

```

#https://stackoverflow.com/questions/48293601/how-to-install-libspatialindex-on-google-colab
#https://colab.research.google.com/drive/1N7i9zm0wVcUzd4eHWZux4p_WTBMZHi8C

#####
### Rodar toda vez que for usar o Osmnx no Google Colaboratory ###
#####

import os
!pip install geopandas
!pip install rtree
!pip install osmnx
!mount -o remount,exec /content
!apt-get install -qq curl g++ make
!curl -L http://download.osgeo.org/libspatialindex/spatialindex-src-1.8.5.tar.gz | tar xz
os.chdir('spatialindex-src-1.8.5')
!./configure
!make
!make install
!pip install rtree
!ldconfig
os.chdir('/content/')
clear_output()

from networkx.algorithms.community import greedy_modularity_communities
from sklearn.metrics.cluster import normalized_mutual_info_score
from networkx.algorithms.community import LFR_benchmark_graph
from sklearn.preprocessing import StandardScaler
from networkx.algorithms import community
from IPython.display import clear_output
from community import community_louvain
from sklearn.decomposition import PCA
from scipy.linalg import expm
from rtree.index import Rtree
from random import randint
from rtree import index
from numpy import *
import matplotlib.pyplot as plt
import statistics as stats
import scipy.stats as st
import networkx as nx
import seaborn as sns
import pandas as pd
import osmnx as ox
import numpy as np
import warnings
import random
import scipy
import os
warnings.filterwarnings('ignore')

```

▼ 1 – For the following networks:

- a) E-road network (http://konect.cc/networks/subelj_euroroad),
- b) Hamsterster friendships (<http://konect.uni-koblenz.de/networks/petsterfriendships-hamster>)
- c) C. elegans neural network ([http://wwwpersonal.umich.edu/~mejn/netdata/celegansneural.](http://wwwpersonal.umich.edu/~mejn/netdata/celegansneural/))
- d) US airport network (<http://toreopsahl.com/datasets/#usairports>)

▼ Construct a correlation matrix between the centrality measures:

- (i) degree,
- (ii) kcore,
- (iii) closeness centrality,
- (iv) betweenness centrality,
- (v) eigenvector centrality,
- (vi) pagerank,
- (vi) random walk accessibility,
- (v) communicability centrality.

Discuss the highest correlations and interpret the results.

```
def refaz_multigraph(G):
    Gnew = nx.Graph()
    for edge in G.edges():
        Gnew.add_edge(edge[0], edge[1])
    return Gnew

def refaz_grafo_ponderado(G):
    Gnew = nx.Graph()
    for (u,v) in G.edges:
        Gnew.add_edge(u, v)
    return Gnew

def trata_rede(G
                , undirected = True
                , convert_to_int = True
                , most_connected_component = True
                , remove_selfedges = True
                , multigraph = False
                , remove_weights = True):
    # Se True:
    # Deixa o Grafo bidirecionado
    # Troca os labels dos nós para inteiros
    # Extrai o componente com maior número de vértices
    # Remove loops
    # Transforma de Multigrafo para grafo
    # Remove pesos

    if multigraph : G = refaz_multigraph(G)
    if remove_selfedges : G.remove_edges_from(G.selfloop_edges())
```

```

if most_connected_component : G = sorted(nx.connected_component_subgraphs(G), key = len,
if convert_to_int : G = nx.convert_node_labels_to_integers(G, first_label=0)
if undirected : G = G.to_undirected()
if remove_weights : G = refaz_grafo_ponderado(G)
return G

def plota_rede(G, fig_size = 6, nd_size = 500, n_color = 0):
    colors = [ 'b', 'g', 'r', 'c', 'm', 'y', 'k', 'w' ]
    plt.figure(figsize=(fig_size,fig_size))
    pos=nx.spring_layout(G)
    nx.draw(G, with_labels = True, pos = pos, node_size = nd_size, node_color = colors[n_color])
    plt.show(True)

def degree_centrality(G):
    vk = dict(G.degree())
    return list(vk.values())

def closeness_centrality(G):
    CLC = dict(nx.closeness_centrality(G))
    return list(CLC.values())

def betweenness_centrality(G):
    B = dict(nx.betweenness_centrality(G))
    return list(B.values())

def eigenvector_centrality(G):
    EC = dict(nx.eigenvector_centrality(G, max_iter = 1000))
    return list(EC.values())

def pagerank(G):
    PR = dict(nx.pagerank(G, alpha=0.85))
    PR = list(PR.values())
    return np.array(PR)

def kcore(G):
    return list(dict(nx.core_number(G)).values())

def communicability_centrality(G):
    return np.asarray(list(nx.subgraph_centrality_exp(G).values()))

def random_walk_accessibility(G):
    N = len(G.nodes())
    vk = dict(G.degree())
    vk = list(vk.values())
    A = nx.adjacency_matrix(G)
    P = np.zeros((N,N), dtype = 'float')
    for i in np.arange(0, N):
        for j in np.arange(i, N):
            P[i,j] = A[i,j]/vk[i]
            P[j,i] = P[i,j]
    P2 = expm(P)/np.exp(1)

```

```

vacc = np.zeros(N, dtype = float)
for i in np.arange(0, N):
    acc = 0
    for j in np.arange(0,N):
        if(P2[i,j] > 0):
            acc = acc + P2[i,j]*log(P2[i,j])
    acc = np.exp(-acc)
    vacc[i] = acc
return vacc

def correlation_matrix(df, type = 1):
    if type == 1 :
        corr = df.corr()
        plt.figure(figsize=(7, 7))
        mask = np.zeros_like(corr)
        mask[np.triu_indices_from(mask)] = True
        with sns.axes_style("white"):ax = sns.heatmap(corr, mask=mask, vmax=1, square=True)
        plt.show()

    elif type == 2 :
        corr = df.corr()
        #Plot Correlation Matrix using Matplotlib
        plt.figure(figsize=(8,8))
        plt.imshow(corr, cmap='Blues', interpolation='none', aspect='auto')
        plt.colorbar()
        plt.xticks(range(len(corr)), corr.columns, rotation='vertical', fontsize=20)
        plt.yticks(range(len(corr)), corr.columns, fontsize=20);
        plt.suptitle('Correlation between centrality measures', fontsize=20)
        plt.grid(False)
        plt.show()
    return

listaGraph = list()
listaIndex = ["E-road network", "Hamsterster friendships", "C.elegans neural network", ""]

G_eroad = nx.read_edgelist("eroad.edges", nodetype=int, data=(('weight',int),))
listaGraph.append(trata_rede(G_eroad))

G_hamster = nx.read_edgelist("Hamsterster.edges", nodetype=int, data=(('weight',int),))
listaGraph.append(trata_rede(G_hamster))

G_celneural = nx.read_gml("celegansneural.gml")
listaGraph.append(trata_rede(G_celneural, multigraph = True))

G_usaairport = nx.read_edgelist("usaairport.edges", nodetype=int, data=(('weight',int),))
listaGraph.append(trata_rede(G_usaairport))

def ex1(G,T):
    VK = degree_centrality(G)
    KC = kcore(G)
    CLC = closeness_centrality(G)
    B = betweenness_centrality(G)
    EC = eigenvector_centrality(G)
    PR = pagerank(G)

```

```

... PUSCUNHUA
RWA = random_walk_accessibility(G)
CC = communicability_centrality(G)
df = pd.DataFrame({'K':VK, 'CLC':CLC, 'B':B, 'EC':EC, 'PR':PR, 'KC':KC, 'RWA':RWA, 'CC': CC})
#df = pd.DataFrame({'K':VK, 'CLC':CLC, 'B':B, 'EC':EC, 'PR':PR, 'KC':KC, 'RWA':RWA})
print("Matriz de correlações entre \nK Degreee Centrality\nKC Kcore\nCLC Closeness Centr")
print("EC Eigenvector Centrality\nPR Pagerank\nRWA Random Walk Accessibility\nCC Communi")
correlation_matrix(df,1)

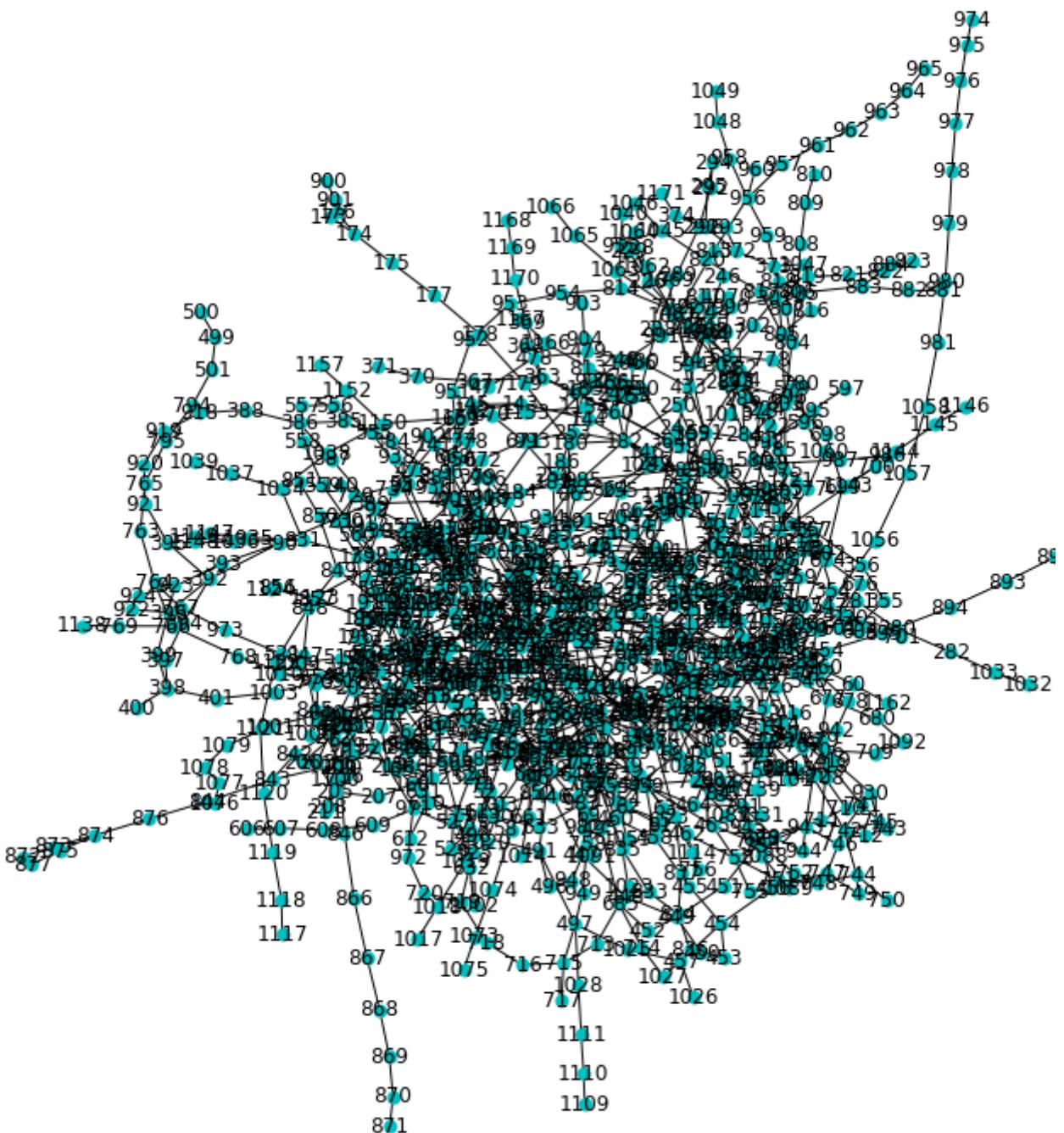
```

```

T = listaIndex[0]
G = listaGraph[0]
print("Rede: ", T)
plota_rede(G, nd_size=50, fig_size=10, n_color = random.randint(0,8))

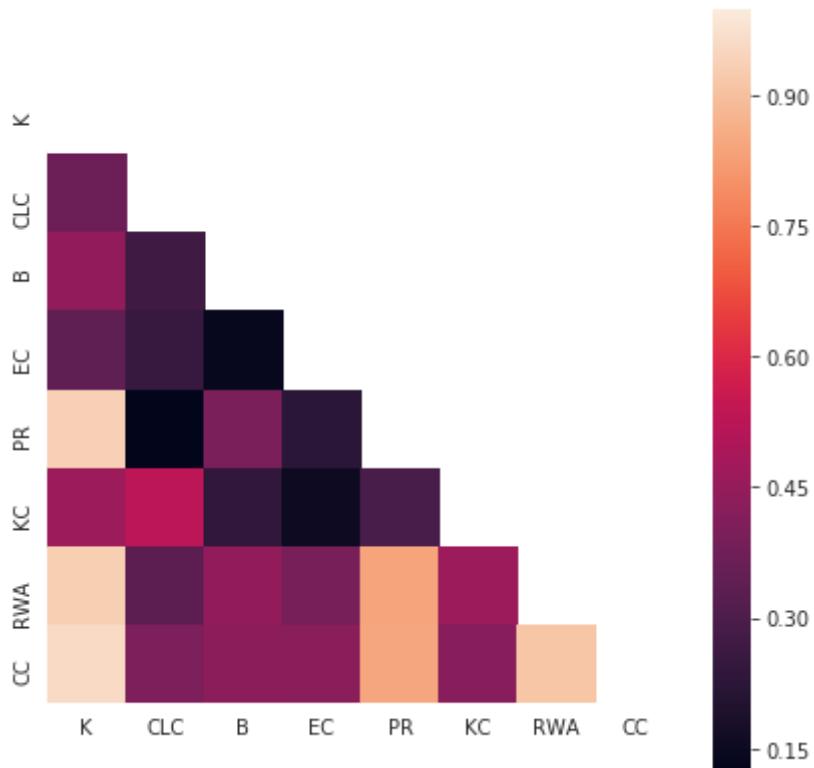
```

□ Rede: E-road network



```
ex1(G,T)
```

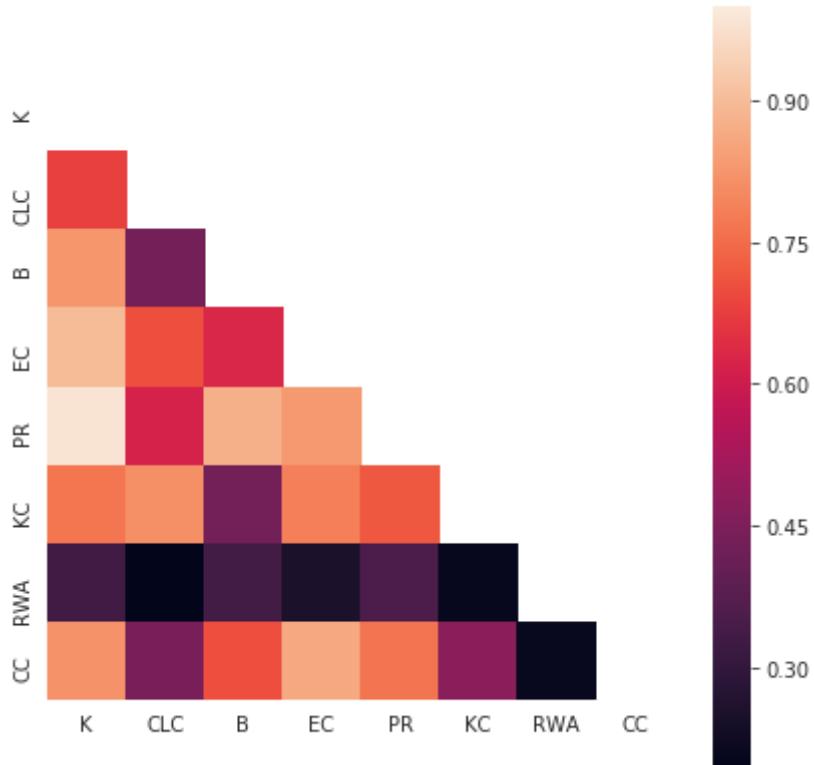
- ⇨ Matriz de correlações entre
 - K Degreee Centrality
 - KC Kcore
 - CLC Closeness Centrality
 - B Betwenesses Centrality
 - EC Eigenvector Centrality
 - PR Pagerank
 - RWA Random Walk Accessibility
 - CC Communicability Centrality



```
T = listaIndex[1]  
G = listaGraph[1]  
ex1(G,T)
```

- ⇨

Matriz de correlações entre
 K Degreee Centrality
 KC Kcore
 CLC Closeness Centrality
 B Betwenesses Centrality
 EC Eigenvector Centrality
 PR Pagerank
 RWA Random Walk Accessibility
 CC Communicability Centrality

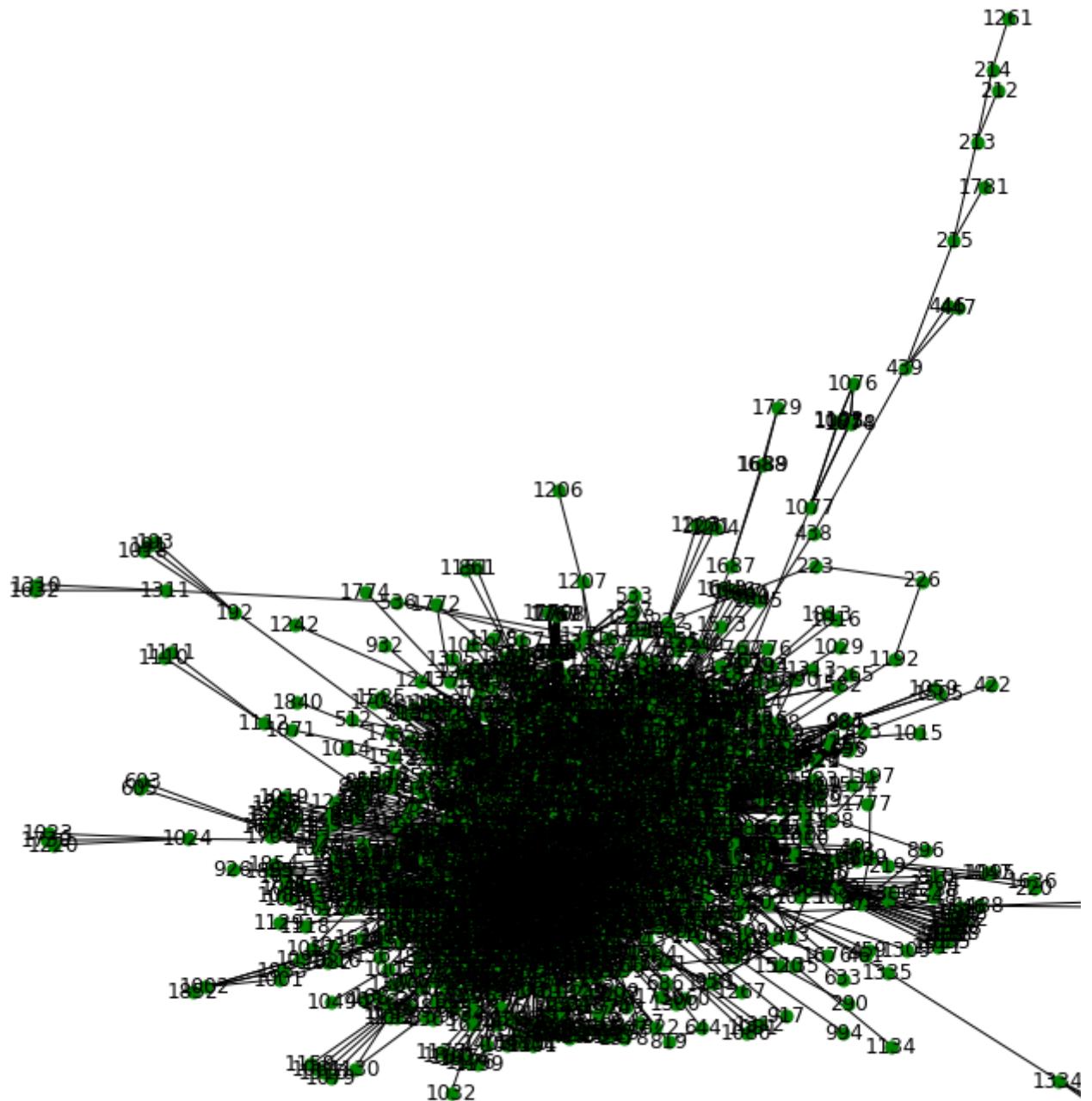


```

print("Rede: ", T)
plota_rede(G, nd_size=50, fig_size=10, n_color = random.randint(0,8))
  
```



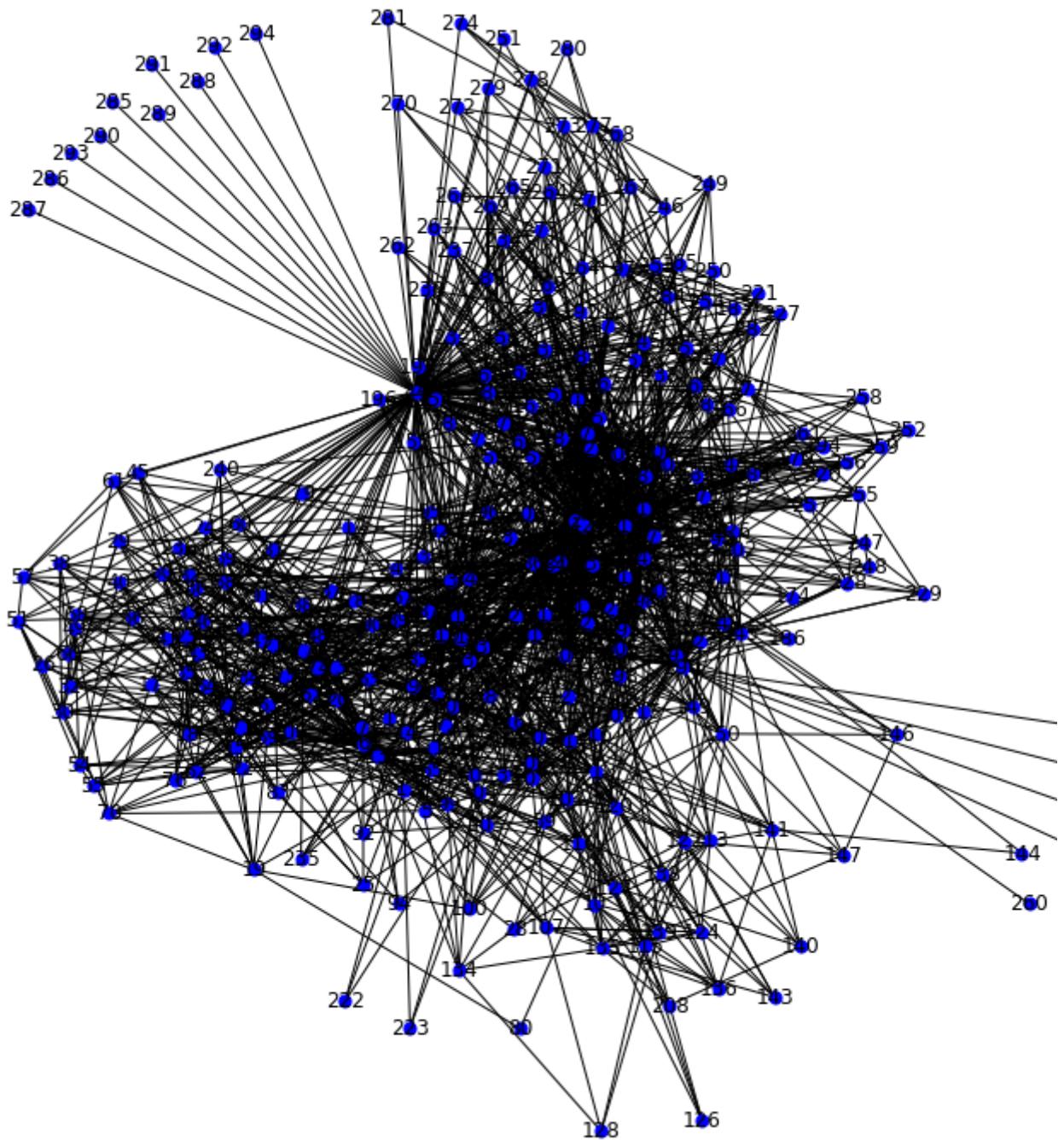
Rede: Hamsterster friendships



```
T = listaIndex[2]
G = listaGraph[2]
print("Rede: ", T)
plota_rede(G, nd_size=50, fig_size=10, n_color = random.randint(0,8))
```



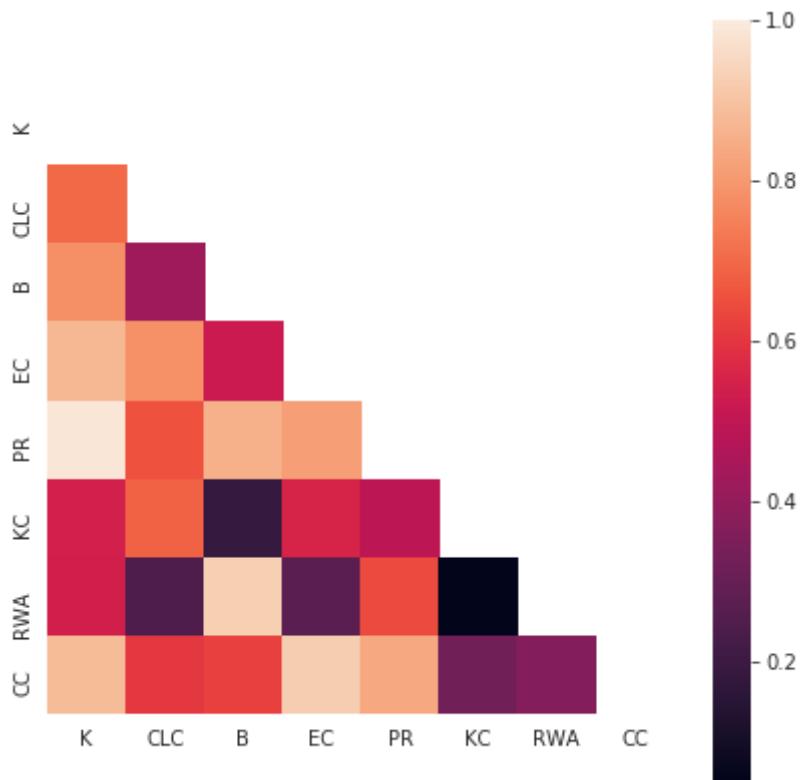
Rede: C.elegans neural network



$\text{ex1}(G, T)$

◻

Matriz de correlações entre
 K Degreee Centrality
 KC Kcore
 CLC Closeness Centrality
 B Betwenesses Centrality
 EC Eigenvector Centrality
 PR Pagerank
 RWA Random Walk Accessibility
 CC Communicability Centrality

