Project Report

of

Digital Assignment—I

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REPORT OF SNA DA 1

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For the preparing repot the first things as question mentioned that there was sudden procedure to build a sudden concastinated things into the SNA.

- Enlist the basic proportion of a particular tabular format
- List item

```
%pip install networkx
```

```
    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
    Requirement already satisfied: networkx in /usr/local/lib/python3.9/dist-packages (3.0)
```

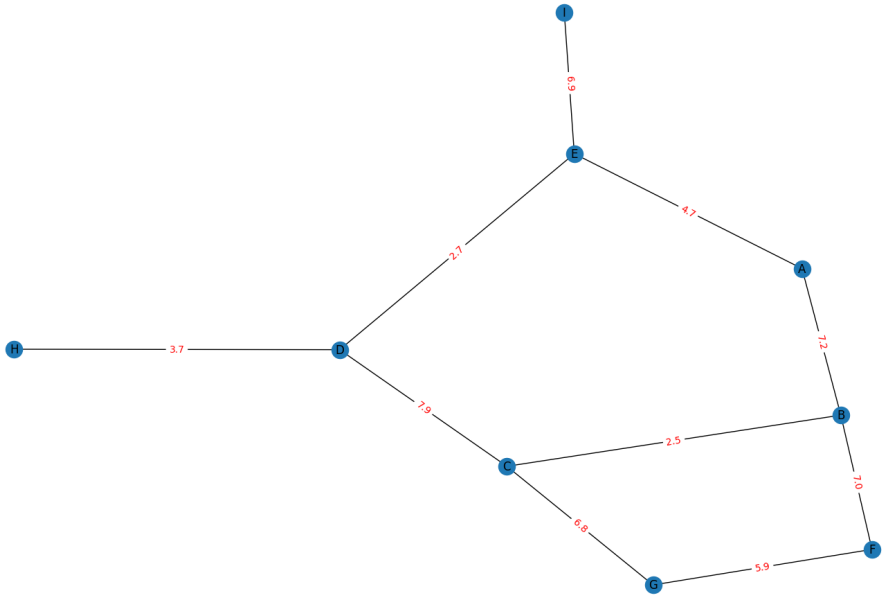
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import networkx as nx
```

For gettiing the values through the dataset used the dataset and then map the nodes into edge fill to it fills. This the adjacency matrix for filling it.

 # Problem of Question 1

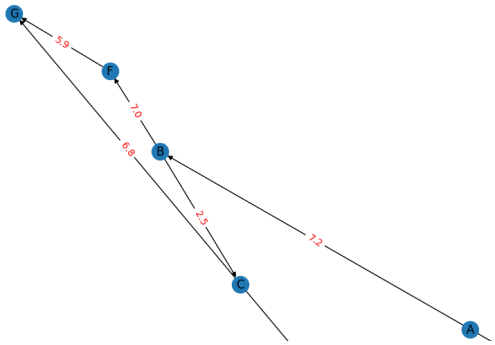
```
# LoadCSV data into a Pandas
df = pd.read_csv('/content/dataset.csv')

# Creating a dictionary that maps node names to indices in the adjacency matrix
node_dict = {node: i for i, node in enumerate(set(df['src']) | set(df['dst']))}

# Create an empty adjacency matrix for filling it
adj_matrix = np.zeros((len(node_dict), len(node_dict)))

# Fill the adjacency matrix with edge weights it fills
for _, row in df.iterrows():
    src_idx = node_dict[row['src']]
    dst_idx = node_dict[row['dst']]
    adj_matrix[src_idx, dst_idx] = row['weight']

# Create a graph using the adjacency matrix first items
UG = nx.Graph(adj_matrix)

# Set the node labels to be the node names

node_labels = {i: node for node, i in node_dict.items()}
nx.set_node_attributes(UG, node_labels, 'label')

