Social network Graph Link Prediction - Facebook Challenge

Problem statement:

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

Data Overview

Taken data from facebook's recruting challenge on kaggle https://www.kaggle.com/c/FacebookRecruiting
data contains two columns source and destination eac edge in graph

> - Data columns (total 2 columns):
> - source_node   int64
> - destination_node   int64

Mapping the problem into supervised learning problem:

- Generated training samples of good and bad links from given directed graph and for each link got some features like no of followers, is he followed back, page rank, katz score, adar index, some svd fetures of adj matrix, some weight features etc. and trained ml model based on these features to predict link.
- Some reference papers and videos :
  - https://www.cs.cornell.edu/home/kleinber/link-pred.pdf
  - https://www3.nd.edu/~dial/publications/lichtenwalter2010new.p
  - 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 [1]:
```
#Importing Libraries
# please do go through this python notebook:
import warnings
warnings.filterwarnings("ignore")

import csv
import pandas as pd#pandas to create small dataframes
import datetime #Convert to unix time
```

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

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

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.

1. Preferential Attachment

In [38]:
```
# estimating how "rich" each vertices are by calculating the nu
mber of friends/neighbourhood (|Γ(x)|)

# reading graph using non_direction
directed_graph=nx.read_edgelist('data/after_eda/train_woheader.
csv',delimiter=',',create_using=nx.DiGraph(),nodetype=int)

# prfrential attachment of each user_i
def ps_attachment_single_user(a):
    try:
        preferential_score=len(set(directed_graph.successors(a
)))
        return preferential_score
```

```
    except:
        return -1
```

In [39]:
```
# reading graph using non_direction as inbuilt Netwotkx.prefere
ntial_attachment does not work on directed graph
non_directed_graph=nx.read_edgelist('data/after_eda/train_wohea
der.csv',delimiter=',',create_using=nx.Graph(),nodetype=int)

# preferential_attachment for (u_i,u_j) using Netwotkx library
 to calculate preferential_attachment score
def ps_attachment(a,b):
    try:
        preferential_score=nx.preferential_attachment(non_direc
ted_graph,[(a,b)])
        for s in preferential_score:
            return s[2]

    except:
        return -1
```

In [40]:
```
from pandas import read_hdf
df_final_train = read_hdf('data/fea_sample/storage_sample_stage
4.h5', 'train_df',mode='r')
df_final_test = read_hdf('data/fea_sample/storage_sample_stage
4.h5', 'test_df',mode='r')

if not os.path.isfile('data/fea_sample/storage_sample_stage5.h
5'):
    #============================================================
=========================================

    # preferential_attachment of source
    ps_attachment_source_train = df_final_train.apply(lambda ro
w: ps_attachment_single_user(row['source_node']),axis=1)
    df_final_train["preferential_score_source"] = ps_attachment
_source_train

    ps_attachment_source_test = df_final_test.apply(lambda row:
ps_attachment_single_user(row['source_node']),axis=1)
    df_final_test["preferential_score_source"] = ps_attachment_
source_test


    # preferential_attachment of destination
    ps_attachment_destination_train = df_final_train.apply(lamb
da row: ps_attachment_single_user(row['destination_node']),axis
=1)
    df_final_train["preferential_score_destination"] = ps_attac
hment_destination_train

    ps_attachment_destination_test = df_final_test.apply(lambda
row: ps_attachment_single_user(row['destination_node']),axis=1)
    df_final_test["preferential_score_destination"] = ps_attach
ment_destination_test


    # preferential_attachment_score by multiplying size neighbo
urhood of source and destination(using networkx library)
    preferential_score_source_destination_train = df_final_trai
n.apply(lambda row:

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

```
1)
    df_final_train["preferential_score_source_destination"] = p
referential_score_source_destination_train

    preferential_score_source_destination_test = df_final_test.
apply(lambda row:

ps_attachment(row['source_node'],row['destination_node']),axis=
1)
    df_final_test["preferential_score_source_destination"] = pr
eferential_score_source_destination_test


    hdf = HDFStore('data/fea_sample/storage_sample_stage5.h5')
    hdf.put('train_df',df_final_train, format='table', data_col
umns=True)
    hdf.put('test_df',df_final_test, format='table', data_colum
ns=True)
    hdf.close()

