

## YOUTUBE NETWORK ANALYSIS

Project by

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### ▼ 1) Load the dataset into NetworkX to create an undirected graph

```
import networkx as nx
from networkx.algorithms import community
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import random
plt.rcParams.update({'figure.max_open_warning': 50})
```

Generates a plot with the degrees of distribution of the connected components. To facilitate the representation it was decided to

▼ also use the loglog contained in numpy. Plot of the histogram degree distribution

-----

Input: G---> Graphs

A networkx graph

Output: a list of values of the degree distribution

```
def plot_degree_dist(G):
    degrees = G.degree()
    degrees = dict(degrees)
    values = sorted(set(degrees.values()))
    histo = [list(degrees.values()).count(x) for x in values]
    P_k = [x / G.order() for x in histo]

    plt.figure()
    plt.plot(values, P_k, "ro-")
```

```

plt.xlabel("k")
plt.ylabel("p(k)")
plt.title("Degree Distribution")
plt.show()

plt.figure()
plt.grid(False)
plt.loglog(values, P_k, "bo-")
plt.xlabel("log k")
plt.ylabel("log p(k)")
plt.title("log Degree Distribution")
plt.show()
plt.figure()
degrees = [G.degree(n) for n in G.nodes()]
counts = dict()
for i in degrees:
    counts[i] = counts.get(i, 0) + 1
axes = plt.gca()
axes.set_xlim([0,100])
axes.set_ylim([0,1000])
plt.grid(False)
plt.bar(list(counts.keys()), counts.values(), color='r')
plt.title("Degree Histogram")
plt.ylabel("Count")
plt.xlabel("Degree")
plt.show()

```

- Generates a plot with the IN/OUT degrees of distribution of the
- ▼ connected components. To facilitate the representation it was decided to also use the loglog contained in numpy

#### Parameters

Input: G---> Graphs

A networkx graph

Output: a list of values of the degree distribution

```

def plot_degree_In(G):
    N = G.order()
    in_degrees = G.in_degree() #built-in function to estimate in-degree distribution
    in_degrees = dict(in_degrees)
    in_values= sorted(set(in_degrees.values()))
    in_hist = [list(in_degrees.values()).count(x) for x in in_values]
    in_P_k = [x / N for x in in_hist]
    out_degrees = G.out_degree() #built-in function to estimate out-degree distribution
    out_degrees = dict(out_degrees)
    out_values = sorted(set(out_degrees.values()))
    out_hist = [list(out_degrees.values()).count(x) for x in out_values]
    out_P_k = [x / N for x in out_hist]

```

```
plt.figure()
plt.grid(False)
plt.plot(in_values ,in_P_k, "r.")
plt.plot(out_values,out_P_k, "b.")
plt.legend(['In-degree','Out-degree'])
plt.xlabel("k")
plt.ylabel("p(k)")
plt.title("Degree Distribution")
plt.show()

plt.figure()
plt.grid(False)
plt.loglog(in_values ,in_P_k, "r.")
plt.loglog(out_values,out_P_k, "b.")
plt.legend(['In-degree','Out-degree'])
plt.xlabel("log k")
plt.ylabel("log p(k)")
plt.title("log log Degree Distribution")
plt.show()
```

Generates a plot with the clustering coefficient. It is a measure of the degree to which nodes in a graph tend to cluster together. To facilitate the representation it was decided to also use the loglog contained in numpy

#### Parameters

Input: G---> Graphs

Output: a list of values of the degree distribution

```
def plot_clustering_coefficient(G):
    clust_coefficients = nx.clustering(G) #built-in function to estimate clustering c
    clust_coefficients = dict(clust_coefficients)
    values1= sorted(set(clust_coefficients.values()))
    histo1 = [list(clust_coefficients.values()).count(x) for x in values1]

    plt.figure()
    plt.grid(False)
    plt.plot(values1,histo1, "r.")
    plt.xlabel("k")
    plt.ylabel("C (Clustering Coeff)")
    plt.title("Clustering Coefficients")
    plt.show()
    plt.figure()
    plt.grid(False)
    plt.loglog(values1,histo1, "r.")
    plt.xlabel("log degree k")
```

```
plt.ylabel("c (clustering coeff)")
plt.title("log log Clustering Coefficients")
plt.show()

plt.figure()
degrees1 = [nx.clustering(G,n) for n in G.nodes()]
plt.hist(degrees1)
plt.xlabel("log degree k")
plt.ylabel("C (Clustering Coeff) hist")
plt.title("Clustering Coefficients")
plt.show()
```

## ▼ Generate a view of lattice graph

Parameters:

- G (NetworkX graph) -
- k (node) - number of adjacent nodes

Returns:

graphs - a graph lattice view

Return type: networkx graph

```
def adjacent_edges(nodes, halfk):
```

```
    n = len(nodes)
    for i, u in enumerate(nodes):
        for j in range(i+1, i+halfk+1):
            v = nodes[j % n]
            yield u,v
```

```
def make_ring_lattice(n,k):
```

```
    G = nx.Graph()
    nodes = range(n)
    G.add_nodes_from(nodes)
    G.add_edges_from(adjacent_edges(nodes, k//2))
    return G
```

```
def flip(p):
```

```
    return np.random.random() < p
```

```
def rewire(G,p):
```

```
    nodes = set(G)
    for u, v in G.edges():
        if flip(p):
            choices = nodes - {u} - set(G[u])
            new_v = np.random.choice(list(choices))
            G.remove_edge(u, v)
            G.add_edge(u, new_v)
```

```
def small_world(n,k,p):
    sw = make_ring_lattice(n,k)
    rewire(sw,p)
    return sw
```

Return the core number for each vertex. A  $k$ -core is a maximal subgraph that contains nodes of degree  $k$  or more. The core number of a node is the largest value  $k$  of a  $k$ -core containing that node.

