Facebook_Models

June 29, 2019

In [1]:
```python
# general purpose packages
import pandas as pd
import numpy as np
from datetime import datetime
# for model saving and loading
import pickle
import os
import math

# viasualizzation related packages
import matplotlib.pylab as plt
import seaborn as sns
sns.set()

# import graph related packages
import networkx as nx

# Model related packages
import xgboost as xgb
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

# Model selection related packages
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import train_test_split
from scipy.stats import randint

# Classifier Evaluation
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import make_scorer

# summarizing results in a table
from prettytable import PrettyTable
```

1 Configs

```
In [2]: print(datetime.now() ,' Started')

        sample_size = -1 # set -1 for using full size # -1 or 0.01 etc.
        df_train_path = './data/Final_graph_train_features.csv'
        df_test_path = './data/Final_graph_test_features.csv'
```

```
2019-06-23 16:52:12.700897  Started
```

2 Data

```
In [3]: df_train = pd.read_csv(df_train_path, index_col=False)
        df_test = pd.read_csv(df_test_path, index_col=False)
        print('Shape of train data frame', df_train.shape)
        print('Shape of test data frame', df_test.shape)
        df_train.head()
```

```
Shape of train data frame (100000, 63)
Shape of test data frame (100000, 63)
```

```
Out[3]:    src_num_followers  src_num_followees  src_common_nodes_count  \
        0                  1                  4                       1
        1                  0                  2                       0
        2                  1                  2                       1
        3                  1                  1                       1
        4                 46                 89                      15

           src_incoming_edge_weight  src_outgoing_edge_weight  src_weight_sum  \
        0                  0.707107                  0.447214        1.154320
        1                  1.000000                  0.577350        1.577350
        2                  0.707107                  0.577350        1.284457
        3                  0.707107                  0.707107        1.414214
        4                  0.145865                  0.105409        0.251274

           src_weight_product  src_liner_sum_1  src_liner_sum_2  dst_num_followers  \
        0            0.316228         1.861427         1.601534                  8
        1            0.577350         2.577350         2.154701                  9
        2            0.408248         1.991564         1.861807                  0
        3            0.500000         2.121320         2.121320                  2
        4            0.015376         0.397139         0.356684                111

           ...      svd_v_s_6     svd_v_d_1     svd_v_d_2     svd_v_d_3     svd_v_d_4  \
        0  ...   4.849544e-20  3.066836e-09 -1.320418e-12 -3.511876e-07 -1.484744e-12
        1  ...   0.000000e+00  2.912995e-14 -8.226035e-11 -5.907914e-12 -8.215418e-13
        2  ...   1.698938e-17  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
```

```
3  ... -1.525110e-21  6.639933e-19 -2.337091e-16 -8.949695e-15 -3.956764e-13
4  ...  2.358748e-14 -8.379303e-11 -7.496258e-02 -9.565510e-10 -3.057344e-10

      svd_v_d_5     svd_v_d_6         U_DOT         V_DOT  Label
0  4.322285e-12  5.413785e-12  4.738274e-25  5.909254e-22      0
1  1.031080e-12  5.646996e-15  1.414967e-20  0.000000e+00      0
2  0.000000e+00  0.000000e+00  3.614572e-26  0.000000e+00      0
3  1.228825e-18  7.163667e-21  1.865929e-33  5.915392e-34      0
4  1.883535e-07  4.559034e-14  2.774752e-03  2.623718e-03      1

[5 rows x 63 columns]
```

In [4]:
```
# Sample the data frame if opted
if sample_size > 0:
    print('Sample from the data frame is taken !!!')
    # sample train dataset
    df_train = df_train.sample(frac=sample_size)
    df_train = df_train.reset_index(drop=False)
    # sample test dataset
    df_test = df_test.sample(frac=sample_size)
    df_test = df_test.reset_index(drop=False)
```

In [5]:
```
# get train features, labels separately
X_train = df_train.drop(['Label'], axis=1)
y_train = df_train['Label']

# get test features, labels separately
X_test = df_test.drop(['Label'], axis=1)
y_test = df_test['Label']
```

3 UTIL Functions

In [6]:
```
def get_confusion_matrix(actual_list, predicted_list, title_suffix=str()):
    """
    This function plots the confusion matrix given ground truth and predicted
    """

    conf_matrix = confusion_matrix(actual_list, predicted_list, labels=[0, 1])

    col_names = ['Not Recommend', 'Recommend']
    conf_df = pd.DataFrame(conf_matrix, columns=col_names)
    conf_df.index = col_names

    # plot confusion matrix
    sns.heatmap(conf_df, annot=True, annot_kws={'size': 16}, fmt='g', cmap='YlGnBu',
                cbar_kws={'label': 'prediction_count', 'format':'%d'})
    plt.yticks(rotation=0)
    plt.xticks(rotation=90)
```

```
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title('Confusion Matrix -' + title_suffix)
    plt.show()

    return conf_df
```

```
In [7]: def get_precision_recall_matrix(conf_matrix, title_suffix=str()):

            # compute precision matrix
            precision_matrix = conf_matrix.div(conf_matrix.sum(axis=0), axis=1) * 100.0

            # compute recall matrix
            recall_matrix = conf_matrix.div(conf_matrix.sum(axis=1), axis=0) * 100.0

            # plot both the matrices

            # plot precision matrix
            sns.heatmap(precision_matrix, annot=True, annot_kws={'size': 16}, fmt='.4f', cmap='Y
                        cbar_kws={'label': 'percentage', 'format':'%.2f'})
            plt.yticks(rotation=0)
            plt.xticks(rotation=90)
            plt.xlabel('Predicted')
            plt.ylabel('Actual')
            plt.title('Precision Matrix -' + title_suffix)
            plt.show()

            # plot recall matrix
            sns.heatmap(recall_matrix, annot=True, annot_kws={'size': 16}, fmt='.4f', cmap='YlGn
                        cbar_kws={'label': 'percentage', 'format':'%.2f'})
            plt.yticks(rotation=0)
            plt.xticks(rotation=90)
            plt.xlabel('Predicted')
            plt.ylabel('Actual')
            plt.title('Recall Matrix -' + title_suffix)
            plt.show()

            # return as a tuple
            return (precision_matrix, recall_matrix,)
```

```
In [8]: def get_classification_report(actual, predicted, title_suffix=str()):

            # set class labels and its corresponding name
            class_labels_list = [0, 1]
            col_names = ['Not Recommend', 'Recommend']

            # compute performance df
            eval_matrix = precision_recall_fscore_support(actual, predicted,
```

```
                                              labels=class_labels_list)

        eval_df = pd.DataFrame(list(eval_matrix), columns=class_labels_list)
        eval_df.index = ['Precision', 'Recall', 'Fscore', 'Support']
        eval_df.columns = col_names


        # normalize the performace df
        eval_df_normed = eval_df * 100.0
        eval_df_normed.loc['Support', col_names] /= eval_df_normed.loc['Support', col_names]
        eval_df_normed.iloc[3:4, :] *= 100.0

        # plot the classification report
        sns.heatmap(eval_df_normed, annot=True, annot_kws={'size': 16}, fmt='.4f', cmap='YlG
                    cbar_kws={'label': 'Percentage', 'format':'%.2f'})
        plt.yticks(rotation=0)
        plt.xticks(rotation=90)

        plt.xlabel('Classes')
        plt.ylabel('Metrics')
        plt.title('Classification Report -' + title_suffix)
        plt.show()

        return eval_df_normed
```

```
In [9]: def evaluate_model(model, X, y):

        # get prediction and its probability
        predicted_labels = model.predict(X)
        predicted_probs = model.predict_proba(X)

        # get confsuion matrix
        conf_matrix = get_confusion_matrix(y, predicted_labels)

        # get precision & recall matrix
        pre_matrix, recall_matrix = get_precision_recall_matrix(conf_matrix)

        # get classification report
        clf_report = get_classification_report(y, predicted_labels)

        # get the fscore value
        prec_neg, prec_pos = tuple(clf_report.loc['Precision',:])
        fscore_neg, fscore_pos = tuple(clf_report.loc['Fscore',:])

        # create table entry tuple
        table_entry = (round(fscore_pos,4),)

        return table_entry
```

4 Models

4.1 A) Random Forest Classifier

In [10]:
```
def get_best_hyperparam_RFClassifier(param_dict, X, y, random_search=False):

    # set the scoring function
    final_scorer = 'f1score'

    # declare a scoring dictionary
    score_dict = {
        'f1score': make_scorer(score_func=f1_score, greater_is_better=True,
                               needs_proba=False, needs_threshold=False)
    }


     #Declare the metric as  'minimization' or 'maximization'
    optimization_dict = {
        'f1score' : 'maximization'
    }


    # statified kfold split
    cv_data = 3


    # declare model
    model = RandomForestClassifier()

    if random_search:
        search_cv = RandomizedSearchCV(estimator=model, param_distributions=param_dict,
                                       cv=cv_data, scoring=score_dict, refit=False,
                                       return_train_score=True, n_iter=20, n_jobs=-1)

    else:
        # declare grid search CV object
        search_cv = GridSearchCV(estimator=model, param_grid=param_dict, cv=cv_data,
                                 scoring=score_dict, refit=False,
                                 return_train_score=True, n_jobs=-1)

    # fit to the data
    search_cv.fit(X, y)


    # get total number of param settings
    param_list = list(param_dict.keys())
    param_field_list = ['param_' + item for item in param_list]
```

```
# get list of train metric list
train_metric_list = ['mean_train_' + item for item in score_dict.keys()]
# get list of test metric list
test_metric_list = ['mean_test_' + item for item in score_dict.keys()]

# get number of rows in the search cv data frame
num_rows = len(search_cv.cv_results_['params'])

# create the grid search info df
grid_info_df = pd.DataFrame(search_cv.cv_results_, index=range(num_rows))

# prepare a list of reqired columns
required_columns = ['params'] + param_field_list + train_metric_list + \
                   test_metric_list

# slice the data frame to only required columns
grid_info_df = grid_info_df[required_columns]

# process individual metrics
for metric, optimization in optimization_dict.items():
    if optimization == 'minimization':
        grid_info_df['mean_train_' + metric] *= -1
        grid_info_df['mean_test_' + metric] *= -1

# Find the best hyperparam & its corresponding scores
if optimization_dict[final_scorer] == 'minimization':
    best_hyperparam_record = grid_info_df.loc[grid_info_df[
                               'mean_test_'+ final_scorer].idxmin(),:]
else:
    best_hyperparam_record = grid_info_df.loc[grid_info_df[
                               'mean_test_'+ final_scorer].idxmax(),:]

# best hyperparam & corresponding scores
best_hyperparam = best_hyperparam_record['params']
best_train_score = best_hyperparam_record['mean_train_'+ final_scorer]
best_validation_score = best_hyperparam_record['mean_test_'+ final_scorer]

# plot the hyper params
if len(param_list) == 1:

    # extract individual fiedls
    x_vals = grid_info_df[param_field_list[0]].tolist()
    y_vals_tr = grid_info_df['mean_train_' + final_scorer].tolist()
    y_vals_val = grid_info_df['mean_test_' + final_scorer].tolist()

    # plot train, validation performances
    plt.plot(x_vals, y_vals_tr, label='Train', color='r', marker='o', linestyle='-'
    plt.plot(x_vals, y_vals_val, label='Validation', color='b', marker='o', linesty
```

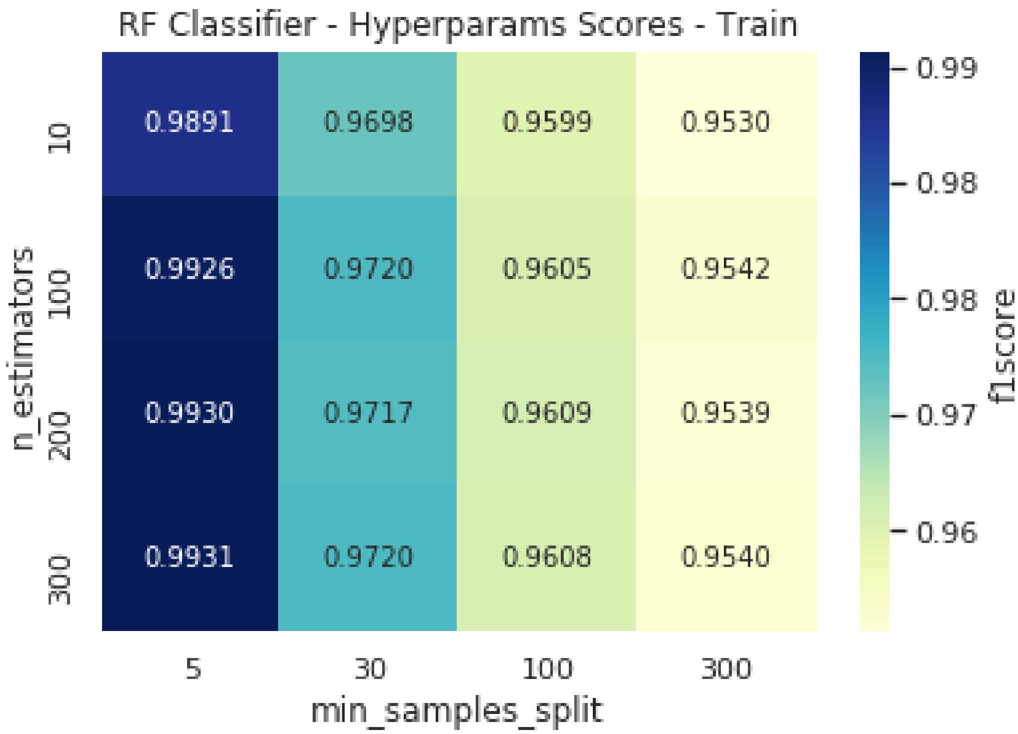
```python
        plt.xlabel('Hyper Params -' + param_list[0])
        plt.ylabel(final_scorer)
        plt.legend()
        plt.title('RF Classifier - Hyperparam Train v/s Validation Scores')
        plt.show()


    # Heatmap plot for pair of hyperparam values
    elif len(param_list) == 2:
        # get pivoted table
        train_hyp_df = pd.pivot_table(data=grid_info_df, index=param_field_list[0],
                                      columns=param_field_list[1],
                                      values='mean_train_' + final_scorer ,
                                      fill_value=np.inf)
        sns.heatmap(train_hyp_df, annot=True, cmap='YlGnBu', fmt='.4f',
                    cbar_kws={'label': final_scorer, 'format':'%.2f'})
        plt.xlabel(param_list[1])
        plt.ylabel(param_list[0])
        plt.title('RF Classifier - Hyperparams Scores - Train')
        plt.show()

        print('\n'*3)

        # Test hyperparam

        # get pivoted table
        train_hyp_df = pd.pivot_table(data=grid_info_df, index=param_field_list[0],
                                      columns=param_field_list[1],
                                      values='mean_test_' + final_scorer, fill_value=np
        sns.heatmap(train_hyp_df, annot=True, cmap='YlGnBu', fmt='.4f',
                    cbar_kws={'label': final_scorer, 'format':'%.2f'})
        plt.xlabel(param_list[1])
        plt.ylabel(param_list[0])
        plt.title('RF Classifier - Hyperparams Scores - Validation')
        plt.show()

    else:
        print(grid_info_df)

    print('Best hyperparam value: ', best_hyperparam, 'Best Train Score: ', best_train_
          'Best Validation Score: ', best_validation_score)


    #best_mse_train = best_hyperparam_record['mean_train_MSE']
    #best_mse_validation = best_hyperparam_record['mean_test_MSE']

    # return tuple
    ret_tuple = (best_hyperparam, best_train_score, best_validation_score,)
```

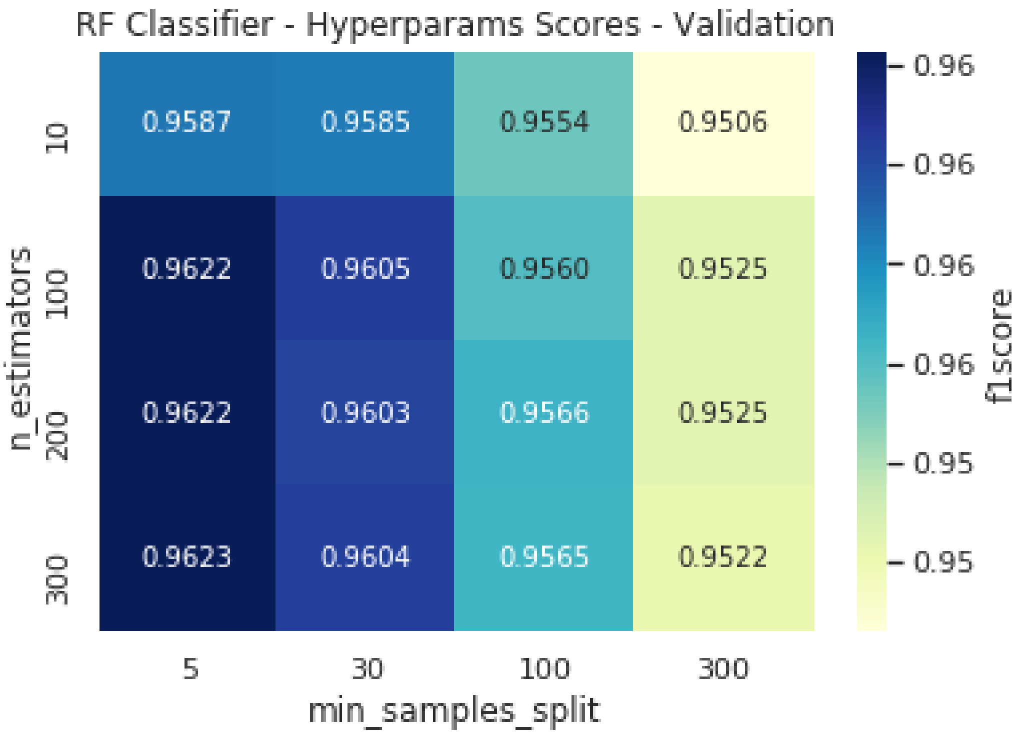
```
            return ret_tuple
```

4.1.1 1. Find the best hyperparameter

```
In [11]: # declare a set of params to search for
         """
         param_dict_rf = {'n_estimators' : randint(20,200),
                          'min_samples_split' : randint(30,180),
                          'min_samples_leaf': randint(25,65),
                          'max_depth' : randint(10,15)
                         }
         """

         param_dict_rf = {'n_estimators' : [10, 100, 200, 300],
                          'min_samples_split' : [5, 30, 100, 300],
                         }


         print(datetime.now() ,' Hyperparam Tuning of RF started')
         hyp_tuned_info_rf = get_best_hyperparam_RFClassifier(param_dict_rf, X_train, y_train, F
         print(datetime.now() ,' Hyperparam Tuning of RF completed')


         best_hyp_rf, best_tr_score_rf, best_val_score_rf = hyp_tuned_info_rf

         rf_clf = RandomForestClassifier(n_estimators=best_hyp_rf['n_estimators'],
                                         min_samples_split=best_hyp_rf['min_samples_split'],
                                         #min_samples_leaf=best_hyp_rf['min_samples_leaf'],
                                         #max_depth=best_hyp_rf['max_depth'])
                                        )
```

```
2019-06-23 16:52:18.758040  Hyperparam Tuning of RF started


/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/pr
  "timeout or by a memory leak.", UserWarning
```


RF Classifier - Hyperparams Scores - Train
0.9891
0.9698
0.9599
0.9530
0.9926
0.9720
0.9605
0.9542
0.9930
0.9717
0.9609
0.9539
0.9931
0.9720
0.9608
0.9540
n_estimators
10
100
200
300
min_samples_split
5
30
100
300
f1score
0.99
0.98
0.98
0.97
0.96




```
Best hyperparam value:  {'min_samples_split': 5, 'n_estimators': 300} Best Train Score:  0.99306
2019-06-23 16:58:36.690489  Hyperparam Tuning of RF completed
```

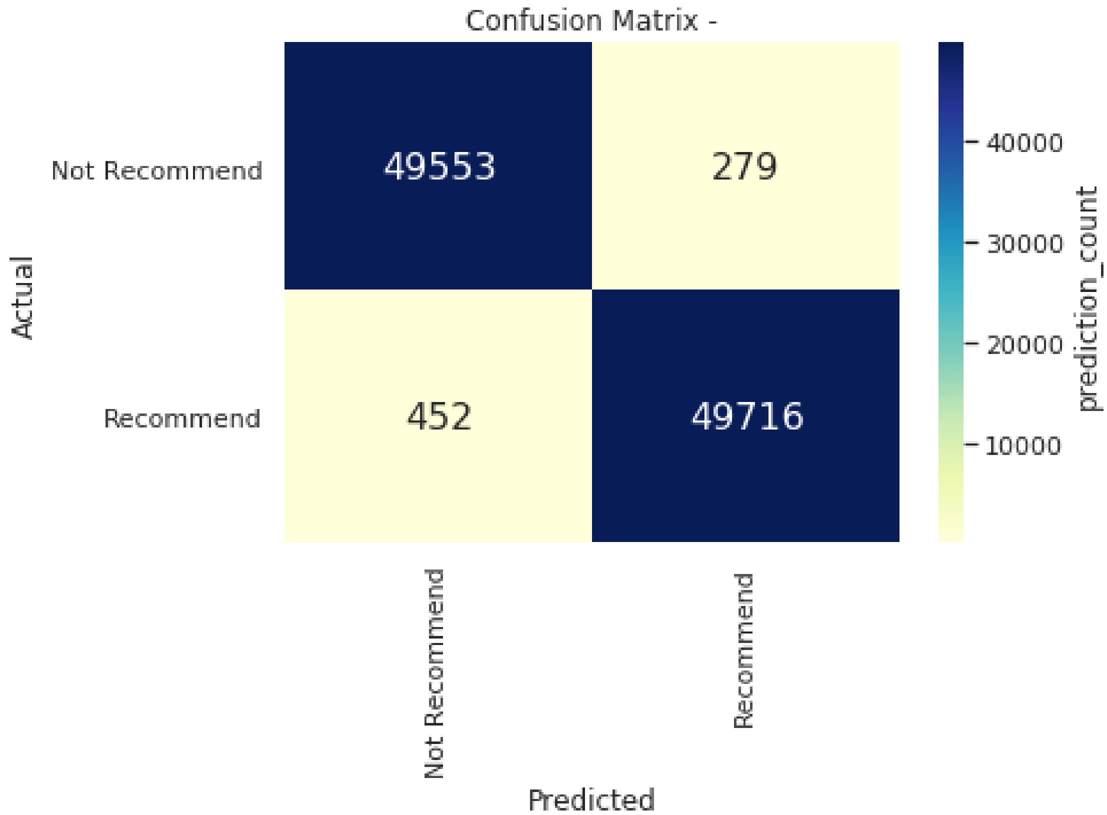
4.1.2 2. Train the model with best hyperparameter

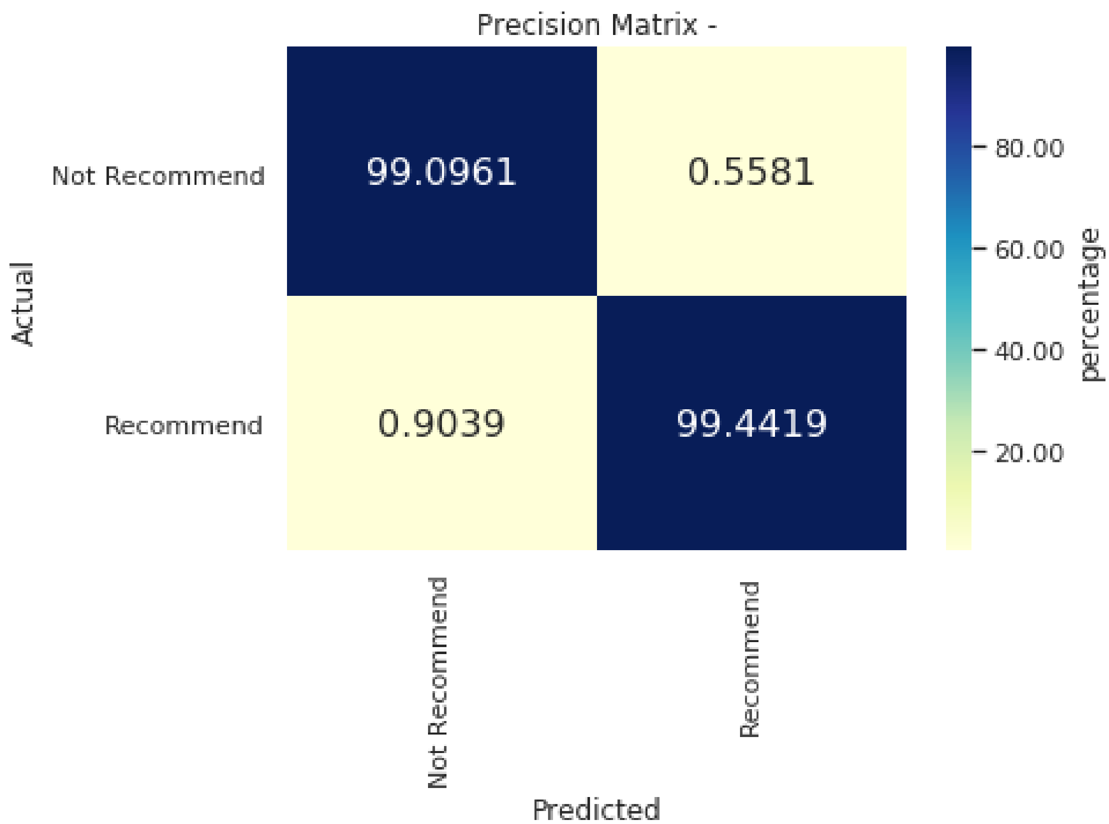
```
In [12]: # train the model using the best hyperparam obtained
         print(datetime.now() ,' Training of RF started')
         rf_clf.fit(X_train, y_train)
         print(datetime.now() ,' Training of RF completed')

         # save model to disk
         pickle_out = open("./model/rf_clf.pkl","wb")
         pickle.dump(rf_clf, pickle_out)
         pickle_out.close()
```

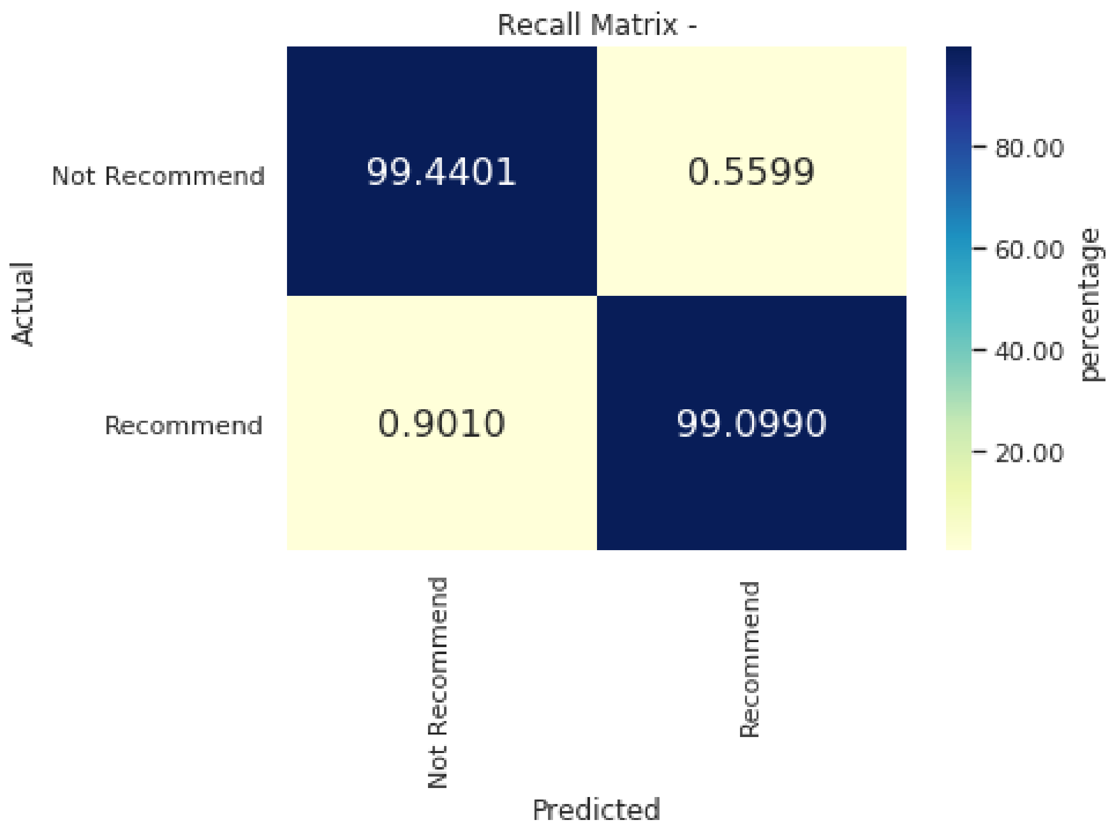
```
2019-06-23 16:58:36.701123  Training of RF started
2019-06-23 16:59:43.622639  Training of RF completed
```

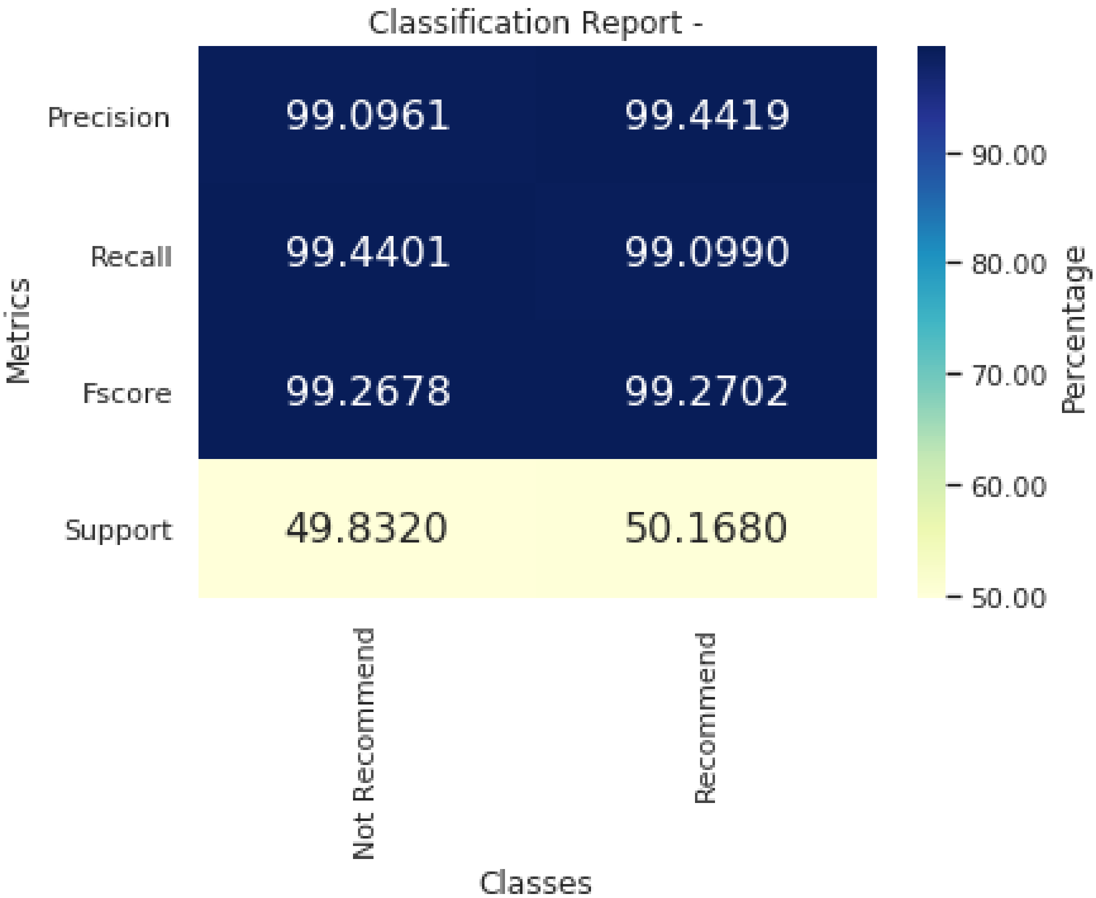
```
In [13]: #load model from disk
         pickle_in = open("./model/rf_clf.pkl","rb")
         rf_clf = pickle.load(pickle_in)
         pickle_in.close()
```

```
table_entry_rf_train = evaluate_model(rf_clf, X_train, y_train)
```



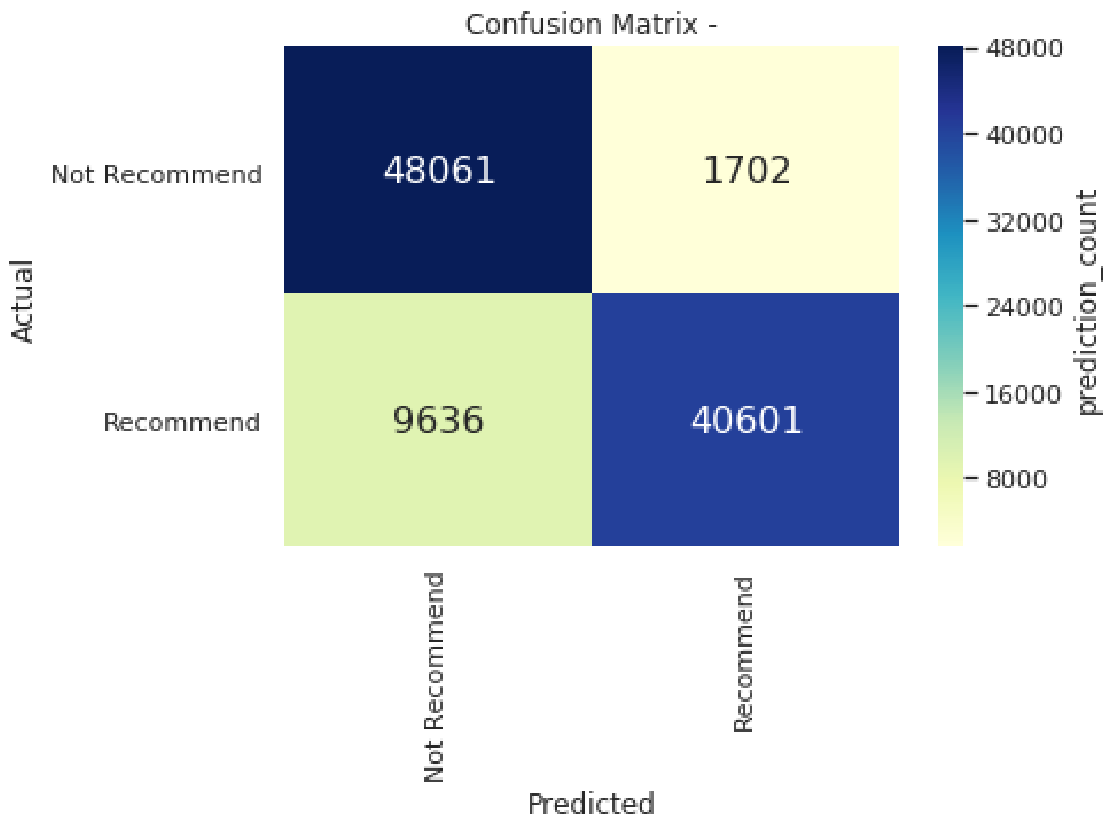

Precision Matrix -
Not Recommend
Recommend
Actual
99.0961
0.5581
0.9039
99.4419
Not Recommend
Recommend
Predicted
80.00
60.00
40.00
20.00
percentage

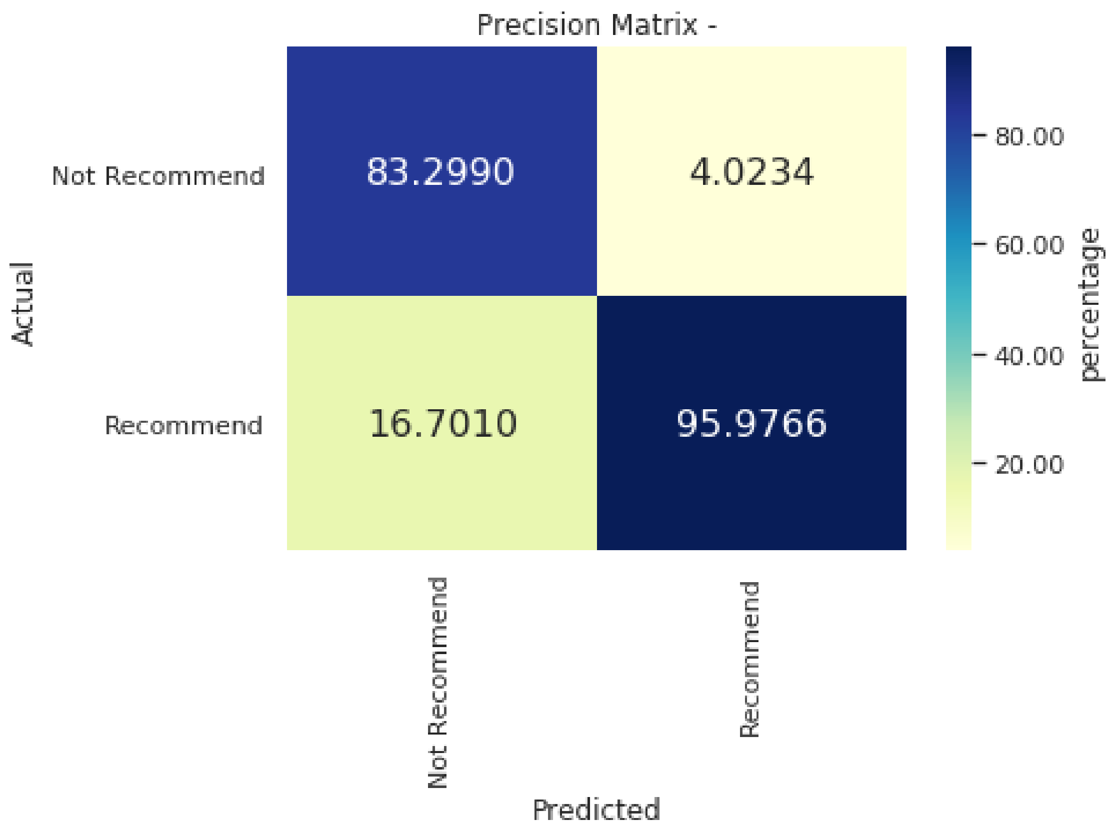

Recall Matrix -
Not Recommend
Recommend
Actual
99.4401
0.5599
0.9010
99.0990
Not Recommend
Recommend
Predicted
80.00
60.00
40.00
20.00
percentage

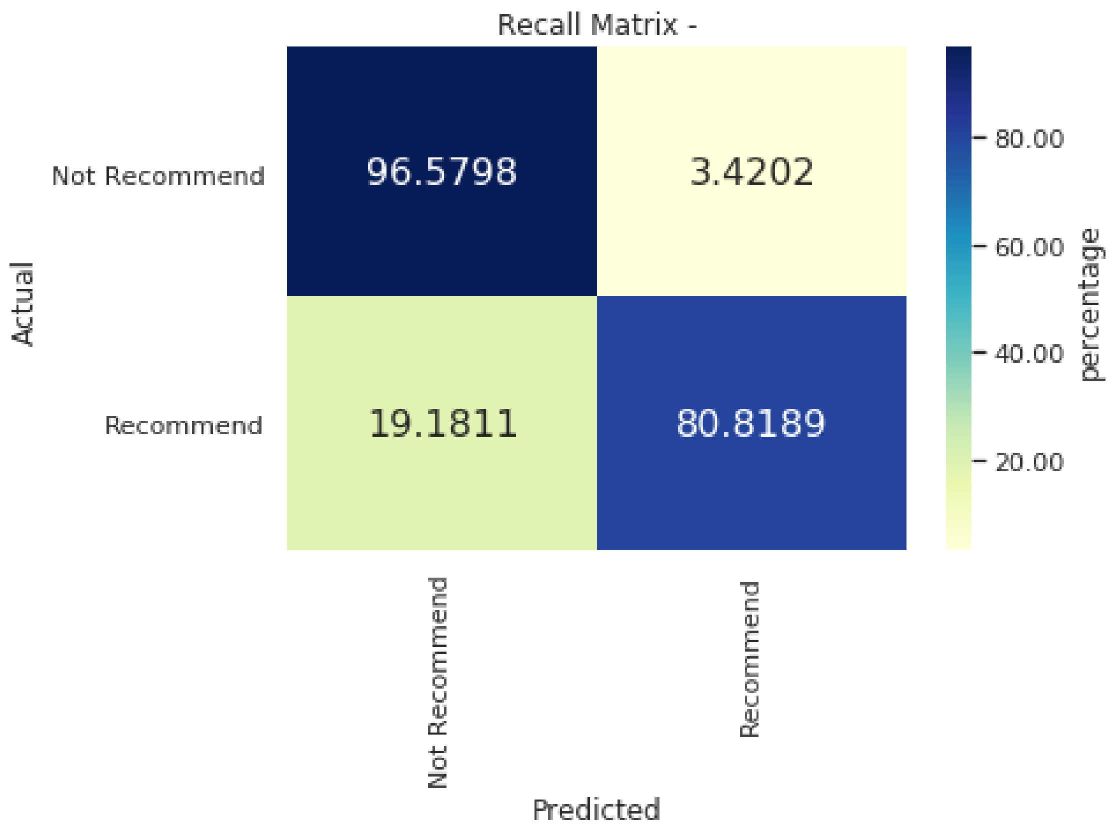


4.1.3 3. Test the model

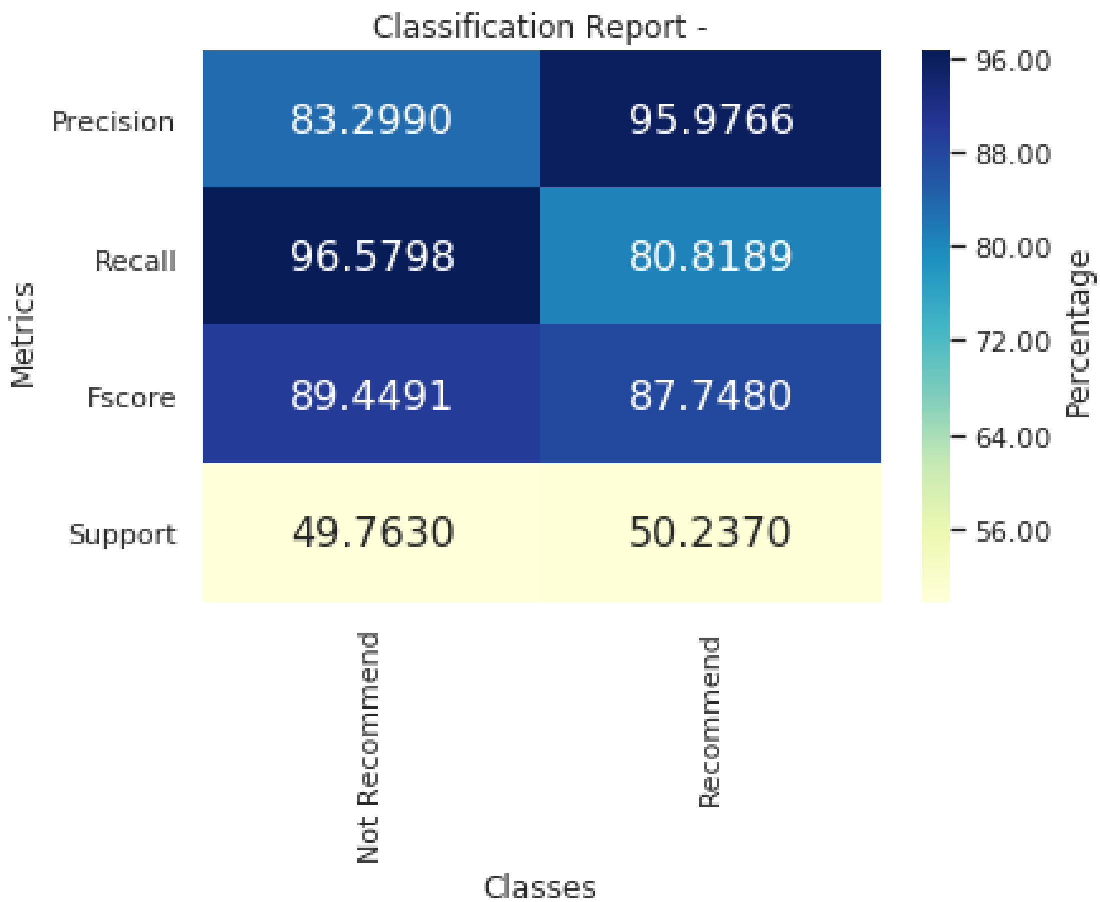
In [14]:
```
table_entry_rf_test = evaluate_model(rf_clf, X_test, y_test)
best_hyp_rf = '\n'.join(str(best_hyp_rf).split(','))
table_entry_rf = ('RF Classifier', best_hyp_rf,) + table_entry_rf_train + table_entry_r
```


Confusion Matrix -
Not Recommend
Recommend
Actual
48061
1702
9636
40601
Not Recommend
Recommend
Predicted
48000
40000
32000
24000
16000
8000
prediction_count


Precision Matrix -
Not Recommend
Recommend
Actual
83.2990
4.0234
16.7010
95.9766
Not Recommend
Recommend
Predicted
80.00
60.00
40.00
20.00
percentage

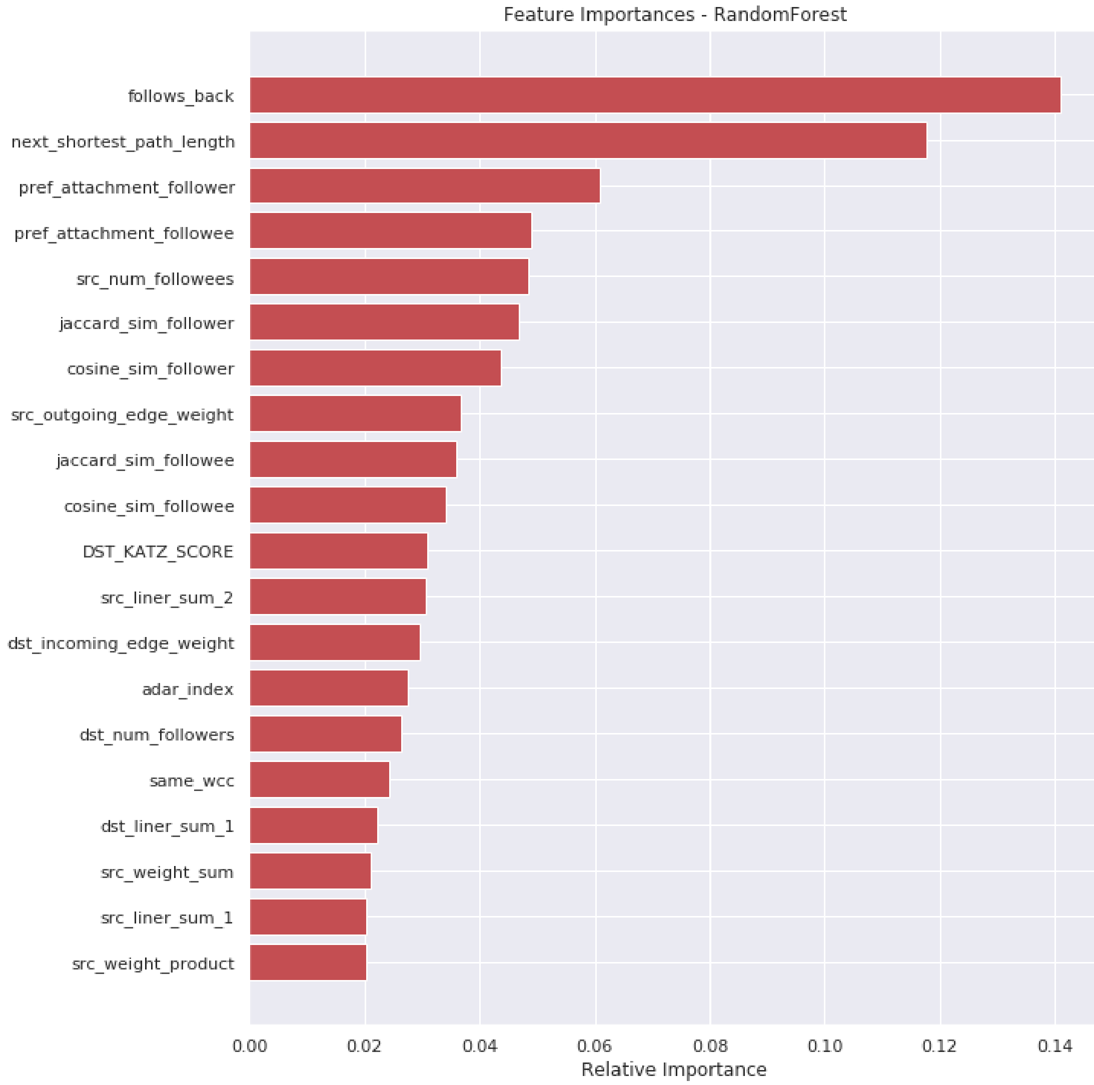


Recall Matrix -
Not Recommend
Recommend
Actual
96.5798
3.4202
19.1811
80.8189
80.00
60.00
40.00
20.00
percentage
Not Recommend
Recommend
Predicted



4.2 Feature Importance

In [15]:
```
features = X_train.columns.values.tolist()
importances = rf_clf.feature_importances_

indices = (np.argsort(importances))[-20:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances - RandomForest')
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()
```



4.3 B) XGB Classifier

In [16]:
```
def get_best_hyperparam_XGBClassifier(param_dict, X, y, random_search=False):

    # set the scoring function
    final_scorer = 'f1score'

    # declare a scoring dictionary
    score_dict = {
        'f1score': make_scorer(score_func=f1_score, greater_is_better=True,
                                needs_proba=False, needs_threshold=False)
    }
```

```
 #Declare the metric as  'minimization' or 'maximization'
optimization_dict = {
    'f1score' : 'maximization'
}


# statified k fold validation
cv_data = 3

# declare model
model = XGBClassifier()

if random_search:
    search_cv = RandomizedSearchCV(estimator=model, param_distributions=param_dict,
                                   cv=cv_data, scoring=score_dict, refit=False,
                                   return_train_score=True, n_iter=6, n_jobs=-1)

else:
    # declare grid search CV object
    search_cv = GridSearchCV(estimator=model, param_grid=param_dict, cv=cv_data,
                             scoring=score_dict, refit=False,
                             return_train_score=True, n_jobs=-1)

# fit to the data
search_cv.fit(X, y)


# get total number of param settings
param_list = list(param_dict.keys())
param_field_list = ['param_' + item for item in param_list]

# get list of train metric list
train_metric_list = ['mean_train_' + item for item in score_dict.keys()]
# get list of test metric list
test_metric_list = ['mean_test_' + item for item in score_dict.keys()]

# get number of rows in the search cv data frame
num_rows = len(search_cv.cv_results_['params'])

# create the grid search info df
grid_info_df = pd.DataFrame(search_cv.cv_results_, index=range(num_rows))

# prepare a list of reqired columns
required_columns = ['params'] + param_field_list + train_metric_list + \
                   test_metric_list

# slice the data frame to only required columns
grid_info_df = grid_info_df[required_columns]
```

```
# process individual metrics
for metric, optimization in optimization_dict.items():
    if optimization == 'minimization':
        grid_info_df['mean_train_' + metric] *= -1
        grid_info_df['mean_test_' + metric] *= -1

# Find the best hyperparam & its corresponding scores
if optimization_dict[final_scorer] == 'minimization':
    best_hyperparam_record = grid_info_df.loc[grid_info_df[
                              'mean_test_'+ final_scorer].idxmin(),:]
else:
    best_hyperparam_record = grid_info_df.loc[grid_info_df[
                              'mean_test_'+ final_scorer].idxmax(),:]

# best hyperparam & corresponding scores
best_hyperparam = best_hyperparam_record['params']
best_train_score = best_hyperparam_record['mean_train_'+ final_scorer]
best_validation_score = best_hyperparam_record['mean_test_'+ final_scorer]

# plot the hyper params
if len(param_list) == 1:

    # extract individual fiedls
    x_vals = grid_info_df[param_field_list[0]].tolist()
    y_vals_tr = grid_info_df['mean_train_' + final_scorer].tolist()
    y_vals_val = grid_info_df['mean_test_' + final_scorer].tolist()

    # plot train, validation performances
    plt.plot(x_vals, y_vals_tr, label='Train', color='r', marker='o', linestyle='-'
    plt.plot(x_vals, y_vals_val, label='Validation', color='b', marker='o', linesty
    plt.xlabel('Hyper Params -' + param_list[0])
    plt.ylabel(final_scorer)
    plt.legend()
    plt.title('XGB Classifier - Hyperparam Train v/s Validation Scores')
    plt.show()


# Heatmap plot for pair of hyperparam values
elif len(param_list) == 2:
    # get pivoted table
    train_hyp_df = pd.pivot_table(data=grid_info_df, index=param_field_list[0],
                                  columns=param_field_list[1],
                                  values='mean_train_' + final_scorer ,
                                  fill_value=np.inf)
    sns.heatmap(train_hyp_df, annot=True, cmap='YlGnBu', fmt='.4f',
                cbar_kws={'label': final_scorer, 'format':'%.2f'})
    plt.xlabel(param_list[1])
```

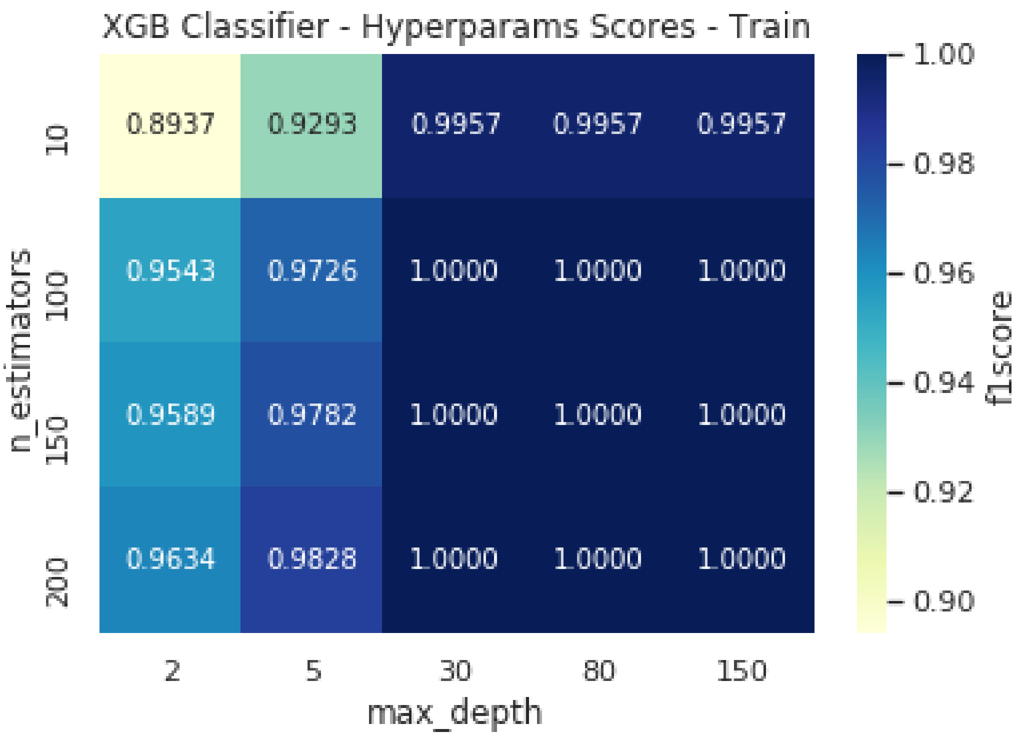
```
            plt.ylabel(param_list[0])
            plt.title('XGB Classifier - Hyperparams Scores - Train')
            plt.show()

            print('\n'*3)

            # Test hyperparam

            # get pivoted table
            train_hyp_df = pd.pivot_table(data=grid_info_df, index=param_field_list[0],
                                          columns=param_field_list[1],
                                          values='mean_test_' + final_scorer, fill_value=np
            sns.heatmap(train_hyp_df, annot=True, cmap='YlGnBu', fmt='.4f',
                        cbar_kws={'label': final_scorer, 'format':'%.2f'})
            plt.xlabel(param_list[1])
            plt.ylabel(param_list[0])
            plt.title('XGB Classifier - Hyperparams Scores - Validation')
            plt.show()

        else:
            print(grid_info_df)

        print('Best hyperparam value: ', best_hyperparam, 'Best Train Score: ', best_train_
              'Best Validation Score: ', best_validation_score)


        #best_mse_train = best_hyperparam_record['mean_train_MSE']
        #best_mse_validation = best_hyperparam_record['mean_test_MSE']

        # return tuple
        ret_tuple = (best_hyperparam, best_train_score, best_validation_score,)


        return ret_tuple
```

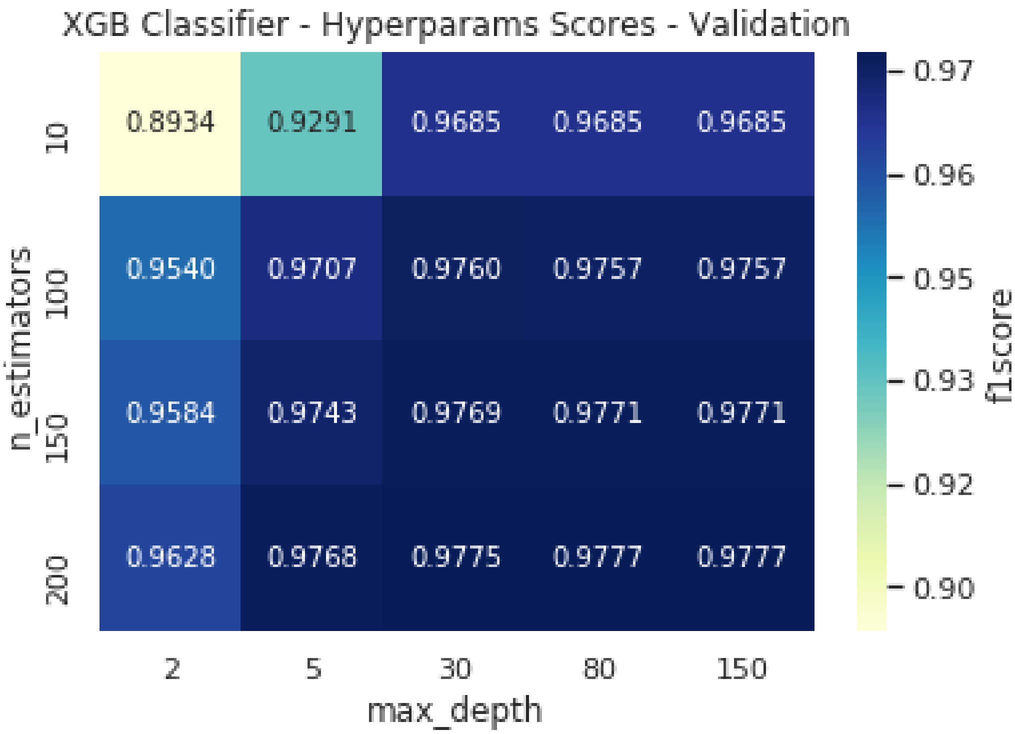
4.3.1 1. Find the best hyperparameter

```
In [17]: # declare a set of params to search for
         """
         param_dict_xgb = {'n_estimators' : randint(60,200),
                           'learning_rate' : [1e-04, 1e-03, 1e-02, 1e-01, 1e+00],
                           'max_depth' : randint(10,15)
                          }
         """

         param_dict_xgb = {'n_estimators' : [10, 100, 150, 200],
                           'max_depth' : [2, 5, 30, 80, 150]
                          }
```

```
print(datetime.now() ,' Hyperparam Tuning of XGB started')
hyp_tuned_info_xgb = get_best_hyperparam_XGBClassifier(param_dict_xgb, X_train, y_train
print(datetime.now() ,' Hyperparam Tuning of XGB completed')

best_hyp_xgb, best_tr_score_xgb, best_val_score_xgb = hyp_tuned_info_xgb

xgb_clf = XGBClassifier(n_estimators=best_hyp_xgb['n_estimators'],
                        max_depth=best_hyp_xgb['max_depth'],
                        #learning_rate=best_hyp_xgb['learning_rate']
                       )
```

```
2019-06-23 17:00:06.295206  Hyperparam Tuning of XGB started
```






```
Best hyperparam value:  {'max_depth': 80, 'n_estimators': 200} Best Train Score:  1.0 Best Valid
2019-06-23 17:27:22.942277  Hyperparam Tuning of XGB completed
```

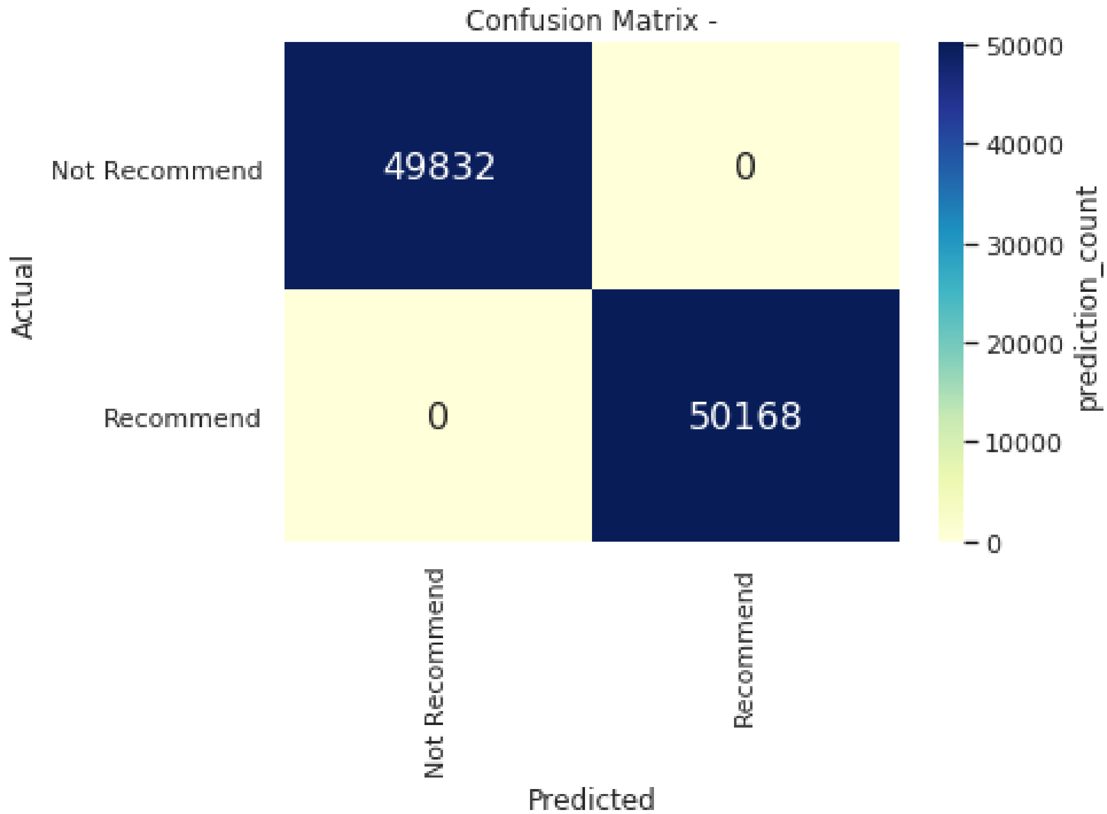
4.3.2 2. Train the model with best hyperparameter

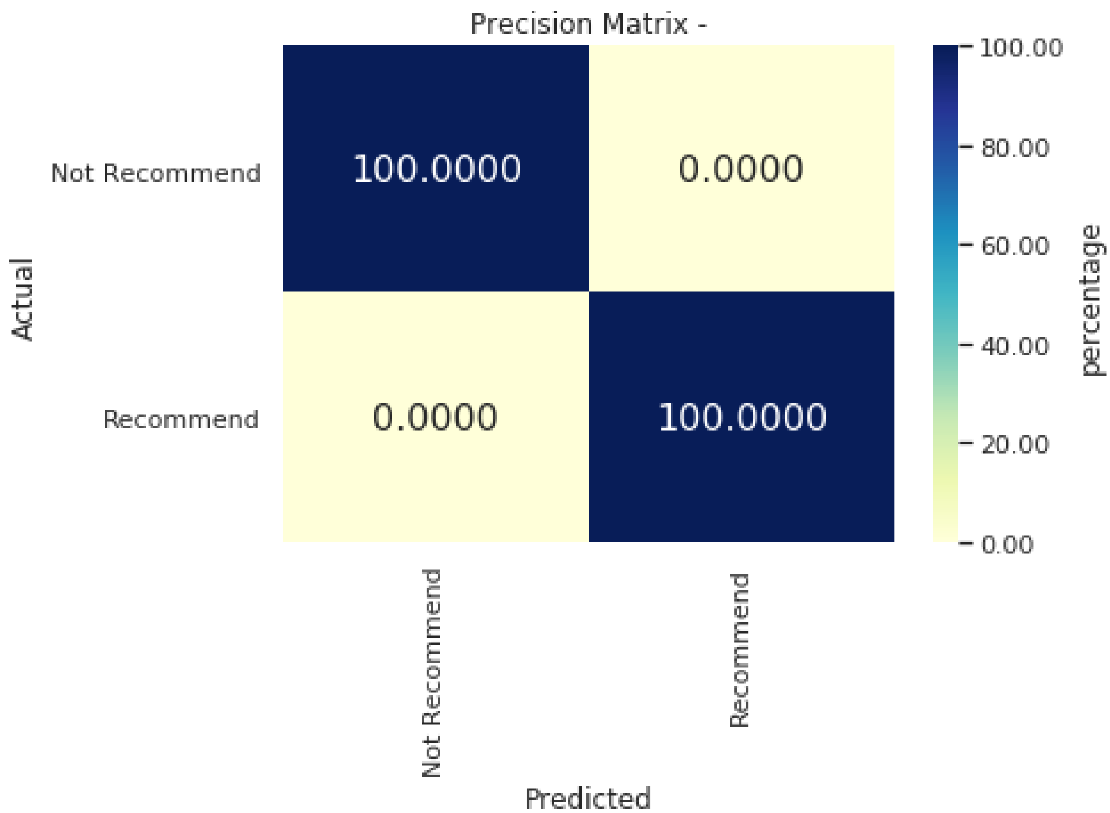
In [18]:
```
# train the model using the best hyperparam obtained
print(datetime.now() ,' Training of XGB started')
xgb_clf.fit(X_train, y_train)
print(datetime.now() ,' Training of XGB completed')

# save model to disk
pickle_out = open("./model/xgb_clf.pkl","wb")
pickle.dump(xgb_clf, pickle_out)
pickle_out.close()
```

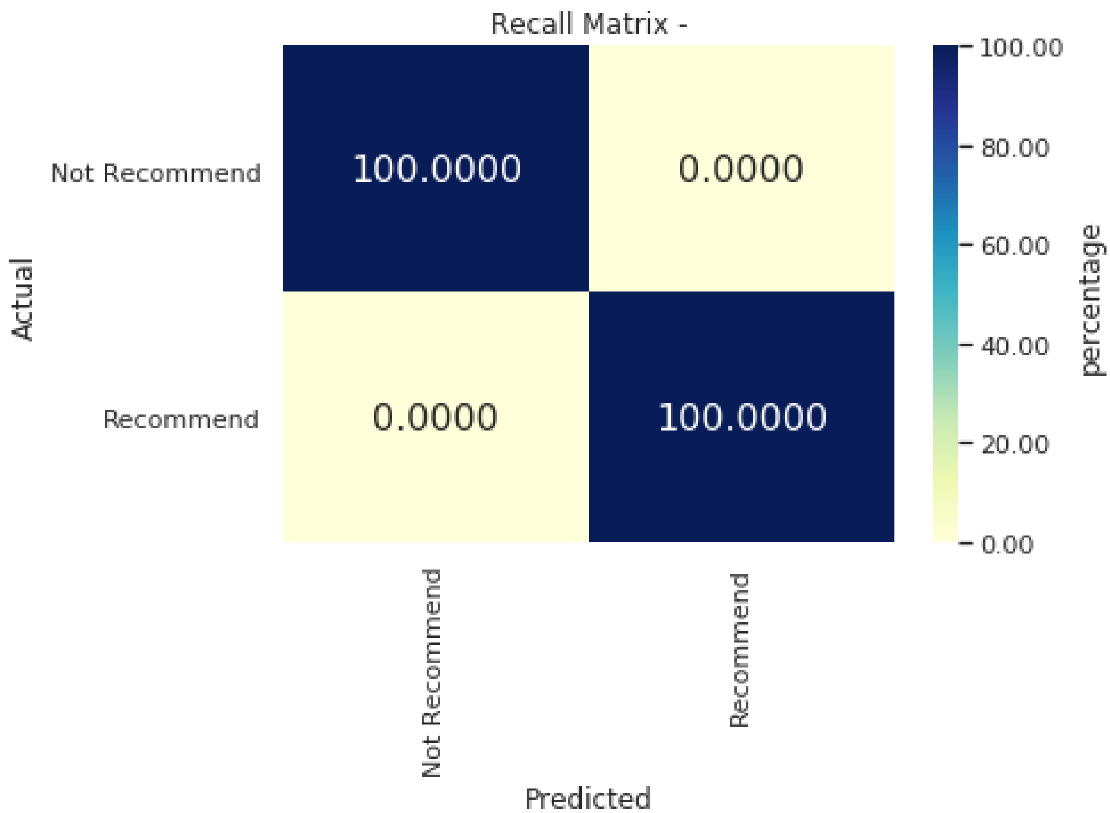
```
2019-06-23 17:27:22.956185  Training of XGB started
2019-06-23 17:33:19.615081  Training of XGB completed
```

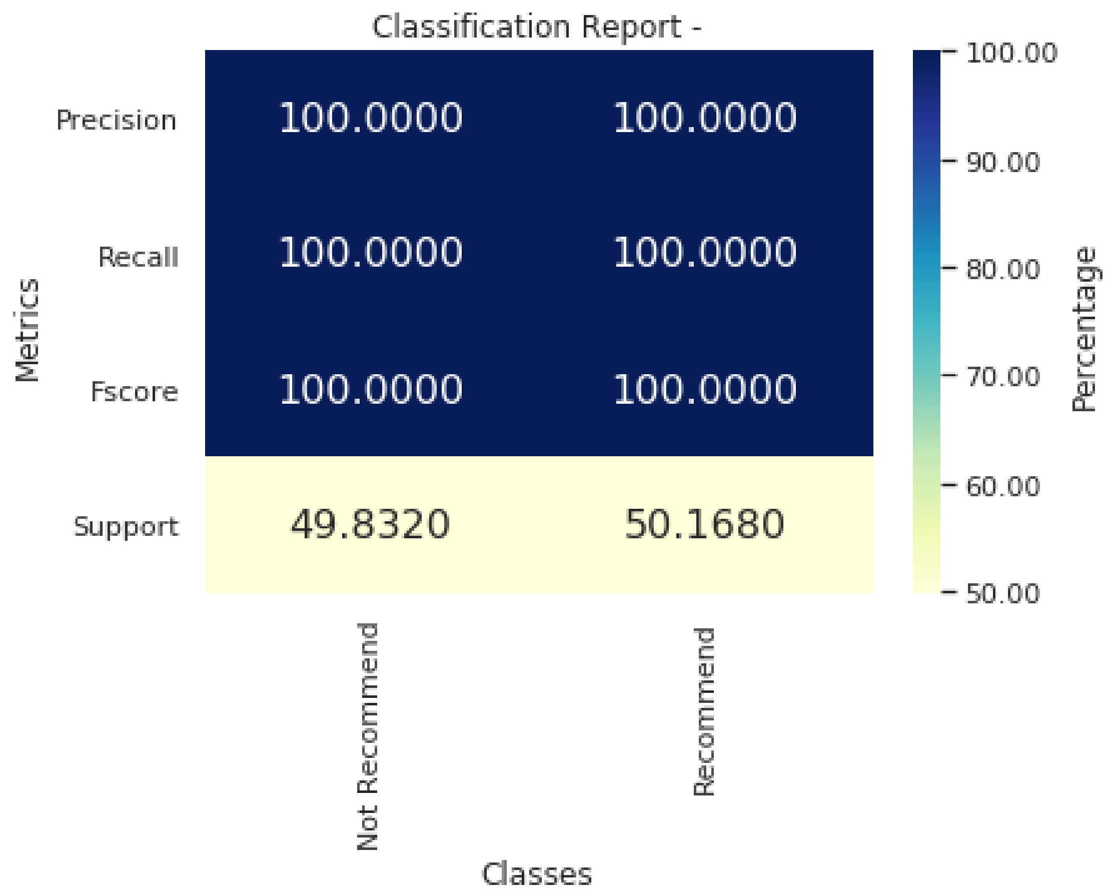
In [19]:
```
#load model from disk
pickle_in = open("./model/xgb_clf.pkl","rb")
xgb_clf = pickle.load(pickle_in)
pickle_in.close()
```

```
table_entry_xgb_train = evaluate_model(xgb_clf, X_train, y_train)
```



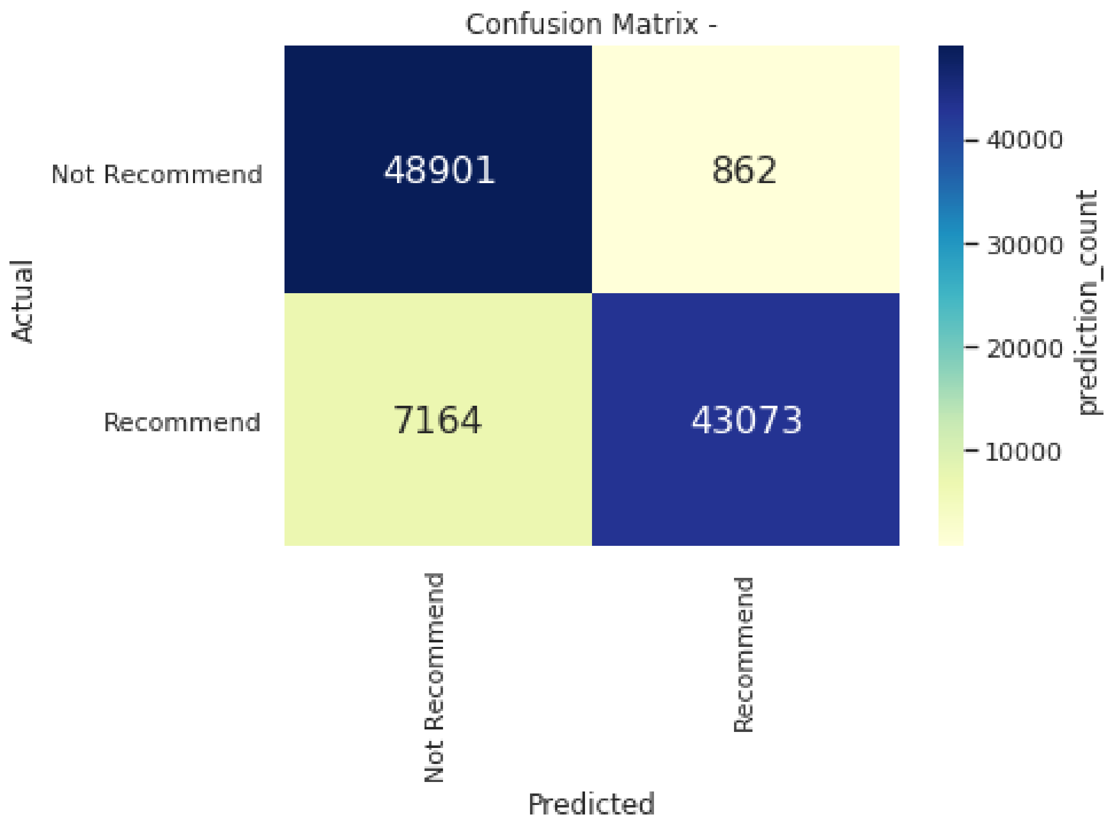

Precision Matrix -
Not Recommend
Recommend
100.0000
0.0000
0.0000
100.0000
Actual
Predicted
Not Recommend
Recommend
100.00
80.00
60.00
40.00
20.00
0.00
percentage


Recall Matrix -
Not Recommend
Recommend
Actual
100.0000
0.0000
0.0000
100.0000
Not Recommend
Recommend
Predicted
100.00
80.00
60.00
40.00
20.00
0.00
percentage

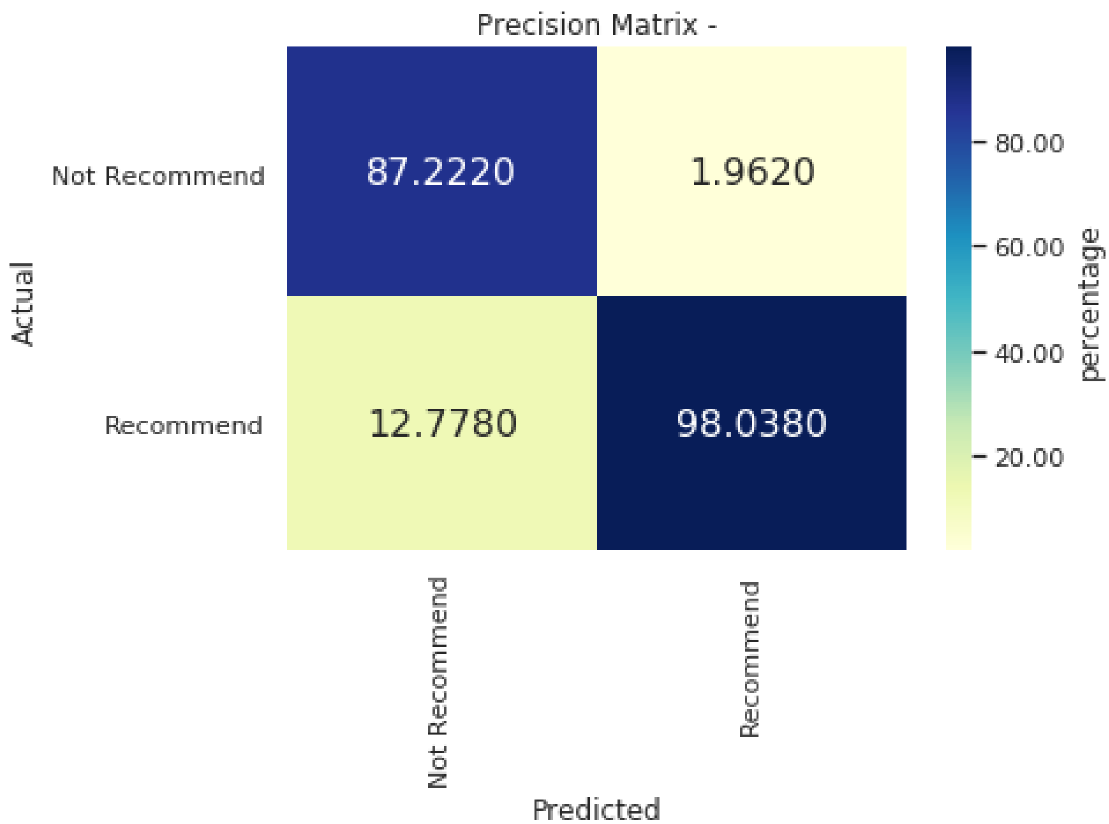


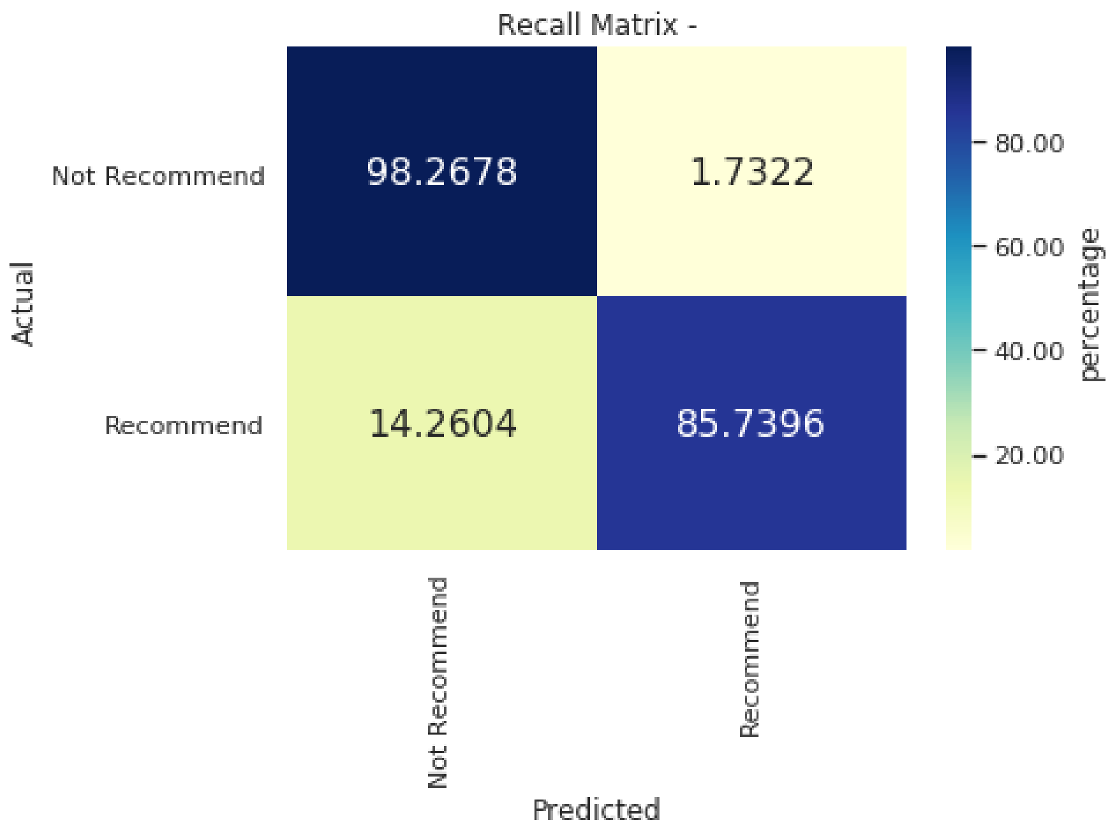
4.3.3 3. Test the model

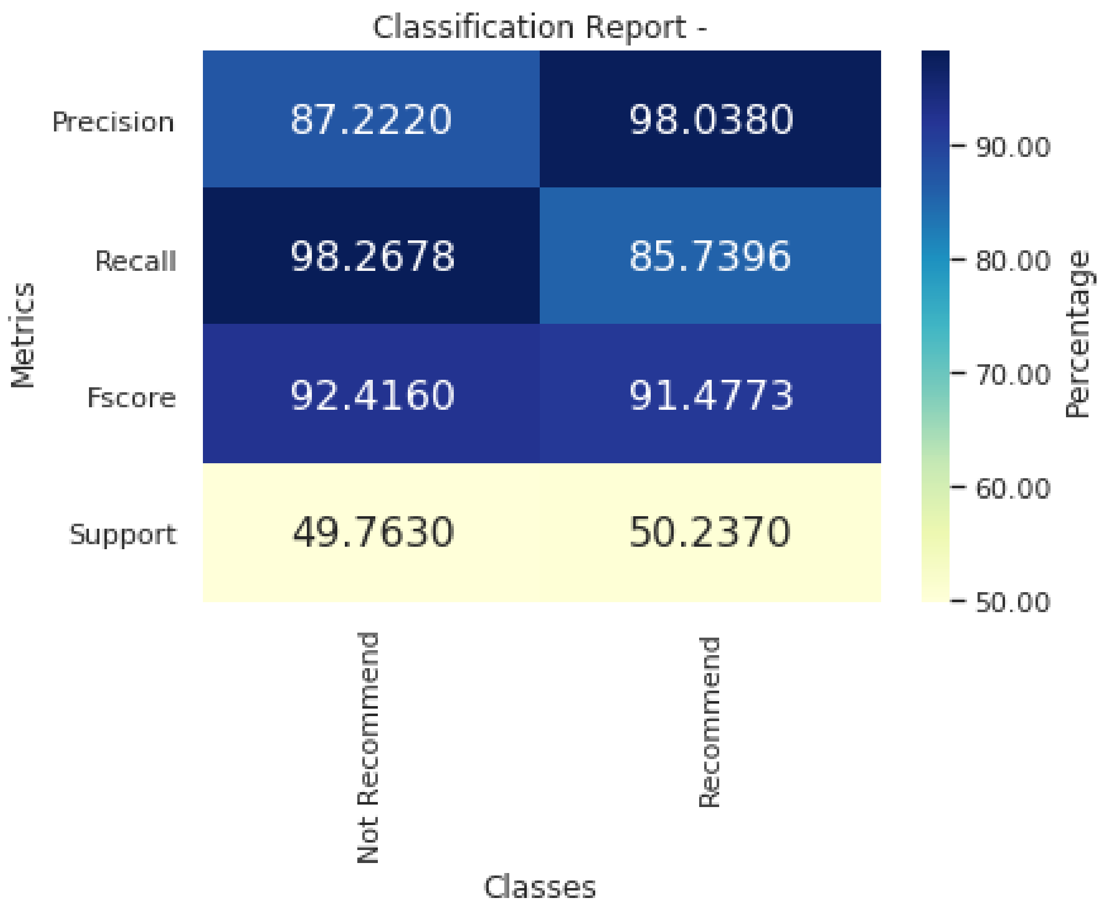
```
In [20]: table_entry_xgb_test = evaluate_model(xgb_clf, X_test, y_test)
         best_hyp_xgb = '\n'.join(str(best_hyp_xgb).split(','))
         table_entry_xgb = ('XGB Classifier', best_hyp_xgb,) + table_entry_xgb_train + table_ent
```



Confusion Matrix -
Not Recommend
Recommend
Actual
48901
862
7164
43073
40000
30000
20000
10000
prediction_count
Not Recommend
Recommend
Predicted

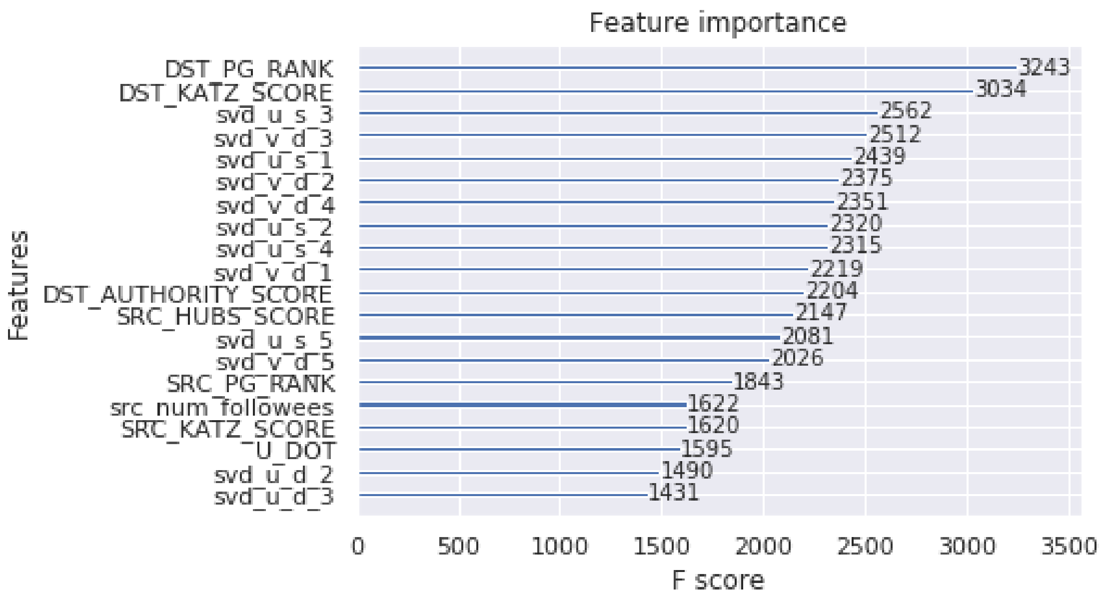

Precision Matrix -
Not Recommend
Recommend
87.2220
1.9620
12.7780
98.0380
Actual
Not Recommend
Recommend
Predicted
80.00
60.00
40.00
20.00
percentage


Recall Matrix -
Not Recommend
Recommend
Actual
98.2678
1.7322
14.2604
85.7396
80.00
60.00
40.00
20.00
percentage
Not Recommend
Recommend
Predicted



4.4 Feature Importance

```
In [21]: xgb.plot_importance(xgb_clf, height=0.2, max_num_features=20)
         plt.show()
```



5 Results Summary

In [22]:
```
Pret_table = PrettyTable()
Pret_table.field_names = ['Model', 'Hyperparam', 'Train F1_Score(%)', 'Test F1_Score(%)
Pret_table.title = 'Classification Model Results Summary'

Pret_table.add_row(table_entry_rf)
Pret_table.add_row(table_entry_xgb)
print(Pret_table)

print(datetime.now() ,' Done !!!')
```

```
+----------------+------------------------+-------------------+------------------+
|     Model      |       Hyperparam       | Train F1_Score(%) | Test F1_Score(%) |
+----------------+------------------------+-------------------+------------------+
| RF Classifier  | {'min_samples_split': 5 |      99.2702      |      87.748      |
|                |   'n_estimators': 300}  |                   |                  |
| XGB Classifier |     {'max_depth': 80     |       100.0       |     91.4773      |
|                |   'n_estimators': 200}  |                   |                  |
+----------------+------------------------+-------------------+------------------+
2019-06-23 17:33:29.566349  Done !!!
```

6 Procedure Summary

Hyperparam tuning is done for RF & XGB

Trained two models RF & XGB on the dataset created
Important features are listed for RF & XGB classifiers
Evaluated both models on the test dataset and compared the performance

7 Conclusion

XGB model (91.47 f1-score) outperformed the RF model (87.74 f1-score)
Both the model showed tendency of overfit, this is more significatnt in random forest model
Feature selection methods can be tried to improve the performace
Page Rank & Katz score are the two most important features for XGB
Follows back & next shorted path are the two most important features for RF
Added engineered feature preferential attachment is identified as the third most important feature for random forest