Facebook_EDA_and_Data_Preparation

June 29, 2019

```
In [1]: # pandas to create small dataframes
        import pandas as pd
        import numpy as np

        # general purpose packages
        import os
        import sys
        import random
        from datetime import datetime
        from itertools import product

        # visualization related packages
        import matplotlib.pylab as plt
        import seaborn as sns
        sns.set()

        # model, file saving packages
        import pickle


        # Graph package
        import networkx as nx

        # singular value decomposition relataed package
        from scipy.sparse.linalg import svds, eigs

        # package for partitioning the dataset into train, test
        from sklearn.model_selection import train_test_split
```

Social network Graph Link Prediction - Facebook Challenge

0.0.1 Problem statement:

Given a directed social graph, have to predict missing links to recommend users (Link Prediction in graph)

0.0.2 Data Overview

Taken data from facebook's recruting challenge on kaggle https://www.kaggle.com/c/FacebookRecruiting
data contains two columns source and destination eac edge in graph - Data columns (total 2 columns):
- source_node int64
- destination_node int64

0.0.3 Mapping the problem into supervised learning problem:

- Generated training samples of good and bad links from given directed graph and for each link got some features like no of followers, is he followed back, page rank, katz score, adar index, some svd fetures of adj matrix, some weight features etc. and trained ml model based on these features to predict link.
- Some reference papers and videos :
  - https://www.cs.cornell.edu/home/kleinber/link-pred.pdf
  - https://www3.nd.edu/~dial/publications/lichtenwalter2010new.pdf
  - https://kaggle2.blob.core.windows.net/forum-message-attachments/2594/supervised_link_predicti
  - https://www.youtube.com/watch?v=2M77Hgy17cg

0.0.4 Business objectives and constraints:

- No low-latency requirement.
- Probability of prediction is useful to recommend ighest probability links

0.0.5 Performance metric for supervised learning:

- Both precision and recall is important so F1 score is good choice
- Confusion matrix

1 Configs

```
In [2]: # path for existing edges & missing edges
        input_graph_csv_path = '/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSets/Facebook/data/t
```

```
In [3]: # The below files will be created if doesnt exist.
        missing_egde_csv_path = './data/missing_edges.csv'

        train_labeled_csv_path = './data/Train_labeled.csv'
        test_labeled_csv_path = './data/Test_labeled.csv'
```

```
In [4]: dataset_sample_size = 100000
```

2 Create G

```
In [5]: def create_graph_from_dataframe(graph_df):
```

```
    # remove duplicates
    duplicated_info_series = graph_df.duplicated(subset=['source_node',
                                                          'destination_node'],
                                                          keep='first')

    graph_df = graph_df[~duplicated_info_series]

    # create graph
    G = nx.from_pandas_edgelist(df=graph_df, source='source_node',
                                target='destination_node',
                                edge_attr=None,
                                create_using=nx.DiGraph())

    # Basic information about this graph
    print('Graph basic info:\n', nx.info(G))

    return G
```

```
In [6]: input_df = pd.read_csv(input_graph_csv_path, index_col=False)
        print('Input df shape : ', input_df.shape)
        input_df.head()
```

```
Input df shape :  (9437519, 2)
```

```
Out[6]:    source_node  destination_node
        0            1            690569
        1            1            315892
        2            1            189226
        3            2            834328
        4            2           1615927
```

```
In [7]: # create input graph
        G_input = create_graph_from_dataframe(input_df)
```

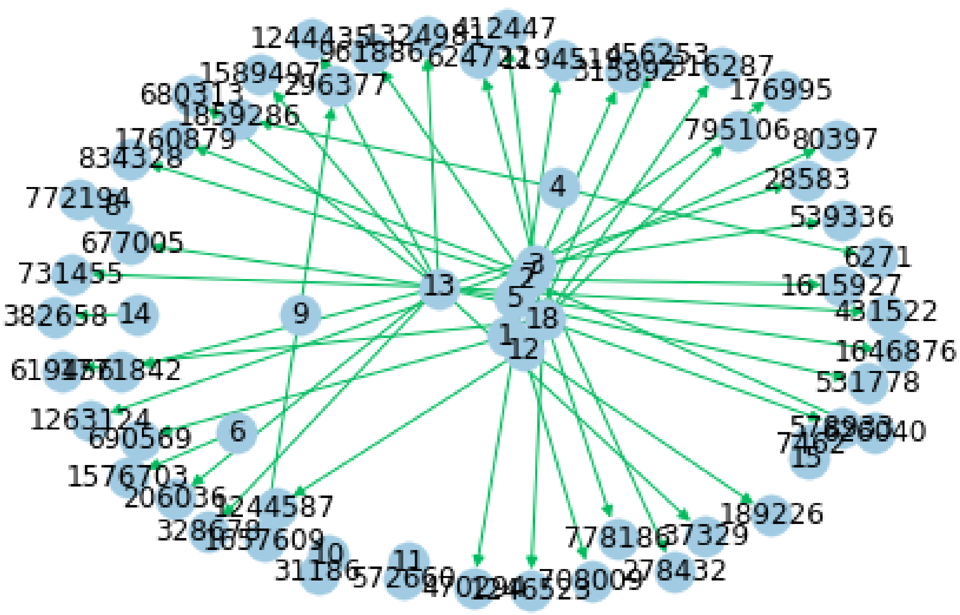
```
Graph basic info:
 Name:
Type: DiGraph
Number of nodes: 1862220
Number of edges: 9437519
Average in degree:   5.0679
Average out degree:   5.0679
```

2.1 Displaying a subgraph

```
In [8]: input_df_sample = input_df.iloc[0:50, :]
        subgraph = create_graph_from_dataframe(input_df_sample)
        pos=nx.spring_layout(subgraph)
```

```
nx.draw(subgraph,pos,node_color='#A0CBE2',edge_color='#00bb5e',width=1,
        edge_cmap=plt.cm.Blues, with_labels=True)
plt.savefig('./data/graph_sample.pdf')
print(nx.info(subgraph))
```

```
Graph basic info:
 Name:
Type: DiGraph
Number of nodes: 66
Number of edges: 50
Average in degree:   0.7576
Average out degree:   0.7576
Name:
Type: DiGraph
Number of nodes: 66
Number of edges: 50
Average in degree:   0.7576
Average out degree:   0.7576
```



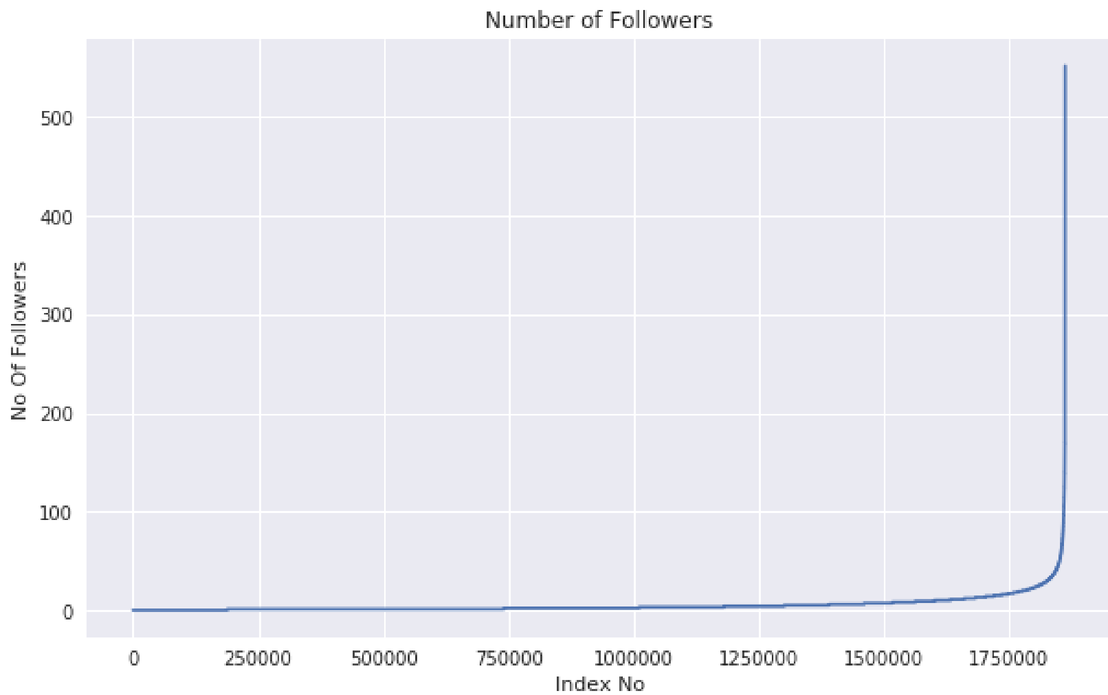
3 Exploratory Data Analysis

```
In [9]: # No of Unique persons
        print('The number of unique persons',len(G_input.nodes()))
```

