf{n}\) : node
A node in the graph

\section*{Raises NetworkXError :}

If n is not in the graph.

\section*{See Also:}
```

remove_nodes_from

```

\section*{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()
[]

```

\section*{networkx.DiGraph.remove_nodes_from}
```

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.

\section*{See Also:}
```

remove_node

```

\section*{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()
[]

\section*{networkx.DiGraph.add_edge}
```

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.

\section*{See Also:}
add_edges_from add a collection of edges

\section*{Notes}

Adding an edge that already exists updates the edge data.
NetworkX algorithms designed for weighted graphs use as the edge weight a numerical value assigned to the keyword 'weight'.

\section*{Examples}

The following all add the edge \(\mathrm{e}=(1,2)\) to graph G :
```

>>> 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:
```

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

```

\section*{networkx.DiGraph.add_edges_from}
```

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.

\section*{See Also:}
add_edge add a single edge
add_weighted_edges_from convenient way to add weighted edges

\section*{Notes}

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

\section*{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')

```
networkx.DiGraph.add_weighted_edges_from
add_weighted_edges_from (ebunch, **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 ( \(\mathrm{u}, \mathrm{v}, \mathrm{w}\) ) where w is a number. attr : keyword arguments, optional (default= no attributes)

Edge attributes to add/update for all edges.

\section*{See Also:}
add_edge add a single edge
add_edges_from add multiple edges

\section*{Notes}

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

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0,1,3.0), (1, 2, 7.5)])

\section*{networkx.DiGraph.remove_edge}
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

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, etc
\(\ggg\) G.add_path ( \([0,1,2,3])\)
\(\ggg\) G.remove_edge \((0,1)\)
\(\ggg e=(1,2)\)
>>> G.remove_edge(*e) \# unpacks e from an edge tuple
\(\ggg\) e \(=\left(2,3,\left\{' w e i g h t^{\prime}: 7\right\}\right)\) \# an edge with attribute data
\(\ggg\) G.remove_edge(*e[:2]) \# select first part of edge tuple

\section*{networkx.DiGraph.remove_edges_from}
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 ( \(\mathrm{u}, \mathrm{v}, \mathrm{k}\) ) where k is ignored.

\section*{See Also:}
remove_edge remove a single edge

\section*{Notes}

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

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2,3])\)
\(\ggg\) ebunch=[(1,2), \((2,3)]\)
>>> G.remove_edges_from (ebunch)

\section*{networkx.DiGraph.add_star}
```

add_star(nlist, **attr)

```

Add a star.
The first node in nlist is the middle of the star. It is connected to all other nodes in nlist.
Parameters nlist : list

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

\section*{See Also:}
add_path, add_cycle

\section*{Examples}
\(\ggg\) G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MuItiDiGraph, etc
\(\ggg\) G.add_star \(([0,1,2,3])\)
>>> G.add_star([10,11,12],weight=2)

\section*{networkx.DiGraph.add_path}
add_path (nlist, **attr)
Add a path.
Parameters nlist : list
A list 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.

\section*{See Also:}
add_star, add_cycle

\section*{Examples}
>>> G=nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2,3])\)
>>> G.add_path([10,11,12],weight=7)

\section*{networkx.DiGraph.add_cycle}
add_cycle (nlist, **attr)
Add a cycle.

\section*{Parameters nlist : list}

A list 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.

\section*{See Also:}
```

add__path,add_star

```

\section*{Examples}
>>> G=nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc \(\ggg\) G.add_cycle([0,1,2,3])
>>> G.add_cycle([10,11,12], weight=7)

\section*{networkx.DiGraph.clear}

\section*{clear()}

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

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path ([0,1,2,3])
>>> G.clear()
>>> G.nodes()
[]
>>> G.edges()
[]

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

\section*{networkx.DiGraph.nodes}

\section*{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).

\section*{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=' 5 pm')
>>> G.nodes (data=True)
[(0, \{\}), (1, \{'time': '5pm'\}), (2, \{\})]

\section*{networkx.DiGraph.nodes_iter}
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)

\section*{Notes}

If the node data is not required it is simpler and equivalent to use the expression 'for n in G '.
>>> G = nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2])\)

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc \(\ggg\) G.add_path ([0,1,2])
>>> [d for \(n, d\) in G.nodes_iter(data=True)]
[\{\}, \{\}, \{\}]
networkx.DiGraph. \(\qquad\)
iter ()

Iterate over the nodes. Use the expression 'for n in G '.
Returns niter : iterator
An iterator over all nodes in the graph.

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2,3])\)
networkx.DiGraph.edges
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).

\section*{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.

\section*{See Also:}
edges_iter return an iterator over the edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{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)]

```

\section*{networkx.DiGraph.edges_iter}

\section*{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.

\section*{See Also:}
edges return a list of edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{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)]

```

\section*{networkx.DiGraph.out_edges}
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).

\section*{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.

\section*{See Also:}
edges_iter return an iterator over the edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{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)]

```
networkx.DiGraph.out_edges_iter
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

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{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)]

```
networkx.DiGraph.in_edges
in_edges (nbunch=None, data=False)
Return a list of the incoming edges.
See Also:
edges return a list of edges

\section*{networkx.DiGraph.in_edges_iter}
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
networkx.DiGraph.get_edge_data
get_edge_data \((u, v\), default=None)
Return the attribute dictionary associated with edge ( \(u, v\) ).
Parameters u,v: nodes

\section*{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.

\section*{Notes}

It is faster to use \(\mathrm{G}[\mathrm{u}][\mathrm{v}]\).
>>> 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

```

\section*{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

```

\section*{networkx.DiGraph.neighbors}
```

neighbors(n)

```

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

\section*{networkx.DiGraph.neighbors_iter}
```

neighbors_iter(n)

```

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

__getitem
(n)

```

Return a dict of neighbors of node \(n\). Use the expression ' \(\mathrm{G}[\mathrm{n}]\) '.
Parameters n : node
A node in the graph.
Returns adj_dict : dictionary
The adjacency dictionary for nodes connected to \(n\).

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

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

\section*{networkx.DiGraph.successors}
```

successors(n)

```

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

\section*{networkx.DiGraph.successors_iter}
```

successors_iter(n)

```

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

\section*{networkx.DiGraph.predecessors}
```

predecessors(n)

```

Return a list of predecessor nodes of \(n\).

\section*{networkx.DiGraph.predecessors_iter}

\section*{predecessors_iter ( \(n\) )}

Return an iterator over predecessor nodes of \(n\).

\section*{networkx.DiGraph.adjacency_list}

\section*{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.

\section*{See Also:}
adjacency_iter

\section*{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]]

\section*{networkx.DiGraph.adjacency_iter}

\section*{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

```

\section*{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: {}})]

```

\section*{networkx.DiGraph.nbunch_iter}
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.

\section*{Raises NetworkXError :}

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

\section*{See Also:}

Graph.__iter__

\section*{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.

\section*{Information about graph structure}
```

DiGraph.has_node(n)
DiGraph.__contains__(n)
DiGraph.has_edge(u,v)
DiGraph.order()
DiGraph.number_of_nodes()
DiGraph.__len__()
DiGraph.degree([nbunch, weighted])
DiGraph.degree_iter([nbunch, weighted])
DiGraph.in_degree([nbunch, weighted])
DiGraph.in_degree([nbunch, weighte
weighted])
DiGraph.out_degree([nbunch, weighted])
DiGraph.out_degree_iter([nbunch,
weighted])
DiGraph.size([weighted]) Return the number of edges.
DiGraph.number_of_edges([u,v])
DiGraph.nodes_with_selfloops()
DiGraph.selfloop_edges([data])
DiGraph.number_of_selfloops()
Return True if the graph contains the node n.
expression
Return True if the edge (u,v) is in the graph.
Return the number of nodes in the graph.
Return the number of nodes in the graph.
DiGraph.-_en_()
Return the number of nodes.
Return the degree of a node or nodes.
Return an iterator for (node, degree).
Return the in-degree of a node or nodes.
Return the out-degree of a node or nodes.
Return the number of edges between two nodes.
Return a list of nodes with self loops.

```

Return True if the graph contains the node n .
Return True if n is a node, False otherwise. Use the expression
Return True if the edge ( \(u, v\) ) is in the graph.
Return the number of nodes in the graph.
Return the number of nodes in the graph.
Return the number of nodes.
Return the degree of a node or nodes.
Return an iterator for (node, degree).
Return the in-degree of a node or nodes.
Return an iterator for (node, in-degree).

Return the out-degree of a node or nodes.
Return an iterator for (node, out-degree).
Return the number of edges.
Retur a
Return a list of selfloop edges.
Return the number of selfloop edges.
networkx.DiGraph.has_node
has_node ( \(n\) )
Return True if the graph contains the node \(n\).
Parameters n: node

\section*{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

```

\section*{networkx.DiGraph.__contains}
\(\qquad\) ( \(n\) )
Return True if n is a node, False otherwise. Use the expression ' n in G '.

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2,3])\)
>>> 1 in G
True

\section*{networkx.DiGraph.has_edge}

\section*{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.

\section*{Returns edge_ind : bool}

True if edge is in the graph, False otherwise.

\section*{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

```

\section*{networkx.DiGraph.order}
```

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__

```

\section*{networkx.DiGraph.number_of_nodes}

\section*{number_of_nodes ()}

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

\section*{See Also:}
```

    order,
    ```
\(\qquad\)
``` len
``` \(\qquad\)

\section*{Examples}
```

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

```

\section*{networkx.DiGraph. \\ \(\qquad\)}
\(\qquad\)
len ( )
Return the number of nodes. Use the expression 'len(G)'.
Returns nnodes : int
The number of nodes in the graph.

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

\section*{networkx.DiGraph.degree}
degree (nbunch=None, weighted=False)
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.
weighted : bool, optional (default=False)

If True return the sum of 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.

\section*{Examples}
```

>>> 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]

```

\section*{networkx.DiGraph.degree_iter}
```

degree_iter(nbunch=None, weighted=False)

```

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.
weighted : bool, optional (default=False)
If True return the sum of edge weights adjacent to the node.
Returns nd_iter : an iterator
The iterator returns two-tuples of (node, degree).

\section*{See Also:}
```

degree, in_degree, out_degree, in_degree_iter, out_degree_iter

```

\section*{Examples}
```

>>> 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)]

```
networkx.DiGraph.in_degree
in_degree ( nbunch=None, weighted=False)
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.
weighted : bool, optional (default=False)
If True return the sum of 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.

\section*{See Also:}
```

degree,out__degree,in_degree_iter

```

\section*{Examples}
```

>>> 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]

```

\section*{networkx.DiGraph.in_degree_iter}
```

in_degree_iter(nbunch=None, weighted=False)

```

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.
weighted : bool, optional (default=False)
If True return the sum of edge weights adjacent to the node.
Returns nd_iter : an iterator
The iterator returns two-tuples of (node, in-degree).

\section*{See Also:}
```

degree, in_degree, out_degree,out_degree_iter

```

\section*{Examples}
```

>>> G = nx.DiGraph()
>>> G.add_path([0,1,2,3])
>>> list(G.in_degree_iter(0)) \# node O with degree 0

```
```

[(0, 0)]
>>> list(G.in_degree_iter([0,1]))
[(0, 0), (1, 1)]

```

\section*{networkx.DiGraph.out_degree}
```

out_degree (nbunch=None, weighted=False)

```

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.
weighted : bool, optional (default=False)
If True return the sum of 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.

\section*{Examples}
```

>>> 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]

```

\section*{networkx.DiGraph.out_degree_iter}
out_degree_iter (nbunch=None, weighted=False)
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.
weighted : bool, optional (default=False)
If True return the sum of edge weights adjacent to the node.
Returns nd_iter : an iterator
The iterator returns two-tuples of (node, out-degree).

\section*{See Also:}
degree, in_degree, out_degree, in_degree_iter

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.DiGraph.size}

\section*{size (weighted=False)}

Return the number of edges.
Parameters weighted : boolean, optional (default=False)
If True return the sum of the edge weights.
Returns nedges : int
The number of edges in the graph.

\section*{See Also:}
```

number_of__edges

```

\section*{Examples}
```

>>> 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(weighted=True)
6.0

```
networkx.DiGraph.number_of_edges
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.

\section*{See Also:}

\section*{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

```

\section*{networkx.DiGraph.nodes_with_selfloops}

\section*{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.

\section*{See Also:}
```

selfloop_edges, number_of_selfloops

```

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_edge \((1,1)\)
>>> G.add_edge \((1,2)\)
>>> G.nodes_with_selfloops()
[1]

\section*{networkx.DiGraph.selfloop_edges}
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.

\section*{See Also:}
```

selfloop_nodes, number_of_selfloops

```

\section*{Examples}
```

>>> 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, {})]

```

\section*{networkx.DiGraph.number_of_selfloops}
```

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.

\section*{See Also:}
```

    selfloop_nodes,selfloop_edges
    ```

\section*{Examples}
>>> G=nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge \((1,1)\)
>>> G.add_edge \((1,2)\)
>>> G.number_of_selfloops()
1

\section*{Making copies and subgraphs}
\begin{tabular}{ll}
\hline DiGraph.copy() & Return a copy of the graph. \\
DiGraph.to_undirected() & Return an undirected representation of the digraph. \\
DiGraph.to_directed() & Return a directed copy of the graph. \\
DiGraph.subgraph(nbunch) & Return the subgraph induced on nodes in nbunch. \\
DiGraph.reverse([copy]) & Return the reverse of the graph. \\
\hline
\end{tabular}

\section*{networkx.DiGraph.copy}
copy ()
Return a copy of the graph.
Returns G: Graph
A copy of the graph.

\section*{See Also:}
to_directed return a directed copy of the graph.

\section*{Notes}

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

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path ( \([0,1,2,3])\)
\(\ggg H=\) G.copy ()

\section*{networkx.DiGraph.to_undirected}

\section*{to_undirected()}

Return an undirected representation of the 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 ( \(v, u, d a t a)\) 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.

\section*{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 \(\mathrm{G}=\mathrm{DiGraph}(\mathrm{D})\) 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.

\section*{networkx.DiGraph.to_directed}
to_directed ()
Return a directed copy of the graph.
Returns G: DiGraph
A deepcopy of the graph.

\section*{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 \(\mathrm{D}=\mathrm{DiGraph}(\mathrm{G})\) 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.

\section*{Examples}
```

>>> 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
```

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

```

\section*{networkx.DiGraph.subgraph}

\section*{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.

\section*{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)])

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.DiGraph.reverse}

\section*{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).

\subsection*{3.2.3 MultiGraph - Undirected graphs with self loops and parallel edges}

\section*{Overview}

MultiGraph (data=None, name=", **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.

\section*{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.

\section*{See Also:}
```

Graph,DiGraph,MultiDiGraph

```

\section*{Examples}

Create an empty graph structure (a "null graph") with no nodes and no edges.
```

>>> G = nx.MultiGraph()

```

G can be grown in several ways.

\section*{Nodes:}

Add one node at a time:
```

>>> 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).
```

>>> 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.
```

>>> G.add_node(H)

```

\section*{Edges:}

G can also be grown by adding edges.
Add one edge,
\(\ggg\) G.add_edge \((1,2)\)
a list of edges,
```

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

```
or a collection of edges,
```

>>> 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.
```

>>> 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}}}

```

\section*{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.
```

>>> G = nx.MultiGraph(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' }
>>> G.node[1]['room'] = 714
>>> G.nodes(data=True)
[(1, {'room' : 714, '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

```

\section*{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)]

```

\section*{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.

\section*{Adding and removing nodes and edges}
```

MultiGraph.__init__(**attr[, data, name]) Initialize a graph with edges, name, graph attributes.
MultiGraph.add_node(n, **attr[, attr_dict]) Add a single node n and update node attributes.
MultiGraph.add_nodes_from(nodes, **attr) Add multiple nodes.
MultiGraph.remove_node(n)
MultiGraph.remove_nodes_from(nodes) Remove multiple nodes.
MultiGraph.add_edge(u, v, **attr[, key, ...]) Add an edge between u and v.
MultiGraph.add_edges_from(ebunch, Add all the edges in ebunch.
**attr[, ..])
MultiGraph.add_weighted_edges_from(ebundlld}\mathrm{ all the edges in ebunch as weighted edges with
...) specified weights.
MultiGraph.remove_edge(u, v[, key]) Remove an edge between u and v.
MultiGraph.remove_edges_from(ebunch) Remove all edges specified in ebunch.
MultiGraph.add_star(nlist, **att) Add a star.
MultiGraph.add_path(nlist, **attr) Add a path.
MultiGraph.add_cycle(nlist, **attr) Add a cycle.
MultiGraph.clear() Remove all nodes and edges from the graph.

```
networkx.MultiGraph.__init__
__init__ (data=None, name=", **attr)
    Initialize a graph with edges, name, graph attributes.

\section*{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.

\section*{See Also:}
convert

\section*{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' }

```

\section*{networkx.MultiGraph.add_node}
```

add_node ( }n\mathrm{ , 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.

\section*{See Also:}
```

add_nodes_from

```

\section*{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.

\section*{Examples}
```

>>> 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:
```

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

```

\section*{networkx.MultiGraph.add_nodes_from}
```

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.

\section*{See Also:}
add_node

\section*{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.
\(\ggg\) 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

```
networkx.MultiGraph.remove_node
```

remove_node ( }n\mathrm{ )

```

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

\section*{Raises NetworkXError :}

If n is not in the graph.

\section*{See Also:}
```

remove_nodes_from

```

\section*{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()
[]

```
networkx.MultiGraph.remove_nodes_from
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.

\section*{See Also:}
```

    remove_node
    ```

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2])\)
\(\ggg\) e \(=\) G.nodes()
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> G.nodes()
[]
networkx.MultiGraph.add_edge
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 \(\mathbf{u}, \mathbf{v}\) : 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.

\section*{See Also:}
add_edges_from add a collection of edges

\section*{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.

\section*{Examples}

The following all add the edge \(\mathrm{e}=(1,2)\) to graph G :
```

>>> 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:
```

>>> 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)

```
networkx.MultiGraph.add_edges_from
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.

\section*{See Also:}
add_edge add a single edge
add_weighted_edges_from convenient way to add weighted edges

\section*{Notes}

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

\section*{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')

```

\section*{networkx.MultiGraph.add_weighted_edges_from}
add_weighted_edges_from (ebunch, **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 ( \(\mathrm{u}, \mathrm{v}, \mathrm{w}\) ) where w is a number.
attr : keyword arguments, optional (default= no attributes)
Edge attributes to add/update for all edges.

\section*{See Also:}
add_edge add a single edge
add_edges_from add multiple edges

\section*{Notes}

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

\section*{Examples}
\(\ggg\) G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MuItiDiGraph, etc
>>> G.add_weighted_edges_from([(0,1,3.0), (1, 2, 7.5)])

\section*{networkx.MultiGraph.remove_edge}
remove_edge ( \(u, v\), key=None)
Remove an edge between \(u\) and \(v\).

\section*{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 (abritrary) edge between u and v .

\section*{Raises NetworkXError :}

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

\section*{See Also:}
remove_edges_from remove a collection of edges

\section*{Examples}
\(\ggg G=n x \cdot M u l t i G r a p h()\)
\(\ggg\) G.add_path \(([0,1,2,3])\)
>>> G.remove_edge \((0,1)\)
\(\ggg \mathrm{e}=(1,2)\)
>>> 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')

```

\section*{networkx.MultiGraph.remove_edges_from}
remove_edges_from (ebunch)
Remove all edges specified in ebunch.

\section*{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.

\section*{See Also:}
remove_edge remove a single edge

\section*{Notes}

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

\section*{Examples}
```

>>> 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
```

>>> 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
[]

```

\section*{networkx.MultiGraph.add_star}
```

add_star(nlist, **attr)

```

Add a star.
The first node in nlist is the middle of the star. It is connected to all other nodes in nlist.
Parameters nlist : list
A list of nodes.
attr : keyword arguments, optional (default= no attributes)
Attributes to add to every edge in star.

See Also:
```

add__path,add_cycle

```

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_star \(([0,1,2,3])\)
\(\ggg\) G.add_star([10,11,12], weight=2)

\section*{networkx.MultiGraph.add_path}
add_path (nlist, **attr)
Add a path.
Parameters nlist : list
A list 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.

\section*{See Also:}
```

add_star,add_cycle

```

\section*{Examples}
```

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

```

\section*{networkx.MultiGraph.add_cycle}
add_cycle (nlist, **attr)
Add a cycle.

\section*{Parameters nlist : list}

A list 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.

\section*{See Also:}
add_path, add_star

\section*{Examples}
```

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

```

\section*{networkx.MultiGraph.clear}
```

clear()

```

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

\section*{Examples}
```

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

```

\section*{Iterating over nodes and edges}
\begin{tabular}{ll}
\hline MultiGraph.nodes([data]) & Return a list of the nodes in the graph. \\
MultiGraph.nodes_iter([data]) & Return an iterator over the nodes. \\
MultiGraph.__iter__() & Iterate over the nodes. \\
MultiGraph.edges([nbunch, data, keys]) & Return a list of edges. \\
MultiGraph.edges_iter([nbunch, data, & Return an iterator over the edges. \\
keys]) & \\
MultiGraph.get_edge_data(u, v[, key, & Return the attribute dictionary associated with edge (u,v). \\
default]) & \\
MultiGraph. neighbors(n) & Return a list of the nodes connected to the node n. \\
MultiGraph. neighbors_iter(n) & Return an iterator over all neighbors of node n. \\
MultiGraph.__getitem__(n) & Return a dict of neighbors of node n. \\
MultiGraph.adjacency_list() & Return an adjacency list representation of the graph. \\
MultiGraph.adjacency_iter() & Return an iterator of (node, adjacency dict) tuples for all nodes. \\
MultiGraph. nbunch_iter([nbunch]) & Return an iterator of nodes contained in nbunch that are also in \\
& the graph. \\
\hline
\end{tabular}

\section*{networkx.MultiGraph.nodes}
```

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).

\section*{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, {})]

```

\section*{networkx.MultiGraph.nodes_iter}
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)

\section*{Notes}

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

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

```

\section*{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)]
[\{\}, \{\}, \{\}]
networkx.MultiGraph.__iter__

Iterate over the nodes. Use the expression 'for n in G '.

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

\section*{Examples}
```

>>> G = nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc

```
\(\ggg\) G.add_path ( \([0,1,2,3])\)

\section*{networkx.MultiGraph.edges}

\section*{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).

\section*{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.

\section*{See Also:}
edges_iter return an iterator over the edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{Examples}
```

>>> 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)
\([(0,1)]\)

\section*{networkx.MultiGraph.edges_iter}
```

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.

\section*{See Also:}
edges return a list of edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{Examples}
>>> 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)) \# default data is \{\} (empty dict)
\([(0,1,\{ \}),(1,2,\{ \}),(2,3,\{ \})]\)
>>> list (G.edges(keys=True)) \# default keys are integers
\([(0,1,0),(1,2,0),(2,3,0)]\)
>>> list (G.edges (data=True, keys=True)) \# default keys are integers
\([(0,1,0,\{ \}),(1,2,0,\{ \}),(2,3,0,\{ \})]\)
>>> list(G.edges_iter([0,3]))
\([(0,1),(3,2)]\)
>>> list(G.edges_iter(0))
\([(0,1)]\)

\section*{networkx.MultiGraph.get_edge_data}
get_edge_data ( \(u, v\), key=None, default=None)
Return the attribute dictionary associated with edge ( \(u, v\) ).
Parameters \(\mathbf{u , v}\) : 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.

\section*{Notes}

It is faster to use \(\mathrm{G}[\mathrm{u}][\mathrm{v}][\mathrm{key}]\).
```

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

```

Warning: Assigning \(G[u][v][k e y]\) 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

```

\section*{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

```

\section*{networkx.MultiGraph.neighbors}
```

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 .

\section*{Raises NetworkXError :}

If the node n is not in the graph.

\section*{Notes}

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

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

```

\section*{Examples}
```

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

```

\section*{networkx.MultiGraph.neighbors_iter}
```

neighbors_iter(n)

```

Return an iterator over all neighbors of node \(n\).

\section*{Notes}

It is faster to use the idiom "in G[0]", e.g. >>> [n for \(n\) in G[0]] [1]

\section*{Examples}
>>> G = nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2,3])
>>> [n for \(n\) in \(\left.G . n e i g h b o r s \_i t e r(0)\right]\)
[1]
networkx.MultiGraph.__getitem_

Return a dict of neighbors of node \(n\). Use the expression ' \(\mathrm{G}[\mathrm{n}]\) '.

Parameters n : node
A node in the graph.
Returns adj_dict : dictionary
The adjacency dictionary for nodes connected to \(n\).

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

\section*{Examples}
```

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

```

\section*{networkx.MultiGraph.adjacency_list}
```

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.

\section*{See Also:}
adjacency_iter

\section*{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]]

\section*{networkx.MultiGraph.adjacency_iter}
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

```

\section*{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()]
\([(0,\{1:\{ \}\}),(1,\{0:\{ \}, 2:\{ \}\}),(2,\{1:\{ \}, 3:\{ \}\}),(3,\{2:\{ \}\})]\)
networkx.MultiGraph.nbunch_iter
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.

\section*{Raises NetworkXError :}

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

\section*{See Also:}

Graph.__iter__

\section*{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.

\section*{Information about graph structure}
```

MultiGraph.has_node(n)
MultiGraph.__contains__(n)
MultiGraph.has_edge(u, v[, key])
MultiGraph.order()
MultiGraph.number_of_nodes()
MultiGraph.__len__()
MultiGraph.degree([nbunch, weighted])
MultiGraph.degree_iter([nbunch, weighted])
MultiGraph.size([weighted])
MultiGraph.number_of_edges([u,v])
MultiGraph.nodes_with_selfloops()
MultiGraph.selfloop_edges([data, keys])
MultiGraph.number_of_selfloops()

```

Return True if the graph contains the node n .
Return True if n is a node, False otherwise. Use the expression
Return True if the graph has an edge between nodes \(u\) and \(v\).
Return the number of nodes in the graph.
Return the number of nodes in the graph.
Return the number of nodes.
Return the degree of a node or nodes.
Return an iterator for (node, degree).
Return the number of edges.
Return the number of edges between two nodes.
Return a list of nodes with self loops.
Return a list of selfloop edges.
Return the number of selfloop edges.

\section*{networkx.MultiGraph.has_node}
```

has_node ( }n\mathrm{ )

```

Return True if the graph contains the node \(n\).
Parameters n : node

\section*{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
networkx.MultiGraph.__contains
```

contains___(n)

```

Return True if \(n\) is a node, False otherwise. Use the expression ' \(n\) in G'.

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

\section*{networkx.MultiGraph.has_edge}
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.

\section*{Examples}

Can be called either using two nodes \(u, v\), an edge tuple ( \(u, v\) ), or an edge tuple ( \(u, v, k e y\) ).
```

>>> 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

```
networkx.MultiGraph.order
order ()
Return the number of nodes in the graph.
Returns nnodes : int
The number of nodes in the graph.

\section*{See Also:}
```

number_of_nodes,__len__

```

\section*{networkx.MultiGraph.number_of_nodes}
```

number_of_nodes()

```

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

\section*{See Also:}
order,__len__

\section*{Examples}
>>> G = nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> len(G)
3
networkx.MultiGraph.__len
len ()

Return the number of nodes. Use the expression 'len(G)'.
Returns nnodes : int
The number of nodes in the graph.

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path ([0, 1, 2, 3])
\(\ggg \operatorname{len}(G)\)
4

\section*{networkx.MultiGraph.degree}

\section*{degree (nbunch=None, weighted=False)}

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.
weighted : bool, optional (default=False)
If True return the sum of 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.

\section*{Examples}
```

>>> 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]

```

\section*{networkx.MultiGraph.degree_iter}
```

degree_iter (nbunch=None, weighted=False)

```

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.
weighted : bool, optional (default=False)
If True return the sum of edge weights adjacent to the node.
Returns nd_iter : an iterator
The iterator returns two-tuples of (node, degree).

\section*{See Also:}
degree

\section*{Examples}
>>> 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]))
\([(0,1),(1,2)]\)

\section*{networkx.MultiGraph.size}
size (weighted=False)
Return the number of edges.
Parameters weighted : boolean, optional (default=False)
If True return the sum of the edge weights.

Returns nedges : int
The number of edges in the graph.

\section*{See Also:}
number_of_edges

\section*{Examples}
```

>>> 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(weighted=True)
6.0

```

\section*{networkx.MultiGraph.number_of_edges}
```

number_of_edges ( }u=\mathrm{ None, v=None)

```

Return the number of edges between two nodes.
Parameters \(\mathbf{u}, \mathbf{v}\) : 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.

\section*{See Also:}
size

\section*{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

```

\section*{networkx.MultiGraph.nodes_with_selfloops}

\section*{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

```

\section*{Examples}
\(\ggg\) G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_edge \((1,1)\)
\(\ggg\) G.add_edge \((1,2)\)
>>> G.nodes_with_selfloops()
[1]

\section*{networkx.MultiGraph.selfloop_edges}
```

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.

\section*{See Also:}
```

selfloop_nodes, number_of_selfloops

```

\section*{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)
\([(1,1,0,\{ \})]\)

\section*{networkx.MultiGraph.number_of_selfloops}
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.

\section*{See Also:}
```

selfloop_nodes,selfloop_edges

```

\section*{Examples}
>>> G=nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge \((1,1)\)
>>> G.add_edge \((1,2)\)
>>> G.number_of_selfloops()
1

\section*{Making copies and subgraphs}
\begin{tabular}{ll}
\hline MultiGraph.copy() & Return a copy of the graph. \\
MultiGraph.to_undirected() & Return an undirected copy of the graph. \\
MultiGraph.to_directed() & Return a directed representation of the graph. \\
MultiGraph.subgraph(nbunch) & Return the subgraph induced on nodes in nbunch. \\
\hline
\end{tabular}
networkx.MultiGraph.copy
copy ()
Return a copy of the graph.
Returns G: Graph
A copy of the graph.

\section*{See Also:}
to_directed return a directed copy of the graph.

\section*{Notes}

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

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path ([0, 1, 2, 3])
\(\ggg H=\) G.copy ()

\section*{networkx.MultiGraph.to_undirected}

\section*{to_undirected()}

Return an undirected copy of the graph.
Returns G: Graph/MultiGraph

> A deepcopy of the graph.

\section*{See Also:}
```

copy,add_edge,add_edges_from

```

\section*{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 \(\mathrm{G}=\mathrm{DiGraph}(\mathrm{D})\) 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.

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.MultiGraph.to_directed}
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).

\section*{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 \(\mathrm{D}=\mathrm{DiGraph}(\mathrm{G})\) 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.

\section*{Examples}
```

>>> 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
```

>>> G = nx.DiGraph() \# or MultiDiGraph, etc

```
\(\ggg\) G.add_path ([0,1])
>>> H = G.to_directed()
>>> H.edges()
\([(0,1)]\)

\section*{networkx.MultiGraph.subgraph}

\section*{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.

\section*{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)])

\section*{Examples}
```

>>> 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)]

```

\subsection*{3.2.4 MultiDiGraph - Directed graphs with self loops and parallel edges}

\section*{Overview}

MultiDiGraph (data=None, name=", **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.
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:
Graph, DiGraph, MultiGraph

\section*{Examples}

Create an empty graph structure (a "null graph") with no nodes and no edges.
>>> G = nx.MultiDiGraph()
G can be grown in several ways.

\section*{Nodes:}

Add one node at a time:
>>> 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).
```

>>> 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.
```

>>> G.add_node(H)

```

\section*{Edges:}

G can also be grown by adding edges.
Add one edge,
>>> G.add_edge (1, 2)
a list of edges,
```

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

```
or a collection of edges,
```

>>> 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.
```

>>> G.add_edges_from([(4,5,dict(route=282)), (4,5,dict(route=37))])
>>> G[4]
{5: {0: {}, 1: {'route': 282}, 2: {'route': 37}}}

```

\section*{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.
```

>>> G = nx.MultiDiGraph(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' }
>>> G.node[1]['room'] = 714
>>> G.nodes(data=True)
[(1, {'room' : 714, '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

```

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

```

\section*{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.

\section*{Adding and Removing Nodes and Edges}
```

MultiDiGraph.__init__(**attr[, data, name]) Initialize a graph with edges, name, graph attributes.
MultiDiGraph.add_node(n, **attr[, attr_dict]) Add a single node n and update node attributes.
MultiDiGraph.add_nodes_from(nodes, Add multiple nodes.
**attr)
MultiDiGraph.remove_node(n) Remove node n.
MultiDiGraph.remove_nodes_from(nbunch) Remove multiple nodes.
MultiDiGraph.add_edge(u,v, **attr[, key,...]) Add an edge between u and v.
MultiDiGraph.add_edges_from(ebunch, Add all the edges in ebunch.
**attr)
MultiDiGraph.add_weighted_edges_from(ebAralchall the edges in ebunch as weighted edges with
...) specified weights.
MultiDiGraph.remove_edge(u,v[, key]) Remove an edge between u and v.
MultiDiGraph.remove_edges_from(ebunch) Remove all edges specified in ebunch.
MultiDiGraph.add_star(nlist,**attr) Add a star.
MultiDiGraph.add_path(nlist, **attr) Add a path.
MultiDiGraph.add_cycle(nlist, **attr) Add a cycle.
MultiDiGraph.clear()
Remove all nodes and edges from the graph.

```

\section*{networkx.MultiDiGraph.__init_}
_init__(data=None, name=", **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.

\section*{See Also:}
convert

\section*{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' }

```

\section*{networkx.MultiDiGraph.add_node}
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.

\section*{See Also:}
```

add__nodes_from

```

\section*{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.

\section*{Examples}
```

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

\section*{networkx.MultiDiGraph.add_nodes_from}
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.

\section*{See Also:}
add_node

\section*{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'})])
>>> G.node[1]['Size']
11
>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))
>>> H.node[1]['size']
11

```
networkx.MultiDiGraph.remove_node
```

remove_node ( }n\mathrm{ )

```

Remove node \(n\).
Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.
Parameters \(\mathbf{n}\) : node
A node in the graph
Raises NetworkXError :
If n is not in the graph.

\section*{See Also:}
```

remove_nodes_from

```

\section*{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()
[]

```
networkx.MultiDiGraph.remove_nodes_from
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.

\section*{See Also:}
```

remove_node

```

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2])\)
\(\ggg\) e \(=\) G.nodes()
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> G.nodes()
[]

\section*{networkx.MultiDiGraph.add_edge}
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

```

\section*{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.

\section*{Examples}

The following all add the edge \(\mathrm{e}=(1,2)\) to graph G :
```

>>> 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:
```

>>> 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)

```

\section*{networkx.MultiDiGraph.add_edges_from}
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

\section*{Notes}

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

\section*{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')

```
networkx.MultiDiGraph.add_weighted_edges_from
add_weighted_edges_from (ebunch, **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 ( \(\mathrm{u}, \mathrm{v}, \mathrm{w}\) ) where w is a number.
attr : keyword arguments, optional (default= no attributes)
Edge attributes to add/update for all edges.

