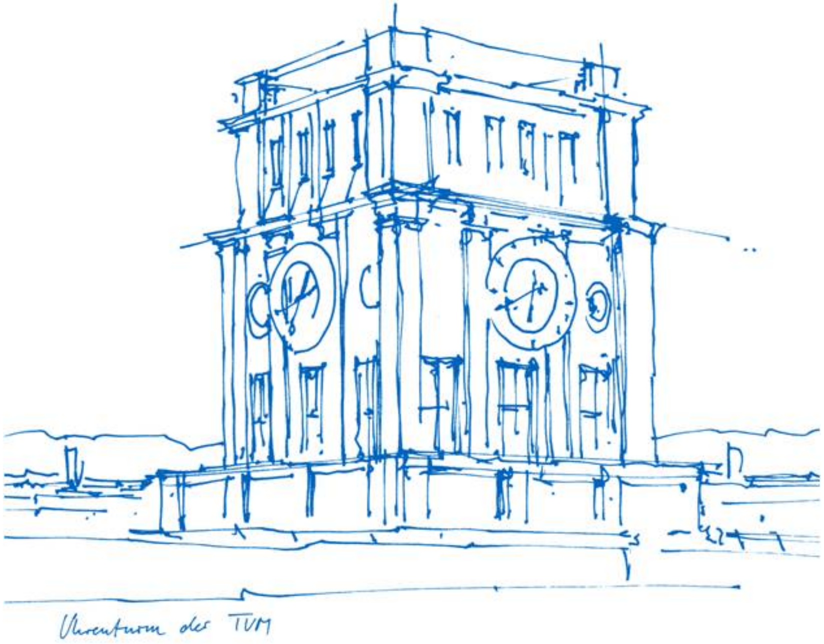
Exercises for Social Gaming and Social Computing (IN2241 + IN0040) – Introduction to

Exercise Sheet 2

Centrality



Exercise Content

Sheet Number	Exercise	Working Time
1	• Introduction to Python and Network Visualization	May 29 - June 11 (sic!)
2	• Centrality Measures	June 5 – June 11 (sic!)
3	• Finding Groups & Clustering Methods	June 12 – 18
4	• Predicting Social Tie Strength with Linear Regression	June 19 - 25
5	• Natural Language Processing: Hate Speech detection + Social Context Influence	June 26 – July 2
6	• Natural Language Processing: Modern Machine Learning Methods and Explainable AI	July 3 – July 9

Exercise Sheet 2: Centrality Measures

- Goals:
  - Being able to compare different centrality measures
  - Being able to judge pros and cons of different c.m.

- Data: UniversityNetwork.graphml
  - represents the faculty of a university
  - consists of individuals (vertices) and their directed and weighted connections (edges)
  - the edges' weights are a measure of the degree of friendship between the persons

Repetition from Lecture: Centrality Indices

- Degree Centrality
  - the more friends a node has, the more central it is

$$C_{deg}(u) = \deg(u)$$

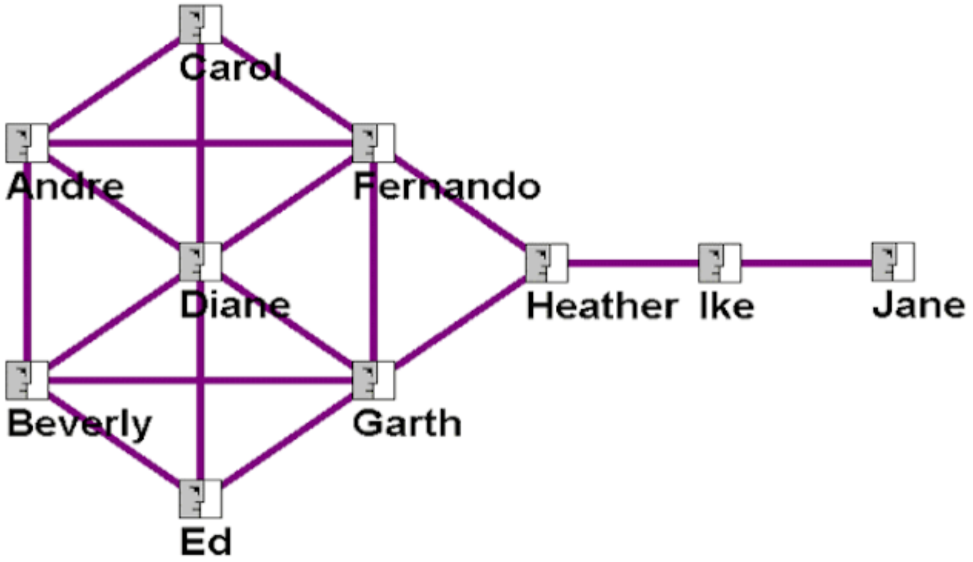
- Closeness Centrality
  - the inverse average length of the shortest path between the node and all other nodes

$$C_{clo}(u) = \frac{1}{\sum_{v \in V} d(u,v)} \text{ or } \frac{|V|-1}{\sum_{v \in V} d(u,v)}$$

- (Shortest Path) Betweenness Centrality
  - probability of a node acting as a bridge along the shortest path between two other nodes

