```
In [2]:
```

```
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
import math
from sklearn.metrics import normalized mutual info score
from sklearn.ensemble import RandomForestClassifier
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
import spacy
from tqdm import tqdm
/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/p roject/six/).

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

4. Machine Learning Models

In [0]:

from google.colab import drive # drive.mount('/content/drive')

In [0]:

cd DONOR_CHOOSE_KNN/quora

4.1 Reading data from file and storing into sqi table

In [0]:

```
# #Creating db file from csv
# if not os.path.isfile('train.db'):
               disk_engine = create_engine('sqlite:///train.db')
              start = dt.datetime.now()
             chunksize = 180000
# j = 0
#
              index_start = 1
                for df in pd.read_csv('../input/quora/Quora/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_diff','mean_len','token_set_ratio','token_sort_ratio','fuzz_rati
o','fuzz_partial_ratio','longest_substr_ratio','freq_qid1','freq_qid2','q1len','q2len','q1_n_words','q2_n_words','word_Common','word_Tot
al','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','1
6_x','17_x','18_x','19_x','20_x','21_x','22_x','23_x','24_x','25_x','26_x','27_x','28_x','29_x','30_x','31_x','32_x','33_x','34_x','35_x','36_x',
37_x','38_x','39_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','78_x','70_x','70_x','71_x','72_x','73_x','74_x','75_x','76_x','77_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','78_x','
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','90_x','91_x','92_x','93_x','94_x','95_x','96_x','97_x','98_x','99_x','90_x','91_x','91_x','92_x','91_x','92_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x','91_x'
   x','100 x','101 x','102 x','103 x','104 x','105 x','106 x','107 x','108 x','109 x','110 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','131_x','132_x','133_x','13
4_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','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', 185\_x', 180\_x', 180_x', 180_
6\_x', 187\_x', 188\_x', 189\_x', 190\_x', 191\_x', 192\_x', 193\_x', 194\_x', 195\_x', 196\_x', 197\_x', 198\_x', 199\_x', 200\_x', 201\_x', 202\_x', 203\_x', 203_x', 203_x'
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','23
8_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','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','255_x','25_x','25_x','25_x','25_x','25_x','25_x','25_x','25_x','25_x','2
x','256_x','257_x','258_x','259_x','260_x','261_x','262_x','263_x','264_x','265_x','266_x','266_x','268_x','269_x','270_x','271_x','272_x',
273_x','274_x','275_x','276_x','277_x','278_x','279_x','280_x','281_x','282_x','283_x','284_x','285_x','286_x','287_x','288_x','289_x','29
0_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','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','308_x','
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_x','321_x','322_x','322_x','324_x',
325_x','326_x','327_x','328_x','329_x','330_x','331_x','332_x','333_x','334_x','335_x','336_x','337_x','338_x','339_x','340_x','341_x','34
2_x','343_x','344_x','345_x','346_x','347_x','348_x','349_x','350_x','351_x','352_x','353_x','354_x','355_x','356_x','356_x','358_x','359_x','359_x','358_x','359_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','358_x','
x','360_x','361_x','362_x','363_x','364_x','365_x','366_x','367_x','368_x','369_x','370_x','371_x','372_x','373_x','374_x','375_x','376_x',
377\_x', \\ 379\_x', \\ 380\_x', \\ 381\_x', \\ 382\_x', \\ 383\_x', \\ 0\_y', \\ 11\_y', \\ 12\_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', \\ 13\_y', \\ 14\_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','3
5_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','11
5_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','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','128_y','
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','146_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_y','161_y','162_y','163_y','164_y','165_y','166_y','16
 7_y','168_y','169_y','170_y','171_y','172_y','173_y','174_y','175_y','176_y','177_y','178_y','179_y','180_y','181_y','182_y','183_y','184_
y','185_y','186_y','187_y','188_y','189_y','190_y','191_y','192_y','193_y','194_y','195_y','196_y','197_y','198_y','198_y','200_y','201_y'
202_y','203_y','204_y','205_y','206_y','207_y','208_y','209_y','210_y','211_y','212_y','213_y','214_y','215_y','216_y','216_y','218_y','218_y','21
9_y','220_y','221_y','222_y','223_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','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','266_y','267_y','268_y','269_y','270_y','27
1_y','272_y','273_y','274_y','275_y','276_y','277_y','278_y','280_y','281_y','282_y','283_y','284_y','285_y','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','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','32
3_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','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y','374_y'
5_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
```

In [0]:

```
## final_data = pd.read_csv('final_features.csv')
# import os
# for dirname, _, filenames in os.walk('/kaggle/input'):
# for filename in filenames:
# print(os.path.join(dirname, filename))
```

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 = 'train.db'
# conn_r = create_connection(read_db)
# checkTableExists(conn_r)
# conn_r.close()
```

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)
#
      conn_r.commit()
#
      conn_r.close()
```

In [7]:

```
# data = pd.read_csv('../input/quora/Quora/final_features.csv')
# data.head(5)
nlp data = pd.read csv('nlp features train.csv', encoding = "latin-1")
preprocessed_data = pd.read_csv("df_fe_without_preprocessing_train.csv",encoding = "latin-1")
preprocessed_data = preprocessed_data.drop(['qid1', 'qid2', 'question1', 'question2', 'is_duplicate'],axis=1)
# df1 = dfnlp.drop(['qid1','qid2','question1','question2'],axis=1)
# df2 = dfppro.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
# df3_q1['id']=df1['id']
# df3_q2['id']=df1['id']
# df1 = df1.merge(df2, on='id',how='left')
\# df2 = df3_q1.merge(df3_q2, on='id',how='left')
# result = df1.merge(df2, on='id',how='left')
# df3 = df.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
# df3_q1 = pd.DataFrame(df3.q1_feats_m.values.tolist(), index= df3.index)
# df3_q2 = pd.DataFrame(df3.q2_feats_m.values.tolist(), index= df3.index)
print(nlp_data.columns)
print(preprocessed_data.columns)
print("preprocessed_data shape =",preprocessed_data.shape)
print("nlp_data shape = ",nlp_data.shape)
Index(['id', 'qid1', 'qid2', 'question1', 'question2', 'is_duplicate',
```

In [8]:

```
nan_rows = nlp_data[nlp_data.isnull().any(1)]
print("Number of null entries = ", nan_rows.shape)

clean_nlp_data = nlp_data.dropna(axis = 0, how ='any')
print("Number of entries left after droping the null entries = ",clean_nlp_data.shape[0])
```

Number of null entries = (6, 21) Number of entries left after droping the null entries = 99994

In [0]:

```
data = clean_nlp_data.merge(preprocessed_data, on="id", how="left")
# remove the first row
# data.drop(data.index[0], inplace=True)
y_true = data['is_duplicate']
data.drop(['is_duplicate'], axis=1, inplace=True)
```

In [10]:

```
nan_rows = data[data.isnull().any(1)]
print("Number of null entries = ", nan_rows.shape)

data.head(5)
# print(type(data['cwc_min']))
# print(data['cwc_min'])
# data['cwc_min'].apply(pd.to_numeric)
#
```

Number of null entries = (0, 31)

Out[10]:

	id	qid1	qid2	question1	question2	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	ał
0	0	1	2	what is the step by step guide to invest in sh	what is the step by step guide to invest in sh	0.999980	0.833319	0.999983	0.999983	0.916659	0.785709	0.0	1.0	
1	1	3	4	what is the story of kohinoor koh i noor dia	what would happen if the indian government sto	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	1.0	
2	2	5	6	how can i increase the speed of my internet co	how can internet speed be increased by hacking	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	1.0	
3	3	7	8	why am i mentally very lonely how can i solve	find the remainder when math 23 24 math i	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	
4	4	9	10	which one dissolve in water quikly sugar	which fish would survive in salt water	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	1.0	

4.2 Converting strings to numerics

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:
# print(i)
# data[i] = data[i].apply(pd.to_numeric)
# print(i)
```

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)

In [0]:

```
X_train,X_test, y_train, y_test = train_test_split(data, y_true, stratify=y_true, test_size=0.3)
```

In [12]:

Tfidf weighted W2Vec

In [0]:

(69995,) (29999,)

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
# merge texts
questions = list(X_train['question1']) + list(X_train['question2'])

tfidf = TfidfVectorizer(lowercase=False, )
tfidf.fit_transform(questions)

# dict key:word and value:tf-idf score
word2tfidf = dict(zip(tfidf.get_feature_names(), tfidf.idf_))
```

```
In [14]:
# en_vectors_web_lg, which includes over 1 million unique vectors.
nlp = spacy.load('en_core_web_sm')
# FOR TRAIN DATA
vecs1 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu1 in tqdm(list(X train['question1'])):
  doc1 = nlp(qu1)
  # 384 is the number of dimensions of vectors
  mean_vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
  for word1 in doc1:
     # word2vec
     vec1 = word1.vector
     # fetch df score
     try:
       idf = word2tfidf[str(word1)]
     except:
       idf = 0
     # compute final vec
     mean vec1 += vec1 * idf
  mean_vec1 = mean_vec1.mean(axis=0)
  vecs1.append(mean_vec1)
X_train['q1_feats_m'] = list(vecs1)
            69995/69995 [11:38<00:00, 100.26it/s]
100%
In [15]:
X_train['q1_feats_m'].head(5)
Out[15]:
77387 [42.92952561378479, -78.06101938523352, 37.328...
34262 [66.40157455205917, -62.90219736099243, -3.168...
83765 [154.74325448274612, -31.549048513174057, -54....
        [68.17155885696411, -59.59435647726059, -51.83...
76827
94493 [118.61638343334198, -199.699702501297, -73.87...
Name: q1_feats_m, dtype: object
In [16]:
vecs2 = []
for qu2 in tqdm(list(X_train['question2'])):
  doc2 = nlp(qu2)
  mean_vec2 = np.zeros([len(doc2), len(doc2[0].vector)])
  for word2 in doc2:
     # word2vec
     vec2 = word2.vector
     # fetch df score
       idf = word2tfidf[str(word2)]
     except:
       #print word
       idf = 0
     # compute final vec
```

In [0]:

mean_vec2 += vec2 * idf

vecs2.append(mean_vec2)
X_train['q2_feats_m'] = list(vecs2)

mean_vec2 = mean_vec2.mean(axis=0)

69995/69995 [11:41<00:00, 99.80it/s]

```
# df3_q1 = pd.DataFrame(X_train.q1_feats_m.values.tolist(), index= X_train.index)
# df3_q2 = pd.DataFrame(X_train.q2_feats_m.values.tolist(), index= X_train.index)
```

```
In [18]:
```

```
Cut[18]:

77387 [89.03142619132996, -66.80487707257271, 18.497...
34262 [-58.02090382575989, 10.582061052322388, -93.9...
83765 [238.44520664215088, 53.86913478374481, -70.78...
76827 [80.08975768089294, -58.981304690241814, -42.7...
94493 [220.2964512705803, -137.26451462507248, -85.9...
Name: q2_feats_m, dtype: object
```

FOR TEST DATA

In [19]:

```
# FOR TEST DATA
vecs1_test = []
# https://github.com/noamraph/tgdm
# tqdm is used to print the progress bar
for qu1 in tqdm(list(X_test['question1'])):
  doc1 = nlp(qu1)
  # 384 is the number of dimensions of vectors
  mean vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
  for word1 in doc1:
     # word2vec
     vec1 = word1.vector
     # fetch df score
     try:
       idf = word2tfidf[str(word1)]
     except:
       idf = 0
     # compute final vec
    mean vec1 += vec1 * idf
  mean vec1 = mean vec1.mean(axis=0)
  vecs1_test.append(mean_vec1)
X_test['q1_feats_m'] = list(vecs1_test)
            29999/29999 [04:58<00:00, 100.52it/s]
```

In [20]:

```
X_test['q1_feats_m'].head(5)
```

Out[20]:

```
22101 [17.958252295851707, -25.70195958018303, 24.60...
81113 [-46.77597823739052, 40.94902968406677, -82.79...
93300 [96.17097091674805, -127.29158794879913, -134....
35918 [108.213887155056, 21.325669050216675, -57.288...
94903 [101.91307735443115, -64.84906335175037, -28.6...
Name: q1_feats_m, dtype: object
```

In [21]:

```
vecs2_test = []
for qu2 in tqdm(list(X_test['question2'])):
    doc2 = nlp(qu2)
    mean_vec2 = np.zeros([len(doc2), len(doc2[0].vector)])
    for word2 in doc2:
        # word2vec
        vec2 = word2.vector
        # fetch df score
        try:
        idf = word2tfidf[str(word2)]
        except:
        #print word
        idf = 0
```

```
iat = 0
     # compute final vec
    mean vec2 += vec2 * idf
  mean_vec2 = mean_vec2.mean(axis=0)
  vecs2_test.append(mean_vec2)
X_test['q2_feats_m'] = list(vecs2_test)
            29999/29999 [04:59<00:00, 100.08it/s]
In [22]:
X_test['q2_feats_m'].head(5)
Out[22]:
22101
        [309.50440019369125, -130.29062724113464, 265....
81113
        [-16.74356174468994, 17.549556016921997, -54.0...
93300
        [138.9835479259491, -95.82764136791229, -158.8...
35918 [66.88981437683105, -30.132676362991333, -20.2...
94903 [64.071160197258, -69.28862392902374, -61.9866...
Name: q2_feats_m, dtype: object
In [0]:
df_train = X_train.drop(['qid1','qid2','question1','question2'],axis=1)
df_train_q1 = pd.DataFrame(X_train.q1_feats_m.values.tolist(), index= df_train.index)
df_train_q2 = pd.DataFrame(X_train.q2_feats_m.values.tolist(), index= df_train.index)
In [24]:
df_train_q1.head(1)
Out[24]:
                         1
                                             3
                                                        4
                                                                 5
                                                                                                                    10
                  78.061019 37.328049
                                      30.88724 52.762367 5.918803 37.552955 59.861208 1.327656 31.216255 24.102007 32.1914
1 rows × 96 columns
In [0]:
df_train_q1['id']=X_train['id']
df_train_q2['id']=X_train['id']
# df1 = df1.merge(df2, on='id',how='left') # X_train
df2_train = df_train_q1.merge(df_train_q2 , on='id', how='left') # df_train_q1 + df_train_q2
X_train_final = X_train.merge(df2_train, on = 'id', how ='left')
In [26]:
nan rows = X_train_final[X_train_final.isnull().any(1)]
print("Number of null entries = ", nan_rows.shape)
X_train_final.drop(['id','qid1','qid2','question1','question2'],axis=1,inplace=True)
X_train_final.head(5)
Number of null entries = (0, 225)
Out[26]:
    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
   0.999967 0.999967 0.999975 0.799984 0.999986 0.874989
                                                                      1.0
                                                                                    1.0
                                                                                                1.0
                                                                                                          7.5
                                                                                                                         100
 0.0
                                                                                    0.0
                                                                                                3.0
                                                                                                          7.5
                                                                                                                          39
```

cwc min 0.199998	cwc max 0.142856	csc min 0.666656	csc max 0.444440	ctc min 0.352939	ctc_max 0.222221	last_word_eq 0.0	first_word_eq 1.0	abs_len_diff 10.0	mean len 22.0	token_set_ratio
3 0.666644	0.399992	0.333328	0.249997	0.444440	0.307690	1.0	0.0	4.0	11.0	68
4 0.000000	0.000000	0.499992	0.428565	0.199999	0.166666	0.0	0.0	3.0	16.5	36
rows × 220) columns									
]										
1 [0]:	df tost – V	tost dron	/[ˈaid1' ˈaid	NO! !au octiv	n1! kulod	tion2'],axis=1)				
f_test_q1 =	pd.DataFr	ame(X_te	st.q1_feats	_m.value	s.tolist(), ir	ndex= df_test.ii ndex= df_test.ii				
n [0]:										
f_test_q1['id f_test_q2['id : df1 = df1.r f2_test = d (_test_final	d']=X_test[' merge(df2, f_test_q1.r	id'] on='id',ho nerge(df_t	est_q2, o	n= <mark>'id</mark> ', how		lf_train_q1 + di	^t _train_q2			
n [0]:										
(_test_final. (_train_final										
n [59]:										
_train_final	.head(1)									
out[59]:										
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
0.999967	0.999967	0.999975	n 79998 <i>4</i>							
			0.733304	0.999986	0.874989	1.0	1.0	1.0	7.5	100
rows × 218	3 columns		0.733304	0.999986	0.874989	1.0	1.0	1.0	7.5	100
rows × 218	columns		0.733304	0.999986	0.874989	1.0	1.0	1.0	7.5	
rows × 218	3 columns		0.733304	0.999986	0.874989	1.0	1.0	1.0	7.5	
 n [30]: an_rows = rint("Numbe	X_test_fina er of null er drop(['id','q	ntries = ", r	inal.isnull() nan_rows.:	.any(1)] shape)		1.0 inplace= True)	1.0	1.0	7.5	
n [30]: an_rows = rint("Number of the standard	X_test_fina er of null er drop(['id','q head(5)	ntries = ", r id1','qid2',	inal.isnull() nan_rows.:	.any(1)] shape)			1.0	1.0	7.5	100
[30]: an_rows = rint("Numbe (_test_final. (_test_final.	X_test_fina er of null er drop(['id','q head(5)	ntries = ", r id1','qid2',	inal.isnull() nan_rows.:	.any(1)] shape)			1.0	1.0	7.5	
n [30]: an_rows = rint("Numbe (_test_final. (_test_final. lumber of near the content o	X_test_fina er of null er drop(['id','q head(5) ull entries =	ntries = ", r id1','qid2', = (0, 223)	inal.isnull() nan_rows.: 'question1	a.any(1)] shape) ,' <mark>question</mark>	2 '],axis=1,	inplace= True)				
n [30]: an_rows = rint("Numbe (_test_final. (_test_final. lumber of near the content o	X_test_fina er of null er drop(['id','q head(5) ull entries =	ntries = ", r id1','qid2', = (0, 223) csc_min	inal.isnull() nan_rows.: 'question1	a.any(1)] shape) ','question ctc_min	2'],axis=1,	inplace= True)				
n [30]: an_rows = rint("Number Lest_final. Lest_final. lumber of no	X_test_fina er of null er drop(['id','q head(5) ull entries = cwc_max 0.076922	csc_min 0.461535	inal.isnull() nan_rows.: 'question1 csc_max	ctc_min	2'],axis=1, ctc_max 0.189189	inplace= True)	first_word_eq	abs_len_diff	mean_len	token_set_ratio

0.0 0.0

6.0 10.0

73

3 0.999967 0.499992 0.249994 0.166664 0.571420 0.307690

