Facebook Friend Recommendation - Social network Graph Link Prediction

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 [0]:

```
#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
```

Mounting Drive

In [0]:

```
!kill -9 -1
```

In [2]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%
b&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.
2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww
ogleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/drive
```

In [3]:

```
!pwd
!ls
```

```
/content
drive  sample_data
```

In [4]:

```
import os
PATH = os.getcwd()
print(PATH)
```

```
/content
```

In [5]:

```
data_path = PATH + '/drive/My Drive/AAIC/Case Studies/Facebook Friend Recommendation/'
data_path
```

Out[5]:

```
'/content/drive/My Drive/AAIC/Case Studies/Facebook Friend Recommendation/'
```

In [0]:

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

```
x.DiGraph(),nodetype=int)
    print(nx.info(g))
```

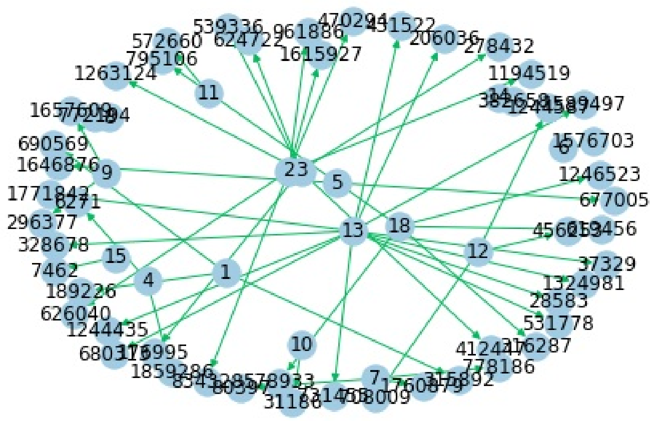
```
Name:
Type: DiGraph
Number of nodes: 1862220
Number of edges: 9437519
Average in degree:   5.0679
Average out degree:   5.0679
```

> Displaying a sub graph

In [0]:

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

subgraph=nx.read_edgelist(data_path + 'train_woheader_sample.csv',delimiter=',',create_using=nx.Di
Graph(),nodetype=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 [0]:

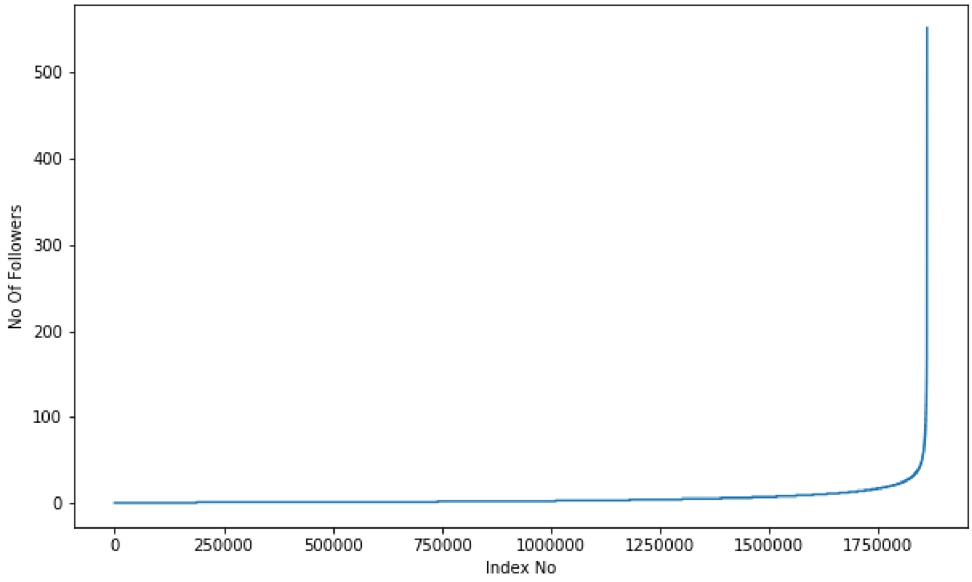
```
# No of Unique persons
print("The number of unique persons",len(g.nodes()))
```

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

1.1 No of followers for each person

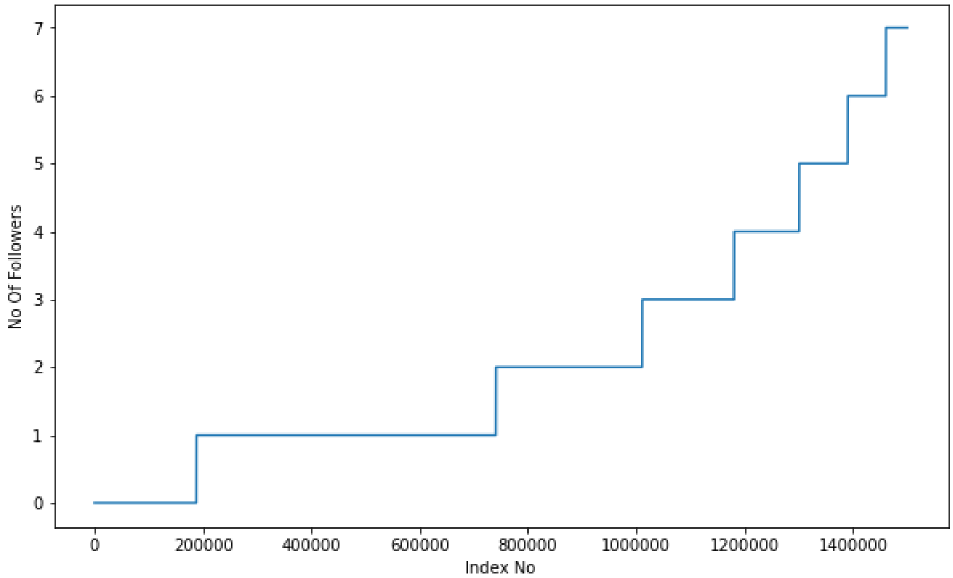
In [0]:

```
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()
```



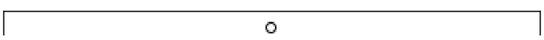
In [0]:

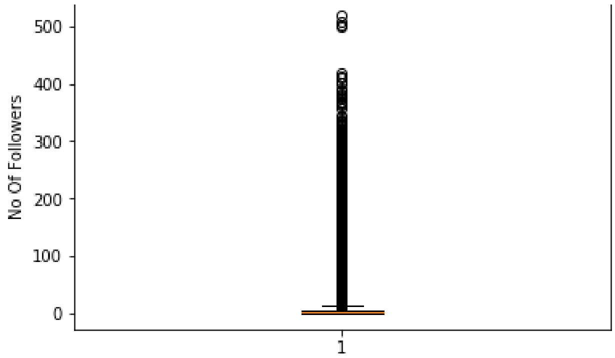
```
indegree_dist = list(dict(g.in_degree()).values())
indegree_dist.sort()
plt.figure(figsize=(10,6))
plt.plot(indegree_dist[0:1500000])
plt.xlabel('Index No')
plt.ylabel('No Of Followers')
plt.show()
```



In [0]:

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





In [0]:

```
### 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.