$$C_{btw}(u) = \sum_{s \neq u, t \neq u} \frac{\sigma_{st}(u)}{\sigma_{st}}$$

Degree Centrality

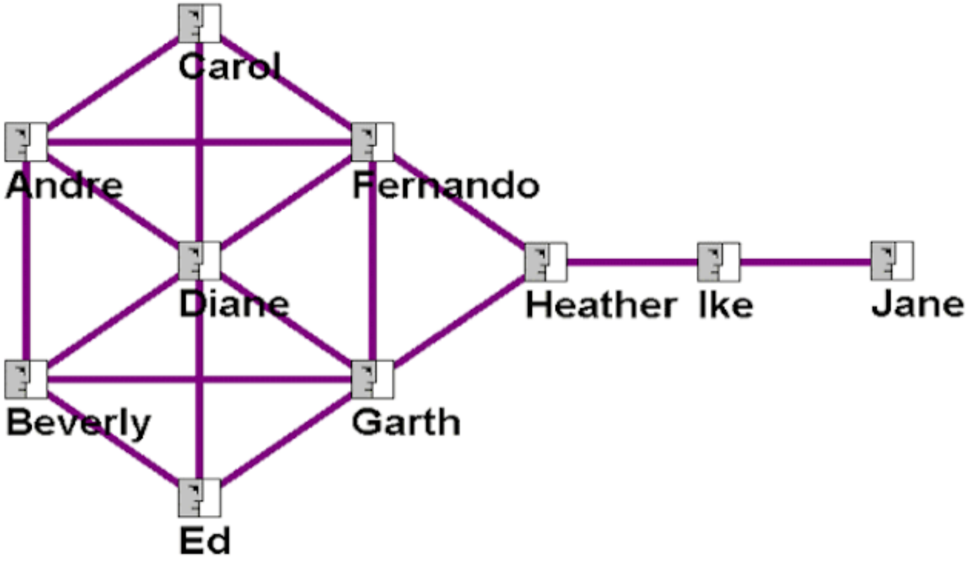


Name	Degree
Andre	4
Beverly	4
Carol	3
Diane	6
Ed	3
Fernando	5
Garth	5
Heather	3
Ike	2
Jane	1

- is the number of connections a node has
- Diane has the most direct connections in the network, making hers the most active node in the network
- however, she only connects people that are already friends with each other

SOURCE: http://www.orgnet.com/sna.html

Closeness Centrality

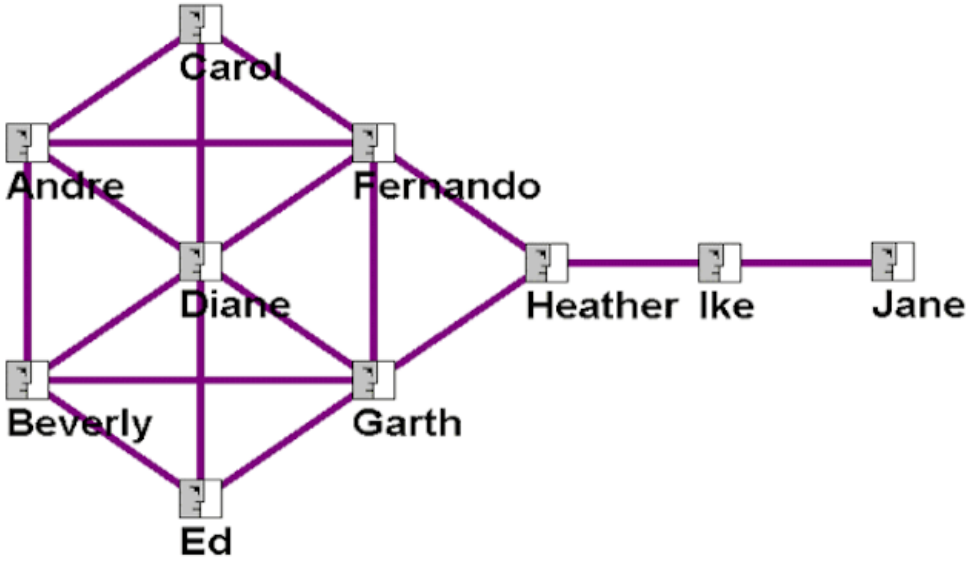


Name	Closeness
Andre	0.529
Beverly	0.529
Carol	0.500
Diane	0.600
Ed	0.500
Fernando	0.643
Garth	0.643
Heather	0.600
Ike	0.429
Jane	0.310

- is the inverse of the average shortest path length to all other nodes in the graph
- Fernando and Garth can access all the nodes in the network more quickly than anyone else
    - they have the shortest average path length to all users

SOURCE: http://www.orgnet.com/sna.html

(Shortest Path) Betweenness Centrality



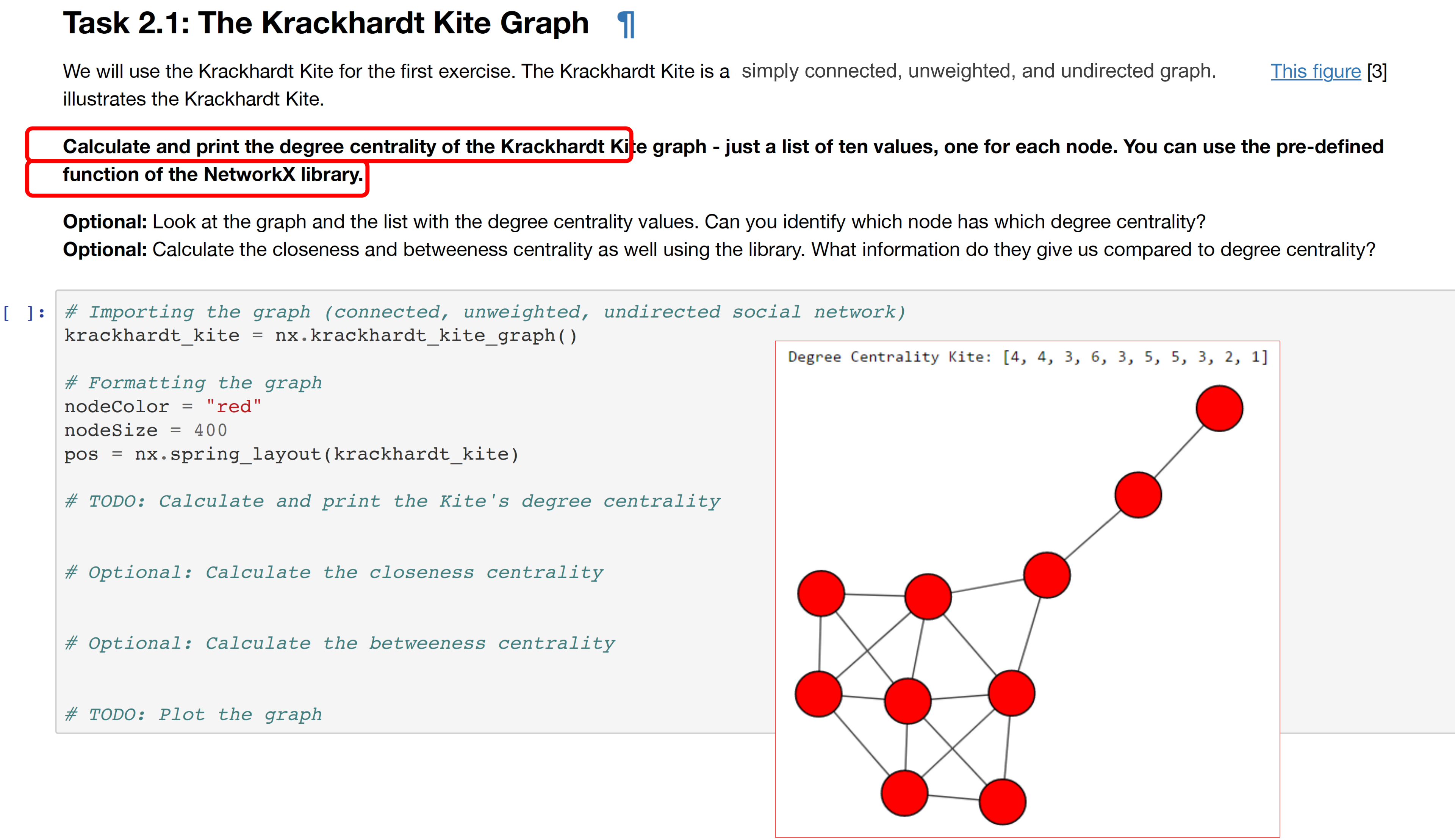
Name	Betweenness
Andre	0.833
Beverly	0.833
Carol	0
Diane	3.667
Ed	0
Fernando	8.333
Garth	8.333
Heather	14
Ike	8
Jane	0

