```
In [2]: from google.colab import drive
               drive.mount('/content/drive')
               Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client id=947318989803-6bn6gk8gdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect uri=ur
               n%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Docs.test%2Do
               googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response type=code
               Enter your authorization code:
               Mounted at /content/drive
In [3]: import pandas as pd
               import matplotlib.pyplot as plt
               import re
               import time
               import warnings
               import sqlite3
               from sqlalchemy import create_engine # database connection
               import csv
               import os
               warnings.filterwarnings("ignore")
               import datetime as dt
               import numpy as np
               from nltk.corpus import stopwords
               from sklearn.decomposition import TruncatedSVD
               from sklearn.preprocessing import normalize
               from sklearn.feature extraction.text import CountVectorizer
               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 sklearn.feature extraction.text import TfidfVectorizer
               from collections import Counter
               from scipy.sparse import hstack
               from sklearn.multiclass import OneVsRestClassifier
               from sklearn.svm import SVC
               from sklearn.model selection import StratifiedKFold
               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
               from sklearn.model selection import RandomizedSearchCV
               import math
               from sklearn.metrics import normalized mutual info score
               from sklearn.ensemble import RandomForestClassifier
               from prettytable import PrettyTable
               from sklearn.model selection import cross val score
               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
```

/usr/local/lib/python3.6/dist-packages/sklearn/externals/six.py:31: DeprecationWarning: The module is deprecated in version 0.21 and will be removed in version 0.23 since we've dropped support for Python 2.7. Please rely on the official version of six (https://pypi.org/project/six/).

"(https://pypi.org/project/six/).", DeprecationWarning)

```
In [4]: table = PrettyTable()
table.field_names= ["Model","Hyperparameters","Log_Loss"]
print(table)

+----+
| Model | Hyperparameters | Log_Loss |
+----+
+----+
```

