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Social network Graph Link Prediction - Facebook Challenge

[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
```

[2]:
```
#reading
from pandas import read_hdf
df_final_train = read_hdf('data/fea_sample/storage_sample_stage4.h5',␣
 ↪'train_df',mode='r')
df_final_test = read_hdf('data/fea_sample/storage_sample_stage4.h5',␣
 ↪'test_df',mode='r')
```

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

[3]:
```
Index(['source_node', 'destination_node', 'indicator_link',
       'jaccard_followers', 'jaccard_followees', 'cosine_followers',
       'cosine_followees', 'num_followers_s', 'num_followers_d',
       'num_followees_s', 'num_followees_d', 'inter_followers',
       'inter_followees', 'adar_index', 'follows_back', 'same_comp',
       'shortest_path', 'weight_in', 'weight_out', 'weight_f1', 'weight_f2',
       'weight_f3', 'weight_f4', 'page_rank_s', 'page_rank_d', 'katz_s',
       'katz_d', 'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d',
       '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')
```

[4]:
```
y_train = df_final_train.indicator_link
y_test = df_final_test.indicator_link
```

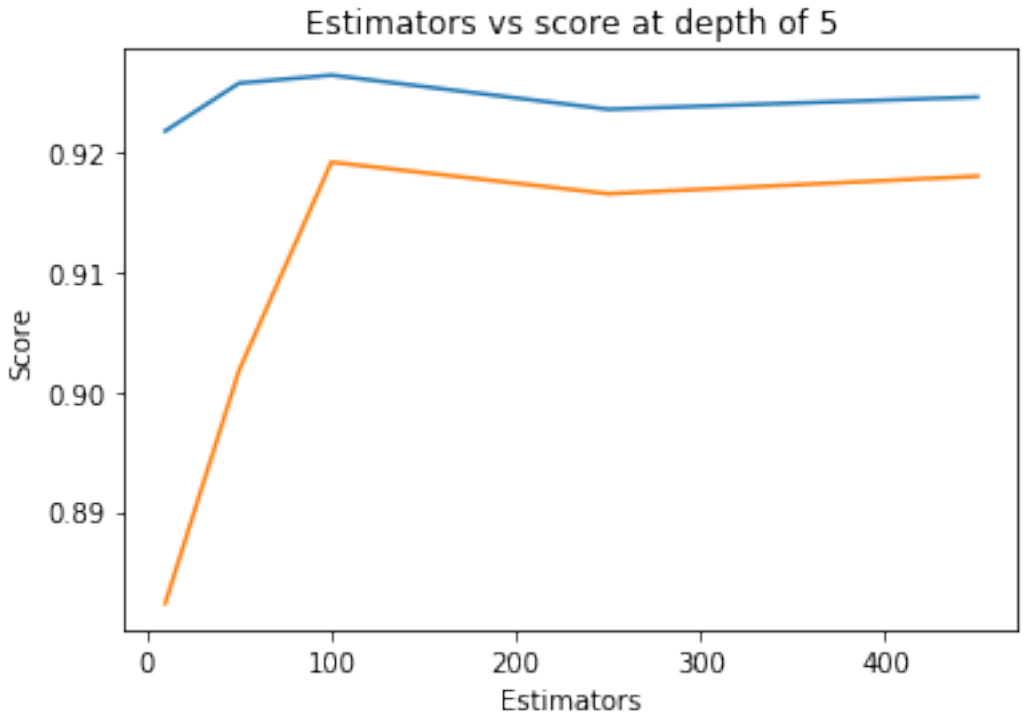
[5]:
```
df_final_train.drop(['source_node',␣
 ↪'destination_node','indicator_link'],axis=1,inplace=True)
df_final_test.drop(['source_node',␣
 ↪'destination_node','indicator_link'],axis=1,inplace=True)
```

[6]:
```
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 0.9218056522778535 test Score 0.8823414718689747
Estimators =  50 Train Score 0.9258003453081772 test Score 0.9017996618946738
