Social network Graph Link Prediction - Facebook Challenge

September 12, 2018

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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

In [1]:
```
#Importing Libraries
# please do go through this python notebook:
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 warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
#reading df
traincsv = pd.read_csv('train.csv')
```

In [3]:
```
#chacking if any null values in given graph
traincsv[traincsv.isna().any(1)]
```

Out[3]:
```
Empty DataFrame
Columns: [source_node, destination_node]
Index: []
```

In [4]:
```
#info of given data set
traincsv.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9437519 entries, 0 to 9437518
Data columns (total 2 columns):
source_node         int64
destination_node    int64
dtypes: int64(2)
memory usage: 144.0 MB
```

In [5]:
```
#no of duplicates
sum(traincsv.duplicated())
```

Out[5]: 0

In [6]:
```
#removing header and saving
traincsv.to_csv('train_woheader.csv',header=False,index=False)
```

In [2]:
```
#Getting basic info from our data
g=nx.read_edgelist('train_woheader.csv',delimiter=',',create_using=nx.DiGraph(),nodetype
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
```

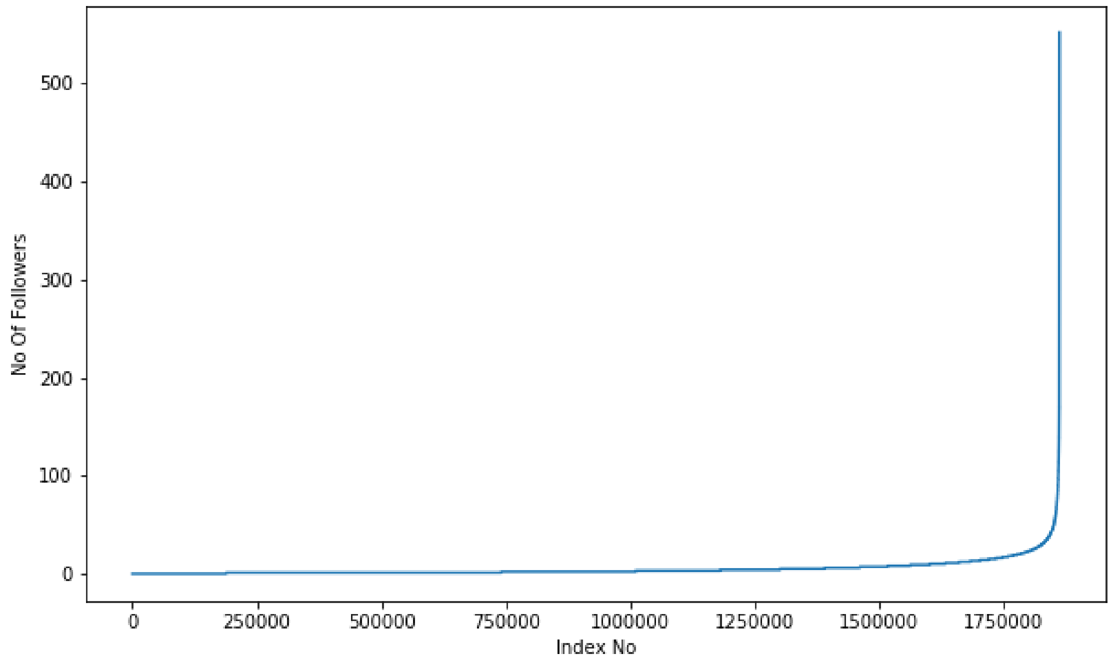
0.1 EDA

In [8]:
```
# No of Unique persons
len(g.nodes())
```

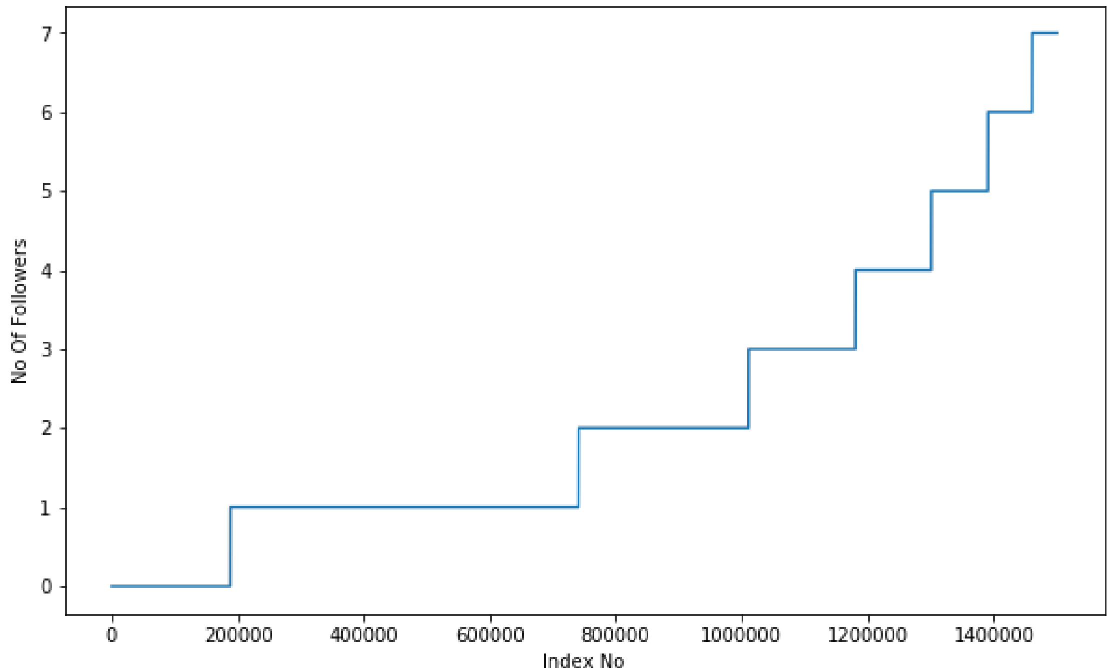
Out[8]: 1862220

No of followers for each person

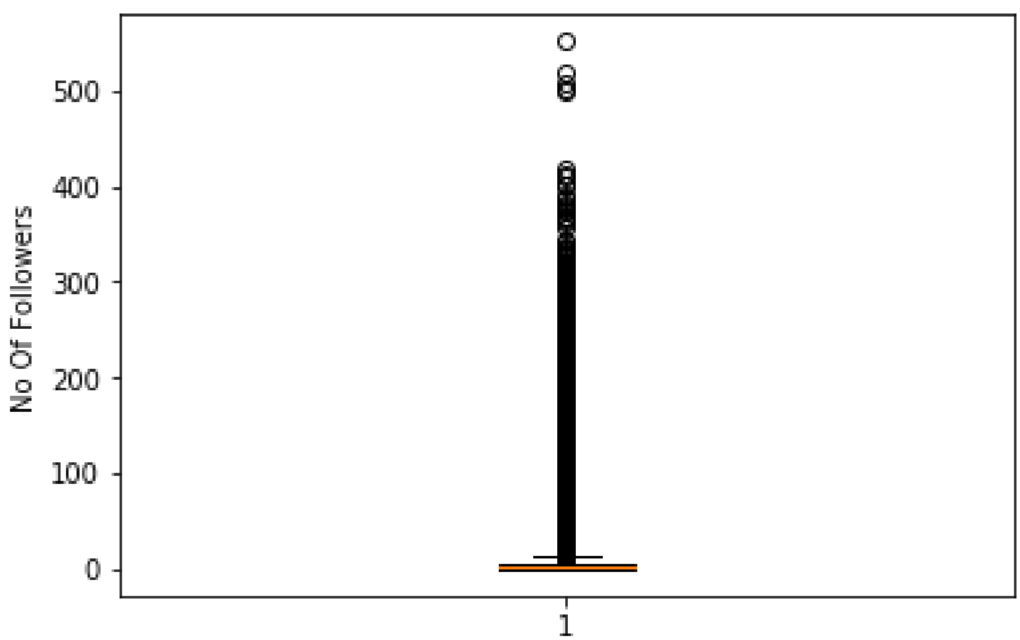
In [9]:
```
indegree_dist = list(dict(g.in_degree()).values())
indegree_dist.sort()
plt.figure(figsize=(10,6))
plt.plot(indegree_dist)
plt.xlabel('Index No')
plt.ylabel('No Of Followers')
plt.show()
```




```
In [10]: 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 [11]: plt.boxplot(indegree_dist)
         plt.ylabel('No Of Followers')
         plt.show()
```



```
In [12]: ### 90-100 percentile
         for i in range(0,11):
             print(90+i,'percentile value is',np.percentile(indegree_dist,90+i))
```

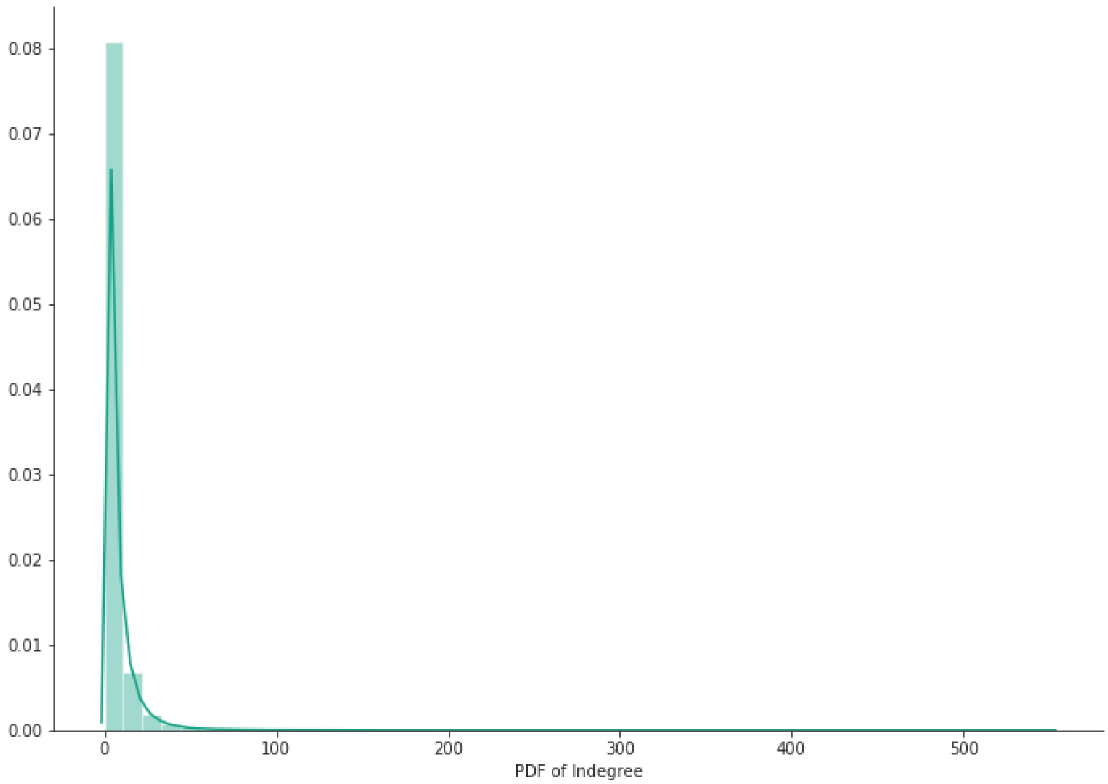
```
90 percentile value is 12.0
91 percentile value is 13.0
92 percentile value is 14.0
93 percentile value is 15.0
94 percentile value is 17.0
95 percentile value is 19.0
96 percentile value is 21.0
97 percentile value is 24.0
98 percentile value is 29.0
99 percentile value is 40.0
100 percentile value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

99% of data having followers of 40 only.