Parameters

-----

G : NetworkX graph

A graph or directed graph

Returns

-----

core\_number : dictionary

A dictionary keyed by node to the core number

```
def k_core(G,k,t):
    H=G.copy()
    i=1
    while (i>0):
        i=0
        for node in list(H.nodes()):
            if H.degree(node)<k:
                H.remove_node(node)
                i+=1
    if (H.order()!=0):
        plt.figure()
        plt.title(str(k) + '-core decomposition of' + t)
        nx.draw(H,with_labels=True)
    return H
```

```
def full_k_core_decomposition(G,t):
    empty = False
    k=1
    while (empty==False):
        H = k_core(G,k,t)
        k+=1
        if (H.order()==0):
            empty = True
```

```
graphs = nx.read_edgelist('com-youtube.ungraph.txt',create_using=nx.Graph(), nodetype=int)
```

```
subset = 1000
edges = graphs.edges()
edges = list(edges)[:int(subset)]
edges = [list(elem) for elem in edges]

#%% formatting necessary to allow performing nx.parse_edgelist

_newlist = []
_list = []

for subsets in edges:
    for element in subsets:
        _list.append(element)

_temp= int(len(_list)*0.5)

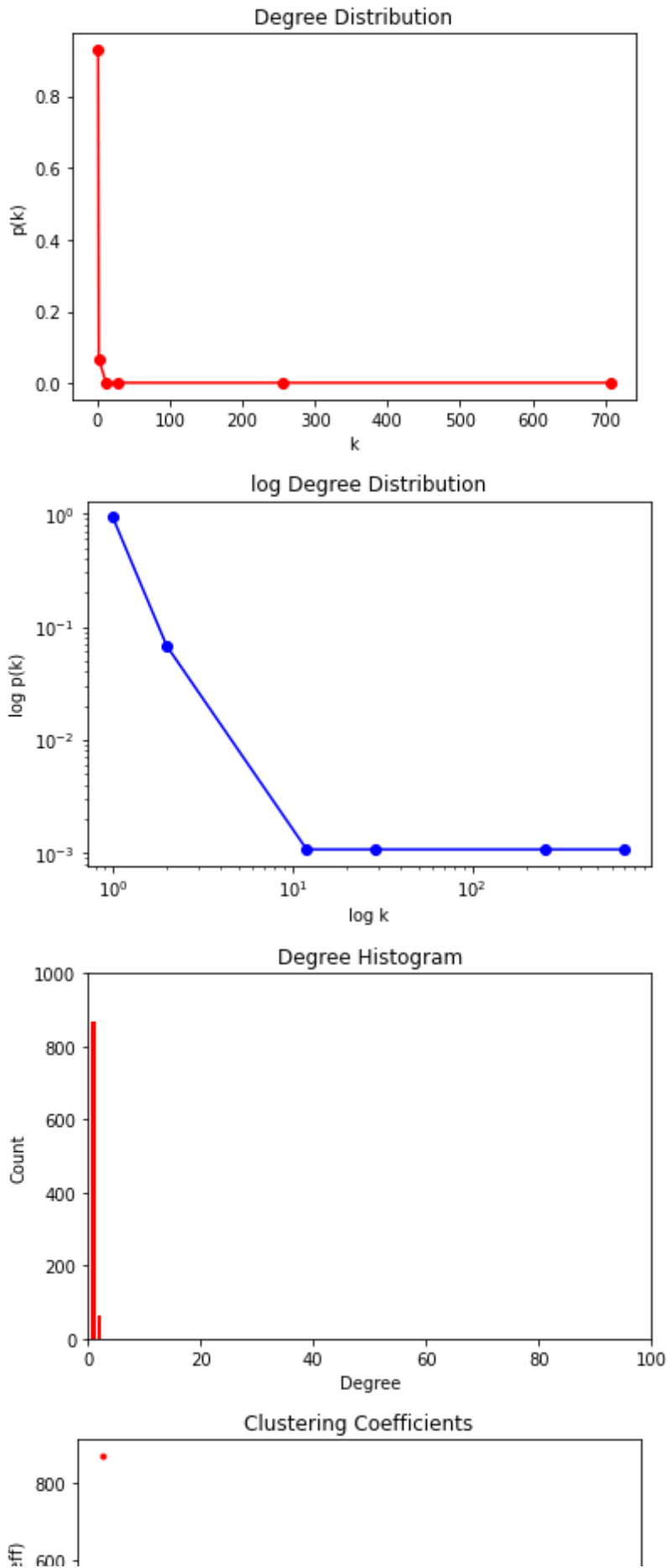
for i in range (_temp):
    _newlist.append(str(_list[2*i]) + " " + str(_list[2*i +1]) )
print(_newlist)
graphs = nx.parse_edgelist(_newlist, nodetype = int)
#%%
"""1 Original Graphs Measures"""
N=graphs.order()
E = graphs.number_of_edges()
Av_deg_undirected = float(2*E)/N

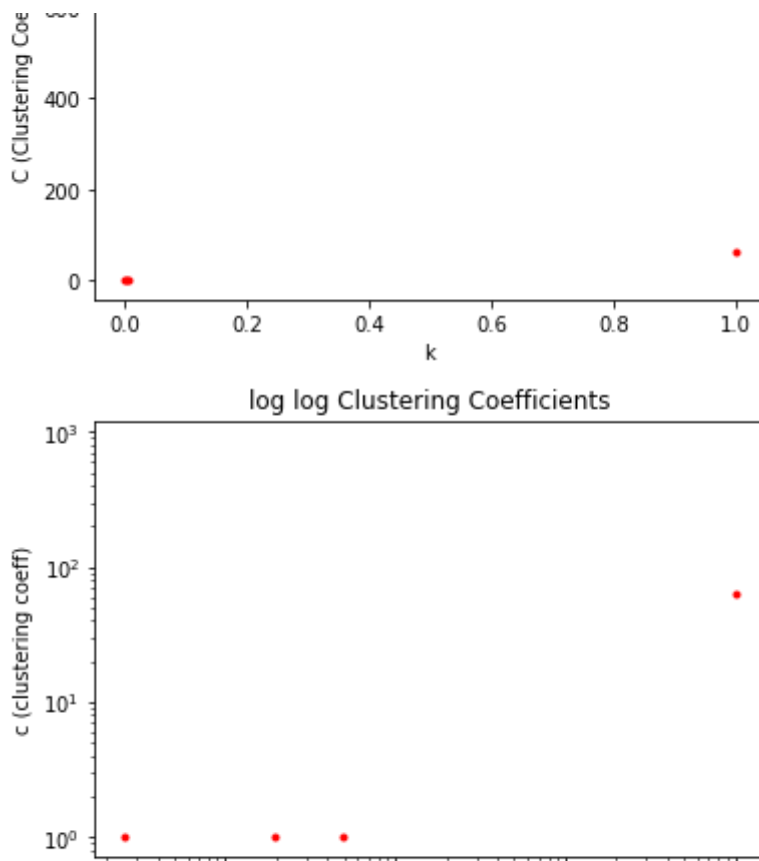
print ("\n ORIGINAL GRAPH: ")
print("The number of nodes is:", N)
print("The number of edges is:", E)
print("The average degree (undirected graph) is:", Av_deg_undirected)

plot_degree_dist(graphs)
plot_clustering_coefficient(graphs)
print ('The average clustering coefficient is: ' + str(nx.average_clustering(graphs)))
```

['1 2', '1 3', '1 4', '1 5', '1 6', '1 7', '1 8', '1 9', '1 10', '1 11', '1 12', '1

ORIGINAL GRAPH:  
The number of nodes is: 937  
The number of edges is: 1000  
The average degree (undirected graph) is: 2.134471718249733





## ▼ Community Generation

```
|        |
```

```
communities_gen = community.girvan_newman(graphs)
top_level_communities = next(communities_gen)
next_level_communities = next(communities_gen)
a=sorted(map(sorted,next_level_communities))
```

```
return a
```

