Social network Graph Link Prediction - Facebook Challenge

Problem statement:

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

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
```

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_prediction.pdf
  - https://www.youtube.com/watch?v=2M77Hgy17cg

Business objectives and constraints:

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

Performance metric for supervised learning:

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

In [103]:

```
#Importing Libraries
# please do go through this python notebook:
import warnings
warnings.filterwarnings("ignore")

import csv
import pandas as pd#pandas to create small dataframes
import datetime #Convert to unix time
import time #Convert to unix time
# if numpy is not installed already : pip3 install numpy
import numpy as np#Do aritmetic operations on arrays
# matplotlib: used to plot graphs
import matplotlib
import matplotlib.pylab as plt
import seaborn as sns#Plots
from matplotlib import rcParams#Size of plots
from sklearn.cluster import MiniBatchKMeans, KMeans#Clustering
import math
import pickle
import os
# to install xgboost: pip3 install xgboost
import xgboost as xgb

import warnings
```

```
import networkx as nx
import pdb
import pickle
```

In [104]:

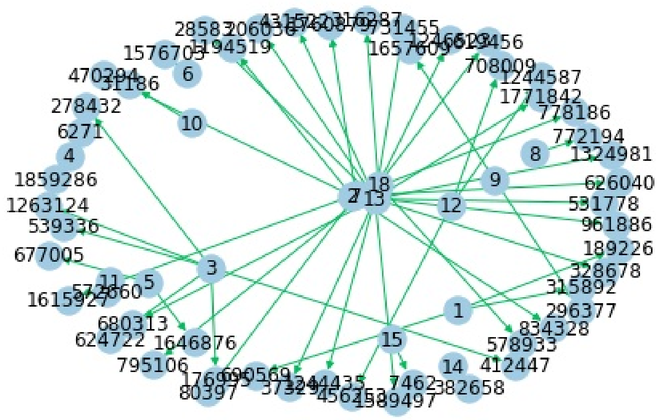
```
#reading graph
if not os.path.isfile('train_woheader.csv'):
    traincsv = pd.read_csv('train.csv')
    print(traincsv[traincsv.isna().any(1)])
    print(traincsv.info())
    print("Number of diplicate entries: ",sum(traincsv.duplicated()))
    traincsv.to_csv('train_woheader.csv',header=False,index=False)
    print("saved the graph into file")
else:
    g=nx.read_edgelist('train_woheader.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=int)
    print(nx.info(g))
```

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

In [105]:

```
if not os.path.isfile('train_woheader_sample.csv'):
    pd.read_csv('train.csv', nrows=50).to_csv('train_woheader_sample.csv',header=False,index=False)

subgraph=nx.read_edgelist('train_woheader_sample.csv',delimiter=',',create_using=nx.DiGraph(),node
type=int)
# https://stackoverflow.com/questions/9402255/drawing-a-huge-graph-with-networkx-and-matplotlib

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("graph_sample.pdf")
print(nx.info(subgraph))
```

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



1. Exploratory Data Analysis

In [106]:

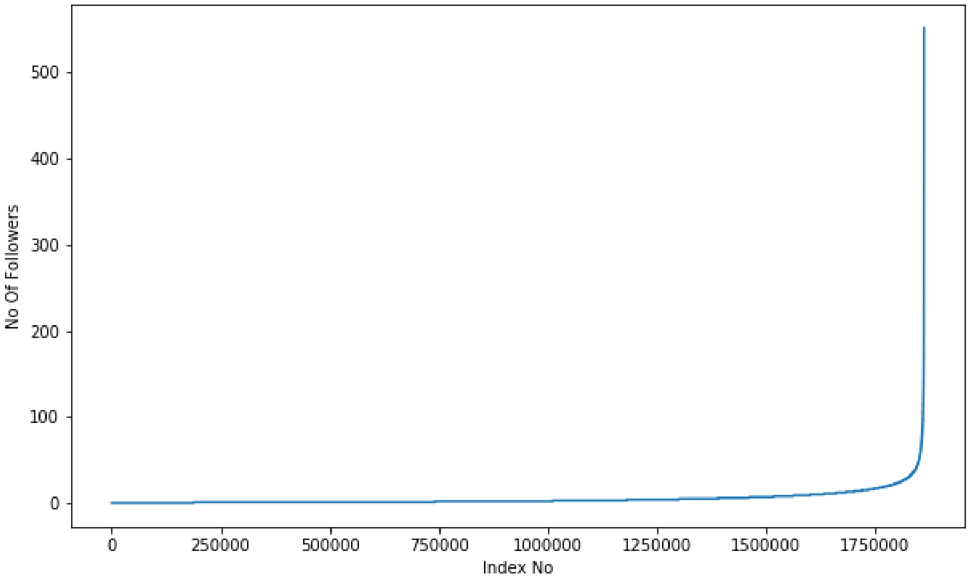
```
# No of Unique persons
print("The number of unique persons",len(g.nodes()))
```

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

1.1 No of followers for each person

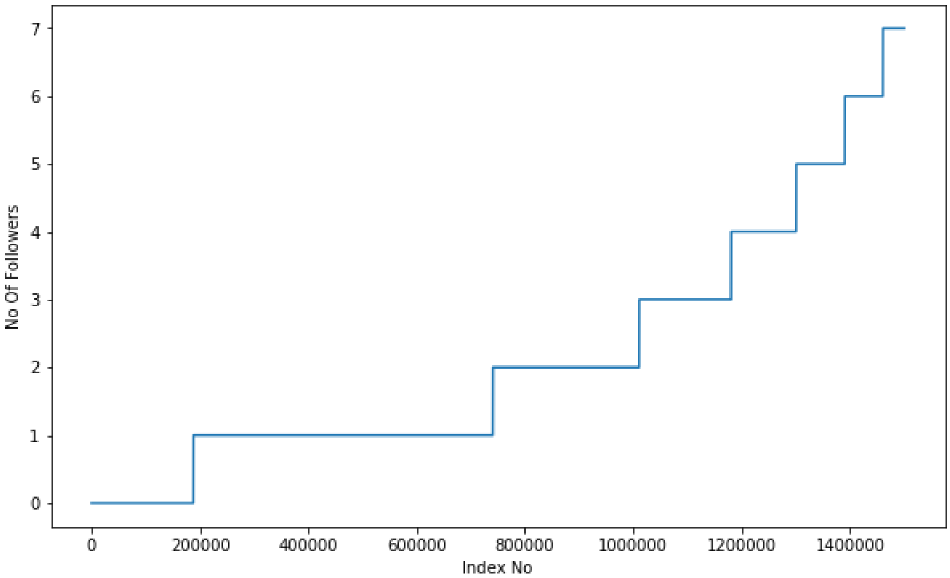
In [107]:

```
indegree_dist = list(dict(g.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.show()
```



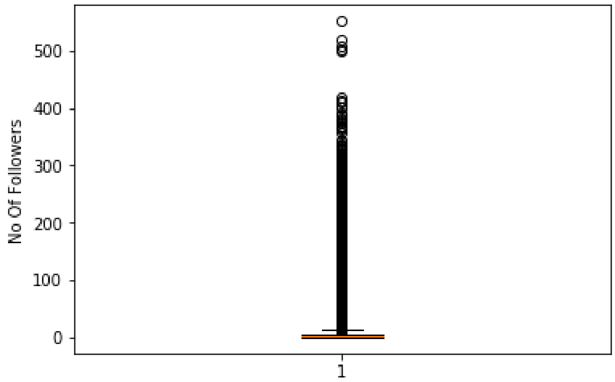
In [108]:

```
indegree_dist = list(dict(g.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.show()
```



In [109]:

```
plt.boxplot(indegree_dist)
plt.ylabel('No Of Followers')
plt.show()
```



In [110]:

```
### 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
```

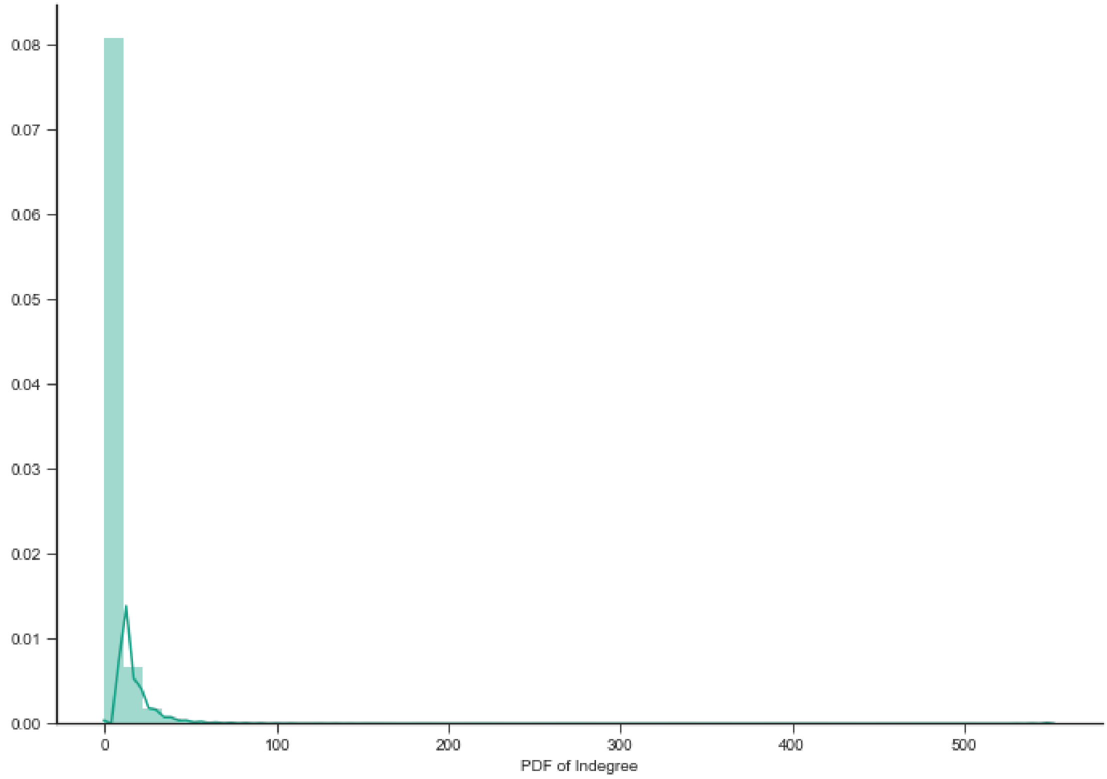
In [111]:

```
### 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 [112]:

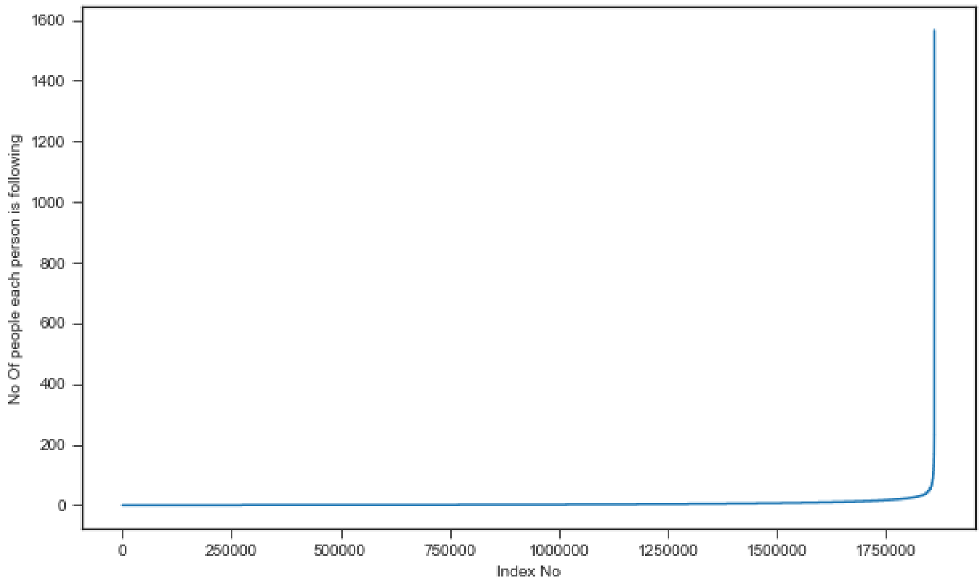
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
sns.set_style('ticks')
fig, ax = plt.subplots()
fig.set_size_inches(11.7, 8.27)
sns.distplot(indegree_dist, color='#16A085')
plt.xlabel('PDF of Indegree')
sns.despine()
#plt.show()
```



1.2 No of people each person is following

In [113]:

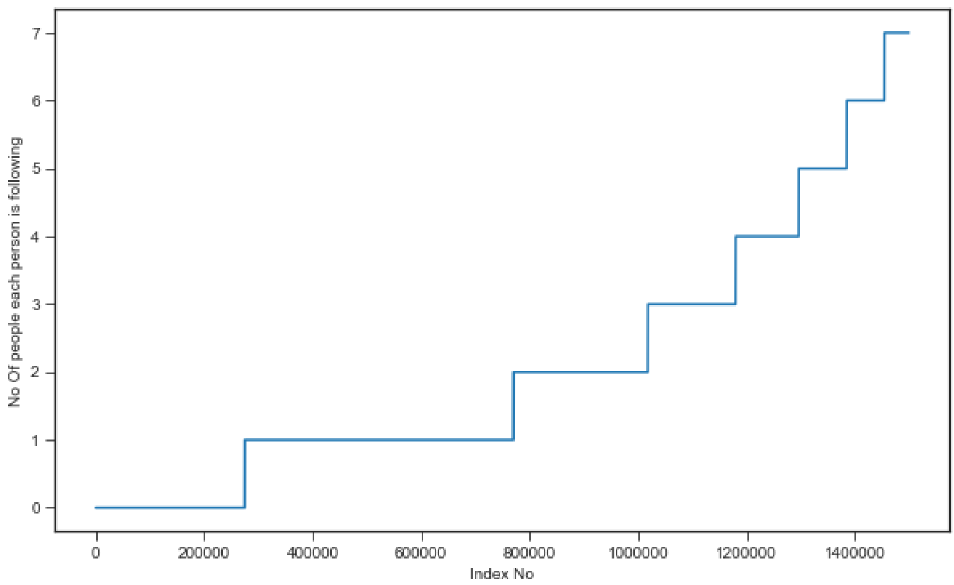
```
outdegree_dist = list(dict(g.out_degree()).values())
outdegree_dist.sort()
plt.figure(figsize=(10,6))
plt.plot(outdegree_dist)
plt.xlabel('Index No')
plt.ylabel('No Of people each person is following')
plt.show()
```



In [114]:

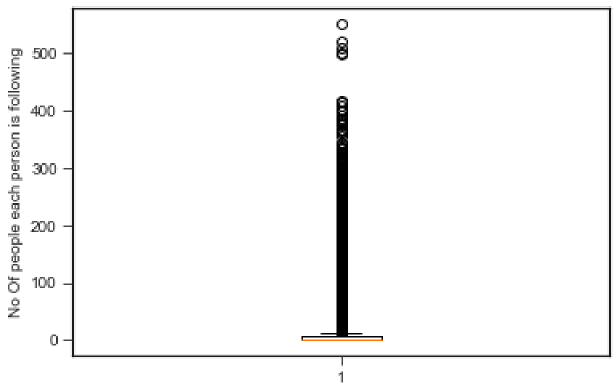
```
indegree_dist = list(dict(g.in_degree()).values())
indegree_dist.sort()
plt.figure(figsize=(10,6))
plt.plot(outdegree_dist[0:1500000])
plt.xlabel('Index No')
```

```
plt.ylabel('No Of people each person is following')
plt.show()
```



In [115]:

```
plt.boxplot(indegree_dist)
plt.ylabel('No Of people each person is following')
plt.show()
```



In [116]:

```
### 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
```

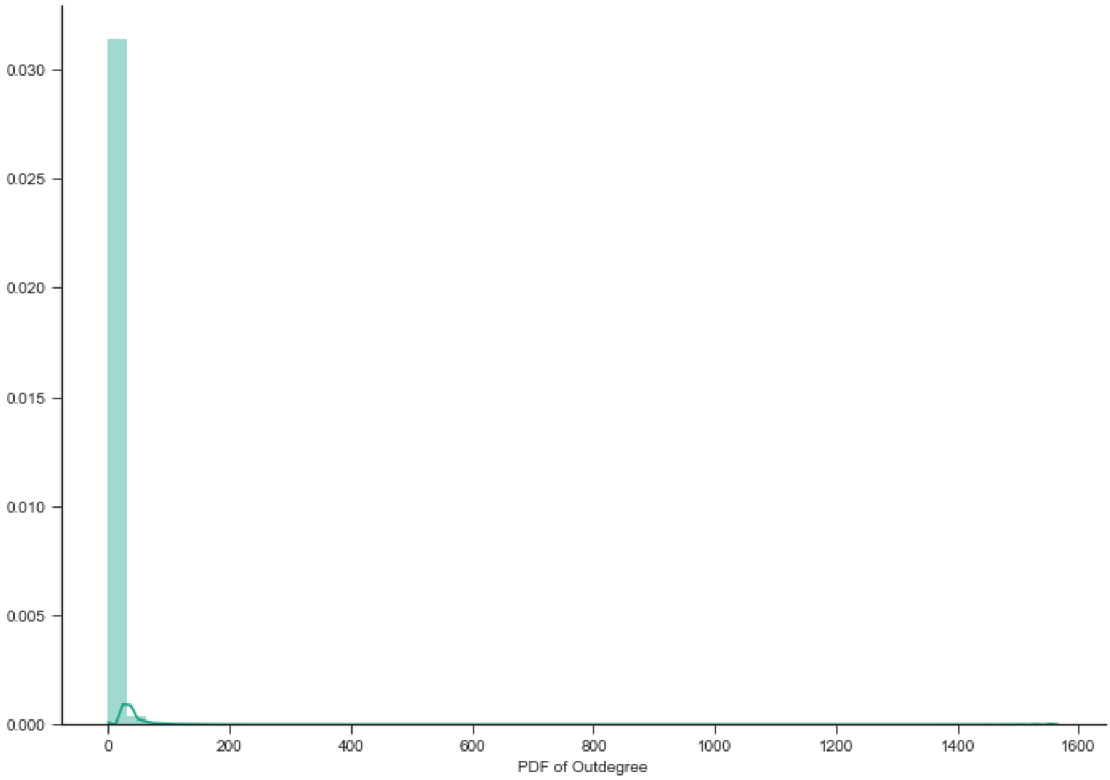
In [117]:

```
### 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 [118]:

```
import warnings
warnings.filterwarnings("ignore")
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')
sns.despine()
```



In [119]:

```
print('No of persons those are not following anyone are' ,sum(np.array(outdegree_dist)==0),'and %
is',
                                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 [120]:

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

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

In [121]:

```
count=0
```

```
for i in g.nodes():
    if len(list(g.predecessors(i)))==0 :
        if len(list(g.successors(i)))==0:
            count+=1
print('No of persons those are not not following anyone and also not having any followers are',cou
nt)
```

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

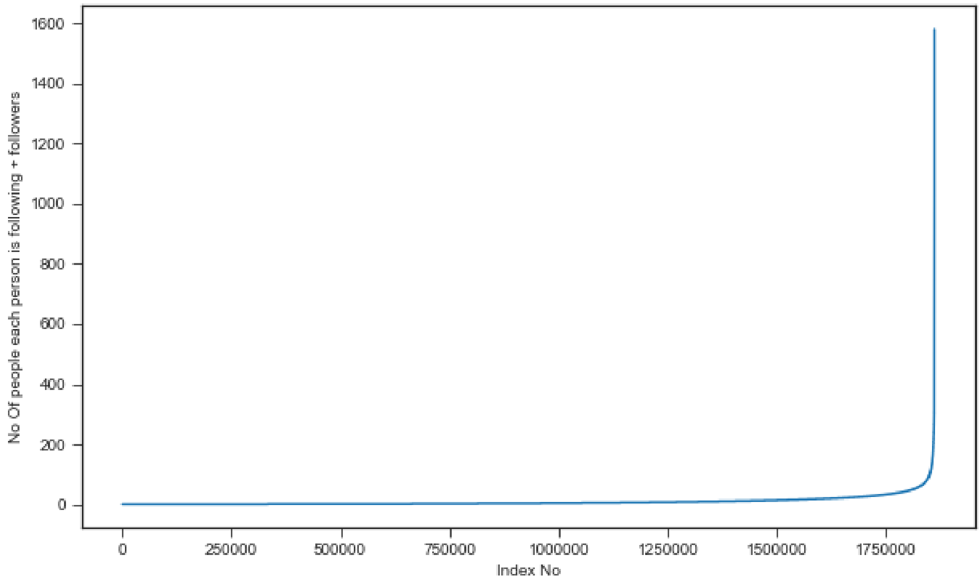
1.3 both followers + following

In [122]:

```
from collections import Counter
dict_in = dict(g.in_degree())
dict_out = dict(g.out_degree())
d = Counter(dict_in) + Counter(dict_out)
in_out_degree = np.array(list(d.values()))
```

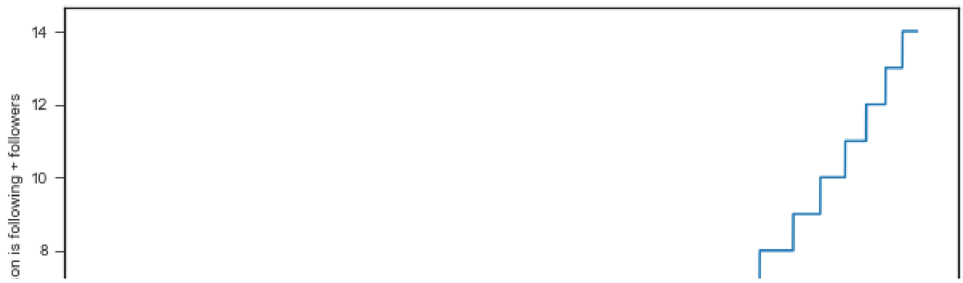
In [21]:

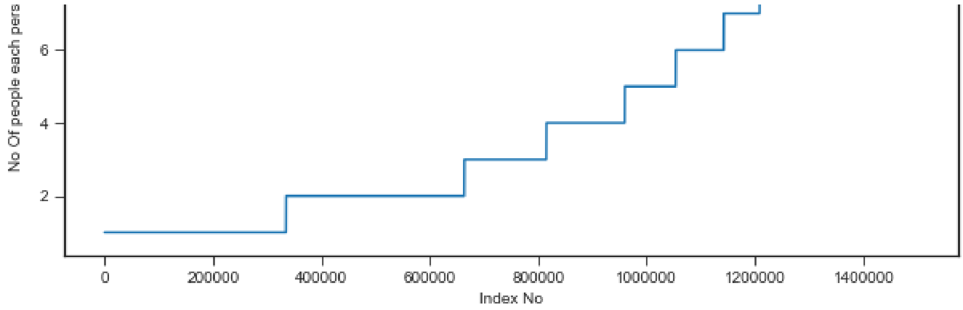
```
in_out_degree_sort = sorted(in_out_degree)
plt.figure(figsize=(10,6))
plt.plot(in_out_degree_sort)
plt.xlabel('Index No')
plt.ylabel('No Of people each person is following + followers')
plt.show()
```



In [22]:

```
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.show()
```





In [23]:

```
### 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 [24]:

```
### 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 [25]:

```
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 followers +
following')
```

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

In [26]:

```
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 followers +
following')
```

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

In [27]:

```
print('No of persons having followers + following less than 10 are',np.sum(in_out_degree<10))
```

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

In [28]:

```
print('No of weakly connected components',len(list(nx.weakly_connected_components(g))))
count=0
for i in list(nx.weakly_connected_components(g)):
    if len(i)==2:
        count+=1
print('weakly connected components wit 2 nodes',count)
```

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

2. Posing a problem as classification problem

2.1 Generating some edges which are not present in graph for supervised learning

Generated Bad links from graph which are not in graph and whose shortest path is greater than 2.

In [46]:

```
%%time
###generating bad edges from given graph
import random
if not os.path.isfile('missing_edges_final.p'):
    #getting all set of edges
    r = csv.reader(open('train_woheader.csv','r'))
    edges = dict()
    for edge in r:
        edges[(edge[0], edge[1])] = 1


    missing_edges = set([])
    while (len(missing_edges)<9437519):
        a=random.randint(1, 1862220)
        b=random.randint(1, 1862220)
        tmp = edges.get((a,b),-1)
        if tmp == -1 and a!=b:
            try:
                if nx.shortest_path_length(g,source=a,target=b) > 2:

                    missing_edges.add((a,b))
                else:
                    continue
            except:
                    missing_edges.add((a,b))
        else:
            continue
    pickle.dump(missing_edges,open('missing_edges_final.p','wb'))
else:
    missing_edges = pickle.load(open('missing_edges_final.p','rb'))
```