```
In [13]: ### 99-100 percentile
         for i in range(10,110,10):
             print(99+(i/100),'percentile value is',np.percentile(indegree_dist,99+(i/100)))
```

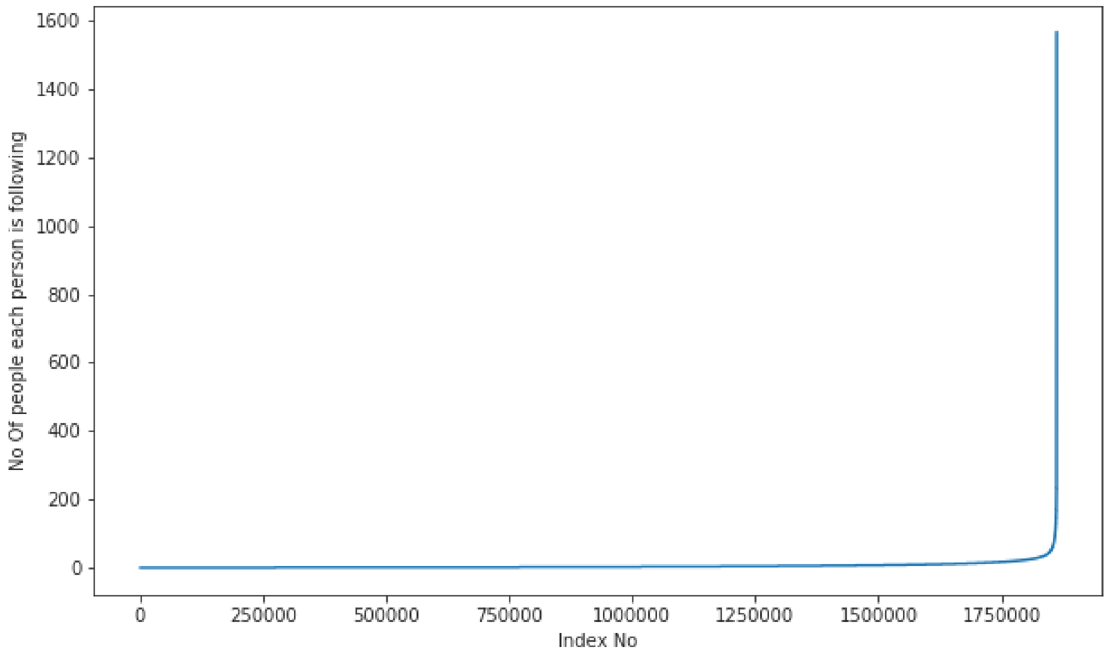
```
99.1 percentile value is 42.0
99.2 percentile value is 44.0
99.3 percentile value is 47.0
99.4 percentile value is 50.0
99.5 percentile value is 55.0
99.6 percentile value is 61.0
99.7 percentile value is 70.0
99.8 percentile value is 84.0
99.9 percentile value is 112.0
100.0 percentile value is 552.0
```

```
In [14]: %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')
         sns.despine()
         #plt.show()
```

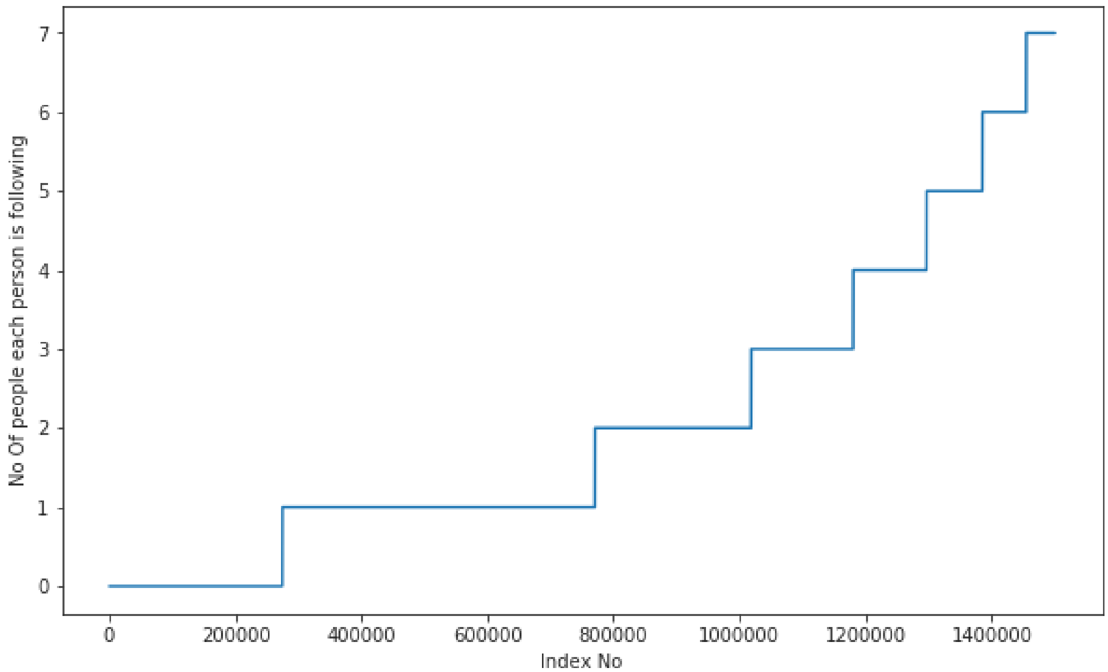


No of people each person is following

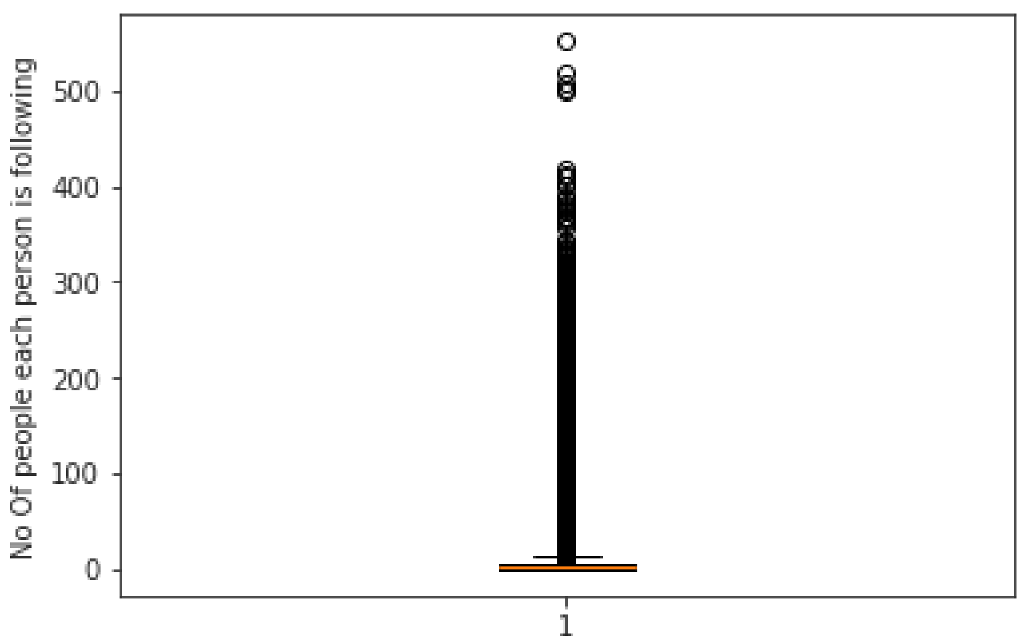
```
In [15]: outdegree_dist = list(dict(g.out_degree()).values())
         outdegree_dist.sort()
         plt.figure(figsize=(10,6))
         plt.plot(outdegree_dist)
         plt.xlabel('Index No')
         plt.ylabel('No Of people each person is following')
         plt.show()
```




```
In [16]: 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 [17]:
```
plt.boxplot(indegree_dist)
plt.ylabel('No Of people each person is following')
plt.show()
```



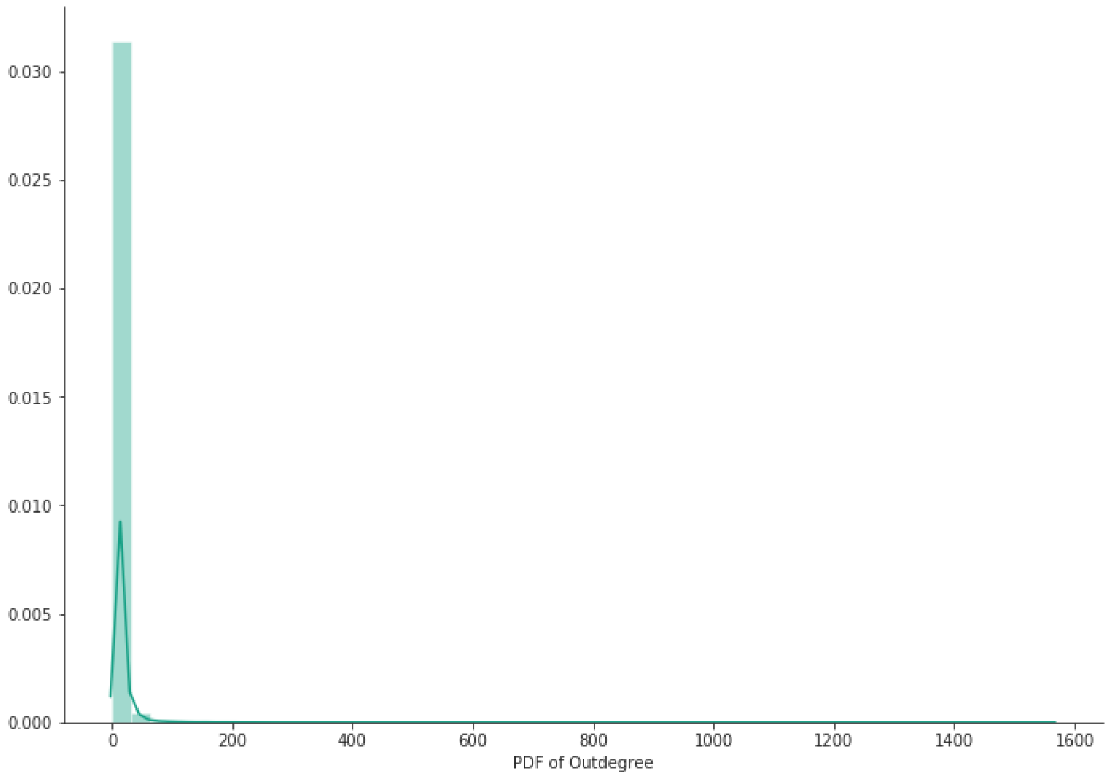
In [18]:
```
### 90-100 percentile
for i in range(0,11):
    print(90+i,'percentile value is',np.percentile(outdegree_dist,90+i))
```

```
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 [19]:
```
### 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 [20]:
```
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 [21]: 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 [22]: 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

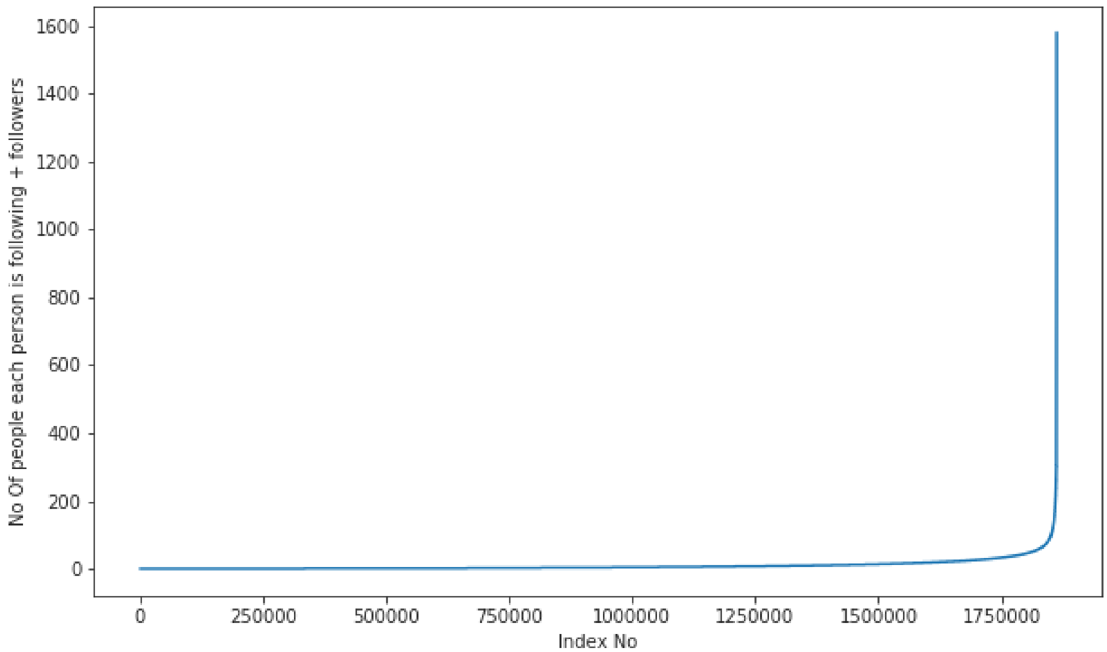
```
In [23]: count=0
         for i in g.nodes():
             if len(list(g.predecessors(i)))==0 :
                 if len(list(g.successors(i)))==0:
                     count+=1
         print('No of persons those are not not following anyone and also not having any followe
```

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

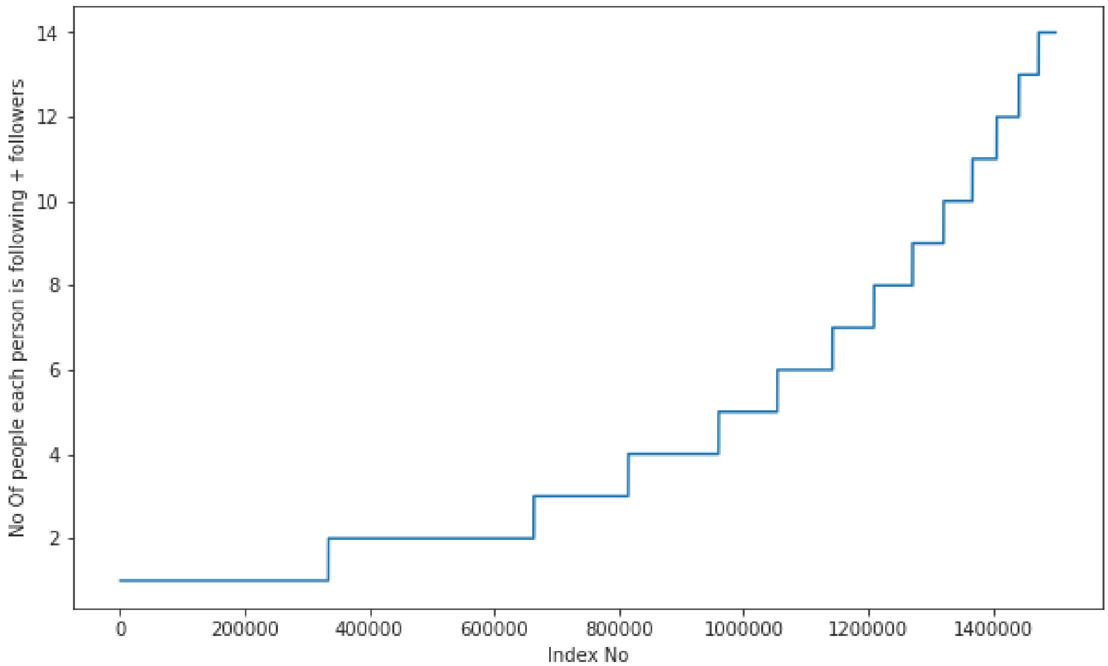
both followers + following