Estimators =  100 Train Score 0.9264686001892619 test Score 0.9192036237227431
Estimators =  250 Train Score 0.9236186855308673 test Score 0.9165666645613592
Estimators =  450 Train Score 0.9246411731715931 test Score 0.91802933686891
```

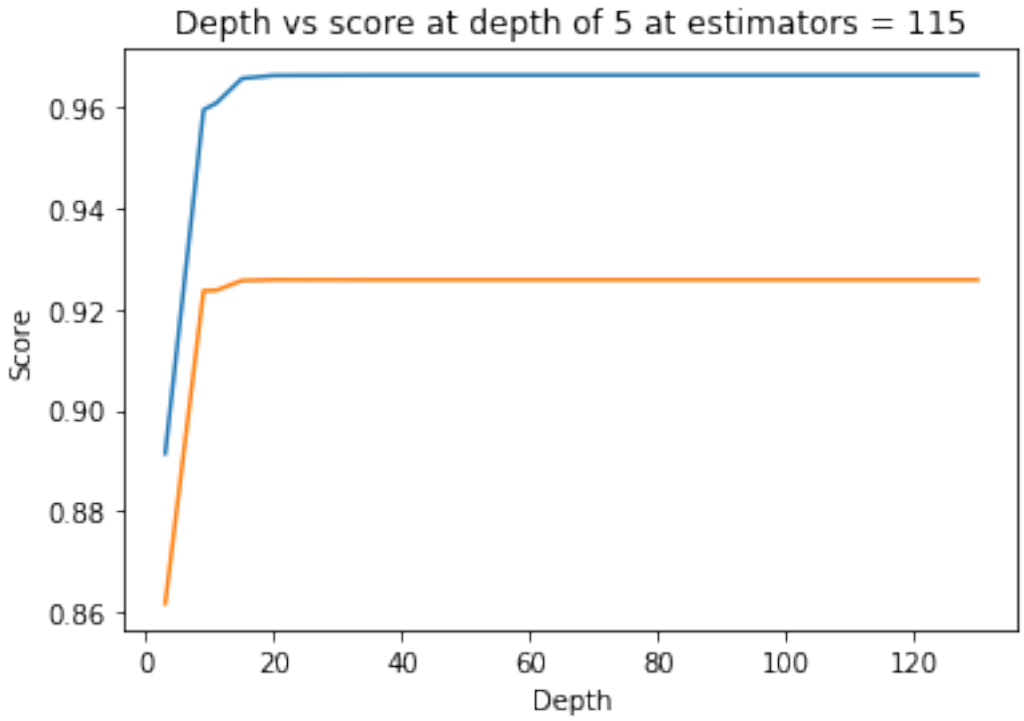
[6]: `Text(0.5, 1.0, 'Estimators vs score at depth of 5')`



[7]:
```
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,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 0.8914243728351001 test Score 0.8616972825261878
depth =  9 Train Score 0.9596061907462927 test Score 0.9237098611755771
depth =  11 Train Score 0.9609335465457562 test Score 0.9238006835154635
depth =  15 Train Score 0.9658021249949501 test Score 0.9257374522266096
depth =  20 Train Score 0.9664092079357867 test Score 0.9258969864633709
depth =  35 Train Score 0.9664658452161101 test Score 0.9258790257903845
depth =  50 Train Score 0.9664658452161101 test Score 0.9258790257903845
depth =  70 Train Score 0.9664658452161101 test Score 0.9258790257903845
depth =  130 Train Score 0.9664658452161101 test Score 0.9258790257903845
```



[8]:
```
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 [0.96368617 0.96324135 0.96129318 0.96308844 0.96541799]
```

[9]:
```
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)
```

[10]:
```
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)
```

[11]:
```
clf.fit(df_final_train,y_train)
y_train_pred = clf.predict(df_final_train)
y_test_pred = clf.predict(df_final_test)
```

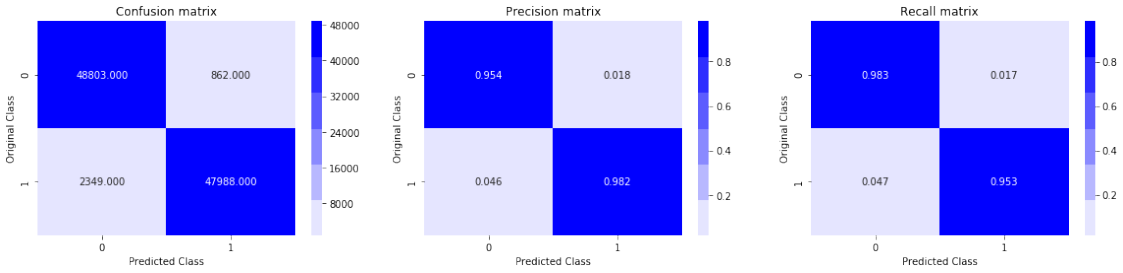
[12]:
```
from sklearn.metrics import f1_score
print('Train f1 score',f1_score(y_train,y_train_pred))
print('Test f1 score',f1_score(y_test,y_test_pred))
```