```
Wall time: 6.49 s
```

In [47]:

```
missing_edges = pickle.load(open('missing_edges_final.p','rb'))
len(missing_edges)
```

Out[47]:

```
9437519
```

2.2 Training and Test data split:

Removed edges from Graph and used as test data and after removing used that graph for creating features for Train and test data

In [48]:

```
from sklearn.model_selection import train_test_split
if (not os.path.isfile('train_pos_after_eda.csv')) and (not os.path.isfile('test_pos_after_eda.csv'
)):
    df_pos = pd.read_csv('train.csv')
    df_neg = pd.DataFrame(list(missing_edges), columns=['source_node', 'destination_node'])

    print("Number of nodes in the graph with edges", df_pos.shape[0])
    print("Number of nodes in the graph without edges", df_neg.shape[0])

    #Trian test split
    #Spiltted data into 80-20
    #positive links and negative links seperatly because we need positive training data only for c
reating graph
    #and for feature generation
    X_train_pos, X_test_pos, y_train_pos, y_test_pos  = train_test_split(df_pos,np.ones(len(df_pos)
),test_size=0.2, random_state=9)
    X_train_neg, X_test_neg, y_train_neg, y_test_neg  = train_test_split(df_neg,np.zeros(len(df_neg
)),test_size=0.2, random_state=9)

    print('='*60)
    print("Number of nodes in the train data graph with edges", X_train_pos.shape[0],"=",y_train_po
s.shape[0])
    print("Number of nodes in the train data graph without edges", X_train_neg.shape[0],"=", y_trai
n_neg.shape[0])
    print('='*60)
    print("Number of nodes in the test data graph with edges", X_test_pos.shape[0],"=",y_test_pos.s
hape[0])
    print("Number of nodes in the test data graph without edges",
X_test_neg.shape[0],"=",y_test_neg.shape[0])

    #removing header and saving
    X_train_pos.to_csv('train_pos_after_eda.csv',header=False, index=False)
    X_test_pos.to_csv('test_pos_after_eda.csv',header=False, index=False)
    X_train_neg.to_csv('train_neg_after_eda.csv',header=False, index=False)
    X_test_neg.to_csv('test_neg_after_eda.csv',header=False, index=False)
else:
    #Graph from Traing data only
    print('deleting ........')
    del missing_edges
```

```
Number of nodes in the graph with edges 9437519
Number of nodes in the graph without edges 9437519
============================================================
Number of nodes in the train data graph with edges 7550015 = 7550015
Number of nodes in the train data graph without edges 7550015 = 7550015
============================================================
Number of nodes in the test data graph with edges 1887504 = 1887504
Number of nodes in the test data graph without edges 1887504 = 1887504
```

In [49]:

```
if (os.path.isfile('train_pos_after_eda.csv')) and (os.path.isfile('test_pos_after_eda.csv')):


train_graph=nx.read_edgelist('train_pos_after_eda.csv',delimiter=',',create_using=nx.DiGraph(),nod
etype=int)

test_graph=nx.read_edgelist('test_pos_after_eda.csv',delimiter=',',create_using=nx.DiGraph(),nodety
pe=int)
    print(nx.info(train_graph))
    print(nx.info(test_graph))

    # finding the unique nodes in the both train and test graphs
    train_nodes_pos = set(train_graph.nodes())
    test_nodes_pos = set(test_graph.nodes())

    trY_teY = len(train_nodes_pos.intersection(test_nodes_pos))
    trY_teN = len(train_nodes_pos - test_nodes_pos)
    teY_trN = len(test_nodes_pos - train_nodes_pos)

    print('no of people common in train and test -- ',trY_teY)
```

```
    print('no of people present in train but not present in test -- ',trY_teN)

    print('no of people present in test but not present in train -- ',teY_trN)
    print(' % of people not there in Train but exist in Test in total Test data are {} %'.format(te
Y_trN/len(test_nodes_pos)*100))
```

```
Name:
Type: DiGraph
Number of nodes: 1780722
Number of edges: 7550015
Average in degree:   4.2399
Average out degree:   4.2399
Name:
Type: DiGraph
Number of nodes: 1144623
Number of edges: 1887504
Average in degree:   1.6490
Average out degree:   1.6490
no of people common in train and test --  1063125
no of people present in train but not present in test --  717597
no of people present in test but not present in train --  81498
 % of people not there in Train but exist in Test in total Test data are 7.1200735962845405 %
```

In [52]:

```
X_train_pos = pd.read_csv('train_pos_after_eda.csv', names=['source_node', 'destination_node'])
X_test_pos = pd.read_csv('test_pos_after_eda.csv', names=['source_node', 'destination_node'])
X_train_neg = pd.read_csv('train_neg_after_eda.csv', names=['source_node', 'destination_node'])
X_test_neg = pd.read_csv('test_neg_after_eda.csv', names=['source_node', 'destination_node'])
print('='*60)
print("Number of nodes in the train data graph with edges", X_train_pos.shape[0])
print("Number of nodes in the train data graph without edges", X_train_neg.shape[0])
print('='*60)
print("Number of nodes in the test data graph with edges", X_test_pos.shape[0])
print("Number of nodes in the test data graph without edges", X_test_neg.shape[0])

X_train = X_train_pos.append(X_train_neg,ignore_index=True)
y_train = np.concatenate((y_train_pos,y_train_neg))
X_test = X_test_pos.append(X_test_neg,ignore_index=True)
y_test = np.concatenate((y_test_pos,y_test_neg))
X_train.to_csv('train_after_eda.csv',header=False,index=False)
X_test.to_csv('test_after_eda.csv',header=False,index=False)
pd.DataFrame(y_train.astype(int)).to_csv('train_y.csv',header=False,index=False)
pd.DataFrame(y_test.astype(int)).to_csv('test_y.csv',header=False,index=False)
```

```
============================================================
Number of nodes in the train data graph with edges 7550015
Number of nodes in the train data graph without edges 7550015
============================================================
Number of nodes in the test data graph with edges 1887504
Number of nodes in the test data graph without edges 1887504
```

In [53]:

```
print("Data points in train data",X_train.shape)
print("Data points in test data",X_test.shape)
print("Shape of traget variable in train",y_train.shape)
print("Shape of traget variable in test", y_test.shape)
```

```
Data points in train data (15100030, 2)
Data points in test data (3775008, 2)
Shape of traget variable in train (15100030,)
Shape of traget variable in test (3775008,)
```

In [1]:

```
#Importing Libraries
# please do go through this python notebook:
import warnings
warnings.filterwarnings("ignore")

import csv
```

```
import pandas as pd#pandas to create small dataframes
import datetime #Convert to unix time
import time #Convert to unix time
# if numpy is not installed already : pip3 install numpy
import numpy as np#Do aritmetic operations on arrays
# matplotlib: used to plot graphs
import matplotlib
import matplotlib.pylab as plt
import seaborn as sns#Plots
from matplotlib import rcParams#Size of plots
from sklearn.cluster import MiniBatchKMeans, KMeans#Clustering
import math
import pickle
import os
# to install xgboost: pip3 install xgboost
import xgboost as xgb

import warnings
import networkx as nx
import pdb
import pickle
from pandas import HDFStore,DataFrame
from pandas import read_hdf
from scipy.sparse.linalg import svds, eigs
import gc
from tqdm import tqdm
```

1. Reading Data

In [2]:

```
train_graph=nx.read_edgelist('train_pos_after_eda.csv',delimiter=',',create_using=nx.DiGraph(),nod
etype=int)
print(nx.info(train_graph))
```

```
Name:
Type: DiGraph
Number of nodes: 1780722
Number of edges: 7550015
Average in degree:   4.2399
Average out degree:   4.2399
```

2. Similarity measures

2.1 Jaccard Distance:

http://www.statisticshowto.com/jaccard-index/

\begin{equation} j = \frac{|X\cap Y|}{|X \cup Y|} \end{equation}

In [3]:

```
#for followees
def jaccard_for_followees(a,b):
    try:
        if len(set(train_graph.successors(a))) == 0  | len(set(train_graph.successors(b))) == 0:
            return 0
        sim = (len(set(train_graph.successors(a)).intersection(set(train_graph.successors(b)))))/\

(len(set(train_graph.successors(a)).union(set(train_graph.successors(b)))))
    except:
        return 0
    return sim
```

In [4]:

```
#one test case
print(jaccard_for_followees(273084,1505602))
```

```
print(jaccard_for_followees(273084,1505602))
```

0.0

In [5]:

```
#node 1635354 not in graph
print(jaccard_for_followees(273084,1505602))
```

0.0

In [6]:

```
#for followers
def jaccard_for_followers(a,b):
    try:
        if len(set(train_graph.predecessors(a))) == 0  | len(set(g.predecessors(b))) == 0:
            return 0
        sim = (len(set(train_graph.predecessors(a)).intersection(set(train_graph.predecessors(b))))
)/\
                                 (len(set(train_graph.predecessors(a)).union(set(train_graph.predec
ssors(b)))))
        return sim
    except:
        return 0
```

In [7]:

```
print(jaccard_for_followers(273084,470294))
```

0

In [8]:

```
#node 1635354 not in graph
print(jaccard_for_followees(669354,1635354))
```

0

2.2 Cosine distance

\begin{equation} CosineDistance = \frac{|X\cap Y|}{|X|\cdot|Y|} \end{equation}

In [9]:

```
#for followees
def cosine_for_followees(a,b):
    try:
        if len(set(train_graph.successors(a))) == 0  | len(set(train_graph.successors(b))) == 0:
            return 0
        sim = (len(set(train_graph.successors(a)).intersection(set(train_graph.successors(b)))))/\

(math.sqrt(len(set(train_graph.successors(a)))*len((set(train_graph.successors(b))))))
        return sim
    except:
        return 0
```

In [10]:

```
print(cosine_for_followees(273084,1505602))
```

0.0

In [11]:

```
print(cosine_for_followees(273084,1635354))
```

```
print(cosine_for_followees(273084,1635354))
```

0

In [12]:

```
def cosine_for_followers(a,b):
    try:

        if len(set(train_graph.predecessors(a))) == 0  | len(set(train_graph.predecessors(b))) == 0
:
            return 0
        sim = (len(set(train_graph.predecessors(a)).intersection(set(train_graph.predecessors(b))))
)/\
                                     (math.sqrt(len(set(train_graph.predecessors(a))))*(len(set(tra
n_graph.predecessors(b)))))
        return sim
    except:
        return 0
```

In [13]:

```
print(cosine_for_followers(2,470294))
```

0.02886751345948129

In [14]:

```
print(cosine_for_followers(669354,1635354))
```

0

3. Ranking Measures

https://networkx.github.io/documentation/networkx-1.10/reference/generated/networkx.algorithms.link_analysis.pagerank_alg.pagerank.html

PageRank computes a ranking of the nodes in the graph G based on the structure of the incoming links.

Mathematical PageRanks for a simple network, expressed as percentages. (Google uses a logarithmic scale.) Page C has a higher PageRank than Page E, even though there are fewer links to C; the one link to C comes from an important page and hence is of high value. If web surfers who start on a random page have an 85% likelihood of choosing a random link from the page they are currently visiting, and a 15% likelihood of jumping to a page chosen at random from the entire web, they will reach Page E 8.1% of the time. **(The 15% likelihood of jumping to an arbitrary page corresponds to a damping factor of 85%.) Without damping, all web surfers would eventually end up on Pages A, B, or C, and all other pages would have PageRank zero. In the presence of damping, Page A effectively links to all pages in the web, even though it has no outgoing links of its own.**

3.1 Page Ranking

https://en.wikipedia.org/wiki/PageRank

In [15]:

```
if not os.path.isfile('page_rank.p'):
    pr = nx.pagerank(train_graph, alpha=0.85)
    pickle.dump(pr,open('page_rank.p','wb'))
else:
    pr = pickle.load(open('page_rank.p','rb'))
```

In [16]:

```
print('min',pr[min(pr, key=pr.get)])
print('max',pr[max(pr, key=pr.get)])
print('mean',float(sum(pr.values())) / len(pr))
```

```
min 1.6556497245737814e-07
max 2.7098251341935827e-05
mean 5.615699699389075e-07
```

In [17]:

```
#for imputing to nodes which are not there in Train data
mean_pr = float(sum(pr.values())) / len(pr)
print(mean_pr)
```

