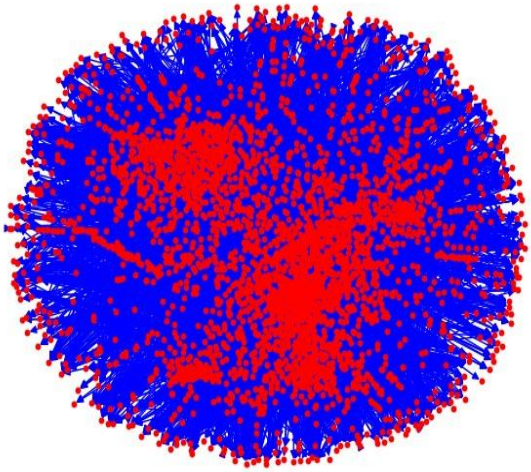

SNA_Origin

SNA Project Round-1

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Github Link: https://github.com/algoviber/SNA_PROJECT

Dataset 1 - Social circles: Facebook

This dataset consists of 'circles' (or 'friends lists') from Facebook. Facebook data was collected from survey participants using this Facebook app. The dataset includes node features (profiles), circles, and ego networks.

Facebook data has been anonymized by replacing the Facebook-internal ids for each user with a new value. Also, while feature vectors from this dataset have been provided, the interpretation of those features has been obscured. For instance, where the original dataset may have contained a feature "political=Democratic Party", the new data would simply contain "political=anonymized feature 1". Thus, using the anonymized data it is possible to determine whether two users have the same political affiliations, but not what their individual political affiliations represent.

Dataset statistics	
Nodes	4039
Edges	88234
Nodes in largest WCC	4039 (1.000)
Edges in largest WCC	88234 (1.000)
Nodes in largest SCC	4039 (1.000)
Edges in largest SCC	88234 (1.000)
Average clustering coefficient	0.6055
Number of triangles	1612010
Fraction of closed triangles	0.2647
Diameter (longest shortest path)	8
90-percentile effective diameter	4.7

Python Libraries/Packages Used

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

pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labeled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real-world data analysis in Python.

NetworkX is a package for the Python programming language that's used to create, manipulate, and study the structure, dynamics, and functions of complex graph networks.

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. Matplotlib makes easy things easy and hard things possible. Create publication quality plots. Make interactive figures that can zoom, pan, update.

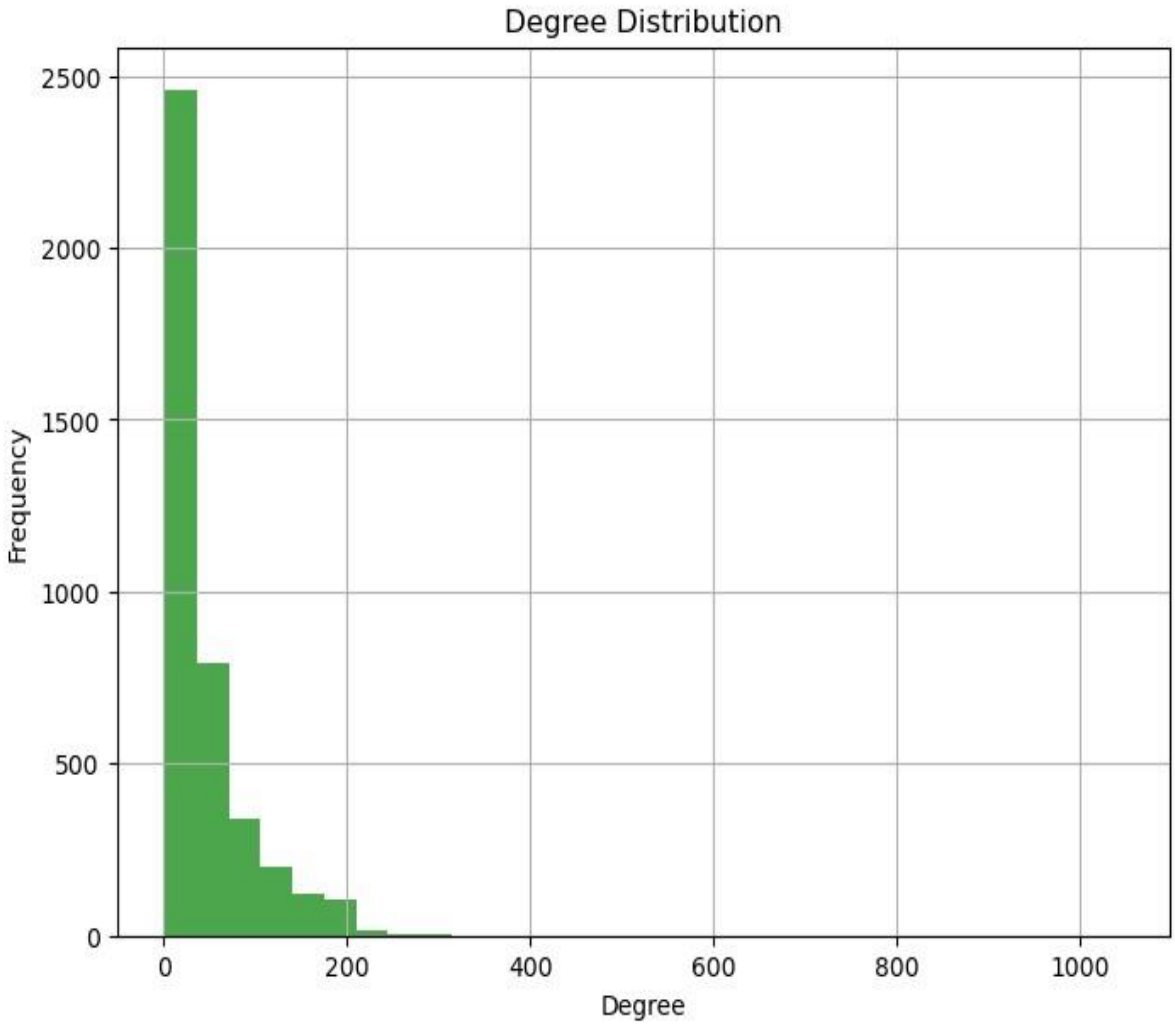
NumPy is a module for Python that allows you to work with multidimensional arrays and matrices. It's perfect for scientific or mathematical calculations because it's fast and efficient. In addition, NumPy includes support for signal processing and linear algebra operations.

```python
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
# Load the CSV file
file_path = 'Snadataset2.csv'
edges = pd.read_csv(file_path)

# Create a directed graph from the DataFrame
G = nx.from_pandas_edgelist(edges, source='node1', target='node2', create_using=nx.DiGraph())

# Function to plot centrality distributions
def plot_centrality_distribution(centrality, title):
    values = list(centrality.values())
    plt.figure(figsize=(8, 6))
    plt.hist(values, bins=20, color='blue', alpha=0.7)
    plt.title(title + ' Distribution')
    plt.xlabel('Centrality value')
    plt.ylabel('Frequency')
    plt.grid(True)
    plt.show()

# Calculate centrality measures
degree_centrality = nx.degree_centrality(G)
eigenvector_centrality = nx.eigenvector_centrality_numpy(G)
katz_centrality = nx.katz_centrality_numpy(G)
pagerank_centrality = nx.pagerank(G)
closeness_centrality = nx.closeness_centrality(G)
betweenness_centrality = nx.betweenness_centrality(G)
```

1. **Data Handling**: The script begins by loading data from a CSV file named 'Snadataset2.csv' using pandas. This data will be used to construct a network graph.
2. **Graph Construction**: Using NetworkX, the script creates a directed graph (**DiGraph**) from the loaded data. The nodes and edges of the graph are derived from the DataFrame created by reading the CSV file.
3. **Centrality Calculation**: Various centrality measures are computed for the nodes in the graph. These measures include degree centrality, eigenvector centrality, Katz centrality, PageRank centrality, closeness centrality, and betweenness centrality. Each of these measures quantifies the importance or centrality of nodes in the network based on different criteria.
4. **Centrality Visualization**: The script defines a function to plot the distribution of centrality values. It then iterates over the centrality measures calculated earlier and generates a histogram for each measure, visualizing the distribution of centrality values across the nodes in the network.

Plotting Degree Distribution:

```
import numpy as np
def plot_degree_distribution(G):
    degrees = [G.degree(n) for n in G.nodes()]
    plt.figure(figsize=(8, 6))
    plt.hist(degrees, bins=30, color='green', alpha=0.7)
    plt.title('Degree Distribution')
    plt.xlabel('Degree')
    plt.ylabel('Frequency')
    plt.grid(True)
    plt.show()

plot_degree_distribution(G)

# Calculate degrees
degrees = [G.degree(n) for n in G.nodes()]

# Calculate and print statistical measures
max_degree = np.max(degrees)
min_degree = np.min(degrees)
average_degree = np.mean(degrees)
std_dev_degree = np.std(degrees)

print(f"Maximum Degree: {max_degree}")
print(f"Minimum Degree: {min_degree}")
print(f"Average Degree: {average_degree:.2f}")
print(f"Standard Deviation of Degree: {std_dev_degree:.2f}")
```



1. **Plot Degree Distribution**: **plot_degree_distribution** function plots the degree distribution of nodes in **G**.
2. **Calculate Degree Statistics**: It computes statistical measures (maximum, minimum, average, and standard deviation) of the degrees of nodes in **G**. 3. **Output Degree Statistics**: It prints the calculated statistical measures.

Inference:

Maximum Degree: 1045

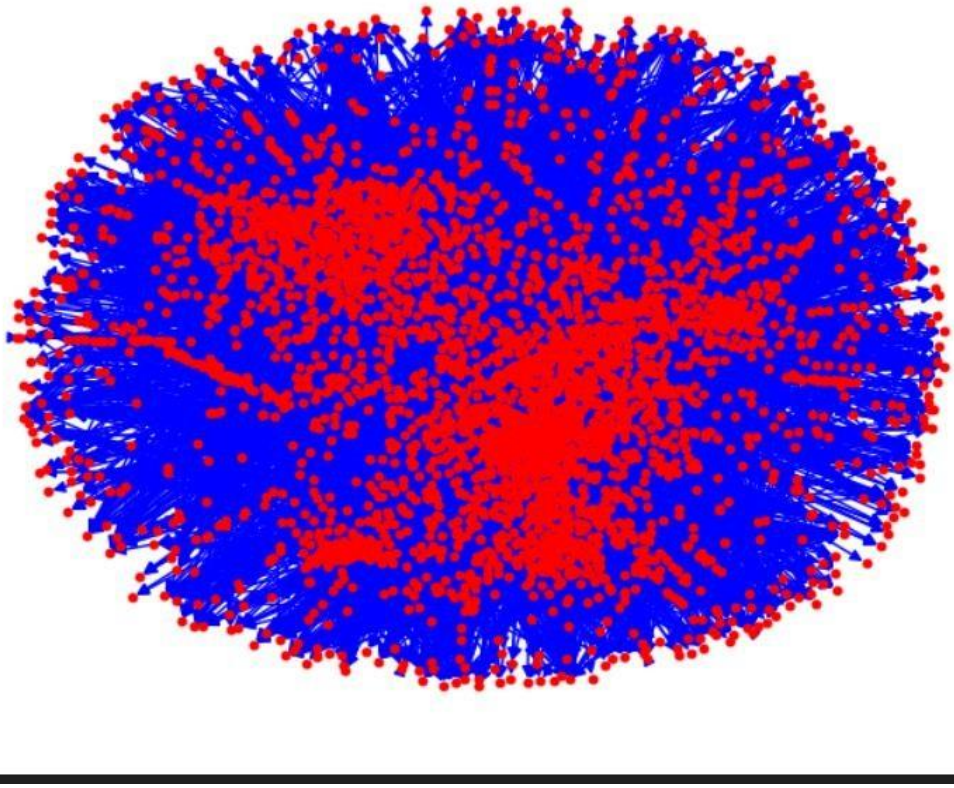
Minimum Degree: 1

Average Degree: 43.69

Standard Deviation of Degree: 52.41

Network Graph Visualization:

```
nx.draw(G, pos=None, node_color='r', edge_color='b',node_size=10)
plt.show()
```



This code snippet utilizes NetworkX's draw function to visualize the graph G. It sets the node color to red (node_color='r'), edge color to blue (edge_color='b'), and node size to 10 (node_size=10). Finally, it displays the plot using plt.show().

```
list1 = sorted(nx.strongly_connected_components(G))
print("Number of nodes in the giant component = " + str(len(list1)) + '\n')
print("Set of nodes in the giant component:")
list1
```

This code snippet calculates the strongly connected components of the graph G using NetworkX's strongly_connected_components function and sorts them. Then, it prints the number of nodes in the giant component and the set of nodes in the giant component.

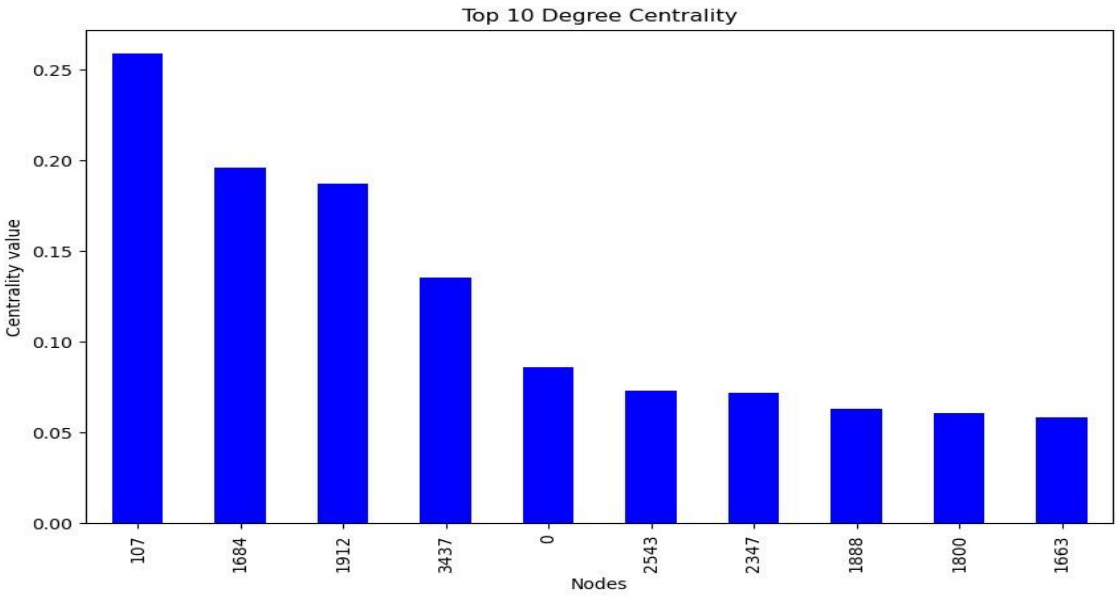
Here's a breakdown of the output:

Number of nodes in the giant component: This line displays the total number of nodes in the largest strongly connected component of the graph G.
Set of nodes in the giant component: It lists the nodes present in the giant component.
This information helps in understanding the structure of the graph and the extent of its connectivity. Strongly connected components represent subsets of nodes where each node is reachable from every other node within the subset. The largest strongly connected component, often referred to as the giant component, is of particular interest in analyzing the overall connectivity and resilience of the network.

```python
degree_centrality = nx.degree_centrality(G)
sorted_degree_centrality = pd.Series(degree_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Degree Centrality:")
print(sorted_degree_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_degree_centrality.plot(kind='bar', color='blue')
plt.title("Top 10 Degree Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 Degree Centrality:
107     0.258791
1684    0.196137
1912    0.186974
3437    0.135463
0       0.085934
2543    0.072808
2347    0.072065
1888    0.062902
1800    0.060674
1663    0.058197
dtype: float64
```

Plot of Top 10 Degree Centralities:

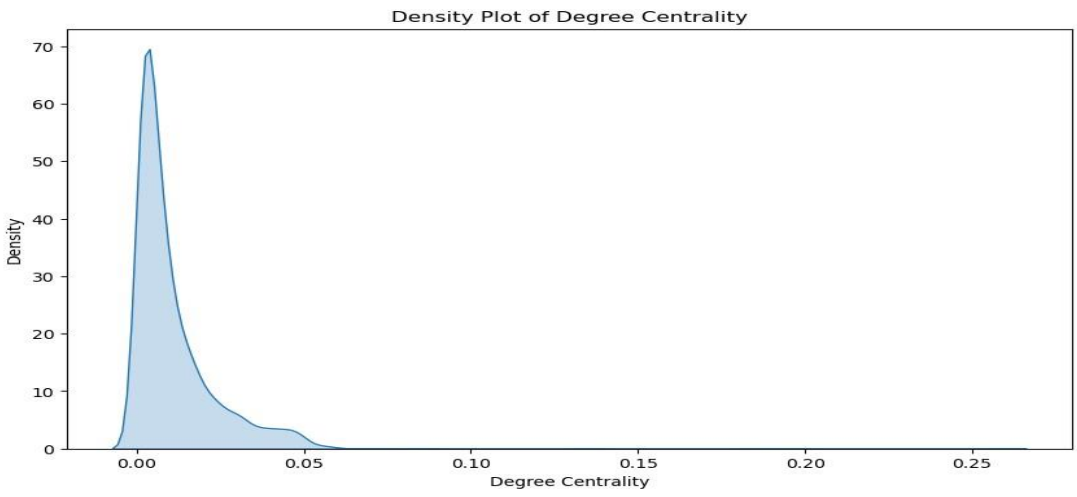


Inferences:

- **Popular users:** Users on the far right side of the graph, with the highest degree centrality, are likely the most popular on Facebook. They have a very large number of friends.
- **Average users:** The center of the graph likely represents the majority of Facebook users who have a typical number of friends.
- **Less connected users:** Users on the left side of the graph, with low degree centrality, have a smaller number of friends on Facebook.

Density Plot of Degree Centrality:

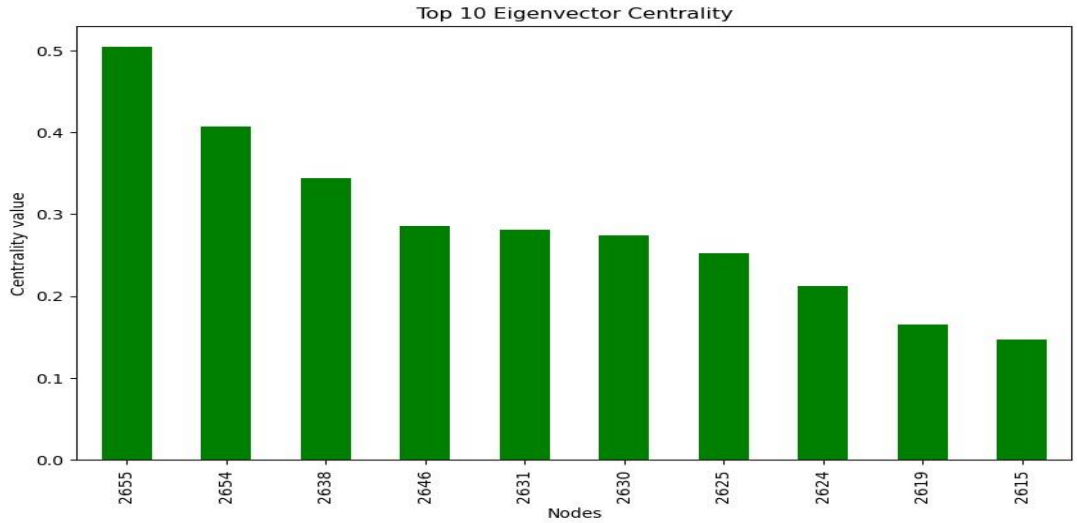
```
import networkx as nx
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

degree_centrality = nx.degree_centrality(G)
degree_df = pd.Series(degree_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(degree_df, fill=True)
plt.title('Density Plot of Degree Centrality')
plt.xlabel('Degree Centrality')
plt.ylabel('Density')
plt.show()
```



Top 10 Eigen Vector Centralities:

```
eigenvector_centrality = nx.eigenvector_centrality_numpy(G)
sorted_eigenvector_centrality = pd.Series(eigenvector_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Eigenvector Centrality:")
print(sorted_eigenvector_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_eigenvector_centrality.plot(kind='bar', color='green')
plt.title("Top 10 Eigenvector Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

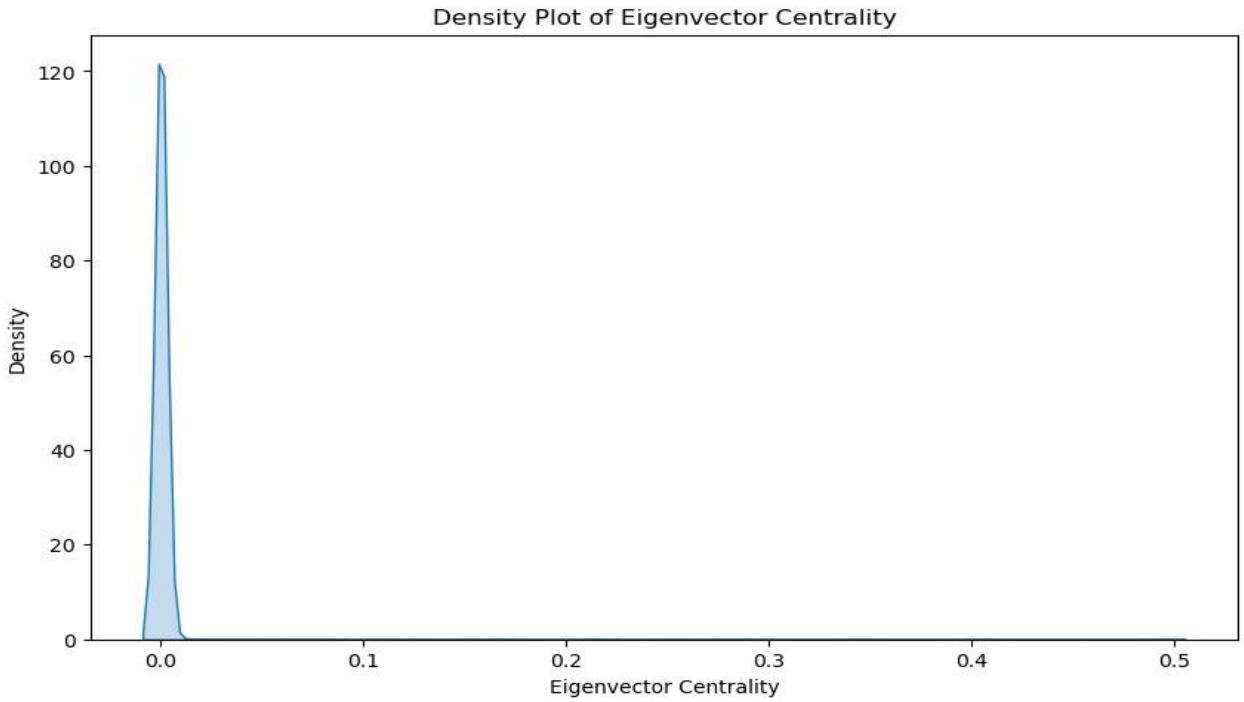
```
Top 10 Eigenvector Centrality:
2655    0.504248
2654    0.407411
2638    0.343954
2646    0.285722
2631    0.281511
2630    0.274160
2625    0.252943
2624    0.212095
2619    0.164936
2615    0.146549
dtype: float64
```



Inferences:

Users on the far right side of the graph, with the highest eigenvector centrality, are likely the most influential on Facebook. But unlike degree centrality (which focuses on the number of friends), eigenvector centrality goes beyond just popularity. These influential users are connected to other influential people, forming a network of significant impact. Imagine a celebrity who befriends other celebrities and public figures – they'd likely score high on eigenvector centrality.