```
Train f1 score 0.967626805932229
Test f1 score 0.9264445381695486
```

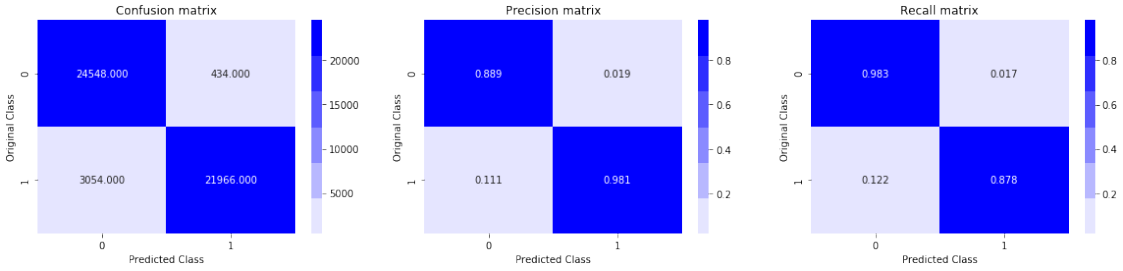
[13]:
```
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    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()
```

[14]:
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

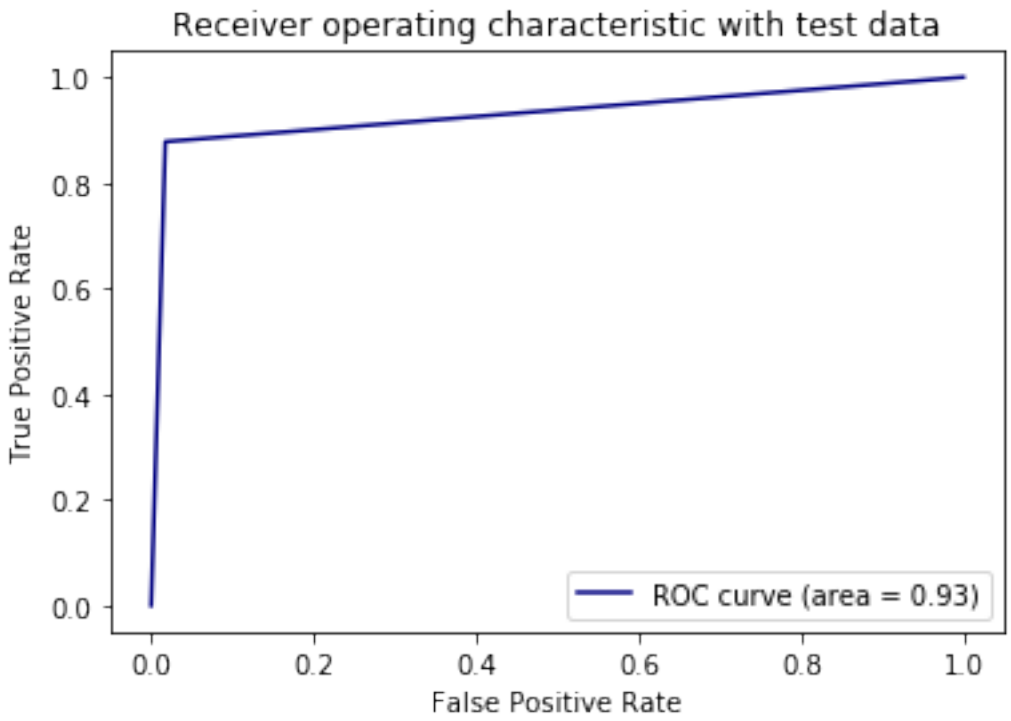
```
Train confusion_matrix
```



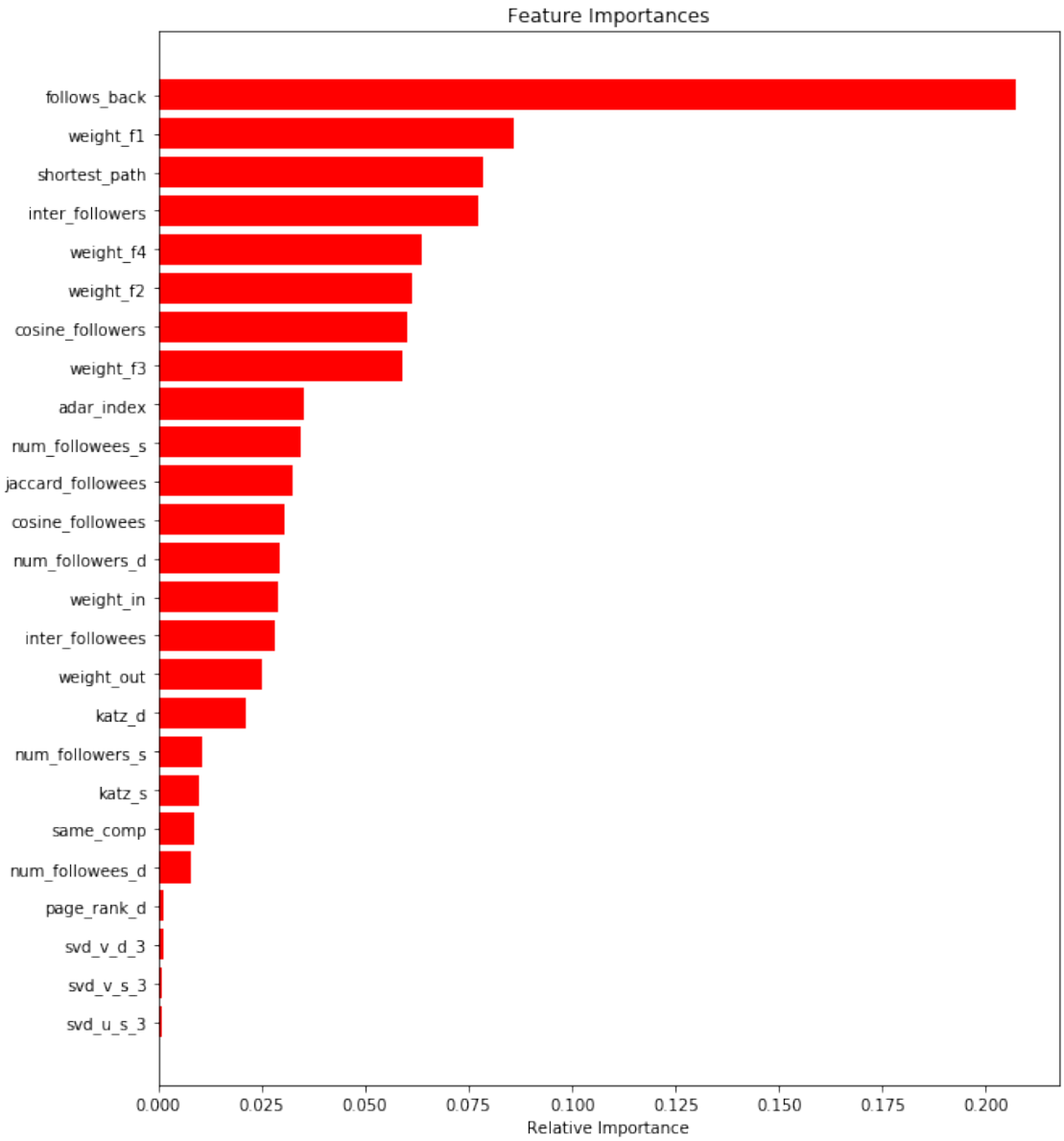
Test confusion_matrix



[15]:
```
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()
```



[16]:
```
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()
```



1 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.

2 Part 1 & part 2 is completed in featurization section so start working on part 3

[28]:
```
#reading
from pandas import read_hdf
df_final_train = read_hdf('data/fea_sample/storage_sample_stage6.h5',␣
 ↪'train_df',mode='r')
df_final_test = read_hdf('data/fea_sample/storage_sample_stage6.h5',␣
 ↪'test_df',mode='r')
```

[29]:
```
df_final_train.columns
```

[29]:
```
Index(['source_node', 'destination_node', 'indicator_link',
       'jaccard_followers', 'jaccard_followees', 'cosine_followers',