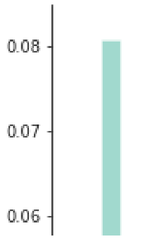
In [0]:

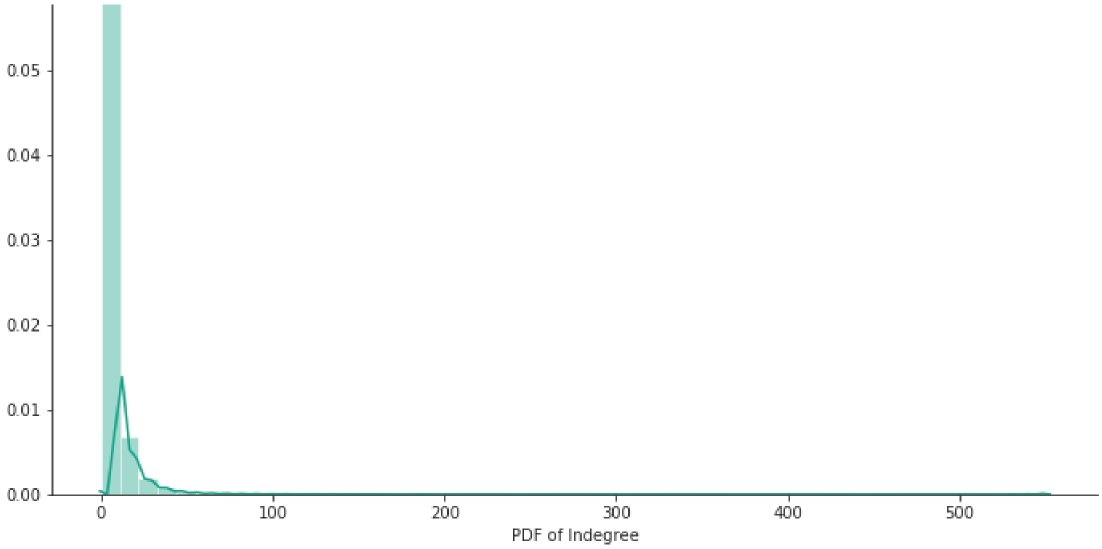
```
### 99-100 percentile
for i in range(10,110,10):
    print(99+(i/100),'percentile value is',np.percentile(indegree_dist,99+(i/100)))
```

```
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 [0]:

```
%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()
```

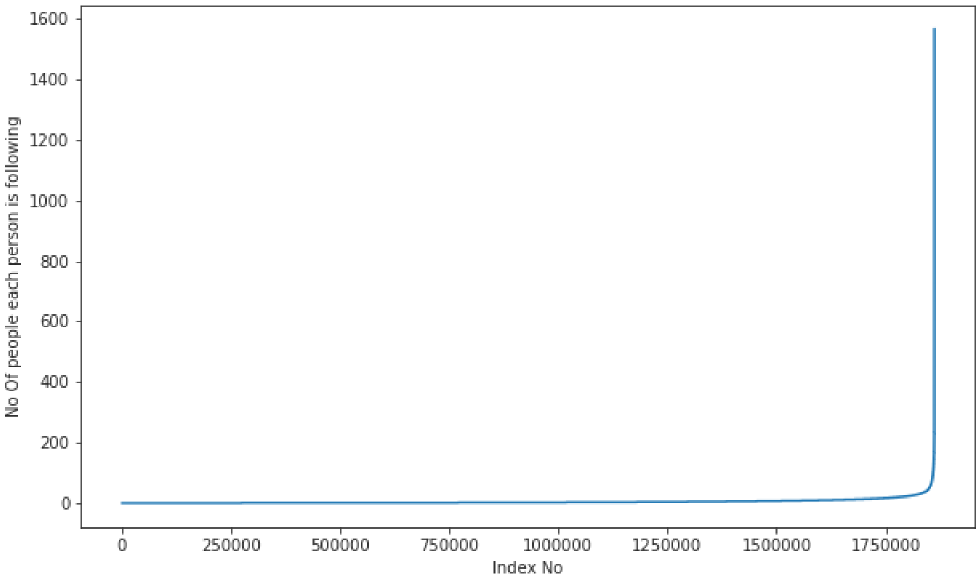




1.2 No of people each person is following

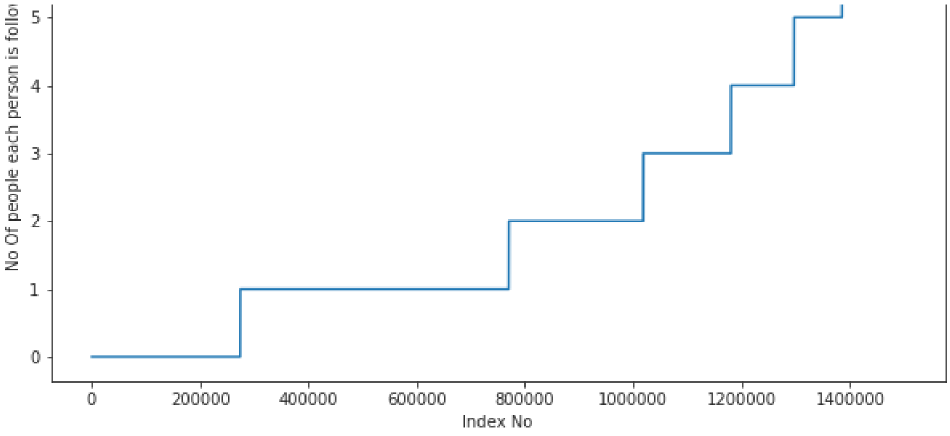
In [0]:

```
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()
```



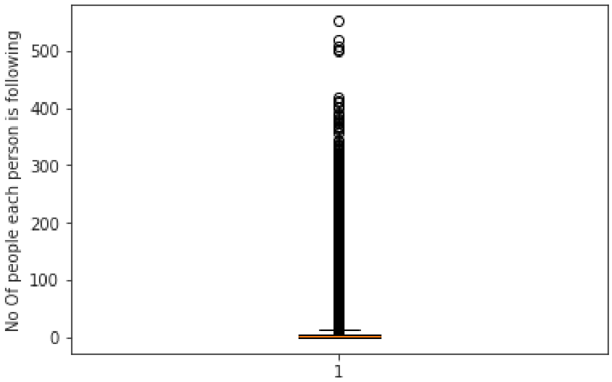
In [0]:

```
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 [0]:

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



In [0]:

```
### 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 [0]:

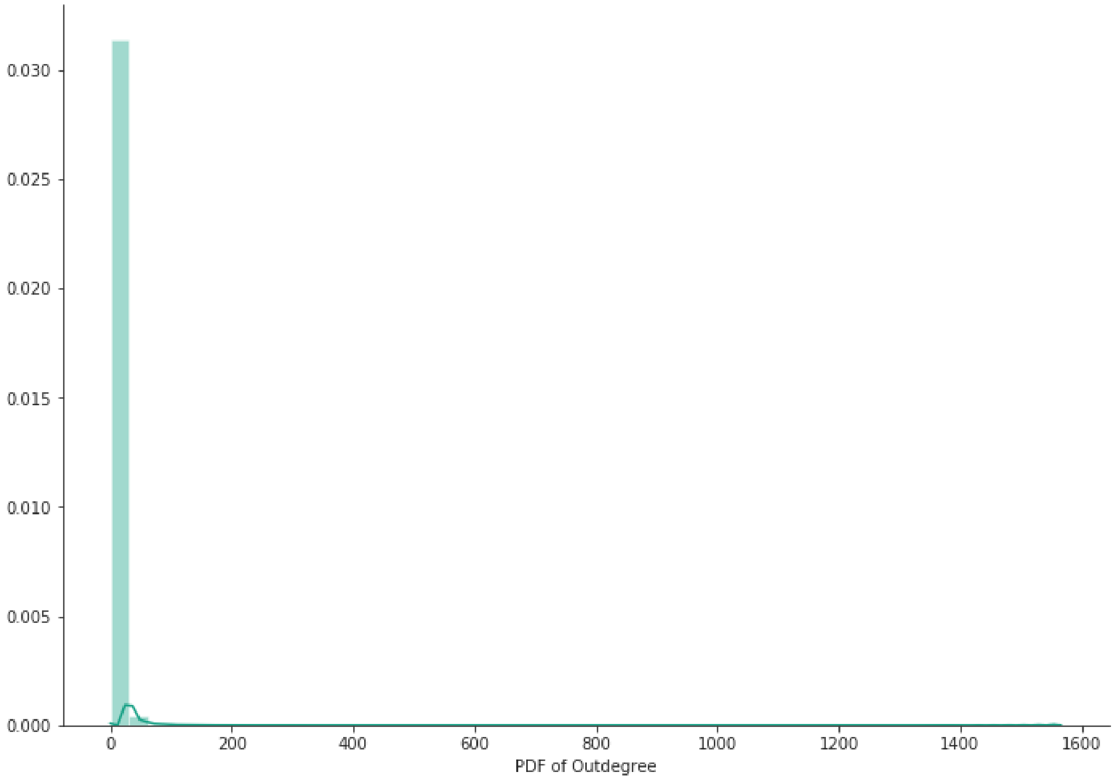
```
### 99-100 percentile
for i in range(10,110,10):
    print(99+(i/100),'percentile value is',np.percentile(outdegree_dist,99+(i/100)))
```