\section*{See Also:}
add_edge add a single edge
add_edges_from add multiple edges

\section*{Notes}

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

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0,1,3.0), (1, 2, 7.5)])

\section*{networkx.MultiDiGraph.remove_edge}
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 (abritrary) edge between \(u\) and \(v\).

\section*{Raises NetworkXError :}

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

\section*{See Also:}
remove_edges_from remove a collection of edges

\section*{Examples}
>>> G = nx.MultiDiGraph()
\(\ggg\) G.add_path \(([0,1,2,3])\)
\(\ggg\) G.remove_edge \((0,1)\)
\(\ggg \mathrm{e}=(1,2)\)
>>> G.remove_edge(*e) \# unpacks e from an edge tuple
For multiple edges
>>> G = nx.MultiDiGraph()
\(\ggg\) G.add_edges_from \(([(1,2),(1,2),(1,2)])\)
\(\ggg\) G.remove_edge \((1,2)\) \# remove a single (arbitrary) edge
For edges with keys
>>> G = nx.MultiDiGraph()
>>> G.add_edge (1, 2, key='first')
\(\ggg\) G.add_edge \(\left(1,2\right.\), key \(=\) ' second' \(\left.^{\prime}\right)\)
\(\ggg\) G.remove_edge ( 1,2 , key \(=^{\prime}\) second')

\section*{networkx.MultiDiGraph.remove_edges_from}
remove_edges_from (ebunch)
Remove all edges specified in ebunch.

\section*{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.

\section*{See Also:}
remove_edge remove a single edge

\section*{Notes}

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

\section*{Examples}
```

>>> 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
```

>>> 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
[]

```

\section*{networkx.MultiDiGraph.add_star}
```

add_star (nlist, **attr)

```

Add a star.
The first node in nlist is the middle of the star. It is connected to all other nodes in nlist.
Parameters nlist : list
A list of nodes.
attr : keyword arguments, optional (default= no attributes)
Attributes to add to every edge in star.

\section*{See Also:}
add_path, add_cycle

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_star \(([0,1,2,3])\)
>>> G.add_star([10,11,12],weight=2)

\section*{networkx.MultiDiGraph.add_path}
add_path (nlist, **attr)
Add a path.

\section*{Parameters nlist : list}

A list 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

```

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

\section*{networkx.MultiDiGraph.add_cycle}
add_cycle (nlist, **attr)
Add a cycle.
Parameters nlist : list
A list 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

```

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

\section*{networkx.MultiDiGraph.clear}

\section*{clear ()}

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

\section*{Examples}
```

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

```

\section*{Iterating over nodes and edges}
```

MultiDiGraph.nodes([data])
MultiDiGraph.nodes_iter([data])
MultiDiGraph.__iter__()
MultiDiGraph.edges([nbunch, data, keys])
MultiDiGraph.edges_iter([nbunch, data,
keys])
MultiDiGraph.out_edges([nbunch, data]) Return a list of edges.
MultiDiGraph.out_edges_iter([nbunch, Return an iterator over the edges.
data, keys])
MultiDiGraph.in_edges([nbunch, data])
MultiDiGraph.in_edges_iter([nbunch,
data, keys])
MultiDiGraph.get_edge_data(u,v[, key, Return the attribute dictionary associated with edge (u,v).
default])
MultiDiGraph.neighbors(n)
MultiDiGraph.neighbors_iter(n)
MultiDiGraph.__getitem__(n)
MultiDiGraph.successors(n)
MultiDiGraph.successors_iter(n)
MultiDiGraph.predecessors(n)
MultiDiGraph.predecessors_iter(n)
MultiDiGraph.adjacency_list()
MultiDiGraph.adjacency_iter()
MultiDiGraph.nbunch_iter([nbunch])

```

Return a list of the nodes in the graph.
Return an iterator over the nodes.
Iterate over the nodes.
Return a list of edges.
Return an iterator over the edges.

Return a list of edges.
Return an iterator over the edges.
Return a list of the incoming edges.
Return an iterator over the incoming edges.
Return the attribute dictionary associated with edge (u,v).
Return a list of successor nodes of \(n\).
Return an iterator over successor nodes of \(n\).
Return a dict of neighbors of node \(n\).
Return a list of successor nodes of \(n\).
Return an iterator over successor nodes of n .
Return a list of predecessor nodes of \(n\).
Return an iterator over predecessor nodes of \(n\).
Return an adjacency list representation of the graph.
Return an iterator of (node, adjacency dict) tuples for all nodes.
Return an iterator of nodes contained in nbunch that are also in the graph.

\section*{networkx.MultiDiGraph.nodes}
```

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).

\section*{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, {})]

```

\section*{networkx.MultiDiGraph.nodes_iter}
```

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)

\section*{Notes}

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

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

```

\section*{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)]
[{}, {}, {}]

```
networkx.MultiDiGraph.__iter_
_iter_()
Iterate over the nodes. Use the expression 'for n in G '.
Returns niter : iterator
An iterator over all nodes in the graph.

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

\section*{networkx.MultiDiGraph.edges}
```

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).

\section*{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.

\section*{See Also:}
edges_iter return an iterator over the edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{Examples}
>>> 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)]

```

\section*{networkx.MultiDiGraph.edges_iter}
```

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.

\section*{See Also:}
edges return a list of edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.MultiDiGraph.out_edges}
out_edges ( \(n b u n c h=\) 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).

\section*{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.

\section*{See Also:}
edges_iter return an iterator over the edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{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)]

```

\section*{networkx.MultiDiGraph.out_edges_iter}
```

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.

\section*{See Also:}
edges return a list of edges

\section*{Notes}

Nodes in nbunch that are not in the graph will be (quietly) ignored.

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.MultiDiGraph.in_edges}
in_edges (nbunch=None, data=False)
Return a list of the incoming edges.

\section*{See Also:}
edges return a list of edges

\section*{networkx.MultiDiGraph.in_edges_iter}
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:
edges_iter return an iterator of edges

\section*{networkx.MultiDiGraph.get_edge_data}
get_edge_data ( \(u, v\), key=None, default=None)
Return the attribute dictionary associated with edge (u,v).
Parameters u,v: nodes

\section*{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.

\section*{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 \(\mathrm{G}[\mathrm{u}][\mathrm{v}][\mathrm{key}]\) 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']
1 0

```

\section*{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

```

\section*{networkx.MultiDiGraph.neighbors}
neighbors ( \(n\) )
Return a list of successor nodes of \(n\).
neighbors() and successors() are the same function.
networkx.MultiDiGraph.neighbors_iter
```

neighbors_iter(n)

```

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

\section*{networkx.MultiDiGraph.__getitem \\ \(\qquad\)}
_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 \(n\).

\section*{Notes}
\(\mathrm{G}[\mathrm{n}]\) 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 \(\mathrm{G}[\mathrm{n}]\) for reading data only.

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

\section*{networkx.MultiDiGraph.successors}

\section*{successors ( \(n\) )}

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

\section*{networkx.MultiDiGraph.successors_iter}
```

successors_iter(n)

```

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

\section*{networkx.MultiDiGraph.predecessors}
```

predecessors(n)

```

Return a list of predecessor nodes of \(n\).

\section*{networkx.MultiDiGraph.predecessors_iter}

\section*{predecessors_iter \((n)\)}

Return an iterator over predecessor nodes of n .

\section*{networkx.MultiDiGraph.adjacency_list}

\section*{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.

\section*{See Also:}
```

    adjacency_iter
    ```

\section*{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]]
networkx.MultiDiGraph.adjacency_iter
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.

\section*{See Also:}
```

adjacency_list

```

\section*{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()]
\([(0,\{1:\{ \}\}),(1,\{0:\{ \}, 2:\{ \}\}),(2,\{1:\{ \}, 3:\{ \}\}),(3,\{2:\{ \}\})]\)

\section*{networkx.MultiDiGraph.nbunch_iter}
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.

\section*{Raises NetworkXError :}

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

\section*{See Also:}
\(\qquad\)

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.

\section*{Information about graph structure}
```

MultiDiGraph.has_node(n) Return True if the graph contains the node n.
MultiDiGraph.__contains___(n)
MultiDiGraph.has_edge(u,v[, key])
MultiDiGraph.order()
MultiDiGraph.number_of_nodes()
MultiDiGraph.__len___()
MultiDiGraph.degree([nbunch, weighted])
MultiDiGraph.degree_iter([nbunch,
weighted])
MultiDiGraph.in_degree([nbunch, weighted]) Return the in-degree of a node or nodes.
MultiDiGraph.in_degree_iter([nbunch, Return an iterator for (node, in-degree).
weighted])
MultiDiGraph.out_degree([nbunch, weighted]) Return the out-degree of a node or nodes.
MultiDiGraph.out_degree_iter([nbunch, Return an iterator for (node, out-degree).
weighted])
MultiDiGraph.size([weighted]) Return the number of edges.
MultiDiGraph.number_of_edges([u,v]) Return the number of edges between two nodes.
MultiDiGraph.nodes_with_selfloops() Return a list of nodes with self loops.
MultiDiGraph.selfloop_edges([data, keys]) Return a list of selfloop edges.
MultiDiGraph.number_of_selfloops() Return the number of selfloop edges.

```

\section*{networkx.MultiDiGraph.has_node}
```

has_node (n)

```

Return True if the graph contains the node \(n\).
Parameters \(\mathbf{n}\) : node

\section*{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

```

\section*{networkx.MultiDiGraph._contains \\ \(\qquad\)}
```

contains (n)

```

Return True if \(n\) is a node, False otherwise. Use the expression ' \(n\) in G'.

\section*{Examples}
>>> G \(=\) nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
\(\ggg\) G.add_path \(([0,1,2,3])\)
>>> 1 in G
True

\section*{networkx.MultiDiGraph.has_edge}
has_edge ( \(u, v\), key \(=\) None )
Return True if the graph has an edge between nodes \(u\) and \(v\).
Parameters \(\mathbf{u , v}\) : 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.

\section*{Examples}

Can be called either using two nodes \(u, v\), an edge tuple ( \(u, v\) ), or an edge tuple ( \(u, v, k e y\) ).
```

>>> 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

```

\section*{networkx.MultiDiGraph.order}
```

order()

```

Return the number of nodes in the graph.

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

\section*{See Also:}
number_of_nodes,__len___

\section*{networkx.MultiDiGraph.number_of_nodes}
number_of_nodes ()
Return the number of nodes in the graph.
Returns nnodes : int
The number of nodes in the graph.

\section*{See Also:}
order,__len__

\section*{Examples}
>>> G = nx.Graph() \# or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_path([0,1,2])
>>> len(G)
3
networkx.MultiDiGraph.__len__

Return the number of nodes. Use the expression 'len(G)'.
Returns nnodes : int
The number of nodes in the graph.

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

\section*{networkx.MultiDiGraph.degree}
degree (nbunch=None, weighted=False)
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.
weighted : bool, optional (default=False)
If True return the sum of 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.

\section*{Examples}
```

>>> 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]

```

\section*{networkx.MultiDiGraph.degree_iter}
```

degree_iter(nbunch=None, weighted=False)

```

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.
weighted : bool, optional (default=False)
If True return the sum of edge weights adjacent to the node.
Returns nd_iter : an iterator
The iterator returns two-tuples of (node, degree).

\section*{See Also:}
```

degree

```

\section*{Examples}
```

>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1,2,3])
>>> list(G.degree_iter(0)) \# node O with degree I
[(0, 1)]
>>> list(G.degree_iter([0,1]))
[(0, 1), (1, 2)]

```

\section*{networkx.MultiDiGraph.in_degree}
in_degree ( nbunch=None, weighted=False)
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.
weighted : bool, optional (default=False)
If True return the sum of 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.

\section*{See Also:}
```

degree,out_degree, in_degree_iter

```

\section*{Examples}
```

>>> 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]

```

\section*{networkx.MultiDiGraph.in_degree_iter}
```

in_degree_iter(nbunch=None, weighted=False)

```

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.
weighted : bool, optional (default=False)
If True return the sum of edge weights adjacent to the node.
Returns nd_iter : an iterator
The iterator returns two-tuples of (node, in-degree).

\section*{See Also:}
```

    degree, in_degree, out_degree, out_degree_iter
    ```

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.MultiDiGraph.out_degree}
out_degree ( \(n\) bunch=None, weighted=False)
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.
weighted : bool, optional (default=False)
If True return the sum of 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.

\section*{Examples}
>>> G \(=\) nx.DiGraph() \# or MultiDiGraph
\(\ggg\) 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]
networkx.MultiDiGraph.out_degree_iter
out_degree_iter (nbunch=None, weighted=False)
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.
weighted : bool, optional (default=False)
If True return the sum of 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

```

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.MultiDiGraph.size}

\section*{size (weighted=False)}

Return the number of edges.
Parameters weighted : boolean, optional (default=False)
If True return the sum of the edge weights.
Returns nedges : int
The number of edges in the graph.

\section*{See Also:}
```

number_of_edges

```

\section*{Examples}
```

>>> 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(weighted=True)
6.0

```

\section*{networkx.MultiDiGraph.number_of_edges}
number_of_edges ( \(u=\) None, \(v=\) None)
Return the number of edges between two nodes.
Parameters \(\mathbf{u , v}\) : 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.

\section*{See Also:}
size

\section*{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

```

\section*{networkx.MultiDiGraph.nodes_with_selfloops}

\section*{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

\section*{A list of nodes with self loops.}

\section*{See Also:}
```

selfloop_edges, number_of_selfloops

```

\section*{Examples}
```

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

```

\section*{networkx.MultiDiGraph.selfloop_edges}
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.

\section*{See Also:}
```

selfloop_nodes, number_of_selfloops

```

\section*{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, {})]

```

\section*{networkx.MultiDiGraph.number_of_selfloops}
```

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.

\section*{See Also:}
```

selfloop_nodes,selfloop_edges

```

\section*{Examples}
```

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

```

\section*{Making copies and subgraphs}
\begin{tabular}{ll}
\hline MultiDiGraph.copy() & Return a copy of the graph. \\
MultiDiGraph.to_undirected() & Return an undirected representation of the digraph. \\
MultiDiGraph.to_directed() & Return a directed copy of the graph. \\
MultiDiGraph.subgraph(nbunch) & Return the subgraph induced on nodes in nbunch. \\
MultiDiGraph.reverse([copy]) & Return the reverse of the graph. \\
\hline
\end{tabular}

\section*{networkx.MultiDiGraph.copy}

\section*{copy ()}

Return a copy of the graph.
Returns G: Graph
A copy of the graph.

\section*{See Also:}
to_directed return a directed copy of the graph.

\section*{Notes}

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

\section*{Examples}
```

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

```

\section*{networkx.MultiDiGraph.to_undirected}
```

to_undirected()

```

Return an undirected representation of the 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.

\section*{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 \(\mathrm{D}=\mathrm{DiGraph}(\mathrm{G})\) 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.

\section*{networkx.MultiDiGraph.to_directed}

\section*{to_directed ()}

Return a directed copy of the graph.
Returns G: MultiDiGraph
A deepcopy of the graph.

\section*{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 \(\mathrm{G}=\mathrm{DiGraph}(\mathrm{D})\) 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.

\section*{Examples}
```

>>> 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
>>> G = nx.MultiDiGraph()
>>> G.add_path([0,1])
>>> H = G.to_directed()
>>> H.edges()
\([(0,1)]\)

\section*{networkx.MultiDiGraph.subgraph}

\section*{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.

\section*{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)])

\section*{Examples}
```

>>> 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)]

```

\section*{networkx.MultiDiGraph.reverse}
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).

\section*{ALGORITHMS}

\subsection*{4.1 Bipartite}
\begin{tabular}{ll}
\hline is_bipartite \((\mathbf{G})\) & Returns True if graph G is bipartite, False if not. \\
bipartite_sets \((\mathbf{G})\) & Returns bipartite node sets of graph G. \\
bipartite_color \((\mathbf{G})\) & Returns a two-coloring of the graph. \\
project \((\mathbf{B}\), nodes[, create_using]) & Return the projection of the graph onto a subset of nodes. \\
\hline
\end{tabular}

\subsection*{4.1.1 networkx.is_bipartite}

\section*{is_bipartite ( \(G\) )}

Returns True if graph G is bipartite, False if not.
Parameters G : NetworkX graph
See Also:
bipartite_color

\section*{Examples}
>>> G=nx.path_graph (4)
>>> print(nx.is_bipartite(G))
True

\subsection*{4.1.2 networkx.bipartite_sets}
bipartite_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.

\section*{See Also:}
bipartite_color

\section*{Examples}
```

>>> G=nx.path_graph(4)
>>> X,Y=nx.bipartite_sets(G)
>>> list(X)
[0, 2]
>>> list(Y)
[1, 3]

```

\subsection*{4.1.3 networkx.bipartite_color}
bipartite_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.

\section*{Examples}
>>> G=nx.path_graph (4)
>>> c=nx.bipartite_color (G)
>>> print (c)
\(\{0: 1,1: 0,2: 1,3: 0\}\)

\subsection*{4.1.4 networkx.project}
project ( \(B\), nodes, create_using=None)
Return the projection of the graph onto a subset of nodes.
The nodes retain their names and are connected in the resulting graph if 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.
Returns Graph : NetworkX graph
A graph that is the projection onto the given nodes.

\section*{See Also:}
```

    is_bipartite, bipartite_sets
    ```

\section*{Notes}

Returns a graph that is the projection of the bipartite graph B onto the set of nodes given in list nodes. No attempt is made to verify that the input graph \(B\) is bipartite.

\section*{Examples}
```

>>> B=nx.path_graph(4)
>>> G=nx.project(B,[1,3])
>>> print(G.nodes())
[1, 3]
>>> print(G.edges())
[(1, 3)]

```

\subsection*{4.2 Blockmodeling}

Functions for creating network blockmodels from node partitions.
Created by Drew Conway <drew.conway @ nyu.edu> Copyright (c) 2010. All rights reserved.
\begin{tabular}{ll}
\begin{tabular}{l} 
blockmodel(G, partitions[, \\
multigraph])
\end{tabular} & \begin{tabular}{l} 
Returns a reduced graph constructed using the generalized block \\
modeling technique.
\end{tabular} \\
\hline
\end{tabular}

\subsection*{4.2.1 networkx.blockmodel}

\section*{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

\section*{References}
[R49]

\section*{Examples}
>>> G=nx.path_graph (6)
\(\ggg\) partition \(=[[0,1],[2,3],[4,5]]\)
>>> M=nx.blockmodel(G, partition)

\subsection*{4.3 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.

\subsection*{4.3.1 networkx.edge_boundary}
edge_boundary ( \(G\), nbunch1, nbunch \(2=\) 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.

\section*{Returns elist : list}

List of edges

\section*{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.

\subsection*{4.3.2 networkx.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.

\section*{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.

\subsection*{4.4 Centrality}

\subsection*{4.4.1 Degree}

Degree centrality measures.
\begin{tabular}{ll}
\hline degree_centrality \((G)\) & Compute the degree centrality for nodes. \\
in_degree_centrality \((G)\) & Compute the in-degree centrality for nodes. \\
out_degree_centrality \((G)\) & Compute the out-degree centrality for nodes. \\
\hline
\end{tabular}
networkx.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 nodes : dictionary
Dictionary of nodes with degree centrality as the value.

\section*{See Also:}
betweenness_centrality, load_centrality, eigenvector_centrality

\section*{Notes}

The degree centrality values are normalized by dividing by the maximum possible degree in a simple graph \(\mathrm{n}-1\) 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.

\section*{networkx.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 nodes : dictionary
Dictionary of nodes with in-degree centrality as values.

\section*{See Also:}
```

degree_centrality,out_degree_centrality, Notes,-----, The, possible, For, be, are

```
```

networkx.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.

\section*{Parameters G: graph}

A NetworkX graph
Returns nodes : dictionary
Dictionary of nodes with out-degree centrality as values.

\section*{See Also:}
```

degree_centrality, in_degree_centrality

```

\section*{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.

\subsection*{4.4.2 Closeness}

Closeness centrality measures.
closeness_centrality(G[, v, weighted_edges, ...]) Compute closeness centrality for nodes.

\section*{networkx.closeness_centrality}
closeness_centrality (G, v=None, weighted_edges=False, normalized=True)
Compute closeness centrality for nodes.
Closeness centrality at a node is \(1 /\) average distance to all other nodes.
Parameters G: graph
A networkx graph
\(\mathbf{v}\) : node, optional
Return only the value for node v .
weighted_edges : bool, optional
Consider the edge weights in determining the shortest paths. If False, all edge weights are considered equal.
normalized : bool, optional
If True normalize the values to the size of the connected compoenent containing v .
Returns nodes: dictionary
Dictionary of nodes with closeness centrality as the value.

\section*{See Also:}
betweenness_centrality, load_centrality, eigenvector_centrality, degree_centrality

\section*{Notes}

The closeness centrality is normalized to to \(n-1 / \operatorname{size}(\mathrm{G})-1\) 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.

\subsection*{4.4.3 Betweenness}

Betweenness centrality measures.
betweenness_centrality \((G[\), normalized, ...]) Compute betweenness centrality for nodes.
edge_betweenness_centrality \((G[\), normalized, ...]) Compute betweenness centrality for edges.

\section*{networkx.algorithms.centrality.betweenness.betweenness_centrality}
betweenness_centrality ( \(G\), normalized=True, weighted_edges=False, endpoints=False)
Compute betweenness centrality for nodes.
Betweenness 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 \(b=b /(n-1)(n-2)\) where \(n\) is the number of nodes in G.
weighted_edges : bool, optional
Consider the edge weights in determining the shortest paths. The edge weights must be greater than zero. If False, all edge weights are considered equal.
Returns nodes : dictionary
Dictionary of nodes with betweenness centrality as the value.

\section*{See Also:}
```

edge_betweenness_centrality,load_centrality

```

\section*{Notes}

The algorithm is from Ulrik Brandes [R38].
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.

\section*{References}
[R38]
networkx.algorithms.centrality.betweenness.edge_betweenness_centrality
edge_betweenness_centrality ( \(G\), normalized=True, weighted_edges=False)
Compute betweenness centrality for edges.
Betweenness centrality of an edge is the fraction of all shortest paths that pass through that edge.
Parameters G: graph
A networkx graph
normalized : bool, optional
If True the betweenness values are normalized by \(b=b /(n-1)(n-2)\) where \(n\) is the number of nodes in G.
weighted_edges : bool, optional
Consider the edge weights in determining the shortest paths. The edge weights must be greater than zero. If False, all edge weights are considered equal.
Returns edges : dictionary
Dictionary of edges with betweenness centrality as the value.

\section*{See Also:}
betweenness_centrality, edge_load

\section*{Notes}

The algorithm is from Ulrik Brandes [R39].
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.

\section*{References}
[R39]

\subsection*{4.4.4 Current Flow Closeness}

Current-flow closeness centrality measures.
```

current_flow_closeness_centrality(G[, ..]) Compute current-flow closeness centrality for nodes.

```
```

networkx.current_flow_closeness_centrality

```
current_flow_closeness_centrality ( \(G\), normalized=True)
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 \(1 /(\mathrm{n}-1)\) where n is the number of nodes in G .
Returns nodes : dictionary
Dictionary of nodes with current flow closeness centrality as the value.

\section*{See Also:}
closeness_centrality

\section*{Notes}

The algorithm is from Brandes [R50].
If the edges have a 'weight' attribute they will be used as weights in this algorithm. Unspecified weights are set to 1 .

See also [R51] for the original definition of information centrality.

\section*{References}
[R50], [R51]

\subsection*{4.4.5 Current-Flow Betweenness}

Current-flow betweenness centrality measures.
```

current_flow_betweenness_centrality(G[, Compute current-flow betweenness centrality for
...])
nodes.
edge_current_flow__betweenness_centrality(GCompute current-flow betweenness centrality for
edges.

```
networkx.algorithms.centrality.current_flow_betweenness.current_flow_betweenness_centrality
current_flow_betweenness_centrality ( \(G\), normalized=True)
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 [R41].
Parameters G: graph
A networkx graph
normalized : bool, optional
If True the betweenness values are normalized by \(b=b /(n-1)(n-2)\) where \(n\) is the number of nodes in G.
Returns nodes : dictionary
Dictionary of nodes with betweenness centrality as the value.

\section*{See Also:}
```

    betweenness_centrality,edge_betweenness_centrality,edge_current_flow_betweenness_centra
    ```

\section*{Notes}

The algorithm is from Brandes [R40].
If the edges have a 'weight' attribute they will be used as weights in this algorithm. Unspecified weights are set to 1 .

\section*{References}
[R40], [R41]
networkx.algorithms.centrality.current_flow_betweenness.edge_current_flow_betweenness_centrality
edge_current_flow_betweenness_centrality ( \(G\), normalized=True)
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 [R43].
Parameters G: graph
A networkx graph
normalized : bool, optional
If True the betweenness values are normalized by \(b=b /(n-1)(n-2)\) where \(n\) is the number of nodes in G.
Returns nodes: dictionary
Dictionary of edge tuples with betweenness centrality as the value.

\section*{See Also:}
```

betweenness_centrality,edge_betweenness_centrality,current_flow_betweenness_centrality

```

\section*{Notes}

The algorithm is from Brandes [R42].
If the edges have a 'weight' attribute they will be used as weights in this algorithm. Unspecified weights are set to 1 .

\section*{References}
[R42], [R43]

\subsection*{4.4.6 Eigenvector}

Eigenvector centrality.

> \begin{tabular}{ll} \hline eigenvector_centrality \(\left(G\left[, \max \_i t e r\right.\right.\), tol, ...] \()\) & Compute the eigenvector centrality for the graph G. \\ eigenvector_centrality_numpy \((G)\) & Compute the eigenvector centrality for the graph G. \end{tabular}

\section*{networkx.eigenvector_centrality}
eigenvector_centrality ( \(G\), max_iter=100, tol=9.9999999999999995e-07, 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 : interger, 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.

\section*{See Also:}
eigenvector_centrality_numpy, pagerank, hits

\section*{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 \((\mathrm{G}) *\) tol has been reached.

For directed graphs this is "right" eigevector centrality. For "left" eigenvector centrality, first reverse the graph with G.reverse().

\section*{Examples}
```

>>> G=nx.path_graph(4)
>>> centrality=nx.eigenvector_centrality(G)
>>> print(['%S %O. 2f'%(node,centrality[node]) for node in centrality])
['0 0.37',' '1 0.60','2 0.60',' '3 0.37']

```

\section*{networkx.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.

\section*{See Also:}
```

eigenvector_centrality, pagerank,hits

```

\section*{Notes}

This algorithm uses the NumPy eigenvalue solver.
For directed graphs this is "right" eigevector centrality. For "left" eigenvector centrality, first reverse the graph with G.reverse().

\section*{Examples}
```

>>> 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']

```

\subsection*{4.4.7 Load}

Load centrality.
\begin{tabular}{ll}
\hline load_centrality(G[, v, cutoff, normalized, ...]) & Compute load centrality for nodes. \\
edge_load(G[, nodes, cutoff]) & Compute edge load. \\
\hline
\end{tabular}

\section*{networkx.algorithms.centrality.load.load_centrality}
load_centrality ( \(G, v=\) None, cutoff=None, normalized=True, weighted_edges=False)
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 \(b=b /(n-1)(n-2)\) where \(n\) is the number of nodes in G.
weighted_edges : bool, optional
Consider the edge weights in determining the shortest paths. If False, all edge weights are considered equal.
cutoff : bool, optional
If specified, only consider paths of length \(<=\) cutoff.
Returns nodes : dictionary
Dictionary of nodes with centrality as the value.

\section*{See Also:}
betweenness_centrality

\section*{Notes}

Load centrality is slightly different than betweenness. For this load algorithm see the reference Scientific collaboration networks: II. Shortest paths, weighted networks, and centrality, M. E. J. Newman, Phys. Rev. E 64, 016132 (2001).
networkx.algorithms.centrality.load.edge_load
edge_load ( \(G\), nodes=None, cutoff=False )
Compute edge load.
WARNING:
This module is for demonstration and testing purposes.

\subsection*{4.5 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.
http://en.wikipedia.org/wiki/Clique_problem
```

find_cliques(G) Search for all maximal cliques in a graph.
make_max_clique_graph(G[, Create the maximal clique graph of a graph.
create_using, name])
make_clique_bipartite(G[, fpos, ...]) Create a bipartite clique graph from a graph G.
graph_clique_number(G[, cliques])
graph_number_of_cliques(G[, cliques])
node_clique_number(G[, nodes, cliques])
number_of_cliques(G[, nodes, cliques])
cliques_containing_node(G[, nodes,
cliques])

```

\subsection*{4.5.1 networkx.find_cliques}

\section*{find_cliques \((G)\)}

\section*{Search for all maximal cliques in a graph.}

This algorithm searches for maximal cliques in a graph. maximal cliques are the largest complete subgraph containing a given point. The largest maximal clique is sometimes called the maximum clique.

This implementation is a generator of lists each of which contains the members of a maximal clique. To obtain a list of cliques, use list(find_cliques(G)). The method essentially unrolls the recursion used in the references to avoid issues of recursion stack depth.

\section*{See Also:}
find_cliques_recursive, A

\section*{Notes}

Based on the algorithm published by Bron \& Kerbosch (1973) [R56] as adapated by Tomita, Tanaka and Takahashi (2006) [R57] and discussed in Cazals and Karande (2008) [R58].

\section*{References}
[R56], [R57], [R58]

\subsection*{4.5.2 networkx.make_max_clique_graph}
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.

\section*{Notes}

This should be the same as make_clique_bipartite followed by project_up, but it saves all the intermediate steps.

\subsection*{4.5.3 networkx.make_clique_bipartite}
make_clique_bipartite \((G, f p o s=N o n e\), 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.

\subsection*{4.5.4 networkx.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.

\subsection*{4.5.5 networkx.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.

\subsection*{4.5.6 networkx.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.

\subsection*{4.5.7 networkx.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.