       'cosine_followees', 'num_followers_s', 'num_followers_d',
       'num_followees_s', 'num_followees_d', 'inter_followers',
       'inter_followees', 'adar_index', 'follows_back', 'same_comp',
       'shortest_path', 'weight_in', 'weight_out', 'weight_f1', 'weight_f2',
       'weight_f3', 'weight_f4', 'page_rank_s', 'page_rank_d', 'katz_s',
       'katz_d', 'hubs_s', 'hubs_d', 'authorities_s', 'authorities_d',
       '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_attachment_followees',
       'preferential_attachment_followers', 'svd_dot_product'],
      dtype='object')
```

[30]:
```
df_final_train.head()
```

[30]:

	source_node	destination_node	indicator_link	jaccard_followers
0	273084	1505602	1	0
1	1092078	1019460	1	0
2	1430596	400599	1	0
3	1013979	1628559	1	0
4	197515	805550	1	0

	jaccard_followees	cosine_followers	cosine_followees	num_followers_s
0	0.000000	0.000000	0.000000	11
1	0.000000	0.142857	0.000000	4
2	0.098039	0.051948	0.233126	49
3	0.333333	0.229081	0.524142	14
4	0.000000	0.161985	0.000000	7

	num_followers_d	num_followees_s	...	svd_v_s_6	svd_v_d_1
0	6	15	...	1.719703e-14	-1.355368e-12
1	7	7	...	1.347584e-14	-1.240513e-12