```
In [24]: 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 [25]: 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 [26]: 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 [27]: ### 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 [28]: ### 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 [29]: 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 [30]: 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 [31]: 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 [32]: 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
```

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 [4]: #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
```

```
In [6]: %%time
        ###generating bad edges from given graph
```

```
import random
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
```

```
CPU times: user 2h 28min 24s, sys: 34.8 s, total: 2h 28min 59s
Wall time: 2h 28min 59s
```

```
In [7]: len(missing_edges)
```

```
Out[7]: 9437519
```

```
In [8]: import pickle
        pickle.dump(missing_edges,open('missing_edges_final.p','wb'))
```

```
In [45]: import pickle
         missing_edges = pickle.load(open('missing_edges_final.p','rb'))
```

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 [46]: #reading total data df
         df_pos = pd.read_csv('train.csv')
         df_neg = pd.DataFrame(list(missing_edges), columns=['source_node', 'destination_node'])
```

```
In [47]: #positive links i.e graph
         df_pos.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9437519 entries, 0 to 9437518
Data columns (total 2 columns):
source_node         int64
destination_node    int64
dtypes: int64(2)
memory usage: 144.0 MB
```

```
In [48]: #negative links synthesized links
         df_neg.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9437519 entries, 0 to 9437518
Data columns (total 2 columns):
source_node         int64
destination_node    int64
dtypes: int64(2)
memory usage: 144.0 MB
```

```
In [49]: #Trian test split
         #Spiltted data into 80-20
         #positive links and negative links seperatly because we need positive training data onl
         #and for feature generation
         from sklearn.model_selection import train_test_split
         X_train_pos, X_test_pos, y_train_pos, y_test_pos  = train_test_split(df_pos,np.ones(len
         X_train_neg, X_test_neg, y_train_neg, y_test_neg  = train_test_split(df_neg,np.zeros(le
```

```
In [50]: df_train_pos = pd.DataFrame(X_train_pos)
         #removing header and saving
         df_train_pos.to_csv('train_data.csv',header=False,index=False)
```

```
In [51]: #Graph from Traing data only
         g=nx.read_edgelist('train_data.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=in
         print(nx.info(g))
```

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

```
In [52]: #Graph of total data without splitting
         G=nx.read_edgelist('train_woheader.csv',delimiter=',',create_using=nx.DiGraph(),nodetyp
         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 [53]: ###total nodes in train positive data
         train_nodes_pos = set(g.nodes())
```

```
###total nodes in total data
total_nodes_pos = set(G.nodes())
###test nodes in pos data
test_nodes_pos = set(X_test_pos.values.flatten())
```

```
In [11]: print('no of people common in train and test -- ',len(train_nodes_pos.intersection(test
         print('no of people present in train but not present in test -- ',len(train_nodes_pos -
         print('no of people present in test but not present in train -- ',len(test_nodes_pos -
```

```
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
```

```
In [57]: print(' % of people not there in Train but exist in Test in total Test data are {} %'.\
                          format(len(test_nodes_pos - train_nodes_pos)/len(test_nodes_pos)*100)
```

```
 % of people not there in Train but exist in Test in total Test data are 7.1200735962845405 %
```

This will cause a cold start problem

```
In [13]: #final train and test data sets
         df_final_train = X_train_pos.append(X_train_neg,ignore_index=True)
         y_final_train = np.concatenate((y_train_pos,y_train_neg))
         df_final_test = X_test_pos.append(X_test_neg,ignore_index=True)
         y_final_test = np.concatenate((y_test_pos,y_test_neg))
```

```
In [14]: df_final_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15100030 entries, 0 to 15100029
Data columns (total 2 columns):
source_node         int64
destination_node    int64
dtypes: int64(2)
memory usage: 230.4 MB
```

```
In [15]: df_final_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3775008 entries, 0 to 3775007
Data columns (total 2 columns):
source_node         int64
destination_node    int64
dtypes: int64(2)
memory usage: 57.6 MB
```

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

```
In [7]: Adj = nx.adjacency_matrix(g,nodelist=sorted(g.nodes()))
```

```
In [8]: Adj = Adj.asfptype()
        Adj
```

```
Out[8]: <1780722x1780722 sparse matrix of type '<class 'numpy.float64'>'
                with 7550015 stored elements in Compressed Sparse Row format>
```

0.2 Feature Engineering

0.2.1 SVD

```
In [9]: from scipy.sparse.linalg import svds, eigs
        U, s, V = svds(Adj,k = 6)
```

```
In [10]: U
```

```
Out[10]: array([[-2.06311438e-15,  4.86280646e-12,  4.32863386e-13,
                  6.34827889e-14,  1.18649118e-14,  1.85940576e-16],
                [-5.39810495e-14,  7.68601596e-13,  1.32207398e-11,
                  2.12945529e-13,  9.80313275e-13,  5.21376923e-16],
                [-1.03323961e-11,  2.77939874e-11,  1.56793759e-09,
                  2.35993376e-11,  3.87897382e-12,  6.99955573e-13],
                ...,
                [-9.08926368e-15,  3.01073958e-14,  6.61712281e-13,
                  1.86989518e-13,  2.39751694e-12,  1.01911935e-14],
                [-4.04926290e-13,  1.66308893e-13,  1.36923604e-06,
                  6.08332634e-14,  1.84662990e-13,  1.79395445e-12],
                [-7.33024975e-15,  7.79261880e-15,  7.97714296e-14,
                  2.89269174e-16,  1.21312591e-15,  2.25623613e-16]])
```

```
In [11]: print('U Shape',U.shape)
         print('V Shape',V.shape)
         print('s Shape',s.shape)
```

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

```
In [12]: del Adj
         del s
```

0.2.2 Similarity measures

Jaccard Distance:

$$j = \frac{|X \cap Y|}{|X \cup Y|} \tag{1}$$

```
In [21]: #for followees
         def jaccard_for_followees(a,b):
             try:
                 if len(set(g.successors(a))) == 0  | len(set(g.successors(b))) == 0:
                     return 0
                 sim = (len(set(g.successors(a)).intersection(set(g.successors(b)))))/\
                                             (len(set(g.successors(a)).union(set(g.successors(b)
             except:
                 return 0
             return sim
```

```
In [22]: #one test case
         jaccard_for_followees(2,1615927)
```

```
Out[22]: 0.0
```

```
In [23]: #node 1635354 not in graph
         jaccard_for_followees(669354,1635354)
```

```
Out[23]: 0
```

```
In [24]: #for followers
         def jaccard_for_followers(a,b):
             try:
                 if len(set(g.predecessors(a))) == 0  | len(set(g.predecessors(b))) == 0:
                     return 0
                 sim = (len(set(g.predecessors(a)).intersection(set(g.predecessors(b)))))/\
                                          (len(set(g.predecessors(a)).union(set(g.predecessors(b
                 return sim
             except:
                 return 0
```

```
In [25]: jaccard_for_followers(2,470294)
```

```
Out[25]: 0.045454545454545456
```

```
In [26]: #node 1635354 not in graph
         jaccard_for_followees(669354,1635354)
```

```
Out[26]: 0
```

Cosine distance

$$CosineDistance = \frac{|X \cap Y|}{|X| \cdot |Y|} \tag{2}$$

```
In [27]: #for followees
         def cosine_for_followees(a,b):
             try:
                 if len(set(g.successors(a))) == 0  | len(set(g.successors(b))) == 0:
                     return 0
```

```
            sim = (len(set(g.successors(a)).intersection(set(g.successors(b)))))/\
                                    (math.sqrt(len(set(g.successors(a)))*len((set(g.suc
            return sim
        except:
            return 0
```

In [28]:
```
cosine_for_followees(2,470294)
```

Out[28]: 0.08944271909999159

In [29]:
```
cosine_for_followees(669354,1635354)
```

Out[29]: 0

In [30]:
```
def cosine_for_followers(a,b):
    try:

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

In [31]:
```
cosine_for_followers(2,470294)
```

Out[31]: 0.02886751345948129

In [32]:
```
cosine_for_followers(669354,1635354)
```

Out[32]: 0

0.2.3 Ranking Measures

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

In [33]:
```
pr = nx.pagerank(g, alpha=0.85)
```

In [34]:
```
pickle.dump(pr,open('page_rank.p','wb'))
```

In [35]:
```
len(pr)
```

Out[35]: 1780722

In [37]:
```
pr = pickle.load(open('page_rank.p','rb'))
```

In [39]:
```
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 [40]: #for imputing to nodes which are not there in Train data
         mean_pr = float(sum(pr.values())) / len(pr)
```

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

```
In [9]: #testing
        compute_shortest_path_length(77697, 826021)
```

```
Out[9]: 10
```

```
In [10]: #testing
         compute_shortest_path_length(669354,1635354)
```

```
Out[10]: -1
```

Checking for same community

```
In [39]: #getting weekly connected edges from graph
         wcc=list(nx.weakly_connected_components(g))
         def belongs_to_same_wcc(a,b):
             index = []
             if g.has_edge(b,a):
                  return 1
             if g.has_edge(a,b):
                     for i in wcc:
                         if a in i:
                             index= i
                             break
                     if (b in index):
```

```
                        g.remove_edge(a,b)
                        if compute_shortest_path_length(a,b)==-1:
                            g.add_edge(a,b)
                            return 0
                        else:
                            g.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 [40]: belongs_to_same_wcc(861, 1659750)
```

```
Out[40]: 0
```

```
In [41]: belongs_to_same_wcc(669354,1635354)
```

```
Out[41]: 0
```

