Fraud Analytics Assignment

Title: Trust Rank

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Importing libraries:

In [1]:
```
import numpy as np
import pandas as pd
from collections import defaultdict
import operator
import math
import random
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Utility Functions:

In [2]:
```
def plot_scatter_plot(x, y, bad_x, bad_y):
    plt.scatter(x = x, y = y, label="Trust-Rank of nodes", color='green')
    plt.axhline(y=0.007, color='red', linestyle='--', label='Threshold Trust Score'
    plt.scatter(x = bad_x, y = bad_y,  marker="d", color="orange", label="Bad nodes
    plt.ylabel("Trust-Rank Score (Bad trust score)")
    plt.xlabel("Node ID [Re-numbered between 0-800]")
    plt.legend()
    plt.show()
```

In [3]:
```
def plot_histogram(df):
    trust_ranks = df['Trust-Score']
    bin_values = sorted({round(val, 3) for val in trust_ranks})
    plt.figure(figsize=(8, 8))
    sns.histplot(data=df, y='Trust-Score', bins = bin_values, color="orange")
```

```
    plt.title("Trust Scores Vs Frequency of Nodes")
    plt.xlabel("Node count (Frequency)")
    plt.ylabel("Trust Score (Bad trust score)")
    plt.show()
```

Loading Payments.csv and bad_sender.csv files:

In [4]:
```
payments_df = pd.read_csv('Payments.csv')
payments_df.head()
```

Out[4]:

	Sender	Receiver	Amount
0	1309	1011	123051
1	1309	1011	118406
2	1309	1011	112456
3	1309	1011	120593
4	1309	1011	166396

In [5]:
```
bad_sender_df = pd.read_csv('bad_sender.csv')
bad_sender_df.head()
```

Out[5]:

	Bad Sender
0	1303
1	1259
2	1562
3	1147
4	1393

Extracting all unique nodes and bad nodes from dataset:

In [6]:
```
all_bad_nodes = bad_sender_df["Bad Sender"].unique().tolist()
all_unique_nodes = sorted(list(set(payments_df["Sender"]) | set(payments_df["Receiv
```

Storing the Node ID mappings in dictionaries:

In [7]:
```
# nodes_dict: Stores original Node ID to new Node ID mapping: {1001: 0, 1002: 1,...
nodes_dict = {node: index for index, node in enumerate(all_unique_nodes)}

# node_index_to_label: Stores new Node ID to original Node ID mapping: {0: 1001, 1
node_index_to_label = {}
for key, value in nodes_dict.items():
    node_index_to_label[value] = key
```

```
# Extracting node indices from the nodes_dict
all_nodes = [nodes_dict[i] for i in all_unique_nodes if i in nodes_dict]
bad_nodes = [nodes_dict[i] for i in all_bad_nodes if i in nodes_dict]

total_nodes_count = len(all_nodes)
bad_nodes_count =  len(bad_nodes)
print(f'Count of all nodes: {total_nodes_count}')
print(f'Count of bad nodes: {bad_nodes_count}')
```

```
Count of all nodes: 799
Count of bad nodes: 20
```

TrustRank implementation:

- Connected nodes having no outlinks back to bad nodes to avoid trust leakage.

In [8]:
```
'''
Creating the adjacency matrix by considering:
'Sender' as source node, 'Receiver' as destination node, and 'Amount' as edge weigh
 adj_list_dict: {
                    0: {188: 88788, 344: 22566},
                    1: {358: 20660, 532: 6760},
                    2: {106: 21277, 332: 54988, 510: 43476, 452: 62765, 666: 48368
                    3: {168: 113338, 193: 99620, 712: 120571},
                    4: {252: 60191},
                    ...
                }
'''
adj_list_dict = {}
for i in all_nodes:
    adj_list_dict[i] = {}
for index, row in payments_df.iterrows():
    from_node = nodes_dict[row.Sender]
    to_node = nodes_dict[row.Receiver]
    amount = row.Amount
    adj_list = adj_list_dict[from_node]
    adj_list[to_node] = amount
```

Constructing Transition Matrix:

In [9]:
```
T = np.zeros((total_nodes_count, total_nodes_count))
for from_node in adj_list_dict:
    adj_list = adj_list_dict[from_node]
    sum_of_amount = sum(adj_list.values())
    for to_node in adj_list:
        T[to_node][from_node] = T[to_node][from_node] + (adj_list[to_node]/sum_of_a
```

Constructing Initial TrustRank Vector:

- d: Denotes the static score distribution vector

- Initially, we assign trust score of '1 / (Number_of_bad_nodes)' to all bad nodes and 0 to all good nodes

In [10]:
```
d = np.full(total_nodes_count, 0.0)
for node in bad_nodes:
    d[node] = (1./bad_nodes_count)
d = d.reshape(-1, 1)
```

Sum of entries of static scores distribution vector should be equal to 1:

In [11]:
```
print('Sum of all elements of r:', sum(d))
```