```
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 [0]:

```
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 [0]:

```
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 [0]:

```
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 [0]:

```
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

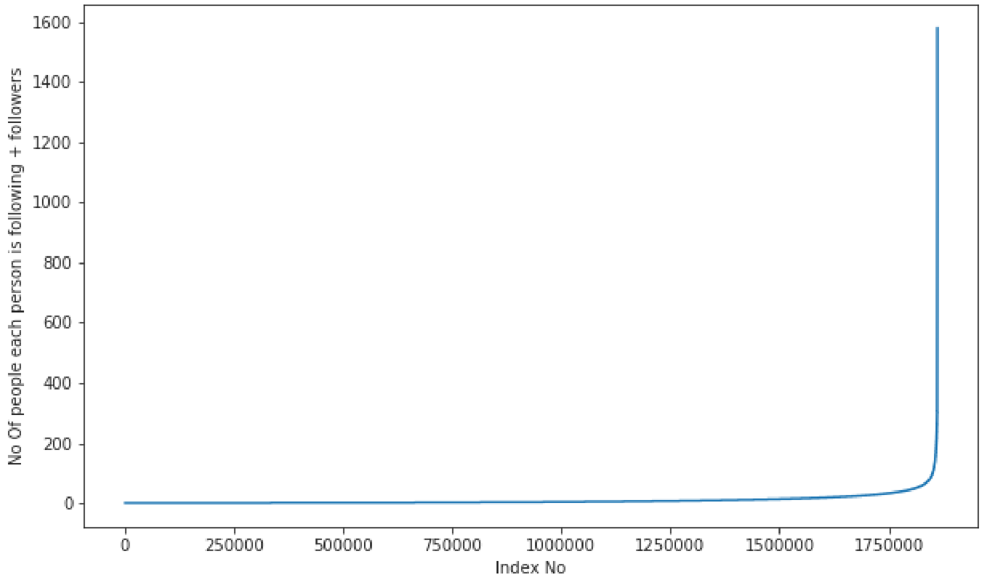
1.3 both followers + following

In [0]:

```
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()))
```

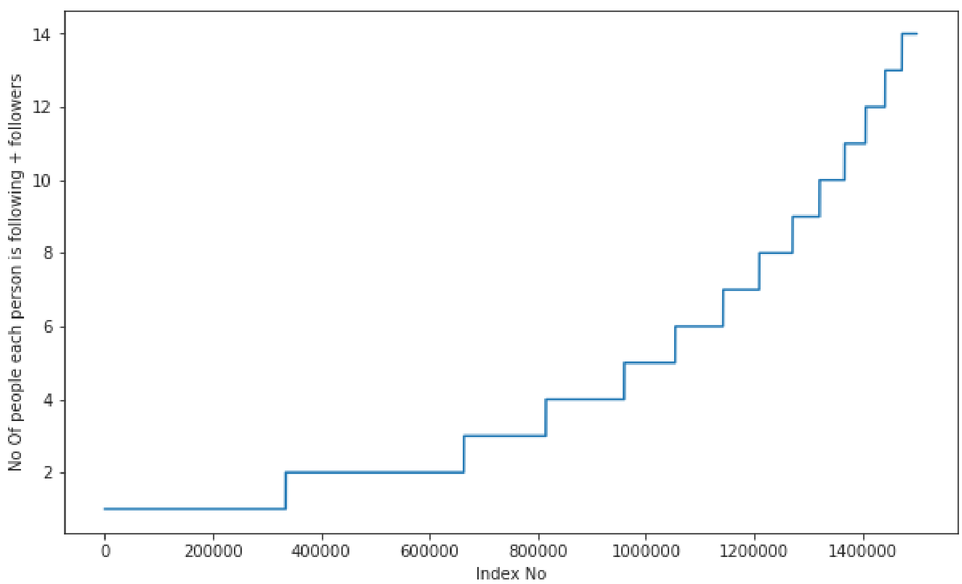
In [0]:

```
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 [0]:

```
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 [0]:

```
### 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 [0]:

```
### 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 [0]:

```
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 [0]:

```
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 [0]:

```
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 [0]:

```
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 [0]:

```
%%time
###generating bad edges from given graph
import random
if not os.path.isfile(data_path + 'data/after_eda/missing_edges_final.p'):
    #getting all set of edges
    r = csv.reader(open(data_path + 'data/after_eda/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(data_path + 'data/after_eda/missing_edges_final.p','wb'))
else:
    missing_edges = pickle.load(open(data_path + 'data/after_eda/missing_edges_final.p','rb'))
```

```
CPU times: user 2.46 s, sys: 1.29 s, total: 3.75 s
Wall time: 5.65 s
```

In [0]:

```
len(missing_edges)
```

Out[0]:

```
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 [0]:

```
from sklearn.model_selection import train_test_split
if (not os.path.isfile(data_path + 'data/after_eda/train_pos_after_eda.csv')) and (not
os.path.isfile(data_path + 'data/after_eda/test_pos_after_eda.csv')):
    #reading total data df
    df_pos = pd.read_csv(data_path + 'data/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(data_path + 'data/after_eda/train_pos_after_eda.csv',header=False, index=Fal
se)
    X_test_pos.to_csv(data_path + 'data/after_eda/test_pos_after_eda.csv',header=False, index=False
)
    X_train_neg.to_csv(data_path + 'data/after_eda/train_neg_after_eda.csv',header=False, index=Fal
se)
    X_test_neg.to_csv(data_path + 'data/after_eda/test_neg_after_eda.csv',header=False, index=False
)
else:
    #Graph from Traing data only
    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 [0]:

```
if (os.path.isfile(data_path + 'data/after_eda/train_pos_after_eda.csv')) and
(os.path.isfile(data_path + 'data/after_eda/test_pos_after_eda.csv')):
    train_graph=nx.read_edgelist(data_path +
'data/after_eda/train_pos_after_eda.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=int)
    test_graph=nx.read_edgelist(data_path + 'data/after_eda/test_pos_after_eda.csv',delimiter=',',c
reate_using=nx.DiGraph(),nodetype=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 %
```

> we have a cold start problem here

In [0]:

```
#final train and test data sets
if (not os.path.isfile(data_path + 'data/after_eda/train_after_eda.csv')) and \
(not os.path.isfile(data_path + 'data/after_eda/test_after_eda.csv')) and \
(not os.path.isfile(data_path + 'data/train_y.csv')) and \
(not os.path.isfile(data_path + 'data/test_y.csv')) and \
(os.path.isfile(data_path + 'data/after_eda/train_pos_after_eda.csv')) and \
(os.path.isfile(data_path + 'data/after_eda/test_pos_after_eda.csv')) and \
(os.path.isfile(data_path + 'data/after_eda/train_neg_after_eda.csv')) and \
(os.path.isfile(data_path + 'data/after_eda/test_neg_after_eda.csv')):

    X_train_pos = pd.read_csv(data_path + 'data/after_eda/train_pos_after_eda.csv', names=['source_node', 'destination_node'])
    X_test_pos = pd.read_csv(data_path + 'data/after_eda/test_pos_after_eda.csv', names=['source_node', 'destination_node'])
    X_train_neg = pd.read_csv(data_path + 'data/after_eda/train_neg_after_eda.csv', names=['source_node', 'destination_node'])
    X_test_neg = pd.read_csv(data_path + 'data/after_eda/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(data_path + 'data/after_eda/train_after_eda.csv',header=False,index=False)
    X_test.to_csv(data_path + 'data/after_eda/test_after_eda.csv',header=False,index=False)
    pd.DataFrame(y_train.astype(int)).to_csv(data_path + 'data/train_y.csv',header=False,index=False)
    pd.DataFrame(y_test.astype(int)).to_csv(data_path + 'data/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 [0]:

```
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,)
```

3. Reading Data

In [0]:

```
if os.path.isfile(data_path + 'data/after_eda/train_pos_after_eda.csv'):
    train_graph=nx.read_edgelist(data_path +
'data/after_eda/train_pos_after_eda.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=int)
    print(nx.info(train_graph))
else:
    print("please run the FB_EDA.ipynb or download the files from drive")
```

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

4. Similarity measures

4.1 Jaccard Distance:

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

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

In [0]:

```
#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 [0]:

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

```
0.0
```

In [0]:

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

```
0.0
```

In [0]:

```
#for followers
def jaccard_for_followers(a,b):
    try:
        if len(set(train_graph.predecessors(a))) == 0  | len(set(g.predecessors(b))) == 0:
```

```
        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 [0]:

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

0

In [0]:

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

0

4.2 Cosine distance

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

In [0]:

```
#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 [0]:

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

0.0

In [0]:

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

0

In [0]:

```
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:
```

```
    except:
        return 0
```

In [0]:

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

```
0.02886751345948129
```

In [0]:

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

```
0
```

5. 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.**

5.1 Page Ranking

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

In [0]:

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

In [0]:

```
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 [0]:

```
#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
```

6. Other Graph Features

6. Other Graph Features

6.1 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 [0]:

```
#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 [0]:

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

Out[0]:

```
10
```

In [0]:

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

Out[0]:

```
-1
```

6.2 Checking for same community

In [0]:

```
#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:
                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 [0]:

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

Out[0]:

0

In [0]:

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

Out[0]:

0

6.3 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 [0]:

```
#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 [0]:

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

Out[0]:

0

In [0]:

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

Out[0]:

0

6.4 Is person was following back:

In [0]:

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

```
        return 0
```

In [0]:

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

Out[0]:

```
1
```

In [0]:

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

Out[0]:

```
0
```

6.5 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 [0]:

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

In [0]:

```
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 [0]:

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

```
0.0007483800935562018
```

6.6 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 [0]:

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

In [0]:

```python
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
```

7. Featurization

7. 1 Reading a sample of Data from both train and test

In [0]:

```python
import random
if os.path.isfile(data_path + 'data/after_eda/train_after_eda.csv'):
    filename = data_path + "data/after_eda/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 [0]:

```python
if os.path.isfile(data_path + 'data/after_eda/train_after_eda.csv'):
    filename = data_path + "data/after_eda/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 [0]:

```python
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
```

In [0]:

```python
df_final_train = pd.read_csv(data_path + 'data/after_eda/train_after_eda.csv', skiprows=skip_train,
names=['source_node', 'destination_node'])
df_final_train['indicator_link'] = pd.read_csv(data_path + 'data/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)
```

Our train matrix size (100002, 5)

Out[0]:

	source_node	destination_node	indicator_link
0	273084	1505602	1
1	832016	1543415	1

In [0]:

```
df_final_test = pd.read_csv(data_path + 'data/after_eda/test_after_eda.csv', skiprows=skip_test, 
names=['source_node', 'destination_node'])
df_final_test['indicator_link'] = pd.read_csv(data_path + 'data/test_y.csv', skiprows=skip_test, na
mes=['indicator_link'])
print("Our test matrix size ",df_final_test.shape)
df_final_test.head(2)
```

Our test matrix size (50002, 3)

Out[0]:

	source_node	destination_node	indicator_link
0	848424	784690	1
1	483294	1255532	1

7.2 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 [0]:

```
if not os.path.isfile(data_path + 'data/fea_sample/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 [0]:

```
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 [0]:

```
if not os.path.isfile(data_path + 'data/fea_sample/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('data/fea_sample/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(data_path + 'data/fea_sample/storage_sample_stage1.h5', 'train_df',mo
de='r')
    df_final_test = read_hdf(data_path + 'data/fea_sample/storage_sample_stage1.h5', 'test_df',mode
='r')
```

7.3 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 [0]:

```
if not os.path.isfile(data_path + 'data/fea_sample/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(data_path + 'data/fea_sample/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(data_path + 'data/fea_sample/storage_sample_stage2.h5', 'train_df',mo
de='r')
    df_final_test = read_hdf(data_path + 'data/fea_sample/storage_sample_stage2.h5', 'test_df',mode
='r')
```

7.4 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
    - 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 [0]:

```
#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
[00:11<00:00, 152682.24it/s]
```

In [0]:

```
if not os.path.isfile(data_path + 'data/fea_sample/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 [0]:

```
if not os.path.isfile(data_path + 'data/fea_sample/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(data_path + 'data/fea_sample/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(data_path + 'data/fea_sample/storage_sample_stage3.h5', 'train_df',mo
de='r')
    df_final_test = read_hdf(data_path + 'data/fea_sample/storage_sample_stage3.h5', 'test_df',mode
='r')
```

7.5 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 [0]:

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

In [0]:

```
#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 [0]:

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

In [0]:

```
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 [0]:

```
if not os.path.isfile(data_path + 'data/fea_sample/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)
#===================================================================================================

    hdf = HDFStore(data_path + 'data/fea_sample/storage_sample_stage4.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()
```

8. Modelling the data

In [0]:

```
#reading
from pandas import read_hdf
df_final_train = read_hdf(data_path + 'data/fea_sample/storage_sample_stage4.h5', 'train_df',mode='
r')
df_final_test = read_hdf(data_path + 'data/fea_sample/storage_sample_stage4.h5',
'test_df',mode='r')
```

In [0]:

```
df_final_train.columns
```

Out[0]:

```
Index(['source_node', 'destination_node', 'indicator_link',
       'jaccard_followers', 'jaccard_followees', 'cosine_followers',
       'cosine_followees', 'num_followers_s', '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', '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 [0]:

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

In [0]:

```
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)
```

8.1 Random Forest

In [0]:

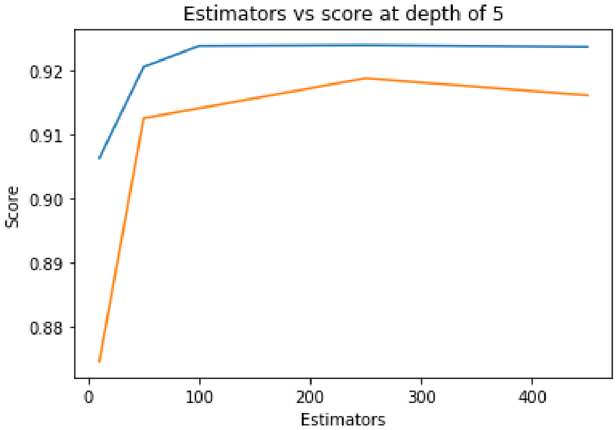
```
estimators = [10,50,100,250,450]
train_scores = []
test_scores = []
for i in estimators:
    clf = RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=5, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            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 0.9063252121775113 test Score 0.8745605278006858
Estimators =  50 Train Score 0.9205725512208812 test Score 0.9125653355634538
Estimators =  100 Train Score 0.9238690848446947 test Score 0.9141199714153599
```

```
Estimators =  250 Train Score 0.9239789348046863 test Score 0.9188007232664732
Estimators =  450 Train Score 0.9237190618658074 test Score 0.9161507685828595
```

Out[0]:

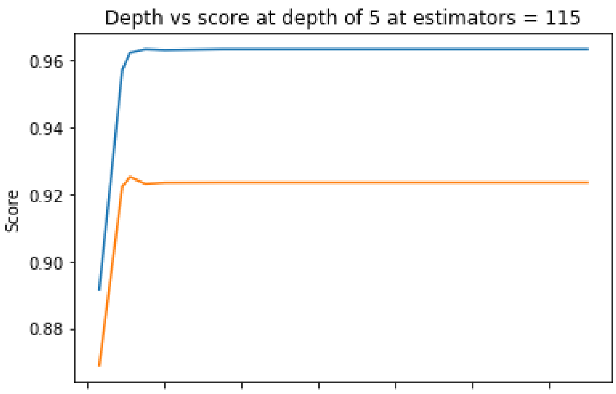
```
Text(0.5,1,'Estimators vs score at depth of 5')
```

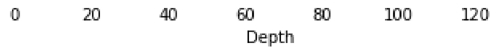


In [0]:

```
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 0.8916120853581238 test Score 0.8687934859875491
depth =  9 Train Score 0.9572226298198419 test Score 0.9222953031452904
depth =  11 Train Score 0.9623451340902863 test Score 0.9252318758281279
depth =  15 Train Score 0.9634267621927706 test Score 0.9231288356496615
depth =  20 Train Score 0.9631629153051491 test Score 0.9235051024711141
depth =  35 Train Score 0.9634333127085721 test Score 0.9235601652753184
depth =  50 Train Score 0.9634333127085721 test Score 0.9235601652753184
depth =  70 Train Score 0.9634333127085721 test Score 0.9235601652753184
depth =  130 Train Score 0.9634333127085721 test Score 0.9235601652753184
```





In [0]:

```
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)
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 [0.96225043 0.96215493 0.96057081 0.96194015 0.96330005]
mean train scores [0.96294922 0.96266735 0.96115674 0.96263457 0.96430539]
```

In [0]:

```
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 [0]:

```
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 [0]:

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

In [0]:

```
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 0.9652533106548414
Test f1 score 0.9241678239279553
```

In [0]:

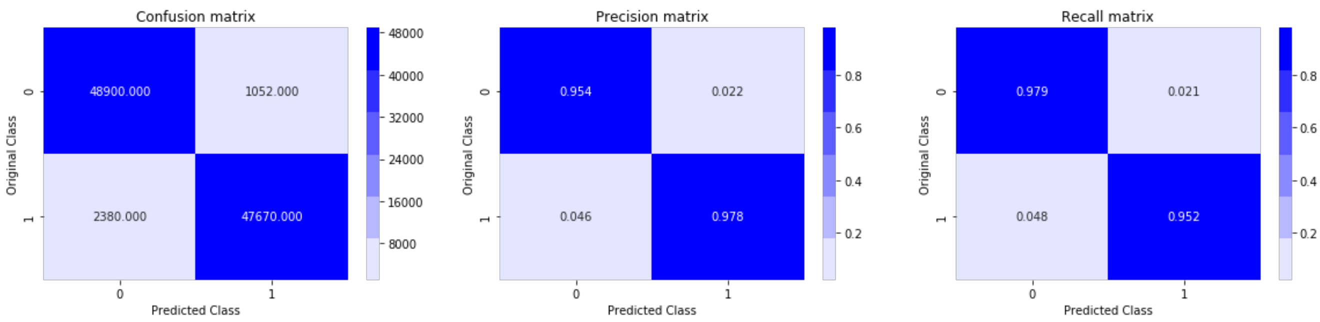
```
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
```

```
    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()
```

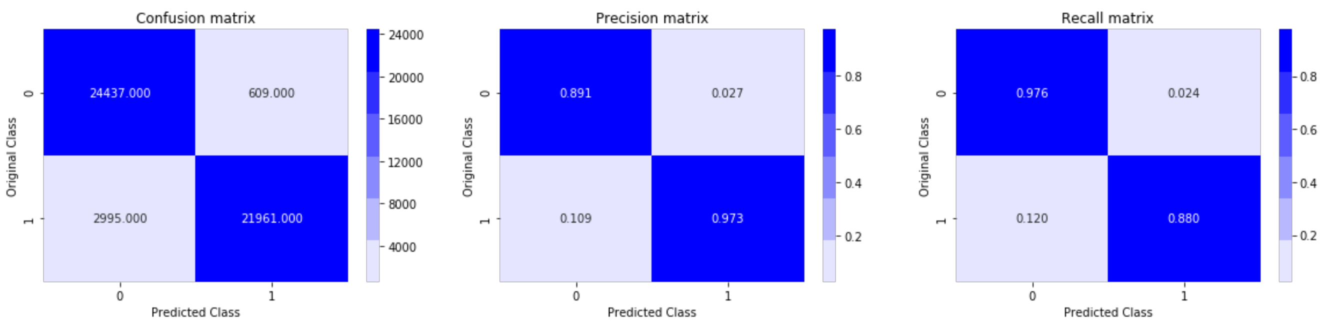
In [0]:

```
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



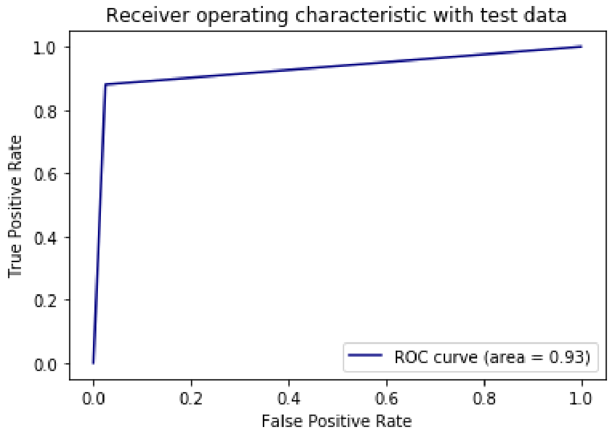
Test confusion_matrix



In [0]:

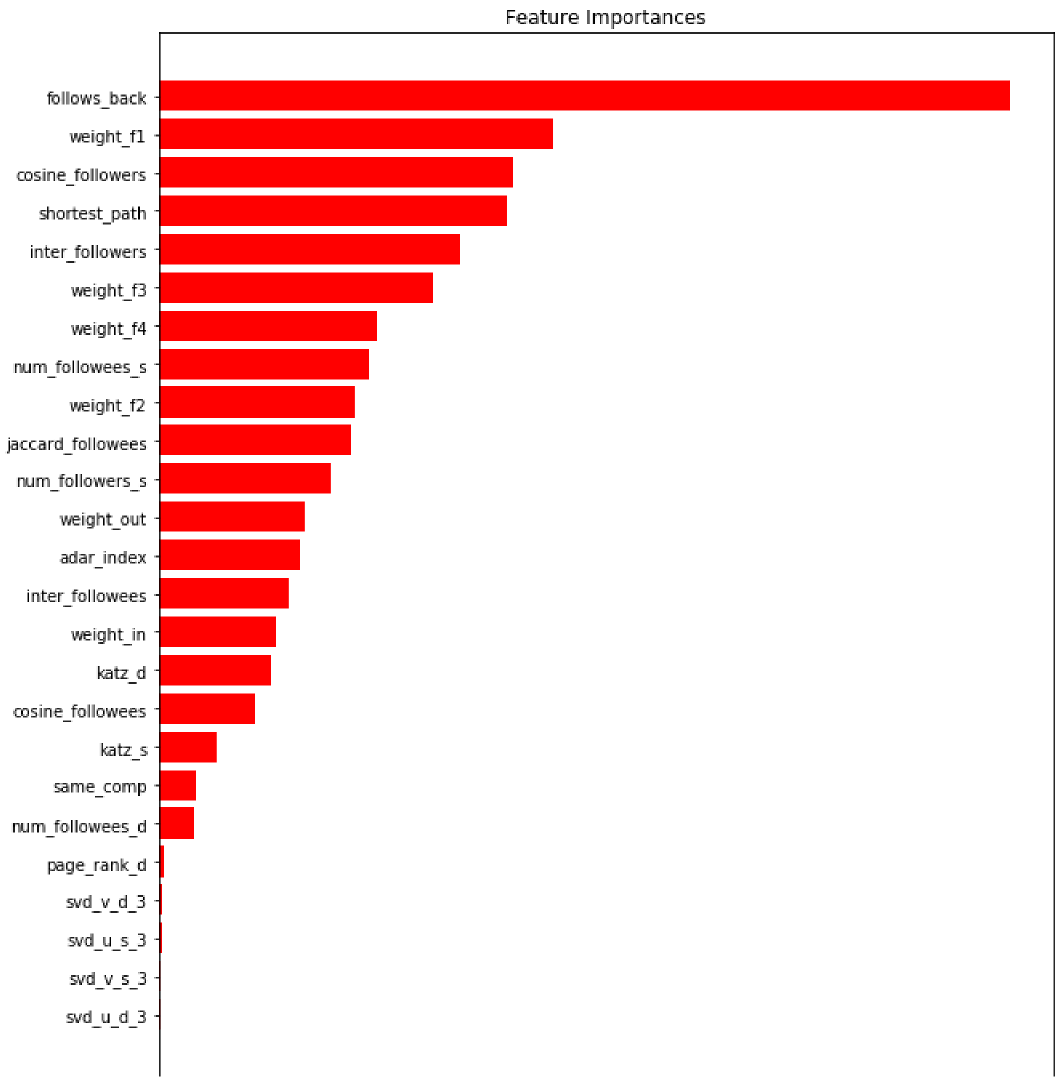
```
from sklearn.metrics import roc_curve, auc
fpr,tpr,ths = roc_curve(y_test,y_test_pred)
auc_sc = auc(fpr, tpr)
plt.plot(fpr, tpr, color='navy',label='ROC curve (area = %0.2f)' % auc_sc)
```