```
5.615699699389075e-07
```

4. Other Graph Features

4.1 Shortest path:

Getting Shortest path between twoo nodes, if nodes have direct path i.e directly connected then we are removing that edge and calculating path.

In [18]:

```
#if has direct edge then deleting that edge and calculating shortest path
def compute_shortest_path_length(a,b):
    p=-1
    try:
        if train_graph.has_edge(a,b):
            train_graph.remove_edge(a,b)
            p= nx.shortest_path_length(train_graph,source=a,target=b)
            train_graph.add_edge(a,b)
        else:
            p= nx.shortest_path_length(train_graph,source=a,target=b)
        return p
    except:
        return -1
```

In [19]:

```
#testing
compute_shortest_path_length(77697, 826021)
```

Out[19]:

```
10
```

In [20]:

```
#testing
compute_shortest_path_length(669354,1635354)
```

Out[20]:

```
-1
```

4.2 Checking for same community

In [21]:

```
#getting weekly connected edges from graph
wcc=list(nx.weakly_connected_components(train_graph))
def belongs_to_same_wcc(a,b):
    index = []
    if train_graph.has_edge(b,a):
        return 1
    if train_graph.has_edge(a,b):
            for i in wcc:
```

```
            for i in wcc:
                if a in i:
                    index= i
                    break
            if (b in index):
                train_graph.remove_edge(a,b)
                if compute_shortest_path_length(a,b)==-1:
                    train_graph.add_edge(a,b)
                    return 0
                else:
                    train_graph.add_edge(a,b)
                    return 1
            else:
                return 0
    else:
            for i in wcc:
                if a in i:
                    index= i
                    break
            if(b in index):
                return 1
            else:
                return 0
```

In [22]:

```
belongs_to_same_wcc(861, 1659750)
```

Out[22]:

0

In [23]:

```
belongs_to_same_wcc(669354,1635354)
```

Out[23]:

0

4.3 Adamic/Adar Index:

Adamic/Adar measures is defined as inverted sum of degrees of common neighbours for given two vertices. $$A(x,y)=\sum_{u \in N(x) \cap N(y)}\frac{1}{log(|N(u)|)}$$

In [24]:

```
#adar index
def calc_adar_in(a,b):
    sum=0
    try:
        n=list(set(train_graph.successors(a)).intersection(set(train_graph.successors(b))))
        if len(n)!=0:
            for i in n:
                sum=sum+(1/np.log10(len(list(train_graph.predecessors(i)))))
            return sum
        else:
            return 0
    except:
        return 0
```

In [25]:

```
calc_adar_in(1,189226)
```

Out[25]:

0

In [26]:

```
calc_adar_in(669354,1635354)
```

Out[26]:

```
0
```

4.4 Is persion was following back:

In [27]:

```
def follows_back(a,b):
    if train_graph.has_edge(b,a):
        return 1
    else:
        return 0
```

In [28]:

```
follows_back(1,189226)
```

Out[28]:

```
1
```

In [29]:

```
follows_back(669354,1635354)
```

Out[29]:

```
0
```

4.5 Katz Centrality:

https://en.wikipedia.org/wiki/Katz_centrality

https://www.geeksforgeeks.org/katz-centrality-centrality-measure/ Katz centrality computes the centrality for a node based on the centrality of its neighbors. It is a generalization of the eigenvector centrality. The Katz centrality for node `i` is

$$x_i = \alpha \sum_{j} A_{ij} x_j + \beta,$$ where `A` is the adjacency matrix of the graph G with eigenvalues $$\lambda$$.

The parameter $$\beta$$ controls the initial centrality and

$$\alpha < \frac{1}{\lambda_{max}}.$$

In [30]:

```
if not os.path.isfile('katz.p'):
    katz = nx.katz.katz_centrality(train_graph,alpha=0.005,beta=1)
    pickle.dump(katz,open('katz.p','wb'))
else:
    katz = pickle.load(open('katz.p','rb'))
```

In [31]:

```
print('min',katz[min(katz, key=katz.get)])
print('max',katz[max(katz, key=katz.get)])
print('mean',float(sum(katz.values())) / len(katz))
```

```
min 0.0007313532484065916
max 0.003394554981699122
mean 0.0007483800935562018
```

In [32]:

```
mean_katz = float(sum(katz.values())) / len(katz)
```

```
print(mean_katz)
```

```
0.0007483800935562018
```

4.6 Hits Score

The HITS algorithm computes two numbers for a node. Authorities estimates the node value based on the incoming links. Hubs estimates the node value based on outgoing links.

https://en.wikipedia.org/wiki/HITS_algorithm

In [33]:

```
if not os.path.isfile('hits.p'):
    hits = nx.hits(train_graph, max_iter=100, tol=1e-08, nstart=None, normalized=True)
    pickle.dump(hits,open('hits.p','wb'))
else:
    hits = pickle.load(open('hits.p','rb'))
```

In [34]:

```
 print('min',hits[0][min(hits[0], key=hits[0].get)])
print('max',hits[0][max(hits[0], key=hits[0].get)])
print('mean',float(sum(hits[0].values())) / len(hits[0]))
```

```
min 0.0
max 0.004868653378780953
mean 5.615699699344123e-07
```

5. Featurization

In [35]:

```
import random
if os.path.isfile('train_after_eda.csv'):
    filename = "train_after_eda.csv"
    # you uncomment this line, if you dont know the lentgh of the file name
    # here we have hardcoded the number of lines as 15100030
    # n_train = sum(1 for line in open(filename)) #number of records in file (excludes header)
    n_train =  15100028
    s = 100000 #desired sample size
    skip_train = sorted(random.sample(range(1,n_train+1),n_train-s))
    #https://stackoverflow.com/a/22259008/4084039
```

In [36]:

```
if os.path.isfile('train_after_eda.csv'):
    filename = "test_after_eda.csv"
    # you uncomment this line, if you dont know the lentgh of the file name
    # here we have hardcoded the number of lines as 3775008
    # n_test = sum(1 for line in open(filename)) #number of records in file (excludes header)
    n_test = 3775006
    s = 50000 #desired sample size
    skip_test = sorted(random.sample(range(1,n_test+1),n_test-s))
    #https://stackoverflow.com/a/22259008/4084039
```

In [37]:

```
print("Number of rows in the train data file:", n_train)
print("Number of rows we are going to elimiate in train data are",len(skip_train))
print("Number of rows in the test data file:", n_test)
print("Number of rows we are going to elimiate in test data are",len(skip_test))
```

```
Number of rows in the train data file: 15100028
Number of rows we are going to elimiate in train data are 15000028
Number of rows in the test data file: 3775006
Number of rows we are going to elimiate in test data are 3725006
```

```
Number of rows we are going to elimiate in test data are 3725006
```

In [38]:

```python
df_final_train = pd.read_csv('train_after_eda.csv', skiprows=skip_train, names=['source_node', 'destination_node'])
df_final_train['indicator_link'] = pd.read_csv('train_y.csv', skiprows=skip_train, names=['indicator_link'])
print("Our train matrix size ",df_final_train.shape)
df_final_train.head(2)
```

```
Our train matrix size  (100002, 3)
```

Out[38]:

	source_node	destination_node	indicator_link
0	273084	1505602	1.0
1	1071699	800041	1.0

In [39]:

```python
df_final_test = pd.read_csv('test_after_eda.csv', skiprows=skip_test, names=['source_node', 'destination_node'])
df_final_test['indicator_link'] = pd.read_csv('test_y.csv', skiprows=skip_test, names=['indicator_link'])
print("Our test matrix size ",df_final_test.shape)
df_final_test.head(2)
```

```
Our test matrix size  (50002, 3)
```

Out[39]:

	source_node	destination_node	indicator_link
0	848424	784690	1
1	1105426	490941	1

5.2 Adding a set of features

we will create these each of these features for both train and test data points

1. jaccard_followers
2. jaccard_followees
3. cosine_followers
4. cosine_followees
5. num_followers_s
6. num_followees_s
7. num_followers_d
8. num_followees_d
9. inter_followers
10. inter_followees

In [40]:

```python
if not os.path.isfile('storage_sample_stage1.h5'):
    #mapping jaccrd followers to train and test data
    df_final_train['jaccard_followers'] = df_final_train.apply(lambda row:

jaccard_for_followers(row['source_node'],row['destination_node']),axis=1)
    df_final_test['jaccard_followers'] = df_final_test.apply(lambda row:

jaccard_for_followers(row['source_node'],row['destination_node']),axis=1)

    #mapping jaccrd followees to train and test data
    df_final_train['jaccard_followees'] = df_final_train.apply(lambda row:
```

```
jaccard_for_followees(row['source_node'],row['destination_node']),axis=1)
    df_final_test['jaccard_followees'] = df_final_test.apply(lambda row:

jaccard_for_followees(row['source_node'],row['destination_node']),axis=1)


        #mapping jaccrd followers to train and test data
    df_final_train['cosine_followers'] = df_final_train.apply(lambda row:

cosine_for_followers(row['source_node'],row['destination_node']),axis=1)
    df_final_test['cosine_followers'] = df_final_test.apply(lambda row:

cosine_for_followers(row['source_node'],row['destination_node']),axis=1)

    #mapping jaccrd followees to train and test data
    df_final_train['cosine_followees'] = df_final_train.apply(lambda row:

cosine_for_followees(row['source_node'],row['destination_node']),axis=1)
    df_final_test['cosine_followees'] = df_final_test.apply(lambda row:

cosine_for_followees(row['source_node'],row['destination_node']),axis=1)
```

In [41]:

```
def compute_features_stage1(df_final):
    #calculating no of followers followees for source and destination
    #calculating intersection of followers and followees for source and destination
    num_followers_s=[]
    num_followees_s=[]
    num_followers_d=[]
    num_followees_d=[]
    inter_followers=[]
    inter_followees=[]
    for i,row in df_final.iterrows():
        try:
            s1=set(train_graph.predecessors(row['source_node']))
            s2=set(train_graph.successors(row['source_node']))
        except:
            s1 = set()
            s2 = set()
        try:
            d1=set(train_graph.predecessors(row['destination_node']))
            d2=set(train_graph.successors(row['destination_node']))
        except:
            d1 = set()
            d2 = set()
        num_followers_s.append(len(s1))
        num_followees_s.append(len(s2))

        num_followers_d.append(len(d1))
        num_followees_d.append(len(d2))

        inter_followers.append(len(s1.intersection(d1)))
        inter_followees.append(len(s2.intersection(d2)))

    return num_followers_s, num_followers_d, num_followees_s, num_followees_d, inter_followers, int
er_followees
```

In [42]:

```
import tables
if not os.path.isfile('storage_sample_stage1.h5'):
    df_final_train['num_followers_s'], df_final_train['num_followers_d'], \
    df_final_train['num_followees_s'], df_final_train['num_followees_d'], \
    df_final_train['inter_followers'], df_final_train['inter_followees']= compute_features_stage1(d
f_final_train)

    df_final_test['num_followers_s'], df_final_test['num_followers_d'], \
    df_final_test['num_followees_s'], df_final_test['num_followees_d'], \
    df_final_test['inter_followers'], df_final_test['inter_followees']=
compute_features_stage1(df_final_test)

    hdf = HDFStore('storage_sample_stage1.h5')
    hdf.put('train_df',df_final_train, format='table', data_columns=True)
```

```
    hdf.put('test_df',df_final_test, format='table', data_columns=True)
    hdf.close()
else:
    df_final_train = read_hdf('storage_sample_stage1.h5', 'train_df',mode='r')
    df_final_test = read_hdf('storage_sample_stage1.h5', 'test_df',mode='r')
```

5.3 Adding new set of features

we will create these each of these features for both train and test data points

1. adar index
2. is following back
3. belongs to same weakly connect components
4. shortest path between source and destination

In [43]:

```
if not os.path.isfile('storage_sample_stage2.h5'):
    #mapping adar index on train
    df_final_train['adar_index'] = df_final_train.apply(lambda row: calc_adar_in(row['source_node']
,row['destination_node']),axis=1)
    #mapping adar index on test
    df_final_test['adar_index'] = df_final_test.apply(lambda row: calc_adar_in(row['source_node'],r
ow['destination_node']),axis=1)

    #------------------------------------------------------------------------------------------------
------
    #mapping followback or not on train
    df_final_train['follows_back'] = df_final_train.apply(lambda row:
follows_back(row['source_node'],row['destination_node']),axis=1)