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

2. SVD svd_dot feature

In [44]:
```
# return the dot product of U,V.T --> SVD feature
def dot(a,b):
    return np.dot(a,b)
```

2.1 SVD Dot product of U,V.T on source node and destination node

In [46]:
```
df_final_train = read_hdf('data/fea_sample/storage_sample_stage
5.h5', 'train_df',mode='r')
df_final_test = read_hdf('data/fea_sample/storage_sample_stage
5.h5', 'test_df',mode='r')

if not os.path.isfile('data/fea_sample/storage_sample_stage6.h
5'):
    #===============================================================
=======================================================
    # applying dot product of U,V.T on source node and destinat
ion node

    df_final_train['source_U.VT']=df_final_train.apply(lambda r
ow: dot(row[['svd_u_s_1', 'svd_u_s_2', 'svd_u_s_3',

'svd_u_s_4','svd_u_s_5', 'svd_u_s_6']],

row[['svd_v_s_1', 'svd_v_s_2','svd_v_s_3',

'svd_v_s_4', 'svd_v_s_5', 'svd_v_s_6']]),axis=1)

    df_final_test['source_U.VT']=df_final_test.apply(lambda row
: dot(row[['svd_u_s_1', 'svd_u_s_2', 'svd_u_s_3',

'svd_u_s_4','svd_u_s_5', 'svd_u_s_6']],

row[['svd_v_s_1', 'svd_v_s_2','svd_v_s_3',
```

```
'svd_v_s_4', 'svd_v_s_5', 'svd_v_s_6']]),axis=1)


    df_final_train["destination_U.VT"] = df_final_train.apply(l
ambda row: dot(row[['svd_u_d_1', 'svd_u_d_2', 'svd_u_d_3',

'svd_u_d_4', 'svd_u_d_5', 'svd_u_d_6']],

row[['svd_v_d_1','svd_v_d_2', 'svd_v_d_3',

'svd_v_d_4', 'svd_v_d_5', 'svd_v_d_6']]),axis=1)

    df_final_test["destination_U.VT"] = df_final_test.apply(lam
bda row: dot(row[['svd_u_d_1', 'svd_u_d_2', 'svd_u_d_3',

'svd_u_d_4', 'svd_u_d_5', 'svd_u_d_6']],

row[['svd_v_d_1','svd_v_d_2', 'svd_v_d_3',

'svd_v_d_4', 'svd_v_d_5', 'svd_v_d_6']]),axis=1)

    hdf = HDFStore('data/fea_sample/storage_sample_stage6.h5')
    hdf.put('train_df',df_final_train, format='table', data_col
umns=True)
    hdf.put('test_df',df_final_test, format='table', data_colum
ns=True)
    hdf.close()

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

2.2 SVD Dot product of U,U.T and V,V.T on source and destination node

In [47]:

```
df_final_train = read_hdf('data/fea_sample/storage_sample_stage
6.h5', 'train_df',mode='r')
df_final_test = read_hdf('data/fea_sample/storage_sample_stage
6.h5', 'test_df',mode='r')

if not os.path.isfile('data/fea_sample/storage_sample_stage7.h
5'):
    #===========================================================
========================================================
    # applying Dot product of U,U.T on source node and V,V.T on
destination node

    df_final_train['source_destination_U.UT']=df_final_train.ap
ply(lambda row: dot(row[['svd_u_s_1', 'svd_u_s_2', 'svd_u_s_3',

'svd_u_s_4','svd_u_s_5', 'svd_u_s_6']],

row[['svd_u_d_1', 'svd_u_d_2', 'svd_u_d_3',

'svd_u_d_4', 'svd_u_d_5', 'svd_u_d_6']]),axis=1)


    df_final_test['source_destination_U.UT']=df_final_test.appl
y(lambda row: dot(row[['svd_u_s_1', 'svd_u_s_2', 'svd_u_s_3',
```

```
'svd_u_s_4','svd_u_s_5', 'svd_u_s_6']],

row[['svd_u_d_1', 'svd_u_d_2', 'svd_u_d_3',

'svd_u_d_4', 'svd_u_d_5', 'svd_u_d_6']]),axis=1)


    df_final_train["source_destination_V.VT"] = df_final_train.
apply(lambda row: dot(row[['svd_v_s_1', 'svd_v_s_2','svd_v_s_3'
,