```
2               11               46  ...  7.171148e-15 -4.091095e-13
3                7               13  ...  1.597539e-18 -1.903970e-16
4                7               12  ...  6.503282e-19 -4.760155e-19

      svd_v_d_2     svd_v_d_3     svd_v_d_4     svd_v_d_5     svd_v_d_6  \
0  4.675302e-13  1.128589e-06  6.616669e-14  9.771059e-13  4.160011e-14
1  4.237680e-13  1.125696e-09  1.917101e-12  1.483785e-12  2.649401e-12
2  4.076675e-14  2.783363e-12  4.809181e-13  9.748510e-14  1.847969e-16
3  4.652690e-16  4.073271e-15  8.574630e-17  1.387813e-15  7.993854e-19
4  2.910335e-16  1.515485e-15  1.854415e-18  3.395863e-18  3.250485e-19

   preferential_attachment_followees  preferential_attachment_followers  \
0                                120                                 66
1                                  0                                 28
2                                460                                539
3                                 91                                 98
4                                  0                                 49

   svd_dot_product
0    1.338835e-11
1    2.384645e-20
2    1.252459e-21
3    2.609823e-28
4    3.974762e-30

[5 rows x 58 columns]
```

[31]:
```
df_final_test.head()
```

[31]:
```
   source_node  destination_node  indicator_link  jaccard_followers  \
0       848424            784690               1                  0
1       182360            205736               1                  0
2       120585            539098               1                  0
3      1286685           1751018               1                  0
4      1284877            979430               1                  0

   jaccard_followees  cosine_followers  cosine_followees  num_followers_s  \
0           0.000000          0.029161          0.000000                6
1           0.187500          0.157485          0.358569                7
2           0.000000          0.051805          0.000000               73
3           0.021739          0.000000          0.050252               43
4           0.000000          0.000000          0.000000                1

   num_followers_d  num_followees_s  ...     svd_v_s_6     svd_v_d_1  \
0               14                6  ...  5.535489e-14 -9.994074e-10
1               12                5  ...  1.262255e-18 -1.152091e-16
2              122               28  ...  2.106447e-06 -1.208154e-12
3               11               36  ...  2.050646e-14 -2.334162e-12
```

```
4                6                0  ...  0.000000e+00 -1.949308e-13

      svd_v_d_2     svd_v_d_3     svd_v_d_4     svd_v_d_5     svd_v_d_6  \
0  5.791890e-10  3.512358e-07  2.486659e-09  2.771126e-09  1.727685e-12
1  1.421397e-11  8.108408e-15  5.273874e-16  1.418345e-13  1.925426e-18
2  2.721133e-14  1.976924e-12 -1.766527e-11  2.396330e-13  8.069914e-05
3  5.258642e-10  1.389547e-10  7.992433e-10  1.078892e-09  2.588075e-13
4  1.340613e-14  1.431608e-13  1.773713e-14  1.016923e-13  4.527517e-15

   preferential_attachment_followees  preferential_attachment_followers  \
0                                 54                                 84
1                                 70                                 84
2                                  0                               8906
3                                396                                473
4                                  0                                  6

   svd_dot_product
0     2.083237e-17
1     3.215717e-22
2     1.699884e-10
3     6.821693e-19
4    -1.575727e-30

[5 rows x 58 columns]
```

[32]:
```
y_train = df_final_train.indicator_link
y_test = df_final_test.indicator_link
```

[33]:
```
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)
```

[34]:
```
df_final_train.head()
```

[34]:
```
   jaccard_followers  jaccard_followees  cosine_followers  cosine_followees  \
0                  0           0.000000          0.000000          0.000000
1                  0           0.000000          0.142857          0.000000
2                  0           0.098039          0.051948          0.233126
3                  0           0.333333          0.229081          0.524142
4                  0           0.000000          0.161985          0.000000

   num_followers_s  num_followers_d  num_followees_s  num_followees_d  \
0               11                6               15                8
1                4                7                7                0
2               49               11               46               10
3               14                7               13                7
4                7                7               12                0
```

```
   inter_followers  inter_followees  ...     svd_v_s_6     svd_v_d_1  \
0                0                0  ...  1.719703e-14 -1.355368e-12
1                2                0  ...  1.347584e-14 -1.240513e-12
2                4                5  ...  7.171148e-15 -4.091095e-13
3                6                5  ...  1.597539e-18 -1.903970e-16
4                3                0  ...  6.503282e-19 -4.760155e-19

      svd_v_d_2     svd_v_d_3     svd_v_d_4     svd_v_d_5     svd_v_d_6  \
0  4.675302e-13  1.128589e-06  6.616669e-14  9.771059e-13  4.160011e-14
1  4.237680e-13  1.125696e-09  1.917101e-12  1.483785e-12  2.649401e-12
2  4.076675e-14  2.783363e-12  4.809181e-13  9.748510e-14  1.847969e-16
3  4.652690e-16  4.073271e-15  8.574630e-17  1.387813e-15  7.993854e-19
4  2.910335e-16  1.515485e-15  1.854415e-18  3.395863e-18  3.250485e-19

   preferential_attachment_followees  preferential_attachment_followers  \
0                                120                                 66
1                                  0                                 28
2                                460                                539
3                                 91                                 98
4                                  0                                 49

   svd_dot_product
0    1.338835e-11
1    2.384645e-20
2    1.252459e-21
3    2.609823e-28
4    3.974762e-30