## ▼ GENERATION OF THE SBM GRAPH

```
|        |
```

```
sizes = []
probs = []
for com in a:
    sizes.append(len(com))

num11 = sizes[0] * (sizes[0]-1)*0.5
num12 = sizes[0] * sizes[1]
num13 = sizes[0] * sizes[2]
num22 = sizes[1] * (sizes[1]-1)*0.5
num23 = sizes[1] * sizes[2]
num33 = sizes[2] * (sizes[2]-1)*0.5

num_edges11,num_edges22,num_edges33,num_edges12,num_edges13,num_edges23 = [0,0,0,0,0,0]
for g in edges:
    g[0] = int(g[0])
    g[1] = int(g[1])
for h in edges:
```



```

    if (h[0] in a[0] and h[1] in a[0]):
        num_edges11+=1
    elif (h[0] in a[1] and h[1] in a[1]):
        num_edges22+=1
    elif (h[0] in a[2] and h[1] in a[2]):
        num_edges33+=1
    elif ((h[0] in a[0] and h[1] in a[1]) or (h[0] in a[1] and h[1] in a[0])):
        num_edges12+=1
    elif ((h[0] in a[0] and h[1] in a[2]) or (h[0] in a[2] and h[1] in a[0])):
        num_edges13+=1
    else:
        (h[0] in a[1] and h[1] in a[2]) or (h[0] in a[2] and h[1] in a[1])
        num_edges23+=1
p11 = float (num_edges11/num11)
p12 = float (num_edges12/num12)
p13 = float (num_edges13/num13)
p22 = float (num_edges22/num22)
p23 = float (num_edges23/num23)
p33 = float (num_edges33/num33)

probs1 = [p11,p12,p13],[p12,p22,p23],[p13,p23,p33]

print(probs1)
#% It is now possible to generate the SBM and calculate some statistic measures on it

SBM = nx.stochastic_block_model(sizes, probs1, seed=0)

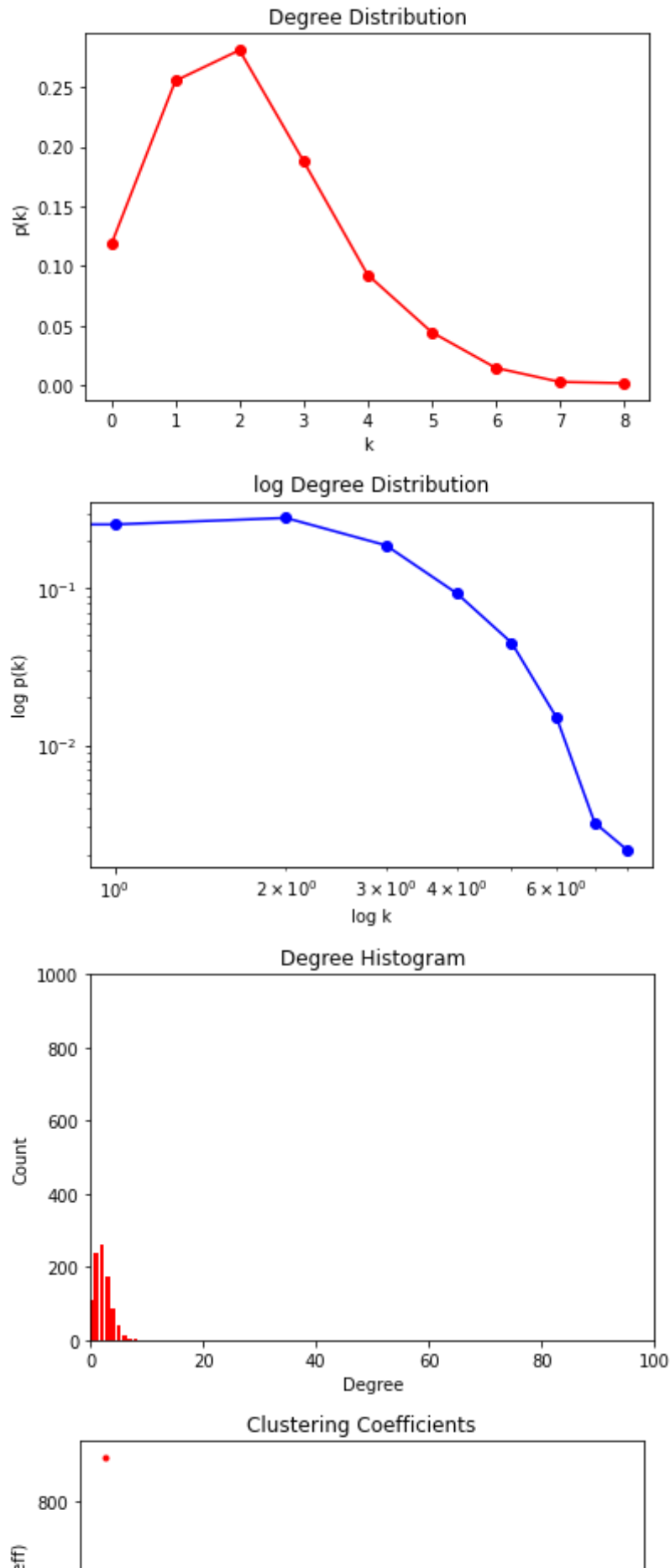
"""2a STATISTICS ABOUT MEASURES - SBM"""
SBM_nodes=SBM.order()
SBM_Edges = SBM.number_of_edges()
Av_deg_SBM = float(2*SBM_Edges)/SBM_nodes

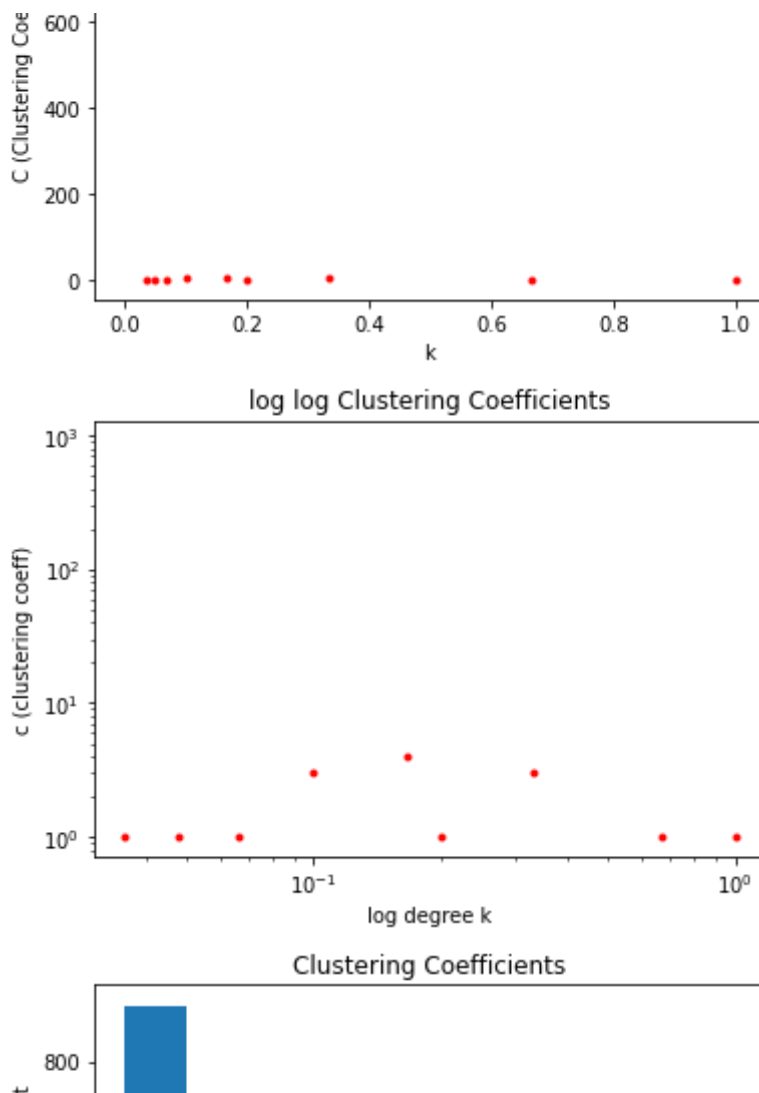
print ("\n SBM GRAPH: ")
print("The number of nodes is:", SBM_nodes)
print("The number of edges is:", SBM_Edges)
print("The average degree (undirected graph) is:", Av_deg_SBM)

plot_degree_dist(SBM)
plot_clustering_coefficient(SBM)
print ('The average clustering coefficient is: ' + str(nx.average_clustering(SBM)))

```

SBM GRAPH:  
The number of nodes is: 937  
The number of edges is: 986  
The average degree (undirected graph) is: 2.104589114194237





## ▼ Generation of Erdos-Renyi random graph

eri ann ↓

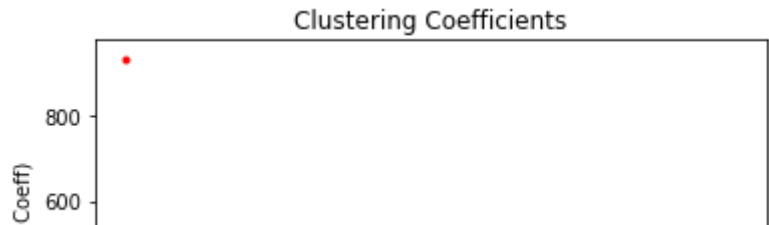
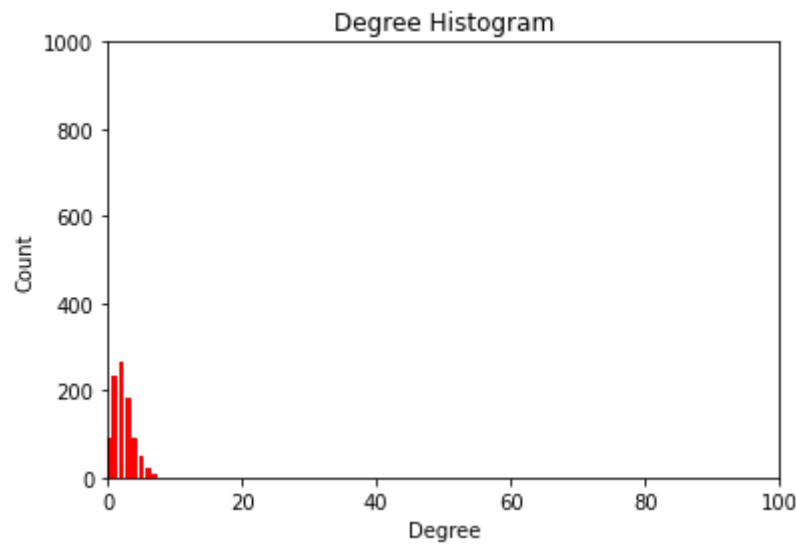
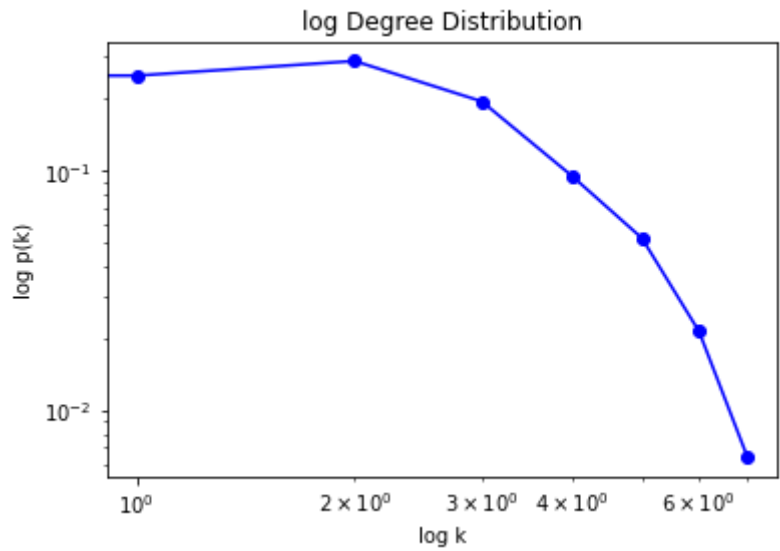
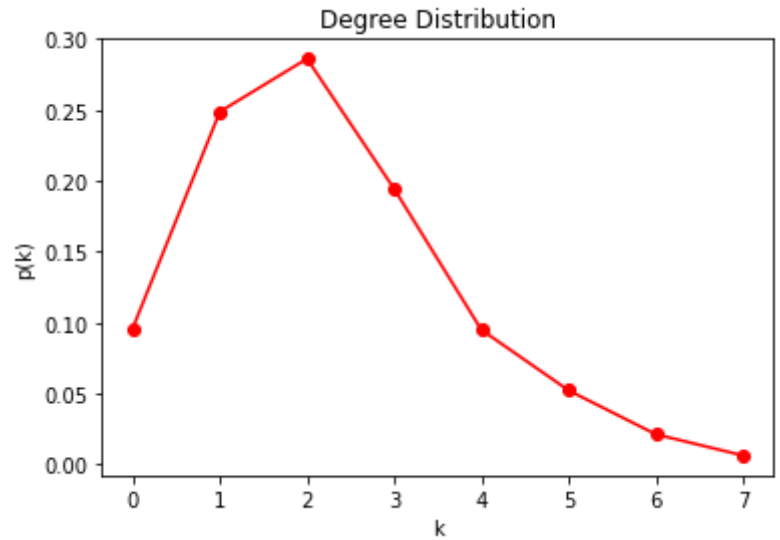
"""2b STATISTICS ABOUT MEASURES - ERDOS-RENYI"""