Adamic/Adar Index

$$A = \sum_{u \in N(x) \cap N(y)} \frac{1}{log|N(u)|} \tag{3}$$

```
In [42]: #adar index
         def calc_adar_in(a,b):
             sum=0
             try:
                 n=list(set(g.successors(a)).intersection(set(g.successors(b))))
                 if len(n)!=0:
                     for i in n:
                         sum=sum+(1/np.log10(len(list(g.predecessors(i)))))
                     return sum
                 else:
                     return 0
             except:
                 return 0
```

```
In [43]: calc_adar_in(1,189226)
```

```
Out[43]: 0
```

```
In [44]: calc_adar_in(669354,1635354)
```

```
Out[44]: 0
```

Is persion was following back:

```
In [45]: def follows_back(a,b):
             if g.has_edge(b,a):
                 return 1
             else:
                 return 0
```

```
In [46]: follows_back(1,189226)
```

```
Out[46]: 1
```

```
In [47]: follows_back(669354,1635354)
```

```
Out[47]: 0
```

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

```
In [119]: katz = nx.katz.katz_centrality(g,alpha=0.005,beta=1)
          #import pickle
          #katz = pickle.load(open('katz.p','rb'))
```

```
In [11]: import pickle
         katz = pickle.load(open('katz.p','rb'))
```

```
In [24]: type(katz)
```

```
Out[24]: dict
```

```
In [32]: 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 [33]: mean_katz = float(sum(katz.values())) / len(katz)
```

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

```
In [40]: hits = nx.hits(g, max_iter=100, tol=1e-08, nstart=None, normalized=True)
         #hits = pickle.load(open('hits.p','rb'))
```

```
In [13]: hits = pickle.load(open('hits.p','rb'))
```

```
In [14]: len(hits)
```

```
Out[14]: 2
```

```
In [15]: len(hits[0])
```

```
Out[15]: 1780722
```

```
In [45]: 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
```

```
In [43]: import pickle
         pickle.dump(hits,open('hits.p','wb'))
```

From all above scores preparing data set

```
In [54]: df_final_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15100030 entries, 0 to 15100029
Data columns (total 2 columns):
source_node         int64
destination_node    int64
dtypes: int64(2)
memory usage: 230.4 MB
```

```
In [55]: df_final_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3775008 entries, 0 to 3775007
Data columns (total 2 columns):
source_node         int64
destination_node    int64
dtypes: int64(2)
memory usage: 57.6 MB
```

```
In [57]: #mapping jaccrd followers to train data
         df_final_train['jaccard_followers'] = df_final_train.apply(lambda row:
                                                 jaccard_for_followers(row['source_node'],row['d
```

```
In [59]: #mapping jaccrd followers to test data
         df_final_test['jaccard_followers'] = df_final_test.apply(lambda row:
                                                 jaccard_for_followers(row['source_node'],row['d
```

In [60]:
```
#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['d
df_final_test['jaccard_followees'] = df_final_test.apply(lambda row:
                                        jaccard_for_followees(row['source_node'],row['d
```

In [65]:
```
#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_train.iterrows():
    try:
        s1=set(g.predecessors(row['source_node']))
        s2=set(g.successors(row['source_node']))
    except:
        s1 = set()
        s2 = set()
    try:
        d1=set(g.predecessors(row['destination_node']))
        d2=set(g.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)))
```

In [66]:
```
df_final_train['num_followers_s']=num_followers_s
df_final_train['num_followees_s']=num_followees_s
df_final_train['num_followers_d']=num_followers_d
df_final_train['num_followees_d']=num_followees_d
df_final_train['inter_followers']=inter_followers
df_final_train['inter_followees']=inter_followees
```

In [67]:
```
#For test data
#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_test.iterrows():
    try:
        s1=set(g.predecessors(row['source_node']))
        s2=set(g.successors(row['source_node']))
    except:
        s1 = set()
        s2 = set()
    try:
        d1=set(g.predecessors(row['destination_node']))
        d2=set(g.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)))
```

In [68]:
```
#assigning
df_final_test['num_followers_s']=num_followers_s
df_final_test['num_followees_s']=num_followees_s
df_final_test['num_followers_d']=num_followers_d
df_final_test['num_followees_d']=num_followees_d
df_final_test['inter_followers']=inter_followers
df_final_test['inter_followees']=inter_followees
```

In [69]:
```
#saving to disk
df_final_train.to_csv('df_final_train_some.csv',index=False)
df_final_test.to_csv('df_final_test_some.csv',index=False)
```

In [71]:
```
#head of df
df_final_train.head()
```

Out[71]:

	source_node	destination_node	jaccard_followers	jaccard_followees	\
0	273084	1505602	0.000000	0.000000	
1	912810	1678443	0.058824	0.058824	
2	365429	1523458	0.033058	0.023077	
3	527014	1605979	0.000000	0.000000	
4	1228116	471233	0.068966	0.162162	

```
   num_followers_s  num_followees_s  num_followers_d  num_followees_d  \
```

```
0              11               15                6                8
1              10               10                8                8
2              40               49               85               84
3               0                1                1                0
4              14               23               48               20

   inter_followers  inter_followees
0                0                0
1                1                1
2                4                3
3                0                0
4                4                6
```

In [72]:
```python
df_final_test.head()
```

Out[72]:
```
   source_node  destination_node  jaccard_followers  jaccard_followees  \
0       848424            784690           0.052632           0.000000
1      1248963            444518           0.000000           0.000000
2       264224            132395           0.375000           0.400000
3       549680            326829           0.115385           0.040000
4       875380           1394902           0.190476           0.184211

   num_followers_s  num_followees_s  num_followers_d  num_followees_d  \
0                6                6               14                9
1                5                8                1                2
2                8                7                3                7
3               17               11               12               15
4               21               20               29               25

   inter_followers  inter_followees
0                1                0
1                0                0
2                3                4
3                3                1
4                8                7
```

In [73]:
```python
#mapping adar index on train
df_final_train['adar_index'] = df_final_train.apply(lambda row:
                                        calc_adar_in(row['source_node'],row['destinatio
```

In [74]:
```python
#mapping adar index on test
df_final_test['adar_index'] = df_final_test.apply(lambda row:
                                        calc_adar_in(row['source_node'],row['destinatio
```

In [75]:
```python
#mapping followback or not on train
df_final_train['follows_back'] = df_final_train.apply(lambda row:
                                        follows_back(row['source_node'],row['destinatio
```

In [76]:
```python
#mapping followback or not on test
df_final_test['follows_back'] = df_final_test.apply(lambda row:
                                        follows_back(row['source_node'],row['destinatio
```

In [77]:
```
##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['des
```

In [78]:
```
##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_node'],row['des
```

In [79]:
```
#saving to disk beacuse above operation takes much time so at every check point saving
df_final_train.to_csv('df_final_train_some1.csv',index=False)
df_final_test.to_csv('df_final_test_some1.csv',index=False)
```

In [16]:
```
df_final_train = pd.read_csv('df_final_train_some1.csv')
df_final_test = pd.read_csv('df_final_test_some1.csv')
```

In [20]:
```
#mapping shortest path on train
df_final_train['shortest_path'] = df_final_train.apply(lambda row:
                                        compute_shortest_path_length(row['source_node']
```

In [21]:
```
#mapping shortest path on test
df_final_test['shortest_path'] = df_final_test.apply(lambda row:
                                        compute_shortest_path_length(row['source_node']
```

In [22]:
```
df_final_train.to_csv('df_final_train_some2.csv',index=False)
df_final_test.to_csv('df_final_test_some2.csv',index=False)
```

In [41]:
```
#page rank for source and destination in Train
#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
df_final_train['page_rank_d'] = df_final_train.destination_node.apply(lambda x:pr.get(x
```

In [42]:
```
#page rank for source and destination in Test
#if anything not there in train graph then adding mean page rank
df_final_test['page_rank_s'] = df_final_test.source_node.apply(lambda x:pr.get(x,mean_p
df_final_test['page_rank_d'] = df_final_test.destination_node.apply(lambda x:pr.get(x,m
```

In [43]:
```
#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_k
df_final_train['katz_d'] = df_final_train.destination_node.apply(lambda x: katz.get(x,m
df_final_test['katz_s'] = df_final_test.source_node.apply(lambda x: katz.get(x,mean_kat
df_final_test['katz_d'] = df_final_test.destination_node.apply(lambda x: katz.get(x,mea
```

In [46]:
```
#Hits algorithm score for source and destination in Train
#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(
df_final_train['authorities_s'] = df_final_train.source_node.apply(lambda x: hits[1].ge
df_final_train['authorities_d'] = df_final_train.destination_node.apply(lambda x: hits[
```

In [47]:
```
#Hits algorithm score for source and destination in Train
#if anything not there in train graph then adding 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,
df_final_test['authorities_s'] = df_final_test.source_node.apply(lambda x: hits[1].get(
df_final_test['authorities_d'] = df_final_test.destination_node.apply(lambda x: hits[1]
```

In [50]:
```
#dependent varible i.e link exist or not
df_final_train['indicator_link'] = y_final_train
df_final_test['indicator_link'] = y_final_test
```

In [48]:
```
#storing to db
from pandas import HDFStore,DataFrame
hdf = HDFStore('storage_temp.h5')
```

In [51]:
```
hdf.put('train_df',df_final_train, format='table', data_columns=True)
```

In [52]:
```
hdf.put('test_df',df_final_test, format='table', data_columns=True)
```

In [14]:
```
del g
```

In [17]:
```
#reading from db
from pandas import read_hdf
df_final_train = read_hdf('storage_temp.h5', 'train_df',mode='r')
df_final_test = read_hdf('storage_temp.h5', 'test_df',mode='r')
```

Adding SVD Features:

In [13]:
```
#for svd features to get feature vector creating a dict node val and inex in svd vector
sadj_col = sorted(g.nodes())
sadj_dict = { val:idx for idx,val in enumerate(sadj_col)}
del sadj_col
```

In [20]:
```
##creating two df for U valuesfor train and test data with two columns source and desti
#and each column will have a list of 6 svd features
train_df_svd_u = pd.DataFrame()
test_df_svd_u = pd.DataFrame()
def svd_s(x):
    try:
        z = sadj_dict[x]
        return U[z]
    except:
        return [0,0,0,0,0,0]
train_df_svd_u['features_s'] = df_final_train.source_node.apply(lambda x: svd_s(x))
train_df_svd_u['features_d'] = df_final_train.destination_node.apply(lambda x: svd_s(x)
test_df_svd_u['features_s'] = df_final_test.source_node.apply(lambda x: svd_s(x))
test_df_svd_u['features_d'] = df_final_test.destination_node.apply(lambda x: svd_s(x))
```

In [21]:
```
##creating two df for V valuesfor train and test data with two columns source and desti
#and each column will have a list of 6 svd features
train_df_svd_v = pd.DataFrame()
test_df_svd_v = pd.DataFrame()
def svd_v(x):
    try:
        z = sadj_dict[x]
        return V.T[z]
    except:
        return [0,0,0,0,0,0]

train_df_svd_v['features_s'] = df_final_train.source_node.apply(lambda x: svd_v(x))
train_df_svd_v['features_d'] = df_final_train.destination_node.apply(lambda x: svd_v(x)
test_df_svd_v['features_s'] = df_final_test.source_node.apply(lambda x: svd_v(x))
test_df_svd_v['features_d'] = df_final_test.destination_node.apply(lambda x: svd_v(x))
```

In [22]:
```
train_df_svd_u.index = df_final_train.index
train_df_svd_v.index = df_final_train.index
test_df_svd_u.index = df_final_test.index
test_df_svd_v.index = df_final_test.index
```

In [23]:
```
#Splitting those each one column into 6 features
#https://stackoverflow.com/questions/35491274/pandas-split-column-of-lists-into-multipl
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_
                            pd.DataFrame(train_df_svd_u.features_s.values.tolist(), ind
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
                            pd.DataFrame(test_df_svd_u.features_s.values.tolist(), inde
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_
                            pd.DataFrame(train_df_svd_u.features_d.values.tolist(), ind
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
                            pd.DataFrame(test_df_svd_u.features_d.values.tolist(), inde
```

In [24]:
```
del train_df_svd_u
del test_df_svd_u
```

In [25]:
```
#Splitting those each one column into 6 features
#https://stackoverflow.com/questions/35491274/pandas-split-column-of-lists-into-multipl
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_
                            pd.DataFrame(train_df_svd_v.features_s.values.tolist(), ind
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
                            pd.DataFrame(test_df_svd_v.features_s.values.tolist(), inde
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_
                            pd.DataFrame(train_df_svd_v.features_d.values.tolist(), ind
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
                            pd.DataFrame(test_df_svd_v.features_d.values.tolist(), inde
```

