Quora Question pair Similarity Case study

In [1]:

```
# Importing all the neccessary libraries and packages

import warnings
warnings.filterwarnings("ignore")
import sqlite3
import csv
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os
import gc
import re
import distance
import math
import spacy

from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
from subprocess import check_output

from datetime import datetime as dt
from collections import Counter
from scipy.sparse import hstack
from mlxtend.classifier import StackingClassifier
from tqdm import tqdm
from datetime import datetime as dt

from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
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 sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
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 sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_curve, auc, roc_curve
```

Reading Data

In [2]:

```
df = pd.read_csv("train.csv")

print("Shape of dataframe : ", df.shape)
print("Total data points : ", df.shape[0])
```

```
Shape of dataframe :  (404290, 6)
Total data points :  404290
```

In [3]:

```
# Printing top Data points
df.head()
```

Out[3]:

	id	qid1	qid2	question1	question2	is_duplicate
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
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0
2	2	5	6	How can I increase the speed of my internet co...	How can Internet speed be increased by hacking...	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
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0

In [5]:

```
# Info of dataFrame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404290 entries, 0 to 404289
Data columns (total 6 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   id            404290 non-null  int64
 1   qid1          404290 non-null  int64
 2   qid2          404290 non-null  int64
 3   question1     404289 non-null  object
 4   question2     404288 non-null  object
 5   is_duplicate  404290 non-null  int64
dtypes: int64(4), object(2)
memory usage: 18.5+ MB
```

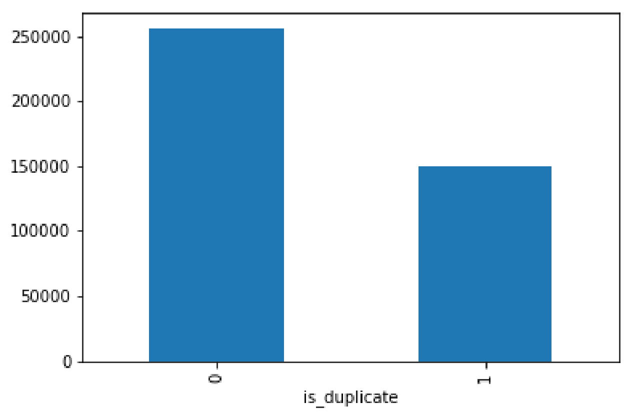
Distribution of data points among output classes

In [6]:

```
df.groupby("is_duplicate")['id'].count().plot.bar()
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x234522035f8>
```



In [11]:

```
print("Total number of question pairs for training :  {}".format(len(df)))
```

```
Total number of question pairs for training :  404290
```

In [10]:

```
print("Question pairs are not Similar (is_duplicate = 0) :  {}%".format(100 - round(df['is_duplicate'].mean()*100, 2)))
print("\nQuestion pairs are Similar (is_duplicate = 1) : {}%".format(round(df['is_duplicate'].mean()*100, 2)))
```

```
Question pairs are not Similar (is_duplicate = 0) :  63.08%

Question pairs are Similar (is_duplicate = 1) :  36.92%
```

Observations

- We can see that there are total 404290 datapoints and out of which 63.08% of datapoints are not similar and arounf 39.62% of data are similar.
- Means there are more number of datapoints that are not similar.

Number of unique questions

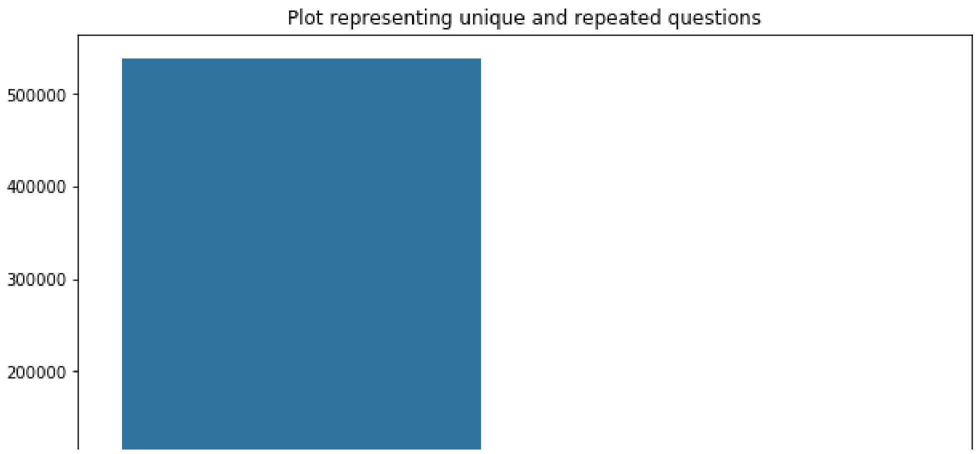
In [12]:

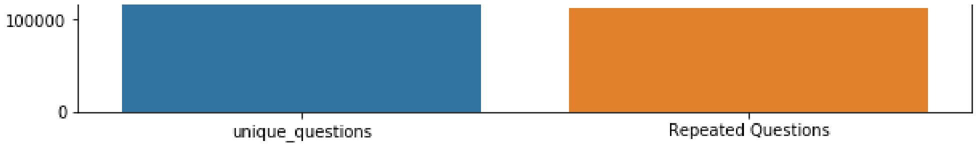
```
qids = pd.Series(df['qid1'].tolist() + df['qid2'].tolist())
unique_qs = len(np.unique(qids))
qs_morethan_onetime = np.sum(qids.value_counts() > 1)

print ("Total number of  Unique Questions are : {}".format(unique_qs))
print ("\nNumber of unique questions that appear more than one time : {} ({}%)".format(qs_morethan_onetime,qs_morethan_onetime/unique_qs*100))
print ("\nMax number of times a single question is repeated: {}".format(max(qids.value_counts())))


q_vals=qids.value_counts()
q_vals=q_vals.values
```

```
Total number of  Unique Questions are : 537933

Number of unique questions that appear more than one time : 111780 (20.77953945937505%)

Max number of times a single question is repeated: 157
```

In [13]:

```
x = ["unique_questions" , "Repeated Questions"]
y = [unique_qs , qs_morethan_onetime]

plt.figure(figsize=(10, 6))
plt.title("Plot representing unique and repeated questions")
sns.barplot(x,y)
plt.show()
```





Observations

- As seen from plot above we can see that the number of unique questions are far more than repeated questions
- There are total of 537933 unique questions
- There are total 111780 repeated questions

checking for Duplicates

In [14]:

```
#checking whether there are any repeated pair of questions

pair_duplicates = 
df[['qid1','qid2','is_duplicate']].groupby(['qid1','qid2']).count().reset_index()
print ("Number of duplicate questions : ", (pair_duplicates).shape[0] - df.shape[0])
```

```
Number of duplicate questions :  0
```

Observations

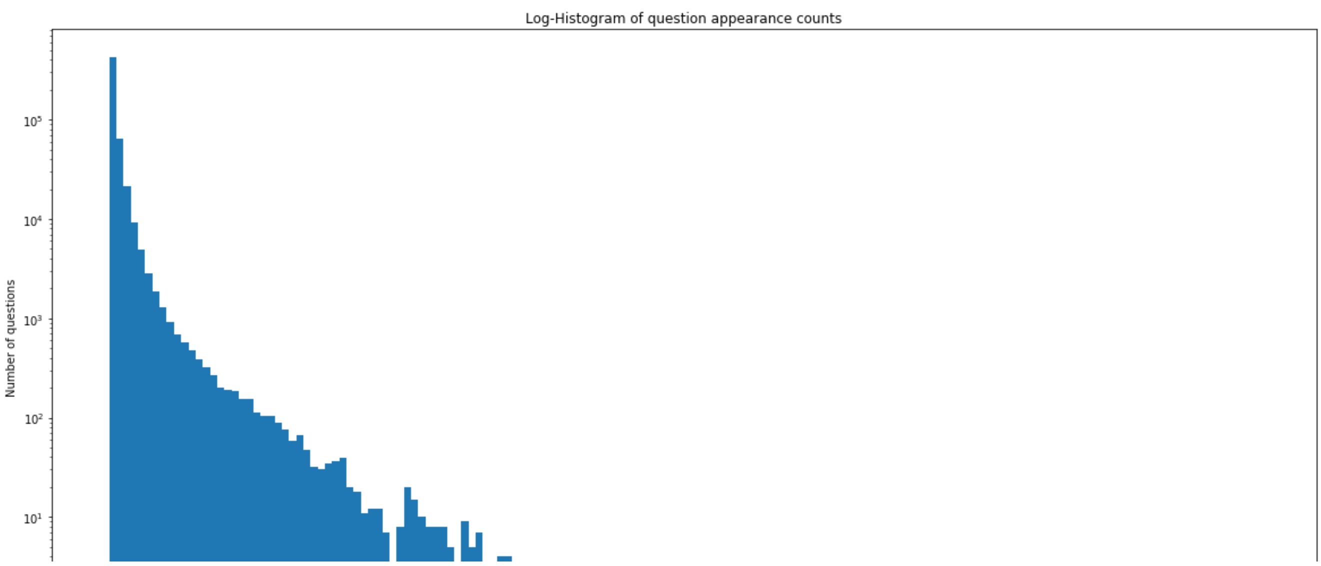
- There are no question pair which are repeated