    #mapping followback or not on test
    df_final_test['follows_back'] = df_final_test.apply(lambda row: follows_back(row['source_node']
,row['destination_node']),axis=1)

    #------------------------------------------------------------------------------------------------
------
    #mapping same component of wcc or not on train
    df_final_train['same_comp'] = df_final_train.apply(lambda row: belongs_to_same_wcc(row['source_
node'],row['destination_node']),axis=1)

    ##mapping same component of wcc or not on train
    df_final_test['same_comp'] = df_final_test.apply(lambda row: belongs_to_same_wcc(row['source_no
de'],row['destination_node']),axis=1)

    #------------------------------------------------------------------------------------------------
------
    #mapping shortest path on train
    df_final_train['shortest_path'] = df_final_train.apply(lambda row: compute_shortest_path_length
(row['source_node'],row['destination_node']),axis=1)
    #mapping shortest path on test
    df_final_test['shortest_path'] = df_final_test.apply(lambda row: compute_shortest_path_length(r
ow['source_node'],row['destination_node']),axis=1)

    hdf = HDFStore('storage_sample_stage2.h5')
    hdf.put('train_df',df_final_train, format='table', data_columns=True)
    hdf.put('test_df',df_final_test, format='table', data_columns=True)
    hdf.close()
else:
    df_final_train = read_hdf('storage_sample_stage2.h5', 'train_df',mode='r')
    df_final_test = read_hdf('storage_sample_stage2.h5', 'test_df',mode='r')
```

5.4 Adding new set of features

we will create these each of these features for both train and test data points

1. Weight Features
    - weight of incoming edges
    - weight of outgoing edges
    - weight of incoming edges + weight of outgoing edges
    - weight of incoming edges * weight of outgoing edges

- weight of incoming edges * weight of outgoing edges
  - 2*weight of incoming edges + weight of outgoing edges
  - weight of incoming edges + 2*weight of outgoing edges
2. Page Ranking of source
3. Page Ranking of dest
4. katz of source
5. katz of dest
6. hubs of source
7. hubs of dest
8. authorities_s of source
9. authorities_s of dest

Weight Features

In order to determine the similarity of nodes, an edge weight value was calculated between nodes. Edge weight decreases as the neighbor count goes up. Intuitively, consider one million people following a celebrity on a social network then chances are most of them never met each other or the celebrity. On the other hand, if a user has 30 contacts in his/her social network, the chances are higher that many of them know each other. `credit` - Graph-based Features for Supervised Link Prediction William Cukierski, Benjamin Hamner, Bo Yang

\begin{equation} W = \frac{1}{\sqrt{1+|X|}} \end{equation}

it is directed graph so calculated Weighted in and Weighted out differently

In [44]:

```
#weight for source and destination of each link
Weight_in = {}
Weight_out = {}
for i in  tqdm(train_graph.nodes()):
    s1=set(train_graph.predecessors(i))
    w_in = 1.0/(np.sqrt(1+len(s1)))
    Weight_in[i]=w_in
    
    s2=set(train_graph.successors(i))
    w_out = 1.0/(np.sqrt(1+len(s2)))
    Weight_out[i]=w_out
    
#for imputing with mean
mean_weight_in = np.mean(list(Weight_in.values()))
mean_weight_out = np.mean(list(Weight_out.values()))
```

```
100%|██████████| 1780722/1780722 [00:20<00:00, 88424.83it/s]
```

In [45]:

```
if not os.path.isfile('storage_sample_stage3.h5'):
    #mapping to pandas train
    df_final_train['weight_in'] = df_final_train.destination_node.apply(lambda x: Weight_in.get(x,m
ean_weight_in))
    df_final_train['weight_out'] = df_final_train.source_node.apply(lambda x: Weight_out.get(x,mean
_weight_out))

    #mapping to pandas test
    df_final_test['weight_in'] = df_final_test.destination_node.apply(lambda x: Weight_in.get(x,mea
n_weight_in))
    df_final_test['weight_out'] = df_final_test.source_node.apply(lambda x: Weight_out.get(x,mean_w
eight_out))


    #some features engineerings on the in and out weights
    df_final_train['weight_f1'] = df_final_train.weight_in + df_final_train.weight_out
    df_final_train['weight_f2'] = df_final_train.weight_in * df_final_train.weight_out
    df_final_train['weight_f3'] = (2*df_final_train.weight_in + 1*df_final_train.weight_out)
    df_final_train['weight_f4'] = (1*df_final_train.weight_in + 2*df_final_train.weight_out)

    #some features engineerings on the in and out weights
    df_final_test['weight_f1'] = df_final_test.weight_in + df_final_test.weight_out
    df_final_test['weight_f2'] = df_final_test.weight_in * df_final_test.weight_out
    df_final_test['weight_f3'] = (2*df_final_test.weight_in + 1*df_final_test.weight_out)
```

```
    df_final_test['weight_f4'] = (1*df_final_test.weight_in + 2*df_final_test.weight_out)
```

In [46]:

```
if not os.path.isfile('storage_sample_stage3.h5'):

    #page rank for source and destination in Train and Test
    #if anything not there in train graph then adding mean page rank
    df_final_train['page_rank_s'] = df_final_train.source_node.apply(lambda x:pr.get(x,mean_pr))
    df_final_train['page_rank_d'] = df_final_train.destination_node.apply(lambda x:pr.get(x,mean_pr
))

    df_final_test['page_rank_s'] = df_final_test.source_node.apply(lambda x:pr.get(x,mean_pr))
    df_final_test['page_rank_d'] = df_final_test.destination_node.apply(lambda x:pr.get(x,mean_pr))
    #================================================================================

    #Katz centrality score for source and destination in Train and test
    #if anything not there in train graph then adding mean katz score
    df_final_train['katz_s'] = df_final_train.source_node.apply(lambda x: katz.get(x,mean_katz))
    df_final_train['katz_d'] = df_final_train.destination_node.apply(lambda x: katz.get(x,mean_katz
))

    df_final_test['katz_s'] = df_final_test.source_node.apply(lambda x: katz.get(x,mean_katz))
    df_final_test['katz_d'] = df_final_test.destination_node.apply(lambda x: katz.get(x,mean_katz))
    #================================================================================

    #Hits algorithm score for source and destination in Train and test
    #if anything not there in train graph then adding 0
    df_final_train['hubs_s'] = df_final_train.source_node.apply(lambda x: hits[0].get(x,0))
    df_final_train['hubs_d'] = df_final_train.destination_node.apply(lambda x: hits[0].get(x,0))

    df_final_test['hubs_s'] = df_final_test.source_node.apply(lambda x: hits[0].get(x,0))
    df_final_test['hubs_d'] = df_final_test.destination_node.apply(lambda x: hits[0].get(x,0))
    #================================================================================

    #Hits algorithm score for source and destination in Train and Test
    #if anything not there in train graph then adding 0
    df_final_train['authorities_s'] = df_final_train.source_node.apply(lambda x: hits[1].get(x,0))
    df_final_train['authorities_d'] = df_final_train.destination_node.apply(lambda x: hits[1].get(x
,0))

    df_final_test['authorities_s'] = df_final_test.source_node.apply(lambda x: hits[1].get(x,0))
    df_final_test['authorities_d'] = df_final_test.destination_node.apply(lambda x: hits[1].get(x,0
))
    #================================================================================

    hdf = HDFStore('storage_sample_stage3.h5')
    hdf.put('train_df',df_final_train, format='table', data_columns=True)
    hdf.put('test_df',df_final_test, format='table', data_columns=True)
    hdf.close()
else:
    df_final_train = read_hdf('storage_sample_stage3.h5', 'train_df',mode='r')
    df_final_test = read_hdf('storage_sample_stage3.h5', 'test_df',mode='r')
```

In [47]:

```
df_final_train.head()
```

Out[47]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees
0	273084	1505602	1.0	0	0.0	0.000000	0.0
1	660560	1272982	1.0	0	0.0	0.000000	0.0
2	1077631	1517929	1.0	0	0.0	0.000000	0.0
3	648133	760360	1.0	0	0.0	0.098039	0.0

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees
4	933781	125939	1.0	0	0.0	0.000000	0.0

5 rows × 31 columns

Preferential Attachement

Preferential attachment means that the more connected a node is, the more likely it is to receive new links.
This algorithm was popularised by Albert-László Barabási and Réka Albert through their work on scale-free networks.
It is computed using the following formula:
PA(X,y)= N(X)*N(Y)

preferential attachment where N(u) is the set of nodes adjacent to u.

A value of 0 indicates that two nodes are not close, while higher values indicate that nodes are closer.
https://neo4j.com/docs/graph-algorithms/current/algorithms/linkprediction-preferential-attachment/index.html

Preferential Attachement for followers

In [48]:

```
#for train dataset
nfs=np.array(df_final_train['num_followers_s'])
nfd=np.array(df_final_train['num_followers_d'])
preferential=[]
for i in range(len(nfs)):
    preferential.append(nfd[i]*nfs[i])
df_final_train['prefer_followers']= preferential
df_final_train.head()
```

Out[48]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees
0	273084	1505602	1.0	0	0.0	0.000000	0.0
1	660560	1272982	1.0	0	0.0	0.000000	0.0
2	1077631	1517929	1.0	0	0.0	0.000000	0.0
3	648133	760360	1.0	0	0.0	0.098039	0.0
4	933781	125939	1.0	0	0.0	0.000000	0.0

5 rows × 32 columns

['num_followers_s'] and ['num_followers_d'] consists of follower of source and ddestination nodes

In [49]:

```
#for test dataset
nfs=np.array(df_final_test['num_followers_s'])
nfd=np.array(df_final_test['num_followers_d'])
preferential=[]
for i in range(len(nfs)):
    preferential.append(nfd[i]*nfs[i])
df_final_test['prefer_followers']= preferential
```

Preferential Attachement for followees

For Train

In [50]:

```
nfs=np.array(df_final_train['num_followees_s'])
nfd=np.array(df_final_train['num_followees_d'])
preferential_followees=[]
for i in range(len(nfs)):
    preferential_followees.append(nfd[i]*nfs[i])
df_final_train['prefer_followees']= preferential_followees
df_final_train.head()
```

Out[50]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees
0	273084	1505602	1.0	0	0.0	0.000000	0.0
1	660560	1272982	1.0	0	0.0	0.000000	0.0
2	1077631	1517929	1.0	0	0.0	0.000000	0.0
3	648133	760360	1.0	0	0.0	0.098039	0.0
4	933781	125939	1.0	0	0.0	0.000000	0.0

5 rows × 33 columns

For test

In [51]:

```
nfs=np.array(df_final_test['num_followees_s'])
nfd=np.array(df_final_test['num_followees_d'])
preferential_followees=[]
for i in range(len(nfs)):
    preferential_followees.append(nfd[i]*nfs[i])
df_final_test['prefer_followees']= preferential_followees
df_final_test.head()
```

Out[51]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees
0	848424	784690	1	0	0.000000	0.029161	0.000000
1	1315983	196578	1	0	0.083333	0.058321	0.158114
2	121108	204025	1	0	0.000000	0.000000	0.000000
3	768391	1439644	1	0	0.000000	0.176777	0.000000
4	1160135	758282	1	0	0.333333	0.144338	0.577350

5 rows × 33 columns

5.5 Adding new set of features

we will create these each of these features for both train and test data points

1. SVD features for both source and destination

In [52]:

```
def svd(x, S):
    try:
        z = sadj_dict[x]
        return S[z]
    except:
        return [0,0,0,0,0,0]
```

In [53]:

```
#for svd features to get feature vector creating a dict node val and inedx in svd vector
sadj_col = sorted(train_graph.nodes())
sadj_dict = { val:idx for idx,val in enumerate(sadj_col)}
```

In [54]:

```
Adj = nx.adjacency_matrix(train_graph,nodelist=sorted(train_graph.nodes())).asfptype()
```

In [55]:

```
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)
```

```
Adjacency matrix Shape (1780722, 1780722)
U Shape (1780722, 6)
V Shape (6, 1780722)
s Shape (6,)
```

In [68]:

```
if os.path.isfile('storage_sample_stage4.h5'):

#===================================================================================================


    df_final_train[['svd_u_s_1', 'svd_u_s_2','svd_u_s_3', 'svd_u_s_4', 'svd_u_s_5', 'svd_u_s_6']] =
\
    df_final_train.source_node.apply(lambda x: svd(x, U)).apply(pd.Series)

    df_final_train[['svd_u_d_1', 'svd_u_d_2', 'svd_u_d_3', 'svd_u_d_4', 'svd_u_d_5','svd_u_d_6']] =
\
    df_final_train.destination_node.apply(lambda x: svd(x, U)).apply(pd.Series)