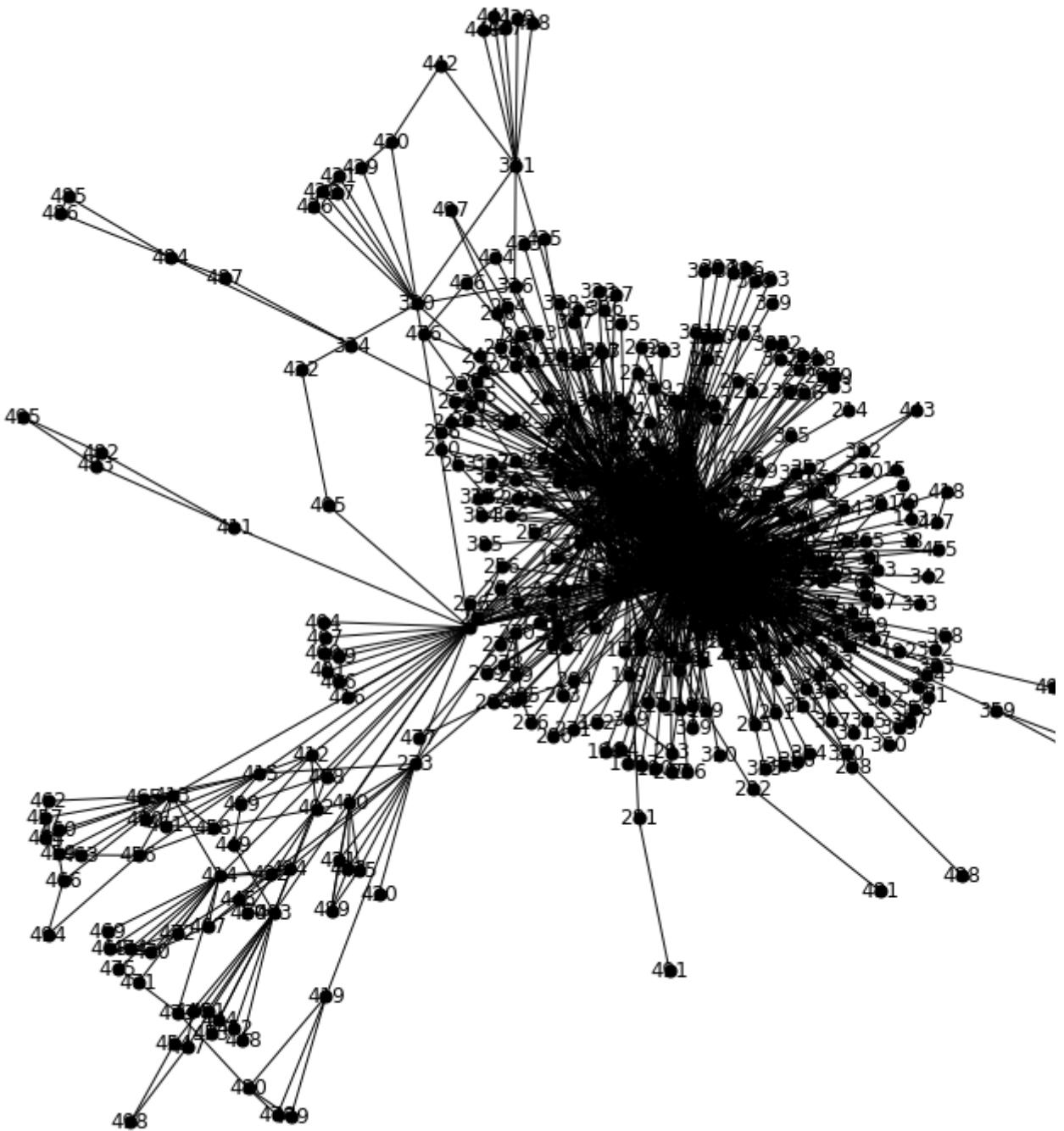


```

T = listaIndex[3]
G = listaGraph[3]
print("Rede: ", T)
plota_rede(G, nd_size=50, fig_size=10, n_color = random.randint(0,8))
  
```



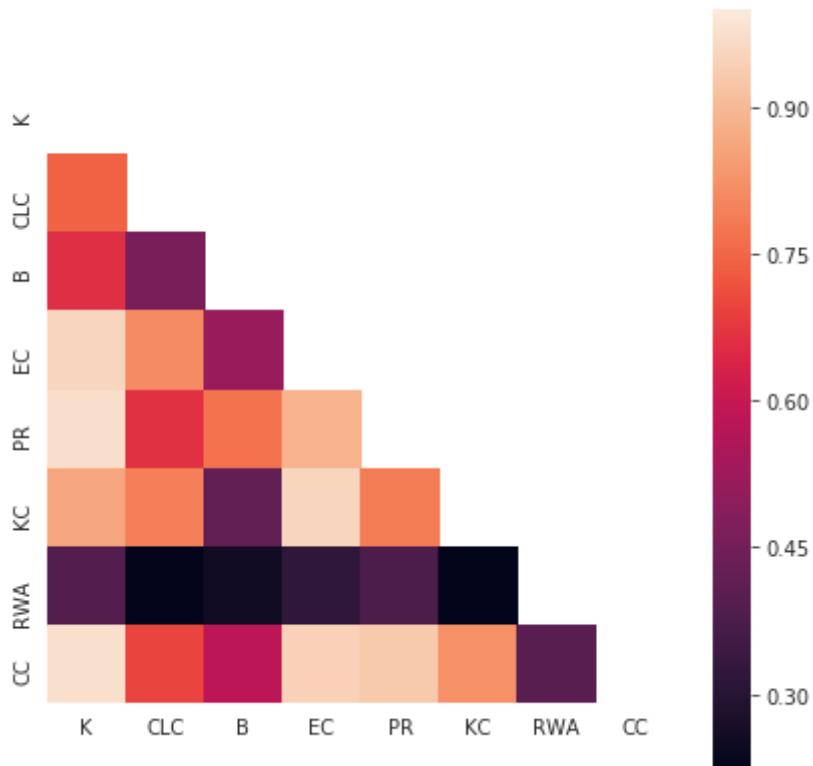
Rede: US airport network



$\text{ex1}(G, T)$



Matriz de correlações entre
 K Degreee Centrality
 KC Kcore
 CLC Closeness Centrality
 B Betwenesses Centrality
 EC Eigenvector Centrality
 PR Pagerank
 RWA Random Walk Accessibility
 CC Communicability Centrality



2 – Choose four dataset of cities (from OSMX or any other dataset) and calculate the centrality measures. That is, construct the histogram of

- (i) degree,**
- (ii) closeness centrality and**
- (iii) betweenness centrality. Discuss which city is easier to navigate in terms of these distributions.**

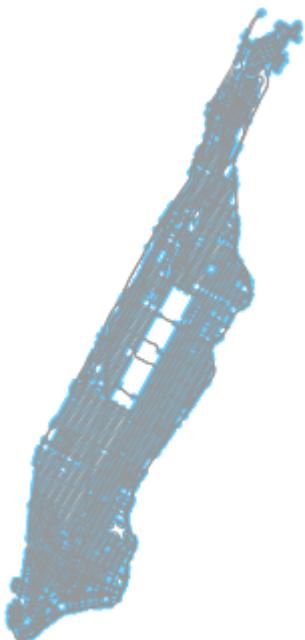
```

listaGraph = list()
listaIndex = ["Manhattan - EUA", "São Carlos - Brasil", "Brest - França", "Veneza - Itália"]

G_manhattan = ox.graph_from_place('Manhattan Island, New York City, New York, USA', network_type='walk')
print("Ilha de Manhattan")
ox.plot_graph(G_manhattan)
listaGraph.append(trata_rede(G_manhattan, multigraph= True, remove_selfedges=False))
  
```

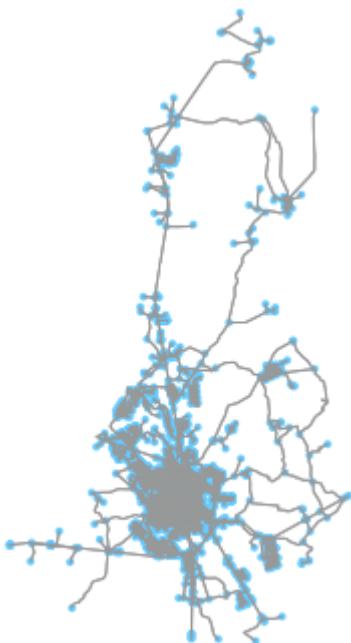


Ilha de Manhattan



```
G_sanca = ox.graph_from_place('São Carlos', network_type='drive')
print("Cidade de São Carlos")
ox.plot_graph(G_sanca)
listaGraph.append(trata_rede(G_sanca, multigraph= True, remove_selfedges=False))
```

↳ Cidade de São Carlos



```
G_brest = ox.graph_from_place('Brest, France', network_type='drive')
print("Cidade de Brest na Bretanha francesa")
ox.plot_graph(G_brest)
listaGraph.append(trata_rede(G_brest, multigraph= True, remove_selfedges=False))
```

↳

Cidade de Brest na Bretanha francesa



```
G_venice = ox.graph_from_place('Venice', network_type='drive')
print("Cidade de Veneza na Itália")
ox.plot_graph(G_venice)
listaGraph.append(trata_rede(G_venice, multigraph= True, remove_selfedges=False))
```

⇨ Cidade de Veneza na Itália



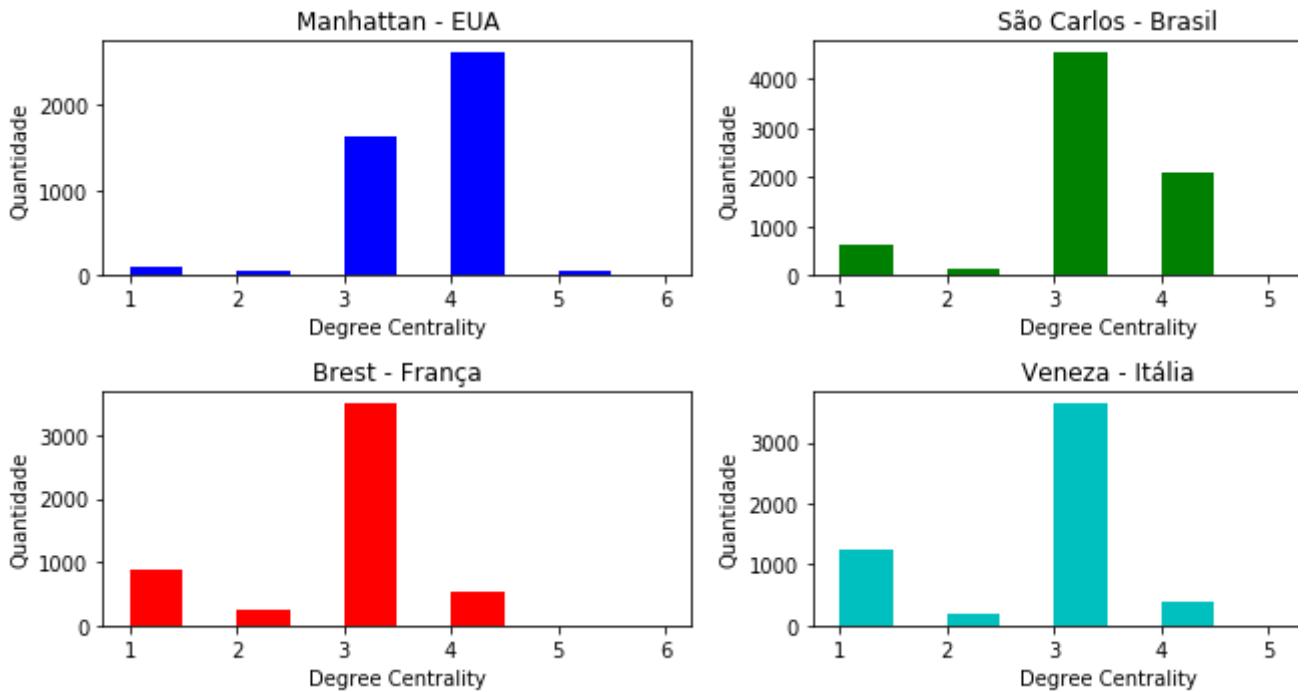
```
print('Histogramas da distribuição de grau de acordo com a cidade')
f,a = plt.subplots(2,2, figsize=(10,5))
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
a = a.ravel()
for idx,ax in enumerate(a):
    ax.hist(degree_centrality(listaGraph[idx]), facecolor=colors[idx])
    ax.set_title(listaIndex[idx])
    ax.set_xlabel("Degree Centrality")
```

```

    ax.set_ylabel("Quantidade")
plt.tight_layout()

```

⇨ Histogramas da distribuição de grau de acordo com a cidade



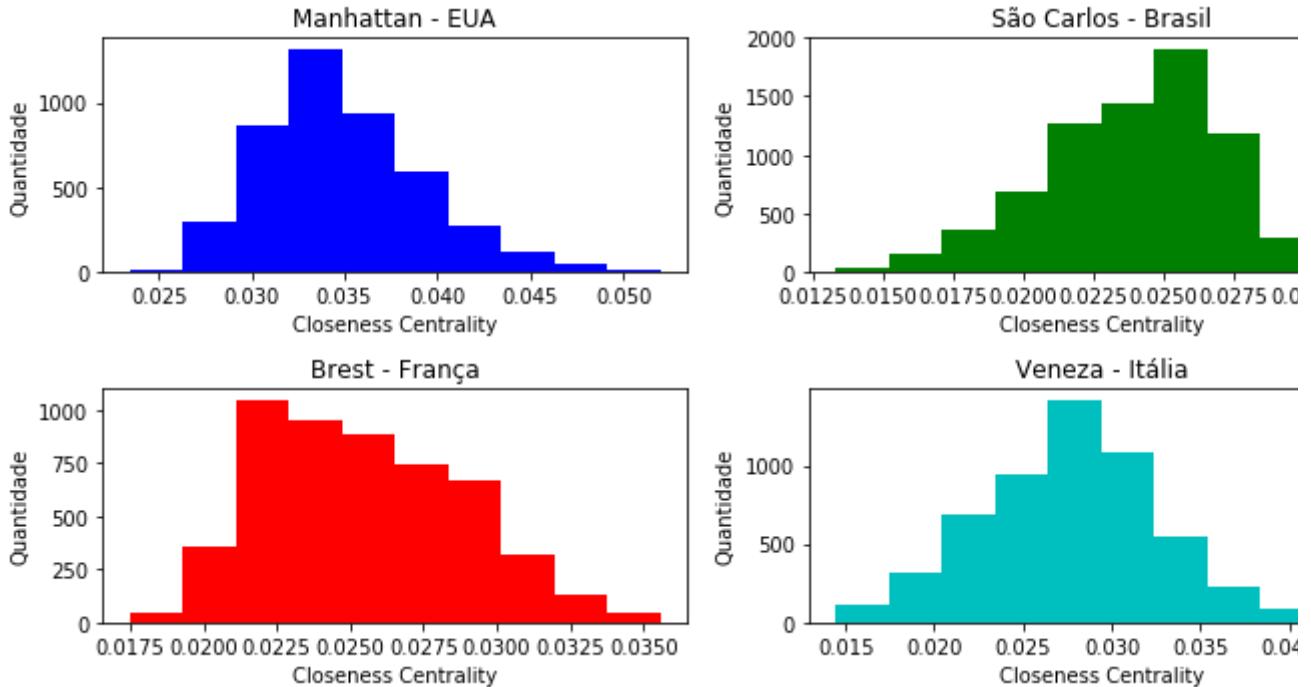
```

print('Histogramas da distribuição de closeness centrality de acordo com a cidade')
f,a = plt.subplots(2,2, figsize=(10,5))
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
a = a.ravel()
for idx,ax in enumerate(a):
    print(round(100*(idx/4),2),"%")
    ax.hist(closeness_centrality(listaGraph[idx]), facecolor=colors[idx])
    ax.set_title(listaIndex[idx])
    ax.set_xlabel("Closeness Centrality")
    ax.set_ylabel("Quantidade")
    clear_output()
print('Histogramas da distribuição de closeness centrality de acordo com a cidade')
plt.tight_layout()

```

⇨

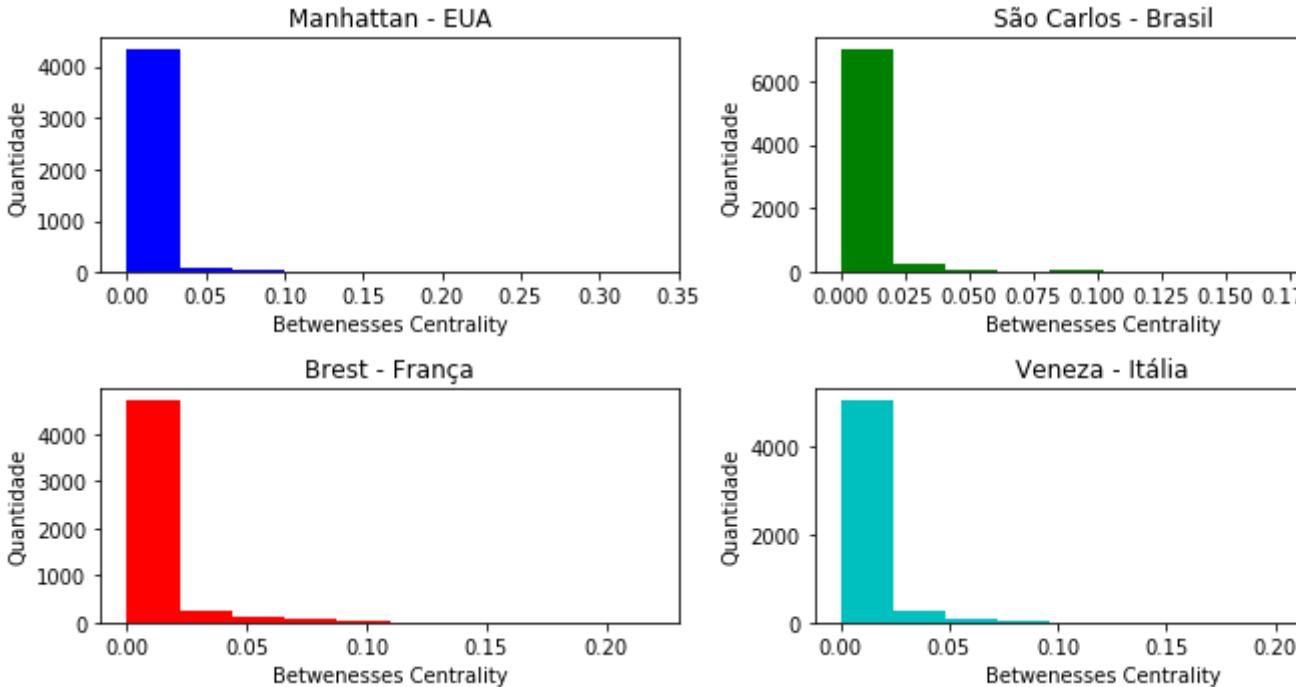
Histogramas da distribuição de closeness centrality de acordo com a cidade



```
print('Histogramas da distribuição de betwenesses centrality de acordo com a cidade')
f,a = plt.subplots(2,2, figsize=(10,5))
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
a = a.ravel()
for idx,ax in enumerate(a):
    print(round(100*(idx/4),2),"%")
    ax.hist(betweenness_centrality(listaGraph[idx]), facecolor=colors[idx])
    ax.set_title(listaIndex[idx])
    ax.set_xlabel("Betwenesses Centrality")
    ax.set_ylabel("Quantidade")
    clear_output()
print('Histogramas da distribuição de betwenesses centrality de acordo com a cidade')
plt.tight_layout()
```



Histogramas da distribuição de betwenesses centrality de acordo com a cidade



▼ 3 – For the following networks:

- Human protein network (<http://konect.cc/networks/maayan-vidal>)
- C. elegans protein network 2007 (http://interactome.dfci.harvard.edu/C_elegans/index.php)
- C. elegans protein network 2004 (http://interactome.dfci.harvard.edu/C_elegans/index.php)
- Western US power grid (<http://wwwpersonal.umich.edu/~mejn/netdata/power.zip>)
- R dependency network (<http://www.mas.ncl.ac.uk/~ncsg3/blog/dependencies.csv>)

▼ Construct the histogram of the centrality measures and compare them. Use the measures

- degree,
- eigenvector centrality,
- pagerank and
- closeness centrality.

Are there similarities between networks of the same type, such as among technological or biological networks?

```
listaGraph = list()
listaIndex = ["Human protein network", "C. elegans protein network 2007", "C. elegans prot
"Western US power grid ", "R dependency network"]

G_maayan_vidal = nx.read_edgelist("maayan-vidal.edges", nodetype=int)
```

```

listaGraph.append(trata_rede(G_maayan_vidal))

G_protein_2007 = nx.read_edgelist("protein2007.edges")
listaGraph.append(trata_rede(G_protein_2007))

G_protein_2005 = nx.read_edgelist("protein2005.edges")
listaGraph.append(trata_rede(G_protein_2005))

G_powergrid = nx.read_edgelist("powergrid.edges", nodetype = int)
listaGraph.append(trata_rede(G_powergrid))

df = pd.read_csv("dependencies.csv")
G_R_dep = nx.Graph()
for i in range(len(df)): G_R_dep.add_edge(df.iloc[i,1],df.iloc[i,2])
listaGraph.append(trata_rede(G_R_dep))

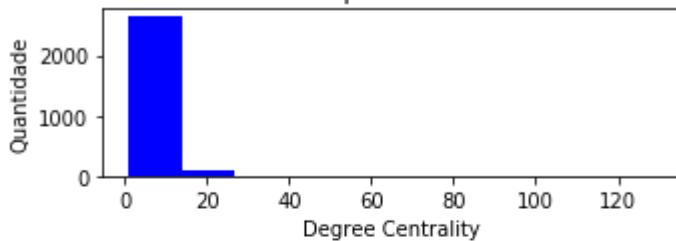
print('Histogramas da distribuição de grau de acordo com cada rede')
f,a = plt.subplots(5,1, figsize=(5,10))
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
a = a.ravel()
for idx,ax in enumerate(a):
    ax.hist(degree_centrality(listaGraph[idx]), facecolor=colors[idx])
    ax.set_title(listaIndex[idx])
    ax.set_xlabel("Degree Centrality")
    ax.set_ylabel("Quantidade")
plt.tight_layout()

```

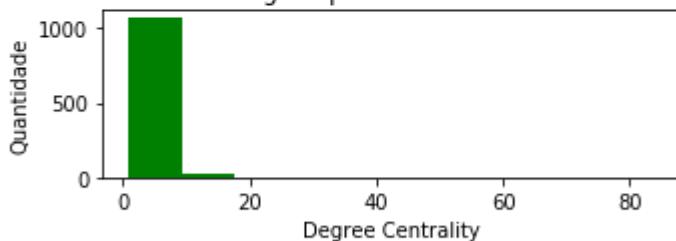


Histogramas da distribuição de grau de acordo com cada rede

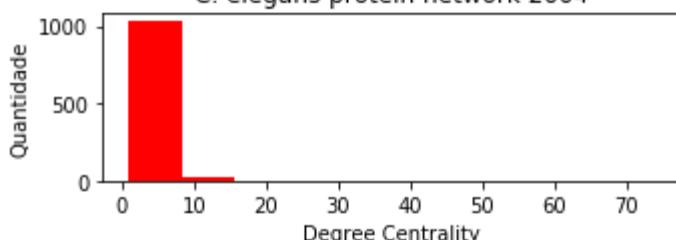
Human protein network



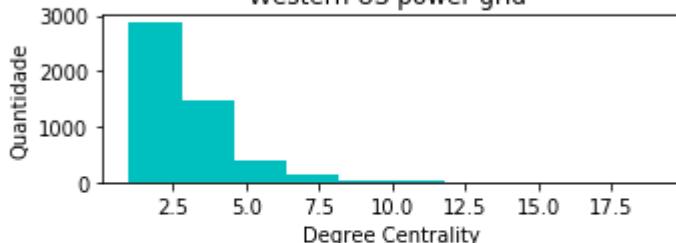
C. elegans protein network 2007



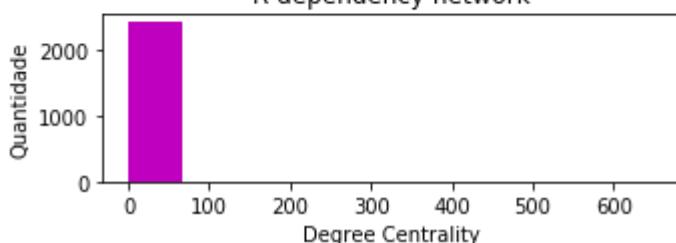
C. elegans protein network 2004



Western US power grid

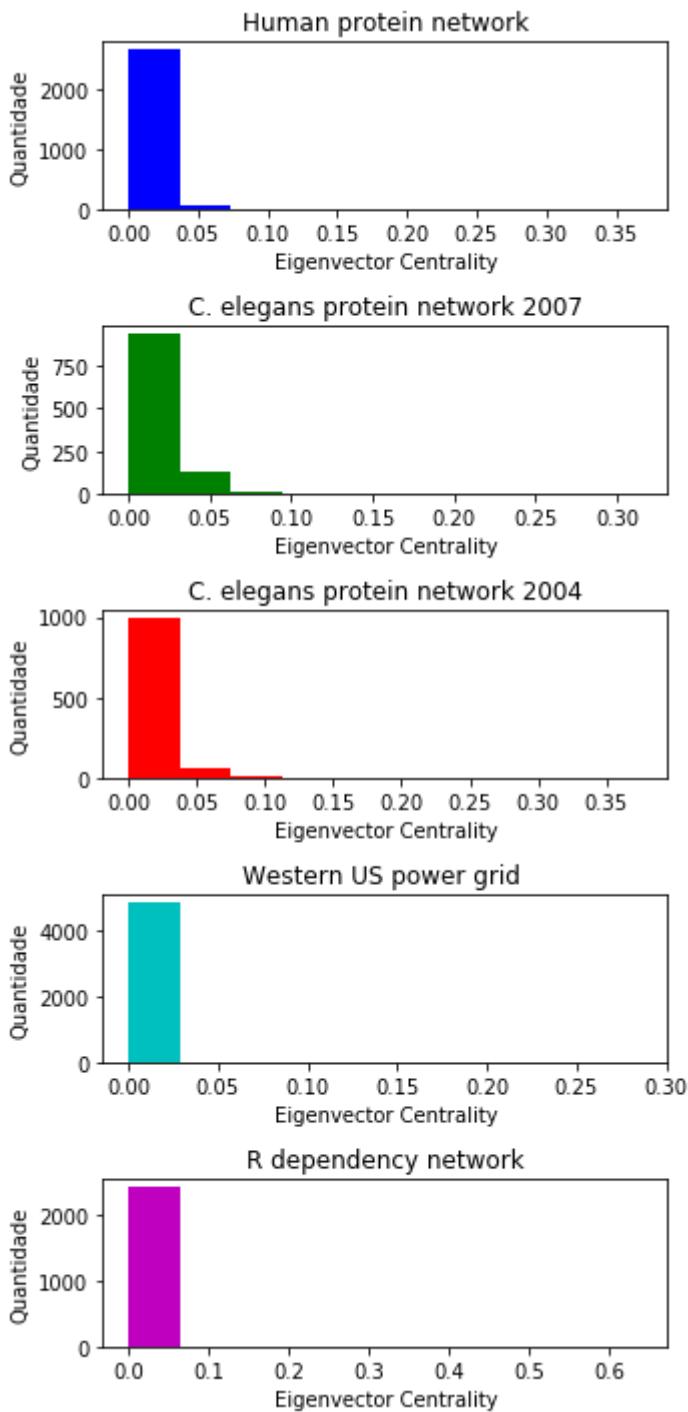


R dependency network



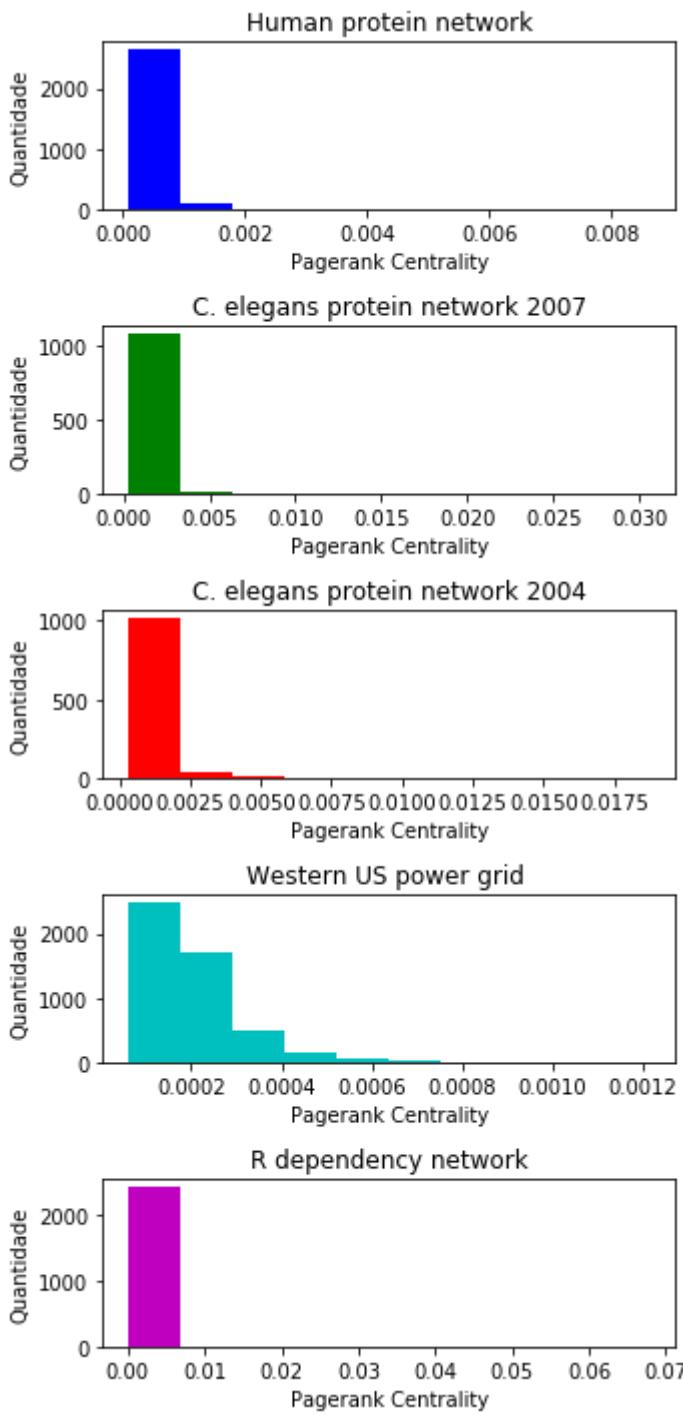
```
print('Histogramas da distribuição de eigenvector centrality de acordo com cada rede')
f,a = plt.subplots(5,1, figsize=(5,10))
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
a = a.ravel()
for idx,ax in enumerate(a):
    print(round(100*(idx/4),2),"%")
    ax.hist(eigenvector_centrality(listaGraph[idx]), facecolor=colors[idx])
    ax.set_title(listaIndex[idx])
    ax.set_xlabel("Eigenvector Centrality")
    ax.set_ylabel("Quantidade")
    clear_output()
print('Histogramas da distribuição de eigenvector centrality de acordo com cada rede')
plt.tight_layout()
```

