

Assignment 1: Network Models Measurements

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ABSTRACT

In this assignment I created randomly generated networks of three types and performed various analysis on each of these networks. For the assignment I used networkx python library along with matplotlib to perform the various network measurements and to also display the results and statistics of those network measurements.

1 ERDŐS-RÉNYI RANDOM GRAPH MODEL

In this section I have created 3 Erdős-Rényi random graph models and for each of these models I have generated 1000 nodes and about 10,000 edges for each of the graphs.

1.1 Erdős-Rényi Model 1(er1)

1.1.1 er1 Part A: Graph Model Generation .

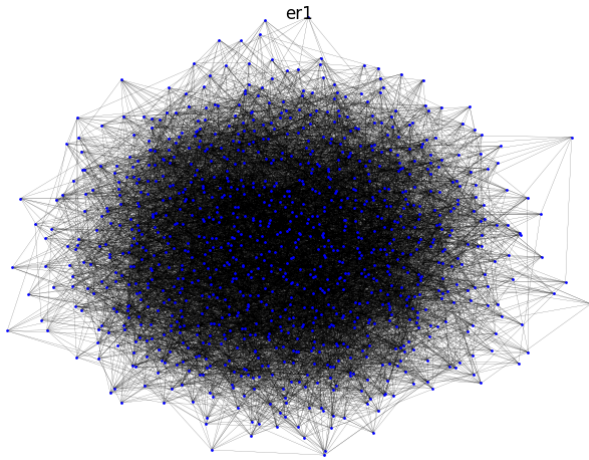


Figure 1

Nodes: 1000

Edges: 9968

Parameter Values: `nx.erdos_renyi(1000,0.02,directed=False)`

1.1.2 er1 Part B: Graph Measurements .

2020-10-25 02:53. Page 1 of 1-10.

er1: Node degree distribution of the graph

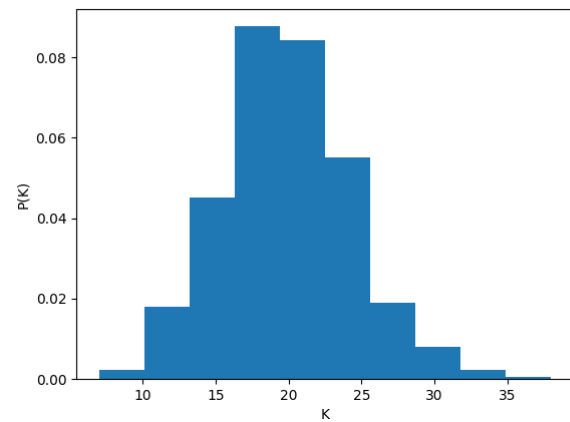


Figure 2

er1: Distribution of the local clustering coefficient

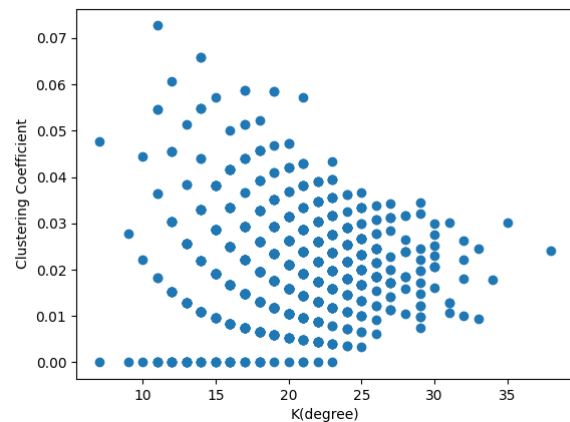


Figure 3

Global Clustering Coefficient: 0.020400615087305177

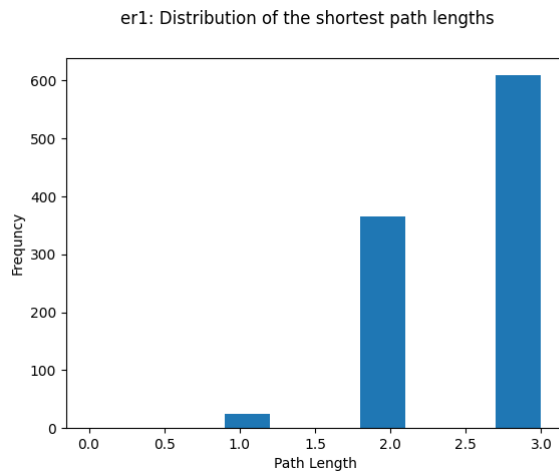


Figure 4

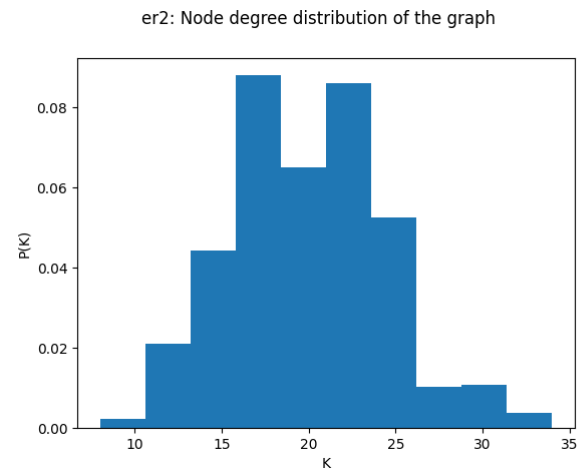


Figure 6

This is average Shortest Path: 2.6414494494494494

this is diameter: 4

1.2 Erdős-Rényi Model 2(er2)

1.2.1 er2 Part A: Graph Model Generation .