- measures the number of times the shortest path between two nodes goes through the investigated node, divided by the total number of shortest paths between the two nodes
- Heather has few direct connections, yet she has an important role for Ike and Jane, who wouldn’t be connected to the network without her
  - she has high control of information flow

PageRank Centrality

- feedback-centrality named after Larry Page, co-founder of Google
- used for the Google search engine
- basic idea: a node is more central the more central its neighbors are

Tasks



Task 2.1: The Krackhardt Kite Graph ¶

We will use the Krackhardt Kite for the first exercise. The Krackhardt Kite is a simply connected, unweighted, and undirected graph. This figure [3] illustrates the Krackhardt Kite.

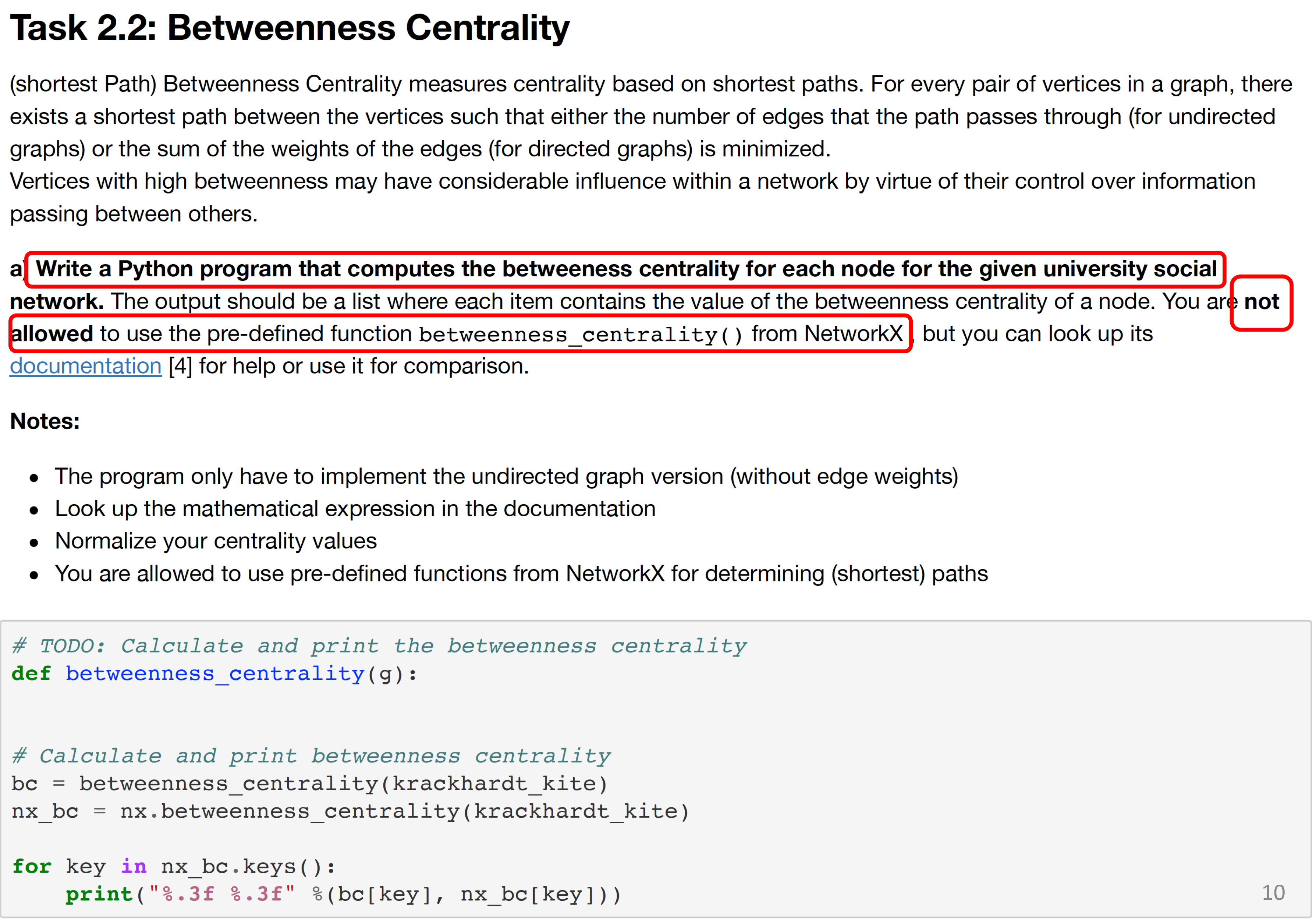
Calculate and print the degree centrality of the Krackhardt Kite graph - just a list of ten values, one for each node. You can use the pre-defined function of the NetworkX library.

