Fraud Analytics (CS6890)

Assignment:	**2**
Title :	**Trust Rank**

Team Details :

Name	Roll Number
Shreesh Gupta	***CS23MTECH12009***
Hrishikesh Hemke	***CS23MTECH14003***
Manan Patel	***CS23MTECH14006***
Yug Patel	***CS23MTECH14019***
Bhargav Patel	***CS23MTECH11026***

In [ ]:
```
# Required Libraries
!pip install pandas numpy matplotlib scikit-learn torch torch-geometric ne

```

In [1]:
```
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
import seaborn as sns

```

In [2]:
```
# Load the datasets
payments_df = pd.read_csv('Payments.csv')
bad_senders_df = pd.read_csv('bad_sender.csv')

# Display the first few rows of each dataframe to understand their structu
payments_df.head(), bad_senders_df.head()
```

Out[2]:
```
(   Sender  Receiver  Amount
 0    1309      1011  123051
 1    1309      1011  118406
 2    1309      1011  112456
 3    1309      1011  120593
 4    1309      1011  166396,
    Bad Sender
 0        1303
 1        1259
 2        1562
 3        1147
 4        1393)
```

In [3]:
```
print(len(payments_df), len(bad_senders_df))
```

```
130535 20
```

In [4]:
```
print(payments_df['Amount'].max(), payments_df['Amount'].min())
```

```
2124500 1501
```

In [5]:
```
unique_transactions = set()
for index, row in payments_df.iterrows():
    # Create a tuple of (Sender, Receiver)
    unique_transactions.add((row['Sender'], row['Receiver']))

print(len(unique_transactions))
```

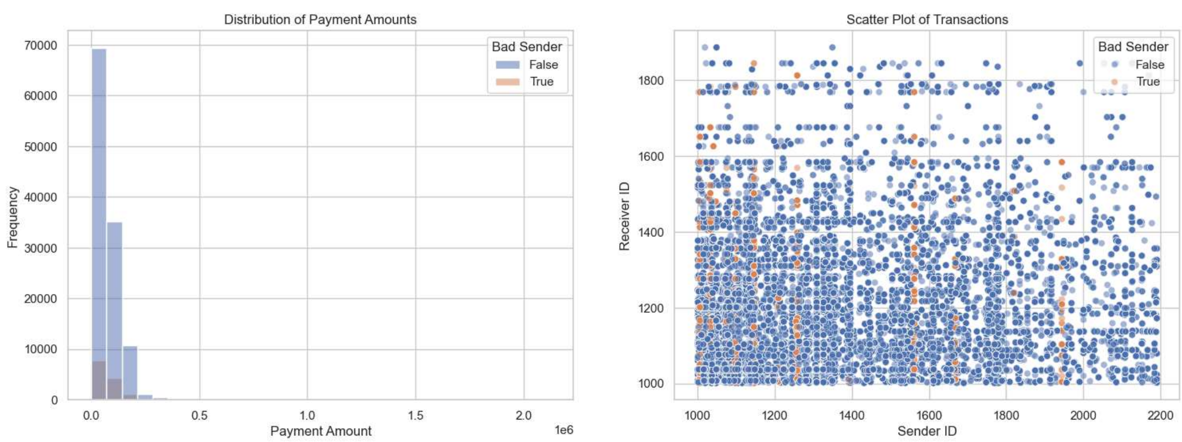
```
5358
```

In [6]:
```
# Mark transactions involving bad senders
payments_df['Bad Sender'] = payments_df['Sender'].isin(bad_senders_df['Bac

# Display a summary of transactions involving bad senders
bad_transactions_summary = payments_df['Bad Sender'].value_counts()
bad_transactions_summary
```

Out[6]:
```
Bad Sender
False    117032
True      13503
Name: count, dtype: int64
```