\subsection*{4.5.8 networkx.cliques_containing_node}
```

cliques_containing_node(G, nodes=None, cliques=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.

\subsection*{4.6 Clustering}

Algorithms to characterize the number of triangles in a graph.
\begin{tabular}{ll}
\hline triangles(G[, nbunch]) & Compute the number of triangles. \\
transitivity(G) & Compute transitivity. \\
clustering(G[, nbunch, weights]) & Compute the clustering coefficient for nodes. \\
average_clustering(G) & Compute average clustering coefficient. \\
\hline
\end{tabular}

\subsection*{4.6.1 networkx.triangles}
triangles ( \(G\), nbunch=None)
Compute the number of triangles.
Finds the number of triangles that include a node as one of the vertices.
Parameters G: graph
A networkx graph
nbunch : container of nodes, optional
Compute triangles for nodes in nbunch. The default is all nodes in G.
Returns out : dictionary
Number of trianges keyed by node label.

\section*{Notes}

When computing triangles for the entire graph each triangle is counted three times, once at each node.
Self loops are ignored.

\section*{Examples}
```

>>> 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]

```

\subsection*{4.6.2 networkx.transitivity}
transitivity ( \(G\) )
Compute transitivity.
Finds the fraction of all possible triangles which are in fact triangles. Possible triangles are identified by the number of "triads" (two edges with a shared vertex).
\(\mathrm{T}=3^{*}\) triangles/triads
Parameters G: graph

A networkx graph
Returns out : float
Transitivity

\section*{Examples}
>>> G=nx.complete_graph (5)
>>> print(nx.transitivity(G))
1.0

\subsection*{4.6.3 networkx.clustering}
clustering (G, nbunch=None, weights=False)
Compute the clustering coefficient for nodes.
For each node find the fraction of possible triangles that exist,
\[
c_{v}=\frac{2 T(v)}{\operatorname{deg}(v)(\operatorname{deg}(v)-1)}
\]
where \(T(v)\) is the number of triangles through node \(v\).
Parameters G: graph
A networkx graph
nbunch : container of nodes, optional
Limit to specified nodes. Default is entire graph.
weights : bool, optional
If True return fraction of connected triples as dictionary
Returns out : float, dictionary or tuple of dictionaries
Clustering coefficient at specified nodes

\section*{Notes}

The weights are the fraction of connected triples in the graph which include the keyed node. Ths is useful for computing transitivity.

Self loops are ignored.

\section*{Examples}
>>> G=nx.complete_graph (5)
>>> print(nx.clustering (G,0))
1.0
>>> print (nx.clustering(G))
\(\{0: 1.0,1: 1.0,2: 1.0,3: 1.0,4: 1.0\}\)

\subsection*{4.6.4 networkx.average_clustering}

\section*{average_clustering ( \(G\) )}

Compute average 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 \(G\).
Parameters G: graph
A networkx graph
Returns out : float
Average clustering

\section*{Notes}

This is a space saving routine; it might be faster to use clustering to get a list and then take the average.
Self loops are ignored.

\section*{Examples}
>>> G=nx.complete_graph (5)
>>> print(nx.average_clustering(G))
1.0

\subsection*{4.7 Components}

\subsection*{4.7.1 Connectivity}

Connected components.
\begin{tabular}{ll}
\hline is_connected \((\mathbf{G})\) & Test graph connectivity. \\
number_connected_components \((G)\) & Return number of connected components in graph. \\
connected_components \((G)\) & Return nodes in connected components of graph. \\
connected_component_subgraphs \((G)\) & Return connected components as subgraphs. \\
node_connected_component \((G, n)\) & Return nodes in connected components of graph containing node n. \\
\hline
\end{tabular}
networkx.algorithms.components.connected.is_connected

\section*{is_connected \((G)\)}

Test graph connectivity.

\section*{Parameters G: NetworkX Graph}

An undirected graph.
Returns connected : bool

True if the graph is connected, false otherwise.
See Also:
```

connected_components

```

\section*{Notes}

For undirected graphs only.

\section*{Examples}
```

>>> G=nx.path_graph(4)
>>> print(nx.is_connected(G))
True

```
networkx.algorithms.components.connected.number_connected_components
number_connected_components ( \(G\) )

Return number of connected components in graph.
Parameters G: NetworkX Graph
An undirected graph.
Returns \(\mathbf{n}\) : integer
Number of connected components
See Also:
connected_components

\section*{Notes}

For undirected graphs only.
networkx.algorithms.components.connected.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
    ```

\section*{Notes}

The list is ordered from largest connected component to smallest. For undirected graphs only.
networkx.algorithms.components.connected.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

\section*{Notes}

The list is ordered from largest connected component to smallest. For undirected graphs only.

\section*{Examples}

Get largest connected component as subgraph
>>> G=nx.path_graph (4)
\(\ggg\) G.add_edge \((5,6)\)
>>> H=nx.connected_component_subgraphs (G) [0]
networkx.algorithms.components.connected.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.
\(\mathbf{n}\) : node label
A node in G
Returns comp : lists
A list of nodes in component of G containing node n .

\section*{See Also:}
connected_components

\section*{Notes}

For undirected graphs only.

\subsection*{4.7.2 Strong connectivity}

Strongly connected components.
\begin{tabular}{ll}
\hline is_strongly_connected(G) & \begin{tabular}{l} 
Test directed graph for strong connectivity. \\
number_strongly_connected_components(G) \\
\\
Return number of strongly connected components in \\
graph.
\end{tabular} \\
strongly_connected_components(G) & \begin{tabular}{l} 
Return nodes in strongly connected components of \\
graph.
\end{tabular} \\
strongly_connected_component_subgraphs(G)
\end{tabular}
networkx.algorithms.components.strongly_connected.is_strongly_connected
is_strongly_connected ( \(G\) )
Test directed graph for strong connectivity.
Parameters G: NetworkX Graph
A directed graph.
Returns connected : bool
True if the graph is strongly connected, False otherwise.

\section*{See Also:}
```

    strongly_connected_components
    ```

\section*{Notes}

For directed graphs only.
networkx.algorithms.components.strongly_connected.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 \(\mathbf{n}\) : integer
Number of strongly connected components

\section*{See Also:}
```

    connected_components
    ```

\section*{Notes}

For directed graphs only.
networkx.algorithms.components.strongly_connected.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.

\section*{See Also:}
connected_components

\section*{Notes}

Uses Tarjan's algorithm with Nuutila's modifications. Nonrecursive version of algorithm.

\section*{References}
[R44], [R45]
networkx.algorithms.components.strongly_connected.strongly_connected_component_subgraphs
strongly_connected_component_subgraphs ( \(G\) )
Return strongly connected components as subgraphs.
Parameters G : NetworkX Graph
A graph.
Returns glist : list
A list of graphs, one for each strongly connected component of G.

\section*{See Also:}
connected_component_subgraphs

\section*{Notes}

The list is ordered from largest strongly connected component to smallest.
networkx.algorithms.components.strongly_connected.strongly_connected_components_recursive
strongly_connected_components_recursive ( \(G\) )
Return nodes in strongly connected components of graph.
Recursive version of algorithm.
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.

See Also:
```

connected_components

```

Notes

Uses Tarjan's algorithm with Nuutila's modifications.

\section*{References}
[R46], [R47]
networkx.algorithms.components.strongly_connected.kosaraju_strongly_connected_components
kosaraju_strongly_connected_components \((G\), source=None)
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.

See Also:
connected_components

\section*{Notes}

Uses Kosaraju's algorithm.

\section*{networkx.algorithms.components.strongly_connected.condensation}
```

condensation(G)

```

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 Graph
A directed graph.
Returns cG: NetworkX DiGraph
The condensation of G.

\section*{Notes}

After contracting all strongly connected components to a single node, the resulting graph is a directed acyclic graph.

\subsection*{4.7.3 Weak connectivity}

Weakly connected components.
```

is_weakly_connected(G) Test directed graph for weak connectivity.
number_weakly_connected_components(G) Return the number of connected components in G.
weakly_connected_components(G) Return weakly connected components of G.
weakly_connected_component_subgraphs(G) Return weakly connected components as subgraphs.

```

\section*{networkx.algorithms.components.weakly_connected.is_weakly_connected}
```

is_weakly_connected ( $G$ )
Test directed graph for weak connectivity.
Parameters G: NetworkX Graph
A directed graph.
Returns connected : bool
True if the graph is weakly connected, False otherwise.

```

\section*{See Also:}
```

    strongly_connected_components
    ```
```

    strongly_connected_components
    ```

\section*{Notes}
```

For directed graphs only.
networkx.algorithms.components.weakly_connected.number_weakly_connected_components
number_weakly_connected_components ( $G$ )
Return the number of connected components in G. For directed graphs only.

```
networkx.algorithms.components.weakly_connected.weakly_connected_components
```

weakly_connected_components(G)

```

Return weakly connected components of G.
networkx.algorithms.components.weakly_connected.weakly_connected_component_subgraphs
weakly_connected_component_subgraphs ( \(G\) )
Return weakly connected components as subgraphs.

\subsection*{4.7.4 Atrracting components}

Attracting components.
```

is_attracting_component(G)
number_attracting_components(G)
attracting_components(G)
attracting_component_subgraphs(G)

```

Returns True if \(G\) consists of a single attracting component.
Returns the number of attracting components in \(G\).
Returns a list of attracting components in \(G\).
Returns a list of attracting component subgraphs from \(G\).

\section*{networkx.algorithms.components.attracting.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.

\section*{See Also:}
attracting_components, number_attracting_components, attracting_component_subgraphs
networkx.algorithms.components.attracting.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 \(\mathbf{n}\) : int
The number of attracting components in G.

\section*{See Also:}

\footnotetext{
attracting_components, is_attracting_component, attracting_component_subgraphs
}

\section*{networkx.algorithms.components.attracting.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.

\section*{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.

\section*{See Also:}
number_attracting_components, is_attracting_component, attracting_component_subgraphs

\section*{networkx.algorithms.components.attracting.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

\subsection*{4.8 Cores}

Find the k -cores of a graph. The k-core is found by recursively pruning nodes with degrees less than k .
\[
\text { find_cores(G) } \quad \text { Return the core number for each vertex. }
\]

\subsection*{4.8.1 networkx.find_cores}

\section*{find_cores ( \(G\) )}

Return the core number for each vertex.
Parameters G: NetworkX graph
A graph
Returns core_number : dictionary
A ditionary keyed by node to the core number.

\section*{References}
[R59]

\subsection*{4.9 Cycles}

> cycle_basis(G[, root]) Returns a list of cycles which form a basis for cycles of G.

\subsection*{4.9.1 networkx.cycle_basis}

\section*{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.

\section*{Parameters G: NetworkX Graph} root : node of G, optional (default=arbitrary choice from G)

Returns A list of cycle lists. Each cycle list is a list of nodes : which forms a cycle (loop) in G. :

\section*{Notes}

This algorithm is adapted from algorithm CACM 491 published: Paton, K. An algorithm for finding a fundamental set of cycles of a graph. Comm. ACM 12, 9 (Sept 1969), 514-518.

\section*{Examples}
>>> G=nx.Graph()
\(\ggg\) G.add_cycle([0,1,2,3])
>>> G.add_cycle([0,3,4,5])
>>> print(nx.cycle_basis (G, 0))
\([[3,4,5,0],[1,2,3,0]]\)

\subsection*{4.10 Directed Acyclic Graphs}

Algorithms for directed acyclic graphs (DAGs).
\begin{tabular}{ll}
\hline topological_sort(G[, nbunch]) & Return a list of nodes in topological sort order. \\
topological_sort_recursive(G[, \\
nbunch]) & Return a list of nodes in topological sort order. \\
is_directed_acyclic_graph(G) & \begin{tabular}{l} 
Return True if the graph G is a directed acyclic graph (DAG) or \\
\\
\hline
\end{tabular} \\
\hline
\end{tabular}

\subsection*{4.10.1 networkx.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

\section*{Raises NetworkXError :}

Topological sort is defined for directed graphs only. If the graph \(G\) is undirected, a NetworkXError is raised.

\section*{NetworkXUnfeasible :}

If G is not a directed acyclic graph (DAG) no topological sort exists and a NetworkXUnfeasible exception is raised.

\section*{See Also:}
is_directed_acyclic_graph

\section*{Notes}

This algorithm is based on a description and proof in The Algorithm Design Manual [R105] .

\section*{References}
[R105]

\subsection*{4.10.2 networkx.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.

\section*{Parameters G : NetworkX digraph}
nbunch : container of nodes (optional)
Explore graph in specified order given in nbunch

\section*{Raises NetworkXError :}

Topological sort is defined for directed graphs only. If the graph \(G\) is undirected, a NetworkXError is raised.

\section*{NetworkXUnfeasible :}

If G is not a directed acyclic graph (DAG) no topological sort exists and a NetworkXUnfeasible exception is raised.

\section*{See Also:}
topological_sort, is_directed_acyclic_graph

\section*{Notes}

This is a recursive version of topological sort.

\subsection*{4.10.3 networkx.is_directed_acyclic_graph}

\section*{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

\subsection*{4.11 Distance Measures}

Graph diameter, radius, eccentricity and other properties.
\begin{tabular}{ll}
\hline center \((\mathrm{G}[, \mathrm{e}])\) & Return the periphery of the graph G. \\
diameter \((\mathrm{G}[, \mathrm{e}])\) & Return the diameter of the graph G. \\
eccentricity \((\mathrm{G}[, \mathrm{v}, \mathrm{sp}])\) & Return the eccentricity of nodes in G. \\
periphery(G[, e]) & Return the periphery of the graph G. \\
radius \((\mathrm{G}[, \mathrm{e}])\) & Return the radius of the graph G. \\
\hline
\end{tabular}

\subsection*{4.11.1 networkx.center}
center ( \(G, e=\) None)
Return the periphery of the graph \(G\).
The center is the set of nodes with eccentricity equal to radius.

\section*{Parameters G: NetworkX graph}

A graph
e: eccentricity dictionary, optional
A precomputed dictionary of eccentricities.
Returns c: list
List of nodes in center

\subsection*{4.11.2 networkx.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

\section*{See Also:}
eccentricity

\subsection*{4.11.3 networkx.eccentricity}
eccentricity ( \(G, v=\) None, \(s p=\) 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
\(\mathbf{v}\) : node, optional
Return value of specified node
\(\mathbf{s p}\) : dict of dicts, optional
All pairs shortest path lenghts as a dictionary of dictionaries
Returns ecc : dictionary
A dictionary of eccentricity values keyed by node.

\subsection*{4.11.4 networkx.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

\subsection*{4.11.5 networkx.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

\subsection*{4.12 Eulerian}

Eulerian circuits and graphs.
\begin{tabular}{ll}
\hline is_eulerian(G) & Return True if G is an Eulerian graph, False otherwise. \\
eulerian_circuit(G[, source]) & Return the edges of an Eulerian circuit in G. \\
\hline
\end{tabular}

\subsection*{4.12.1 networkx.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: NetworkX graph

\section*{Notes}

This implementation requires the graph to be connected (or strongly connected for directed graphs).

\section*{Examples}
>>> 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

\subsection*{4.12.2 networkx.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: NetworkX graph
source : node, optional
Starting node for circuit.
Returns edges : generator
A generator that produces edges in the Eulerian circuit.

\section*{Notes}

Uses Fleury's algorithm [R54],[R55]_

\section*{References}
[R54], [R55]

\section*{Examples}
```

>>> 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]

```

\subsection*{4.13 Flows}

\subsection*{4.13.1 Ford-Fulkerson}
_(Gax, s, [, capacity]
max_flow(G, s, t[, capacity])
min_cut(G, s, t[, capacity])
ford_fulkerson(G, s, t , capacity])
ford_fulkerson_flow(G, s, t[, capacity]) -

Find the value of a maximum single-commodity flow. Compute the value of a minimum ( \(\mathrm{s}, \mathrm{t}\) )-cut.
Find a maximum single-commodity flow using the Ford-Fulkerson algorithm.
Return a maximum flow for a single-commodity flow problem.
networkx.max_flow
max_flow ( \(G, s, t\), capacity='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.

\section*{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 flowValue : integer, float
Value of the maximum flow, i.e., net outflow from the source.

\section*{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.

\section*{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.

\section*{Examples}
```

>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge(' x','a', capacity = 3.0)
>>> G.add_edge(' }\mp@subsup{\textrm{X}}{}{\prime},\mp@subsup{'}{}{\prime}\mp@subsup{\textrm{b}}{}{\prime}, 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

```

\section*{networkx.min_cut}
```

min_cut (G, s,t, capacity='capacity')

```

Compute the value of a minimum ( \(\mathrm{s}, \mathrm{t}\) )-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.

\section*{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.

\section*{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.

\section*{Raises NetworkXUnbounded :}

If the graph has a path of infinite capacity, all cuts have infinite capacity and the function raises a NetworkXError.

\section*{Examples}
```

>>> 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

```

\section*{networkx.ford_fulkerson}

\section*{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 \(\mathrm{O}\left(\mathrm{nm}^{\wedge} 2\right)\) for n nodes and \(m\) edges.

\section*{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 flowValue : integer, float
Value of the maximum flow, i.e., net outflow from the source.

\section*{flowDict : dictionary}

Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge (u, v).

\section*{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.

\section*{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.

\section*{Examples}
```

>>> 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,F=nx.ford_fulkerson(G, 'x', 'y')
>>> flow
3.0

```

\section*{networkx.ford_fulkerson_flow}
ford_fulkerson_flow ( \(G\), \(s, t\), capacity='capacity')
Return a maximum flow for a single-commodity flow problem.

\section*{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.
\(\mathbf{s}\) : 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 flowDict : dictionary

Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge (u, v).

\section*{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.

\section*{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.

\section*{Examples}
```

>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge(' x',' a', capacity = 3.0)
>>> G.add_edge(' }\mp@subsup{\textrm{X}}{}{\prime},\mp@subsup{'}{}{\prime}\mp@subsup{\textrm{b}}{}{\prime}, 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')
>>> for u, v in G.edges_iter():
... print('(%S, %S) %.2f' % (u, v, F[u][v]))
...
(a, c) 2.00
(c, y) 2.00
(b, c) 0.00
(b, d) 1.00
(e, y) 1.00
(d, e) 1.00
(x, a) 2.00
(x, b) 1.00

```

\subsection*{4.13.2 Network Simplex}
\begin{tabular}{ll}
\hline network_simplex(G[, demand, capacity, & Find a minimum cost flow satisfying all demands in digraph \\
weight \(])\) & G. \\
min_cost_flow_cost \((G[\), demand, & Find the cost of a minimum cost flow satisfying all demands \\
capacity, weight \(])\) & in digraph G. \\
min_cost_flow(G[, demand, capacity, & Return a minimum cost flow satisfying all demands in digraph \\
weight \(])\) & G. \\
cost_of_flow(G, flowDict[, weight \(])\) & Compute the cost of the flow given by flowDict on graph G. \\
max_flow_min_cost(G, s, t[, capacity, & Return a maximum (s, t)-flow of minimum cost. \\
weight \(])\) & \\
\hline
\end{tabular}

\section*{networkx.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.

\section*{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'.

\section*{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'.

\section*{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'.

\section*{Returns flowCost: integer, float :}

Cost of a minimum cost flow satisfying all demands.

\section*{flowDict: dictionary :}

Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge ( \(u\), v).

\section*{Raises NetworkXError :}

This exception is raised if the input graph is not directed or not connected.

\section*{NetworkXUnfeasible :}

\section*{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.

\section*{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.

\section*{See Also:}
```

cost_of_flow,max_flow_min_cost,min_cost_flow,min_cost_flow_cost

```

\section*{References}
W. J. Cook, W. H. Cunningham, W. R. Pulleyblank and A. Schrijver. Combinatorial Optimization. WileyInterscience, 1998.

\section*{Examples}

A simple example of a min cost flow problem.
```

>>> 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}\mp@subsup{\textrm{b}}{}{\prime}:4}, '\mp@subsup{c}{}{\prime}: {' d': 1}, 'b': {' (' : 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.
```

>>> 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), (' }\mp@subsup{x}{}{\prime},'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', weighted = True)
True
>>> [(u, v) for u in flowDict for v in flowDict[u] if flowDict[u][v] > 0]
[('x', 'u'), ('S', 'x'), ('u', 'v')]
>>> nx.shortest_path(G, 's', 'v', weighted = True)

```


It is possible to change the name of the attributes used for the algorithm.
```

>>> 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

```

```

networkx.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.

\section*{Parameters G: NetworkX graph}

DiGraph on which a minimum cost flow satisfying all demands is to be found.

\section*{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'.

\section*{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'.

\section*{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'.

\section*{Returns flowCost: integer, float :}

Cost of a minimum cost flow satisfying all demands.

\section*{Raises NetworkXError :}

This exception is raised if the input graph is not directed or not connected.

\section*{NetworkXUnfeasible :}

\section*{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.

\section*{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.

\section*{See Also:}
```

cost_of_flow,max_flow_min_cost,min_cost_flow, network_simplex

```

\section*{Examples}

A simple example of a min cost flow problem.
```

>>> 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

```
networkx.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.

\section*{Parameters G : NetworkX graph}

DiGraph on which a minimum cost flow satisfying all demands is to be found.

\section*{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'.

\section*{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'.

\section*{Returns flowDict: dictionary :}

Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge ( \(u\), v).

\section*{Raises NetworkXError :}

This exception is raised if the input graph is not directed or not connected.

\section*{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.

\section*{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.

\section*{See Also:}
```

cost_of_flow,max_flow_min_cost,min_cost_flow__cost, network_simplex

```

\section*{Examples}

A simple example of a min cost flow problem.
```

>>> 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)
>>> flowDict
{' a': {' C' : 1, 'b b': 4}, ' c': {' d': 1}, ' b' : {' d': 4}, '' d': {}}

```

\section*{networkx.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.

\section*{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'.

\section*{flowDict: dictionary :}

Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge ( \(u\), v).

\section*{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.

\section*{See Also:}
```

max_flow_min_cost,min_cost_flow, min_cost_flow_cost, network_simplex

```

\section*{networkx.max_flow_min_cost}
max_flow_min_cost ( \(G, s, t\), capacity='capacity', weight='weight')
Return a maximum ( \(\mathrm{s}, \mathrm{t}\) )-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'.

\section*{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'.

\section*{Returns flowDict: dictionary :}

Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge ( \(u\), v).

\section*{Raises NetworkXError :}

This exception is raised if the input graph is not directed or not connected.

\section*{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.

\section*{See Also:}
```

cost_of_flow, ford_fulkerson, min__cost_flow, min_cost_flow_cost,
network_simplex

```

\section*{Examples}
>>> 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

```

\subsection*{4.14 Isolates}

Functions for identifying isolate (degree zero) nodes.
```

is_isolate(G, n) Determine of node n is an isolate (degree zero).
isolates(G) Return list of isolates in the graph.

```

\subsection*{4.14.1 networkx.is_isolate}
```

is_isolate(G,n)

```

Determine of node n is an isolate (degree zero).
Parameters G: graph
A networkx graph
\(\mathbf{n}\) : node
A node in G
Returns isolate : bool
True if \(n\) has no neighbors, False otherwise.

\section*{Examples}
\(\ggg G=n x\). Graph ()
\(\ggg\) G.add_edge \((1,2)\)
\(\ggg\) G.add_node (3)
>>> nx.is_isolate ( \(\mathrm{G}, 2\) )
False
>>> nx.is_isolate (G, 3)
True

\subsection*{4.14.2 networkx.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.

\section*{Examples}
```

>>> 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]

\subsection*{4.15 Isomorphism}
```

is_isomorphic(G1, G2[,weighted, rtol,
atol])
could_be_isomorphic(G1,G2) Returns False if graphs are definitely not isomorphic.
fast_could_be_isomorphic(G1, Returns False if graphs are definitely not isomorphic.
G2)
faster_could_be_isomorphic(G1, Returns False if graphs are definitely not isomorphic.
G2)

```

\subsection*{4.15.1 networkx.is_isomorphic}
is_isomorphic (G1, G2, weighted=False, rtol=9.9999999999999995e-07, atol=1.0000000000000001e-09)
Returns True if the graphs G1 and G2 are isomorphic and False otherwise.

\section*{Parameters G1, G2: NetworkX graph instances :}

The two graphs G1 and G2 must be the same type.
weighted: bool, optional :
Optionally check isomorphism for weighted graphs. G1 and G2 must be valid weighted graphs.
rtol: float, optional :
The relative error tolerance when checking weighted edges
atol: float, optional :
The absolute error tolerance when checking weighted edges

\section*{See Also:}
```

isomorphvf2

```

\section*{Notes}

Uses the vf2 algorithm. Works for Graph, DiGraph, MultiGraph, and MultiDiGraph

\subsection*{4.15.2 networkx.could_be_isomorphic}

\section*{could_be_isomorphic (G1, G2)}

Returns False if graphs are definitely not isomorphic. True does NOT guarantee isomorphism.
Parameters G1, G2 : NetworkX graph instances
The two graphs G1 and G2 must be the same type.

\section*{Notes}

Checks for matching degree, triangle, and number of cliques sequences.

\subsection*{4.15.3 networkx.fast_could_be_isomorphic}
fast_could_be_isomorphic (G1, G2)
Returns False if graphs are definitely not isomorphic. True does NOT guarantee isomorphism.
Parameters G1, G2 : NetworkX graph instances
The two graphs G1 and G2 must be the same type.

\section*{Notes}

Checks for matching degree and triangle sequences.

\subsection*{4.15.4 networkx.faster_could_be_isomorphic}

\section*{faster_could_be_isomorphic (G1, G2)}

Returns False if graphs are definitely not isomorphic. True does NOT guarantee isomorphism.
Parameters G1, G2 : NetworkX graph instances
The two graphs G1 and G2 must be the same type.

\section*{Notes}

Checks for matching degree sequences.

\subsection*{4.15.5 Advanced Interface to VF2 Algorithm}

\section*{VF2 Algorithm}

\section*{Graph Matcher}
\begin{tabular}{ll}
\hline GraphMatcher.__init_(G1, G2) & Initialize GraphMatcher. \\
GraphMatcher.initialize() & Reinitializes the state of the algorithm. \\
GraphMatcher.is_isomorphic() & Returns True if G1 and G2 are isomorphic graphs. \\
GraphMatcher.subgraph_is_isomorphic() & Returns True if a subgraph of G1 is isomorphic to G2. \\
GraphMatcher.isomorphisms_iter() & Generator over isomorphisms between G1 and G2. \\
GraphMatcher.subgraph_isomorphisms_iteG(enerator over isomorphisms between a subgraph of G1 \\
& and G2. \\
GraphMatcher.candidate_pairs_iter() & Iterator over candidate pairs of nodes in G1 and G2. \\
GraphMatcher.match() & Extends the isomorphism mapping. \\
GraphMatcher.semantic_feasibility(G1_noReturns True if adding (G1_node, G2_node) is \\
..) & symantically feasible. \\
GraphMatcher.syntactic_feasibility(G1_nRdeurns True if adding (G1_node, G2_node) is \\
...) & syntactically feasible. \\
\hline
\end{tabular}

\section*{networkx.GraphMatcher.__init_}
__init__(G1, G2)
Initialize GraphMatcher.

\section*{Parameters G1,G2: NetworkX Graph or MultiGraph instances. :}

The two graphs to check for isomorphism.

\section*{Examples}

To create a GraphMatcher which checks for syntactic feasibility:
\(\ggg\) G1 \(=\) nx.path_graph (4)
>>> G2 = nx.path_graph (4)
>>> GM \(=\) nx. GraphMatcher (G1, G2)

\section*{networkx.GraphMatcher.initialize}

\section*{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.
```

networkx.GraphMatcher.is_isomorphic
is_isomorphic()

```

Returns True if G1 and G2 are isomorphic graphs.
```

networkx.GraphMatcher.subgraph_is_isomorphic
subgraph_is_isomorphic()

```

Returns True if a subgraph of G1 is isomorphic to G2.

\author{
networkx.GraphMatcher.isomorphisms_iter \\ isomorphisms_iter() \\ Generator over isomorphisms between G1 and G2.
}

\section*{networkx.GraphMatcher.subgraph_isomorphisms_iter \\ subgraph_isomorphisms_iter()}

Generator over isomorphisms between a subgraph of G1 and G2.

\section*{networkx.GraphMatcher.candidate_pairs_iter \\ candidate_pairs_iter()}

Iterator over candidate pairs of nodes in G1 and G2.

\section*{networkx.GraphMatcher.match \\ 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.

\section*{networkx.GraphMatcher.semantic_feasibility}
semantic_feasibility (G1_node, G2_node)
Returns True if adding (G1_node, G2_node) is symantically feasible.
The semantic feasibility function should return True if it is acceptable to add the candidate pair (G1_node, G2_node) to the current partial isomorphism mapping. The logic should focus on semantic information contained in the edge data or a formalized node class.

By acceptable, we mean that the subsequent mapping can still become a complete isomorphism mapping. Thus, if adding the candidate pair definitely makes it so that the subsequent mapping cannot become a complete isomorphism mapping, then this function must return False.

The default semantic feasibility function always returns True. The effect is that semantics are not considered in the matching of G1 and G2.
The semantic checks might differ based on the what type of test is being performed. A keyword description of the test is stored in self.test. Here is a quick description of the currently implemented tests:
test='graph' Indicates that the graph matcher is looking for a graph-graph isomorphism.
test='subgraph' Indicates that the graph matcher is looking for a subgraph-graph isomorphism such that a subgraph of G1 is isomorphic to G2.

Any subclass which redefines semantic_feasibility() must maintain the above form to keep the match() method functional. Implementations should consider multigraphs.

\section*{networkx.GraphMatcher.syntactic_feasibility}
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.

\section*{DiGraph Matcher}
```

DiGraphMatcher.__init__(G1,G2) Initialize DiGraphMatcher.
DiGraphMatcher.initialize() Reinitializes the state of the algorithm.
DiGraphMatcher.is_isomorphic() Returns True if G1 and G2 are isomorphic graphs.
DiGraphMatcher.subgraph_is_isomorphic() Returns True if a subgraph of G1 is isomorphic to G2.
DiGraphMatcher.isomorphisms_iter() Generator over isomorphisms between G1 and G2.
DiGraphMatcher.subgraph_isomorphisms_itGen()rator over isomorphisms between a subgraph of G1
and G2.
DiGraphMatcher.candidate_pairs_iter() Iterator over candidate pairs of nodes in G1 and G2.
DiGraphMatcher.match() Extends the isomorphism mapping.
DiGraphMatcher.semantic_feasibility(G1_Rodherns True if adding(G1_node, G2_node) is
...) symantically feasible.
DiGraphMatcher.syntactic_feasibility(...)Returns True if adding(G1_node, G2_node) is
syntactically feasible.

```
```

networkx.DiGraphMatcher.__init__

```
    init__(G1, G2)
        Initialize DiGraphMatcher.
        G1 and G2 should be nx. Graph or nx. MultiGraph instances.
    Examples

To create a GraphMatcher which checks for syntactic feasibility:
>>> G1 = nx.DiGraph(nx.path_graph(4, create_using=nx.DiGraph()))
>>> G2 = nx.DiGraph(nx.path_graph(4, create_using=nx.DiGraph()))
>>> DiGM \(=\) nx.DiGraphMatcher (G1, G2)

\section*{networkx.DiGraphMatcher.initialize initialize()}

Reinitializes the state of the algorithm.
This method should be redefined if using something other than DiGMState. If only subclassing GraphMatcher, a redefinition is not necessary.

\section*{networkx.DiGraphMatcher.is_isomorphic \\ is_isomorphic()}

Returns True if G1 and G2 are isomorphic graphs.

\section*{networkx.DiGraphMatcher.subgraph_is_isomorphic subgraph_is_isomorphic()}

Returns True if a subgraph of G1 is isomorphic to G2.
```

networkx.DiGraphMatcher.isomorphisms_iter isomorphisms_iter()

```

Generator over isomorphisms between G1 and G2.

\author{
networkx.DiGraphMatcher.subgraph_isomorphisms_iter \\ subgraph_isomorphisms_iter() \\ Generator over isomorphisms between a subgraph of G1 and G2.
}

\section*{networkx.DiGraphMatcher.candidate_pairs_iter}
candidate_pairs_iter()
Iterator over candidate pairs of nodes in G1 and G2.

\section*{networkx.DiGraphMatcher.match \\ 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.

\section*{networkx.DiGraphMatcher.semantic_feasibility}
semantic_feasibility (G1_node, G2_node)
Returns True if adding (G1_node, G2_node) is symantically feasible.
The semantic feasibility function should return True if it is acceptable to add the candidate pair (G1_node, G2_node) to the current partial isomorphism mapping. The logic should focus on semantic information contained in the edge data or a formalized node class.

By acceptable, we mean that the subsequent mapping can still become a complete isomorphism mapping. Thus, if adding the candidate pair definitely makes it so that the subsequent mapping cannot become a complete isomorphism mapping, then this function must return False.
The default semantic feasibility function always returns True. The effect is that semantics are not considered in the matching of G1 and G2.

The semantic checks might differ based on the what type of test is being performed. A keyword description of the test is stored in self.test. Here is a quick description of the currently implemented tests:
test='graph' Indicates that the graph matcher is looking for a graph-graph isomorphism.
test='subgraph' Indicates that the graph matcher is looking for a subgraph-graph isomorphism such that a subgraph of G1 is isomorphic to G2.

Any subclass which redefines semantic_feasibility() must maintain the above form to keep the match() method functional. Implementations should consider multigraphs.

\section*{networkx.DiGraphMatcher.syntactic_feasibility}
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.

\section*{Weighted Graph Matcher}
```

WeightedGraphMatcher.__init__(G1, G2[, Initialize WeightedGraphMatcher.
...])
WeightedGraphMatcher.initialize() Reinitializes the state of the algorithm.
WeightedGraphMatcher.is_isomorphic() Returns True if G1 and G2 are isomorphic graphs.
WeightedGraphMatcher.subgraph_is_isomorRRetur(n)s True if a subgraph of G1 is isomorphic to G2.
WeightedGraphMatcher.isomorphisms_iter() Generator over isomorphisms between G1 and G2.
WeightedGraphMatcher.sulbgraph_isomorphiGGeneratorn(yer isomorphisms between a subgraph of
G1 and G2.
WeightedGraphMatcher.candidate_pairs_it\&terrator over candidate pairs of nodes in G1 and G2.
WeightedGraphMatcher.match() Extends the isomorphism mapping.
WeightedGraphMatcher.semantic_feasibilitRefturms True if mapping G1_node to G2_node is
semantically feasible.
WeightedGraphMatcher.syntactic_feasibil Rethrn\$ True if adding(G1_node, G2_node) is
syntactically feasible.

```
networkx.WeightedGraphMatcher.__init
    init__(G1, G2, rtol \(=9.9999999999999995 e-07\), atol \(=1.0000000000000001 e-09\) )
        Initialize WeightedGraphMatcher.
            Parameters G1, G2 : nx.Graph instances

G1 and G2 must be weighted graphs.
rtol : float, optional
The relative tolerance used to compare weights.
atol : float, optional
The absolute tolerance used to compare weights.

\section*{networkx.WeightedGraphMatcher.initialize}

\section*{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.

\section*{networkx.WeightedGraphMatcher.is_isomorphic}
is_isomorphic()
Returns True if G1 and G2 are isomorphic graphs.
```

networkx.WeightedGraphMatcher.subgraph_is_isomorphic
subgraph_is_isomorphic()

```

Returns True if a subgraph of G1 is isomorphic to G2.

\section*{networkx.WeightedGraphMatcher.isomorphisms_iter}
```

isomorphisms_iter()

```

Generator over isomorphisms between G1 and G2.
```

networkx.WeightedGraphMatcher.subgraph_isomorphisms_iter
subgraph_isomorphisms_iter()
Generator over isomorphisms between a subgraph of G1 and G2.

```

\section*{networkx.WeightedGraphMatcher.candidate_pairs_iter}
```

candidate_pairs_iter()

```

Iterator over candidate pairs of nodes in G1 and G2.

\section*{networkx.WeightedGraphMatcher.match \\ 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.

\section*{networkx.WeightedGraphMatcher.semantic_feasibility}
semantic_feasibility (G1_node, G2_node)
Returns True if mapping G1_node to G2_node is semantically feasible.

\section*{networkx.WeightedGraphMatcher.syntactic_feasibility \\ 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.

\section*{Weighted DiGraph Matcher}
\begin{tabular}{|c|c|}
\hline WeightedDiGraphMatcher.__init__(G1, G2[, ...]) & itialize WeightedGraphMatcher. \\
\hline WeightedDiGraphMatcher.initialize() & Reinitializes the state of the algorithm. \\
\hline WeightedDiGraphMatcher.is_isomorphic() & Returns True if G1 and G2 are isomorphic graphs. \\
\hline WeightedDiGraphMatcher.subgraph_is_iso & Returns()True if a subgraph of G1 is isomorphic to G2. \\
\hline WeightedDiGraphMatcher.isomorphisms_it & Oenerator over isomorphisms between G1 and G2. \\
\hline WeightedDiGraphMatcher.subgraph_isomor & Generator evety isomorphisms between a subgraph of G1 and G2. \\
\hline WeightedDiGraphMatcher.candidate_pa & erattor over candidate pairs of nodes in G1 and G2. \\
\hline WeightedDiGraphMatcher.match() & Extends the isomorphism mapping. \\
\hline WeightedDiGraphMatcher.semantic_feasi & Retar(rns) True if mapping G1_node to G2_node is semantically feasible. \\
\hline WeightedDiGraphMatcher.syntactic_feas & Returns.True if adding (G1_node, G2_node) is syntactically feasible. \\
\hline
\end{tabular}
networkx.WeightedDiGraphMatcher.__init__
__init__ (G1, G2, rtol=9.9999999999999995e-07, atol=1.0000000000000001e-09)
Initialize WeightedGraphMatcher.
Parameters G1, G2 : nx.DiGraph instances
G1 and G2 must be weighted graphs.
rtol : float, optional
The relative tolerance used to compare weights.
atol : float, optional
The absolute tolerance used to compare weights.

\section*{networkx.WeightedDiGraphMatcher.initialize \\ initialize()}

Reinitializes the state of the algorithm.
This method should be redefined if using something other than DiGMState. If only subclassing GraphMatcher, a redefinition is not necessary.

\section*{networkx.WeightedDiGraphMatcher.is_isomorphic \\ is_isomorphic()}

Returns True if G1 and G2 are isomorphic graphs.
```

networkx.WeightedDiGraphMatcher.subgraph_is_isomorphic
subgraph_is_isomorphic()
Returns True if a subgraph of G1 is isomorphic to G2.

```
```

networkx.WeightedDiGraphMatcher.isomorphisms_iter
isomorphisms_iter()

```

Generator over isomorphisms between G1 and G2.
```

networkx.WeightedDiGraphMatcher.subgraph_isomorphisms_iter
subgraph_isomorphisms_iter()
Generator over isomorphisms between a subgraph of G1 and G2.

```
```

networkx.WeightedDiGraphMatcher.candidate_pairs_iter
candidate_pairs_iter()

```

Iterator over candidate pairs of nodes in G1 and G2.
```

networkx.WeightedDiGraphMatcher.match
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.

\section*{networkx.WeightedDiGraphMatcher.semantic_feasibility}
semantic_feasibility (G1_node, G2_node)
Returns True if mapping G1_node to G2_node is semantically feasible.

\section*{networkx.WeightedDiGraphMatcher.syntactic_feasibility}
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.

