

### Basic graph manipulation

```
import networkx as nx
```

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

```
G=nx.MultiGraph()
```

Create a graph allowing parallel edges

```
G.add_edges_from([(0, 1), (0, 2), (1, 3), (2, 4)])
```

Create graph from edges

```
nx.draw_networkx(G)
```

Draw the graph

```
G.add_node('A', role='manager')
```

Add a node

```
G.add_edge('A', 'B', relation = 'friend')
```

Add an edge

```
G.node['A']['role'] = 'team member'
```

Set attribute of a node

```
G.node['A'], G.edge[('A', 'B')]
```

View attributes of node, edge

```
G.edges(), G.nodes()
```

Show edges, nodes

```
list(G.edges())
```

Return as list instead of EdgeView class

```
G.nodes(data=True), G.edges(data=True)
```

Include node/edge attributes

```
G.nodes(data='relation')
```

Return specific attribute

### Creating graphs from data

```
G=nx.read_adjlist('G_adjlist.txt', nodetype=int)
```

Create from adjacency list

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

Create from matrix (np.array)

```
G=nx.read_edgelist('G_edgelist.txt', data=[('Weight', int)])
```

Create from edgelist

```
G=nx.from_pandas_dataframe(G_df, 'n1', 'n2', edge_attr='weight')
```

Create from df

#### Adjacency list format

```
0 1 2 3 5
1 3 6 ...
```

#### Edgelist format:

```
0 1 14
0 2 17
```

### Bipartite graphs

```
from networkx.algorithms import bipartite
```

```
bipartite.is_bipartite(B)
```

Check if graph B is bipartite

```
bipartite.is_bipartite_node_set(B, set)
```

Check if set of nodes is bipartition of graph

```
bipartite.sets(B)
```

Get each set of nodes of bipartite graph

```
bipartite.projected_graph(B, X)
```

Bipartite projected graph - nodes with bipartite friends in common

```
P=bipartite.weighted_projected_graph(B, X)
```

projected graph with weights (number of friends in common)

### Network Connectivity

```
nx.clustering(G, node)
```

Local clustering coefficient

```
nx.average_clustering(G)
```

Global clustering coefficient

```
nx.transitivity(G)
```

Transitivity (% of open triads)

```
nx.shortest_path(G, n1, n2)
```

Outputs the path itself

```
nx.shortest_path_length(G, n1, n2)
```

```
T=nx.bfs_tree(G, n1)
```

Create breadth-first search tree from node n1

```
nx.average_shortest_path_length(G)
```

Average distance between all pairs of nodes

```
nx.diameter(G)
```

Maximum distance between any pair of nodes

```
nx.eccentricity(G)
```

Returns each node's distance to furthest node

```
nx.radius(G)
```

Minimum eccentricity in the graph

```
nx.periphery(G)
```

Set of nodes where eccentricity=diameter

```
nx.center(G)
```

Set of nodes where eccentricity=radius



### Connectivity: Network Robustness

<code>nx.node_connectivity(G)</code>	Min nodes removed to disconnect a network
<code>nx.minimum_node_cut()</code>	Which nodes?
<code>nx.edge_connectivity(G)</code>	Min edges removed to disconnect a network
<code>nx.minimum_edge_cut(G)</code>	Which edges?
<code>nx.all_simple_paths(G, n1, n2)</code>	Show all paths between two nodes

### Network Connectivity: Connected Components

<code>nx.is_connected(G)</code>	Is there a path between every pair of nodes?
<code>nx.number_connected_components(G)</code>	# separate components
<code>nx.node_connected_component(G, N)</code>	Which connected component does N belong to?
<code>nx.is_strongly_connected(G)</code>	Is the network connected directionally?
<code>nx.is_weakly_connected(G)</code>	Is the directed network connected if assumed undirected?