In [7]:

```


# Setting up the visual environment
sns.set(style="whitegrid")

# Create the plots
fig, ax = plt.subplots(1, 2, figsize=(18, 6))

# Histogram of payment amounts
sns.histplot(data=payments_df, x='Amount', hue='Bad Sender', ax=ax[0], bir
ax[0].set_title('Distribution of Payment Amounts')
ax[0].set_xlabel('Payment Amount')
ax[0].set_ylabel('Frequency')

# Scatter plot of transactions
sns.scatterplot(data=payments_df, x='Sender', y='Receiver', hue='Bad Sende
ax[1].set_title('Scatter Plot of Transactions')
ax[1].set_xlabel('Sender ID')
ax[1].set_ylabel('Receiver ID')

plt.show()

```



TrustRank Algorithm Explanation

Initialization

Step 1: Initial Score Assignment

Every node v in the graph G is assigned an initial TrustRank score, $TR(v)$. The scores are uniformly distributed across all nodes:

$$TR_0(v) = \frac{1}{N}$$

where N is the total number of nodes in the graph.

Personalization Vector

Step 2: Personalization Vector Creation

A personalization vector p is created to adjust initial scores based on node trustworthiness, specifically reducing the influence of known bad nodes:

$$p(v) = \begin{cases} 0.1 & \text{if } v \text{ is a bad node} \\ 1 & \text{otherwise} \end{cases}$$

The vector is normalized to ensure that its elements sum to 1:

$$p(v) = \frac{p(v)}{\sum_{u \in G} p(u)}$$

Iterative Calculation

Step 3: Iterative Score Update

The TrustRank score for each node is updated iteratively. At each iteration, the new score for a node v is calculated based on the scores of its predecessors (nodes that point to v) adjusted by their transaction amounts as weights:

$$TR_{i+1}(v) = (1 - d) \cdot p(v) + d \cdot \sum_{u \in P(v)} \frac{TR_i(u) \cdot w(u, v)}{\sum_{w \in S(u)} w(u, w)}$$

where:

- $P(v)$ is the set of predecessors of v,
- $S(u)$ is the set of successors of u,
- $w(u, v)$ is the weight of the edge from u to v (transaction amount),
- d is the damping factor, typically set to 0.85, representing the probability of continuing the random walk through the network.

Convergence

Step 4: Convergence Check

The algorithm iterates until the TrustRank scores converge, which is typically determined by the total change in scores between iterations falling below a predefined threshold ϵ:

$$\sum_{v \in G} |TR_{i+1}(v) - TR_i(v)| < \epsilon$$

Conclusion

This mathematical framework ensures that the TrustRank scores reflect not only the direct financial interactions between entities but also the broader network dynamics, particularly penalizing entities closely connected to known bad actors. The damping factor d and the personalized initialization help to simulate a biased random walk that favors trustworthy nodes

In [8]:

```
def trustrank_stable(G, bad_nodes, damping_factor=0.85, max_iter=100, tol=
    # Initialize trust scores uniformly
    n = G.number_of_nodes()
    trust_scores = {node: 1 / n for node in G.nodes()}

    # Initialize personalization vector, where bad nodes have lower initia
    personalization = {node: (0.1 if node in bad_nodes else 1) for node in
    total_personalization = sum(personalization.values())
    personalization = {node: p / total_personalization for node, p in pers

    # Normalize initial trust scores based on personalization
    trust_scores = {node: trust_scores[node] * personalization[node] for n

    # Iterative calculation of TrustRank
    for _ in range(max_iter):
        prev_trust_scores = trust_scores.copy()
        # Each node gets a share of the score of its in-neighbors, adjuste
        for node in G.nodes():
            incoming_trust = sum(prev_trust_scores[neighbor] * G[neighbor]
                                 sum(G[n][node]['weight'] for n in G.prede
                                 for neighbor in G.predecessors(node))
            trust_scores[node] = (1 - damping_factor) * personalization[no

        # Check for convergence
        err = sum(abs(trust_scores[node] - prev_trust_scores[node]) for no
        if err < n * tol:
            break

    return trust_scores


# Create the directed graph from the transactions data
G = nx.DiGraph()

# Add edges from the payment data; considering each transaction as an edge
for index, row in payments_df.iterrows():
    # Use the payment amount as the weight of the edge
    G.add_edge(row['Sender'], row['Receiver'], weight=row['Amount'])

# Identifying bad nodes (from bad_senders_df)
bad_nodes = set(bad_senders_df['Bad Sender'].unique())

# Initialize node attributes (good = 1, bad = 0)
for node in G.nodes():
    G.nodes[node]['trust'] = 0 if node in bad_nodes else 1

# Compute TrustRank with stability adjustments
stable_trust_ranks = trustrank_stable(G, bad_nodes)
stable_trust_rank_results = pd.DataFrame(list(stable_trust_ranks.items()),
stable_trust_rank_results = stable_trust_rank_results.sort_values(by='Trus
stable_trust_rank_results.head()