# Draw the graph using NetworkX and Matplotlib
print("The Values are mentioned over here : \n")
pos = nx.spring_layout(UG)
nx.draw(UG, pos, labels=node_labels, with_labels=True)
edge_labels = nx.get_edge_attributes(UG, 'weight')
nx.draw_networkx_edge_labels(UG, pos, edge_labels=edge_labels, font_color='red')
print(adj_matrix)
fig = plt.gcf()
fig.set_size_inches(15, 10)
fig.savefig('undirected_graph.png', dpi=100)
plt.show()
print("\n")
```

```
The Values are mentioned over here :

[[0.  0.  0.  0.  0.  0.  0.  0.  0. ]
 [0.  0.  0.  2.5 7.  0.  0.  0.  0. ]
 [3.7 0.  0.  0.  0.  2.7 0.  0.  0. ]
 [0.  0.  7.9 0.  0.  0.  0.  6.8 0. ]
 [0.  0.  0.  0.  0.  0.  0.  5.9 0. ]
 [0.  0.  0.  0.  0.  0.  0.  0.  6.9]
 [0.  7.2 0.  0.  0.  4.7 0.  0.  0. ]
 [0.  0.  0.  0.  0.  0.  0.  0.  0. ]
 [0.  0.  0.  0.  0.  0.  0.  0.  0. ]]
```



Creating the graph using the adjacency into the matrix port and then rebuilding the name nodes into the label

```
# Create a graph using the adjacency matrix
DG = nx.DiGraph(adj_matrix)

# Set the node labels to be the node names
node_labels = {i: node for node, i in node_dict.items()}
nx.set_node_attributes(DG, node_labels, 'label')

# Draw the graph using NetworkX and Matplotlib
pos = nx.spring_layout(DG)
nx.draw(DG, pos, labels=node_labels, with_labels=True)
edge_labels = nx.get_edge_attributes(DG, 'weight')
nx.draw_networkx_edge_labels(DG, pos, edge_labels=edge_labels, font_color='red')
fig = plt.gcf()
fig.set_size_inches(15, 10)
fig.savefig('directed_graph.png', dpi=100)
plt.show()
```



 # Question 2

For undirected Graph status

```
# Number of nodes
print("\nNumber of nodes: " + str(UG.number_of_nodes()))

# Nnumber of edges
print("\nNumber of edges: " + str(UG.number_of_edges()))
```

```
Number of nodes: 9

Number of edges: 10
```

Another centrality measure, called the degree centrality, is based on the degrees in the graph. It can be summarized by “He with the most toys, wins.” In other words, the number of neighbors a vertex has is important. If the network is spread out, then there should be low centralization. If the centralization is high, then vertices with large degrees should dominate the graph.

```
# Node with max degree
max_degree = max(UG.degree(), key=lambda x: x[1])[1] # (index, degree)
print(f"\nNodes with maximum degree of {max_degree} are {[UG.nodes[idx]['label'] for idx, deg in UG.degree() if deg == max_degree]}")

# Node with min degree
min_degree = min(UG.degree(), key=lambda x: x[1])[1]
print(f"\nNodes with minimum degree of {min_degree} are {[UG.nodes[idx]['label'] for idx, deg in UG.degree() if deg == min_degree]}")
```

```
Nodes with maximum degree of 3 are ['B', 'D', 'C', 'E']

Nodes with minimum degree of 1 are ['H', 'I']
```

For directed GRAPHS

```
# Number of nodes
print("Number of nodes: " + str(DG.number_of_nodes()))

# Nnumber of edges
print("Number of edges: " + str(DG.number_of_edges()))
```

```
Number of nodes: 9
Number of edges: 10
```

```
in_degrees = DG.in_degree()
out_degrees = DG.out_degree()

# Node with the maximum in-degree
max_indegree = max(in_degrees, key=lambda x: x[1])[1] # (index, degree)
print(f"Nodes with maximum in-degree of {max_indegree} are {[DG.nodes[idx]['label'] for idx, deg in in_degrees if deg == max_indegree]}"

# Node with the minimum in-degree
min_indegree = min(in_degrees, key=lambda x: x[1])[1] # (index, degree)
print(f"Nodes with minimum in-degree of {min_indegree} are {[DG.nodes[idx]['label'] for idx, deg in in_degrees if deg == min_indegree]}"