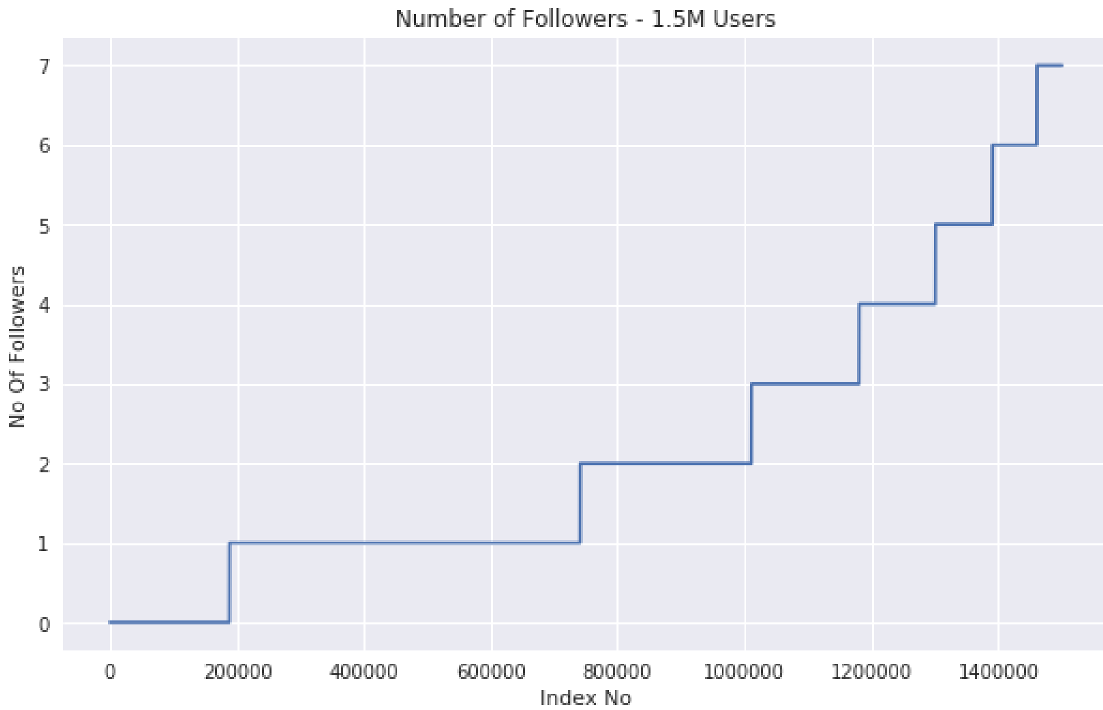
```
The number of unique persons 1862220
```

3.1 Number of followers of each person

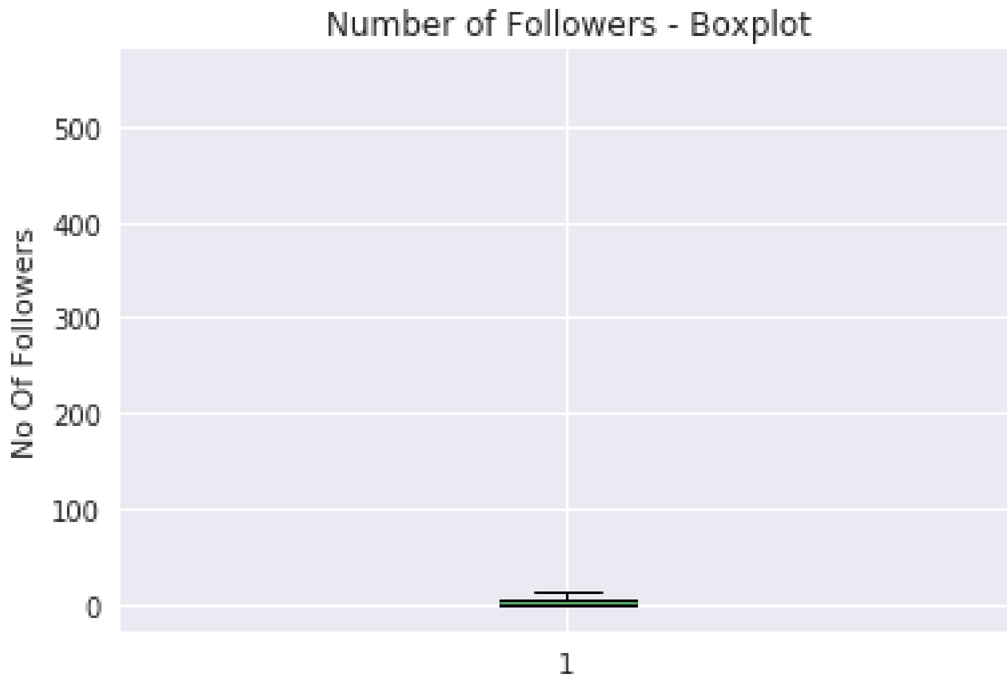
```
In [10]: indegree_dist = list(dict(G_input.in_degree()).values())
         indegree_dist.sort()
         plt.figure(figsize=(10,6))
         plt.plot(indegree_dist)
         plt.xlabel('Index No')
         plt.ylabel('No Of Followers')
         plt.title('Number of Followers')
         plt.show()
         plt.close()
```




```
In [11]: indegree_dist = list(dict(G_input.in_degree()).values())
         indegree_dist.sort()
         plt.figure(figsize=(10,6))
         plt.plot(indegree_dist[0:1500000])
         plt.xlabel('Index No')
         plt.ylabel('No Of Followers')
         plt.title('Number of Followers - 1.5M Users')
         plt.show()
         plt.close()
```




```
In [12]: plt.boxplot(indegree_dist)
         plt.ylabel('No Of Followers')
         plt.title('Number of Followers - Boxplot')
         plt.show()
         plt.close()
```




```
In [13]: ### 90-100 percentile
         for i in range(0,11):
             print(90+i,'percentile value is',np.percentile(indegree_dist,90+i))
```

```
90 percentile value is 12.0
91 percentile value is 13.0
92 percentile value is 14.0
93 percentile value is 15.0
94 percentile value is 17.0
95 percentile value is 19.0
96 percentile value is 21.0
97 percentile value is 24.0
98 percentile value is 29.0
99 percentile value is 40.0
100 percentile value is 552.0
```

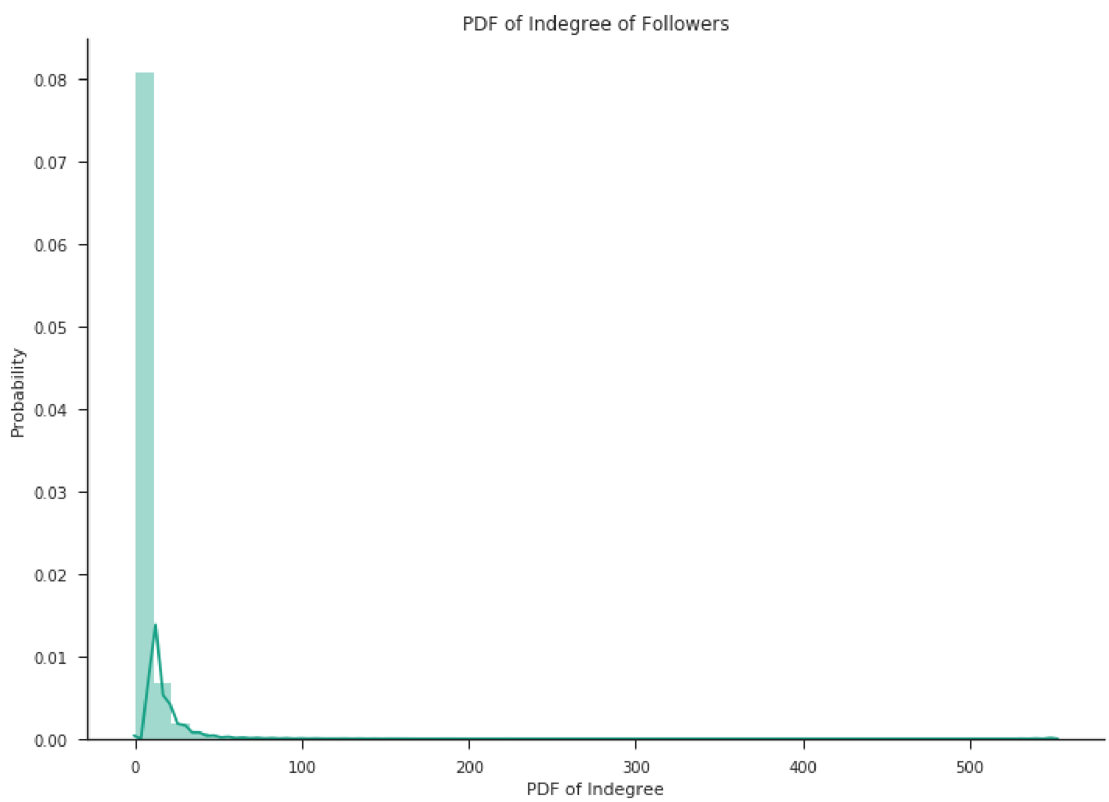
```
In [14]: ### 99-100 percentile
         for i in range(10,110,10):
             print(99+(i/100),'percentile value is',np.percentile(indegree_dist,99+(i/100)))
```

```
99.1 percentile value is 42.0
99.2 percentile value is 44.0
99.3 percentile value is 47.0
99.4 percentile value is 50.0
```

```
99.5 percentile value is 55.0
99.6 percentile value is 61.0
99.7 percentile value is 70.0
99.8 percentile value is 84.0
99.9 percentile value is 112.0
100.0 percentile value is 552.0
```