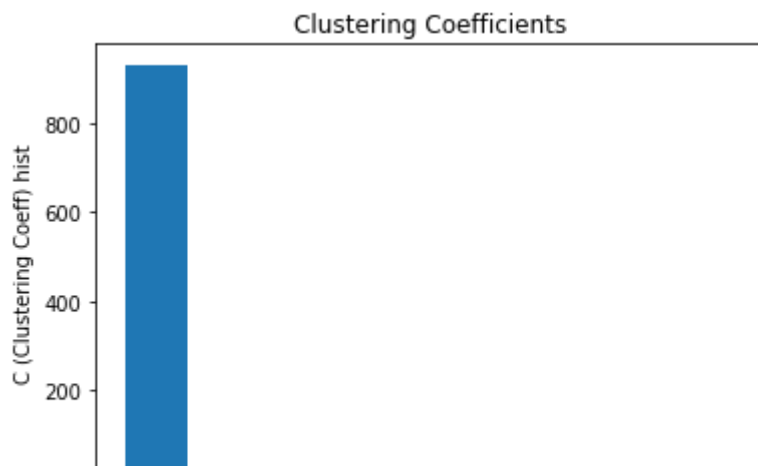
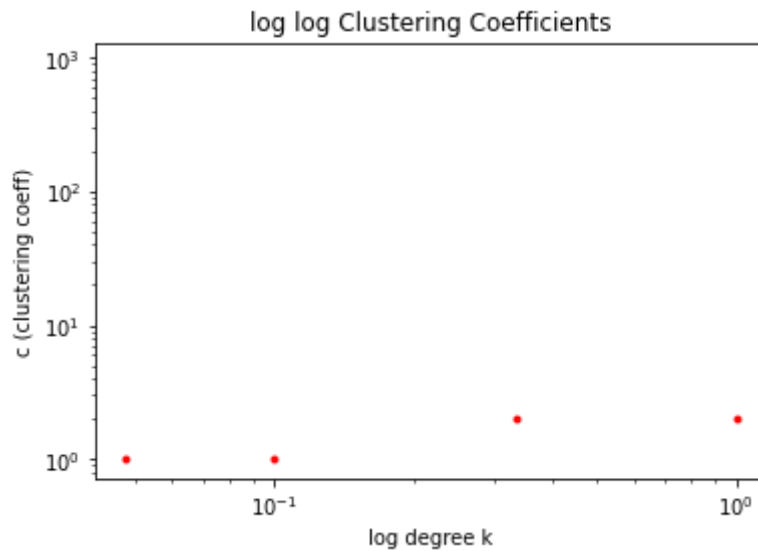
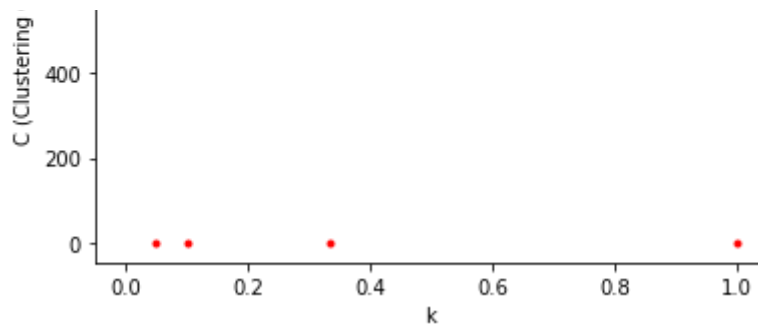
```
Proba = E/(N*(N-1)/2)
Erdos_renyi = nx.erdos_renyi_graph (N, Proba)
Nodes_erdos=Erdos_renyi.order()
Edges_erdos = Erdos_renyi.number_of_edges()
Av_deg_und_erdos = float(2*Edges_erdos)/Nodes_erdos

print ("\n ERDOS-RENYI GRAPH: ")
print("The number of nodes is:", Nodes_erdos)
print("The number of edges is:", Edges_erdos)
print("The average degree (undirected graph) is:", Av_deg_und_erdos)

plot_degree_dist(Erdos_renyi)
plot_clustering_coefficient(Erdos_renyi)
print ('The average clustering coefficient is: ' + str(nx.average_clustering(Erdos_renyi)))
```

ERDOS-RENYI GRAPH:  
The number of nodes is: 937  
The number of edges is: 1039  
The average degree (undirected graph) is: 2.2177161152614726





""2b STATISTICS ABOUT MEASURES - SMALL WORLD""

```
Small_World = small_world(N,4,0.2)
nx.draw_circular(Small_World)
```

```
Nodes_SW=Small_World.order()
Edge_SW = Small_World.number_of_edges()
Av_deg_SW = float(2*Edge_SW)/Nodes_SW
print ("\n SMALL WORLD GRAPH: ")
print("The number of nodes is:", Nodes_SW)
print("The number of edges is:", Edge_SW)
print("The average degree (undirected graph) is:", Av_deg_SW)
```

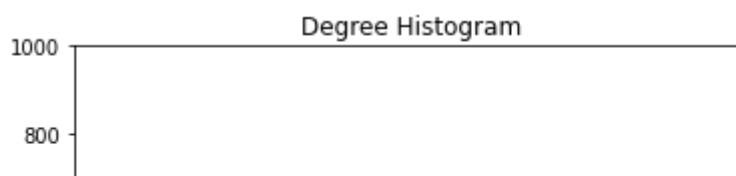
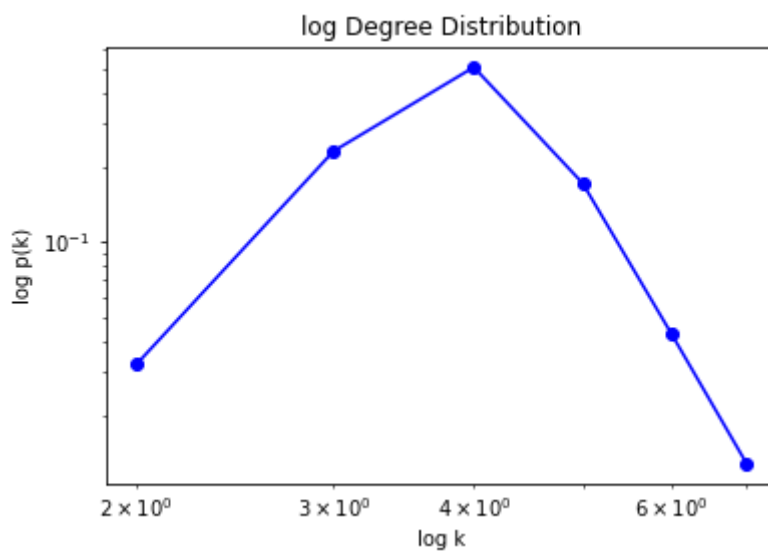
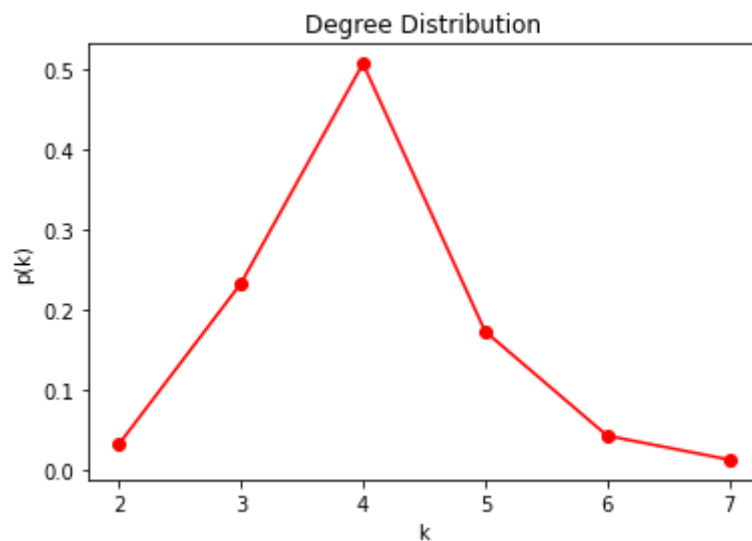
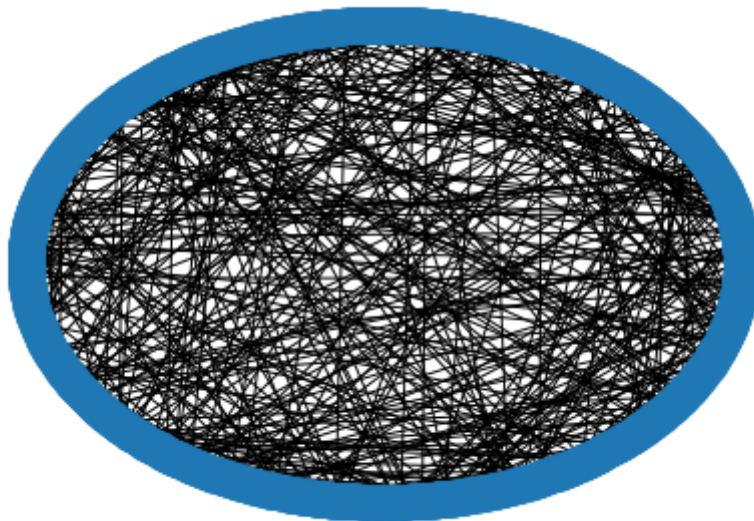
```
plot_degree_dist(Small_World)
plot_clustering_coefficient(Small_World)
print ('The average clustering coefficient is: ' + str(nx.average_clustering(Small_World)))
```