In [26]:
```
del train_df_svd_v
del test_df_svd_v
del U
```

```
del V
del sadj_dict
```

```
In [28]: #data frame
         df_final_train.columns
```

```
Out[28]: Index(['source_node', 'destination_node', 'jaccard_followers',
                'jaccard_followees', 'num_followers_s', 'num_followees_s',
                'num_followers_d', 'num_followees_d', 'inter_followers',
                'inter_followees', 'adar_index', 'follows_back', 'same_comp',
                'shortest_path', 'page_rank_s', 'page_rank_d', 'katz_s', 'katz_d',
                'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d', 'indicator_link',
                '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')
```

Storing data in HDF format

```
In [29]: from pandas import HDFStore,DataFrame
         hdf1 = HDFStore('storage_final_df.h5')
```

```
In [30]: hdf1.put('train_df',df_final_train, format='table', data_columns=True)
```

```
In [31]: hdf1.put('test_df',df_final_test, format='table', data_columns=True)
```

```
In [32]: hdf1.close()
```

```
In [2]: #reading
        from pandas import read_hdf
        df_final_train = read_hdf('storage_final_df.h5', 'train_df',mode='r')
        df_final_test = read_hdf('storage_final_df.h5', 'test_df',mode='r')
```

```
In [3]: df_final_train.columns
```

```
Out[3]: Index(['source_node', 'destination_node', 'jaccard_followers',
               'jaccard_followees', 'num_followers_s', 'num_followees_s',
               'num_followers_d', 'num_followees_d', 'inter_followers',
               'inter_followees', 'adar_index', 'follows_back', 'same_comp',
               'shortest_path', 'page_rank_s', 'page_rank_d', 'katz_s', 'katz_d',
               'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d', 'indicator_link',
               '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')
```

indicator_link is target varible.

```
In [4]: #dependent varible
        y_train = df_final_train.indicator_link
        y_test = df_final_test.indicator_link
```

```
In [5]: #dropping some columns
        df_final_train.drop(['source_node', 'destination_node','indicator_link'],axis=1,inplace=
        df_final_test.drop(['source_node', 'destination_node','indicator_link'],axis=1,inplace=T
```

```
In [6]: df_final_train.columns
```

```
Out[6]: Index(['jaccard_followers', 'jaccard_followees', 'num_followers_s',
               'num_followees_s', 'num_followers_d', 'num_followees_d',
               'inter_followers', 'inter_followees', 'adar_index', 'follows_back',
               'same_comp', 'shortest_path', 'page_rank_s', 'page_rank_d', 'katz_s',
               'katz_d', 'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d',
               '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')
```

```
In [7]: df_final_test.columns
```

```
Out[7]: Index(['jaccard_followers', 'jaccard_followees', 'num_followers_s',
               'num_followees_s', 'num_followers_d', 'num_followees_d',
               'inter_followers', 'inter_followees', 'adar_index', 'follows_back',
               'same_comp', 'shortest_path', 'page_rank_s', 'page_rank_d', 'katz_s',
               'katz_d', 'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d',
               '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')
```

```
In [8]: print('Train Shape',df_final_train.shape)
        print('Test Shape',df_final_test.shape)
```

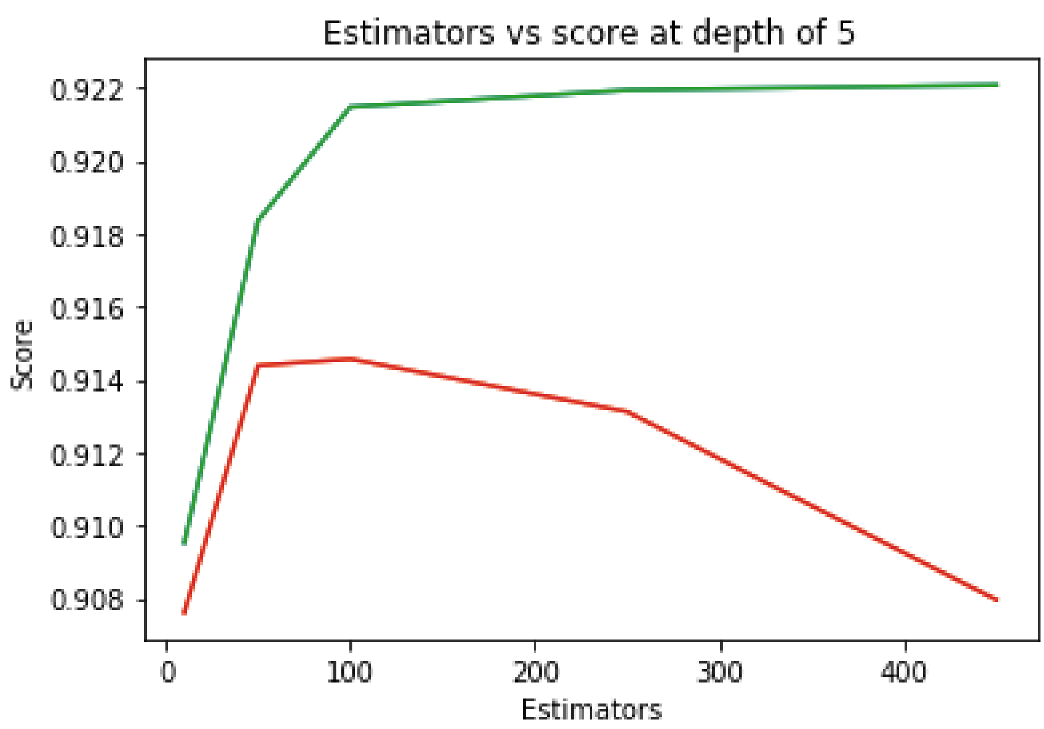
```
Train Shape (15100030, 44)
Test Shape (3775008, 44)
```

0.2.4 Machine learning Models

```
In [9]: from sklearn.ensemble import RandomForestClassifier
        from sklearn.metrics import f1_score
```

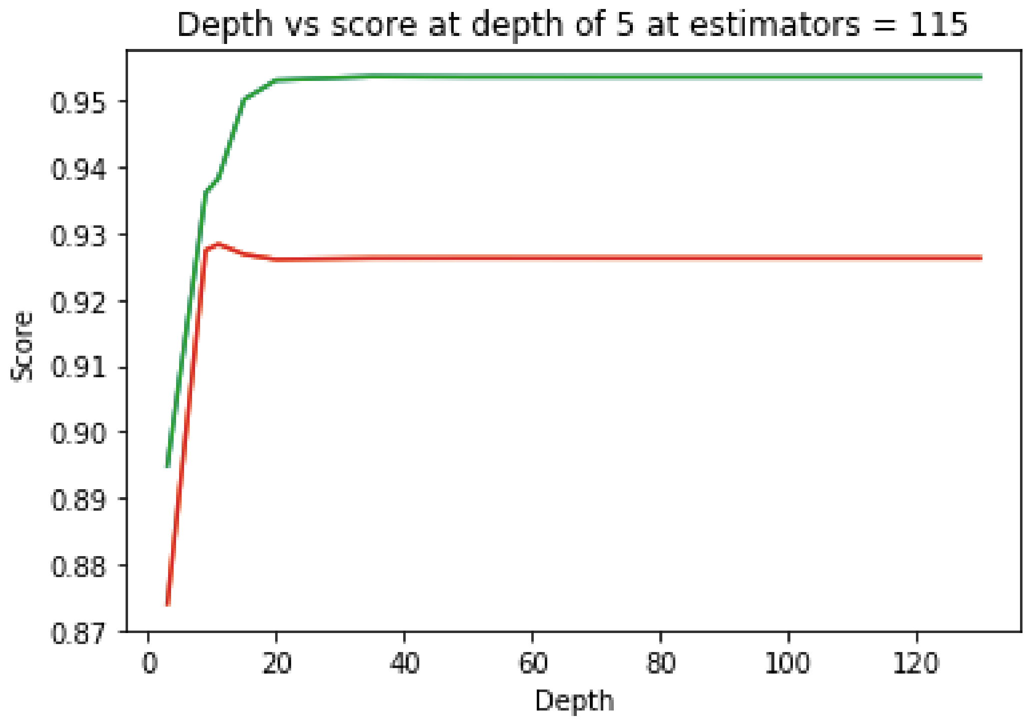
```
In [54]: estimators = [10,50,100,250,450]
         train_scores = []
         test_scores = []
         for i in estimators:
             clf = RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=5, max_features='auto', max_leaf_nodes=None,
                     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,ver
             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 0.909522473891829 test Score 0.9076068019574423
Estimators =  50 Train Score 0.9183594774113881 test Score 0.9143837381083021
Estimators =  100 Train Score 0.9214777800537078 test Score 0.9145669218732931
Estimators =  250 Train Score 0.9219390207399591 test Score 0.9131197428892744
Estimators =  450 Train Score 0.922078108477195 test Score 0.9079599330754532
```



In [37]:
```
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,v
    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 0.8949603900952848 test Score 0.8741052014942736
depth =  9 Train Score 0.9360254429127565 test Score 0.9273782435689065
depth =  11 Train Score 0.9382050540742228 test Score 0.9282749447838731
depth =  15 Train Score 0.9500877674602457 test Score 0.9267378494825711
depth =  20 Train Score 0.9529872894706812 test Score 0.9259543094148095
depth =  35 Train Score 0.9535361101001514 test Score 0.9261583609015455
depth =  50 Train Score 0.9534687885463979 test Score 0.9261677119534877
depth =  70 Train Score 0.9534623667394676 test Score 0.9261637624878941
depth =  130 Train Score 0.9534623667394676 test Score 0.9261637624878941
```




```
In [11]: 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)

         import pickle
         pickle.dump(rf_random,open('rf_random_2.p','wb'))

In [12]: rf_random.grid_scores_
```

```
Out[12]: [mean: 0.94717, std: 0.00143, params: {'max_depth': 14, 'min_samples_leaf': 51, 'min_sa
          mean: 0.94104, std: 0.00162, params: {'max_depth': 12, 'min_samples_leaf': 33, 'min_sa
          mean: 0.93796, std: 0.00125, params: {'max_depth': 11, 'min_samples_leaf': 56, 'min_sa
          mean: 0.94485, std: 0.00120, params: {'max_depth': 13, 'min_samples_leaf': 49, 'min_sa
          mean: 0.94772, std: 0.00114, params: {'max_depth': 14, 'min_samples_leaf': 28, 'min_sa
```

```
In [13]: print('mean test scores',rf_random.cv_results_['mean_test_score'])
         print('mean train scores',rf_random.cv_results_['mean_train_score'])
```

```
mean test scores [0.94716991 0.94103944 0.93796448 0.94485387 0.94772461]
mean train scores [0.94719986 0.94105021 0.93797457 0.94487586 0.94775144]
```

```
In [14]: #best estimator
         rf_random.best_estimator_
```

```
Out[14]: 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 [15]: 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)
         clf.fit(df_final_train,y_train)

         import pickle
         pickle.dump(clf,open('clf_rf.p','wb'))
```

```
In [22]: print('Train f1 score',f1_score(y_train,y_pred_train))
         print('Test f1 score',f1_score(y_test,y_pred_test))
```

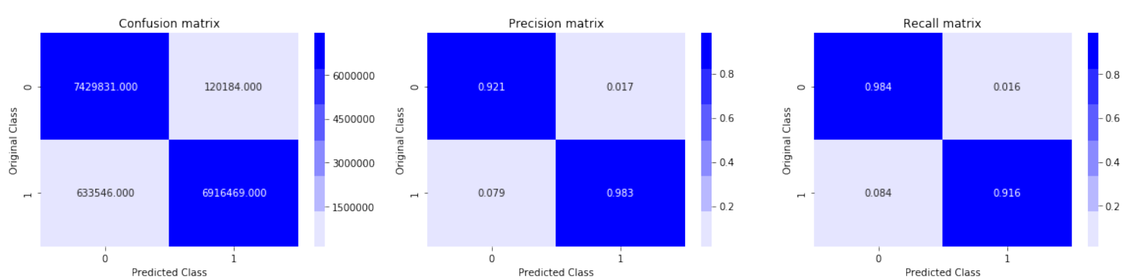
```
Train f1 score 0.9483274727305785
Test f1 score 0.926825556291337
```

```
In [18]: 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))
```