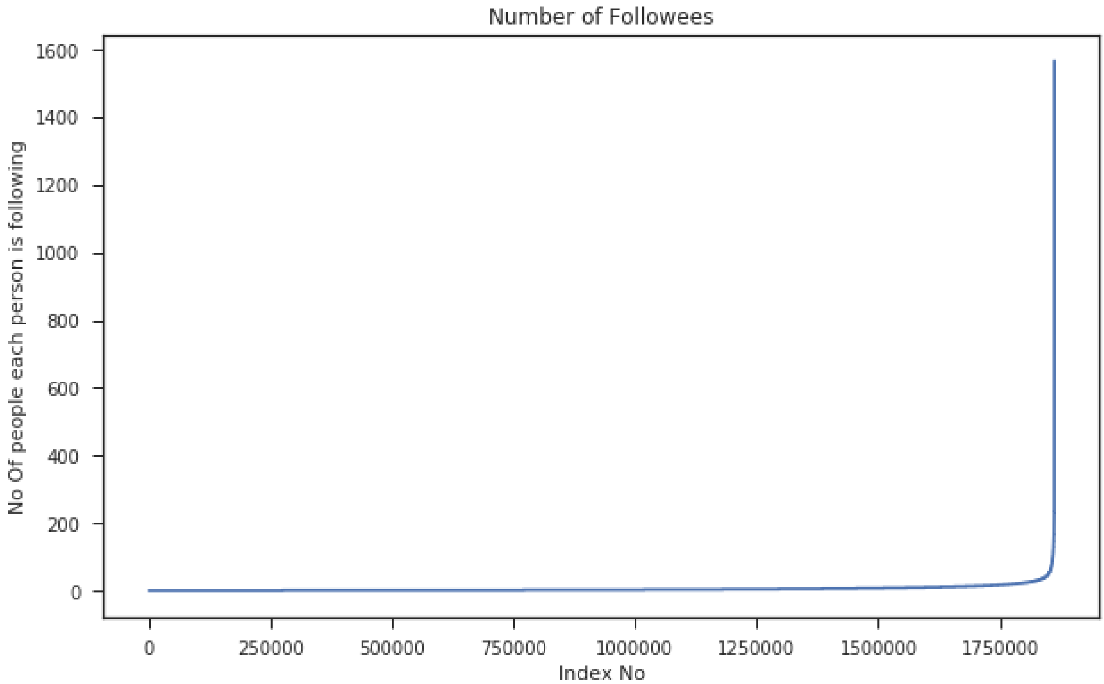
```
In [15]: %matplotlib inline
         sns.set_style('ticks')
         fig, ax = plt.subplots()
         fig.set_size_inches(11.7, 8.27)
         sns.distplot(indegree_dist, color='#16A085')
         plt.xlabel('PDF of Indegree')
         plt.ylabel('Probability')
         plt.title('PDF of Indegree of Followers')
         sns.despine()
         plt.show()
         plt.close()
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

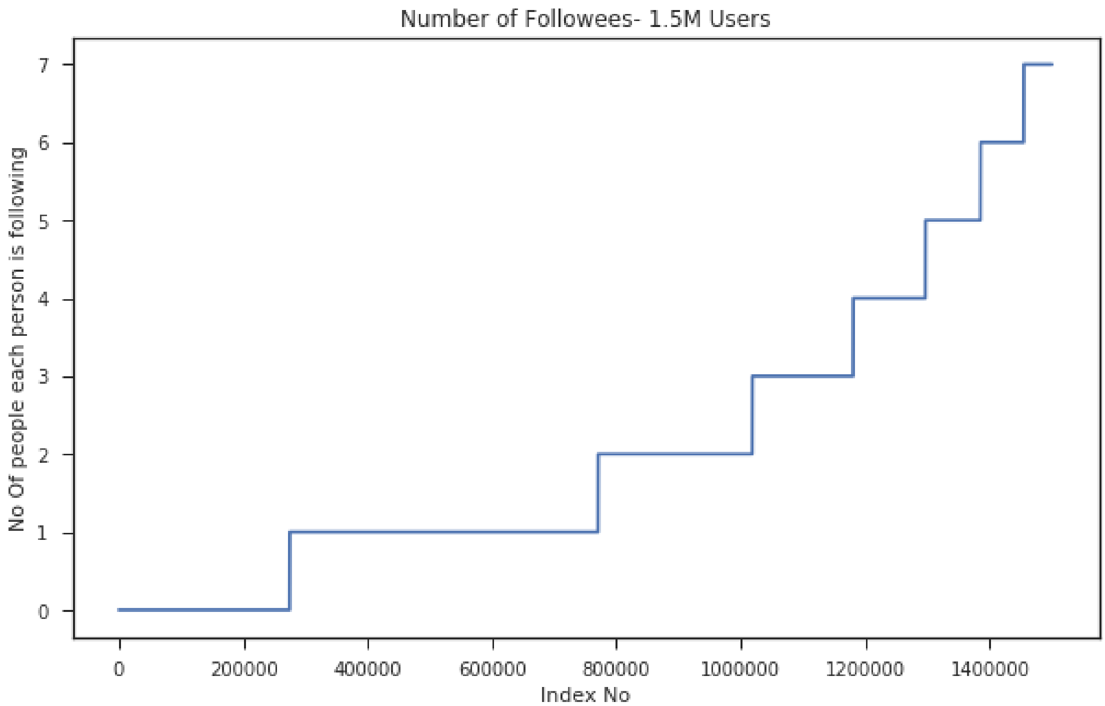


3.2 Number of followees of each person

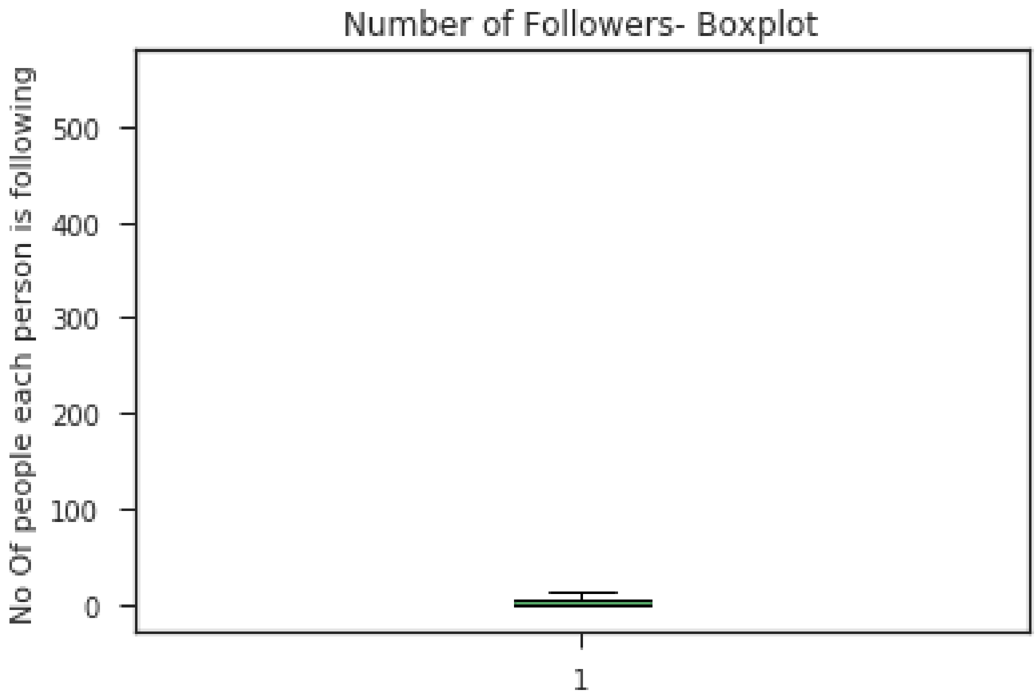
```
In [16]: outdegree_dist = list(dict(G_input.out_degree()).values())
         outdegree_dist.sort()
         plt.figure(figsize=(10,6))
         plt.plot(outdegree_dist)
         plt.xlabel('Index No')
         plt.ylabel('No Of people each person is following')
         plt.title('Number of Followees')
         plt.show()
         plt.close()
```