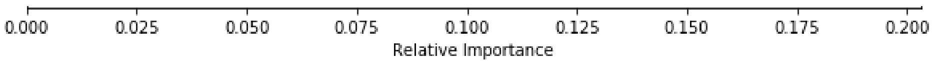
```
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic with test data')
plt.legend()
plt.show()
```



In [0]:

```
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()
```





9. Assignments:

1. Add another feature called Preferential Attachment with followers and followees data of vertex. you can check about Preferential Attachment in below link http://be.amazd.com/link-prediction/
2. Add feature called svd_dot. you can calculate svd_dot as Dot product between sourse node svd and destination node svd features. you can read about this in below pdf https://storage.googleapis.com/kaggle-forum-message-attachments/2594/supervised_link_prediction.pdf
3. Tune hyperparameters for XG boost with all these features and check the error metric.

In [0]:

```
#reading
from pandas import read_hdf
df_final_train = read_hdf(data_path + 'data/fea_sample/storage_sample_stage4.h5', 'train_df',mode='
r')
df_final_test = read_hdf(data_path + 'data/fea_sample/storage_sample_stage4.h5',
'test_df',mode='r')
```

In [7]:

```
df_final_train.columns
```

Out[7]:

```
Index(['source_node', 'destination_node', 'indicator_link',
       'jaccard_followers', 'jaccard_followees', 'cosine_followers',
       'cosine_followees', 'num_followers_s', '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', '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 [0]:

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

In [9]:

```
df_final_train.head()
```

Out[9]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees	num_followe
0	273084	1505602	1	0	0.000000	0.000000	0.000000	
1	832016	1543415	1	0	0.187135	0.028382	0.343828	
2	1325247	760242	1	0	0.369565	0.156957	0.566038	
3	1368400	1006992	1	0	0.000000	0.000000	0.000000	
4	140165	1708748	1	0	0.000000	0.000000	0.000000	

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees	num_followe

In [10]:

```
if os.path.isfile(data_path + 'data/after_eda/train_pos_after_eda.csv') and
os.path.isfile(data_path + 'data/after_eda/test_pos_after_eda.csv'):
    train_graph=nx.read_edgelist(data_path +
'data/after_eda/train_pos_after_eda.csv',delimiter=',',create_using=nx.DiGraph(),nodetype=int)
    test_graph=nx.read_edgelist(data_path + 'data/after_eda/test_pos_after_eda.csv',delimiter=',',c
reate_using=nx.DiGraph(),nodetype=int)
    print(nx.info(train_graph))
    print(nx.info(test_graph))
```

```
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
```

9.1 Addigng SVD Dot product as one of the feature

In [12]:

```
from tqdm import tqdm
svd_dot_u = []
svd_dot_v = []
for i in tqdm(range(len(df_final_train))):
  svd_s_u = list(df_final_train[df_final_train.columns[30:36]].iloc[i])
  svd_s_v = list(df_final_train[df_final_train.columns[42:48]].iloc[i])
  svd_d_u = list(df_final_train[df_final_train.columns[36:42]].iloc[i])
  svd_d_v = list(df_final_train[df_final_train.columns[48:]].iloc[i])
  svd_dot_u.append(np.dot(svd_s_u,svd_d_u))
  svd_dot_v.append(np.dot(svd_s_v,svd_d_v))
print(len(svd_dot_u), len(svd_dot_v))
```

```
100%|██████████| 100002/100002 [15:28<00:00, 107.67it/s]
```

```
100002 100002
```

In [13]:

```
df_final_train['svd_dot_u'] = svd_dot_u
df_final_train['svd_dot_v'] = svd_dot_v
df_final_train.head()
```

Out[13]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees	num_followe
0	273084	1505602	1	0	0.000000	0.000000	0.000000	
1	832016	1543415	1	0	0.187135	0.028382	0.343828	
2	1325247	760242	1	0	0.369565	0.156957	0.566038	
3	1368400	1006992	1	0	0.000000	0.000000	0.000000	

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees	num_followe
4	140165	1708748	1	0	0.000000	0.000000	0.000000	

In [14]:

```
svd_dot_u = []
svd_dot_v = []
for i in tqdm(range(len(df_final_test))):
  svd_s_u = list(df_final_test[df_final_test.columns[30:36]].iloc[i])
  svd_s_v = list(df_final_test[df_final_test.columns[42:48]].iloc[i])
  svd_d_u = list(df_final_test[df_final_test.columns[36:42]].iloc[i])
  svd_d_v = list(df_final_test[df_final_test.columns[48:]].iloc[i])
  svd_dot_u.append(np.dot(svd_s_u,svd_d_u))
  svd_dot_v.append(np.dot(svd_s_v,svd_d_v))
df_final_test['svd_dot_u'] = svd_dot_u
df_final_test['svd_dot_v'] = svd_dot_v
df_final_test.head()
```

```
100%|██████████| 50002/50002 [06:04<00:00, 137.11it/s]
```

Out[14]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees	num_followe
0	848424	784690	1	0	0.0	0.029161	0.000000	
1	483294	1255532	1	0	0.0	0.000000	0.000000	
2	626190	1729265	1	0	0.0	0.000000	0.000000	
3	947219	425228	1	0	0.0	0.000000	0.000000	
4	991374	975044	1	0	0.2	0.042767	0.347833	

9.2 Adding Preferential Attachment as one feature

In [0]:

```
def compute_features(df_final, graph):
    #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=[]
    for i,row in df_final.iterrows():
        try:
            s1=set(graph.predecessors(row['source_node']))
            s2=set(graph.successors(row['source_node']))
        except:
            s1 = set()
            s2 = set()
        try:
            d1=set(graph.predecessors(row['destination_node']))
            d2=set(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))
```

```
    return num_followers_s, num_followers_d, num_followees_s, num_followees_d
```

In [0]:

```
followers_s, followers_d, followees_s, followees_d = compute_features(df_final_train, train_graph)
```

In [17]:

```
df_final_train['pref_attachment_followers'] = [a*b for a,b in zip(followers_s,followers_d)]
df_final_train['pref_attachment_followees'] = [a*b for a,b in zip(followees_s,followees_d)]
df_final_train.head()
```

Out[17]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees	num_followe
0	273084	1505602	1	0	0.000000	0.000000	0.000000	
1	832016	1543415	1	0	0.187135	0.028382	0.343828	
2	1325247	760242	1	0	0.369565	0.156957	0.566038	
3	1368400	1006992	1	0	0.000000	0.000000	0.000000	
4	140165	1708748	1	0	0.000000	0.000000	0.000000	

In [18]:

```
followers_s, followers_d, followees_s, followees_d = compute_features(df_final_test, test_graph)
df_final_test['pref_attachment_followers'] = [a*b for a,b in zip(followers_s,followers_d)]
df_final_test['pref_attachment_followees'] = [a*b for a,b in zip(followees_s,followees_d)]
df_final_test.head()
```

Out[18]:

	source_node	destination_node	indicator_link	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees	num_followe
0	848424	784690	1	0	0.0	0.029161	0.000000	
1	483294	1255532	1	0	0.0	0.000000	0.000000	
2	626190	1729265	1	0	0.0	0.000000	0.000000	
3	947219	425228	1	0	0.0	0.000000	0.000000	
4	991374	975044	1	0	0.2	0.042767	0.347833	

In [0]:

```
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)
```

9.3 Applying XGBoost

In [0]:

```python
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import RandomizedSearchCV
from datetime import datetime
```

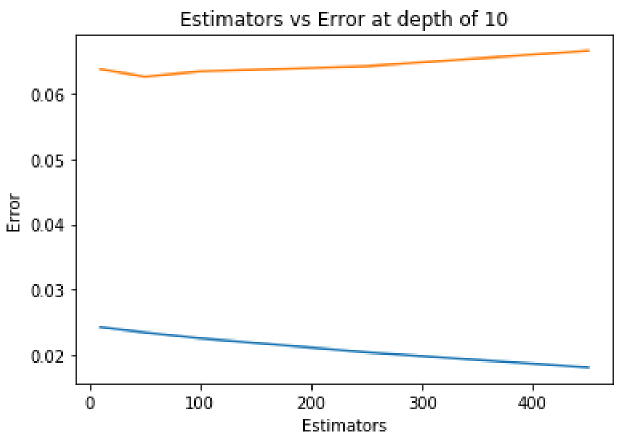
In [21]:

```python
estimators = [10,50,100,250,450]
train_error = []
test_error = []
for i in estimators:
    model = XGBClassifier(max_depth=10,
                            subsample=0.33,
                            n_estimators=i,
                            learning_rate = 0.01)
    model.fit(df_final_train,y_train)
    train_er = 1 - accuracy_score(y_train,model.predict(df_final_train))
    test_er = 1 - accuracy_score(y_test,model.predict(df_final_test))
    test_error.append(test_er)
    train_error.append(train_er)
    print('Estimators = ',i,'Train Error',train_er,'test Error',test_er)
plt.plot(estimators,train_error,label='Train Error')
plt.plot(estimators,test_error,label='Test Error')
plt.xlabel('Estimators')
plt.ylabel('Error')
plt.title('Estimators vs Error at depth of 10')
```

```
Estimators =  10 Train Error 0.024259514809703786 test Error 0.06373745050197988
Estimators =  50 Train Error 0.023449531009379854 test Error 0.06259749610015597
Estimators =  100 Train Error 0.022549549009019842 test Error 0.06339746410143599
Estimators =  250 Train Error 0.020419591608167864 test Error 0.06419743210271589
Estimators =  450 Train Error 0.018099638007239904 test Error 0.06657733690652379
```

Out[21]:

```
Text(0.5, 1.0, 'Estimators vs Error at depth of 10')
```

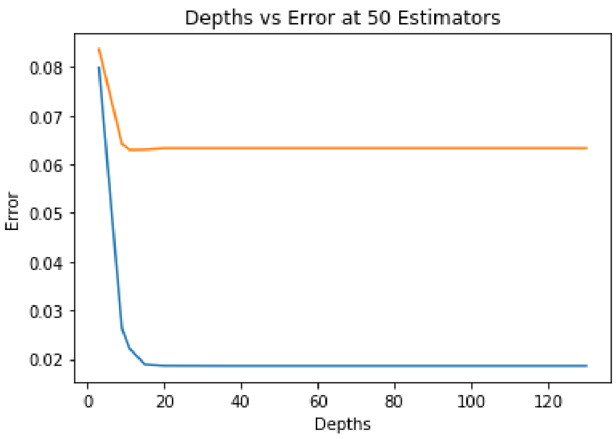


In [22]:

```python
depths = [3,9,11,15,20,35,50,70,130]
train_error = []
test_error = []
for i in depths:
    model = XGBClassifier(max_depth=i,
                            subsample=0.33,
                            n_estimators=50,
                            learning_rate = 0.01)
    model.fit(df_final_train,y_train)
    train_er = 1 - accuracy_score(y_train,model.predict(df_final_train))
    test_er = 1 - accuracy_score(y_test,model.predict(df_final_test))
    test_error.append(test_er)
    train_error.append(train_er)
    print('Depth = ',i,'Train Error',train_er,'test Error',test_er)
plt.plot(depths,train_error,label='Train Error')
plt.plot(depths,test_error,label='Test Error')
plt.xlabel('Depths')
```

```
plt.ylabel('Error')
plt.title('Depths vs Error at 50 Estimators')
plt.show()
```

```
Depth =  3 Train Error 0.07985840283194334 test Error 0.0836766529338826
Depth =  9 Train Error 0.026239475210495744 test Error 0.06423743050277986
Depth =  11 Train Error 0.022119557608847873 test Error 0.06297748090076394
Depth =  15 Train Error 0.01885962280754383 test Error 0.06301747930082802
Depth =  20 Train Error 0.01857962840743188 test Error 0.0632974681012759
Depth =  35 Train Error 0.018549629007419854 test Error 0.0632974681012759
Depth =  50 Train Error 0.018549629007419854 test Error 0.0632974681012759
Depth =  70 Train Error 0.018549629007419854 test Error 0.0632974681012759
Depth =  130 Train Error 0.018549629007419854 test Error 0.0632974681012759
```



In [0]:

```
params = {
        'n_estimators': [5, 10, 50, 100, 200, 500],
        'gamma': [0.5, 1, 1.5, 2, 5],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'learning_rate': [0.01,0.1,0.3,0.5,1],
        'max_depth': [2, 5, 9, 10, 11, 13, 15, 20]
}
```

In [0]:

```
#https://www.kaggle.com/tilii7/hyperparameter-grid-search-with-xgboost
def timer(start_time=None):
    if not start_time:
        start_time = datetime.now()
        return start_time
    elif start_time:
        thour, temp_sec = divmod((datetime.now() - start_time).total_seconds(), 3600)
        tmin, tsec = divmod(temp_sec, 60)
        print('\n Time taken: %i hours %i minutes and %s seconds.' % (thour, tmin, round(tsec, 2)))
```

In [25]:

```
xgb = XGBClassifier()
clf = RandomizedSearchCV(xgb, params, cv=5, scoring='f1')
start_time = timer(None) # timing starts from this point for "start_time" variable
clf.fit(df_final_train, y_train)
timer(start_time) # timing ends here for "start_time" variable
```

```
 Time taken: 1 hours 11 minutes and 39.79 seconds.
```

In [26]:

```
clf.best_params_
```

Out[26]:

```
{'colsample_bytree': 0.6,
```

```
 'gamma': 1,
 'learning_rate': 0.1,
 'max_depth': 9,
 'n_estimators': 500}
```

In [0]:

```
clf = XGBClassifier(learning_rate=0.1, colsample_bytree=0.6, max_depth=9, gamma=1, n_estimators=500
)
```

In [0]:

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

In [29]:

```
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 1.0
Test f1 score 0.9250450068834057
```

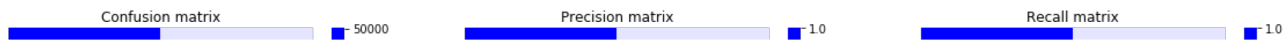
In [0]:

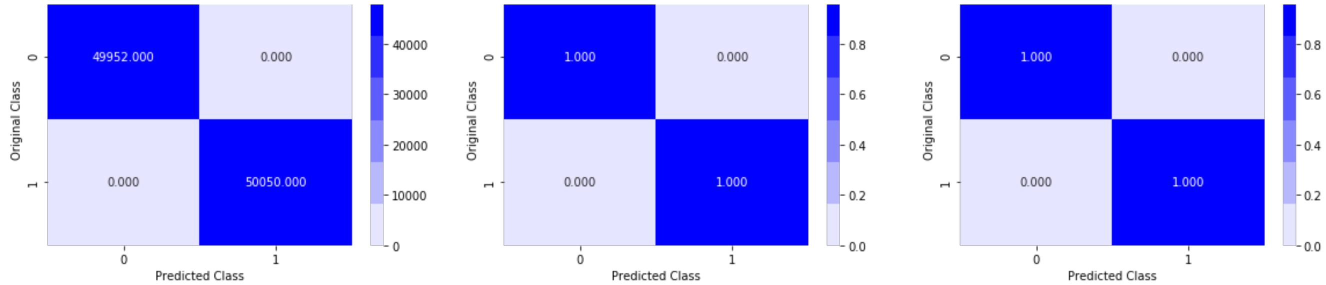
```
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    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 [31]:

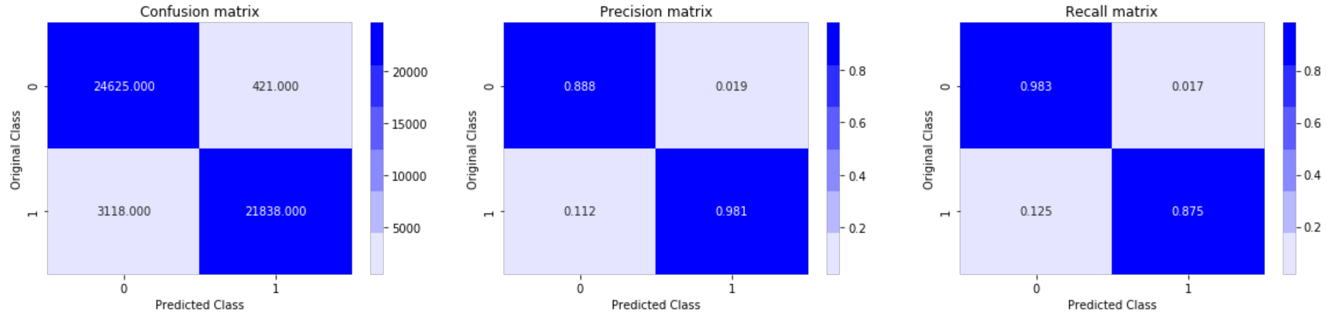
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```



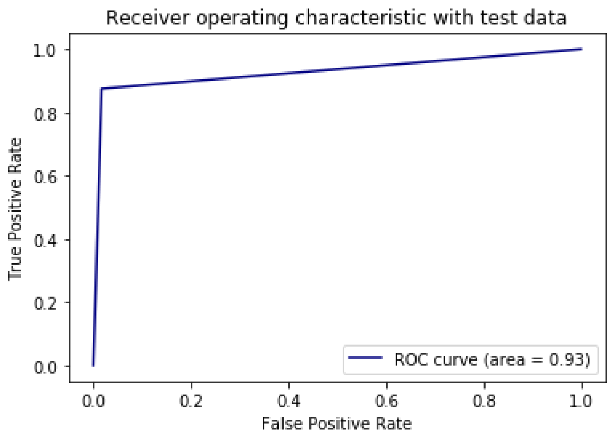


Test confusion_matrix



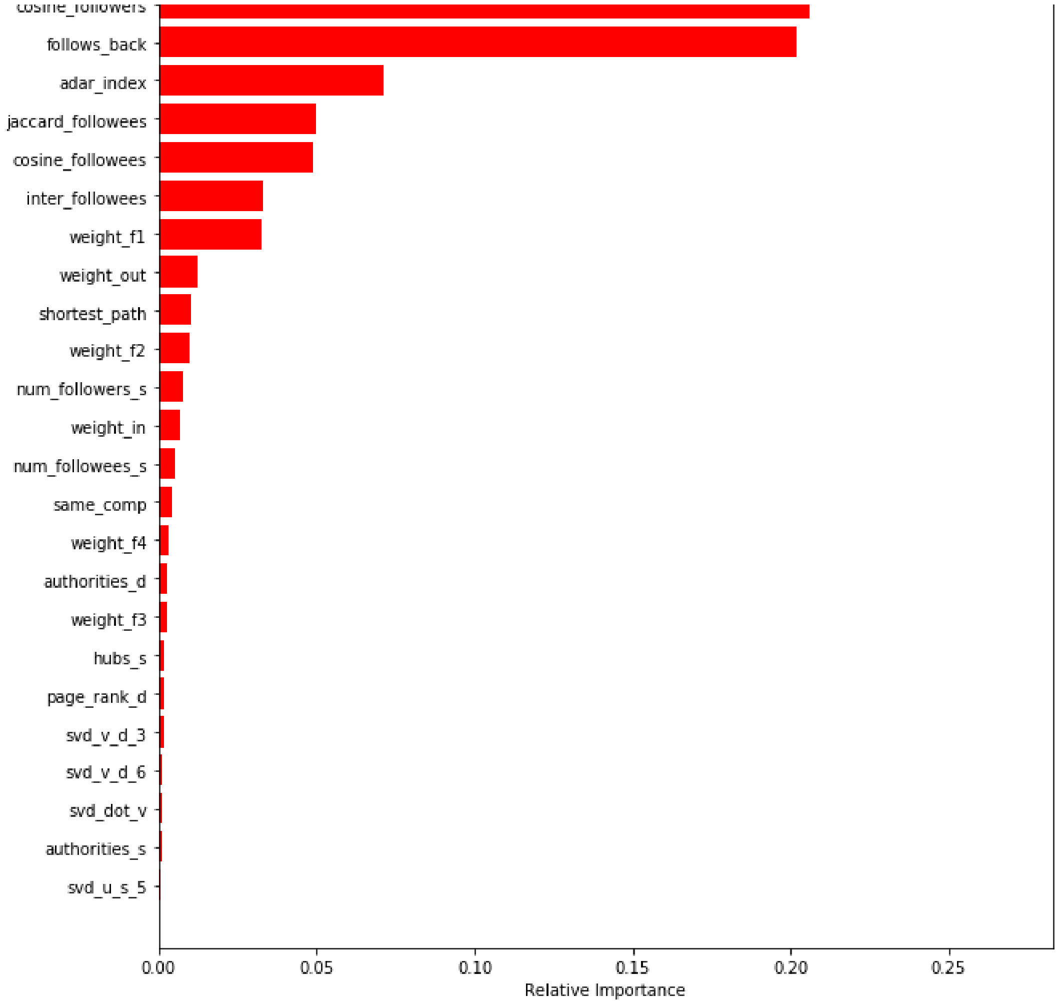
In [32]:

```
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 [33]:

```
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()
```



10 Conclusion

In [0]:

```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Algorithm", "Hyper Parameters", "F1 Score-Train", "F1 Score-Test", "ROC-AUC Score
(test)"]
```

In [35]:

```
x.add_row(["Random Forest","n_estimators=121, max_depth=14", 0.965, 0.924, 0.93])
x.add_row(["XGBoost","learning_rate=0.1, colsample_bytree=0.6, max_depth=9, gamma=1,
n_estimators=500", 1.0, 0.925, 0.93])
print(x)
```

```
+----------------+-------------------------------------------------------------------------------+
------------+--------------+--------------------+
|   Algorithm    |                                 Hyper Parameters                              |
F1 Score-Train | F1 Score-Test | ROC-AUC Score(test) |
+----------------+-------------------------------------------------------------------------------+
------------+--------------+--------------------+
| Random Forest |                         n_estimators=121, max_depth=14                         |
0.965       |     0.924     |          0.93         |
|    XGBoost     | learning_rate=0.1, colsample_bytree=0.6, max_depth=9, gamma=1, n_estimators=500
|      1.0        |      0.925      |          0.93         |
+----------------+-------------------------------------------------------------------------------+
------------+--------------+--------------------+
```

Steps that were followed during this case study

1. The data was analysed for the initial steps and the actual data had to be prepared to apply models on top of that.

2. The need was to have certain features to help train the model and so proper featurization was done.
3. Features were then extracted from the data available and a numerous type of featurizations were applied which eventually gave 47 Features at the end
4. These features are then used for the purpose of modelling.
5. 2 models have been applied after hyperparameter tuning which are XGBoost and Random Forest and the results seen are mentioned above.