Optional: Look at the graph and the list with the degree centrality values. Can you identify which node has which degree centrality?
Optional: Calculate the closeness and betweeness centrality as well using the library. What information do they give us compared to degree centrality?

```
[ ]: # Importing the graph (connected, unweighted, undirected social network)
     krackhardt_kite = nx.krackhardt_kite_graph()

     # Formatting the graph
     nodeColor = "red"
     nodeSize = 400
     pos = nx.spring_layout(krackhardt_kite)

     # TODO: Calculate and print the Kite's degree centrality


     # Optional: Calculate the closeness centrality


     # Optional: Calculate the betweeness centrality


     # TODO: Plot the graph
```

```
Degree Centrality Kite: [4, 4, 3, 6, 3, 5, 5, 3, 2, 1]
```

Tasks



Task 2.2: Betweenness Centrality

(shortest Path) Betweenness Centrality measures centrality based on shortest paths. For every pair of vertices in a graph, there exists a shortest path between the vertices such that either the number of edges that the path passes through (for undirected graphs) or the sum of the weights of the edges (for directed graphs) is minimized.
Vertices with high betweenness may have considerable influence within a network by virtue of their control over information passing between others.

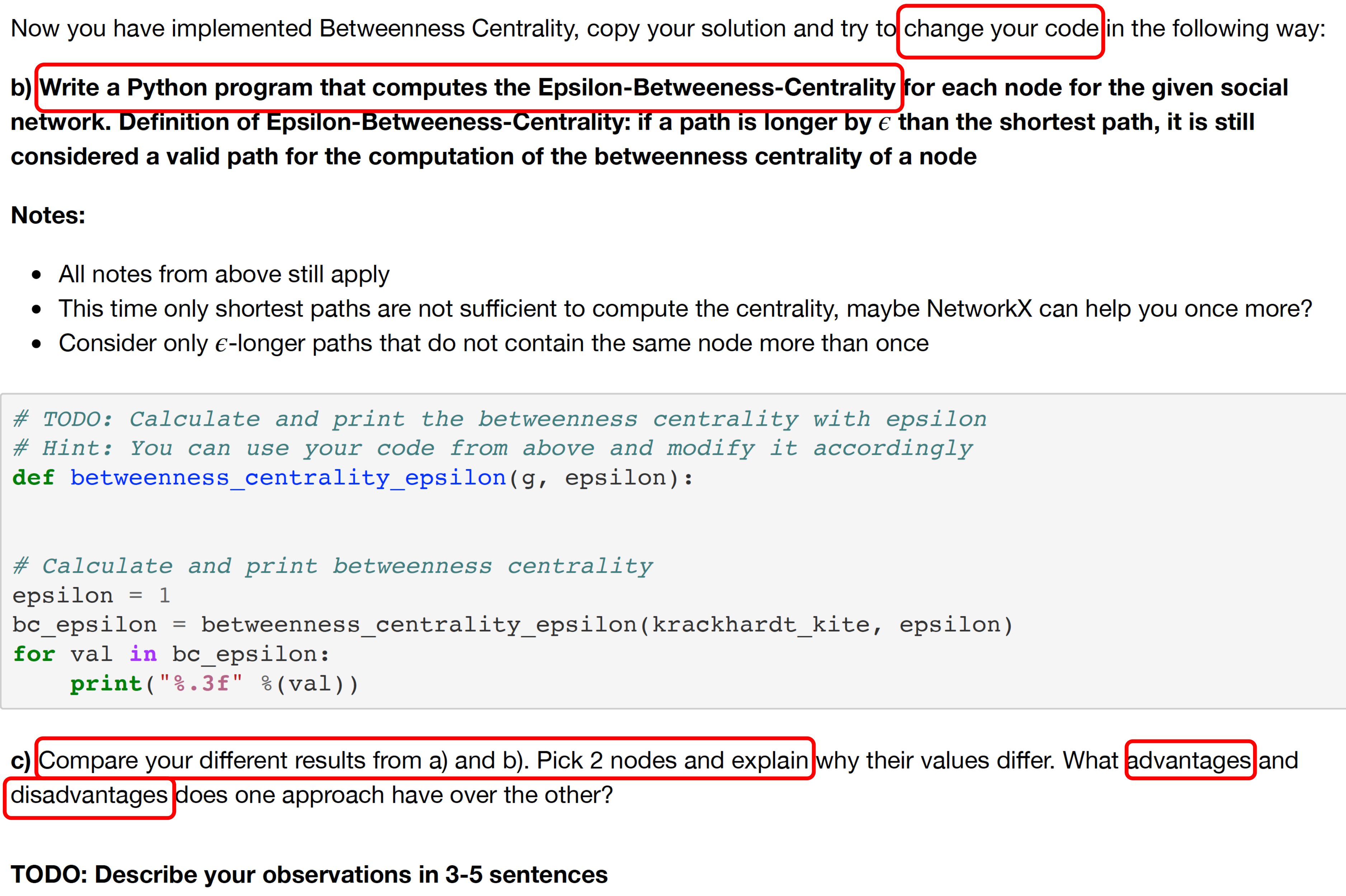
a) Write a Python program that computes the betweeness centrality for each node for the given university social network. The output should be a list where each item contains the value of the betweenness centrality of a node. You are **not allowed** to use the pre-defined function `betweenness_centrality()` from NetworkX, but you can look up its documentation [4] for help or use it for comparison.