```
In [17]: indegree_dist = list(dict(G_input.in_degree()).values())
         indegree_dist.sort()
         plt.figure(figsize=(10,6))
         plt.plot(outdegree_dist[0:1500000])
         plt.xlabel('Index No')
         plt.ylabel('No Of people each person is following')
         plt.title('Number of Followees- 1.5M Users')
         plt.show()
         plt.close()
```




```
In [18]: plt.boxplot(indegree_dist)
         plt.ylabel('No Of people each person is following')
         plt.title('Number of Followers- Boxplot')
         plt.show()
         plt.close()
```




```
In [19]: ### 90-100 percentile
         for i in range(0,11):
             print(90+i,'percentile value is',np.percentile(outdegree_dist,90+i))
```

```
90 percentile value is 12.0
91 percentile value is 13.0
92 percentile value is 14.0
93 percentile value is 15.0
94 percentile value is 17.0
95 percentile value is 19.0
96 percentile value is 21.0
97 percentile value is 24.0
98 percentile value is 29.0
99 percentile value is 40.0
100 percentile value is 1566.0
```

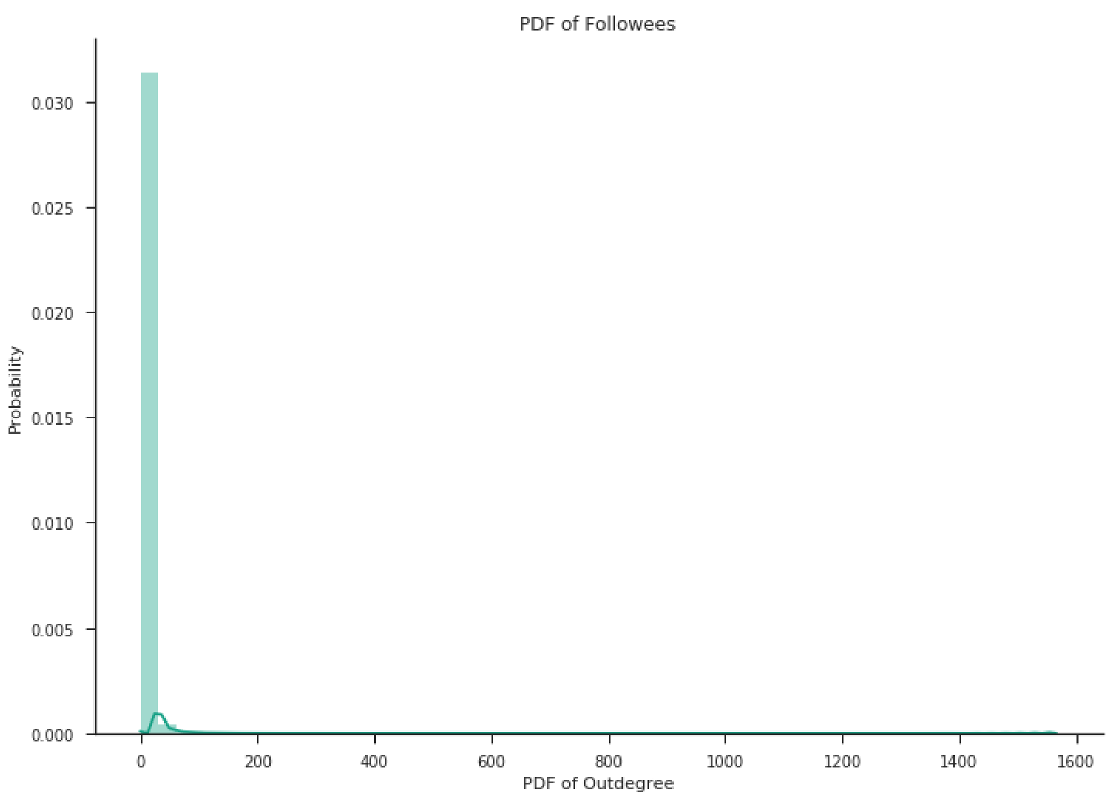
```
In [20]: ### 99-100 percentile
         for i in range(10,110,10):
             print(99+(i/100),'percentile value is',np.percentile(outdegree_dist,99+(i/100)))
```

```
99.1 percentile value is 42.0
99.2 percentile value is 45.0
99.3 percentile value is 48.0
99.4 percentile value is 52.0
```

```
99.5 percentile value is 56.0
99.6 percentile value is 63.0
99.7 percentile value is 73.0
99.8 percentile value is 90.0
99.9 percentile value is 123.0
100.0 percentile value is 1566.0
```

In [21]:
```
sns.set_style('ticks')
fig, ax = plt.subplots()
fig.set_size_inches(11.7, 8.27)
sns.distplot(outdegree_dist, color='#16A085')
plt.xlabel('PDF of Outdegree')
plt.ylabel('Probability')
sns.despine()
plt.title('PDF of Followees')
plt.show()
plt.close()
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



In [22]:
```
print('No of persons those are not following anyone are' ,sum(np.array(outdegree_dist)=
                                              sum(np.array(outdegree_dist)==0)*100/len(outdegree_dist
```

```
No of persons those are not following anyone are 274512 and % is 14.741115442858524
```

In [23]:
```
print('No of persons having zero followers are' ,sum(np.array(indegree_dist)==0),'and %
                                              sum(np.array(indegree_dist)==0)*100/len(indegree_dist)
```

```
No of persons having zero followers are 188043 and % is 10.097786512871734
```

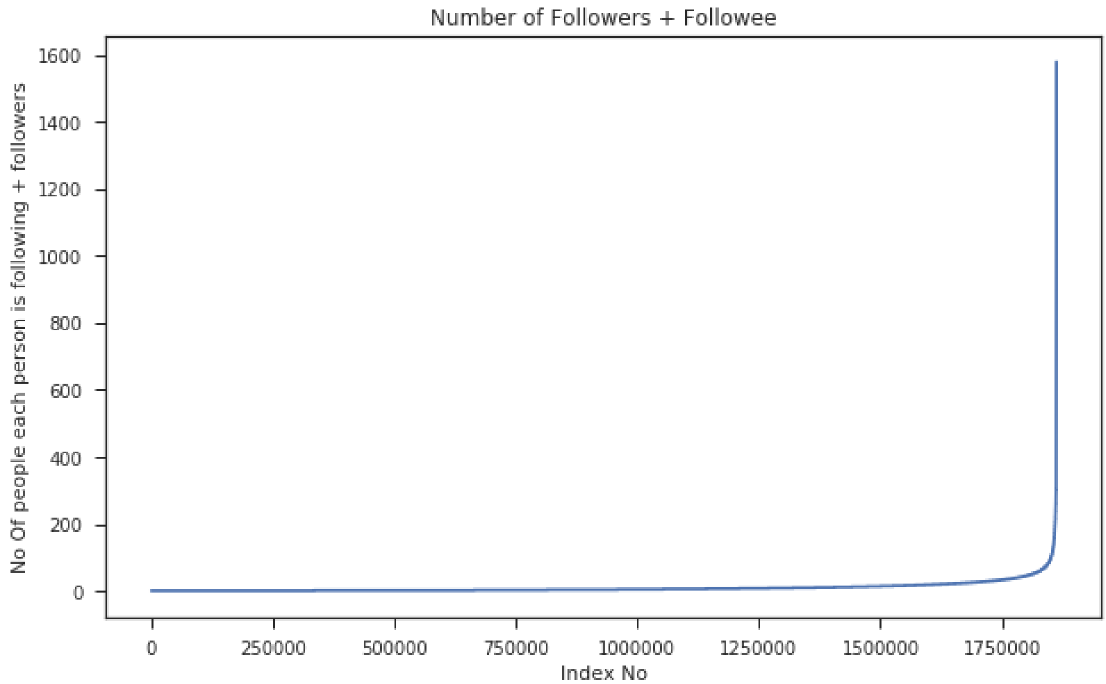
In [24]:
```
count=0
for i in G_input.nodes():
    if len(list(G_input.predecessors(i)))==0 :
        if len(list(G_input.successors(i)))==0:
            count+=1
print('No of persons those are not not following anyone and also not having any followe
```

```
No of persons those are not not following anyone and also not having any followers are 0
```