⇨ Histogramas da distribuição de eigenvector centrality de acordo com cada rede



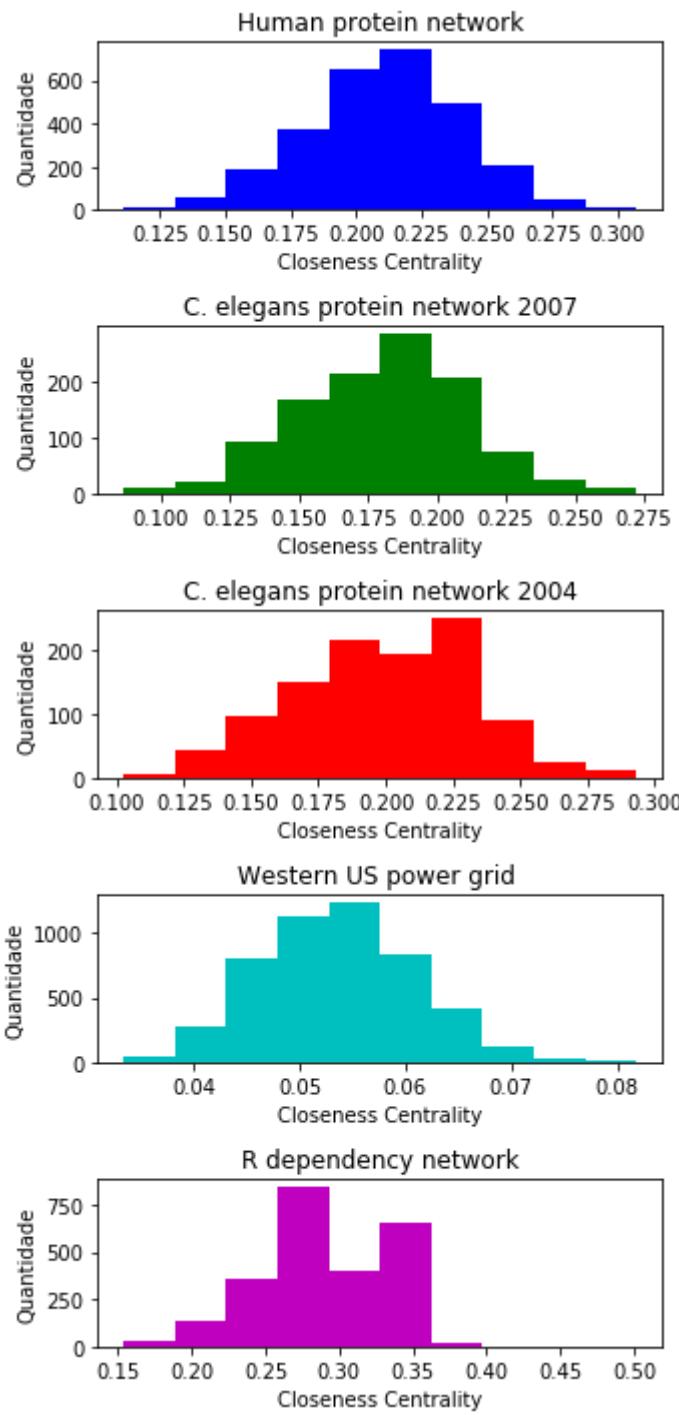
```
print('Histogramas da distribuição de pagerank centrality de acordo com cada rede')
f,a = plt.subplots(5,1, figsize=(5,10))
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
a = a.ravel()
for idx,ax in enumerate(a):
    print(round(100*(idx/4),2),"%")
    ax.hist(pagerank(listaGraph[idx]), facecolor=colors[idx])
    ax.set_title(listaIndex[idx])
    ax.set_xlabel("Pagerank Centrality")
    ax.set_ylabel("Quantidade")
    clear_output()
print('Histogramas da distribuição de pagerank centrality de acordo com cada rede')
plt.tight_layout()
```

⇨ Histogramas da distribuição de pagerank centrality de acordo com cada rede



```
print('Histogramas da distribuição de closeness centrality de acordo com cada rede')
f,a = plt.subplots(5,1, figsize=(5,10))
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
a = a.ravel()
for idx,ax in enumerate(a):
    print(round(100*(idx/4),2),"%")
    ax.hist(closeness_centrality(listaGraph[idx]), facecolor=colors[idx])
    ax.set_title(listaIndex[idx])
    ax.set_xlabel("Closeness Centrality")
    ax.set_ylabel("Quantidade")
    clear_output()
print('Histogramas da distribuição de closeness centrality de acordo com cada rede')
plt.tight_layout()
```

⇨ Histogramas da distribuição de closeness centrality de acordo com cada rede



▼ 4 – Consider the networks in the last exercise. For each network, consider

- (i) degree,
- (ii) k-core,
- (iii) closeness centrality,
- (iv) betweenness centrality,
- (v) eigenvector centrality,

(vi) pagerank,

(vi) random walk accessibility,

(v) communicability centrality.

And for each measure, calculate:

(i) average,

(ii) standard deviation,

(iii) second moment,

(iii) Shannon entropy.

Thus, each network will be represented by a feature vector with 20 elements. Project the netw Principal Component Analysis (PCA). Discuss the similarities of the networks in terms of their

```
def momment_of_degree_distribution(m):
    return(np.sum(m**2) / len(m))
```

```
def shannon_entropy(m):
    value,counts = np.unique(m, return_counts=True)
    pk = counts / counts.sum()
    H = st.entropy(counts, base=2)
    return H
```

```
def ex4(measure):
    return np.mean(measure), stats.stdev(measure) , momment_of_degree_distribution(measure)
```

```
matrix_values = np.zeros((5, 8*4))
```

```
for i in range(len(listaGraph)):
    G = listaGraph[i]
    print("Network ",listaIndex[i])
```

```
VK = np.asarray(degree_centrality(G))
matrix_values[i,0],matrix_values[i,1],matrix_values[i,2],matrix_values[i,3] = ex4(VK)
print("\n VK", VK)
```

```
KC = np.asarray(kcore(G))
matrix_values[i,4],matrix_values[i,5],matrix_values[i,6],matrix_values[i,7] = ex4(KC)
print("\n KC", KC)
```

```
CLC = np.asarray(closeness_centrality(G))
matrix_values[i,8],matrix_values[i,9],matrix_values[i,10],matrix_values[i,11] = ex4(CLC)
print("\n CLC", CLC)
```

```
B = np.asarray(betweenness_centrality(G))
matrix_values[i,12],matrix_values[i,13],matrix_values[i,14],matrix_values[i,15] = ex4(B)
print("\n B", B)
```

```

EC = np.asarray(eigenvector_centrality(G))
matrix_values[i,16],matrix_values[i,17],matrix_values[i,18],matrix_values[i,19] = ex4(EC)
print("\n EC", EC)

PR = np.asarray(pagerank(G))
matrix_values[i,20],matrix_values[i,21],matrix_values[i,22],matrix_values[i,23] = ex4(PR)
print("\n PR", PR)

RWA = np.asarray(random_walk_accessibility(G))
matrix_values[i,24],matrix_values[i,25],matrix_values[i,26],matrix_values[i,27] = ex4(RWA)
print("\n RWA", RWA)

CC = np.asarray(communicability_centrality(G))
matrix_values[i,28],matrix_values[i,29],matrix_values[i,30],matrix_values[i,31] = ex4(CC)
print("\n CC", CC)

clear_output()

df = pd.DataFrame(matrix_values)
names = pd.DataFrame(listaIndex)

# Standardizing the features
x = StandardScaler().fit_transform(df)

pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents
                           , columns = ['principal component 1', 'principal component 2'])

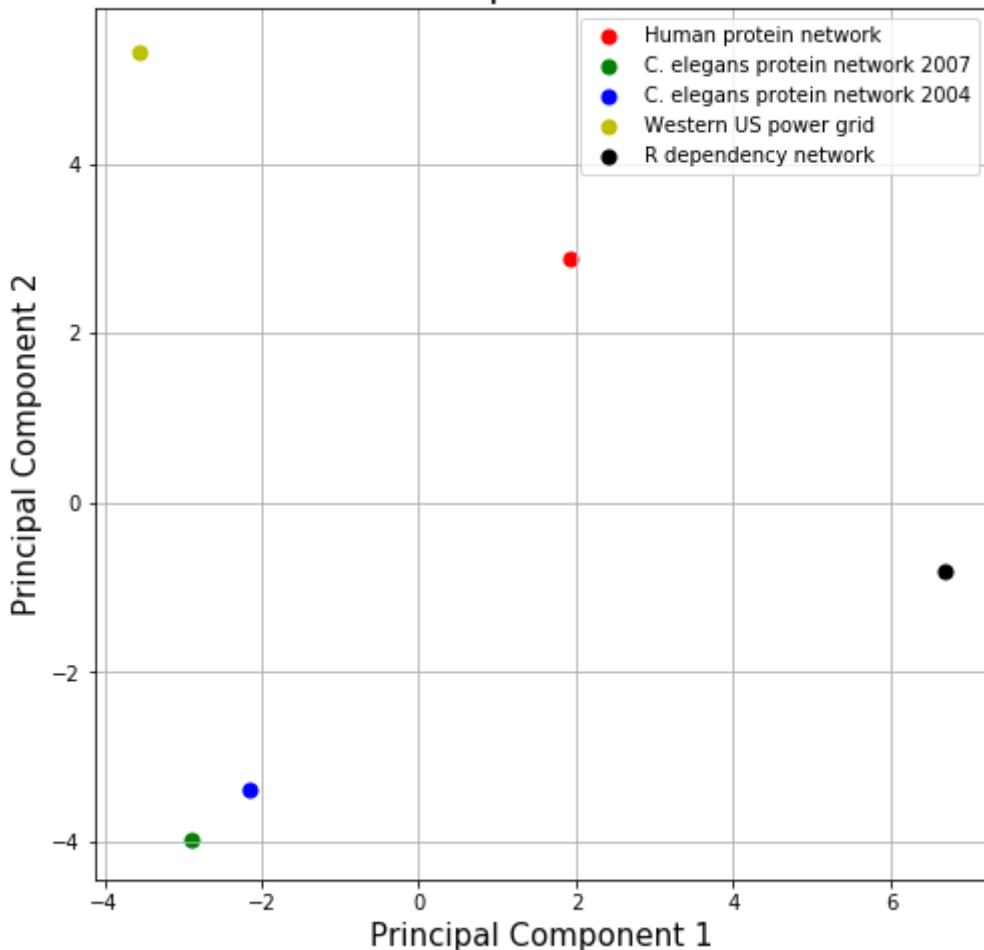
finalDf = pd.concat([principalDf, names],axis=1)

fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
targets = ["Human protein network", "C. elegans protein network 2007", "C. elegans protein network 2003", "Western US power grid ", "R dependency network"]
colors = ['r', 'g', 'b', 'y', 'k']
for target, color in zip(targets,colors):
    indicesToKeep = finalDf[0] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
              , finalDf.loc[indicesToKeep, 'principal component 2']
              , c = color
              , s = 50)
ax.legend(targets)
ax.grid()

```



2 component PCA



▼ 5 – For the following networks:

- a) E-road network (http://konect.cc/networks/subelj_euroroad),
- b) C. elegans neural network (<http://www-personal.umich.edu/~mejn/netdata/celegansneural>)
- c) US airport network (<http://toreopsahl.com/datasets/#usairports>)
- d) Human protein network (<http://konect.cc/networks/maayan-vidal>)

Obtain the scatterplot of knn(k) X k and calculate the Pearson correlation coefficient between assortativity coefficient. Comment the results.

```

listaGraph = list()
listaIndex = ["E-road network", "C. elegans neural network", "US airport network ", "Human
G_eroad = nx.read_edgelist("eroad.edges", nodetype=int, data=(('weight',int),))
listaGraph.append(trata_rede(G_eroad))

G_celneural = nx.read_gml("celegansneural.gml")
listaGraph.append(trata_rede(G_celneural, multigraph = True))

G_usaairport = nx.read_edgelist("usaairport.edges", nodetype=int, data=(('weight',int),))

```

```

listaGraph.append(trata_rede(G_usaairport))

G_maayan_vidal = nx.read_edgelist("maayan-vidal.edges", nodetype=int)
listaGraph.append(trata_rede(G_maayan_vidal))

def ex5(G):
    knn = []
    for i in G.nodes():
        aux = nx.average_neighbor_degree(G, nodes = [i])
        knn.append(float(aux[i]))
    knn = np.array(knn)
    vk = dict(G.degree())
    vk = list(vk.values())
    knnk = list()
    ks = list()
    for k in arange(np.min(vk), np.max(vk)):
        aux = vk == k
        if(len(knn[aux]) > 0):
            av_knn = mean(knn[aux]) #average clustering among all the nodes with degree k
            knnk.append(av_knn)
            ks.append(k)
    plt.plot(ks, knnk, 'ro')
    #plt.loglog(ks,knnk,'bo', basex=10, basey=10)
    #plt.title("Average neighborhood connectivity vs degree")
    plt.ylabel("knn(k)")
    plt.xlabel("k")
    plt.grid(True)
    #plt.savefig('knnk.eps')

    # determine best fit line
    par = np.polyfit(ks, knnk, 1, full=True)
    slope=par[0][0]
    intercept=par[0][1]
    xl = [min(ks), max(ks)]
    yl = [slope*xx + intercept for xx in xl]
    plt.plot(xl, yl, '-b')

    #plt.savefig('knn.eps') #save the figure into a file
    plt.show(True)

    rho = corrcoef(ks, knnk)[0,1]
    print('Pearson correlation coefficient:', rho)

    r=nx.degree_assortativity_coefficient(G)
    print("Assortativity = ", "%3.4f"%r)
    return rho,r

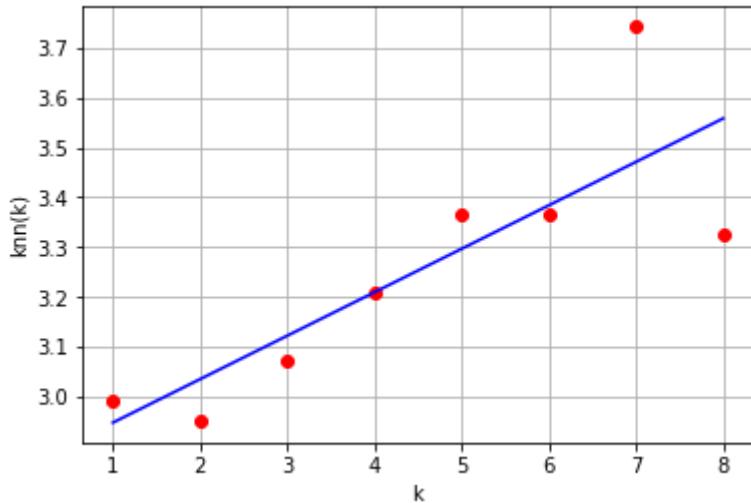
matrix_values = np.zeros((4,2))

print(listaIndex[0])
matrix_values[0,0],matrix_values[0,1] = ex5(listaGraph[0])

```



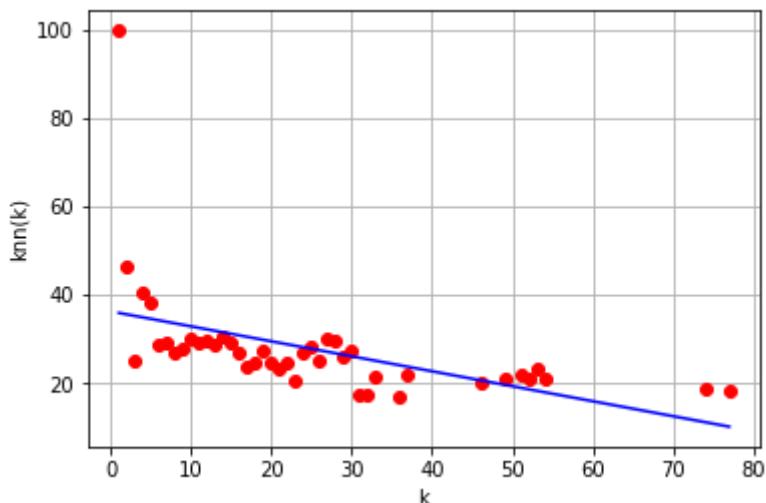
E-road network



Pearson correlation coefficient: 0.8296047846722235
Assortativity = 0.0900

```
print(listaIndex[1])
matrix_values[1,0],matrix_values[1,1] = ex5(listaGraph[1])
```

C. elegans neural network

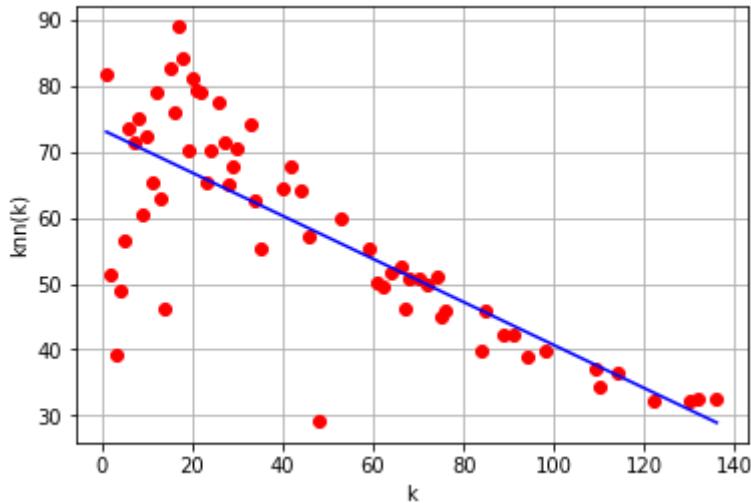


Pearson correlation coefficient: -0.4947811319324024
Assortativity = -0.1632

```
print(listaIndex[2])
matrix_values[2,0],matrix_values[2,1] = ex5(listaGraph[2])
```

?

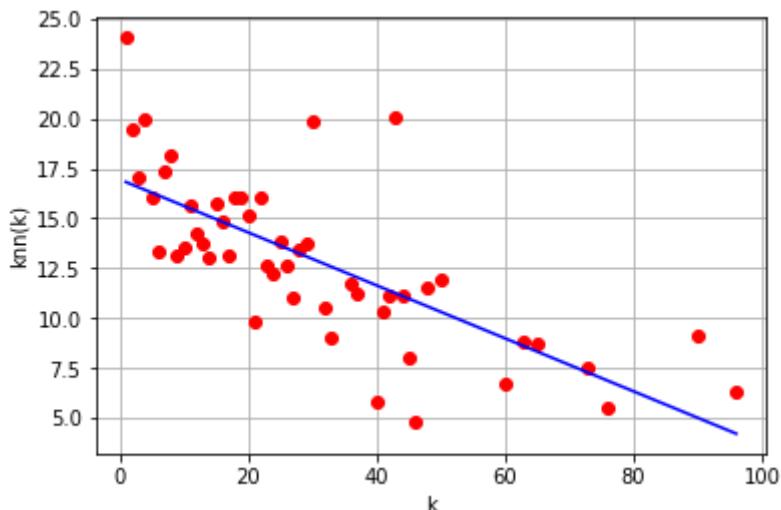
US airport network



Pearson correlation coefficient: -0.7756491513624391
Assortativity = -0.2679

```
print(listaIndex[3])
matrix_values[3,0],matrix_values[3,1] = ex5(listaGraph[3])
```

Human protein network

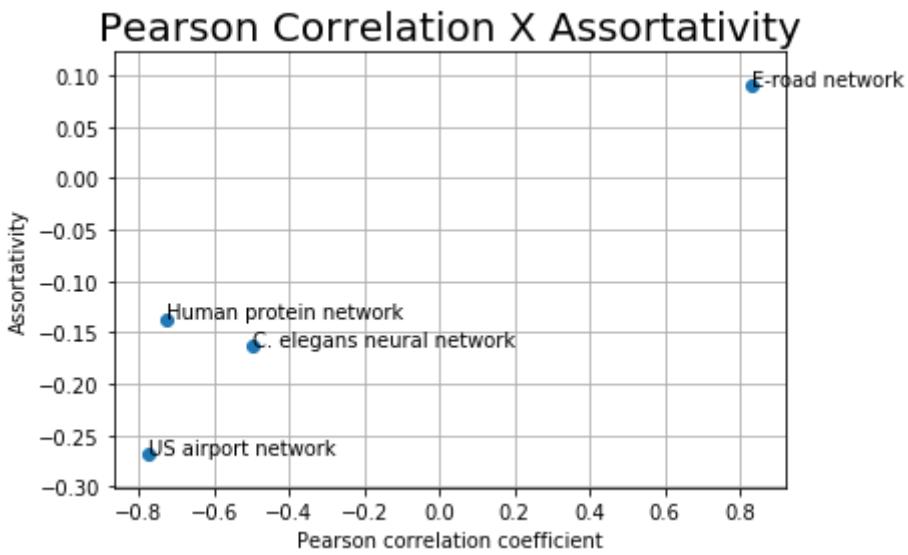


Pearson correlation coefficient: -0.7264791351157311
Assortativity = -0.1366

```
df = pd.DataFrame(matrix_values, columns = ["Pearson correlation coefficient", "Assortativity"])
names = pd.DataFrame(listaIndex, columns = ["Networks"])
df = pd.concat([df, names], axis=1)
```

```
fig, ax = plt.subplots()
ax.scatter(df["Pearson correlation coefficient"], df["Assortativity"])
ax.set_title('Pearson Correlation X Assortativity', fontsize = 20)
plt.ylabel("Assortativity")
plt.xlabel("Pearson correlation coefficient")
plt.grid(True)
for i, txt in enumerate(listaIndex):
    ax.annotate(txt, (df["Pearson correlation coefficient"][i], df["Assortativity"][i]))
```





▼ 6 – Construct the Givan-Newman benchmark (N=128, kin+kout = 16 and $\epsilon = 0.05$)

You can use:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.LFR_benchmark_graph.html

Compare the following methods:

Fastgreedy:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.modularity_communities.html#networkx.algorithms.community.modularity_max.greedy_modularity_max

Label propagation:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.community_label_propagation.html#networkx.algorithms.community_label_propagation.label_propagation

Givan Newman:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.community.centrality.girvan_newman.html#networkx.algorithms.community.centrality.girvan_newman

Louvain: <https://github.com/taynaud/python-louvain>

Use the normalized mutual information as a measure of accuracy.

```
def drawing_graph_and_communities(G,partition, T):
    #drawing
    plt.figure(figsize=(10,10))
    colors = []
    for i in range(max(list(partition.values())) + 5):
        colors.append('#%06X' % randint(0, 0xFFFFFF))
    #colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
    size = float(len(set(partition.values())))
    #size = len(partition)
    pos = nx.spring_layout(G, k=1.5, iterations=T)
    nx.draw(G, pos, node_color=[colors[partition.get(n)] for n in G.nodes()],
            node_size=[size for n in G.nodes()])
    nx.draw_networkx_labels(G, pos)
```

```

count = 0.
pos=nx.spring_layout(G)
for com in set(partition.values()) :
    count = count + 1.
    list_nodes = [nodes for nodes in partition.keys() if partition[nodes] == com]
    nx.draw_networkx_nodes(G, pos, list_nodes, node_size = 50, node_color = colors[int(com)])
nx.draw_networkx_edges(G, pos, alpha=0.5)
plt.title(T)
plt.show()

def greedy(G, draw = True):
    p = greedy_modularity_communities(G)

    p = ([list(x) for x in p])

    partition_greedy = {}
    for i in range(len(p)):
        for j in range(len(p[i])):
            partition_greedy[p[i][j]] = i

    if draw: drawing_graph_and_communities(G,partition_greedy,"Modularity Method: FastGreedy")
    return partition_greedy

def label(G, draw = True):
    p = nx.algorithms.community.label_propagation.label_propagation_communities(G)
    p = ([list(x) for x in p])

    partition_label = {}
    for i in range(len(p)):
        for j in range(len(p[i])):
            partition_label[p[i][j]] = i

    if draw: drawing_graph_and_communities(G,partition_label, "Modularity Method: Label Prop")
    return partition_label

def givan_newman_method(G,k, draw = True):
    communities = community.girvan_newman(G)
    for i in arange(0, k-1):
        next_level_communities = next(communities)
    p = sorted(map(sorted, next_level_communities))

    partition_givan_newman = {}
    for i in range(len(p)):
        for j in range(len(p[i])):
            partition_givan_newman[p[i][j]] = i
    if draw : drawing_graph_and_communities(G,partition_givan_newman, "Modularity Method: Giv")
    return partition_givan_newman

def louvain(G, draw = True):
    partition_lovain = community_louvain.best_partition(G)
    if draw: drawing_graph_and_communities(G,partition_lovain, "Modularity Method: Louvain ")
    return partition_lovain