'svd_v_s_4', 'svd_v_s_5', 'svd_v_s_6']],

row[['svd_v_d_1','svd_v_d_2', 'svd_v_d_3',

'svd_v_d_4', 'svd_v_d_5', 'svd_v_d_6']]),axis=1)

    df_final_test["source_destination_V.VT"] = df_final_test.ap
ply(lambda row: dot(row[['svd_v_s_1', 'svd_v_s_2','svd_v_s_3',

'svd_v_s_4', 'svd_v_s_5', 'svd_v_s_6']],


row[['svd_v_d_1','svd_v_d_2', 'svd_v_d_3',

'svd_v_d_4', 'svd_v_d_5', 'svd_v_d_6']]),axis=1)
    hdf = HDFStore('data/fea_sample/storage_sample_stage7.h5')
    hdf.put('train_df',df_final_train, format='table', data_col
umns=True)
    hdf.put('test_df',df_final_test, format='table', data_colum
ns=True)
    hdf.close()

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

3. Modeling

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

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

```
Index(['source_node', 'destination_node', 'indicator_li
nk',
       'jaccard_followers', 'jaccard_followees', 'cosin
e_followers',
       'cosine_followees', 'num_followers_s', 'num_foll
owees_s',
       'num_followees_d', 'inter_followers', 'inter_fol
lowees', 'adar_index',
       'follows_back', 'same_comp', 'shortest_path', 'w
eight_in', 'weight_out',
       'weight_f1', 'weight_f2', 'weight_f3', 'weight_f
```

```
4', 'page_rank_s',
       'page_rank_d', 'katz_s', 'katz_d', 'hubs_s', 'hu
bs_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',
       'preferential_score_source', 'preferential_score
_destination',
       'preferential_score_source_destination', 'source
_U.VT',
       'destination_U.VT', 'source_destination_U.UT',
       'source_destination_V.VT'],
      dtype='object')
```

In [4]:
```
df_final_train.shape
```

```
(100002, 61)
```

In [5]:
```
df_final_train.head()
```

	source_node	destination_node	indicator_link	jaccard_followers
0	273084	1505602	1	0
1	832016	1543415	1	0
2	1325247	760242	1	0
3	1368400	1006992	1	0
4	140165	1708748	1	0

5 rows × 61 columns

In [6]:
```
y_train = df_final_train.indicator_link
y_test = df_final_test.indicator_link
```

In [7]:
```
df_final_train.drop(['source_node', 'destination_node','indicat
or_link'],axis=1,inplace=True)
df_final_test.drop(['source_node', 'destination_node','indicato
r_link'],axis=1,inplace=True)
```

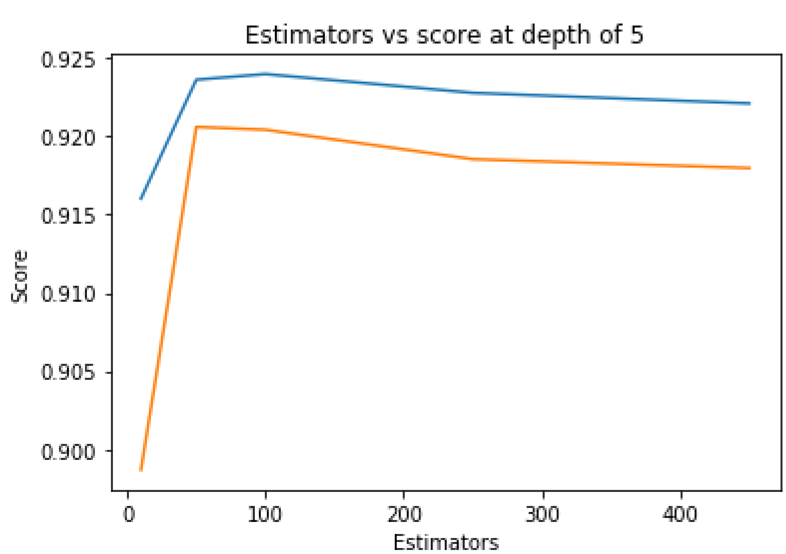
3.1 RandomForestClassifier using various n_estimator parameter