\section*{Weighted MultiGraph Matcher}


\section*{networkx.WeightedMultiGraphMatcher.__init} init__(G1, G2, rtol=9.9999999999999995e-07, atol=1.0000000000000001e-09)

Initialize WeightedGraphMatcher.
Parameters G1, G2 : nx.MultiGraph instances
G1 and G2 must be weighted graphs.
rtol : float, optional
The relative tolerance used to compare weights.
atol : float, optional
The absolute tolerance used to compare weights.

\section*{networkx.WeightedMultiGraphMatcher.initialize}

\section*{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.

\section*{networkx.WeightedMultiGraphMatcher.is_isomorphic \\ is_isomorphic()}

Returns True if G1 and G2 are isomorphic graphs.
```

networkx.WeightedMultiGraphMatcher.subgraph_is_isomorphic
subgraph_is_isomorphic()
Returns True if a subgraph of G1 is isomorphic to G2.

```
```

networkx.WeightedMultiGraphMatcher.isomorphisms_iter
isomorphisms_iter()

```

Generator over isomorphisms between G1 and G2.
```

networkx.WeightedMultiGraphMatcher.subgraph_isomorphisms_iter
subgraph_isomorphisms_iter()
Generator over isomorphisms between a subgraph of G1 and G2.

```
networkx.WeightedMultiGraphMatcher.candidate_pairs_iter
candidate_pairs_iter ()
    Iterator over candidate pairs of nodes in G1 and G2.

\section*{networkx.WeightedMultiGraphMatcher.match}
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.

\author{
networkx.WeightedMultiGraphMatcher.semantic_feasibility \\ semantic_feasibility (G1_node, G2_node)
}

Returns True if mapping G1_node to G2_node is semantically feasible.

\section*{networkx.WeightedMultiGraphMatcher.syntactic_feasibility \\ 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.

\section*{Weighted MultiDiGraph Matcher}
```

WeightedMultiDiGraphMatcher.__init__(G1, Initialize WeightedGraphMatcher.
G2)
WeightedMultiDiGraphMatcher.initialize() Reinitializes the state of the algorithm.
WeightedMultiDiGraphMatcher.is_isomorphic()Returns True if G1 and G2 are isomorphic graphs.
WeightedMultiDiGraphMatcher.subgraph_is_isRetarnshTrue)if a subgraph of G1 is isomorphic to
G2.
WeightedMultiDiGraphMatcher.isomorphisms_iGeme()ator over isomorphisms between G1 and G2.
WeightedMultiDiGraphMatcher.subgraph_isomoGemeratosoveresomorphisms between a subgraph
of G1 and G2.
WeightedMultiDiGraphMatcher.candidate_pairHeratomo(ver candidate pairs of nodes in G1 and G2.
WeightedMultiDiGraphMatcher.match() Extends the isomorphism mapping.
WeightedMultiDiGraphMatcher.semantic_feasiReturnsT(rue if mapping G1_node to G2_node is
semantically feasible.
WeightedMultiDiGraphMatcher.syntactic_feasRetuinnstTr(e.)f adding (G1_node, G2_node) is
syntactically feasible.

```
networkx.WeightedMultiDiGraphMatcher._init_
init__(G1, G2, rtol=9.9999999999999995e-07, atol=1.0000000000000001e-09)

Initialize WeightedGraphMatcher.
Parameters G1, G2 : nx.MultiDiGraph instances
G1 and G2 must be weighted graphs.
rtol : float, optional
The relative tolerance used to compare weights.
atol : float, optional
The absolute tolerance used to compare weights.

\section*{networkx.WeightedMultiDiGraphMatcher.initialize \\ initialize()}

Reinitializes the state of the algorithm.
This method should be redefined if using something other than DiGMState. If only subclassing GraphMatcher, a redefinition is not necessary.
networkx.WeightedMultiDiGraphMatcher.is_isomorphic
is_isomorphic()
Returns True if G1 and G2 are isomorphic graphs.
networkx.WeightedMultiDiGraphMatcher.subgraph_is_isomorphic
subgraph_is_isomorphic ()
Returns True if a subgraph of G1 is isomorphic to G2.
```

networkx.WeightedMultiDiGraphMatcher.isomorphisms_iter
isomorphisms_iter()
Generator over isomorphisms between G1 and G2.

```
```

networkx.WeightedMultiDiGraphMatcher.subgraph_isomorphisms_iter
subgraph_isomorphisms_iter()
Generator over isomorphisms between a subgraph of G1 and G2.

```

\section*{networkx.WeightedMultiDiGraphMatcher.candidate_pairs_iter}
candidate_pairs_iter()
Iterator over candidate pairs of nodes in G1 and G2.

\section*{networkx.WeightedMultiDiGraphMatcher.match \\ 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.

\section*{networkx. WeightedMultiDiGraphMatcher.semantic_feasibility \\ semantic_feasibility (G1_node, G2_node)}

Returns True if mapping G1_node to G2_node is semantically feasible.

\section*{networkx.WeightedMultiDiGraphMatcher.syntactic_feasibility \\ 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.

\subsection*{4.16 Link Analysis}

\subsection*{4.16.1 PageRank}

PageRank analysis of graph structure.
\begin{tabular}{ll}
\hline pagerank(G[, alpha, max_iter, tol, nstart]) & Return the PageRank of the nodes in the graph. \\
pagerank_numpy(G[, alpha]) & Return the PageRank of the nodes in the graph. \\
pagerank_scipy(G[, alpha, max_iter, tol, ...]) & Return the PageRank of the nodes in the graph. \\
google_matrix(G[, alpha, nodelist \(])\) & Return the Google matrix of the graph. \\
\hline
\end{tabular}

\section*{networkx.pagerank}
pagerank ( \(G\), alpha=0.84999999999999998, max_iter=100, tol=1e-08, nstart=None)
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 \(=0.85\)
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.
Returns nodes : dictionary
Dictionary of nodes with value as PageRank

\section*{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 \((\mathrm{G}) *\) 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.

\section*{References}
[R95], [R96]

\section*{Examples}
>>> G=nx.DiGraph(nx.path_graph (4))
>>> pr=nx.pagerank (G,alpha=0.9)
networkx.pagerank_numpy
pagerank_numpy ( \(G\), alpha=0.849999999999999998)
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 \(=0.85\)
Returns nodes : dictionary
Dictionary of nodes with value as PageRank

\section*{Notes}

The eigenvector calculation uses NumPy's interface to the LAPACK eigenvalue solvers.
This implementation works with Multi(Di)Graphs.

\section*{References}
[R97], [R98]

\section*{Examples}
>>> G=nx.DiGraph(nx.path_graph(4))
>>> pr=nx.pagerank_numpy (G,alpha=0.9)
networkx.pagerank_scipy
pagerank_scipy \((G, \quad\) alpha=0.849999999999999998, max_iter=100, tol=9.9999999999999995e-07, nodelist=None)
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 \(=0.85\)
Returns nodes : dictionary
Dictionary of nodes with value as PageRank

\section*{Notes}

The eigenvector calculation uses power iteration with a SciPy sparse matrix representation.

\section*{References}
[R99], [R100]

\section*{Examples}
>>> G=nx.DiGraph(nx.path_graph (4))
>>> pr=nx.pagerank_numpy (G,alpha=0.9)

\section*{networkx.google_matrix}
google_matrix (G, alpha=0.84999999999999998, nodelist=None)
Return the Google matrix of the graph.
Parameters G: graph
A NetworkX graph
alpha : float
The damping factor
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().

Returns A: NumPy matrix
Google matrix of the graph

\subsection*{4.16.2 Hits}

Hubs and authorities analysis of graph structure.
\begin{tabular}{ll}
\hline hits(G[, max_iter, tol, nstart]) & Return HITS hubs and authorities values for nodes. \\
hits_numpy(G) & Return HITS hubs and authorities values for nodes. \\
hits_scipy(G[, max_iter, tol]) & Return HITS hubs and authorities values for nodes. \\
hub_matrix(G[, nodelist]) & Return the HITS hub matrix. \\
authority_matrix(G[, nodelist]) & Return the HITS authority matrix. \\
\hline
\end{tabular}

\section*{networkx.hits}
hits (G, max_iter \(=100\), tol=le-08, nstart=None)
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 : interger, 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.
Returns (hubs,authorities) : two-tuple of dictionaries
Two dictionaries keyed by node containing the hub and authority values.

\section*{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 \((\mathrm{G}) *\) 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.

\section*{References}
[R86], [R87]

\section*{Examples}
>>> G=nx.path_graph (4)
\(\ggg h, a=n x . h i t s(G)\)

\section*{networkx.hits_numpy}

\section*{hits_numpy ( \(G\) )}

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
Returns (hubs,authorities) : two-tuple of dictionaries
Two dictionaries keyed by node containing the hub and authority values.

\section*{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.

\section*{References}
[R88], [R89]

\section*{Examples}
```

>>> G=nx.path_graph(4)

```
>>> h,a=nx.hits (G)

\section*{networkx.hits_scipy}
hits_scipy (G, max_iter \(=100\), tol=9.99999999999999995e-07)
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 : interger, 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.
Returns (hubs,authorities) : two-tuple of dictionaries
Two dictionaries keyed by node containing the hub and authority values.

\section*{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.

\section*{References}
[R90], [R91]

\section*{Examples}
>>> G=nx.path_graph (4)
>>> h, a=nx.hits (G)
networkx.hub_matrix
hub_matrix (G, nodelist=None)
Return the HITS hub matrix.

\section*{networkx.authority_matrix}
authority_matrix (G, nodelist=None)
Return the HITS authority matrix.

\subsection*{4.17 Matching}

The algorithm is taken from "Efficient Algorithms for Finding Maximum Matching in Graphs" by Zvi Galil, ACM Computing Surveys, 1986. It 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.
max_weight_matching(G[, maxcardinality]) Compute a maximum-weighted matching of G.

\subsection*{4.17.1 networkx.max_weight_matching}
max_weight_matching ( \(G\), 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.

\section*{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] \(==\mathrm{w}\) if node v is matched to node w. Unmatched nodes do not occur as a key in mate.

\section*{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(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.

\section*{References}
[R93]

\subsection*{4.18 Mixing Patterns}

Mixing matrices and assortativity coefficients.

\subsection*{4.18.1 Assortativity}
\begin{tabular}{ll}
\hline degree_assortativity \((G)\) & Compute degree assortativity of graph. \\
attribute_assortativity \((G\), attribute \()\) & Compute assortativity for node attributes. \\
numeric_assortativity \((G\), attribute \()\) & Compute assortativity for numerical node attributes. \\
neighbor_connectivity \((G)\) & Compute neighbor connectivity of graph. \\
degree_pearsonr \((\mathbf{G})\) & Compute degree assortativity of graph. \\
\hline
\end{tabular}
networkx.degree_assortativity

\section*{degree_assortativity ( \(G\) )}

Compute degree assortativity of graph.
Assortativity measures the similarity of connections in the graph with respect to the node degree.
Parameters G : NetworkX graph
Returns r:float
Assortativity of graph by degree.

\section*{See Also:}
attribute_assortativity, numeric_assortativity, neighbor_connectivity, degree_mixing_dict, degree_mixing_matrix

\section*{Notes}

This computes Eq. (21) in Ref. [R52], 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 out-degree and in-degree.

\section*{References}
[R52]

\section*{Examples}
```

    >>> G=nx.path_graph(4)
    >>> r=nx.degree_assortativity(G)
    >>> print("%3.1f"%r)
    -0.5
    ```

\section*{networkx.attribute_assortativity}
attribute_assortativity ( \(G\), attribute)
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
Node attribute key
Returns a: float :
Assortativity of given attribute

\section*{Notes}

This computes Eq. (2) in Ref. [R48], (trace(e)-sum(e))/(1-sum(e)), where e is the joint probability distribution (mixing matrix) of the specified attribute.

\section*{References}
[R48]

\section*{Examples}
>>> 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(G,'color'))
1.0
networkx.numeric_assortativity
numeric_assortativity (G, attribute)
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
Returns a: float :
Assortativity of given attribute

\section*{Notes}

This computes Eq. (21) in Ref. [R94], where e is the joint probability distribution (mixing matrix) of the specified attribute.

\section*{References}
[R94]

\section*{Examples}
```

>>> 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(G,'size'))
1.0

```
networkx.neighbor_connectivity
neighbor_connectivity ( \(G\) )

Compute neighbor connectivity of graph.
The neighbor connectivity is the average nearest neighbor degree of a node of degree \(k\).
Parameters G: NetworkX graph
Returns d: dictionary :
A dictionary keyed by degree k with the value of average neighbor degree.

\section*{Examples}
>>> G=nx.cycle_graph (4)
>>> nx.neighbor_connectivity(G)
\(\{2: 2.0\}\)
>>> G=nx.complete_graph (4)
>>> nx.neighbor_connectivity(G)
\(\{3: 3.0\}\)
networkx.degree_pearsonr
degree_pearsonr ( \(G\) )
Compute degree assortativity of graph.
Assortativity measures the similarity of connections in the graph with respect to the node degree.
Parameters G: NetworkX graph
Returns \(\mathbf{r}\) : float

Assortativity of graph by degree.

\section*{Notes}

This calls scipy.stats.pearsonr().

\section*{References}
[R53]

\section*{Examples}
```

>>> G=nx.path_graph(4)
>>> r=nx.degree_pearsonr(G)
>>> r
-0.5

```

\subsection*{4.18.2 Mixing}
\begin{tabular}{ll}
\hline attribute_mixing_matrix(G, attribute[, ...]) & Return mixing matrix for attribute. \\
degree_mixing_matrix(G[, normalized]) & Return mixing matrix for attribute. \\
degree_mixing_dict(G[, normalized]) & Return dictionary representation of mixing matrix for \\
& \begin{tabular}{l} 
degree.
\end{tabular} \\
\begin{tabular}{ll} 
attribute_mixing_dict(G, attribute[, & Return dictionary representation of mixing matrix for \\
normalized \(])\) & attribute.
\end{tabular} \\
\hline
\end{tabular}
networkx.attribute_mixing_matrix
attribute_mixing_matrix(G, attribute, mapping=None, normalized=True)
Return mixing matrix for attribute.
Parameters G: graph
NetworkX graph object.
attribute : string
Node attribute key.
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.
networkx.degree_mixing_matrix
degree_mixing_matrix (G, normalized=True)
Return mixing matrix for attribute.
Parameters G: graph
NetworkX graph object.
normalized : bool (default=False)
Return counts if False or probabilities if True.

\section*{Returns m: numpy array :}

Counts, or joint probability, of occurrence of node degree.
networkx.degree_mixing_dict
degree_mixing_dict ( \(G\), normalized=False)
Return dictionary representation of mixing matrix for degree.
Parameters G: graph
NetworkX graph object.
normalized : bool (default=False)
Return counts if False or probabilities if True.

\section*{Returns d: dictionary :}

Counts or joint probability of occurrence of degree pairs.
```

networkx.attribute_mixing_dict
attribute_mixing_dict (G, attribute, normalized=False)

```

Return dictionary representation of mixing matrix for attribute.
Parameters G: graph
NetworkX graph object.
attribute : string
Node attribute key.
normalized : bool (default=False)
Return counts if False or probabilities if True.
Returns d : dictionary
Counts or joint probability of occurrence of attribute pairs.

\section*{Examples}
>>> G=nx.Graph()
>>> G.add_nodes_from ([0,1], color='red')
>>> G.add_nodes_from([2,3],color='blue')
>>> G.add_edge \((1,3)\)
```

>>> d=nx.attribute_mixing_dict(G,'color')
>>> print(d['red']['blue'])
1
>>> print(d['blue']['red']) \# d symmetric for undirected graphs
1

```

\subsection*{4.19 Minimum Spanning Tree}

Computes minimum spanning tree of a weighted graph.
minimum_spanning_tree(G) Return a minimum spanning tree or forest of an undirected weighted graph. minimum_spanning_edges(G) Generate edges in a minimum spanning forest of an undirected weighted graph.

\subsection*{4.19.1 networkx.minimum_spanning_tree}

\section*{minimum_spanning_tree ( \(G\) )}

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
Returns G: NetworkX Graph
A minimum spanning tree or forest.

\section*{Notes}

Uses Kruskal's algorithm.
If the graph edges do not have a weight attribute a default weight of 1 will be assigned.

\section*{Examples}
```

>>> 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, {'weight': 1}), (1, 2, {'weight': 1}), (2, 3, {'weight': 1})]

```

\subsection*{4.19.2 networkx.minimum_spanning_edges}
```

minimum_spanning_edges (G)

```

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

Returns edges : iterator
A generator that produces edges in the minimum spanning tree. The edges are threetuples ( \(\mathrm{u}, \mathrm{v}, \mathrm{w}\) ) where w is the weight.

\section*{Notes}

Uses Kruskal's algorithm.
If the graph edges do not have a weight attribute a default weight of 1 will be assigned.
Modified code from David Eppstein, April 2006 http://www.ics.uci.edu/~eppstein/PADS/

\section*{Examples}
```

>>> 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) \# a generator of MST edges
>>> edgelist=list(mst) \# make a list of the edges
>>> print(sorted(edgelist))
[(0, 1, {'weight': 1}), (1, 2, {'weight': 1}), (2, 3, {'weight': 1})]
>>> T=nx.Graph(edgelist) \# build a graph of the MST.
>>> print(sorted(T.edges(data=True)))
[(0, 1, {'weight': 1}), (1, 2, {'weight': 1}), (2, 3, {'weight': 1})]

```

\subsection*{4.20 Operators}

Operations on graphs including union, intersection, difference, complement, subgraph.
\begin{tabular}{|c|c|}
\hline ```
cartesian_product(G, H[,
create_using])
``` & Return the Cartesian product of G and H. \\
\hline compose(G, H[, create_using, name]) & Return a new graph of G composed with H. \\
\hline complement(G[, create_using, name]) & Return graph complement of G. \\
\hline union( \(\mathrm{G}, \mathrm{H}\), create_using, rename, name]) & Return the union of graphs G and H. \\
\hline disjoint_union(G, H) & Return the disjoint union of graphs G and H , forcing distinct integer node labels. \\
\hline intersection(G, H[, create_using]) & Return a new graph that contains only the edges that exist in both G and H . \\
\hline difference(G, H[, create_using]) & Return a new graph that contains the edges that exist in G but not in H. \\
\hline symmetric_difference(G, H[, create_using]) & Return new graph with edges that exist in either G or H but not both. \\
\hline
\end{tabular}

\subsection*{4.20.1 networkx.cartesian_product}
cartesian_product ( \(G, H\), create_using=None)
Return the Cartesian product of G and H .
Parameters G,H : graph
A NetworkX graph
create_using : NetworkX graph
Use specified graph for result. Otherwise a new graph is created with the same type as G.

\section*{Notes}

Only tested with Graph class. Graph, node, and edge attributes are not copied to the new graph.

\subsection*{4.20.2 networkx.compose}
```

compose(G,H,create_using=None, name=None)

```

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
create_using : NetworkX graph
Use specified graph for result. Otherwise a new graph is created with the same type as G
name : string
Specify name for new graph

\section*{Notes}

A new graph is returned, of the same class as \(G\). It is recommended that G and H be either both directed or both undirected. Attributes from G take precedent over attributes from H .

\subsection*{4.20.3 networkx.complement}
complement (G, create_using=None, name=None)
Return graph complement of \(G\).
Parameters G: graph
A NetworkX graph
create_using : NetworkX graph
Use specified graph for result. Otherwise a new graph is created.
name : string
Specify name for new graph

\section*{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.

\subsection*{4.20.4 networkx.union}
```

union(G,H, create_using=None, rename=False,name=None)

```

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
create_using : NetworkX graph
Use specified graph for result. Otherwise a new graph is created with the same type as G.
rename : bool (default=False)
Node names of G and H can be changed be specifying the tuple rename=('G-','H-') (for example). Node \(u\) in \(G\) is then renamed "G-u" and v in H is renamed " \(\mathrm{H}-\mathrm{v}\) ".
name : string
Specify the name for the union graph

\section*{See Also:}
```

    disjoint_union
    ```

\section*{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 G is used.

\subsection*{4.20.5 networkx.disjoint_union}
```

disjoint_union(G, H)

```

Return the disjoint union of graphs G and H , forcing distinct integer node labels.
Parameters G,H : graph
A NetworkX graph

\section*{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.

\subsection*{4.20.6 networkx.intersection}
intersection ( \(G, H\), create_using=None)
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.
create_using : NetworkX graph
Use specified graph for result. Otherwise a new graph is created with the same type as G.

\section*{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
```

>>> 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)

```

\subsection*{4.20.7 networkx.difference}

\section*{difference \((G, H\), create_using \(=\) None \()\)}

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.
create_using : NetworkX graph
Use specified graph for result. Otherwise a new graph is created with the same type as G.

\section*{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
>>> 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 \(H\) )

\subsection*{4.20.8 networkx.symmetric_difference}
symmetric_difference \((G, H\), create_using=None)
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.
create_using : NetworkX graph

Use specified graph for result. Otherwise a new graph is created with the same type as G.

\section*{Notes}

Attributes from the graph, nodes, and edges are not copied to the new graph.

\subsection*{4.21 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).
shortest_path(G[, source, target, weighted]) Compute shortest paths in the graph.
shortest_path_length(G[, source, target, ...]) Compute shortest path lengths in the graph.
average_shortest_path_length(G[, weighted]) Return the average shortest path length.

\subsection*{4.21.1 networkx.shortest_path}
shortest_path \((G\), source \(=\) None, target=None, weighted \(=\) False \()\)
Compute shortest paths in the graph.
Parameters G : NetworkX graph
source : node, optional
Starting node for path. If not specified compute shortest paths for all connected node pairs.
target : node, optional
Ending node for path. If not specified compute shortest paths for every node reachable from the source.
weighted : bool, optional
If True consider weighted edges when finding shortest path.

\section*{Returns path: list or dictionary :}

If the source and target are both specified return a single list of nodes in a shortest path. If only the source is specified return a dictionary keyed by targets with a list of nodes in a shortest path. If neither the source or target is specified return a dictionary of dictionaries with path[source][target]=[list of nodes in path].

\section*{Notes}

There may be more than one shortest path between a source and target. This returns only one of them.
If weighted=True and the graph has no 'weight' edge attribute the value 1 will be used.
For digraphs this returns a shortest directed path. To find paths in the reverse direction use G.reverse(copy=False) first to flip the edge orientation.

\section*{Examples}
```

>>> 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) \# source,target not specified
>>> p[0][4]
[0, 1, 2, 3, 4]

```

\subsection*{4.21.2 networkx.shortest_path_length}

\section*{shortest_path_length \((G\), source \(=\) None, target=None, weighted \(=\) False \()\)}

Compute shortest path lengths in the graph.
This function can compute the single source shortest path lengths by specifying only the source or all pairs shortest path lengths by specifying neither the source or target.

\section*{Parameters G : NetworkX graph}
source : node, optional
Starting node for path. If not specified compute shortest pats lenghts for all connected node pairs.
target : node, optional
Ending node for path. If not specified compute shortest path lenghts for every node reachable from the source.
weighted : bool, optional
If True consider weighted edges when finding shortest path length.
Returns length : number, or container of numbers
If the source and target are both specified return a single number for the shortest path. If only the source is specified return a dictionary keyed by targets with a the shortest path as keys. If neither the source or target is specified return a dictionary of dictionaries with length[source][target]=value.

\section*{Raises NetworkXError :}

If no path exists between source and target.

\section*{Notes}

If weighted=True and the graph has no 'weight' edge attribute the value 1 will be used.
For digraphs this returns the shortest directed path. To find path lengths in the reverse direction use G.reverse(copy=False) first to flip the edge orientation.

\section*{Examples}
```

>>> 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) \# source,target not specified
>>> p[0][4]
4

```

\subsection*{4.21.3 networkx.average_shortest_path_length}

\section*{average_shortest_path_length ( \(G\), weighted=False)}

Return the average shortest path length.
The average shortest path length is the sum of path lengths \(\mathrm{d}(\mathrm{u}, \mathrm{v})\) between all pairs of nodes (assuming the length is zero if \(v\) is not reachable from \(v\) ) normalized by \(n *(n-1)\) where \(n\) is the number of nodes in \(G\).

Parameters G: NetworkX graph
weighted : bool, optional, default=False
If True use edge weights on path.

\section*{Notes}

If weighted=True and the graph has no 'weight' edge attribute the value 1 will be used.

\section*{Examples}
```

>>> G=nx.path_graph(5)
>>> print(nx.average_shortest_path_length(G))
2.0

```

\subsection*{4.21.4 Advanced Interface}

Shortest path algorithms for unweighted graphs.
```

single_source_shortest_path(G, Compute shortest path between source and all other nodes
source[, cutoff]) reachable from source.
single_source_shortest_path_length_Compute the shortest path lengths from source to all reachable
source) nodes.
all_pairs_shortest_path(G[, cutoff]) Compute shortest paths between all nodes.
all_pairs_shortest_path_length(G[, Compute the shortest path lengths between all nodes in G.
cutoff])
predecessor(G, source[, target, cutoff, ..]) Returns dictionary of predecessors for the path from source to
all nodes in G.
floyd_warshall(G) The Floyd-Warshall algorithm for all pairs shortest paths.

```

\section*{networkx.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 \(<=\) cutoff are returned.
Returns lengths: dictionary
Dictionary, keyed by target, of shortest paths.
See Also:
shortest_path

\section*{Notes}

There may be more than one shortest path between the source and target nodes. This function returns only one of them.

\section*{Examples}
>>> G=nx.path_graph (5)
\(\ggg\) path=nx.single_source_shortest_path (G, 0)
\(\ggg\) path[4]
\([0,1,2,3,4]\)
networkx.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 \(<=\) cutoff are returned.
Returns lengths: dictionary
Dictionary of shortest path lengths keyed by target.

\section*{See Also:}
```

shortest_path_length

```

\section*{Examples}
```

>>> 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}

```
networkx.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.

\section*{See Also:}
```

floyd_warshall

```

\section*{Examples}
>>> G=nx.path_graph (5)
>>> path=nx.all_pairs_shortest_path (G)
>>> print (path[0][4])
[0, 1, 2, 3, 4]
networkx.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.

\section*{Notes}

The dictionary returned only has keys for reachable node pairs.

\section*{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}

```

\section*{networkx.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 source : node label

Starting node for path
target : node label, optional
Ending node for path. If provided only predecessors between source and target are returned
cutoff : integer, optional
Depth to stop the search. Only paths of length \(<=\) cutoff are returned.
Returns pred : dictionary
Dictionary, keyed by node, of predecessors in the shortest path.

\section*{Examples}
>>> G=nx.path_graph (4)
>>> print(G.nodes())
\([0,1,2,3]\)
>>> nx.predecessor (G, 0)
\(\{0:[], 1:[0], 2:[1], 3:[2]\}\)
networkx.floyd_warshall
floyd_warshall (G)
The Floyd-Warshall algorithm for all pairs shortest paths.
Parameters G: NetworkX graph
Returns distance,pred : dictionaries
A dictionary, keyed by source and target, of shortest path distance and predecessors in the shortest path.

\section*{See Also:}
```

all_pairs_shortest_path,all_pairs_shortest_path_length

```

\section*{Notes}

This algorithm is most appropriate for dense graphs. The running time is \(\mathrm{O}\left(\mathrm{n}^{\wedge} 3\right)\), and running space is \(\mathrm{O}\left(\mathrm{n}^{\wedge} 2\right)\) where n is the number of nodes in G .

Shortest path algorithms for weighed graphs.
```

dijkstra_path(G, source, target[, Returns the shortest path from source to target in a weighted graph
weight])
dijkstra_path_length(G, source, Returns the shortest path length from source to target in a weighted
target[, weight])
single_source_dijkstra_path(G, Compute shortest path between source and all other reachable
source[,weight]) nodes for a weighted graph.
single_source_dijkstra_path_lenGomqute shortest path length between source and all other
source) reachable nodes for a weighted graph.
all_pairs_dijkstra_path(G[, Compute shortest paths between all nodes in a weighted graph.
weight])
all_pairs_dijkstra_path_length(Glompute shortest path lengths between all nodes in a weighted
weight]) graph.
single_source_dijkstra(G, Compute shortest paths and lengths in a weighted graph G.
source[, target, ...])
bidirectional_dijkstra(G, Dijkstra's algorithm for shortest paths using bidirectional search.
source, target[, ...])
bidirectional_shortest_path(G, Return a list of nodes in a shortest path between source and target.
source, target)
dijkstra_predecessor_and_distanCe@pute shorest path length and predecessors on shortest paths in
source) weighted graphs.
bellman_ford(G, source[,weight]) Compute shortest path lengths and predecessors on shortest paths in
weighted graphs.

```

\section*{networkx.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 :
Edge data key corresponding to the edge weight
Returns path : list
List of nodes in a shortest path.

\section*{See Also:}
bidirectional_dijkstra

\section*{Notes}

Uses a bidirectional version of Dijkstra's algorithm. Edge weight attributes must be numerical.

\section*{Examples}
>>> G=nx.path_graph (5)
>>> print(nx.dijkstra_path(G, 0, 4))
\([0,1,2,3,4]\)
networkx.dijkstra_path_length
dijkstra_path_length ( \(G\), source, target, weight='weight')
Returns the shortest path length from source to target in a weighted graph G.
Parameters G: NetworkX graph, weighted
source : node label
starting node for path
target : node label
ending node for path
weight: string, optional :
Edge data key corresponding to the edge weight
Returns length : number
Shortest path length.
Raises NetworkXError :
If no path exists between source and target.
See Also:
bidirectional_dijkstra

\section*{Notes}

Edge weight attributes must be numerical.

\section*{Examples}
```

>>> G=nx.path_graph(5) \# a weighted graph by default
>>> print(nx.dijkstra_path_length(G,0,4))
4

```
networkx.single_source_dijkstra_path
single_source_dijkstra_path (G, source, weight='weight')
Compute shortest path between source and all other reachable nodes for a weighted graph.
Parameters G: NetworkX graph
source : node
Starting node for path.
weight: string, optional :
Edge data key corresponding to the edge weight
Returns paths : dictionary
Dictionary of shortest path lengths keyed by target.
See Also:
single_source_dijkstra

Notes

Edge weight attributes must be numerical.

\section*{Examples}
>>> G=nx.path_graph (5)
>>> path=nx.single_source_dijkstra_path(G,0)
>>> path[4]
\([0,1,2,3,4]\)
networkx.single_source_dijkstra_path_length
single_source_dijkstra_path_length ( \(G\), source, weight='weight')
Compute 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 :
Edge data key corresponding to the edge weight
Returns paths: dictionary
Dictionary of shortest paths keyed by target.

\section*{See Also:}
```

single_source_dijkstra

```

\section*{Notes}

Edge data must be numerical values for XGraph and XDiGraphs.

\section*{Examples}
```

>>> 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}

```
networkx.all_pairs_dijkstra_path
all_pairs_dijkstra_path (G, weight='weight')
Compute shortest paths between all nodes in a weighted graph.
Parameters G : NetworkX graph
weight: string, optional :
Edge data key corresponding to the edge weight
Returns distance : dictionary
Dictionary, keyed by source and target, of shortest paths.
See Also:
floyd_warshall

\section*{Examples}
>>> G=nx.path_graph (5)
>>> path=nx.all_pairs_dijkstra_path(G)
>>> print (path[0][4])
[0, 1, 2, 3, 4]
networkx.all_pairs_dijkstra_path_length
all_pairs_dijkstra_path_length ( \(G\), weight='weight')
Compute shortest path lengths between all nodes in a weighted graph.
Parameters G: NetworkX graph
weight: string, optional :
Edge data key corresponding to the edge weight
Returns distance : dictionary
Dictionary, keyed by source and target, of shortest path lengths.

\section*{Notes}

The dictionary returned only has keys for reachable node pairs.

\section*{Examples}
```

>>> 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}

```

\section*{networkx.single_source_dijkstra}
```

single_source_dijkstra(G, source, target=None, cutoff=None, weight='weight')

```

Compute shortest paths and lengths in a weighted graph G.
Uses Dijkstra's algorithm for shortest paths.
Parameters G: NetworkX graph
source : node label
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 \(<=\) 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.

\section*{See Also:}
```

single_source_dijkstra_path, single_source_dijkstra__path_length

```

\section*{Notes}

Distances are calculated as sums of weighted edges traversed. Edges must hold numerical values for Graph and DiGraphs.

Based on the Python cookbook recipe (119466) at 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).

\section*{Examples}
```

>>> 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]

```

\section*{networkx.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 :
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 dicdtionary stores distance from the source. :
The second stores the path from the source to that node. :

\section*{Raise an exception if no path exists. :}

\section*{Raises NetworkXError :}

If no path exists between source and target.

\section*{See Also:}
```

shortest_path,shortest_path_length

```

\section*{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 \(\mathrm{pi} * \mathrm{r} * \mathrm{r}\) while the others are \(2 * \mathrm{pi} * \mathrm{r} / 2 * \mathrm{r} / 2\), 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).

\section*{Examples}
```

>>> G=nx.path_graph(5)
>>> length,path=nx.bidirectional_dijkstra(G, 0, 4)
>>> print(length)
4
>>> print (path)
[0, 1, 2, 3, 4]

```

\section*{networkx.bidirectional_shortest_path}
bidirectional_shortest_path (G, source, target)
Return a list of nodes in a shortest path between source and target.
Parameters G: NetworkX graph
source : node label
starting node for path
target : node label
ending node for path

\section*{Returns path: list :}

List of nodes in a path from source to target.

\section*{See Also:}
```

shortest_path

```

\section*{Notes}

This algorithm is used by shortest_path(G,source,target).
networkx.dijkstra_predecessor_and_distance
dijkstra_predecessor_and_distance (G, source, weight='weight')
Compute shorest path length and predecessors on shortest paths in weighted graphs.
Parameters G: NetworkX graph
source : node label
Starting node for path
weight: string, optional :
Edge data key corresponding to the edge weight
Returns pred,distance : dictionaries
Returns two dictionaries representing a list of predecessors of a node and the distance to each node.

\section*{Notes}

The list of predecessors contains more than one element only when there are more than one shortest paths to the key node.

\section*{networkx.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 \(\mathrm{O}(\mathrm{mn})\) where n is the number of nodes and n is the number of edges.
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 :
Edge data key corresponding to the edge weight
Returns pred,dist : dictionaries
Returns two dictionaries representing a list of predecessors of a node and the distance from the source to each node. The dictionaries are keyed by target node label.

\section*{Raises NetworkXError :}

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.

\section*{Notes}

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.