```

Out[8]:

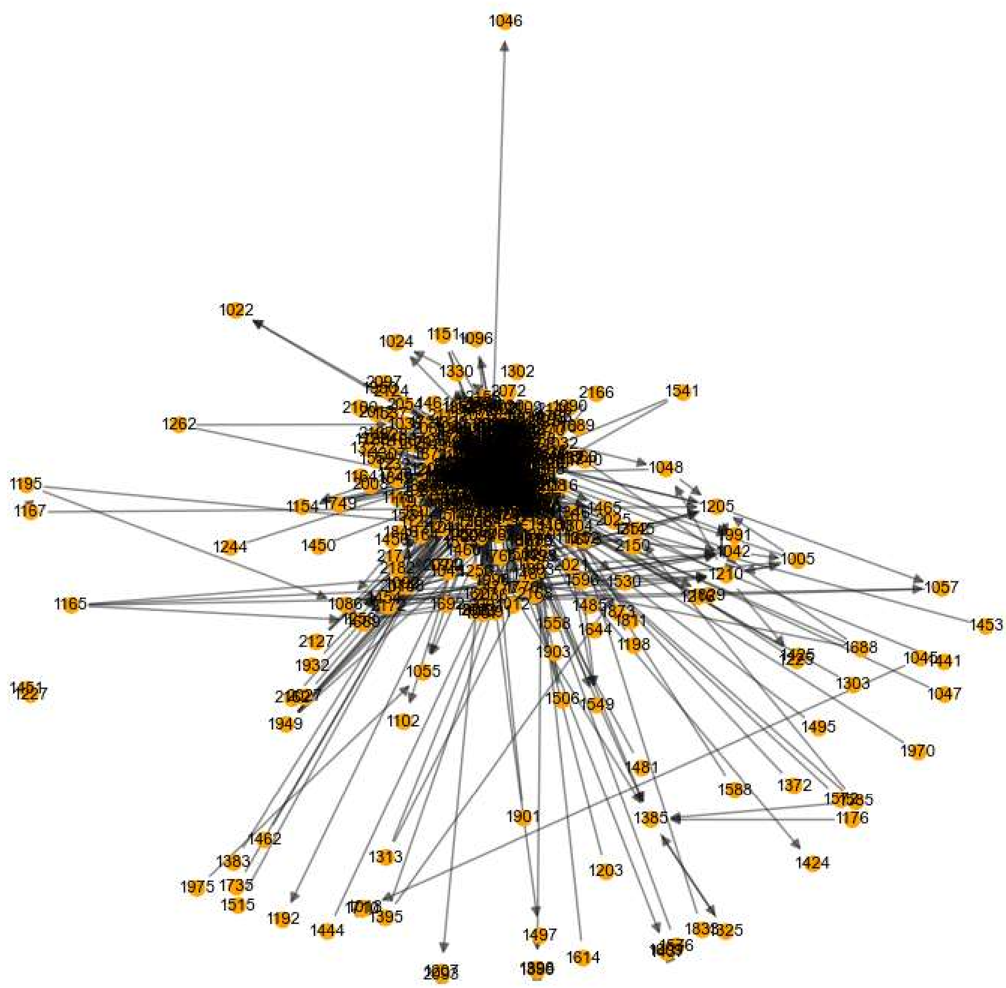
	Node	TrustRank
143	1058	0.000744
692	1325	0.000722
142	1019	0.000685
702	1567	0.000669
542	1041	0.000633