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,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')
```

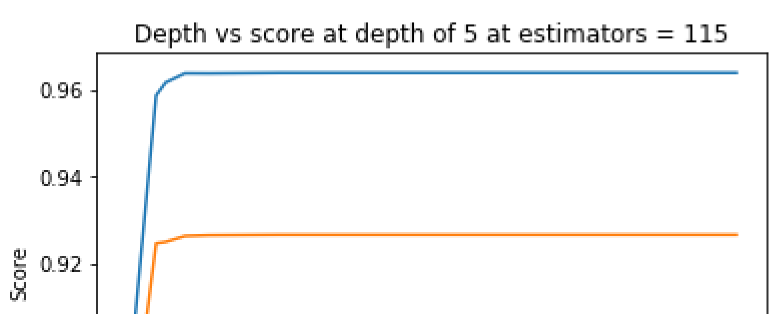
```
Estimators =  10 Train Score 0.9160210656883666 test Score 0.8986979722518678
Estimators =  50 Train Score 0.9236173001310616 test Score 0.9206015353875276
Estimators =  100 Train Score 0.9239773429238517 test Score 0.9204208934534687
Estimators =  250 Train Score 0.9227762915900352 test Score 0.9185402684563759
Estimators =  450 Train Score 0.9221044726301736 test Score 0.917974471646788
```

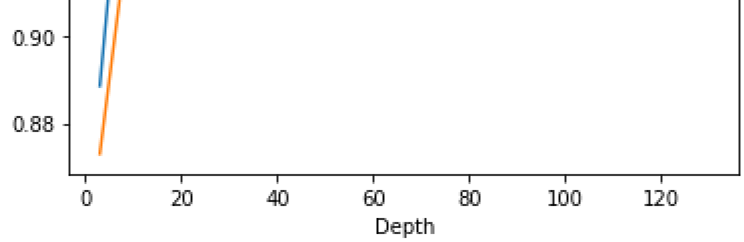
```
Text(0.5, 1.0, 'Estimators vs score at depth of 5')
```



In [55]:
```
depths = [3,9,11,15,20,35,50,70,130]
train_scores = []
test_scores = []
for i in depths:
    clf = RandomForestClassifier(bootstrap=True, class_weight=N
one, criterion='gini',
            max_depth=i, max_features='auto', max_leaf_nodes=No
ne,
            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_j
obs=-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('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 0.8885341622734241 test Score 0.8
729199472273056
depth =  9 Train Score 0.9586056644880175 test Score 0.9
245207583696314
depth =  11 Train Score 0.9615954230995517 test Score 0.
9248649671087199
depth =  15 Train Score 0.9637023225649549 test Score 0.
9262246870010924
depth =  20 Train Score 0.963679995139782 test Score 0.9
264041994750656
depth =  35 Train Score 0.963817854178056 test Score 0.9
265067069714719
depth =  50 Train Score 0.963817854178056 test Score 0.9
265067069714719
depth =  70 Train Score 0.963817854178056 test Score 0.9
265067069714719
depth =  130 Train Score 0.963817854178056 test Score 0.
9265067069714719
```





3.2 RandomForestClassifier hypertuning using RandonSearchCV

In [56]:
```
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_d
ist,
                                   n_iter=5,cv=10,scoring='f1',
random_state=25, return_train_score=True)

rf_random.fit(df_final_train,y_train)
print('mean test scores',rf_random.cv_results_['mean_test_scor
e'])
print('mean train scores',rf_random.cv_results_['mean_train_sco
re'])
```

```
mean test scores [0.96241759 0.96203769 0.9607686  0.961
76077 0.96259747]
mean train scores [0.96287389 0.96265065 0.96118371 0.96
245331 0.9634601 ]
```

In [57]:
```
rf_random.best_estimator_
```

```
RandomForestClassifier(bootstrap=True, class_weight=Non
e, criterion='gini',
                       max_depth=14, max_features='aut
o', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_i
mpurity_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, rand
```

```
om_state=25, verbose=0,
                             warm_start=False)
```

In [58]:
```
#best hyperparameter after hypertuning
rf_random.best_params_
```

```
{'max_depth': 14,
 'min_samples_leaf': 28,
 'min_samples_split': 111,
 'n_estimators': 121}
```

In [59]:
```
# best score
rf_random.best_score_
```