4. Machine Learning Models

4.1 Reading data from file and storing into sql table

```
In [0]: data_dir='/content/drive/My Drive/Colab Notebooks/AppliedAI/Quora_Assignment/'
```

```
In [0]: #Creating db file from csv
                                       if not os.path.isfile(data dir+'Quora/train.db'):
                                                        disk engine = create engine('sqlite:///'+data dir+'Quora/train.db')
                                                        start = dt.datetime.now()
                                                                   chunksize = 180000
                                                        chunksize = 50000
                                                        j = 0
                                                        index start = 1
                                                        for df in pd.read csv(data dir+'final features.csv',
                                                                                                                                                            names=['Unnamed: 0','id','is duplicate','cwc min','cwc max','csc min','csc max','ctc min','ctc max','last word eq','first word eq','abs len dif
                                       f','mean len','token set ratio','token sort ratio','fuzz ratio','fuzz partial ratio','longest substr ratio','freq qid1','freq qid2','q1len','q2len','q1 n words','q2 n wo
                                       rds','word_Common','word_Total','word_share','freq_q1+q2','freq_q1-q2','0_x','1_x','2_x','3_x','4_x','5_x','6_x','7_x','8_x','9_x','10_x','11_x','12_x','13_x','14_x','15_x','15_x','16_x','17_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_x','18_
                                        x', 16x', 17x', 18x', 19x', 19x', 120x', 121x', 122x', 123x', 124x', 125x', 126x', 127x', 128x', 129x', 130x', 131x', 132x', 132x', 134x', 135x', 136x', 137x', 138x', 139x', 130x', 131x', 132x', 132x', 134x', 135x', 136x', 137x', 138x', 139x', 130x', 131x', 1
                                       x','40 x','41 x','42 x','43 x','44 x','45 x','46 x','47 x','48 x','49 x','50 x','51 x','52 x','53 x','54 x','55 x','56 x','57 x','58 x','59 x','60 x','61 x','62 x','63
                                       x','64 x','65 x','66 x','67 x','68 x','69 x','70 x','71 x','72 x','73 x','74 x','75 x','76 x','77 x','78 x','79 x','80 x','81 x','82 x','83 x','84 x','85 x','86 x','87
                                       x','88_x','89_x','90_x','91_x','92_x','93_x','94_x','95_x','96_x','97_x','98_x','99_x','100_x','101_x','102_x','103_x','104_x','105_x','106_x','106_x','107_x','108_x','109_x','1
                                       10\_x', 111\_x', 112\_x', 113\_x', 114\_x', 115\_x', 116\_x', 117\_x', 118\_x', 119\_x', 120\_x', 121\_x', 122\_x', 123\_x', 124\_x', 125\_x', 126\_x', 127\_x', 128\_x', 129\_x', 130\_x', 130\_x', 130\_x', 130\_x', 130\_x', 130\_x', 130_x', 130_x
                                       1_x','132_x','133_x','134_x','135_x','136_x','137_x','138_x','139_x','140_x','141_x','142_x','143_x','144_x','145_x','146_x','147_x','148_x','149_x','150_x','151_x','152_x','152_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','134_x','
                                         _x','153_x','154_x','155_x','156_x','157_x','158_x','159_x','160_x','161_x','162_x','163_x','164_x','165_x','166_x','167_x','168_x','169_x','170_x','171_x','172_x','173_
                                       x','174_x','175_x','176_x','177_x','178_x','179_x','180_x','181_x','182_x','183_x','184_x','185_x','186_x','187_x','188_x','189_x','190_x','191_x','192_x','193_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','194_x','19
                                       x','195 x','196 x','197 x','198 x','199 x','200 x','201 x','202 x','203 x','204 x','205 x','206 x','207 x','208 x','209 x','210 x','211 x','212 x','213 x','214 x','215
                                       x','216 x','217 x','218 x','219 x','220 x','221 x','222 x','223 x','224 x','225 x','226 x','227 x','228 x','229 x','230 x','231 x','232 x','233 x','234 x','235 x','236
                                       x','237_x','238_x','239_x','240_x','241_x','242_x','243_x','244_x','245_x','246_x','247_x','248_x','249_x','250_x','251_x','252_x','253_x','254_x','255_x','256_x','257_x','266_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x','27_x
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                                       x','279 x','280 x','281 x','282 x','283 x','284 x','285 x','286 x','287 x','288 x','289 x','290 x','291 x','292 x','293 x','294 x','295 x','296 x','297 x','298 x','299
                                       x','300 x','301 x','302 x','303 x','304 x','305 x','306 x','307 x','308 x','309 x','310 x','311 x','312 x','313 x','314 x','315 x','316 x','317 x','318 x','319 x','320
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                                       x','0_y','1_y','2_y','3_y','4_y','5_y','6_y','7_y','8_y','9_y','10_y','11_y','12_y','13_y','14_y','15_y','16_y','17_y','18_y','19_y','20_y','21_y','22_y','23_y','24_y'
                                       '25_y','26_y','27_y','28_y','29_y','30_y','31_y','32_y','33_y','34_y','35_y','36_y','37_y','38_y','39_y','40_y','41_y','42_y','43_y','44_y','45_y','46_y','47_y','48_y'
                                         '49 y','50 y','51 y','52 y','53 y','54 y','55 y','56 y','57 y','58 y','59 y','60 y','61 y','62 y','63 y','64 y','65 y','66 y','67 y','68 y','69 y','70 y','71 y','72 y'
                                        '73_y','74_y','75_y','76_y','77_y','78_y','79_y','80_y','81_y','82_y','83_y','84_y','85_y','86_y','87_y','88_y','89_y','90_y','91_y','92_y','93_y','94_y','95_y','96_y',
                                       '97_y','98_y','99_y','100_y','101_y','102_y','103_y','104_y','105_y','106_y','107_y','108_y','109_y','110_y','111_y','112_y','113_y','114_y','115_y','116_y','117_y','118
                                         _y','119_y','120_y','121_y','122_y','123_y','124_y','125_y','126_y','127_y','128_y','129_y','130_y','131_y','132_y','133_y','134_y','135_y','136_y','137_y','138_y','139_
                                       y','140_y','141_y','142_y','143_y','144_y','145_y','146_y','147_y','148_y','149_y','150_y','151_y','152_y','153_y','154_y','155_y','156_y','157_y','158_y','159_y','160_
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                                       y','224 y','225 y','226 y','227 y','228 y','229 y','230 y','231 y','232 y','233 y','234 y','235 y','236 y','237 y','238 y','239 y','240 y','241 y','242 y','243 y','244 y','244 y','247 y','248 y','247 y','248 y','24
                                      y','245_y','246_y','247_y','248_y','249_y','250_y','251_y','252_y','253_y','254_y','255_y','256_y','257_y','258_y','259_y','260_y','261_y','262_y','263_y','264_y','265_y','265_y','260_y','260_y','260_y','261_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','260_y','26
                                      ŷ','266_ŷ','267_ŷ','268_ŷ','269_ŷ','270_ŷ','271_ŷ','272_ŷ','273_ŷ','274_ŷ','275_ŷ','276_ŷ','277_ŷ','278_ŷ','279_ŷ','280_ŷ','281_ŷ','282_ŷ','283_ŷ','284_ŷ','285_ŷ','286_
                                       y','287_y','288_y','289_y','290_y','291_y','292_y','293_y','294_y','295_y','296_y','297_y','298_y','299_y','300_y','301_y','302_y','303_y','304_y','305_y','306_y','307_y','287_y','288_y','288_y','288_y','289_y','288_y','288_y','288_y','288_y','288_y','288_y','288_y','288_y','288_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','308_y','30
                                       y','308 y','309 y','310 y','311 y','312 y','313 y','314 y','315 y','316 y','317 y','318 y','319 y','320 y','321 y','322 y','323 y','324 y','325 y','326 y','327 y','328
                                       y','329 y','330 y','331 y','332 y','333 y','334 y','335 y','336 y','337 y','338 y','339 y','340 y','341 y','342 y','343 y','344 y','345 y','346 y','347 y','348 y','349
                                       y','350_y','351_y','352_y','353_y','354_y','355_y','356_y','357_y','358_y','359_y','360_y','361_y','362_y','363_y','364_y','365_y','366_y','367_y','368_y','369_y','370_
                                       y','371 y','372 y','373 y','374 y','375 y','376 y','377 y','378 y','379 y','380 y','381 y','382 y','383 y'],
                                                                                                                                                             chunksize=chunksize, iterator=True, encoding='utf-8', ):
                                                                            df.index += index start
                                                                            print('{} rows'.format(j*chunksize))
                                                                            df.to sql('data', disk engine, if exists='append')
                                                                            index start = df.index[-1] + 1
                                       else:
                                                print("train.db found..!")
```

```
In [0]: #http://www.sqlitetutorial.net/sqlite-python/create-tables/
        def create connection(db file):
             """ create a database connection to the SQLite database
                specified by db file
             :param db file: database file
            :return: Connection object or None
            try:
                conn = sqlite3.connect(db file)
                return conn
            except Error as e:
                print(e)
            return None
        def checkTableExists(dbcon):
            cursr = dbcon.cursor()
            str = "select name from sqlite_master where type='table'"
            table names = cursr.execute(str)
            print("Tables in the databse:")
            tables =table_names.fetchall()
            print(tables[0][0])
            return(len(tables))
In [0]: read db = data dir+'Quora/train.db'
        conn r = create connection(read db)
        checkTableExists(conn_r)
        conn_r.close()
        Tables in the databse:
        data
In [0]: # try to sample data according to the computing power you have
        if os.path.isfile(read_db):
            conn r = create connection(read db)
            if conn r is not None:
                # for selecting first 1M rows
                # data = pd.read_sql_query("""SELECT * FROM data LIMIT 100001;""", conn_r)
                # for selecting random points
                # data = pd.read sql query("SELECT * From data ORDER BY RANDOM() LIMIT 100001;", conn r)
                # changing the number to 50k as it is taking ages for 100k
                data = pd.read sql query("SELECT * From data ORDER BY RANDOM() LIMIT 50001;", conn r)
                conn_r.commit()
                conn_r.close()
In [0]: # remove the first row
        data.drop(data.index[0], inplace=True)
        y true = data['is duplicate']
        data.drop(['Unnamed: 0', 'id', 'index', 'is_duplicate'], axis=1, inplace=True)
In [0]: data.shape
```

Out[0]: (50000, 794)

1 0.999950002499875 0.18 2 0.499987500312492 0.49			0.285710204139941	0.799984000319994	0.199999000005	0.0	1.0	15.0	10.5				
2 0.499987500312492 0.49	99987500312492				0.2000000000	0.0	1.0	15.0	12.5	94	41	33	
	33301300012432	0.599988000239995	0.428565306209911	0.555549382784636	0.454541322351615	1.0	1.0	2.0	10.0	73	71	71	
3 0.666655555740738 0.57	71420408279882	0.499987500312492	0.399992000159997	0.545449586821938	0.545449586821938	0.0	0.0	0.0	11.0	73	69	67	
4 0.599988000239995 0.49	99991666805553	0.999975000624984	0.799984000319994	0.77776913589849	0.636357851292261	1.0	0.0	2.0	10.0	85	84	62	
5 0.399992000159997 0.33	33327777870369	0.499975001249937	0.166663888935184	0.374995312558593	0.249997916684028	0.0	0.0	4.0	10.0	56	52	50	

4.2 Converting strings to numerics

In [0]: data.head()

```
In [0]: # after we read from sql table each entry was read it as a string
    # we convert all the features into numaric before we apply any model
    # cols = list(data.columns)
    # for i in cols:
    # data[i] = data[i].apply(pd.to_numeric)
    # print(i)

# Faster and cleaner code
    data=data.astype(float)
In [0]: # https://stackoverflow.com/questions/7368789/convert-all-strings-in-a-list-to-int
    y_true = list(map(int, y_true.values))
```