Notes:

- The program only have to implement the undirected graph version (without edge weights)
- Look up the mathematical expression in the documentation
- Normalize your centrality values
- You are allowed to use pre-defined functions from NetworkX for determining (shortest) paths

```
# TODO: Calculate and print the betweenness centrality
def betweenness_centrality(g):


# Calculate and print betweenness centrality
bc = betweenness_centrality(krackhardt_kite)
nx_bc = nx.betweenness_centrality(krackhardt_kite)

for key in nx_bc.keys():
    print("%.3f %.3f" %(bc[key], nx_bc[key]))
```

Tasks (cont.)



Now you have implemented Betweenness Centrality, copy your solution and try to change your code in the following way:

b) Write a Python program that computes the Epsilon-Betweeness-Centrality for each node for the given social network. Definition of Epsilon-Betweeness-Centrality: if a path is longer by ϵ than the shortest path, it is still considered a valid path for the computation of the betweenness centrality of a node

Notes:

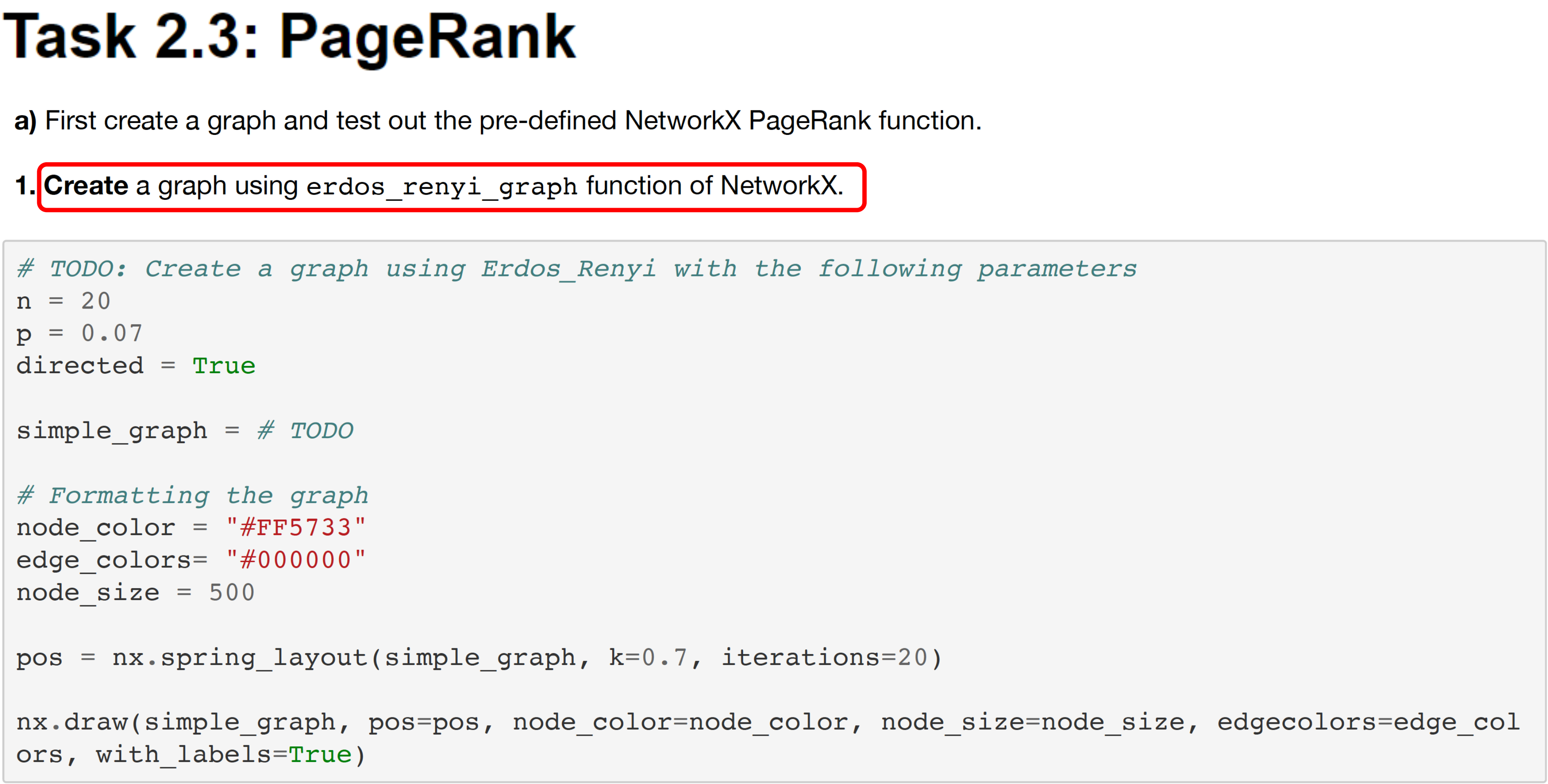
- All notes from above still apply
- This time only shortest paths are not sufficient to compute the centrality, maybe NetworkX can help you once more?
- Consider only ϵ-longer paths that do not contain the same node more than once

```
# TODO: Calculate and print the betweenness centrality with epsilon
# Hint: You can use your code from above and modify it accordingly
def betweenness_centrality_epsilon(g, epsilon):


# Calculate and print betweenness centrality
epsilon = 1
bc_epsilon = betweenness_centrality_epsilon(krackhardt_kite, epsilon)
for val in bc_epsilon:
    print("%.3f" %(val))
```

c) Compare your different results from a) and b). Pick 2 nodes and explain why their values differ. What advantages and disadvantages does one approach have over the other?

TODO: Describe your observations in 3-5 sentences

Tasks (cont.)