```
0.9625974691596553
```

3.2.1 Traning using best hyperparameter

In [8]:
```
# traning using best hyperparameter
clf = RandomForestClassifier(bootstrap=True, class_weight=None,
criterion='gini',
                       max_depth=14, max_features='auto', max_l
eaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_
split=None,
                       min_samples_leaf=28, min_samples_split=1
11,
                       min_weight_fraction_leaf=0.0, n_estimato
rs=121,
                       n_jobs=-1, oob_score=False, random_state
=25, verbose=0,
                       warm_start=False)
```

In [9]:
```
clf.fit(df_final_train,y_train)
y_train_pred = clf.predict(df_final_train)
y_test_pred = clf.predict(df_final_test)
```

In [10]:
```
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))
```

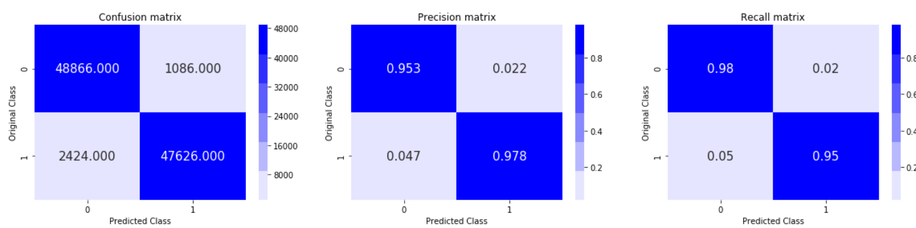
```
Train f1 score 0.9644600149855206
Test f1 score 0.9267012408927708
```

In [11]:
```
# utility function
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
```

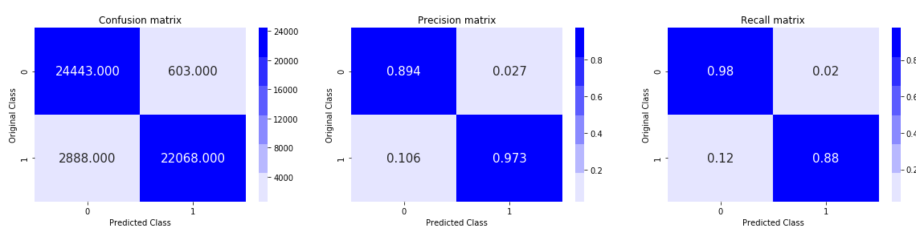
```
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", annot_kws=
{"size": 15}, xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f",annot_kws={
"size": 15}, 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='.2f', annot_kws=
{"size": 15}, xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()
```

In [12]:
```
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
```

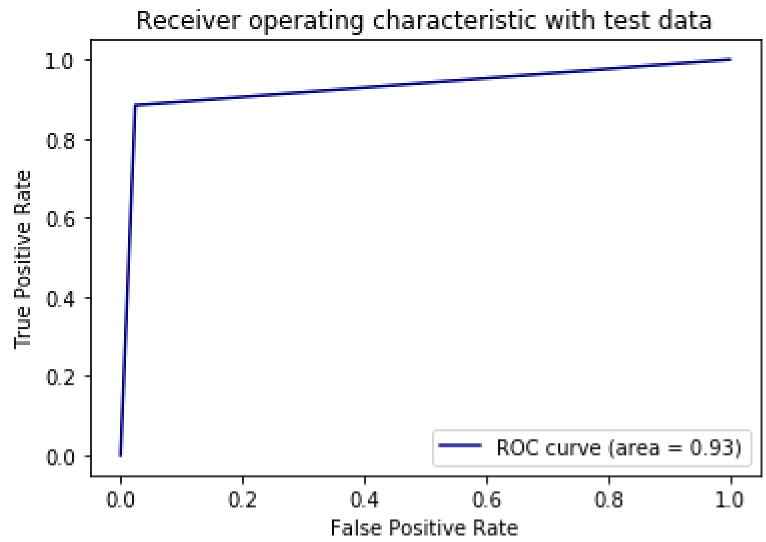