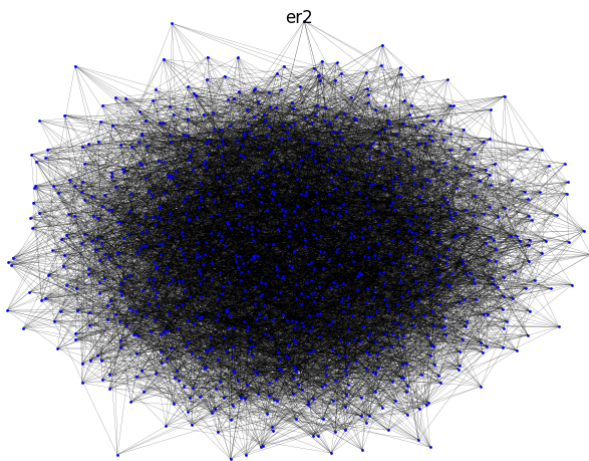


Figure 5

Nodes: 1000

Edges: 9911

Parameter Values: `nx.erdos_renyi(1000,0.02,directed=False)`

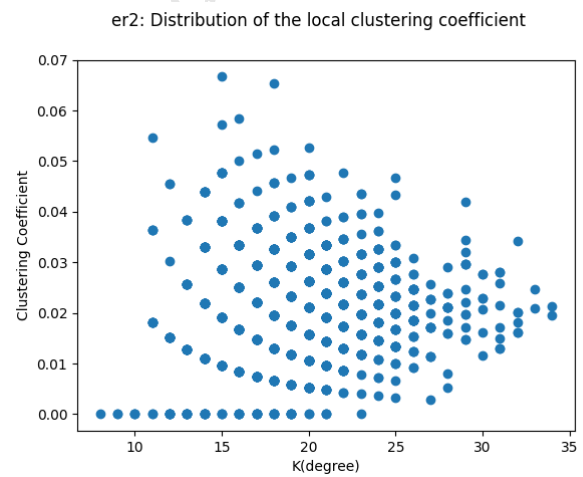


Figure 7

Global Clustering Coefficient: 0.020400615087305177

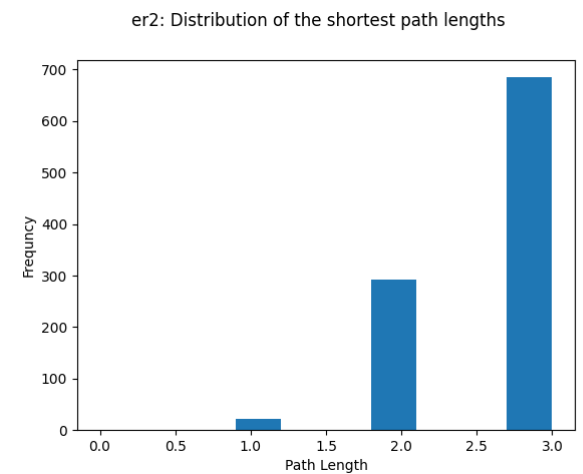


Figure 8

1.2.2 er2 Part B: Graph Measurements .

This is average Shortest Path: 2.6414494494494494

this is diameter: 4

1.3 Erdős-Rényi Model 3(er3)

1.3.1 er3 Part A: Graph Model Generation .

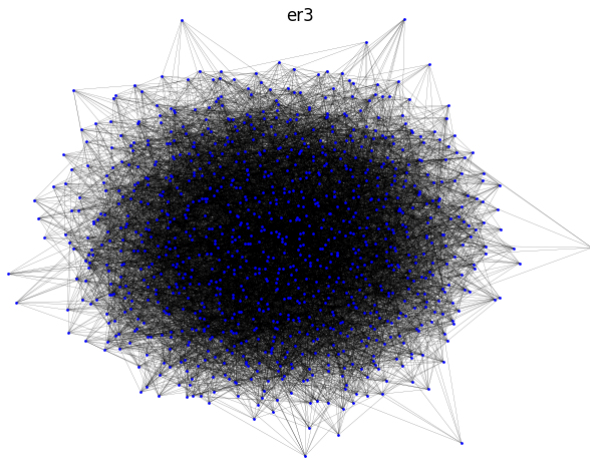


Figure 9

Nodes: 1000

Edges: 10437

Parameter Values: `nx.erdos_renyi(1000,0.021,directed=False)`

1.3.2 er3 Part B: Graph Measurements .

