IV.Basic Structural Properties of Networks

January 29, 2018

1 All imports

```
In [1]: import numpy as np
        import networkx as nx
        import math
        import itertools
        import matplotlib.pyplot as plt
        import pandas as pd
        import seaborn as sns
```

2 Utils

```
In [2]: def draw(G,**kwargs):
            if len(G)<20:
                nx.draw_spring(G,
                               node_size=400,
                               with_labels=True)
            else:
                nx.draw_spring(G,
                               node_size=10,
                               with_labels=False)
```

```
In [3]: def create_undirected_graph(edges):
            G=nx.Graph()
            G.add_edges_from(edges)
            return G
```

```
In [4]: def create_directed_graph(edges):
            DG=nx.DiGraph()
            DG.add_edges_from(edges)
            return DG
```

```
In [5]: def load_graph_from_tsv(file):
            f = open(file,"r")
            text = f.readlines()
            clean = lambda x:x.strip("\n").split(" ")
            node_pairs = list(map(clean,text[2:]))
```

```
    node_pairs = [(int(x[0]),int(x[1])) for x in node_pairs]
    node_pairs[:4]
    G = nx.Graph()
    G.add_edges_from(node_pairs)
    return G
```

3 IV.5

Take an undirected network and measure the correlation between different centrality measures. The correlation can either be estimated with the centrality values (Spearman) or with their associated ranking (Kendall). Construct an example of a graph where one node has a small degree centrality but a high betweenness centrality.

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Given 2 random variables (or sets of observation) X and Y, we have

Pearson Correlation: $\frac{\mathrm{Cov}(X,Y)}{\sigma(X)\sigma(Y)}$

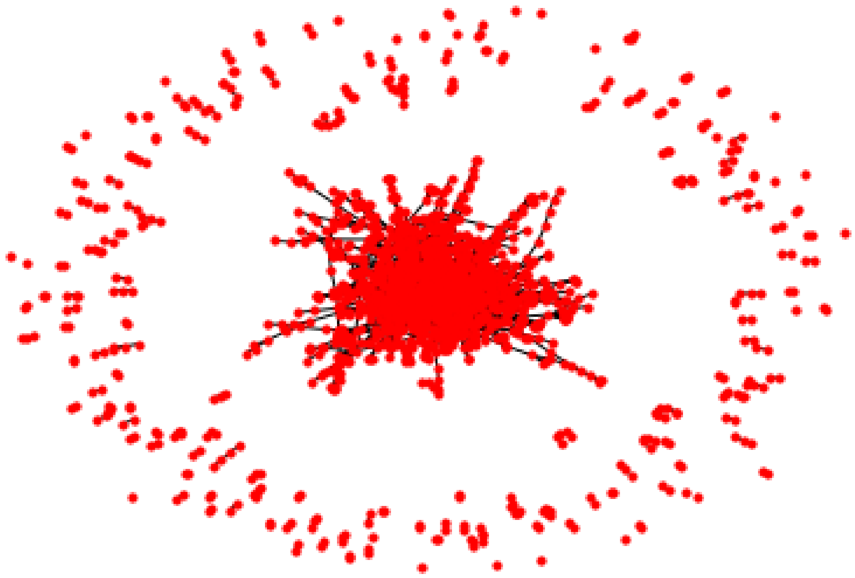
Kendall Correlation: After ordering the observation pairs, use $\frac{(number.of.concordant.pairs)-(number.of.discordant.pairs)}{\frac{1}{2}n(n-1)}$

Spearman Correlation: Pearson correlation after mapping the observations X_i, Y_i to their ranks.

```
In [6]: def build_centrality_measures_dataframe(G):

            # Builds dictionaries with the different metrics
            betweenness = nx.betweenness_centrality(G)
            degree = dict(nx.degree(G))
            closeness = nx.closeness_centrality(G)
            katz = nx.katz_centrality(G)
            pagerank = nx.pagerank(G,alpha=0.5) # The $ \alpha=.85 $ was chosen randomly. Is the

            # Builds a dataframe with the measures as columns and the nodes as rows
            df = pd.DataFrame({'betweenness':betweenness,
                               'degree':degree,
                               'closeness':closeness,
                               'katz':katz,
                               'pagerank':pagerank})
            return df

        # Requires the centrality_measures_dataframe as input
        def correlation_of_centrality_metrics(df):
            # Builds correlation matrices for the different metrics
            for metric in ['pearson', 'kendall', 'spearman']:
                print("\n\n" + str(metric.capitalize()) + ' correlation:')
                print(df.corr(metric))
```

Dataset used: The propo dataset used consists of nodes representing proteins and edges representing pairs of interacting proteins.

In [7]:
```
G = load_graph_from_tsv("datasets/propo.tsv")
draw(G)
```



In [8]:
```
df = build_centrality_measures_dataframe(G)
df.describe()
```

Out[8]:

	betweenness	closeness	degree	katz	pagerank
count	1870.000000	1870.000000	1870.000000	1870.000000	1870.000000
mean	0.001891	0.091932	2.435294	0.020112	0.000535
std	0.006035	0.051226	3.164618	0.011416	0.000374
min	0.000000	0.000000	1.000000	0.013533	0.000313
25%	0.000000	0.080883	1.000000	0.014203	0.000362
50%	0.000000	0.112335	1.000000	0.016208	0.000446
75%	0.001219	0.126392	3.000000	0.021312	0.000548
max	0.129420	0.183020	56.000000	0.200559	0.009283