```
Test confusion_matrix
```

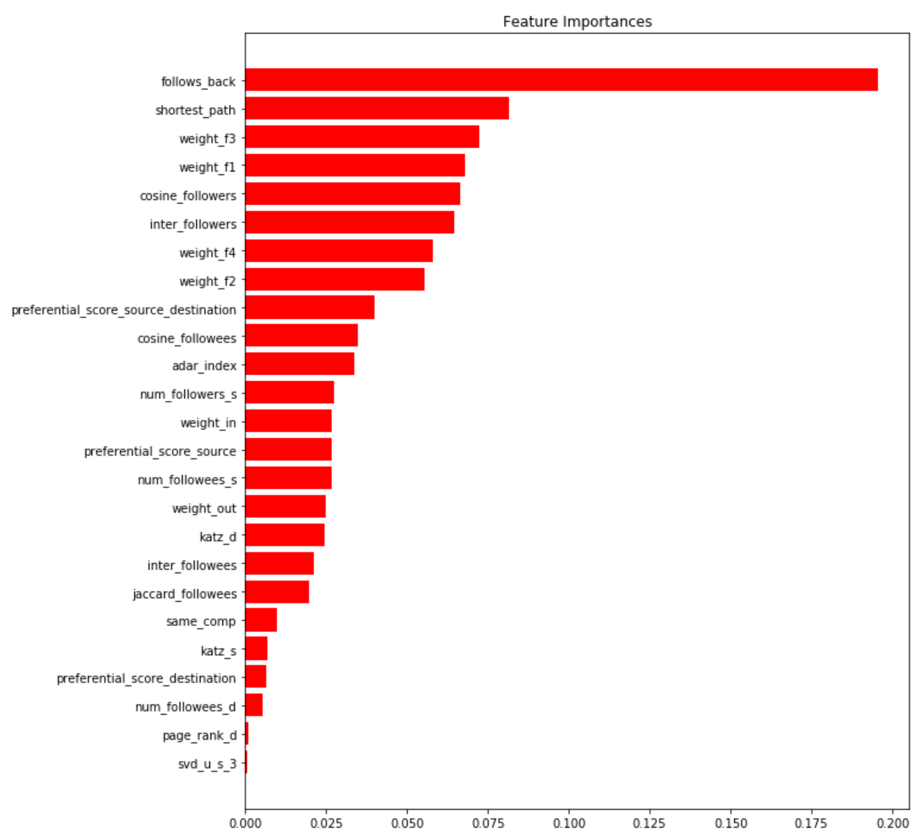


In [13]:
```
from sklearn.metrics import roc_curve, auc
fpr,tpr,ths = roc_curve(y_test,y_test_pred)
auc_sc = auc(fpr, tpr)
plt.plot(fpr, tpr, color='navy',label='ROC curve (area = %0.2f
)' % auc_sc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic with test data')
```

```
plt.legend()
plt.show()
```




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



3.3 Xgboost hypertuning using

RandonSearchCV

In [74]:
```
from sklearn.metrics import f1_score
from sklearn.metrics import f1_score
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from scipy.stats import uniform

param_dist = {"n_estimators":[10,25,50,100,150],
              "max_depth": [3,5,7,10,15,20,25],
              "learning_rate": [0.01,0.05,0.1,0.3,0.5]}

clf = xgb.XGBClassifier(random_state=25,n_jobs=-1)

gscv_xgboost = RandomizedSearchCV(clf, param_distributions=para
m_dist,
                                   n_iter=5,cv=10,scoring='f1',
random_state=20, return_train_score=True)

gscv_xgboost.fit(df_final_train,y_train)

print('mean test scores',gscv_xgboost.cv_results_['mean_test_sc
ore'])
print('mean train scores',gscv_xgboost.cv_results_['mean_train_
score'])
```

```
mean test scores [0.97275645 0.97191409 0.96317531 0.973
69547 0.97616364]
mean train scores [0.97361705 0.97236247 0.96455085 0.97
454971 0.99949719]
```

In [75]:
```
gscv_xgboost.best_estimator_
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsamp
le_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, g
amma=0,
              learning_rate=0.3, max_delta_step=0, max_
depth=25,
              min_child_weight=1, missing=None, n_estim
ators=10, n_jobs=-1,
              nthread=None, objective='binary:logisti
c', random_state=25,
              reg_alpha=0, reg_lambda=1, scale_pos_weig
ht=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [78]:
```
#best hyperparameter after hypertuning
gscv_xgboost.best_params_
```

```
{'n_estimators': 10, 'max_depth': 25, 'learning_rate':
0.3}
```

In [79]:
```
# best score
```

```
gscv_xgboost.best_score_
```

```
0.9761636355560456
```