er3: Node degree distribution of the graph

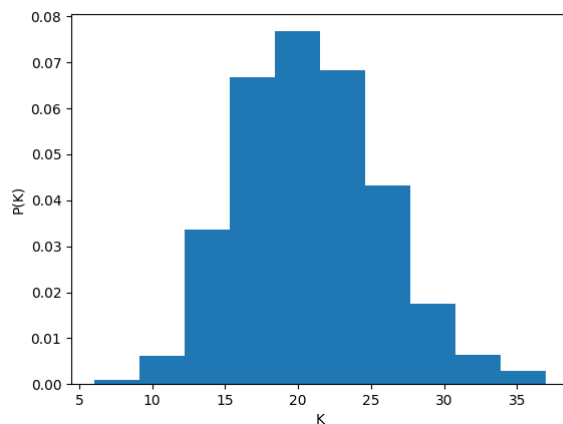


Figure 10

er3: Distribution of the local clustering coefficient

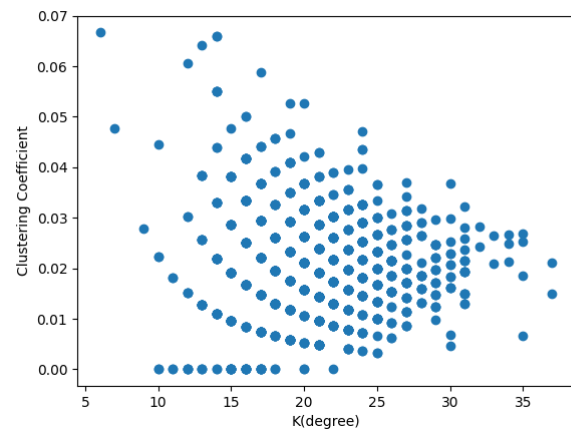


Figure 11

Global Clustering Coefficient: 0.020501113509304558

er3: Distribution of the shortest path lengths

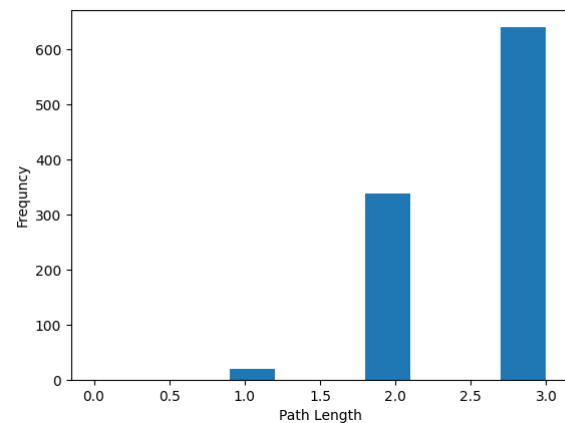


Figure 12

This is average Shortest Path: 2.611981981981982

this is diameter: 4

2 BARABÁSI-ALBERT PREFERENTIAL ATTACHMENT MODEL

In this section I have created 3 W Barabási-Albert preferential attachment models and for each of these models I have generated 1000 nodes and about 10,000 edges for each of the graphs.

2.1 Barabási-Albert Model 1(ba1)

2.1.1 ba1 Part A: Graph Model Generation .

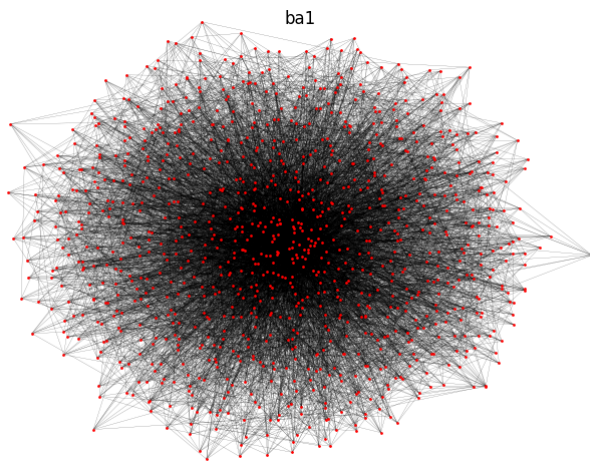


Figure 13

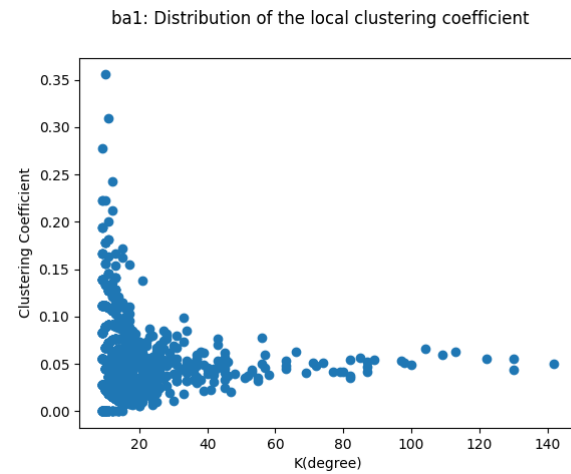


Figure 15

Nodes: 1000
Edges: 8919
Parameter Values: `nx.barabasi_albert_graph(1000, 9)`

Global Clustering Coefficient: 0.054335136597017344

2.1.2 ba1 Part B: Graph Measurements .