[5 rows x 55 columns]
```

[35]:
```
df_final_test.head()
```

[35]:
```
   jaccard_followers  jaccard_followees  cosine_followers  cosine_followees  \
0                  0           0.000000          0.029161          0.000000
1                  0           0.187500          0.157485          0.358569
2                  0           0.000000          0.051805          0.000000
3                  0           0.021739          0.000000          0.050252
4                  0           0.000000          0.000000          0.000000

   num_followers_s  num_followers_d  num_followees_s  num_followees_d  \
0                6               14                6                9
1                7               12                5               14
2               73              122               28                0
3               43               11               36               11
4                1                6                0                3

   inter_followers  inter_followees  ...     svd_v_s_6     svd_v_d_1  \
0                1                0  ...  5.535489e-14 -9.994074e-10
```

```
1                5                3  ...  1.262255e-18 -1.152091e-16
2               54                0  ...  2.106447e-06 -1.208154e-12
3                0                1  ...  2.050646e-14 -2.334162e-12
4                0                0  ...  0.000000e+00 -1.949308e-13

      svd_v_d_2     svd_v_d_3     svd_v_d_4     svd_v_d_5     svd_v_d_6  \
0  5.791890e-10  3.512358e-07  2.486659e-09  2.771126e-09  1.727685e-12
1  1.421397e-11  8.108408e-15  5.273874e-16  1.418345e-13  1.925426e-18
2  2.721133e-14  1.976924e-12 -1.766527e-11  2.396330e-13  8.069914e-05
3  5.258642e-10  1.389547e-10  7.992433e-10  1.078892e-09  2.588075e-13
4  1.340613e-14  1.431608e-13  1.773713e-14  1.016923e-13  4.527517e-15

   preferential_attachment_followees  preferential_attachment_followers  \
0                                 54                                 84
1                                 70                                 84
2                                  0                               8906
3                                396                                473
4                                  0                                  6

   svd_dot_product
0    2.083237e-17
1    3.215717e-22
2    1.699884e-10
3    6.821693e-19
4   -1.575727e-30

[5 rows x 55 columns]
```

[38]:
```
from xgboost import XGBClassifier
```

[41]:
```
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 = XGBClassifier(random_state=25,n_jobs=-1)

xgb_random = RandomizedSearchCV(clf, param_distributions=param_dist,
                                n_iter=5,cv=10,scoring='f1',random_state=25,␣
 ↪verbose=3,n_jobs=-1)

xgb_random.fit(df_final_train,y_train)
print('mean test scores',xgb_random.cv_results_['mean_test_score'])
# print('mean train scores',rf_random.cv_results_['mean_train_score'])
```

```
Fitting 10 folds for each of 5 candidates, totalling 50 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed: 29.8min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 51.8min finished

mean test scores [0.98157049 0.98153097 0.98164212 0.98184261 0.98200255]
```

[43]:
```
print(xgb_random.best_estimator_)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=11,
              min_child_weight=1, missing=None, n_estimators=112, n_jobs=-1,
              nthread=None, objective='binary:logistic', random_state=25,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