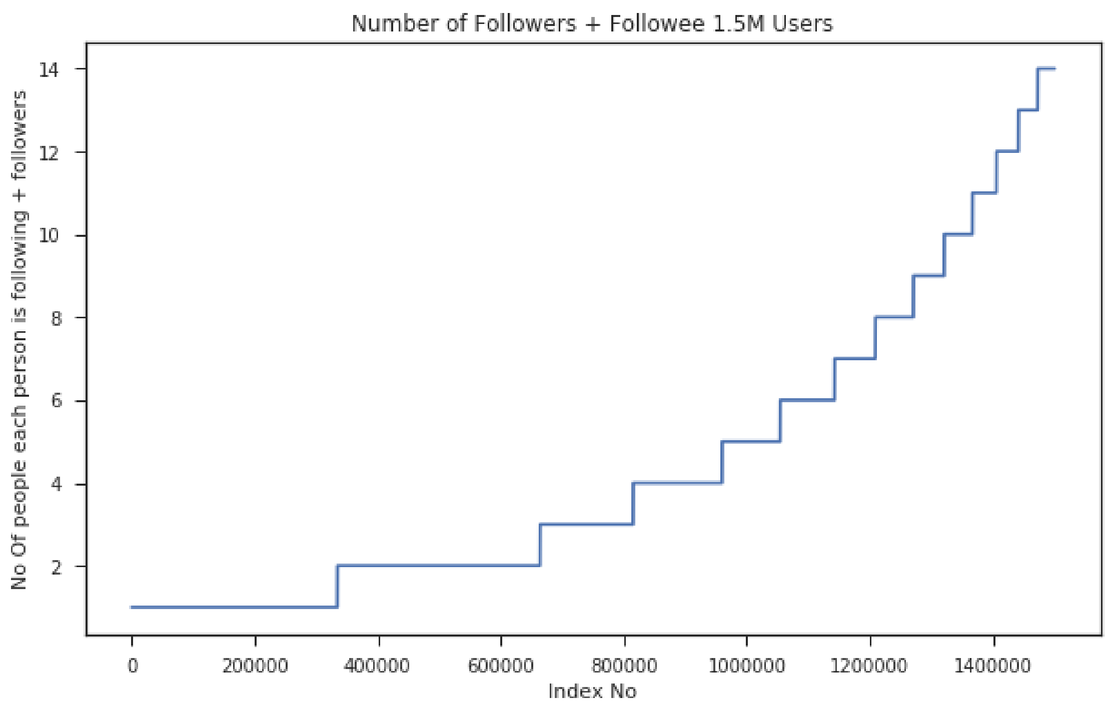
3.3 3) both followers + following

In [25]:
```
from collections import Counter
dict_in = dict(G_input.in_degree())
dict_out = dict(G_input.out_degree())
d = Counter(dict_in) + Counter(dict_out)
in_out_degree = np.array(list(d.values()))
```

In [26]:
```
in_out_degree_sort = sorted(in_out_degree)
plt.figure(figsize=(10,6))
plt.plot(in_out_degree_sort)
plt.xlabel('Index No')
plt.ylabel('No Of people each person is following + followers')
plt.title('Number of Followers + Followee')
plt.show()
plt.close()
```




```
In [27]: in_out_degree_sort = sorted(in_out_degree)
         plt.figure(figsize=(10,6))
         plt.plot(in_out_degree_sort[0:1500000])
         plt.xlabel('Index No')
         plt.ylabel('No Of people each person is following + followers')
         plt.title('Number of Followers + Followee 1.5M Users')
         plt.show()
         plt.close()
```




```
In [28]: ### 90-100 percentile
         for i in range(0,11):
             print(90+i,'percentile value is',np.percentile(in_out_degree_sort,90+i))
```

```
90 percentile value is 24.0
91 percentile value is 26.0
92 percentile value is 28.0
93 percentile value is 31.0
94 percentile value is 33.0
95 percentile value is 37.0
96 percentile value is 41.0
97 percentile value is 48.0
98 percentile value is 58.0
99 percentile value is 79.0
100 percentile value is 1579.0
```

```
In [29]: ### 99-100 percentile
         for i in range(10,110,10):
             print(99+(i/100),'percentile value is',np.percentile(in_out_degree_sort,99+(i/100))
```

```
99.1 percentile value is 83.0
99.2 percentile value is 87.0
99.3 percentile value is 93.0
99.4 percentile value is 99.0
```

```
99.5 percentile value is 108.0
99.6 percentile value is 120.0
99.7 percentile value is 138.0
99.8 percentile value is 168.0
99.9 percentile value is 221.0
100.0 percentile value is 1579.0
```

```
In [30]: print('Min of no of followers + following is',in_out_degree.min())
         print(np.sum(in_out_degree==in_out_degree.min()),' persons having minimum no of followe
```

```
Min of no of followers + following is 1
334291  persons having minimum no of followers + following
```

```
In [31]: print('Max of no of followers + following is',in_out_degree.max())
         print(np.sum(in_out_degree==in_out_degree.max()),' persons having maximum no of followe
```

```
Max of no of followers + following is 1579
1  persons having maximum no of followers + following
```

```
In [32]: print('No of persons having followers + following less than 10 are',np.sum(in_out_degre
```

```
No of persons having followers + following less than 10 are 1320326
```

```
In [33]: print('No of weakly connected components',
               len(list(nx.weakly_connected_components(G_input))))
         count=0
         for i in list(nx.weakly_connected_components(G_input)):
             if len(i)==2:
                 count+=1
         print('weakly connected components with 2 nodes',count)
```

```
No of weakly connected components 45558
weakly connected components with 2 nodes 32195
```

4 Generate the edges not present

```
In [34]: def two_rechable_nodes(G, node):

             # get all the followees of this node in a set
             node_followees = set(G.successors(node))

             # get followees followees (i.e. length 2)
             for temp_node in node_followees:
                 node_followees = node_followees.union(set(G.successors(temp_node)))
```

```
        # add the node itself in the set
        node_followees.add(node)

        return node_followees
```

In [35]:
```
def get_missing_edges(index_dict, current_node, lb, ub, node_set, num_edges):

        # declare an empty list for adding all the missig edges
        selected_edge_list = list()

        while(len(selected_edge_list) < num_edges):
            # generate a random index in the range
            index = np.random.randint(lb,ub)
            # get the node corresponding to this index
            index_node = index_dict[index]

            # test the node already present in the node_set
            if  index_node in node_set:
                continue

            # update the selected edge list
            selected_edge_list.append((current_node, index_node,))

        return set(selected_edge_list)
```

