Quora_Model

June 29, 2019

In [1]:
```
# general purpose packages
import pandas as pd
import numpy as np

import os
from datetime import datetime
import pickle

# visualization related packages
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import train_test_split

# generate random distributions for hyperparams
from scipy.stats import randint
from scipy.stats import beta
from scipy.stats import gamma
from scipy.stats import expon
from scipy.stats import uniform
from scipy.stats import poisson


# Classifier Evaluation
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.metrics import log_loss
from sklearn.metrics import make_scorer

# data preprocessing
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import normalize
```

```
# import model related packages
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.linear_model import SGDClassifier
import xgboost
from xgboost import XGBClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.model_selection import StratifiedKFold

from wordcloud import WordCloud
from sklearn.manifold import TSNE


from prettytable import PrettyTable
```

1 Configs

```
In [2]: sample_size = -1 # set -1 if we want to use full size # set fractional value for sample

        train_df_path = './data/Final_train_df.csv'
        test_df_path = './data/Final_test_df.csv'
```

2 Util Functions

```
In [3]: 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 = ['Non Duplicate', 'Duplicate']
            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 [4]: 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 [5]: def get_classification_report(actual, predicted, title_suffix=str()):

            # set class labels and its corresponding name
            class_labels_list = [0, 1]
            col_names = ['Non Duplicate', 'Duplicate']

            # 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 [6]: def show_class_distribution(df, title):
            """
            This function displays the distribution of each class as a barchart
            """
            count_df = pd.DataFrame(list(dict(df['is_duplicate'].value_counts()).items()),
                                    columns=['is_duplicate', 'Count'])

            plt.title('Class Distribution of '+ title + ' Data')
            plt.xlabel('is_duplicate')
            plt.ylabel('Count')
            sns.barplot(x='is_duplicate', y =count_df['Count'], data=count_df)

            plt.show()
```

```
In [7]: 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 logistic loss
        log_loss_value = log_loss(y, predicted_probs, labels=[0, 1], eps=1e-15)
        log_loss_value = round(log_loss_value, 4)

        table_entry = (log_loss_value,)

        return table_entry
```

3 Data

In [8]:
```
df_train = pd.read_csv(train_df_path, index_col=False)
df_test = pd.read_csv(test_df_path, index_col=False)

print('Shape of train data : ', df_train.shape)
print('Shape of test data :', df_test.shape)

if sample_size > 0:
    print('Sample is taken ', sample_size)
    # train sample
    df_train = df_train.sample(frac=sample_size)
    df_train = df_train.reset_index(drop=True)
    # test sample
    df_test = df_test.sample(frac=sample_size)
    df_test = df_test.reset_index(drop=True)

    print('Shape of train data : ', df_train.shape)
    print('Shape of test data :', df_test.shape)
```

```
Shape of train data :  (84000, 123)
Shape of test data : (36000, 123)
```

In [9]:
```
df_train.head()
```

Out[9]:
```
        id  is_duplicate  q1len  q2len  q1_n_words  q2_n_words  word_Common  \
0   223477             0     73     61          12          13            2
1   111372             0     32     40           6           6            3
2   291123             0     67     46          13          10            2
3   317134             1     33     37           7           6            4
4   246990             0     94     58          16          10            1

   word_Total  word_share   ctc_min  ...  q2_start  q2_think  q2_time  q2_use  \
0          23    0.086957  0.999999  ...       0.0       0.0      0.0     0.0
1          12    0.250000  0.999998  ...       0.0       0.0      0.0     0.0
2          22    0.090909  0.923076  ...       0.0       0.0      0.0     0.0
3          13    0.307692  0.999999  ...       0.0       0.0      0.0     0.0
```

```
4          25    0.040000  0.937499  ...       0.0        0.0       0.0     0.0

   q2_want  q2_way  q2_without  q2_work  q2_would  q2_year
0      0.0     0.0         0.0      0.0       0.0      0.0
1      0.0     0.0         0.0      0.0       0.0      0.0
2      0.0     0.0         0.0      0.0       0.0      0.0
3      0.0     0.0         0.0      0.0       0.0      0.0
4      0.0     0.0         0.0      0.0       0.0      0.0

[5 rows x 123 columns]
```

In [10]:
```
X_train = df_train.drop(['id', 'is_duplicate'], axis=1)
y_train = df_train['is_duplicate']

X_test = df_test.drop(['id', 'is_duplicate'], axis=1)
y_test = df_test['is_duplicate']
```

3.1 Scale the data

In [11]:
```
col_names = X_train.columns.values.tolist()

# fit to data
std_scaler = StandardScaler()
std_scaler.fit(X_train)

# scale the datasets
X_train = pd.DataFrame(std_scaler.transform(X_train), columns=col_names)
X_test = pd.DataFrame(std_scaler.transform(X_test), columns=col_names)

X_train.head()
```

```
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: DataCon
  return self.partial_fit(X, y)
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:8: DataConversionWar

/home/nisheel-s/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:9: DataConversionWar
  if __name__ == '__main__':
```

Out[11]:
```
      q1len     q2len  q1_n_words  q2_n_words  word_Common  word_Total  \
0  0.449286  0.027934    0.195881    0.288942    -0.811405    0.222577
1 -0.921050 -0.589063   -0.910307   -0.812989    -0.487533   -1.063037
2  0.248749 -0.412778    0.380245   -0.183314    -0.811405    0.105703
3 -0.887627 -0.677205   -0.725942   -0.812989    -0.163660   -0.946163
4  1.151165 -0.060208    0.933339   -0.183314    -1.135278    0.456325

   word_share   ctc_min   ctc_max   cwc_min  ...  q2_start  q2_think  \
0   -1.061825  0.537775  0.537775  0.013822  ... -0.109526 -0.119748
1    0.207553  0.537762  0.537762  0.013725  ... -0.109526 -0.119748
```

```
2   -1.031052 -0.637190 -0.637190  0.013876  ... -0.109526 -0.119748
3    0.656718  0.537765  0.537765  0.013725  ... -0.109526 -0.119748
4   -1.427406 -0.416882 -0.416882  0.013846  ... -0.109526 -0.119748

    q2_time    q2_use   q2_want    q2_way  q2_without   q2_work  q2_would  \
0 -0.133215 -0.123439 -0.108397 -0.148691   -0.105842 -0.116595 -0.156094
1 -0.133215 -0.123439 -0.108397 -0.148691   -0.105842 -0.116595 -0.156094
2 -0.133215 -0.123439 -0.108397 -0.148691   -0.105842 -0.116595 -0.156094
3 -0.133215 -0.123439 -0.108397 -0.148691   -0.105842 -0.116595 -0.156094
4 -0.133215 -0.123439 -0.108397 -0.148691   -0.105842 -0.116595 -0.156094

    q2_year
0 -0.102217
1 -0.102217
2 -0.102217
3 -0.102217
4 -0.102217

[5 rows x 121 columns]
```

4 Model

In [12]:
```python
def predict_using_random_model(df, df_type):

    # create a random prediction dataframe
    rand_df = pd.DataFrame(np.random.rand(df.shape[0], 2))

    # convert each row into a probability distribution
    rand_df = rand_df.div(rand_df.sum(axis=1), axis=0)

    # compute log loss
    log_loss_val = log_loss(df['is_duplicate'], rand_df.values, labels=[0,1] ,eps=1e-15

    # get log loss on validation from the random model prediction
    print('Log loss on %s data using Random Model : %f'%(df_type, log_loss_val,))

    #return rand_df
```

In [13]:
```python
predict_using_random_model(df_train, 'Train')
predict_using_random_model(df_test, 'Train')
```

```
Log loss on Train data using Random Model : 0.883145
Log loss on Train data using Random Model : 0.884132
```

4.1 1. Logistic Regression

In [14]:
```
def get_best_hyperparam_LogisticRegression(param_dict, X, y, random_search=False):

    print(datetime.now() ,' Hyper param tuning of logistic regression started')

    # set the scoring function
    final_scorer = 'log_loss'

    # declare a scoring dictionary
    score_dict = {
        'log_loss': make_scorer(score_func=log_loss, greater_is_better=False,
                                needs_proba=True, needs_threshold=False,
                                eps=1e-15, labels=[0,1])
    }


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


    # set data partitioning method
    cv_data = 3


    # declare model
    model = LogisticRegression()

    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 = np.log10(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='-'
```

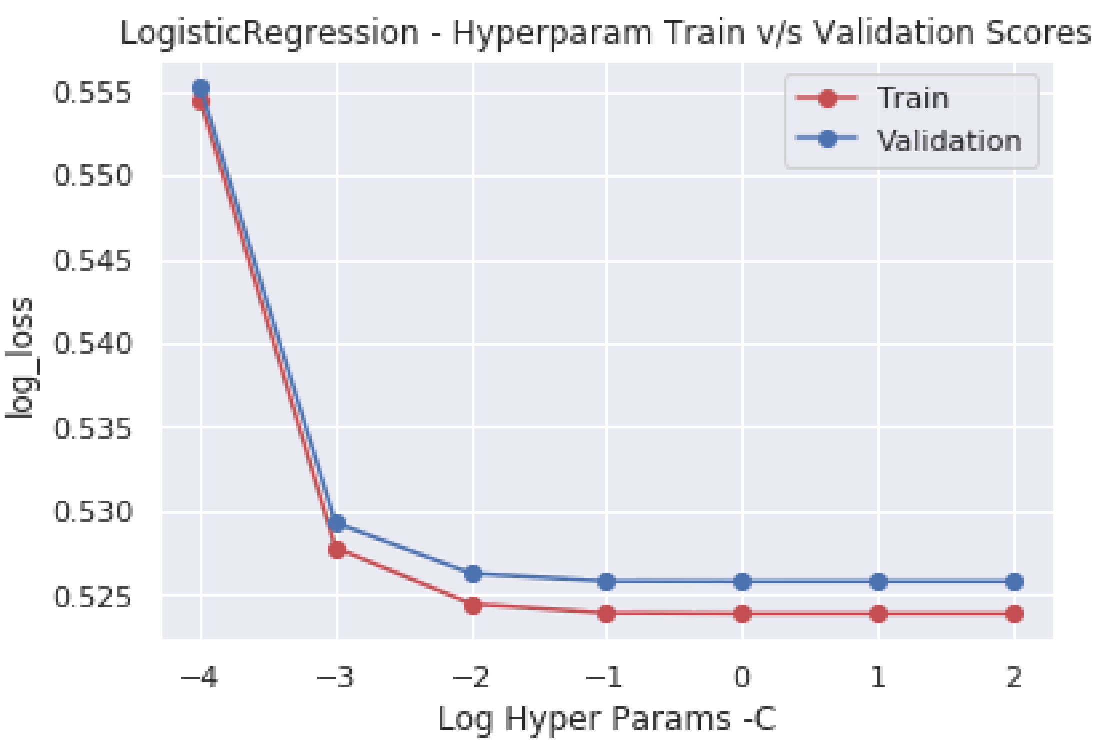
```
            plt.plot(x_vals, y_vals_val, label='Validation', color='b', marker='o', linesty
            plt.xlabel('Log Hyper Params -' + param_list[0])
            plt.ylabel(final_scorer)
            plt.legend()
            plt.title('LogisticRegression - Hyperparam Train v/s Validation Scores')
            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('LogisticRegression - 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('LogisticRegression - 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,)

    print(datetime.now() ,' Hyper param tuning of logistic regression Completed')

    return ret_tuple
```

4.1.1 1. Find best hyperparameter

```
In [15]: # declare a set of params to search for
         param_dict_lr = {'C' : [1e-04, 1e-03, 1e-02, 1e-01, 1e+00, 1e+01, 1e+02]}

         hyp_tuned_info = get_best_hyperparam_LogisticRegression(param_dict_lr, X_train,
                                                                  y_train, False)
         best_hyp_lr, best_tr_score_lr, best_val_score_lr = hyp_tuned_info
         lr_clf = LogisticRegression(C=best_hyp_lr['C'])
```

```
2019-06-26 14:36:52.765010  Hyper param tuning of logistic regression started
```



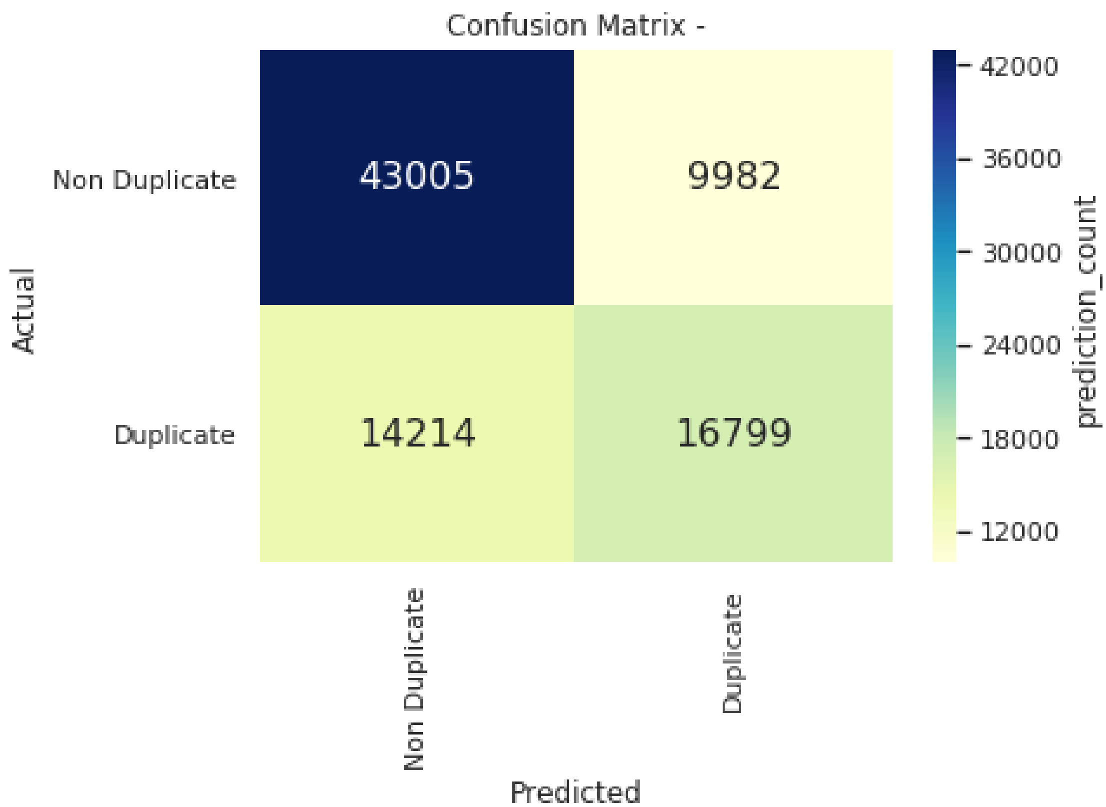

```
Best hyperparam value:  {'C': 1.0} Best Train Score:  0.523874261103707 Best Validation Score:
2019-06-26 14:37:51.933136  Hyper param tuning of logistic regression Completed
```