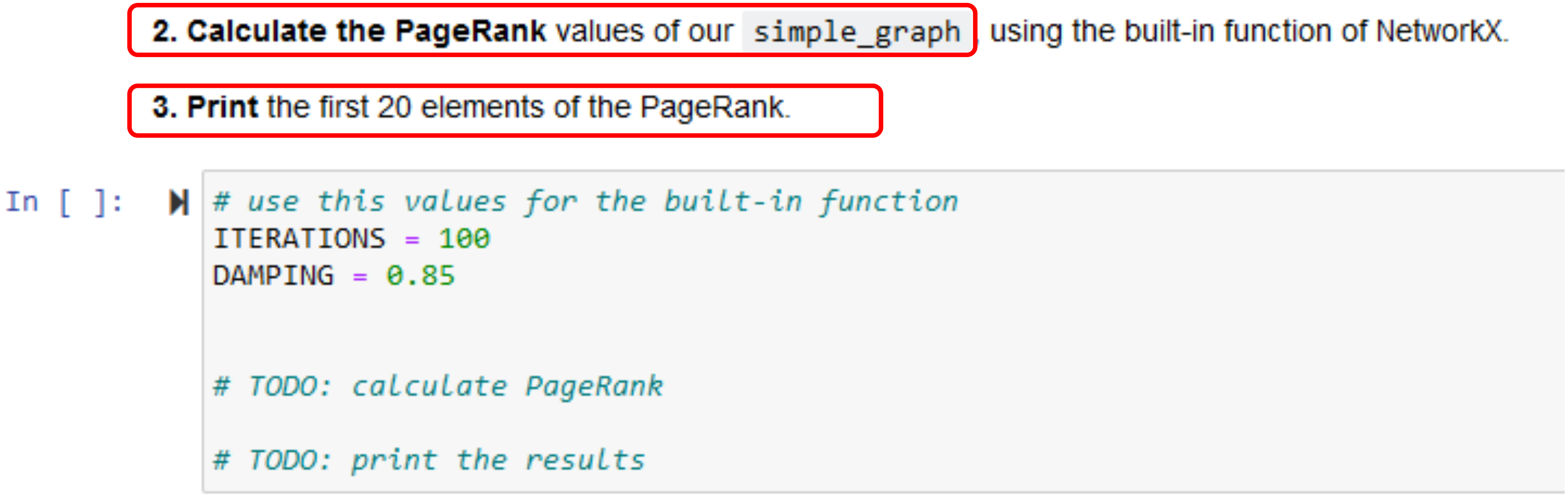
Task 2.3: PageRank

a) First create a graph and test out the pre-defined NetworkX PageRank function.

1. **Create** a graph using `erdos_renyi_graph` function of NetworkX.

```
# TODO: Create a graph using Erdos_Renyi with the following parameters
n = 20
p = 0.07
directed = True

simple_graph = # TODO

# Formatting the graph
node_color = "#FF5733"
edge_colors= "#000000"
node_size = 500

pos = nx.spring_layout(simple_graph, k=0.7, iterations=20)

nx.draw(simple_graph, pos=pos, node_color=node_color, node_size=node_size, edgecolors=edge_col
ors, with_labels=True)
```

Tasks (cont.)



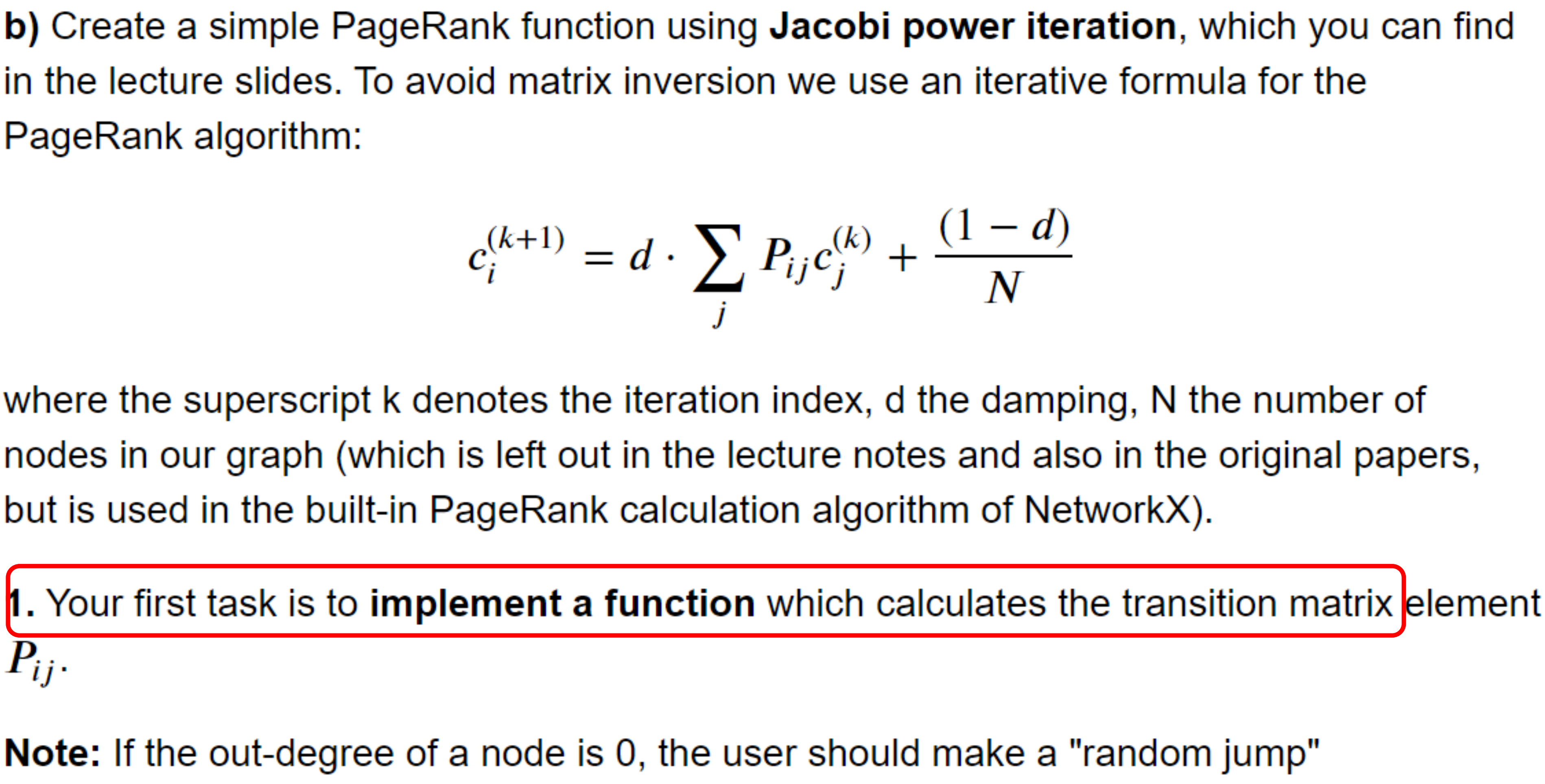
2. Calculate the PageRank values of our `simple_graph` using the built-in function of NetworkX.

