network lab

May 4, 2022

```
[]: # Initialize Otter
import otter
grader = otter.Notebook("network lab.ipynb")

[]: import numpy as np
import pandas as pd
import seaborn as sns
import networkx as nx
SEED = 3383
```

1 0. Data preparation

The following is a network of connections within part of the brain of a fly.

```
[]: fly = nx.read_edgelist("bn-fly-drosophila_medulla_1.edges",nodetype=int)
n = fly.number_of_nodes()
print(n,"nodes")
```

This network has a feature that we have not allowed so far: some nodes link to themselves. These appear, for example, as nonzeros on the diagonal of the adjacency matrix.

```
[ ]: A = nx.adjacency_matrix(fly).toarray()
print(sum(A[i,i] for i in range(n)), "self-linked nodes")
```

We will get rid of these self-links by zeroing out the diagonal and reconstructing the graph from the modified adjacency matrix. This will also relabel the nodes to go in order from 0 to n-1.

```
[]: np.fill_diagonal(A,0)
fly = nx.from_numpy_array(A)
nodes = pd.Index(fly.nodes)
```

2 1. Basic info

2.1 1.1

Compute the average node degree of the network.

```
[]: kbar = ...

# No need to change this line.
print("average degree is",kbar)
```

```
[]: grader.check("info-kbar")
```

2.2 1.2

Draw the ego graph of node 80, with labels for the nodes.

```
[]:
```

2.3 1.3

Create a list of all the nodes that are adjacent to node 9.

```
[]: nbrs9 = ...
# No need to change the following line.
print("neighbors of node 9:",nbrs9)
```

```
[]: grader.check("info-neighbors")
```

3 2. Clustering and distance

3.1 2.1

Create a Series for the local clustering coefficients in the network.

```
[]: cluster = ...

# No need to change the following lines.
print("clustering coeffs:")
print(cluster.describe())
```

```
[]: grader.check("cluster-values")
```

$3.2 \ 2.2$

Compute T(110), the number of triangles that have node 110 as a vertex. Then, apply the formula

$$\frac{2T(110)}{d_{110}(d_{110}-1)},$$

where d_{110} is the degree of node 110, to get the clustering coefficient of 110.

```
[]: # Set this to the number of triangles.
T110 = ...
```

```
# Set this to the local clustering coefficient.
C110 = ...

# No need to change the following line.
print(T110, "adjacent triangles, giving clustering coefficient", C110)
```

```
[]: grader.check("cluster-110")
```

3.3 2.3

Let k be the integer closest to kbar. For each $q = 0, 0.02, 0.04, 0.06, \ldots$, compute and print out the average clustering coefficient of a Watts-Strogatz graph for n, k, and q, with random seed equal to SEED. When the average coefficient is smaller than the average clustering coefficient of the fly graph, stop.

```
[]: # Exit this loop when the average WS clustering exceeds the average clustering

in the fly graph.

for q in np.arange(0,0.5,0.02):

# No need to change the following line.

print("final value of q is",q)
```

```
[]: grader.check("cluster-WS")
```

3.4 2.4

Compute the mean shortest path length between all pairs of nodes in the largest connected component of the fly graph. (This computation might take 20-60 seconds, depending on the speed of the computer you use.)

```
[]: avg_dist = ...

# No need to change the following line.
print("average shortest path length:",avg_dist)
[]: grader.check("distance-average")
```

4 3. Degree distribution

4.1 3.1

Create a Series of the node degrees in the fly graph.

```
[]: degrees = ...

# No need to change the following line.
print("node degrees for fly graph:\n",degrees.describe())
```

```
[]: grader.check("degree-series")
```

4.2 3.2

Using log scales on both axes, plot a histogram of the degree distribution. You should see a rough linear trend in the resulting plot.

[]:

4.3 3.4

Create a Barabási-Albert graph with random seed SEED, the same number of nodes as the fly graph, and parameter m equal to the integer nearest to half the average degree of the fly graph. Find the standard deviation of its degree distribution.

```
[]: grader.check("degree-BA")
```

5 4. Centrality

5.1 4.1

Create a data frame indexed by node and with columns named degree, betweenness, and eigenvector for centrality measures.

```
[]: # This should be a data frame indexed by nodes and with 3 columns for □ □ □ centrality measures. Fidn the mean value in each column.

centrality = ...

# These should be assigned to the means of the three columns.

dc_mean = ...

bc_mean = ...

ec_mean = ...

# No need to change the following lines.

print("centrality scores\n:",centrality)

print("with means",dc_mean,",",bc_mean,",",ec_mean)
```

```
[]: grader.check("central-columns")
```

5.2 4.2

Of the three pairings degree-betweenness, degree-eigenvector, and betweenness-eigenvector, find the Pearson correlation coefficient of centrality scores for the pairing that is the *least* strongly correlated.

```
[]: min_correlation = ...
# No need to change the following line.
print("weakest correlation is", min_correlation)
```

```
[]: grader.check("central-corr")
```

5.3 4.3

For each type of centrality score, find the 10 highest-scoring nodes.

```
[]: # Each should be an array, list, or Series.

top_degree = ...

top_betweenness = ...

top_eigenvector = ...

# No need to change these lines.

results = pd.DataFrame({"degree":top_degree, "betweenness":

→top_betweenness, "eigenvector":top_eigenvector})

print(results)
```

```
[]: grader.check("central-rank")
```

To double-check your work, the cell below will rerun all of the autograder tests.

```
[]: grader.check_all()
```

5.4 Submission

Make sure you have run all cells in your notebook in order before running the cell below, so that all images/graphs appear in the output. The cell below will generate a zip file for you to submit.

Select $Kernel/Restart \ \mathcal{C}$ Run All, then save, then run this export cell again. Submit by pushing the resulting zip file to your GitHub assignment repo.

```
[]: grader.export(pdf=False, force_save=True)
```