```
eigenvector_centrality = nx.eigenvector_centrality_numpy(G)
eigenvector_df = pd.Series(eigenvector_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(eigenvector_df, fill=True)
plt.title('Density Plot of Eigenvector Centrality')
plt.xlabel('Eigenvector Centrality')
plt.ylabel('Density')
plt.show()
```



Inferences:

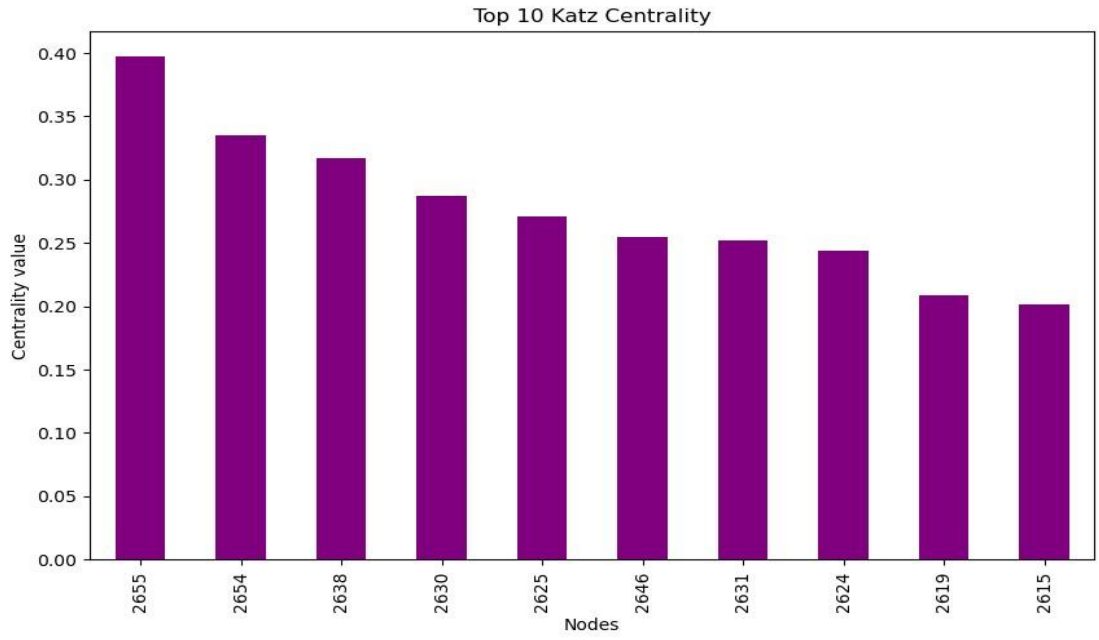
- **Most users have low to moderate influence:** The majority of users likely fall in the center of the distribution, with eigenvector centrality scores between 0.1 and 0.2. This suggests that they are connected to some moderately influential users, but don't wield a huge amount of influence themselves.
- **There's a small number of highly influential users:** The tail of the distribution on the right side suggests a small number of users with very high eigenvector centrality scores. These are the heavy hitters on Facebook, likely celebrities, public figures, or brands with a massive network of connections to other influential users.
- **There might be niche influencers:** The plot doesn't reveal specific communities, but bumps or clusters of users in the distribution could indicate communities or hubs of users with high centrality around

specific topics or niches. These users may not be widely known but hold significant influence within their particular areas of interest.

Top 10 Katz Centralities:

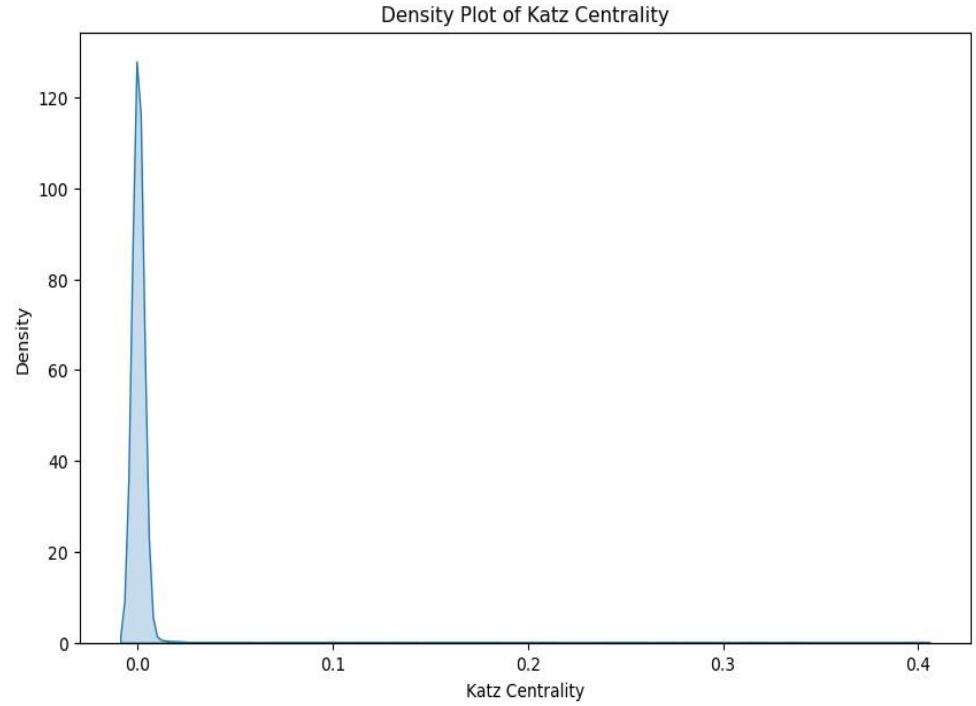
```
katz_centrality = nx.katz_centrality_numpy(G)
sorted_katz_centrality = pd.Series(katz_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Katz Centrality:")
print(sorted_katz_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_katz_centrality.plot(kind='bar', color='purple')
plt.title("Top 10 Katz Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 Katz Centrality:
2655    0.397174
2654    0.335130
2638    0.316972
2630    0.287424
2625    0.271248
2646    0.254795
2631    0.251948
2624    0.243761
2619    0.208479
2615    0.201767
dtype: float64
```



Density Plot:

```
katz_centrality = nx.katz_centrality_numpy(G)
katz_df = pd.Series(katz_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(katz_df, fill=True)
plt.title('Density Plot of Katz Centrality')
plt.xlabel('Katz Centrality')
plt.ylabel('Density')
plt.show()
```



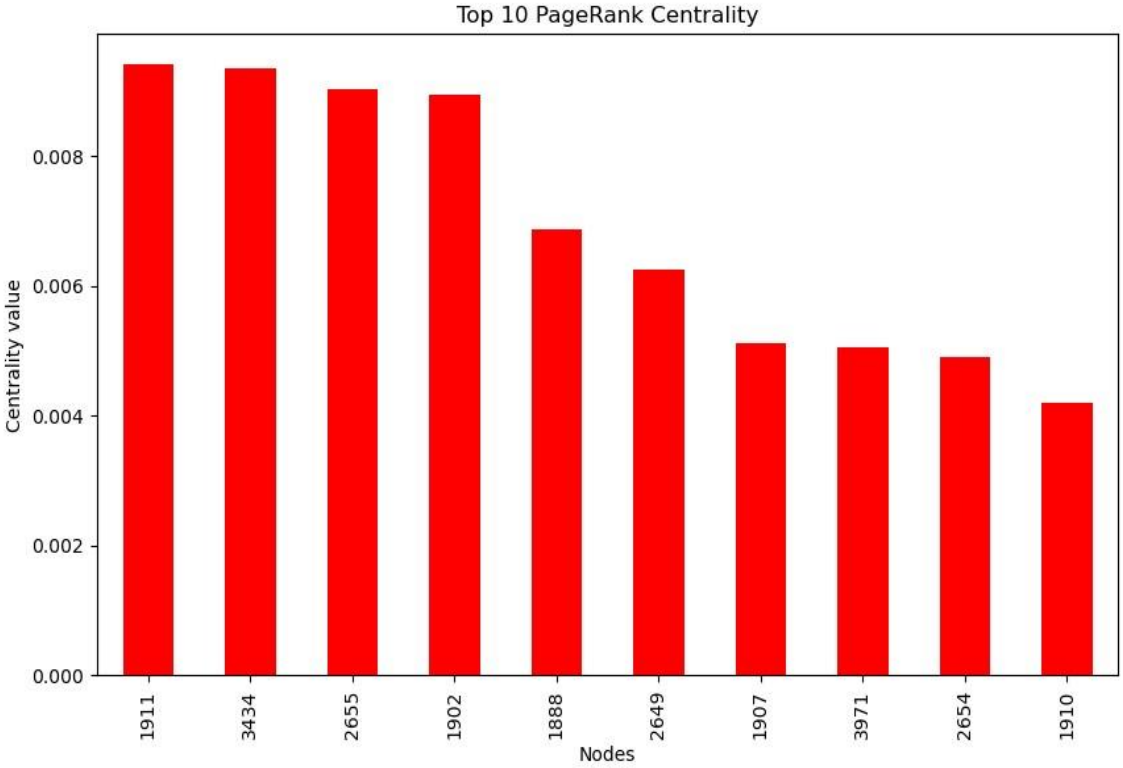
Inferences:

By analyzing the Katz centrality plot of a Facebook network, we gain insights into the distribution of connectivity and reach among users. It reveals a spectrum, with many users having limited reach and a smaller group acting as potential information hubs due to their extensive connections. This knowledge can be valuable for understanding information flow and spread on the platform.

Top 10 PageRank Centralities:

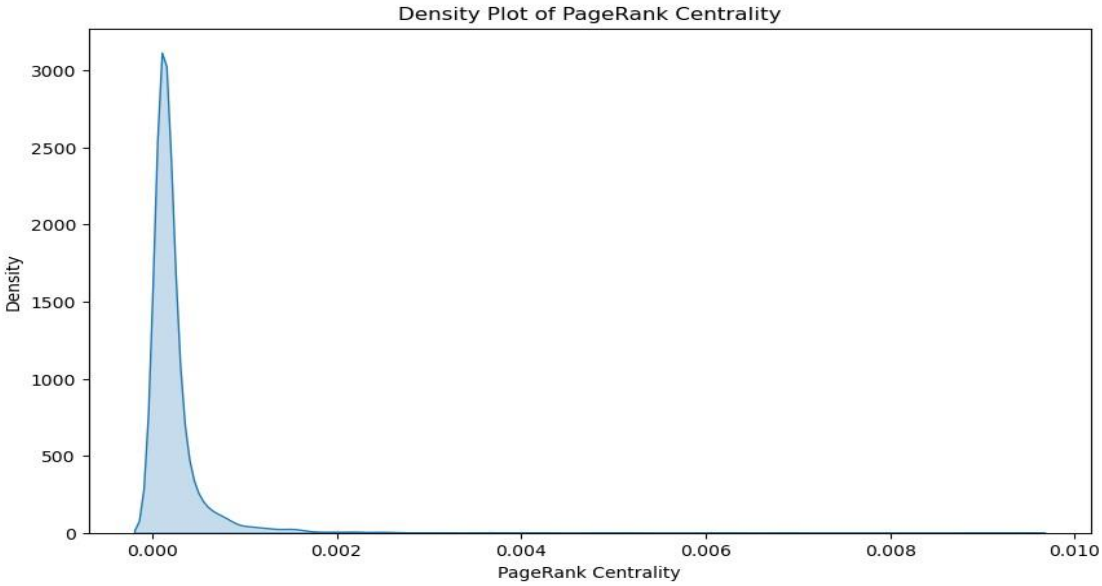
```
pagerank_centrality = nx.pagerank(G)
sorted_pagerank_centrality = pd.Series(pagerank_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 PageRank Centrality:")
print(sorted_pagerank_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_pagerank_centrality.plot(kind='bar', color='red')
plt.title("Top 10 PageRank Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 PageRank Centrality:
1911    0.009409
3434    0.009341
2655    0.009030
1902    0.008947
1888    0.006871
2649    0.006248
1907    0.005120
3971    0.005050
2654    0.004907
1910    0.004187
dtype: float64
```



Density Plot:

```
pagerank_centrality = nx.pagerank(G)
pagerank_df = pd.Series(pagerank_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(pagerank_df, fill=True)
plt.title('Density Plot of PageRank Centrality')
plt.xlabel('PageRank Centrality')
plt.ylabel('Density')
plt.show()
```



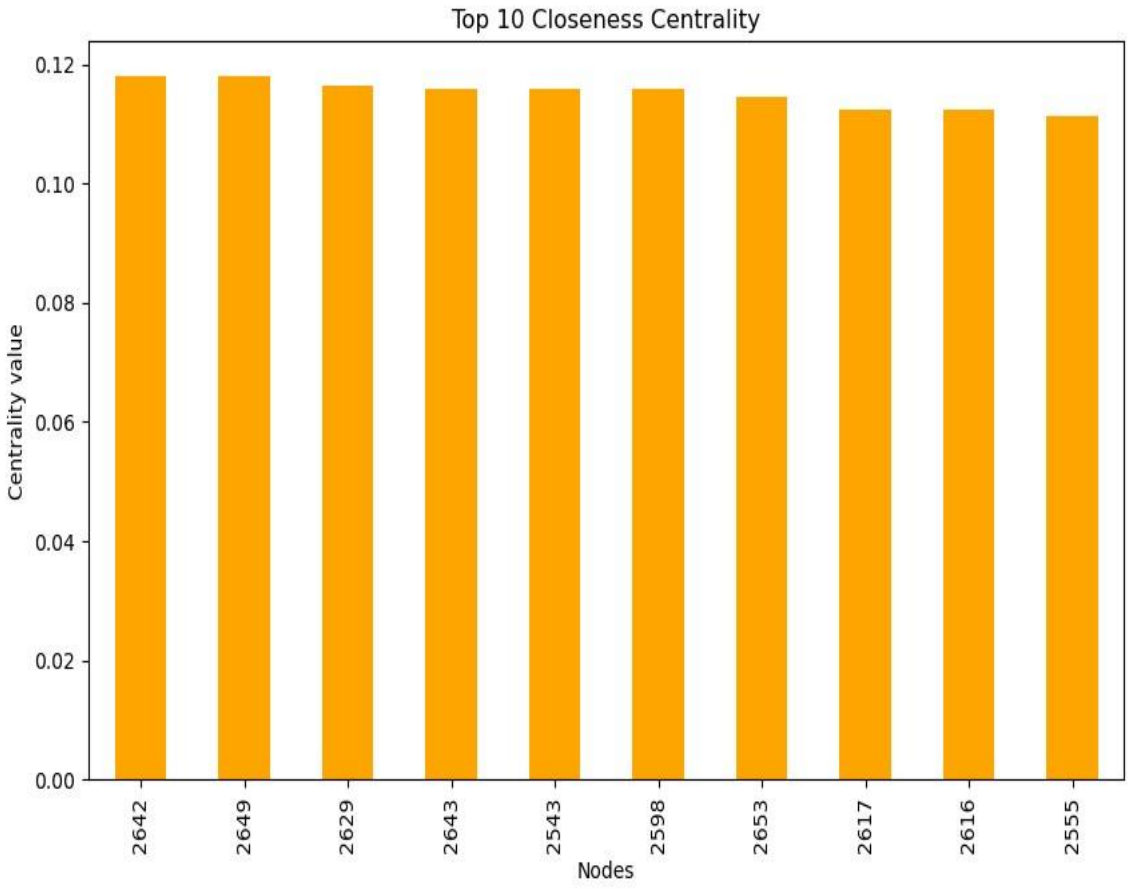
Inferences:

- **Many users have a small number of friends:** The density appears to be highest at the lower end of the x-axis, suggesting that a large portion of Facebook users have a low number of connections (friends).
- **There's a smaller number of users with a large number of friends:** The tail on the right side of the distribution suggests a smaller number of users with a high degree centrality. These are likely the most popular users on Facebook, with a very large number of friends.

Top 10 Closeness Centralities:

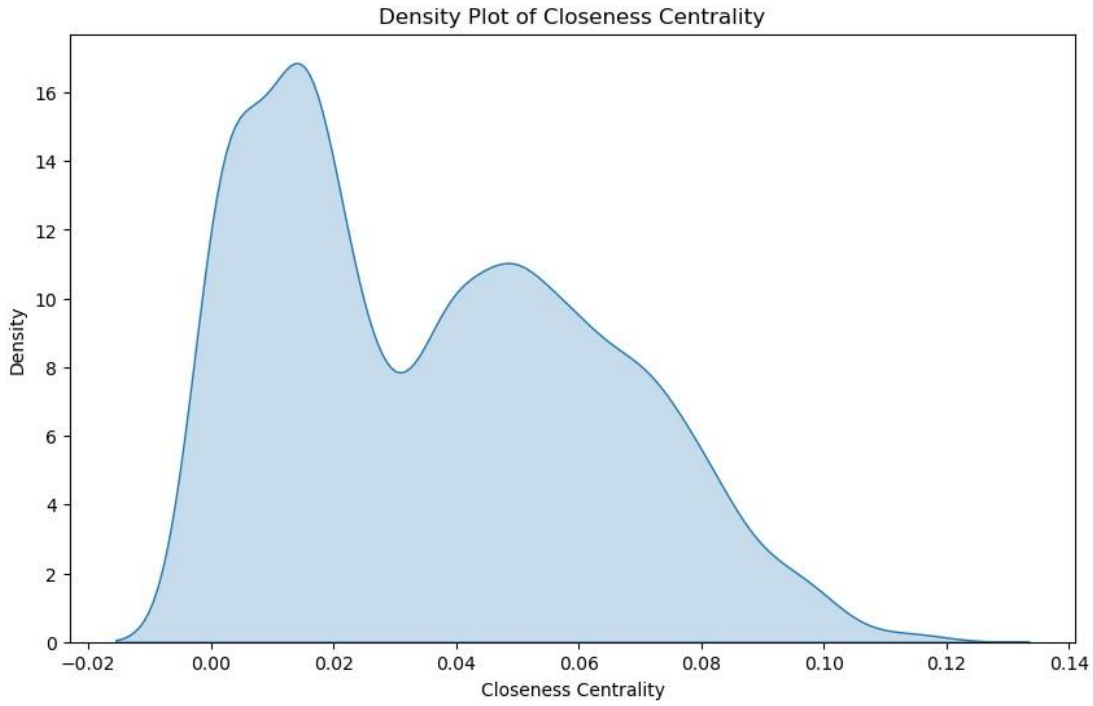
```python
closeness_centrality = nx.closeness_centrality(G)
sorted_closeness_centrality = pd.Series(closeness_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Closeness Centrality:")
print(sorted_closeness_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_closeness_centrality.plot(kind='bar', color='orange')
plt.title("Top 10 Closeness Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 Closeness Centrality:
2642    0.117975
2649    0.117932
2629    0.116293
2643    0.115918
2543    0.115902
2598    0.115758
2653    0.114452
2617    0.112444
2616    0.112349
2555    0.111385
dtype: float64
```



Density Plot:

```python
closeness_centrality = nx.closeness_centrality(G)
closeness_df = pd.Series(closeness_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(closeness_df, fill=True)
plt.title('Density Plot of Closeness Centrality')
plt.xlabel('Closeness Centrality')
plt.ylabel('Density')
plt.show()
```



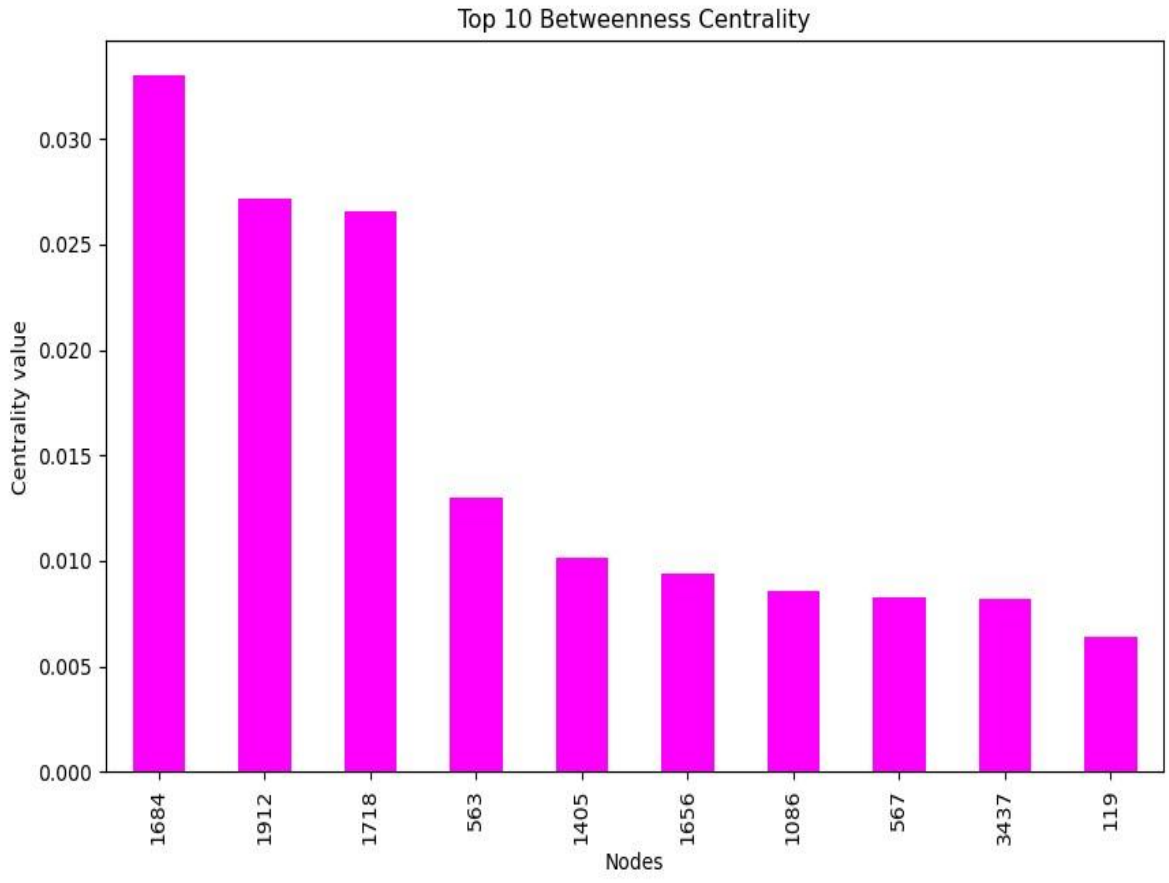
Inferences:

Overall, the density plot of closeness centrality provides valuable insights into how close users are to each other on the Facebook network. It reveals a spectrum, with many users having moderate closeness centrality, and smaller groups at either extreme. This knowledge can be helpful for understanding how information and influence flow on the platform.

Top 10 Betweenness Centralities:

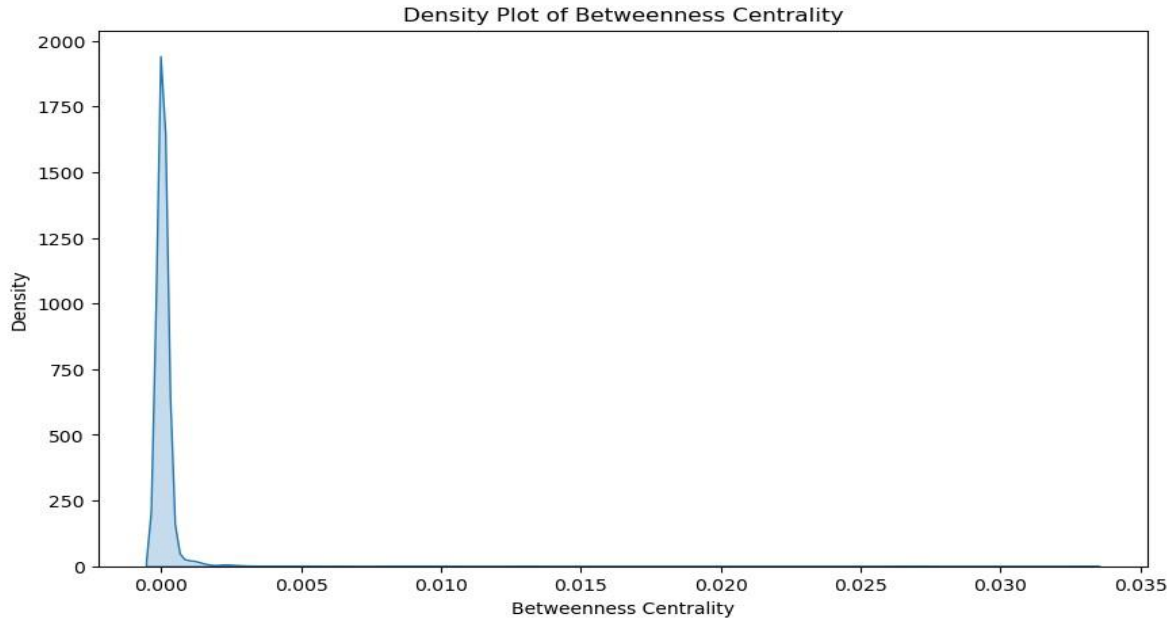
```
betweenness_centrality = nx.betweenness_centrality(G)
sorted_betweenness_centrality = pd.Series(betweenness_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Betweenness Centrality:")
print(sorted_betweenness_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_betweenness_centrality.plot(kind='bar', color='magenta')
plt.title("Top 10 Betweenness Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 Betweenness Centrality:
1684    0.033000
1912    0.027146
1718    0.026578
563     0.013010
1405    0.010124
1656    0.009426
1086    0.008554
567     0.008300
3437    0.008194
119     0.006359
dtype: float64
```



Density Plot:

```
betweenness_centrality = nx.betweenness_centrality(G)
betweenness_df = pd.Series(betweenness_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(betweenness_df, fill=True)
plt.title('Density Plot of Betweenness Centrality')
plt.xlabel('Betweenness Centrality')
plt.ylabel('Density')
plt.show()
```



Inferences:

The density plot likely shows a peak in the middle with tails on either side.
The central peak represents users with moderate betweenness centrality. These users act as bridges between different communities or groups within Facebook. Information or trends might flow through them as they connect various parts of the network.

The tail on the left side (low betweenness centrality) likely represents users who are on the outskirts of the network.

The tail on the right side (high betweenness centrality) represents a smaller group of influential users who lie on the shortest paths between many other users.

```
reciprocity_value = nx.reciprocity(G)
print("Reciprocity of the graph:", reciprocity_value)
```

```
Reciprocity of the graph: 0.0
```

```
transitivity_value = nx.transitivity(G)
print("Transitivity (Global Clustering Coefficient) of the graph:", transitivity_value)
```

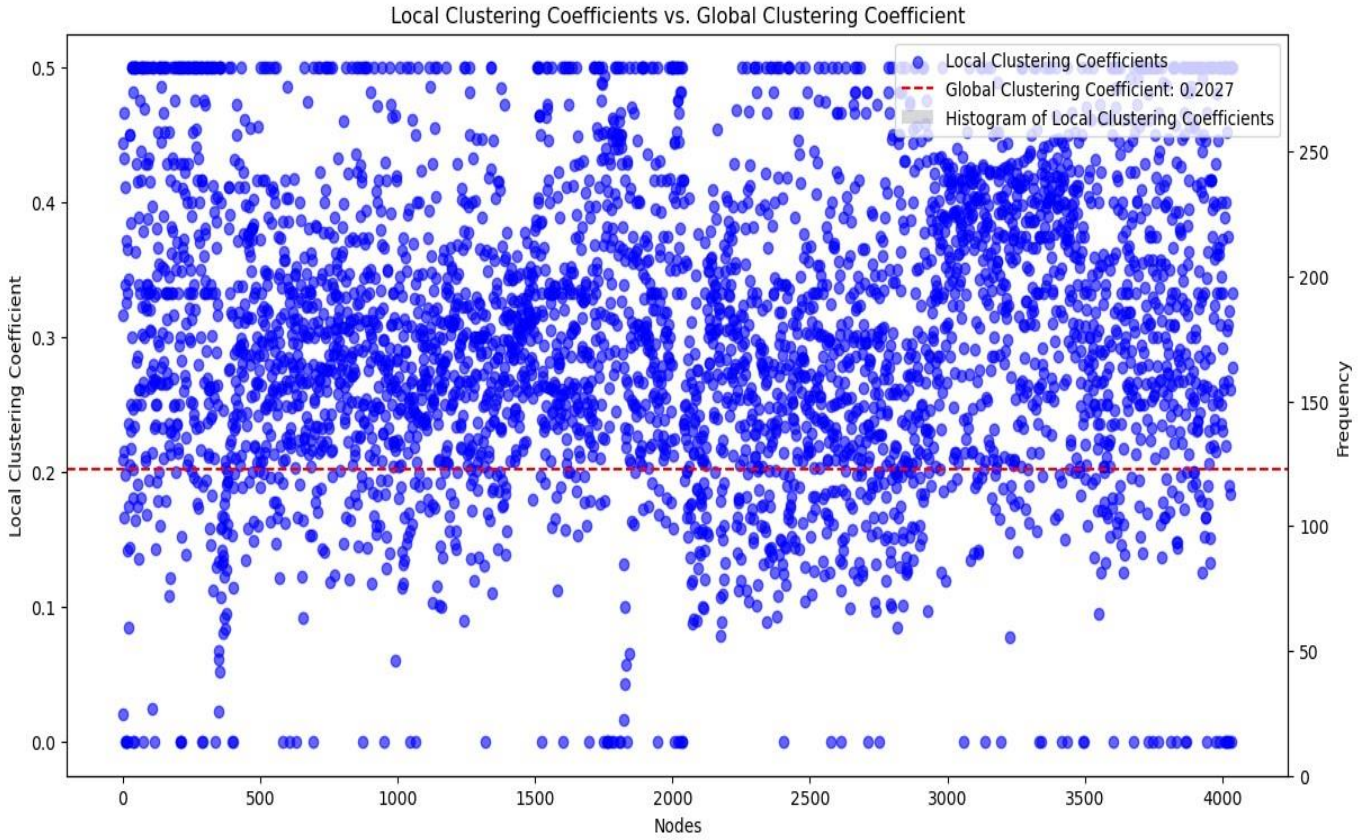
```
Transitivity (Global Clustering Coefficient) of the graph: 0.2027449891358539
```

Local Clustering & Global Clustering:

```
local_clustering = nx.clustering(G)
global_clustering = nx.transitivity(G)

# Creating a DataFrame from the local clustering data
local_clustering_df = pd.DataFrame(list(local_clustering.items()), columns=['Node', 'LocalClustering'])

# Set up the figure and axes for a combined plot
fig, ax1 = plt.subplots(figsize=(14, 7))

# Scatter plot for local clustering coefficients
scatter = ax1.scatter(local_clustering_df.index, local_clustering_df['LocalClustering'], alpha=0.6, color='blue', label='Local Clustering Coefficients')
ax1.set_ylabel('Local Clustering Coefficient')
ax1.set_xlabel('Nodes')
ax1.set_title('Local Clustering Coefficients vs. Global Clustering Coefficient')

# Add a horizontal line for global clustering coefficient
ax1.axhline(y=global_clustering, color='red', linestyle='--', label=f'Global Clustering Coefficient: {global_clustering:.4f}')

# Secondary axis for histogram
ax2 = ax1.twinx()
sns.histplot(local_clustering_df['LocalClustering'], bins=30, ax=ax2, color='gray', alpha=0.3, label='Histogram of Local Clustering Coefficients')
ax2.set_ylabel('Frequency')

# Adding legend
lines, labels = ax1.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
ax2.legend(lines + lines2, labels + labels2, loc='upper right')

plt.show()
```

- Local clustering might be used to identify groups of friends who frequently interact with each other, share similar posts, or belong to the same groups.
- Global clustering could be used to identify communities based on interests (e.g., sports fans, music lovers), demographics (e.g., parents of young children,

professionals in a specific industry), or online behavior (e.g., news sharers, content creators).



Inferences:

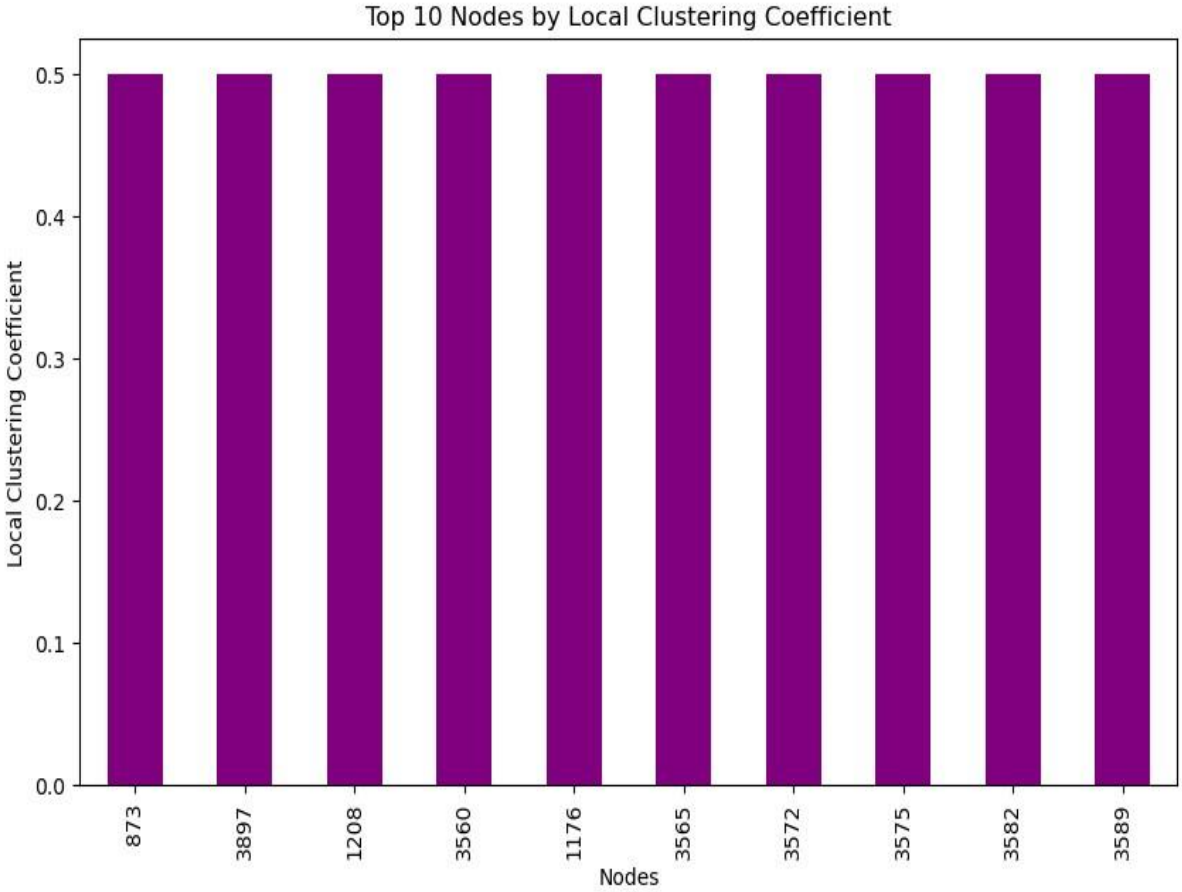
- **Generally higher local clustering coefficient:** Most of the data points appear to be above the diagonal line, suggesting that for most users, their friends (local connections) also tend to be friends with each other (high local clustering coefficient). This indicates that the network is made up of many small communities or groups where users tend to be well-connected to each other.

- **Variation in global clustering coefficient:** There seems to be more spread in the data points along the y-axis (global clustering coefficient) compared to the x-axis (local clustering coefficient). This suggests that while most users are in locally clustered communities, the network

itself might not be globally well-clustered. In other words, these local communities may not be strongly interconnected with each other.

```
local_clustering_df = pd.Series(local_clustering).sort_values(ascending=False).head(10)
print("Top 10 Nodes by Local Clustering Coefficient:")
print(local_clustering_df)

# Plotting top 10 local clustering coefficients
plt.figure(figsize=(10, 6))
local_clustering_df.plot(kind='bar', color='purple')
plt.title("Top 10 Nodes by Local Clustering Coefficient")
plt.ylabel('Local Clustering Coefficient')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 Nodes by Local Clustering Coefficient:
873     0.5
3897    0.5
1208    0.5
3560    0.5
1176    0.5
3565    0.5
3572    0.5
3575    0.5
3582    0.5
3589    0.5
dtype: float64
```


Top 10 Nodes by Local Clustering Coefficient
Local Clustering Coefficient
0.0
0.1
0.2
0.3
0.4
0.5
873
3897
1208
3560
1176
3565
3572
3575
3582
3589
Nodes

Dataset 2: Gnutella peer-to-peer network

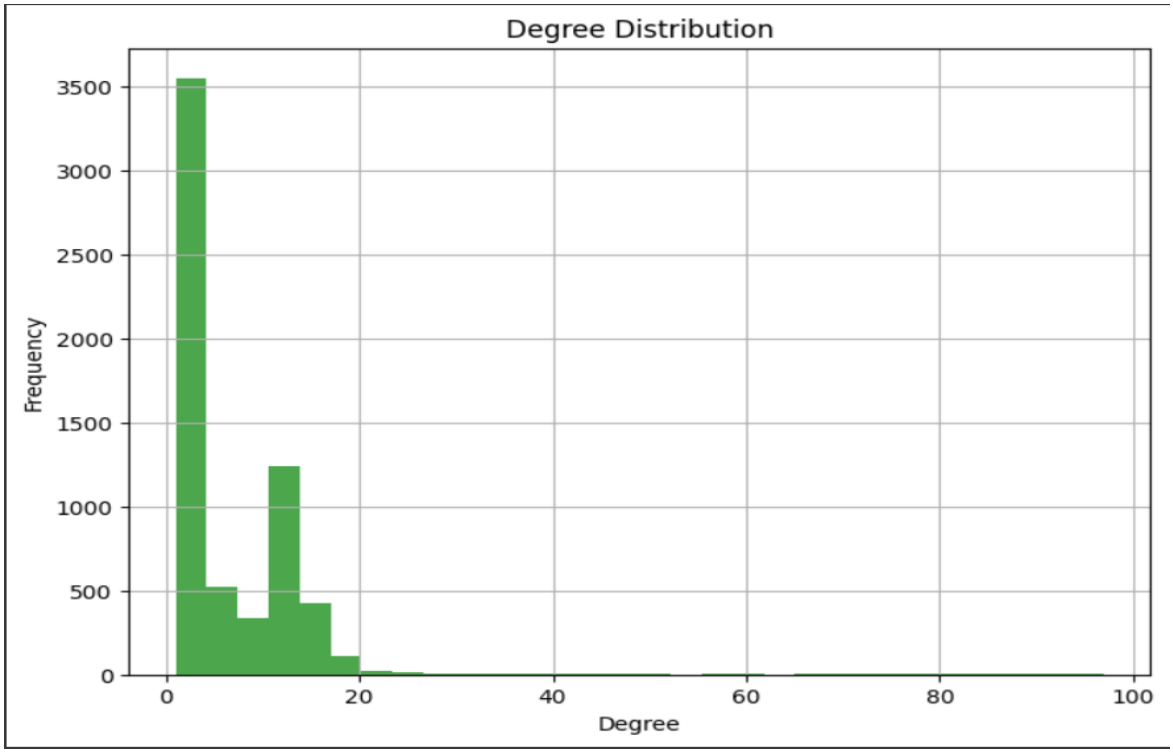
A sequence of snapshots of the Gnutella peer-to-peer file-sharing network from August 2002. There are a total of 9 snapshots of the Gnutella network collected in August 2002. Nodes represent hosts in the Gnutella network topology and edges represent connections between the Gnutella hosts.

What is Gnutella?

Gnutella was designed to be a file-sharing system based on an unstructured P2P overlay that allows for the decentralized, scalable, reliable, and anonymous sharing of files between participating nodes.

Dataset statistics	
Nodes	6301
Edges	20777
Nodes in largest WCC	6299 (1.000)
Edges in largest WCC	20776 (1.000)
Nodes in largest SCC	2068 (0.328)
Edges in largest SCC	9313 (0.448)
Average clustering coefficient	0.0109
Number of triangles	2383
Fraction of closed triangles	0.006983
Diameter (longest shortest path)	9
90-percentile effective diameter	5.5

Degree of distribution



Inference

Maximum Degree: 97

Minimum Degree: 1

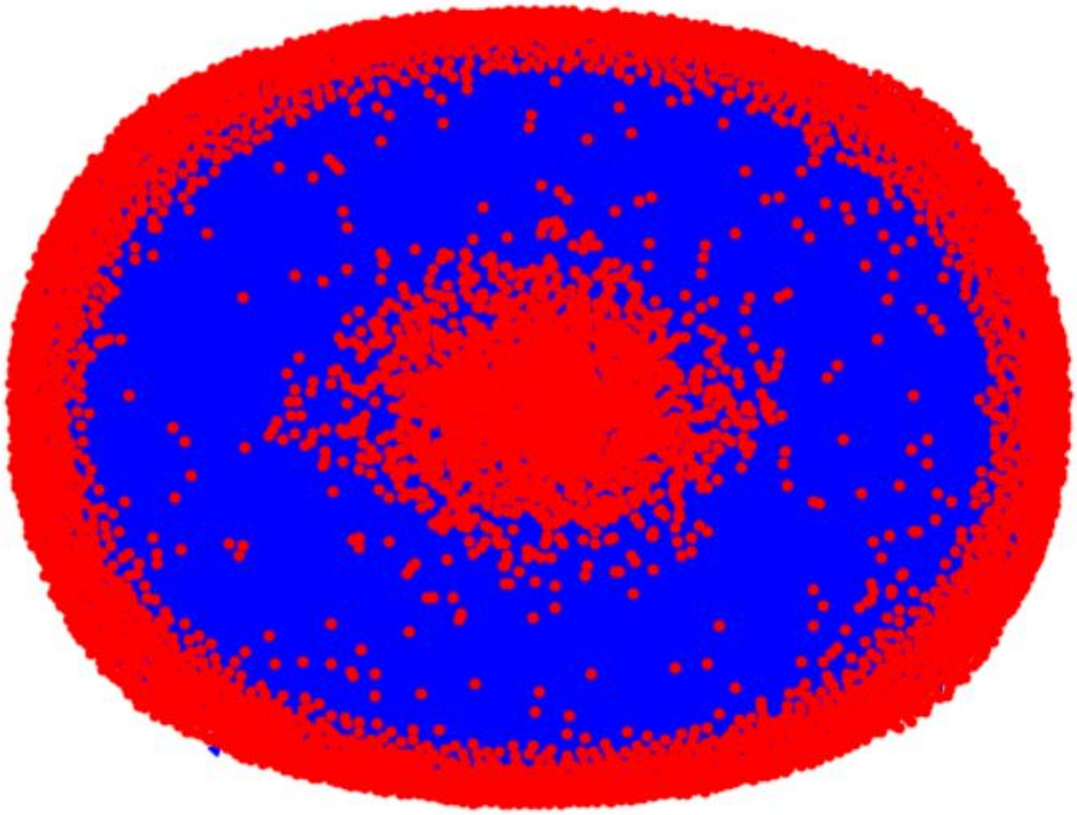
Average Degree: 6.59

Standard Deviation of Degree: 8.54

Comparison with Dataset-1

- Both graphs share the same trend of having more low-degree nodes and fewer high-degree nodes.
- The specific values may differ, but the overall shape remains consistent.

Network graph visualization



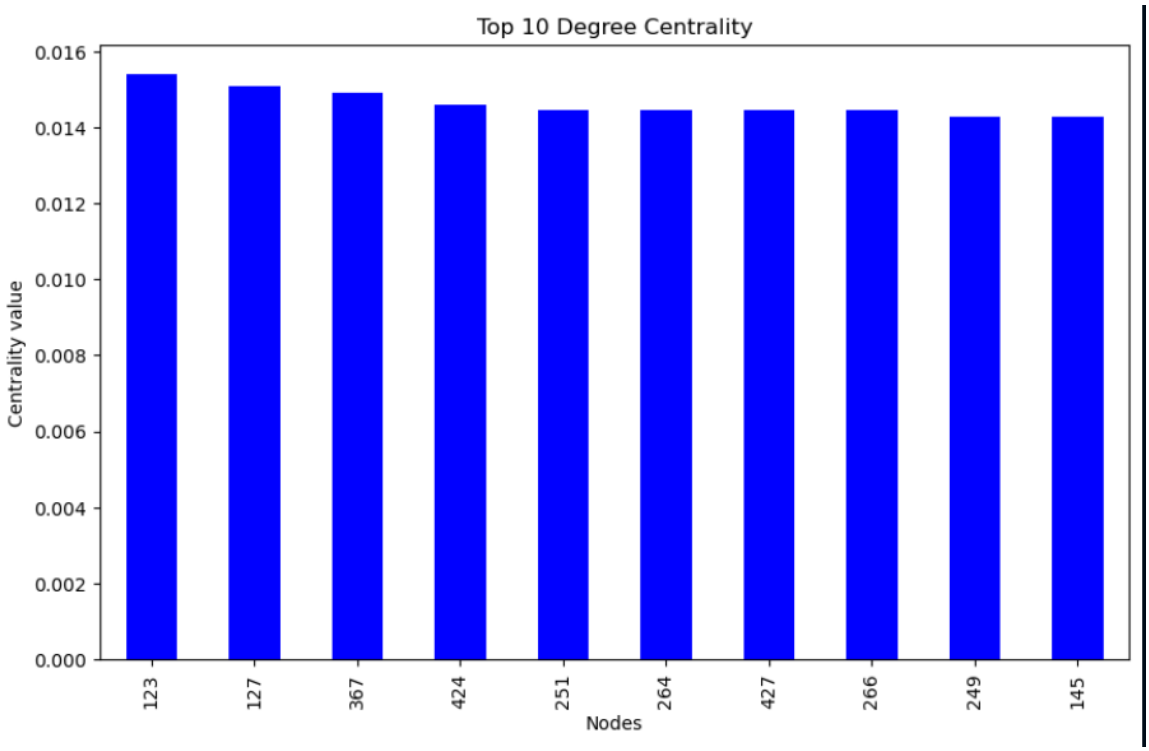
Top 10 degree of centrality of dataset -2