4.3 Random train test split(70:30)

----- Distribution of output variable in test data ------

Class 0: 0.3719333333333334 Class 1: 0.3719333333333334

```
In [0]: X_train,X_test, y_train, y_test = train_test_split(data, y_true,
                                          stratify=y true, test size=0.3)
In [0]: print("Number of data points in train data :",X_train.shape)
        print("Number of data points in test data :",X test.shape)
        Number of data points in train data: (35000, 794)
        Number of data points in test data: (15000, 794)
In [0]: 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])/train_len)
        print("-"*10, "Distribution of output variable in test 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_len)
        ----- Distribution of output variable in train data ------
        Class 0: 0.6280571428571429 Class 1: 0.37194285714285713
```

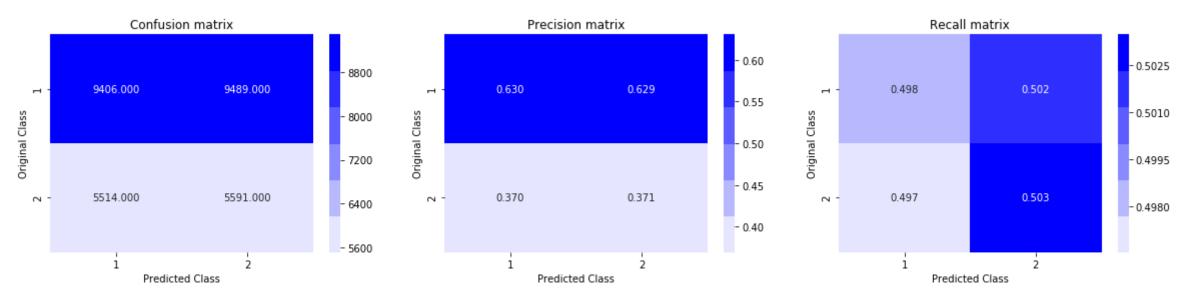
```
In [0]: # This function plots the confusion matrices given y_i, y_i_hat.
        def plot confusion matrix(test y, predict y):
            C = confusion matrix(test y, predict y)
            # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predicted class j
            A = (((C.T)/(C.sum(axis=1))).T)
            #divid each element of the confusion matrix with the sum of elements in that column
            \# C = [[1, 2],
            # [3, 4]]
            \# C.T = [[1, 3],
                     [2, 4]]
            # C.sum(axis = 1) axis=0 corresonds to columns and axis=1 corresponds to rows in two diamensional array
            \# C.sum(axix = 1) = [[3, 7]]
            \# ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
                                        [2/3, 4/7]]
            \# ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
                                        [3/7, 4/7]]
            # sum of row elements = 1
            B = (C/C.sum(axis=0))
            #divid each element of the confusion matrix with the sum of elements in that row
            \# C = [[1, 2],
            # [3, 4]]
            # C.sum(axis = 0) axis=0 corresponds to columns and axis=1 corresponds to rows in two diamensional array
            \# C.sum(axix = 0) = [[4, 6]]
            \# (C/C.sum(axis=0)) = [[1/4, 2/6],
                                   [3/4, 4/6]]
            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=labels)
            plt.xlabel('Predicted Class')
            plt.ylabel('Original Class')
            plt.title("Confusion matrix")
            plt.subplot(1, 3, 2)
            sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
            plt.xlabel('Predicted Class')
            plt.ylabel('Original Class')
            plt.title("Precision matrix")
            plt.subplot(1, 3, 3)
            # representing B in heatmap format
            sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
            plt.xlabel('Predicted Class')
            plt.ylabel('Original Class')
            plt.title("Recall matrix")
            plt.show()
```

4.4 Building a random model (Finding worst-case log-loss)

```
In [0]: # we need to generate 9 numbers and the sum of numbers should be 1
# one solution is to genarate 9 numbers and divide each of the numbers by their sum
# ref: https://stackoverflow.com/a/18662466/4084039
# we create a output array that has exactly same size as the CV data
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-15))

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

Log loss on Test Data using Random Model 0.8869456220491898



4.4 Logistic Regression with hyperparameter tuning

```
In [0]: alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
        # read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear model.SGDClassifier.html
        # default parameters
        # SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1 ratio=0.15, fit intercept=True, max iter=None, tol=None,
        # shuffle=True, verbose=0, epsilon=0.1, n jobs=1, random state=None, learning rate='optimal', eta0=0.0, power t=0.5,
        # class weight=None, warm start=False, average=False, n iter=None)
        # some of methods
        # fit(X, y[, coef init, intercept init, ...]) Fit linear model with Stochastic Gradient Descent.
        # predict(X) Predict class labels for samples in X.
        #-----
        # video link:
        #-----
        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, labels=clf.classes_, eps=1e-15))
        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 loss(y train, predict y, labels=clf.classes , eps=1e-15))
        predict y = sig clf.predict proba(X test)
        print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
        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: 0.56662713178077

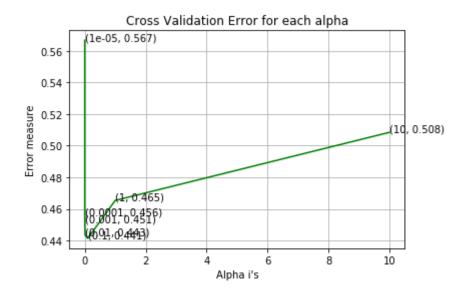
For values of alpha = 0.0001 The log loss is: 0.45626538982765824

For values of alpha = 0.001 The log loss is: 0.451440451281298

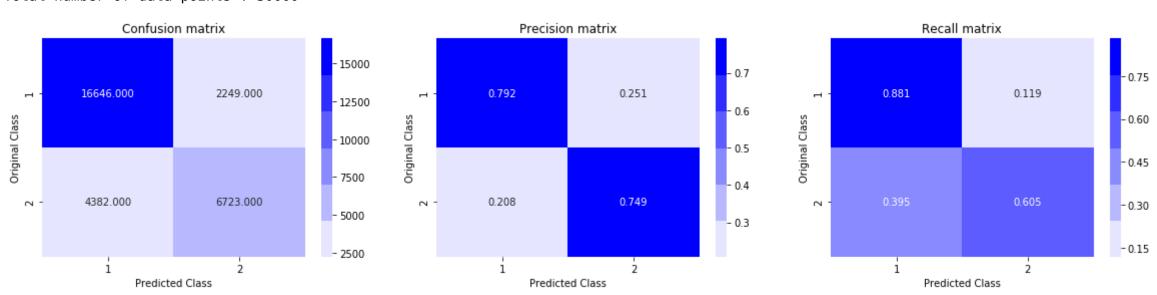
For values of alpha = 0.01 The log loss is: 0.44340750607505

For values of alpha = 0.1 The log loss is: 0.4414283106295279

For values of alpha = 10 The log loss is: 0.5084292621090118



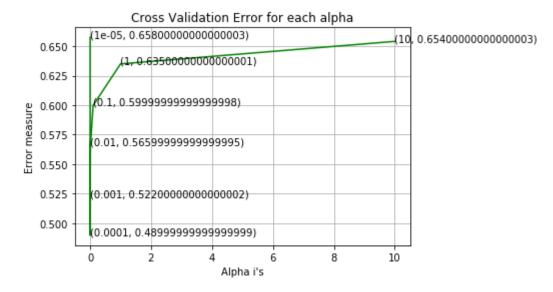
For values of best alpha = 0.1 The train log loss is: 0.43291199173090306 For values of best alpha = 0.1 The test log loss is: 0.4414283106295279 Total number of data points : 30000