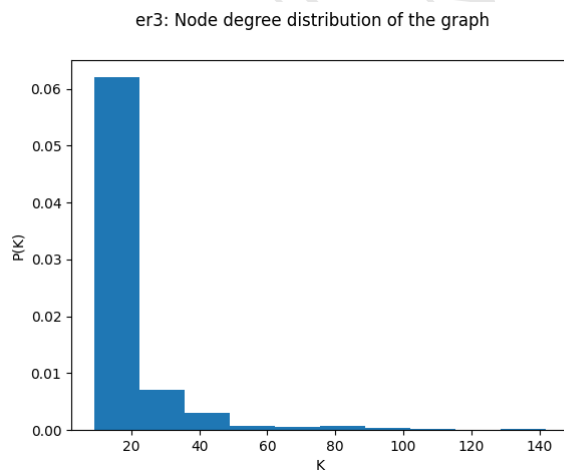


Figure 14: Should be ba1: not er3:

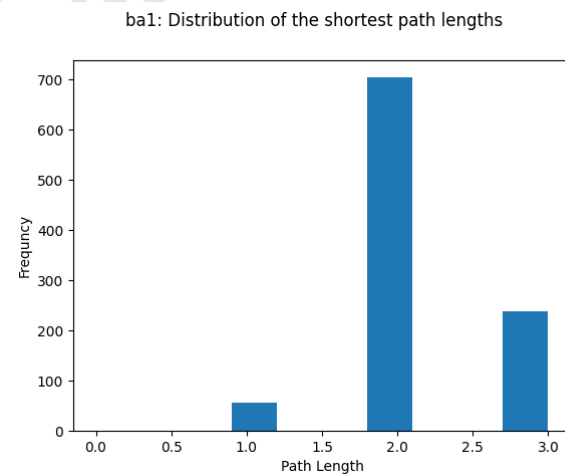


Figure 16

This is average Shortest Path: 2.6196676676676676

this is diameter: 4

2.2 Barabási–Albert model 2(ba2)

2.2.1 ba2 Part A: Graph Model Generation .

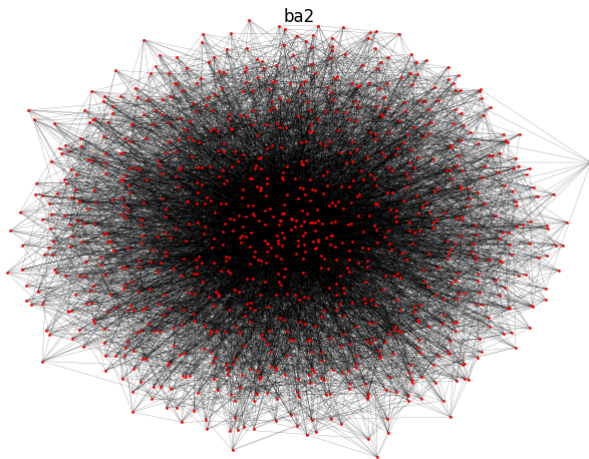


Figure 17

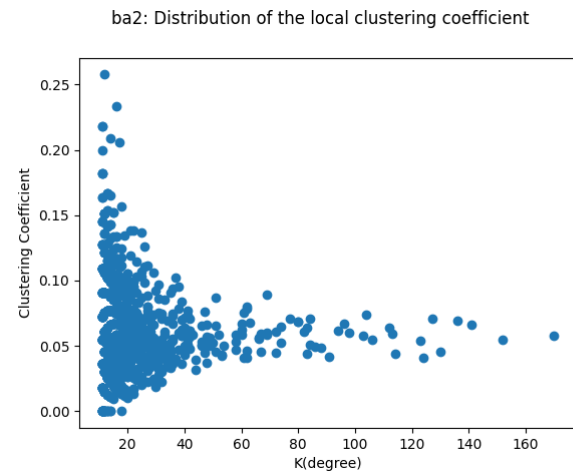


Figure 19

Nodes: 1000

Edges: 10879

Parameter Values: `nx.barabasi_albert_graph(1000, 11)`

Global Clustering Coefficient: 0.06372649651757713

2.2.2 ba2 Part B: Graph Measurements .