\section*{Examples}
```

>>> 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)
>>> G[1][2]['weight'] = -7
>>> assert_raises(nx.NetworkXError, nx.bellman_ford, G, 0)

```

\subsection*{4.21.5 A* Algorithm}

Shortest paths and path lengths using A* ("A star") algorithm.
\begin{tabular}{ll}
\hline astar_path(G, source, target[, & \begin{tabular}{l} 
Return a list of nodes in a shortest path between source and target using \\
heuristic] \()\)
\end{tabular} \\
\begin{tabular}{ll} 
astar_path_length(G, source, ("A-star") algorithm. \\
target[, heuristic] \()\)
\end{tabular} & \begin{tabular}{l} 
Return a list of nodes in a shortest path between source and target using \\
the A* ("A-star") algorithm.
\end{tabular} \\
\hline
\end{tabular}

\section*{networkx.astar_path}

\section*{astar_path (G, source, target, heuristic=None)}

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.

See Also:
shortest_path, dijkstra_path

\section*{Examples}
>>> G=nx.path_graph (5)
>>> print(nx.astar_path (G, 0, 4))
[0, 1, 2, 3, 4]
\(\ggg\) G=nx.grid_graph (dim=[3,3]) \# nodes are two-tuples (x,y)
>>> def dist (a, b):
... \((x 1, y 1)=a\)
\(\ldots \quad\left(x 2, y^{2}\right)=b\)
... return \(((x 1-x 2)\) ** \(2+(y 1-y 2) * * 2)\) ** 0.5
>>> print (nx.astar_path (G, \((0,0),(2,2)\), dist))
\([(0,0),(0,1),(1,1),(1,2),(2,2)]\)
networkx.astar_path_length
astar_path_length (G, source, target, heuristic=None)
Return a list of nodes in a 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.

\section*{See Also:}
```

astar_path

```

\subsection*{4.22 Traversal}

\subsection*{4.22.1 Depth First Search}

Search algorithms.
\begin{tabular}{|c|c|}
\hline dfs_preorder(G[, source, reverse_graph]) & Return list of nodes connected to source in depth-first-search preorder. \\
\hline dfs_postorder(G[, source, reverse_graph]) & Return list of nodes connected to source in depth-first-search postorder. \\
\hline dfs_predecessor(G[, source, reverse_graph]) & Return predecessors of depth-first-search with root at source. \\
\hline dfs_successor(G[, source, reverse_graph]) & Return succesors of depth-first-search with root at source. \\
\hline dfs_tree(G[, source, reverse_graph]) & Return directed graph (tree) of depth-first-search with root at source. \\
\hline
\end{tabular}

\section*{networkx.dfs_preorder}
```

dfs_preorder (G, source=None, reverse_graph=False)

```

Return list of nodes connected to source in depth-first-search preorder.
Traverse the graph G with depth-first-search from source. Non-recursive algorithm.
```

networkx.dfs_postorder

```
dfs_postorder \((G\), source \(=\) None, reverse_graph=False \()\)

Return list of nodes connected to source in depth-first-search postorder.
Traverse the graph G with depth-first-search from source. Non-recursive algorithm.

\section*{networkx.dfs_predecessor}
dfs_predecessor ( \(G\), source=None, reverse_graph=False)
Return predecessors of depth-first-search with root at source.
```

networkx.dfs_successor

```
dfs_successor ( \(G\), source \(=\) None, reverse_graph=False \()\)

Return succesors of depth-first-search with root at source.
networkx.dfs_tree
dfs_tree ( \(G\), source=None, reverse_graph=False)
Return directed graph (tree) of depth-first-search with root at source.
If the graph is disconnected, return a disconnected graph (forest).

\subsection*{4.23 Vitality}

Vitality measures.
\[
\text { closeness_vitality }(G[, \text { v, weighted_edges]) } \quad \text { Compute closeness vitality for nodes. }
\]

\subsection*{4.23.1 networkx.closeness_vitality}
closeness_vitality ( \(G, v=\) None, weighted_edges=False)
Compute closeness vitality for nodes.
Closeness vitality at a node is the change in the sum of distances between all node pairs when excluding a that node.

Parameters G: graph
A networkx graph
\(\mathbf{v}\) : node, optional
Return only the value for node v .
weighted_edges : bool, optional
Consider the edge weights in determining the shortest paths. If False, all edge weights are considered equal.

Returns nodes : dictionary
Dictionary with nodes as keys and closeness vitality as the value.

\section*{See Also:}
closeness_centrality

\section*{Examples}
>>> G=nx.cycle_graph (3)
>>> nx.closeness_vitality(G)
\{0: 4.0, 1: 4.0, 2: 4.0\}

\section*{FUNCTIONS}

Functional interface to graph methods and assorted utilities.

\subsection*{5.1 Graph functions}
\begin{tabular}{ll}
\hline density \((G)\) & Return the density of a graph. \\
info(G[, \(n])\) & Print short summary of information for the graph G or the node n. \\
degree_histogram(G) & Return a list of the frequency of each degree value. \\
freeze(G) & Modify graph to prevent addition of nodes or edges. \\
is_frozen(G) & Return True if graph is frozen. \\
create_empty_copy(G[, with_nodes]) & Return a copy of the graph G with all of the edges removed. \\
\hline
\end{tabular}

\subsection*{5.1.1 networkx.density}
density \((G)\)
Return the density of a graph.
The density for undirected graphs is
\[
d=\frac{2 m}{n(n-1)}
\]
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 \(G\).

\section*{Notes}

The density is 0 for an graph without edges and 1.0 for a complete graph.
The density of multigraphs can be higher than 1 .

\subsection*{5.1.2 networkx.info}
info ( \(G, n=\) None)
Print short summary of information for the graph \(G\) or the node \(n\).

Parameters G : Networkx graph
A graph
\(\mathbf{n}\) : node (any hashable)
A node in the graph G

\subsection*{5.1.3 networkx.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.

\section*{Notes}

Note: the bins are width one, hence len(list) can be large (Order(number_of_edges))

\subsection*{5.1.4 networkx.freeze}
freeze ( \(G\) )
Modify graph to prevent addition of nodes or edges.
Parameters G : graph
A NetworkX graph

\section*{See Also:}
is_frozen

\section*{Notes}

This does not prevent modification of edge data.
To "unfreeze" a graph you must make a copy.

\section*{Examples}
>>> 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

\subsection*{5.1.5 networkx.is_frozen}
is_frozen ( \(G\) )
Return True if graph is frozen.
Parameters G: graph
A NetworkX graph

\section*{See Also:}
freeze

\subsection*{5.1.6 networkx.create_empty_copy}

\section*{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.

\section*{Notes}

Graph, node, and edge data is not propagated to the new graph.

\section*{GRAPH GENERATORS}

\subsection*{6.1 Atlas}

Generators for the small graph atlas.
See "An Atlas of Graphs" by Ronald C. Read and Robin J. Wilson, Oxford University Press, 1998.
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.

```

\subsection*{6.1.1 networkx.generators.atlas.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)

\subsection*{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.
barbell_graph(m1, m2[, Return the Barbell Graph: two complete graphs connected by a path.
create_using])
complete_graph(n[, create_using]) Return the Complete graph K_n with n nodes.
complete_bipartite_graph(n1, Return the complete bipartite graph K_{n1_n2}.
n2[, create_using])
circular_ladder_graph(n[, Return the circular ladder graph CL_n of length n.
create_using])
cycle_graph(n[, create_using]) Return the cycle graph C_n over n nodes.
dorogovtsev_goltsev_mendes_gra_Retn{n the hierarchically constructed Dorogovtsev-Goltsev-Mendes
...]) graph.
empty_graph([n, create_using]) Return the empty graph with n nodes and zero edges.
grid_2d_graph(m, n[, periodic, Return the 2d grid graph of mxn nodes, each connected to its nearest
create_using])
grid_graph(dim[, periodic, Return the n-dimensional grid graph.
create_using])
hypercube_graph(n[, create_using]) Return the n-dimensional hypercube.
ladder_graph(n[, create_using]) Return the Ladder graph of length n.
lollipop_graph(m, n[, Return the Lollipop Graph; K_m connected to P_n.
create_using])
null_graph([create_using]) Return the Null graph with no nodes or edges.
path_graph(n[, create_using]) Return the Path graph P_n of n nodes linearly connected by n-1
edges.
star_graph(n[, create_using]) Return the Star graph with n+1 nodes: one center node, connected to
n}\mathrm{ outer nodes.
trivial_graph([create_using]) Return the Trivial graph with one node (with integer label 0) and no
edges.
wheel_graph(n[, create_using]) Return the wheel graph: a single hub node connected to each node of
the (n-1)-node cycle graph.

```

\subsection*{6.2.1 networkx.generators.classic.balanced_tree}

\section*{balanced_tree (r,h, create_using=None)}

Return the perfectly balanced r-tree of height \(h\).
For \(\mathrm{r}>=2, \mathrm{~h}>=1\), 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 \(\mathrm{r}+1\).
number_of_nodes \(=1+\mathrm{r}+\mathrm{r}^{* *} 2+\ldots+\mathrm{r}^{* *} \mathrm{~h}=\left(\mathrm{r}^{* *}(\mathrm{~h}+1)-1\right) /(\mathrm{r}-1)\), number_of_edges \(=\) number_of_nodes -1 .
Node labels are the integers 0 (the root) up to number_of_nodes -1 .

\subsection*{6.2.2 networkx.generators.classic.barbell_graph}

\section*{barbell_graph (m1, m2, create_using=None)}

Return the Barbell Graph: two complete graphs connected by a path.
For \(\mathrm{m} 1>1\) and \(\mathrm{m} 2>=0\).
Two identical complete graphs \(K_{-}\{m 1\}\) form the left and right bells, and are connected by a path \(P_{-}\{m 2\}\).
The \(2 * \mathrm{~m} 1+\mathrm{m} 2\) nodes are numbered \(0, \ldots, \mathrm{~m} 1-1\) for the left barbell, \(\mathrm{m} 1, \ldots, \mathrm{~m} 1+\mathrm{m} 2-1\) for the path, and \(\mathrm{m} 1+\mathrm{m} 2, \ldots, 2 * \mathrm{~m} 1+\mathrm{m} 2-1\) for the right barbell.

The 3 subgraphs are joined via the edges \((\mathrm{m} 1-1, \mathrm{~m} 1)\) and \((\mathrm{m} 1+\mathrm{m} 2-1, \mathrm{~m} 1+\mathrm{m} 2)\). If \(\mathrm{m} 2=0\), 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.

\subsection*{6.2.3 networkx.generators.classic.complete_graph}
```

complete_graph (n, create_using=None)

```

Return the Complete graph \(\mathrm{K} \_\mathrm{n}\) with n nodes.
Node labels are the integers 0 to \(\mathrm{n}-1\).

\subsection*{6.2.4 networkx.generators.classic.complete_bipartite_graph}
complete_bipartite_graph (n1, n2, create_using=None)
Return the complete bipartite graph K_\{n1_n2\}.
Composed of two partitions with n1 nodes in the first and n2 nodes in the second. Each node in the first is connected to each node in the second.

Node labels are the integers 0 to \(\mathrm{n} 1+\mathrm{n} 2-1\)

\subsection*{6.2.5 networkx.generators.classic.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 \(\mathrm{n}-1\)

\subsection*{6.2.6 networkx.generators.classic.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 \(\mathrm{n}-1\) If create_using is a DiGraph, the direction is in increasing order.

\subsection*{6.2.7 networkx.generators.classic.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.

\subsection*{6.2.8 networkx.generators.classic.empty_graph}
empty_graph ( \(n=0\), create_using=None)
Return the empty graph with n nodes and zero edges.
Node labels are the integers 0 to \(\mathrm{n}-1\)
For example: >>> G=nx.empty_graph(10) >>> G.number_of_nodes() \(10 \ggg\) 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,
```

>>> 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).

\subsection*{6.2.9 networkx.generators.classic.grid_2d_graph}
grid_2d_graph ( \(m\), \(n\), periodic=False, create_using=None)
Return the 2 d grid graph of mxn nodes, each connected to its nearest neighbors. Optional argument periodic=True will connect boundary nodes via periodic boundary conditions.

\subsection*{6.2.10 networkx.generators.classic.grid_graph}
grid_graph (dim, periodic=False, create_using=None)
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. \(G=\) grid_graph \((\operatorname{dim}=[2,3])\) produces a \(2 \times 3\) grid graph.

If periodic=True then join grid edges with periodic boundary conditions.

\subsection*{6.2.11 networkx.generators.classic.hypercube_graph}
hypercube_graph ( \(n\), create_using=None)
Return the \(n\)-dimensional hypercube.
Node labels are the integers 0 to \(2 * * n-1\).

\subsection*{6.2.12 networkx.generators.classic.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 \(2 * \mathrm{n}-1\).

\subsection*{6.2.13 networkx.generators.classic.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 \(0, \ldots, \mathrm{~m}-1\) for the complete graph and \(\mathrm{m}, \ldots, \mathrm{m}+\mathrm{n}-1\) for the path. The 2 subgraphs are joined via the edge \((\mathrm{m}-1, \mathrm{~m})\). 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.)

\subsection*{6.2.14 networkx.generators.classic.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.

\subsection*{6.2.15 networkx.generators.classic.path_graph}
path_graph (n, create_using=None)
Return the Path graph \(\mathrm{P}_{-} \mathrm{n}\) of n nodes linearly connected by \(\mathrm{n}-1\) edges.
Node labels are the integers 0 to \(n-1\). If create_using is a DiGraph then the edges are directed in increasing order.

\subsection*{6.2.16 networkx.generators.classic.star_graph}
star_graph (n, create_using=None)
Return the Star graph with \(\mathrm{n}+1\) nodes: one center node, connected to n outer nodes.
Node labels are the integers 0 to n .

\subsection*{6.2.17 networkx.generators.classic.trivial_graph}
trivial_graph (create_using=None)
Return the Trivial graph with one node (with integer label 0 ) and no edges.

\subsection*{6.2.18 networkx.generators.classic.wheel_graph}
wheel_graph ( \(n\), create_using=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 \(\mathrm{n}-1\).

\subsection*{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.
LCF_graph(n, shift_list, repeats[, create_using]) Return the cubic graph specified in LCF notation.
bull_graph([create_using])
chvatal_graph([create_using])
cubical_graph([create_using])
desargues_graph([create_using])
diamond_graph([create_using])
dodecahedral_graph([create_using])
frucht_graph([create_using])
heawood_graph([create_using])
house_graph([create_using])
house_x_graph([create_using])
icosahedral_graph([create_using])
krackhardt_kite_graph([create_using])
moebius_kantor_graph([create_using])
octahedral_graph([create_using])
pappus_graph()
petersen_graph([create_using])
sedgewick_maze_graph([create_using])
tetrahedral_graph([create_using])
truncated_cube_graph([create_using])
truncated_tetrahedron_graph([create_using]) Return the skeleton of the truncated Platonic tetrahedron.
tutte_graph([create_using])
Return the small graph described by graph_description.
Return the cubic graph specified in LCF notation.
Return the Bull graph.
Return the Chvátal graph.
Return the 3-regular Platonic Cubical graph.
Return the Desargues graph.
Return the Diamond graph.
Return the Platonic Dodecahedral graph.
Return the Frucht Graph.
Return the Heawood graph, a $(3,6)$ cage.
Return the House graph (square with triangle on top).
Return the House graph with a cross inside the house square.
Return the Platonic Icosahedral graph.
Return the Krackhardt Kite Social Network.
Return the Moebius-Kantor graph.
Return the Platonic Octahedral graph.
Return the Pappus graph.
Return the Petersen graph.
Return a small maze with a cycle.
Return the 3-regular Platonic Tetrahedral graph.
Return the skeleton of the truncated cube.
Return the skeleton of the truncated Platonic tetrahedron.
Return the Tutte graph.

```

\subsection*{6.3.1 networkx.generators.small.make_small_graph}
make_small_graph (graph_description, create_using=None)
Return the small graph described by graph_description.
graph_description is a list of the form [ltype, name, \(n, x l i s t\) ]
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 \(0, . ., \mathrm{n}-1\).

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
```

>>> 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 \(\mathrm{C}_{-} 4\) 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.

\subsection*{6.3.2 networkx.generators.small.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 \(0, \ldots, n-1\). (The null graph is returned if \(n<\) 0.\()\)
shift_list \(=[\mathrm{s} 1, \mathrm{~s} 2, . ., \mathrm{sk}]\), 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 \(\mathrm{v}_{\mathbf{\prime}}\) current and \(\mathrm{v}_{\mathbf{\prime}}\) current+shift mod n .

For v 1 cycling through the n -cycle a total of \(\mathrm{k} *\) repeats with shift cycling through shiftlist repeats times connect v1 with \(\mathrm{v} 1+\) shift \(\bmod \mathrm{n}\)

The utility graph \(K_{-}\{3,3\}\)
>>> \(G=n x . \operatorname{LCF}\) _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.

\subsection*{6.3.3 networkx.generators.small.bull_graph}

\section*{bull_graph (create_using=None)}

Return the Bull graph.

\subsection*{6.3.4 networkx.generators.small.chvatal_graph}
```

chvatal_graph (create_using=None)

```

Return the Chvátal graph.

\subsection*{6.3.5 networkx.generators.small.cubical_graph}
```

cubical_graph(create_using=None)

```

Return the 3-regular Platonic Cubical graph.

\subsection*{6.3.6 networkx.generators.small.desargues_graph}
desargues_graph (create_using=None)
Return the Desargues graph.

\subsection*{6.3.7 networkx.generators.small.diamond_graph}
diamond_graph (create_using=None)
Return the Diamond graph.

\subsection*{6.3.8 networkx.generators.small.dodecahedral_graph}
dodecahedral_graph (create_using=None)
Return the Platonic Dodecahedral graph.

\subsection*{6.3.9 networkx.generators.small.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.

\subsection*{6.3.10 networkx.generators.small.heawood_graph}
heawood_graph (create_using=None)
Return the Heawood graph, a \((3,6)\) cage.

\subsection*{6.3.11 networkx.generators.small.house_graph}
house_graph (create_using=None)
Return the House graph (square with triangle on top).

\subsection*{6.3.12 networkx.generators.small.house_x_graph}
```

house_x_graph (create_using=None)

```

Return the House graph with a cross inside the house square.

\subsection*{6.3.13 networkx.generators.small.icosahedral_graph}
icosahedral_graph (create_using=None)
Return the Platonic Icosahedral graph.

\subsection*{6.3.14 networkx.generators.small.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.

\subsection*{6.3.15 networkx.generators.small.moebius_kantor_graph}
```

moebius_kantor_graph(create_using=None)

```

Return the Moebius-Kantor graph.

\subsection*{6.3.16 networkx.generators.small.octahedral_graph}
```

octahedral_graph (create_using=None)

```

Return the Platonic Octahedral graph.

\subsection*{6.3.17 networkx.generators.small.pappus_graph}
```

pappus_graph()

```

Return the Pappus graph.

\subsection*{6.3.18 networkx.generators.small.petersen_graph}
```

petersen_graph (create_using=None)

```

Return the Petersen graph.

\subsection*{6.3.19 networkx.generators.small.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 \(0, . ., 7\)

\subsection*{6.3.20 networkx.generators.small.tetrahedral_graph}

\section*{tetrahedral_graph (create_using=None)}

Return the 3-regular Platonic Tetrahedral graph.

\subsection*{6.3.21 networkx.generators.small.truncated_cube_graph}
```

truncated_cube_graph (create_using=None)

```

Return the skeleton of the truncated cube.

\subsection*{6.3.22 networkx.generators.small.truncated_tetrahedron_graph}
truncated_tetrahedron_graph (create_using=None)
Return the skeleton of the truncated Platonic tetrahedron.

\subsection*{6.3.23 networkx.generators.small.tutte_graph}
```

tutte_graph (create_using=None)
Return the Tutte graph.

```

\subsection*{6.4 Random Graphs}

Generators for random graphs.
```

fast_gnp_random_graph(n, p[,
Return a random graph G_{n,p}.
create_using, seed])
gnp_random_graph(n, p[, create_using, Return a random graph G_{n,p}.
seed])
directed_gnp_random_graph(n, p[, ...]) Return a directed random graph.
dense_gnm_random_graph(n, m[,
create_using, ...])
gnm_random_graph(n, m[, create_using, Return the random graph G_{n,m}.
seed])
erdos_renyi_graph(n, p[, create_using, Return a random graph G_{n,p}.
seed])
binomial_graph(n, p[, create_using, seed]) Return a random graph G_{n,p}.
newman_watts_strogatz_graph(n, k, p[, Return a Newman-Watts-Strogatz small world graph.
...])
watts_strogatz_graph(n, k, p[, ..]) Return a Watts-Strogatz small-world graph.
connected_watts_strogatz_graph(n,
k, p[, ..])
random_regular_graph(d, n[, Return a random regular graph of n nodes each with degree d.
create_using, seed])
barabasi_albert_graph(n, m[, Return random graph using Barabási-Albert preferential
create_using, seed])
powerlaw_cluster_graph(n, m, p[,...])
random_lobster(n, p1, p2[, create_using,
seed])
random_shell_graph(constructor[, ...])
random_powerlaw_tree(n[, gamma,...])
random_powerlaw_tree_sequence(n[,
gamma, ...])
Return a random graph $\mathrm{G}_{-}\{\mathrm{n}, \mathrm{p}\}$.
Return the random graph G_{n,m}.
Return a connected Watts-Strogatz small-world graph.
attachment model.
Holme and Kim algorithm for growing graphs with powerlaw
Return a random lobster.
Return a random shell graph for the constructor given.
Return a tree with a powerlaw degree distribution.
Return a degree sequence for a tree with a powerlaw
distribution.

```

\subsection*{6.4.1 networkx.generators.random_graphs.fast_gnp_random_graph}
```

fast_gnp_random_graph (n, p,create_using=None, seed=None)

```

Return a random graph \(\mathrm{G}_{-}\{\mathrm{n}, \mathrm{p}\}\).
The \(G_{-}\{n, p\}\) graph choses each of the possible \([n(n-1)] / 2\) edges with probability \(p\).
Sometimes called Erdős-Rényi graph, or binomial graph.
Parameters \(\mathbf{n}\) : int
The number of nodes.
p: float
Probability for edge creation.
create_using : graph, optional (default Graph)
Use specified graph as a container.
seed : int, optional
Seed for random number generator (default=None).

\section*{Notes}

This algorithm is \(\mathrm{O}(\mathrm{n}+\mathrm{m})\) where m is the expected number of edges \(\mathrm{m}=\mathrm{p} * \mathrm{n} *(\mathrm{n}-1) / 2\).
It should be faster than gnp_random_graph when p is small, and the expected number of edges is small, (sparse graph).

\section*{References}
[R78]

\subsection*{6.4.2 networkx.generators.random_graphs.gnp_random_graph}
```

gnp_random_graph ( n, p, create_using=None, seed=None)

```

Return a random graph \(\mathrm{G}_{-}\{\mathrm{n}, \mathrm{p}\}\).
Choses each of the possible \([\mathrm{n}(\mathrm{n}-1)] / 2\) edges with probability p . This is the same as binomial_graph and erdos_renyi_graph.

Sometimes called Erdős-Rényi graph, or binomial graph.
Parameters n : int
The number of nodes.
\(\mathbf{p}\) : float
Probability for edge creation.
create_using : graph, optional (default Graph)
Use specified graph as a container.
seed : int, optional
Seed for random number generator (default=None).
See Also:
```

fast_gnp_random_graph

```

\section*{Notes}

This is an \(\mathrm{O}\left(\mathrm{n}^{\wedge} 2\right)\) algorithm. For sparse graphs (small p) see fast_gnp_random_graph.

\section*{References}
[R79], [R80]

\subsection*{6.4.3 networkx.generators.random_graphs.directed_gnp_random_graph}
directed_gnp_random_graph ( \(n, p\), create_using=None, seed=None)
Return a directed random graph.
Chooses each of the possible \(n(n-1)\) edges with probability p .

This is a directed version of G_np.
Parameters \(\mathbf{n}\) : int
The number of nodes.
p: float
Probability for edge creation.
create_using : graph, optional (default DiGraph)
Use specified graph as a container.
seed : int, optional
Seed for random number generator (default=None).
See Also:
```

gnp_random_graph, fast_gnp_random_graph

```

\section*{Notes}

This is an \(\mathrm{O}\left(\mathrm{n}^{\wedge} 2\right)\) algorithm.

\section*{References}
[R74], [R75]

\subsection*{6.4.4 networkx.generators.random_graphs.dense_gnm_random_graph}
dense_gnm_random_graph ( \(n, m\), create_using=None, 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.
create_using : graph, optional (default Graph)
Use specified graph as a container.
seed : int, optional
Seed for random number generator (default=None).

\section*{See Also:}
gnm_random_graph

\section*{Notes}

Algorithm by Keith M. Briggs Mar 31, 2006. Inspired by Knuth's Algorithm S (Selection sampling technique), in section 3.4.2 of

\section*{References}
[R73]

\subsection*{6.4.5 networkx.generators.random_graphs.gnm_random_graph}
gnm_random_graph ( \(n, m\), create_using \(=\) None, 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.
Parameters n: int
The number of nodes.
m : int
The number of edges.
create_using : graph, optional (default Graph)
Use specified graph as a container.
seed : int, optional
Seed for random number generator (default=None).

\subsection*{6.4.6 networkx.generators.random_graphs.erdos_renyi_graph}
erdos_renyi_graph ( \(n, p\), create_using=None, seed=None)
Return a random graph \(\mathrm{G}_{-}\{\mathrm{n}, \mathrm{p}\}\).
Choses each of the possible \([\mathrm{n}(\mathrm{n}-1)] / 2\) edges with probability p . This is the same as binomial_graph and erdos_renyi_graph.

Sometimes called Erdős-Rényi graph, or binomial graph.
Parameters \(\mathbf{n}\) : int
The number of nodes.
p : float
Probability for edge creation.
create_using : graph, optional (default Graph)
Use specified graph as a container.
seed : int, optional
Seed for random number generator (default=None).

\section*{See Also:}
```

fast_gnp_random_graph

```

\section*{Notes}

This is an \(\mathrm{O}\left(\mathrm{n}^{\wedge} 2\right)\) algorithm. For sparse graphs (small p) see fast_gnp_random_graph.

\section*{References}
[R76], [R77]

\subsection*{6.4.7 networkx.generators.random_graphs.binomial_graph}
binomial_graph ( \(n, p\), create_using \(=\) None, seed \(=\) None \()\)
Return a random graph \(\mathrm{G}_{-}\{\mathrm{n}, \mathrm{p}\}\).
Choses each of the possible \([\mathrm{n}(\mathrm{n}-1)] / 2\) edges with probability p . This is the same as binomial_graph and erdos_renyi_graph.

Sometimes called Erdős-Rényi graph, or binomial graph.
Parameters n : int
The number of nodes.
p: float
Probability for edge creation.
create_using : graph, optional (default Graph)
Use specified graph as a container.
seed : int, optional
Seed for random number generator (default=None).
See Also:
fast_gnp_random_graph
Notes

This is an \(\mathrm{O}\left(\mathrm{n}^{\wedge} 2\right)\) algorithm. For sparse graphs (small p) see fast_gnp_random_graph.

\section*{References}
[R71], [R72]

\subsection*{6.4.8 networkx.generators.random_graphs.newman_watts_strogatz_graph}
newman_watts_strogatz_graph ( \(n, k, p\), create_using=None, seed=None)
Return a Newman-Watts-Strogatz small world graph.

\section*{Parameters \(\mathbf{n}\) : 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
create_using : graph, optional (default Graph)
The graph instance used to build the graph.
seed : int, optional
seed for random number generator (default=None)

\section*{See Also:}
```

watts_strogatz_graph

```

\section*{Notes}

First create a ring over n nodes. Then each node in the ring is connected with its k nearest neighbors ( \(\mathrm{k}-1\) 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.

\section*{References}
[R81]

\subsection*{6.4.9 networkx.generators.random_graphs.watts_strogatz_graph}
```

watts_strogatz_graph (n,k,p,create_using=None, seed=None)

```

Return a Watts-Strogatz small-world graph.
Parameters \(n\) : int
The number of nodes
\(\mathbf{k}\) : int
Each node is connected to k nearest neighbors in ring topology
p : float
The probability of rewiring each edge
create_using : graph, optional (default Graph)
The graph instance used to build the graph.
seed : int, optional
Seed for random number generator (default=None)

\section*{See Also:}
newman_watts_strogatz_graph, connected_watts_strogatz_graph

\section*{Notes}

First create a ring over n nodes. Then each node in the ring is connected with its k nearest neighbors ( \(\mathrm{k}-1\) neighbors if k is odd). Then shortcuts are created by replacing some edges as follows: for each edge \(u-v\) in the underlying " \(n\)-ring with k nearest neighbors" with probability p replace it with a new edge \(\mathrm{u}-\mathrm{w}\) 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().

\section*{References}
[R85]

\subsection*{6.4.10 networkx.generators.random_graphs.connected_watts_strogatz_graph}
connected_watts_strogatz_graph ( \(n, k, p\), tries \(=100\), create_using \(=\) None, 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
\(\mathbf{k}\) : int
Each node is connected to k nearest neighbors in ring topology
p : float
The probability of rewiring each edge
tries : int
Number of attempts to generate a connected graph.
create_using : graph, optional (default Graph)
The graph instance used to build the graph.
seed : int, optional
The seed for random number generator.

\section*{See Also:}
newman_watts_strogatz_graph, watts_strogatz_graph

\subsection*{6.4.11 networkx.generators.random_graphs.random_regular_graph}
random_regular_graph (d, n, create_using=None, 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
\(\mathbf{n}\) : integer
Number of nodes. The value of \(n * d\) must be even.
create_using : graph, optional (default Graph)
The graph instance used to build the graph.
seed : hashable object
The seed for random number generator.

\section*{Notes}

The nodes are numbered form 0 to \(\mathrm{n}-1\).
Kim and Vu's paper [R84] shows that this algorithm samples in an asymptotically uniform way from the space of random graphs when \(\mathrm{d}=\mathrm{O}\left(\mathrm{n}^{* *}(1 / 3-\mathrm{epsilon})\right)\).

\section*{References}
[R83], [R84]

\subsection*{6.4.12 networkx.generators.random_graphs.barabasi_albert_graph}
barabasi_albert_graph ( \(n, m\), create_using=None, 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
create_using : graph, optional (default Graph)
The graph instance used to build the graph.
seed : int, optional
Seed for random number generator (default=None).
Returns G: Graph

\section*{Notes}

The initialization is a graph with with m nodes and no edges.

\section*{References}
[R70]

\subsection*{6.4.13 networkx.generators.random_graphs.powerlaw_cluster_graph}
powerlaw_cluster_graph ( \(n, m, p\), create_using=None, 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
create_using : graph, optional (default Graph)
The graph instance used to build the graph.
seed : int, optional
Seed for random number generator (default=None).

\section*{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 modes may not be all linked to a new node on the first iteration like the B-A model.

\section*{References}
[R82]

\subsection*{6.4.14 networkx.generators.random_graphs.random_lobster}
random_lobster ( \(n, p 1, p 2\), create_using=None, 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 \((\mathrm{p} 2=0)\).
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
create_using : graph, optional (default Graph)
The graph instance used to build the graph.
seed : int, optional
Seed for random number generator (default=None).

\subsection*{6.4.15 networkx.generators.random_graphs.random_shell_graph}
random_shell_graph (constructor, create_using=None, seed=None)
Return a random shell graph for the constructor given.
Parameters constructor: a list of three-tuples :
( \(\mathrm{n}, \mathrm{m}, \mathrm{d}\) ) for each shell starting at the center shell.
\(\mathbf{n}\) : 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. \(\mathrm{d}=0\) means no intra shell edges, \(\mathrm{d}=1\) for the last shell
create_using : graph, optional (default Graph)
The graph instance used to build the graph.
seed : int, optional
Seed for random number generator (default=None).

\section*{Examples}
>>> constructor=[(10,20,0.8), (20,40,0.8)]
>>> G=nx.random_shell_graph (constructor)

\subsection*{6.4.16 networkx.generators.random_graphs.random_powerlaw_tree}
random_powerlaw_tree ( \(n\), gamma \(=3\), create_using \(=\) None, 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
create_using : graph, optional (default Graph)

The graph instance used to build the graph.
seed : int, optional
Seed for random number generator (default=None).
tries: int
Number of attempts to adjust sequence to make a tree

\section*{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).

\subsection*{6.4.17 networkx.generators.random_graphs.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 \(\mathbf{n}\) : 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

\section*{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).

\subsection*{6.5 Degree Sequence}

Generate graphs with a given degree sequence or expected degree sequence.
configuration_model(deg_sequeReturn a random graph with the given degree sequence.
...])
directed_configuration_modRRetu.un, a directed_random graph with the given degree sequences.
...])
expected_degree_graph(w[, Return a random graph \(G(w)\) with expected degrees given by w. create_using, seed])
havel_hakimi_graph(deg_sequenRetturn a simple graph with given degree sequence, constructed using the create_using]) Havel-Hakimi algorithm.

...])
is_valid_degree_sequence(deRequetine if deg_sequence is a valid sequence of integer degrees equal to the degree sequence of some simple graph.
create_degree_sequence(n, Attempt to create a valid degree sequence of length \(n\) using specified
**kwds[, ...]) function sfunction(n,**kwds).
double_edge_swap(G[, Attempt nswap double-edge swaps on the graph G.
nswap])
connected_double_edge_swap(AVttempt nswap double-edge swaps on the graph G.
nswap])
li_smax_graph(degree_seq[, Generates a graph based with a given degree sequence and maximizing the create_using]) s-metric.

\subsection*{6.5.1 networkx.generators.degree_seq.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.

\section*{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.

\section*{Raises NetworkXError :}

If the degree sequence does not have an even sum.

\section*{See Also:}
is_valid_degree_sequence

\section*{Notes}

As described by Newman [R60].

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.

\section*{References}
[R60]

\section*{Examples}
```

>>> from networkx.utils import powerlaw_sequence
>>> z=nx.create_degree_sequence(100,powerlaw_sequence)
>>> G=nx.configuration_model(z)

```

To remove parallel edges:
```

>>> G=nx.Graph(G)

```

To remove self loops:
>>> G.remove_edges_from(G.selfloop_edges())

\subsection*{6.5.2 networkx.generators.degree_seq.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 \(\operatorname{deg}_{-}\)sequence.

Raises NetworkXError :

If the degree sequences do not have the same sum.
See Also:
```

configuration_model

```

\section*{Notes}

Algorithm as described by Newman [R62].
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.

\section*{References}
[R62]

\section*{Examples}
```