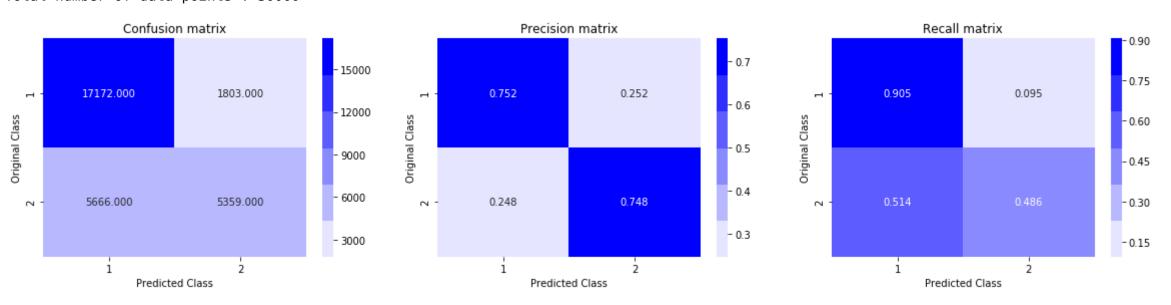
4.5 Linear SVM with hyperparameter tuning

```
In [0]: alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
        # read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear model.SGDClassifier.html
        # default parameters
        # SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1 ratio=0.15, fit intercept=True, max iter=None, tol=None,
        # shuffle=True, verbose=0, epsilon=0.1, n jobs=1, random state=None, learning rate='optimal', eta0=0.0, power t=0.5,
        # class weight=None, warm start=False, average=False, n iter=None)
        # some of methods
        # fit(X, y[, coef init, intercept init, ...]) Fit linear model with Stochastic Gradient Descent.
        # predict(X) Predict class labels for samples in X.
        #-----
        # video link:
        #-----
        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, labels=clf.classes_, eps=1e-15))
        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=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 loss(y train, predict y, labels=clf.classes , eps=1e-15))
        predict y = sig clf.predict proba(X test)
        print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
        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: 0.657611721261
For values of alpha = 0.0001 The log loss is: 0.489669093534
For values of alpha = 0.001 The log loss is: 0.521829068562
For values of alpha = 0.01 The log loss is: 0.566295616914
For values of alpha = 0.1 The log loss is: 0.599957866217
For values of alpha = 10 The log loss is: 0.635059427016
For values of alpha = 10 The log loss is: 0.654159467907

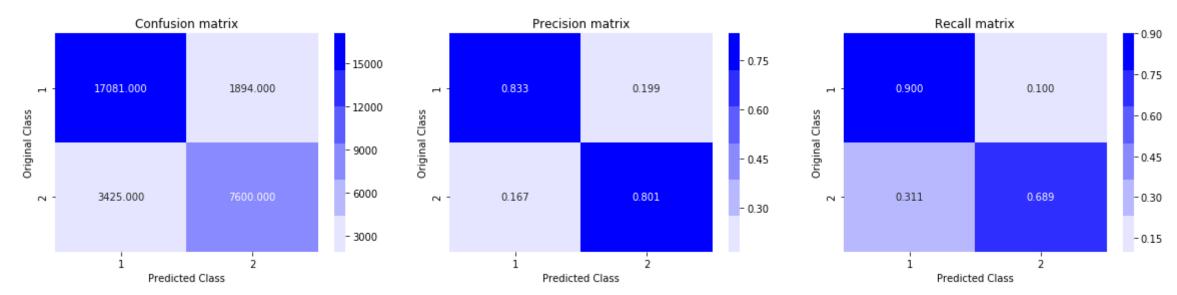


For values of best alpha = 0.0001 The train log loss is: 0.478054677285 For values of best alpha = 0.0001 The test log loss is: 0.489669093534 Total number of data points : 30000



4.6 XGBoost

```
In [0]: import xgboost as xgb
        params = \{\}
        params['objective'] = 'binary:logistic'
        params['eval metric'] = 'logloss'
        params['eta'] = 0.02
        params['max depth'] = 4
        d train = xgb.DMatrix(X train, label=y train)
        d test = xgb.DMatrix(X test, label=y test)
        watchlist = [(d train, 'train'), (d test, 'valid')]
        bst = xgb.train(params, d_train, 400, watchlist, early_stopping_rounds=20,
                        verbose eval=10)
        xgdmat = xgb.DMatrix(X train,y train)
        predict y = bst.predict(d test)
        print("The test log loss is:",log_loss(y_test, predict_y, eps=1e-15))
In [0]: predicted_y =np.array(predict_y>0.5,dtype=int)
        print("Total number of data points :", len(predicted y))
        plot_confusion_matrix(y_test, predicted_y)
        Total number of data points : 30000
```



5. Assignments

1. Try out models (Logistic regression, Linear-SVM) with simple TF-IDF vectors instead of TD_IDF weighted word2Vec.

correctly get the tf-Idf values without data leakage

2. Hyperparameter tune XgBoost using RandomSearch to reduce the log-loss.

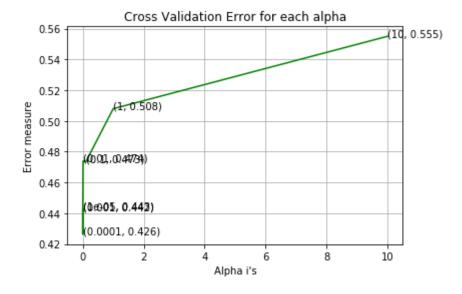
```
In [0]: import spacy
from scipy.sparse import csr_matrix, hstack
In [0]: # To prepare data to solve the given assignment we will use the stored dataframe
# for some of the prepared features, and use the original Quora questions again to
```