[44]:
```
clf = XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=11,
              min_child_weight=1, missing=None, n_estimators=112, n_jobs=-1,
              nthread=None, objective='binary:logistic', random_state=25,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

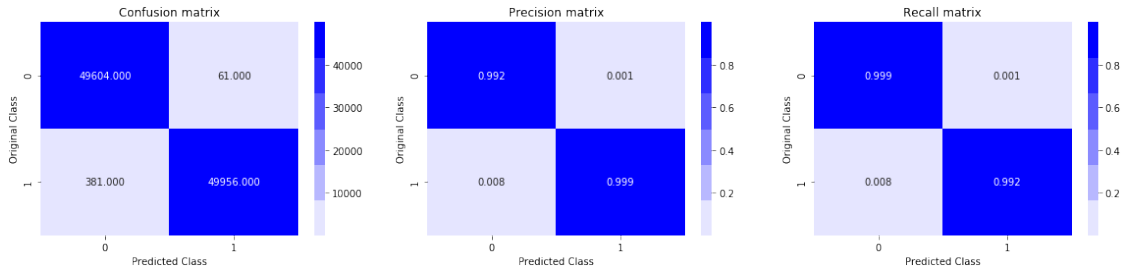
[45]:
```
clf.fit(df_final_train,y_train)
y_train_pred = clf.predict(df_final_train)
y_test_pred = clf.predict(df_final_test)
```

[46]:
```
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))
```

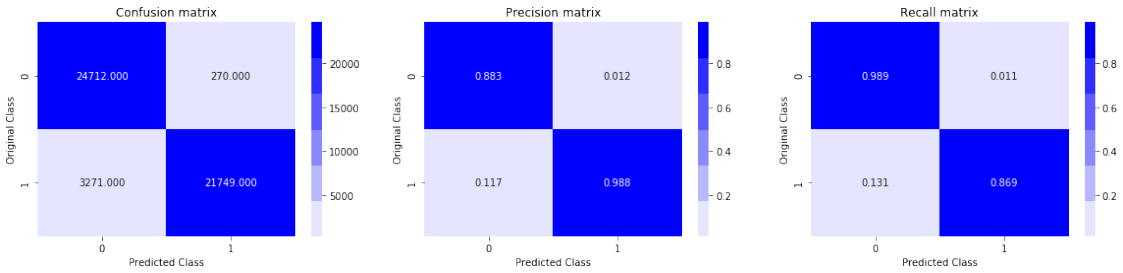
```
Train f1 score 0.9955955916057158
Test f1 score 0.9247220391589956
```

[47]:
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

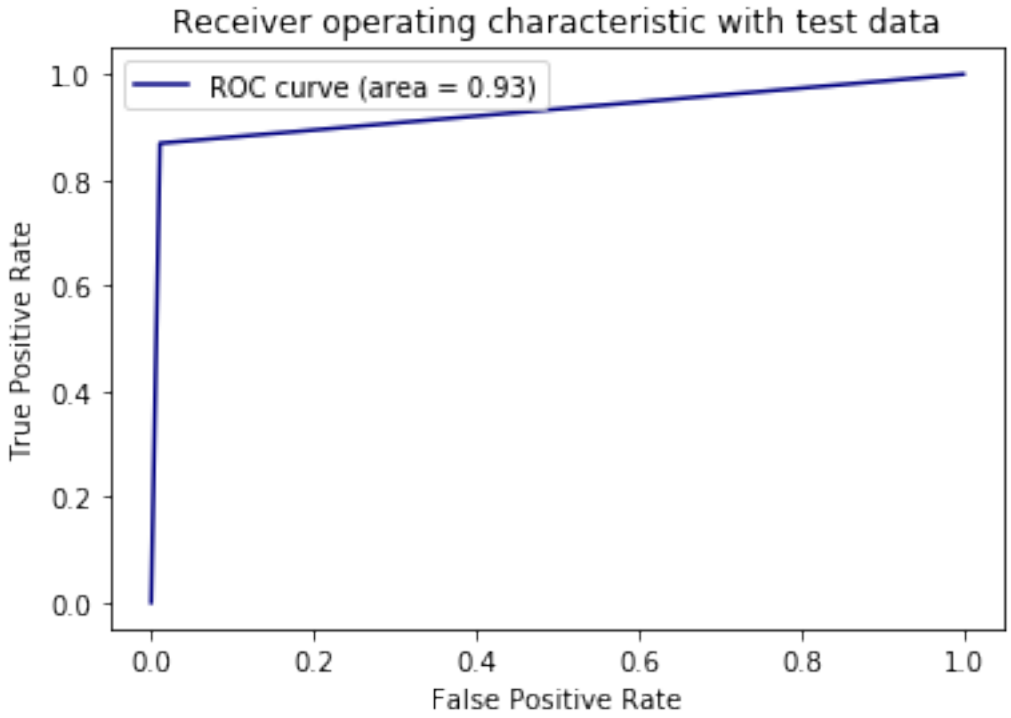
```
Train confusion_matrix
```



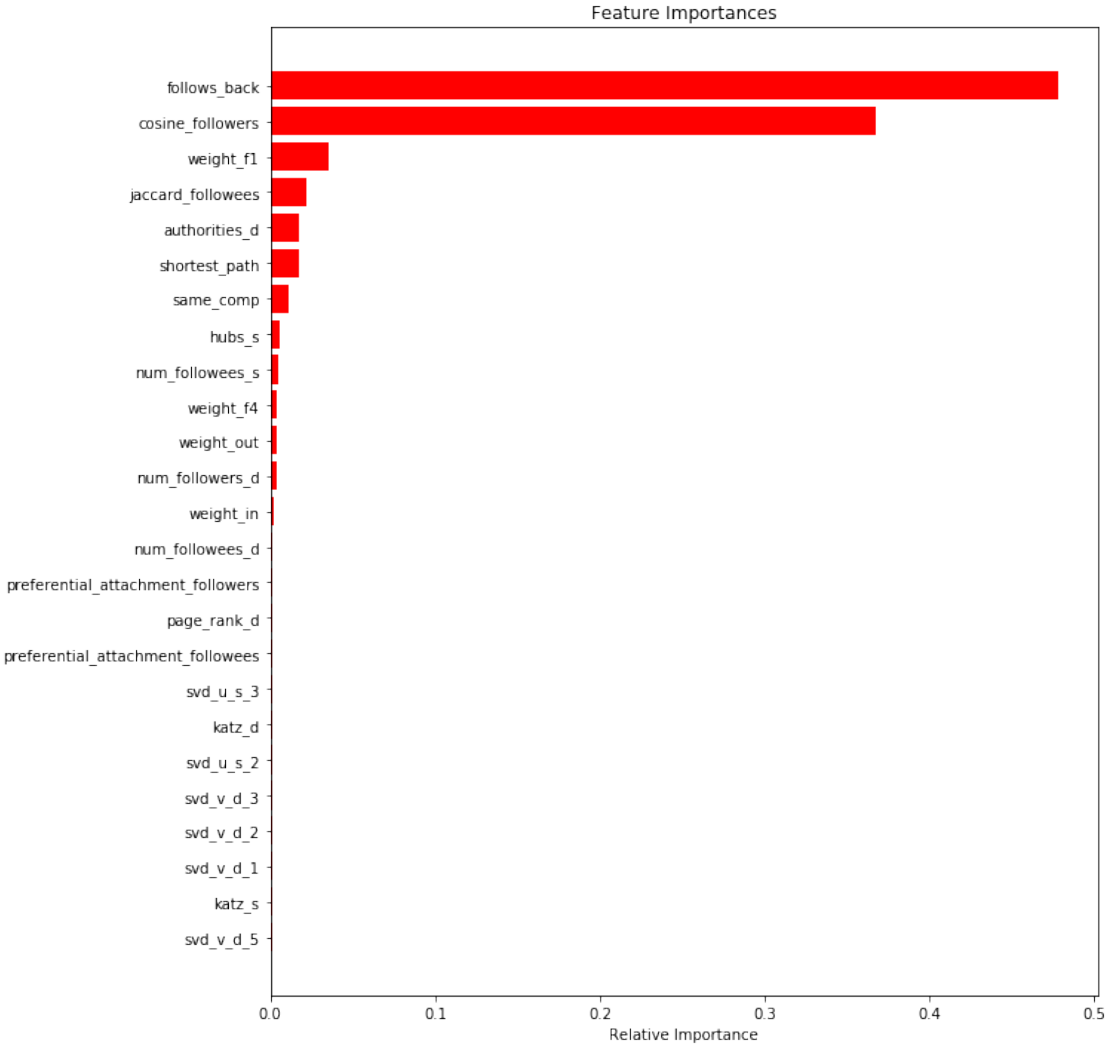
Test confusion_matrix



[48]:
```
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()
```



[49]:
```
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 Model Comparision

[50]:
```
from prettytable import PrettyTable

table = PrettyTable()
table.field_names = ['Model', 'HyperParameter', 'Train F1 Score', 'Test F1␣
↪Score']
table.add_row(['RandomForestClassifier',␣
↪'n_estimators=121,max_depth=14,min_samples_split=111,min_samples_leaf=28', 0.
↪967626805932229, 0.9264445381695486])
table.add_row(['XgboostClassifier', 'n_estimators=112,max_depth=11', 0.
↪9955955916057158, 0.9247220391589956])

print(table)
```

```
+------------------------+-------------------------------------------------------
------------------+--------------------+--------------------+
|         Model          |                                HyperParameter
|   Train F1 Score   |   Test F1 Score    |
+------------------------+-------------------------------------------------------
------------------+--------------------+--------------------+
| RandomForestClassifier |
n_estimators=121,max_depth=14,min_samples_split=111,min_samples_leaf=28 |
0.967626805932229  | 0.9264445381695486 |
|   XgboostClassifier    |                       n_estimators=112,max_depth=11
| 0.9955955916057158 | 0.9247220391589956 |
+------------------------+-------------------------------------------------------
------------------+--------------------+--------------------+
```

4 Observations

- Did EDA on FB friend recommendation
- Calculated three new features (preferential_attachment_followees, preferential_attachment_followers and svd_dot_product)
- Implement Xgboost Model with newly added features
- Hyperparameter tune Xgboost Model

[ ]:
```

```