```
        cwc
        max
        csc
        min
        csc
        max
        ctc
        min
        ctc
        max
        last_word_eq
        first_word_eq
        abs_len_diff
        mean_len
        token_set_ratio

        0.999980
        0.999900
        0.249994
        0.999983
        0.666659
        1.0
        0.0
        3.0
        7.5
        100

    cwc_min
0.999980
5 rows × 218 columns
In [0]:
# print(type(X_train_final))
# print(type(X_test_final))
In [0]:
# print("Number of data points in train data:",X_train.shape)
# print("Number of data points in test data :",X_test.shape)
In [49]:
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: 0.6274305307521966 Class 1: 0.37256946924780343
----- Distribution of output variable in test data -----
Class 0: 0.3725457515250508 Class 1: 0.3725457515250508
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 corresonds 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')
```

```
pit.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.ylabel('Original Class')
plt.title("Recall matrix")
```

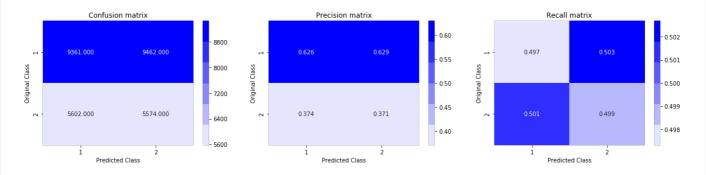
4.4 Building a random model (Finding worst-case log-loss)

In [51]:

```
# 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 0.8899443787399149



In [32]:

```
# y_train = y_train.tolist()
# y_test = y_test.tolist()
# type(y_train),type(y_test),type(X_train_final),type(X_test_final)
X_train_final.head(5)
```

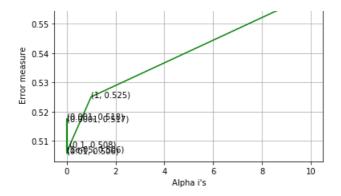
Out[32]:

	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
0	0.999967	0.999967	0.999975	0.799984	0.999986	0.874989	1.0	1.0	1.0	7.5	100
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	3.0	7.5	39
2	0.199998	0.142856	0.666656	0.444440	0.352939	0.222221	0.0	1.0	10.0	22.0	51
3	0.666644	0.399992	0.333328	0.249997	0.444440	0.307690	1.0	0.0	4.0	11.0	68
4	0.000000	0.000000	0.499992	0.428565	0.199999	0.166666	0.0	0.0	3.0	16.5	36

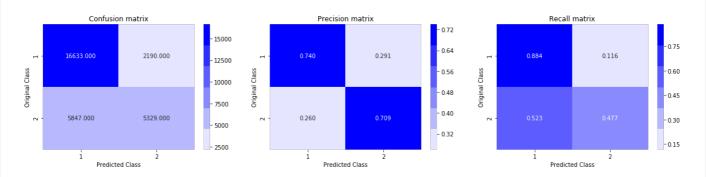
4.4 Logistic Regression with hyperparameter tuning

In [53]:

```
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_final, y_train)
  sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
  sig_clf.fit(X_train_final, y_train)
  predict_y = sig_clf.predict_proba(X_test_final)
  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.arid()
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 final, y train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_final, y_train)
predict_y = sig_clf.predict_proba(X_train_final)
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-1
5))
predict_y = sig_clf.predict_proba(X_test_final)
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: 0.5063727374740048
For values of alpha = 0.0001 The log loss is: 0.5167159185514054
For values of alpha = 0.001 The log loss is: 0.5176136436939562
For values of alpha = 0.01 The log loss is: 0.5057223026944383
For values of alpha = 0.1 The log loss is: 0.508105471628662
For values of alpha = 1 The log loss is: 0.5250693289796764
For values of alpha = 10 The log loss is: 0.5599229563483208
```



For values of best alpha = 0.01 The train log loss is: 0.5046804357200726 For values of best alpha = 0.01 The test log loss is: 0.5057223026944383 Total number of data points: 29999



4.5 Linear SVM with hyperparameter tuning

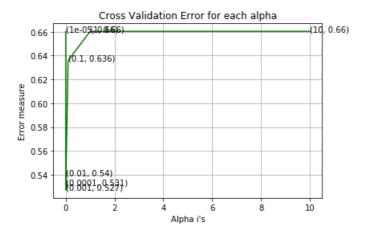
In [54]:

```
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 final, y train)
  sig clf = CalibratedClassifierCV(clf, method="sigmoid")
  sig_clf.fit(X_train_final, y_train)
  predict_y = sig_clf.predict_proba(X_test_final)
  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.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
```