```
In [0]: data=pd.merge(pd.read_csv(data_dir+'Quora/final_features.csv', index_col='id',
                      usecols=['id','is_duplicate','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',
                                'freq_qid1', 'freq_qid2', 'q1len', 'q2len', 'q1_n_words',
                                'q2 n words', 'word Common', 'word_Total', 'word_share',
                                'freq q1+q2', 'freq q1-q2']),
                      pd.read csv(data dir+'Quora/train.csv', index col='id',
                      usecols=['id','question1','question2']),
                      how='inner', on='id')
In [0]: #Select 50k duplicates and 50k non-duplicates for balanced dataset
        data=data[data.is duplicate==1][:50000].append(
                            data[data.is_duplicate==0][:50000],ignore_index=True)
In [0]: #Re-shuffling the dataframe
        data=data.sample(frac=1).reset_index(drop=True)
In [0]: #Code for pre-processing of questions text
        nlp=spacy.load('en_core_web_sm')
        def preprocess(text):
            # lower case
            text = str(text).lower()
            # decontractions and replacement
            text = text.replace(",000,000", "m").replace(",000", "k").replace("'", "'")\
                    .replace("'", "'").replace("won't", "will not").replace("cannot", "can not")\
                    .replace("can't", "can not").replace("n't", " not")\
                    .replace("what's", "what is").replace("it's", "it is")\
                    .replace("'ve", " have").replace("i'm", "i am").replace("'re", " are")\
                    .replace("he's", "he is").replace("she's", "she is").replace("'s", " own")\
                   .replace("%", " percent ").replace("₹", " rupee ").replace("$", " dollar ")\
                    .replace("€", " euro ").replace("'ll", " will")
            text = re.sub(r"([0-9]+)000000", r"\1m", text)
            text = re.sub(r"([0-9]+)000", r"\1k", text)
            # nlp processing using spacy. We will use lemma as different forms of the same
            # word unnecessarily increase the feature size and create noise rather than adding
            # information
            tokens = nlp(text)
            text = ' '.join([t.lemma_ for t in tokens if t.lemma_ != '-PRON-' and \
                                            t.is_alpha and not t.is_digit and \
                                           not t.is punct and not t.is stop])
            return text
In [0]: | # Apply pre-processing and save
        data.question1=data.question1.apply(preprocess)
        data.question2=data.question2.apply(preprocess)
In [0]: | data['question_pair']=data.question1+' '+data.question2
In [0]: data.drop(columns=['question1', 'question2'],inplace=True)
In [0]: # data.to csv(data dir+'final data pp.csv',index=False)
In [0]: | data=pd.read_csv(data_dir+'final_data_pp.csv')
In [0]: # Split data and proceed for vectorization
```

```
In [0]: data.columns
Out[0]: Index(['is_duplicate', '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', 'freq_qid1', 'freq_qid2',
               'qllen', 'q2len', 'q1 n words', 'q2 n words', 'word Common',
               'word Total', 'word share', 'freq q1+q2', 'freq q1-q2',
               'question pair'],
              dtype='object')
In [0]: # Y data is the 'is duplicate'
        Y_data=data.is_duplicate.to numpy()
        # X data is all the features excluding 'is duplicate'
        X data=data.drop(columns=['is duplicate'])
In [0]: # Split in 70:30 ratio
        X train, X test, Y train, Y test = train test split(X data, Y data,
                                     stratify=Y data, test size=0.3,random state=1234)
In [0]: | tf idf vect = TfidfVectorizer(ngram range=(1,2), min df=5, max features=15000)
        tf idf vect.fit(X train.question pair)
        print("some sample features(unique words in the corpus)",
                                       tf_idf_vect.get_feature_names()[0:10])
        print('='*50)
        tfIdf_train = tf_idf_vect.transform(X train.question pair)
        tfIdf test = tf idf vect.transform(X test.question pair)
        print("the type of count vectorizer ",type(tfIdf_train))
        print("the shape of out text TFIDF vectorizer ",tfIdf_train.get_shape())
        print("the number of unique words including both unigrams and bigrams ",
                           tfIdf train.get shape()[1])
        some sample features(unique words in the corpus) ['00', '04', '10', '10 cgpa', '10 day', '10 favourite', '10 good', '10 hour', '10 kg', '10 million']
        the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
        the shape of out text TFIDF vectorizer (70000, 15000)
        the number of unique words including both unigrams and bigrams 15000
In [0]: # Drop the 'question pair' column
        X train.drop(columns=['question pair'],inplace=True)
        X_test.drop(columns=['question pair'],inplace=True)
In [0]: # Add the Tf-Idf vectors with the other features
        X train=hstack([X train.to sparse().astype(float),tfIdf train])
        X test=hstack([X test.to sparse().astype(float),tfIdf test])
```

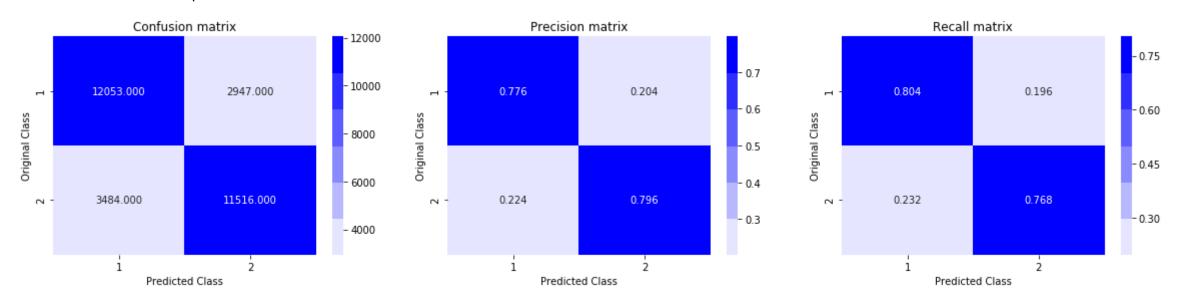
```
In [0]: # Using the classification code from above
        alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
        log error array=[]
        for i in alpha:
            print("Working for alpha : ",i)
            clf = SGDClassifier(alpha=i, penalty='l2', loss='log',
                                random state=1234, n jobs=-1)
            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)
            loss value=log loss(Y test, predict y, labels=clf.classes , eps=1e-15)
            log error array.append(loss value)
            print('For values of alpha = ', i, "The log loss is:",loss value)
        Working for alpha: 1e-05
        For values of alpha = 1e-05 The log loss is: 0.4427934371192924
        Working for alpha: 0.0001
        For values of alpha = 0.0001 The log loss is: 0.4263252404402409
        Working for alpha: 0.001
        For values of alpha = 0.001 The log loss is: 0.4423823907181991
        Working for alpha: 0.01
        For values of alpha = 0.01 The log loss is: 0.4739527428386096
        Working for alpha: 0.1
        For values of alpha = 0.1 The log loss is: 0.473400739483149
        Working for alpha: 1
        For values of alpha = 1 The log loss is: 0.5079527165965277
        Working for alpha: 10
        For values of alpha = 10 The log loss is: 0.5550171046260312
In [0]: # Best figures for 7k features
        # For values of alpha = 0.01 The log loss is: 0.45523614249492544
        # Best figures for 15k features
        # For values of alpha = 0.0001 The log loss is: 0.4263252404402409
        # Finally we use all features(21540)
        # For values of alpha = 1e-05 The log loss is: 0.4321301625022141
        # If we increase the max df to 10 and for all features (9900)
```

For values of alpha = 0.0001 The log loss is: 0.4363398372482077



```
In [0]: best_alpha = np.argmin(log_error_array)
        clf = SGDClassifier(alpha=alpha[best alpha], penalty='l2', loss='log',
                             random state=1234)
        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 loss(Y train, predict y,
                                      labels=clf.classes , eps=1e-15))
        predict y = sig clf.predict proba(X test)
        print('For values of best alpha = ', alpha[best_alpha],
               "The test log loss is: ", log loss(Y test, predict y,
                                      labels=clf.classes , eps=1e-15))
        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 = 0.0001 The train log loss is: 0.4310660274785347 For values of best alpha = 0.0001 The test log loss is: 0.4263252404402409 Total number of data points : 30000



