**Network generation and analysis** Prerequisites: • Basic data types in Python: integer, float, string, boolean Basic math operations: + - / . Exponentiation , integer division // · Lists: creating, adding, removing, testing membership, testing index, indexing and slicing, iterating, enumerate • Tuples (immutable lists): creating, indexing, iterating, enumerating • Sets (unordered container that only allows unique elements): creation, testing membership, adding, deleting, logical operations • Dictionaries (map a key to a value): creating, adding, number of keys, testing membership, removing, iterating over keys / values / items • numpy arrays (ndarray can represent vectors, matrices, etc.): vectors and vector operations, matrices and matrix operations Import modules In [2]: import numpy as np import networkx as nx import matplotlib.pyplot as plt import matplotlib as mplb import collections In [3]: # see NetworkX documentation: https://networkx.org/ # dir(nx)In [4]: nx.\_\_version\_ Out[4]: '2.4' Basic data types in NetworkX Classes provided to represent network-related data: Graph - Undirected graph with self loops DiGraph - Directed graph with self loops MultiGraph - Undirected Graph with self loops and multiple edges MultiDiGraph - Directed Graph with self loops and multiple edges **Getting started** In [18]: G = nx.Graph() #create an empty undirected graph **Nodes** In [19]: G.add node(0) # int G.add\_node("John") # string pos = (1.2, 3.4) # tupleG.add node (pos) G.add\_nodes\_from([1,2,3]) # add several nodes from a list In [20]: G.nodes() Out[20]: NodeView((0, 'John', (1.2, 3.4), 1, 2, 3)) **Node attributes** A node can have attributes: given as string-index dictionary. In [21]: G.add\_node("Carla", eye\_color="blue", height=170) # add new node with attributes using keyword argument G.add\_node("Camelia") In [22]: G.nodes["Camelia"]["publications"] = 100 # add an attribute to an existing node In [23]: print(G.nodes) [0, 'John', (1.2, 3.4), 1, 2, 3, 'Carla', 'Camelia'] print(G.nodes(data=True)) In [24]: [(0, {}), ('John', {}), ((1.2, 3.4), {}), (1, {}), (2, {}), (3, {}), ('Carla', {'eye\_color': 'blue', 'height': 170}), ('Camelia', {'publications': 100})] G.nodes['Carla'] In [25]: Out[25]: {'eye\_color': 'blue', 'height': 170} In [27]: G.nodes[1] Out[27]: {} In [28]: print("Carla has ", G.nodes["Carla"]["eye\_color"], " eyes. Height = ", G.nodes["Carla"]["height"]) Carla has blue eyes. Height = 170 In [30]: # KeyError: G.nodes[1]["height"] **Edges** An edge between node1 and node2 is represented as a tuple (node1, node2) In [32]: # add edge between nodes 0 and 1  $G.add\_edge(0, 1)$ # add multiple edges edge\_list = [ (1, 2), ("Carla", "Camelia"), (3, 4)] G.add\_edges\_from(edge\_list) Note: Nodes will be automatically created if they do not already exist. **Edge attributes** Edges can also have arbitrary attributes. An important and special attribute if "weight". G.edges[node1, node2] is a dictionary with all attribute:value pairs associated with the edge from node1 and node2 In [33]: G.add edge("Carla", "Timi", weight=10) G.add edge("Cluj", "Budapest") G.edges["Cluj", "Budapest"]['distance'] = 