>>> 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())

```

\subsection*{6.5.3 networkx.generators.degree_seq.expected_degree_graph}
expected_degree_graph ( \(w\), create_using=None, seed=None)
Return a random graph \(G(w)\) with expected degrees given by w.
Parameters w : list
The list of expected degrees.
create_using : graph, optional (default Graph)
Return graph of this type. The instance will be cleared.
seed : hashable object, optional

The seed for the random number generator.

\section*{References}
[R63]

\section*{Examples}
\(\ggg z=[10\) for \(i\) in range (100)]
>>> G=nx.expected_degree_graph (z)

\subsection*{6.5.4 networkx.generators.degree_seq.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. Multigraphs and directed graphs are not allowed.

\section*{Raises NetworkXException :}

For a non-graphical degree sequence (i.e. one not realizable by some simple graph).

\section*{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.

See Theorem 1.4 in [chartrand-graphs-1996]. This algorithm is also used in the function is_valid_degree_sequence.

\section*{References}
[R64]

\subsection*{6.5.5 networkx.generators.degree_seq.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) \(/ 2=1\)

\subsection*{6.5.6 networkx.generators.degree_seq.is_valid_degree_sequence}

\section*{is_valid_degree_sequence (deg_sequence)}

Return True if deg_sequence is a valid sequence of integer degrees equal to the degree sequence of some simple graph.
-deg_sequence: degree sequence, a list of integers with each entry corresponding to the degree of a node (need not be sorted). A non-graphical degree sequence (i.e. one not realizable by some simple graph) will raise an exception.

See Theorem 1.4 in [R65]. This algorithm is also used in havel_hakimi_graph()

\section*{References}
[R65]

\subsection*{6.5.7 networkx.generators.degree_seq.create_degree_sequence}
create_degree_sequence ( \(n\), sfunction=None, max_tries=50, **kwds)
Attempt to create a valid degree sequence of length \(n\) using specified function sfunction( \(n,{ }^{* *} \mathrm{kwds}\) ).
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, \({ }^{* * k w d s) " . ~}\)
max_tries: int :
Max number of attempts at creating valid degree sequence.

\section*{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.

\section*{Examples}
>>> from networkx.utils import uniform_sequence
>>> seq=nx.create_degree_sequence(10, uniform_sequence)

\subsection*{6.5.8 networkx.generators.degree_seq.double_edge_swap}
double_edge_swap ( \(G, n s w a p=1\) )
Attempt nswap double-edge swaps on the graph G.
Return count of successful swaps. The graph \(G\) is modified in place. A double-edge swap removes two randomly choseen edges \(u-v\) and \(x-y\) and creates the new edges \(u-x\) and \(v-y\) :
\begin{tabular}{ccc}
\(u--v\) & & \(u\) \\
& becomes & I \\
\(x--y\) & & \(x\)
\end{tabular}

If either the edge \(u-x\) or \(v-y\) already exist no swap is performed so the actual count of swapped edges is always <= nswap
Does not enforce any connectivity constraints.

\subsection*{6.5.9 networkx.generators.degree_seq.connected_double_edge_swap}
connected_double_edge_swap ( \(G, n s w a p=1\) )
Attempt nswap double-edge swaps on the graph G.
Returns the count of successful swaps. Enforces connectivity. The graph G is modified in place.

\section*{Notes}

A double-edge swap removes two randomly choseen edges \(u-v\) and \(x-y\) and creates the new edges \(u-x\) and \(v-y\) :
\begin{tabular}{ccc}
\(u--v\) & & \(u\) \\
& becomes & \(\mid\) \\
\(x--y\) & & \(x\)
\end{tabular}

If either the edge \(u-x\) or \(v-y\) already exist no swap is performed so the actual count of swapped edges is always <= nswap

The initial graph G must be connected and the resulting graph is connected.

\section*{References}
[R61]

\subsection*{6.5.10 networkx.generators.degree_seq.li_smax_graph}
li_smax_graph (degree_seq, create_using=None)
Generates a graph based with a given degree sequence and maximizing the s-metric. Experimental implementation.

Maximum s-metrix means that high degree nodes are connected to high degree nodes.
-degree_seq: degree sequence, a list of integers with each entry corresponding to the degree of a node. A non-graphical degree sequence raises an Exception.
Reference:
```

    @unpublished{li-2005,
    author = {Lun Li and David Alderson and Reiko Tanaka
                and John C. Doyle and Walter Willinger},
    title = {Towards a Theory of Scale-Free Graphs:
                Definition, Properties, and Implications (Extended Version)},
    url = {http://arxiv.org/abs/cond-mat/0501169},
    ```
```

year = {2005}
}

```

The algorithm:
```

STEP 0 - Initialization
A = {0}
B}={1,2,3,···,n
O = {(i; j), ..., (k, l),...} where i < j, i <= k < l and
d_i * d_j >= d_k *d_l
wA = d_1
dB = sum(degrees)
STEP 1 - Link selection
(a) If |O| = O TERMINATE. Return graph A.
(b) Select element(s) (i, j) in O having the largest d_i * d_j , if for
any i or j either w_i = 0 or w_j = 0 delete (i, j) from O
(c) If there are no elements selected go to (a).
(d) Select the link (i, j) having the largest value w_i (where for each
(i, j) w_i is the smaller of w_i and w_j ), and proceed to STEP 2.
STEP 2 - Link addition
Type 1: i in A and j in B.
Add j to the graph A and remove it from the set B add a link
(i, j) to the graph A. Update variables:
wA = wA + d_j -2 and dB = dB - d_j
Decrement w_i and w_j with one. Delete (i, j) from O
Type 2: i and j in A.
Check Tree Condition: If dB = 2 * |B| - wA.
Delete (i, j) from O, continue to STEP 3
Check Disconnected Cluster Condition: If wA = 2.
Delete (i, j) from O, continue to STEP 3
Add the link (i, j) to the graph A
Decrement w_i and w_j with one, and wA = wA -2
STEP 3
Go to STEP 1

```

The article states that the algorithm will result in a maximal s-metric. This implementation can not guarantee such maximality. I may have misunderstood the algorithm, but I can not see how it can be anything but a heuristic. Please contact me at sundsdal@gmail.com if you can provide python code that can guarantee maximality. Several optimizations are included in this code and it may be hard to read. Commented code to come.

\section*{A POSSIBLE ALTERNATIVE:}

For an 'unconstrained' graph, that is one they describe as having the sum of the degree sequence be even(ie all undirected graphs) they present a simpler algorithm. It is as follows
"For each vertex i: if di is even then attach di/2 self-loops; if di is odd, then attach (di-1)/2 self-loops, leaving one available "stub". Second for all remaining vertices with "stubs" connect them in pairs according to decreasing values of di." \([1]\)

Since this only works for undirected graphs anyway, perhaps this is the better method? Note this also returns a graph with a larger s_metric than the other method, and it seems to have the same degree sequence, though I haven't tested it extensively.

\subsection*{6.6 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 directed graph
\begin{tabular}{ll}
\hline gn_graph(n[, kernel, create_using, seed] \()\) & Return the GN digraph with n nodes. \\
gnr_graph(n, p[, create_using, seed] \()\) & Return the GNR digraph with n nodes and redirection \\
& probability p. \\
gnc_graph(n[, create_using, seed]) & Return the GNC digraph with n nodes. \\
scale_free_graph(n[, alpha, beta, gamma, & Return a scale free directed graph. \\
\(\ldots . .]\). & \\
\hline
\end{tabular}

\subsection*{6.6.1 networkx.generators.directed.gn_graph}
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.

\section*{References}
[R66]

\section*{Examples}
```

>>> D=nx.gn_graph(10) \# the GN graph
>>> G=D.to_undirected() \# the undirected version

```

To specify an attachment kernel use the kernel keyword
```

>>> D=nx.gn_graph(10,kernel=lambda x:x**1.5) \# A_k=k^1.5

```

\subsection*{6.6.2 networkx.generators.directed.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 probabiliy 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.

\section*{References}
[R68]

\section*{Examples}
\(\ggg\) D=nx.gnr_graph \((10,0.5)\) \# the GNR graph
>>> G=D.to_undirected() \# the undirected version

\subsection*{6.6.3 networkx.generators.directed.gnc_graph}
gnc_graph (n, create_using=None, seed=None)
Return the GNC digraph with n nodes.
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 \(\mathbf{n}\) : 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.

\section*{References}
[R67]

\subsection*{6.6.4 networkx.generators.directed.scale_free_graph}
```

scale_free_graph ( }n,\quad\mathrm{ alpha=0.40999999999999998, beta=0.54000000000000004, gamma=0.050000000000000003, delta_in=0.20000000000000001, delta_out=0, create_using=None, seed $=$ None)

```

Return a scale free directed graph.
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 the in-degree distribution and the other chosen randomly according to the out-degree distribution.
gamma : float
Probability for adding a new node conecgted to an existing node chosen randomly according to the out-degree distribution.
delta_in : float
Bias for choosing ndoes from in-degree distribution.
delta_out : float
Bias for choosing ndoes from out-degree distribution.
create_using : graph, optional (default MultiDiGraph)
Use this graph instance to start the process (default=3-cycle).
seed : integer, optional
Seed for random number generator

\section*{Notes}

The sum of alpha, beta, and gamma must be 1 .

\section*{References}
[R69]

\section*{Examples}
```

>>> G=nx.scale_free_graph(100)

```

\subsection*{6.7 Geometric}

Generators for geometric graphs.
random_geometric_graph(n, radius[, ..]) Random geometric graph in the unit cube.

\subsection*{6.7.1 networkx.generators.geometric.random_geometric_graph}
random_geometric_graph ( \(n\), radius, create_using \(=\) None, repel \(=0.0\), verbose \(=\) False, dim \(=2\) )
Random geometric graph in the unit cube.
Returned Graph has added attribute G.pos which is a dict keyed by node to the position tuple for the node.

\subsection*{6.8 Hybrid}

Hybrid
kl_connected_subgraph(G, k, l[, low_memory, Returns the maximum locally (k,l) connected subgraph

Returns True if G is kl connected.

\subsection*{6.8.1 networkx.generators.hybrid.kl_connected_subgraph}
kl_connected_subgraph ( \(G\), \(k\), l, low_memory=False, same_as_graph=False)
Returns the maximum locally ( \(\mathrm{k}, \mathrm{l}\) ) 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

\subsection*{6.8.2 networkx.generators.hybrid.is_kl_connected}
is_kl_connected ( \(G, k\), l, low_memory=False)
Returns True if G is kl connected.

\subsection*{6.9 Bipartite}

Generators and functions for bipartite graphs.
bipartite_configuration_model(aRequrn a random bipartite graph from two given degree sequences. bseq[, ...])
bipartite_havel_hakimi_graph(asketurn a bipartite graph from two given degree sequences using a bseq[, ...]) Havel-Hakimi style construction.
bipartite_reverse_havel_hakimiRetumpabaipeqtite graph from two given degree sequences using a bseq) Havel-Hakimi style construction.
bipartite_alternating_havel_haRèturn ab bipartite)graph from two given degree sequences using a alternating Havel-Hakimi style construction.
bipartite_preferential_attachmCreategabipartaseqraph with a preferential attachment model from a p) given single degree sequence.
bipartite_random_regular_graph(dNTESTED: Generate a random bipartite graph.
\(\mathrm{n}[, \ldots]\) )

\subsection*{6.9.1 networkx.generators.bipartite.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.

\section*{Nodes from the set \(\mathbf{A}\) are connected to nodes in the set \(\mathbf{B}\) by :}
choosing randomly from the possible free stubs, one in \(\mathbf{A}\) and :
one in B. :

\section*{Notes}

The sum of the two sequences must be equal: 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.

\subsection*{6.9.2 networkx.generators.bipartite.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.
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.
Nodes from the set \(A\) are connected to nodes in the set \(B\) by :
connecting the highest degree nodes in set \(\mathbf{A}\) to :
the highest degree nodes in set \(B\) until all stubs are connected. :

\section*{Notes}

The sum of the two sequences must be equal: 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.

\subsection*{6.9.3 networkx.generators.bipartite.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.
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.
Nodes from the set \(\mathbf{A}\) 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. :

\section*{Notes}

The sum of the two sequences must be equal: 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.

\subsection*{6.9.4 networkx.generators.bipartite.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 a alternating Havel-Hakimi style construction.
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.
Nodes from the set \(A\) are connected to nodes in the set \(B\) by :
connecting the highest degree nodes in set \(\mathbf{A}\) to :
alternatively the highest and the lowest degree nodes in set :
B until all stubs are connected. :

\section*{Notes}

The sum of the two sequences must be equal: 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.

\subsection*{6.9.5 networkx.generators.bipartite.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.

\section*{Notes}
@article\{guillaume-2004-bipartite, author \(=\{\) Jean-Loup Guillaume and Matthieu Latapy \(\}\), title \(=\{\) Bipartite structure of all complex networks \(\}\), journal \(=\{\) Inf. Process. Lett. \(\}\), volume \(=\{90\}\), number \(=\{5\}\), year \(=\{2004\}\), issn \(=\{0020-0190\}\), pages \(=\{215-221\}\), doi \(=\{\) http://dx.doi.org/10.1016/j.ipl.2004.03.007 \(\}\), publisher \(=\{\) Elsevier North-Holland, Inc. \(\}\), address \(=\{\) Amsterdam, The Netherlands, The Netherlands \(\}\), \}

\subsection*{6.9.6 networkx.generators.bipartite.bipartite_random_regular_graph}
bipartite_random_regular_graph (d, n, create_using=None, seed=None)
UNTESTED: Generate a random bipartite graph.
Parameters d: integer
Degree of graph.
n : integer
Number of nodes in graph.
create_using : NetworkX graph instance, optional
Return graph of this type.
seed : integer, optional
Seed for random number generator.

\section*{Notes}

Nodes are numbered 0...n-1.

\section*{Restrictions on \(\mathbf{n}\) and d:}
- n must be even
- \(\mathrm{n}>=2 * \mathrm{~d}\)

Algorithm inspired by random_regular_graph()

\subsection*{6.10 Line Graph}

Line graphs.
line_graph(G) Return the line graph of the graph or digraph G.

\subsection*{6.10.1 networkx.generators.line.line_graph}

\section*{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

\section*{Notes}

Not implemented for MultiGraph or MultiDiGraph classes.
Graph, node, and edge data are not propagated to the new graph.

\section*{Examples}
```

>>> 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))]

```

\subsection*{6.11 Ego Graph}

Ego graph.
ego_graph(G, n[, radius, center, undirected]) Returns induced subgraph of neighbors centered at node n.

\subsection*{6.11.1 networkx.generators.ego.ego_graph}
ego_graph ( \(G, n\), radius \(=1\), center=True, undirected=False)
Returns induced subgraph of neighbors centered at node n .
Parameters G: graph
A NetworkX Graph or DiGraph
\(\mathbf{n}\) : node
A single node
radius : integer, 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.

\section*{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.

\subsection*{6.12 Stochastic}

Stocastic graph.
stochastic_graph(G[, copy]) \(\quad\) Return a right-stochastic representation of G.

\subsection*{6.12.1 networkx.generators.stochastic.stochastic_graph}
stochastic_graph ( \(G\), copy=True)
Return a right-stochastic representation of \(G\).
A right-stochastic graph is a weighted graph in which all of the node (out) neighbors edge weights sum to 1 .
Parameters G: graph
A NetworkX graph, must have valid edge weights
copy : boolean, optional
If True make a copy of the graph, otherwise modify original graph

\section*{LINEAR ALGEBRA}

\subsection*{7.1 Spectrum}

Laplacian, adjacency matrix, and spectrum of graphs.
\begin{tabular}{ll}
\hline adj_matrix(G[, nodelist \(])\) & Return adjacency matrix of G. \\
laplacian(G[, nodelist \(])\) & Return the Laplacian matrix of G. \\
normalized_laplacian(G[, nodelist \(])\) & Return the normalized Laplacian matrix of G. \\
laplacian_spectrum(G) & Return eigenvalues of the Laplacian of G \\
adjacency_spectrum(G) & Return eigenvalues of the adjacency matrix of G. \\
\hline
\end{tabular}

\subsection*{7.1.1 networkx.linalg.spectrum.adj_matrix}

\section*{adj_matrix (G, nodelist=None)}

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().

Returns A: numpy matrix
Adjacency matrix representation of G.

\section*{See Also:}
to_numpy_matrix, to_dict_of_dicts

\section*{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.

\subsection*{7.1.2 networkx.linalg.spectrum.laplacian}
laplacian ( \(G\), nodelist=None)
Return the Laplacian matrix of G.
The graph Laplacian is the matrix \(\mathrm{L}=\mathrm{D}-\mathrm{A}\), 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, then the ordering is produced by G.nodes().
Returns L: NumPy matrix
Laplacian of G.
See Also:
normalized_laplacian

\subsection*{7.1.3 networkx.linalg.spectrum.normalized_laplacian}
normalized_laplacian ( \(G\), nodelist=None)
Return the normalized Laplacian matrix of G.
The normalized graph Laplacian is the matrix \(\mathrm{NL}^{=} \mathrm{D}^{\wedge}(-1 / 2) \mathrm{L} \mathrm{D}^{\wedge}(-1 / 2) \mathrm{L}\) 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, then the ordering is produced by G.nodes().
Returns L: NumPy matrix
Normalized Laplacian of G.

\section*{See Also:}
laplacian

\section*{References}
[R92]

\subsection*{7.1.4 networkx.linalg.spectrum.laplacian_spectrum}

\section*{laplacian_spectrum ( \(G\) )}

Return eigenvalues of the Laplacian of G
Parameters G: graph

A NetworkX graph
Returns evals : NumPy array
Eigenvalues

\section*{See Also:}
laplacian

\subsection*{7.1.5 networkx.linalg.spectrum.adjacency_spectrum}
```

adjacency_spectrum (G)

```

Return eigenvalues of the adjacency matrix of G.
Parameters G: graph
A NetworkX graph
Returns evals : NumPy array
Eigenvalues

\section*{See Also:}
adj_matrix

\subsection*{7.2 Attribute Matrices}

Functions for constructing matrix-like objects from graph attributes.
attr_matrix(G[, edge_attr, node_attr, ...]) Returns a NumPy matrix using attributes from G.
attr_sparse_matrix(G[, edge_attr, ...]) Returns a SciPy sparse matrix using attributes from G.

\subsection*{7.2.1 networkx.linalg.attrmatrix.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 \(\mathrm{e}=(\mathrm{u}, \mathrm{v})\) 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 matirx. 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 \(r\) c_order was specified, then only the matrix is returned. However, if \(r c \_o r d e r\) was None, then the ordering used to construct the matrix is returned as well.

\section*{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:
\(\operatorname{Pr}(\mathrm{v}\) has color Y I 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):
\(\operatorname{Pr}(\mathrm{v}\) is red l u is red \()=1 / 3 \operatorname{Pr}(\mathrm{v}\) is blue \(\mid \mathrm{u}\) is red \()=2 / 3\)
\(\operatorname{Pr}(\mathrm{v}\) is red l u is blue \()=1 \operatorname{Pr}(\mathrm{v}\) is blue l u is blue \()=0\)
Finally, we can obtain the total weights listed by the node colors.
```

>>> 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

\subsection*{7.2.2 networkx.linalg.attrmatrix.attr_sparse_matrix}
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_attr. Then the elements of A represent the rows and columns of the constructed matrix. Now, iterate through every edge \(\mathrm{e}=(\mathrm{u}, \mathrm{v})\) 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 matirx. 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.

\section*{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.

\section*{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)
>>> 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.
```

>>> 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:
\(\operatorname{Pr}(\mathrm{v}\) has color Y I u has color X\()\)
```

>>> 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',
>>> M.todense()
matrix([[ 0.33333333, 0.66666667],
[ 1. , 0. ] ])

```

For example, the above tells us that for all edges ( \(\mathrm{u}, \mathrm{v}\) ):
\(\operatorname{Pr}(\mathrm{v}\) is red u is red \()=1 / 3 \operatorname{Pr}(\mathrm{v}\) is blue l u is red \()=2 / 3\)
\(\operatorname{Pr}(\mathrm{v}\) is red l u is blue \()=1 \operatorname{Pr}(\mathrm{v}\) is blue l u is blue \()=0\)
Finally, we can obtain the total weights listed by the node colors.
```

>>> M = nx.attr_sparse_matrix(G, edge_attr='weight',
>>> 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

\title{
CONVERTING TO AND FROM OTHER DATA FORMATS
}

\subsection*{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.

\subsection*{8.1.1 Examples}

Create a 10 node random graph from a numpy matrix
```

>>> import numpy
>>> a=numpy.reshape(numpy.random.random_integers(0,1,size=100),(10,10))
>>> D=nx.DiGraph(a)

```
or equivalently
```

>>> D=nx.to_networkx_graph(a,create_using=nx.DiGraph())

```

Create a graph with a single edge from a dictionary of dictionaries
```

>> d={0: {1: 1}} \# dict-of-dicts single edge (0,1)
>>> G=nx.Graph(d)

```

\subsection*{8.1.2 See Also}
nx_pygraphviz, nx_pydot
to_networkx_graph(data[, create_using, ...]) Make a NetworkX graph from a known data structure.

\subsection*{8.1.3 networkx.convert.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
```

>>> d={0: {1: {'weight':I}}} \# dict-of-dicts single edge (0,1)
>>> G=nx.Graph(d)

```
instead of the equivalent
```

>>> 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 multigraph from a multigraph.

\subsection*{8.2 Relabeling}
convert_node_labels_to_integers(G[,...]) Return a copy of G node labels replaced with integers.
relabel_nodes(G, mapping) Return a copy of G with node labels transformed by mapping.

\subsection*{8.2.1 networkx.convert.convert_node_labels_to_integers}
convert_node_labels_to_integers (G, first_label=0, ordering='default', discard_old_labels=True)
Return a copy of \(G\) node labels replaced with integers.
Parameters G: graph
A NetworkX graph
first_label : int, optional (default=0)
An integer specifying the offset in numbering nodes. The n new integer labels are numbered first_label, ..., n+first_label.
ordering : string
"default" : inherit node ordering from G.nodes() "sorted" : inherit node ordering from sorted(G.nodes()) "increasing degree" : nodes are sorted by increasing degree "decreasing degree" : nodes are sorted by decreasing degree
discard_old_labels : bool, optional (default=True)
if True (default) discard old labels if False, create a dict self.node_labels that maps new labels to old labels

\subsection*{8.2.2 networkx.convert.relabel_nodes}

\section*{relabel_nodes ( \(G\), mapping)}

Return a copy of \(G\) with node labels transformed by mapping.
Parameters G: graph
A NetworkX graph
mapping : dictionary or function
Either a dictionary with the old labels as keys and new labels as values or a function transforming an old label with a new label. In either case, the new labels must be hashable Python objects.

\section*{See Also:}
```

convert_node_labels_to_integers

```

\section*{Examples}
mapping as dictionary
```

>>> G=nx.path_graph(3) \# nodes 0-1-2

```
>>> mapping=\{0:' \(\left.a^{\prime}, 1:{ }^{\prime} b^{\prime}, 2:^{\prime} c^{\prime}\right\}\)
>>> H=nx.relabel_nodes (G, mapping)
>>> print (H.nodes())
['a', 'c', 'b']
>>> G=nx.path_graph(26) \# nodes 0.. 25
>>> mapping=dict(zip(G.nodes(),"abcdefghijklmnopqrstuvwxyz"))
>>> H=nx.relabel_nodes(G,mapping) \# nodes a..z
>>> mapping=dict(zip(G.nodes(),range (1,27)))
>>> G1=nx.relabel_nodes (G, mapping) \# nodes 1.. 26
mapping as function
```

>>> G=nx.path_graph(3)
>>> def mapping(x):
... return x**2
>>> H=nx.relabel_nodes(G,mapping)
>>> print(H.nodes())
[0, 1, 4]

```

\subsection*{8.3 Dictionaries}
```

to_dict_of_dicts(G[, nodelist, Return adjacency representation of graph as a dictionary of
edge_data]) dictionaries.
from_dict_of_dicts(d[, create_using, Return a graph from a dictionary of dictionaries.
...])

```

\subsection*{8.3.1 networkx.convert.to_dict_of_dicts}
to_dict_of_dicts (G, nodelist=None, edge_data=None)
Return adjacency representation of graph as a dictionary of dictionaries.
Parameters G: graph
A NetworkX graph

\section*{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 ( \(u, v\) ).

\subsection*{8.3.2 networkx.convert.from_dict_of_dicts}
from_dict_of_dicts (d, create_using=None, multigraph_input=False)
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.

\section*{Examples}
```

>>> dod= {0: {1:{'weight':1}}} \# single edge (0,1)

```
>>> G=nx.from_dict_of_dicts(dod)
or \(\ggg \mathrm{G}=\mathrm{nx}\).Graph(dod) \# use Graph constructor

\subsection*{8.4 Lists}
\begin{tabular}{ll}
\hline to_dict_of_lists(G[, nodelist]) & Return adjacency representation of graph as a dictionary of lists. \\
from_dict_of_lists \((d[\), create_using] \()\) & Return a graph from a dictionary of lists. \\
to_edgelist(G[, nodelist]) & Return a list of edges in the graph. \\
from_edgelist(edgelist[, create_using]) & Return a graph from a list of edges. \\
\hline
\end{tabular}

\subsection*{8.4.1 networkx.convert.to_dict_of_lists}

\section*{to_dict_of_lists (G, nodelist=None)}

Return adjacency representation of graph as a dictionary of lists.
Parameters G: graph
A NetworkX graph
nodelist : list
Use only nodes specified in nodelist

\section*{Notes}

Completely ignores edge data for MultiGraph and MultiDiGraph.

\subsection*{8.4.2 networkx.convert.from_dict_of_lists}
from_dict_of_lists (d, create_using=None)
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.

\section*{Examples}
>>> dol= \{0:[1]\} \# single edge \((0,1)\)
>>> G=nx.from_dict_of_lists(dol)
or \(\ggg\) G=nx.Graph(dol) \# use Graph constructor

\subsection*{8.4.3 networkx.convert.to_edgelist}
to_edgelist ( \(G\), nodelist=None)
Return a list of edges in the graph.
Parameters G: graph
A NetworkX graph
nodelist : list
Use only nodes specified in nodelist

\subsection*{8.4.4 networkx.convert.from_edgelist}
from_edgelist (edgelist, create_using=None)
Return a graph from a list of edges.
Parameters edgelist : list or iterator
Edge tuples
create_using : NetworkX graph
Use specified graph for result. Otherwise a new graph is created.

\section*{Examples}
>>> edgelist \(=[(0,1)]\) \# single edge \((0,1)\)
>>> G=nx.from_edgelist (edgelist)
or >>> G=nx.Graph(edgelist) \# use Graph constructor

\subsection*{8.5 Numpy}
to_numpy_matrix(G[, nodelist, dtype, order]) from_numpy_matrix(A[, create_using]) Return a graph from numpy matrix adjacency list.

\subsection*{8.5.1 networkx.convert.to_numpy_matrix}
to_numpy_matrix ( \(G\), nodelist=None, dtype=None, order=None)
Return the graph adjacency matrix as a NumPy 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.
order : \{ 'C', 'F'\}, optional
Whether to store multidimensional data in C- or Fortran-contiguous (row- or columnwise) order in memory. If None, then the NumPy default is used.
Returns M: NumPy matrix
Graph adjacency matrix.

\section*{Notes}

The matrix entries are populated using the '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.

\section*{Examples}
```

>>> 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.]])

```

\subsection*{8.5.2 networkx.convert.from_numpy_matrix}
from_numpy_matrix (A, create_using=None)
Return a graph from numpy matrix adjacency list.
Parameters A : numpy matrix
An adjacency matrix representation of a graph
create_using : NetworkX graph
Use specified graph for result. The default is Graph()

\section*{Examples}
>>> import numpy
\(\ggg A=\) numpy.matrix([ \([1,1],[2,1]])\)
>>> G=nx.from_numpy_matrix(A)

\subsection*{8.6 Scipy}
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.

\subsection*{8.6.1 networkx.convert.to_scipy_sparse_matrix}
to_scipy_sparse_matrix (G, nodelist=None, dtype=None)
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.

Returns M: SciPy sparse matrix
Graph adjacency matrix.

\section*{Notes}

The matrix entries are populated using the '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.

Uses lil_matrix format. To convert to other formats see the documentation for scipy.sparse.

\section*{Examples}
```

>>> 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])
>>> S.todense()
matrix([[ 0., 2., 0.],
[ 1., 0., 0.],
[ 0., 0., 4.]])

```

\subsection*{8.6.2 networkx.convert.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()

\section*{Examples}
```

>>> import scipy.sparse
>>> A=scipy.sparse.eye (2, 2,1)
>>> G=nx.from_scipy_sparse_matrix(A)

```

\section*{CHAPTER}

NINE

\section*{READING AND WRITING GRAPHS}

\subsection*{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.

\subsection*{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.
write_adjlist(G, path[, comments, ...])
Write graph G in single-line adjacency-list format to path.
parse_adjlist(lines[, comments, delimiter, ...]) Parse lines of a graph adjacency list representation.
generate_adjlist(G[, delimiter]) Generate a single line of the graph G in adjacency list format.

```

\subsection*{9.1.2 networkx.read_adjlist}
read_adjlist (path, comments='\#', delimiter=' ', create_using=None, nodetype=None, encoding='utf-8')
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
create_using: NetworkX graph container :
Use given NetworkX graph for holding nodes or edges.

\section*{Returns G: NetworkX graph :}

The graph corresponding to the lines in adjacency list format.

\section*{See Also:}
```

write_adjlist

```

\section*{Notes}

This format does not store graph or node data.

\section*{Examples}
```

>>> 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.
```

>>> fh=open("test.adjlist", 'rb')
>>> G=nx.read_adjlist(fh)

```

Filenames ending in .gz or .bz2 will be compressed.
```

>>> 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
```

>>> 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
```

>>> G=nx.read_adjlist("test.adjlist", create_using=nx.DiGraph())

```

\subsection*{9.1.3 networkx.write_adjlist}
write_adjlist ( \(G\), path, comments='\#', delimiter=' ', encoding='utf-8')
Write graph G in single-line adjacency-list format to path.
Parameters G : NetworkX graph
path : string or file
Filename or file handle for data output. Filenames ending in .gz or .bz2 will be compressed.
comments : string, optional
Marker for comment lines
delimiter : string, optional
Separator for node labels
encoding : string, optional
Text encoding.

\section*{See Also:}
read_adjlist, generate_adjlist

\section*{Notes}

This format does not store graph, node, or edge data.

\section*{Examples}
```

>>> 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.
```

>>> fh=open("test.adjlist",'wb')
>>> nx.write_adjlist(G, fh)

```

\subsection*{9.1.4 networkx.parse_adjlist}
parse_adjlist (lines, comments='\#', delimiter=' ', create_using=None, nodetype=None)
Parse lines of a graph adjacency list representation.
Parameters lines: list or iterator of strings
Input data in 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 create_using: NetworkX graph container :

Use given NetworkX graph for holding nodes or edges.

\section*{Returns G: NetworkX graph :}

The graph corresponding to the lines in adjacency list format.
See Also:
```

read_adjlist

```

\section*{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)]

```

\subsection*{9.1.5 networkx.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
See Also:
```

write_adjlist,read_adjlist

```

\section*{Examples}
>>> G = nx.lollipop_graph(4, 3)
>>> for line in nx.generate_adjlist(G):
... print(line)
0123
123
23
34

\subsection*{9.2 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.

\subsection*{9.2.1 Format}

You can read or write three formats of edge lists with these functions.
Node pairs with no data:
```

12

```

Python dictionary as data:
```

1 2 {'weight':7, 'color':'green'}

```

Arbitrary data:

\section*{127 green}
\begin{tabular}{ll}
\hline read_edgelist(path[, comments, delimiter, ...]) & Read a graph from a list of edges. \\
write_edgelist(G, path[, comments, ...]) & Write graph as a list of edges. \\
read_weighted_edgelist(path[, comments, ...]) & Read a graph as list of edges with numeric weights. \\
write_weighted_edgelist(G, path[, comments, ...]) & Write graph G as a list of edges with numeric weights. \\
generate_edgelist(G[, delimiter, data]) & Generate a single line of the graph G in edge list format. \\
parse_edgelist(lines[, comments, delimiter, ...]) & Parse lines of an edge list representation of a graph. \\
\hline
\end{tabular}

\subsection*{9.2.2 networkx.read_edgelist}
read_edgelist (path, comments='\#', delimiter=' ', create_using \(=\) None, nodetype \(=\) None, data \(=\) True, edgetype \(=\) None, encoding \(=\) 'utf-8')
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

\section*{See Also:}
parse_edgelist

\section*{Notes}

Since nodes must be hashable, the function nodetype must return hashable types (e.g. int, float, str, frozenset or tuples of those, etc.)

\section*{Examples}
```

>>> 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)
>>> G=nx.read_edgelist("test.edgelist", nodetype=int)
>>> G=nx.read_edgelist("test.edgelist",create_using=nx.DiGraph())

```

See parse_edgelist() for more examples of formatting.

\subsection*{9.2.3 networkx.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

```

\section*{Examples}
```

>>> 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'])

```

\subsection*{9.2.4 networkx.read_weighted_edgelist}
read_weighted_edgelist (path, comments='\#', delimiter=', 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
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

\section*{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:
```


# read with

# >>> G=nx.read_weighted_edgelist(fh)

# source target data

a b 1
a c 3.14159
d e 42

```

\subsection*{9.2.5 networkx.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

```

\section*{Examples}
```

>>> G=nx.Graph()
>>> G.add_edge(1,2,weight=7)
>>> nx.write_weighted_edgelist(G, 'weighted.edgelist')

```

\subsection*{9.2.6 networkx.generate_edgelist}
```

generate_edgelist (G, delimiter=' ', data=True)

```

Generate a single line of the graph \(G\) in edge list format.

\section*{Parameters G : NetworkX graph}
delimiter : string, optional
Separator for node labels
data : bool or list of keys
If False generate no edge data. If True use a dictionary representation of edge data. If a list of keys use a list of data values corresponding to the keys.

\section*{See Also:}
```

write_adjlist,read_adjlist

```

\section*{Examples}
>>> 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)
01
02
03
12
13
23
34
45
56
>>> for line in \(n x . g e n e r a t e \_e d g e l i s t(G):\)
... print(line)
01 \{\}
02 \{\}
03 \{\}
12 \{'weight': 3\}
13 \{\}
23 \{\}
34 \{'capacity': 12\}
45 \{\}
56 \{\}
```

>>> for line in nx.generate_edgelist(G,data=['weight']):
print(line)
O
O}
0
2 3
3
2 3
3 4
5
56

```

\subsection*{9.2.7 networkx.parse_edgelist}
parse_edgelist (lines, comments='\#', delimiter=' ', create_using=None, nodetype=None, data=True) Parse lines of an edge list representation of a graph.

\section*{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.

\section*{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

\section*{create_using: NetworkX graph container :}

Use given NetworkX graph for holding nodes or edges.