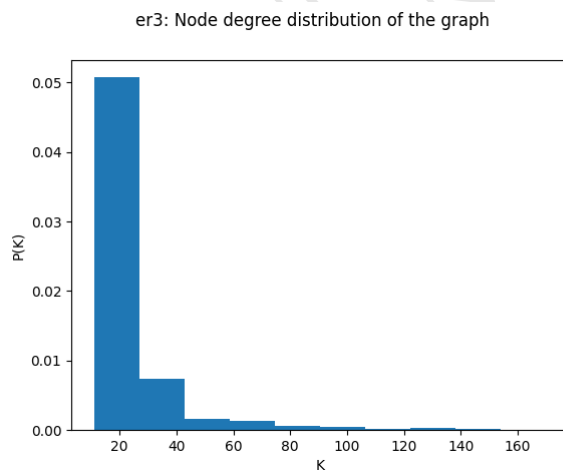


Figure 18: Should be ba2: not er3:

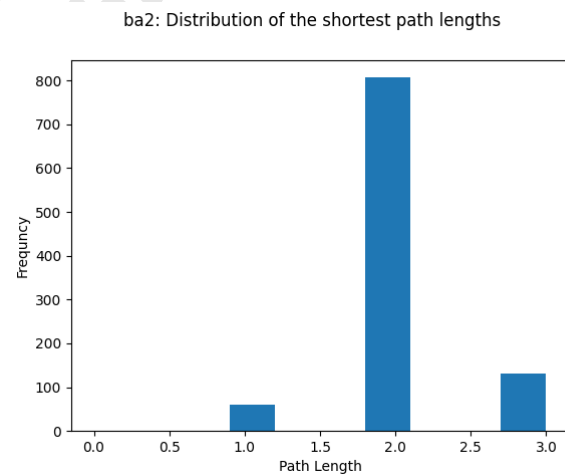


Figure 20

This is average Shortest Path: 2.5130150150150152

this is diameter: 4

2.3 Barabási–Albert model 3(ba3)

2.3.1 ba3 Part A: Graph Model Generation .

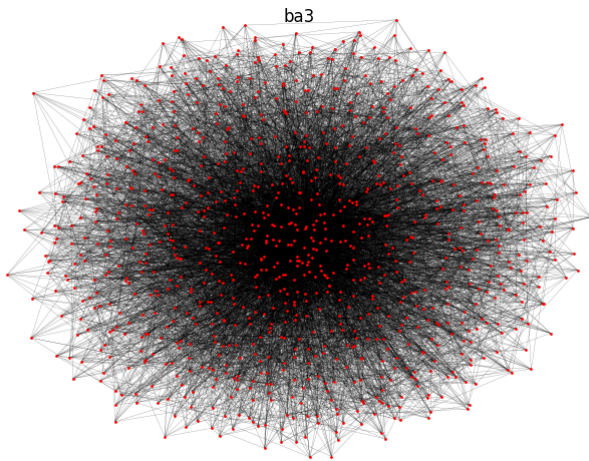


Figure 21

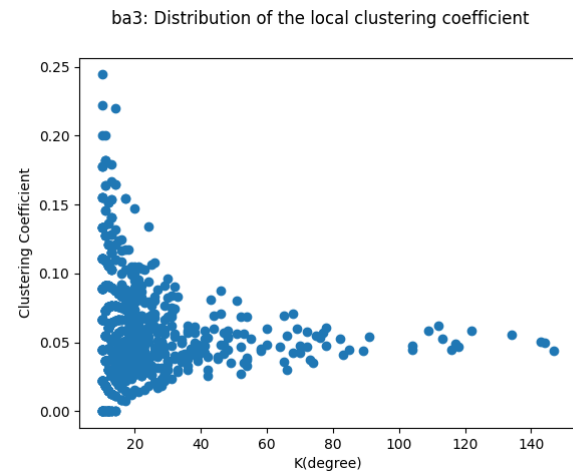


Figure 23

Global Clustering Coefficient: 0.058388625867178114

Nodes: 1000
Edges: 9900
Parameter Values: `nx.barabasi_albert_graph(1000, 10)`

2.3.2 ba3 Part B: Graph Measurements .

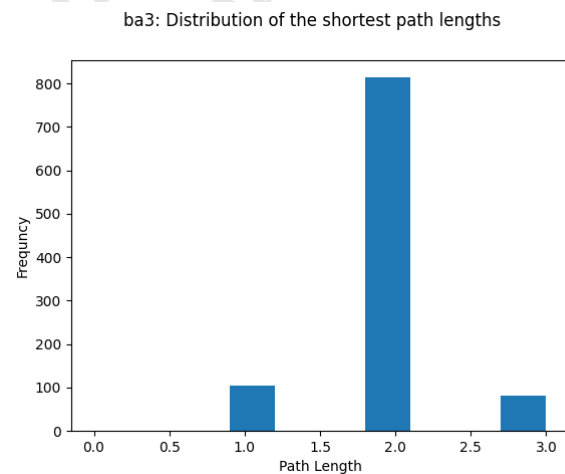


Figure 24

This is average Shortest Path: 2.556142142142142

this is diameter: 4

3 WATTS-STROGATZ SMALL-WORLD GRAPH MODEL

In this section I have created 3 Watts–Strogatz small-world graph models and for each of these models I have generated 1000 nodes and about 10,000 edges for each of the graphs.