```

```

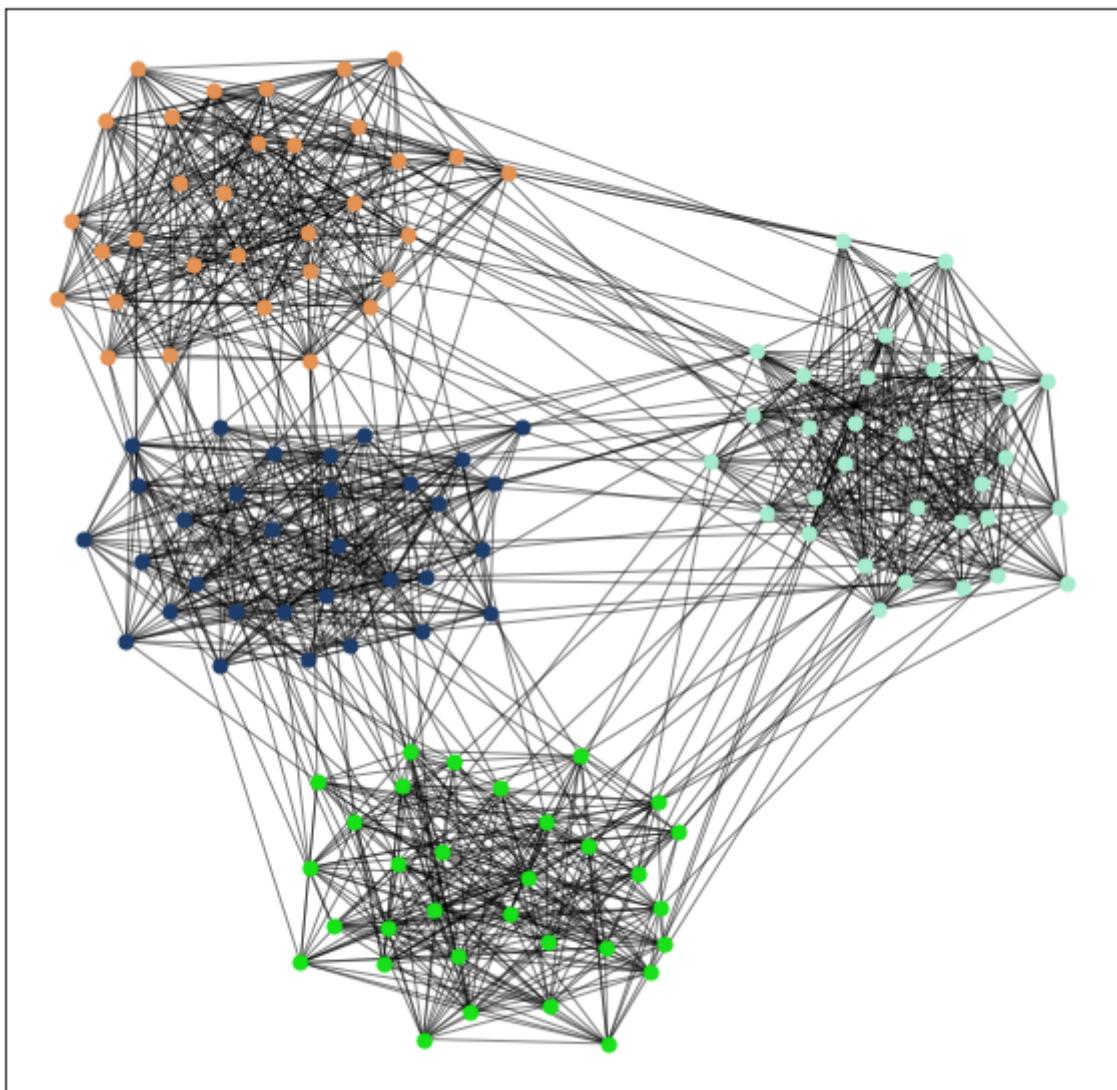
N = 128
tau1 = 3
tau2 = 1.5
mu = 0.04
k = 16
minc = 32
maxc = 32
G_benchmark_graph = LFR_benchmark_graph(n = N, tau1 = tau1, tau2 = tau2, mu = mu, min_degr
    max_degree = k, min_community=minc, max_community = maxc, seed = 1
communities = {frozenset(G_benchmark_graph.nodes[v]['community']) for v in G_benchmark_gra
p = ([list(x) for x in communities])

partition_communities = {}
for i in range(len(p)):
    for j in range(len(p[i])):
        partition_communities[p[i][j]] = i
drawing_graph_and_communities(G_benchmark_graph,partition_communities, "LFT Communities")

```

↳

LFT Communities



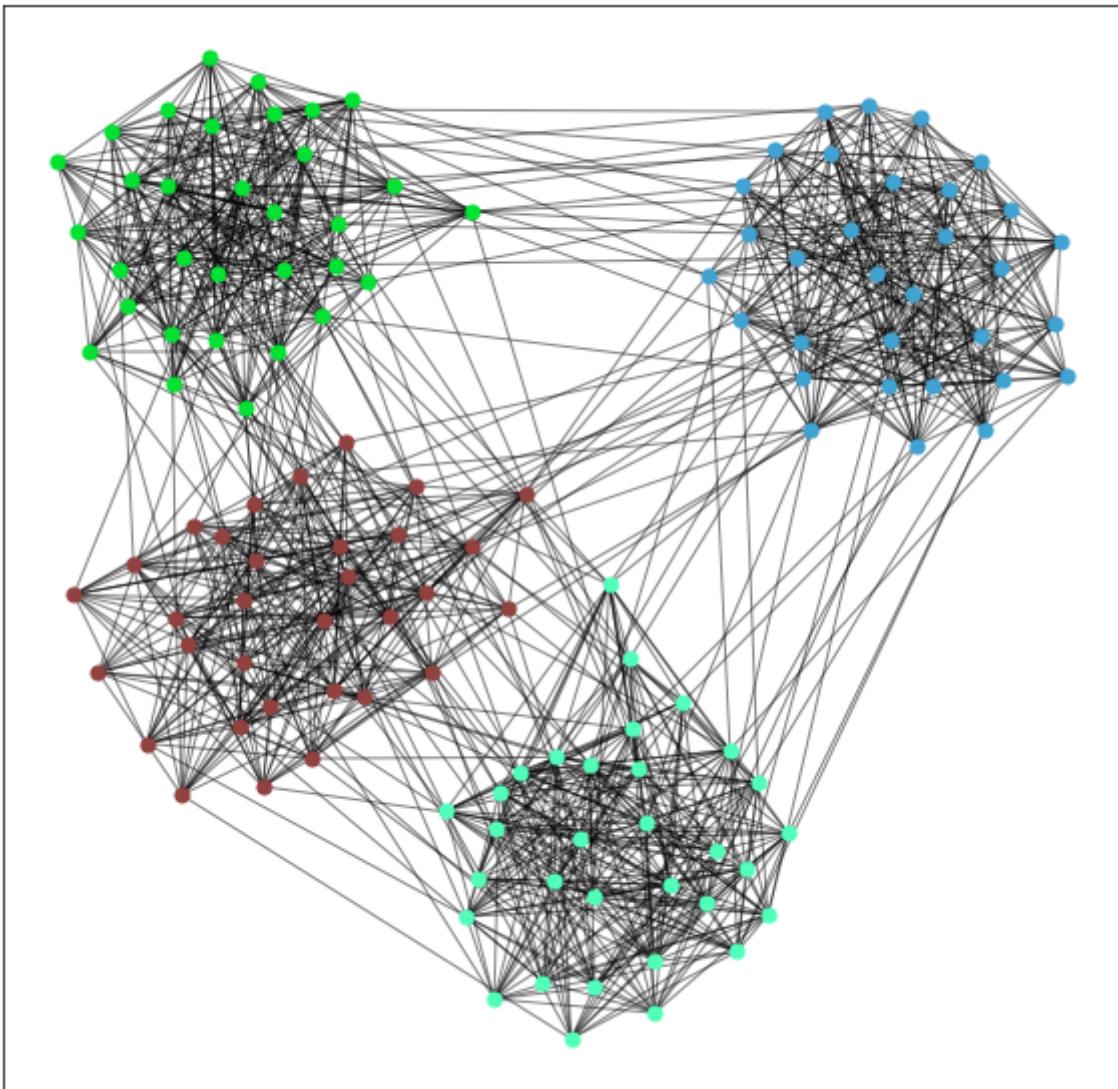
```

listaClusters = list()
partition_greedy = greedy(G_benchmark_graph)
listaClusters.append(partition_greedy)

```

↳

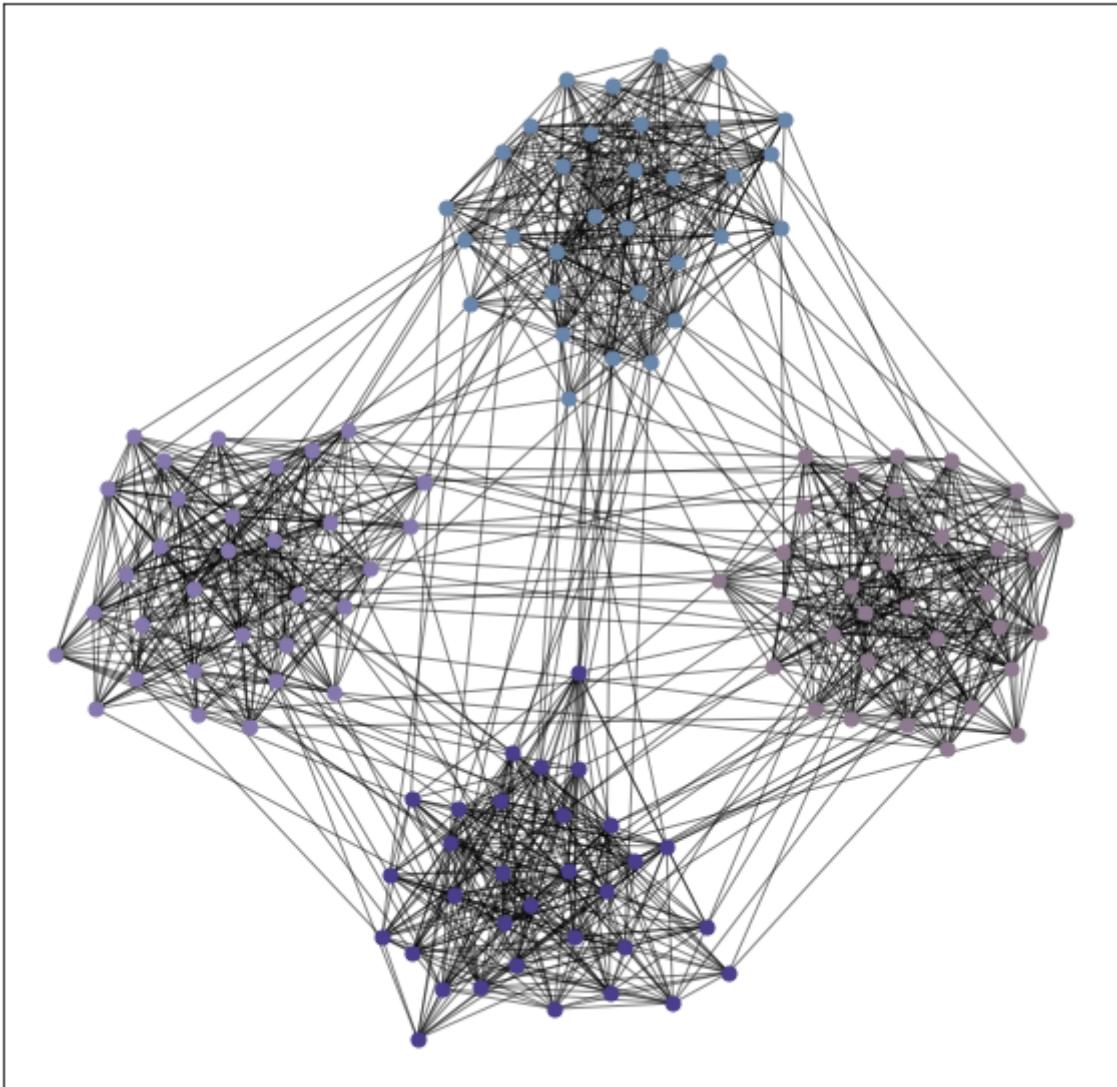
Modularity Method: FastGreedy



```
partition_label = label(G_benchmark_graph)
listaClusters.append(partition_label)
```



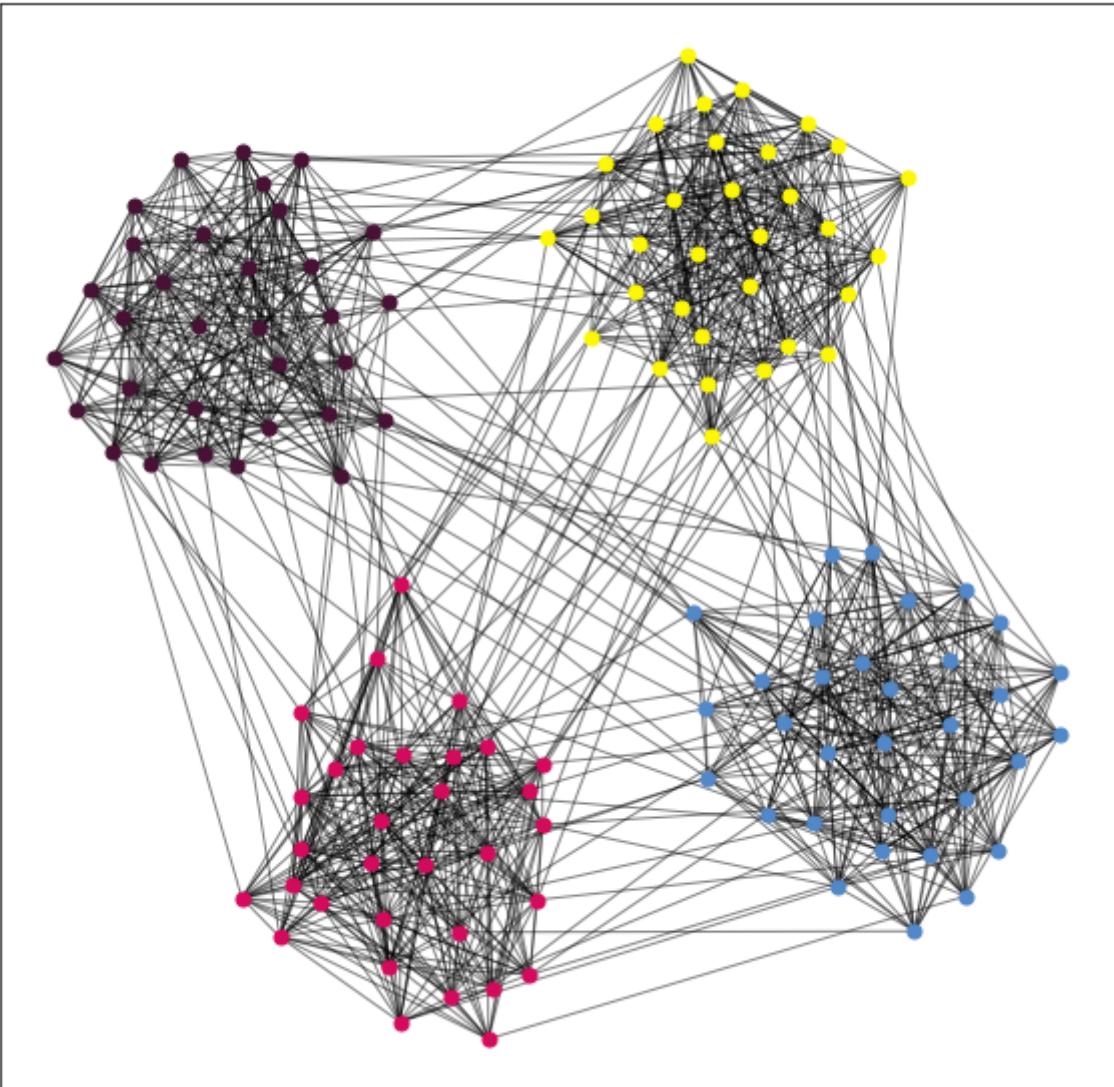
Modularity Method: Label Propagation



```
partition_givan_newman = givan_newman_method(G_benchmark_graph,4)
listaClusters.append(partition_givan_newman)
```



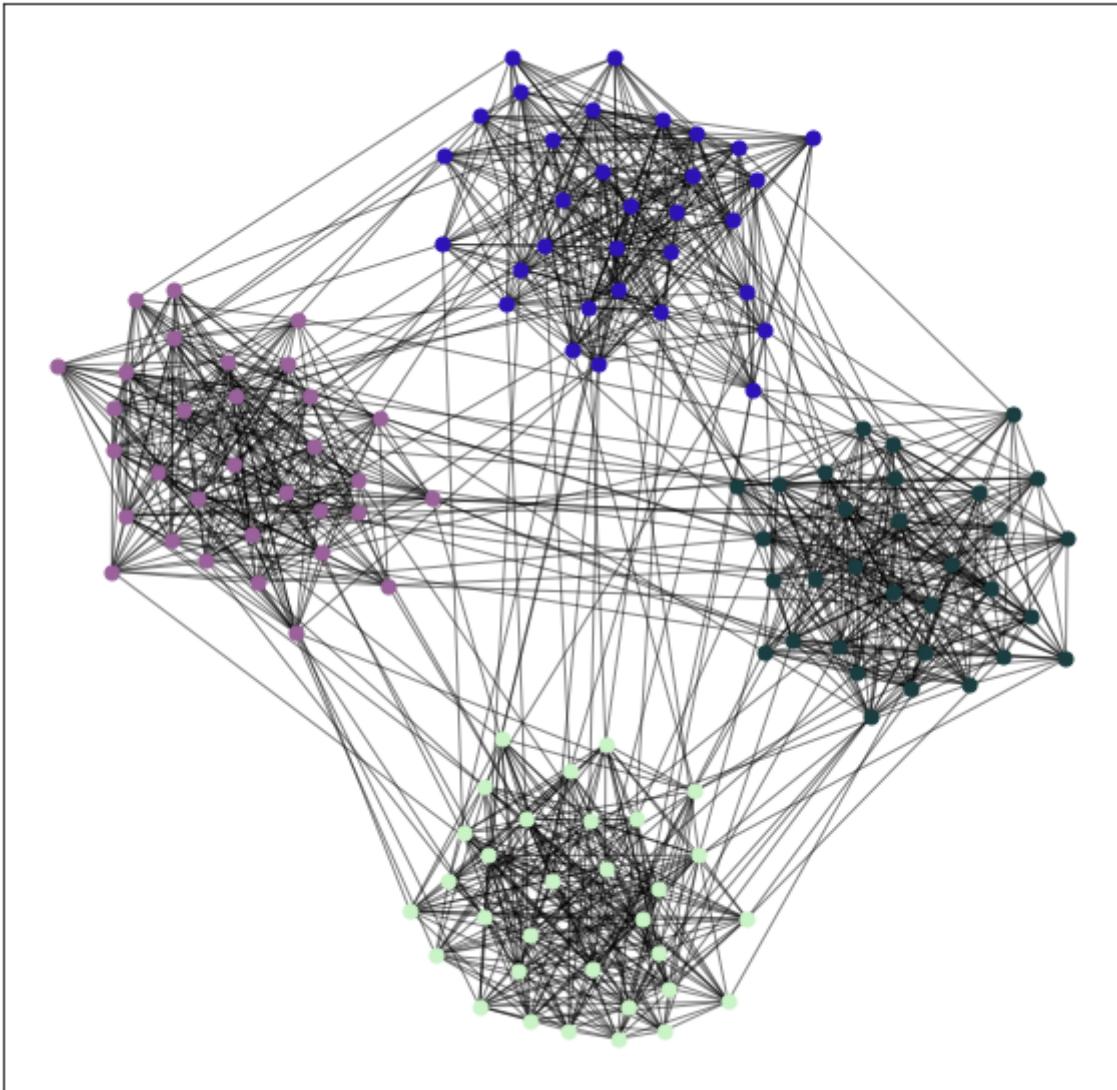
Modularity Method: Givan Newman



```
partition_louvain = louvain(G_benchmark_graph)
listaClusters.append(partition_louvain)
```



Modularity Method: Louvain



```
matrix_values = np.zeros((len(listaClusters[0]),len(listaClusters) ))
for i in range(len(listaClusters)):
    for j in range(len(listaClusters[i])):
        matrix_values[j,i] = listaClusters[i][j]
df = pd.DataFrame(matrix_values)
matrix_values = np.zeros((len(partition_communities)))
for i in range(len(partition_communities)):
    matrix_values[i] = partition_communities[i]
matrix_final = np.zeros((4))
for i in range(4):
    matrix_final[i] = normalized_mutual_info_score(df[i],matrix_values)
final_df = pd.DataFrame(matrix_final, columns = ["Communities"], index = ["FastGreedy", "Louvain", "GirvanNewman", "Spectral"])
print("Normalized Mutual Information Score between each clustering method")
final_df
```



Normalized Mutual Information Score between each clustering method

Communities	
FastGreedy	1.0
Label_propagation	1.0
Givan_Newman	1.0
Louvain	1.0

▼ 7 –Consider the methods for community identification:

Netcarto: <https://amaral.northwestern.edu/resources/software/netcarto>

Informap: <https://www.mapequation.org/code.html>

Fastgreedy:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.modularity_communities.html#networkx.algorithms.community.modularity_max.greedy_modularity_communities

Label propagation:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.propagation_communities.html#networkx.algorithms.community.label_propagation.label_propagation_communities

Givan Newman:

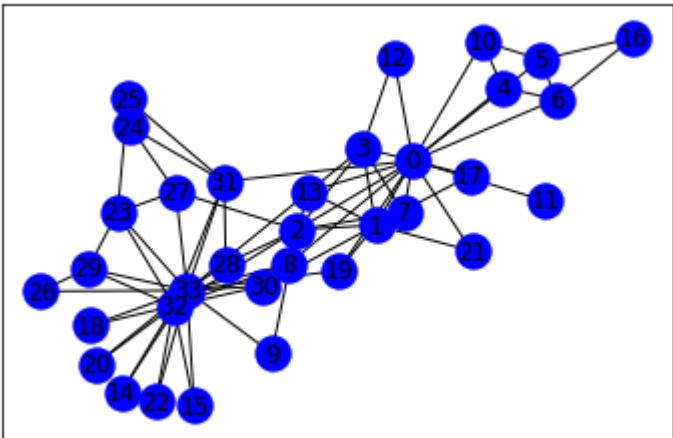
https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.community.centrality.girvan_newman.html#networkx.algorithms.community.centrality.girvan_newman

Louvain: <https://github.com/taynaud/python-louvain>

Show the partition of the Zachary karate club for these networks.

```
G=nx.karate_club_graph()
G = trata_rede(G)
pos=nx.nx.fruchterman_reingold_layout(G)
nx.draw_networkx(G, pos=pos, node_color = 'b')
plt.show(True)
```





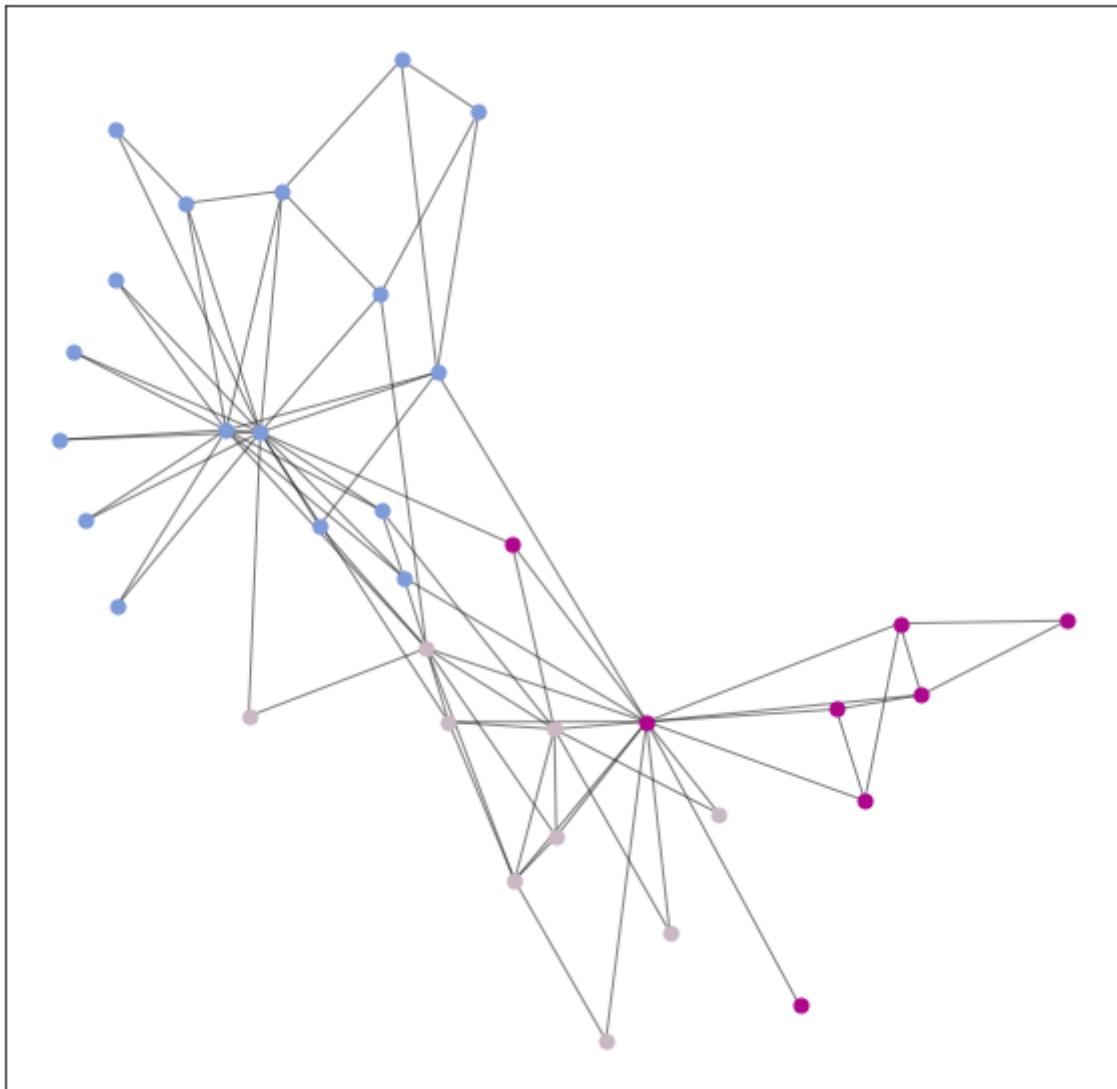
```
listaClusters = list()
partition_netcarto = np.zeros((len(G)))
listaClusters.append(partition_netcarto)

partition_informap = np.zeros((len(G)))
listaClusters.append(partition_informap)

partition_greedy = greedy(G)
listaClusters.append(partition_greedy)
```