```
Top 10 Degree Centrality:
123    0.015397
127    0.015079
367    0.014921
424    0.014603
251    0.014444
264    0.014444
427    0.014444
266    0.014444
249    0.014286
145    0.014286
dtype: float64
```

1. Nodes with higher degree centrality values play more influential roles in the network.
2. These top 10 nodes likely have significant connections or interactions with other nodes.

Comparison with the Dataset-1

The previous table had higher degree centrality values, while the current table shows lower values.



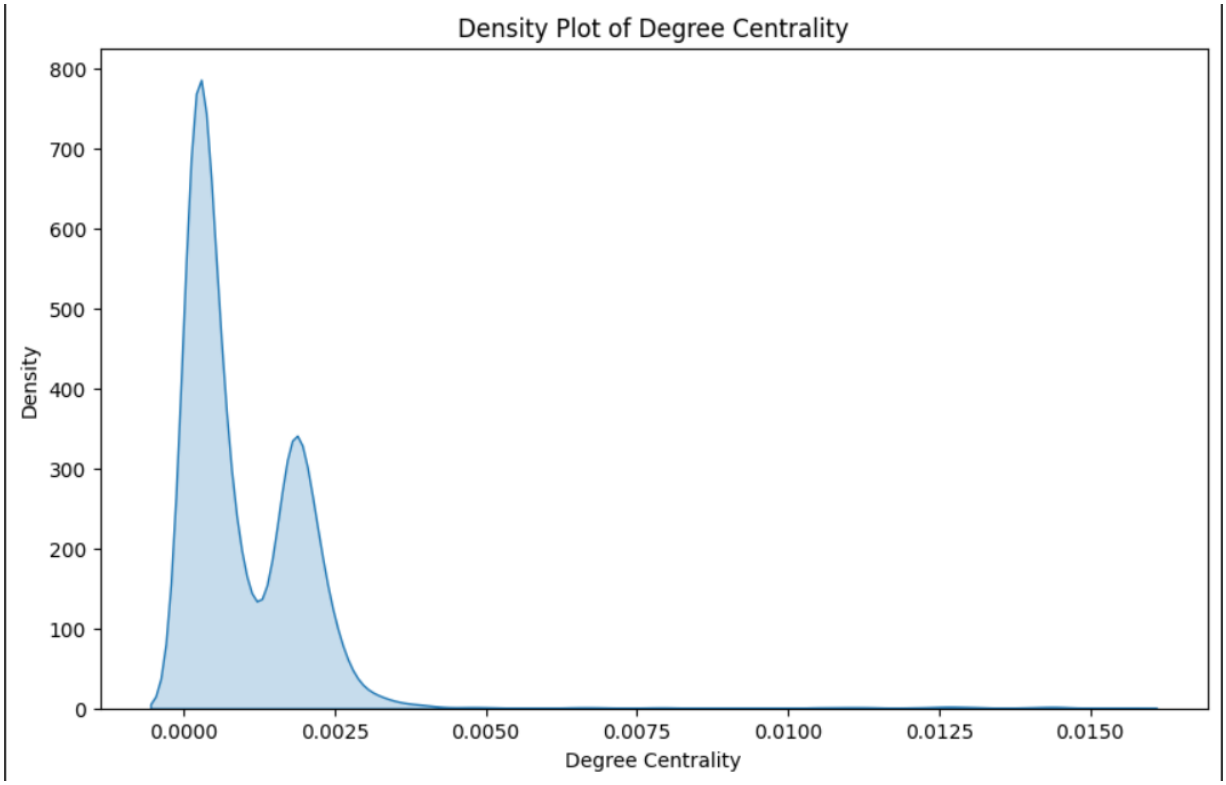
Inference

The graph represents the **top 10 nodes** within a network based on their **degree of centrality**. Here are the key takeaways:

1. **Node 123**: Has a degree centrality of approximately **0.015397**.
2. **Node 127**: Also has a degree centrality of approximately **0.015079**.
3. **Node 367**: Exhibits a degree centrality value of approximately **0.014921**.
4. **Node 424**: Shows a degree centrality of approximately **0.014603**.
5. **Node 251**: Has a degree centrality value of approximately **0.014444**.

These nodes play influential roles in the network due to their connections. The degree centrality values are relatively close, indicating similar importance among these top 10 nodes.

Density plot of degree of centrality



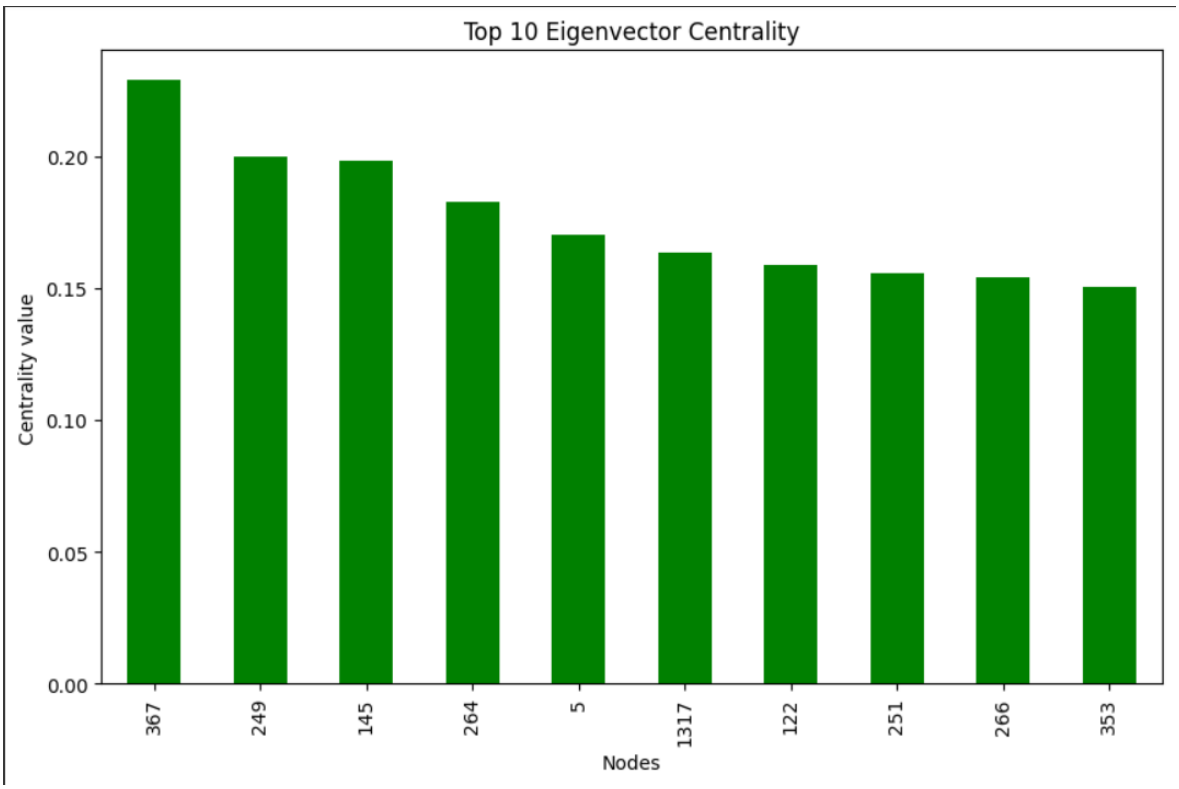
Comparison with dataset-1

The current distribution is more concentrated around a higher degree of centrality value.

Top 10 Eigen Vector Centrality

Dataset-2

```
Top 10 Eigenvector Centrality:
367     0.228702
249     0.199973
145     0.198424
264     0.182862
5       0.170008
1317    0.163589
122     0.158768
251     0.155446
266     0.154309
353     0.150357
dtype: float64
```



Inference

The graph of eigenvector centrality reveals the influence of nodes within a network. Here are the key insights:

1. Node 367: Has the highest eigenvector centrality value, approximately 0.20.

This node

is most central within the network according to this measure.

2. Other nodes (249, 145, 264, 5, 1317, 122, 251, 256, and 353) also exhibit moderate to

high eigenvector centrality values, ranging from approximately 0.15 to 0.20.

3. These nodes likely play crucial roles in information flow and influence propagation within the network.

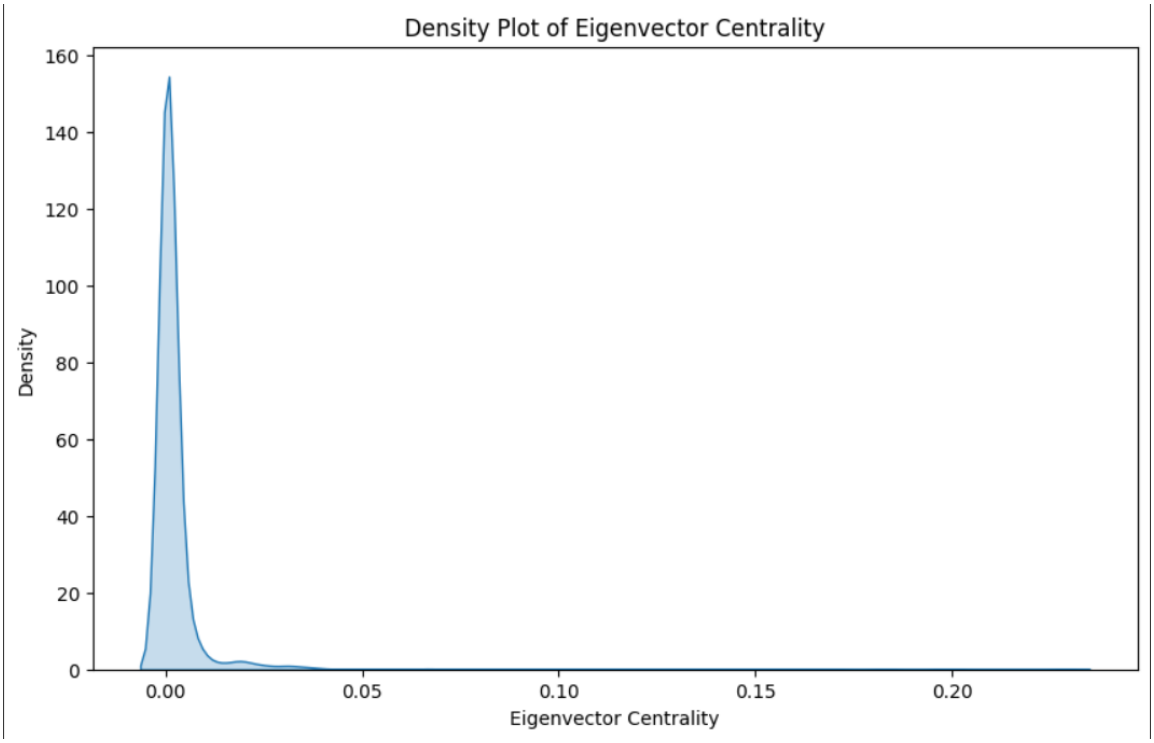
Remember that eigenvector centrality emphasizes both the node's direct connections and the centrality of its neighbors. These influential nodes can significantly impact the network dynamics.

Comparison with dataset-1

- The previous table had higher eigenvector centrality values, while the the table shows lower values.
- Both tables highlight influential nodes within their respective networks.

Density plot of Eigenvector centrality

Plot for dataset -2



Inferences

The graph of eigenvector centrality reveals the influence of nodes within a network. Here are the key insights:

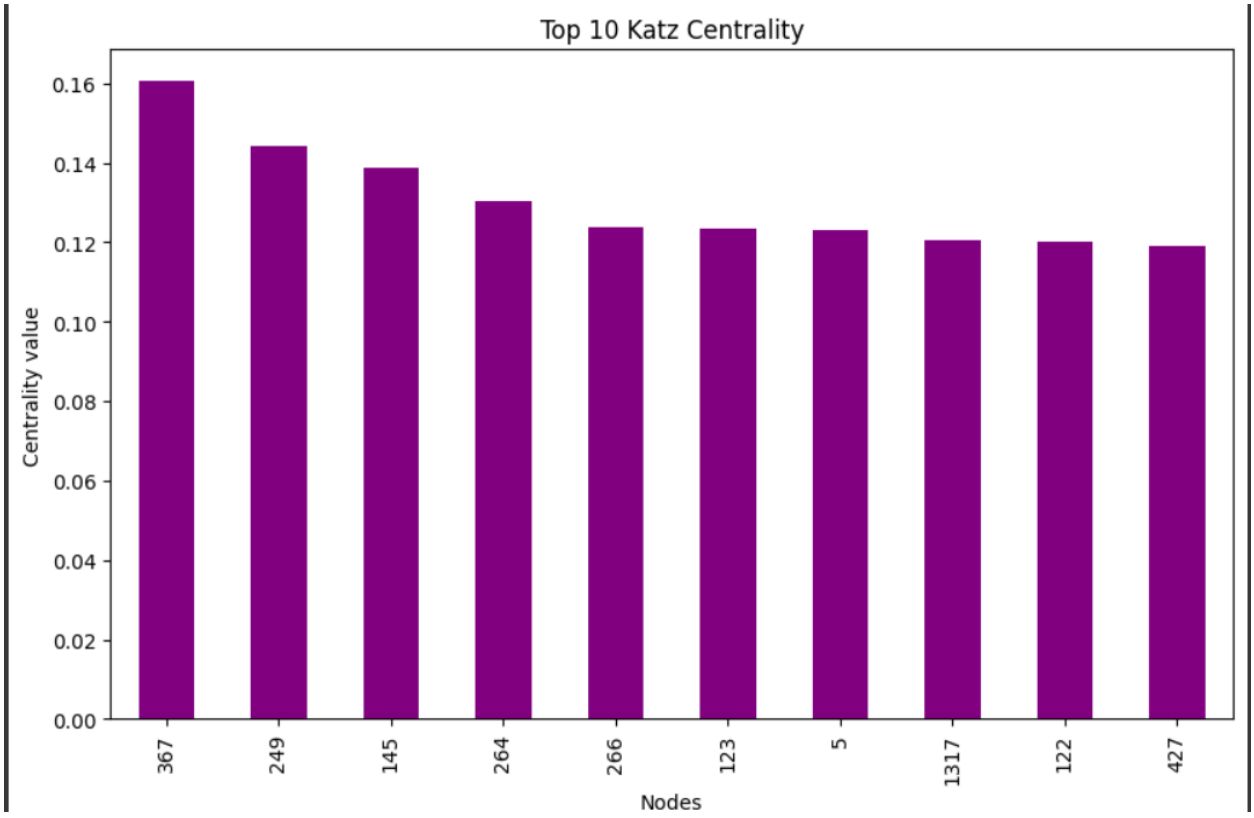
1. **Node 367**: Has the highest eigenvector centrality value of approximately **0.228702**. This node is the most central within the network according to this measure.
2. Other nodes (249, 145, 264, 5, 1317, 122, 251, 256, and 353) also exhibit moderate to high eigenvector centrality values, ranging from approximately **0.15** to **0.20**.
3. These nodes likely play crucial roles in information flow and influence propagation within the network.

Remember that eigenvector centrality emphasizes both the node's direct connections and the centrality of its neighbors. These influential nodes can significantly impact the network dynamics.

Top 10 Katz Centrality

Dataset-2

```
Top 10 Katz Centrality:
367     0.160454
249     0.144380
145     0.138631
264     0.130439
266     0.123885
123     0.123538
5       0.123031
1317    0.120449
122     0.120281
427     0.119091
dtype: float64
```

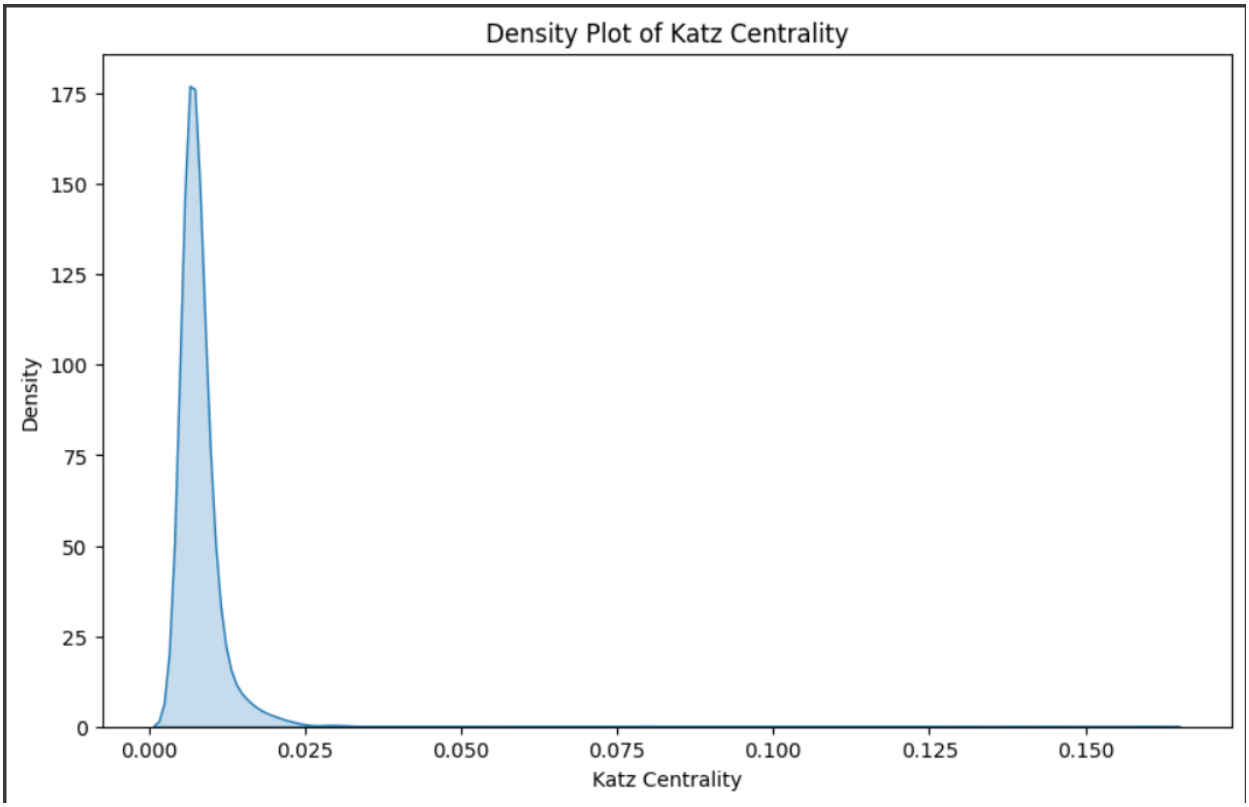


Comparison with dataset-1

1. The previous table had higher Katz centrality values, while the current table shows lower values.
2. Nodes with higher Katz centrality are more influential within the network.
3. Both tables highlight influential nodes based on their connectivity and influence propagation.

Remember that Katz's centrality considers both direct connections and the influence of neighbors, making it a valuable measure for understanding node importance.

Density plot



Inference for the output

The density plot of Katz's Centrality provides insights into the distribution of centrality values within a network. Here are the key observations:

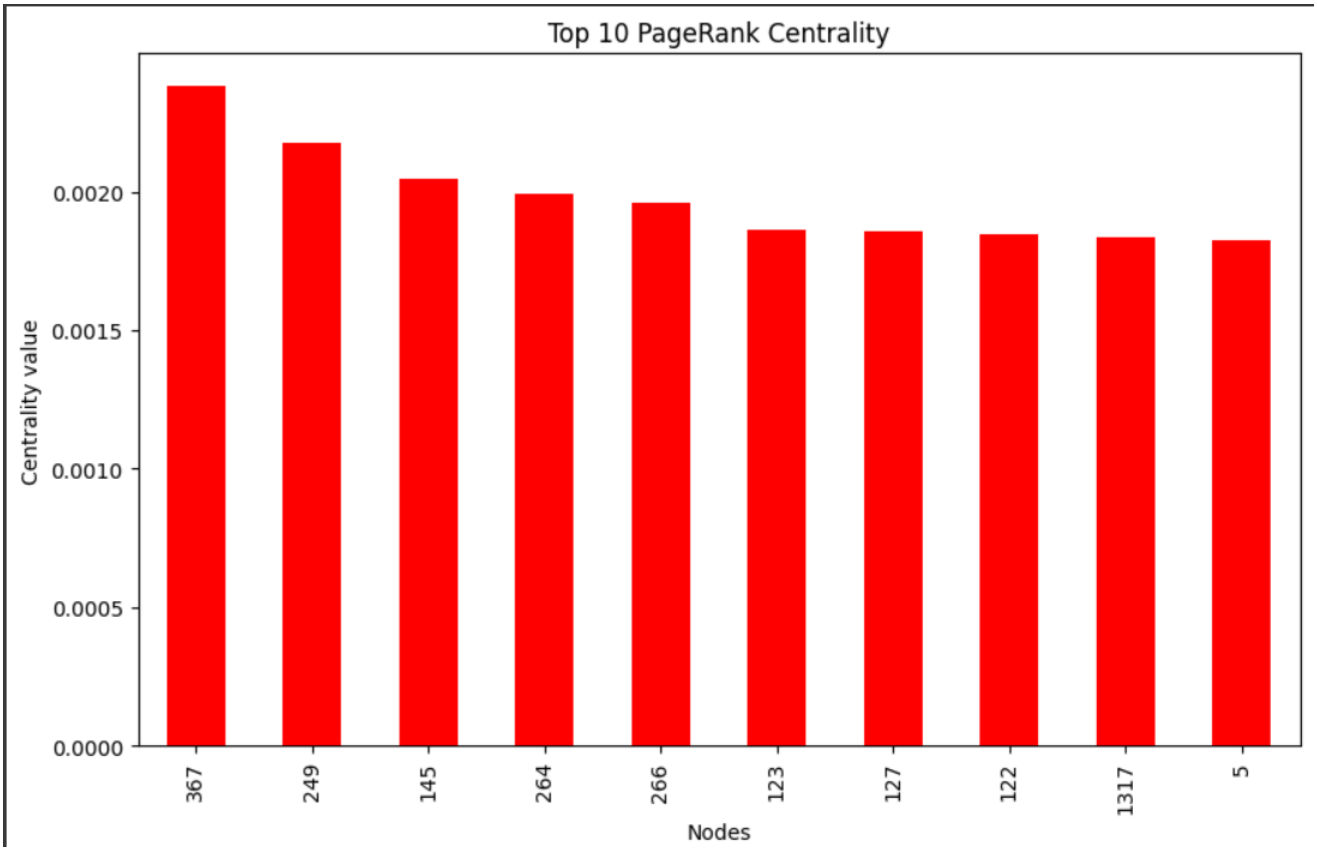
- The x-axis represents Katz Centrality values, ranging from 0 to approximately 0.15.
- The y-axis represents density, indicating how many nodes fall within a specific Katz Centrality intervals.
- The plot shows a peak in density near a Katz Centrality of 0, suggesting that many nodes have low centrality.
- As Katz's Centrality increases, the density sharply decreases, indicating fewer nodes with higher centrality values.

In summary, this density plot highlights the prevalence of low centrality nodes and the rapid decline in density as centrality values rise. It provides valuable information about the distribution of influence within the network.

Top 10 PageRank centrality

```
Top 10 PageRank Centrality:
367     0.002379
249     0.002177
145     0.002047
264     0.001990
266     0.001958
123     0.001860
127     0.001857
122     0.001848
1317    0.001836
5       0.001824
dtype: float64
```

For Dataset-2

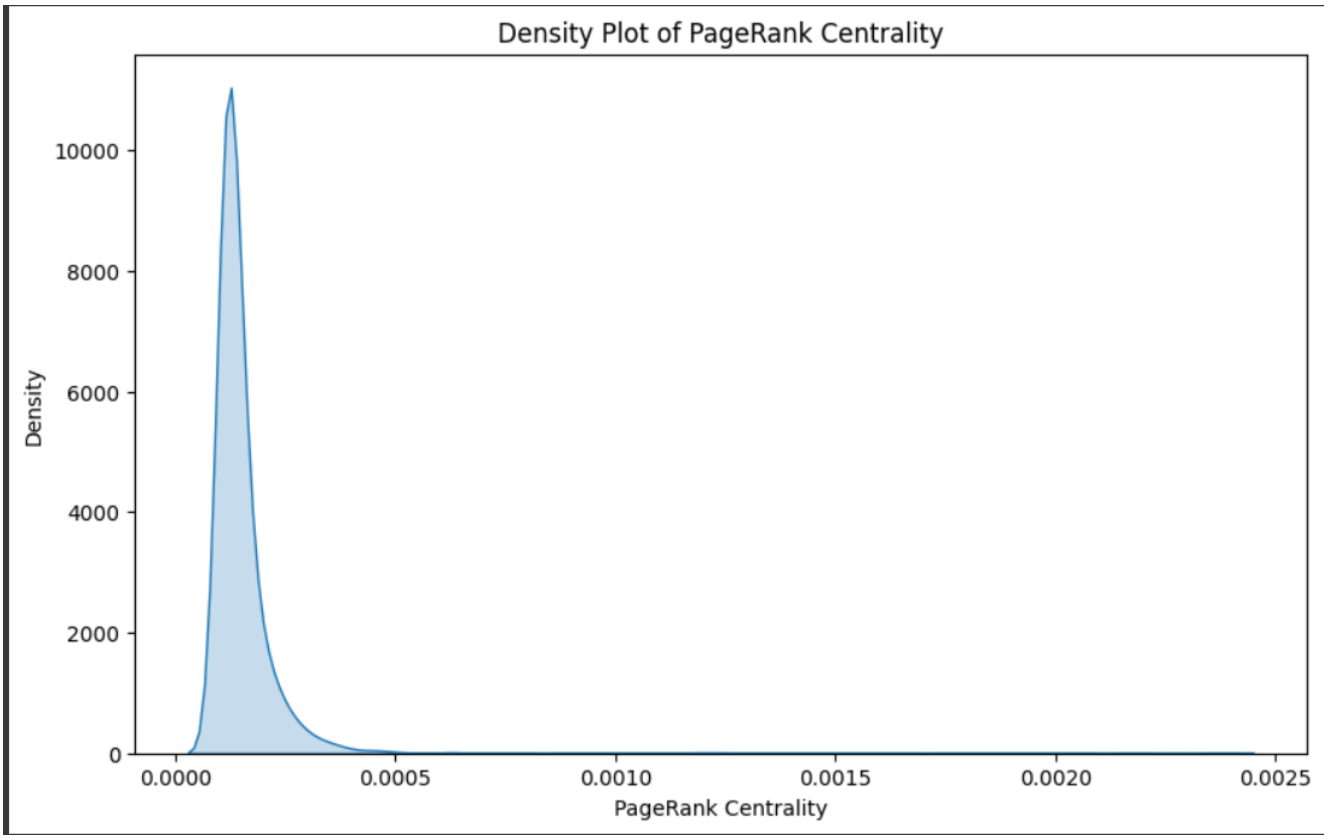


Comparison with dataset-1

1. The PageRank Centrality values in the current network are significantly lower than those in the previous network.
2. Nodes with higher PageRank Centrality are more influential within their respective networks.
3. The current network seems to have less overall influence compared to the previous one.

PageRank Centrality is a valuable measure for understanding node importance in various contexts, such as web pages, social networks, and citation networks

Density Plot graph



Inference

The plot shows a sharp peak in density near a very low PageRank Centrality value (close to zero), suggesting that a large number of nodes have low centrality.

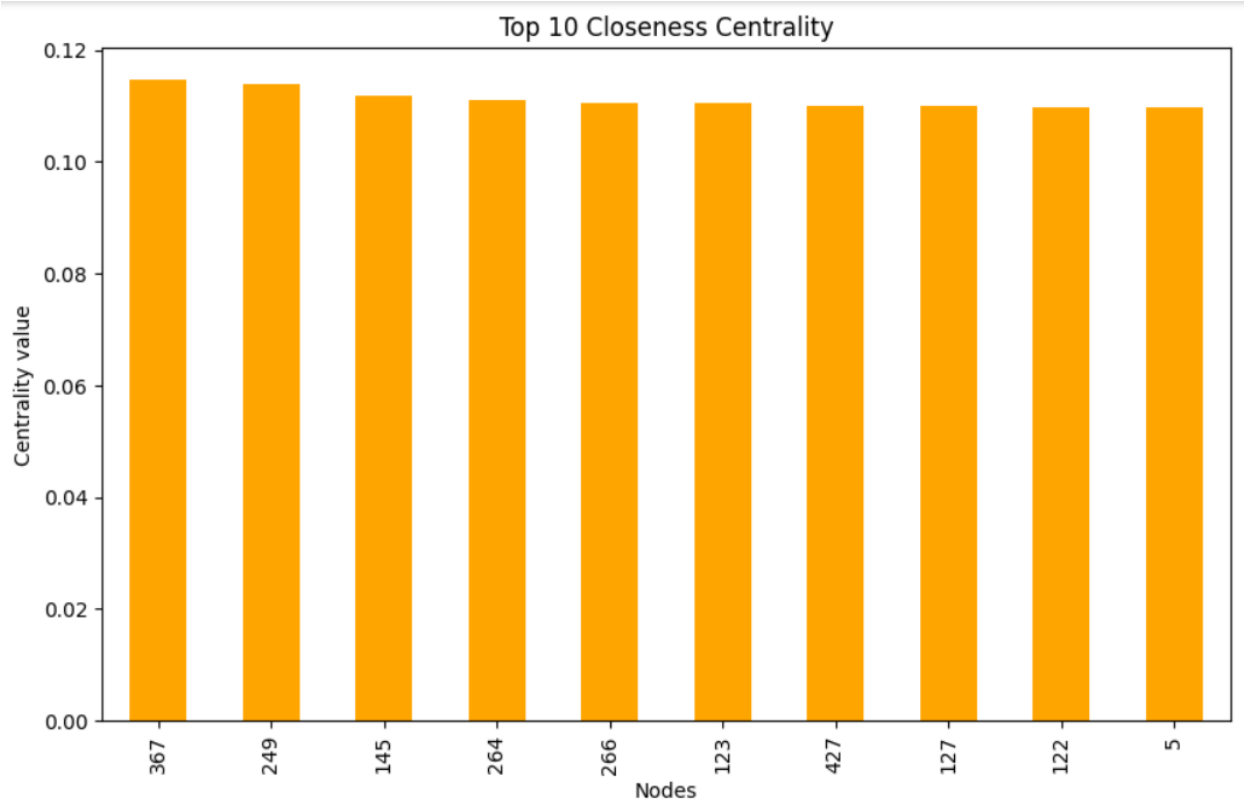
As PageRank Centrality increases, the density rapidly decreases, indicating fewer nodes with higher centrality values.

In summary, this density plot highlights the prevalence of low centrality nodes and the scarcity of highly influential nodes within the network**.**

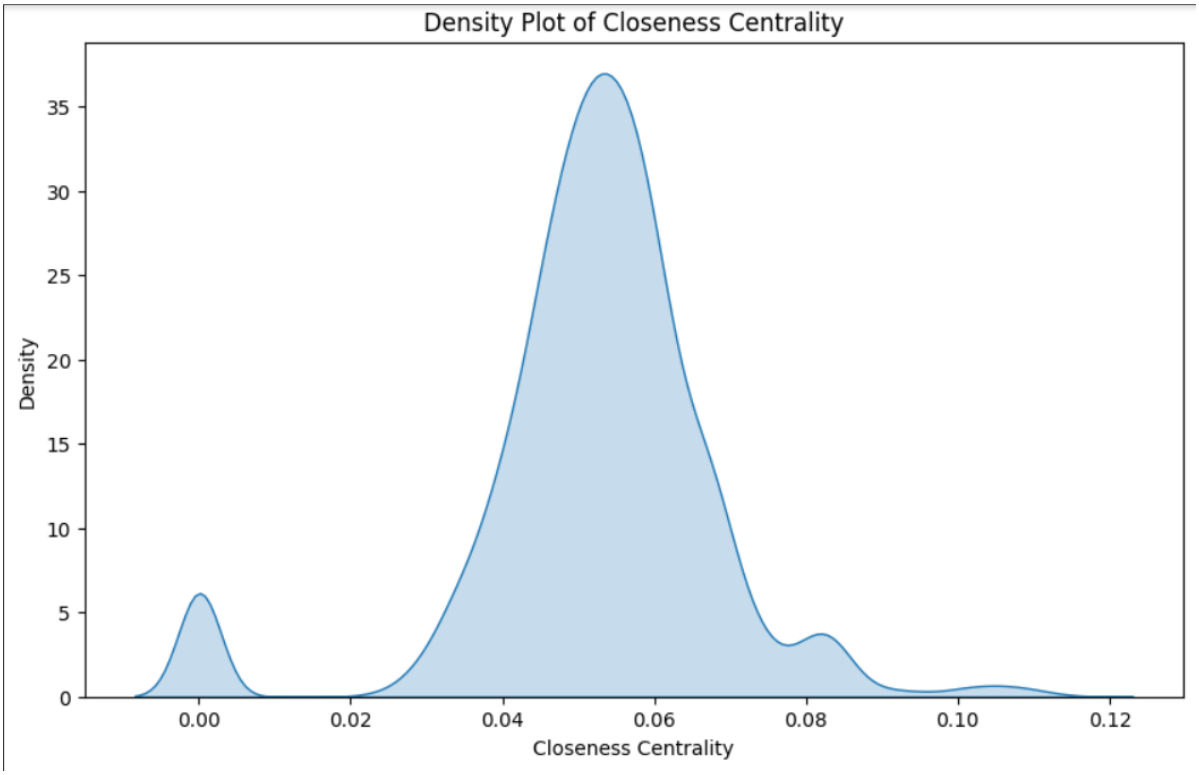
Top 10 Closeness centrality

Dataset-2

```
Top 10 Closeness Centrality:
367    0.114660
249    0.113881
145    0.111855
264    0.111081
266    0.110677
123    0.110479
427    0.110156
127    0.110092
122    0.109787
5      0.109692
dtype: float64
```



Density plot



Inference for the output

The density plot of closeness centrality reveals the following insights:

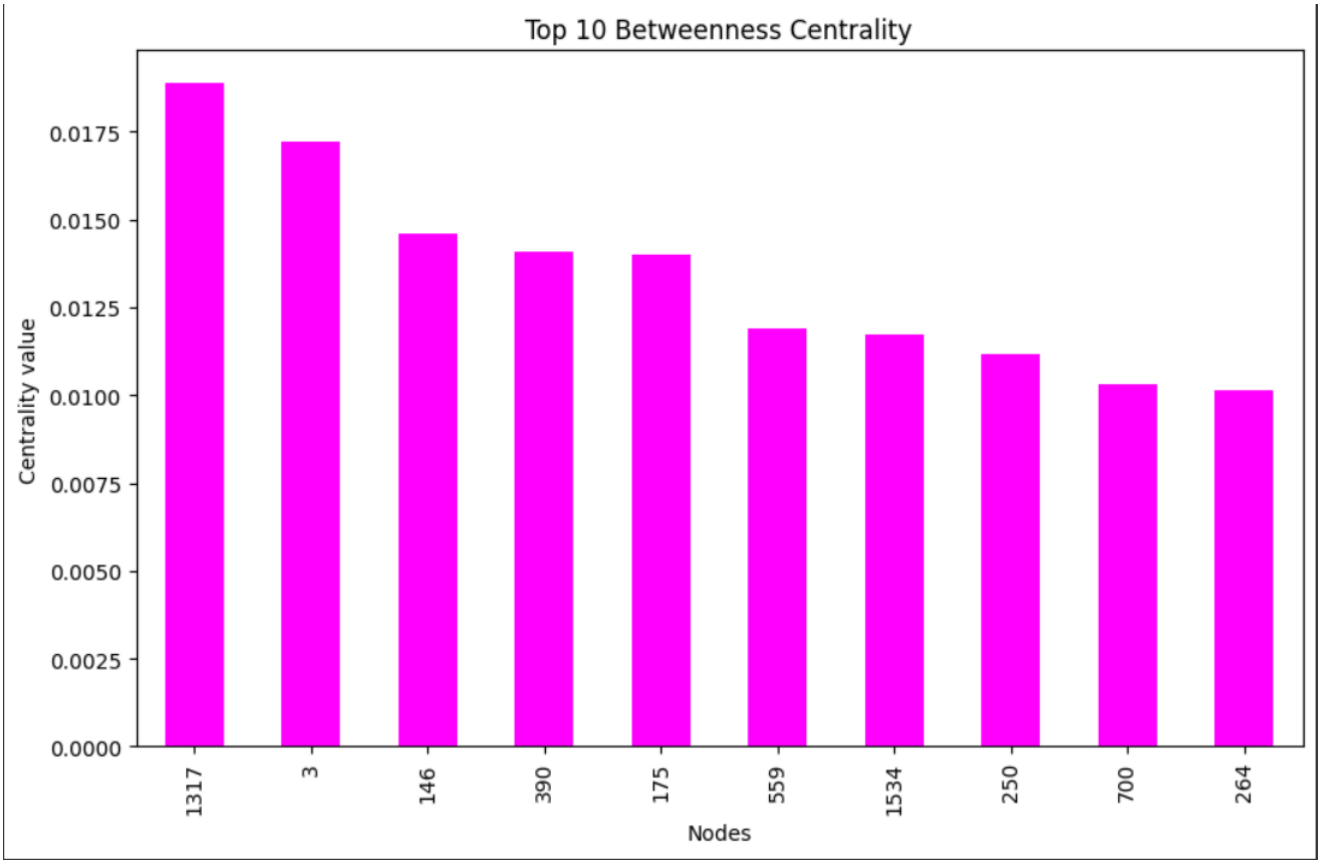
- Peak at 0.06: The majority of nodes in the network exhibit a closeness centrality around 0.06. This suggests that many nodes are well-connected and can efficiently transmit information to other nodes.
- Spread: As we move away from the peak, the density decreases. There are fewer nodes with higher or lower closeness centrality values. This indicates that some nodes act as critical bridges, while others are more isolated.
- Importance of Central Nodes: Nodes with centrality values significantly higher than 0.06 play a crucial role in maintaining efficient communication within the network.

In summary, this density plot highlights the distribution of closeness centrality values, emphasizing the significance of well-connected nodes in the network's overall structure.

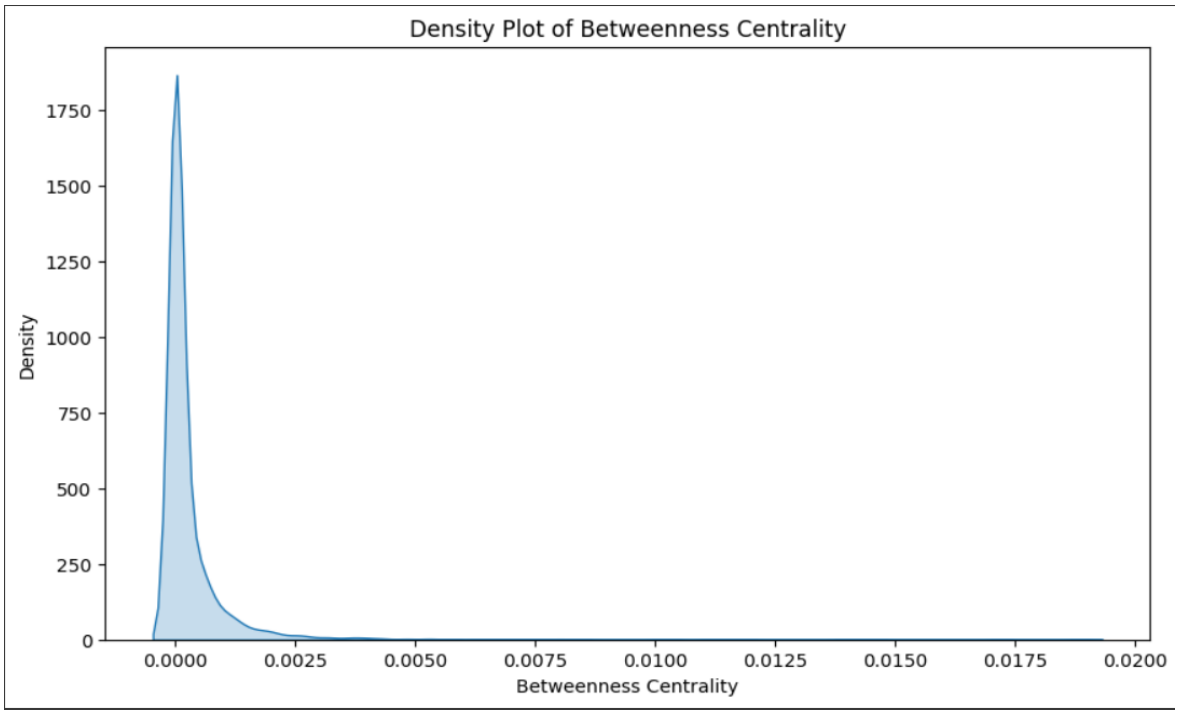
Top 10 Betweenness Centrality

For Dataset-2

```
Top 10 Betweenness Centrality:
1317    0.018869
3       0.017235
146     0.014611
390     0.014068
175     0.014000
559     0.011889
1534    0.011710
250     0.011175
700     0.010316
264     0.010158
dtype: float64
```



Density plot



Inference for the Output

The density plot of betweenness centrality provides insights into the distribution of this centrality measure within the network:

Peak at Low Betweenness Centrality:

- The majority of nodes exhibit low betweenness centrality, as indicated by the peak on the left side of the plot.
- These nodes are not central in terms of controlling information flow or acting as bridges.

Decreasing Density with Higher Betweenness Centrality:

- As we move toward higher betweenness centrality values, the density decreases sharply.
- Fewer nodes have higher influence or act as critical connectors.

Importance of Central Nodes:

- Nodes with significantly higher betweenness centrality play a crucial role in maintaining efficient communication within the network.

In summary, this plot emphasizes the distribution of betweenness centrality values, highlighting the significance of well-connected nodes in the network's overall structure.

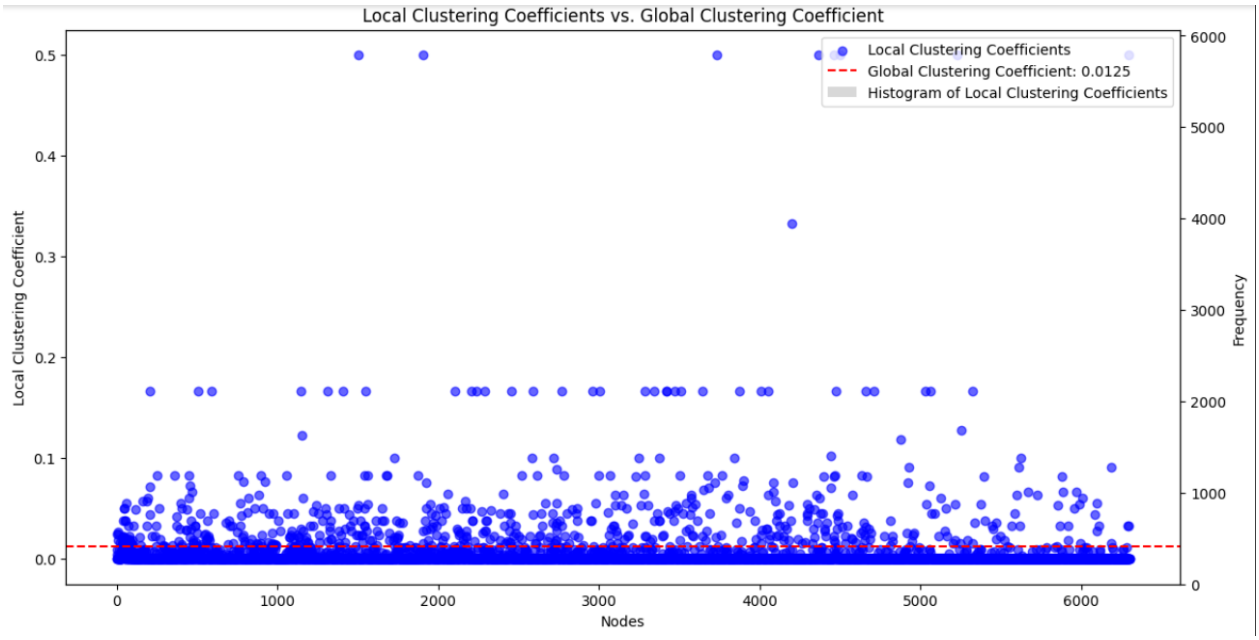
Transitivity and Reciprocity

Transitivity refers to the tendency for connections to "cluster" together, forming triangles in the network. If A is connected to B, and B is connected to C, then transitivity suggests there's a higher likelihood of A being connected to C as well.

```
[52] reciprocity_value = nx.reciprocity(G)
     print("Reciprocity of the graph:", reciprocity_value)

     Reciprocity of the graph: 0.0

[53] transitivity_value = nx.transitivity(G)
     print("Transitivity (Global Clustering Coefficient) of the graph:", transitivity_value)

     Transitivity (Global Clustering Coefficient) of the graph: 0.012464558925801101
```

Reciprocity focuses on the two-way nature of connections. It describes the tendency for connections to be mutual, meaning if A follows B on social media, B is also likely to follow A back.

Local vs Global Clustering coefficient



Inference for the output

the global clustering coefficient (0.0125) is lower than the average local clustering coefficient. This suggests that while there may be clustering of connections locally within the network, overall, the network does not exhibit a high degree of clustering.

Here's a more detailed explanation:

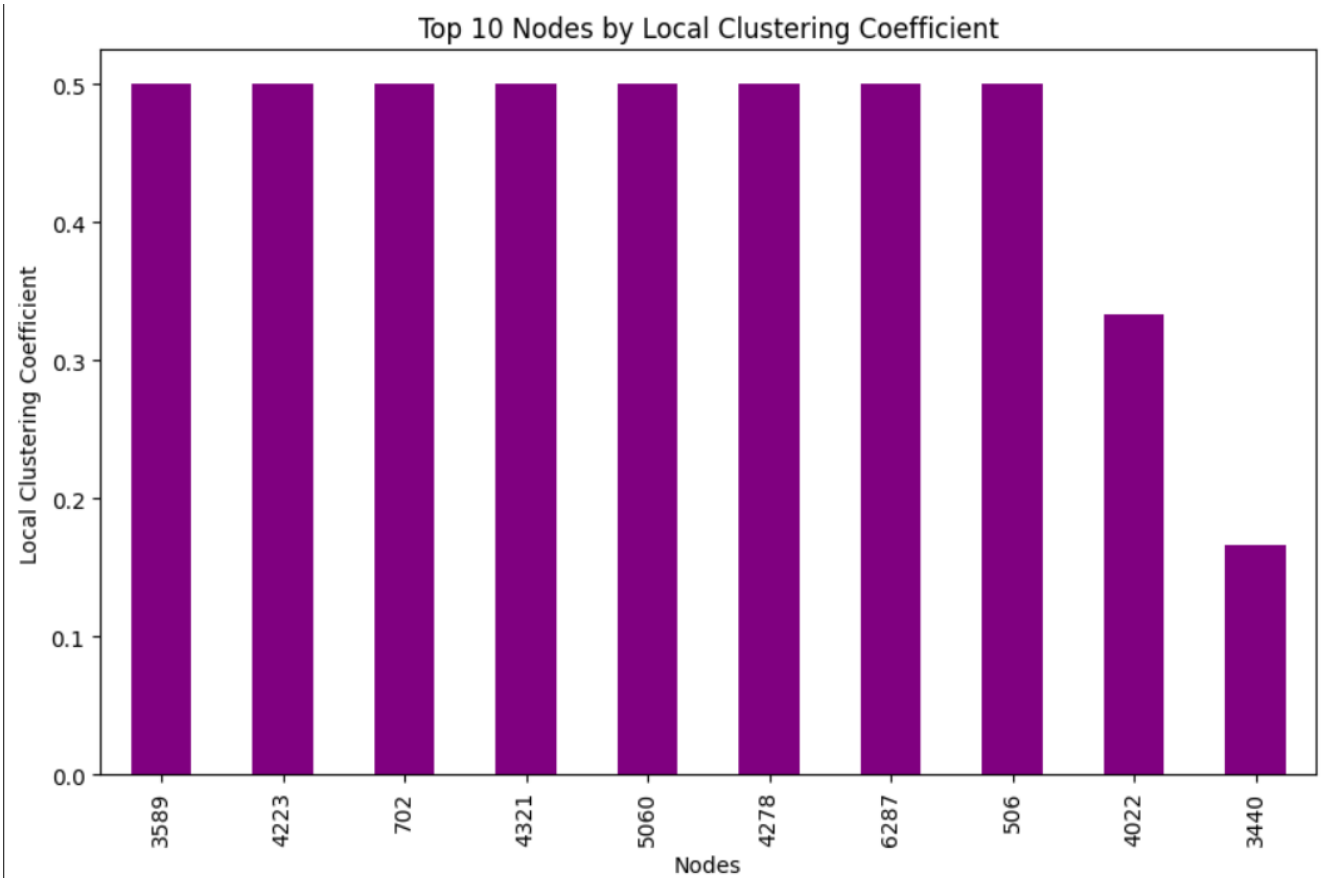
- Local clustering coefficient: This refers to the proportion of triangles around a specific node. In simpler terms, it measures how well a node's neighbors are connected.
-
- The histogram shows the distribution of local clustering coefficients for different nodes in the network. The fact that some nodes have higher coefficients than others indicates that there's clustering happening in some local areas of the network.

- Global clustering coefficient: This is a single value that represents the overall clustering tendency of the entire network. It is calculated by averaging the local clustering coefficients of all nodes. Here, the global value (0.0125) is low, signifying that overall, connections are not highly clustered across the network.

Possible reasons for low global clustering coefficient despite local clustering:

- The network may be sparse, meaning there are fewer connections overall compared to the number of nodes.
- The network may have a specific structure, like a star topology, where most nodes connect to a central hub but not necessarily to each other.

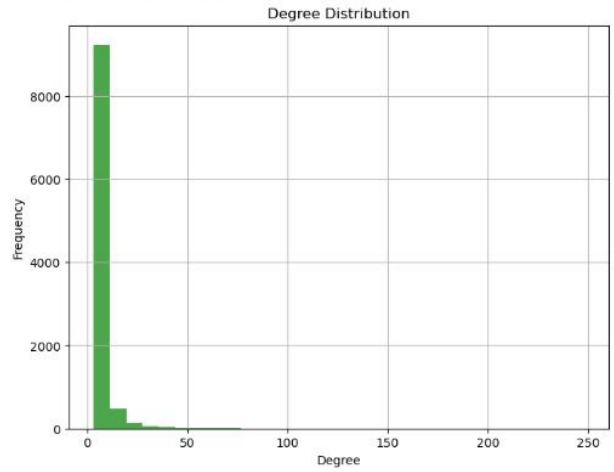
```
Top 10 Nodes by Local Clustering Coefficient:
3589    0.500000
4223    0.500000
702     0.500000
4321    0.500000
5060    0.500000
4278    0.500000
6287    0.500000
506     0.500000
4022    0.333333
3440    0.166667
dtype: float64
```


Top 10 Nodes by Local Clustering Coefficient
Local Clustering Coefficient
0.0
0.1
0.2
0.3
0.4
0.5
3589
4223
702
4321
5060
4278
6287
506
4022
3440
Nodes

Scale Free Network

Degree Distribution for Scale free Network

In [5]:
```
def plot_degree_distribution(G):
    degrees = [G.degree(n) for n in G.nodes()]
    plt.figure(figsize=(8, 6))
    plt.hist(degrees, bins=30, color='green', alpha=0.7)
    plt.title('Degree Distribution')
    plt.xlabel('Degree')
    plt.ylabel('Frequency')
    plt.grid(True)
    plt.show()

plot_degree_distribution(G1)

# Calculate degrees
degrees = [G1.degree(n) for n in G1.nodes()]

# Calculate and print statistical measures
max_degree = np.max(degrees)
min_degree = np.min(degrees)
average_degree = np.mean(degrees)
std_dev_degree = np.std(degrees)

print(f"Maximum Degree: {max_degree}")
print(f"Minimum Degree: {min_degree}")
print(f"Average Degree: {average_degree:.2f}")
print(f"Standard Deviation of Degree: {std_dev_degree:.2f}")
```




```
Maximum Degree: 248
Minimum Degree: 3
Average Degree: 6.00
Standard Deviation of Degree: 8.58
```

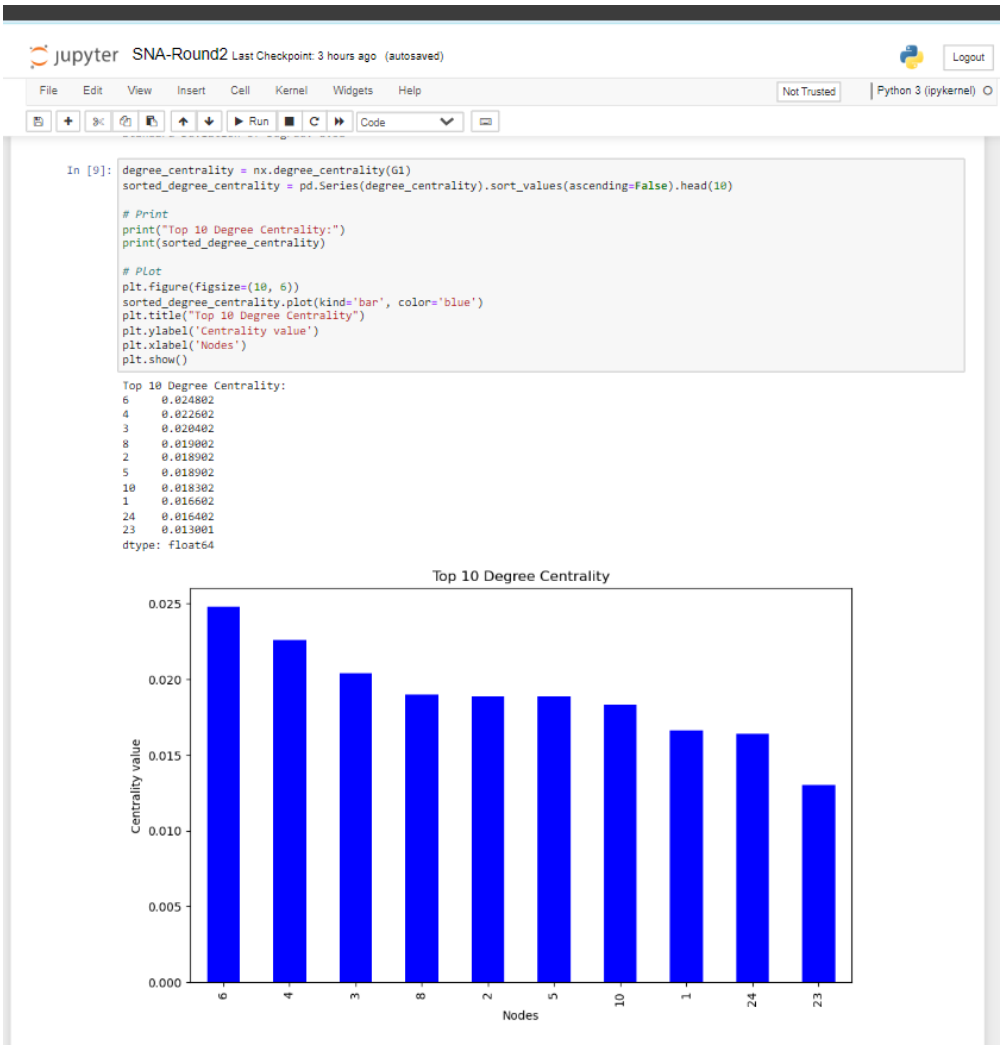
- **Maximum degree: 248**
- **Minimum degree: 3**
- **Average degree: 6.00**
- **Standard deviation of degree: 8.58**

Here are some additional inferences that can be made from the degree distribution:

The network is likely to be growing or evolving over time, as this is a common feature of scale-free Networks.

New nodes are likely to be preferentially attached to existing hubs, as this is another mechanism that can lead to scale-free degree distribution.

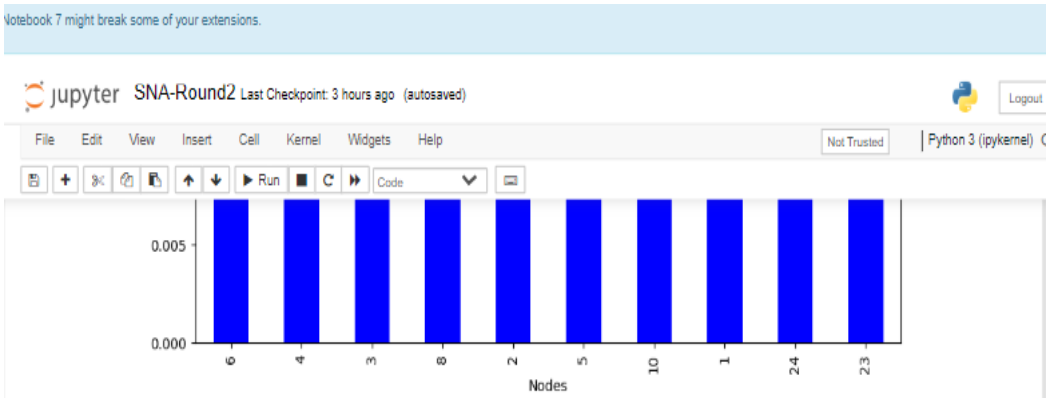
Degree centrality for scale free network



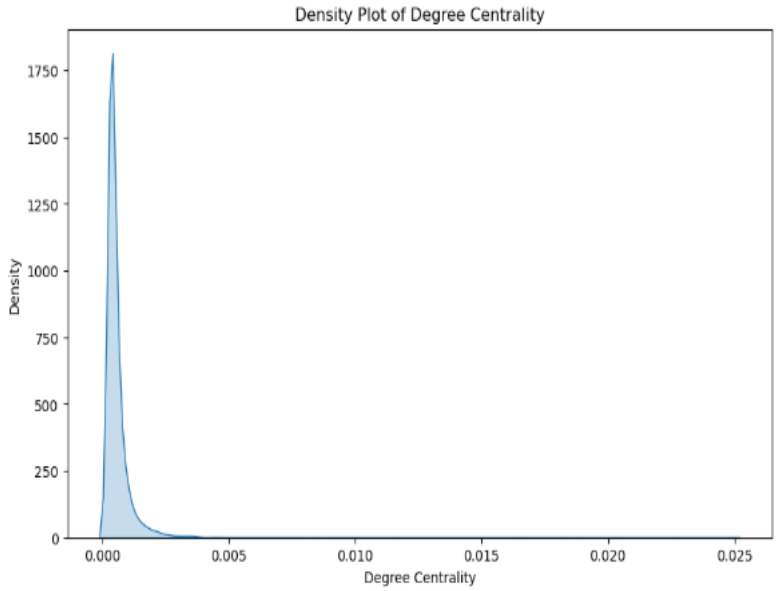
The Graph confirms a scale-free network with few highly connected hubs (high degree) and many nodes with fewer connections.

This suggests the network is evolving and new nodes connect to hubs, making it resilient to random failures but vulnerable to targeted hub attacks.

Density plot of Degree Centrality



In [12]:
```
degree_centrality = nx.degree_centrality(G1)
degree_df = pd.Series(degree_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(degree_df, fill=True)
plt.title('Density Plot of Degree Centrality')
plt.xlabel('Degree Centrality')
plt.ylabel('Density')
plt.show()
```

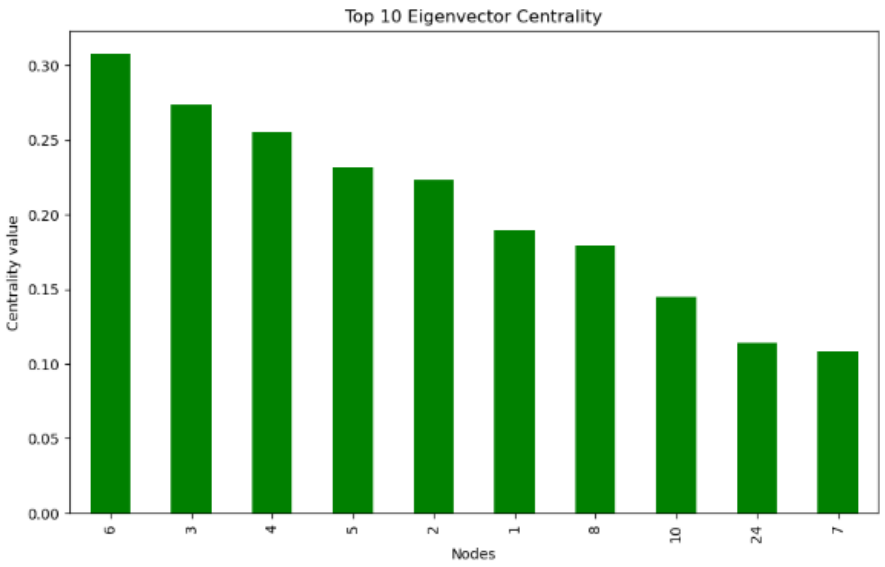


In [13]:
```
eigenvector_centrality = nx.eigenvector_centrality_numpy(G1)
sorted_eigenvector_centrality = pd.Series(eigenvector_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Eigenvector Centrality:")
print(sorted_eigenvector_centrality)
```

Top 10 eigen Vector centrality

```
In [13]: eigenvector_centrality = nx.eigenvector_centrality_numpy(G1)
sorted_eigenvector_centrality = pd.Series(eigenvector_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Eigenvector Centrality:")
print(sorted_eigenvector_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_eigenvector_centrality.plot(kind='bar', color='green')
plt.title("Top 10 Eigenvector Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 Eigenvector Centrality:
6     0.307759
3     0.273469
4     0.255149
5     0.231214
2     0.222994
1     0.189380
8     0.178912
10    0.144677
24    0.113697
7     0.108706
dtype: float64
```

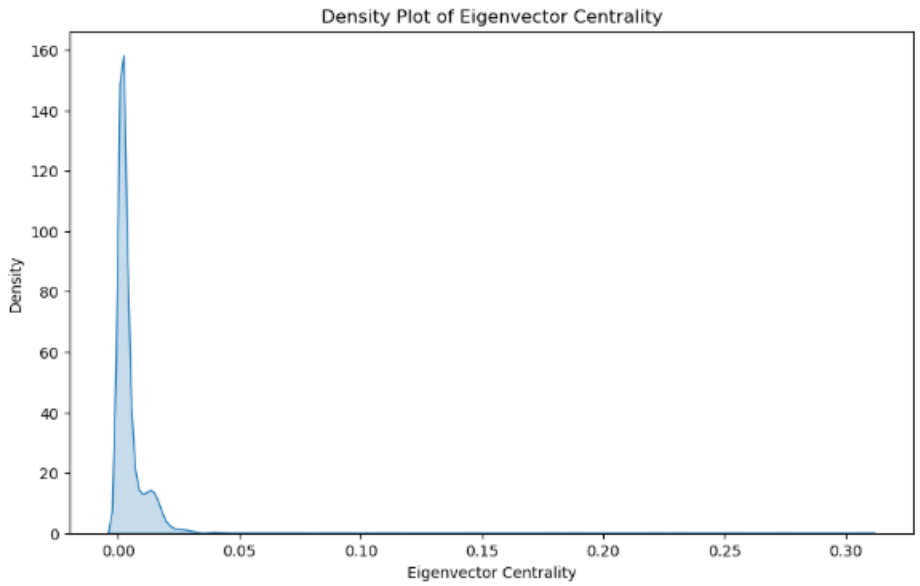


Eigenvector centrality is a measure of a node's influence in a network, based on the influence of its neighbours. Nodes with connections to other influential nodes will have higher eigenvector centrality

The image shows the top 10 nodes with the highest eigenvector centrality scores.

Density Plot for Eigen Vector Centrality

In [14]:
```
eigenvector_centrality = nx.eigenvector_centrality_numpy(G1)
eigenvector_df = pd.Series(eigenvector_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(eigenvector_df, fill=True)
plt.title('Density Plot of Eigenvector Centrality')
plt.xlabel('Eigenvector Centrality')
plt.ylabel('Density')
plt.show()
```



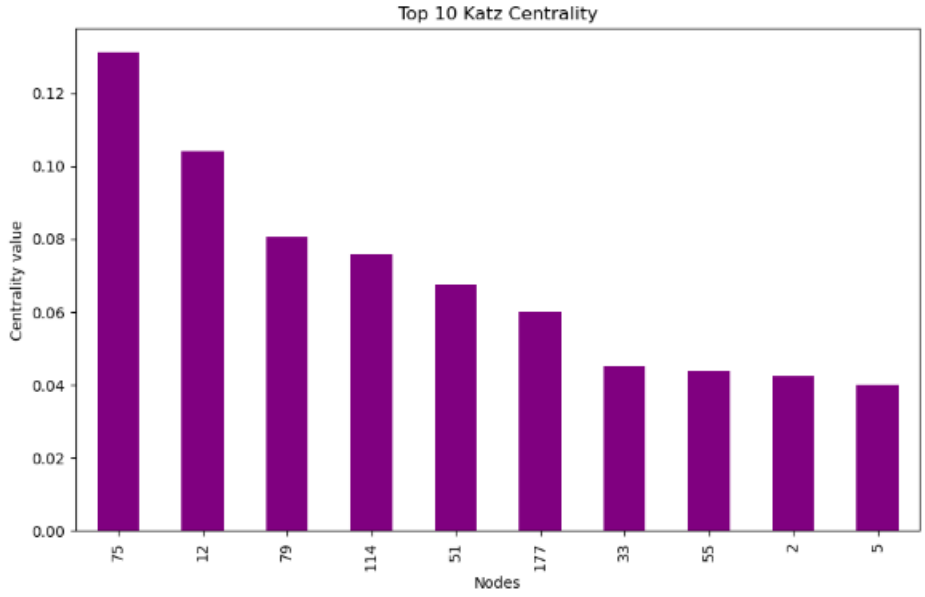
The distribution of eigenvector centrality is likely skewed. There are more nodes with lower centrality scores (toward the left of the plot) than nodes with higher centrality scores (toward the right). This suggests that a small number of nodes have much higher influence than most nodes in the network.

Top 10 Katz Centrality

- **The height of each bar represents the number of nodes that have that centrality value.** For. example, a tall bar at a particular value on the x-axis would indicate that there are many nodes in the network with that centrality value.
- **The distribution of nodes across centrality values can provide insights into the structure of the network.** For example, a network with a scale-free distribution would have many nodes with low centrality and a few nodes with very high centrality

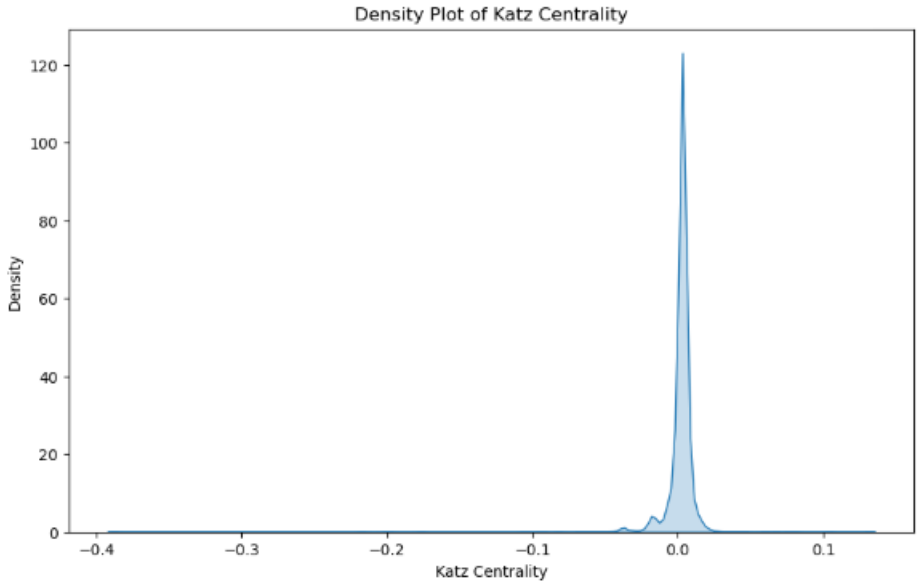
In [15]:
```
katz_centrality = nx.katz_centrality_numpy(G1)
sorted_katz_centrality = pd.Series(katz_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Katz Centrality:")
print(sorted_katz_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_katz_centrality.plot(kind='bar', color='purple')
plt.title("Top 10 Katz Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 Katz Centrality:
75     0.131172
12     0.104184
79     0.080508
114    0.075607
51     0.067452
177    0.060055
33     0.045016
55     0.043730
2      0.042480
5      0.039887
dtype: float64
```



Density plot for Katz Centrality

```
In [16]: katz_centrality = nx.katz_centrality_numpy(G1)
         katz_df = pd.Series(katz_centrality)

         # Plotting
         plt.figure(figsize=(10, 6))
         sns.kdeplot(katz_df, fill=True)
         plt.title('Density Plot of Katz Centrality')
         plt.xlabel('Katz Centrality')
         plt.ylabel('Density')
         plt.show()
```



The distribution of Katz centrality is likely skewed. There are more nodes with lower centrality scores (toward the left of the plot) than nodes with higher centrality scores (toward the right). This suggests that a small number of nodes have much higher influence than most nodes in the network.

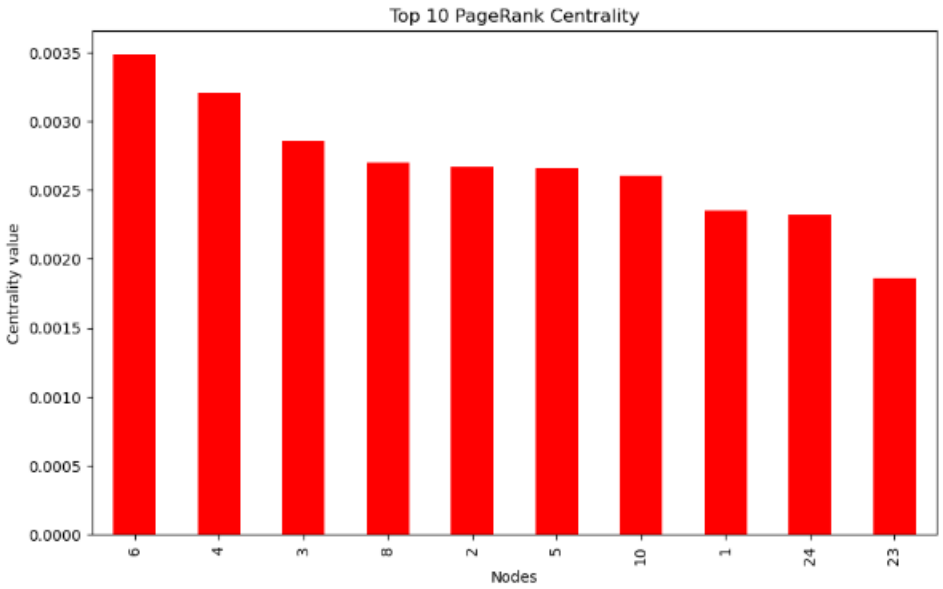
Katz centrality takes into account not only a node's direct neighbours but also the neighbours of its neighbours, and so on, up to a certain number of steps. This means that nodes that are connected to many influential nodes, even if they are not themselves very well-connected, can have high Katz centrality.

Overall, the density plot of Katz centrality suggests that the network may have a hierarchical structure, where some nodes have more influence than others.

Top 10 Page Rank Centrality

In [17]:
```
pagerank_centrality = nx.pagerank(G1)
sorted_pagerank_centrality = pd.Series(pagerank_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 PageRank Centrality:")
print(sorted_pagerank_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_pagerank_centrality.plot(kind='bar', color='red')
plt.title("Top 10 PageRank Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 PageRank Centrality:
6     0.003484
4     0.003203
3     0.002859
8     0.002701
2     0.002665
5     0.002663
10    0.002608
1     0.002355
24    0.002319
23    0.001862
dtype: float64
```

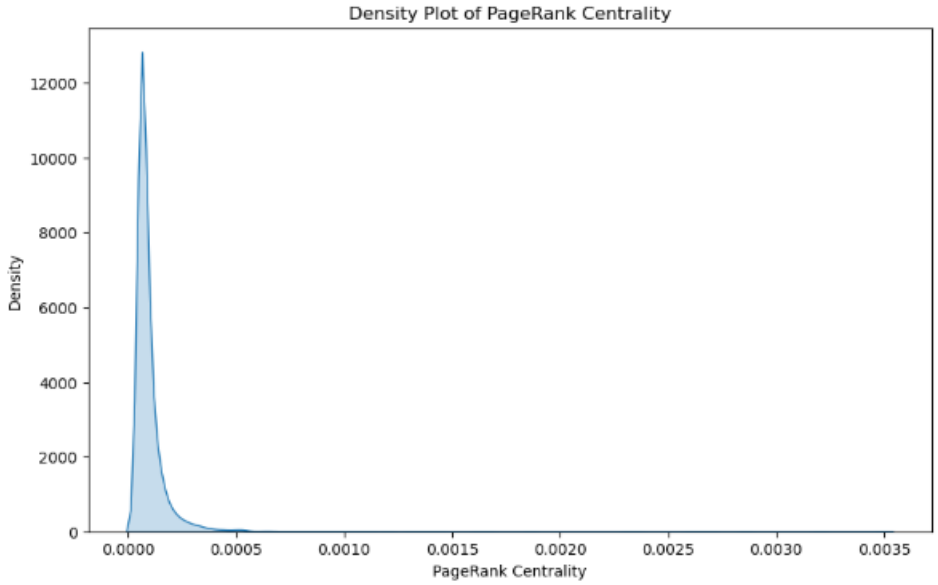


- **The nodes are ranked by their PageRank centrality score.** PageRank centrality is a measure of a node's importance in a network, based on the quality and quantity of its incoming links. Nodes with higher PageRank centrality scores are considered more important or influential than nodes with lower scores.
- **The distribution of PageRank centrality is likely skewed.** There seems to be a node with a much higher centrality score (6) compared to the other nodes. This suggests that a small number of nodes have much higher influence than most nodes in the network.

The remaining nodes have a similar PageRank centrality score. This suggests that these nodes may have similar importance or influence within the network.

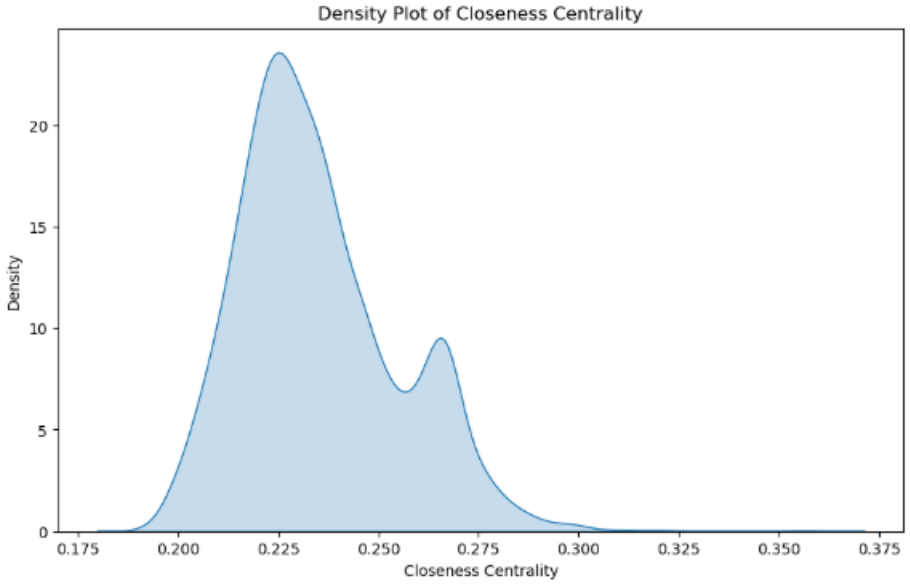
Density Plot page rank Centrality

```
In [19]: pagerank_centrality = nx.pagerank(G1)
         pagerank_df = pd.Series(pagerank_centrality)

         # Plotting
         plt.figure(figsize=(10, 6))
         sns.kdeplot(pagerank_df, fill=True)
         plt.title('Density Plot of PageRank Centrality')
         plt.xlabel('PageRank Centrality')
         plt.ylabel('Density')
         plt.show()
```



Density plot of closeness centrality

In [21]:
```
closeness_centrality = nx.closeness_centrality(G1)
closeness_df = pd.Series(closeness_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(closeness_df, fill=True)
plt.title('Density Plot of Closeness Centrality')
plt.xlabel('Closeness Centrality')
plt.ylabel('Density')
plt.show()
```

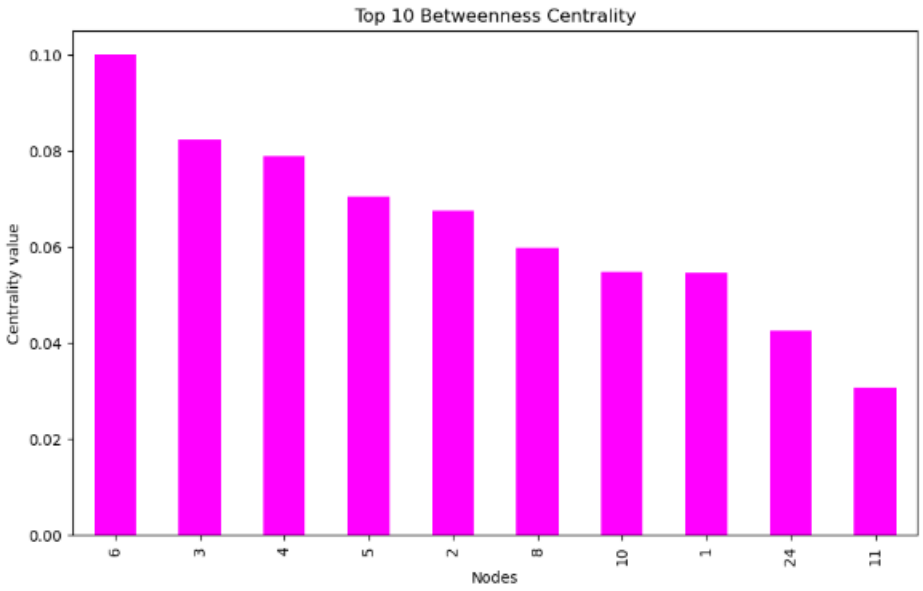


- **The distribution of closeness centrality is likely skewed.** There are more nodes with lower centrality scores (toward the left of the plot) than nodes with higher centrality scores (toward the right). This suggests that a small number of nodes are very close to all other nodes in the network, while most nodes are farther away from some nodes in the network.

Top 10 Betweenness Centrality

In [22]:
```
betweenness_centrality = nx.betweenness_centrality(G1)
sorted_betweenness_centrality = pd.Series(betweenness_centrality).sort_values(ascending=False).head(10)

# Print
print("Top 10 Betweenness Centrality:")
print(sorted_betweenness_centrality)

# Plot
plt.figure(figsize=(10, 6))
sorted_betweenness_centrality.plot(kind='bar', color='magenta')
plt.title("Top 10 Betweenness Centrality")
plt.ylabel('Centrality value')
plt.xlabel('Nodes')
plt.show()
```

```
Top 10 Betweenness Centrality:
6     0.100064
3     0.082328
4     0.079003
5     0.070442
2     0.067522
8     0.059743
10    0.054872
1     0.054556
24    0.042427
11    0.030782
dtype: float64
```

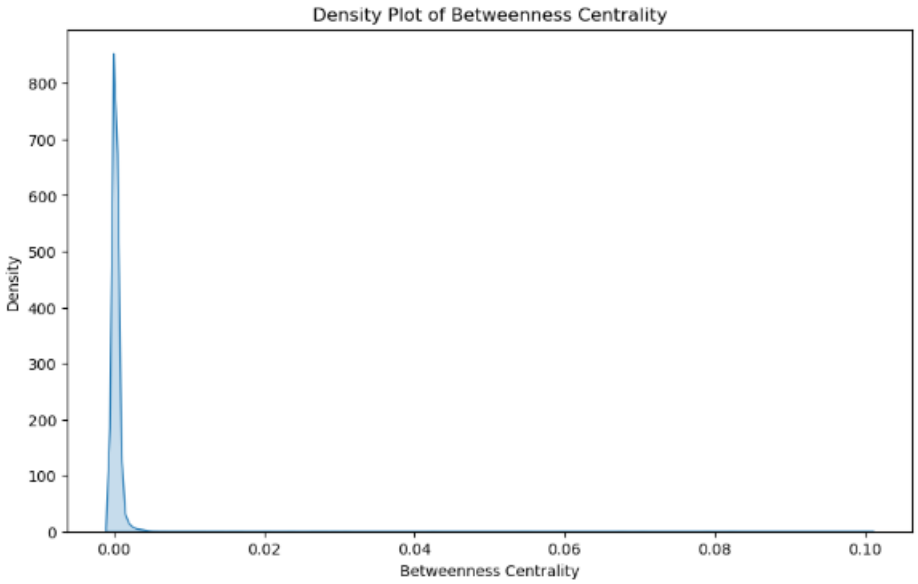


- **The distribution of betweenness centrality is likely skewed.** There are more nodes with lower centrality scores (toward the bottom of the plot) than nodes with higher centrality scores (toward the top). This suggests that a small number of nodes act as bridges between many other nodes in the network, while most nodes do not play a central role in communication between other nodes.

- **The presence of nodes with high betweenness centrality suggests the network may have a small-world property.** In a small-world network, most nodes can be reached from any other node in a small number of steps, even if the network is large. The nodes with high betweenness centrality likely play a key role in facilitating these short connections between distant parts of the network.

Density plot for betweenness centrality

In [23]:
```
betweenness_centrality = nx.betweenness_centrality(G1)
betweenness_df = pd.Series(betweenness_centrality)

# Plotting
plt.figure(figsize=(10, 6))
sns.kdeplot(betweenness_df, fill=True)
plt.title('Density Plot of Betweenness Centrality')
plt.xlabel('Betweenness Centrality')
plt.ylabel('Density')
plt.show()
```



In [24]:
```
reciprocity_value = nx.reciprocity(G1)
print("Reciprocity of the graph:", reciprocity_value)
```

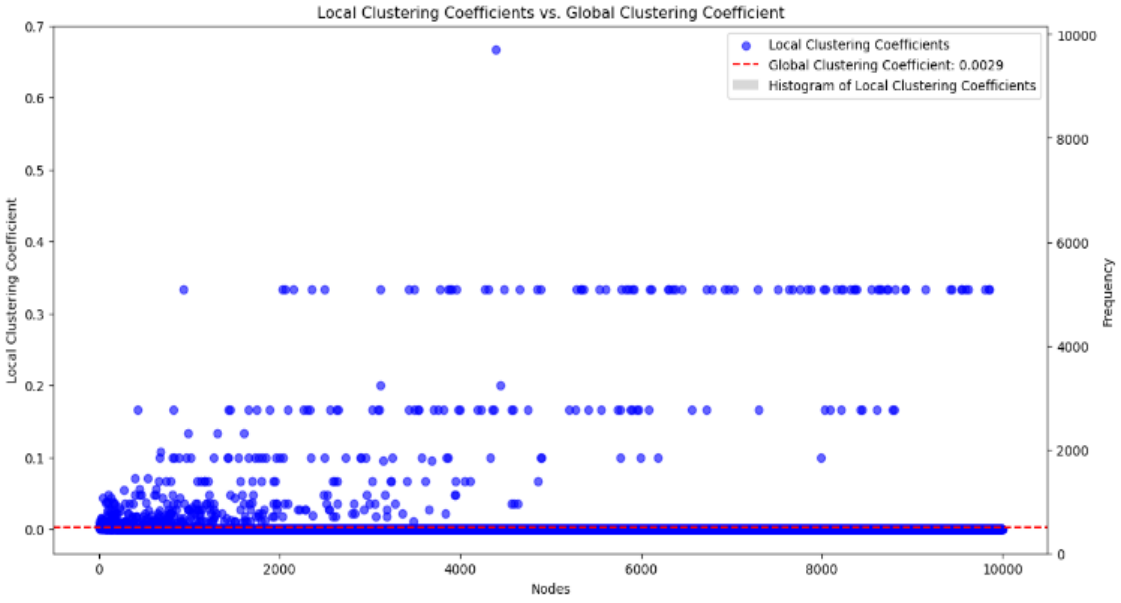
```
Reciprocity of the graph: 0.0
```

In [25]:
```
transitivity_value = nx.transitivity(G1)
print("Transitivity (Global Clustering Coefficient) of the graph:", transitivity_value)
```

```
Transitivity (Global Clustering Coefficient) of the graph: 0.002879568006859977
```

Local Clustering V/S Global Coefficient

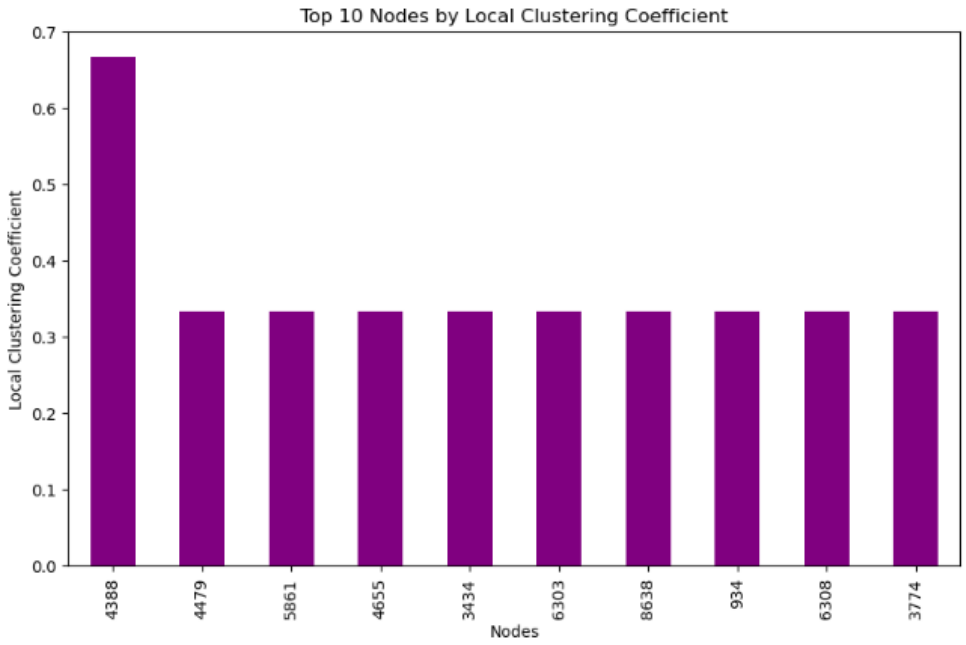
In [26]:
```
local_clustering = nx.clustering(G1)
global_clustering = nx.transitivity(G1)

# Creating a DataFrame from the local clustering data
local_clustering_df = pd.DataFrame(list(local_clustering.items()), columns=['Node', 'LocalClustering'])

# Set up the figure and axes for a combined plot
fig, ax1 = plt.subplots(figsize=(14, 7))

# Scatter plot for local clustering coefficients
scatter = ax1.scatter(local_clustering_df.index, local_clustering_df['LocalClustering'], alpha=0.6, color='blue', label='Local C
ax1.set_ylabel('Local Clustering Coefficient')
ax1.set_xlabel('Nodes')
ax1.set_title('Local Clustering Coefficients vs. Global Clustering Coefficient')

# Add a horizontal line for global clustering coefficient
ax1.axhline(y=global_clustering, color='red', linestyle='--', label=f'Global Clustering Coefficient: {global_clustering:.4f}')

# Secondary axis for histogram
ax2 = ax1.twinx()
sns.histplot(local_clustering_df['LocalClustering'], bins=30, ax=ax2, color='gray', alpha=0.3, label='Histogram of Local Cluster
ax2.set_ylabel('Frequency')

# Adding legend
lines, labels = ax1.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
ax2.legend(lines + lines2, labels + labels2, loc='upper right')

plt.show()
```



(Top 10 Local Clustering Coefficient

```
In [27]: local_clustering_df = pd.Series(local_clustering).sort_values(ascending=False).head(10)
         print("Top 10 Nodes by Local Clustering Coefficient:")
         print(local_clustering_df)

         # Plotting top 10 local clustering coefficients
         plt.figure(figsize=(10, 6))
         local_clustering_df.plot(kind='bar', color='purple')
         plt.title("Top 10 Nodes by Local Clustering Coefficient")
         plt.ylabel('Local Clustering Coefficient')
         plt.xlabel('Nodes')
         plt.show()
```

```
Top 10 Nodes by Local Clustering Coefficient:
4388    0.666667
4479    0.333333
5861    0.333333
4655    0.333333
3434    0.333333
6303    0.333333
8638    0.333333
934     0.333333
6308    0.333333
3774    0.333333
dtype: float64
```



The graph shows the distribution of local clustering coefficients for nodes in a network. The local clustering coefficient measures how well-connected a node's neighbours are to each other. A higher coefficient indicates a node is part of a tightly knit community. The chart suggests that there are many nodes with low coefficients, and a few nodes with high coefficients. This implies the network may have a modular structure with some well-defined communities, but also many nodes that are not part of such communities.

Giant Component Networks

In [32]:
```
giant_component = max(nx.connected_components(G1), key=len)
giant_component2 = max(nx.connected_components(G), key=len)
giant_component3 = max(nx.connected_components(G2), key=len)
```

In [33]:
```
giant_component_subgraph = G1.subgraph(giant_component)
giant_component_subgraph2 = G.subgraph(giant_component2)
giant_component_subgraph3 = G2.subgraph(giant_component3)
```

In [34]:
```
num_nodes_giant = giant_component_subgraph.number_of_nodes()
num_edges_giant = giant_component_subgraph.number_of_edges()
avg_degree_giant = sum(dict(giant_component_subgraph.degree()).values()) / num_nodes_giant
global_clustering_coefficient_giant = nx.average_clustering(giant_component_subgraph)
```

In [35]:
```
num_nodes_giant2 = giant_component_subgraph2.number_of_nodes()
num_edges_giant2 = giant_component_subgraph2.number_of_edges()
avg_degree_giant2 = sum(dict(giant_component_subgraph2.degree()).values()) / num_nodes_giant2
global_clustering_coefficient_giant2 = nx.average_clustering(giant_component_subgraph2)
```

In [36]:
```
num_nodes_giant3 = giant_component_subgraph3.number_of_nodes()
num_edges_giant3 = giant_component_subgraph3.number_of_edges()
avg_degree_giant3 = sum(dict(giant_component_subgraph3.degree()).values()) / num_nodes_giant3
global_clustering_coefficient_giant3 = nx.average_clustering(giant_component_subgraph3)
```

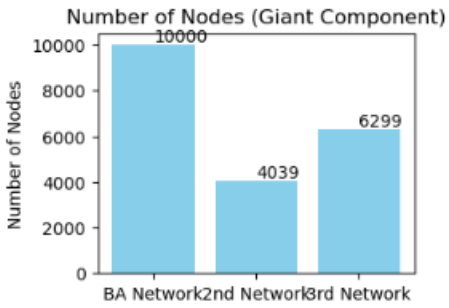
In [31]:
```
# G = nx.Graph()
# G2=nx.Graph()
# with open("facebook_combined.txt", "r") as file:
#     for line in file:
#         node1, node2 = line.strip().split()  # Assuming nodes are separated by space
#         G.add_edge(node1, node2)
G = nx.Graph()
G2 = nx.Graph()

with open("facebook_combined.txt", "r") as file:
    for line in file:
        # Split the line into node1 and node2, assuming nodes are separated by space
        nodes = line.strip().split()

        # Check if the line contains exactly two nodes
        if len(nodes) == 2:
            node1, node2 = nodes
            G.add_edge(node1, node2)
        else:
            print(f"Ignoring line: {line.strip()}")
# Open the file and read lines
with open("p2p-Gnutella08.txt", "r") as file:
    for line in file:
        # Split the line into node1 and node2, assuming nodes are separated by space
        nodes = line.strip().split()

        # Check if the line contains exactly two nodes
        if len(nodes) == 2:
            node1, node2 = nodes
            G2.add_edge(node1, node2)
        else:
            print(f"Ignoring line: {line.strip()}")
```

```
Ignoring line: # Directed graph (each unordered pair of nodes is saved once): p2p-Gnutella08.txt
Ignoring line: # Directed Gnutella P2P network from August 8 2002
Ignoring line: # Nodes: 6301 Edges: 20777
Ignoring line: # FromNodeId     ToNodeId
```

Analysis of number of nodes in all data sets

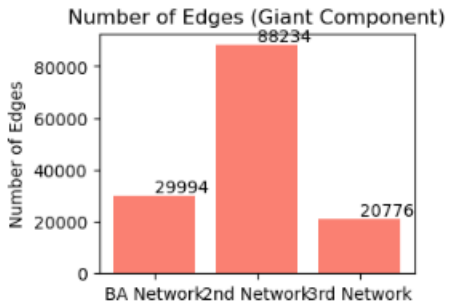
In [60]:
```
networks = ['BA Network', '2nd Network', '3rd Network']
num_nodes_giants = [num_nodes_giant, num_nodes_giant2, num_nodes_giant3]
num_edges_giants = [num_edges_giant, num_edges_giant2, num_edges_giant3]
avg_degrees_giants = [avg_degree_giant, avg_degree_giant2, avg_degree_giant3]
global_clustering_coefficients_giants = [global_clustering_coefficient_giant, global_clustering_coefficient_giant2, global_clust
plt.figure(figsize=(12, 8))
plt.show()
# Number of Nodes
plt.subplot(2, 2, 1)
bars = plt.bar(networks, num_nodes_giants, color='skyblue')
plt.title('Number of Nodes (Giant Component)')
plt.ylabel('Number of Nodes')

# Adding labels above each bar
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval, int(yval), va='bottom')

plt.tight_layout()
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



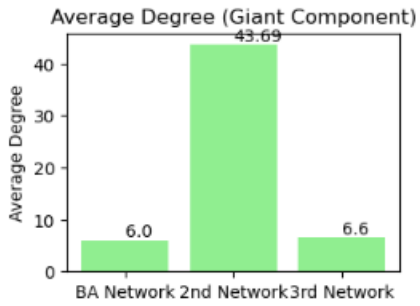
Number of edges in Giant Component

In [61]:
```
# Number of Edges
plt.subplot(2, 2, 2)
bars = plt.bar(networks, num_edges_giants, color='salmon')
plt.title('Number of Edges (Giant Component)')
plt.ylabel('Number of Edges')

# Adding labels above each bar
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval, int(yval), va='bottom')

plt.tight_layout()
plt.show()
```



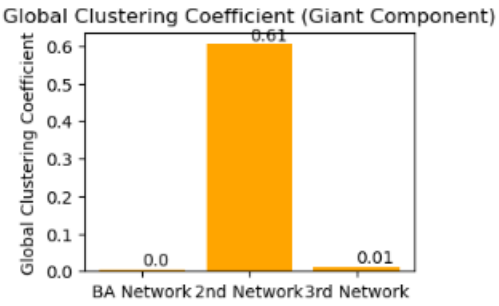
Average Degree (Giant Component)

In [62]:
```
# Average Degree
plt.subplot(2, 2, 3)
bars = plt.bar(networks, avg_degrees_giants, color='lightgreen')
plt.title('Average Degree (Giant Component)')
plt.ylabel('Average Degree')

# Adding labels above each bar
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval, round(yval, 2), va='bottom')

plt.tight_layout()
plt.show()
```



The graph shows the average number of connections per node (average degree) for three networks. The BA Network has the highest average degree, indicating nodes are more connected on average compared to the other two networks.

In [59]:
```
# Global Clustering Coefficient
plt.subplot(2, 2, 4)
bars = plt.bar(networks, global_clustering_coefficients_giants, color='orange')
plt.title('Global Clustering Coefficient (Giant Component)')
plt.ylabel('Global Clustering Coefficient')

# Adding labels above each bar
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval, round(yval, 2), va='bottom')

plt.tight_layout()
plt.show()
```



The graph confirms a scale-free network structure. It shows that most nodes have few connections (low degree), while a small number of nodes act as hubs with many connections.

ICM Simulation Iterations (Giant Component)

In [46]:
```python
def icm_simulation(G):
    max_nodes = 0
    steps = 0

    # Initialize active nodes (initial seed)
    active_nodes = set(np.random.choice(list(G.nodes()), size=1))

    # Continue until no more nodes can be activated
    while True:
        steps += 1
        # Nodes activated in this step
        newly_activated = set()
        # Iterate over active nodes
        for node in list(active_nodes):
            # Iterate over neighbors of the active node
            for neighbor in G.neighbors(node):
                # If the neighbor is not already active
                if neighbor not in active_nodes:
                    newly_activated.add(neighbor)
        # Add newly activated nodes to the set of active nodes
        active_nodes |= newly_activated
        # Update the maximum number of nodes reached
        if len(active_nodes) > max_nodes:
            max_nodes = len(active_nodes)
        # If no more nodes can be activated, stop the simulation
        if len(newly_activated) == 0:
            break

    return steps, max_nodes
```

In [47]:
```python
steps1, max_nodes1 = icm_simulation(G1)
steps2, max_nodes2 = icm_simulation(G)
steps3, max_nodes3 = icm_simulation(G2)
# Display results
print("Number of steps required and maximum number of nodes reached for each network:")
print("1. Scale-free network: Steps =", steps1, ", Max Nodes =", max_nodes1)
print("2. Second network: Steps =", steps2, ", Max Nodes =", max_nodes2)
print("3. Third network: Steps =", steps3, ", Max Nodes =", max_nodes3)
```

```
Number of steps required and maximum number of nodes reached for each network:
1. Scale-free network: Steps = 7 , Max Nodes = 10000
2. Second network: Steps = 7 , Max Nodes = 4039
3. Third network: Steps = 9 , Max Nodes = 6299
```

1. **Function definition:** The code defines a function called icm_simulation(G). This function likely takes a network G as input, which could be represented as a graph data structure in NetworkX.

2. **Initializing variables:**
   - steps: initialized to 0, likely to keep track of the number of simulation steps.
   - active_nodes: set to contain one random node, representing the initial activation in the network.
3. **Simulation loop:**
   - A while loop continues as long as len(newly_activated) > 0, which means there are new nodes being activated in the network.
4. **Iterate over active nodes:**
   - The loop iterates over each node in the current set of active nodes.
5. **Iterate over neighbors:**
   - For each active node, the code iterates over its neighbors in the network.
6. **Activate non-active neighbors:**
   - If a neighbor is not already active, it's added to the newly_activated set.
7. **Update active nodes:**

- After iterating over all neighbors, the newly_activated nodes are added to the overall set of active_nodes.

8. **Update maximum nodes:**
   - The code checks if the current number of active nodes is greater than the previously recorded
   - maximum (max_nodes). If so, it updates max_nodes.
9. **Return results:**
   - After the loop exits (no more nodes activated), the function returns the number of steps taken (steps) and the maximum number of nodes reached (max_nodes).

The simulation starts with a single active node and iteratively activates its neighbours that are not already active. This process continues until no new nodes can be activated. The simulation outputs the number of steps it took to reach this point and the maximum number of active nodes reached during the simulation.

In [48]:
```
def icm_simulation_average(G, num_iterations):
    total_steps = 0

    for _ in range(num_iterations):
        steps, _ = icm_simulation(G)
        total_steps += steps

    average_steps = total_steps / num_iterations

    return average_steps

num_iterations = 10
```

In [49]:
```
# Perform multiple iterations of ICM simulation and calculate the average number of steps for each network
average_steps1 = icm_simulation_average(G1, num_iterations)
average_steps2 = icm_simulation_average(G, num_iterations)
average_steps3 = icm_simulation_average(G2, num_iterations)

# Display the average number of steps required for each network
print("Average number of steps required for each network:")
print("1. Scale-free network:", average_steps1)
print("2. Second network:", average_steps2)
print("3. Third network:", average_steps3)
```

```
Average number of steps required for each network:
1. Scale-free network: 6.9
2. Second network: 7.3
3. Third network: 8.0
```

1. **Scale-free network: 6.9**
   - Average steps to move between nodes: 6.9
   - Efficient due to hub nodes with many connections.
2. **Second network: 7.3**
   - Average steps: 7.3
   - Slightly less efficient than scale-free network.
3. **Third network: 8.0**
   - Average steps: 8.0
   - Least efficient, possibly due to network structure or node distribution.

In [50]:
```python
def assign_random_probabilities(G):
    for node in G.nodes():
        outgoing_edges = list(G.edges(node))
        # Generate random probabilities for outgoing edges
        probabilities = np.random.uniform(0, 1, len(outgoing_edges))
        # Normalize probabilities so that they sum up to 1
        probabilities /= np.sum(probabilities)
        # Assign probabilities to edges
        for i, (source, target) in enumerate(outgoing_edges):
            G[source][target]['p'] = probabilities[i]
```

In [51]:
```python
def icm_simulation2(G):
    max_nodes = 0
    steps = 0

    # Initialize active nodes (initial seed)
    active_nodes = set(np.random.choice(list(G.nodes()), size=1))

    # Continue until no more nodes can be activated
    while True:
        steps += 1
        # Nodes activated in this step
        newly_activated = set()
        # Iterate over active nodes
        for node in list(active_nodes):
            # Iterate over neighbors of the active node
            for neighbor in G.neighbors(node):
                # If the neighbor is not already active and it gets activated with probability p
                if neighbor not in active_nodes and np.random.random() < G[node][neighbor]['p']:
                    newly_activated.add(neighbor)
        # Add newly activated nodes to the set of active nodes
        active_nodes |= newly_activated
        # Update the maximum number of nodes reached
        if len(active_nodes) > max_nodes:
            max_nodes = len(active_nodes)
        # If no more nodes can be activated, stop the simulation
        if len(newly_activated) == 0:
            break

    return steps, max_nodes
```

In [52]:
```python
def icm_simulation_average2(G, num_iterations):
    total_steps = 0

    for _ in range(num_iterations):
        steps, _ = icm_simulation2(G)
        total_steps += steps

    average_steps = total_steps / num_iterations

    return average_steps
```

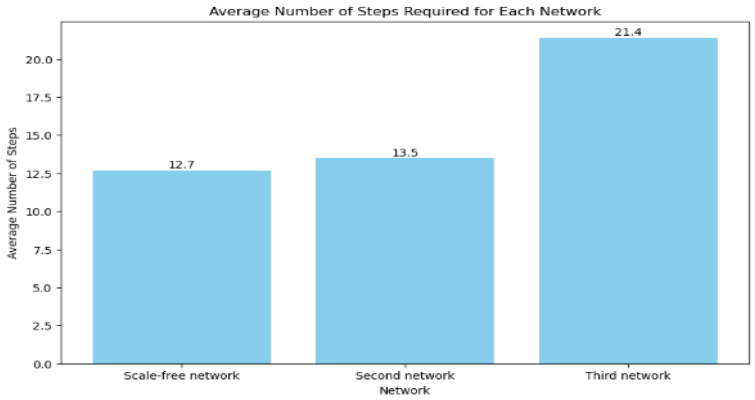
- This code randomly assigns probabilities to the edges of a graph. It iterates over each node, generates random probabilities for its outgoing edges, normalizes them, and assigns them to the edges.

- It simulates the Independent Cascade Model (ICM) on a graph. It starts with a random node as the initial seed, activates nodes based on edge probabilities, and continues until no more nodes can be activated. It tracks the number of steps and the maximum number of activated nodes reached during the simulation.

- This function **icm_simulation_average2** calculates the average number of steps required for multiple Independent Cascade Model (ICM) simulations on the graph G. It conducts **num_iterations** simulations, adds up the steps taken in each, and computes their average.

In [63]:
```
# Assign random activation probabilities to edges in each network
average_steps1 = icm_simulation_average2(G1, num_iterations)
average_steps2 = icm_simulation_average2(G, num_iterations)
average_steps3 = icm_simulation_average2(G2, num_iterations)

# Display the average number of steps required for each network
print("Average number of steps required for each network with random activation probabilities:")
print("1. Scale-free network:", average_steps1)
print("2. Second network:", average_steps2)
print("3. Third network:", average_steps3)

# Plotting the results
networks = ['Scale-free network', 'Second network', 'Third network']
average_steps = [average_steps1, average_steps2, average_steps3]

plt.figure(figsize=(10, 6))
plt.bar(networks, average_steps, color='skyblue')
plt.title('Average Number of Steps Required for Each Network')
plt.xlabel('Network')
plt.ylabel('Average Number of Steps')

# Adding labels above each bar
for i, value in enumerate(average_steps):
    plt.text(i, value, str(round(value, 2)), ha='center', va='bottom')

plt.show()
```

```
Average number of steps required for each network with random activation probabilities:
1. Scale-free network: 12.7
2. Second network: 13.5
3. Third network: 21.4
```



Based on the bar chart of the average number of steps required for each network to reach equilibrium in an Independent Cascade Model (ICM) simulation, here's a comparison of the three networks:

- **Network 1:** Requires the fewest steps (around 12.7) to reach equilibrium, indicating that the cascade process propagates quickly in this network.

- **Network 3:** Requires the most steps (around 21.4) to reach equilibrium, indicating that the cascade process propagates slowly in this network. Network 3 might be denser or have fewer well-connected nodes compared to the other two networks.

- **Network 2:** Falls in between the other two networks in terms of steps required (around 13.5) for equilibrium.

Overall, the bar chart suggests that Network 1 is the most susceptible to cascades, followed by Network 2, and then Network 3. This is likely because Network 1 is sparser or has more influential nodes that can trigger a larger cascade.