### Common Graphs

<code>G=nx.karate_club_graph()</code>	Karate club graph (social network)
<code>G=nx.path_graph(n)</code>	Path graph with n nodes
<code>G=nx.complete_graph(n)</code>	Complete graph on n nodes
<code>G=random_regular_graph(d, n)</code>	Random d-regular graph on n-nodes

See NetworkX Graph Generators reference for more.  
Also see "An Atlas of Graphs" by Read and Wilson (1998).

### Influence Measures and Network Centralization

<code>dc=nx.degree_centrality(G)</code>	Degree centrality for network
<code>dc[node]</code>	Degree centrality for a node
<code>nx.in_degree_centrality(G), nx.out_degree_centrality(G)</code>	DC for directed networks
<code>cc=nx.closeness_centrality(G, normalized=True)</code>	Closeness centrality (normalised) for the network
<code>cc[node]</code>	Closeness centrality for an individual node
<code>bC=nx.betweenness_centrality(G, ..., normalized=True, ...)</code>	Betweenness centrality
<code>..., endpoints=False, ...)</code>	BC excluding endpoints
<code>..., K=10, ...)</code>	BC approximated using random sample of K nodes
<code>nx.betweenness_centrality_subset(G, {subset})</code>	BC calculated on subset
<code>nx.edge_betweenness_centrality(G)</code>	BC on edges
<code>nx.edge_betweenness_centrality_subset(G, {subset})</code>	BC on subset of edges

Normalization: Divide by number of pairs of nodes.

### PageRank and Hubs & Authorities Algorithms

<code>nx.pagerank(G, alpha=0.8)</code>	Scaled PageRank of G with dampening parameter
<code>h,a=nx.hits(G)</code>	HITS algorithm - outputs 2 dictionaries (hubs, authorities)
<code>h,a=nx.hits(G, max_iter=10, normalized=True)</code>	Constrained HITS and normalized by sum at each stage

Centrality measures make different assumptions about what it means to be a "central" node. Thus, they produce different rankings.



### Network Evolution - Real-world Applications

<code>G.degree()</code> , <code>G.in_degree()</code> , <code>G.out_degree()</code>	Distribution of node degrees
<b>Preferential Attachment Model</b>	Results in power law -> many nodes with low degrees; few with high degrees
<code>G=barabasi_albert_graph(n,m)</code>	Preferential Attachment Model with $n$ nodes and each new node attaching to $m$ existing nodes
<b>Small World model</b>	High average degree (global clustering) and low average shortest path
<code>G=watts_strogatz_graph(n,k,p)</code>	Small World network of $n$ nodes, connected to its $k$ nearest neighbours, with chance $p$ of rewiring
<code>G=connected_watts_strogatz_graph(n,k,p,t)</code>	$t$ = max iterations to try to ensure connected graph
<code>G=newman_watts_strogatz_graph(n,k,p)</code>	$p$ = probability of adding (not rewiring)
<b>Link Prediction measures</b>	How likely are 2 nodes to connect, given an existing network
<code>nx.common_neighbors(G,n1,n2)</code>	Calc common neighbors of nodes $n1, n2$
<code>nx.jaccard_coefficient(G)</code>	Normalised common neighbors measure
<code>nx.resource_allocation_index(G)</code>	Calc RAI of all nodes not already connected by an edge
<code>nx.adamic_adar_index(G)</code>	As per RAI but with log of degree of common neighbor
<code>nx.preferential_attachment(G)</code>	Product of two nodes' degrees

### Network Evolution - Real-world Applications (cont)

<b>Community Common Neighbors</b>	Common neighbors but with bonus if they belong in same 'community'
<code>nx.cn_soundarajan_hopcroft(n1, n2)</code>	CCN score for $n1, n2$
<code>G.node['A']['community']=1</code>	Add community attribute to node
<code>nx.ra_index_soundarajan_hopcroft(G)</code>	Community Resource Allocation score
<p>These scores give only an indication of whether 2 nodes are likely to connect.</p> <p>To make a link prediction, you would use these scores as features in a classification ML model.</p>	