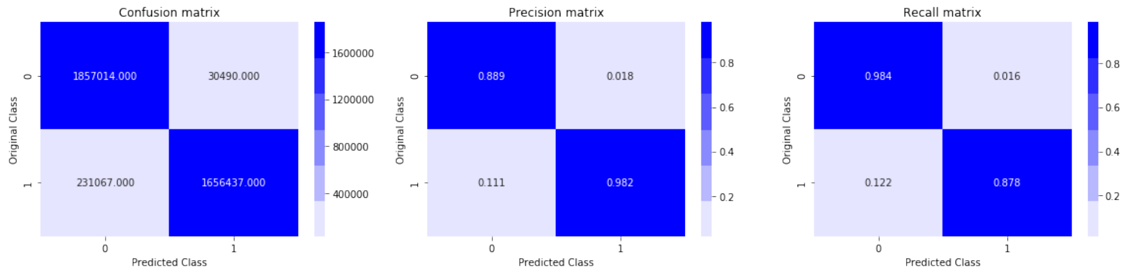
```
            labels = [0,1]
            # representing A in heatmap format
            cmap=sns.light_palette("blue")
            plt.subplot(1, 3, 1)
            sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=la
            plt.xlabel('Predicted Class')
        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

            plt.show()
```

```
In [18]: y_pred_train = clf.predict(df_final_train)
         y_pred_test = clf.predict(df_final_test)
         print('Train confusion_matrix')
         plot_confusion_matrix(y_train,y_pred_train)
         print('Test confusion_matrix')
         plot_confusion_matrix(y_test,y_pred_test)
```

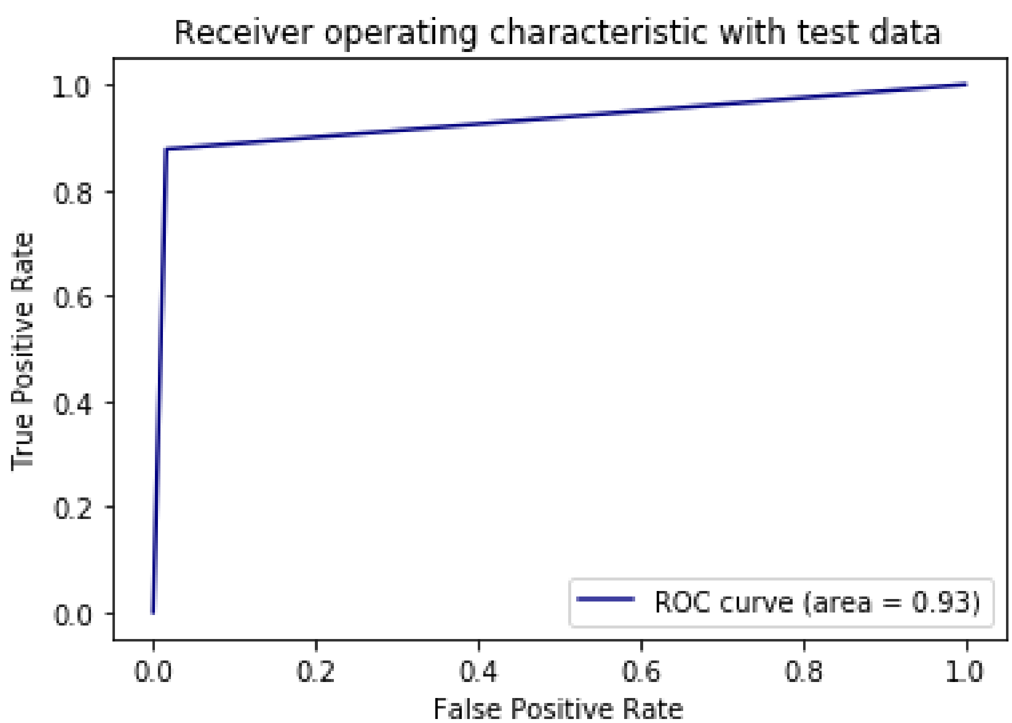
```
Train confusion_matrix
```




```
Test confusion_matrix
```

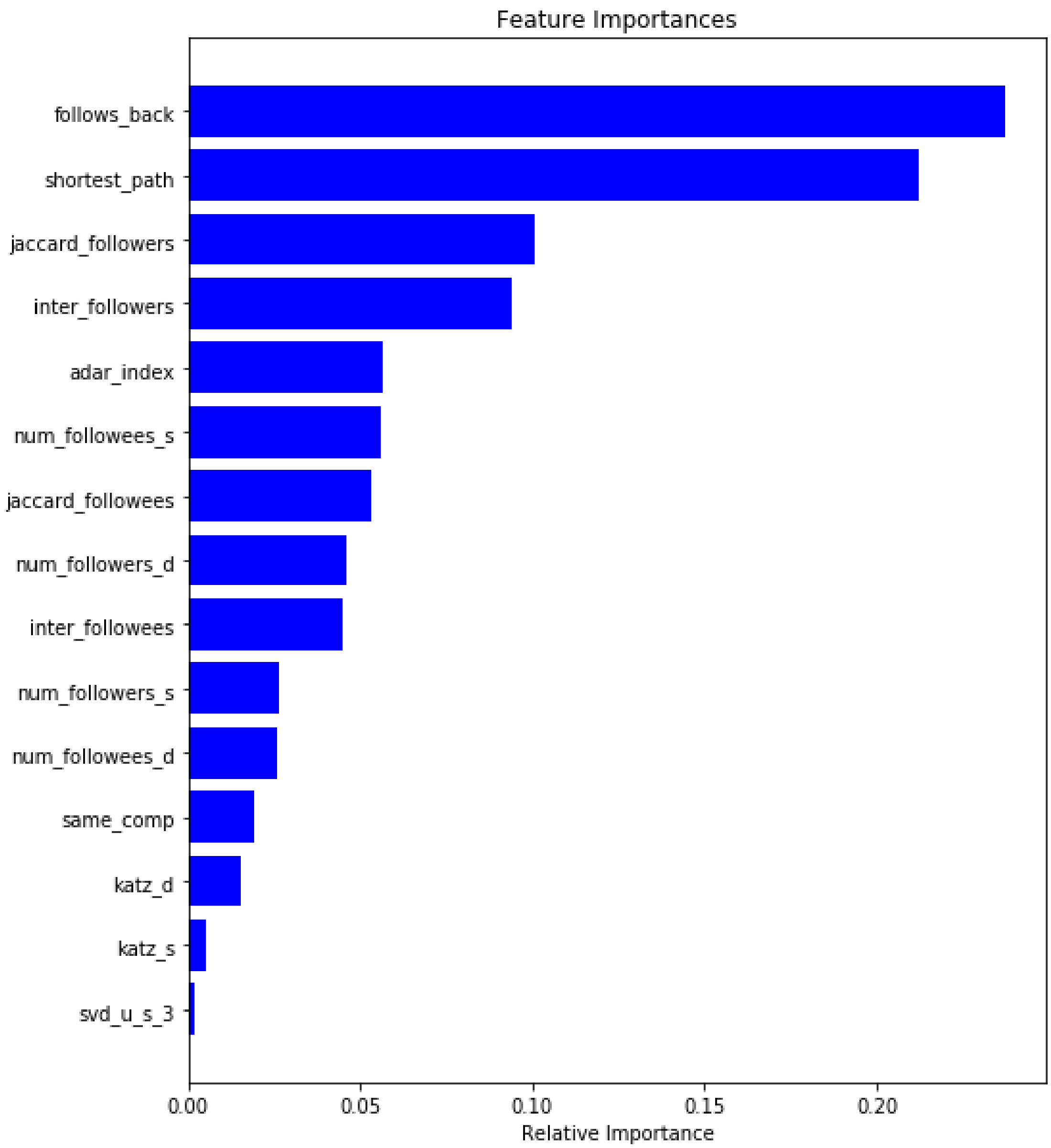



```
In [19]: from sklearn.metrics import roc_curve, auc
         fpr,tpr,ths = roc_curve(y_test,y_pred_test)
         auc_sc = auc(fpr, tpr)
         plt.plot(fpr, tpr, color='navy',label='ROC curve (area = %0.2f)' % auc_sc)
         plt.xlabel('False Positive Rate')
         plt.ylabel('True Positive Rate')
         plt.title('Receiver operating characteristic with test data')
         plt.legend()
         plt.show()
```




```
In [21]: features = df_final_train.columns
         importances = clf.feature_importances_
```

```
indices = (np.argsort(importances))[-15:]
plt.figure(figsize=(8,10))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



Some other features:

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

```
In [2]: ##reading data
        from pandas import read_hdf
        df_final_train = read_hdf('storage_final_df.h5', 'train_df',mode='r')
        df_final_test = read_hdf('storage_final_df.h5', 'test_df',mode='r')
```

```
In [38]: #Getting basic info from our data
         g=nx.read_edgelist('train_data.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=in
         print(nx.info(g))
```

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

```
In [39]: from tqdm import tqdm
```

$$W = \frac{1}{\sqrt{1 + |X|}} \tag{4}$$

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

```
In [40]: #weight for source and destination of each link
         Weight_in = []
         Weight_out = []
         for i in  tqdm(g.nodes()):
             s1=set(g.predecessors(i))
             w_in = 1.0/(np.sqrt(1+len(s1)))
             s2=set(g.successors(i))
             w_out = 1.0/(np.sqrt(1+len(s2)))
             Weight_in.append((i,w_in))
             Weight_out.append((i,w_out))
```

```
100%|| 1780722/1780722 [00:14<00:00, 122313.55it/s]
```

```
In [42]: #converting as dict to map DataFrame
         Weight_in_dict = dict(Weight_in)
         Weight_out_dict = dict(Weight_out)
```

```
In [45]: #saving to disk
         import pickle
         pickle.dump(Weight_in_dict,open('Weight_in_dict.p','wb'))
         pickle.dump(Weight_out_dict,open('Weight_out_dict.p','wb'))
```

```
In [6]: import pickle
        Weight_in_dict = pickle.load(open('Weight_in_dict.p','rb'))
        Weight_out_dict = pickle.load(open('Weight_out_dict.p','rb'))
```

```
In [7]: #for imputing
        mean_weight_in = np.mean(list(Weight_in_dict.values()))
        mean_weight_out = np.mean(list(Weight_out_dict.values()))
```

```
In [8]: #mapping to pandas train
        df_final_train['Weight_in'] = df_final_train.destination_node.apply(lambda x: Weight_in_
        df_final_train['Weight_out'] = df_final_train.source_node.apply(lambda x: Weight_out_dic
        #mapping to pandas test
        df_final_test['Weight_in'] = df_final_test.destination_node.apply(lambda x: Weight_in_di
        df_final_test['Weight_out'] = df_final_test.source_node.apply(lambda x: Weight_out_dict.
```

From above derived some other features

```
In [9]: #some features engineerings on tose in and out weigts
        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 tose in and out weigts
        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 [11]: df_final_train.columns
```

```
Out[11]: Index(['source_node', 'destination_node', 'jaccard_followers',
                'jaccard_followees', 'num_followers_s', 'num_followees_s',
                'num_followers_d', 'num_followees_d', 'inter_followers',
                'inter_followees', 'adar_index', 'follows_back', 'same_comp',
                'shortest_path', 'page_rank_s', 'page_rank_d', 'katz_s', 'katz_d',
                'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d', 'indicator_link',
                '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', 'Weight_in',
                'Weight_out', 'Weight_f1', 'Weight_f2', 'Weight_f3', 'Weight_f4'],
               dtype='object')
```

```
In [13]: del Weight_in_dict
         del Weight_out_dict
```

Some Other SVD Features:

In [14]:
```
#adj matrix
g=nx.read_edgelist('train_data.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=in
Adj = nx.adjacency_matrix(g,nodelist=sorted(g.nodes()))
Adj = Adj.asfptype()
Adj
```

Out[14]:
```
<1780722x1780722 sparse matrix of type '<class 'numpy.float64'>'
        with 7550015 stored elements in Compressed Sparse Row format>
```

In [15]:
```
#nodes list sorted
nodes_list = list(g.nodes())
nodes_list = sorted(nodes_list)
#node and index as key value pairs, i need it because getting index from list is O(n) c
# but from dict its O(1)
nodes_list_dict = {k:v for v,k in enumerate(nodes_list)}
```

In [16]:
```
# deleting because of sapce constraint
del g
del nodes_list
```

In [17]:
```
### svd decomposition
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components=200, n_iter=7, random_state=42)
svd_mat = svd.fit_transform(Adj)
```

In [18]:
```
# deleting because of sapce constraint
del Adj
```

In [19]:
```
import pickle
pickle.dump(svd_mat,open('svd_mat.p','wb'))
pickle.dump(nodes_list_dict,open('nodes_list_dict.p','wb'))
```

In [5]:
```
import pickle
svd_mat = pickle.load(open('svd_mat.p','rb'))
nodes_list_dict = pickle.load(open('nodes_list_dict.p','rb'))
```

In [21]:
```
#for Train
### SVD dot product of source and destination vectores
### SVD mean of source and destination vector
from tqdm import tqdm
svd_dot = []
svd_mean_dest = []
svd_mean_source = []
for idx,temp_series in tqdm(df_final_train.iterrows(),total=df_final_train.shape[0]):
    in_idx = nodes_list_dict.get(temp_series.destination_node,'X')
    out_idx = nodes_list_dict.get(temp_series.source_node,'X')
    if in_idx != 'X':
```