In [9]:
```
correlation_of_centrality_metrics(df)
```

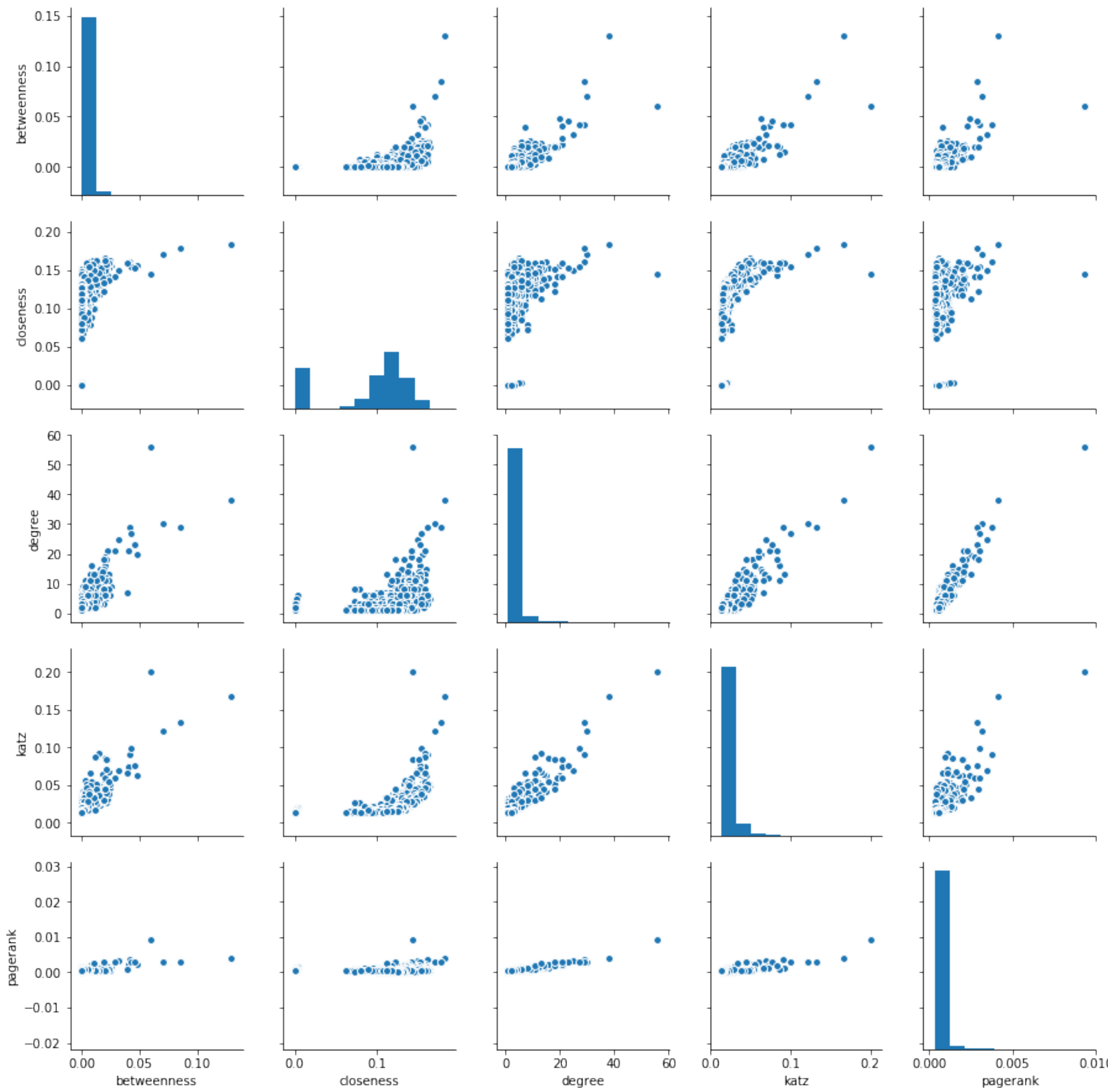
Pearson correlation:

	betweenness	closeness	degree	katz	pagerank
betweenness	1.000000	0.297399	0.837694	0.818457	0.739478
closeness	0.297399	1.000000	0.302620	0.456009	0.090823

```
degree           0.837694   0.302620  1.000000  0.868335  0.929309
katz             0.818457   0.456009  0.868335  1.000000  0.726429
pagerank         0.739478   0.090823  0.929309  0.726429  1.000000


Kendall correlation:
             betweenness  closeness    degree      katz  pagerank
betweenness     1.000000   0.409058  0.813356  0.548139  0.548832
closeness       0.409058   1.000000  0.359753  0.713957 -0.081977
degree          0.813356   0.359753  1.000000  0.569681  0.638604
katz            0.548139   0.713957  0.569681  1.000000  0.064198
pagerank        0.548832  -0.081977  0.638604  0.064198  1.000000


Spearman correlation:
             betweenness  closeness    degree      katz  pagerank
betweenness     1.000000   0.523995  0.897253  0.676930  0.699047
closeness       0.523995   1.000000  0.463058  0.880813 -0.064068
degree          0.897253   0.463058  1.000000  0.687259  0.764166
katz            0.676930   0.880813  0.687259  1.000000  0.176845
pagerank        0.699047  -0.064068  0.764166  0.176845  1.000000
```

In [10]:
```
# Pairplots comparing the different metrics
sns.pairplot(df)
```

Out[10]:
```
<seaborn.axisgrid.PairGrid at 0x7f36d0163ac8>
```


betweenness
closeness
degree
katz
pagerank