In [0]: table.add_row(['Logistic Reg',' alpha = 0.0001', 'Train Log=0.43 Test Log=0.42'])
print(table)

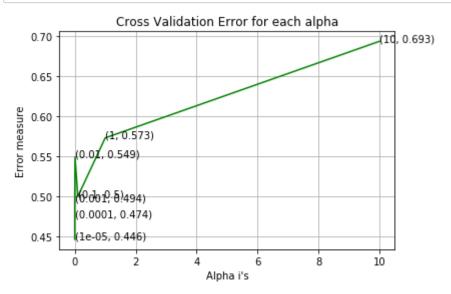
Model	Hyperparameters	+ Log_Loss +			
Logistic Reg	C = 0.0001	Train Log=0.43 Test Log=0.42			
Logistic Reg	alpha = 0.0001	Train Log=0.43 Test Log=0.42			

In [0]: # Lets go for Linear SVM now

```
In [0]: alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
        log_error array=[]
        for i in alpha:
            print("Working for alpha : ",i)
            clf = SGDClassifier(alpha=i, penalty='l1', loss='hinge',
                                random state=1234, n jobs=-1)
            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)
            loss value=log loss(Y test, predict y,labels=clf.classes , eps=1e-15)
            log error array.append(loss value)
            print('For values of alpha = ', i, "The log loss is:",loss_value)
        Working for alpha: 1e-05
        For values of alpha = 1e-05 The log loss is: 0.4464618542962933
        Working for alpha: 0.0001
        For values of alpha = 0.0001 The log loss is: 0.4737792548089313
        Working for alpha: 0.001
        For values of alpha = 0.001 The log loss is: 0.4936783681321137
        Working for alpha: 0.01
        For values of alpha = 0.01 The log loss is: 0.5489273580706926
        Working for alpha: 0.1
        For values of alpha = 0.1 The log loss is: 0.49973248365944906
        Working for alpha: 1
        For values of alpha = 1 The log loss is: 0.5727954914635746
        Working for alpha: 10
        For values of alpha = 10 The log loss is: 0.6931471805599453
In [0]: # Best figures for 15k features
        # For values of alpha = 1e-05 The log loss is: 0.4464618542962933
        # Finally we use all features(21540)
        # For values of alpha = 1e-05 The log loss is: 0.44670317676117144
        # If we increase the max_df to 10 and for all features(9900)
```

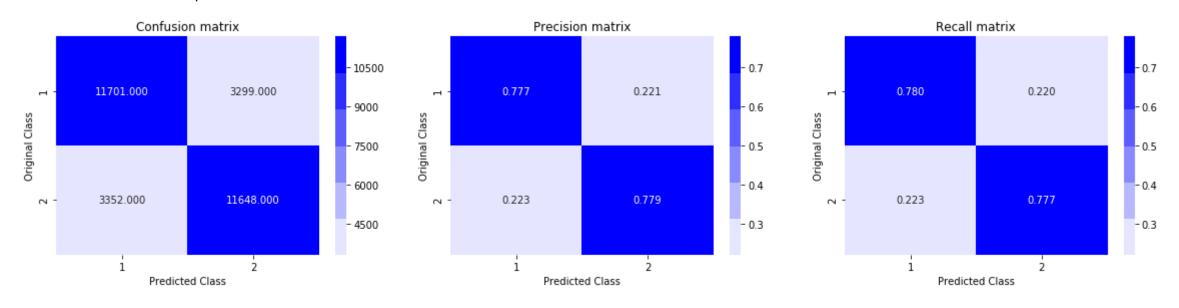
For values of alpha = 1e-05 The log loss is: 0.46394818579735897

```
In [0]: 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()
```



```
In [0]: best_alpha = np.argmin(log_error_array)
        clf = SGDClassifier(alpha=alpha[best alpha], penalty='l1', loss='hinge',
                             random state=1234, n jobs=-1)
        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 loss(Y train, predict y,
                                     labels=clf.classes , eps=1e-15))
        predict y = sig clf.predict proba(X test)
        print('For values of best alpha = ', alpha[best_alpha],
               "The test log loss is: ", log loss(Y test, predict y,
                                     labels=clf.classes , eps=1e-15))
        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: 0.45074353360243696 For values of best alpha = 1e-05 The test log loss is: 0.4464618542962933 Total number of data points : 30000



In [0]: table.add_row(['Simple SVM',' alpha = 0.0001', 'Train Log=0.45 Test Log=0.44'])
print(table)

Model	Hyperparameters	Log_Loss	İ
Logistic Reg	alpha = 0.0001	Train Log=0.43 Test Log=0.42	
Simple SVM	alpha = 0.0001	Train Log=0.45 Test Log=0.44	

In [0]: # Now for working on XGBoost we have to reload the old data. For that we re-run the # code from the above cells

In [0]: from xgboost import XGBClassifier

```
In [7]: # !python -m spacy download en core web md
         Collecting en core web md==2.1.0 from https://github.com/explosion/spacy-models/releases/download/en core web md-2.1.0/en core web md-2.1.0.tar.gz#egg=en core web md==2.
        1.0
           Downloading https://github.com/explosion/spacy-models/releases/download/en core web md-2.1.0/en core web md-2.1.0.tar.gz (95.4MB)
                                               | 95.4MB 2.7MB/s
         Building wheels for collected packages: en-core-web-md
           Building wheel for en-core-web-md (setup.py) ... done
           Created wheel for en-core-web-md: filename=en core web md-2.1.0-cp36-none-any.whl size=97126237 sha256=0ad61ae499ad1fd2c54494dfbfeeb6ade526f92b83ce57211ac6425bae7ce4b9
           Stored in directory: /tmp/pip-ephem-wheel-cache-8jw cg4l/wheels/c1/2c/5f/fd7f3ec336bf97b0809c86264d2831c5dfb00fc2e239d1bb01
         Successfully built en-core-web-md
         Installing collected packages: en-core-web-md
         Successfully installed en-core-web-md-2.1.0
         ✓ Download and installation successful
         You can now load the model via spacy.load('en core web md')
In [0]: | import en_core_web_md
         from bs4 import BeautifulSoup
         from tqdm import tqdm
         import nltk
In [0]: # Read dataframe and filter balanced data. Using only 50k
         # due to resource constraints
         df = pd.read_csv(data_dir+"Quora/train.csv")
In [0]: | df = df[df.is_duplicate==0][:25000].append(df[df.is_duplicate==1][:25000])
         df = df.sample(frac=1).reset_index(drop=True)
In [11]: # nltk.download('stopwords')
         [nltk_data] Downloading package stopwords to /root/nltk_data...
         [nltk data] Unzipping corpora/stopwords.zip.
Out[11]: True
```