400 **Basic operations** In [34]: print(G.number of nodes()) # number of nodes print(len(G)) # same as above print(G.number\_of\_edges()) # number of edges print(G.size()) # same as above print("G has {0} nodes and {1} edges.".format(len(G), G.size())) # how to do string formatting 12 6 G has 12 nodes and 6 edges. Test if a node exists In [35]: G.has\_node("Carla") Out[35]: True "Camelia" in G In [38]: Out[38]: True In [37]: 1 in G.nodes Out[37]: True Test if an edge exists In [39]: G.has edge(3,4) # must use has edge Out[39]: True In [40]: G.has\_edge("Carla", 1) Out[40]: False Finding neighbors of a node In [41]: G.neighbors(1) Out[41]: <dict\_keyiterator at 0x183efc88ae0> In [42]: list(G.neighbors(1)) Out[42]: [0, 2] Note: • In DiGraph objects, G.neighbors (node) gives the successors of node, as does G.successors (node) • Predecessors of node can be obtained with G.predecessors (node) Iterating over nodes and edges This can be done with G.nodes() and G.edges() In [43]: G.nodes() Out[43]: NodeView((0, 'John', (1.2, 3.4), 1, 2, 3, 'Carla', 'Camelia', 4, 'Timi', 'Cluj', 'Budapest')) In [54]: for node in G.nodes(): print(node) John (1.2, 3.4)1 2 3 Carla Camelia Timi Cluj Budapest In [53]: for node in G.nodes(): print(node, " --- ", type(node)) 0 --- <class 'int'> John --- <class 'str'> (1.2, 3.4) --- <class 'tuple'> 1 --- <class 'int'> 2 --- <class 'int'> 3 --- <class 'int'> Carla --- <class 'str'> Camelia --- <class 'str'> 4 --- <class 'int'> Timi --- <class 'str'> Cluj --- <class 'str'> Budapest --- <class 'str'> In [50]: for node, data in G.nodes(data=True): # date=True includes node attributes as dictionaries print("Node: ", node, " --- ", data) Node: 0 --- {} Node: John --- {} Node: (1.2, 3.4) --- {} Node: 1 --- {} Node: 2 --- {} Node: 3 --- {} Node: Carla --- {'eye\_color': 'blue', 'height': 170} Node: Camelia --- { 'publications': 100} Node: 4 --- {} Node: Timi --- {} Node: Cluj --- {} Node: Budapest --- {} In [51]: for n1, n2, data in G.edges(data=True): print("{0} <---> {1}: {2}".format(n1, n2, data)) 0 <---> 1: {} 1 <---> 2: {} 3 <---> 4: {} Carla <---> Camelia: {} Carla <---> Timi: {'weight': 10} Cluj <---> Budapest: {'distance': 400} In [55]: for n1, n2 in G.edges(): print(n1, n2) 0 1 1 2 Carla Camelia Carla Timi Cluj Budapest Calculating degrees In [57]: G.degree() # returns a view of a dictionary with node: degree pairs for all nodes Out[57]: DegreeView({0: 1, 'John': 0, (1.2, 3.4): 0, 1: 2, 2: 1, 3: 1, 'Carla': 2, 'Camelia': 1, 4: 1, 'Timi': 1, 'Cluj': 1, 'Budapest': 1}) In [59]: print(G.degree()) [(0, 1), ('John', 0), ((1.2, 3.4), 0), (1, 2), (2, 1), (3, 1), ('Carla', 2), ('Camelia', 1), (4, 1), ('Timi', 1), ('Cluj', 1), ('Budapest', 1)] In [56]: G.degree("Carla") Out[56]: 2 In [58]: print([G.degree(node) for node in G]) [1, 0, 0, 2, 1, 1, 2, 1, 1, 1, 1, 1] Note: In directed graphs (of class <code>DiGraph</code> ) there are two types of degree. Things work just as you expect • G.in degree(node) • G.out\_degree(node) # same as G.degree() Adjacency matrix In [60]: nx.to numpy array(G, weight=None) Out[60]: array([[0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.], [1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0.][0., 