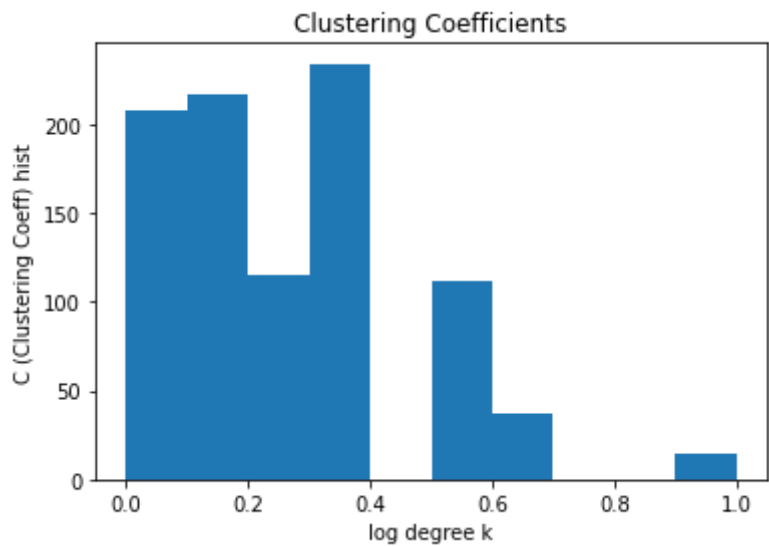
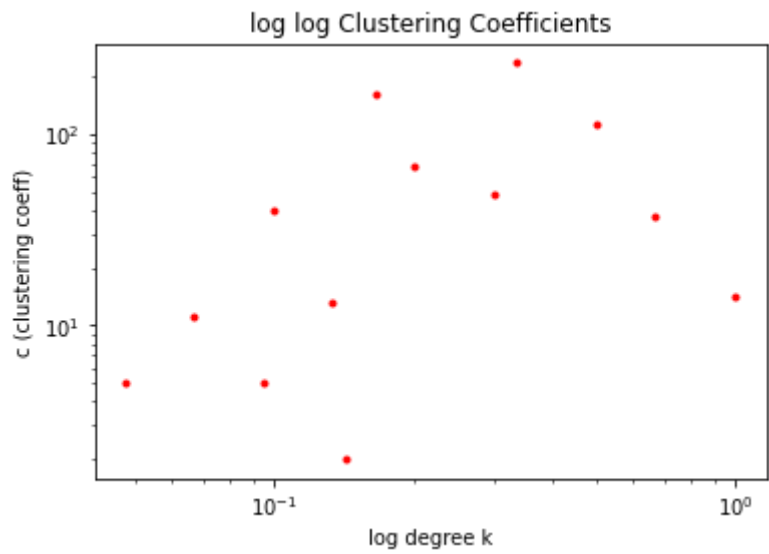
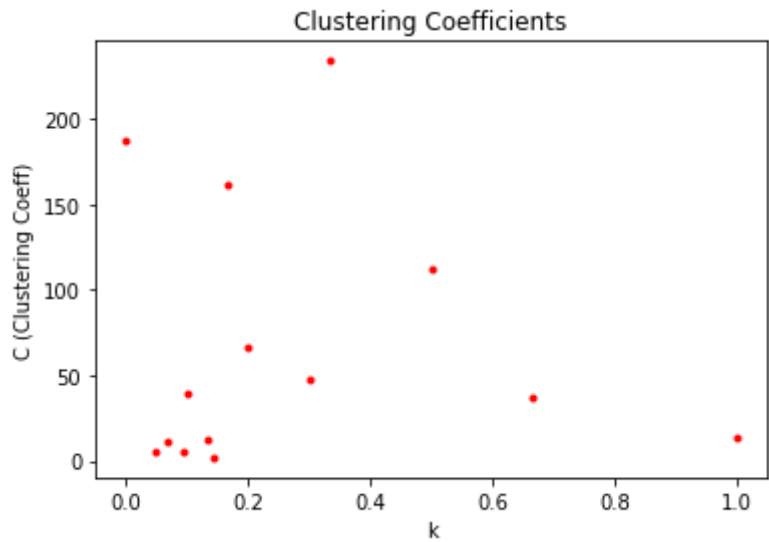
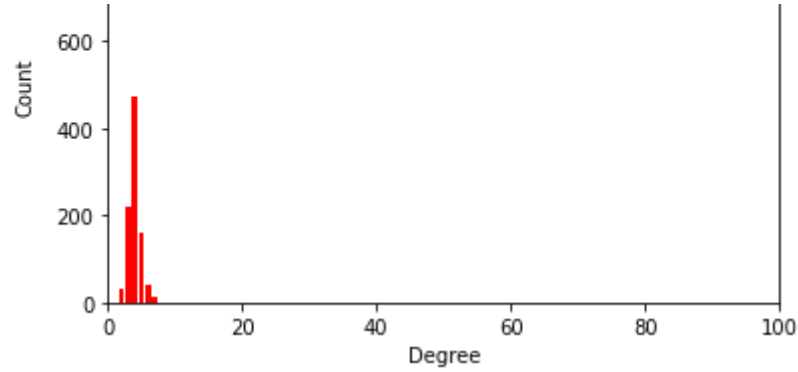
## SMALL WORLD GRAPH:

The number of nodes is: 937

The number of edges is: 1874

The average degree (undirected graph) is: 4.0





```
"""4 DIRECTED VERSION WITHOUT 25% OF THE LINKS"""
```

```
k = int(E*0.25)
DG = graphs.copy()
DG = DG.to_directed()
edges_d = DG.edges()
list_edges_d = list(edges_d)
random.shuffle(list_edges_d)

for edgee in list_edges_d:
    if (DG.degree(edgee[0]) != 1 and DG.degree(edgee[1]) != 1):
        DG.remove_edge(edgee[0],edgee[1])
        k-=1
    if (k==0):
        break

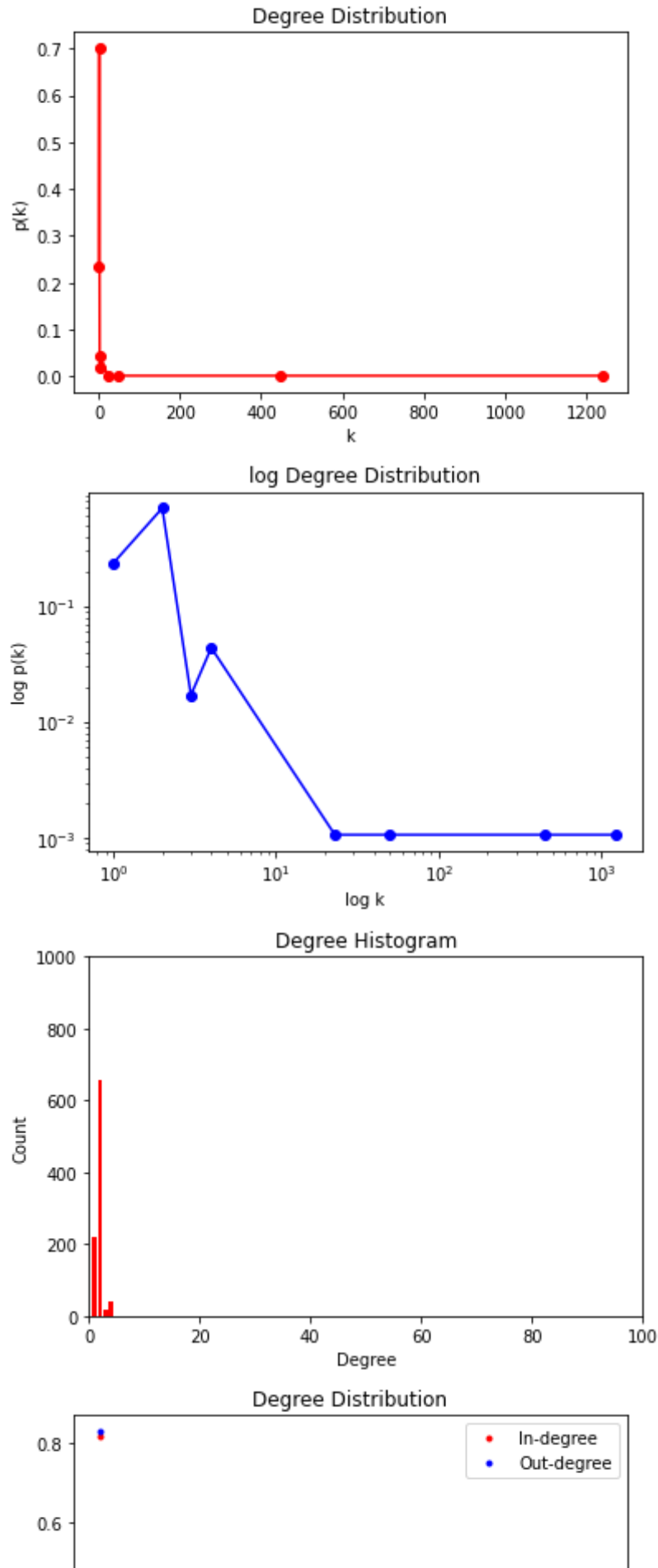
N4=DG.order()
E4 = DG.number_of_edges()
Av_deg_d = float(E)/N

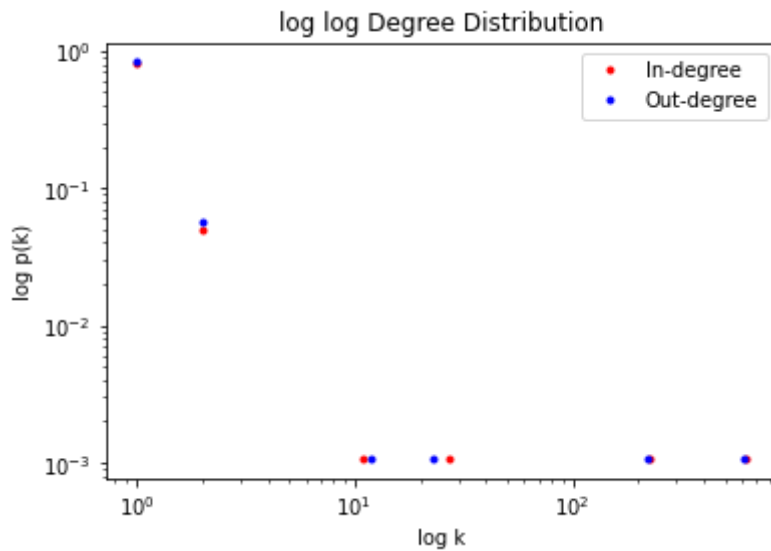
print ("\n DIRECTED VERSION WITHOUT 25% OF THE LINKS: ")
print("The number of nodes is:", N4)
print("The number of edges is:", E4)
print("The average degree (directed graph) is:", Av_deg_d)

plot_degree_dist(DG)
plot_degree_In(DG)
plot_clustering_coefficient(DG)
DG = DG.to_undirected()
print ('The average clustering coefficient is: ' + str(nx.average_clustering(DG)))
```



DIRECTED VERSION WITHOUT 25% OF THE LINKS:  
The number of nodes is: 937  
The number of edges is: 1750  
The average degree (directed graph) is: 1.0672358591248665





```
nodes = dict()
val = 0
for node in list(graphs.nodes()):
```

```
nodes[node] = val
val -= 1

# We have calculated page rank using three measures - simple pagerank, personalized pagerank
simple_pagerank = nx.pagerank(graphs, alpha=0.85)
personalized_pagerank = nx.pagerank(graphs, alpha=0.85, personalization=nodes)
nstart_pagerank = nx.pagerank(graphs, alpha=0.85, nstart=nodes)
weighted_pagerank = nx.pagerank(graphs, alpha=0.85)
weighted_personalized_pagerank = nx.pagerank(graphs, alpha=0.85, personalization=nodes)

df_metrics = pd.DataFrame(dict(
    simple_pagerank = simple_pagerank,
    personalized_pagerank = personalized_pagerank,
    nstart_pagerank = nstart_pagerank,
    weighted_pagerank = weighted_pagerank,
    weighted_personalized_pagerank = weighted_personalized_pagerank,
))
df_metrics.index.name='Nodes'
df_metrics
```

	simple_pagerank	personalized_pagerank	nstart_pagerank	weighted_pagerank
Nodes				
1	0.013706	0.003337	0.013704	0.013706
2	0.112634	0.063337	0.112636	0.112634
3	0.006097	0.003030	0.006096	0.006097
4	0.329266	0.390945	0.329277	0.329266
5	0.000562	0.000099	0.000562	0.000562
...	...	...	...	...
18008	0.000556	0.000788	0.000556	0.000556
18009	0.000556	0.000789	0.000556	0.000556
18010	0.000556	0.000789	0.000556	0.000556
18011	0.000556	0.000789	0.000556	0.000556
18012	0.000556	0.000790	0.000556	0.000556

937 rows × 5 columns

```
page_rank = nx.pagerank(graphs)
page_rank
391: 0.0005555972112576775,
402: 0.0005555972112576775,
404: 0.0009292361516007721,
406: 0.0005555972112576775,
407: 0.0005555972112576775,
412: 0.0005555972112576775,
420: 0.0005555972112576775,
446: 0.0005337243192118247,
448: 0.0005555972112576775,
455: 0.0009292361516007721.
```

```

468: 0.0005555972112576775,
470: 0.0005555972112576775,
480: 0.0009292361516007721,
495: 0.0009292361516007721,
496: 0.0005555972112576775,
511: 0.0005555972112576775,
514: 0.0009292361516007721,
518: 0.0005555972112576775,
519: 0.0005555972112576775,
530: 0.0005555972112576775,
534: 0.0005337243192118247,
556: 0.0005555972112576775,
559: 0.0005555972112576775,
617: 0.0005555972112576775,
622: 0.0005555972112576775,
624: 0.0005555972112576775,
631: 0.0005555972112576775,
688: 0.0009292361516007721,
701: 0.0005555972112576775,
707: 0.0005555972112576775,
710: 0.0005555972112576775,
718: 0.0009292361516007721,
723: 0.0009292361516007721,
727: 0.0005555972112576775,
730: 0.0009292361516007721,
743: 0.0005555972112576775,
745: 0.0005555972112576775,
760: 0.0005555972112576775,
762: 0.0005337243192118247,
773: 0.0005555972112576775,
776: 0.0009292361516007721,
797: 0.0005337243192118247,
803: 0.0009292361516007721,
806: 0.0005555972112576775,
811: 0.0005555972112576775,
822: 0.0005555972112576775,
826: 0.0005555972112576775,
832: 0.0005555972112576775,
834: 0.0005555972112576775,
839: 0.0005337243192118247,
840: 0.0005337243192118247,
844: 0.0005555972112576775,
845: 0.0005555972112576775,
847: 0.0005337243192118247,
848: 0.0009292361516007721,
850: 0.0005555972112576775,
851: 0.0005337243192118247,
863: 0.0005555972112576775,
866: 0.0005555972112576775.

```

## ▼ Degree Centrality

```
dict_degree centrality = nx.degree centrality (graphs)
dict_degree centrality
```

```

{1: 0.030982905982905987,
 2: 0.27350427350427353,

```

```
3: 0.012820512820512822,  
4: 0.7553418803418804,  
5: 0.0010683760683760685,  
6: 0.0010683760683760685,  
7: 0.0010683760683760685,  
8: 0.0010683760683760685,  
9: 0.0010683760683760685,  
10: 0.0010683760683760685,  
11: 0.002136752136752137,  
12: 0.0010683760683760685,  
13: 0.0010683760683760685,  
14: 0.0010683760683760685,  
15: 0.0010683760683760685,  
16: 0.0010683760683760685,  
17: 0.0010683760683760685,  
18: 0.0010683760683760685,  
19: 0.0010683760683760685,  
20: 0.0010683760683760685,  
21: 0.0010683760683760685,  
22: 0.0010683760683760685,  
40: 0.0010683760683760685,  
45: 0.0010683760683760685,  
47: 0.0010683760683760685,  
63: 0.0010683760683760685,  
68: 0.0010683760683760685,  
77: 0.0010683760683760685,  
78: 0.0010683760683760685,  
91: 0.0010683760683760685,  
100: 0.0010683760683760685,  
104: 0.0010683760683760685,  
106: 0.002136752136752137,  
107: 0.0010683760683760685,  
114: 0.0010683760683760685,  
115: 0.0010683760683760685,  
117: 0.0010683760683760685,  
121: 0.0010683760683760685,  
126: 0.0010683760683760685,  
134: 0.0010683760683760685,  
140: 0.0010683760683760685,  
142: 0.0010683760683760685,  
154: 0.0010683760683760685,  
165: 0.0010683760683760685,  
183: 0.0010683760683760685,  
195: 0.0010683760683760685,  
204: 0.0010683760683760685,  
210: 0.0010683760683760685,  
213: 0.0010683760683760685,  
225: 0.0010683760683760685,  
242: 0.0010683760683760685,  
247: 0.002136752136752137,  
249: 0.0010683760683760685,  
269: 0.0010683760683760685,  
276: 0.002136752136752137,  
291: 0.002136752136752137,  
297: 0.0010683760683760685,  
304: 0.0010683760683760685.
```