#===================================================================================================


    df_final_train[['svd_v_s_1','svd_v_s_2', 'svd_v_s_3', 'svd_v_s_4', 'svd_v_s_5', 'svd_v_s_6',]]
= \
    df_final_train.source_node.apply(lambda x: svd(x, V.T)).apply(pd.Series)

    df_final_train[['svd_v_d_1', 'svd_v_d_2', 'svd_v_d_3', 'svd_v_d_4', 'svd_v_d_5','svd_v_d_6']] =
\
    df_final_train.destination_node.apply(lambda x: svd(x, V.T)).apply(pd.Series)

#===================================================================================================


    df_final_test[['svd_u_s_1', 'svd_u_s_2','svd_u_s_3', 'svd_u_s_4', 'svd_u_s_5', 'svd_u_s_6']] =
\
    df_final_test.source_node.apply(lambda x: svd(x, U)).apply(pd.Series)

    df_final_test[['svd_u_d_1', 'svd_u_d_2', 'svd_u_d_3', 'svd_u_d_4', 'svd_u_d_5','svd_u_d_6']] =
\
    df_final_test.destination_node.apply(lambda x: svd(x, U)).apply(pd.Series)


#===================================================================================================
```

```
    df_final_test[['svd_v_s_1','svd_v_s_2', 'svd_v_s_3', 'svd_v_s_4', 'svd_v_s_5', 'svd_v_s_6',]] =
\
    df_final_test.source_node.apply(lambda x: svd(x, V.T)).apply(pd.Series)

    df_final_test[['svd_v_d_1', 'svd_v_d_2', 'svd_v_d_3', 'svd_v_d_4', 'svd_v_d_5','svd_v_d_6']] =
\
    df_final_test.destination_node.apply(lambda x: svd(x, V.T)).apply(pd.Series)

#==================================================================================================
```

In [69]:

```
df_final_train.head()
```

Out[69]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees
0	273084	1505602	1.0	0	0.0	0.000000	0.0
1	660560	1272982	1.0	0	0.0	0.000000	0.0
2	1077631	1517929	1.0	0	0.0	0.000000	0.0
3	648133	760360	1.0	0	0.0	0.098039	0.0
4	933781	125939	1.0	0	0.0	0.000000	0.0

5 rows × 57 columns

In [70]:

```
df_final_train.columns
```

Out[70]:

```
Index(['source_node', 'destination_node', 'indicator_link',
       'jaccard_followers', 'jaccard_followees', 'cosine_followers',
       'cosine_followees', 'num_followers_s', 'num_followers_d',
       'num_followees_s', 'num_followees_d', 'inter_followers',
       'inter_followees', 'adar_index', 'follows_back', 'same_comp',
       'shortest_path', 'weight_in', 'weight_out', 'weight_f1', 'weight_f2',
       'weight_f3', 'weight_f4', 'page_rank_s', 'page_rank_d', 'katz_s',
       'katz_d', 'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d',
       'prefer_followers', 'prefer_followees', 'svd_u_s_1', 'svd_u_s_2',
       'svd_u_s_3', 'svd_u_s_4', 'svd_u_s_5', 'svd_u_s_6', 'svd_u_d_1',
       'svd_u_d_2', 'svd_u_d_3', 'svd_u_d_4', 'svd_u_d_5', 'svd_u_d_6',
       'svd_v_s_1', 'svd_v_s_2', 'svd_v_s_3', 'svd_v_s_4', 'svd_v_s_5',
       'svd_v_s_6', 'svd_v_d_1', 'svd_v_d_2', 'svd_v_d_3', 'svd_v_d_4',
       'svd_v_d_5', 'svd_v_d_6'],
      dtype='object')
```

svd_dot

svd_dot is dot product between sourse node svd and destination node svd features

In [71]:

```
#for train datasets
s1,s2,s3,s4,s5,s6=df_final_train['svd_u_s_1'],df_final_train['svd_u_s_2'],df_final_train['svd_u_s_3
'],df_final_train['svd_u_s_4'],df_final_train['svd_u_s_5'],df_final_train['svd_u_s_6']
s7,s8,s9,s10,s11,s12=df_final_train['svd_v_s_1'],df_final_train['svd_v_s_2'],df_final_train['svd_v_
s_3'],df_final_train['svd_v_s_4'],df_final_train['svd_v_s_5'],df_final_train['svd_v_s_6']

sd1,sd2,sd3,sd4,sd5,sd6=df_final_train['svd_u_d_1'],df_final_train['svd_u_d_2'],df_final_train['svd
_u_d_3'],df_final_train['svd_u_d_4'],df_final_train['svd_u_d_5'],df_final_train['svd_u_d_6']
sd7,sd8,sd9,sd10,sd11,sd12=df_final_train['svd_v_d_1'],df_final_train['svd_v_d_2'],df_final_train['
svd_v_d_3'],df_final_train['svd_v_d_4'],df_final_train['svd_v_d_5'],df_final_train['svd_v_d_6']
```

In [72]:

```
svd_dot=[]
for i in range(len(np.array(s1))):
    a=[]
    b=[]
    a.append(np.array(s1[i]))
    a.append(np.array(s2[i]))
    a.append(np.array(s3[i]))
    a.append(np.array(s4[i]))
    a.append(np.array(s5[i]))
    a.append(np.array(s6[i]))
    a.append(np.array(s7[i]))
    a.append(np.array(s8[i]))
    a.append(np.array(s9[i]))
    a.append(np.array(s10[i]))
    a.append(np.array(s11[i]))
    a.append(np.array(s12[i]))
    b.append(np.array(sd1[i]))
    b.append(np.array(sd2[i]))
    b.append(np.array(sd3[i]))
    b.append(np.array(sd4[i]))
    b.append(np.array(sd5[i]))
    b.append(np.array(sd6[i]))
    b.append(np.array(sd7[i]))
    b.append(np.array(sd8[i]))
    b.append(np.array(sd9[i]))
    b.append(np.array(sd10[i]))
    b.append(np.array(sd11[i]))
    b.append(np.array(sd12[i]))
    svd_dot.append(np.dot(a,b))
df_final_train['svd_dot']=svd_dot
```

In [73]:

```
df_final_train.head()
```

Out[73]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees
0	273084	1505602	1.0	0	0.0	0.000000	0.0
1	660560	1272982	1.0	0	0.0	0.000000	0.0
2	1077631	1517929	1.0	0	0.0	0.000000	0.0
3	648133	760360	1.0	0	0.0	0.098039	0.0
4	933781	125939	1.0	0	0.0	0.000000	0.0

5 rows × 58 columns

In [74]:

```
#for test dataset
s1,s2,s3,s4,s5,s6=df_final_test['svd_u_s_1'],df_final_test['svd_u_s_2'],df_final_test['svd_u_s_3']
,df_final_test['svd_u_s_4'],df_final_test['svd_u_s_5'],df_final_test['svd_u_s_6']
s7,s8,s9,s10,s11,s12=df_final_test['svd_v_s_1'],df_final_test['svd_v_s_2'],df_final_test['svd_v_s_3
'],df_final_test['svd_v_s_4'],df_final_test['svd_v_s_5'],df_final_test['svd_v_s_6']

sd1,sd2,sd3,sd4,sd5,sd6=df_final_test['svd_u_d_1'],df_final_test['svd_u_d_2'],df_final_test['svd_u_
d_3'],df_final_test['svd_u_d_4'],df_final_test['svd_u_d_5'],df_final_test['svd_u_d_6']
sd7,sd8,sd9,sd10,sd11,sd12=df_final_test['svd_v_d_1'],df_final_test['svd_v_d_2'],df_final_test['svd
_v_d_3'],df_final_test['svd_v_d_4'],df_final_test['svd_v_d_5'],df_final_test['svd_v_d_6']
```

In [75]:

```
svd_dot=[]
for i in range(len(np.array(s1))):
    a=[]
    b=[]
    a.append(np.array(s1[i]))
    a.append(np.array(s2[i]))
    a.append(np.array(s3[i]))
    a.append(np.array(s4[i]))
    a.append(np.array(s5[i]))
    a.append(np.array(s6[i]))
    a.append(np.array(s7[i]))
    a.append(np.array(s8[i]))
    a.append(np.array(s9[i]))
    a.append(np.array(s10[i]))
    a.append(np.array(s11[i]))
    a.append(np.array(s12[i]))
    b.append(np.array(sd1[i]))
    b.append(np.array(sd2[i]))
    b.append(np.array(sd3[i]))
    b.append(np.array(sd4[i]))
    b.append(np.array(sd5[i]))
    b.append(np.array(sd6[i]))
    b.append(np.array(sd7[i]))
    b.append(np.array(sd8[i]))
    b.append(np.array(sd9[i]))
    b.append(np.array(sd10[i]))
    b.append(np.array(sd11[i]))
    b.append(np.array(sd12[i]))
    svd_dot.append(np.dot(a,b))
df_final_test['svd_dot']=svd_dot
```

In [76]:

```
df_final_test.head()
```

Out[76]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees
0	848424	784690	1	0	0.000000	0.029161	0.000000
1	1315983	196578	1	0	0.083333	0.058321	0.158114
2	121108	204025	1	0	0.000000	0.000000	0.000000
3	768391	1439644	1	0	0.000000	0.176777	0.000000
4	1160135	758282	1	0	0.333333	0.144338	0.577350

5 rows × 58 columns

In [77]:

```
#Importing Libraries
# please do go through this python notebook:
import warnings
warnings.filterwarnings("ignore")

import csv
import pandas as pd#pandas to create small dataframes
import datetime #Convert to unix time
import time #Convert to unix time
# if numpy is not installed already : pip3 install numpy
import numpy as np#Do aritmetic operations on arrays
# matplotlib: used to plot graphs
import matplotlib
import matplotlib.pylab as plt
import seaborn as sns#Plots
from matplotlib import rcParams#Size of plots
from sklearn.cluster import MiniBatchKMeans, KMeans#Clustering
import math
import pickle
import os
# to install xgboost: pip3 install xgboost
import xgboost as xgb

import warnings
import networkx as nx
import pdb
import pickle
from pandas import HDFStore,DataFrame
from pandas import read_hdf
from scipy.sparse.linalg import svds, eigs
import gc
from tqdm import tqdm
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score
```

In [78]:

```
df_final_train.columns
```

Out[78]:

```
Index(['source_node', 'destination_node', 'indicator_link',
       'jaccard_followers', 'jaccard_followees', 'cosine_followers',
       'cosine_followees', 'num_followers_s', 'num_followers_d',
       'num_followees_s', 'num_followees_d', 'inter_followers',
       'inter_followees', 'adar_index', 'follows_back', 'same_comp',
       'shortest_path', 'weight_in', 'weight_out', 'weight_f1', 'weight_f2',
       'weight_f3', 'weight_f4', 'page_rank_s', 'page_rank_d', 'katz_s',
       'katz_d', 'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d',
       'prefer_followers', 'prefer_followees', 'svd_u_s_1', 'svd_u_s_2',
       'svd_u_s_3', 'svd_u_s_4', 'svd_u_s_5', 'svd_u_s_6', 'svd_u_d_1',
       'svd_u_d_2', 'svd_u_d_3', 'svd_u_d_4', 'svd_u_d_5', 'svd_u_d_6',
       'svd_v_s_1', 'svd_v_s_2', 'svd_v_s_3', 'svd_v_s_4', 'svd_v_s_5',
       'svd_v_s_6', 'svd_v_d_1', 'svd_v_d_2', 'svd_v_d_3', 'svd_v_d_4',
       'svd_v_d_5', 'svd_v_d_6', 'svd_dot'],
      dtype='object')
```

In [79]:

```
y_train = df_final_train.indicator_link
y_test = df_final_test.indicator_link
```

In [80]:

```
y_train=pd.Series(np.nan_to_num(y_train))
```

In [81]:

```
y_test=pd.Series(np.nan_to_num(y_test))
```

```
y_test=pd.Series(np.nan_to_num(y_test))
```

In [82]:

```
df_final_train.drop(['source_node', 'destination_node','indicator_link'],axis=1,inplace=True)
df_final_test.drop(['source_node', 'destination_node','indicator_link'],axis=1,inplace=True)
```

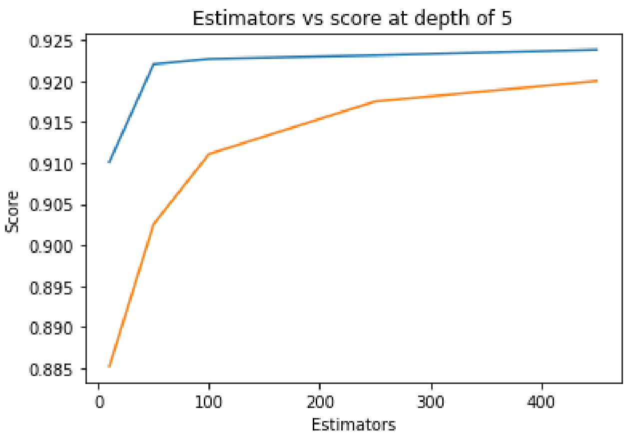
In [83]:

```
estimators = [10,50,100,250,450]
train_scores = []
test_scores = []
for i in estimators:
    clf = RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=5, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=52, min_samples_split=120,
            min_weight_fraction_leaf=0.0, n_estimators=i, n_jobs=-1,random_state=25,verbose=0,warm_
start=False)
    clf.fit(df_final_train,y_train)
    train_sc = f1_score(y_train,clf.predict(df_final_train))
    test_sc = f1_score(y_test,clf.predict(df_final_test))
    test_scores.append(test_sc)
    train_scores.append(train_sc)
    print('Estimators = ',i,'Train Score',train_sc,'test Score',test_sc)
plt.plot(estimators,train_scores,label='Train Score')
plt.plot(estimators,test_scores,label='Test Score')
plt.xlabel('Estimators')
plt.ylabel('Score')
plt.title('Estimators vs score at depth of 5')
```

```
Estimators =  10 Train Score 0.9101399255670831 test Score 0.8852067981428633
Estimators =  50 Train Score 0.9220746784331681 test Score 0.9025521550354759
Estimators =  100 Train Score 0.9227207308679056 test Score 0.911116258501969
Estimators =  250 Train Score 0.9231620602883903 test Score 0.9175346312634909
Estimators =  450 Train Score 0.923845896986393 test Score 0.920024254082422
```

Out[83]:

```
Text(0.5,1,'Estimators vs score at depth of 5')
```

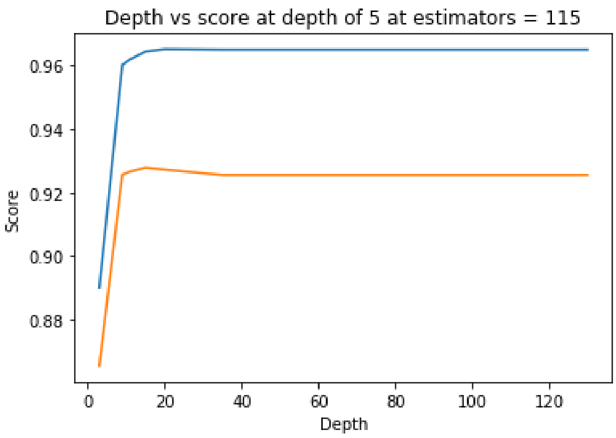


In [84]:

```
depths = [3,9,11,15,20,35,50,70,130]
train_scores = []
test_scores = []
for i in depths:
    clf = RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=i, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=52, min_samples_split=120,
            min_weight_fraction_leaf=0.0, n_estimators=115, n_jobs=-1,random_state=25,verbose=0,war
m_start=False)
    clf.fit(df_final_train,y_train)
    train_sc = f1_score(y_train,clf.predict(df_final_train))
    test_sc = f1_score(y_test,clf.predict(df_final_test))
```

```
    test_scores.append(test_sc)
    train_scores.append(train_sc)
    print('depth = ',i,'Train Score',train_sc,'test Score',test_sc)
plt.plot(depths,train_scores,label='Train Score')
plt.plot(depths,test_scores,label='Test Score')
plt.xlabel('Depth')
plt.ylabel('Score')
plt.title('Depth vs score at depth of 5 at estimators = 115')
plt.show()
```

```
depth =  3 Train Score 0.8900029304642693 test Score 0.8653747213170982
depth =  9 Train Score 0.9602389321197098 test Score 0.9256579637202476
depth =  11 Train Score 0.9619365202008906 test Score 0.9266112789526686
depth =  15 Train Score 0.9644125946527539 test Score 0.9278367826707528
depth =  20 Train Score 0.9651640383347702 test Score 0.9272334445073732
depth =  35 Train Score 0.9650081623961956 test Score 0.9255361606486441
depth =  50 Train Score 0.9650081623961956 test Score 0.9255361606486441
depth =  70 Train Score 0.9650081623961956 test Score 0.9255361606486441
depth =  130 Train Score 0.9650081623961956 test Score 0.9255361606486441
```



In [ ]:

```
from sklearn.metrics import f1_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform

param_dist = {"n_estimators":sp_randint(105,125),
              "max_depth": sp_randint(10,15),
              "min_samples_split": sp_randint(110,190),
              "min_samples_leaf": sp_randint(25,65)}

clf = RandomForestClassifier(random_state=25,n_jobs=-1)

rf_random = RandomizedSearchCV(clf, param_distributions=param_dist,
                                   n_iter=5,cv=10,scoring='f1',random_state=25)

rf_random.fit(df_final_train,y_train)
```

In [87]:

```
print(rf_random.best_estimator_)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=14, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=28, min_samples_split=111,
                       min_weight_fraction_leaf=0.0, n_estimators=121,
                       n_jobs=-1, oob_score=False, random_state=25, verbose=0,
                       warm_start=False)
```

In [88]:

```
clf=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=14, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=28, min_samples_split=111,
            min_weight_fraction_leaf=0.0, n_estimators=121, n_jobs=-1,
            oob_score=False, random_state=25, verbose=0, warm_start=False)
```

In [89]:

```
clf.fit(df_final_train,y_train)
y_train_pred = clf.predict(df_final_train)
y_test_pred = clf.predict(df_final_test)
```

In [90]:

```
from sklearn.metrics import f1_score
print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
```

```
Train f1 score 0.9659107030664152
Test f1 score 0.9254603548305725
```

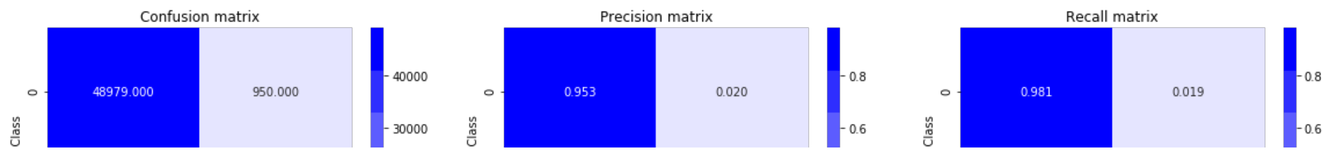
In [91]:

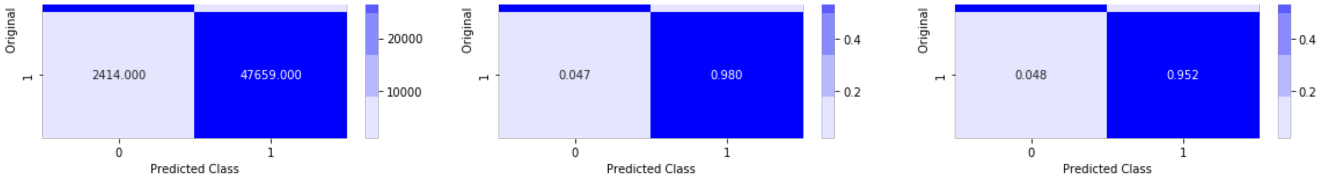
```
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    A =(((C.T)/(C.sum(axis=1))).T)

    B =(C/C.sum(axis=0))
    plt.figure(figsize=(20,4))

    labels = [0,1]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()
```

In [92]:

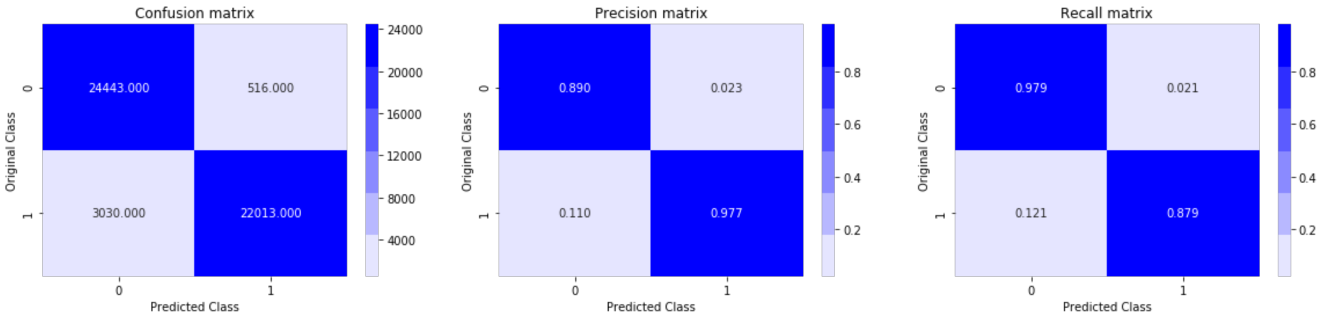
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```



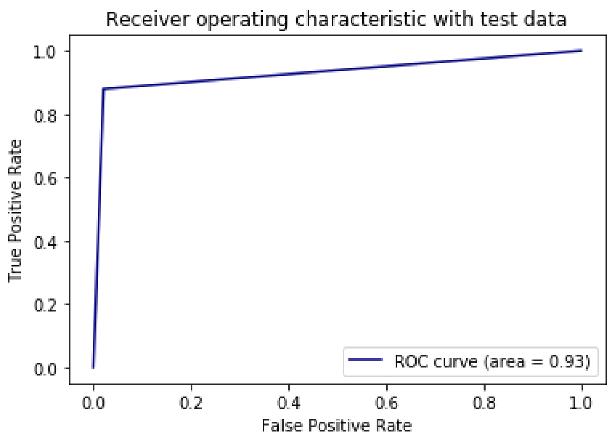


Test confusion_matrix



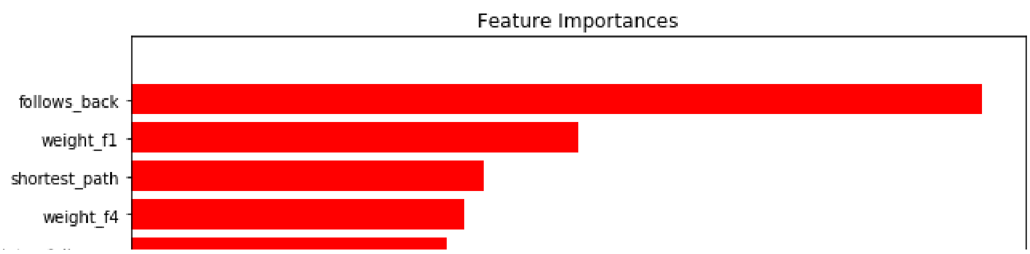
In [93]:

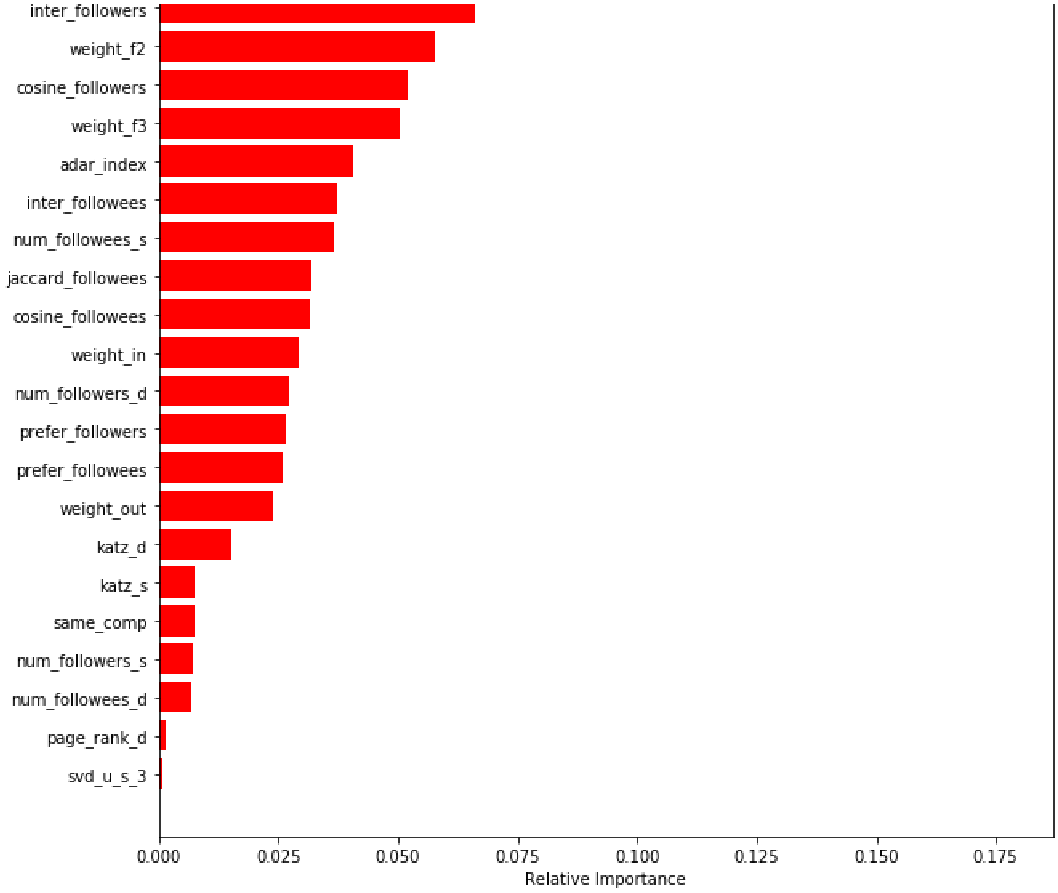
```python
from sklearn.metrics import roc_curve, auc
fpr,tpr,ths = roc_curve(y_test,y_test_pred)
auc_sc = auc(fpr, tpr)
plt.plot(fpr, tpr, color='navy',label='ROC curve (area = %0.2f)' % auc_sc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic with test data')
plt.legend()
plt.show()
```



In [94]:

```python
features = df_final_train.columns
importances = clf.feature_importances_
indices = (np.argsort(importances))[-25:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```





Applying XGBOOST

In [95]:

```
import xgboost as xgb
clf = xgb.XGBClassifier()
param_dist = {"n_estimators":sp_randint(105,125),
              "max_depth": sp_randint(10,15)
              }
model = RandomizedSearchCV(clf, param_distributions=param_dist,
                                   n_iter=5,cv=3,scoring='f1',random_state=25)


model.fit(df_final_train,y_train)
print('mean test scores',model.cv_results_['mean_test_score'])
```

```
mean test scores [0.98084932 0.98108994 0.98076536 0.98107463 0.98114554]
```

In [118]:

```
print(model.best_estimator_)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=11,
              min_child_weight=1, missing=None, n_estimators=112, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [96]:

```
clf=xgb.XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=11, min_child_weight=1, missing=None, n_estimators=112,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=1,verbosity=1)
```

In [97]:

```
clf.fit(df_final_train,y_train)
y_train_pred = clf.predict(df_final_train)
y_test_pred = clf.predict(df_final_test)
```

In [98]:

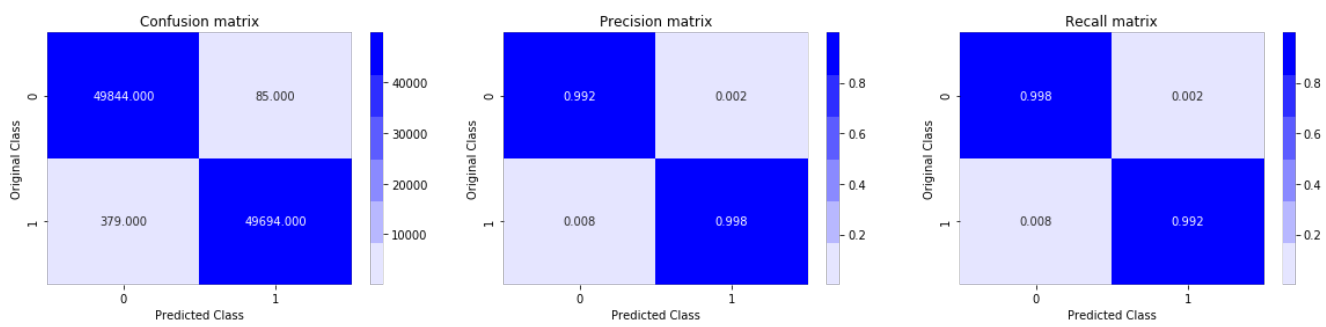
```
from sklearn.metrics import f1_score
print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
```

```
Train f1 score 0.9953531226214797
Test f1 score 0.9303582360515927
```

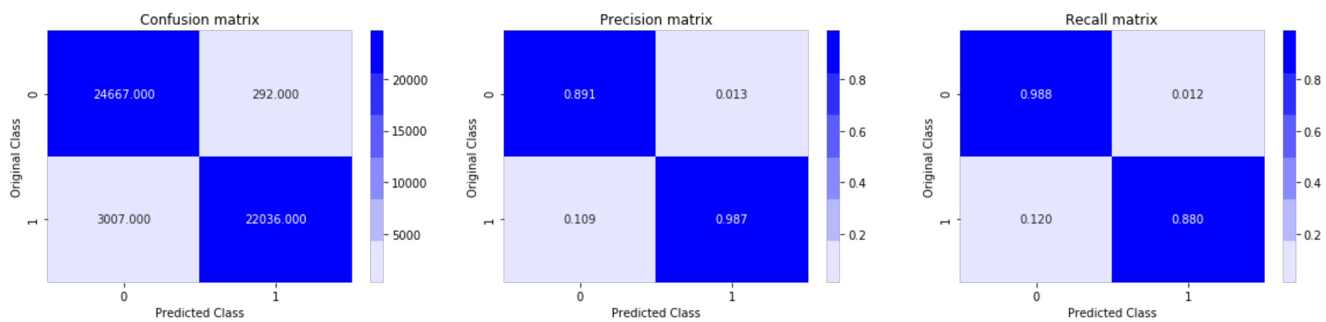
In [99]:

```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```

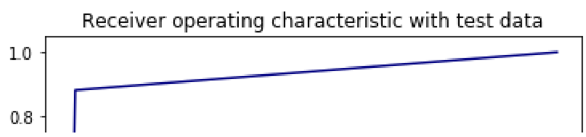


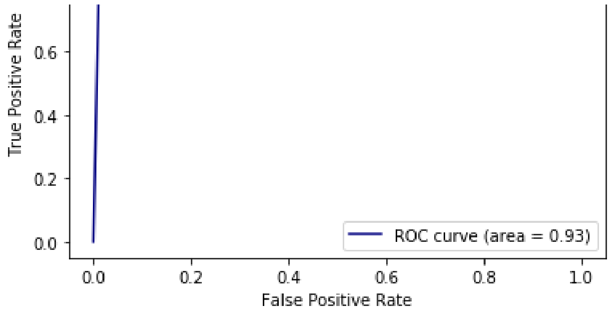

```
Test confusion_matrix
```



In [100]:

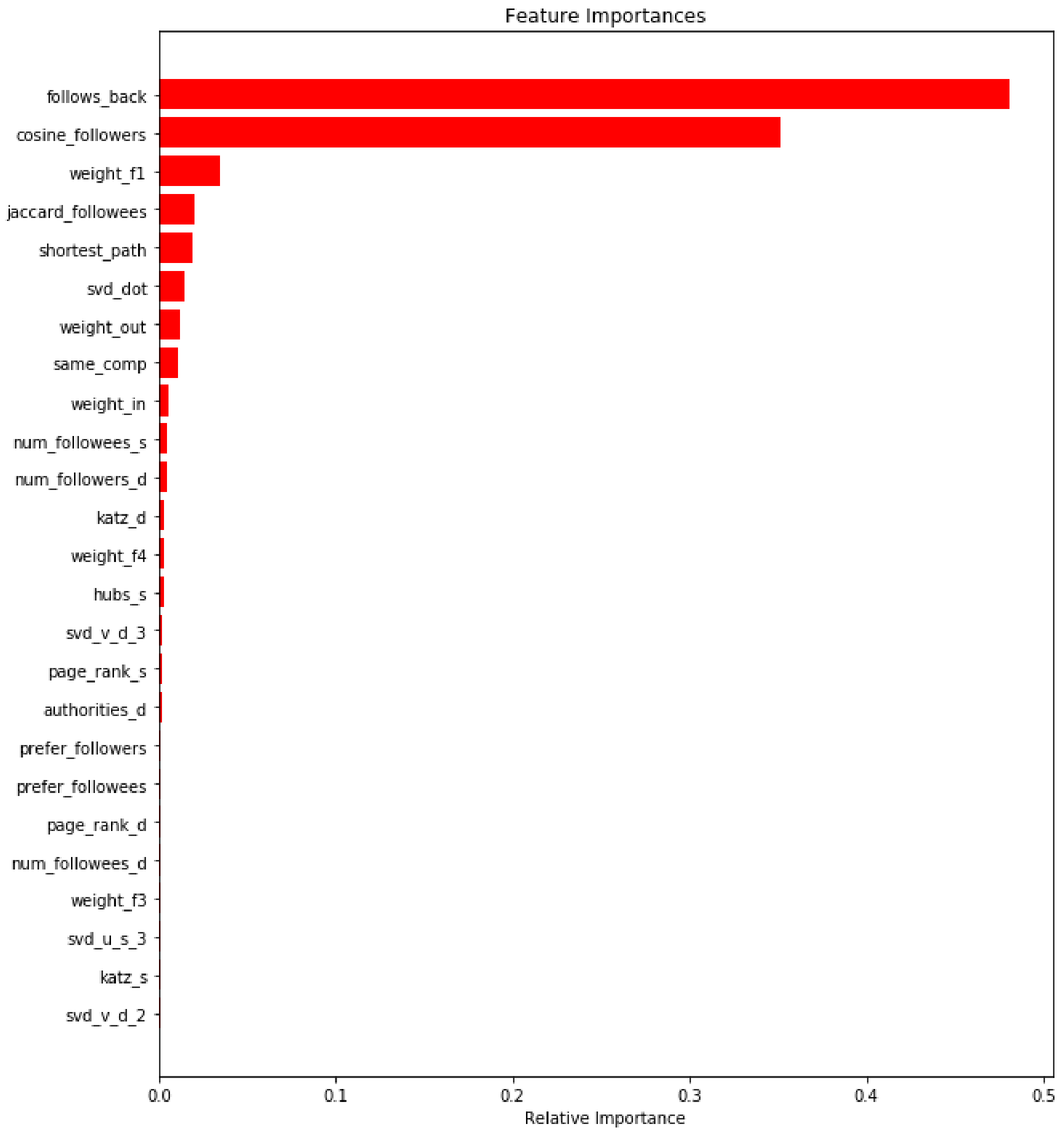
```
from sklearn.metrics import roc_curve, auc
fpr,tpr,ths = roc_curve(y_test,y_test_pred)
auc_sc = auc(fpr, tpr)
plt.plot(fpr, tpr, color='navy',label='ROC curve (area = %0.2f)' % auc_sc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic with test data')
plt.legend()
plt.show()
```





In [101]:

```
features = df_final_train.columns
importances = clf.feature_importances_
indices = (np.argsort(importances))[-25:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



Conclusion

In [102]:

```
from prettytable import PrettyTable
x = PrettyTable()
```

```
x = PrettyTable()
x.field_names = ["Model", "n_estimators", "max_depth", "Train f1-Score","Test f1-Score"]
x.add_row(['Random Forest','121','14','0.965','0.925'])
x.add_row(['XGBOOST','109','10','0.995','0.93'])
print(x)
```

```
+---------------+--------------+-----------+----------------+---------------+
|     Model     | n_estimators | max_depth | Train f1-Score | Test f1-Score |
+---------------+--------------+-----------+----------------+---------------+
| Random Forest |     121      |     14    |     0.965      |     0.925     |
|    XGBOOST    |     109      |     10    |     0.995      |      0.93     |
+---------------+--------------+-----------+----------------+---------------+
```

Summary-:

1. Since we are provided with only two features (source and nodes) we have to add more features
2. We add features like kartz distance , cosine distance , adar_index and shortest path etc.
3. We then combine all the features and store into DataFrame and compute F1 score with various models.
4. Both model performs well because they give F1 score greater than 0.90 .

END