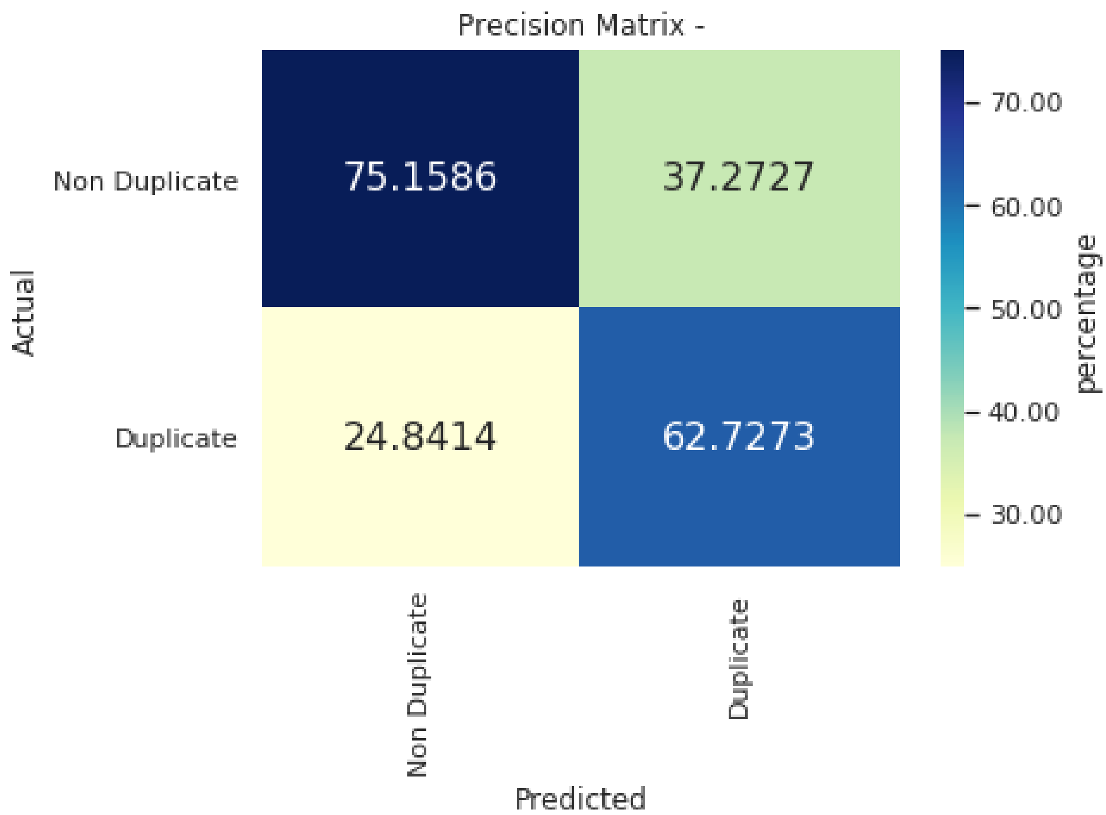
4.1.2 2. Train the model with best hyperparameter

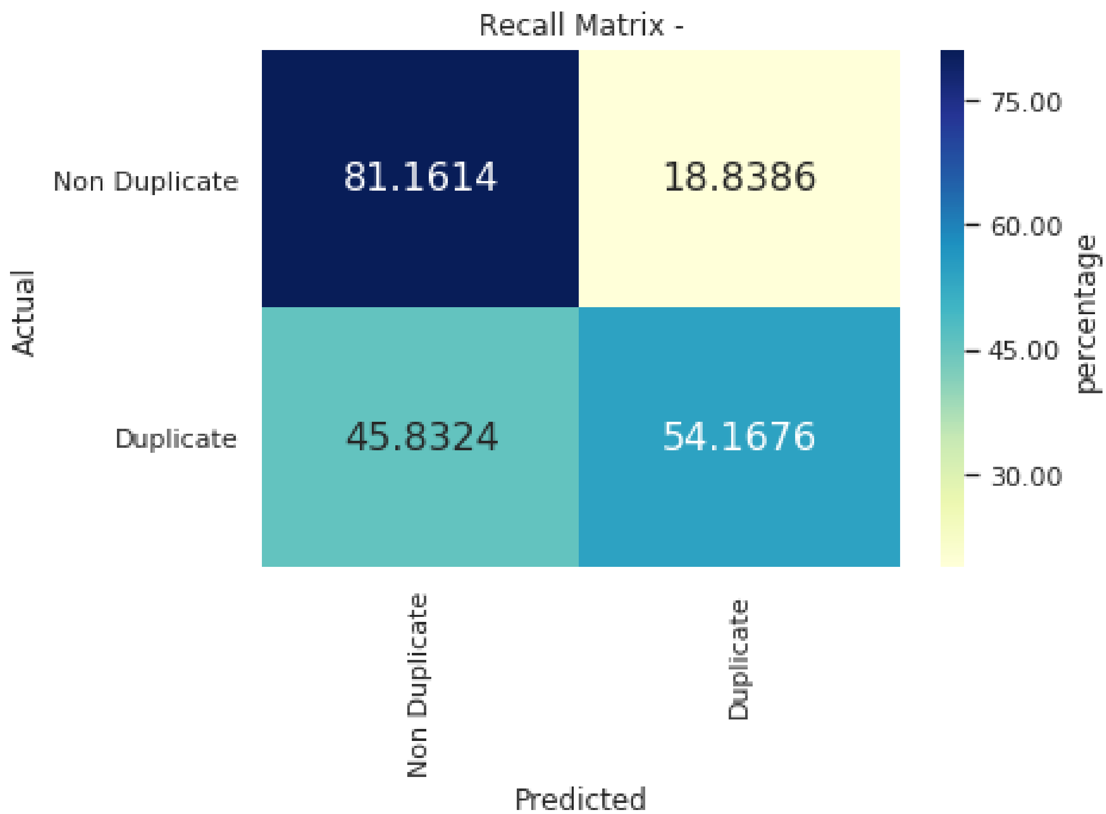
In [16]:
```
# train the model using the best hyperparam obtained
print(datetime.now() ,' Training of logistic regression started')
sig_lr_clf = CalibratedClassifierCV(base_estimator=lr_clf, method='sigmoid', cv=3)
sig_lr_clf.fit(X_train, y_train)
print(datetime.now() ,' Training of logistic regression Completed')

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

```
2019-06-26 14:37:51.941957  Training of logistic regression started


/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: Futu
  FutureWarning)
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: Futu
  FutureWarning)
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: Futu
  FutureWarning)