3.1 Watts–Strogatz Model 1(ws1)

3.1.1 ws1 Part A: Graph Model Generation .

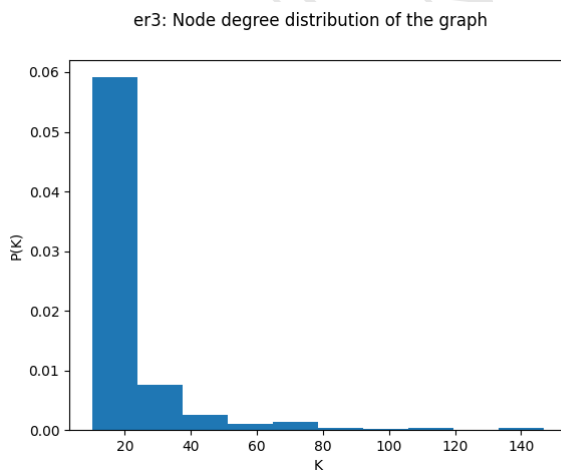


Figure 22: Should be ba3: not er3:

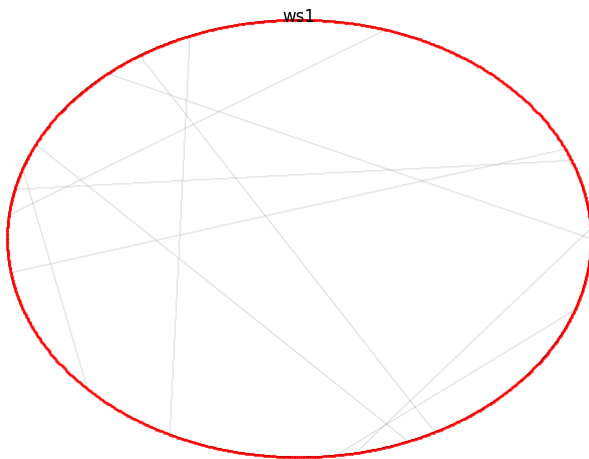


Figure 25: W

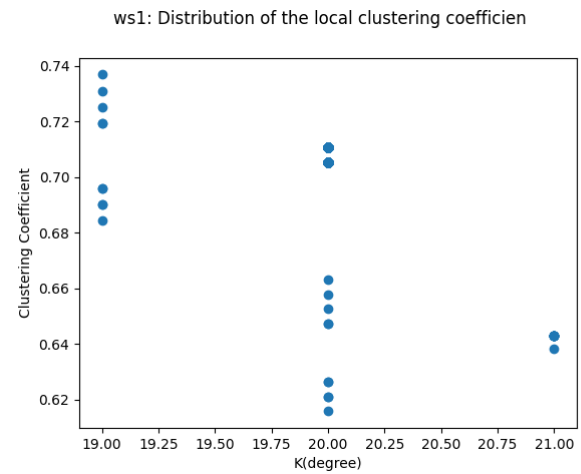


Figure 27: W

Nodes: 1000
Edges: 10,000
Parameter Values: `nx.watts_strogatz_graph(1000, 20, 0.001)`

Global Clustering Coefficient: 0.7083799498746914

3.1.2 ws1 Part B: Graph Measurements .

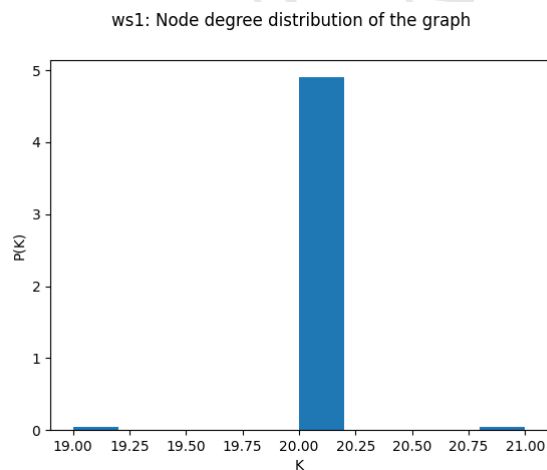


Figure 26: W

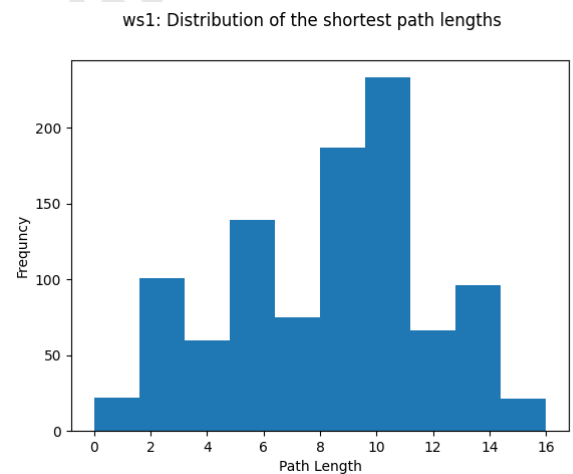


Figure 28: W

This is average Shortest Path: 10.195653653653654

this is diameter: 24

3.2 Watts–Strogatz Model 2(ws2)

3.2.1 ws2 Part A: Graph Model Generation .