⇨

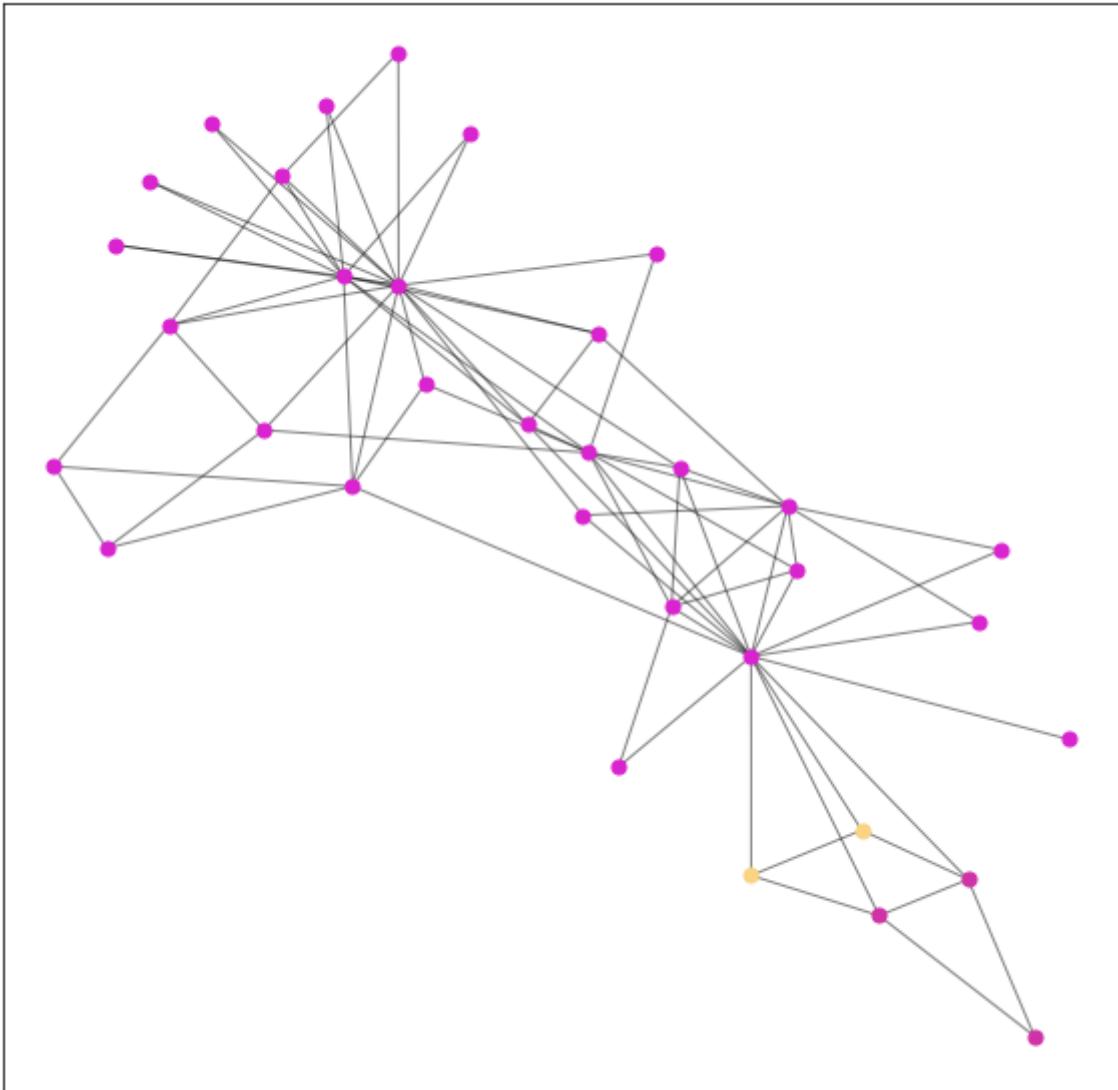
Modularity Method: FastGreedy



```
partition_label = label(G)
listaClusters.append(partition_label)
```



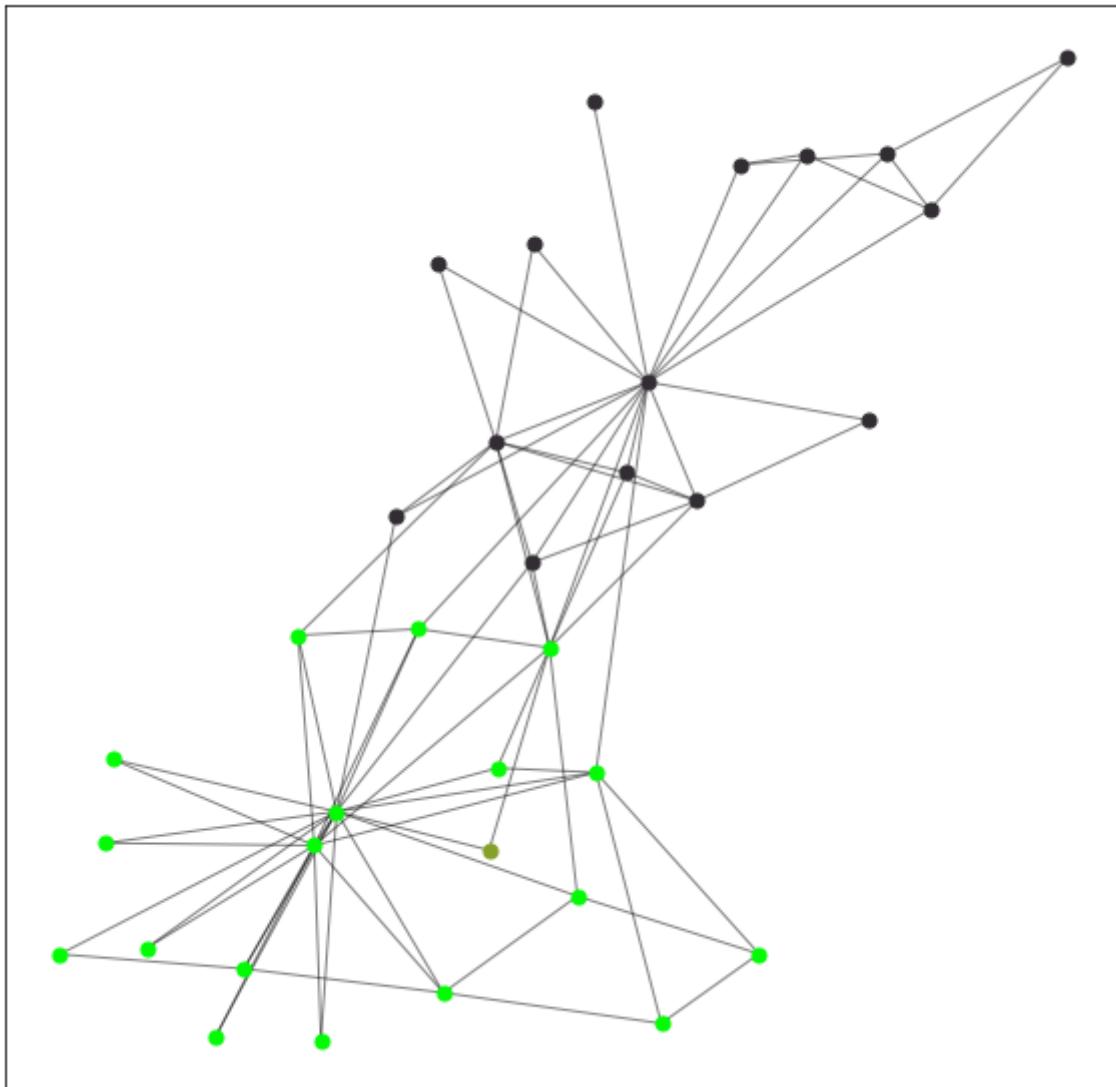
Modularity Method: Label Propagation



```
partition_givan_newman = givan_newman_method(G,3)
listaClusters.append(partition_givan_newman)
```



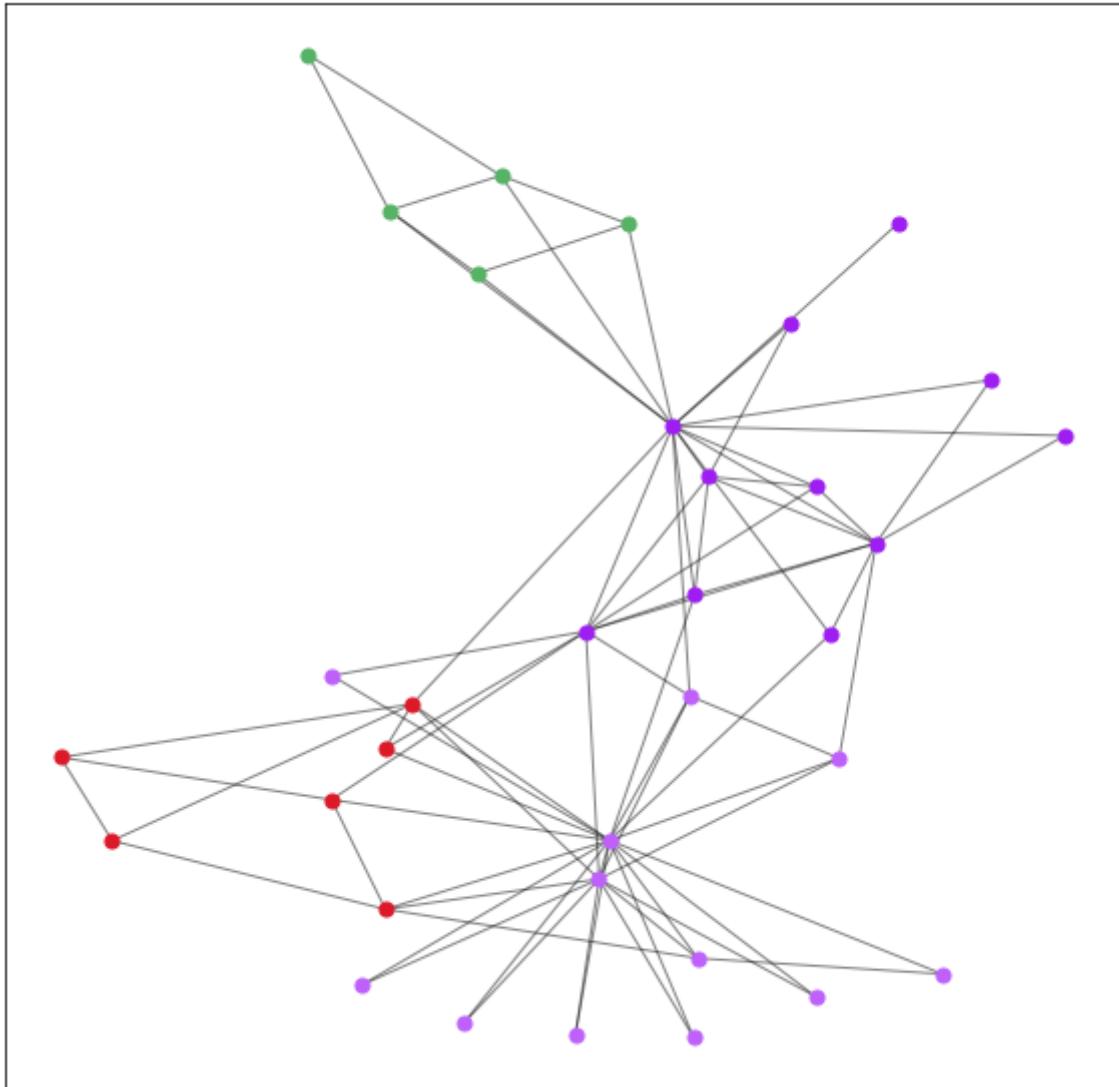
Modularity Method: Givan Newman



```
partition_louvain = louvain(G)
listaClusters.append(partition_louvain)
```



Modularity Method: Louvain



```
def corrplot_NMI_between_modularities(listaClusters, T):
    matrix_values = np.zeros((len(listaClusters[0]),len(listaClusters) ))
    for i in range(len(listaClusters)):
        for j in range(len(listaClusters[i])):
            matrix_values[j,i] = listaClusters[i][j]
    df = pd.DataFrame(matrix_values)
    from sklearn.metrics.cluster import normalized_mutual_info_score
    matrix_values = np.zeros((len(listaClusters),len(listaClusters)))
    for i in range(len(listaClusters)):
        for j in range(len(listaClusters)):
            matrix_values[i,j] = normalized_mutual_info_score(df[i],df[j])
    final_df = pd.DataFrame(matrix_values, index = T, columns = T)

    corr = final_df
    plt.figure(figsize=(8,8))
    plt.imshow(corr, cmap='Blues', interpolation='none', aspect='auto')
    plt.colorbar()
    plt.xticks(range(len(corr)), corr.columns, rotation='vertical', fontsize=20)
    plt.yticks(range(len(corr)), corr.columns, fontsize=20);
    plt.suptitle('NMI between centrality measures', fontsize=20)
    plt.grid(False)
```

```

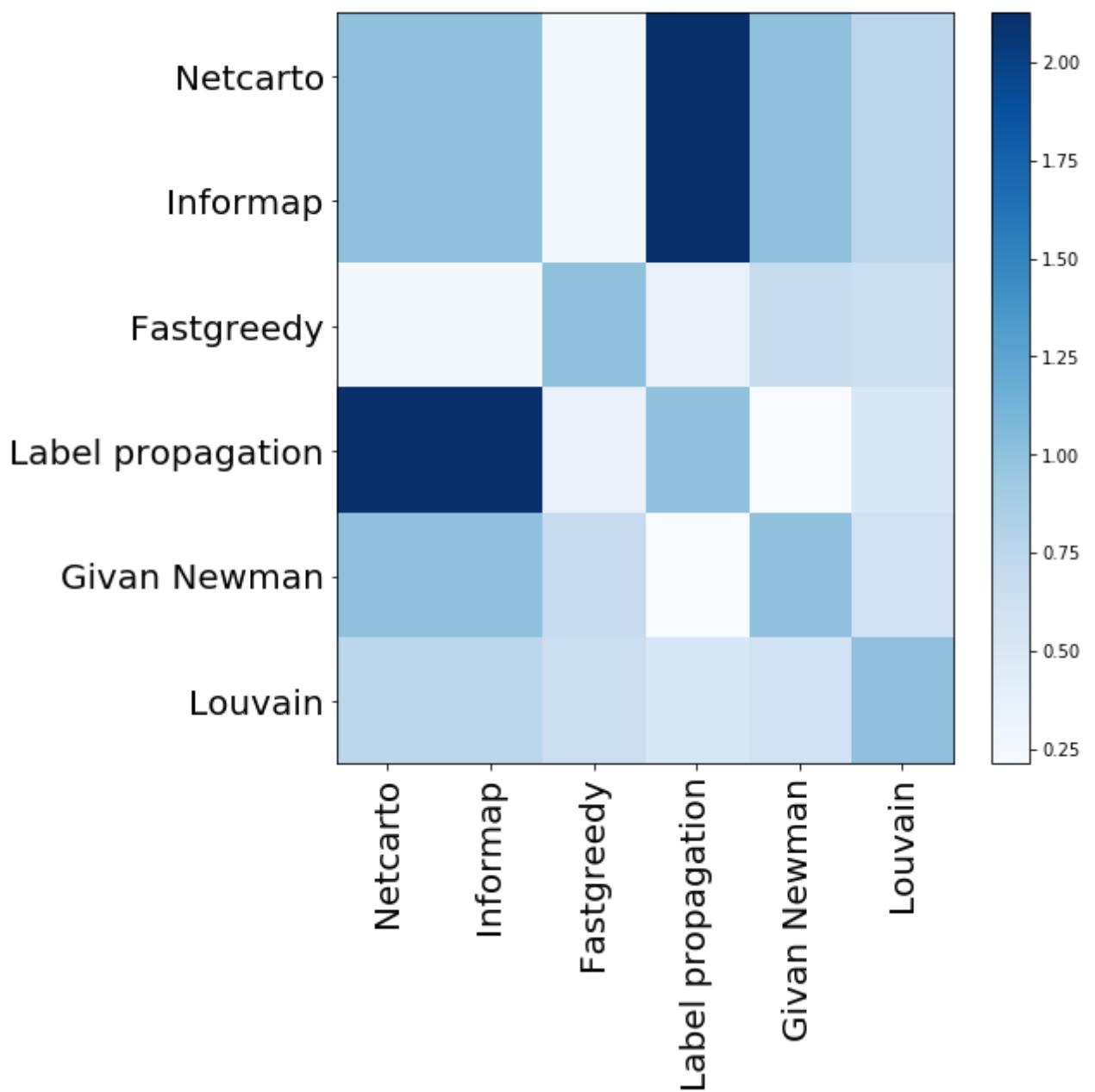
plt.show()

corrplot_NMI_between_modularities(listaClusters
    ,["Netcarto", "Informap", "Fastgreedy", "Label propagation", "Givan Newman", "Lou

```

⇨

Correlation between centrality measures



▼ 8 – Consider the Fortunato benchmark:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.LFR_benchmark_graph.html

Compare the following methods. Consider the Normalized Mutual Information (NMI) measure

Netcarto: <https://amaral.northwestern.edu/resources/software/netcarto>

Informap: <https://www.mapequation.org/code.html>

Fastgreedy:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.modularity_communities.html#networkx.algorithms.community.modularity_max.greedy_modularity_communities

Label propagation:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.propagation_communities.html#networkx.algorithms.community.label_propagation.label_propagation

Givan Newman:

https://networkx.github.io/documentation/stable/reference/algorithms/generated/networkx.algorithms.community.centrality.girvan_newman.html#networkx.algorithms.community.centrality.girvan_newman

Louvain: <https://github.com/tavaud/python-louvain>

```
N = 128
tau1 = 3
tau2 = 1.5
#mu = 0.04
k = 16
minc = 32
maxc = 32
listaGraph = list()
listaMu_x = list()

for i in range(0,100):
    mu = i/100
    listaMu_x.append(mu)
    G_benchmark_graph = LFR_benchmark_graph(n = N, tau1 = tau1, tau2 = tau2, mu = mu, min_degree = k, min_community=minc, max_community = maxc, seed = 1)
    communities = {frozenset(G_benchmark_graph.nodes[v]['community']) for v in G_benchmark_graph}
    N = 128
    tau1 = 3
    tau2 = 1.5
    mu = 0.04
    k = 16
    minc = 32
    maxc = 32
    points_x = list()
    points_y = list()

    for mu in range(1,101):
        mu = mu/100
        print( round(mu*100,2), "% Concluded")
        G_benchmark_graph = LFR_benchmark_graph(n = N, tau1 = tau1, tau2 = tau2, mu = mu, min_degree = k, min_community=minc, max_community = maxc, seed = 1)
        communities = {frozenset(G_benchmark_graph.nodes[v]['community']) for v in G_benchmark_graph}
        p = ([list(x) for x in communities])

        partition_communities = {}
        for i in range(len(n)):
```

```

for i in range(len(p)):
    for j in range(len(p[i])):
        partition_communities[p[i][j]] = i
#drawing_graph_and_communities(G_benchmark_graph,partition_communities, "LFT Communities")

listaClusters = list()
partition_greedy = greedy(G_benchmark_graph, False)
listaClusters.append(partition_greedy)

partition_label = label(G_benchmark_graph, False)
listaClusters.append(partition_label)

partition_givan_newman = givan_newman_method(G_benchmark_graph, 4, False)
listaClusters.append(partition_givan_newman)

partition_louvain = louvain(G_benchmark_graph, False)
listaClusters.append(partition_louvain)

matrix_values = np.zeros((len(listaClusters[0]), len(listaClusters) ))
for i in range(len(listaClusters)):
    for j in range(len(listaClusters[i])):
        matrix_values[j,i] = listaClusters[i][j]
df = pd.DataFrame(matrix_values)

matrix_values = np.zeros((len(partition_communities)))
for i in range(len(partition_communities)):
    matrix_values[i] = partition_communities[i]

matrix_final = np.zeros((4))
for i in range(4):
    nmi = normalized_mutual_info_score(df[i],matrix_values)
    if nmi > 1 or nmi < 0 : nmi = 0
    matrix_final[i] = nmi
points_x.append(mu)
points_y.append(matrix_final)
clear_output()
points_y = np.asmatrix(points_y)
points_y = pd.DataFrame(points_y, columns = ["FastGreedy", "Label_propagation", "Givan_Newman", "Louvain"])

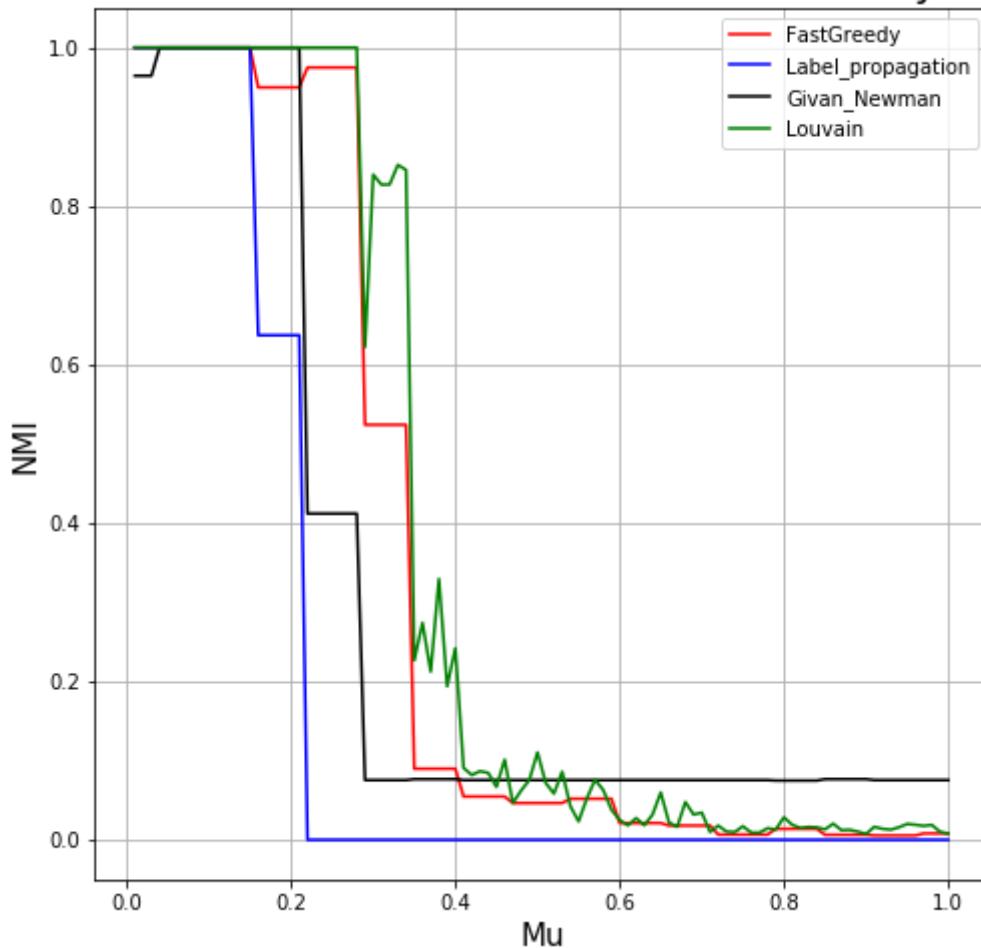
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Mu', fontsize = 15)
ax.set_ylabel('NMI', fontsize = 15)
ax.set_title('NMI for different Methods of Modularity', fontsize = 20)
targets = ["FastGreedy", "Label_propagation", "Givan_Newman", "Louvain"]
colors = ['r', 'g', 'b', 'y', 'k']

ax.plot(points_x ,points_y["FastGreedy"], color = 'r')
ax.plot(points_x ,points_y["Label_propagation"], color = 'b')
ax.plot(points_x ,points_y["Givan_Newman"], color = 'k')
ax.plot(points_x ,points_y["Louvain"], color = 'g')
ax.legend(targets)
ax.grid()

```



NMI for different Methods of Modularity



▼ 9 – Consider the following networks:

- E-road network (http://konect.cc/networks/subelj_euroroad),
- C. elegans neural network (<http://www-personal.umich.edu/~mejn/netdata/celegansneural>)
- US airport network (<http://toreopsahl.com/datasets/#usairports>)
- Human protein network (<http://konect.cc/networks/maayan-vidal>)

Construct a table showing the following properties of these networks:

N,

Average degree,

assortativity coefficient,

average shortest path length,

modularity.

In the case of modularity, show the values for the following methods:

(i) Fastgreedy,

(ii) Label propagation,

(iii) Givan Newman,

(iv)Louvain.

(a) Compare the results in terms of the modularity.