# Node with the maximum out-degree
max_outdegree = max(out_degrees, key=lambda x: x[1])[1] # (index, degree)
print(f"Nodes with maximum out-degree of {max_outdegree} are {[DG.nodes[idx]['label'] for idx, deg in out_degrees if deg == max_outdegre
```

```
# Print the node with the minimum out-degree
min_outdegree = min(in_degrees, key=lambda x: x[1])[1] # (index, degree)
print(f"Nodes with minimum out-degree of {min_outdegree} are {[DG.nodes[idx]['label'] for idx, deg in out_degrees if deg == min_outdegre
```

```
Nodes with maximum in-degree of 2 are ['E', 'G']
Nodes with minimum in-degree of 0 are ['A']
Nodes with maximum out-degree of 2 are ['B', 'D', 'C', 'A']
Nodes with minimum out-degree of 0 are ['H', 'G', 'I']
```

Question 3

```
print(UG.edges(2, data=True))
```

```
[(2, 0, {'weight': 3.7}), (2, 5, {'weight': 2.7}), (2, 3, {'weight': 7.9})]
```

Wlog we can assume the graph is connected.

Notice that the number of edges is, by handshake lemma, even.

This graph is Eulerian since each node has even degree. So we have Euler cycle E in it. Let start at node v and label ecah edge on E alternatively with 1 and −1 on this cycle starting with +1 at v .

Clearly this procedure gives the desired labelling.

```
# Get the sum of weights of all outgoing edges for each vertex
outgoing_weights = {}
for node in UG.nodes():
    outgoing_weights[node] = sum([edge[2]['weight'] for edge in UG.edges(node, data=True)])

# Print the sum of weights of outgoing edges for each vertex
for node, weight in outgoing_weights.items():
    print(f"Node {UG.nodes[node]['label']}: Sum of weights edges = {round(weight, 2)}")
```

```
Node H: Sum of weights edges = 3.7
Node B: Sum of weights edges = 16.7
Node D: Sum of weights edges = 14.3
Node C: Sum of weights edges = 17.2
Node F: Sum of weights edges = 12.9
Node E: Sum of weights edges = 14.3
Node A: Sum of weights edges = 11.9
Node G: Sum of weights edges = 12.7
Node I: Sum of weights edges = 6.9
```

The degree of a vertex (sometimes called degree centrality) is a count of the number of unique edges that are connected to it. Diane has a degree of 6 because she is directly connected to six other individuals. In comparison, Jane has a degree of only 1 because she is connected to only one other person.

```
# Get the sum of weights of all outgoing edges for each vertex
outgoing_weights = {}
for node in DG.nodes():
    outgoing_weights[node] = sum([edge[2]['weight'] for edge in DG.out_edges(node, data=True)])

# Get the sum of weights of all incoming edges for each vertex
incoming_weights = {}
for node in DG.nodes():
    incoming_weights[node] = sum([edge[2]['weight'] for edge in DG.in_edges(node, data=True)])

# Print the sum of weights of incoming and outgoing edges for each vertex
for node, outgoing_weight in outgoing_weights.items():
    incoming_weight = incoming_weights[node]
    print(f"Node {DG.nodes[node]['label']}: Sum of weights of outgoing edges = {round(outgoing_weight, 2)}, Sum of weights of incoming e
```

```
Node H: Sum of weights of outgoing edges = 0, Sum of weights of incoming edges = 3.7
Node B: Sum of weights of outgoing edges = 9.5, Sum of weights of incoming edges = 7.2
Node D: Sum of weights of outgoing edges = 6.4, Sum of weights of incoming edges = 7.9
Node C: Sum of weights of outgoing edges = 14.7, Sum of weights of incoming edges = 2.5
Node F: Sum of weights of outgoing edges = 5.9, Sum of weights of incoming edges = 7.0
Node E: Sum of weights of outgoing edges = 6.9, Sum of weights of incoming edges = 7.4
Node A: Sum of weights of outgoing edges = 11.9, Sum of weights of incoming edges = 0
Node G: Sum of weights of outgoing edges = 0, Sum of weights of incoming edges = 12.7
Node I: Sum of weights of outgoing edges = 0, Sum of weights of incoming edges = 6.9
```

Question 4

Undirected graPH

Here we can see the as per the questioned the degree centrality is determined and then betweeness centrality and closenedd centrality is determined