2019-06-26 14:38:16.352678  Training of logistic regression Completed
```

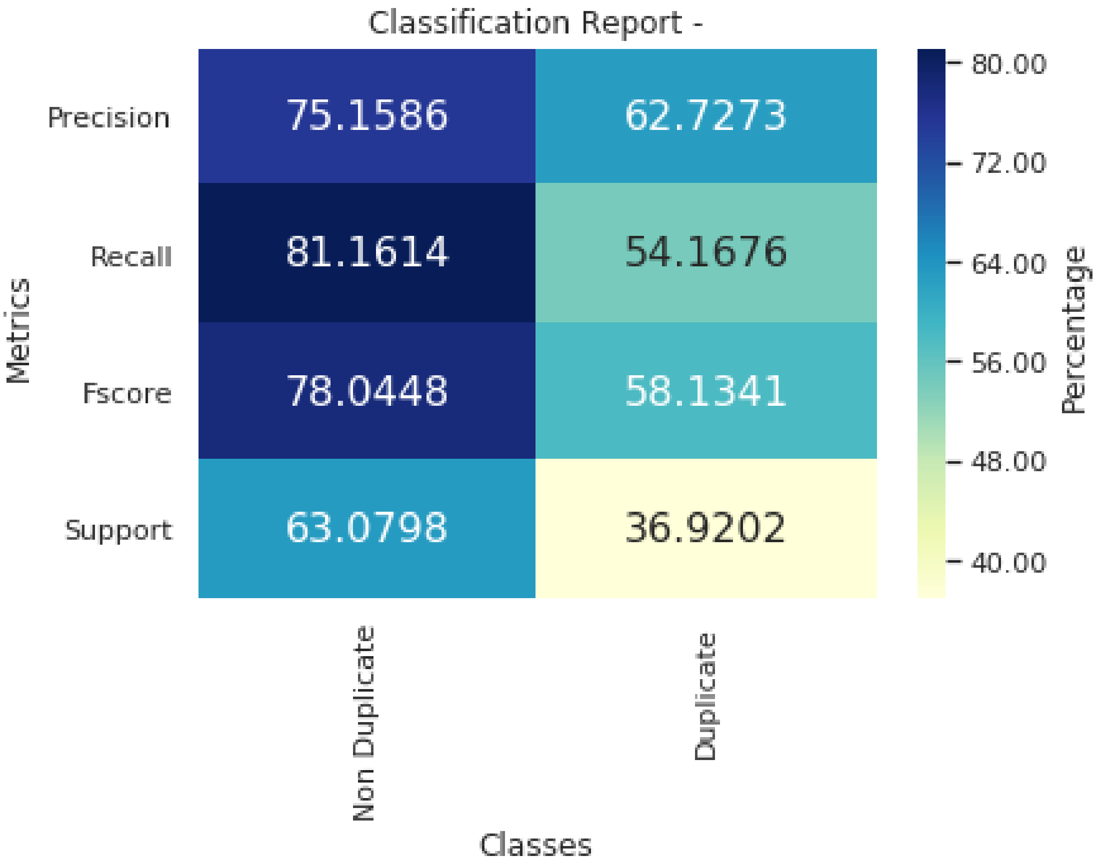
In [17]:
```
# get table entry for training data
#load model from disk
pickle_in = open("./model/logistic_regression.pkl","rb")
sig_lr_clf = pickle.load(pickle_in)
pickle_in.close()
table_entry_lr_train = evaluate_model(sig_lr_clf, X_train, y_train)
```


Confusion Matrix -
Non Duplicate
Duplicate
Actual
43005
9982
14214
16799
Non Duplicate
Duplicate
Predicted
42000
36000
30000
24000
18000
12000
prediction_count


Precision Matrix -
Non Duplicate
Duplicate
Actual
75.1586
37.2727
24.8414
62.7273
Non Duplicate
Duplicate
Predicted
70.00
60.00
50.00
40.00
30.00
percentage

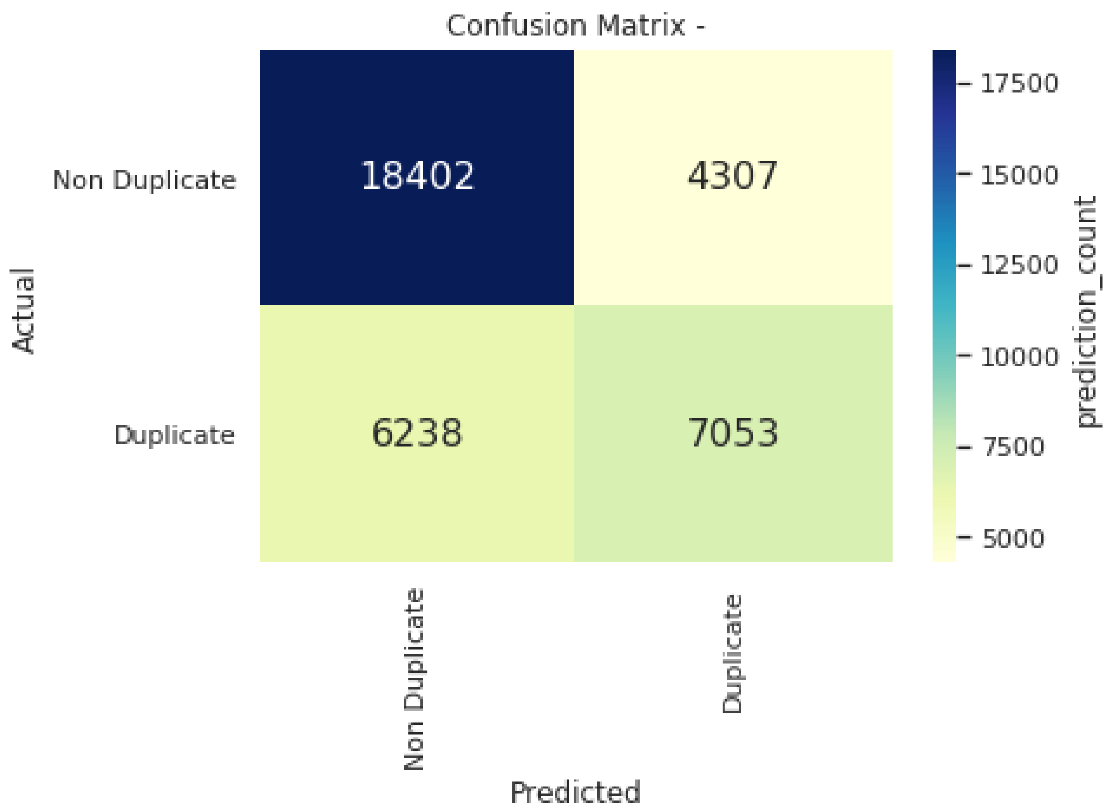


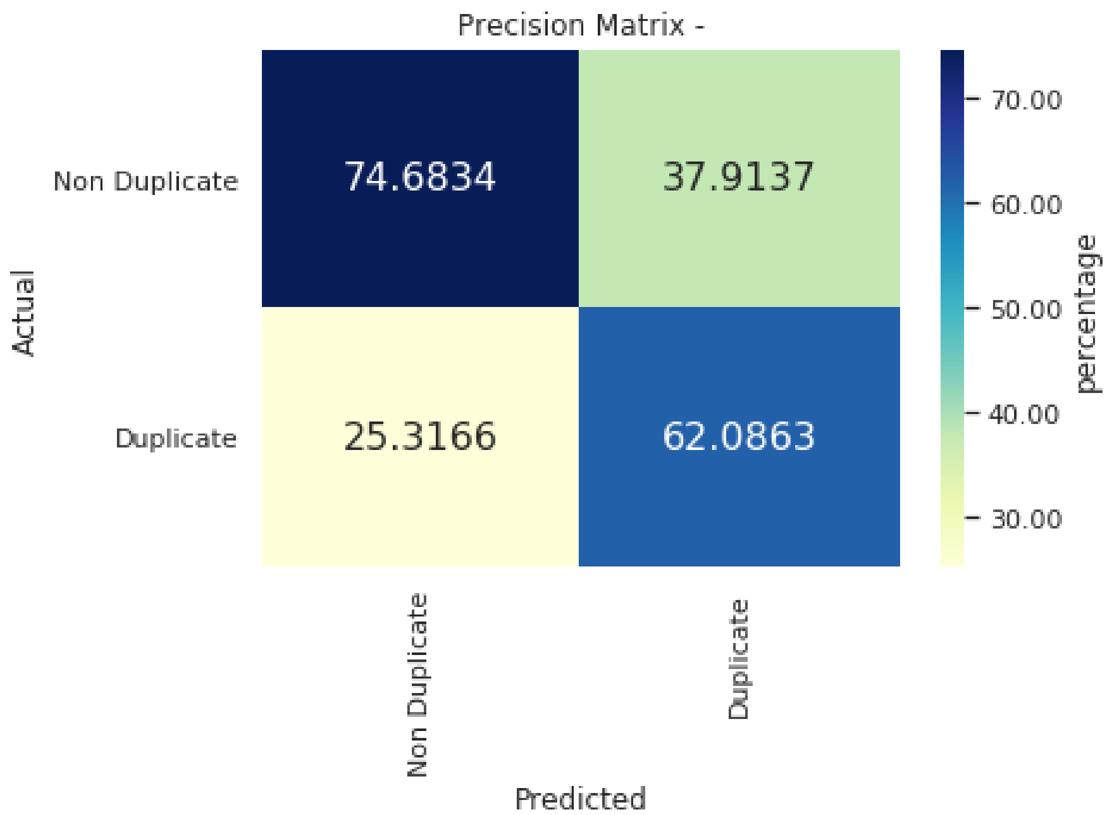
Recall Matrix -
Non Duplicate
Duplicate
Actual
81.1614
18.8386
45.8324
54.1676
75.00
60.00
45.00
30.00
percentage
Non Duplicate
Duplicate
Predicted

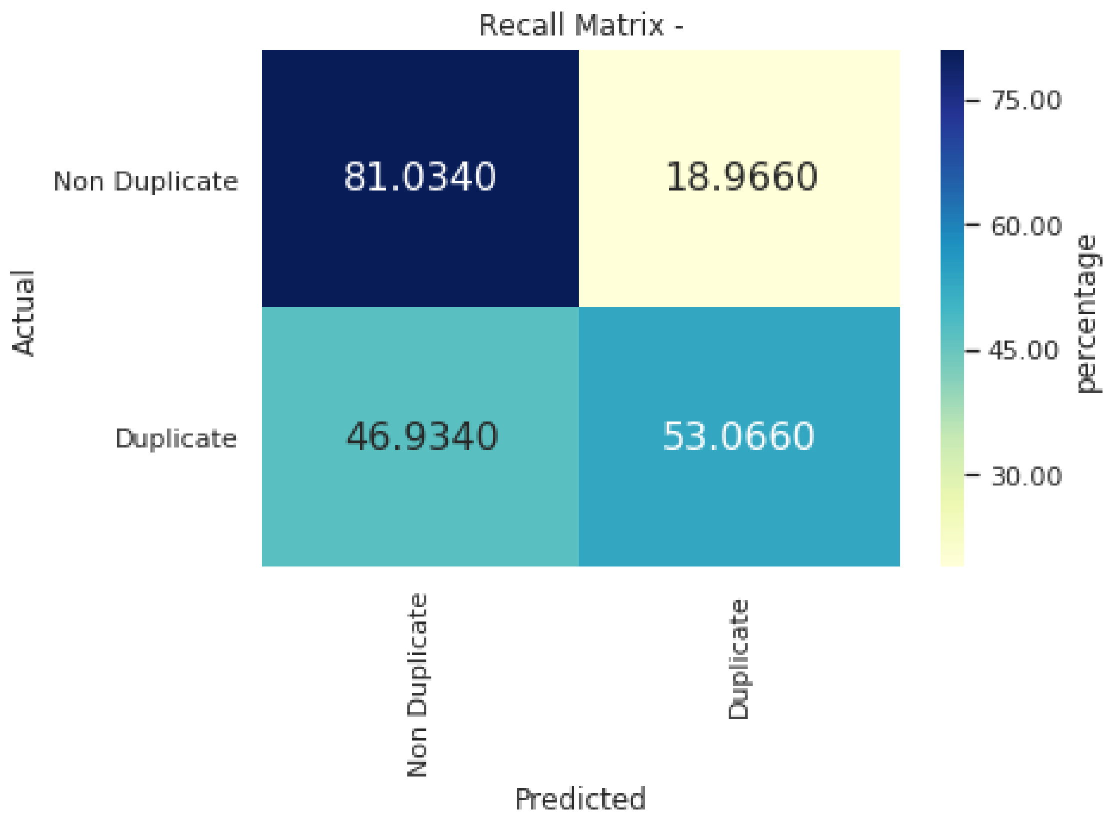


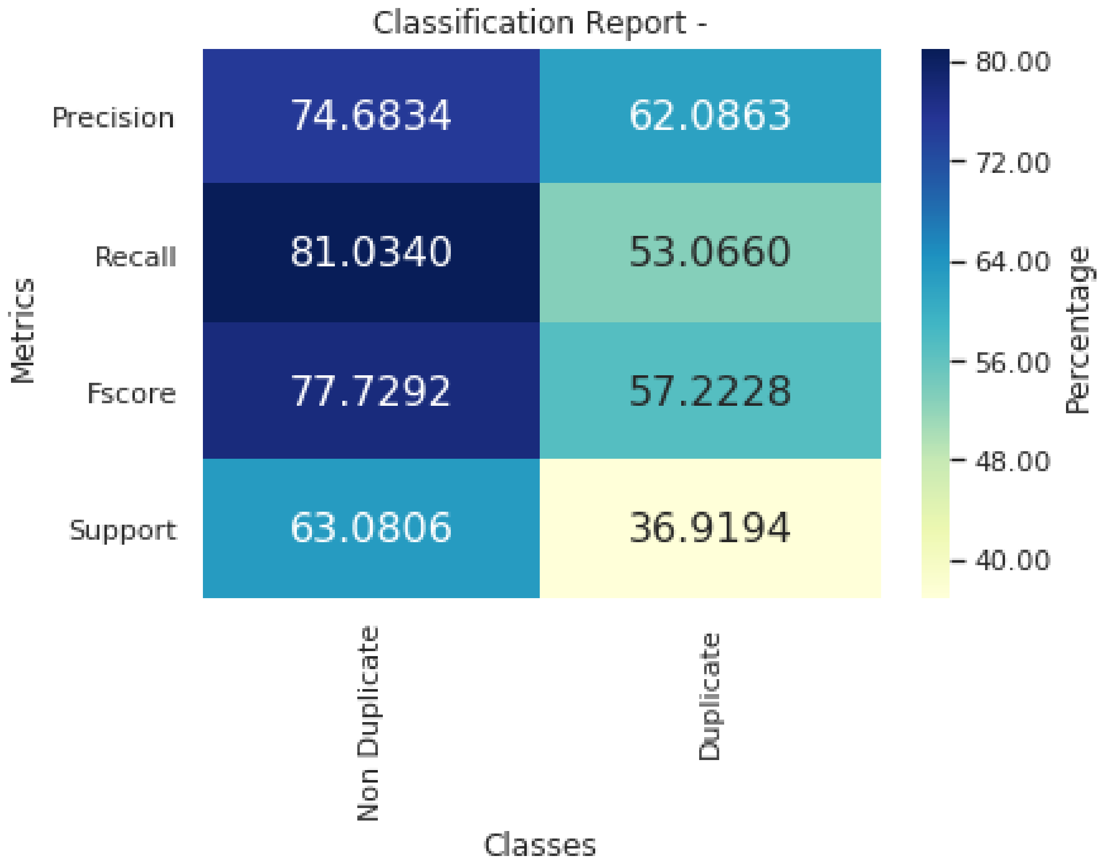
4.1.3 3. Test the model

```
In [18]: table_entry_lr_test = evaluate_model(sig_lr_clf, X_test, y_test)
```

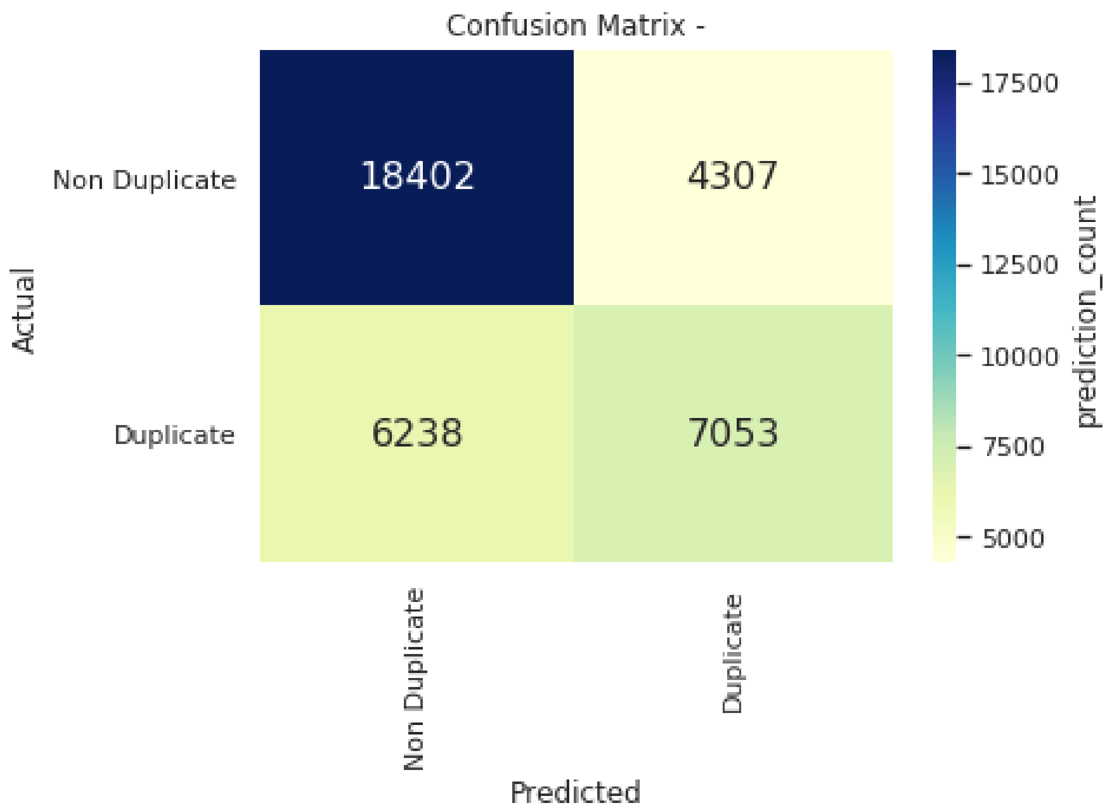

Confusion Matrix -
Non Duplicate
Duplicate
Actual
18402
4307
6238
7053
Non Duplicate
Duplicate
Predicted
17500
15000
12500
10000
7500
5000
prediction_count

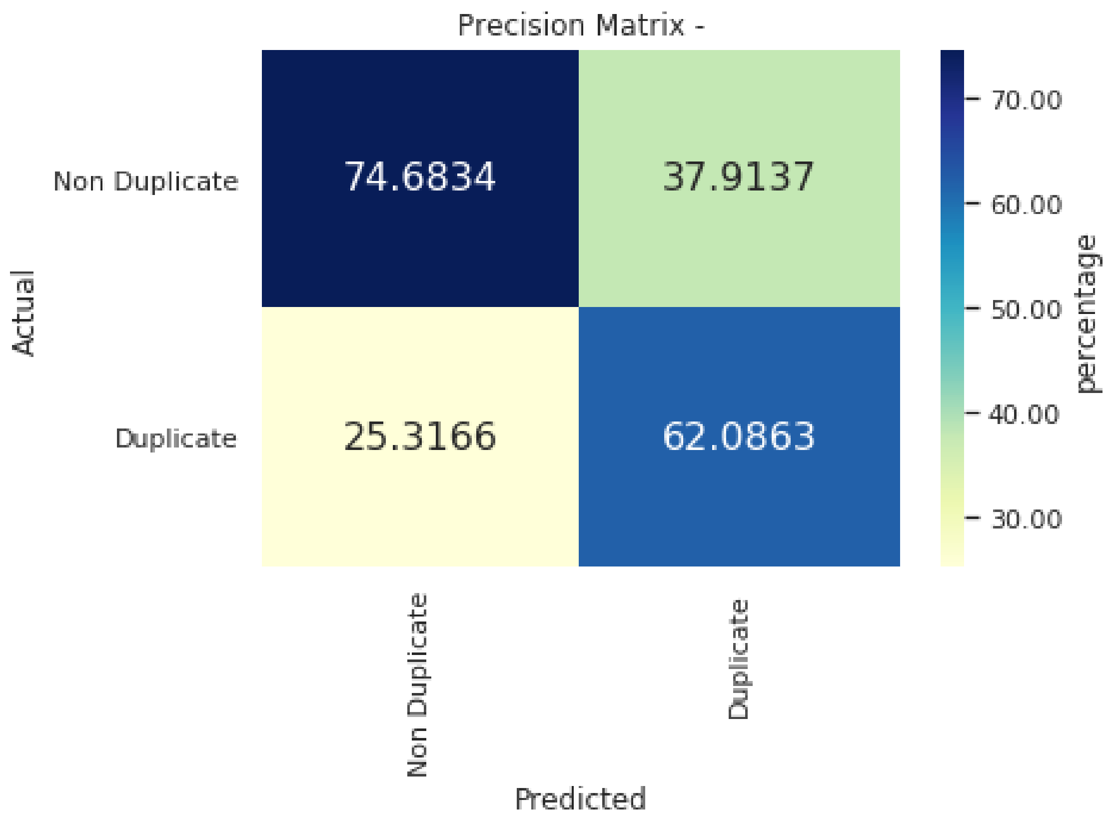

Precision Matrix -
Non Duplicate
Duplicate
Actual
74.6834
37.9137
25.3166
62.0863
Non Duplicate
Duplicate
Predicted
70.00
60.00
50.00
40.00
30.00
percentage


Recall Matrix -
Non Duplicate
Duplicate
Actual
81.0340
18.9660
46.9340
53.0660
Non Duplicate
Duplicate
Predicted
75.00
60.00
45.00
30.00
percentage

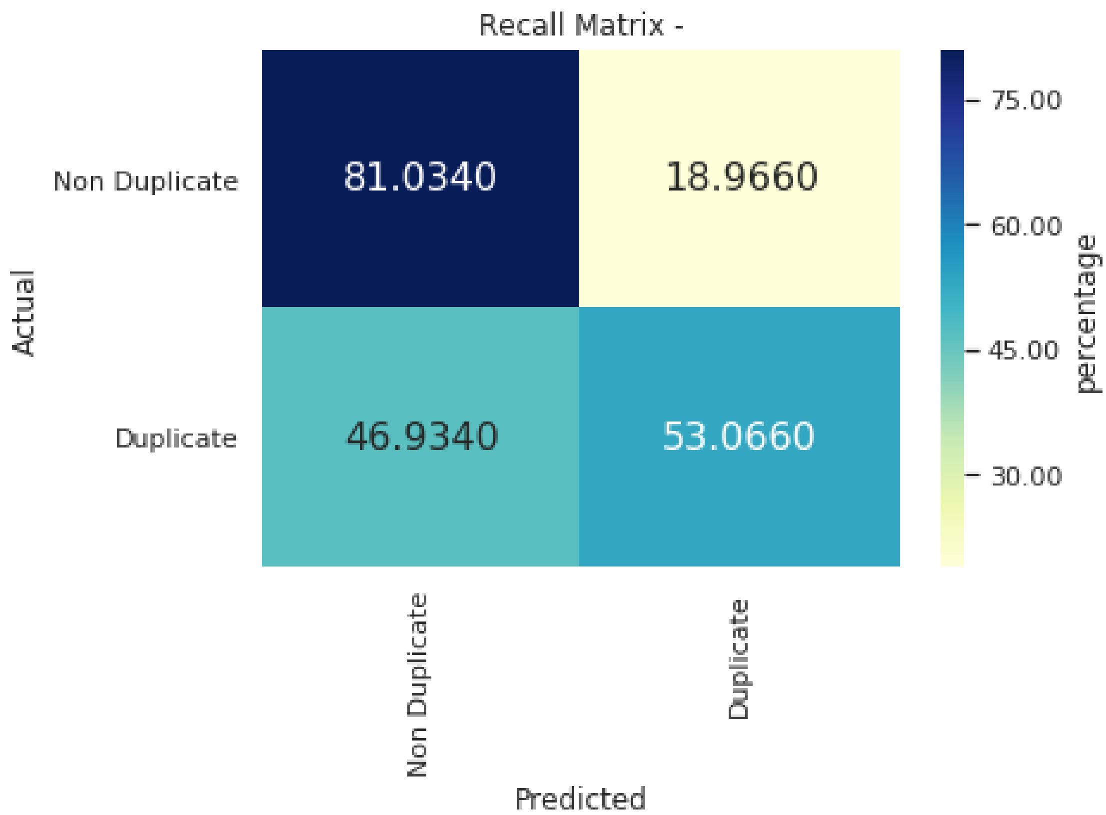


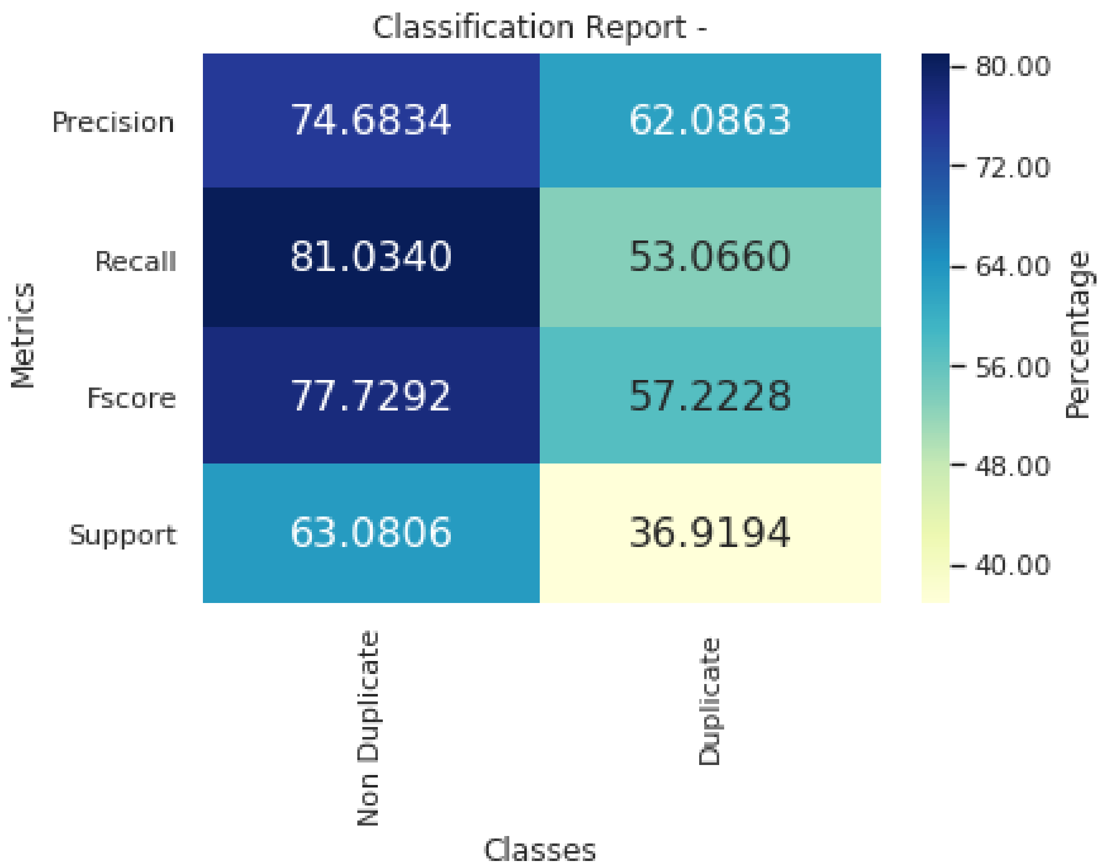