3.3.1 Traning using best hyperparameter

In [15]:
```
# traning using best hyperparameter
clf = xgb.XGBClassifier(base_score=0.5, booster='gbtree', colsa
mple_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.3, max_delta_step=0, max_depth=25
,
              min_child_weight=1, missing=None, n_estimators=10
, n_jobs=-1,
              nthread=None, objective='binary:logistic', random
_state=25,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, se
ed=None,
              silent=None, subsample=1, verbosity=1)
```

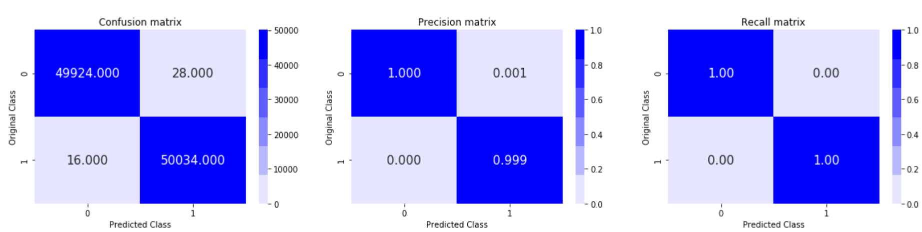
In [16]:
```
clf.fit(df_final_train,y_train)
y_train_pred = clf.predict(df_final_train)
y_test_pred = clf.predict(df_final_test)
```

In [17]:
```
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))
```

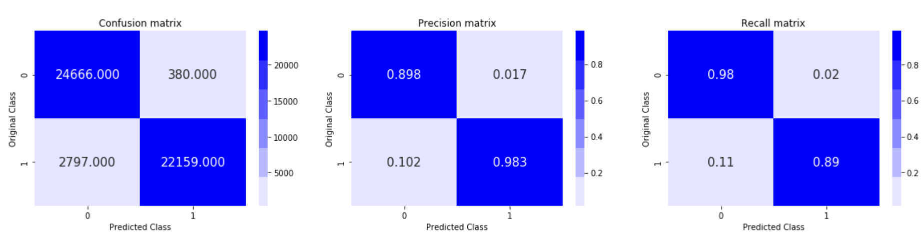
```
Train f1 score 0.9995604922486815
Test f1 score 0.9331087482892935
```