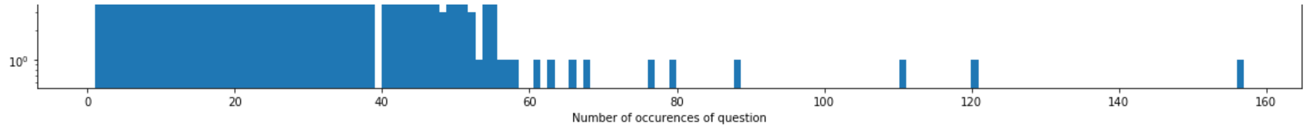
Number of occurrences of each question

In [15]:

```
plt.figure(figsize=(20, 10))
plt.hist(qids.value_counts(), bins=160)
plt.yscale('log', nonposy='clip')

plt.title('Log-Histogram of question appearance counts')
plt.xlabel('Number of occurences of question')
plt.ylabel('Number of questions')
print("Maximum number of times a single question is repeated: {}".format(max(qids.value_counts()))
)
```

```
Maximum number of times a single question is repeated: 157
```





Observations

- Most of Questions occur less than 60 times
- There is a question which occured 157 times

Checking for NULL values

In [16]:

```
#Checking whether there are any rows with null values

nan_rows = df[df.isnull().any(1)]
print(nan_rows)
```

```
            id    qid1    qid2                         question1  \
105780  105780  174363  174364    How can I develop android app?
201841  201841  303951  174364  How can I create an Android app?
363362  363362  493340  493341                               NaN

                                                question2  is_duplicate
105780                                                NaN             0
201841                                                NaN             0
363362  My Chinese name is Haichao Yu. What English na...             0
```

Observations

- There are some null values in our data
- We need to fill all the null values

In [17]:

```
# Filling the null values with ' '

df = df.fillna('')
nan_rows = df[df.isnull().any(1)]
print (nan_rows)
```

```
Empty DataFrame
Columns: [id, qid1, qid2, question1, question2, is_duplicate]
Index: []
```

Basic Feature Extraction (before cleaning)

Let us now construct a few features like:

- freq_qid1 = Frequency of qid1's
- freq_qid2 = Frequency of qid2's
- q1len = Length of q1
- q2len = Length of q2
- q1_n_words = Number of words in Question 1
- q2_n_words = Number of words in Question 2
- word_Common = (Number of common unique words in Question 1 and Question 2)
- word_Total =(Total num of words in Question 1 + Total num of words in Question 2)
- word_share = (word_common)/(word_Total)
- freq_q1+freq_q2 = sum total of frequency of qid1 and qid2
- freq_q1-freq_q2 = absolute difference of frequency of qid1 and qid2