In [9]:

```
# Define a color, this will be used for the nodes in the graph.
# Here we're using a light blue color in RGB format, divided by 255 to use
CLR = (255, 165, 0)
CLR = [x/255 for x in CLR]

# A simple function to plot the graph using NetworkX
def plot_graph(graph):
    """A simple function to plot the graph using NetworkX."""
    # Set the color for each node. Here, all nodes will have the same colo
    node_colors = [CLR] * len(graph.nodes())

    # Set the figure size
    plt.figure(figsize=(10, 10))

    # Define the layout for the graph. You can experiment with different l
    pos = nx.kamada_kawai_layout(graph)

    # Draw the networkx graph -- nodes, edges, and labels.
    nx.draw_networkx_edges(graph, pos, alpha=0.5)
    nx.draw_networkx_nodes(graph, pos, node_color=node_colors, cmap='autur
    nx.draw_networkx_labels(graph, pos, font_size=8, font_color='black')

    # Turn off the axis, as they are not meaningful for this kind of plot.
    plt.axis('off')

    # Display the plot.
    plt.show()
```

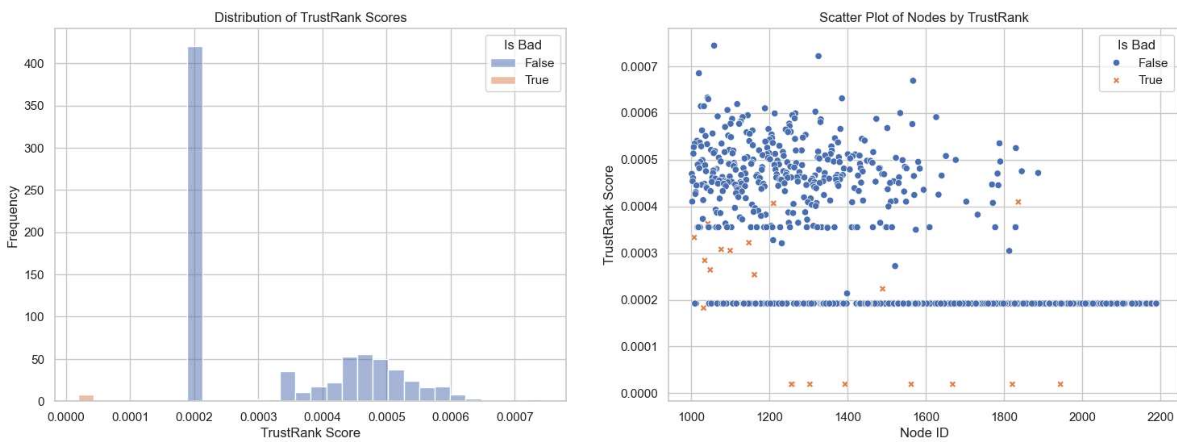
In [10]:
```
plot_graph(G)
```

```
c:\Users\gupta\anaconda3\envs\farudA\Lib\site-packages\networkx\drawing\nx_py
lab.py:450: UserWarning: No data for colormapping provided via 'c'. Parameter
s 'cmap' will be ignored
  node_collection = ax.scatter(
```