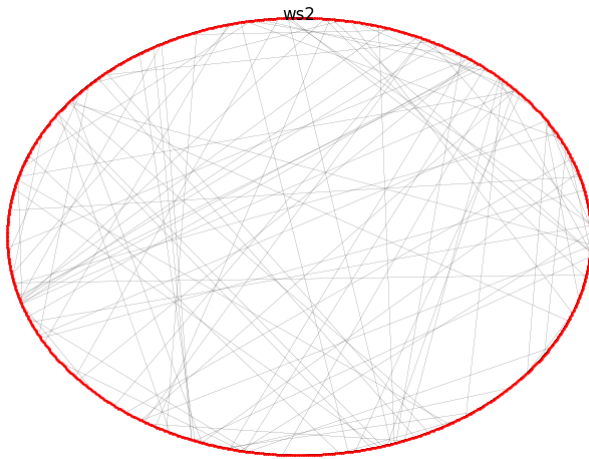


Figure 29: W

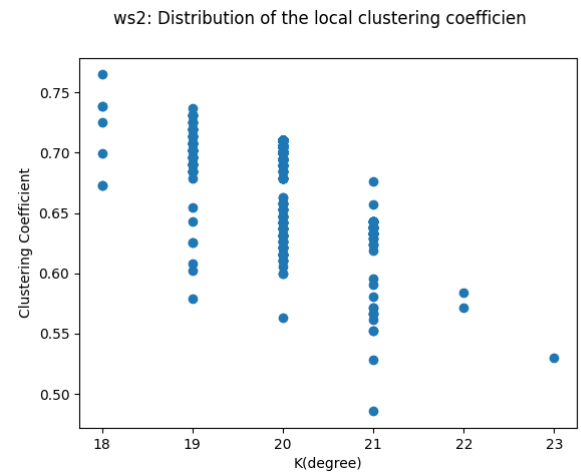


Figure 31: W

Nodes: 1000
Edges: 10,000
Parameter Values: $nx.watts_strogatz_graph(1000, 20, 0.01)$

Global Clustering Coefficient: 0.6908531133693352

3.2.2 ws2 Part B: Graph Measurements .

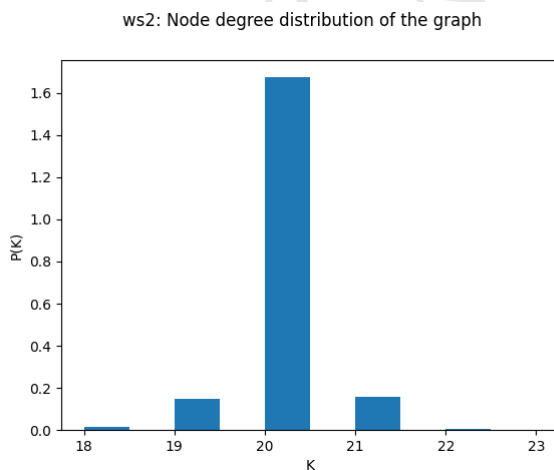


Figure 30: W

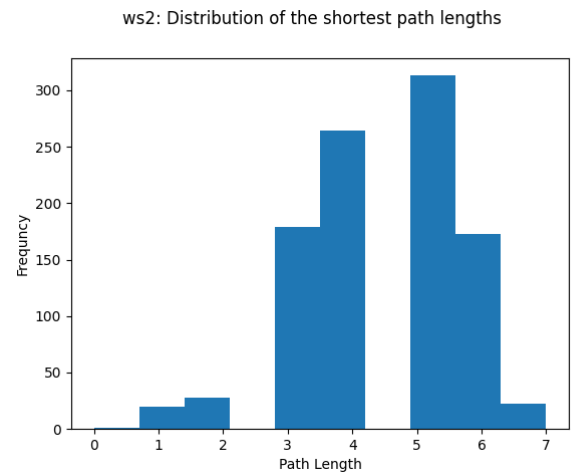


Figure 32: W

This is average Shortest Path: 5.047309309309309

this is diameter: 9

3.3 Watts–Strogatz Model 3(ws3)

3.3.1 ws3 Part A: Graph Model Generation .