In [18]:

```
if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    df = pd.read_csv("df_fe_without_preprocessing_train.csv",encoding='latin-1')
else:
    df['freq_qid1'] = df.groupby('qid1')['qid1'].transform('count')
    df['freq_qid2'] = df.groupby('qid2')['qid2'].transform('count')
    df['q1len'] = df['question1'].str.len()
    df['q2len'] = df['question2'].str.len()
    df['q1_n_words'] = df['question1'].apply(lambda row: len(row.split(" ")))
    df['q2_n_words'] = df['question2'].apply(lambda row: len(row.split(" ")))

    def normalized_word_Common(row):
        w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * len(w1 & w2)
    df['word_Common'] = df.apply(normalized_word_Common, axis=1)

    def normalized_word_Total(row):
        w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * (len(w1) + len(w2))
    df['word_Total'] = df.apply(normalized_word_Total, axis=1)

    def normalized_word_share(row):
        w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * len(w1 & w2)/(len(w1) + len(w2))
    df['word_share'] = df.apply(normalized_word_share, axis=1)

    df['freq_q1+q2'] = df['freq_qid1']+df['freq_qid2']
    df['freq_q1-q2'] = abs(df['freq_qid1']-df['freq_qid2'])

    df.to_csv("df_fe_without_preprocessing_train.csv", index=False)

df.head()
```

Out[18]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common
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	1	1	66	57	14	12	10.0
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0	4	1	51	88	8	13	4.0
2	2	5	6	How can I increase the speed of my internet co...	How can Internet speed be increased by hacking...	0	1	1	73	59	14	10	4.0
3	3	7	8	Why am I mentally very lonely? How can I solve...	Find the remainder when [math]23^{24}[/math] i...	0	1	1	50	65	11	9	0.0
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0	3	1	76	39	13	7	2.0

Analysis of some of the extracted features

In [19]:

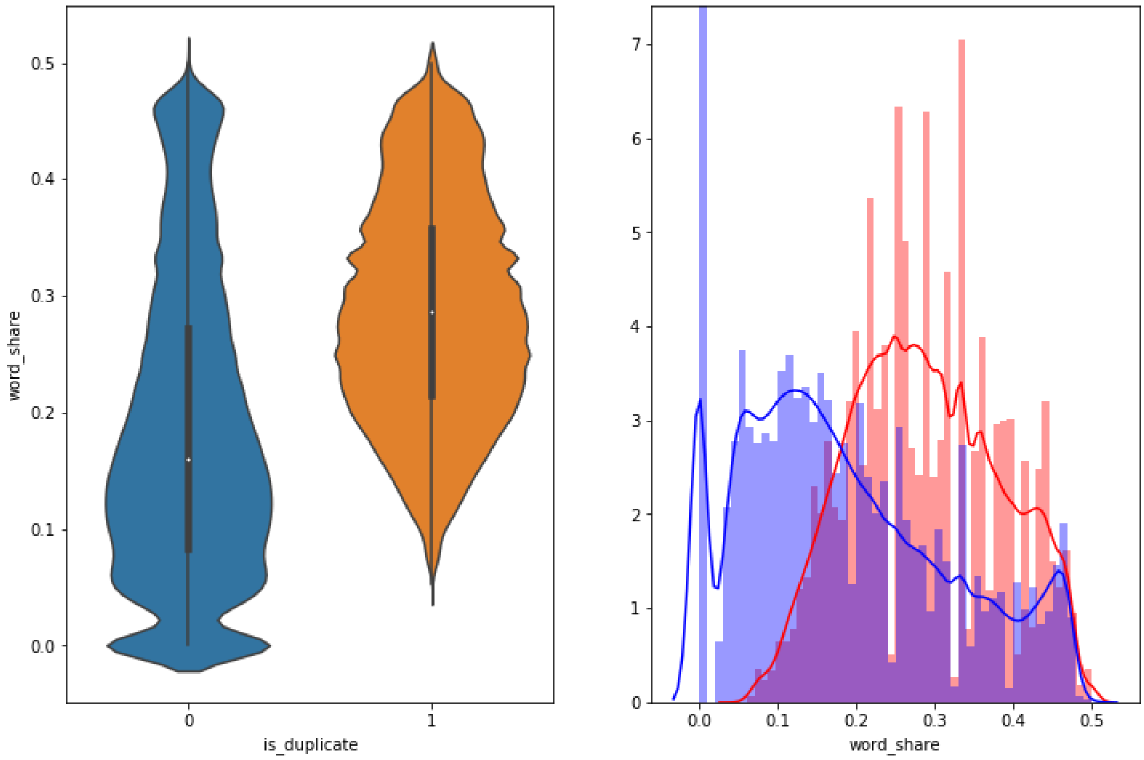
```
print ("Minimum length of the questions in question1 : " , min(df['q1_n_words']))
print ("Minimum length of the questions in question2 : " , min(df['q2_n_words']))

print ("Number of Questions with minimum length [question1] : ", df[df['q1_n_words']== 1].shape[0]
)
print ("Number of Questions with minimum length [question2] : ", df[df['q2_n_words']== 1].shape[0]
)
```

```
Minimum length of the questions in question1 :  1
Minimum length of the questions in question2 :  1
Number of Questions with minimum length [question1] :  67
Number of Questions with minimum length [question2] :  24
```