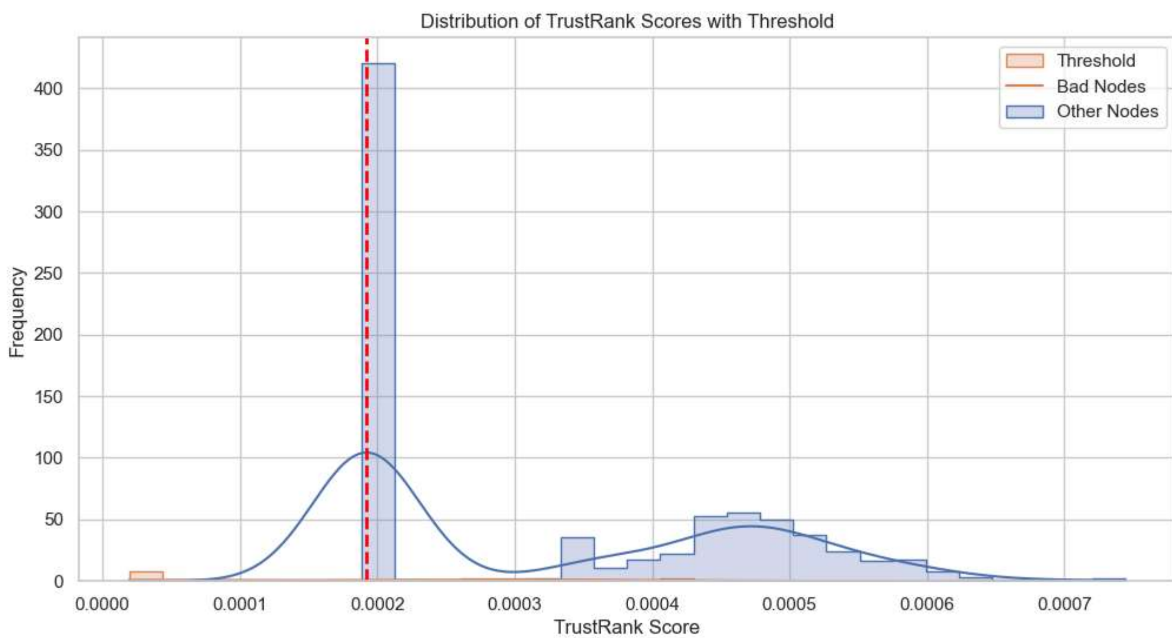
In [11]:

```
# Merge trust rank data with bad sender information for visualization
stable_trust_rank_results['Is Bad'] = stable_trust_rank_results['Node'].is

# Setting up the visual environment
sns.set(style="whitegrid")

# Create the plots
fig, ax = plt.subplots(1, 2, figsize=(18, 6))

# Distribution of TrustRank scores
sns.histplot(data=stable_trust_rank_results, x='TrustRank', hue='Is Bad',
ax[0].set_title('Distribution of TrustRank Scores')
ax[0].set_xlabel('TrustRank Score')
ax[0].set_ylabel('Frequency')

# Scatter plot of TrustRank scores
sns.scatterplot(data=stable_trust_rank_results, x='Node', y='TrustRank', h
ax[1].set_title('Scatter Plot of Nodes by TrustRank')
ax[1].set_xlabel('Node ID')
ax[1].set_ylabel('TrustRank Score')

plt.show()

```



In [12]:

```
# Calculate the 10th percentile of the TrustRank scores
threshold = stable_trust_rank_results['TrustRank'].quantile(0.1)

# Visualize the threshold on the histogram
fig, ax = plt.subplots(figsize=(12, 6))

# Plot histogram with threshold line
sns.histplot(data=stable_trust_rank_results, x='TrustRank', hue='Is Bad',
ax.axvline(x=threshold, color='red', linestyle='--', linewidth=2)
ax.set_title('Distribution of TrustRank Scores with Threshold')
ax.set_xlabel('TrustRank Score')
ax.set_ylabel('Frequency')
ax.legend(['Threshold', 'Bad Nodes', 'Other Nodes'])

plt.show()

threshold
```



Out[12]: 0.0001920614596670935

In [13]:

```
# Initial classification count based on provided bad senders list
initial_bad_nodes_count = len(bad_nodes)

# Post-TrustRank classification count based on the computed threshold
post_trustrank_bad_nodes_count = stable_trust_rank_results[stable_trust_ra
total_nodes_count = stable_trust_rank_results.shape[0]

initial_bad_nodes_count, post_trustrank_bad_nodes_count, total_nodes_count
```

Out[13]: (20, 429, 799)