```
# Degree Centrality
degree_centrality = nx.degree_centrality(UG)

# Betweenness Centrality
betweenness_centrality = nx.betweenness_centrality(UG)

# Closeness Centrality
closeness_centrality = nx.closeness_centrality(UG)

# PageRank
page_rank = nx.pagerank(UG)

# Eigenvector Centrality
eigenvector_centrality = nx.eigenvector_centrality(UG)

# Create a dictionary to hold the centrality measures for each node
centrality = {'Node': [], 'Degree Centrality': [], 'Betweenness Centrality': [], 'Closeness Centrality': [], 'PageRank': [], 'Eigenvecto

# Populate the dictionary with the centrality measures for each node
for node in UG.nodes():
    centrality['Node'].append(UG.nodes[node]['label'])
    centrality['Degree Centrality'].append(round(degree_centrality[node], 2))
    centrality['Betweenness Centrality'].append(round(betweenness_centrality[node], 2))
    centrality['Closeness Centrality'].append(round(closeness_centrality[node], 2))
    centrality['PageRank'].append(round(page_rank[node], 2))
    centrality['Eigenvector Centrality'].append(round(eigenvector_centrality[node], 2))

# Create a Pandas dataframe from the centrality dictionary
df2 = pd.DataFrame(centrality)
df2 = df2.sort_values(by=['Node'])

# Print the dataframe
print(df2.to_string(index=False))
```

```
 Node  Degree Centrality  Betweenness Centrality  Closeness Centrality  PageRank  Eigenvector Centrality
    A               0.25                    0.14                  0.50      0.11                    0.32
    B               0.38                    0.23                  0.53      0.14                    0.44
    C               0.38                    0.32                  0.57      0.15                    0.46
    D               0.38                    0.39                  0.57      0.14                    0.39
    E               0.38                    0.32                  0.53      0.14                    0.34
    F               0.25                    0.04                  0.40      0.11                    0.30
    G               0.25                    0.05                  0.42      0.11                    0.31
    H               0.12                    0.00                  0.38      0.05                    0.16
    I               0.12                    0.00                  0.36      0.07                    0.14
```

```
# Create a list of dictionaries containing centrality measures and corresponding nodes
centrality_list = [
    {
        'centrality': 'degree centrality',
        'min node': df2['Node'].iloc[df2['Degree Centrality'].idxmin()],
        'min score': df2['Degree Centrality'].min(),
        'max node': df2['Node'].iloc[df2['Degree Centrality'].idxmax()],
        'max score': df2['Degree Centrality'].max()
    },
    {
        'centrality': 'betweenness centrality',
        'min node': df2['Node'].iloc[df2['Betweenness Centrality'].idxmin()],
        'min score': df2['Betweenness Centrality'].min(),
        'max node': df2['Node'].iloc[df2['Betweenness Centrality'].idxmax()],
        'max score': df2['Betweenness Centrality'].max()
    },
    {
        'centrality': 'closeness centrality',
        'min node': df2['Node'].iloc[df2['Closeness Centrality'].idxmin()],
        'min score': df2['Closeness Centrality'].min(),
        'max node': df2['Node'].iloc[df2['Closeness Centrality'].idxmax()],
        'max score': df2['Closeness Centrality'].max()
    },
    {
        'centrality': 'page rank',
        'min node': df2['Node'].iloc[df2['PageRank'].idxmin()],
        'min score': df2['PageRank'].min(),
        'max node': df2['Node'].iloc[df2['PageRank'].idxmax()],
```

```
        'max score': df2['PageRank'].max()
    },
    {
        'centrality': 'eigenvector centrality',
        'min node': df2['Node'].iloc[df2['Eigenvector Centrality'].idxmin()],
        'min score': df2['Eigenvector Centrality'].min(),
        'max node': df2['Node'].iloc[df2['Eigenvector Centrality'].idxmax()],
        'max score': df2['Eigenvector Centrality'].max()
    },
]