3. Print the first 20 elements of the PageRank.

In [ ]:

```
# use this values for the built-in function
ITERATIONS = 100
DAMPING = 0.85


# TODO: calculate PageRank

# TODO: print the results
```

Tasks (cont.)



b) Create a simple PageRank function using **Jacobi power iteration**, which you can find in the lecture slides. To avoid matrix inversion we use an iterative formula for the PageRank algorithm:

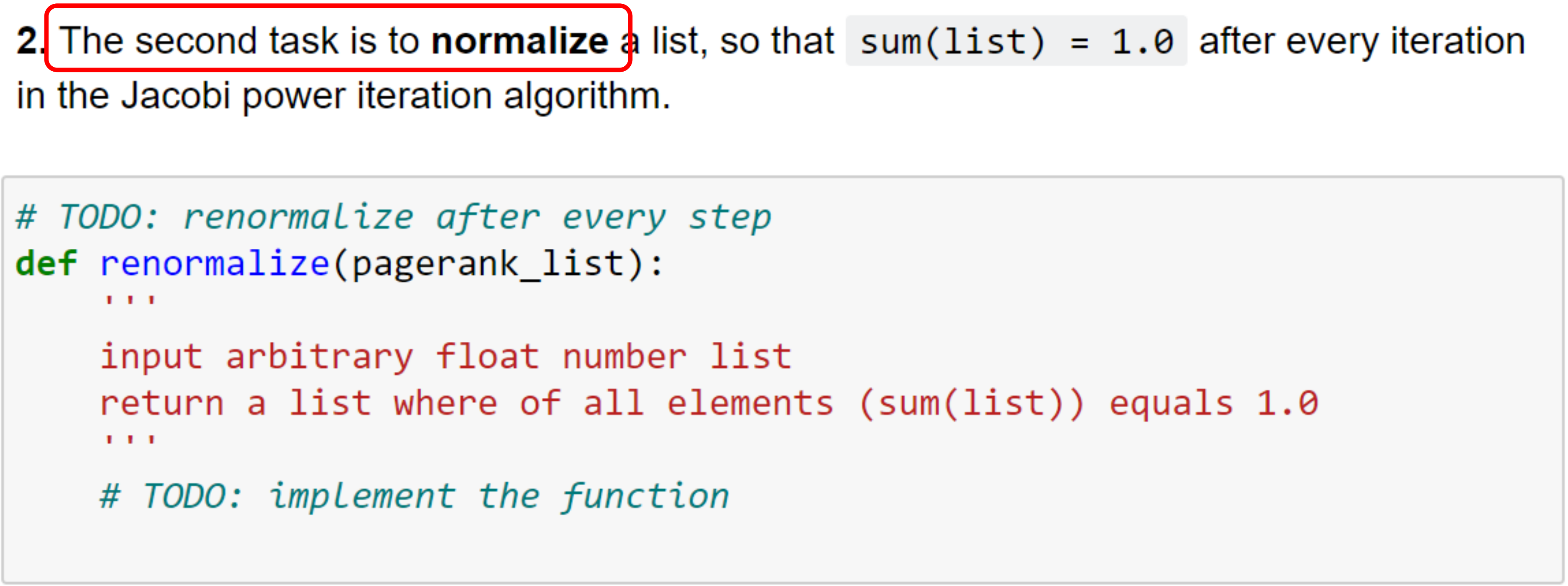
$$c_i^{(k+1)} = d \cdot \sum_j P_{ij} c_j^{(k)} + \frac{(1-d)}{N}$$

where the superscript k denotes the iteration index, d the damping, N the number of nodes in our graph (which is left out in the lecture notes and also in the original papers, but is used in the built-in PageRank calculation algorithm of NetworkX).

1. Your first task is to **implement a function** which calculates the transition matrix element P_{ij}.

Note: If the out-degree of a node is 0, the user should make a "random jump"

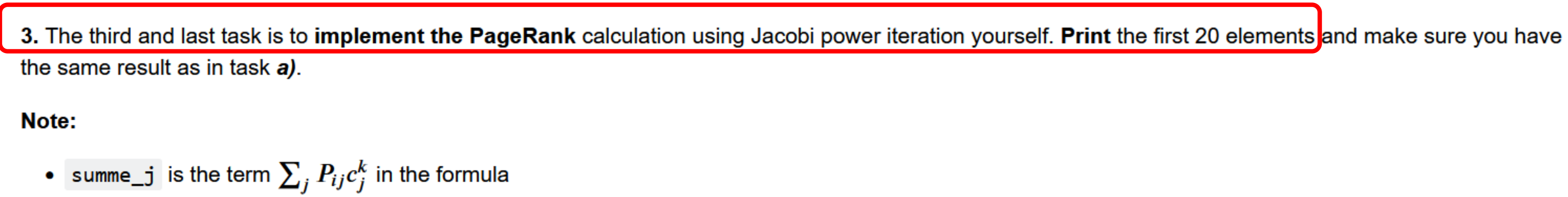
Tasks (cont.)



2. The second task is to **normalize** a list, so that `sum(list) = 1.0` after every iteration in the Jacobi power iteration algorithm.

```
# TODO: renormalize after every step
def renormalize(pagerank_list):
    '''
    input arbitrary float number list
    return a list where of all elements (sum(list)) equals 1.0
    '''
    # TODO: implement the function
```

Tasks (cont.)