```
            #mean of total svd vector
            svd_mean_dest.append(np.squeeze(np.mean(svd_mat[in_idx,:])))
        else:
            svd_mean_dest.append(0)

        if out_idx != 'X':
            #mean of total svd vector
            svd_mean_source.append(np.squeeze(np.mean(svd_mat[out_idx,:])))
        else:
            svd_mean_source.append(0)

        if ( in_idx != 'X' and out_idx != 'X' ):
            #dot product of svd vector of Source and destination
            svd_temp = np.dot(svd_mat[in_idx,:],svd_mat[out_idx,:])
            svd_dot.append(svd_temp)
        else:
            svd_dot.append(0)
```

```
100%|| 15100030/15100030 [16:53<00:00, 14894.68it/s]
```

In [22]:
```
import pickle
pickle.dump(svd_dot,open('svd_dot_train.p','wb'))
pickle.dump(svd_mean_source,open('svd_mean_source_train.p','wb'))
pickle.dump(svd_mean_dest,open('svd_mean_dest_train.p','wb'))
```

In [23]:
```
###mappng above features into
df_final_train['svd_dot'] = svd_dot
df_final_train['svd_mean_s'] = svd_mean_source
df_final_train['svd_mean_d'] = svd_mean_dest
```

In [24]:
```
del svd_dot
del svd_mean_dest
del svd_mean_source
```

In [25]:
```
###for test
### SVD dot product of source and destination vectores
### SVD mean of source and destination vector
from tqdm import tqdm
svd_dot = []
svd_mean_dest = []
svd_mean_source = []
for idx,temp_series in tqdm(df_final_test.iterrows(),total=df_final_test.shape[0]):
    in_idx = nodes_list_dict.get(temp_series.destination_node,'X')
    out_idx = nodes_list_dict.get(temp_series.source_node,'X')
    if in_idx != 'X':
        svd_mean_dest.append(np.squeeze(np.mean(svd_mat[in_idx,:])))
    else:
        svd_mean_dest.append(0)
```

```
            if out_idx != 'X':
                svd_mean_source.append(np.squeeze(np.mean(svd_mat[out_idx,:])))
            else:
                svd_mean_source.append(0)

            if ( in_idx != 'X' and out_idx != 'X' ):
                svd_temp = np.dot(svd_mat[in_idx,:],svd_mat[out_idx,:])
                svd_dot.append(svd_temp)
            else:
                svd_dot.append(0)
```

```
100%|| 3775008/3775008 [04:14<00:00, 14830.45it/s]
```

```
In [26]: import pickle
         pickle.dump(svd_dot,open('svd_dot_test.p','wb'))
         pickle.dump(svd_mean_source,open('svd_mean_source_test.p','wb'))
         pickle.dump(svd_mean_dest,open('svd_mean_dest_test.p','wb'))
```

```
In [27]: ###mappng above features into
         df_final_test['svd_dot'] = svd_dot
         df_final_test['svd_mean_s'] = svd_mean_source
         df_final_test['svd_mean_d'] = svd_mean_dest
```

```
In [28]: del svd_dot
         del svd_mean_dest
         del svd_mean_source
         del nodes_list_dict
```

```
In [32]: #saving to db
         from pandas import HDFStore,DataFrame
         hdf2 = HDFStore('storage_all_features.h5')
```

```
In [33]: #saving to disk
         hdf2.put('train_df',df_final_train, format='table', data_columns=True)
```

```
In [34]: #saving to disk
         hdf2.put('test_df',df_final_test, format='table', data_columns=True)
```

```
In [35]: hdf2.close()
```

```
In [2]: ## reading
        from pandas import read_hdf
        df_final_train = read_hdf('storage_all_features.h5', 'train_df',mode='r')
        df_final_test = read_hdf('storage_all_features.h5', 'test_df',mode='r')
```

```
In [3]: #dependent varible
        y_train = df_final_train.indicator_link
        y_test = df_final_test.indicator_link
```

In [4]:
```
#dropping some columns
df_final_train.drop(['source_node', 'destination_node','indicator_link'],axis=1,inplace=
df_final_test.drop(['source_node', 'destination_node','indicator_link'],axis=1,inplace=T
```

In [5]:
```
df_final_train.columns
```

Out[5]:
```
Index(['jaccard_followers', 'jaccard_followees', 'num_followers_s',
       'num_followees_s', 'num_followers_d', 'num_followees_d',
       'inter_followers', 'inter_followees', 'adar_index', 'follows_back',
       'same_comp', 'shortest_path', 'page_rank_s', 'page_rank_d', 'katz_s',
       'katz_d', 'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d',
       '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', 'Weight_in',
       'Weight_out', 'Weight_f1', 'Weight_f2', 'Weight_f3', 'Weight_f4',
       'svd_dot', 'svd_mean_s', 'svd_mean_d'],
      dtype='object')
```

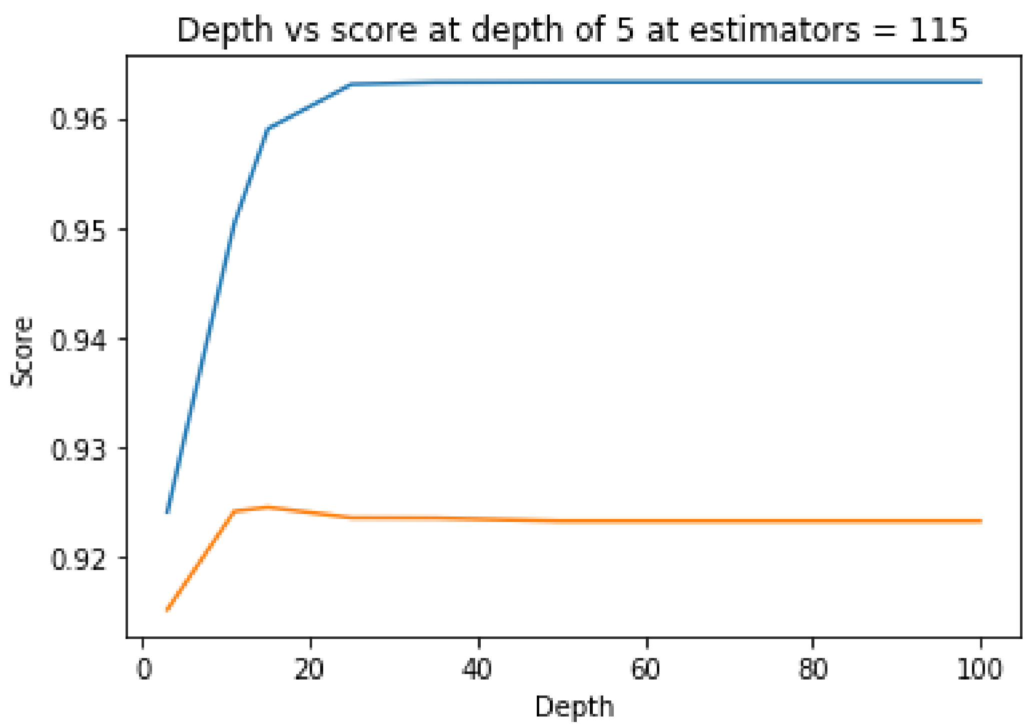
In [6]:
```
df_final_test.columns
```

Out[6]:
```
Index(['jaccard_followers', 'jaccard_followees', 'num_followers_s',
       'num_followees_s', 'num_followers_d', 'num_followees_d',
       'inter_followers', 'inter_followees', 'adar_index', 'follows_back',
       'same_comp', 'shortest_path', 'page_rank_s', 'page_rank_d', 'katz_s',
       'katz_d', 'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d',
       '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', 'Weight_in',
       'Weight_out', 'Weight_f1', 'Weight_f2', 'Weight_f3', 'Weight_f4',
       'svd_dot', 'svd_mean_s', 'svd_mean_d'],
      dtype='object')
```

In [7]:
```
depths = [3,11,15,25,35,50,100]
train_scores = []
test_scores = []

for i in depths:
    clf = RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=i, max_features=11, 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,ve
    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 0.924170984571304 test Score 0.9152763777461715
depth =  11 Train Score 0.9503796519459076 test Score 0.924220959419516
depth =  15 Train Score 0.9590027669458241 test Score 0.9245986302407551
depth =  25 Train Score 0.9630456634334905 test Score 0.9236317354926886
depth =  35 Train Score 0.9632218097809785 test Score 0.9236077277146334
depth =  50 Train Score 0.9632496325083799 test Score 0.9233378118527031
depth =  100 Train Score 0.9632496325083799 test Score 0.9233378118527031
```




```
In [8]: param_dist = {"n_estimators":sp_randint(105,125),
                      "max_depth": sp_randint(10,17),
                      "min_samples_split": sp_randint(110,190),
                      "min_samples_leaf": sp_randint(25,65),
                     "max_features":['auto',11]}
```

```
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)

print(rf_random.grid_scores_)

print()

print(rf_random.cv_results_)

import pickle
pickle.dump(rf_random,open('rf_random_final.p','wb'))
```

In [10]:
```
rf_random.grid_scores_
```

Out[10]:
```
[mean: 0.95251, std: 0.00109, params: {'max_depth': 14, 'max_features': 'auto', 'min_sa
 mean: 0.95499, std: 0.00083, params: {'max_depth': 12, 'max_features': 11, 'min_sample
 mean: 0.95229, std: 0.00054, params: {'max_depth': 11, 'max_features': 11, 'min_sample
 mean: 0.95015, std: 0.00092, params: {'max_depth': 13, 'max_features': 'auto', 'min_sa
 mean: 0.94129, std: 0.00128, params: {'max_depth': 11, 'max_features': 'auto', 'min_sa
```

In [11]:
```
print('mean test scores',rf_random.cv_results_['mean_test_score'])
print('mean train scores',rf_random.cv_results_['mean_train_score'])
```

```
mean test scores [0.95250539 0.95498837 0.95228519 0.95015108 0.94129217]
mean train scores [0.95258963 0.95503648 0.95233589 0.95022736 0.94129525]
```

In [12]:
```
rf_random.best_estimator_
```

Out[12]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=12, max_features=11, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=33, min_samples_split=138,
            min_weight_fraction_leaf=0.0, n_estimators=109, n_jobs=-1,
            oob_score=False, random_state=25, verbose=0, warm_start=False)
```

In [13]:
```
clf_1 =  RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=12, max_features=11, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=33, min_samples_split=138,
            min_weight_fraction_leaf=0.0, n_estimators=109, n_jobs=-1,
            oob_score=False, random_state=25, verbose=0, warm_start=False)
clf_1.fit(df_final_train,y_train)

import pickle
pickle.dump(clf_1,open('clf2_1.p','wb'))
```

```
In [6]: clf_1 = pickle.load(open('/home/u19292/clf2_1.p','rb'))

In [7]: y_train_pred1 = clf_1.predict(df_final_train)
        y_test_pred1 = clf_1.predict(df_final_test)

In [29]: from sklearn.metrics import f1_score
         print('Train f1 score',f1_score(y_train,y_train_pred1))
         print('Test f1 score',f1_score(y_test,y_test_pred1))
```

```
Train f1 score 0.9550800890664483
Test f1 score 0.9243521371699511
```

```
In [8]: df_final_test1 = read_hdf('storage_all_features.h5', 'test_df',mode='r')

In [9]: train_nodes_pos = pickle.load(open('train_nodes_pos.p','rb'))

In [32]: from tqdm import tqdm
         count_error  = 0
         count_cold_err = 0
         total_cold_nodes = 0
         for i,row in tqdm(df_final_test1.iterrows(),total=df_final_test1.shape[0]):
             if row['source_node'] not in train_nodes_pos or row['destination_node'] not in trai
                 total_cold_nodes = total_cold_nodes + 1
                 if y_test.values[i] != y_test_pred1[i]:
                     count_error = count_error + 1
                     count_cold_err = count_cold_err + 1
             else:
                 if y_test.values[i] != y_test_pred1[i]:
                     count_error = count_error + 1
```

```
100%|| 3775008/3775008 [02:07<00:00, 29524.56it/s]
```

```
In [35]: print('Length of Total Test data',len(df_final_test1))
         print('Total no of errors in test data',count_error)
         print('Leghth of test data where any one of nodes are not there in Train',total_cold_no
         print('Total no of error Where any one of nodes are not there in Train',count_cold_err)
```