\section*{See Also:}
```

read_weighted_edgelist

```

\section*{Examples}

Edgelist with no data:
```

>>> lines = ["1 2",
... "2 3",
... "3 4"]
>>> G $=$ nx.parse_edgelist(lines, nodetype $=$ int)
>>> G.nodes()

```
```

[1, 2, 3, 4]
>>> G.edges()
[(1, 2), (2, 3), (3, 4)]

```

Edgelist with data in Python dictionary representation:
```

>>> 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:
```

>>> lines = ["11 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})]

```

\subsection*{9.3 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
Requires pyparsing: http://pyparsing.wikispaces.com/

\subsection*{9.3.1 Format}

See 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/
\begin{tabular}{ll}
\hline read_gml(path[, encoding]) & Read graph in GML format from path. \\
write_gml(G, path) & Write the graph G in GML format to the file or file handle path. \\
parse_gml(lines) & Parse GML graph from a string or iterable. \\
generate_gml \((G)\) & Generate a single entry of the graph G in GML format. \\
\hline
\end{tabular}

\subsection*{9.3.2 networkx.read_gml}
read_gml (path, encoding ='UTF-8')
Read graph in GML format from path.
Parameters path : filename or filehandle
The filename or filehandle to read from.
Returns G: MultiGraph or MultiDiGraph

\section*{Raises ImportError :}

If the pyparsing module is not available.

\section*{See Also:}
```

write_gml, parse_gml

```

\section*{Notes}

This doesn't implement the complete GML specification for nested attributes for graphs, edges, and nodes.
Requires pyparsing: http://pyparsing.wikispaces.com/

\section*{References}

GML specification: http://www.infosun.fim.uni-passau.de/Graphlet/GML/gml-tr.html

\section*{Examples}
>>> G=nx.path_graph (4)
>>> nx.write_gml (G,'test.gml')
>>> H=nx.read_gml('test.gml')

\subsection*{9.3.3 networkx.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.

\section*{See Also:}
read_gml, parse_gml

\section*{Notes}

GML specifications indicate that the file should only use 7bit ASCII text encoding.iso8859-1 (latin-1).
For nested attributes for graphs, nodes, and edges you should use dicts for the value of the attribute.

\section*{Examples}
```

>>> G=nx.path_graph(4)
>>> nx.write_gml(G,"test.gml")

```

Filenames ending in .gz or .bz2 will be compressed.
>>> nx.write_gml(G,"test.gml.gz")

\subsection*{9.3.4 networkx.parse_gml}
parse_gml (lines)
Parse GML graph from a string or iterable.
Parameters lines : string or iterable
Data in GML format.
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 dicts in the NetworkX Graph attribute structures.
Requires pyparsing: http://pyparsing.wikispaces.com/

\section*{References}

GML specification: http://www.infosun.fim.uni-passau.de/Graphlet/GML/gml-tr.html

\subsection*{9.3.5 networkx.generate_gml}
generate_gml ( \(G\) )
Generate a single entry of the graph G in GML format.
Parameters G: NetworkX graph

\subsection*{9.4 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.

\subsection*{9.4.1 Format}

See http://docs.python.org/library/pickle.html
read_gpickle(path) Read graph object in Python pickle format.
write_gpickle(G, path) Write graph in Python pickle format.

\subsection*{9.4.2 networkx.read_gpickle}
read_gpickle (path)
Read graph object in Python pickle format.
Pickles are a serialized byte stream of a Python object [R102]. 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

\section*{References}
[R102]

\section*{Examples}
>>> G=nx.path_graph (4)
>>> nx.write_gpickle(G,"test.gpickle")
>>> G=nx.read_gpickle("test.gpickle")

\subsection*{9.4.3 networkx.write_gpickle}
write_gpickle (G, path)
Write graph in Python pickle format.
Pickles are a serialized byte stream of a Python object [R106]. 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.

\section*{References}
[R106]

\section*{Examples}
>>> G=nx.path_graph (4)
>>> nx.write_gpickle(G,"test.gpickle")

\subsection*{9.5 GraphML}

Read and write graphs in GraphML format.
This implementation does not support mixed graphs (directed and unidirected 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/

\subsection*{9.5.1 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.
\begin{tabular}{ll}
\hline read_graphml(path[, node_type]) & Read graph in GraphML format from path. \\
write_graphml(G, path[, encoding]) & Write G in GraphML XML format to path \\
\hline
\end{tabular}

\subsection*{9.5.2 networkx.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.

\section*{Returns graph: NetworkX graph :}

If no parallel edges are found a Graph or DiGraph is returned. Otherwise a MultiGraph or MultiDiGraph is returned.

\section*{Notes}

This implementation does not support mixed graphs (directed and unidirected edges together), hypergraphs, nested graphs, or ports.

\subsection*{9.5.3 networkx.write_graphml}
write_graphml (G, path, encoding='utf-8')
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.

\section*{Notes}

This implementation does not support mixed graphs (directed and unidirected edges together) hyperedges, nested graphs, or ports.

\section*{Examples}
>>> G=nx.path_graph (4)
>>> nx.write_graphml(G, "test.graphml")

\subsection*{9.6 LEDA}

Read graphs in LEDA format.
LEDA is a C++ class library for efficient data types and algorithms.

\subsection*{9.6.1 Format}

See http://www.algorithmic-solutions.info/leda_guide/graphs/leda_native_graph_fileformat.html
\begin{tabular}{ll} 
read_leda(path[, encoding]) & Read graph in LEDA format from path. \\
parse_leda(lines) & Read graph in LEDA format from string or iterable. \\
\hline
\end{tabular}

\subsection*{9.6.2 networkx.read_leda}
read_leda (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

\section*{References}
[R103]

\section*{Examples}

G=nx.read_leda('file.leda’)

\subsection*{9.6.3 networkx.parse_leda}
parse_leda (lines)
Read graph in LEDA format from string or iterable.
Parameters lines : string or iterable
Data in LEDA format.
Returns G: NetworkX graph

\section*{References}
[R101]

\section*{Examples}
\(\mathrm{G}=\mathrm{nx}\). parse_leda(string)

\subsection*{9.7 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.

\subsection*{9.7.1 Format}
http://pyyaml.org/wiki/PyYAML
\begin{tabular}{ll} 
read_yaml(path) & Read graph in YAML format from path. \\
write_yaml(G, path, **kwds[, encoding]) & Write graph G in YAML format to path. \\
\hline
\end{tabular}

\subsection*{9.7.2 networkx.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 [R104].

Parameters path : file or string
File or filename to read. Filenames ending in .gz or .bz2 will be uncompressed.
Returns G: NetworkX graph

\section*{References}
[R104]

\section*{Examples}
>>> G=nx.path_graph (4)
>>> nx.write_yaml (G,'test.yaml')
>>> G=nx.read_yaml('test.yaml')

\subsection*{9.7.3 networkx.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 [R107].

\section*{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.

\section*{References}
[R107]

\section*{Examples}
>>> G=nx.path_graph (4)
>>> nx.write_yaml (G,'test.yaml')

\subsection*{9.8 SparseGraph6}

Read graphs in graph6 and sparse6 format.

\subsection*{9.8.1 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

See http://cs.anu.edu.au/~bdm/data/formats.txt for details.
\begin{tabular}{ll}
\hline read_graph6(path) & Read simple undirected graphs in graph6 format from path. \\
parse_graph6(str) & Read a simple undirected graph in graph6 format from string. \\
read_graph6_list(path) & Read simple undirected graphs in graph6 format from path. \\
read_sparse6(path) & Read simple undirected graphs in sparse6 format from path. \\
parse_sparse6(string) & Read undirected graph in sparse6 format from string. \\
read_sparse6_list(path) & Read undirected graphs in sparse6 format from path. \\
\hline
\end{tabular}

\subsection*{9.8.2 networkx.read_graph6}
read_graph6 (path)
Read simple undirected graphs in graph6 format from path.
Returns a single Graph.

\subsection*{9.8.3 networkx.parse_graph6}
```

parse_graph6(str)

```

Read a simple undirected graph in graph6 format from string.
Returns a single Graph.

\subsection*{9.8.4 networkx.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.

\subsection*{9.8.5 networkx.read_sparse6}
read_sparse6 (path)
Read simple undirected graphs in sparse6 format from path.
Returns a single MultiGraph.

\subsection*{9.8.6 networkx.parse_sparse6}

\section*{parse_sparse6 (string)}

Read undirected graph in sparse6 format from string.
Returns a MultiGraph.

\subsection*{9.8.7 networkx.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.

\subsection*{9.9 Pajek}

Read graphs in Pajek format.
This implementation handles directed and undirected graphs including those with self loops and parallel edges.

\subsection*{9.9.1 Format}

See http://vlado.fmf.uni-lj.si/pub/networks/pajek/doc/draweps.htm for format information.
\begin{tabular}{ll}
\hline read_pajek(path[, encoding]) & Read graph in Pajek format from path. \\
write_pajek(G, path[, encoding]) & Write graph in Pajek format to path. \\
parse_pajek(lines) & Parse Pajek format graph from string or iterable. \\
\hline
\end{tabular}

\subsection*{9.9.2 networkx.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.

\section*{References}

See http://vlado.fmf.uni-lj.si/pub/networks/pajek/doc/draweps.htm for format information.

\section*{Examples}
>>> 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
>>> G1=nx.Graph (G)

\subsection*{9.9.3 networkx.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.

\section*{References}

See http://vlado.fmf.uni-lj.si/pub/networks/pajek/doc/draweps.htm for format information.

\section*{Examples}
>>> G=nx.path_graph (4)
>>> nx.write_pajek(G, "test.net")

\subsection*{9.9.4 networkx.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

\section*{See Also:}
```

    read_pajek
    ```

\section*{DRAWING}

\subsection*{10.1 Matplotlib}

Draw networks with matplotlib (pylab).

\subsection*{10.1.1 See Also}
matplotlib: http://matplotlib.sourceforge.net/
pygraphviz: http://networkx.lanl.gov/pygraphviz/
\begin{tabular}{|c|c|}
\hline draw(G, **kwds[, pos, ax, hold]) & Draw the graph G with Matplotlib (pylab). \\
\hline draw_networkx(G, **kwds[, pos, with_labels]) & Draw the graph G using Matplotlib. \\
\hline draw_networkx_nodes(G, pos, **kwds[, ...]) & Draw the nodes of the graph G. \\
\hline draw_networkx_edges(G, pos, **kwds[, ...]) & Draw the edges of the graph G. \\
\hline draw_networkx_labels(G, pos, **kwds[, ...]) & Draw node labels on the graph G. \\
\hline raw_networkx_edge_labels(G, pos, **kwds[, ...]) & Draw edge labels. \\
\hline draw_circular(G, **kwargs) & Draw the graph G with a circular layout. \\
\hline draw_random(G, **kwargs) & Draw the graph G with a random layout. \\
\hline draw_spectral(G, **kwargs) & Draw the graph G with a spectral layout. \\
\hline draw_spring(G, **kwargs) & Draw the graph G with a spring layout. \\
\hline draw_shell(G, **kwargs) & Draw networkx graph with shell layout. \\
\hline draw_graphviz(G, **kwargs[, prog]) & Draw networkx graph with graphviz layout. \\
\hline
\end{tabular}

\subsection*{10.1.2 networkx.draw}
draw (G, pos=None, ax=None, hold=None, **kwds)
Draw the graph G with Matplotlib (pylab).
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.

\section*{See Also:}
```

draw_networkx, draw_networkx_nodes, draw_networkx_edges, draw_networkx_labels,
draw__networkx_edge_labels

```

\section*{Notes}

This function has the same name as pylab.draw and pyplot.draw so beware when using
>>> from networkx import *
since you might overwrite the pylab.draw function.
Good alternatives are:
With pylab:
```

>>> import pylab as P \#
>>> import networkx as nx
>>> G=nx.dodecahedral_graph()
>>> nx.draw(G) \# networkx draw()
>>> P.draw() \# pylab draw()

```

With pyplot
```

>>> 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

\section*{Examples}
```

>>> G=nx.dodecahedral_graph()
>>> nx.draw(G)
>>> nx.draw(G,pos=nx.spring_layout(G)) \# use spring layout

```

\subsection*{10.1.3 networkx.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.
ax : Matplotlib Axes object, optional
Draw the graph in the specified Matplotlib axes.
with_labels: bool, optional :
Set to True (default) to draw labels on the nodes.

\section*{nodelist: list, optional :}

Draw only specified nodes (default G.nodes())
edgelist: list :
Draw only specified edges(default=G.edges())
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)
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.
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)

\section*{style: string :}

Edge line style (default='solid') (solidldashedldotted,dashdot)

\section*{labels: dictionary :}

Node labels in a dictionary keyed by node of text labels (default=None)

\section*{font_size: int :}

Font size for text labels (default=12)

\section*{font_color: string :}

Font color string (default='k' black)
font_weight: string :
Font weight (default='normal')
font_family: string :
Font family (default='sans-serif')

\section*{See Also:}
draw, draw_networkx_nodes, draw_networkx_edges, draw_networkx_labels, draw__networkx_edge_labels

\section*{Notes}

Any keywords not listed above are passed through to draw_networkx_nodes(), draw_networkx_edges(), and draw_networkx_labels(). For finer control of drawing you can call those functions directly.

\section*{Examples}
```

>>> G=nx.dodecahedral_graph()
>>> nx.draw(G)
>>> nx.draw(G,pos=nx.spring_layout(G)) \# use spring layout
>>> import pylab
>>> limits=pylab.axis('off') \# turn of axis

```

Also see the NetworkX drawing examples at http://networkx.lanl.gov/gallery.html

\subsection*{10.1.4 networkx.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, **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())
edgelist: list :
Draw only specified edges(default=G.edges())
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)
width': float :
Line width of edges \((\) default \(=1.0)\)

\section*{See Also:}
```

draw, draw_networkx, draw_networkx_edges, draw_networkx_labels,
draw_networkx_edge_labels

```

\section*{Notes}

Any keywords not listed above are passed through to Matplotlib's scatter function.

\section*{Examples}
```

>>> G=nx.dodecahedral_graph()
>>> nodes=nx.draw_networkx_nodes(G,pos=nx.spring_layout (G))

```

Also see the NetworkX drawing examples at http://networkx.lanl.gov/gallery.html

\subsection*{10.1.5 networkx.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, **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.
\(\mathbf{a x}\) : Matplotlib Axes object, optional
Draw the graph in the specified Matplotlib axes.
alpha: float :
The edge transparency (default=1.0)
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.

\section*{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)
style: string :
Edge line style (default='solid') (solidldashedldotted,dashdot)

\section*{See Also:}
```

draw, draw_networkx, draw_networkx_nodes, draw_networkx_labels,
draw__networkx_edge_labels

```

\section*{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.

\section*{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

\subsection*{10.1.6 networkx.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 \(\bar{G}\).
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.
ax : Matplotlib Axes object, optional
Draw the graph in the specified Matplotlib axes.
alpha: float :
The text transparency (default=1.0)
labels: dictionary :
Node labels in a dictionary keyed by node of text labels (default=None)
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')

\section*{See Also:}
```

draw, draw_networkx, draw_networkx_nodes, draw_networkx_edges,
draw__networkx_edge_labels

```

\section*{Examples}
>>> 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

\subsection*{10.1.7 networkx.draw_networkx_edge_labels}
draw_networkx_edge_labels (G, pos, edge_labels=None, font_size =10, font_color=' \(k\) ', font_family='sansserif', font_weight='normal', alpha=1.0, bbox=None, ax=None, **kwds)
Draw edge labels.

\section*{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)

\section*{labels: dictionary :}

Node labels in a dictionary keyed by edge two-tuple of text labels (default=None), Only labels for the keys in the dictionary are drawn.
font_size: int :
Font size for text labels (default=12)
font_color: string :
Font color string (default='k' black)

\section*{font_weight: string :}

Font weight (default='normal')
font_family: string :
Font family (default='sans-serif')

\section*{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

```

\section*{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

\subsection*{10.1.8 networkx.draw_circular}
draw_circular (G, **kwargs)
Draw the graph G with a circular layout.

\subsection*{10.1.9 networkx.draw_random}
draw_random ( \(G\), **kwargs)
Draw the graph G with a random layout.

\subsection*{10.1.10 networkx.draw_spectral}

\section*{draw_spectral (G, **kwargs)}

Draw the graph \(G\) with a spectral layout.

\subsection*{10.1.11 networkx.draw_spring}
draw_spring ( \(G, * * k w a r g s\) )
Draw the graph \(G\) with a spring layout.

\subsection*{10.1.12 networkx.draw_shell}
draw_shell (G, **kwargs)
Draw networkx graph with shell layout.

\subsection*{10.1.13 networkx.draw_graphviz}
draw_graphviz (G, prog='neato', **kwargs)
Draw networkx graph with graphviz layout.

\subsection*{10.2 Graphviz AGraph (dot)}

Interface to pygraphviz AGraph class.

\subsection*{10.2.1 Examples}
```

>>> G=nx.complete_graph(5)
>>> A=nx.to_agraph(G)
>>> H=nx.from_agraph(A)

```

\subsection*{10.2.2 See Also}

Pygraphviz: http://networkx.lanl.gov/pygraphviz
\begin{tabular}{ll}
\hline from_agraph(A[, create_using]) & Return a NetworkX Graph or DiGraph from a PyGraphviz graph. \\
to_agraph(N) & Return a pygraphviz graph from a NetworkX graph N. \\
write_dot(G, path) & Write NetworkX graph G to Graphviz dot format on path. \\
read_dot(path) & Return a NetworkX graph from a dot file on path. \\
graphviz_layout(G[, prog, root, args]) & Create node positions for G using Graphviz. \\
pygraphviz_layout(G[, prog, root, args]) & Create node positions for G using Graphviz. \\
\hline
\end{tabular}

\subsection*{10.2.3 networkx.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

\section*{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.

\section*{Examples}
```

>>> K5=nx.complete_graph(5)
>>> A=nx.to_agraph(K5)
>>> G=nx.from_agraph(A)
>>>G=nx.from_agraph(A)

```

\subsection*{10.2.4 networkx.to_agraph}
to_agraph ( \(N\) )
Return a pygraphviz graph from a NetworkX graph N .

Parameters \(\mathbf{N}\) : NetworkX graph
A graph created with NetworkX

\section*{Notes}

If N has an 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.

\section*{Examples}
```

>>> K5=nx.complete_graph(5)
>>> A=nx.to_agraph(K5)

```

\subsection*{10.2.5 networkx.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.

\subsection*{10.2.6 networkx.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.

\subsection*{10.2.7 networkx.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.

\section*{Notes}

This is a wrapper for pygraphviz_layout.

\section*{Examples}
>>> G=nx.petersen_graph()
>>> pos=nx.graphviz_layout (G)
>>> pos=nx.graphviz_layout (G,prog=' dot \(^{\prime}\) )

\subsection*{10.2.8 networkx.pygraphviz_layout}
pygraphviz_layout ( \(G\), prog='neato', root=None, \(\operatorname{args=")~}\)
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.

\section*{Examples}
>>> G=nx.petersen_graph()
\(\ggg\) pos=nx.graphviz_layout (G)
>>> pos=nx.graphviz_layout (G,prog=' dot')

\subsection*{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.

\subsection*{10.3.1 See Also}

Pydot: http://www.dkbza.org/pydot.html Graphviz: http://www.research.att.com/sw/tools/graphviz/ DOT Language: http://www.graphviz.org/doc/info/lang.html
\begin{tabular}{ll}
\hline from_pydot(P) & Return a NetworkX graph from a Pydot graph. \\
to_pydot(N[, strict]) & Return a pydot graph from a NetworkX graph N. \\
write_dot(G, path) & Write NetworkX graph G to Graphviz dot format on path. \\
read_dot(path) & Return a NetworkX graph from a dot file on path. \\
graphviz_layout(G[, prog, root, args]) & Create node positions for G using Graphviz. \\
pydot_layout(G, **kwds[, prog, root]) & Create node positions using Pydot and Graphviz. \\
\hline
\end{tabular}

\subsection*{10.3.2 networkx.from_pydot}

\section*{from_pydot ( \(P\) )}

Return a NetworkX graph from a Pydot graph.
Parameters P : Pydot graph
A graph created with Pydot

\section*{Examples}
>>> K5=nx.complete_graph (5)
\(\ggg A=n x . t o \_p y d o t(K 5)\)
>>> G=nx.from_pydot (A)

\subsection*{10.3.3 networkx.to_pydot}

\section*{to_pydot ( \(N\), strict=True)}

Return a pydot graph from a NetworkX graph N.
Parameters \(\mathbf{N}\) : NetworkX graph
A graph created with NetworkX

\section*{Examples}
>>> K5=nx.complete_graph (5)
>>> P=nx.to_pydot(K5)

\subsection*{10.3.4 networkx.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.

\subsection*{10.3.5 networkx.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.

\subsection*{10.3.6 networkx.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 \(\mathrm{x}, \mathrm{y}\), positions keyed by node.

\section*{Notes}

This is a wrapper for pygraphviz_layout.

\section*{Examples}
>>> G=nx.petersen_graph()
>>> pos=nx.graphviz_layout (G)
>>> pos=nx.graphviz_layout (G,prog='dot')

\subsection*{10.3.7 networkx.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.

\section*{Examples}
```

>>> G=nx.complete_graph(4)
>>> pos=nx.pydot_layout(G)
>>> pos=nx.pydot_layout(G,prog='dot')

```

\subsection*{10.4 Graph Layout}

Node positioning algorithms for graph drawing.
\begin{tabular}{ll}
\hline circular_layout(G[, dim, scale \(])\) & Position nodes on a circle. \\
random_layout(G[, dim]) & Position nodes uniformly at random in the unit square. \\
shell_layout(G[, nlist, dim, scale]) & \begin{tabular}{l} 
Position nodes in concentric circles. \\
spring_layout(G[, dim, pos, fixed, ...])
\end{tabular} \\
\begin{tabular}{l} 
Position nodes using Fruchterman-Reingold force-directed \\
algorithm.
\end{tabular} \\
\begin{tabular}{l} 
spectral_layout(G[, dim, weighted,, \\
scale] \()\)
\end{tabular} & Position nodes using the eigenvectors of the graph Laplacian. \\
\hline
\end{tabular}

\subsection*{10.4.1 networkx.circular_layout}
circular_layout ( \(G\), dim=2, scale \(=1\) )
Position nodes on a circle.

\section*{Parameters G : NetworkX graph}
\(\operatorname{dim}\) : 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

\section*{Notes}

This algorithm currently only works in two dimensions and does not try to minimize edge crossings.

\section*{Examples}
>>> G=nx.path_graph (4)
>>> pos=nx.circular_layout(G)

\subsection*{10.4.2 networkx.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 \(G\).
\(\operatorname{dim}\) : int
Dimension of layout.

\section*{Returns dict : :}

A dictionary of positions keyed by node

\section*{Examples}
>>> G \(=\) nx.lollipop_graph(4, 3)
>>> pos = nx.random_layout (G)

\subsection*{10.4.3 networkx.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 dict : :
A dictionary of positions keyed by node

\section*{Notes}

This algorithm currently only works in two dimensions and does not try to minimize edge crossings.

\section*{Examples}
>>> G=nx.path_graph (4)
>>> shells=[[0],[1,2,3]]
>>> pos=nx.shell_layout (G,shells)

\subsection*{10.4.4 networkx.spring_layout}
spring_layout ( \(G\), dim=2, pos=None, fixed \(=\) None, iterations \(=50\), weighted \(=\) True, scale \(=1\) )
Position nodes using Fruchterman-Reingold force-directed algorithm.
Parameters G : NetworkX graph
\(\operatorname{dim}\) : int
Dimension of layout
pos: dict
Initial positions for nodes as a dictionary with node as keys and values as a list or tuple.
fixed : list
Nodes to keep fixed at initial position.
iterations : int
Number of iterations of spring-force relaxation
weighted : boolean
If True, use edge weights in layout
scale : float
Scale factor for positions

\section*{Returns dict : :}

A dictionary of positions keyed by node

\section*{Examples}
>>> G=nx.path_graph (4)
>>> pos=nx.spring_layout (G)
\# The same using longer function name >>> pos=nx.fruchterman_reingold_layout(G)

\subsection*{10.4.5 networkx.spectral_layout}
spectral_layout ( \(G\), dim=2, weighted=True, scale=1)
Position nodes using the eigenvectors of the graph Laplacian.

\section*{Parameters G : NetworkX graph}
\(\operatorname{dim}\) : int
Dimension of layout
weighted : boolean
If True, use edge weights in layout
scale : float
Scale factor for positions

\section*{Returns dict : :}

A dictionary of positions keyed by node

\section*{Notes}

Directed graphs will be considered as unidrected graphs when positioning the nodes.
For larger graphs (>500 nodes) this will use the SciPy sparse eigenvalue solver (ARPACK).

\section*{Examples}
```

>>> G=nx.path_graph(4)
>>> pos=nx.spectral_layout (G)

```

\section*{EXCEPTIONS}

Base exceptions and errors for NetworkX.
class NetworkXException ()
Base class for exceptions in NetworkX.

\section*{class NetworkXError ()}

Exception for a serious error in NetworkX
class NetworkXPointlessConcept ()
Harary, F. and Read, R. "Is the Null Graph a Pointless Concept?" In Graphs and Combinatorics Conference, George Washington University. New York: Springer-Verlag, 1973.

\section*{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.

\section*{class NetworkXNoPath ()}

Exception for algorithms that should return a path when running on graphs where such a path does not exist.

\section*{class NetworkXUnbounded ()}

Exception raised by algorithms trying to solve a maximization or a minimization problem instance that is unbounded.

\section*{UTILITIES}

Helpers for NetworkX.
These are not imported into the base networkx namespace but can be accessed, for example, as
```

>>> import networkx
>>> networkx.utils.is_string_like('spam')
True

```

\subsection*{12.1 Helper functions}
\begin{tabular}{ll}
\hline is_string_like(obj) & Check if obj is string. \\
flatten(obj[, result]) & Return flattened version of (possibly nested) iterable object. \\
iterable(obj) & Return True if obj is iterable with a well-defined len(). \\
is_list_of_ints(intlist) & Return True if list is a list of ints. \\
_get_fh(path[, mode]) & Return a file handle for given path. \\
\hline
\end{tabular}

\subsection*{12.1.1 networkx.utils.is_string_like}
is_string_like (obj)
Check if obj is string.

\subsection*{12.1.2 networkx.utils.flatten}
flatten (obj, result=None)
Return flattened version of (possibly nested) iterable object.

\subsection*{12.1.3 networkx.utils.iterable}

\section*{iterable (obj)}

Return True if obj is iterable with a well-defined len().

\subsection*{12.1.4 networkx.utils.is_list_of_ints}
is_list_of_ints (intlist)
Return True if list is a list of ints.

\subsection*{12.1.5 networkx.utils._get_fh}
_get_fh (path, mode='r')
Return a file handle for given path.
Path can be a string or a file handle.
Attempt to uncompress/compress files ending in '.gz' and '.bz2'.

\subsection*{12.2 Data structures and Algorithms}

> \begin{tabular}{ll} \hline UnionFind.union(*objects) \(\quad\) Find the sets containing the objects and merge them all. \\ \hline \end{tabular}

\subsection*{12.2.1 networkx.utils.UnionFind.union}
```

union (*objects)

```

Find the sets containing the objects and merge them all.

\subsection*{12.3 Random sequence generators}
```

pareto_sequence(n[, Return sample sequence of length n from a Pareto distribution.
exponent])
powerlaw_sequence(n[, Return sample sequence of length n from a power law distribution.
exponent])
uniform_sequence(n) Return sample sequence of length n from a uniform distribution.
cumulative_distribution(disRributtinmormalized cumulative distribution from discrete distribution.
discrete_sequence(n[, Return sample sequence of length n from a given discrete distribution or
distribution, ...])
discrete cumulative distribution.

```

\subsection*{12.3.1 networkx.utils.pareto_sequence}
pareto_sequence ( \(n\), exponent=1.0)
Return sample sequence of length n from a Pareto distribution.

\subsection*{12.3.2 networkx.utils.powerlaw_sequence}
powerlaw_sequence ( \(n\), exponent \(=2.0\) )
Return sample sequence of length \(n\) from a power law distribution.

\subsection*{12.3.3 networkx.utils.uniform_sequence}
```

uniform_sequence ( }n\mathrm{ )

```

Return sample sequence of length n from a uniform distribution.

\subsection*{12.3.4 networkx.utils.cumulative_distribution}

\section*{cumulative_distribution (distribution)}

Return normalized cumulative distribution from discrete distribution.

\subsection*{12.3.5 networkx.utils.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

\subsection*{12.4 SciPy random sequence generators}
```

scipy_pareto_sequence(n[, exponent])
scipy_powerlaw_sequence(n[,
exponent])
scipy_poisson_sequence(n[,mu])
scipy_uniform_sequence(n)
scipy_discrete_sequence(n[,
distribution])

```

Return sample sequence of length n from a Pareto distribution. Return sample sequence of length \(n\) from a power law distribution.
Return sample sequence of length \(n\) from a Poisson distribution. Return sample sequence of length \(n\) from a uniform distribution. Return sample sequence of length \(n\) from a given discrete distribution.

\subsection*{12.4.1 networkx.utils.scipy_pareto_sequence}
scipy_pareto_sequence ( \(n\), exponent \(=1.0\) )
Return sample sequence of length n from a Pareto distribution.

\subsection*{12.4.2 networkx.utils.scipy_powerlaw_sequence}
scipy_powerlaw_sequence ( \(n\), exponent \(=2.0\) )
Return sample sequence of length \(n\) from a power law distribution.

\subsection*{12.4.3 networkx.utils.scipy_poisson_sequence}
scipy_poisson_sequence ( \(n, m u=1.0\) )
Return sample sequence of length n from a Poisson distribution.

\subsection*{12.4.4 networkx.utils.scipy_uniform_sequence}
scipy_uniform_sequence ( \(n\) )
Return sample sequence of length n from a uniform distribution.

\subsection*{12.4.5 networkx.utils.scipy_discrete_sequence}
scipy_discrete_sequence ( \(n\), distribution=False) Return sample sequence of length n from a given discrete distribution. distribution=histogram of values, will be normalized

\section*{LICENSE}

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```

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\section*{CITING}

To cite NetworkX please use the following publication:
Aric A. Hagberg, Daniel A. Schult and Pieter J. Swart, "Exploring network structure, dynamics, and function using NetworkX", in Proceedings of the 7th Python in Science Conference (SciPy2008), Gäel Varoquaux, Travis Vaught, and Jarrod Millman (Eds), (Pasadena, CA USA), pp. 11-15, Aug 2008

\section*{CREDITS}

NetworkX was originally written by Aric Hagberg, Dan Schult, and Pieter Swart with the help of many others.
Thanks to Guido van Rossum for the idea of using Python for implementing a graph data structure http://www.python.org/doc/essays/graphs.html

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 \(\mathrm{G}[\mathrm{n}]\) are node n's neighbors.

Thanks to all those who have improved NetworkX by contributing code, bug reports (and fixes), documentation, and input on design, featues, and the future of NetworkX.
Thanks especially to the following contributors.
- Katy Bold contributed the Karate Club graph
- Hernan Rozenfeld added dorogovtsev_goltsev_mendes_graph and did stress testing
- Brendt Wohlberg added examples from the Stanford GraphBase
- Jim Bagrow reported bugs in the search methods
- Holly Johnsen helped fix the path based centrality measures
- Arnar Flatberg fixed the graph laplacian routines
- Chris Myers suggested using None as a default datatype, suggested improvements for the IO routines, added grid generator index tuple labeling and associated routines, and reported bugs
- Joel Miller tested and improved the connected components methods fixed bugs and typos in the graph generators, and contributed the random clustered graph generator.
- Keith Briggs sorted out naming issues for random graphs and wrote dense_gnm_random_graph
- Ignacio Rozada provided the Krapivsky-Redner graph generator
- Phillipp Pagel helped fix eccentricity etc. for disconnected graphs
- Sverre Sundsdal contributed bidirectional shortest path and Dijkstra routines, s-metric computation and graph generation
- Ross M. Richardson contributed the expected degree graph generator and helped test the pygraphviz interface
- Christopher Ellison implemented the VF2 isomorphism algorithm and contributed the code for matching all the graph types.
- Eben Kenah contributed the strongly connected components and DFS functions.
- Sasha Gutfriend contributed edge betweenness algorithms.
- Udi Weinsberg helped develop intersection and difference operators.
- Matteo Dell'Amico wrote the random regular graph generator.
- Andrew Conway contributed ego_graph, eigenvector centrality, line graph and much more.
- Raf Guns wrote the GraphML writer.
- Salim Fadhley and Matteo Dell'Amico contributed the A* algorithm.
- Fabrice Desclaux contributed the Matplotlib edge labeling code.
- Arpad Horvath fixed the barabasi_albert_graph() generator.
- Minh Van Nguyen contributed the connected_watts_strogatz_graph() and documentation for the Graph and MultiGraph classes.
- Willem Ligtenberg contributed the directed scale free graph generator.
- Loïc Séguin-C. contributed the Ford-Fulkerson max flow and min cut algorithms, and ported all of NetworkX to Python3.

\section*{GLOSSARY}

\section*{dictionary FIXME}
ebunch An iteratable 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 \([\mathrm{u}][\mathrm{v}]\) attribute dictionary for the specified edge \(\mathrm{u}-\mathrm{v}\).
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 \(\operatorname{id}()\).