In [18]:
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

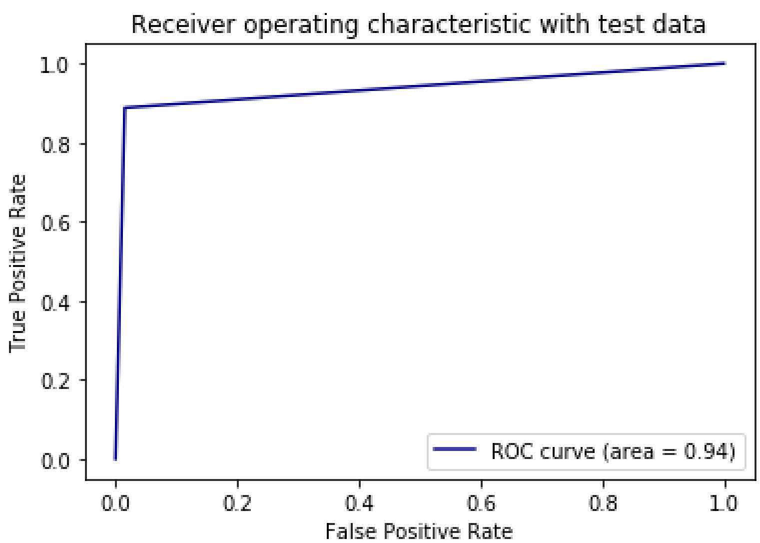
```
Train confusion_matrix
```



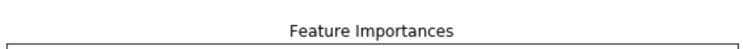

```
Test confusion_matrix
```

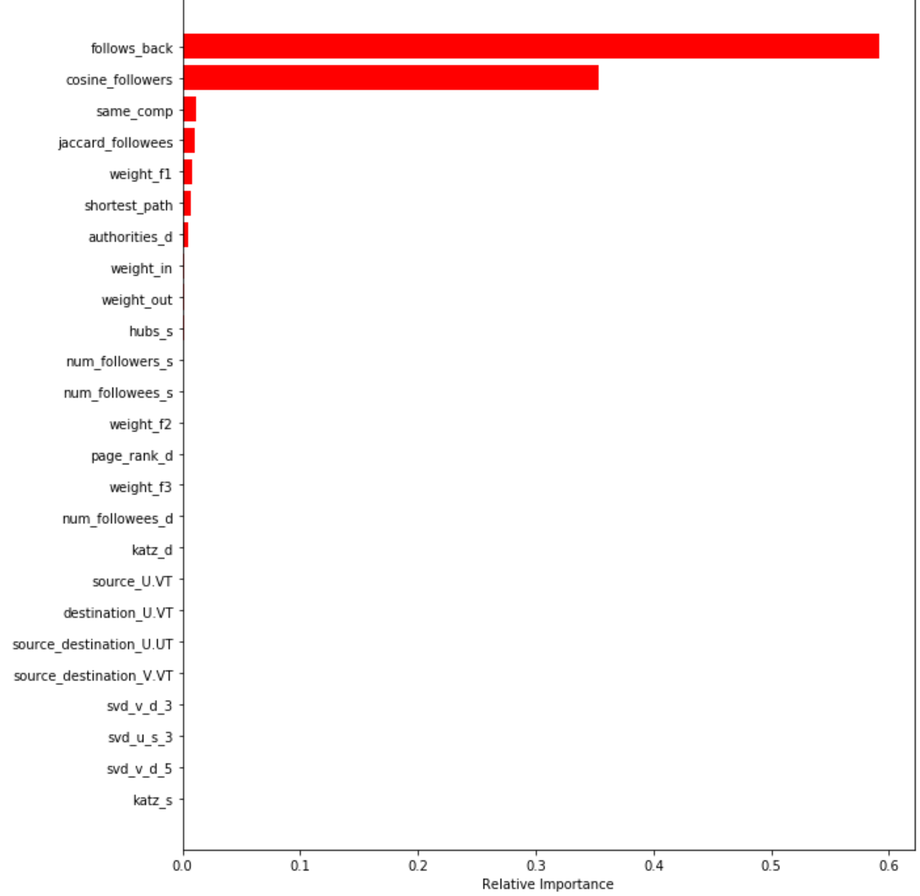


In [21]:
```python
from sklearn.metrics import roc_curve, auc
fpr,tpr,ths = roc_curve(y_test,y_test_pred)
auc_sc = auc(fpr, tpr)
plt.plot(fpr, tpr, color='navy',label='ROC curve (area = %0.2f)' % auc_sc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic with test data')
plt.legend()
plt.show()
```



In [22]:
```python
features = df_final_train.columns
importances = clf.feature_importances_
indices = (np.argsort(importances))[-25:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```





4. Conclusion

In [58]:

```
from prettytable import PrettyTable
# After adding prefrential_attachment and SVDdot feature
print("========Before adding prefrential_attachment and SVDdot
 feature========")
x=PrettyTable()
x.field_names = ["Model","train_f1_score","test_f1_score"]
x.add_row(["Random forest",0.965,0.924])
print(x)
print("="*70,"\n")

# After adding prefrential_attachment and SVDdot feature
print("========After adding prefrential_attachment and SVDdot f
eature========")
x=PrettyTable()
x.field_names = ["Model","train_f1_score","test_f1_score"]
x.add_row(["Random forest",0.964,0.926])
x.add_row(["Xgboost",0.999, 0.933])
print(x)
print("="*70)
```

```
========Before adding prefrential_attachment and SVDdot
feature========
+---------------+----------------+---------------+
|     Model     | train_f1_score | test_f1_score |
+---------------+----------------+---------------+

| Random forest |     0.965      |     0.924     |
+---------------+----------------+---------------+
========================================================
==============
```

```
==============

========After adding prefrential_attachment and SVDdot f
eature========
+----------------+----------------+----------------+
|     Model      | train_f1_score | test_f1_score |
+----------------+----------------+----------------+
| Random forest |     0.963      |     0.926      |
|    Xgboost     |      0.99      |     0.932      |
+----------------+----------------+----------------+
========================================================
==============
```

1. Although difference in result in RandomForest model is not much after adding prefrential_attachment and SVDdot feature, but feature importance of model is clearly showing prefrential_attachment is an important feature

1. Using Xgboost with hyperparameter tuning is giving best result among all.

   > `test_f1_score = 0.933`

END:)