```
Sum of all elements of r: [1.]
```

Executing the Trust-Rank algorithm:

// compute TrustRank scores

$\mathbf{t}^* = \mathbf{d}$

$\underline{\text{for}}\ i = 1\ \underline{\text{to}}\ M_B\ \underline{\text{do}}$

$\qquad \mathbf{t}^* = \alpha_B \cdot \mathbf{T} \cdot \mathbf{t}^* + (1 - \alpha_B) \cdot \mathbf{d}$

$\underline{\text{return}}\ \mathbf{t}^*$

In [12]:
```
t = d
damping_factor = 0.85
t = damping_factor * T.dot(t) + (1 - damping_factor) * d
iteration = 1
total_iterations = 100

while iteration <= total_iterations:
    t = damping_factor * T.dot(t) + (1 - damping_factor) * d
    iteration += 1
    if iteration % 10 == 0:
        print("Iteration:", iteration)
```

```
Iteration: 10
Iteration: 20
Iteration: 30
Iteration: 40
Iteration: 50
Iteration: 60
Iteration: 70
Iteration: 80
Iteration: 90
Iteration: 100
```

In [13]:
```
trust_rank_node_score = [] # to store the node and the corresponding trustrank scor
for k in range(0, len(t)):
        trust_rank_node_score.append([k, t[k]])

# sort the trustrank scores in the decreasing order
trust_rank_node_score = sorted(trust_rank_node_score, key = operator.itemgetter(1),
```

In [14]:
```
columns = ['Node', 'Trust-Score']
df = pd.DataFrame(columns=columns)

for [node_index, score] in trust_rank_node_score:
    new_row = {'Node': node_index, 'Trust-Score': score[0]}
    df = pd.concat([df, pd.DataFrame([new_row])], ignore_index=True)
```

Printing few computed Trust rank values:

In [15]:
```
df.head(n = 25)
```

Out[15]:

	Node	Trust-Score
0	203	0.021315
1	41	0.018441
2	198	0.017904
3	85	0.015963
4	6	0.014853
5	529	0.013112
6	33	0.012231
7	75	0.011430
8	93	0.011229
9	97	0.010573
10	144	0.010256
11	119	0.010137
12	47	0.009839
13	247	0.009226
14	157	0.007991
15	433	0.007822
16	650	0.007593
17	30	0.007500
18	246	0.007500
19	248	0.007500
20	284	0.007500
21	363	0.007500
22	487	0.007500
23	552	0.007500
24	640	0.007500

In [16]:

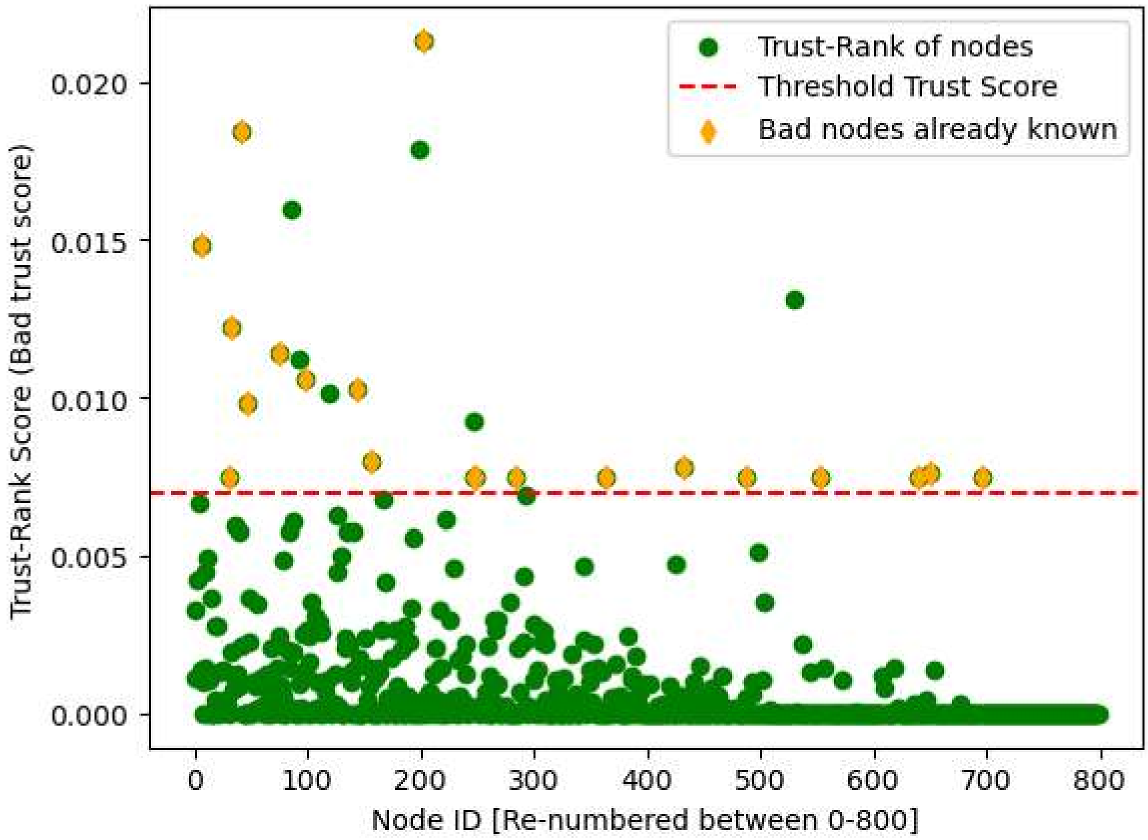
```
columns = ['Node', 'Trust-Score']
bad_node_score_df = pd.DataFrame(columns=columns)