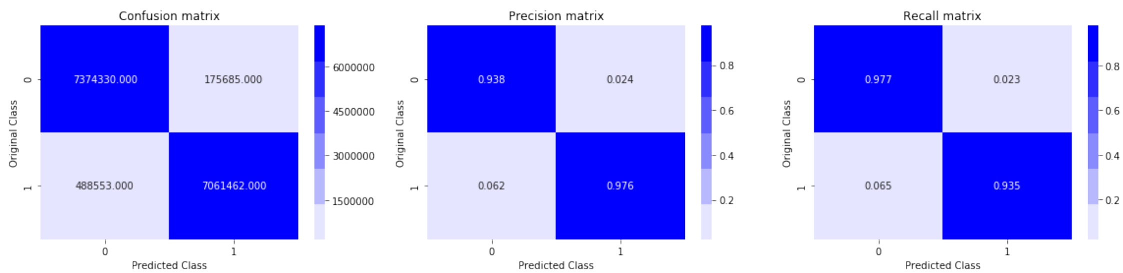
```
Length of Total Test data 3775008
Total no of errors in test data 271739
Leghth of test data where any one of nodes are not there in Train 253173
Total no of error Where any one of nodes are not there in Train 91728
```

```
In [41]: print('Total Error is {}%'.format(count_error/len(df_final_test1)*100))
         print('Error Where nodes not in Train Data is {}%'.format(count_cold_err/len(df_final_t
```

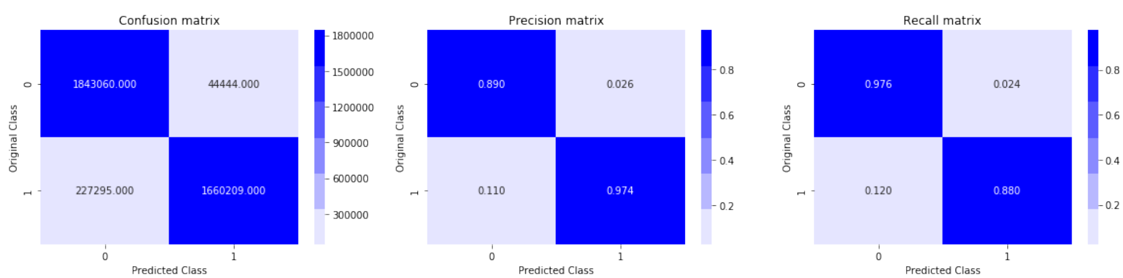
```
Total Error is 7.198368851138859%
Error Where nodes not in Train Data is 2.429875645296646%
```

```
In [30]: print('Train confusion_matrix')
         plot_confusion_matrix(y_train,y_train_pred1)
         print('Test confusion_matrix')
         plot_confusion_matrix(y_test,y_test_pred1)
```

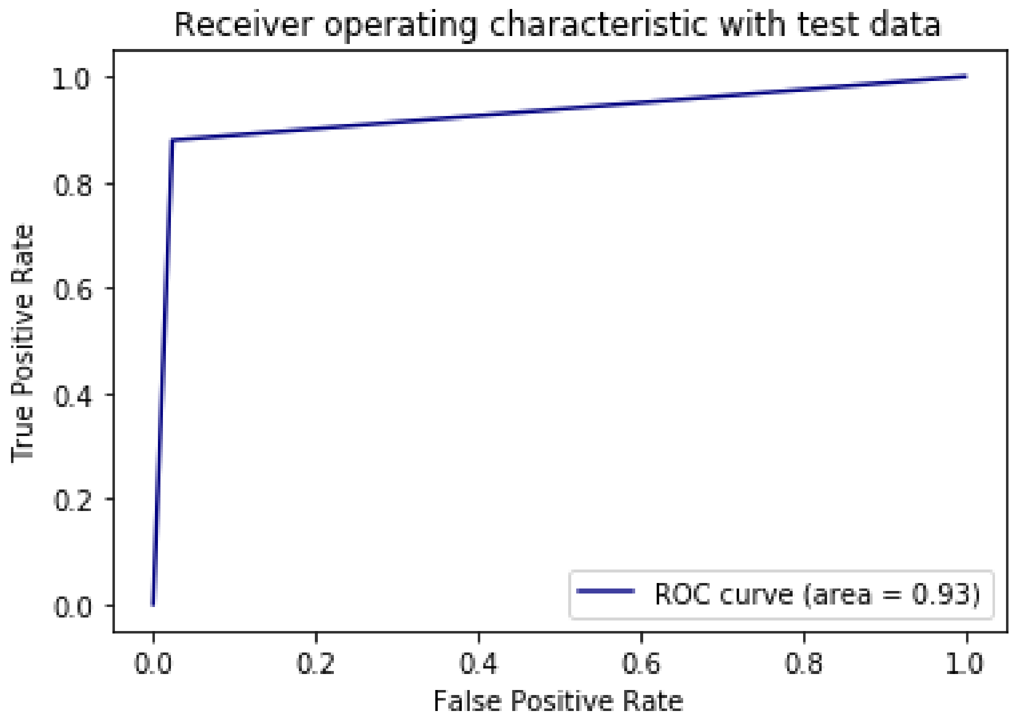
```
Train confusion_matrix
```



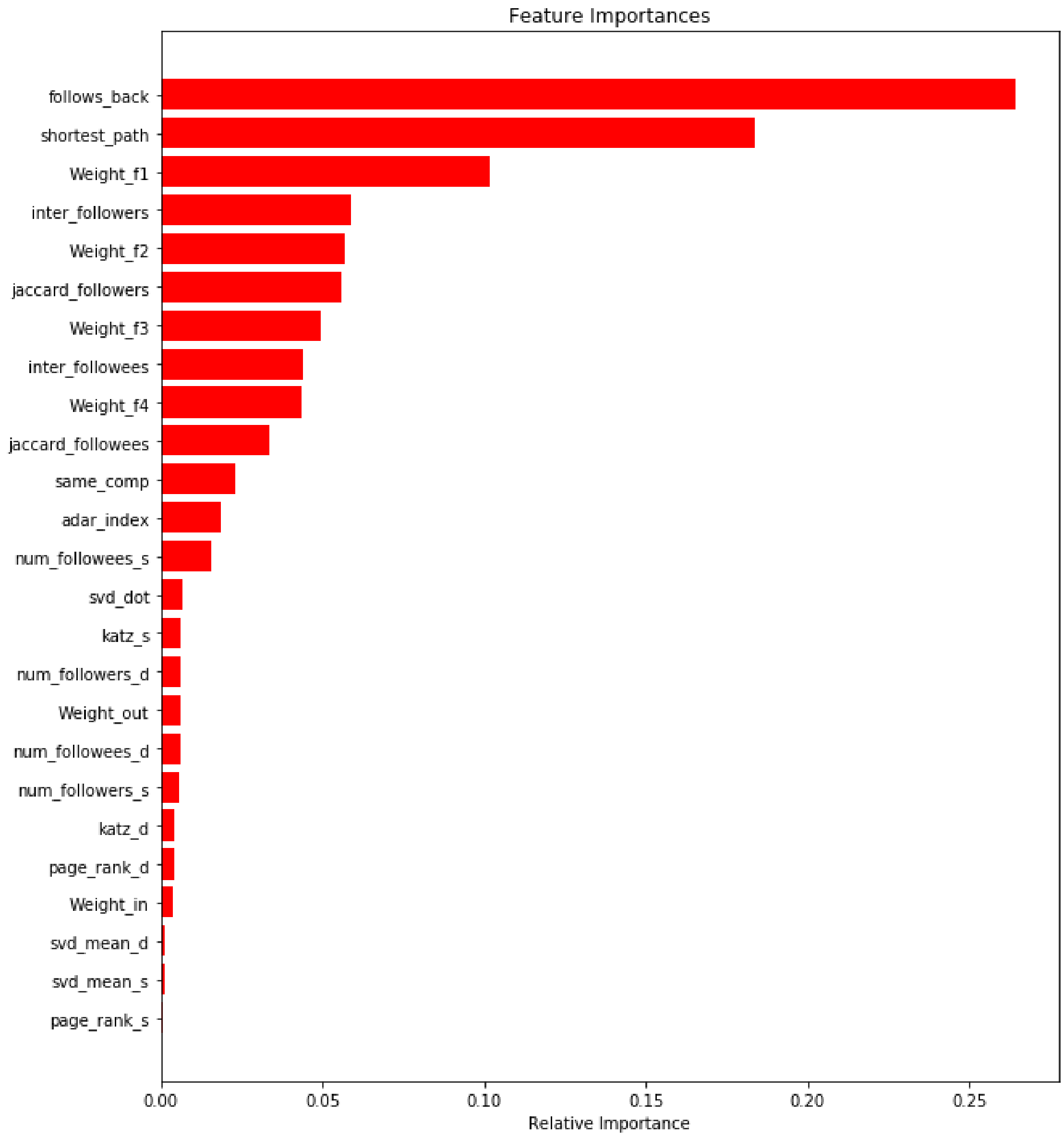

```
Test confusion_matrix
```




```
In [31]: from sklearn.metrics import roc_curve, auc
         fpr,tpr,ths = roc_curve(y_test,y_test_pred1)
         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 [32]: features = df_final_train.columns
         importances = clf_1.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()
```



improved some score and we can observe that Weight features and svd dot produts is somewhat better features than so many features.

In [34]:
```
feature_importances = pd.DataFrame(clf_1.feature_importances_,index = df_final_train.co
                                   columns=['importance']).sort_values('importance',asc
feature_importances
```

Out[34]:

	importance
follows_back	2.644804e-01
shortest_path	1.838595e-01
Weight_f1	1.016269e-01
inter_followers	5.900783e-02

Weight_f2	5.704880e-02
jaccard_followers	5.575706e-02
Weight_f3	4.926787e-02
inter_followees	4.368723e-02
Weight_f4	4.320862e-02
jaccard_followees	3.365333e-02
same_comp	2.304795e-02
adar_index	1.836028e-02
num_followees_s	1.532252e-02
svd_dot	6.457175e-03
katz_s	6.271872e-03
num_followers_d	6.163456e-03
Weight_out	6.068274e-03
num_followees_d	5.916338e-03
num_followers_s	5.488586e-03
katz_d	4.136551e-03
page_rank_d	4.104543e-03
Weight_in	3.734412e-03
svd_mean_d	1.305648e-03
svd_mean_s	1.046256e-03
page_rank_s	4.384363e-04
svd_v_d_3	1.556681e-04
svd_u_s_3	1.194442e-04
svd_u_d_3	1.100387e-04
svd_v_s_3	5.851178e-05
svd_u_s_6	2.462293e-05
svd_v_s_6	1.759360e-05
svd_v_d_6	1.725545e-05
svd_u_d_6	1.137179e-05
hubs_s	5.677168e-06
svd_u_s_2	3.717209e-06
svd_v_s_2	3.399203e-06
authorities_s	2.399581e-06
authorities_d	2.198454e-06
hubs_d	1.640633e-06
svd_v_d_2	1.500757e-06
svd_v_s_1	1.477797e-06
svd_u_d_2	1.179593e-06
svd_u_s_5	5.564461e-07
svd_v_s_5	5.549624e-07
svd_u_s_4	4.290664e-07
svd_u_s_1	4.018964e-07
svd_u_d_5	1.630302e-07
svd_v_d_5	1.376959e-07
svd_v_d_4	1.319796e-07
svd_v_s_4	7.132748e-08
svd_u_d_4	3.841453e-08
svd_u_d_1	3.704987e-09

```
svd_v_d_1            0.000000e+00
```