(b) Are there some relation between assortativity and other network measures?

```
listaGraph = list()
listaIndex = ["E-road network", "C. elegans neural network", "US airport network ", "Human protein network"]

G_eroad = nx.read_edgelist("eroad.edges", nodetype=int, data=(('weight',int),))
listaGraph.append(trata_rede(G_eroad))

G_celneural = nx.read_gml("celegansneural.gml")
listaGraph.append(trata_rede(G_celneural, multigraph = True))

G_usaairport = nx.read_edgelist("usaairport.edges", nodetype=int, data=(('weight',int),))
listaGraph.append(trata_rede(G_usaairport))

G_maayan_vidal = nx.read_edgelist("maayan-vidal.edges", nodetype=int)
listaGraph.append(trata_rede(G_maayan_vidal))

matrix_values = np.zeros((4, 4))
for i in range(len(listaGraph)):
    G = listaGraph[i]
    matrix_values[i,0] = len(G)
    matrix_values[i,1] = mean(np.array(list(dict(G.degree()).values())))
    matrix_values[i,2] = nx.degree_assortativity_coefficient(G)
    matrix_values[i,3] = nx.average_shortest_path_length(G)
df = pd.DataFrame(matrix_values, columns = [ "N", "Avg Degree", "AssortCoef", "Avg SPL"],
                   index = ["E-road network", "C. elegans neural network", "US airport network ", "Human protein network"])
```

df

	N	Avg Degree	AssortCoef	Avg SPL
E-road network	1039.0	2.512031	0.090040	18.395146
C. elegans neural network	297.0	14.464646	-0.163199	2.455319
US airport network	500.0	11.920000	-0.267863	2.991030
Human protein network	2783.0	4.316924	-0.136560	4.839802

```
print("Network : ", listaIndex[0],"\n")
G = listaGraph[0]
```

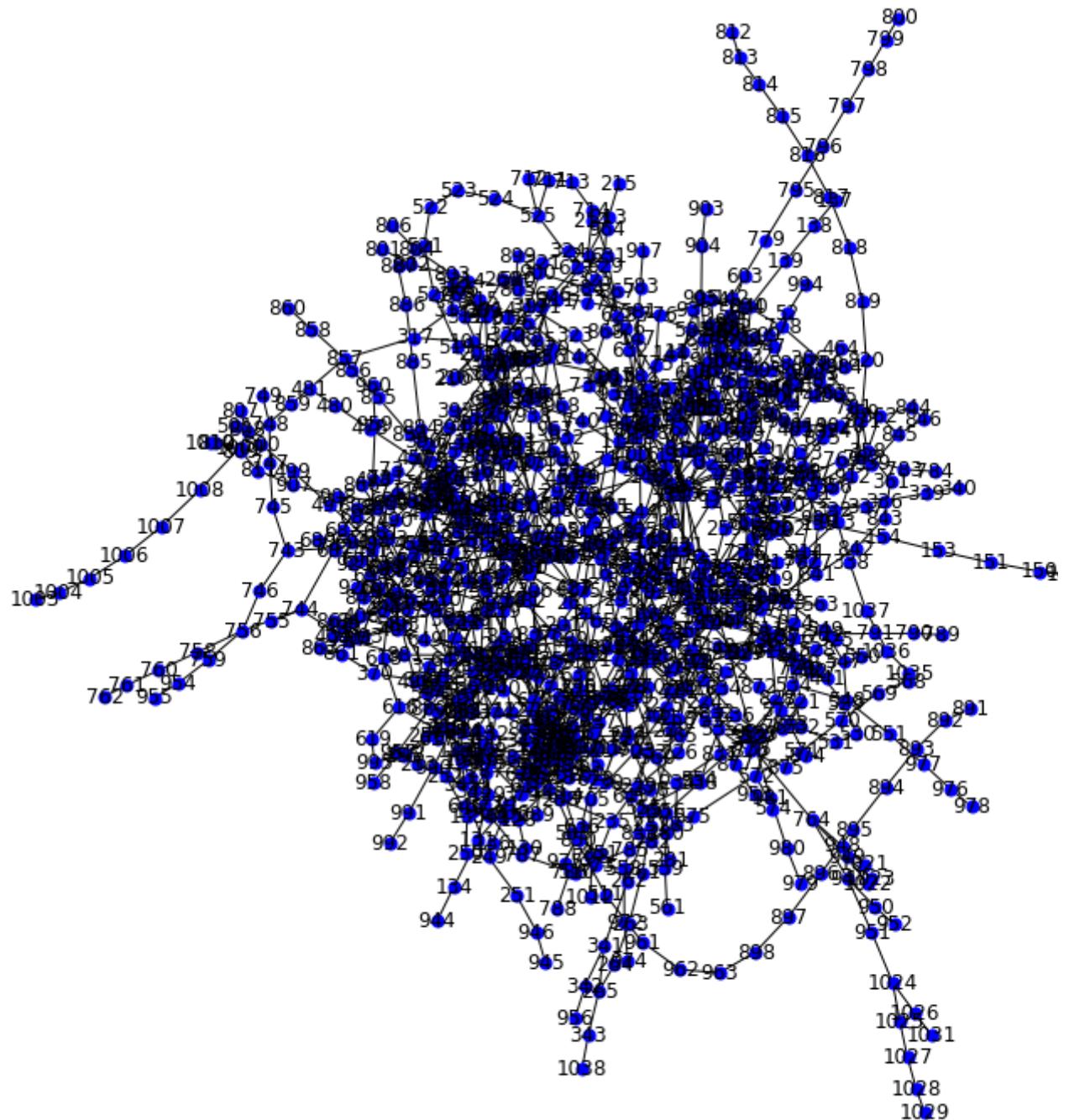
```
df.loc["E-road network",:]
```

Network : E-road network

```
N           1039.000000
Avg Degree    2.512031
AssortCoef     0.090040
Avg SPL        18.395146
Name: E-road network, dtype: float64
```

```
plota_rede(G, nd_size=50, fig_size=10, n_color = random.randint(0,8))
```

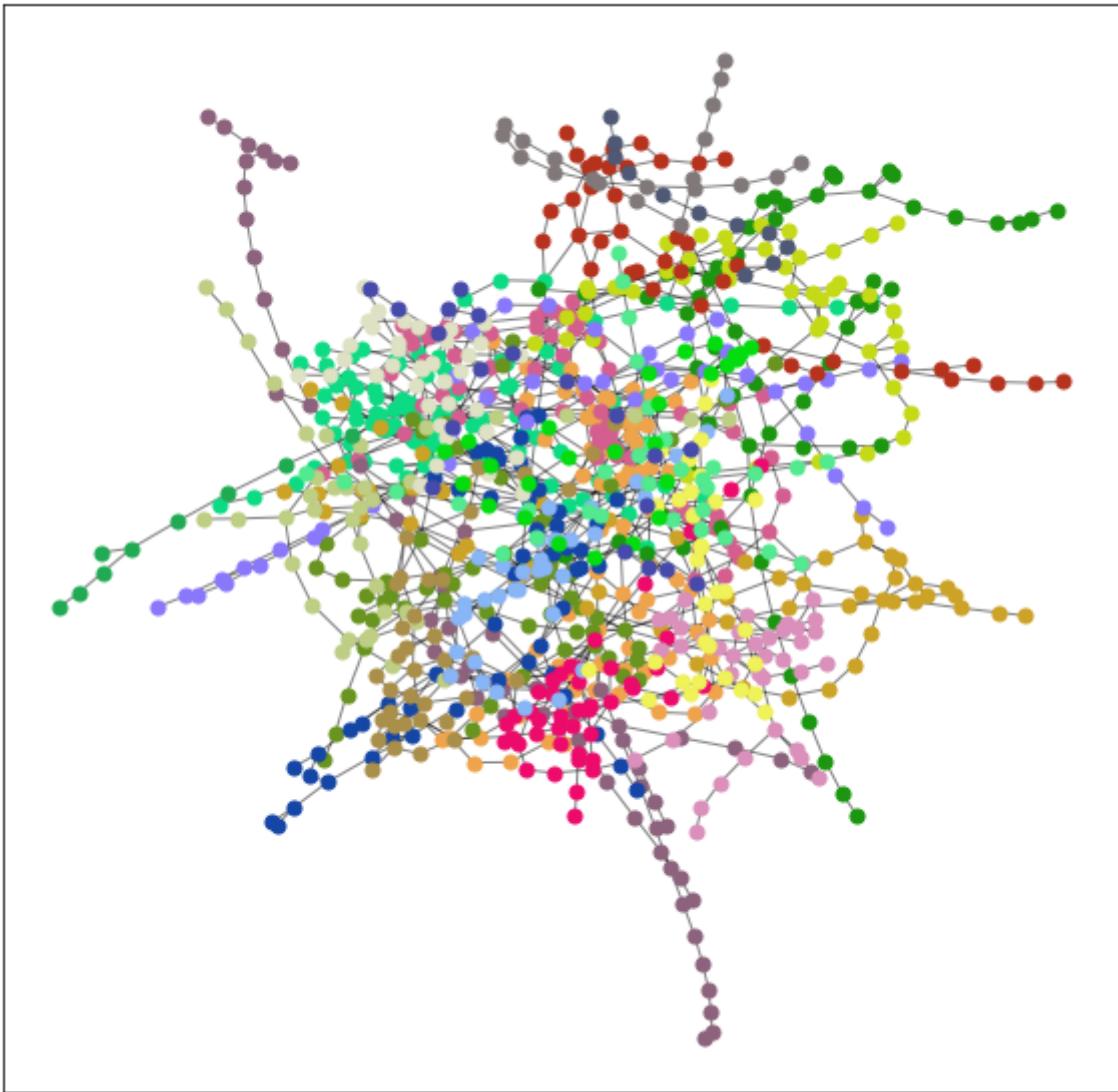
⇨



```
listaClusters = list()
partition_greedy = greedy(G)
listaClusters.append(partition_greedy)
```



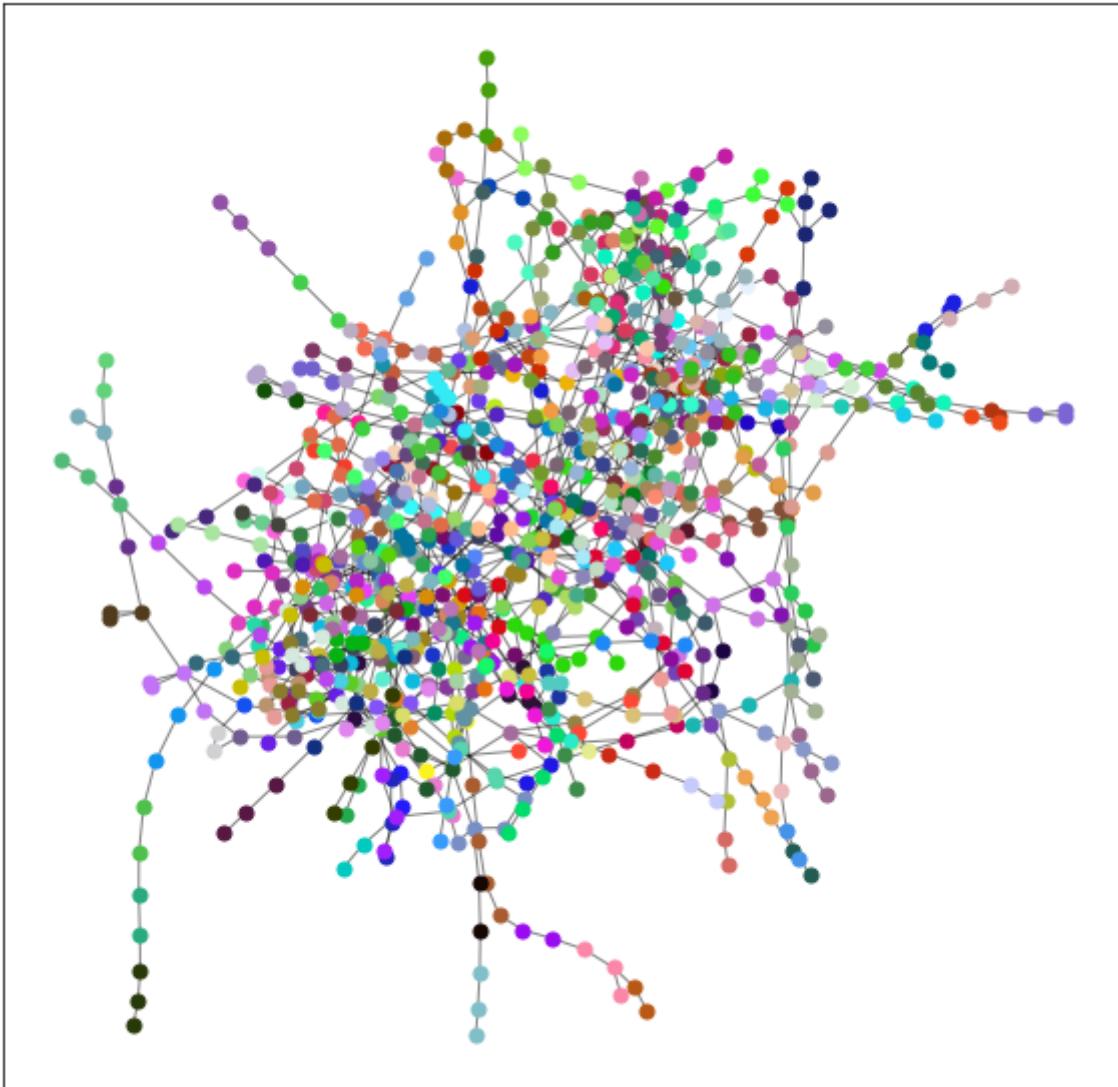
Modularity Method: FastGreedy



```
partition_label = label(G)
listaClusters.append(partition_label)
```



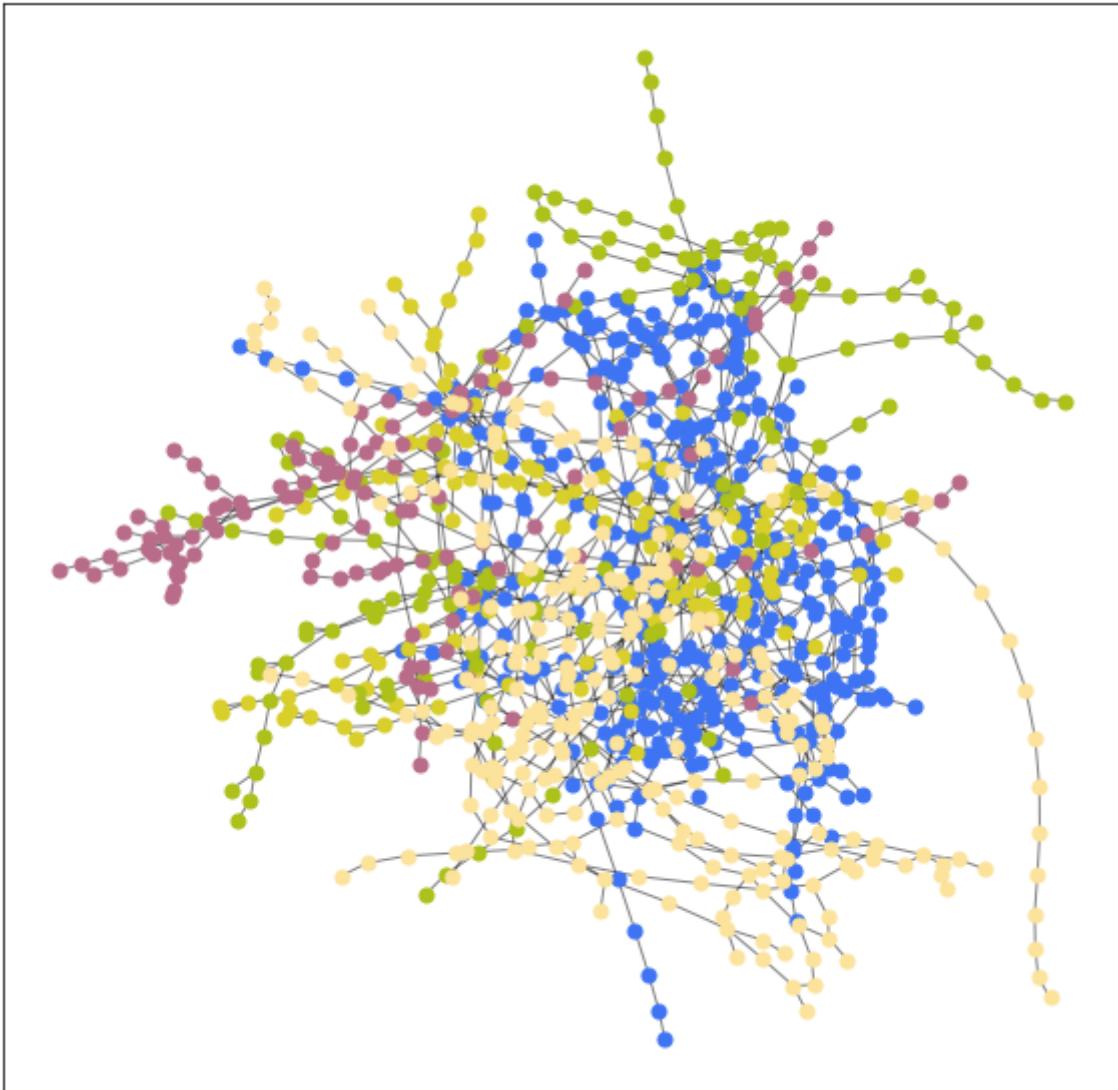
Modularity Method: Label Propagation



```
partition_givan_newman = givan_newman_method(G,5)
listaClusters.append(partition_givan_newman)
```



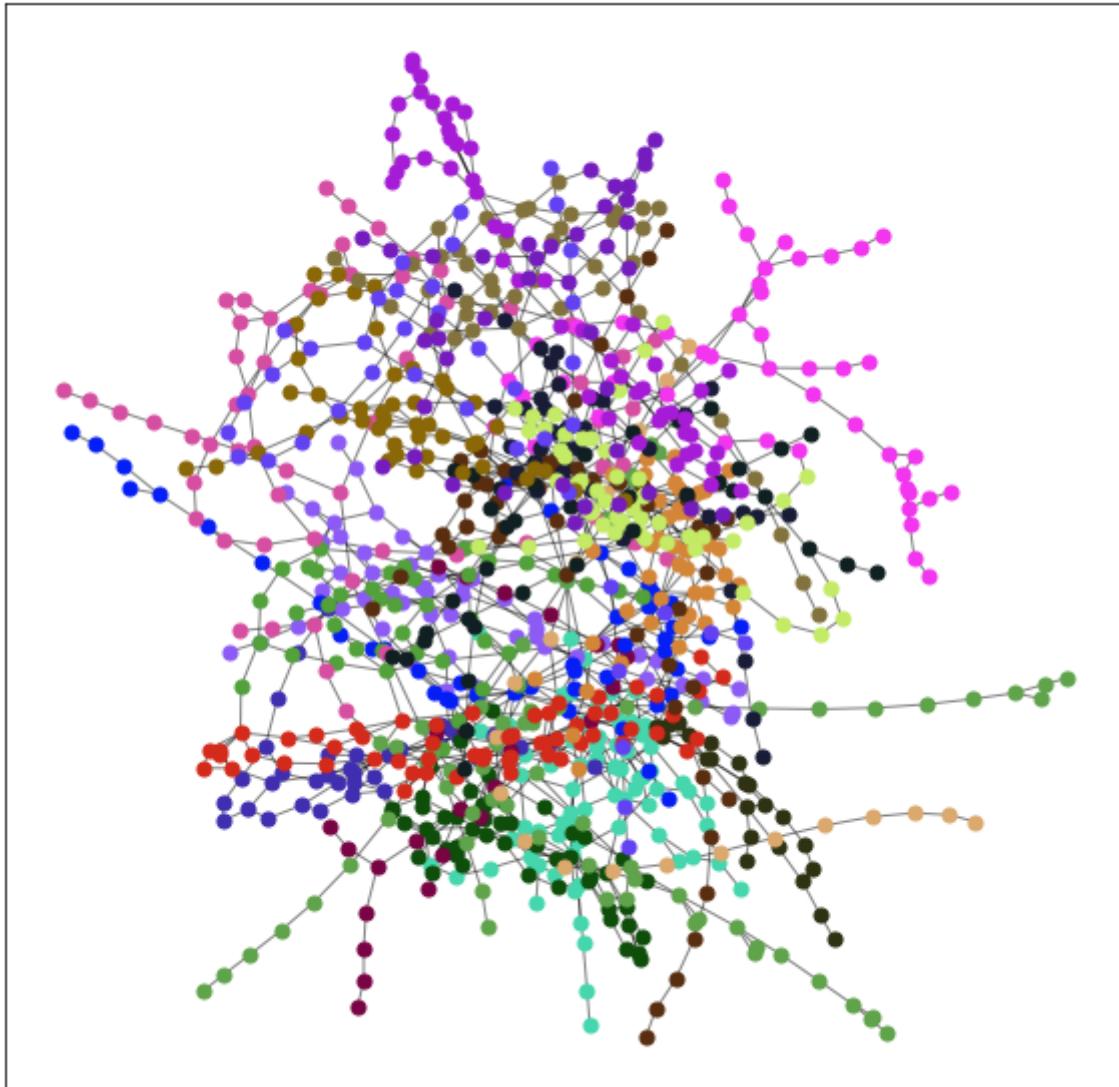
Modularity Method: Givan Newman



```
partition_louvain = louvain(G)
listaClusters.append(partition_louvain)
```



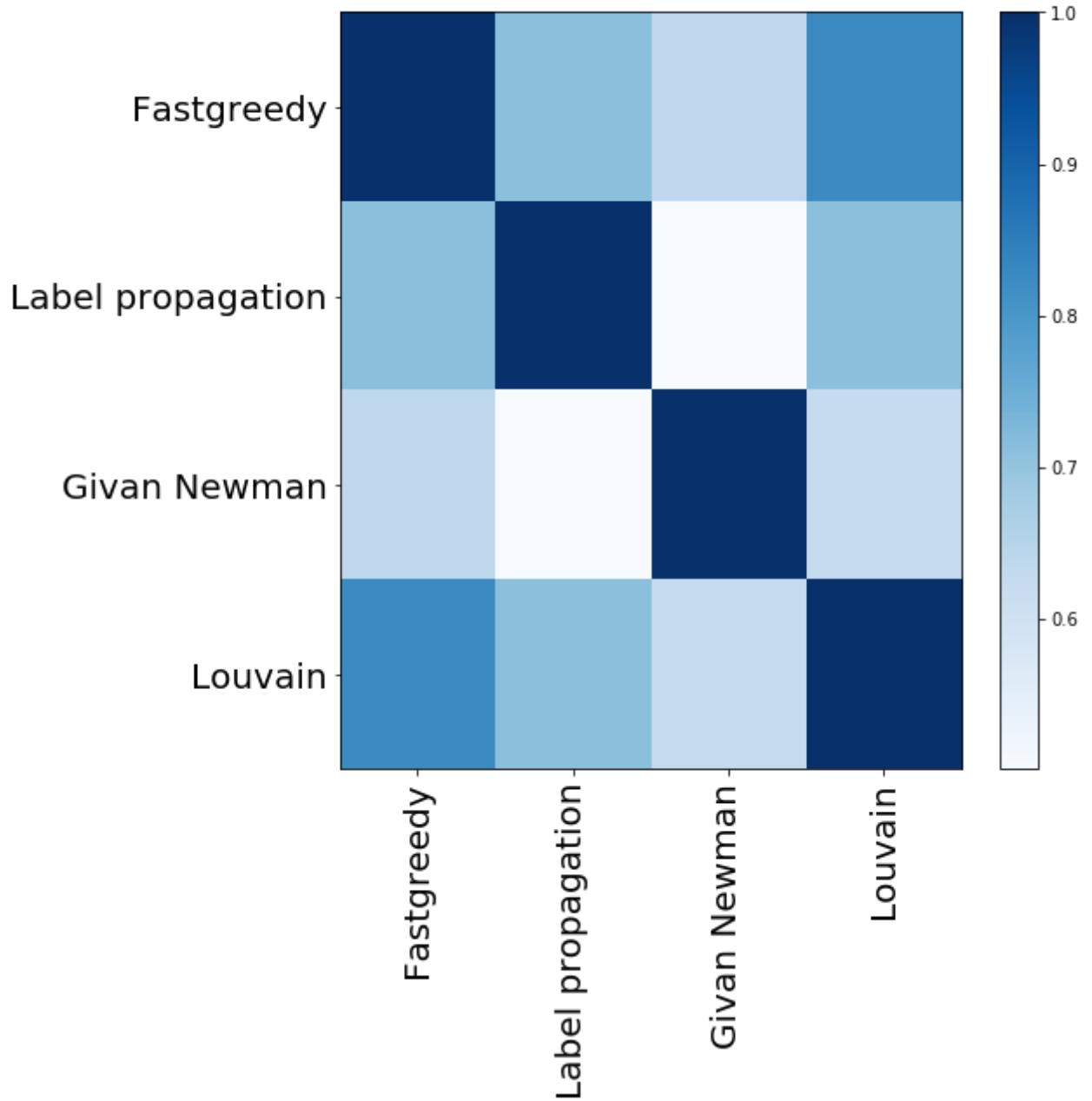
Modularity Method: Louvain



```
corrplot_NMI_between_modularities(listaClusters  
,[ "Fastgreedy", "Label propagation", "Givan Newman", "Louvain"])
```



Correlation between centrality measures



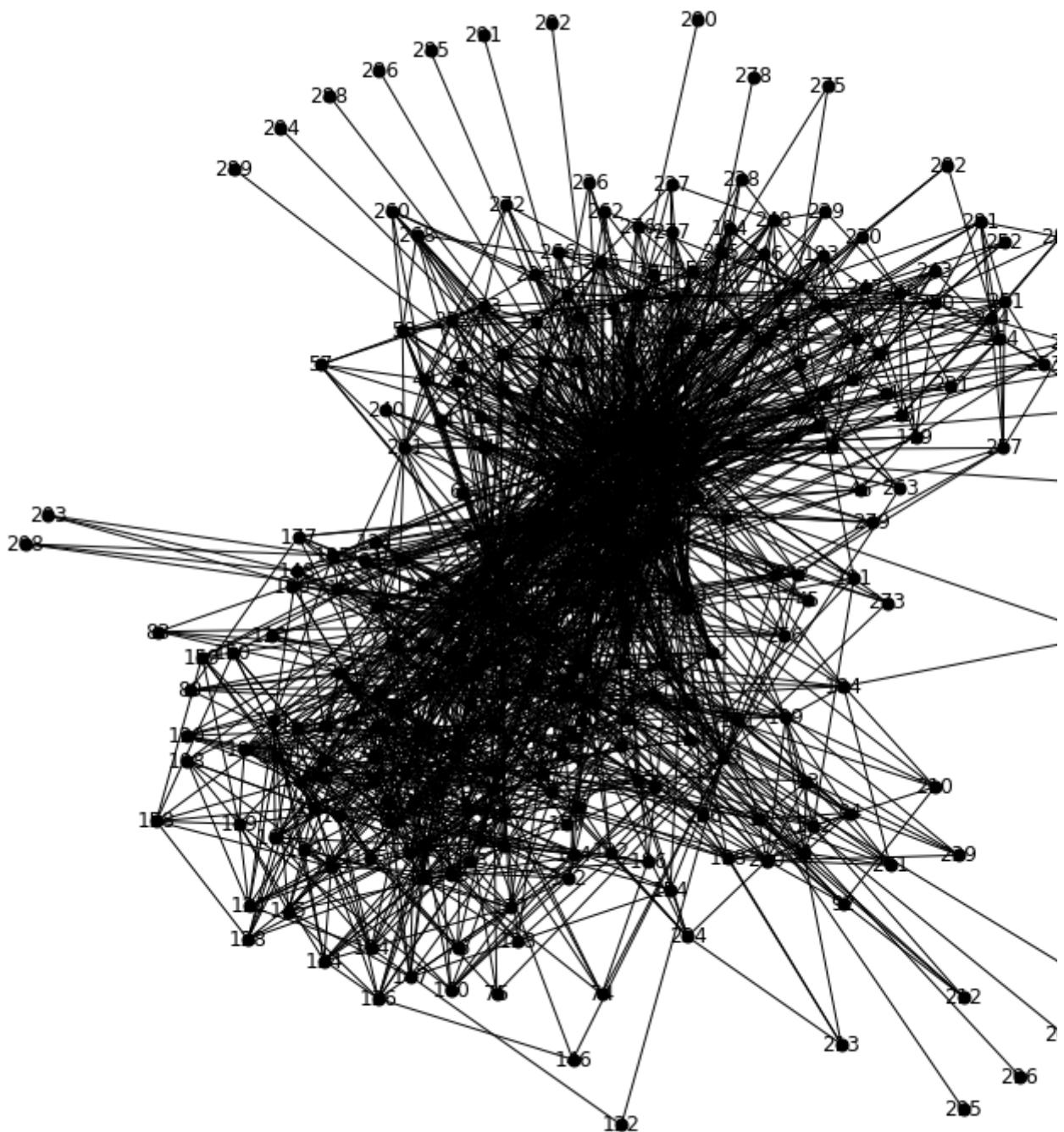
```
print("Network : ", listaIndex[1],"\n")
G = listaGraph[1]
df.loc["C. elegans neural network",:]

⇒ Network : C. elegans neural network

N           297.000000
Avg Degree   14.464646
AssortCoef    -0.163199
Avg SPL      2.455319
Name: C. elegans neural network, dtype: float64
```

```
plota_rede(G, nd_size=50, fig_size=10, n_color = random.randint(0,8))
```