```
In [0]: SAFE DIV = 0.0001
          STOP WORDS = stopwords.words("english")
          def preprocess(x):
               x = str(x).lower()
               x = x.replace(",000,000", "m").replace(",000", "k").replace("'", "'")
                             .replace("'", "'").replace("won't", "will not")\
                             .replace("cannot", "can not").replace("can't", "can not")\
                             .replace("n't", " not").replace("what's", "what is")\
                             .replace("it's", "it is").replace("'ve", " have")\
                             .replace("i'm", "i am").replace("'re", " are")\
                             .replace("he's", "he is").replace("she's", "she is")\
                             .replace("'s", " own").replace("%", " percent ")\
                             .replace("₹", " rupee ").replace("$", " dollar ")\
.replace("€", " euro ").replace("'ll", " will")
               x = re.sub(r''([0-9]+)000000'', r''\setminus 1m'', x)
               x = re.sub(r''([0-9]+)000'', r''\setminus 1k'', x)
               pattern = re.compile('\W')
               if type(x) == type(''):
                   x = re.sub(pattern, ' ', x)
               if type(x) == type(''):
                   example1 = BeautifulSoup(x)
                   x = example1.get_text().strip()
               return x
In [0]: | df['question1'] = df['question1'].apply(lambda x: preprocess(x))
          df['question2'] = df['question2'].apply(lambda x: preprocess(x))
In [14]: | df = df.drop(columns=['id', 'qid1', 'qid2'])
          df.head()
Out[14]:
                                          question1
                                                                               question2 is_duplicate
                  what is the most popular app at your school
           0
                                                    what is the most popular app at your university
                                                                                                0
                is world war 3 on the way with the us elections
                                                                      is world war 3 coming
                                                                                                1
               can a boy join the indian armed forces after a...
                                                             how can i join indian armed forces
                                                                                                1
           3
                      was the isc 2016 accounts paper easy
                                                          was the isc accounts 2016 paper tough
                                                                                                1
                                                                                                0
           4 what are some good ways to insult a dartmouth ... what makes some students unable to fit in at d...
In [0]: | df['question_pair'] = df.question1+' '+df.question2
          df = df.drop(columns=['question1', 'question2'])
In [0]: X data=np.array(df.question pair.tolist())
          y data=np.array(df.is duplicate.tolist())
In [0]: from sklearn.feature extraction.text import TfidfVectorizer
In [0]: X_train, X_test, y_train, y_test = train_test_split(X_data, y_data,
                                      test size=0.30, stratify=y data,random state =1234)
```

```
In [0]: tfidf = TfidfVectorizer(lowercase=False, )
        tfidf.fit transform(X train)
        # dict key:word and value:tf-idf score
        word2tfidf = dict(zip(tfidf.get feature names(), tfidf.idf ))
In [0]: # en vectors web md, having 300 vectors.
        nlp = en core web md.load()
        # nlp = spacy.load('en_core_web_sm')
        vecs1 = []
        for qp in X train:
          doc1 = nlp(str(qp).strip())
          mean_vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
          for i, word1 in enumerate(doc1):
              # word2vec
              vec1 = word1.vector
              # fetch df score
              try:
                  idf = word2tfidf[str(word1)]
              except:
                  idf = 0
              # compute final vec
              mean vec1[i] += vec1 * idf
          mean_vec1 = mean_vec1.mean(axis=0)
          vecs1.append(mean_vec1)
In [0]: vecs2=[]
        for qp in X test:
          doc2 = nlp(str(qp).strip())
          mean_vec2 = np.zeros([len(doc2), len(doc2[0].vector)])
          for i, word2 in enumerate(doc2):
              # word2vec
              vec2 = word2.vector
              # fetch df score
                  idf = word2tfidf[str(word2)]
              except:
                  #print word
                  idf = 0
              # compute final vec
              mean vec2[i] += vec2 * idf
          mean_vec2 = mean_vec2.mean(axis=0)
          vecs2.append(mean vec2)
In [0]: | X_train=np.array(vecs1)
        X test=np.array(vecs2)
```

```
In [38]: | clf = XGBClassifier(random state=1234)
         params = {
         # 'gamma': [0, 0.25, 0.5, 1.0],
         # 'reg lambda': [0.1, 1.0, 5.0, 10.0],
         # 'eta' : [0.02, 0.2],
         # 'max depth' : [5, 15, 30, 50, 75, 100, 125, 150],
         # 'min samples leaf' : [1, 3, 5, 10, 20, 50],
         # 'n estimators' : [50, 150, 300, 500]
         # 'eta' : [0.02],
         'max_depth' : [5, 15, 30, 50, 80],
          'min samples leaf' : [5, 10, 20, 30, 50],
         'n estimators' : [100, 150, 200, 400]
         # d train = xgb.DMatrix(X train, label=y train)
         # d_test = xgb.DMatrix(X_test, label=y_test)
         # watchlist = [(d train, 'train'), (d test, 'valid')]
         # bst = xgb.train(params, d_train, 400, watchlist, early_stopping_rounds=20,
                           verbose eval=10)
         split method = StratifiedKFold(n splits=3, shuffle = True, random state = 1234)
         randomSearch = RandomizedSearchCV(clf, params, n iter=10, n jobs=-1, verbose=3,
                         cv=split_method.split(X_train,y_train),
                       cv=3, return train score=True,
                       scoring='neg_log_loss', refit=False, random_state=1234)
         randomSearch.fit(X_train,y_train)
         # xgdmat = xgb.DMatrix(X_train,y_train)
         # predict y = bst.predict(d test)
         # print("The test log loss is:",log_loss(y_test, predict_y, eps=1e-15))
         Fitting 3 folds for each of 10 candidates, totalling 30 fits
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
         [Parallel(n_jobs=-1)]: Done 30 out of 30 | elapsed: 272.8min finished
Out[38]: RandomizedSearchCV(cv=3, error_score='raise-deprecating',
                            estimator=XGBClassifier(base score=0.5, booster='gbtree',
                                                    colsample_bylevel=1,
                                                    colsample bynode=1,
                                                    colsample bytree=1, gamma=0,
                                                    learning rate=0.1, max delta step=0,
                                                    max depth=3, min child weight=1,
                                                    missing=None, n_estimators=100,
                                                    n jobs=1, nthread=None,
```

objective='binary:logistic',
random_state=1234, reg_alpha=0,
reg_lambda=1, scale_pos_weight=1,
seed=None, silent=None, subsample=1,

'min_samples_leaf': [5, 10, 20, 30, 50], 'n estimators': [100, 150, 200, 400]},

verbosity=1),

param distributions={'max depth': [5, 15, 30, 50, 80],

pre_dispatch='2*n_jobs', random_state=1234, refit=False,
return train score=True, scoring='neg log loss', verbose=3)

iid='warn', n iter=10, n jobs=-1,