```
In [19]: table_entry_lr_test = evaluate_model(sig_lr_clf, X_test, y_test)
         table_entry_lr = ('Logistic Regression', best_hyp_lr,) + table_entry_lr_train + table_e
```


Confusion Matrix -
Non Duplicate
Duplicate
Actual
18402
4307
6238
7053
Non Duplicate
Duplicate
Predicted
17500
15000
12500
10000
7500
5000
prediction_count



Precision Matrix -
Non Duplicate
Duplicate
Actual
74.6834
37.9137
25.3166
62.0863
Non Duplicate
Duplicate
Predicted
70.00
60.00
50.00
40.00
30.00
percentage


Recall Matrix -
Non Duplicate
Duplicate
Actual
81.0340
18.9660
46.9340
53.0660
75.00
60.00
45.00
30.00
percentage
Non Duplicate
Duplicate
Predicted



4.2 2. Linear SVM Classifier

In [20]:
```
def get_best_hyperparam_SVM_Classifier(param_list, X, y):

    print(datetime.now() ,' Hyperparam tuning of SVM started')

    # set the scoring function
    final_scorer = 'log_loss'


    # set data partitioning method
    cv_data = 3

    # set stratified K fold validation
    skf = StratifiedKFold(n_splits=cv_data)

    #declare two list for holding the loss for train, validation
    tr_loss_all = list()
    val_loss_all = list()
```

```python
for alpha_val in param_list:

    # declare model
    model = SGDClassifier(loss='hinge', alpha=alpha_val, tol=1e-03,
                          max_iter=1e+03, penalty='l2', n_jobs=-1)

    # decalre calibrated classifier
    calib_model = CalibratedClassifierCV(base_estimator=model,
                                         method='sigmoid',
                                         cv='prefit')

    # declare two lists for train, validation loss for each fold
    train_loss_list = list()
    val_loss_list = list()

    # evaluate for each fold
    for train_index, val_index in skf.split(X, y):

        # get train test split for this fold
        X_train, X_val = X.loc[train_index,:], X.loc[val_index,:]
        y_train, y_val = y[train_index], y[val_index]

        # fit to data
        model.fit(X_train, y_train)
        calib_model.fit(X_val, y_val)

        # get train, test log loss
        tr_probs = calib_model.predict_proba(X_train)
        val_probs = calib_model.predict_proba(X_val)

        # insert into log loss list
        train_loss_list.append(log_loss(y_train, tr_probs,
                                        labels=[0,1], eps=1e-15))
        val_loss_list.append(log_loss(y_val, val_probs,
                                      labels=[0,1], eps=1e-15))

    # compute mean loss values
    mean_tr_loss = np.mean(train_loss_list)
    mean_val_loss = np.mean(val_loss_list)

    # update the lists
    tr_loss_all.append(mean_tr_loss)
    val_loss_all.append(mean_val_loss)

# get total number of param settings
# get number of rows in the search cv data frame
num_rows = len(param_list)
```

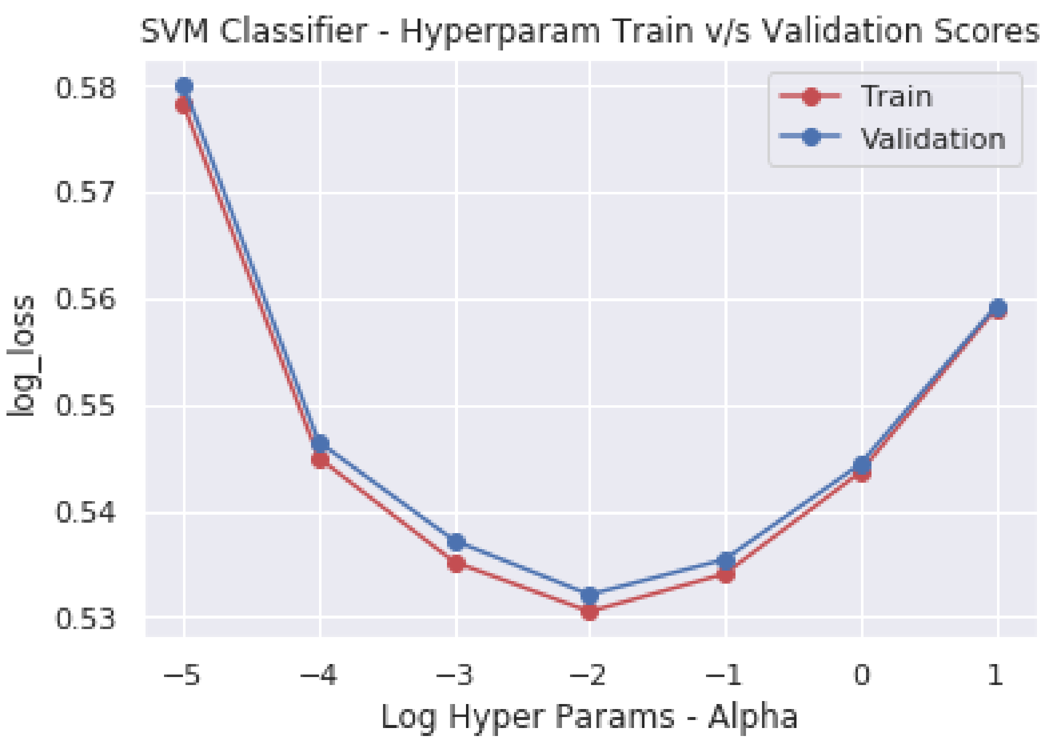
```
# create the grid search info df
cv_results_dict = {'alpha': param_list,
                   'mean_train_log_loss': tr_loss_all,
                   'mean_test_log_loss': val_loss_all}

grid_info_df = pd.DataFrame(cv_results_dict, index=range(num_rows))

# prepare a list of reqired columns
required_columns = ['alpha', 'mean_train_log_loss',
                    'mean_test_log_loss']

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


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

# best hyperparam & corresponding scores
best_hyperparam = {'alpha':best_hyperparam_record['alpha']}
best_train_score = best_hyperparam_record['mean_train_'+ final_scorer]
best_validation_score = best_hyperparam_record['mean_test_'+ final_scorer]

# plot the hyper params
# extract individual fiedls
x_vals = np.log10(param_list)
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', linestyle='
plt.xlabel('Log Hyper Params - Alpha')
plt.ylabel(final_scorer)
plt.legend()
plt.title('SVM Classifier - Hyperparam Train v/s Validation Scores')
plt.show()

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


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

print(datetime.now() ,' Hyperparam tuning of SVM completed')
```

```
        return ret_tuple
```

4.2.1 1. Find best hyperparameter

```
In [21]: # declare a set of params to search for
         param_list_svm = [1e-05, 1e-04, 1e-03, 1e-02, 1e-01, 1e+00, 1e+01]

         hyp_tuned_info = get_best_hyperparam_SVM_Classifier(param_list_svm, X_train,
                                                             y_train)
         best_hyp_svm, best_tr_score_svm, best_val_score_svm = hyp_tuned_info

         svm_clf = SGDClassifier(loss='hinge', alpha=best_hyp_svm['alpha'], tol=1e-03,
                                 max_iter=1e+03, penalty='l2', n_jobs=-1)

         svm_sig_clf = CalibratedClassifierCV(base_estimator=svm_clf,
                                              method='sigmoid', cv=3)
```

```
2019-06-26 14:38:18.633282  Hyperparam tuning of SVM started
```



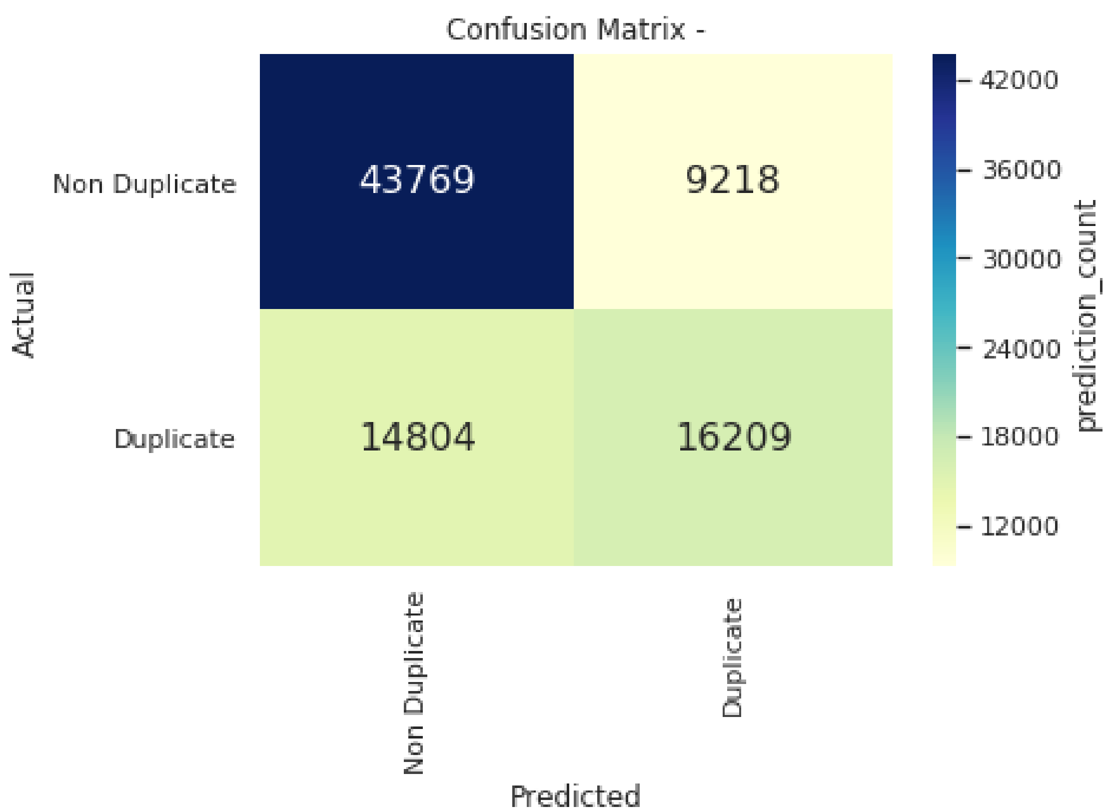

```
Best hyperparam value:  {'alpha': 0.01} Best Train Score:  0.5305024792875814 Best Validation Sc
2019-06-26 14:38:52.919826  Hyperparam tuning of SVM completed
```

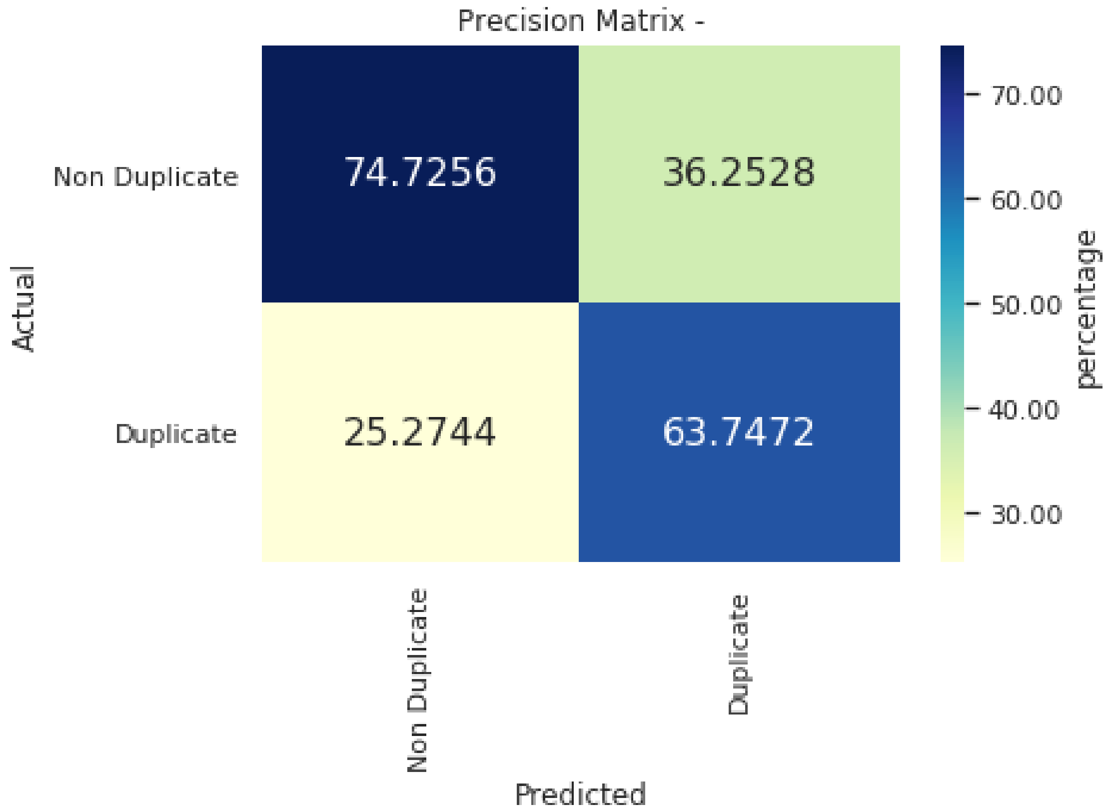
4.2.2 2. Train the model with best hyperparameter

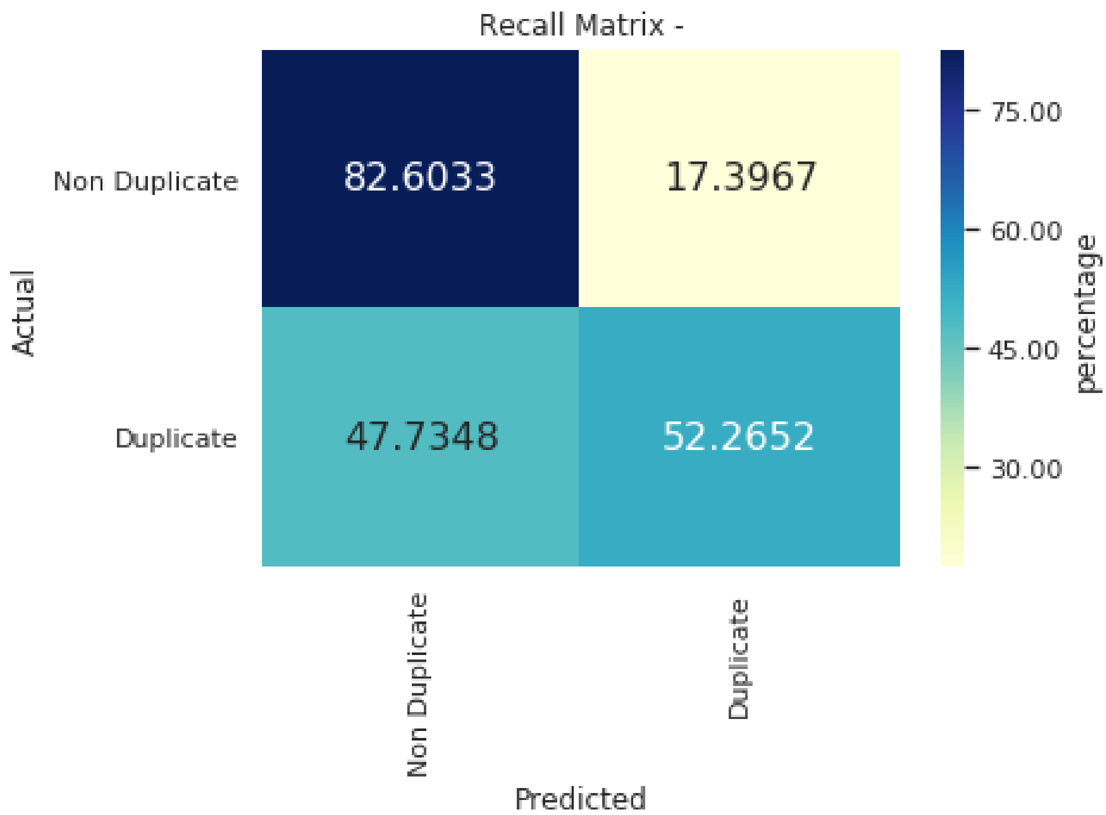
In [22]:
```
# train the model using the best hyperparam obtained
print(datetime.now() ,' Training of SVM started')
svm_sig_clf.fit(X_train, y_train)
print(datetime.now() ,' Training of SVM completed')

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

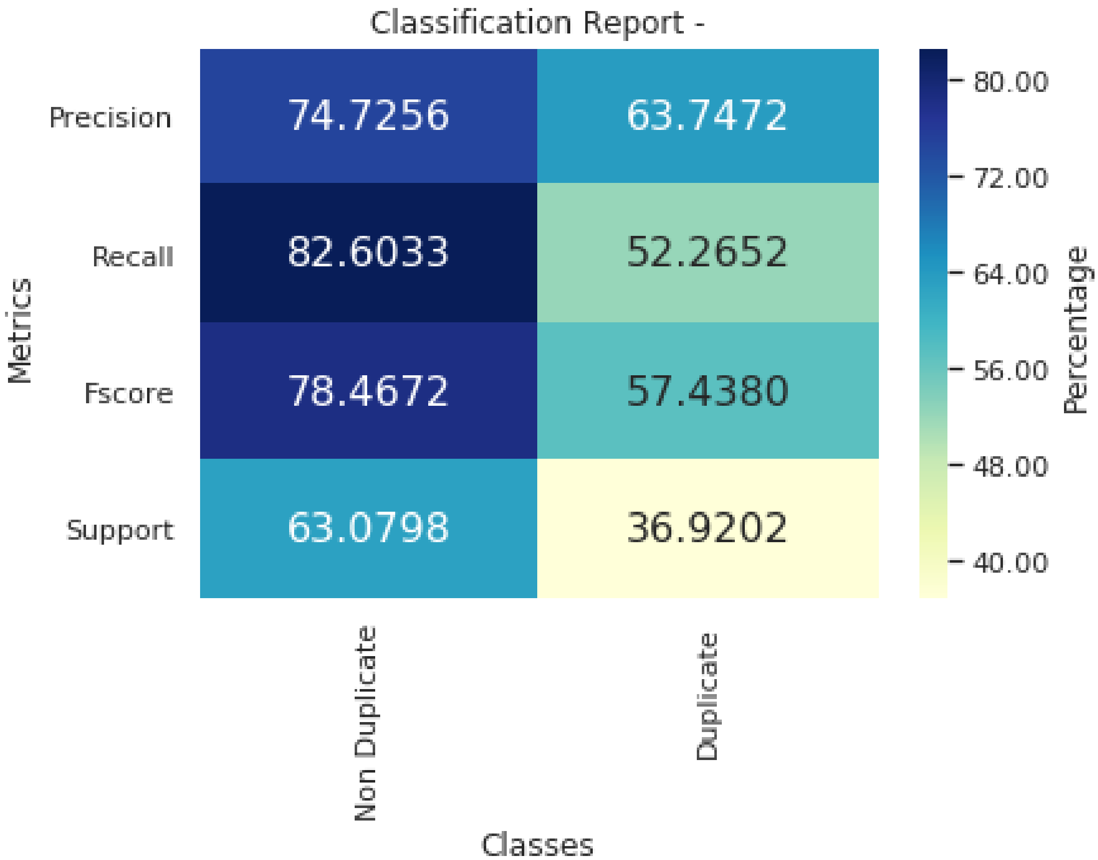
```
2019-06-26 14:38:52.930837  Training of SVM started
2019-06-26 14:38:54.522214  Training of SVM completed
```

In [23]:
```
pickle_in = open("./model/svm.pkl","rb")
svm_sig_clf = pickle.load(pickle_in)
pickle_in.close()
table_entry_svm_train = evaluate_model(svm_sig_clf, X_train, y_train)
```



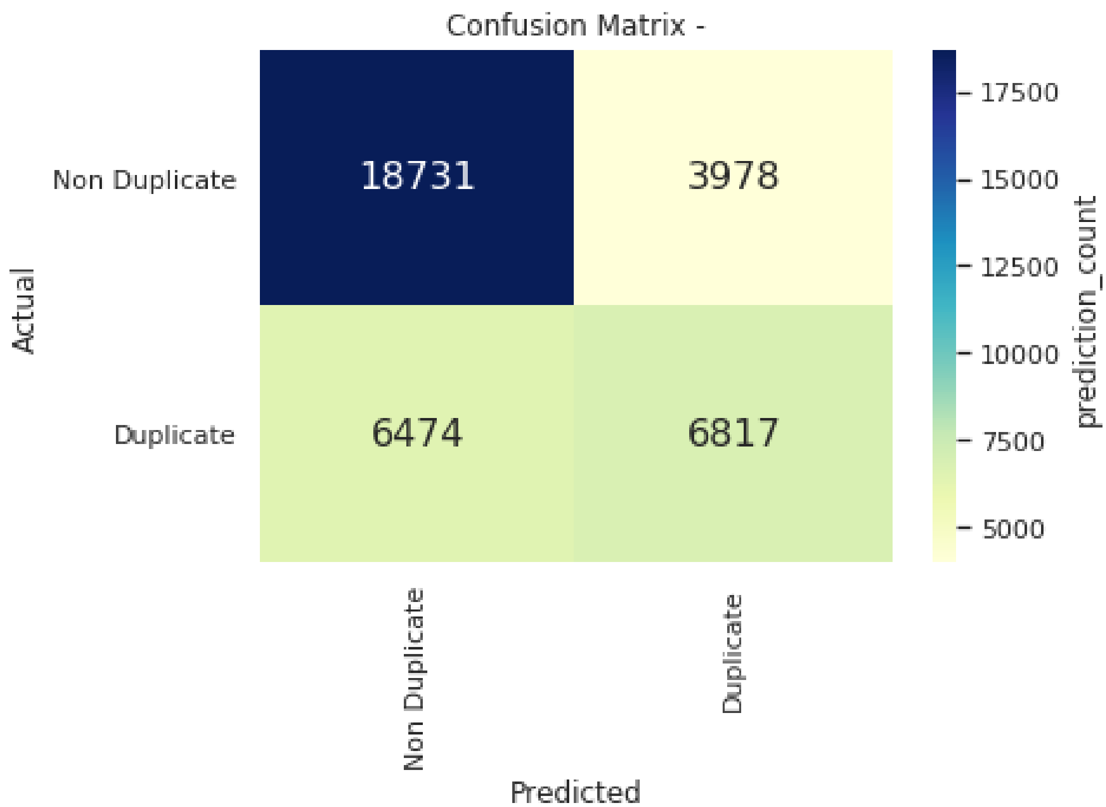

Precision Matrix -
Non Duplicate
Duplicate
Actual
74.7256
36.2528
25.2744
63.7472
70.00
60.00
50.00
40.00
30.00
percentage
Non Duplicate
Duplicate
Predicted

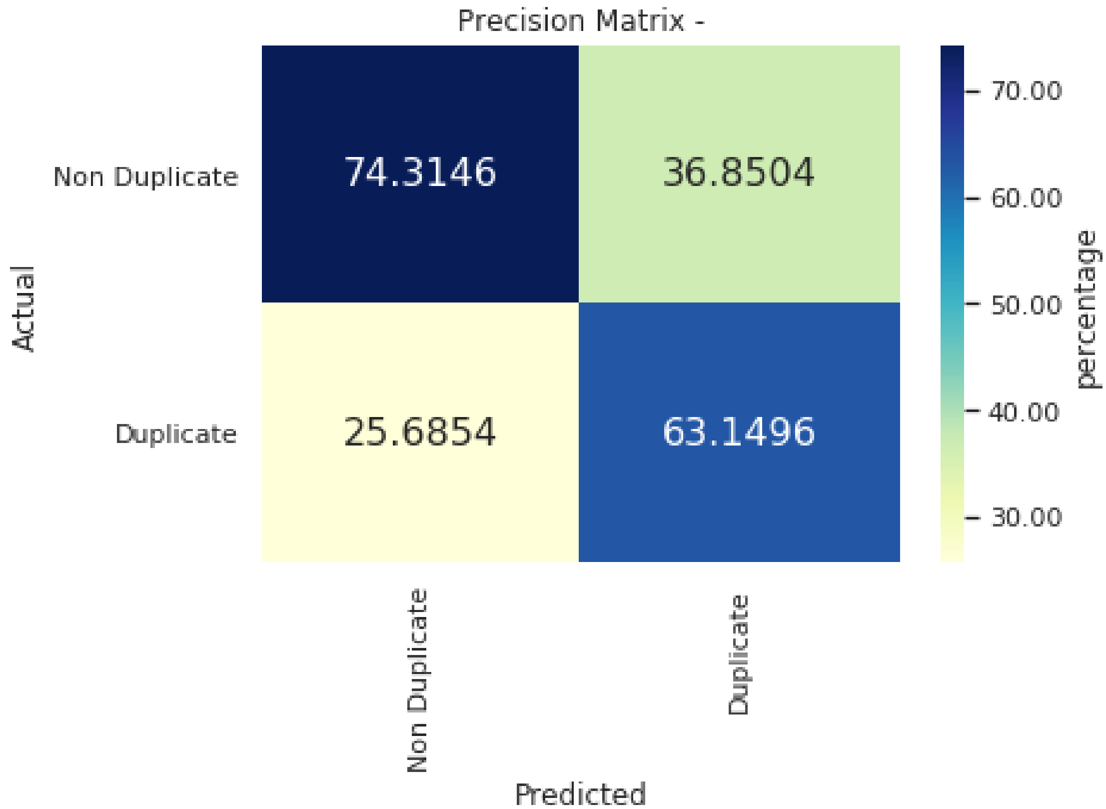

Recall Matrix -
Non Duplicate
Duplicate
Actual
82.6033
17.3967
47.7348
52.2652
Non Duplicate
Duplicate
Predicted
75.00
60.00
45.00
30.00
percentage



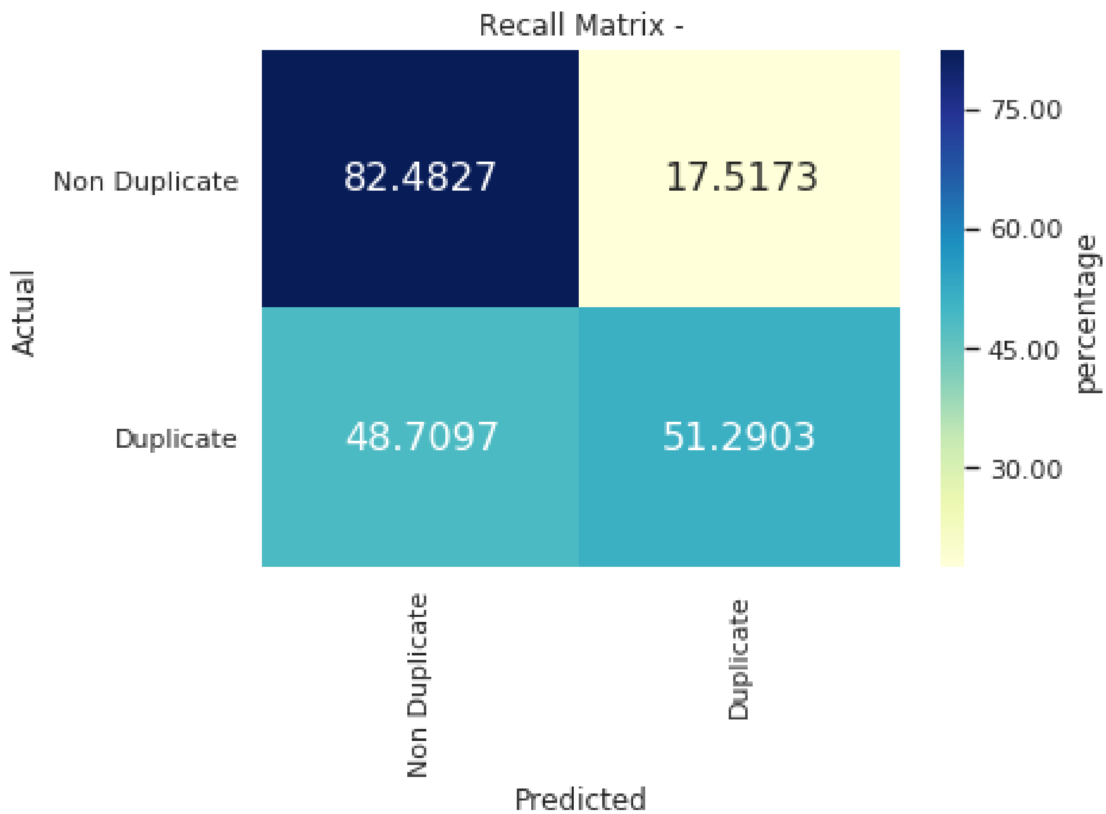
4.2.3 3. Test the model

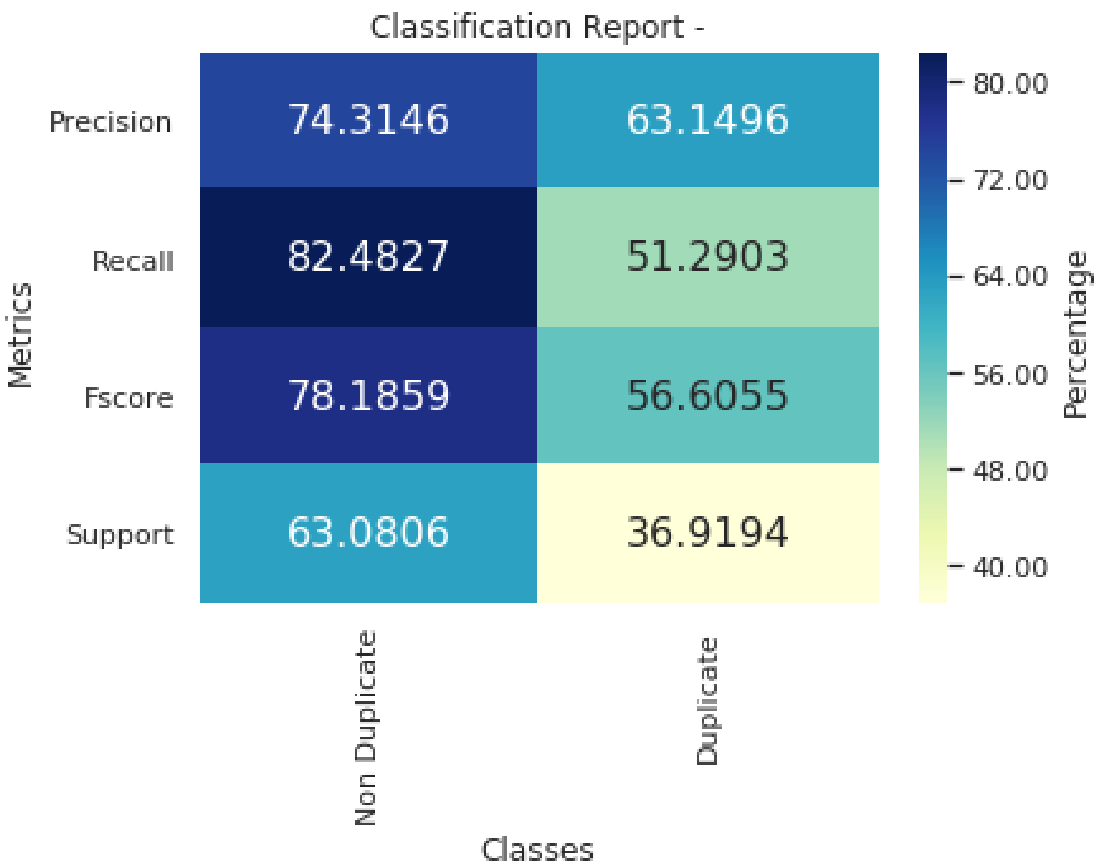
```
In [24]: table_entry_svm_test = evaluate_model(svm_sig_clf, X_test, y_test)
         table_entry_svm = ('Linear SVM', best_hyp_svm,) + table_entry_svm_train + table_entry_s
```


Confusion Matrix -
Non Duplicate
Duplicate
Actual
18731
3978
6474
6817
Non Duplicate
Duplicate
Predicted
17500
15000
12500
10000
7500
5000
prediction_count



Precision Matrix -
Non Duplicate
Duplicate
Actual
74.3146
36.8504
25.6854
63.1496
Non Duplicate
Duplicate
Predicted
70.00
60.00
50.00
40.00
30.00
percentage


Recall Matrix -
Non Duplicate
Duplicate
Actual
82.4827
17.5173
48.7097
51.2903
Non Duplicate
Duplicate
Predicted
75.00
60.00
45.00
30.00
percentage



4.3 3. XG Boost Classifier

```
In [25]: def get_best_hyperparam_XGBClassifier(param_dict, X, y, random_search=False):

             print(datetime.now() ,' Hyperparam Tuning of XGB started')

             # set the scoring function
             final_scorer = 'log_loss'

             # declare a scoring dictionary
             score_dict = {
                 'log_loss': make_scorer(score_func=log_loss, greater_is_better=False,
                                         needs_proba=True, needs_threshold=False,
                                         eps=1e-15, labels=[0,1])
             }


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

```
    'log_loss' : 'minimization'
}

# set data partitioning method
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()
```

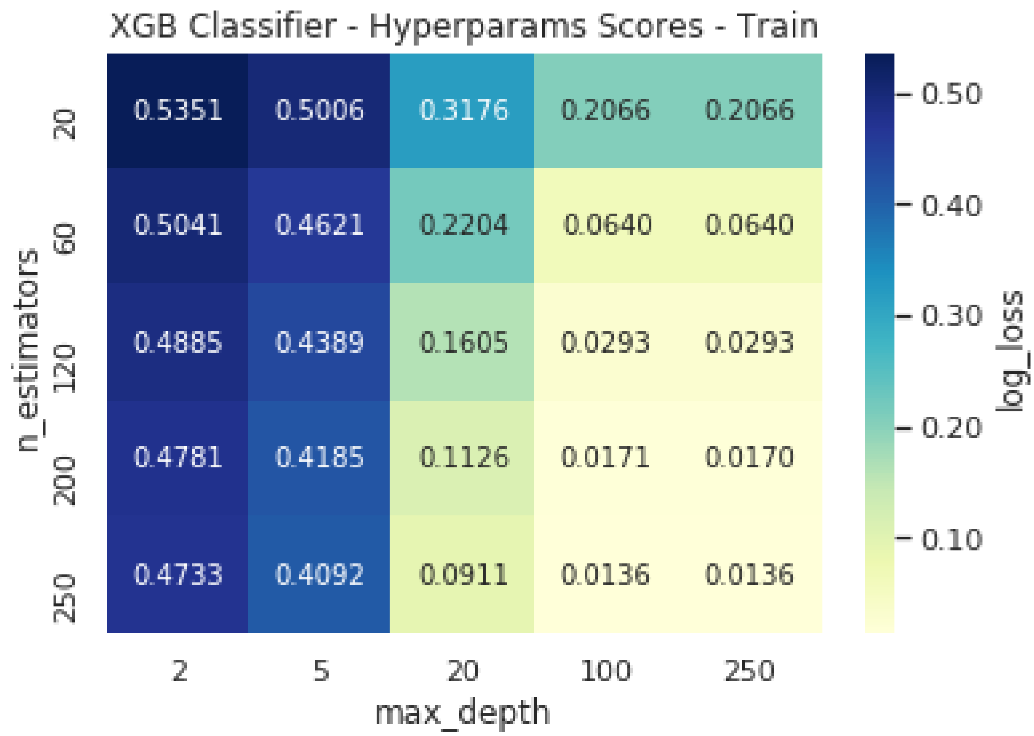
```
            print('\n'*3)

            # 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,)

        print(datetime.now() ,' Hyperparam Tuning of XGB completed')


        return ret_tuple
```

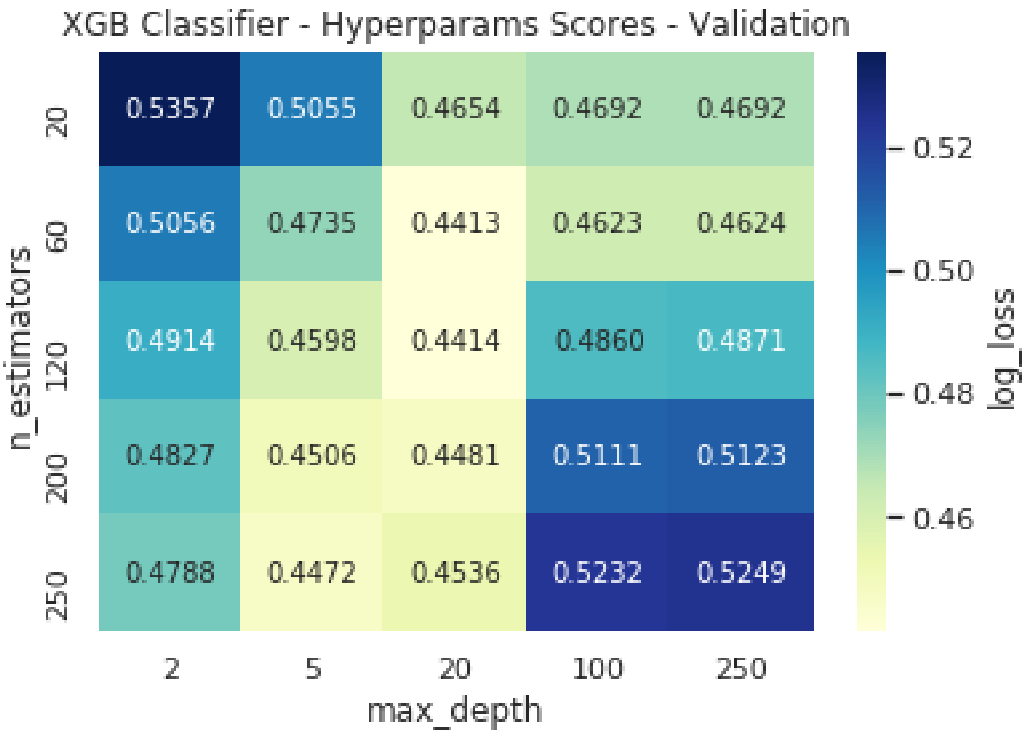
4.3.1 1. Find best hyperparameter