## ▼ Closeness Centrality

```
dict_closeness centrality = nx.closeness centrality(graphs)
dict_closeness centrality
```

```
{1: 0.5078676071622354,
 2: 0.5752919483712354,
 3: 0.33962264150943394,
 4: 0.7959183673469388,
 5: 0.3369330453563715,
 6: 0.3369330453563715,
 7: 0.3369330453563715,
 8: 0.3369330453563715,
 9: 0.3369330453563715,
10: 0.3369330453563715,
11: 0.4515195369030391,
12: 0.3369330453563715,
13: 0.3369330453563715,
14: 0.3369330453563715,
15: 0.3369330453563715,
16: 0.3369330453563715,
17: 0.3369330453563715,
18: 0.3369330453563715,
19: 0.3369330453563715,
20: 0.3369330453563715,
21: 0.3369330453563715,
22: 0.3369330453563715,
40: 0.36533957845433257,
45: 0.443391757460919,
47: 0.443391757460919,
63: 0.443391757460919,
68: 0.443391757460919,
77: 0.443391757460919,
78: 0.443391757460919,
91: 0.443391757460919,
100: 0.443391757460919,
104: 0.443391757460919,
106: 0.4880083420229406,
107: 0.36533957845433257,
114: 0.443391757460919,
115: 0.443391757460919,
117: 0.443391757460919,
121: 0.443391757460919,
126: 0.36533957845433257,
134: 0.36533957845433257,
140: 0.443391757460919,
142: 0.443391757460919,
154: 0.443391757460919,
165: 0.443391757460919,
183: 0.443391757460919,
195: 0.443391757460919,
204: 0.443391757460919,
210: 0.443391757460919,
213: 0.443391757460919,
225: 0.443391757460919,
242: 0.36533957845433257,
247: 0.4880083420229406,
249: 0.443391757460919,
269: 0.443391757460919,
276: 0.4880083420229406,
```

```
291: 0.4880083420229406,  
297: 0.443391757460919,  
-- -- -- -- --
```

## ▼ Harmonic Centrality

```
dict_harmonic Centrality = nx.harmonic Centrality(graphs)  
dict_harmonic Centrality
```

```
{1: 482.5,  
2: 594.1666666666665,  
3: 324.66666666666658,  
4: 819.6666666666667,  
5: 317.33333333333275,  
6: 317.33333333333275,  
7: 317.33333333333275,  
8: 317.33333333333275,  
9: 317.33333333333275,  
10: 317.33333333333275,  
11: 435.16666666666623,  
12: 317.33333333333275,  
13: 317.33333333333275,  
14: 317.33333333333275,  
15: 317.33333333333275,  
16: 317.33333333333275,  
17: 317.33333333333275,  
18: 317.33333333333275,  
19: 317.33333333333275,  
20: 317.33333333333275,  
21: 317.33333333333275,  
22: 317.33333333333275,  
40: 354.2499999999977,  
45: 429.41666666666634,  
47: 429.41666666666634,  
63: 429.41666666666634,  
68: 429.41666666666634,  
77: 429.41666666666634,  
78: 429.41666666666634,  
91: 429.41666666666634,  
100: 429.41666666666634,  
104: 429.41666666666634,  
106: 461.9166666666667,  
107: 354.2499999999977,  
114: 429.41666666666634,  
115: 429.41666666666634,  
117: 429.41666666666634,  
121: 429.41666666666634,  
126: 354.2499999999977,  
134: 354.2499999999977,  
140: 429.41666666666634,  
142: 429.41666666666634,  
154: 429.41666666666634,  
165: 429.41666666666634,  
183: 429.41666666666634,  
195: 429.41666666666634,  
204: 429.41666666666634,  
210: 429.41666666666634,  
213: 429.41666666666634,
```

```
225: 429.41666666666634,  
242: 354.24999999999977,  
247: 461.91666666666667,  
249: 429.41666666666634,  
269: 429.41666666666634,  
276: 461.91666666666667,  
291: 461.91666666666667,  
297: 429.41666666666634,  
304: 429.41666666666634,
```

## ▼ Betweenness Centrality

```
dict_betweeness=nx.betweenness centrality(graphs)  
dict_betweeness
```

```
4950: 0.0,  
4952: 0.0,  
4966: 0.0,  
4983: 0.0,  
5011: 0.0,  
5025: 0.0,  
5038: 0.0,  
5050: 0.0,  
5054: 0.0,  
5057: 0.0,  
5061: 0.0,  
5073: 0.0,  
  
5094: 0.0,  
5135: 0.0,  
5157: 0.0,  
5171: 0.0,  
5173: 0.0,  
5205: 0.0,  
5220: 0.0,  
5229: 0.0,  
5235: 0.0,  
5274: 0.0,  
5425: 0.0,  
5426: 0.0,  
5451: 0.0,  
5457: 0.0,  
5559: 0.0,  
5721: 0.0,  
5738: 0.0,  
5764: 0.0,  
5804: 0.0,  
5819: 0.0,  
5904: 0.0,  
5906: 0.0,  
5927: 0.0,  
5976: 0.0,  
5996: 0.0,  
6068: 0.0,  
6094: 0.0,  
6138: 0.0,  
6245: 0.0,  
6288: 0.0,  
6349: 0.0,
```

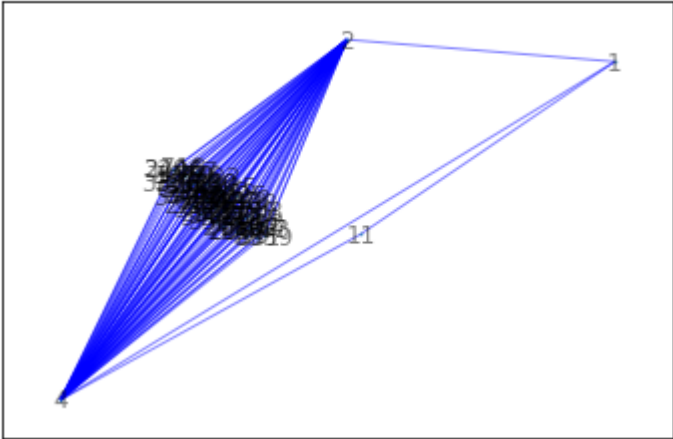


```
6358: 0.0,  
6361: 0.0,  
6386: 0.0,  
6387: 0.0,  
6428: 0.0,  
6430: 0.0,  
6447: 0.0,  
6454: 0.0,  
6470: 0.0,  
6479: 0.0,  
6482: 0.0,  
6524: 0.0,  
6541: 0.0,  
6551: 0.0,  
6559: 0.0,  
6573: 0.0.
```

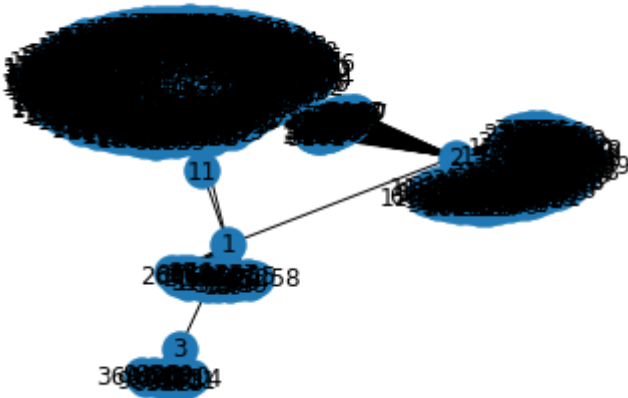
## ▼ 6 K-CORE DECOMPOSITION

```
_G_CORE = nx.k_core(graphs, 2)  
pos = nx.spring_layout(graphs)  
plt.figure()  
plt.title(' networkx 2-core decomposition of Original graph')  
nx.draw_networkx(_G_CORE , pos = pos, node_size = 1, edge_color = "blue", alpha = 0.5, wit  
Original_Graph = full_k_core_decomposition(graphs, ' Original graph')  
SBM_graph = full_k_core_decomposition(SBM, ' Stochastic Block Model graph')  
Erdos_Renyi_graph = full_k_core_decomposition(Erdos_renyi, ' Erdos Renyi graph')  
Smal_Word_graph = full_k_core_decomposition(Small_World, ' Small World graph')  
Degraded_Graphs = full_k_core_decomposition(DG, ' degraded graph')
```