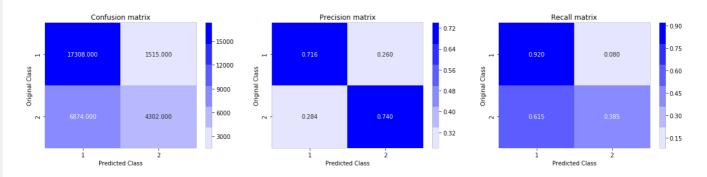
```
best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge', random_state=42)
clf.fit(X_train_final, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_final, y_train)

predict_y = sig_clf.predict_proba(X_train_final)
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-1
5))
predict_y = sig_clf.predict_proba(X_test_final)
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: 0.6602966866509733
For values of alpha = 0.0001 The log loss is: 0.5314219356432783
For values of alpha = 0.001 The log loss is: 0.5273670365703893
For values of alpha = 0.01 The log loss is: 0.5397009610152068
For values of alpha = 0.1 The log loss is: 0.635886855424519
For values of alpha = 1 The log loss is: 0.6602966866509733
For values of alpha = 10 The log loss is: 0.6602966866509733



For values of best alpha = 0.001 The train log loss is: 0.5243945761542032 For values of best alpha = 0.001 The test log loss is: 0.5273670365703893 Total number of data points: 29999



4.6 XGBoost

In [55]:

```
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_final, label=y_train)
d_test = xgb.DMatrix(X_test_final, 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_final,y_train)
predict y = bst.predict(d test)
print("The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
[0] train-logloss:0.685498 valid-logloss:0.685682
Multiple eval metrics have been passed: 'valid-logloss' will be used for early stopping.
Will train until valid-logloss hasn't improved in 20 rounds.
[10] train-logloss:0.623831 valid-logloss:0.62429
[20] train-logloss:0.578631 valid-logloss:0.579297
[30] train-logloss:0.544742 valid-logloss:0.545435
[40] train-logloss:0.518342 valid-logloss:0.519185
[50] train-logloss:0.497807 valid-logloss:0.49875
[60] train-logloss: 0.481548 valid-logloss: 0.482633
[70] train-logloss: 0.468331 valid-logloss: 0.469568
[80] train-logloss: 0.457864 valid-logloss: 0.459311
[90] train-logloss: 0.449296 valid-logloss: 0.450815
[100] train-logloss:0.442168 valid-logloss:0.443801
[110] train-logloss:0.435876 valid-logloss:0.43767
[120] train-logloss:0.430517 valid-logloss:0.432278
[130] train-logloss:0.426018 valid-logloss:0.427905
[140] train-logloss:0.422194 valid-logloss:0.424166
[150] train-logloss:0.418956 valid-logloss:0.421139
[160] train-logloss:0.416271 valid-logloss:0.418558
[170] train-logloss:0.413808 valid-logloss:0.416208
[180] train-logloss:0.411563 valid-logloss:0.414119
[190] train-logloss:0.409571 valid-logloss:0.412271
[200] train-logloss: 0.407646 valid-logloss: 0.410499
[210] train-logloss:0.405749 valid-logloss:0.40876
[220] train-logloss:0.404282 valid-logloss:0.40745
[230] train-logloss:0.402488 valid-logloss:0.405832
[240] train-logloss:0.400895 valid-logloss:0.404464
[250] train-logloss:0.399381 valid-logloss:0.403186
[260] train-logloss:0.397842 valid-logloss:0.401811
[270] train-logloss:0.396337 valid-logloss:0.400536
[280] train-logloss:0.394913 valid-logloss:0.39942
[290] train-logloss:0.393505 valid-logloss:0.398252
```

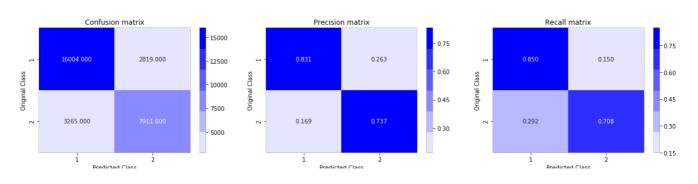
[399] train-logloss:0.381667 valid-logloss:0.389374 The test log loss is: 0.38937737766138825

In [56]:

```
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)
```

[300] train-logloss:0.3922 valid-logloss:0.397225 [310] train-logloss:0.390965 valid-logloss:0.396271 [320] train-logloss:0.389736 valid-logloss:0.395303 [330] train-logloss:0.388481 valid-logloss:0.394327 [340] train-logloss:0.387476 valid-logloss:0.39356 [350] train-logloss:0.386395 valid-logloss:0.39274 [360] train-logloss:0.385402 valid-logloss:0.391996 [370] train-logloss:0.384382 valid-logloss:0.391239 [380] train-logloss:0.383396 valid-logloss:0.390574 [390] train-logloss:0.382493 valid-logloss:0.389941

Total number of data points: 29999



Freducted class Freducted class

5. Assignments

- 1. Try out models (Logistic regression, Linear-SVM) with simple TF-IDF vectors instead of TD_IDF weighted word2Vec.
- 2. Hyperparameter tune XgBoost using RandomSearch to reduce the log-loss.

Simple Tfidf

In [33]:

data.head(5)

Out[33]:

	i	id	qid1	qid2	question1	question2	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	ał
	0	0	1	2	what is the step by step guide to invest in sh	what is the step by step guide to invest in sh	0.999980	0.833319	0.999983	0.999983	0.916659	0.785709	0.0	1.0	
	1	1	3	4	what is the story of kohinoor koh i noor dia	what would happen if the indian government sto	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	1.0	
	2	2	5	6	how can i increase the speed of my internet co	how can internet speed be increased by hacking	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	1.0	
	3	3	7	8	why am i mentally very lonely how can i solve	find the remainder when math 23 24 math i	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	
	4	4	9	10	which one dissolve in water quikly sugar salt	which fish would survive in salt water	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	1.0	
4															Þ

In [0]:

```
##final_data.head(5)
#nlp_data = pd.read_csv('../input/quora/Quora/nlp_features_train.csv', encoding = 'latin-1')
#nlp_data.columns
```

In [0]:

In [36]:

```
\label{eq:data_drop} $$ $  \text{data.drop}(['id','qid1', 'qid2', 'question1', 'question2'], axis=1, inplace=True) $$ $  \text{data.head}(5) $$
```

Out[36]:

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

0	OV9999180	Ø%833949	C.99 9 960	C9999988	00946819	@.tc 8 57108	last_word_@Q	first_word_ <u>req</u>	abs_len_ d iff	mean1le0	token_set_r atio
1	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	1.0	5.0	12.5	86
2	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	1.0	4.0	12.0	63
3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	2.0	12.0	28
4	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	1.0	6.0	10.0	67
4											<u>,</u>

splitting of data for tfidf

In [0]:

 $X_train_tdif, X_test_tdif, y_train_tdif, y_test_tdif = train_test_split(data, y_true, stratify=y_true, test_size=0.3)$

In [40]:

print(X_train_tdif.shape)
print(X_test_tdif.shape)
print(y_train_tdif.shape)
print(y_test_tdif.shape)

(69995, 27) (29999, 27) (69995,) (29999,)

TFIDF Vectorization

In [41]:

vectorizer_tfidf_question_1 = TfidfVectorizer()

X_train_question_tfidf = vectorizer_tfidf_question_1.fit_transform(X_train_tdif['question'])

X_test_question_tfidf = vectorizer_tfidf_question_1.transform(X_test_tdif['question'])

print("Shape of X_train_question_1_tfidf matrix",X_train_question_tfidf.shape)

print("Shape of X_test_question_1_tfidf matrix",X_test_question_tfidf.shape)

Shape of X_train_question_1_tfidf matrix (69995, 39173) Shape of X_test_question_1_tfidf matrix (29999, 39173)

In [0]:

X_train_tdif.drop(['question'],axis=1,inplace=**True**)
X_test_tdif.drop(['question'],axis=1,inplace=**True**)

```
In [0]:

# X_test_tdif.head(1)

In [48]:

print(type(X_train_tdif))
print(type(X_train_tdif.values))
print(X_train_tdif.values)
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'numpy.ndarray'>
[[0.2857102 0.24999688 0.44443951 ... 0.18181818 2.
                                                               1
               0.49999167 ... 0.10714286 3.
       0.
                                             1.
[0.74998125\ 0.74998125\ 0.99996667\ ...\ 0.42857143\ 2.
[0.599988 0.49999167 0.
                                       2.
                                               0.
                              ... 0.
[0.66664445 0.399992 0.499975 ... 0.23076923 6.
                                                       4.
                                                             ]
               0.33332778 ... 0.05555556 2.
```

In [0]:

print()

```
from scipy.sparse import csr_matrix, hstack
Xtr = csr_matrix(X_train_tdif.values)
Xte = csr_matrix(X_test_tdif.values)
```

stacking the data

In [0]:

```
X_tr_final = hstack((Xtr,X_train_question_tfidf)).tocsr()
X_te_final = hstack((Xte,X_test_question_tfidf)).tocsr()
```

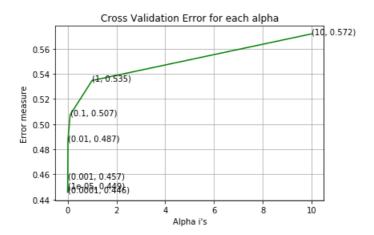
logistic regression

In [51]:

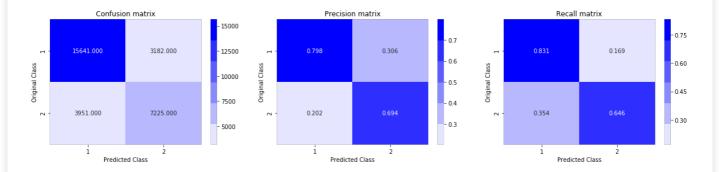
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
log_error_array=[]
for i in alpha:
  clf = SGDClassifier(alpha=i, penalty='l2', loss='log', class_weight='balanced', random_state=42)
  clf.fit(X_tr_final, y_train_tdif)
  sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
  sig_clf.fit(X_tr_final, y_train_tdif)
  predict y = sig clf.predict proba(X te final)
  log_error_array.append(log_loss(y_test_tdif, predict_y, labels=clf.classes_, eps=1e-15))
  print('For values of alpha = ', i, "The log loss is:",log_loss(y_test_tdif, 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.arid()
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',class_weight='balanced', random_state=42)
clf.fit(X tr final, y train tdif)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_tr_final, y_train_tdif)
predict_y = sig_clf.predict_proba(X_tr_final)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train_tdif, predict_y, labels=clf.classes_, eps=
predict v = sig clf.predict proba(X te final)
```

```
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test_tdif, predict_y, labels=clf.classes_, eps=1
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points:", len(predicted y))
plot_confusion_matrix(y_test_tdif, predicted_y)
```

For values of alpha = 1e-05 The log loss is: 0.4490815726865206 For values of alpha = 0.0001 The log loss is: 0.44567587708209017 For values of alpha = 0.001 The log loss is: 0.45681719091051576 For values of alpha = 0.01 The log loss is: 0.4866837089216423 For values of alpha = 0.1 The log loss is: 0.5072952038448704 For values of alpha = 1 The log loss is: 0.5346835943548855 For values of alpha = 10 The log loss is: 0.5718005542194372



For values of best alpha = 0.0001 The train log loss is: 0.4476527789934901 For values of best alpha = 0.0001 The test log loss is: 0.44567587708209017 Total number of data points: 29999



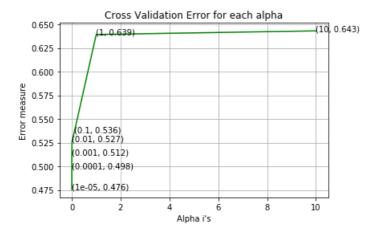
SVM

In [52]:

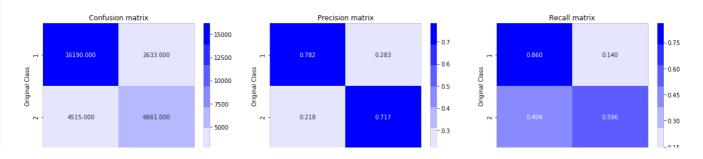
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, 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='11', loss='hinge', random_state=42)
  clf.fit(X tr final, y train tdif)
  sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
  sig_clf.fit(X_tr_final, y_train_tdif)
  predict y = sig clf.predict proba(X te final)
  log_error_array.append(log_loss(y_test_tdif, predict_y, labels=clf.classes_, eps=1e-15))
  print('For values of alpha = ', i, "The log loss is:",log_loss(y_test_tdif, 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 tr final, y train tdif)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig clf.fit(X tr final, y train tdif)
predict_y = sig_clf.predict_proba(X_tr_final)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train_tdif, predict_y, labels=clf.classes_, eps=
1e-15))
predict_y = sig_clf.predict_proba(X_te_final)
print('For values of best alpha = ', alpha[best alpha], "The test log loss is:",log loss(y test tdif, predict y, labels=clf.classes , eps=1
e-15))
predicted y =np.argmax(predict y,axis=1)
print("Total number of data points :", len(predicted y))
plot_confusion_matrix(y_test_tdif, predicted_y)
```

For values of alpha = 1e-05 The log loss is: 0.4756269340349187
For values of alpha = 0.0001 The log loss is: 0.4975739112080212
For values of alpha = 0.001 The log loss is: 0.5120498927141428
For values of alpha = 0.01 The log loss is: 0.5266907873108821
For values of alpha = 0.1 The log loss is: 0.5359308131261725
For values of alpha = 1 The log loss is: 0.6392545439398802
For values of alpha = 10 The log loss is: 0.643123379432156



For values of best alpha = 1e-05 The train log loss is: 0.47345498999409064 For values of best alpha = 1e-05 The test log loss is: 0.4756269340349187 Total number of data points: 29999



. 2 1 2 1 2 Predicted Class Predicted Class Predicted Class

XGBOOST

In [0]:

```
#For memory issue batch wise prediction

def batch_predict(clf, data):

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class

# not the predicted outputs

y_data_pred = []

tr_loop = data.shape[0] - data.shape[0]%1000

# consider you X_tr shape is 49041, then your tr_loop will be 49041 - 49041%1000 = 49000

# in this for loop we will iterate unti the last 1000 multiplier

for i in range(0, tr_loop, 1000):

y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])

# we will be predicting for the last data points

if data.shape[0]%1000 !=0:

y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])

return y_data_pred
```

Hyperparameter tunning on Tfidf Weighted W2Vec data

In [54]:

```
# Please write all the code with proper documentation
# Selecting the best alpha using RnadomSearch
#selecting the hyperparameter using RandomSearch
from scipy.stats import randint as sp_randint
import time
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
start_time = time.clock()
xg_clf = XGBClassifier()
parameters = {'n_estimators':sp_randint(5, 1000), 'max_depth': sp_randint(1, 10)}
clf_xg_1 = RandomizedSearchCV(xg_clf, parameters, cv=3, scoring='neg_log_loss',n_jobs= -1,verbose=10,return_train_score=True
clf_xg_1.fit(X_train_final, y_train)
max_depth_list = list(clf_xg_1.cv_results_['param_max_depth'].data)
n_estimator_list = list(clf_xg_1.cv_results_['param_n_estimators'].data)
neg_log_loss = clf_xg_1.cv_results_['mean_test_score']
print("Max Depth = ",max_depth_list)
print("Number of estimators = ",n estimator list)
print("Negative log loss = ",neg log loss)
for i in range(len(max depth list)):
  print("for n estimators =", n estimator list[i], "and max depth = ", max depth list[i])
  print("neg log loss= ",neg_log_loss[i] )
best_alpha = np.argmax(neg_log_loss)
print("best log loss= ",neg_log_loss[best_alpha])
print("best n_estimators and max_depth = ",n_estimator_list[best_alpha], and max_depth_list[best_alpha])
# print('Time took for preprocessing the text:',time.clock() - start_time, "seconds")
```

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 1 tasks | elapsed: 2.5min

[Parallel(n_jobs=-1)]: Done 4 tasks | elapsed: 5.4min

[Parallel(n_jobs=-1)]: Done 9 tasks | elapsed: 69.9min

[Parallel(n_jobs=-1)]: Done 14 tasks | elapsed: 133.3min

[Parallel(n_jobs=-1)]: Done 21 tasks | elapsed: 177.3min

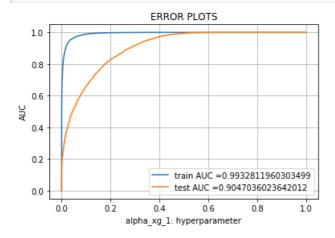
[Parallel(n_jobs=-1)]: Done 30 out of 30 | elapsed: 226.9min finished
```

```
Max Depth = [1, 3, 8, 9, 9, 2, 8, 1, 2, 5]
Number of estimators = [380, 162, 618, 857, 119, 667, 472, 636, 960, 419]
Negative log loss = [-0.41214218 -0.38656689 -0.39808985 -0.43323535 -0.36838166 -0.38090659
```

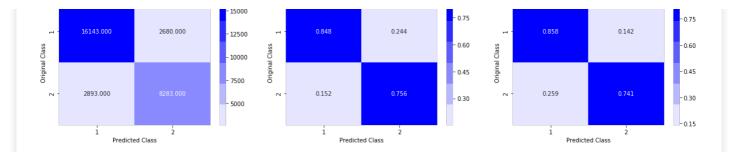
```
-0.38476648 -0.40503909 -0.37854222 -0.3697411 ]
for n estimators = 380 and max depth = 1
neg log loss= -0.4121421777177348
for n estimators = 162 and max depth = 3
neg log loss= -0.3865668930337774
for n estimators = 618 and max depth = 8
neg log loss= -0.3980898469159556
for n estimators = 857 and max depth = 9
neg log loss= -0.43323534852275714
for n estimators = 119 and max depth = 9
neg log loss= -0.3683816604810309
for n estimators = 667 and max depth = 2
neg log loss= -0.38090658675171485
for n_estimators = 472 and max depth = 8
neg log loss= -0.3847664757467235
for n estimators = 636 and max depth = 1
neg log loss= -0.40503908974339614
for n estimators = 960 and max depth = 2
neg log loss= -0.37854222184091546
for n estimators = 419 and max depth = 5
neg log loss= -0.3697411000230001
best log loss= -0.3683816604810309
best n_estimators and max_depth = 119 and 9
```