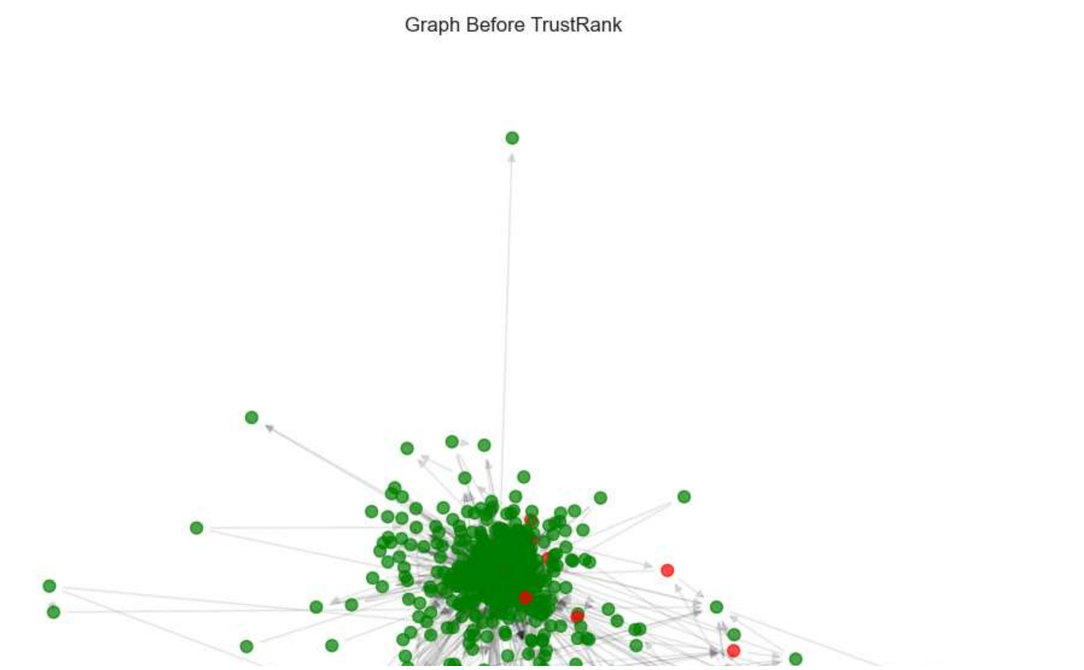
Here are the results:

- **Total Number of Nodes:** 799

- **Initially Classified as Bad Nodes:** 20 (based on the provided bad senders list)
- **Classified as Bad Nodes After TrustRank Calculation:** 429 (nodes with TrustRank scores below the threshold)