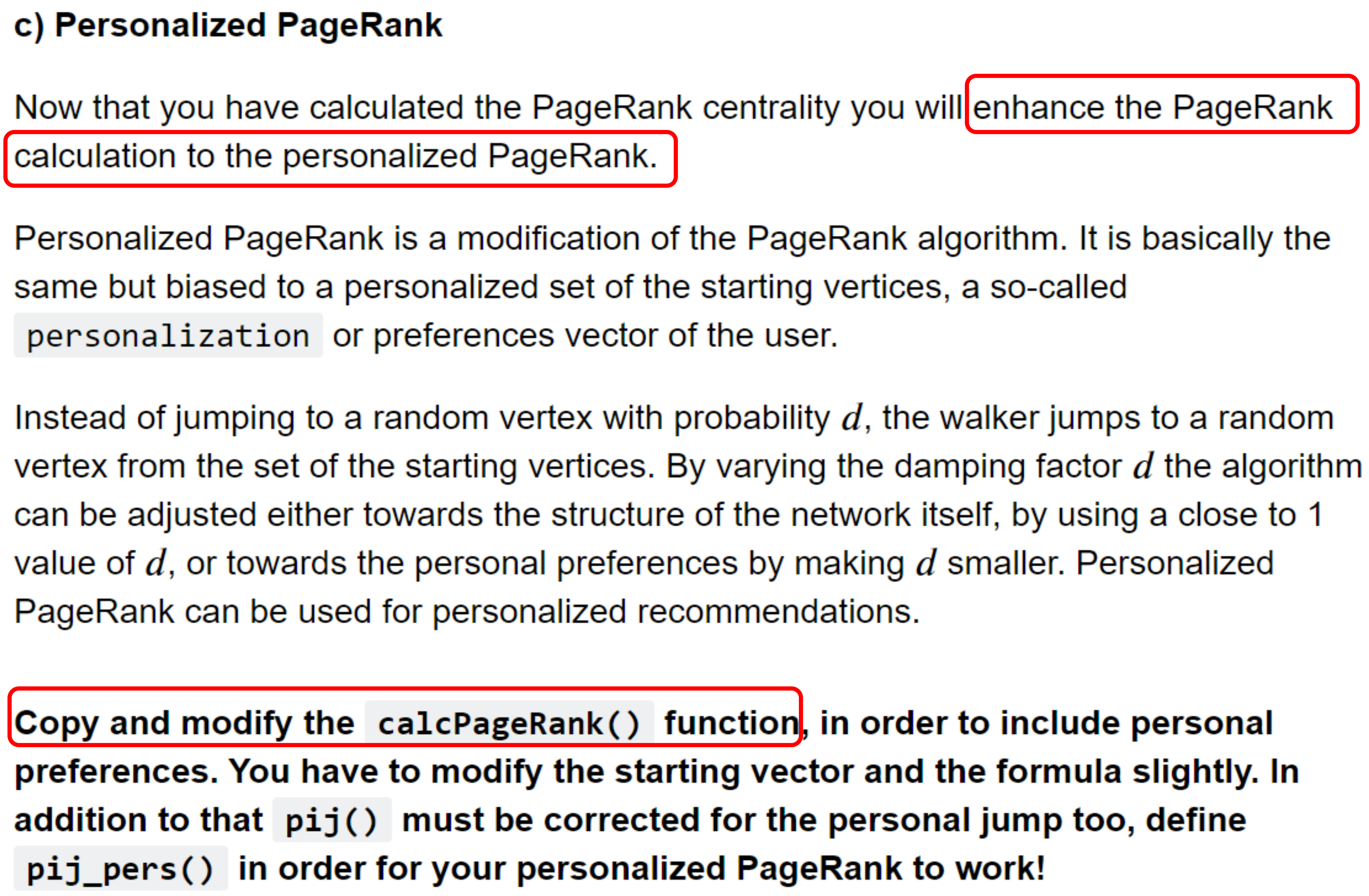


3. The third and last task is to **implement the PageRank** calculation using Jacobi power iteration yourself. **Print** the first 20 elements and make sure you have the same result as in task ***a)***.

Note:

- `summe_j` is the term $\sum_j P_{ij}c_j^k$ in the formula

Tasks (cont.)



c) Personalized PageRank

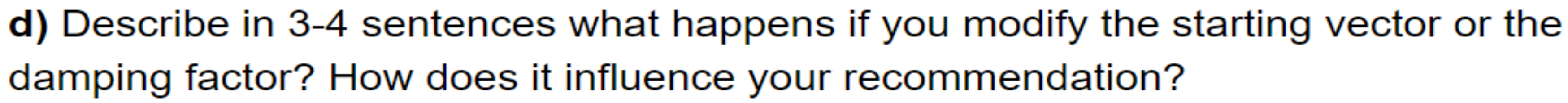
Now that you have calculated the PageRank centrality you will enhance the PageRank calculation to the personalized PageRank.

Personalized PageRank is a modification of the PageRank algorithm. It is basically the same but biased to a personalized set of the starting vertices, a so-called `personalization` or preferences vector of the user.

Instead of jumping to a random vertex with probability d, the walker jumps to a random vertex from the set of the starting vertices. By varying the damping factor d the algorithm can be adjusted either towards the structure of the network itself, by using a close to 1 value of d, or towards the personal preferences by making d smaller. Personalized PageRank can be used for personalized recommendations.

Copy and modify the `calcPageRank()` function, in order to include personal preferences. You have to modify the starting vector and the formula slightly. In addition to that `pij()` must be corrected for the personal jump too, define `pij_pers()` in order for your personalized PageRank to work!

Tasks (cont.)



d) Describe in 3-4 sentences what happens if you modify the starting vector or the damping factor? How does it influence your recommendation?

Submitting your solution

- work by expanding the .ipynb iPython notebook for the exercise that you downloaded from Moodle
- save your expanded .ipynb iPython notebook in your working directory
- submit your .ipynb iPython notebook via Moodle (nothing else)
- remember: working in groups is not permitted. Each student must submit their own .ipynb notebook!
- we check for plagiarism. Each detected case will be graded with 5.0 for the whole exercise
- deadline: check Moodle