In [57]:

```
n_estimators = 119
max depth = 9
xg clf 1 = XGBClassifier(max depth = max depth, n estimators = n estimators, n jobs=1)
xg_clf_1.fit(X_train_final, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs
y_train_pred_xg_1 = batch_predict(xg_clf_1, X_train_final)
y test pred xg 1 = batch predict(xg clf 1, X test final)
train_fpr_xg_1, train_tpr_xg_1, tr_thresholds_xg_1 = roc_curve(y_train, y_train_pred_xg_1)
test fpr xg 1, test tpr xg 1, te thresholds xg 1 = roc curve(y test, y test pred xg 1)
plt.plot(train_fpr_xg_1, train_tpr_xg_1, label="train AUC ="+str(auc(train_fpr_xg_1, train_tpr_xg_1)))
plt.plot(test_fpr_xg_1, test_tpr_xg_1, label="test AUC ="+str(auc(test_fpr_xg_1, test_tpr_xg_1)))
plt.legend()
plt.xlabel("alpha_xg_1: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
print("Confsion matrix, precision, recall plots")
predicted_y =np.array(np.array(y_test_pred_xg_1)>0.5,dtype=int)
print("Total number of data points :", len(predicted_y))
plot confusion matrix(y test, predicted y)
```



Confsion matrix, precision, recall plots Total number of data points: 29999



In [60]:

```
predict_y = xg_clf_1.predict_proba(X_train_final)
# log_loss/
print('For values of best alpha = ', n_estimator_list[best_alpha], 'Max_depth= ',max_depth_list[best_alpha], "The train log loss is:",log
_loss(y_train, predict_y, labels=xg_clf_1.classes_, eps=1e-15))
predict_y = xg_clf_1.predict_proba(X_test_final)
print('For values of best alpha = ', n_estimator_list[best_alpha], 'Max_depth= ',max_depth_list[best_alpha], "The test log loss is:",log_l
oss(y_test, predict_y, labels=xg_clf_1.classes_, eps=1e-15))
# print(predict_y)
# print(type(predict_y))
```

For values of best alpha = 119 Max_depth= 9 The train log loss is: 0.1946405829977869 For values of best alpha = 119 Max_depth= 9 The test log loss is: 0.3642663376609388

In [0]:

Conclusions

Step by Step explanation for the solution

- 1. First I identify which type of machine learning problem this case study is.
- 2. Then I did the exploratory data analysis such as: Distribution of data points among output classes, Number of unique questions, Number of occurrences of each question etc.
- 3. Then I removed the null values.
- 4. Now before processing the text Extracted so basic feature which were as follows
 - A. Frequency of qid1's
 - B. Frequency of gid2's
 - C. Length of q1
 - D. Length of q2
 - E. Number of words in Question 1
 - F. Number of words in Question 2
 - G. Number of common unique words in Question 1 and Question 2
 - H. word Total in question 1 and question 2
 - I. word share between question 1 and question 2
 - J. sum total of frequency of qid1 and qid2
 - K. absolute difference of frequency of qid1 and qid2
- 5. Then I did some analysis on these extracted data
- 6. After that I did the preprocessing of the text data
- 7. Then I did some advanced feature extraction
- 8. Then I did some word cloud plot to know some frequent occusing words for both the class 0 and 1
- 9. Then visualiz the data using T-SNE
- 10. Then I vectorize the data using tfidf and tfidf weighted w2vec
- 11. After that I trained a random model to get the clue of the max value of the log-loss
- 12. Then I trained the logistic regression, linear SVM and XGBOOST models and calculated there precission and recall values for both class 0 and 1

Model comparision

In [62]: from prettytable import PrettyTable x = PrettyTable()x.field_names = ["MODEL","VECORIZATION","MIN_LOG_LOSS(test)","PRECISSION Class 1","PRECISSION Class 2","RECALL CI ass 1","RECALL Class 2"] x.add row(["LOGISTIC REGRESSION", 'weighted w2vec', 0.505,74.0,70.9,88.4,47.7]) x.add_row(["SVM", 'weighted w2vec', 0.527,71.6,74.0,92.0,38.5]) x.add_row(["XGBOOST (without parameter tunning)", 'weighted w2vec', 0.389,83.1,73.7,85.0,70.8]) MODEL | VECORIZATION | MIN_LOG_LOSS(test) | PRECISSION Class 1 | PRECISSION Class 2 | RECALL Class 1 | RECALL Class 2 | LOGISTIC REGRESSION | weighted w2vec | 0.505 | 74.0 | 70.9 | 88.4 | 47.7 | | SVM | weighted w2vec | 0.527 | 71.6 | 74.0 | 92.0 | 38.5 | | | XGBOOST (without parameter tunning) | weighted w2vec | 0.389 | 83.1 | 73.7 | 85.0 | 70.8 | +-----+----+ Model trained on simple tfidf with hyperparamter tunning for XGBOOST(trained on tfidf weighted w2vec) In [63]: y = PrettyTable() y.field names = ["MODEL","VECORIZATION","MIN LOG LOSS(test)","PRECISSION Class 1","PRECISSION Class 2","RECALL CI ass 1","RECALL Class 2"] y.add_row(["LOGISTIC REGRESSION", 'simple tfidf', 0.455,79.6,69.4,83.1,64.6]) y.add row(["SVM", 'simple tfidf', 0.475,78.2,71.7,86.0,59.6]) y.add_row(["XGBOOST(with parameter tunning on tfidf weighted w2vec vector)", 'weighted w2vec', 0.364,84.8,75.6,85.8,74.1]) print(y) | VECORIZATION | MIN LOG LOSS(test) | PRECISSION Class 1 | PRECISSION CI MODEL ass 2 | RECALL Class 1 | RECALL Class 2 | LOGISTIC REGRESSION | simple tfidf | 0.455 | 79.6 | 69.4 | 83.1 | 64.6 | simple tfidf | 0.475 | 78.2 | 71.7 | 86.0 | 59.6 | XGBOOST(with parameter tunning on tfidf weighted w2vec vector) | weighted w2vec | 0.364 | 84.8 | 85.8 | 74.1 | In [0]: