Social network Graph Link Prediction - Facebook Challenge

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
```

In [18]:

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

In [19]:

```
df_final_train.columns
```

Out[19]:

```
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 [20]:

```
y_train = df_final_train.indicator_link
```

```
y_test = df_final_test.indicator_link
```

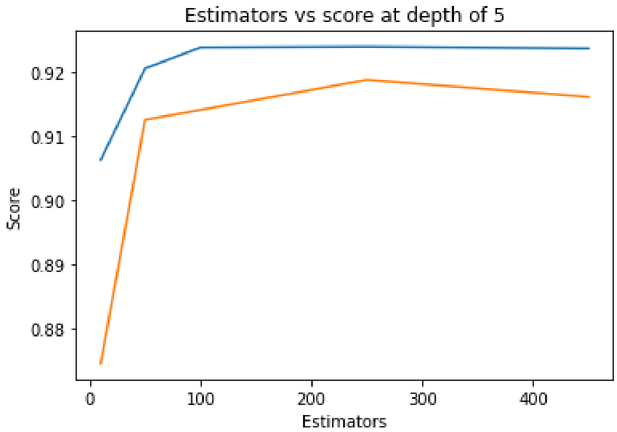
In [0]:

```
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')
```

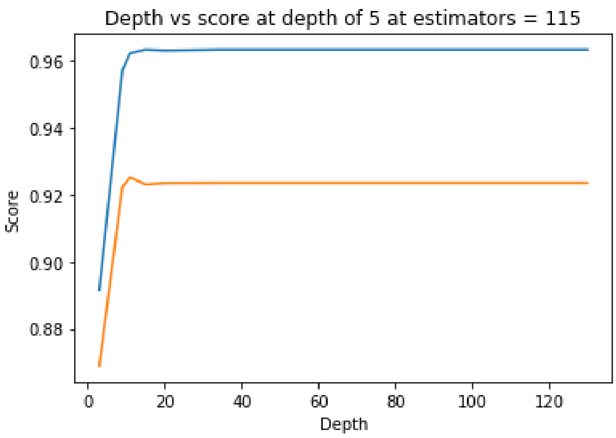


In [0]:

```
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 0.963162915305149l test Score 0.923505102471114l
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
```

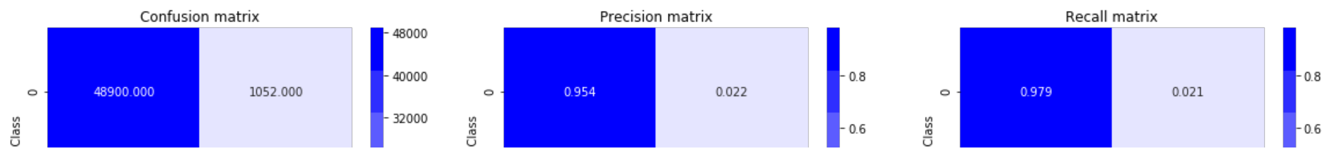
In [36]:

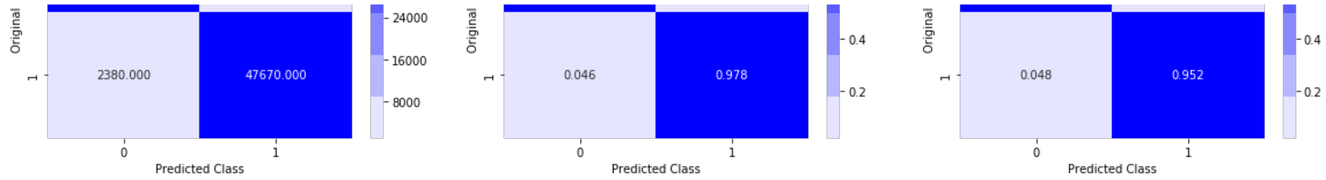
```
from sklearn.metrics import confusion_matrix
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    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]:

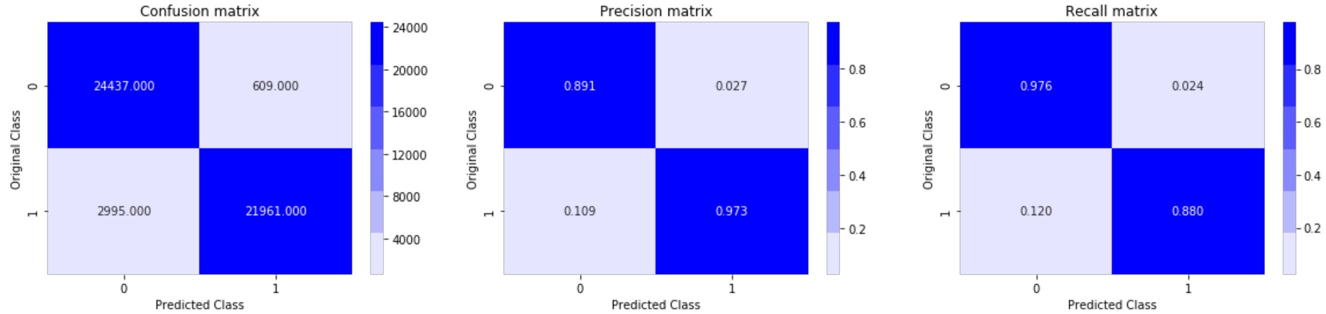
```
print('Train confusion_matrix')
plot_confusion_matrix(y_train,y_train_pred)
print('Test confusion_matrix')
plot_confusion_matrix(y_test,y_test_pred)
```

```
Train confusion_matrix
```



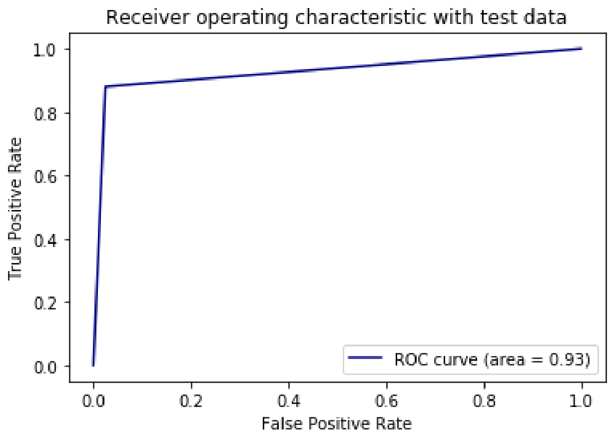


Test confusion_matrix



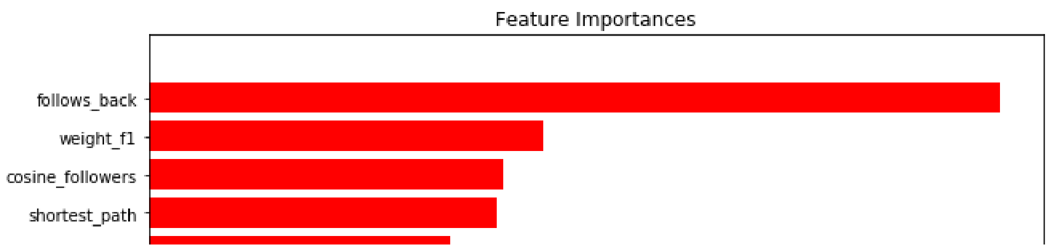
In [0]:

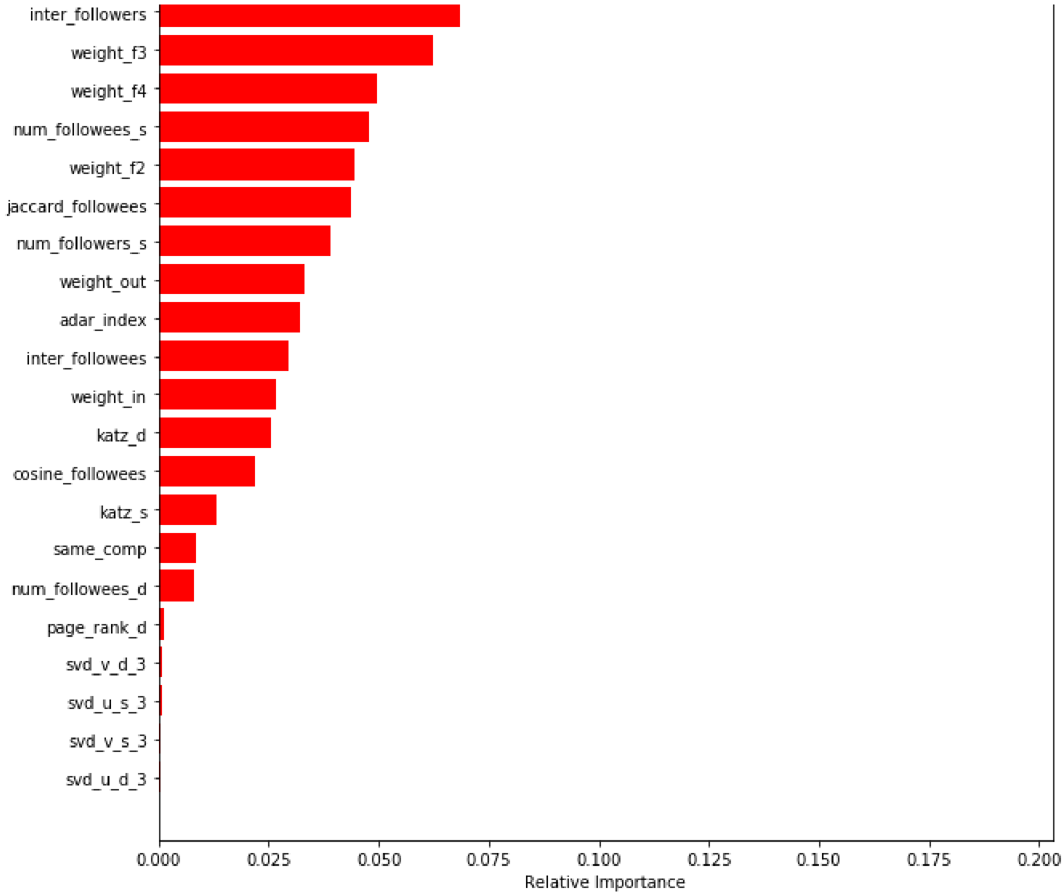
```
from sklearn.metrics import roc_curve, auc
fpr,tpr,ths = roc_curve(y_test,y_test_pred)
auc_sc = auc(fpr, tpr)
plt.plot(fpr, tpr, color='navy',label='ROC curve (area = %0.2f)' % auc_sc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic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





