Quora_Question_Similarity

August 2, 2019

In [1]:
```
import matplotlib.pyplot as plt
import re
import time
import warnings
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
warnings.filterwarnings("ignore")
import sys
import numpy as np
from tqdm import tqdm
from joblib import dump, load

# importing Cross validation libs
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn import model_selection
from collections import Counter, defaultdict

import pandas as pd
import sqlite3
from sqlalchemy import create_engine # database connection
import csv
import os
warnings.filterwarnings("ignore")
import datetime as dt
from nltk.corpus import stopwords
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics.classification import accuracy_score, log_loss
from collections import Counter
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
```

```
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
import math
from sklearn.metrics import normalized_mutual_info_score
from sklearn.ensemble import RandomForestClassifier


import scipy.sparse as sp

from sklearn.linear_model import SGDClassifier
from mlxtend.classifier import StackingClassifier

from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_curve, auc, roc_curve
from sklearn.model_selection import RandomizedSearchCV

from xgboost import XGBClassifier
from sklearn.model_selection import StratifiedKFold

# exctract word2vec vectors
# https://github.com/explosion/spaCy/issues/1721
# http://landinghub.visualstudio.com/visual-cpp-build-tools
import spacy
```

In [4]:
```
# avoid decoding problems
df = pd.read_csv("train.csv")

# encode questions to unicode
# https://stackoverflow.com/a/6812069
# ---------------- python 2 ---------------------
# df['question1'] = df['question1'].apply(lambda x: unicode(str(x),"utf-8"))
# df['question2'] = df['question2'].apply(lambda x: unicode(str(x),"utf-8"))
# ---------------- python 3 ---------------------
df['question1'] = df['question1'].apply(lambda x: str(x))
df['question2'] = df['question2'].apply(lambda x: str(x))
```

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

Out[5]:

	id	qid1	qid2	question1	\
0	0	1	2	What is the step by step guide to invest in sh...	
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	
2	2	5	6	How can I increase the speed of my internet co...	
3	3	7	8	Why am I mentally very lonely? How can I solve...	

```
4   4     9    10  Which one dissolve in water quikly sugar, salt...

                                                question2  is_duplicate
0  What is the step by step guide to invest in sh...             0
1  What would happen if the Indian government sto...             0
2  How can Internet speed be increased by hacking...             0
3  Find the remainder when [math]23^{24}[/math] i...             0
4             Which fish would survive in salt water?             0
```

Common functions

```
In [6]: # This function plots the confusion matrices given y_i, y_i_hat.
        def plot_confusion_matrix(test_y, predict_y):
            C = confusion_matrix(test_y, predict_y)
            # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predi

            A =(((C.T)/(C.sum(axis=1))).T)
            B =(C/C.sum(axis=0))

            plt.figure(figsize=(20,4))

            labels = [1,2]
            # 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=la
            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=la
            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=la
            plt.xlabel('Predicted Class')
            plt.ylabel('Original Class')
            plt.title("Recall matrix")

            plt.show()



        depth_ = [2,3,5,7,9]
```

```
depth_ = np.asarray(depth_)

estimators = [100,500,1000,1200,1300]
estimators_list = np.asarray(estimators)

colsample_bytree = [0.1, 0.3, 0.5, 0.7]
colsample_bytree = np.asarray(colsample_bytree)

subsample = [0.1,0.3,0.5,0.7]
colsample_bytree = np.asarray(subsample)


def finding_best_hyperparam(X_tr,y_tr):
    # instantiate a GBDT model
    xgb = XGBClassifier(class_weight='balanced', random_state=1)

    cross_val = StratifiedKFold(n_splits=5, shuffle=True)

    param_grid=dict(n_estimators=estimators_list,max_depth=depth_,colsample_bytree = co
                    subsample = subsample)

    # instantiate the training random search model
    train_grid = RandomizedSearchCV(xgb, param_grid, cv=cross_val, scoring='neg_log_los

    # fit the training data to train model
    train_grid.fit(X_tr, y_tr)

    return train_grid
```

0.1 1. TFIDF

In [7]:
```
#prepro_features_train.csv (Simple Preprocessing Feartures)
#nlp_features_train.csv (NLP Features)
if os.path.isfile('nlp_features_train.csv'):
    dfnlp = pd.read_csv("nlp_features_train.csv",encoding='latin-1')
else:
    print("download nlp_features_train.csv from drive or run previous notebook")

if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    dfppro = pd.read_csv("df_fe_without_preprocessing_train.csv",encoding='latin-1')
else:
    print("download df_fe_without_preprocessing_train.csv from drive or run previous no
```

In [8]:
```
# drop 'qid1' and 'qid2'
dfppro = dfppro.drop(['qid1','qid2'],axis=1)

# drop 'qid1','qid2', 'question1', 'question2','is_duplicate'
dfnlp = dfnlp.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
```

```
        # join operation
        df_final_features  = dfppro.merge(dfnlp, on='id',how='left')
```

```
In [12]: df_final_features.columns
```

```
Out[12]: Index(['id', 'question1', 'question2', 'is_duplicate', 'freq_qid1',
                'freq_qid2', 'q1len', 'q2len', 'q1_n_words', 'q2_n_words',
                'word_Common', 'word_Total', 'word_share', 'freq_q1+q2', 'freq_q1-q2',
                'cwc_min', 'cwc_max', 'csc_min', 'csc_max', 'ctc_min', 'ctc_max',
                'last_word_eq', 'first_word_eq', 'abs_len_diff', 'mean_len',
                'token_set_ratio', 'token_sort_ratio', 'fuzz_ratio',
                'fuzz_partial_ratio', 'longest_substr_ratio'],
               dtype='object')
```

```
In [13]: # not null check
         df_final_features = df_final_features[df_final_features['question1'].notnull()]
         df_final_features = df_final_features[df_final_features['question2'].notnull()]
```

```
In [14]: y = df_final_features['is_duplicate'][:100000]
```

0.2 3. Split data

```
In [15]: X = df_final_features[:100000]

         X_train,X_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0.
         X_train, X_cv, y_train, y_cv = model_selection.train_test_split(X_train, y_train, tes


         X_train.shape, X_test.shape,X_cv.shape, y_train.shape, y_test.shape, y_cv.shape
```

```
Out[15]: ((64000, 30), (20000, 30), (16000, 30), (64000,), (20000,), (16000,))
```

```
In [16]: tfidf =  TfidfVectorizer(ngram_range=(1,3), min_df=10) #in scikit-learn

         X_tr_tfidf_vect1 = tfidf.fit_transform(X_train['question1'])
         X_cv_tfidf_vect1 = tfidf.transform(X_cv['question1'])
         X_test_tfidf_vect1 = tfidf.transform(X_test['question1'])

         X_tr_tfidf_vect2 = tfidf.fit_transform(X_train['question2'])
         X_cv_tfidf_vect2 = tfidf.transform(X_cv['question2'])
         X_test_tfidf_vect2 = tfidf.transform(X_test['question2'])
```

```
In [17]: X_train.columns
```

```
Out[17]: Index(['id', 'question1', 'question2', 'is_duplicate', 'freq_qid1',
                'freq_qid2', 'q1len', 'q2len', 'q1_n_words', 'q2_n_words',
                'word_Common', 'word_Total', 'word_share', 'freq_q1+q2', 'freq_q1-q2',
                'cwc_min', 'cwc_max', 'csc_min', 'csc_max', 'ctc_min', 'ctc_max',
```

```
       'last_word_eq', 'first_word_eq', 'abs_len_diff', 'mean_len',
       'token_set_ratio', 'token_sort_ratio', 'fuzz_ratio',
       'fuzz_partial_ratio', 'longest_substr_ratio'],
      dtype='object')
```

In [18]:
```
# as we need only features data, we can eliminate unneccasary
X_train.drop(['id','is_duplicate','question1','question2'], axis=1, inplace=True)
X_cv.drop(['id','is_duplicate','question1','question2'], axis=1, inplace=True)
X_test.drop(['id','is_duplicate','question1','question2'], axis=1, inplace=True)
```

In [19]:
```
# https://stackoverflow.com/questions/34710281/use-featureunion-in-scikit-learn-to-co
# dtype=np.float64 will convert string to numeric features

# stacking tfidf_que1 with tfidf_que2
X_tr_stack = sp.hstack([X_tr_tfidf_vect1, X_tr_tfidf_vect2], format='csr', dtype='flo

# stacking all features
X_train = sp.hstack((X_train, X_tr_stack),format="csr",dtype='float64')

X_cv_stack = sp.hstack([X_cv_tfidf_vect1, X_cv_tfidf_vect2], format='csr', dtype='flo
X_cv  = sp.hstack((X_cv, X_cv_stack),format="csr",dtype='float64')

X_test_stack = sp.hstack([X_test_tfidf_vect1, X_test_tfidf_vect2], format='csr', dtyp
X_test  = sp.hstack((X_test, X_test_stack),format="csr",dtype='float64')

X_train.shape, X_test.shape,X_cv.shape, y_train.shape, y_test.shape, y_cv.shape
```

Out[19]:
```
((64000, 29191), (20000, 29191), (16000, 29191), (64000,), (20000,), (16000,))
```

In [20]:
```
print("-"*10, "Distribution of output variable in train data", "-"*10)
train_distr = Counter(y_train)
train_len = len(y_train)
print("Class 0: ",int(train_distr[0])/train_len,"Class 1: ", int(train_distr[1])/trai
print("-"*10, "Distribution of output variable in train data", "-"*10)
test_distr = Counter(y_test)
test_len = len(y_test)
print("Class 0: ",int(test_distr[1])/test_len, "Class 1: ",int(test_distr[1])/test_le
```

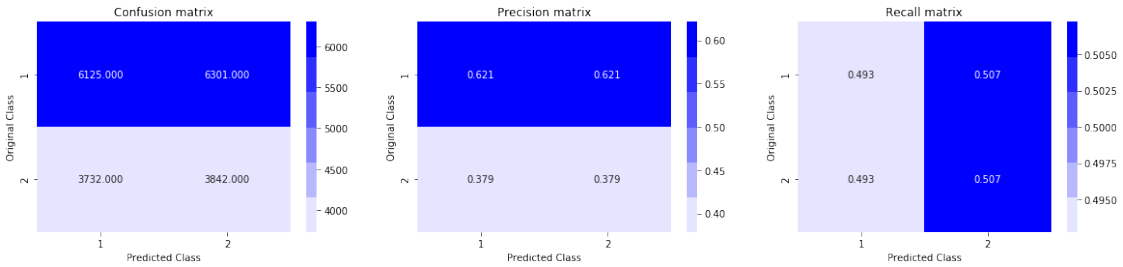
```
---------- Distribution of output variable in train data ----------
Class 0:  0.6275 Class 1:  0.3725
---------- Distribution of output variable in train data ----------
Class 0:  0.3787 Class 1:  0.3787
```

0.3 2. Building a random model (Finding worst-case log-loss)

In [21]:
```
predicted_y = np.zeros((test_len,2))
for i in range(test_len):
    rand_probs = np.random.rand(1,2)
```

```
        predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
    print("Log loss on Test Data using Random Model",log_loss(y_test, predicted_y, eps=1e-

    predicted_y =np.argmax(predicted_y, axis=1)
    plot_confusion_matrix(y_test, predicted_y)
```

```
Log loss on Test Data using Random Model 0.8849129142714491
```



0.4 4. Machine Learning Models

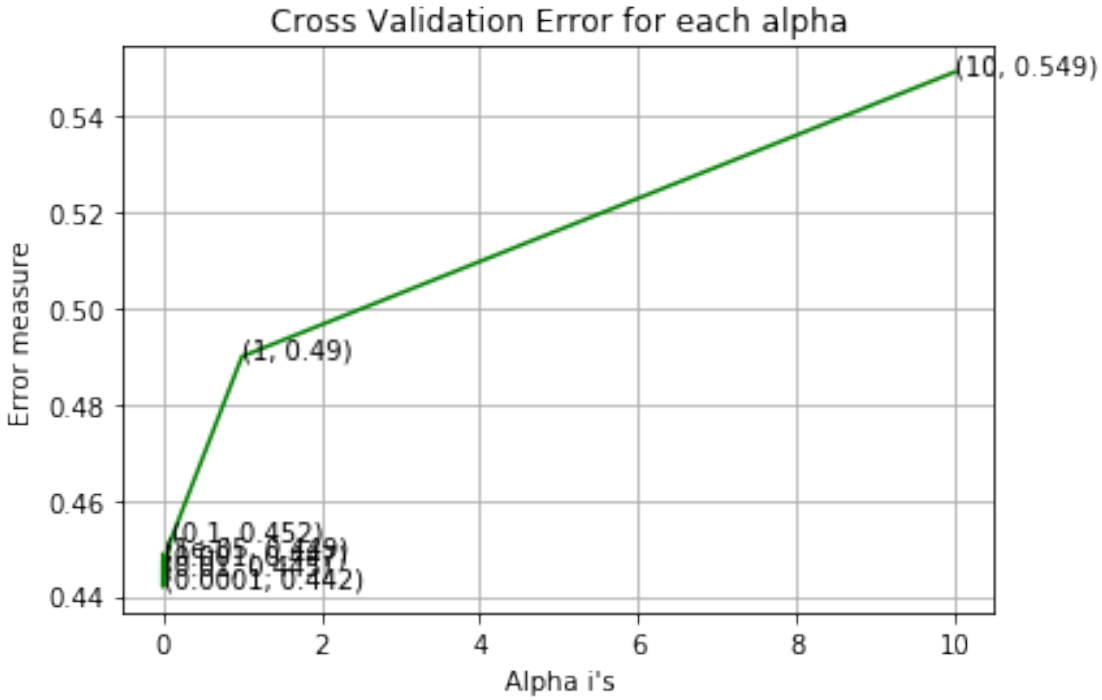
0.5 4.1 Logistic Regression with hyperparameter tuning

```
In [30]: alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
```

```
    log_error_array=[]
    for i in alpha:
        clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
        clf.fit(X_train, y_train)
        sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
        sig_clf.fit(X_train, y_train)
        predict_y = sig_clf.predict_proba(X_test)
        log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15)
        print('For values of alpha = ', i, "The log loss is:",log_loss(y_test, predict_y,

    fig, ax = plt.subplots()
    ax.plot(alpha, log_error_array,c='g')
    for i, txt in enumerate(np.round(log_error_array,3)):
        ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
    plt.grid()
    plt.title("Cross Validation Error for each alpha")
    plt.xlabel("Alpha i's")
    plt.ylabel("Error measure")
    plt.show()
```

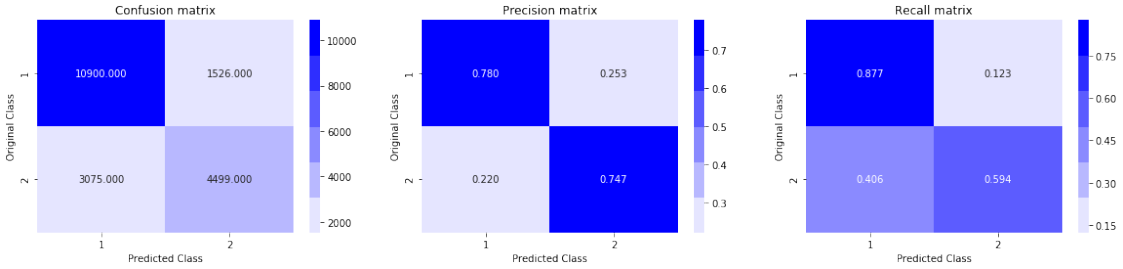
```
best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log', random_state=42
clf.fit(X_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train, y_train)

predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha =  1e-05 The log loss is: 0.44876895419894147
For values of alpha =  0.0001 The log loss is: 0.44198186097701403
For values of alpha =  0.001 The log loss is: 0.4471844116688919
For values of alpha =  0.01 The log loss is: 0.4448723999609054
For values of alpha =  0.1 The log loss is: 0.451698897035198
For values of alpha =  1 The log loss is: 0.48990628376450607
For values of alpha =  10 The log loss is: 0.549087506232412
```




```
For values of best alpha =  0.0001 The train log loss is: 0.4492720654380141
For values of best alpha =  0.0001 The test log loss is: 0.44198186097701403
```

```
Total number of data points : 20000
```

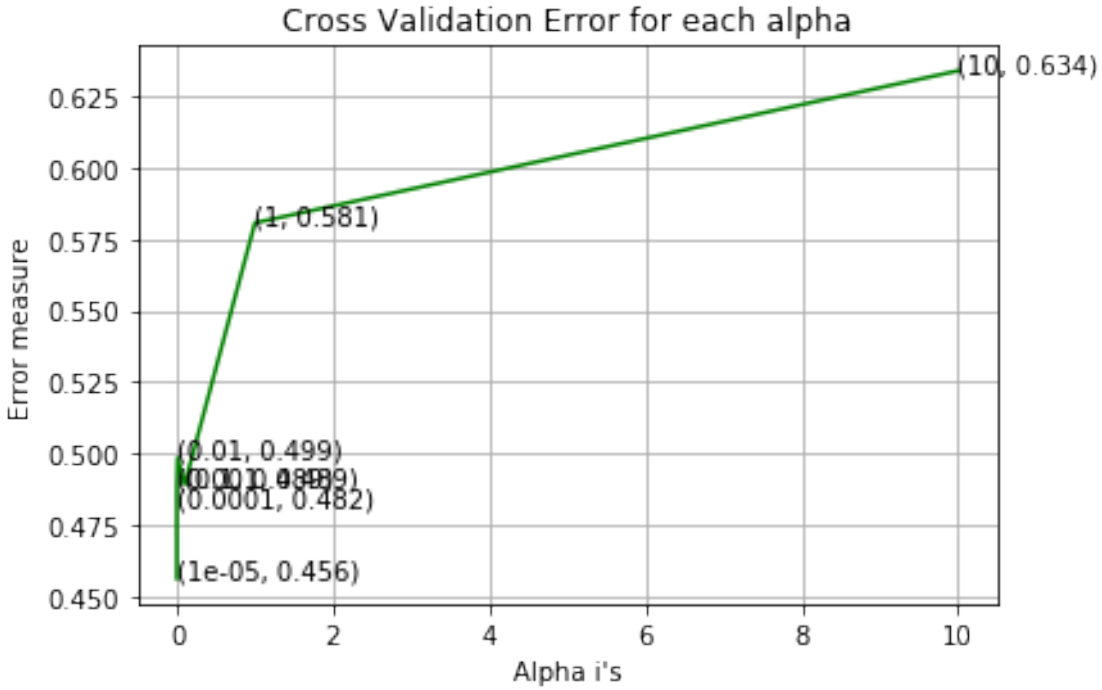


0.6 4.2 Linear SVM with hyperparameter tuning

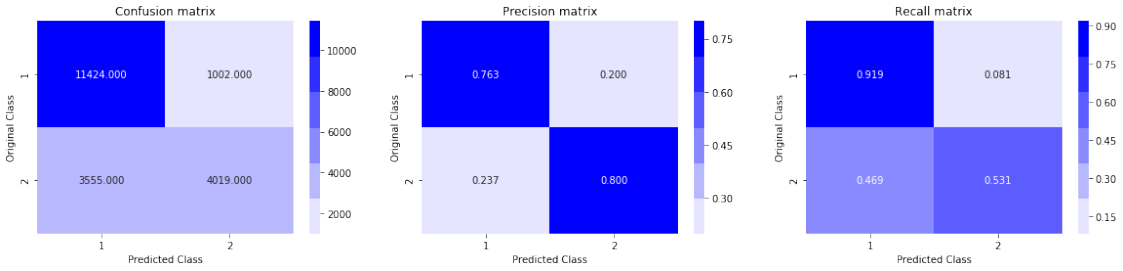
In [31]:
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l1', loss='hinge', random_state=42)
    clf.fit(X_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15)
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test, predict_y,

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge', random_state=
clf.fit(X_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train, y_train)

predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_
predict_y = sig_clf.predict_proba(X_test)
```

```
        print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_l
        predicted_y =np.argmax(predict_y,axis=1)
        print("Total number of data points :", len(predicted_y))
        plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha =  1e-05 The log loss is: 0.4564755096759054
For values of alpha =  0.0001 The log loss is: 0.4816810055256412
For values of alpha =  0.001 The log loss is: 0.48871223690306725
For values of alpha =  0.01 The log loss is: 0.49865661077196854
For values of alpha =  0.1 The log loss is: 0.4892970712272376
For values of alpha =  1 The log loss is: 0.5805943036947876
For values of alpha =  10 The log loss is: 0.6336572993591096
```




```
For values of best alpha =  1e-05 The train log loss is: 0.4648256994859472
For values of best alpha =  1e-05 The test log loss is: 0.4564755096759054
Total number of data points : 20000
```



0.7 4.3 Hyperparam Tuning using XGBOOST

In [24]:
```
hyp_train_= finding_best_hyperparam(X_train,y_train)
```

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


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed: 10.2min
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed: 16.1min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 22.2min remaining:    0.0s
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 22.2min finished
```

In [25]:
```
print("Best: %f using %s" % (hyp_train_.best_score_, hyp_train_.best_params_))
print('=='*50)
means = hyp_train_.cv_results_['mean_test_score']
params = hyp_train_.cv_results_['params']

for mean, param in zip(means, params):
    print("%f with: %r" % (mean, param))
```

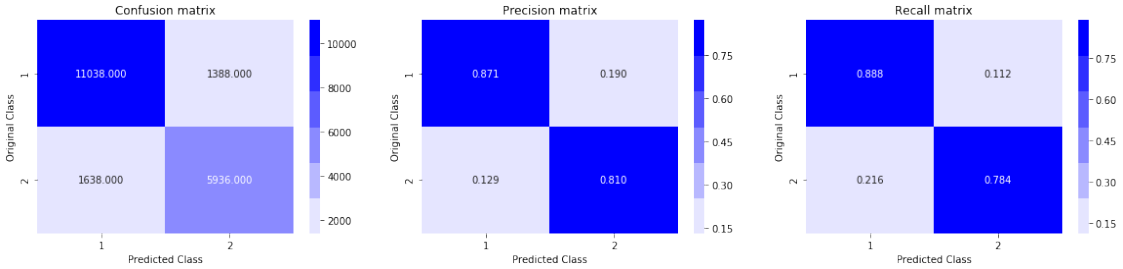
```
Best: -0.330698 using {'subsample': 0.5, 'n_estimators': 1200, 'max_depth': 3, 'colsample_bytre
====================================================================================================
-0.330698 with: {'subsample': 0.5, 'n_estimators': 1200, 'max_depth': 3, 'colsample_bytree': 0
-0.339120 with: {'subsample': 0.7, 'n_estimators': 1000, 'max_depth': 2, 'colsample_bytree': 0
-0.367988 with: {'subsample': 0.7, 'n_estimators': 100, 'max_depth': 3, 'colsample_bytree': 0.3
-0.360434 with: {'subsample': 0.1, 'n_estimators': 1200, 'max_depth': 7, 'colsample_bytree': 0
-0.358152 with: {'subsample': 0.1, 'n_estimators': 100, 'max_depth': 5, 'colsample_bytree': 0.3
-0.386373 with: {'subsample': 0.7, 'n_estimators': 100, 'max_depth': 3, 'colsample_bytree': 0.1
-0.353068 with: {'subsample': 0.1, 'n_estimators': 1000, 'max_depth': 2, 'colsample_bytree': 0
-0.346672 with: {'subsample': 0.1, 'n_estimators': 500, 'max_depth': 3, 'colsample_bytree': 0.5
-0.350379 with: {'subsample': 0.1, 'n_estimators': 1300, 'max_depth': 2, 'colsample_bytree': 0
-0.335191 with: {'subsample': 0.3, 'n_estimators': 1000, 'max_depth': 3, 'colsample_bytree': 0
```

In [26]:
```
xgb_model = XGBClassifier(class_weight='balanced', n_estimators=1300,max_depth=9,colsa
                          subsample = 0.5,random_state=1)

xgb_model.fit(X_train,y_train)
```

Out[26]:
```
XGBClassifier(base_score=0.5, booster='gbtree', class_weight='balanced',
       colsample_bylevel=1, colsample_bytree=0.5, gamma=0,
       learning_rate=0.1, max_delta_step=0, max_depth=9,
       min_child_weight=1, missing=None, n_estimators=1300, n_jobs=1,
       nthread=None, objective='binary:logistic', random_state=1,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=0.5)
```

```
In [27]: predict_y = xgb_model.predict_proba(X_train)
         print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
         predict_y = xgb_model.predict_proba(X_test)
         print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
         predicted_y =np.argmax(predict_y,axis=1)
         print("Total number of data points :", len(predicted_y))
         plot_confusion_matrix(y_test, predicted_y)
```

```
For values of best alpha =  1e-05 The train log loss is: 0.11545512084550494
For values of best alpha =  1e-05 The test log loss is: 0.3217635831075882
Total number of data points : 20000
```



Above we can see that though test loss it '0.32176' which is excellent on other it is also notice that train loss is '0.11545'

There is large difference between train loss and test lost so our model might be **OVERFIT**.

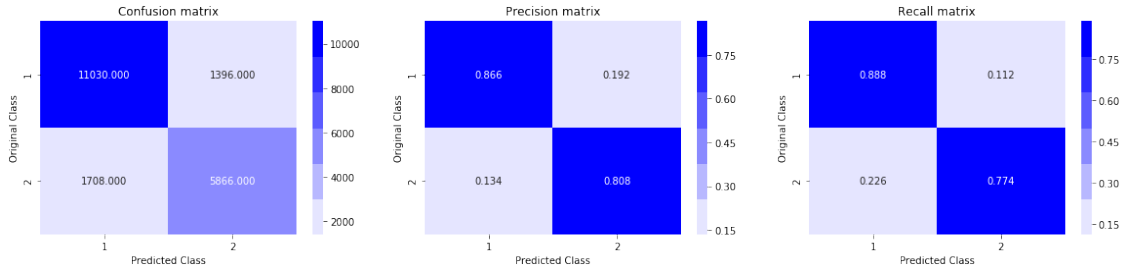
So we will adjust hyperparam tune values.

Try below values

max_depth = 5 n_estimators = 1000

```
In [28]: xgb_model = XGBClassifier(class_weight='balanced', n_estimators=1000,max_depth=5,colsa
                                  subsample = 0.5,random_state=1)

         xgb_model.fit(X_train,y_train)

         predict_y = xgb_model.predict_proba(X_train)
         print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_l
         predict_y = xgb_model.predict_proba(X_test)
         print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_lo
         predicted_y =np.argmax(predict_y,axis=1)
         print("Total number of data points :", len(predicted_y))
         plot_confusion_matrix(y_test, predicted_y)
```

```
For values of best alpha =  1e-05 The train log loss is: 0.23319731846422492
For values of best alpha =  1e-05 The test log loss is: 0.3188408678021985
Total number of data points : 20000
```



1 5. Conclusion

```
In [32]: import pandas as pd
         from prettytable import PrettyTable

         print('\t\t\t\t Model Comparision  ')
         print('\n')

         print('We have considered 100k points')


         x = PrettyTable()
         x.field_names =  ['Metric','Random Model','Logistic Regression','Linear SVM', 'GBDT']

         x.add_row(["Train Log Loss ",0.88491, 0.44927,0.46482,0.23319])
         x.add_row(["Test Log Loss ",0.88491, 0.44198,0.45647,0.31884])


         print('\n')
         print(x)
```

```
                                Model Comparision


We have considered 100k points


+-----------------+--------------+----------------------+------------+---------+
|      Metric     | Random Model | Logistic Regression | Linear SVM |   GBDT  |
+-----------------+--------------+----------------------+------------+---------+
| Train Log Loss  |   0.88491    |       0.44927        |  0.46482   | 0.23319 |
|  Test Log Loss  |   0.88491    |       0.44198        |  0.45647   | 0.31884 |
+-----------------+--------------+----------------------+------------+---------+
```

We have built Logistic Regression, Linear SVM and GBDT based models. It is clear cut GBDT perfoming best in all of them.

Also it is notice that Train log loss and Test Log loss value are closer for all models so we can say that all mode performing well, no overfitting nothing

While performig GBDT we seems model was slightly tends to overfitt, but we adjust some value now its look better.

Logistic Regression and LinearSVM models work better in Higher Dimensions

It is rule of thumb that GBDT works better in small dimension, yet here in HIGHER dimension also it is working well.