In [36]:
```
def create_missing_edges(G):

        if os.path.isfile(missing_egde_csv_path):
            print(datetime.now(), ' Missing edges file already created !!!')
            missing_df = pd.read_csv(missing_egde_csv_path, index_col=False)
            return missing_df

        print(datetime.now(), ' Started adding the missing edges')

        num_edges = G.number_of_edges()
        print(datetime.now(), ' Number of edges present in the graph :', num_edges)

        # separate source nodes, destination edges
        src_nodes_set = set([item[0] for item in nx.edges(G)])
        dst_nodes_set = set([item[1] for item in  nx.edges(G)])
        # compute nodes which are present both in src as well as destination
        common_nodes = src_nodes_set.intersection(dst_nodes_set)

        print(datetime.now(), ' Common nodes count ', len(common_nodes))

        # get all nodes of a graph
        nodes_set = set(G.nodes)
```

```
# get missing nodes in source , dst positions
missing_src_nodes = nodes_set - src_nodes_set
missing_dst_nodes = nodes_set - dst_nodes_set


print(datetime.now(),' Number of missing src nodes', len(missing_src_nodes))
print(datetime.now(), ' Number of missing dst nodes', len(missing_dst_nodes))


######### Generate missing edges

# Get 10% samples from persons who are not following anyone
missing_src_nodes = set(random.sample(missing_src_nodes, 1032))
missing_dst_nodes = set(random.sample(missing_dst_nodes, 1032))

# CASE 1: Missing src x missing dst (10 % sample)
sampled_missing_edges_case1 = set(product(missing_src_nodes,
                                          missing_dst_nodes))
sampled_missing_edges_case1 = set(filter(lambda x : x[0]!=x[1],
                                         sampled_missing_edges_case1))
sampled_missing_edges_case1 = set(random.sample(sampled_missing_edges_case1,
                                            1000000))

# CASE 2 : Missing src x dst (10 % sample)
dst_nodes_set_sampled = random.sample(dst_nodes_set, 1032)
sampled_missing_edges_case2 = set(product(missing_src_nodes,
                                          dst_nodes_set_sampled))
sampled_missing_edges_case2 = set(filter(lambda x : x[0]!=x[1],
                                         sampled_missing_edges_case2))
sampled_missing_edges_case2 = set(random.sample(sampled_missing_edges_case2,
                                            1000000))


# CASE 3: src x Missing dst (10 % sample)
src_nodes_set_sampled = random.sample(src_nodes_set, 1032)
sampled_missing_edges_case3 = set(product(src_nodes_set_sampled,
                                          missing_dst_nodes))
sampled_missing_edges_case3 = set(filter(lambda x : x[0]!=x[1],
                                         sampled_missing_edges_case3))
sampled_missing_edges_case3 = set(random.sample(sampled_missing_edges_case3,
                                            1000000))

# find all missing edges
missing_edges_set = sampled_missing_edges_case1.union(sampled_missing_edges_case2)
missing_edges_set = missing_edges_set.union(sampled_missing_edges_case3)

print(datetime.now(),' Number of missing edges generated from CASE 1 to CASE 3:',
```

```
      len(missing_edges_set))


# CASE 4: Generate 6.4M missing edges from 800K SRC nodes
sampled_src_nodes = set(random.sample(src_nodes_set, 800000))

# declare a dictionary having index and corresponding node name
index_dict = {index:item for index, item in enumerate(common_nodes)}
# declare the number of missing edges to be generated for a node
num_edges_required = 8

# LB & UB for generating random indices
lb = 0
ub = len(common_nodes)

# declare a set for saving all generated missing edges
edges_taken_list = list()

# for each edge in the set test two reachabel condition
for index, node in enumerate(sampled_src_nodes):

    # get all two reachable nodes of this node
    two_reachable_nodes_set = two_rechable_nodes(G, node)
    # generate the missing edges for this node
    node_missing_edges = get_missing_edges(index_dict, node, lb, ub,
                                           two_reachable_nodes_set,
                                           num_edges_required)

    # add the gerated missing edges to the set
    edges_taken_list += list(node_missing_edges)

    if (index+1) % 100000 == 0:
        print(datetime.now(),' Added %d missing edges'%((index+1)*num_edges_require

# form the complete set of missing edges
missing_edges_set = set(list(missing_edges_set) + edges_taken_list)
print(datetime.now(), 'Total number of missing edges created: ',
      len(missing_edges_set))

missing_df = pd.DataFrame(list(missing_edges_set), columns=['source_node',
                                                             'destination_node'])

# writing missing DF to disk
missing_df.to_csv(missing_egde_csv_path, index=False)

print(datetime.now(), ' Creating missing edge graph for verification')

# create missing edge graph
```

```
        G_input_missing = create_graph_from_dataframe(missing_df)

         # verify the created graph
        print('Number of common edges between input graph & missing edge graph: ',
              len(set(nx.edges(G)).intersection(set(nx.edges(G_input_missing)))))


        print(datetime.now(), ' Done !!!')

        return missing_df
```

```
In [37]: # create missing edge df
         input_missing_edge_df = create_missing_edges(G_input)
```

```
2019-06-22 00:27:43.183990  Missing edges file already created !!!
```

5 Create train test dataset

```
In [38]: def prepare_train_test_labeled_data(input_df, input_missing_edge_df):

             if os.path.isfile(train_labeled_csv_path) and os.path.isfile(test_labeled_csv_path)
                 print('Both train, test csv files are present in the path')
                 return

             # add labels
             input_df['Label'] = 1
             input_missing_edge_df['Label'] = 0
             # combine data frames & shuffle it
             combined_df = input_df.append(input_missing_edge_df)
             combined_df = combined_df.reset_index(drop=True)


             # train, test split
             train_df, test_df = train_test_split(combined_df, test_size=0.30,
                                                  stratify=combined_df['Label'])
             train_df = train_df.reset_index(drop=True)
             test_df = test_df.reset_index(drop=True)

             # save the above files
             train_df.to_csv(train_labeled_csv_path, index=False)
             test_df.to_csv(test_labeled_csv_path, index=False)
```

```
In [39]: prepare_train_test_labeled_data(input_df, input_missing_edge_df)
```

```
Both train, test csv files are present in the path
```

6 Extract Global Params

In [40]:
```
train_df = pd.read_csv(train_labeled_csv_path, index_col=False)
train_df_pos = train_df[train_df['Label']==1]
```

In [41]:
```
G_train = create_graph_from_dataframe(train_df_pos)
```

```
Graph basic info:
 Name:
Type: DiGraph
Number of nodes: 1726788
Number of edges: 6606263
Average in degree:   3.8258
Average out degree:   3.8258
```

In [42]:
```
def get_svd_components(G):

        # sort all the nodes present in the graph
        sorted_nodes = sorted(G.nodes())

        # assign the nodes with index from 0 to num_nodes
        node_index_dict = { val : idx for idx, val in enumerate(sorted_nodes)}

        # create adjancency matrix
        Adj = nx.adjacency_matrix(G, nodelist=sorted_nodes).asfptype()

        # decompose the adjacency matrix into SVD components
        U, s, V = svds(Adj, k = 6)
        print('Adjacency matrix Shape', Adj.shape)
        print('U Shape', U.shape)
        print('V Shape', V.shape)
        print('s Shape', s.shape)

        return (U, s, V, node_index_dict, Adj, )
```

In [43]:
```
def estimate_global_params(G):

        if os.path.isfile('./model/global_params_dict.pkl'):
            print('Glboal params dict already exist in the disk !!!')

            param_file = open('./model/global_params_dict.pkl','rb')
            global_params_dict = pickle.load( param_file)
            param_file.close()

            return global_params_dict

        # compute page rank values
        print(datetime.now(), ' Start page rank values')
```

```python
page_rank = nx.pagerank(G, alpha=0.85)
print(datetime.now(), ' End page rank values')

# compute katz centrality values
print(datetime.now(), ' Start katz centrality values')
katz_values = nx.katz.katz_centrality(G, alpha=0.005,beta=1)
print(datetime.now(), ' End katz centrality values')

# compute hits score to find hubs & authorities
print(datetime.now(), ' Start hits score')
hubs_scores, authorities = nx.hits(G, max_iter=100, tol=1e-08, nstart=None,
                                   normalized=True)
print(datetime.now(), ' End hits score')


# get components of this graph G
print(datetime.now(), ' Start SVD components of this graph G')
U, s, V, node_index_dict, Adj = get_svd_components(G)
print(datetime.now(), ' End SVD components of this graph G')

# get list of weekly connected components
print(datetime.now(), ' Start weekly connected components')
wcc_list = list(nx.weakly_connected_components(G))
print(datetime.now(), ' End weekly connected components')

# create a dictionary of parameters
print(datetime.now(), ' Start global params dictionary')
global_params_dict = {
    'Page_Rank': page_rank,
    'Kats_Score': katz_values,
    'Hubs_Scores': hubs_scores,
    'Authorities': authorities,
    'Adj_Matrix': Adj,
    'U': U,
    's': s,
    'V': V,
    'Node_Index_Dict': node_index_dict,
    'WCC': wcc_list
    }

param_file = open('./model/global_params_dict.pkl','wb')
pickle.dump(global_params_dict, param_file)
param_file.close()
print(datetime.now(), ' End global params dictionary')

print(datetime.now(), ' Done !!!')
return global_params_dict
```

In [44]:
```
global_params_dict = estimate_global_params(G_train)
```

```
Glboal params dict already exist in the disk !!!
```