0., 0., 0., 0., 0., 0., 1., 0., 1., 0., 0.],[0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0.][0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0.][0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0.][0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0.]]) Reading network data from files Node and edge data can be read from an appropriate data file. In NetworkX, several commmon graph formats can be used: edge lists · adjacency lists GML GEXF Python 'pickle' GraphML Pajek LEDA YAML File with edge list (test.txt): lines starting with # are treated as comments and ignored • use a Graph object to hold the data (i.e., network is undirected) data are separated by whitespace (' ') nodes should be treated as integers ( int ) encoding of the text file containing the edge list is utf-8 **Allowed formats**  Node pairs with no data 1 2 Node pairs with python dictionary 1 2 {weight:7, color:"green"} In [3]: G = nx.read\_edgelist("test.txt", comments="#", create\_using=nx.Graph(), delimiter=' ', nodetype=int, en coding='utf-8') **Basic analysis** In [4]: N = len(G)L = G.size()degrees = [G.degree(node) for node in G] kmin = min(degrees) kmax = max(degrees)In [32]: print("Number of nodes: ", N) print("Number of edges: ", L) print() print("Average degree: ", 2\*L/N) #print("Average degree (alternate calculation)", np.mean(degrees)) print() print("Minimum degree: ", kmin) print("Maximum degree: ", kmax) print("All degrees: ", degrees) Number of nodes: 443 Number of edges: 540 Average degree: 2.4379232505643342 Minimum degree: 1 Maximum degree: All degrees: [5, 2, 5, 5, 4, 3, 2, 2, 1, 2, 2, 3, 5, 2, 2, 2, 3, 3, 1, 3, 5, 8, 3, 6, 7, 6, 3, 1, 3, 3, 1, 1, 2, 4, 3, 2, 4, 5, 1, 3, 2, 7, 6, 3, 1, 2, 5, 3, 3, 1, 1, 5, 3, 5, 4, 1, 2, 2, 3, 1, 1, 2, 4, 1, 2, 5, 1, 4, 2, 3, 3, 3, 1, 4, 1, 1, 3, 3, 4, 3, 1, 1, 2, 2, 1, 4, 1, 5, 2, 6, 3, 2, 6, 3, 1, 1, 5, 4, 4, 4, 2, 3, 3, 2, 3, 3, 2, 3, 3, 2, 3, 2, 3, 3, 1, 3, 2, 3, 3, 3, 3, 3, 1, 2, 1, 1, 4, 1, 1, 2, 5, 2, 3, 5, 3, 1, 3, 6, 2, 2, 1, 1, 1, 2, 2, 2, 3, 3, 3, 4, 3, 2, 2, 4, 3, 2, 2, 3, 3, 3, 1, 3, 5, 2, 2, 2, 2, 3, 2, 1, 4, 1, 4, 2, 2, 3, 2, 5, 2, 2, 1, 3, 2, 3, 2, 3, 3, 2, 3, 1, 2, 7, 3, 2, 4, 2, 1, 4, 5, 3, 4, 3, 1, 1, 1, 4, 2, 2, 3, 3, 3, 4, 2, 4, 5, 1, 3, 4, 3, 4, 1, 1, 4, 1, 1, 2, 1, 3, 2, 3, 4, 3, 1, 1, 3, 1, 2, 3, 2, 3, 3, 4, 2, 3, 5, 2, 1, 2, 4, 4, 2, 4, 2, 5, 2, 4, 2, 2, 2, 4, 3, 2, 1, 2, 1, 2, 2, 2, 2, 2, 2, 1, 3, 2, 1, 2, 2, 1, 5, 1, 2, 1, 5, 6, 2, 4, 2, 1, 2, 2, 2, 2, 2, 4, 2, 4, 1, 2, 1, 3, 1, 3, 4, 6, 2, 2, 1, 2, 2, 3, 2, 1, 3, 1, 2, 1, 1, 1, 2, 1, 3, 2, 2, 3, 2, 2, 1, 2, 3, 2, 1, 1, 2, 2, 1, 3, 2, 2, 1, 2, 3, 1, 1, 2, 2, 2, 2, 2, 2, 3, 4, 2, 4, 2, 2, 3, 2, 4, 3, 2, 2, 2, 1, 2, 3, 3, 1, 2, 2, 2, 2, 1, 3, 1, 1, 2, 2, 4, 2, 1, 3, 1, 5, 2, 2, 2, 3, 1, 1, 1, 1, 2, 2, 2, 3, 4, 2, 1, 2, 4, 2, 1, 1, 2, 1, 2, 1, 1, 2, 2, 3, 1, 1, 2, 1, 1, 1, 2, 3, 1, 2, 2, 1, 1, 1, 1, 3, 2, 1, 2, 2, 1, 1, 3, 1, 1, 3, 2, 1, 1, 1] **Drawing the network** In [75]: # using the force-based or "spring" layout algorithm fig = plt.figure(figsize=(10,10)) nx.draw\_spring(G, node\_size=40) In [76]: # using the fcircular layout algorithm fig = plt.figure(figsize=(8,8)) nx.draw circular(G, node size=40) Degree histogram In [19]: degree sequence = sorted([d for n, d in G.degree()], reverse=True) # degree sequence #print(degree sequence) degreeCount = collections.Counter(degree sequence) #print(degreeCount) #print(degreeCount.items()) deg, cnt = zip(\*degreeCount.items()) plt.bar(deg, cnt, width=0.80, color="b") plt.title("Degree Histogram") plt.ylabel("Count") plt.xlabel("Degree") plt.show() Degree Histogram 160 140 120 100 80 60 20 1 2 3 6 Degree In [94]: plt.plot(deg,cnt,'bo-') plt.show() 160 140 120 100 80 60 40 20 In [96]: plt.loglog(deg,cnt,'bo') plt.show() 10<sup>1</sup> 10° 10°  $2 \times 10^{0}$ 3×10° 4×10° 6×10° Plotting the degree distribution Log-log scale: In [68]: # numpy can be used to get logarithmically-spaced bins between the minimum and maximum degree # Get 10 logarithmically spaced bins between kmin and kmax bin edges = np.logspace(np.log10(kmin), np.log10(kmax), num=10) # histogram the data into these bins density, = np.histogram(degrees, bins=bin edges, density=True) fig = plt.figure(figsize=(6,4)) # "x" should be midpoint (IN LOG SPACE) of each bin log be = np.log10(bin edges) print(log be) x = 10\*\*((log be[1:] + log be[:-1])/2)plt.loglog(x, density, marker='o', linestyle='none') plt.xlabel(r"degree \$k\$", fontsize=16) plt.ylabel(r"\$P(k)\$", fontsize=16) # remove right and top boundaries because they're ugly ax = plt.gca()ax.spines['right'].set visible(False) ax.spines['top'].set\_visible(False) ax.yaxis.set\_ticks\_position('left') ax.xaxis.set ticks position('bottom') # Show the plot plt.show() 0.10034333 0.20068666 0.30103 0.40137333 0.50171666 0.60205999 0.70240332 0.80274666 0.90308999] [1.12246205 1.41421356 1.78179744 2.2449241 2.82842712 3.56359487 4.48984819 5.65685425 7.12718975] 10° £ 10⁻¹  $10^{-2}$ 3 × 10° 4 × 10°  $2 \times 10^{0}$ 6 × 10<sup>6</sup> degree k In [78]: #using the bin edges generated by np.histogram fig = plt.figure(figsize=(6, 4)) y, bin edges = np.histogram(degrees, density=True, bins=10)  $x = [(bin\_edges[i] + bin\_edges[i+1])/2$  **for** i **in** range(len(bin edges)-1)]plt.loglog(x, y, marker="o", markersize=10, color="r", linestyle='none') plt.xlabel(r"degree \$k\$", fontsize=16) plt.ylabel(r"\$P(k)\$", fontsize=16) plt.show()  $10^{-1}$  $10^{-2}$  $2 \times 10^{0}$ 3 × 10° 4 × 10° degree k linear-linear scale: In [55]: # Get 20 logarithmically spaced bins between kmin and kmax bin edges = np.linspace(kmin, kmax, num=10) # histogram the data into these bins density, \_ = np.histogram(degrees, bins=bin edges, density=True) In [56]: fig = plt.figure(figsize=(6,4)) # "x" should be midpoint (IN LOG SPACE) of each bin log\_be = np.log10(bin\_edges)  $x = 10**((log_be[1:] + log_be[:-1])/2)$ plt.plot(x, density, marker='o', linestyle='none') plt.xlabel(r"degree \$k\$", fontsize=16) plt.ylabel(r"\$P(k)\$", fontsize=16) # remove right and top boundaries because they're ugly ax = plt.gca()ax.spines['right'].set\_visible(False) ax.spines['top'].set visible(False) ax.yaxis.set ticks position('left') ax.xaxis.set\_ticks\_position('bottom') # Show the plot plt.show() 0.4 0.3 0.1 0.0 degree *k*