# Create a new dataframe with the list of dictionaries
df3 = pd.DataFrame(centrality_list)

# Set the index to be the centrality measure
df3 = df3.set_index('centrality')

# Display the dataframe with formatted values
print("Centrality Measures and Corresponding Nodes:\n")
print(df3.to_string(formatters={
    'min score': '{:.2f}'.format,
    'max score': '{:.2f}'.format
}))
```

```
     Centrality Measures and Corresponding Nodes:

                           min node min score max node max score
     centrality
     degree centrality             A      0.12        B      0.38
     betweenness centrality        A      0.00        C      0.39
     closeness centrality          I      0.36        D      0.57
     page rank                     A      0.05        D      0.15
     eigenvector centrality        I      0.14        D      0.46
```

Directed

There are a lot of strategies to select the source node, which is defined by Brandes. On the basis of some random degree selection strategy, the implementation of GDS is performed. In this strategy, the nodes will be selected on the basis of a probability proportional to their degree. The reason to use this strategy is that these types of nodes are likely to lie on a lot of the shortest paths in the graph. That's why this strategy will contain a higher contribution to the score of betweenness centrality.

```
# Degree Centrality
in_degree_centrality = nx.in_degree_centrality(DG)
out_degree_centrality = nx.out_degree_centrality(DG)

# Betweenness Centrality
betweenness_centrality = nx.betweenness_centrality(DG)

# Closeness Centrality
closeness_centrality = nx.closeness_centrality(DG)

# PageRank
page_rank = nx.pagerank(DG)

# Eigenvector Centrality
eigenvector_centrality = nx.eigenvector_centrality_numpy(DG)

# Create a dictionary to hold the centrality measures for each node
centrality = {'Node': [], 'In-Degree Centrality': [], 'Out-Degree Centrality': [], 'Betweenness Centrality': [], 'Closeness Centrality':

# Populate the dictionary with the centrality measures for each node
for node in DG.nodes():
    centrality['Node'].append(DG.nodes[node]['label'])
    centrality['In-Degree Centrality'].append(round(in_degree_centrality[node], 2))
    centrality['Out-Degree Centrality'].append(round(out_degree_centrality[node], 2))
    centrality['Betweenness Centrality'].append(round(betweenness_centrality[node], 2))
    centrality['Closeness Centrality'].append(round(closeness_centrality[node], 2))
    centrality['PageRank'].append(round(page_rank[node], 2))
    centrality['Eigenvector Centrality'].append(round(eigenvector_centrality[node], 2))

# Create a Pandas dataframe from the centrality dictionary
df4 = pd.DataFrame(centrality)
df4 = df4.sort_values(by=['Node'])

# Print the dataframe
print(df4.to_string(index=False))
```

Node	In-Degree Centrality	Out-Degree Centrality	Betweenness Centrality	Closeness Centrality	PageRank	Eigenvector Centrality
A	0.00	0.25	0.00	0.00	0.06	0.0
B	0.12	0.25	0.09	0.12	0.09	0.0
C	0.12	0.25	0.12	0.17	0.08	0.0
D	0.12	0.25	0.12	0.19	0.10	0.0
E	0.25	0.12	0.07	0.29	0.11	0.0
F	0.12	0.12	0.02	0.17	0.12	0.0
G	0.25	0.00	0.00	0.29	0.19	0.0
H	0.12	0.00	0.00	0.20	0.11	0.0
I	0.12	0.00	0.00	0.26	0.16	1.0