```
In [39]: print(randomSearch.best params )
         print(randomSearch.cv results ['mean train score'].mean())
         {'n estimators': 100, 'min samples leaf': 20, 'max depth': 50}
         -0.010713534025180634
In [0]: # We tweaked the XGBoost to include the sklearn-XGBClassifier flavour and also
         # because it is intuitive to make it work with RandomSearchCV. We initially
         # tried to get a hang of the hyperparamas by running on short data points and the
         # we tried to run on the full 100k datapoints using the hyper-params range we
         # set up. But even the Google Colab in GPU mode crashed, so we reduced the data
         # to 50k balanced points and finally after around 8+ hours we got the results.
         # The above code has the final set of hyperparams.
         # The detailed experiments :
In [0]: # randomSearch.best params # best params after randomized search
         # {'eta': 0.02, 'max depth': 5, 'min samples leaf': 20, 'n estimators': 200}
         # randomSearch.best params #100 points
         # print(randomSearch.best_params_) #500 points
         # print(randomSearch.best score )
         # {'n estimators': 50, 'min samples leaf': 3, 'max depth': 3, 'eta': 0.02}
         # -0.5017438927479089
         # print(randomSearch.best_params_) #500 points, with pruned hyperparams
         # print(randomSearch.best score )
         # {'n estimators': 100, 'min samples leaf': 70, 'max depth': 10, 'eta': 0.02}
         # -0.5701361708370969
         # print(randomSearch.best_params_)#5000 points
         # print(randomSearch.best score )
         # {'n estimators': 150, 'min samples leaf': 50, 'max depth': 3, 'eta': 0.02}
         # -0.37187250680599826
         # print(randomSearch.best_params_)
         # print(randomSearch.cv results ['mean test score'])
         # print(randomSearch.best score )
         # {'reg_lambda': 10.0, 'n_estimators': 100, 'min_samples_leaf': 20, 'max_depth': 20, 'gamma': 0.25, 'eta': 0.02}
         # [-0.54784296 -0.55312863 -0.54542933 -0.57557731 -0.53977786 -0.52132554
         # -0.53746365 -0.56679342 -0.5277555 -0.5277555 ]
         # -0.5213255383633077
         # print(randomSearch.best params )
         # print(randomSearch.cv results ['mean test score'])
         # print(randomSearch.best score )
         # {'reg_lambda': 10.0, 'n_estimators': 200, 'min_samples_leaf': 15, 'max_depth': 3, 'gamma': 0.5, 'eta': 0.02}
         # [-0.37403748 -0.37403748 -0.375991 -0.37579951 -0.38147701 -0.37183126
         # -0.37517306 -0.38735439 -0.37514236 -0.38105273]
         # -0.3718312576468452
         # print(randomSearch.best params )
         # print(randomSearch.cv results ['mean test score'])
         # print(randomSearch.best score )
         # {'n_estimators': 100, 'min_samples_leaf': 20, 'max_depth': 3, 'eta': 0.02}
         # [-0.61247562 -0.57013617 -0.58998491 -0.59483405 -0.5399712 -0.57013617
         # -0.57013617 -0.59483405 -0.57213978 -0.59523224]
         # -0.5399712001821027
```

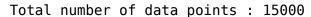
```
In [24]: | clf = XGBClassifier(random state=1234, max depth=50, min samples leaf=20,
                             n estimators=100)
         clf.fit(X train, y train)
Out[24]: XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
                      colsample bynode=1, colsample bytree=1, gamma=0,
                      learning rate=0.1, max delta step=0, max depth=50,
                      min child weight=1, min samples leaf=20, missing=None,
                      n estimators=100, n jobs=1, nthread=None,
                      objective='binary:logistic', random state=1234, reg alpha=0,
                      reg lambda=1, scale pos weight=1, seed=None, silent=None,
                      subsample=1, verbosity=1)
In [27]: clf = XGBClassifier(random state=1234, max depth=5, min samples leaf=20,
                             n estimators=200)
         clf.fit(X train, y train)
Out[27]: XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
                      colsample bynode=1, colsample bytree=1, gamma=0,
                      learning rate=0.1, max delta step=0, max depth=5,
                      min child weight=1, min samples leaf=20, missing=None,
                      n estimators=200, n jobs=1, nthread=None,
                      objective='binary:logistic', random state=1234, reg alpha=0,
                      reg_lambda=1, scale_pos weight=1, seed=None, silent=None,
                      subsample=1, verbosity=1)
In [25]: # This is result for the optimal params, not considering due to extreme overfitting
         predict trainy = clf.predict(X train)
         print("The train log loss is:",log loss(y train, predict trainy, eps=1e-15))
        The train log loss is: 0.0009868450283535956
In [28]: predict trainy = clf.predict(X train)
         print("The train log loss is:",log loss(y train, predict trainy, eps=1e-15))
        The train log loss is: 4.567060443449054
In [29]: predict testy = clf.predict(X test)
         print("The test log loss is:",log loss(y test, predict testy, eps=1e-15))
        The test log loss is: 10.421612181144269
In [40]: table.add_row(['XGBoost', 'max_depth=5, min_samples_leaf=20, n_estimators=200',
                  'Train Log=4.5 Test Log=10.4'])
         print(table)

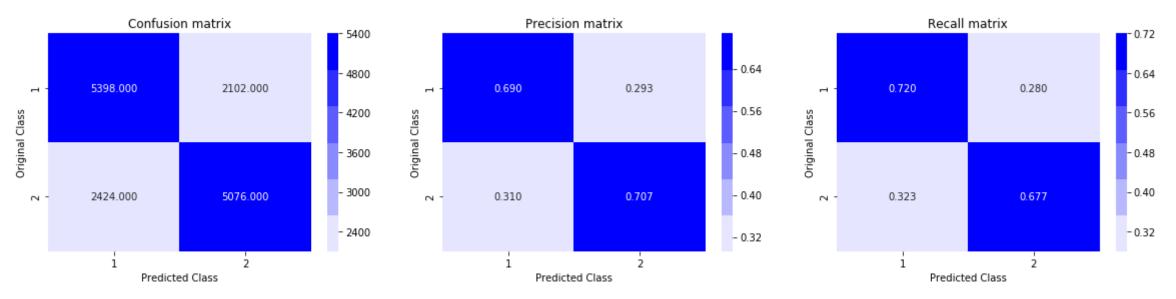
      Logistic Reg |
      alpha = 0.0001
      | Train Log=0.43 Test Log=0.42 |

      Simple SVM |
      alpha = 0.0001
      | Train Log=0.45 Test Log=0.44 |

           XGBoost | max_depth=5, min_samples_leaf=20, n_estimators=200 | Train Log=4.5 Test Log=10.4
```

In [43]: predict_testy =np.array(predict_testy>0.5,dtype=int)
print("Total number of data points :", len(predict_testy))
plot_confusion_matrix(y_test, predict_testy)





In [0]: ## Conclusions

- # So, in the end we figure out that the Logistic Regression comes out as the best
- # classifier so far, based on the given data points.
- # The Simple SVM is also close by, but both do not seem to improve much given the data
- # points we are using and the computing power we have.
- # Lastly, theoretical understanding tells us that the Randomforests should have performed
- # weel too, but it didn't come out well, given the hyperparameters and the data