```
In [26]: # declare a set of params to search for
         param_dict_xgb = {'n_estimators' : [20, 60, 120, 200, 250],
                           'max_depth' : [2, 5, 20, 100, 250]
                          }

         hyp_tuned_info = get_best_hyperparam_XGBClassifier(param_dict_xgb, X_train,
                                                            y_train, False)
         best_hyp_xgb, best_tr_score_xgb, best_val_score_xgb = hyp_tuned_info

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

```
xgb_sig_clf = CalibratedClassifierCV(base_estimator=xgb_clf, method='sigmoid', cv=3)
```

```
2019-06-26 14:38:55.850678  Hyperparam Tuning of XGB started


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





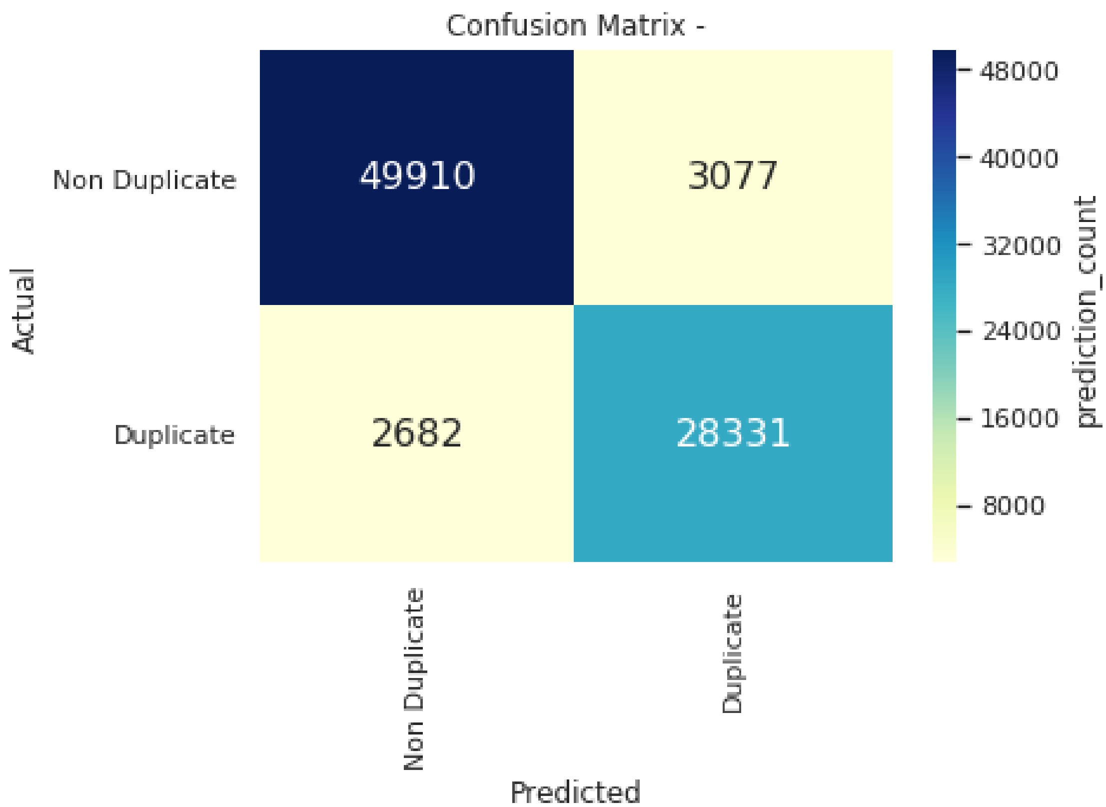

```
Best hyperparam value:  {'max_depth': 20, 'n_estimators': 60} Best Train Score:  0.2204272962825
2019-06-26 15:58:46.269411  Hyperparam Tuning of XGB completed
```

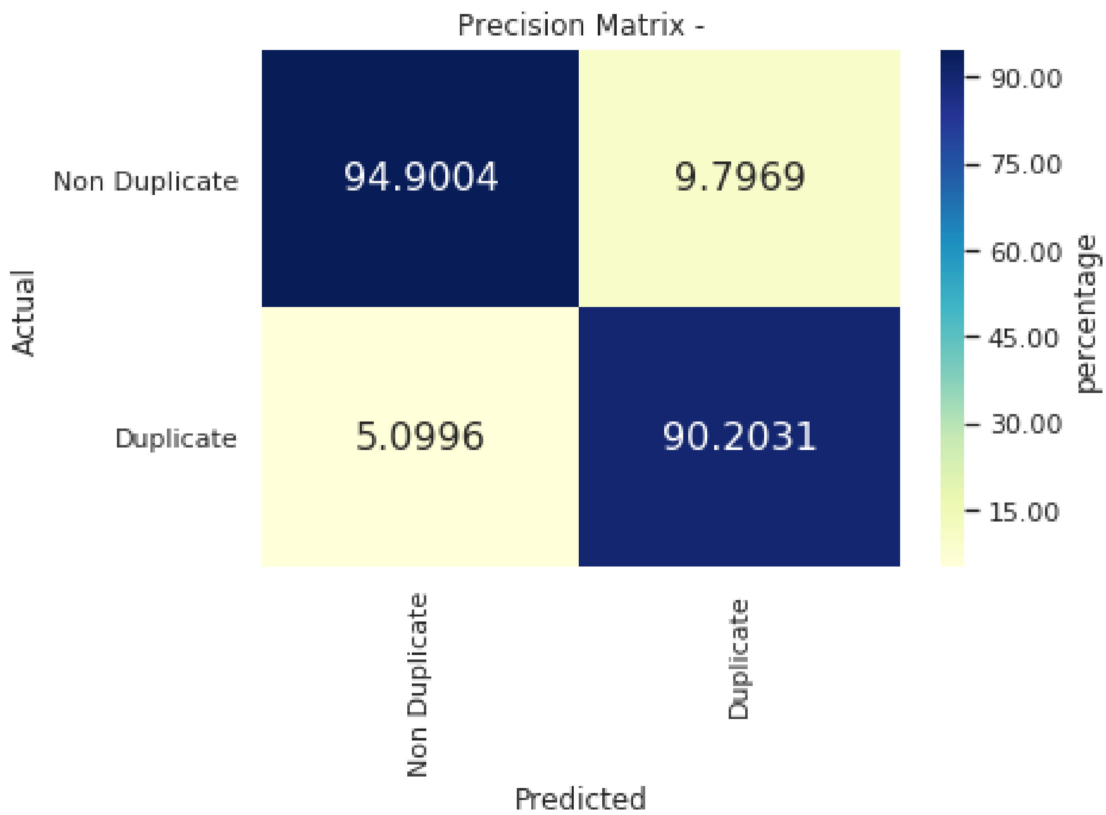
4.3.2 2. Train the model with best hyperparameter

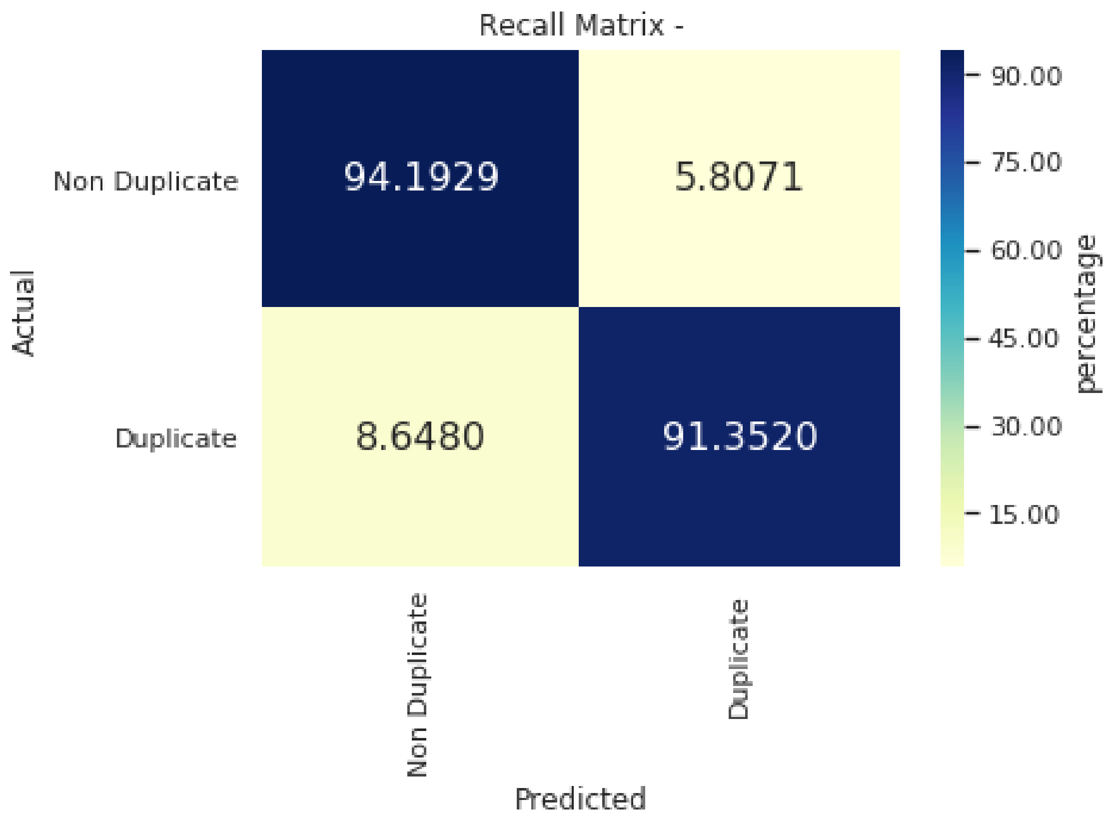
In [27]:
```
# train the model using the best hyperparam obtained
print(datetime.now() ,' Training of XGB started')
xgb_sig_clf.fit(X_train, y_train)
print(datetime.now() ,' Training of XGB completed')

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

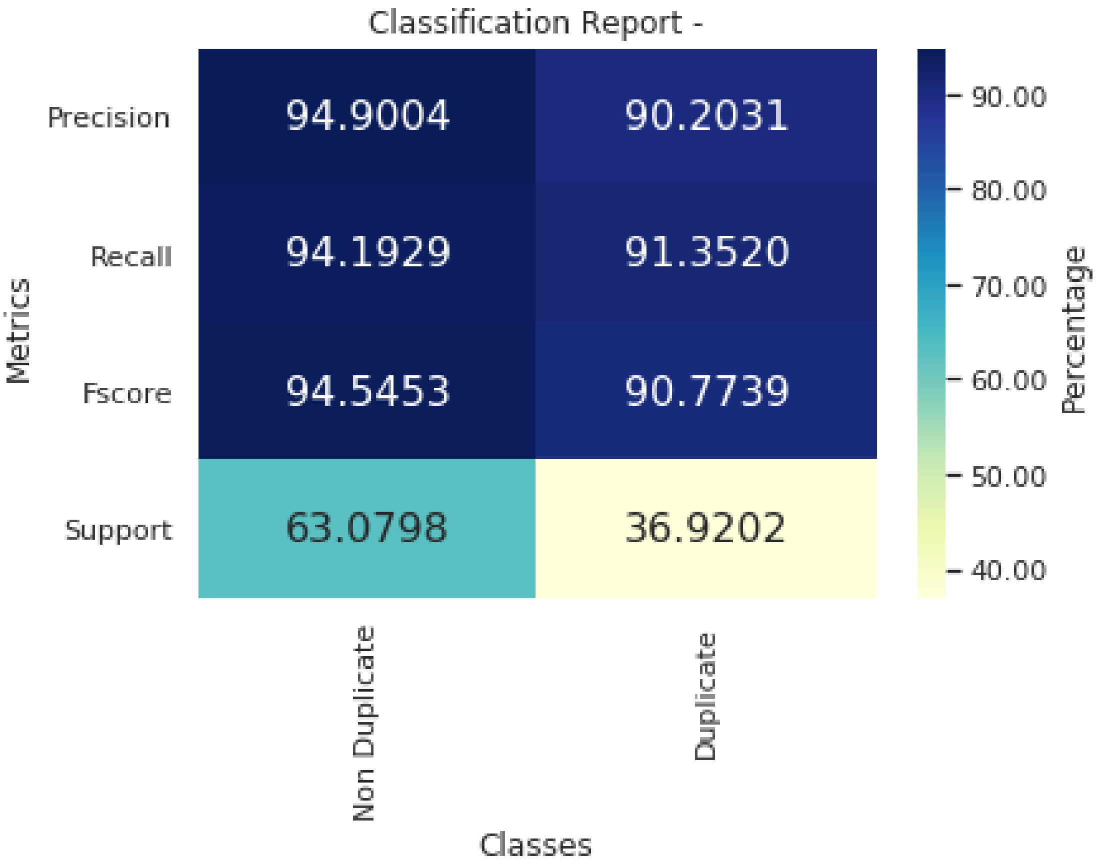
```
2019-06-26 15:58:46.280307  Training of XGB started
2019-06-26 16:01:21.236148  Training of XGB completed
```

In [28]:
```
pickle_in = open("./model/xgb.pkl","rb")
xgb_sig_clf = pickle.load(pickle_in)
pickle_in.close()
table_entry_xgb_train = evaluate_model(xgb_sig_clf, X_train, y_train)
```


Confusion Matrix -
Non Duplicate
Duplicate
Actual
49910
3077
2682
28331
Non Duplicate
Duplicate
Predicted
48000
40000
32000
24000
16000
8000
prediction_count