In [45]:
```
wcc_list = global_params_dict['WCC']
U = global_params_dict['U']
s = global_params_dict['s']
V = global_params_dict['V']
node_index_dict = global_params_dict['Node_Index_Dict']

page_rank = global_params_dict['Page_Rank']
katz_values = global_params_dict['Kats_Score']
hubs_scores = global_params_dict['Hubs_Scores']
authorities = global_params_dict['Authorities']
```

7 Sampling of Train, Test datasets

In [46]:
```
# sample train df
sample_train_df = train_df.sample(n=dataset_sample_size)
sample_train_df = sample_train_df.reset_index(drop=True)

# sample test df
test_df = pd.read_csv(test_labeled_csv_path, index_col=False)
sample_test_df = test_df.sample(n=dataset_sample_size)
sample_test_df = sample_test_df.reset_index(drop=True)
```

8 Feature Extraction

8.1 Feature set 1

In [47]:
```
def get_num_followers(G, node):

    try:
        followers = set(G.predecessors(node))
    except:
        followers = set()

    num_followers = len(followers)

    return num_followers
```

In [48]:
```
def get_num_followees(G, node):
    try:
        followees = set(G.successors(node))
    except:
        followees = set()
```

```
        num_followers = len(followees)

        return num_followers
```

```
In [49]: def mine_node_features(G, node):

             # get successors & predecessors of this node
             try:
                 node_followers = set(G.predecessors(node))
             except:
                 node_followers = set()

             try:
                 node_followees = set(G.successors(node))
             except:
                 node_followees = set()

             # 1) get number of followers of this node
             num_followers = len(node_followers)
             # 2) get number of followees of this node
             num_followees = len(node_followees)
             # 3) get number of common followees & followers
             common_nodes_count = len(node_followers.intersection(node_followees))
             # 4) compute incoming edge weight
             incoming_edge_weight = np.sqrt(1 / (1 + num_followers))
             # 5) compute outgoing edge weight
             outgoing_edge_weight = np.sqrt(1 / (1 + num_followees))
             # 6) Sum of weights
             weight_sum = incoming_edge_weight + outgoing_edge_weight
             # 7) Product of weights
             weight_product = incoming_edge_weight * outgoing_edge_weight
             # 8) 2x + y linear sum-1
             liner_sum_1 = 2 * incoming_edge_weight + outgoing_edge_weight
             # 9) x + 2y linear sum-2
             liner_sum_2 = incoming_edge_weight + 2 * outgoing_edge_weight


             # form the feature tuple
             feat_tuple = (num_followers, num_followees, common_nodes_count, incoming_edge_weigh
                           outgoing_edge_weight, weight_sum, weight_product, liner_sum_1,
                           liner_sum_2)

             return feat_tuple
```

```
In [50]: def mine_features_set_1(df, G):

             # set feature name_list
             feat_name_list = ['num_followers', 'num_followees', 'common_nodes_count',
```

```
                    'incoming_edge_weight', 'outgoing_edge_weight', 'weight_sum',
                    'weight_product', 'liner_sum_1','liner_sum_2']

    # set reqiored feature names in a list
    src_feat_name_list = ['src_' + name for name in feat_name_list]
    dst_feat_name_list = ['dst_' + name for name in feat_name_list]
    edge_feat_name_list = src_feat_name_list + dst_feat_name_list

    edge_feat_list = list()

    # do for all edges in the graph
    for index, row in df.iterrows():

        src_node_features = mine_node_features(G, row['source_node'])
        dst_node_features = mine_node_features(G, row['destination_node'])

        # concatenate both nodes features into single vector
        edge_featues = src_node_features + dst_node_features

        edge_feat_list.append(edge_featues)

    # create edge name list
    edge_feat_df = pd.DataFrame(edge_feat_list, columns=edge_feat_name_list)

    return edge_feat_df
```

8.2 Feature set 2

```
In [51]: def follows_back_fn(G, a, b):

             if G.has_edge(b, a):
                 return 1
             return 0
```

```
In [52]: def belong_to_same_wcc(wcc_list, a, b):

             for component in wcc_list:

                 if ((a in component) and (b in component)):
                     return 1

             return 0
```

```
In [53]: def next_shortest_path(G, a, b):

             # default value for shortest path
             shortest_path_length = -1
```

```
        # if edge already exists
        if G.has_edge(a, b):

            # remove the edge temporaly
            G.remove_edge(a, b)

            try:
                # compute the shortest path length
                shortest_path_length = nx.shortest_path_length(G, source=a, target=b)
            except:
                shortest_path_length = -1
            finally:
                # add the edge back
                G.add_edge(a, b)

        # if no edge exists
        else:
            try:
                shortest_path_length = nx.shortest_path_length(G, source=a, target=b)
            except:
                shortest_path_length = -1


        # returns the shortest path computed
        return shortest_path_length
```

```
In [54]: def mine_edge_features(G, wcc_list, a, b):

             # 1) Follows back (followee)
             follows_back = follows_back_fn(G, a, b)

             # 2) get next shortest path- remove any existing edge and compute shortest path
             next_shortest_path_length = next_shortest_path(G, a, b)

             # 3) belongs to same wcc
             same_wcc = belong_to_same_wcc(wcc_list, a, b)


             # compute followers, sucessors of a, b
             try:
                 a_followers = set(G.predecessors(a))
             except:
                 a_followers = set()

             try:
                 b_followers = set(G.predecessors(b))
             except:
                 b_followers = set()
```

```
try:
    b_followees = set(G.successors(b))
except:
    b_followees = set()

try:
    a_followees = set(G.successors(a))
except:
    a_followees = set()

# compute common followers & common successors
common_followers = a_followers.intersection(b_followers)
common_followees = a_followees.intersection(b_followees)

common_followers_count = len(common_followers)
common_followees_count = len(common_followees)



# compute union of followers & followee
union_followers = a_followers.union(b_followers)
union_followees = a_followees.union(b_followees)

union_followers_count = len(union_followers)
union_followees_count = len(union_followees)

# Preferential attachment
pref_attachment_follower = len(a_followers) * len(b_followers)
pref_attachment_followee = len(a_followees) * len(b_followees)

# Compute similariy matrix such as Jaccard, Cosine, Adar index,

# Compute each similarity matrix
if common_followers_count == 0:
    jaccard_sim_follower = 0.0
    cosine_sim_follower = 0.0
else:

    # compute jaccard_sim_followee
    try:
        jaccard_sim_follower =  (common_followers_count /  union_followers_count)
    except:
        jaccard_sim_follower = 0.0

    # compute cosine_sim_followee
    try:
        cosine_sim_follower = (common_followers_count /
```

```
                                    (np.sqrt(len(a_followers)*len(b_followers))))
        except:
            cosine_sim_follower = 0.0


    if common_followees_count == 0 :
        jaccard_sim_followee = 0.0
        cosine_sim_followee = 0.0
        adar_index = 0.0
    else:

        # compute adar index
        adar_index = 0.0

        for node in common_followees:

            try:
                loc_followers = set(G.predecessors(node))
            except:
                loc_followers = set()

            if loc_followers:
                adar_index += (1/np.log10(len(loc_followers)))

        # compute jaccard_sim_followee
        try:
            jaccard_sim_followee =  (common_followees_count/union_followees_count)
        except:
            jaccard_sim_followee = 0.0

        # compute cosine_sim_followee
        try:
            cosine_sim_followee = (common_followees_count /
                                        np.sqrt(len(a_followees)*len(b_followees)))
        except:
            cosine_sim_followee = 0.0


     # Form feature tuple
    feat_tuple = (follows_back, next_shortest_path_length, same_wcc, adar_index,
                  jaccard_sim_follower, cosine_sim_follower, pref_attachment_follower,
                  jaccard_sim_followee,cosine_sim_followee,pref_attachment_followee,)


    return feat_tuple
```

```
In [55]: def mine_features_set_2(df, G, wcc_list):
```

```
    edge_feat_list = list()

    feat_name_list = ['follows_back', 'next_shortest_path_length', 'same_wcc',
                      'adar_index', 'jaccard_sim_follower', 'cosine_sim_follower',
                      'pref_attachment_follower','jaccard_sim_followee',
                      'cosine_sim_followee', 'pref_attachment_followee']


    for index, row in df.iterrows():
        # edge features
        edge_features = mine_edge_features(G, wcc_list, row['source_node'],
                                           row['destination_node'])
        # update edge feature list
        edge_feat_list.append(edge_features)

    # create a data frame using feature vector list
    edge_feat_df = pd.DataFrame(edge_feat_list, columns=feat_name_list)

    return edge_feat_df
```

8.3 Feature Set 3

```
In [56]: def mine_features_set_3(df, G, page_rank, katz_values, hubs_scores, authorities):

    # form source & destination node list
    src_node_list = df['source_node']
    dst_node_list = df['destination_node']

    # source node related features
    source_page_rank = [page_rank.get(node, 0) for node in src_node_list]
    dst_page_rank = [page_rank.get(node, 0) for node in dst_node_list]

    source_katz_values = [katz_values.get(node, 0) for node in src_node_list]
    dst_katz_values = [katz_values.get(node, 0) for node in dst_node_list]

    source_hubs_scores = [hubs_scores.get(node, 0) for node in src_node_list]
    dst_hubs_scores = [hubs_scores.get(node, 0) for node in dst_node_list]

    source_authorities = [authorities.get(node, 0) for node in src_node_list]
    dst_authorities = [authorities.get(node, 0) for node in dst_node_list]

    feat_df = pd.DataFrame({'SRC_PG_RANK' : source_page_rank,
                            'DST_PG_RANK' : dst_page_rank,
                            'SRC_KATZ_SCORE' : source_katz_values,
                            'DST_KATZ_SCORE' : dst_katz_values,
                            'SRC_HUBS_SCORE' : source_hubs_scores,
                            'DST_HUBS_SCORE' : dst_hubs_scores,
                            'SRC_AUTHORITY_SCORE' : source_authorities,
```

```
                                 'DST_AUTHORITY_SCORE' : dst_authorities},
                                index=range(df.shape[0]))

        feat_df = feat_df[['SRC_PG_RANK', 'DST_PG_RANK', 'SRC_KATZ_SCORE', 'DST_KATZ_SCORE'
                          'SRC_HUBS_SCORE', 'DST_HUBS_SCORE', 'SRC_AUTHORITY_SCORE',
                          'DST_AUTHORITY_SCORE']]


        return feat_df
```

9 Featue Set 4

```
In [57]: def svd(Matrix, node_number):
             try:
                 z = node_index_dict[node_number]
                 return Matrix[z]
             except:
                 return ([0] * 6)

In [58]: def mine_features_set_4(df, U, s, V):

             print(df.head())

             # get feature vectors from U matrix
             u_src_cols = ['svd_u_s_1', 'svd_u_s_2','svd_u_s_3',
                           'svd_u_s_4', 'svd_u_s_5', 'svd_u_s_6']
             u_dst_cols = ['svd_u_d_1', 'svd_u_d_2', 'svd_u_d_3',
                           'svd_u_d_4', 'svd_u_d_5','svd_u_d_6']

             # source node
             U_src_array = df['source_node'].apply(lambda node_number: svd(U, node_number))
             U_src_array = [list(item) for item in list(U_src_array)]
             U_src_array = pd.DataFrame(U_src_array, columns=u_src_cols)
             # destination node
             U_dst_array = df['destination_node'].apply(lambda node_number: svd(U, node_number))
             U_dst_array = [list(item) for item in list(U_dst_array)]
             U_dst_array = pd.DataFrame(U_dst_array, columns=u_dst_cols)


             # get feature vectors from V matrix
             v_src_cols = ['svd_v_s_1','svd_v_s_2', 'svd_v_s_3',
                           'svd_v_s_4', 'svd_v_s_5', 'svd_v_s_6']
             v_dst_cols = ['svd_v_d_1', 'svd_v_d_2', 'svd_v_d_3',
                           'svd_v_d_4','svd_v_d_5','svd_v_d_6']


             # source node
```

```
    V_src_array = df['source_node'].apply(lambda node_number: svd(V.T, node_number))
    V_src_array = [list(item) for item in list(V_src_array)]
    V_src_array = pd.DataFrame(V_src_array, columns=v_src_cols)

    # destination
    V_dst_array = df['destination_node'].apply(lambda node_number: svd(V.T, node_number
    V_dst_array = [list(item) for item in list(V_dst_array)]
    V_dst_array = pd.DataFrame(V_dst_array, columns=v_dst_cols)

    # create SVD featue Dataframe
    svd_feature_df = pd.concat([U_src_array, U_dst_array, V_src_array, V_dst_array], ax

    # add dot product of svd featrues
    svd_feature_df['U_DOT'] = svd_feature_df.apply(lambda x : np.dot(x[u_src_cols],
                                                  x[u_dst_cols]), axis=1)
    svd_feature_df['V_DOT'] = svd_feature_df.apply(lambda x : np.dot(x[v_src_cols],
                                                  x[v_dst_cols]), axis=1)


    return svd_feature_df
```

10 Graph Mining - Feature Extraction

```
In [59]: def mine_features(df, G):

             # mine feature set -1
             print(datetime.now(), ' Started mine_features_set_1')
             feat_df_1 = mine_features_set_1(df, G)
             print(datetime.now(), ' mine_features_set_1 completed !!!')

             # mine feature set-2
             print(datetime.now(), ' Started mine_features_set_2')
             feat_df_2 = mine_features_set_2(df, G, wcc_list)
             print(datetime.now(), ' mine_features_set_2 completed !!!')

             # mine feature set-3
             print(datetime.now(), '  Started mine_features_set_3')
             feat_df_3 = mine_features_set_3(df, G, page_rank, katz_values,
                                             hubs_scores, authorities)
             print(datetime.now(), ' mine_features_set_3 completed !!!')

             # mine featue set-4
             print(datetime.now(), ' Started mine_features_set_4')
             feat_df_4 = mine_features_set_4(df, U, s, V)
             print(datetime.now(), ' mine_features_set_4 completed !!!')

             # create final data frame
```

```
    final_features_df = pd.concat([feat_df_1, feat_df_2,
                                   feat_df_3, feat_df_4], axis=1)

    # add label colum to the dataset
    final_features_df['Label'] = df['Label']

    print('Final feature df shape:', final_features_df.shape)

    print(datetime.now(), ' Featurization completed !!!')

    return final_features_df
```

11 Save final ML dataset

```
In [60]: final_train_features_df = mine_features(sample_train_df, G_train)
         final_test_features_df = mine_features(sample_test_df, G_train)
```

```
2019-06-22 00:28:38.257715  Started mine_features_set_1
2019-06-22 00:28:46.949583  mine_features_set_1 completed !!!
2019-06-22 00:28:46.949685  Started mine_features_set_2
2019-06-22 00:30:41.871410  mine_features_set_2 completed !!!
2019-06-22 00:30:41.871516   Started mine_features_set_3
2019-06-22 00:30:42.835645  mine_features_set_3 completed !!!
2019-06-22 00:30:42.835762  Started mine_features_set_4
   source_node  destination_node  Label
0      1663332            517966      0
1       888857            914745      0
2      1350917            280693      0
3       233770           1624840      0
4       538698           1076250      1
2019-06-22 00:34:48.922123  mine_features_set_4 completed !!!
Final feature df shape: (100000, 63)
2019-06-22 00:34:48.933873  Featurization completed !!!
2019-06-22 00:34:48.934123  Started mine_features_set_1
2019-06-22 00:34:57.756905  mine_features_set_1 completed !!!
2019-06-22 00:34:57.756996  Started mine_features_set_2
2019-06-22 00:36:58.492786  mine_features_set_2 completed !!!
2019-06-22 00:36:58.492876   Started mine_features_set_3
2019-06-22 00:36:59.148978  mine_features_set_3 completed !!!
2019-06-22 00:36:59.149098  Started mine_features_set_4
   source_node  destination_node  Label
0      1311734            608284      0
1       204267            422639      0
2       570292            225447      1
3      1649996            422952      1
4      1234538            909373      0
2019-06-22 00:40:54.812781  mine_features_set_4 completed !!!
```

```
Final feature df shape: (100000, 63)
2019-06-22 00:40:54.824774  Featurization completed !!!
```

```
In [61]: final_train_features_df.to_csv('./data/Final_graph_train_features.csv', index=False)
         final_test_features_df.to_csv('./data/Final_graph_test_features.csv', index=False)
```

12 Procedure Summary

Basic EDA on degree of vertex, followees, followers, followees + followers is done on the dataset

Generated the missing edges from the dataset by considering only those missing edges with shortest path > 2

Added the featue set by grpah mining methods such as page rank, hits score, adar index, follows back, cosine distance, jaccard distance etc.

Added svd features of follower as well as followee

Added an engineered feature of svd dot

Added preferential attachment feature

Saved the train, test feature sets

13 Conclusion

Graph mining is done on the social media dataset

Generated train, test sets for the ML model