```
centrality_list = [
  {
    'centrality': 'in-degree centrality',
    'min node': df4['Node'].iloc[df4['In-Degree Centrality'].idxmin()],
    'min score': df4['In-Degree Centrality'].min(),
    'max node': df4['Node'].iloc[df4['In-Degree Centrality'].idxmax()],
    'max score': df4['In-Degree Centrality'].max()
  },
  {
    'centrality': 'out-degree centrality',
    'min node': df4['Node'].iloc[df4['Out-Degree Centrality'].idxmin()],
    'min score': df4['Out-Degree Centrality'].min(),
    'max node': df4['Node'].iloc[df4['Out-Degree Centrality'].idxmax()],
    'max score': df4['Out-Degree Centrality'].max()
  },
  {
    'centrality': 'betweenness centrality',
    'min node': df4['Node'].iloc[df4['Betweenness Centrality'].idxmin()],
    'min score': df4['Betweenness Centrality'].min(),
    'max node': df4['Node'].iloc[df4['Betweenness Centrality'].idxmax()],
    'max score': df4['Betweenness Centrality'].max()
  },
  {
    'centrality': 'closeness centrality',
    'min node': df4['Node'].iloc[df4['Closeness Centrality'].idxmin()],
    'min score': df4['Closeness Centrality'].min(),
    'max node': df4['Node'].iloc[df4['Closeness Centrality'].idxmax()],
    'max score': df4['Closeness Centrality'].max()
  },
  {
    'centrality': 'page rank',
    'min node': df4['Node'].iloc[df4['PageRank'].idxmin()],
    'min score': df4['PageRank'].min(),
    'max node': df4['Node'].iloc[df4['PageRank'].idxmax()],
    'max score': df4['PageRank'].max()
  },
  {
    'centrality': 'eigenvector centrality',
    'min node': df4['Node'].iloc[df4['Eigenvector Centrality'].idxmin()],
    'min score': df4['Eigenvector Centrality'].min(),
    'max node': df4['Node'].iloc[df4['Eigenvector Centrality'].idxmax()],
    'max score': df4['Eigenvector Centrality'].max()
  },
]

# Create a new dataframe with the list of dictionaries
df5 = pd.DataFrame(centrality_list)

# Set the index to be the centrality measure
df5 = df5.set_index('centrality')

# Display the dataframe with formatted values
print("Centrality Measures and Corresponding Nodes:\n")
print(df5.to_string(formatters={
  'min score': '{:.2f}'.format,
  'max score': '{:.2f}'.format
}))
```

```
Centrality Measures and Corresponding Nodes:

                        min node min score max node max score
centrality
in-degree centrality          G      0.00        F      0.25
out-degree centrality         H      0.00        G      0.25
betweenness centrality        G      0.00        D      0.12
closeness centrality          G      0.00        F      0.29
page rank                     G      0.06        H      0.19
eigenvector centrality        G      0.00        I      1.00
```

As the summery of this repot the IN Degree Centrality and out degree centrality and betweenness and page rank are determined by In graph theory, the degree (or valency) of a vertex of a graph is the number of edges incident to the vertex, with loops counted twice.[1] The degree of a vertex v is denoted \deg(v) or \deg v. The maximum degree of a graph G, denoted by \Delta (G), and the minimum degree of a graph, denoted by \delta (G), are the maximum and minimum degree of its vertices. In the graph on the right, the maximum degree is 5 and the minimum degree is 0. In a regular graph, all degrees are the same, and so we can speak of the degree of the graph.

In the network theory, there is a wide application of Betweenness centrality, i.e., It has the ability to represent the degree of nodes that stands between each other. For example, we can use it in a telecommunication network. If there is a higher betweenness centrality in a node, then that node will have more control over the network. Due to this, we can pass more information with the help of that node. The betweenness can be derived in the form of a general measure of centrality, i.e., In the network theory, we can apply it to a wide range of problems such as transport problems, social networks problems, scientific cooperation problems, and biology problems.

The resource-intensive can vary with the help of Betweenness centrality to compute many things. The single-source shortest path (SSSP) can be computed with the help of Brandes' approximate algorithm for a set of source nodes. This algorithm will generate extra results if all the nodes are selected as source nodes. In this algorithm, the runtimes will become very long for the large graphs. Thus, we can say that approximating the results with the help of computing SSSPs will be useful only for a subset of nodes. This technique will be referred to as sampling in the GDS. Here there is also sampling size which is the size of a source node set.