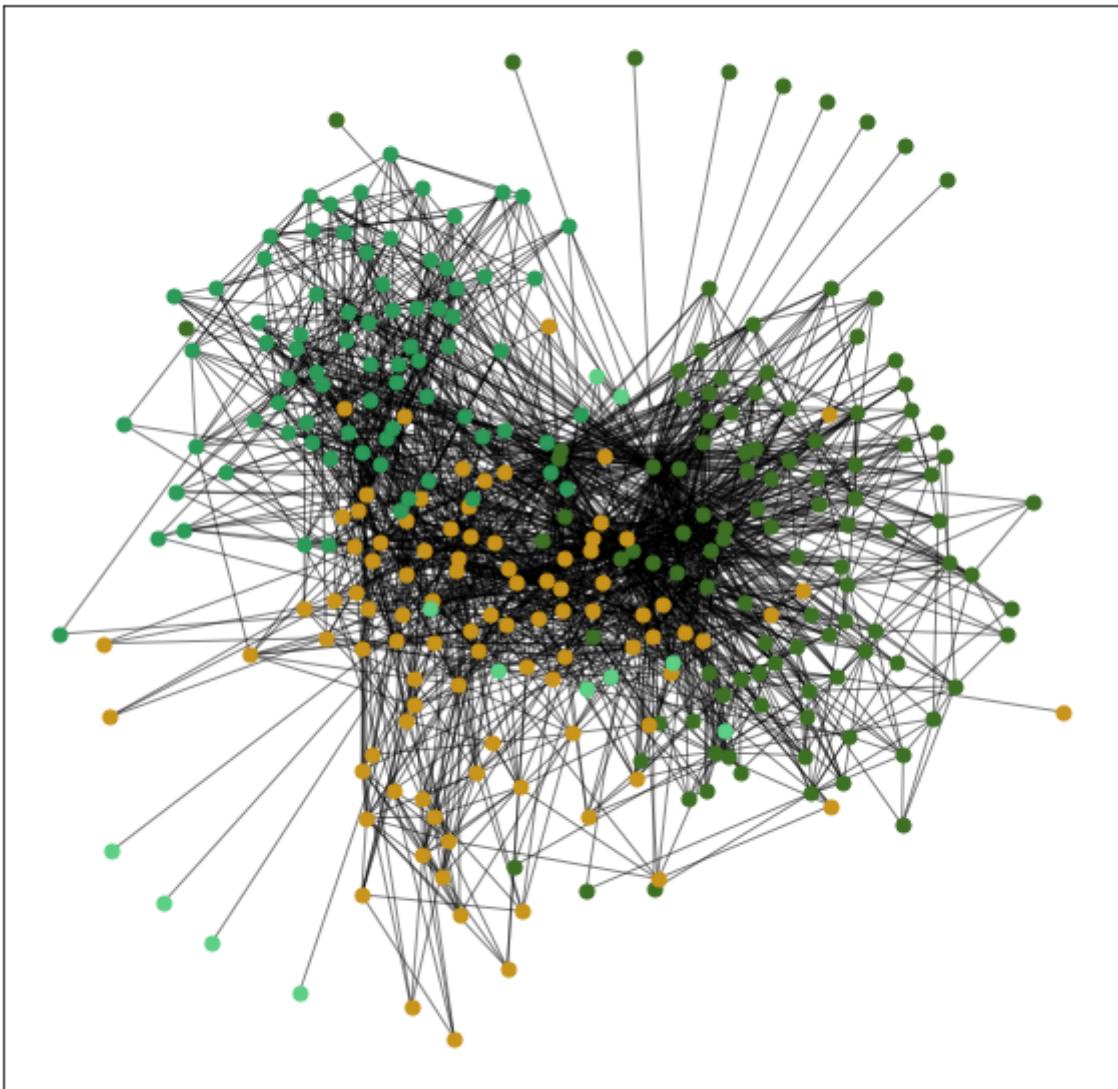
1



```
listaClusters = list()
partition_greedy = greedy(G)
listaClusters.append(partition_greedy)
```

1

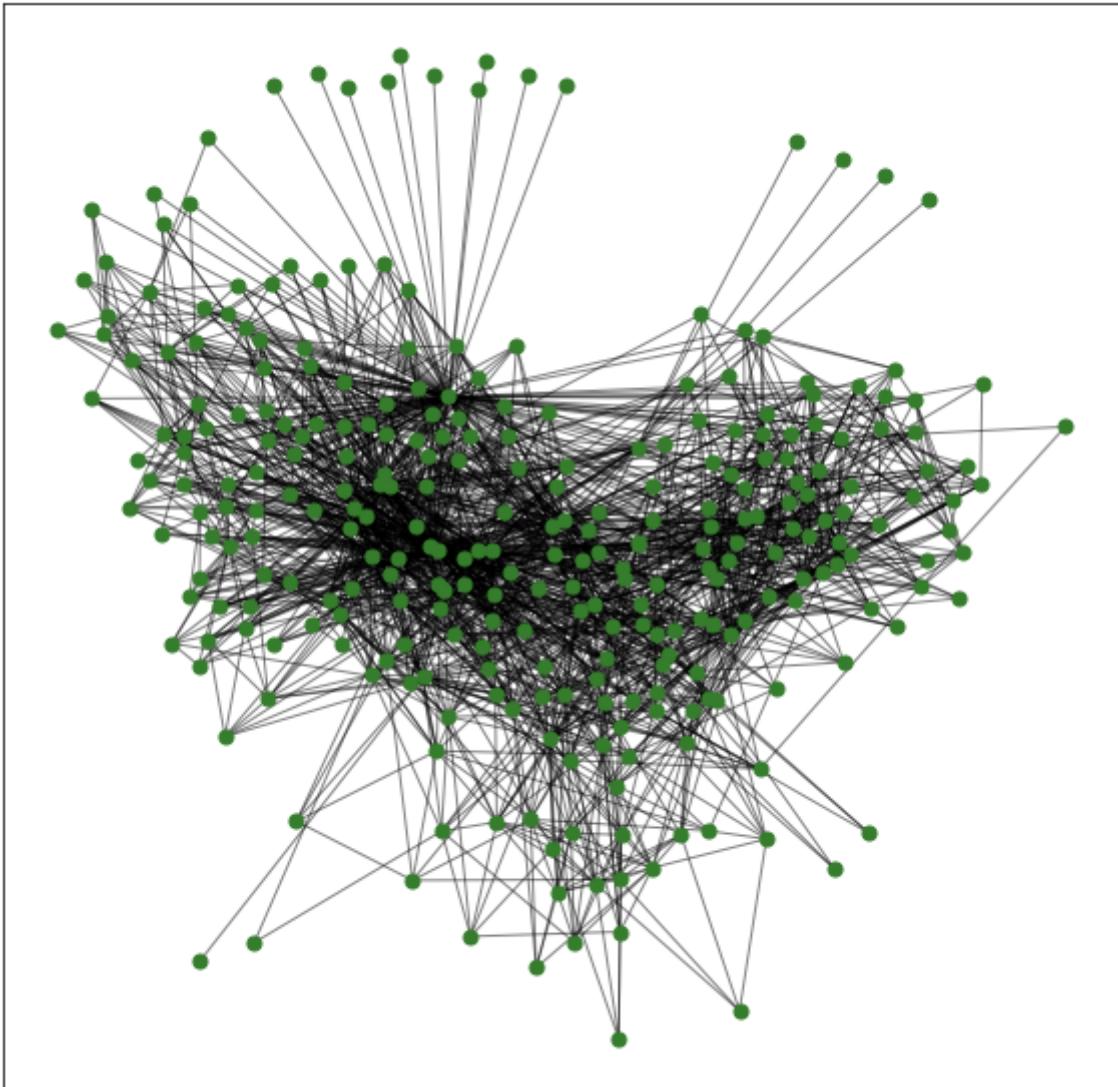
Modularity Method: FastGreedy



```
partition_label = label(G)
listaClusters.append(partition_label)
```



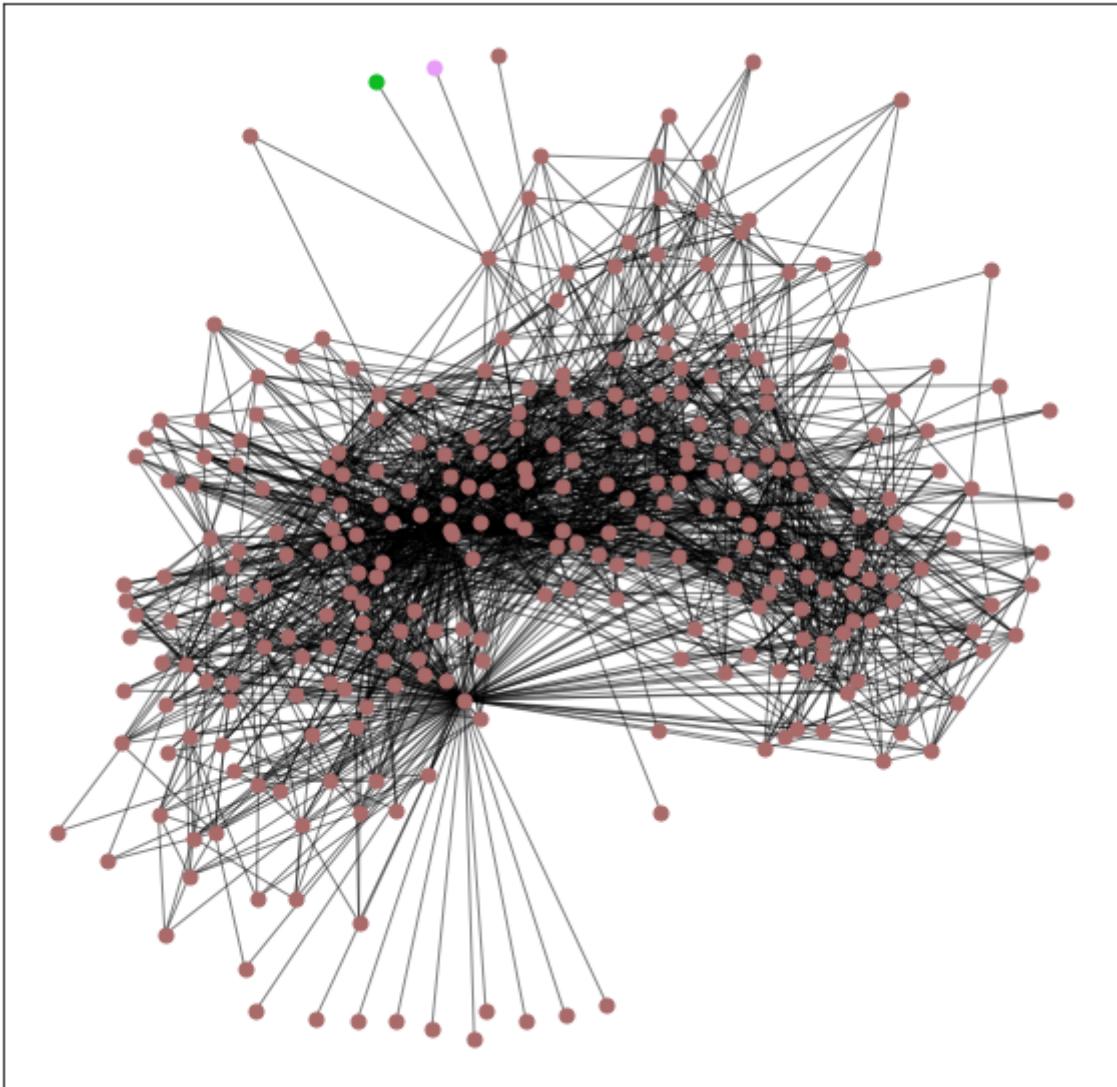
Modularity Method: Label Propagation



```
partition_givan_newman = givan_newman_method(G,3)
listaClusters.append(partition_givan_newman)
```



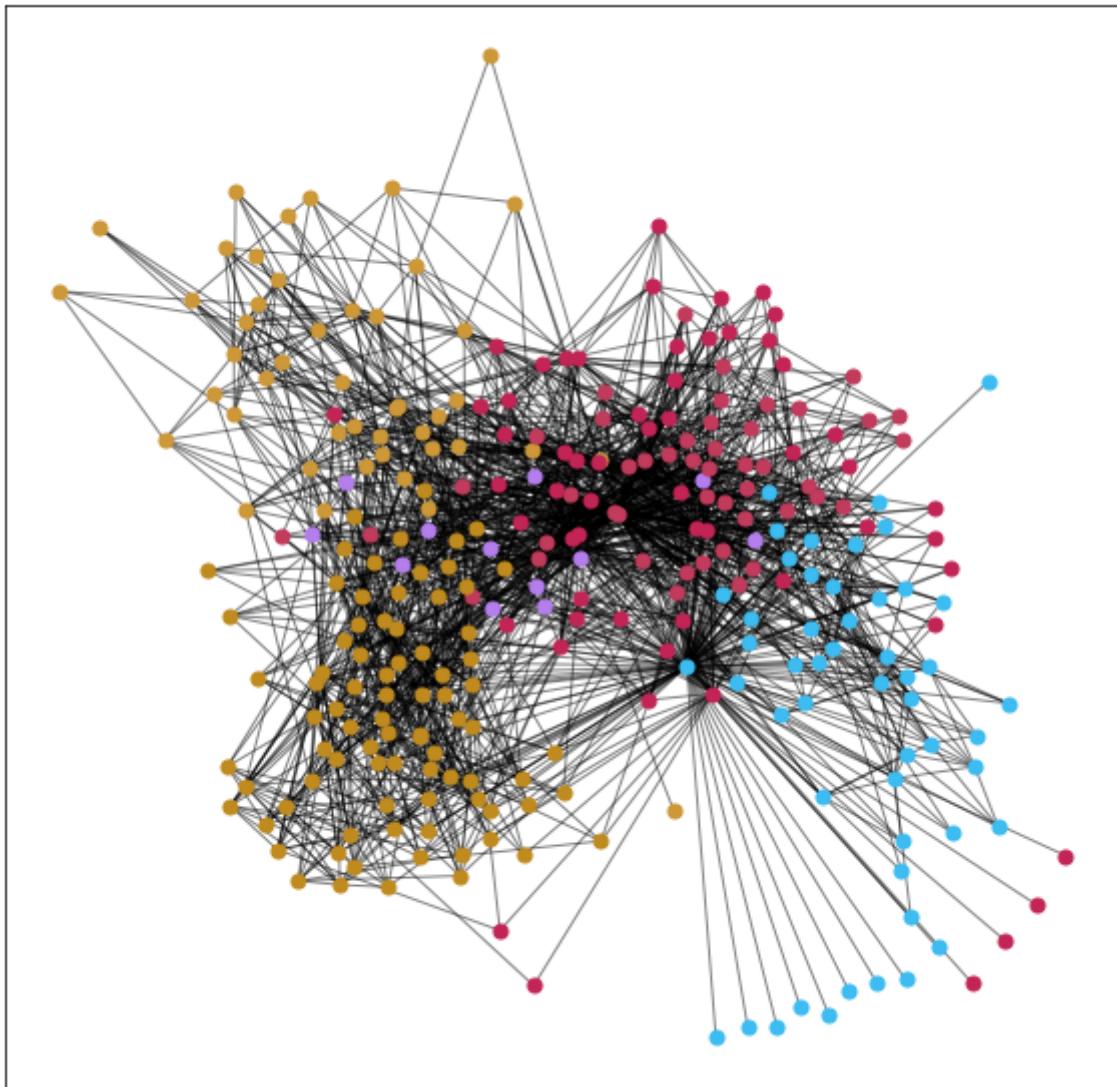
Modularity Method: Givan Newman



```
partition_louvain = louvain(G)
listaClusters.append(partition_louvain)
```



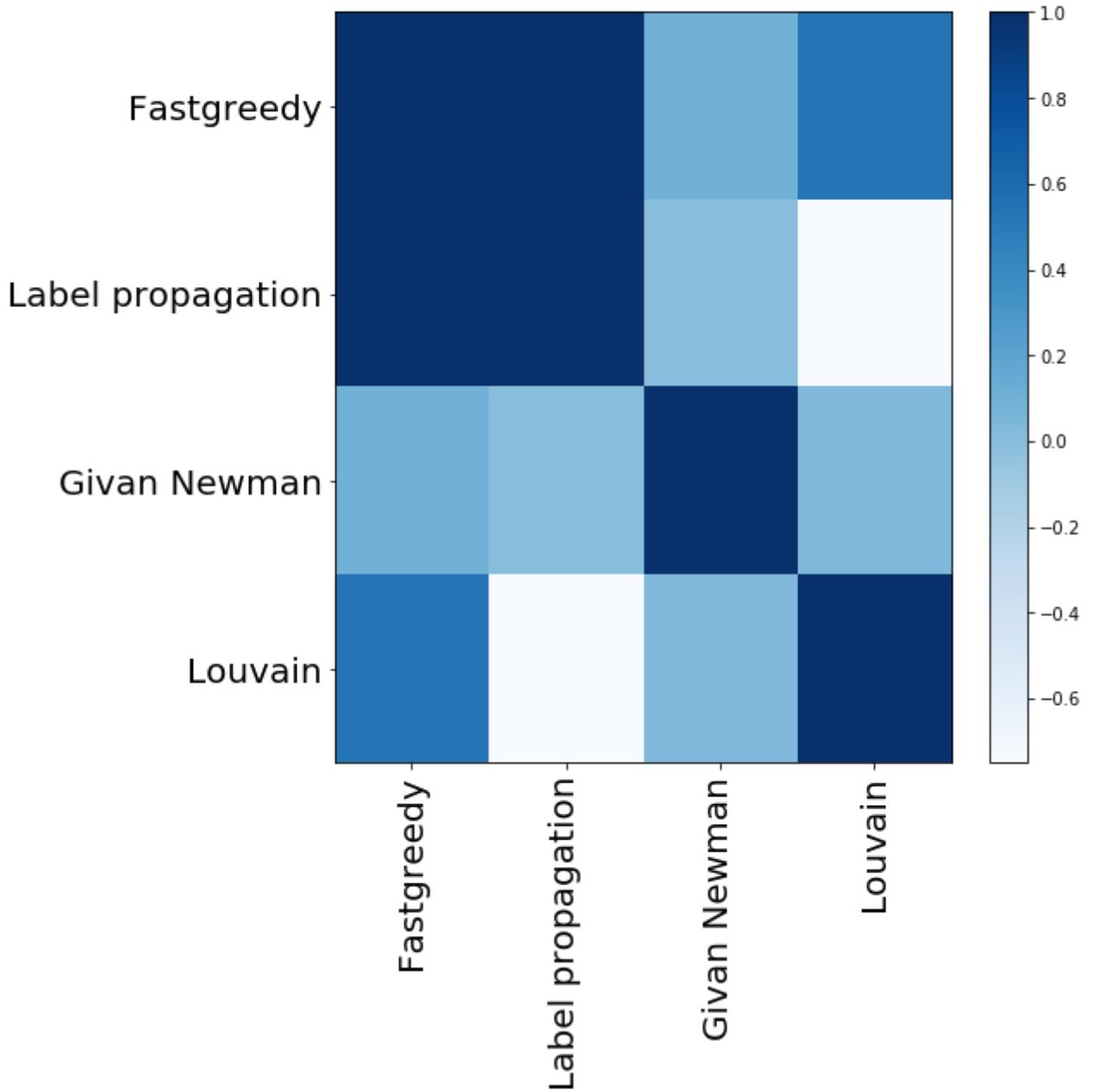
Modularity Method: Louvain



```
corrplot_NMI_between_modularities(listaClusters  
      ,["Fastgreedy", "Label propagation", "Givan Newman", "Louvain"])
```



Correlation between centrality measures



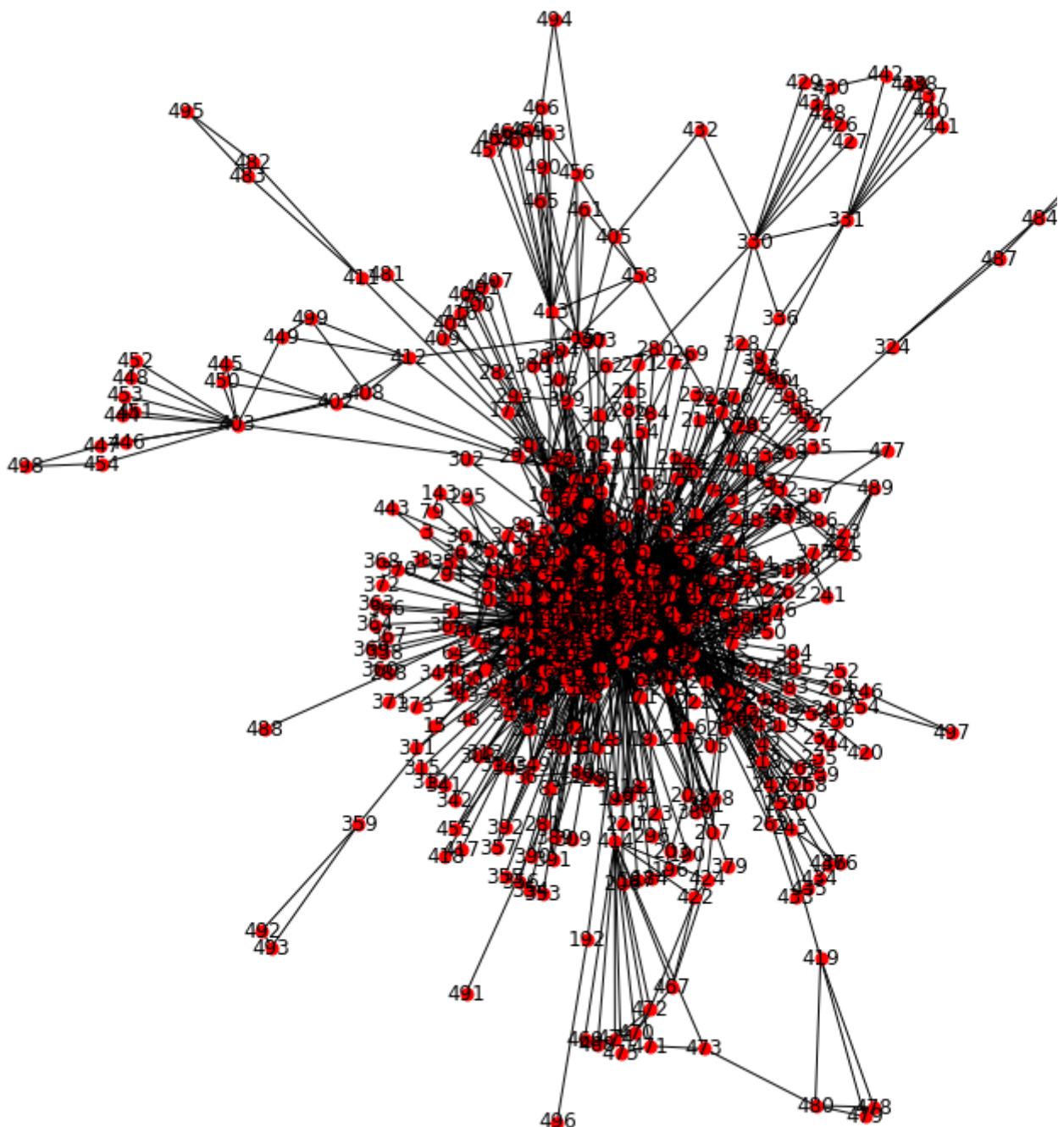
```
print("Network : ", listaIndex[2],"\n")
G = listaGraph[2]
df.loc["US airport network ",:]
```

Network : US airport network

N	500.000000
Avg Degree	11.920000
AssortCoef	-0.267863
Avg SPL	2.991030
Name: US airport network , dtype: float64	

```
plota_rede(G, nd_size=50, fig_size=10, n_color = random.randint(0,8))
```

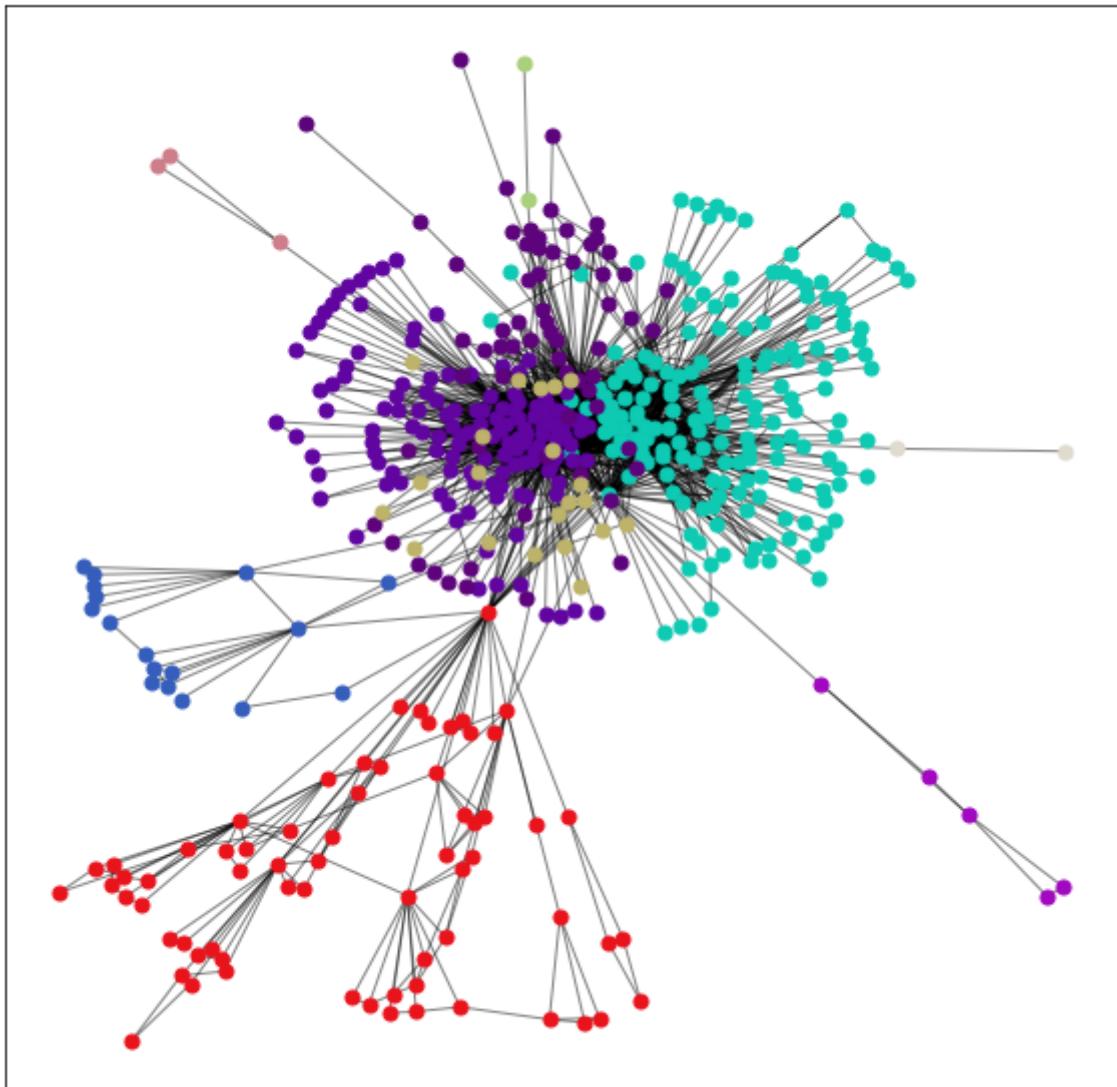
➡



```
listaClusters = list()
partition_greedy = greedy(G)
listaClusters.append(partition_greedy)
```