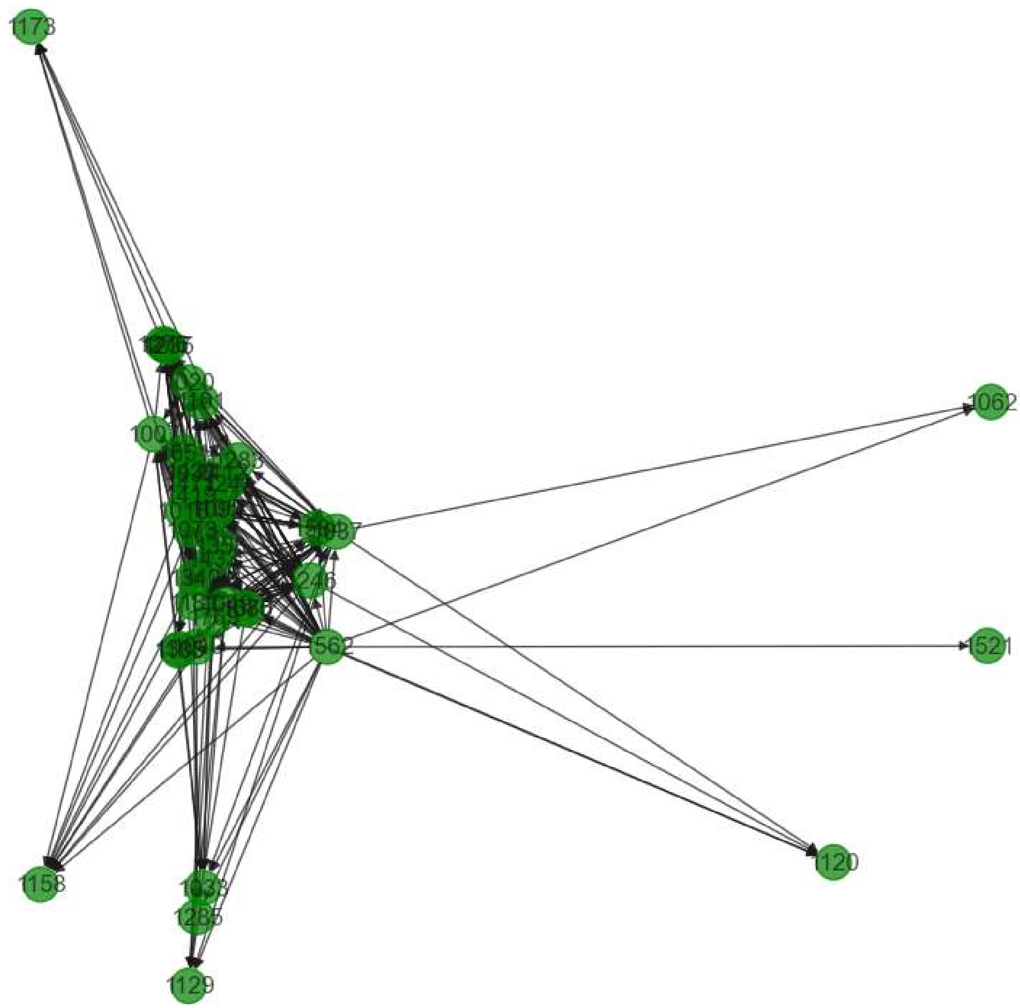
In [15]:

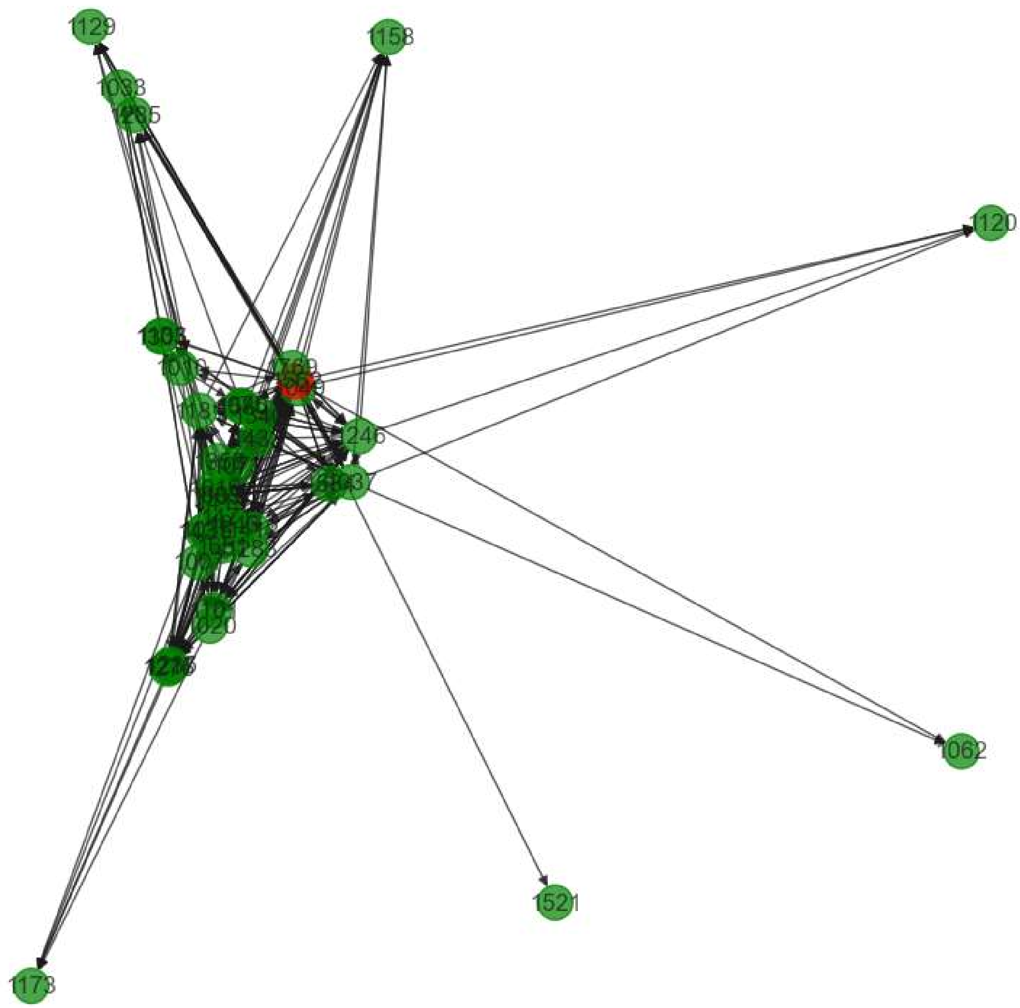
```
# Visualize the graph before applying TrustRank, using the initial bad ser
def visualize_graph(G, pos, bad_nodes, title, trust_scores=None, threshold
    plt.figure(figsize=(12, 12))
    # Determine node colors based on bad node classification
    if trust_scores is None:
        # Initial classification based on provided bad senders list
        node_colors = ['red' if node in bad_nodes else 'green' for node in
    else:
        # Classification based on TrustRank scores
        node_colors = ['red' if trust_scores[node] <= threshold else 'gree

    # Node sizes can be uniform or based on TrustRank scores
    if trust_scores is None:
        node_sizes = [50 for _ in G.nodes()]  # uniform size if scores not
    else:
        # node_sizes = [trust_scores[node] * 5000 for node in G.nodes()]
        node_sizes = [50 for _ in G.nodes()]  # uniform size if scores not

    # Draw nodes and edges
    nx.draw_networkx_nodes(G, pos, node_size=node_sizes, node_color=node_c
    nx.draw_networkx_edges(G, pos, alpha=0.1)
    plt.title(title)
    plt.axis('off')
    plt.show()

# Layout for visualizing the nodes
pos = nx.kamada_kawai_layout(G)

# Visualize the graph before TrustRank scores are applied
visualize_graph(G, pos, bad_nodes, "Graph Before TrustRank")

# Visualize the graph after applying TrustRank, using the computed TrustRa
visualize_graph(G, pos, bad_nodes, "Graph After TrustRank", trust_scores=s

```



In [16]:

```
def visualize_subgraph(G, node_id, trust_scores=None, threshold=None):
    # Extract the subgraph for the specified node and its neighbors
    subgraph = G.subgraph([node_id] + list(G.neighbors(node_id)))

    # Determine the layout
    pos = nx.spring_layout(subgraph)

    # Determine the color of the nodes based on the TrustRank score
    node_colors = []
    for node in subgraph:
        if trust_scores and trust_scores[node] <= threshold:
            node_colors.append('red')  # Color for nodes below the TrustRa
        else:
            node_colors.append('green')  # Color for nodes above the Trust

    # Draw the subgraph
    plt.figure(figsize=(8, 8))
    nx.draw(subgraph, pos, node_color=node_colors, with_labels=True, alpha
    plt.show()

# Use the function to visualize the subgraph before TrustRank scores are c
selected_node_id =1562 #1259 #1944
visualize_subgraph(G, selected_node_id)

# Use the function to visualize the subgraph after TrustRank scores are ap
visualize_subgraph(G, selected_node_id, trust_scores=stable_trust_ranks, t

```


1062
1521
1120
1158
1285
1129
562
246



In [ ]:
```
1
```