networkx 2-core decomposition of Original graph



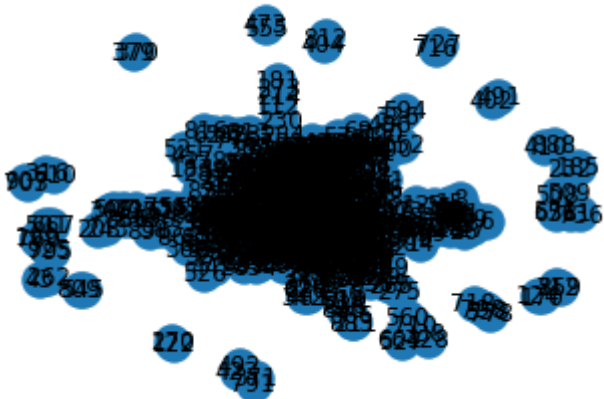
1-core decomposition of Original graph



2-core decomposition of Original graph



1-core decomposition of Stochastic Block Model graph

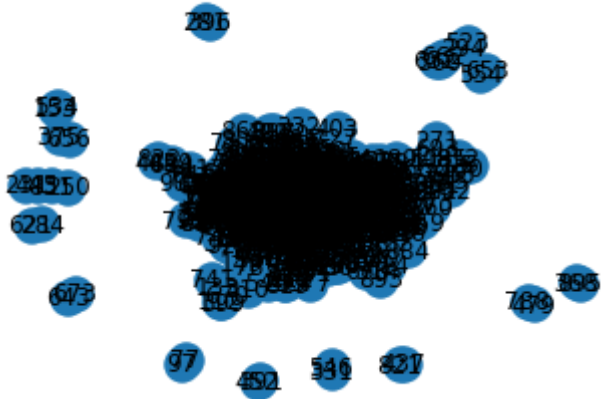


2-core decomposition of Stochastic Block Model graph





1-core decomposition of Erdos Renyi graph



2-core decomposition of Erdos Renyi graph

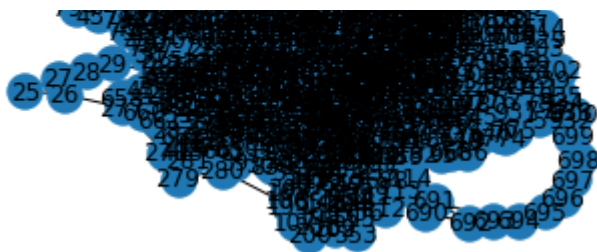


1-core decomposition of Small World graph



2-core decomposition of Small World graph

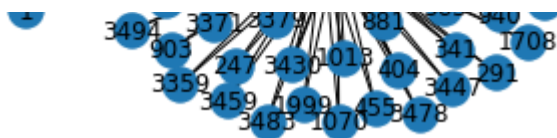




A complex network graph visualization, likely representing a social network or a system of interconnected entities. The graph is composed of numerous nodes (represented by small circles) and edges (represented by lines connecting the nodes). The nodes are densely packed in the center and become sparser towards the periphery. Many nodes are labeled with numbers, including 699, 698, 697, 696, 695, 694, 693, 692, 691, 690, 689, 688, 687, 686, 685, 684, 683, 682, 681, 680, 679, 678, 677, 676, 675, 674, 673, 672, 671, 670, 669, 668, 667, 666, 665, 664, 663, 662, 661, 660, 659, 658, 657, 656, 655, 654, 653, 652, 651, 650, 649, 648, 647, 646, 645, 644, 643, 642, 641, 640, 639, 638, 637, 636, 635, 634, 633, 632, 631, 630, 629, 628, 627, 626, 625, 624, 623, 622, 621, 620, 619, 618, 617, 616, 615, 614, 613, 612, 611, 610, 609, 608, 607, 606, 605, 604, 603, 602, 601, 600, 599, 598, 597, 596, 595, 594, 593, 592, 591, 590, 589, 588, 587, 586, 585, 584, 583, 582, 581, 580, 579, 578, 577, 576, 575, 574, 573, 572, 571, 570, 569, 568, 567, 566, 565, 564, 563, 562, 561, 560, 559, 558, 557, 556, 555, 554, 553, 552, 551, 550, 549, 548, 547, 546, 545, 544, 543, 542, 541, 540, 539, 538, 537, 536, 535, 534, 533, 532, 531, 530, 529, 528, 527, 526, 525, 524, 523, 522, 521, 520, 519, 518, 517, 516, 515, 514, 513, 512, 511, 510, 509, 508, 507, 506, 505, 504, 503, 502, 501, 500, 499, 498, 497, 496, 495, 494, 493, 492, 491, 490, 489, 488, 487, 486, 485, 484, 483, 482, 481, 480, 479, 478, 477, 476, 475, 474, 473, 472, 471, 470, 469, 468, 467, 466, 465, 464, 463, 462, 461, 460, 459, 458, 457, 456, 455, 454, 453, 452, 451, 450, 449, 448, 447, 446, 445, 444, 443, 442, 441, 440, 439, 438, 437, 436, 435, 434, 433, 432, 431, 430, 429, 428, 427, 426, 425, 424, 423, 422, 421, 420, 419, 418, 417, 416, 415, 414, 413, 412, 411, 410, 409, 408, 407, 406, 405, 404, 403, 402, 401, 400, 399, 398, 397, 396, 395, 394, 393, 392, 391, 390, 389, 388, 387, 386, 385, 384, 383, 382, 381, 380, 379, 378, 377, 376, 375, 374, 373, 372, 371, 370, 369, 368, 367, 366, 365, 364, 363, 362, 361, 360, 359, 358, 357, 356, 355, 354, 353, 352, 351, 350, 349, 348, 347, 346, 345, 344, 343, 342, 341, 340, 339, 338, 337, 336, 335, 334, 333, 332, 331, 330, 329, 328, 327, 326, 325, 324, 323, 322, 321, 320, 319, 318, 317, 316, 315, 314, 313, 312, 311, 310, 309, 308, 307, 306, 305, 304, 303, 302, 301, 300, 299, 298, 297, 296, 295, 294, 293, 292, 291, 290, 289, 288, 287, 286, 285, 284, 283, 282, 281, 280, 279, 278, 277, 276, 275, 274, 273, 272, 271, 270, 269, 268, 267, 266, 265, 264, 263, 262, 261, 260, 259, 258, 257, 256, 255, 254, 253, 252, 251, 250, 249, 248, 247, 246, 245, 244, 243, 242, 241, 240, 239, 238, 237, 236, 235, 234, 233, 232, 231, 230, 229, 228, 227, 226, 225, 224, 223, 222, 221, 220, 219, 218, 217, 216, 215, 214, 213, 212, 211, 210, 209, 208, 207, 206, 205, 204, 203, 202, 201, 200, 199, 198, 197, 196, 195, 194, 193, 192, 191, 190, 189, 188, 187, 186, 185, 184, 183, 182, 181, 180, 179, 178, 177, 176, 175, 174, 173, 172, 171, 170, 169, 168, 167, 166, 165, 164, 163, 162, 161, 160, 159, 158, 157, 156, 155, 154, 153, 152, 151, 150, 149, 148, 147, 146, 145, 144, 143, 142, 141, 140, 139, 138, 137, 136, 135, 134, 133, 132, 131, 130, 129, 128, 127, 126, 125, 124, 123, 122, 121, 120, 119, 118, 117, 116, 115, 114, 113, 112, 111, 110, 109, 108, 107, 106, 105, 104, 103, 102, 101, 100, 99, 98, 97, 96, 95, 94, 93, 92, 91, 90, 89, 88, 87, 86, 85, 84, 83, 82, 81, 80, 79, 78, 77, 76, 75, 74, 73, 72, 71, 70, 69, 68, 67, 66, 65, 64, 63, 62, 61, 60, 59, 58, 57, 56, 55, 54, 53, 52, 51, 50, 49, 48, 47, 46, 45, 44, 43, 42, 41, 40, 39, 38, 37, 36, 35, 34, 33, 32, 31, 30, 29, 28, 27, 26, 25, 24, 23, 22, 21, 20, 19, 18, 17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1, 0. The graph is colored in shades of blue and black, with the nodes and edges forming a dense, interconnected structure.

### 1-core decomposition of degraded graph

The k-core decomposition on the original network generates graphs that seem to follow a preferential attachment behavior. There are nodes with very high degree and very few with low degree. This is compatible with the starting network, which is a natural. The decomposition of the Random and Small world graphs is not easily observable but surely for ER the subgraphs are random because the original distribution is normal and consequentially the sub graph distribution are normal and thus random. The same evaluation applies to SW. Degraded graphs also follow how it is possible to observe a power law.



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✓ 1m 28s    completed at 9:27 PM ● ✕