for node in bad_nodes:
    if node in df['Node']:
        index = df['Node'].index[df['Node'] == node][0]
        new_row = {'Node': node, 'Trust-Score': df['Trust-Score'][index]}
        bad_node_score_df = pd.concat([bad_node_score_df, pd.DataFrame([new_row])],
```

Scatter-Plot showing Node ID vs Trust Score of respective nodes:

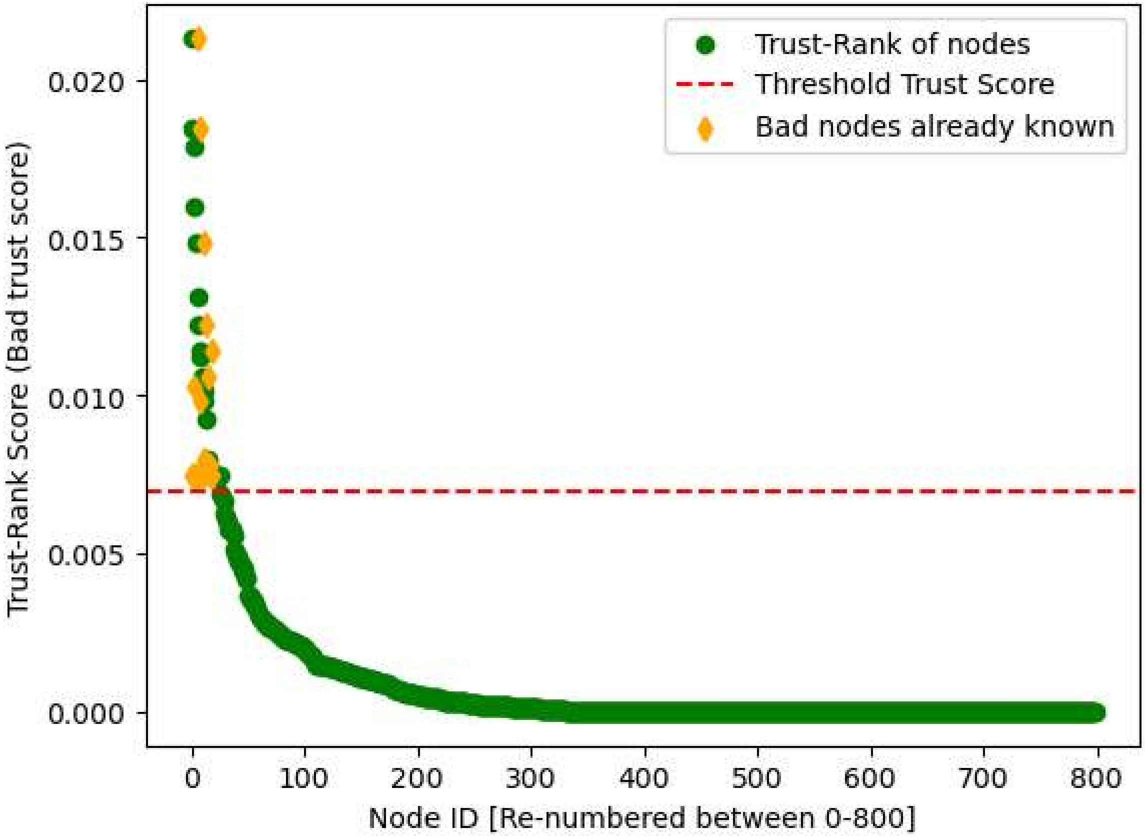
- Here, high Trust score shows that the node is bad

In [17]:
```
plot_scatter_plot(x = df['Node'], y = df['Trust-Score'], bad_x = bad_node_score_df[
```



Plotting Trust Scores of all nodes in Descending Order:

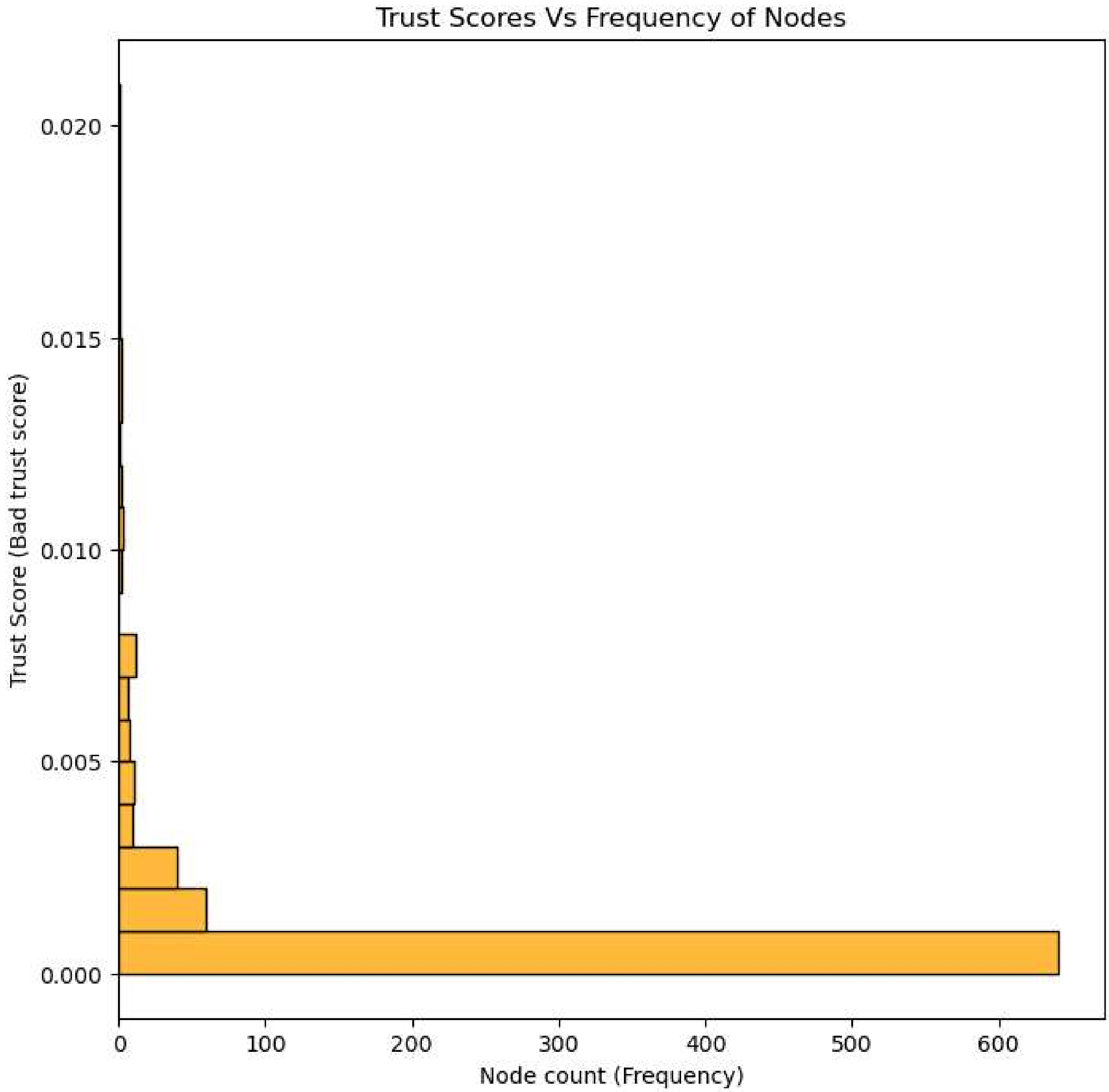
In [18]:
```
plot_scatter_plot(x = np.arange(total_nodes_count), y = df['Trust-Score'], bad_x =
```



Plotting histogram of Trust Score Vs Frequency of Nodes:

- From the plot below we can observe that most of the nodes are good with trust scores ranging from 0.000 to 0.003 (Approx)

In [19]:
```
plot_histogram(df)
```



Results & Observations:

- We can observe that, all the bad nodes have the trust score (bad trust score) above the threshold (0.007).
- Bad nodes are highlited by diamond symbol in above plots.
- Hence, all the good nodes (non-diamond nodes) that lie above the threshold are the **possible bad nodes**.