➡

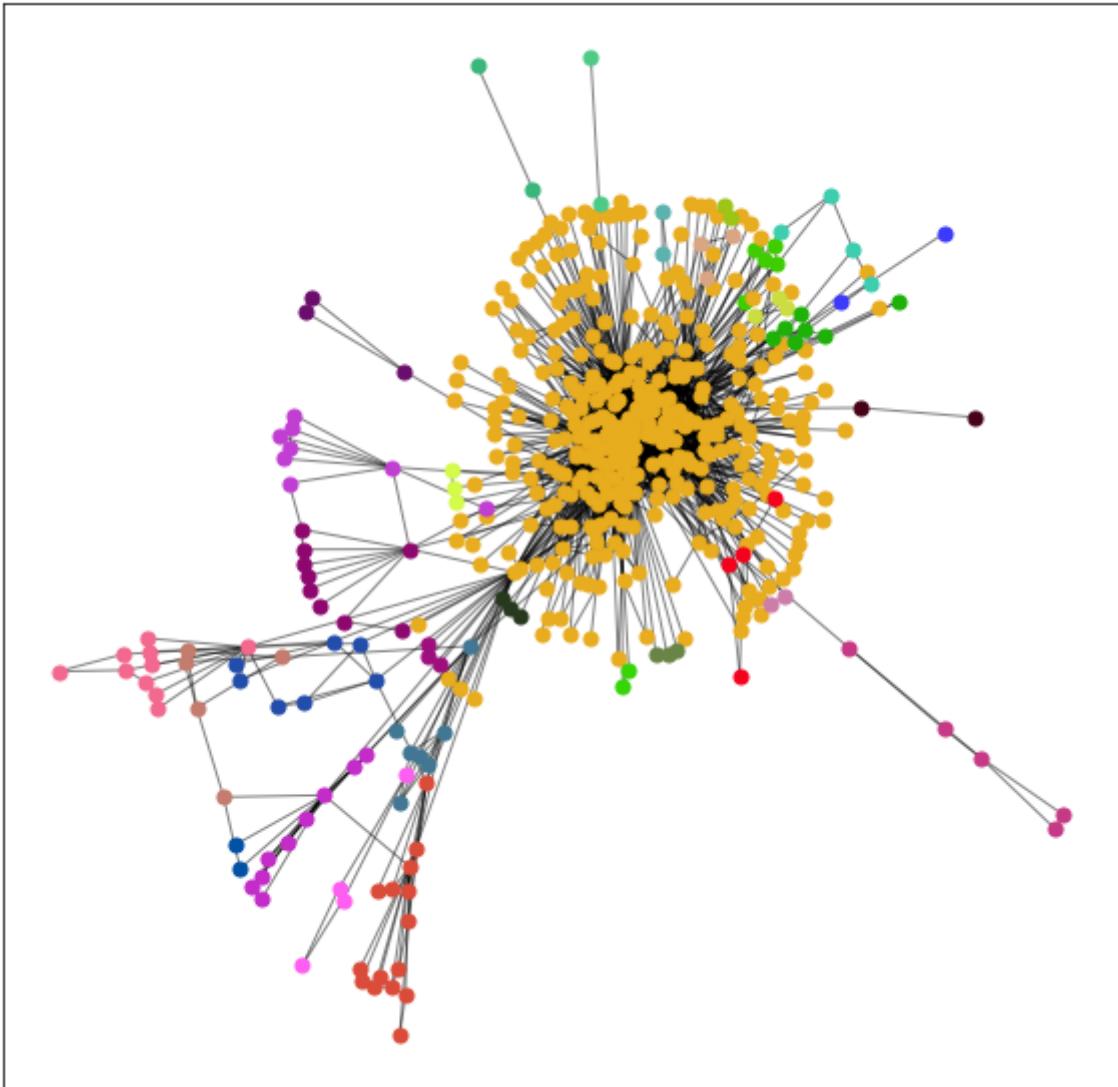
Modularity Method: FastGreedy



```
partition_label = label(G)
listaClusters.append(partition_label)
```



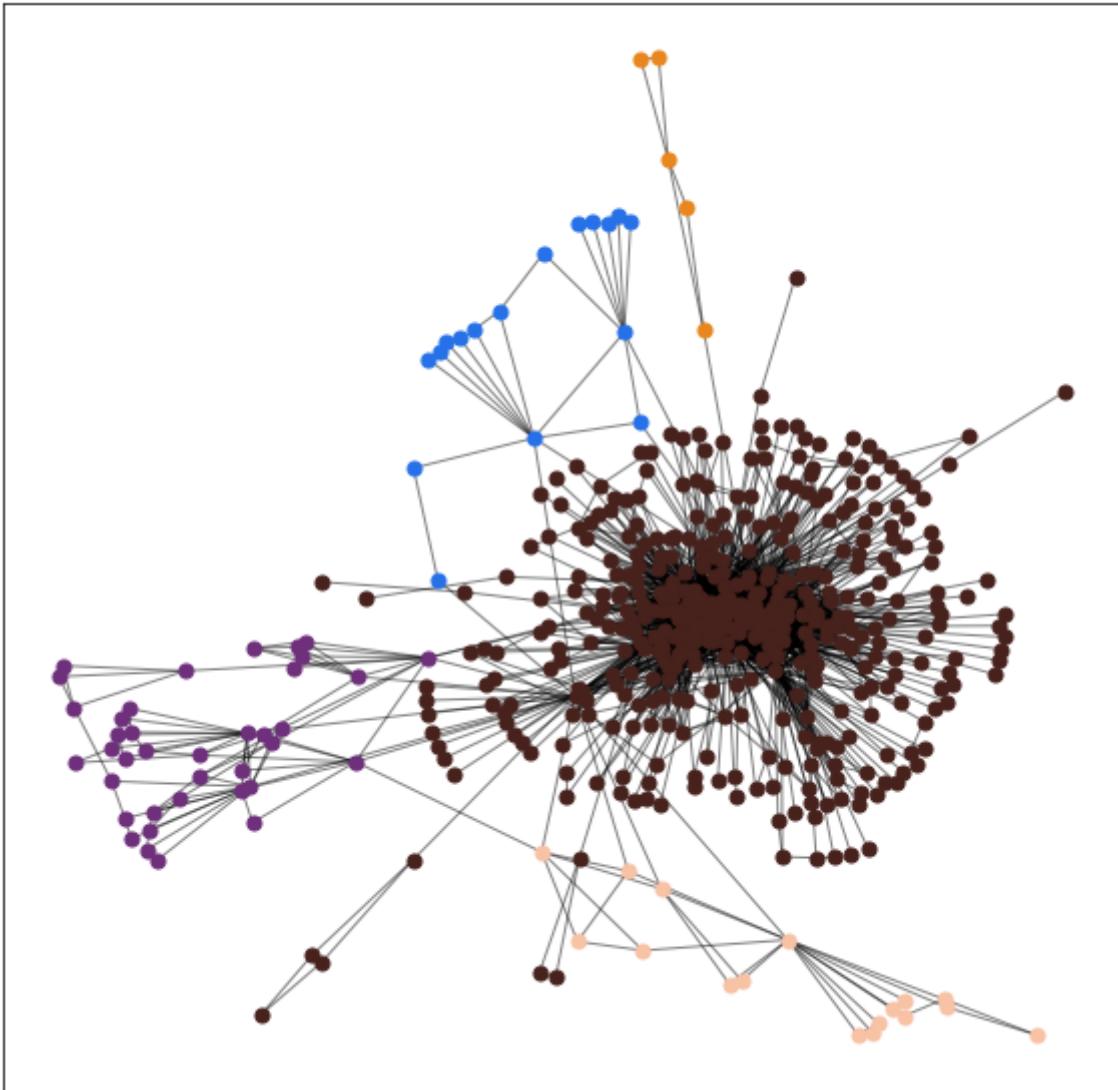
Modularity Method: Label Propagation



```
partition_givan_newman = givan_newman_method(G,5)
listaClusters.append(partition_givan_newman)
```



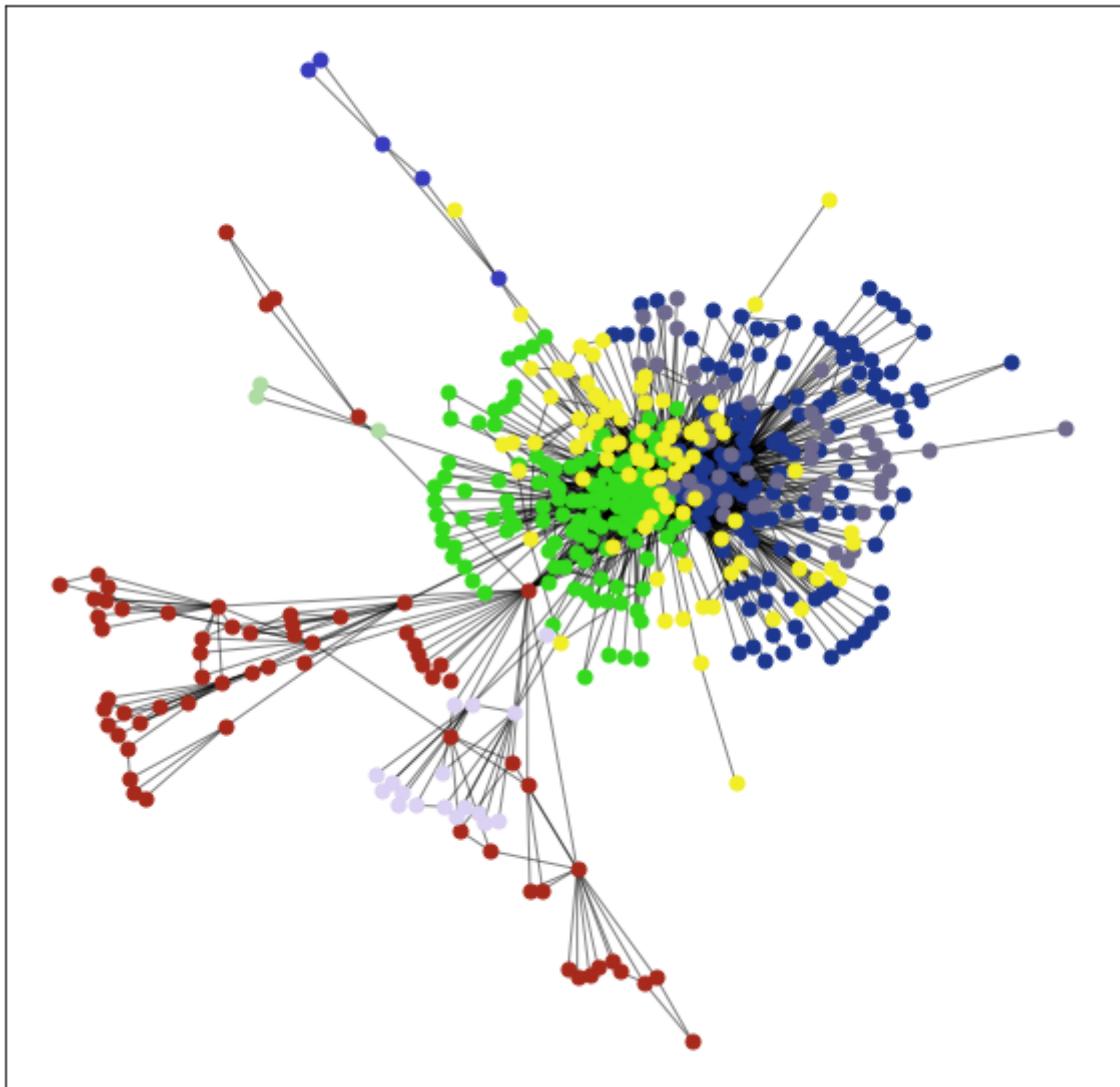
Modularity Method: Givan Newman



```
partition_louvain = louvain(G)
listaClusters.append(partition_louvain)
```



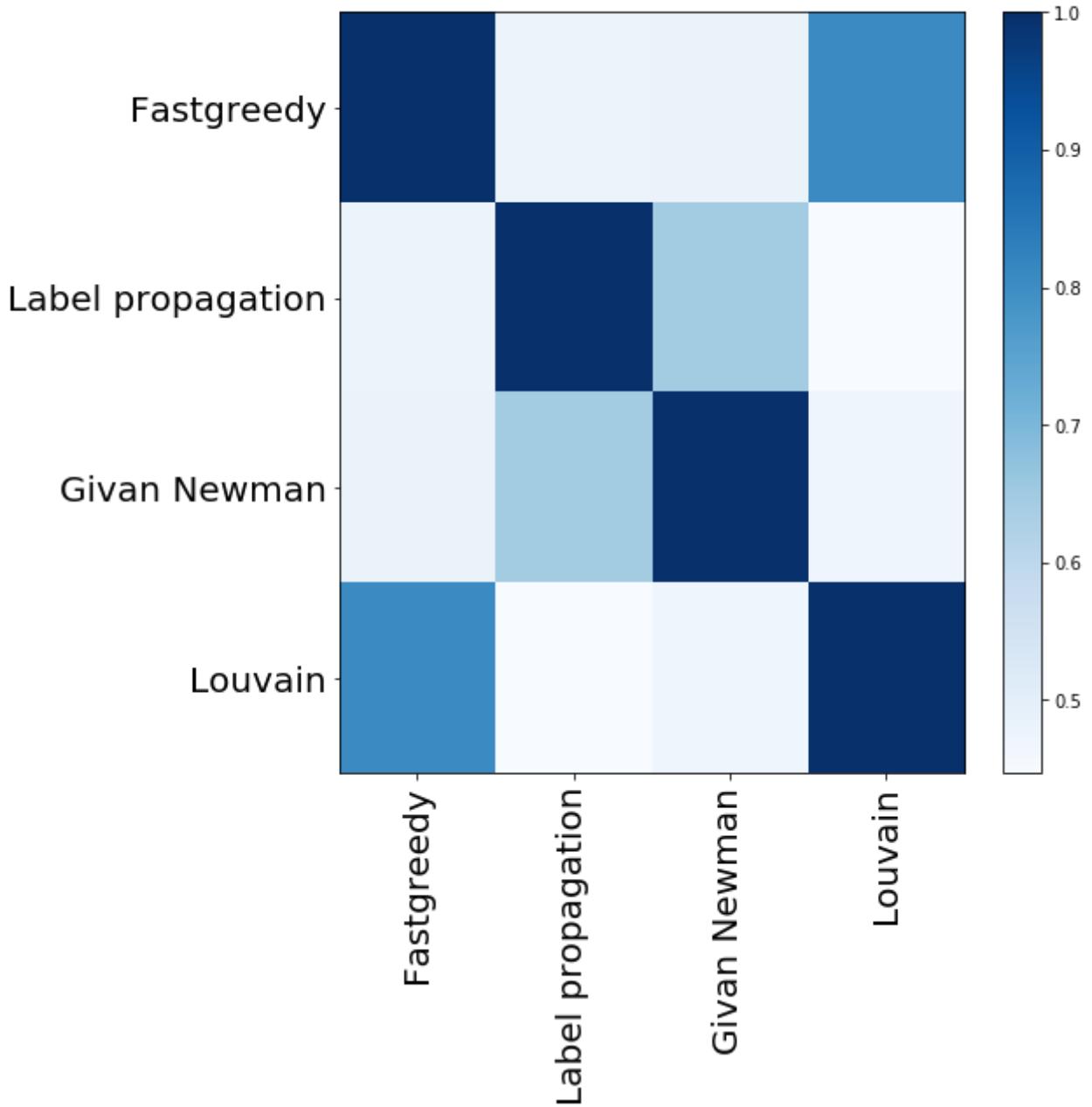
Modularity Method: Louvain



```
corrplot_NMI_between_modularities(listaClusters  
 ,["Fastgreedy", "Label propagation", "Givan Newman", "Louvain"])
```



Correlation between centrality measures



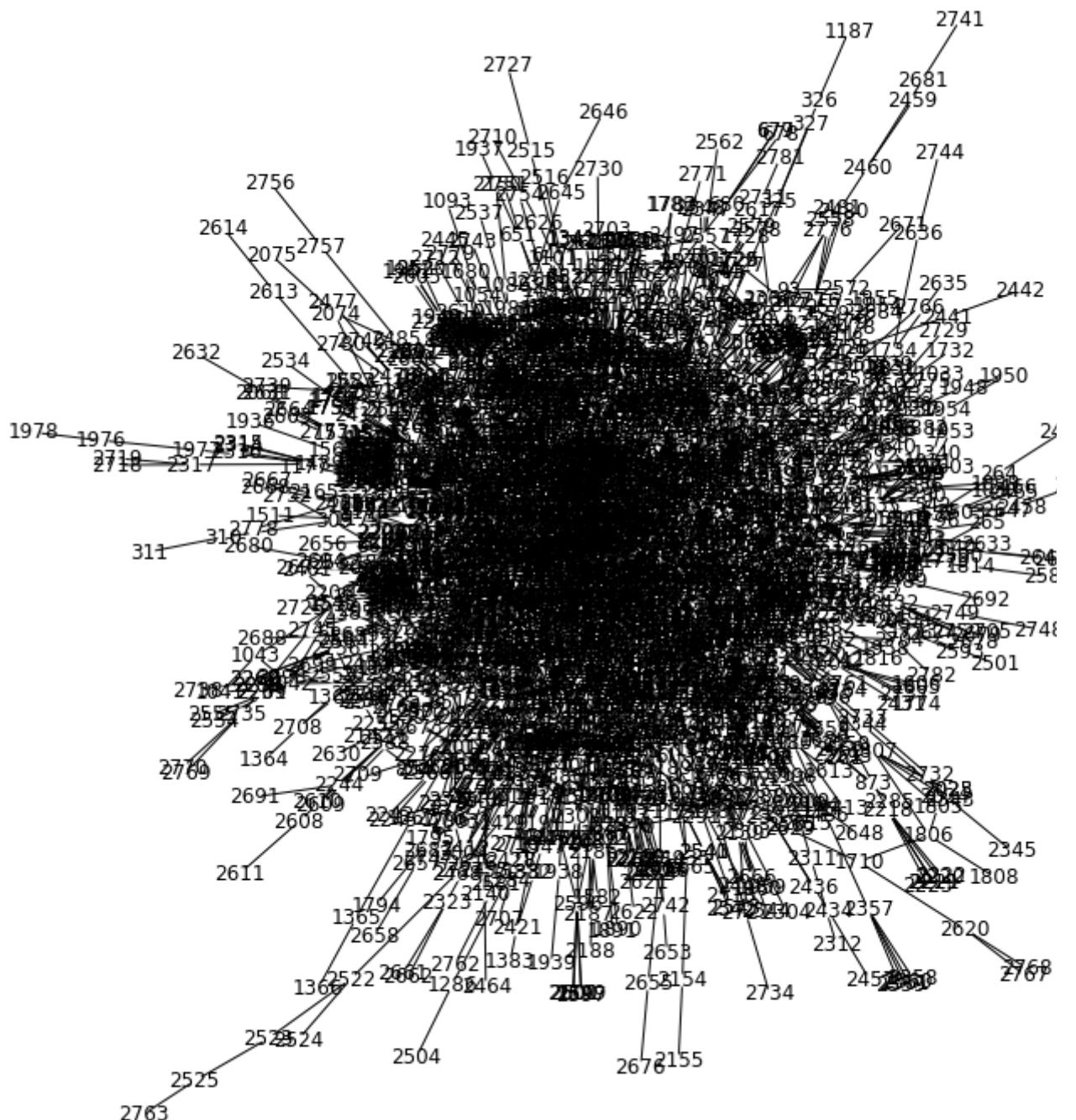
```
print("Network : ", listaIndex[3],"\n")
G = listaGraph[3]
df.loc["Human protein network",:]

⇒ Network : Human protein network

N           2783.000000
Avg Degree      4.316924
AssortCoef     -0.136560
Avg SPL        4.839802
Name: Human protein network, dtype: float64
```

```
plota_rede(G, nd_size=50, fig_size=10, n_color = random.randint(0,7))
```

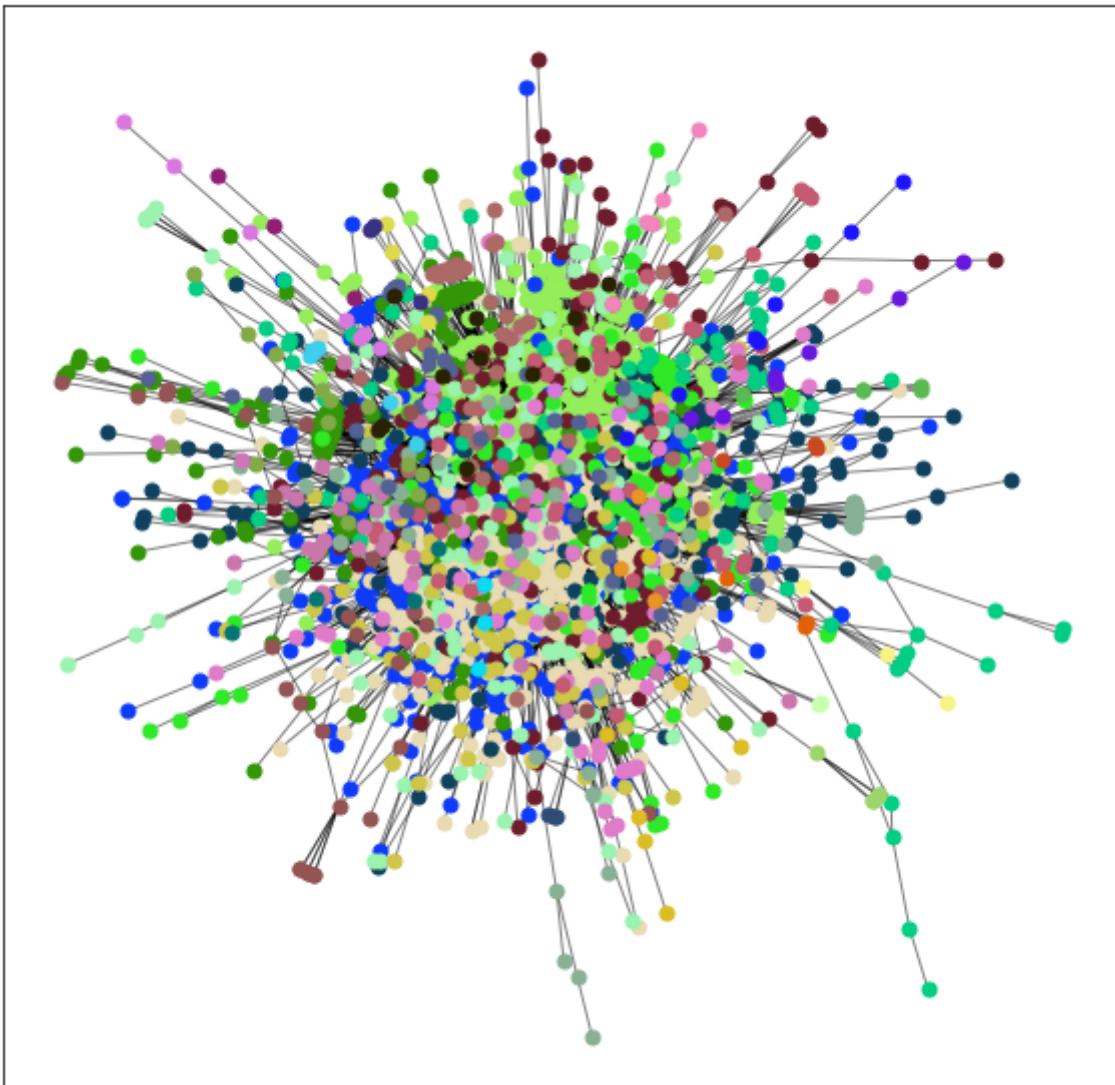
⇒



```
listaClusters = list()
partition_greedy = greedy(G)
listaClusters.append(partition_greedy)
```



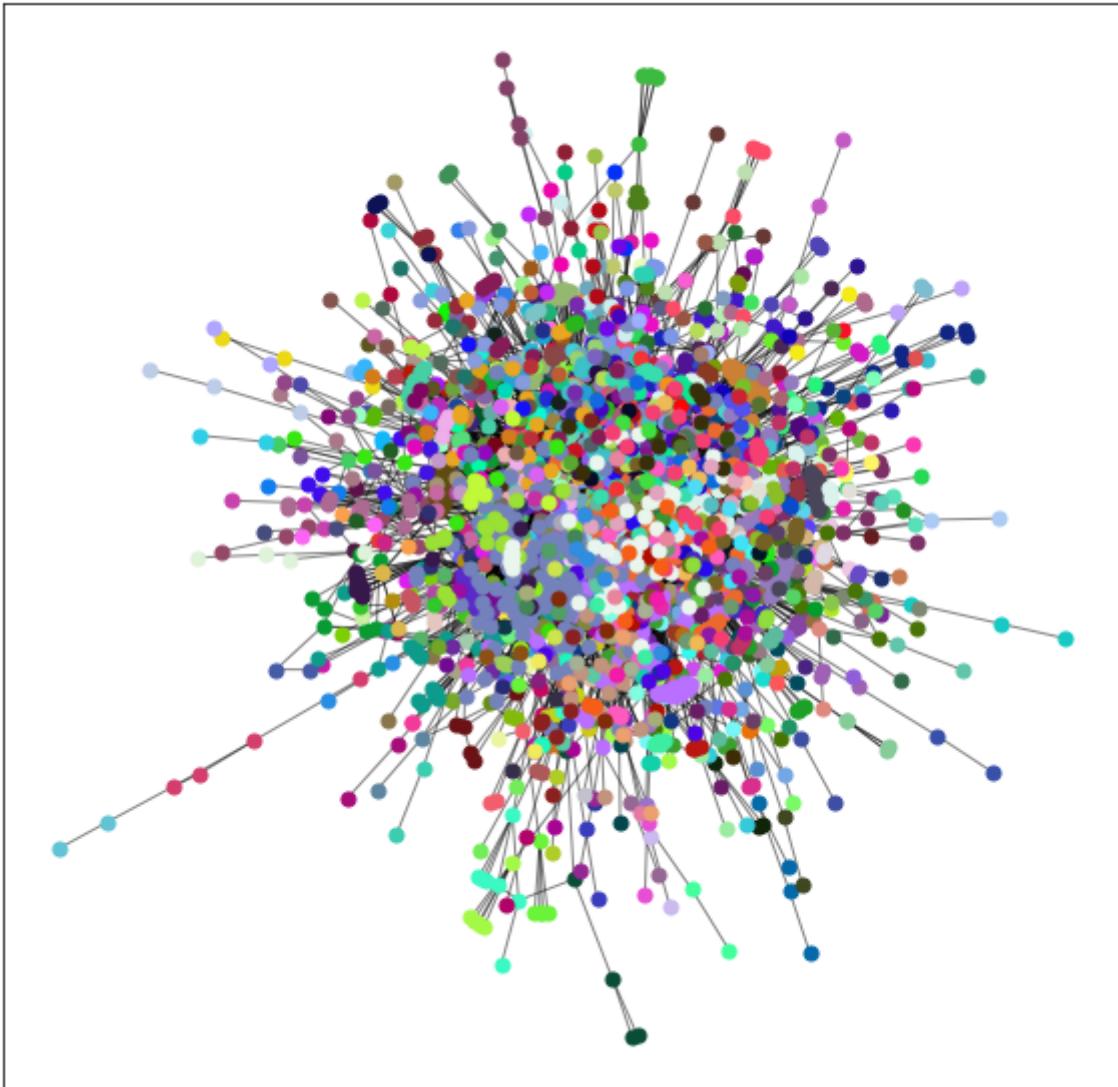
Modularity Method: FastGreedy



```
partition_label = label(G)
listaClusters.append(partition_label)
```



Modularity Method: Label Propagation



```
partition_givan_newman = givan_newman_method(G,10)
listaClusters.append(partition_givan_newman)

partition_louvain = louvain(G)
listaClusters.append(partition_louvain)

corrplot_NMI_between_modularities(listaClusters
    ,["Fastgreedy", "Label propagation", "Givan Newman", "Louvain"])

correlation_matrix(df,2)
```