Definition from 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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[R104] http://www.yaml.org
[R107] http://www.yaml.org

\section*{MODULE INDEX}

\section*{N}
networkx.algorithms.bipartite, 133 networkx.algorithms.block, 135 networkx.algorithms.boundary, 136 networkx.algorithms.centrality, 137
networkx.algorithms.matching, 194
networkx.algorithms.mixing, 195
networkx.algorithms.mst, 200
networkx.algorithms.operators, 201
networkx.algorithms.shortest_paths.astar, 219
networkx.algorithms.shortest_paths.generic, 205
networkx.algorithms.centrality.closeness 138
networkx.algorithms.shortest_paths.unweighted,
networkx.algorithms.centrality.current_flow_bet \({ }^{2}\). \({ }^{2}\) eenness, 141
networkx.algorithms.shortest_paths.weighted,
networkx.algorithms. centrality.current_flow_clofdness,
141
networkx.algorithms.traversal.depth_first_search,
networkx.algorithms.centrality.degree_alg, 220
137 networkx.algorithms.vitality, 221
networkx.algorithms.centrality.eigenvect \(\begin{aligned} & \text { getworkx.classes.function, } 223\end{aligned}\) 143
networkx.algorithms.centrality.load, 144
networkx. convert, 269
networkx.drawing.layout, 315
networkx.drawing.nx_agraph, 309
networkx.drawing.nx_pydot, 312
networkx.algorithms.cluster, 148
networkx.algorithms.components, 150
networkx.drawing.nx_pylab, 301
networkx.algorithms.components.attracting,tworkx.exception, 319
157 networkx.generators.atlas, 227
networkx.algorithms.components.connected, , etworkx.generators.bipartite, 257
150 networkx.generators.classic, 227
networkx.algorithms. components.strongly_Egh\#\&eked,generators.degree_seq, 246 153
networkx.generators.directed, 253
networkx.algorithms.components.weakly_coffewerkx.generators.ego, 262 156
networkx.algorithms.core, 158
networkx.algorithms.cycles, 159
networkx.algorithms.dag, 159
networkx.algorithms.distance_measures, 161
networkx.algorithms.euler, 163
networkx.algorithms.flow, 164
networkx.algorithms.isolates, 175
networkx. generators.geometric, 257
networkx.generators.hybrid, 257
networkx.generators.line, 261
networkx.generators.random_graphs, 236
networkx.generators.small, 232
networkx.generators.stochastic, 262
networkx.linalg.attrmatrix, 265
networkx.linalg.spectrum, 263
networkx.algorithms.isolates, 175 networkx.readwrite.adjlist, 279
networkx.algorithms.link_analysis.hits_angt,workx.readwrite.edgelist, 283 191
networkx.readwrite.gml, 289
networkx.algorithms.link_analysis.pagerafktwogkx.readwrite.gpickle, 291 188
networkx.readwrite.graphml, 293
```

networkx.readwrite.leda,294
networkx.readwrite.nx_yaml,295
networkx.readwrite.pajek, 298
networkx.readwrite.sparsegraph6,297
networkx.utils,321

```

\section*{Symbols}
__contains_ () (DiGraph method), 58
__contains__() (Graph method), 28
__contains__() (MultiDiGraph method), 120
__contains__() (MultiGraph method), 89
__getitem__() (DiGraph method), 55
__getitem__() (Graph method), 25
__getitem__() (MultiDiGraph method), 117
__getitem__() (MultiGraph method), 86
__init__() (DiGraph method), 40
__init__() (DiGraphMatcher method), 180
__init__() (Graph method), 12
__init__() (GraphMatcher method), 178
__init__() (MultiDiGraph method), 101
__init__() (MultiGraph method), 72
__init__() (WeightedDiGraphMatcher method), 183
__init__() (WeightedGraphMatcher method), 182
__init__() (WeightedMultiDiGraphMatcher method), 187
__init__() (WeightedMultiGraphMatcher method), 185
__iter__() (DiGraph method), 50
__iter__() (Graph method), 22
__iter__() (MultiDiGraph method), 112
__iter__() (MultiGraph method), 82
__len__() (DiGraph method), 60
__len__() (Graph method), 30
__len_() (MultiDiGraph method), 122
__len__() (MultiGraph method), 91
_get_fh() (in module networkx.utils), 322

\section*{A}
add_cycle() (DiGraph method), 47
add_cycle() (Graph method), 20
add_cycle() (MultiDiGraph method), 109
add_cycle() (MultiGraph method), 80
add_edge() (DiGraph method), 43
add_edge() (Graph method), 15
add_edge() (MultiDiGraph method), 104
add_edge() (MultiGraph method), 75
add_edges_from() (DiGraph method), 44
add_edges_from() (Graph method), 16
add_edges_from() (MultiDiGraph method), 105
add_edges_from() (MultiGraph method), 76
add_node() (DiGraph method), 41
add_node() (Graph method), 13
add_node() (MultiDiGraph method), 102
add_node() (MultiGraph method), 73
add_nodes_from() (DiGraph method), 41
add_nodes_from() (Graph method), 14
add_nodes_from() (MultiDiGraph method), 102
add_nodes_from() (MultiGraph method), 74
add_path() (DiGraph method), 47
add_path() (Graph method), 19
add_path() (MultiDiGraph method), 109
add_path() (MultiGraph method), 80
add_star() (DiGraph method), 46
add_star() (Graph method), 19
add_star() (MultiDiGraph method), 108
add_star() (MultiGraph method), 79
add_weighted_edges_from() (DiGraph method), 45
add_weighted_edges_from() (Graph method), 17
add_weighted_edges_from() (MultiDiGraph method), 106
add_weighted_edges_from() (MultiGraph method), 77
adj_matrix() (in module networkx.linalg.spectrum), 263
adjacency_iter() (DiGraph method), 57
adjacency_iter() (Graph method), 26
adjacency_iter() (MultiDiGraph method), 118
adjacency_iter() (MultiGraph method), 87
adjacency_list() (DiGraph method), 56
adjacency_list() (Graph method), 26
adjacency_list() (MultiDiGraph method), 118
adjacency_list() (MultiGraph method), 87
adjacency_spectrum() (in module networkx.linalg.spectrum), 265
all_pairs_dijkstra_path() (in module networkx), 214
all_pairs_dijkstra_path_length() (in module networkx), 214
all_pairs_shortest_path() (in module networkx), 209
all_pairs_shortest_path_length() (in module networkx), 209
astar_path() (in module networkx), 219
astar_path_length() (in module networkx), 219
attr_matrix() (in module networkx.linalg.attrmatrix), 265
attr_sparse_matrix() (in module
workx.linalg.attrmatrix), 267
attracting_component_subgraphs() (in module workx.algorithms.components.attracting), 158
attracting_components() (in module networkx.algorithms.components.attracting), 158
attribute_assortativity() (in module networkx), 196
attribute_mixing_dict() (in module networkx), 199
attribute_mixing_matrix() (in module networkx), 198
authority_matrix() (in module networkx), 194
average_clustering() (in module networkx), 150
average_shortest_path_length() (in module networkx), 207

\section*{B}
balanced_tree() (in module networkx.generators.classic), 228
barabasi_albert_graph() (in module networkx.generators.random_graphs), 243
barbell_graph() (in module networkx.generators.classic), 228
bellman_ford() (in module networkx), 218
betweenness_centrality() (in module networkx.algorithms.centrality.betweenness), 139
bidirectional_dijkstra() (in module networkx), 216
bidirectional_shortest_path() (in module networkx), 217
binomial_graph() (in module networkx.generators.random_graphs), 240
bipartite_alternating_havel_hakimi_graph() (in module networkx.generators.bipartite), 259
bipartite_color() (in module networkx), 134
bipartite_configuration_model() (in module networkx.generators.bipartite), 258
bipartite_havel_hakimi_graph() (in module networkx.generators.bipartite), 258
bipartite_preferential_attachment_graph() (in module networkx.generators.bipartite), 260
bipartite_random_regular_graph() (in module networkx.generators.bipartite), 260
bipartite_reverse_havel_hakimi_graph() (in module networkx.generators.bipartite), 259
bipartite_sets() (in module networkx), 133
blockmodel() (in module networkx), 135
bull_graph() (in module networkx.generators.small), 233

\section*{C}
candidate_pairs_iter() (DiGraphMatcher method), 181
candidate_pairs_iter() (GraphMatcher method), 179
candidate_pairs_iter() (WeightedDiGraphMatcher method), 184
net- candidate_pairs_iter() (WeightedGraphMatcher method), 183
candidate_pairs_iter() (WeightedMultiDiGraphMatcher method), 188
candidate_pairs_iter() (WeightedMultiGraphMatcher method), 186
cartesian_product() (in module networkx), 201
center() (in module networkx), 161
chvatal_graph() (in module networkx.generators.small), 233
circular_ladder_graph() (in module networkx.generators.classic), 229
circular_layout() (in module networkx), 315
clear() (DiGraph method), 48
clear() (Graph method), 20
clear() (MultiDiGraph method), 110
clear() (MultiGraph method), 81
cliques_containing_node() (in module networkx), 147
closeness_centrality() (in module networkx), 139
closeness_vitality() (in module networkx), 221
clustering() (in module networkx), 149
complement() (in module networkx), 202
complete_bipartite_graph() (in module networkx.generators.classic), 229
complete_graph() (in module networkx.generators.classic), 229
compose() (in module networkx), 202
condensation() (in module networkx.algorithms.components.strongly_connected), 156
configuration_model() (in module networkx.generators.degree_seq), 247
connected_component_subgraphs() (in module networkx.algorithms.components.connected), 152
connected_components() (in module networkx.algorithms.components.connected), 151
connected_double_edge_swap() (in module networkx.generators.degree_seq), 252
connected_watts_strogatz_graph() (in module networkx.generators.random_graphs), 242
convert_node_labels_to_integers() (in module networkx.convert), 270
copy() (DiGraph method), 67
copy() (Graph method), 34
copy() (MultiDiGraph method), 129
copy() (MultiGraph method), 95
cost_of_flow() (in module networkx), 173
could_be_isomorphic() (in module networkx), 177
create_degree_sequence() (in module networkx.generators.degree_seq), 251
create_empty_copy() (in module networkx), 225
cubical_graph() (in module networkx.generators.small),

\section*{233}
cumulative_distribution() (in module networkx.utils), 323 current_flow_betweenness_centrality() (in module networkx.algorithms.centrality.current_flow_between 142
current_flow_closeness_centrality() (in module networkx), 141
cycle_basis() (in module networkx), 159
cycle_graph() (in module networkx.generators.classic), 229

\section*{D}
degree() (DiGraph method), 60
degree() (Graph method), 30
degree() (MultiDiGraph method), 122
degree() (MultiGraph method), 91
degree_assortativity() (in module networkx), 195
degree_centrality() (in module networkx), 137
degree_histogram() (in module networkx), 224
degree_iter() (DiGraph method), 61
degree_iter() (Graph method), 31
degree_iter() (MultiDiGraph method), 123
degree_iter() (MultiGraph method), 92
degree_mixing_dict() (in module networkx), 199
degree_mixing_matrix() (in module networkx), 199
degree_pearsonr() (in module networkx), 197
degree_sequence_tree() (in module workx.generators.degree_seq), 250
dense_gnm_random_graph() (in module workx.generators.random_graphs), 238
density() (in module networkx), 223
desargues_graph() (in module networkx.generators.small), 233
dfs_postorder() (in module networkx), 220
dfs_predecessor() (in module networkx), 220
dfs_preorder() (in module networkx), 220
dfs_successor() (in module networkx), 220
dfs_tree() (in module networkx), 221
diameter() (in module networkx), 162
diamond_graph() (in module networkx.generators.small), 234
dictionary, 331
difference() (in module networkx), 204
DiGraph() (in module networkx), 37
dijkstra_path() (in module networkx), 211
dijkstra_path_length() (in module networkx), 212
dijkstra_predecessor_and_distance() (in module networkx), 217
directed_configuration_model() (in module networkx.generators.degree_seq), 248
directed_gnp_random_graph() (in module workx.generators.random_graphs), 237
discrete_sequence() (in module networkx.utils), 323
disjoint_union() (in module networkx), 203
dodecahedral_graph() (in module networkx.generators.small), 234
dorogovtsev_goltsev_mendes_graph() (in module netness), workx.generators.classic), 229
double_edge_swap() (in module networkx.generators.degree_seq), 251
draw() (in module networkx), 301
draw_circular() (in module networkx), 309
draw_graphviz() (in module networkx), 309
draw_networkx() (in module networkx), 303
draw_networkx_edge_labels() (in module networkx), 308
draw_networkx_edges() (in module networkx), 306
draw_networkx_labels() (in module networkx), 307
draw_networkx_nodes() (in module networkx), 305
draw_random() (in module networkx), 309
draw_shell() (in module networkx), 309
draw_spectral() (in module networkx), 309
draw_spring() (in module networkx), 309

\section*{E}
ebunch, 331
eccentricity() (in module networkx), 162
edge, 331
edge attribute, 331
edge_betweenness_centrality() (in module networkx.algorithms.centrality.betweenness), 140
edge_boundary() (in module networkx), 136
edge_current_flow_betweenness_centrality()
(in module networkx.algorithms.centrality.current_flow_betweenness), 142
edge_load() (in module networkx.algorithms.centrality.load), 145
edges() (DiGraph method), 50
edges() (Graph method), 22
edges() (MultiDiGraph method), 112
edges() (MultiGraph method), 83
edges_iter() (DiGraph method), 51
edges_iter() (Graph method), 23
edges_iter() (MultiDiGraph method), 113
edges_iter() (MultiGraph method), 84
ego_graph() (in module networkx.generators.ego), 262
eigenvector_centrality() (in module networkx), 143
eigenvector_centrality_numpy() (in module networkx), 144
empty_graph() (in module networkx.generators.classic), 229
erdos_renyi_graph() (in module networkx.generators.random_graphs), 239
net- eulerian_circuit() (in module networkx), 163
expected_degree_graph() (in module networkx.generators.degree_seq), 249

\section*{F}
fast_could_be_isomorphic() (in module networkx), 177
fast_gnp_random_graph() (in module networkx.generators.random_graphs), 236
faster_could_be_isomorphic() (in module networkx), 177
find_cliques() (in module networkx), 146
find_cores() (in module networkx), 158
flatten() (in module networkx.utils), 321
floyd_warshall() (in module networkx), 210
ford_fulkerson() (in module networkx), 166
ford_fulkerson_flow() (in module networkx), 167
freeze() (in module networkx), 224
from_agraph() (in module networkx), 310
from_dict_of_dicts() (in module networkx.convert), 272
from_dict_of_lists() (in module networkx.convert), 273
from_edgelist() (in module networkx.convert), 274
from_numpy_matrix() (in module networkx.convert), 275
from_pydot() (in module networkx), 313
from_scipy_sparse_matrix() (in module networkx.convert), 276
frucht_graph() (in module networkx.generators.small), 234

\section*{G}
generate_adjlist() (in module networkx), 282
generate_edgelist() (in module networkx), 287
generate_gml() (in module networkx), 291
get_edge_data() (DiGraph method), 54
get_edge_data() (Graph method), 24
get_edge_data() (MultiDiGraph method), 116
get_edge_data() (MultiGraph method), 85
gn_graph() (in module networkx.generators.directed), 254
gnc_graph() (in module networkx.generators.directed), 255
gnm_random_graph() (in module networkx.generators.random_graphs), 239
gnp_random_graph() (in module networkx.generators.random_graphs), 237
gnr_graph() (in module networkx.generators.directed), 255
google_matrix() (in module networkx), 191
Graph() (in module networkx), 9
graph_atlas_g() (in module networkx.generators.atlas), 227
graph_clique_number() (in module networkx), 147
graph_number_of_cliques() (in module networkx), 147
graphviz_layout() (in module networkx), 311, 314
grid_2d_graph() (in module networkx.generators.classic), 230
grid_graph() (in module networkx.generators.classic), 230

\section*{H}
has_edge() (DiGraph method), 59
has_edge() (Graph method), 29
has_edge() (MultiDiGraph method), 121
has_edge() (MultiGraph method), 90
has_node() (DiGraph method), 58
has_node() (Graph method), 28
has_node() (MultiDiGraph method), 120
has_node() (MultiGraph method), 89
hashable, 331
havel_hakimi_graph() (in module networkx.generators.degree_seq), 250
heawood_graph() (in module networkx.generators.small), 234
hits() (in module networkx), 191
hits_numpy() (in module networkx), 192
hits_scipy() (in module networkx), 193
house_graph() (in module networkx.generators.small), 234
house_x_graph() (in module networkx.generators.small), 234
hub_matrix() (in module networkx), 193
hypercube_graph() (in module networkx.generators.classic), 230

I
icosahedral_graph() (in module networkx.generators.small), 234
in_degree() (DiGraph method), 61
in_degree() (MultiDiGraph method), 124
in_degree_centrality() (in module networkx), 138
in_degree_iter() (DiGraph method), 62
in_degree_iter() (MultiDiGraph method), 124
in_edges() (DiGraph method), 53
in_edges() (MultiDiGraph method), 115
in_edges_iter() (DiGraph method), 54
in_edges_iter() (MultiDiGraph method), 115
net- info() (in module networkx), 223
initialize() (DiGraphMatcher method), 180
initialize() (GraphMatcher method), 178
initialize() (WeightedDiGraphMatcher method), 184
initialize() (WeightedGraphMatcher method), 182
initialize() (WeightedMultiDiGraphMatcher method), 187
initialize() (WeightedMultiGraphMatcher method), 185
intersection() (in module networkx), 203
is_attracting_component() (in module networkx.algorithms.components.attracting), 157
is_bipartite() (in module networkx), 133
is_connected() (in module networkx.algorithms.components.connected), 150
is_directed_acyclic_graph() (in module networkx), 161
is_eulerian() (in module networkx), 163
is_frozen() (in module networkx), 225
is_isolate() (in module networkx), 175
is_isomorphic() (DiGraphMatcher method), 180
is_isomorphic() (GraphMatcher method), 178
is_isomorphic() (in module networkx), 176
is_isomorphic() (WeightedDiGraphMatcher method), 184
is_isomorphic() (WeightedGraphMatcher method), 182
is_isomorphic() (WeightedMultiDiGraphMatcher method), 187
is_isomorphic() (WeightedMultiGraphMatcher method), 185
is_kl_connected() (in module networkx.generators.hybrid), 257
is_list_of_ints() (in module networkx.utils), 321
is_string_like() (in module networkx.utils), 321
is_strongly_connected() (in module networkx.algorithms.components.strongly_connect 153
is_valid_degree_sequence() (in module networkx.generators.degree_seq), 251
is_weakly_connected() (in module networkx.algorithms.components.weakly_connected 156
isolates() (in module networkx), 176
isomorphisms_iter() (DiGraphMatcher method), 180
isomorphisms_iter() (GraphMatcher method), 179
isomorphisms_iter() (WeightedDiGraphMatcher method), 184
isomorphisms_iter() (WeightedGraphMatcher method), 182
isomorphisms_iter() (WeightedMultiDiGraphMatcher method), 187
isomorphisms_iter() (WeightedMultiGraphMatcher method), 186
iterable() (in module networkx.utils), 321

\section*{K}
kl_connected_subgraph() (in module networkx.generators.hybrid), 257
kosaraju_strongly_connected_components() (in module networkx.algorithms.components.strongly_connect 155
krackhardt_kite_graph() (in module workx.generators.small), 234

L
ladder_graph() (in module networkx.generators.classic), 230
laplacian() (in module networkx.linalg.spectrum), 264
laplacian_spectrum() (in module networkx.linalg.spectrum), 264
LCF_graph() (in module networkx.generators.small), 233
li_smax_graph() (in module networkx.generators.degree_seq), 252
line_graph() (in module networkx.generators.line), 261
load_centrality() (in module networkx.algorithms.centrality.load), 145
lollipop_graph() (in module networkx.generators.classic), 231

\section*{M}
make_clique_bipartite() (in module networkx), 147
make_max_clique_graph() (in module networkx), 146
make_small_graph() (in module networkx.generators.small), 232
match() (DiGraphMatcher method), 181
match() (GraphMatcher method), 179
match() (WeightedDiGraphMatcher method), 184
match() (WeightedGraphMatcher method), 183
dhatch() (WeightedMultiDiGraphMatcher method), 188 match() (WeightedMultiGraphMatcher method), 186 max_flow() (in module networkx), 164 max_flow_min_cost() (in module networkx), 174 max_weight_matching() (in module networkx), 194 )nin_cost_flow() (in module networkx), 172
min_cost_flow_cost() (in module networkx), 171
min_cut() (in module networkx), 165
minimum_spanning_edges() (in module networkx), 200 minimum_spanning_tree() (in module networkx), 200
moebius_kantor_graph() (in module networkx.generators.small), 235
MultiDiGraph() (in module networkx), 98
MultiGraph() (in module networkx), 69

\section*{N}
nbunch, 331
nbunch_iter() (DiGraph method), 57
nbunch_iter() (Graph method), 27
nbunch_iter() (MultiDiGraph method), 119
nbunch_iter() (MultiGraph method), 88
neighbor_connectivity() (in module networkx), 197
neighbors() (DiGraph method), 55
neighbors() (Graph method), 24
neighbors() (MultiDiGraph method), 117
d)eighbors() (MultiGraph method), 85
neighbors_iter() (DiGraph method), 55
neighbors_iter() (Graph method), 25
neighbors_iter() (MultiDiGraph method), 117
neighbors_iter() (MultiGraph method), 86
network_simplex() (in module networkx), 168
networkx.algorithms.bipartite (module), 133
networkx.algorithms.block (module), 135
networkx.algorithms.boundary (module), 136
networkx.algorithms.centrality (module), 137
networkx.algorithms.centrality.betweenness (module), 139
networkx.algorithms.centrality.closeness (module), 138
networkx.algorithms.centrality.current_flow_betweenness (module), 141
networkx.algorithms.centrality.current_flow_closeness (module), 141
networkx.algorithms.centrality.degree_alg (module), 137
networkx.algorithms.centrality.eigenvector (module), 143
networkx.algorithms.centrality.load (module), 144
networkx.algorithms.clique (module), 145
networkx.algorithms.cluster (module), 148
networkx.algorithms.components (module), 150
networkx.algorithms.components.attracting (module), 157
networkx.algorithms.components.connected (module), 150
networkx.algorithms.components.strongly_connected (module), 153
networkx.algorithms.components.weakly_connected (module), 156
networkx.algorithms.core (module), 158
networkx.algorithms.cycles (module), 159
networkx.algorithms.dag (module), 159
networkx.algorithms.distance_measures (module), 161
networkx.algorithms.euler (module), 163
networkx.algorithms.flow (module), 164
networkx.algorithms.isolates (module), 175
networkx.algorithms.link_analysis.hits_alg 191
networkx.algorithms.link_analysis.pagerank_alg (module), 188
networkx.algorithms.matching (module), 194
networkx.algorithms.mixing (module), 195
networkx.algorithms.mst (module), 200
networkx.algorithms.operators (module), 201
networkx.algorithms.shortest_paths.astar (module), 219
networkx.algorithms.shortest_paths.generic (module), 205
networkx.algorithms.shortest_paths.unweighted (module), 207
networkx.algorithms.shortest_paths.weighted (module), 211
networkx.algorithms.traversal.depth_first_search (module), 220
networkx.algorithms.vitality (module), 221
networkx.classes.function (module), 223
networkx.convert (module), 269
networkx.drawing.layout (module), 315
networkx.drawing.nx_agraph (module), 309
networkx.drawing.nx_pydot (module), 312
networkx.drawing.nx_pylab (module), 301
networkx.exception (module), 319
networkx.generators.atlas (module), 227
networkx.generators.bipartite (module), 257
networkx.generators.classic (module), 227
networkx.generators.degree_seq (module), 246
networkx.generators.directed (module), 253
networkx.generators.ego (module), 262
networkx.generators.geometric (module), 257
networkx.generators.hybrid (module), 257
networkx.generators.line (module), 261
networkx.generators.random_graphs (module), 236
networkx.generators.small (module), 232
networkx.generators.stochastic (module), 262
networkx.linalg.attrmatrix (module), 265
networkx.linalg.spectrum (module), 263
networkx.readwrite.adjlist (module), 279
networkx.readwrite.edgelist (module), 283
networkx.readwrite.gml (module), 289
networkx.readwrite.gpickle (module), 291
networkx.readwrite.graphml (module), 293
networkx.readwrite.leda (module), 294
networkx.readwrite.nx_yaml (module), 295
networkx.readwrite.pajek (module), 298
networkx.readwrite.sparsegraph6 (module), 297
networkx.utils (module), 321
NetworkXAlgorithmError (class in networkx), 319
NetworkXError (class in networkx), 319
NetworkXException (class in networkx), 319
NetworkXNoPath (class in networkx), 319
NetworkXPointlessConcept (class in networkx), 319
(module), NetworkXUnbounded (class in networkx), 319
NetworkXUnfeasible (class in networkx), 319
newman_watts_strogatz_graph() (in module networkx.generators.random_graphs), 240
node, 331
node attribute, 331
node_boundary() (in module networkx), 137
node_clique_number() (in module networkx), 147
node_connected_component() (in module networkx.algorithms.components.connected), 152
nodes() (DiGraph method), 49
nodes() (Graph method), 21
nodes() (MultiDiGraph method), 110
nodes() (MultiGraph method), 81
nodes_iter() (DiGraph method), 50
nodes_iter() (Graph method), 21
nodes_iter() (MultiDiGraph method), 111
nodes_iter() (MultiGraph method), 82
nodes_with_selfloops() (DiGraph method), 65
nodes_with_selfloops() (Graph method), 33
nodes_with_selfloops() (MultiDiGraph method), 127
nodes_with_selfloops() (MultiGraph method), 94
normalized_laplacian() (in module networkx.linalg.spectrum), 264
null_graph() (in module networkx.generators.classic), 231
number_attracting_components() (in module networkx.algorithms.components.attracting), 157
number_connected_components() (in module networkx.algorithms.components.connected), 151
number_of_cliques() (in module networkx), 147
number_of_edges() (DiGraph method), 64
number_of_edges() (Graph method), 32
number_of_edges() (MultiDiGraph method), 126
number_of_edges() (MultiGraph method), 93
number_of_nodes() (DiGraph method), 60
number_of_nodes() (Graph method), 29
number_of_nodes() (MultiDiGraph method), 122
number_of_nodes() (MultiGraph method), 91
number_of_selfloops() (DiGraph method), 66
number_of_selfloops() (Graph method), 34
number_of_selfloops() (MultiDiGraph method), 128
number_of_selfloops() (MultiGraph method), 95
number_strongly_connected_components()
(in module networkx.algorithms.components.strongly_connecteф)ygraphviz_layout() (in module networkx), 312 153
number_weakly_connected_components()
(in module net- radius() (in module networkx), 163
workx.algorithms.components.weakly_connected) sandom_geometric_graph() (in module net156
numeric_assortativity() (in module networkx), 196

\section*{0}
octahedral_graph() (in module workx.generators.small), 235
order() (DiGraph method), 59
order() (Graph method), 29
order() (MultiDiGraph method), 121
order() (MultiGraph method), 90
out_degree() (DiGraph method), 63
out_degree() (MultiDiGraph method), 125
out_degree_centrality() (in module networkx), 138
out_degree_iter() (DiGraph method), 63
out_degree_iter() (MultiDiGraph method), 125
out_edges() (DiGraph method), 52
out_edges() (MultiDiGraph method), 114
out_edges_iter() (DiGraph method), 53
out_edges_iter() (MultiDiGraph method), 114

\section*{P}
pagerank() (in module networkx), 188
pagerank_numpy() (in module networkx), 189
pagerank_scipy() (in module networkx), 190
pappus_graph() (in module networkx.generators.small), 235
pareto_sequence() (in module networkx.utils), 322
parse_adjlist() (in module networkx), 281
parse_edgelist() (in module networkx), 288
parse_gml() (in module networkx), 291
parse_graph6() (in module networkx), 297
parse_leda() (in module networkx), 295
parse_pajek() (in module networkx), 299
parse_sparse6() (in module networkx), 298
path_graph() (in module networkx.generators.classic), 231
periphery() (in module networkx), 162
petersen_graph() (in module networkx.generators.small), 235
powerlaw_cluster_graph() (in module networkx.generators.random_graphs), 244
powerlaw_sequence() (in module networkx.utils), 322
predecessor() (in module networkx), 210
predecessors() (DiGraph method), 56
predecessors() (MultiDiGraph method), 118
predecessors_iter() (DiGraph method), 56
predecessors_iter() (MultiDiGraph method), 118
project() (in module networkx), 134
pydot_layout() (in module networkx), 314

\section*{R} workx.generators.geometric), 257
random_layout() (in module networkx), 315
random_lobster() (in module networkx.generators.random_graphs), 244
net- random_powerlaw_tree() (in module networkx.generators.random_graphs), 245
random_powerlaw_tree_sequence() (in module networkx.generators.random_graphs), 246
random_regular_graph() (in module networkx.generators.random_graphs), 242
random_shell_graph() (in module networkx.generators.random_graphs), 245
read_adjlist() (in module networkx), 279
read_dot() (in module networkx), 311, 314
read_edgelist() (in module networkx), 283
read_gml() (in module networkx), 290
read_gpickle() (in module networkx), 292
read_graph6() (in module networkx), 297
read_graph6_list() (in module networkx), 297
read_graphml() (in module networkx), 293
read_leda() (in module networkx), 295
read_pajek() (in module networkx), 298
read_sparse6() (in module networkx), 297
read_sparse6_list() (in module networkx), 298
read_weighted_edgelist() (in module networkx), 285
read_yaml() (in module networkx), 296
relabel_nodes() (in module networkx.convert), 271
remove_edge() (DiGraph method), 45
remove_edge() (Graph method), 18
remove_edge() (MultiDiGraph method), 107
remove_edge() (MultiGraph method), 78
remove_edges_from() (DiGraph method), 46
remove_edges_from() (Graph method), 18
remove_edges_from() (MultiDiGraph method), 107
remove_edges_from() (MultiGraph method), 79
remove_node() (DiGraph method), 42
remove_node() (Graph method), 14
remove_node() (MultiDiGraph method), 103
remove_node() (MultiGraph method), 74
remove_nodes_from() (DiGraph method), 43
remove_nodes_from() (Graph method), 15
remove_nodes_from() (MultiDiGraph method), 104
remove_nodes_from() (MultiGraph method), 75
reverse() (DiGraph method), 69
reverse() (MultiDiGraph method), 131

\section*{S}
scale_free_graph() (in module networkx.generators.directed), 256
scipy_discrete_sequence() (in module networkx.utils), 324
scipy_pareto_sequence() (in module networkx.utils), 323
scipy_poisson_sequence() (in module networkx.utils), 323
scipy_powerlaw_sequence() (in module networkx.utils), 323
scipy_uniform_sequence() (in module networkx.utils), 323
sedgewick_maze_graph() (in module networkx.generators.small), 235
selfloop_edges() (DiGraph method), 65
selfloop_edges() (Graph method), 33
selfloop_edges() (MultiDiGraph method), 127
selfloop_edges() (MultiGraph method), 94
semantic_feasibility() (DiGraphMatcher method), 181
semantic_feasibility() (GraphMatcher method), 179
semantic_feasibility() (WeightedDiGraphMatcher method), 184
semantic_feasibility() (WeightedGraphMatcher method), 183
semantic_feasibility() (WeightedMultiDiGraphMatcher method), 188
semantic_feasibility() (WeightedMultiGraphMatcher method), 186
shell_layout() (in module networkx), 316
shortest_path() (in module networkx), 205
shortest_path_length() (in module networkx), 206
single_source_dijkstra() (in module networkx), 215
single_source_dijkstra_path() (in module networkx), 213
single_source_dijkstra_path_length() (in module networkx), 213
single_source_shortest_path() (in module networkx), 208
single_source_shortest_path_length() (in module networkx), 208
size() (DiGraph method), 64
size() (Graph method), 31
size() (MultiDiGraph method), 126
size() (MultiGraph method), 92
spectral_layout() (in module networkx), 317
spring_layout() (in module networkx), 317
star_graph() (in module networkx.generators.classic), 231
stochastic_graph() (in module networkx.generators.stochastic), 262
strongly_connected_component_subgraphs() (in module networkx.algorithms.components.strongly_connected), 154
strongly_connected_components() (in module networkx.algorithms.components.strongly_connected), 154
strongly_connected_components_recursive() (in module networkx.algorithms.components.strongly_connected), 155
subgraph() (DiGraph method), 68
subgraph() (Graph method), 36
subgraph() (MultiDiGraph method), 130
subgraph() (MultiGraph method), 97
subgraph_is_isomorphic() (DiGraphMatcher method), 180
subgraph_is_isomorphic() (GraphMatcher method), 178
subgraph_is_isomorphic() (WeightedDiGraphMatcher method), 184
subgraph_is_isomorphic() (WeightedGraphMatcher method), 182
subgraph_is_isomorphic() (WeightedMultiDiGraphMatcher method), 187
subgraph_is_isomorphic() (WeightedMultiGraphMatcher method), 186
subgraph_isomorphisms_iter() (DiGraphMatcher method), 181
subgraph_isomorphisms_iter() (GraphMatcher method), 179
subgraph_isomorphisms_iter() (WeightedDiGraphMatcher method), 184
subgraph_isomorphisms_iter() (WeightedGraphMatcher method), 183
subgraph_isomorphisms_iter() (WeightedMultiDiGraphMatcher method), 188
subgraph_isomorphisms_iter() (WeightedMultiGraphMatcher method), 186
successors() (DiGraph method), 56
successors() (MultiDiGraph method), 117
successors_iter() (DiGraph method), 56
successors_iter() (MultiDiGraph method), 118
symmetric_difference() (in module networkx), 204
syntactic_feasibility() (DiGraphMatcher method), 181
syntactic_feasibility() (GraphMatcher method), 179
syntactic_feasibility() (WeightedDiGraphMatcher method), 185
syntactic_feasibility() (WeightedGraphMatcher method), 183
syntactic_feasibility() (WeightedMultiDiGraphMatcher method), 188
syntactic_feasibility() (WeightedMultiGraphMatcher method), 186

\section*{T}
tetrahedral_graph() (in module
workx.generators.small), 235
to_agraph() (in module networkx), 310
to_dict_of_dicts() (in module networkx.convert), 272
to_dict_of_lists() (in module networkx.convert), 273
to_directed() (DiGraph method), 68
to_directed() (Graph method), 35
to_directed() (MultiDiGraph method), 130
to_directed() (MultiGraph method), 96
to_edgelist() (in module networkx.convert), 273
to_networkx_graph() (in module networkx.convert), 269
to_numpy_matrix() (in module networkx.convert), 274
to_pydot() (in module networkx), 313
to_scipy_sparse_matrix() (in module networkx.convert), 275
to_undirected() (DiGraph method), 67
to_undirected() (Graph method), 35
to_undirected() (MultiDiGraph method), 129
to_undirected() (MultiGraph method), 96
topological_sort() (in module networkx), 160
topological_sort_recursive() (in module networkx), 160
transitivity() (in module networkx), 148
triangles() (in module networkx), 148
trivial_graph() (in module networkx.generators.classic), 231
truncated_cube_graph() (in module networkx.generators.small), 235
truncated_tetrahedron_graph() (in module net-
workx.generators.small), 235
tutte_graph() (in module networkx.generators.small), 235

\section*{U}
uniform_sequence() (in module networkx.utils), 322
union() (in module networkx), 203
union() (UnionFind method), 322

\section*{W}
\begin{tabular}{ccc} 
watts_strogatz_graph () & (in \(\quad\) module & net- \\
workx.generators.random_graphs), 241 & \\
weakly_connected_component_subgraphs() & \\
(in & module & net-
\end{tabular}
workx.algorithms.components.weakly_connected), 157
weakly_connected_components() (in module networkx.algorithms.components.weakly_connected), 157
wheel_graph() (in module networkx.generators.classic), 231
write_adjlist() (in module networkx), 281
write_dot() (in module networkx), 311, 313
write_edgelist() (in module networkx), 284
write_gml() (in module networkx), 290
write_gpickle() (in module networkx), 292
write_graphml() (in module networkx), 294
write_pajek() (in module networkx), 299
write_weighted_edgelist() (in module networkx), 286
write_yaml() (in module networkx), 296```


[^0]:    1 "It's dictionaries all the way down."