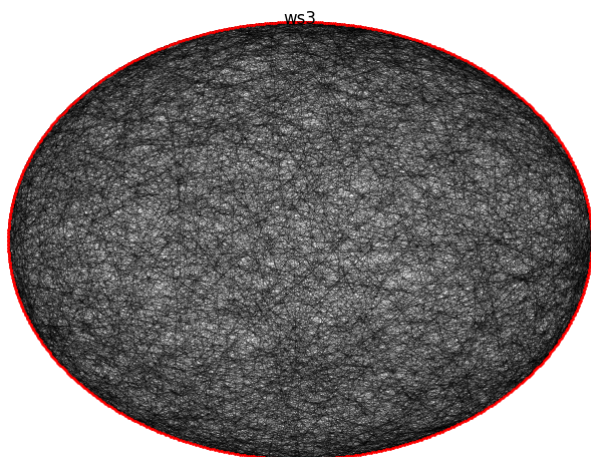


Figure 33: W

Nodes: 1000
Edges: 10,000
Parameter Values: `nx.watts_strogatz_graph(1000, 20, 0.5)`

3.3.2 ws3 Part B: Graph Measurements

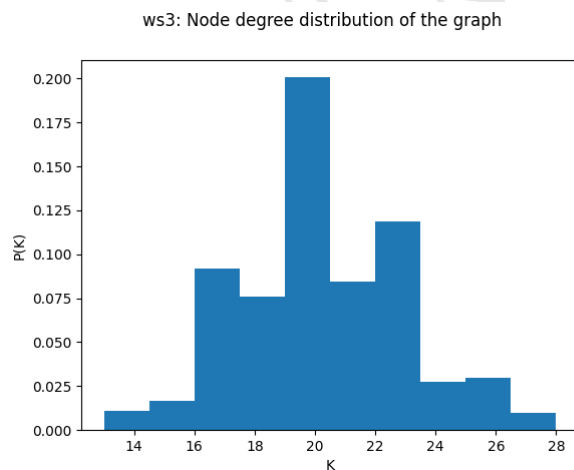


Figure 34: W

ws3: Distribution of the local clustering coefficient

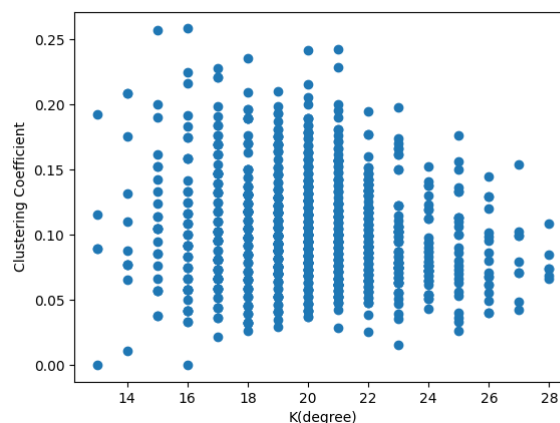


Figure 35: W

Global Clustering Coefficient: 0.10333738696415277

ws3: Distribution of the shortest path lengths

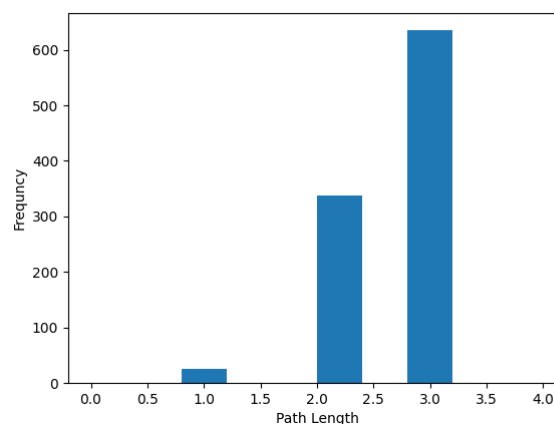


Figure 36: W

This is average Shortest Path: 2.6966746746746746

this is diameter: 4

4 PART C: DISCUSSION

4.1 how the properties of the graphs coming from the same graph model compare to each other?

Erdős-Rényi: For the Erdős-Rényi random graph model the properties of the graphs generally remain the same. This is due to the fact that each of the graphs has a very similar probability of edge creation. The reason each of the graphs have a similar probability of edge creation is because the amount of edges need to remain around 10,000.

Barabási-Albert: For the Barabási-Albert preferential attachment model the graphs generally remained consistent through.

Similarly to the Erdős graphs the Barabási graphs also had to be around 10,000 edges and the variable for number of edges to attach from a new node to an existing node had to remain around 10 in order to generate 10,000 edges.

Watts–Strogatz: Watts–Strogatz small-world graph model showed significant change as the variable for the probability of rewiring each edge was changed. As the variable for rewiring each edge was increased average path clustering coefficient and diameter began rapidly decreasing.

4.2 how the properties of the graphs coming from different graph models compare to each other?

For Erdős-Rényi the node degree distribution was relatively binomial unlike the distribution of Barabási-Albert where the $P(k)$ decreased as the degree increased. As the variable for rewiring each edge was increased in Watts–Strogatz the graph reached a more binomial distribution. Clustering coefficients were also very different as we moved from Erdős-Rényi's more evenly distributed cluster coefficient to Barabási's steep cluster coefficient which peaked at the beginning of the graph. Watts–Strogatz cluster coefficient was more evenly distributed and its frequency increased as the value for rewiring increased. The path length changed from Erdős-Rényi to the other types of graphs.

Unpublished working draft.
Not for distribution.