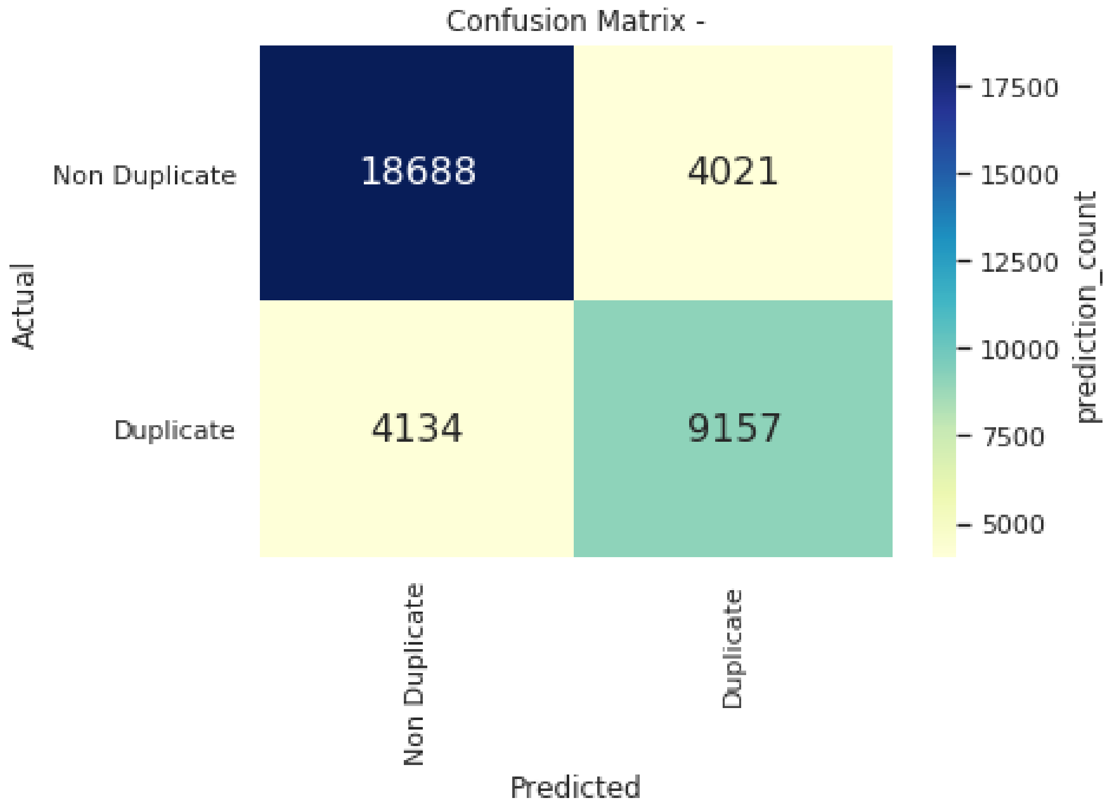

Precision Matrix -
Non Duplicate
Duplicate
Actual
94.9004
9.7969
5.0996
90.2031
Non Duplicate
Duplicate
Predicted
90.00
75.00
60.00
45.00
30.00
15.00
percentage


Recall Matrix -
Non Duplicate
Duplicate
94.1929
5.8071
8.6480
91.3520
Actual
Non Duplicate
Duplicate
Predicted
90.00
75.00
60.00
45.00
30.00
15.00
percentage

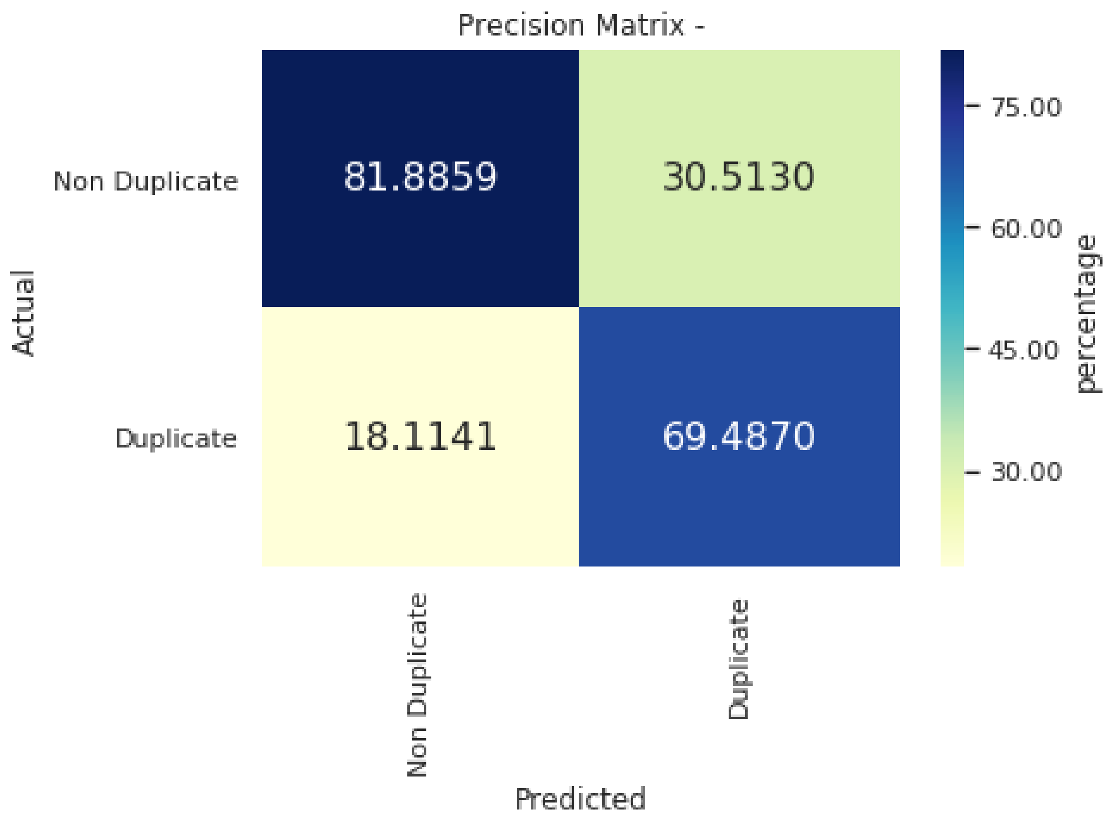


4.3.3 3. Test the model

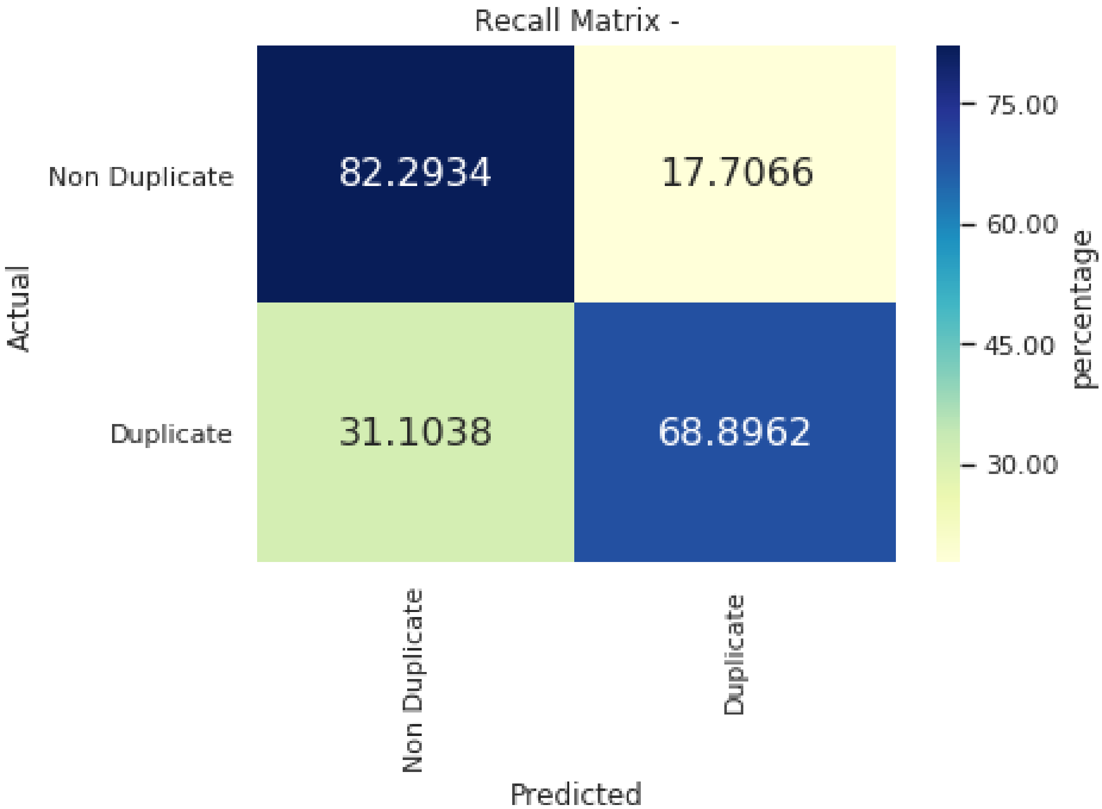
```
In [29]: table_entry_xgb_test = evaluate_model(xgb_sig_clf, X_test, y_test)
         best_hyp_xgb = '\n'.join(str(best_hyp_xgb).split(','))
         table_entry_xgb = ('XG Boost', best_hyp_xgb,) + table_entry_xgb_train + table_entry_xgb
```

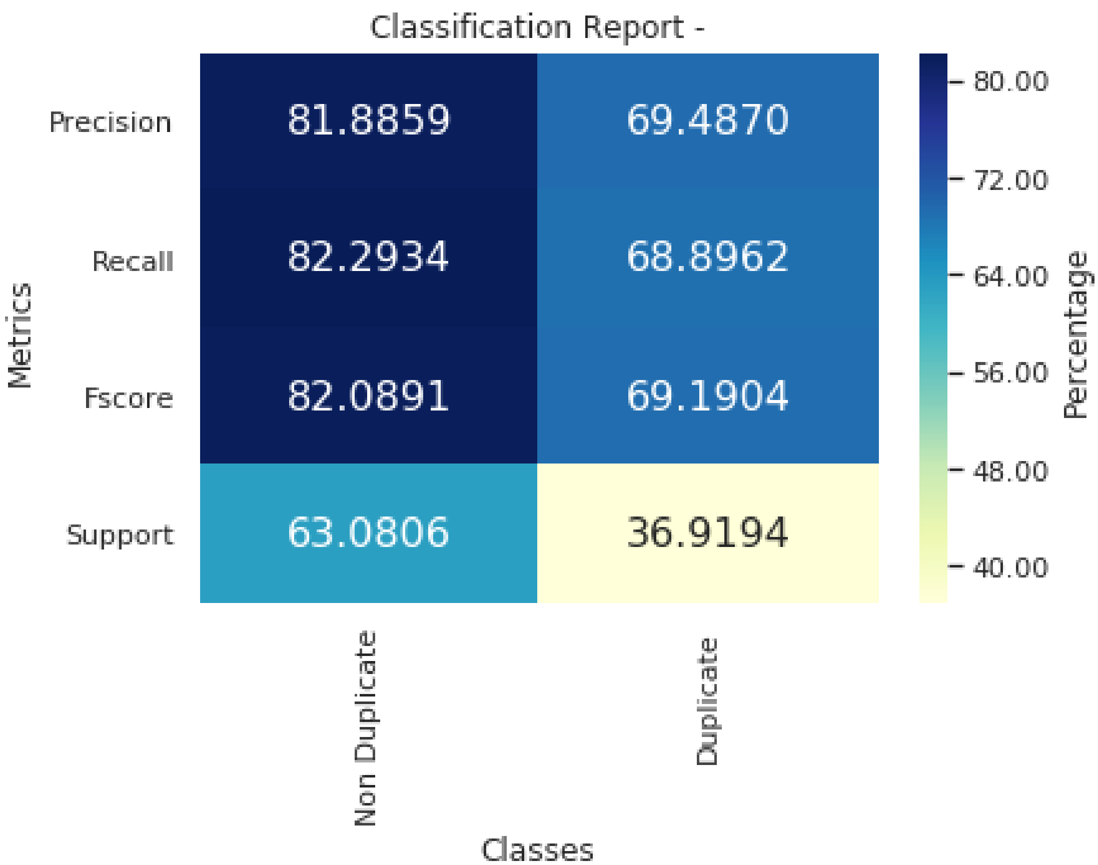


Confusion Matrix -
Non Duplicate
Duplicate
Actual
18688
4021
4134
9157
Non Duplicate
Duplicate
Predicted
17500
15000
12500
10000
7500
5000
prediction_count



Precision Matrix -
Non Duplicate
Duplicate
Actual
81.8859
30.5130
18.1141
69.4870
75.00
60.00
45.00
30.00
percentage
Non Duplicate
Duplicate
Predicted


Recall Matrix -
Non Duplicate
Duplicate
Actual
82.2934
17.7066
31.1038
68.8962
Non Duplicate
Duplicate
Predicted
75.00
60.00
45.00
30.00
percentage



5 Results

```
In [30]: Pret_table = PrettyTable()
         Pret_table.field_names = ['Model', 'Hyperparam', 'Train_Log_Loss', 'Test_Log_Loss']
         Pret_table.title = 'Classification Model Results Summary'

         # enter model performance metrics
         Pret_table.add_row(table_entry_lr)
         Pret_table.add_row(table_entry_svm)
         Pret_table.add_row(table_entry_xgb)
         print(Pret_table)
```

```
+---------------------+---------------------+----------------+---------------+
|        Model        |      Hyperparam     | Train_Log_Loss | Test_Log_Loss |
+---------------------+---------------------+----------------+---------------+
| Logistic Regression |      {'C': 1.0}     |     0.5242     |     0.5313    |
|      Linear SVM     |   {'alpha': 0.01}   |     0.5301     |     0.5372    |
|       XG Boost      |   {'max_depth': 20  |     0.2753     |     0.4493    |
|                     | 'n_estimators': 60} |                |               |
```

+---------------------+---------------------+----------------+---------------+

6 Procedure Summary

Three ML models (LogisticRegression, LinearSVM, XGB) are used to solve the problem
Hyperparam tuning of all models done
All models are trained with the best hyperparam values
The performacne of each model is evaluated on a test set

7 Conclusion

The best log loss obtained is for XGB model (0.4493)
The XGB model showed a tendency to overfit due to quiet large deviation of loss between train test data
More feature engineering methods can be tried to imporove the results further
The f1-score for XGB test is 69.19 % , and SVM - 56.70%, Logistic regression- 57.22%
XGB model outperformed other models interms of f1-score