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.

Adding Preferential Attachment feature

Source : https://www.programcreek.com/python/example/62033/networkx.read_edgelist

https://medium.com/@vgnshiyer/link-prediction-in-a-social-network-df230c3d85e6

In [7]:

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

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

In [13]:

```
def prefential_attachment_followers(a,b):
    try:
        if len(set(train_graph.predecessors(a))) == 0  | len(set(train_graph.predecessors(b))) == 0
:
```

```
            return 0
        pref_attach = (len(set(train_graph.predecessors(a))*len(set(train_graph.predecessors(b)))))

    except:
            return 0

    return pref_attach
```

In [16]:

```
def prefential_attachment_followees(a,b):
    try:
        if len(set(train_graph.successors(a))) == 0  | len(set(train_graph.successors(b))) == 0:
            return 0
        pref_attach = (len(set(train_graph.successors(a))*len(set(train_graph.successors(b)))))

    except:
            return 0

    return pref_attach
```

In [21]:

```
df_final_train['prefential_followers'] = df_final_train.apply(lambda 
row:prefential_attachment_followers(row['source_node'],row['destination_node']),axis=1)
df_final_train['prefential_followees'] = df_final_train.apply(lambda 
row:prefential_attachment_followees(row['source_node'],row['destination_node']),axis=1)

df_final_test['prefential_followers'] = df_final_test.apply(lambda 
row:prefential_attachment_followers(row['source_node'],row['destination_node']),axis=1)
df_final_test['prefential_followees'] = df_final_test.apply(lambda 
row:prefential_attachment_followees(row['source_node'],row['destination_node']),axis=1)
```

In [22]:

```
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)
```

Adding SVD-Dot feature

In [23]:

```
df_final_train['svd_u_dot'] = ((df_final_train['svd_u_s_1']*(df_final_train['svd_u_d_1']))+
                               (df_final_train['svd_u_s_2']*(df_final_train['svd_u_d_2']))+
                               (df_final_train['svd_u_s_3']*(df_final_train['svd_u_d_3']))+
                               (df_final_train['svd_u_s_4']*(df_final_train['svd_u_d_4']))+
                               (df_final_train['svd_u_s_5']*(df_final_train['svd_u_d_5']))+
                               (df_final_train['svd_u_s_6']*(df_final_train['svd_u_d_6'])))

df_final_train['svd_v_dot'] = ((df_final_train['svd_v_s_1']*(df_final_train['svd_v_d_1']))+
                               (df_final_train['svd_v_s_2']*(df_final_train['svd_v_d_2']))+
                               (df_final_train['svd_v_s_3']*(df_final_train['svd_v_d_3']))+
                               (df_final_train['svd_v_s_4']*(df_final_train['svd_v_d_4']))+
                               (df_final_train['svd_v_s_5']*(df_final_train['svd_v_d_5']))+
                               (df_final_train['svd_v_s_6']*(df_final_train['svd_v_d_6'])))
```

In [24]:

```
df_final_train.columns
```

Out[24]:

```
Index(['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_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',
       'prefential_followers', 'prefential_followees', 'svd_u_dot',
       'svd_v_dot'],
      dtype='object')
```

In [25]:

```
df_final_test['svd_u_dot'] = ((df_final_test['svd_u_s_1']*(df_final_test['svd_u_d_1']))+
                              (df_final_test['svd_u_s_2']*(df_final_test['svd_u_d_2']))+
                              (df_final_test['svd_u_s_3']*(df_final_test['svd_u_d_3']))+
                              (df_final_test['svd_u_s_4']*(df_final_test['svd_u_d_4']))+
                              (df_final_test['svd_u_s_5']*(df_final_test['svd_u_d_5']))+
                              (df_final_test['svd_u_s_6']*(df_final_test['svd_u_d_6'])))

df_final_test['svd_v_dot'] = ((df_final_test['svd_v_s_1']*(df_final_test['svd_v_d_1']))+
                              (df_final_test['svd_v_s_2']*(df_final_test['svd_v_d_2']))+
                              (df_final_test['svd_v_s_3']*(df_final_test['svd_v_d_3']))+
                              (df_final_test['svd_v_s_4']*(df_final_test['svd_v_d_4']))+
                              (df_final_test['svd_v_s_5']*(df_final_test['svd_v_d_5']))+
                              (df_final_test['svd_v_s_6']*(df_final_test['svd_v_d_6'])))
```

In [26]:

```
df_final_test.columns
```

Out[26]:

```
Index(['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',
       'prefential_followers', 'prefential_followees', 'svd_u_dot',
       'svd_v_dot'],
      dtype='object')
```

In [27]:

```
df_final_train.head()
```

Out[27]:

	jaccard_followers	jaccard_followees	cosine_followers	cosine_followees	num_followers_s	num_followees_s	num_followees_d	inter
0	0	0.000000	0.000000	0.000000	6	15	8	
1	0	0.187135	0.028382	0.343828	94	61	142	
2	0	0.369565	0.156957	0.566038	28	41	22	
3	0	0.000000	0.000000	0.000000	11	5	7	
4	0	0.000000	0.000000	0.000000	1	11	3	

5 rows × 55 columns

In [28]:

```
import xgboost as xgb

from sklearn.metrics import f1_score
from sklearn.model_selection import GridSearchCV
```

```
params = {
          "n_estimators":[5,15,25,50,100,150,200],
          "max_depth": [2,5,10,15,25]
         }

clf = xgb.XGBClassifier()

xg_grid = GridSearchCV(clf, param_grid=params, cv =3, scoring='f1', verbose = 1, return_train_score
=True, n_jobs=-1)

xg_grid.fit(df_final_train,y_train)

train_error = xg_grid.cv_results_['mean_train_score']
cv_error = xg_grid.cv_results_['mean_test_score']

print('mean test scores',cv_error)
print('mean train scores',train_error)
```

```
Fitting 3 folds for each of 35 candidates, totalling 105 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done 105 out of 105 | elapsed: 39.4min finished
```

```
mean test scores [0.9093935  0.91401278 0.92293747 0.94300771 0.96438198 0.97150018
 0.97300302 0.92818631 0.93702803 0.96344347 0.97193336 0.97526257
 0.97765709 0.97900841 0.97265926 0.9740531  0.97537627 0.97656874
 0.97908447 0.98060856 0.98137781 0.97285756 0.97495136 0.9757658
 0.97732781 0.9791213  0.97974681 0.98001428 0.97267874 0.974778
 0.97580614 0.97720709 0.97873396 0.97938576 0.97970486]
mean train scores [0.91019882 0.91427111 0.92358349 0.94388957 0.9649739  0.97185908
 0.97338012 0.9283499  0.93777802 0.96380831 0.97245427 0.9768479
 0.98118547 0.98459241 0.97717446 0.97958595 0.98125922 0.98350513
 0.99225097 0.9987748  0.99994505 0.9883703  0.99209788 0.99509984
 0.99778277 0.99994505 1.         1.         0.99313963 0.99762446
 0.99924065 0.99991509 1.         1.         1.        ]
```

In [29]:

```
print(xg_grid.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=10,
              min_child_weight=1, missing=None, n_estimators=200, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [30]:

```
clf_best = xgb.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=10,
              min_child_weight=1, missing=None, n_estimators=200, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

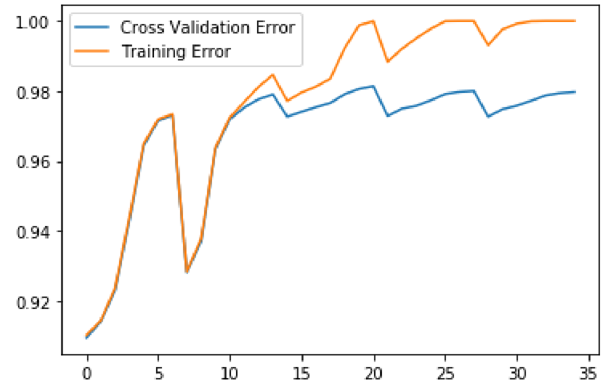
In [32]:

```
clf_best.fit(df_final_train,y_train)

y_train_pred = clf_best.predict(df_final_train)
y_test_pred = clf_best.predict(df_final_test)
```

Error Plots

In [33]:

```
plt.plot(cv_error, label='Cross Validation Error')
plt.plot(train_error, label='Training Error')
plt.legend()
plt.show()
```



In [34]:

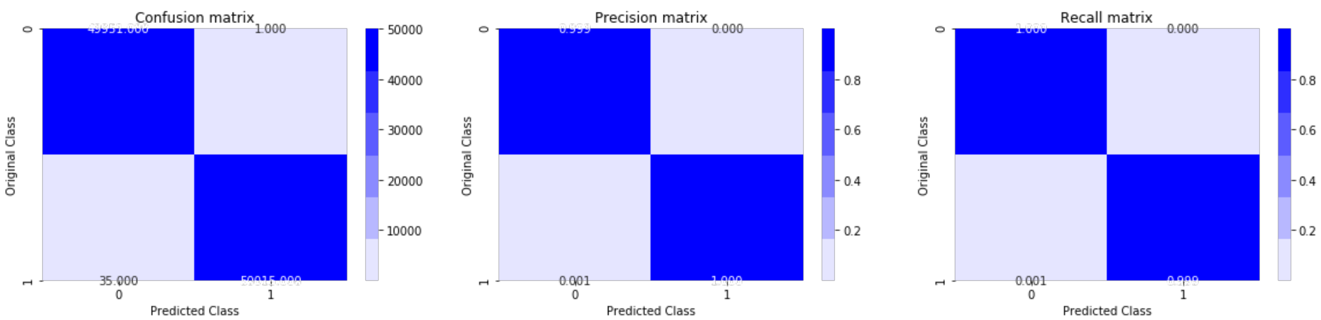
```
from sklearn.metrics import f1_score

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 0.9996402374432874
Test f1 score 0.9258597967946265
```

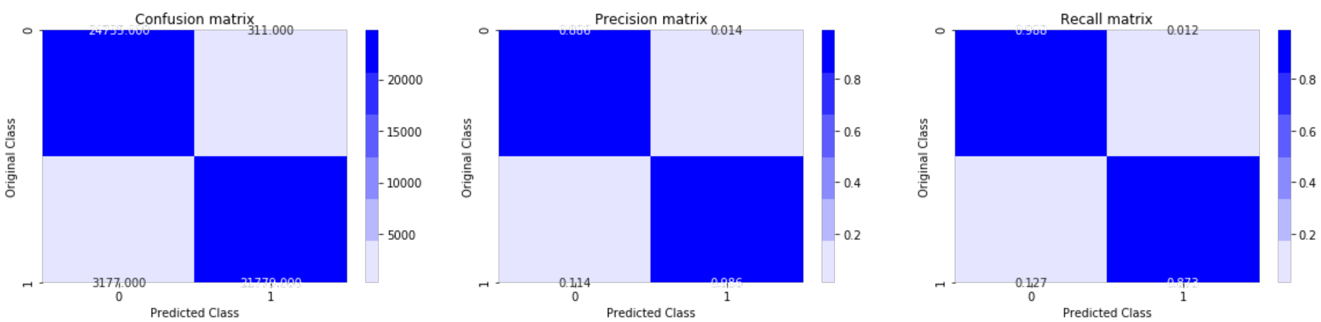
In [37]:

```
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
```

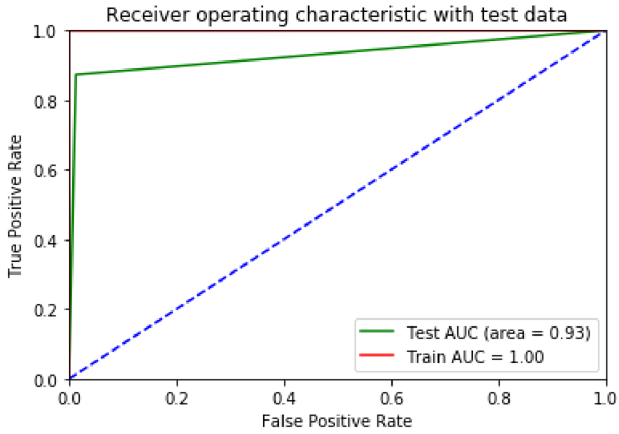



```
Test confusion_matrix
```



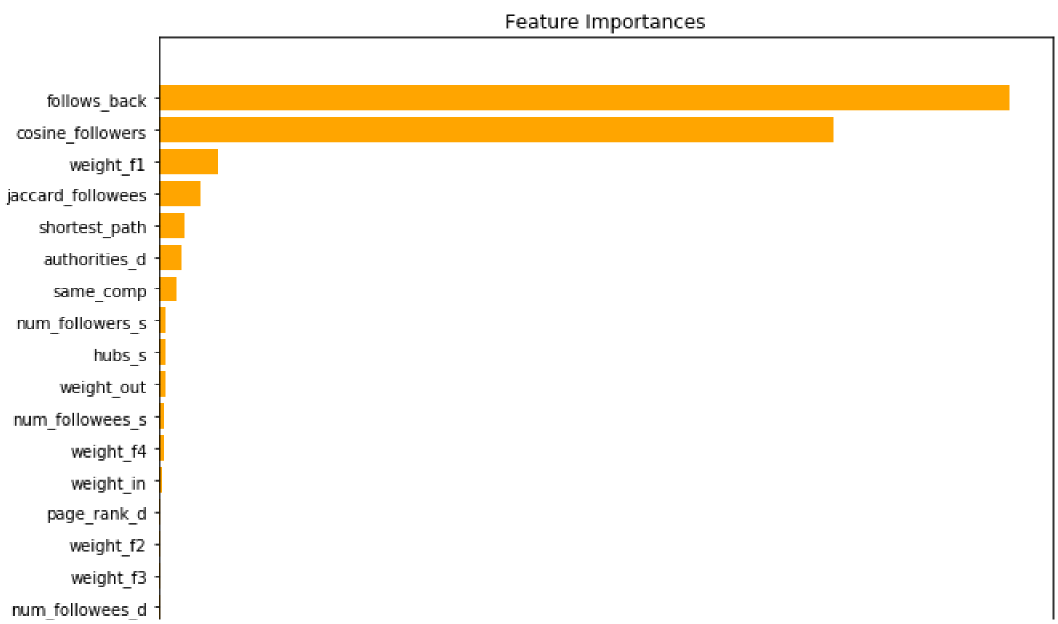
In [38]:

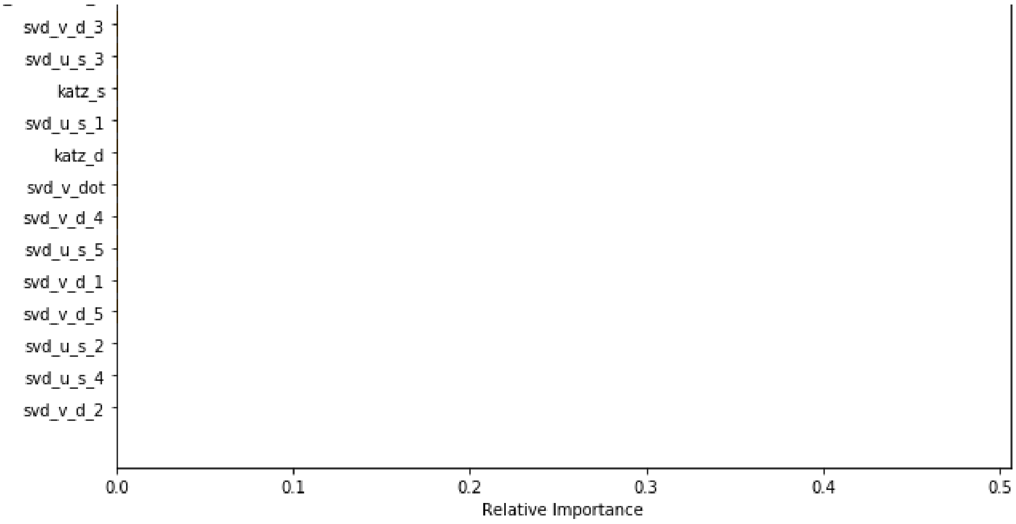
```
from sklearn.metrics import roc_curve, auc

fpr,tpr,threshold = roc_curve(y_test,y_test_pred)
fpr2,tpr2,threshold = roc_curve(y_train,y_train_pred)

auc_sc = auc(fpr, tpr)
auc_sc_train = auc(fpr2, tpr2)

plt.plot(fpr, tpr, color='green',label='Test AUC (area = %0.2f)' % auc_sc)
plt.plot(fpr2, tpr2, 'red', label = 'Train AUC = %0.2f' % auc_sc_train)

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')

plt.plot([0, 1], [0, 1],'b--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.title('Receiver operating characteristic with test data')
plt.legend()
plt.show()
```



In [39]:

```
features = df_final_train.columns
importances = clf_best.feature_importances_
indices = (np.argsort(importances))[-30:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='orange', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```





from the above graph we can infer "follows back" and "cosine followers" are most important features.

Conclusion

In [40]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model", "Train AUC", "Test AUC"]

x.add_row(["Random Forest hyper tunning", 0.97, 0.93])
x.add_row(["XGBoost hyper tunning", 1.0, 0.93 ])


print(x)
```

```
+-----------------------------+-----------+----------+
|            Model            | Train AUC | Test AUC |
+-----------------------------+-----------+----------+
| Random Forest hyper tunning |    0.97   |   0.93   |
|    XGBoost hyper tunning    |    1.0    |   0.93   |
+-----------------------------+-----------+----------+
```