Feature: word_share

In [21]:

```
plt.figure(figsize=(12, 8))

plt.subplot(1,2,1)
sns.violinplot(x = 'is_duplicate', y = 'word_share', data = df[0:])
plt.subplot(1,2,2)
sns.distplot(df[df['is_duplicate'] == 1.0]['word_share'][0:] , label = "1", color = 'red')
sns.distplot(df[df['is_duplicate'] == 0.0]['word_share'][0:] , label = "0", color = 'blue' )
plt.show()
```



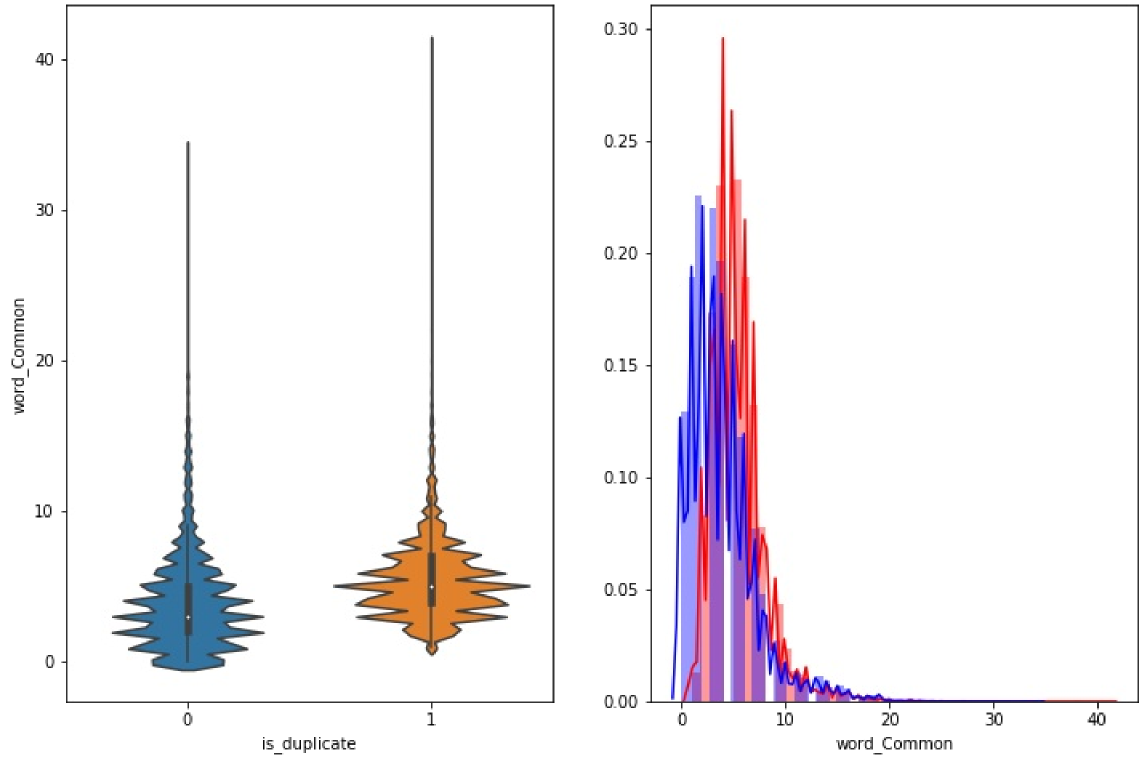
- The distributions for normalized word_share have some overlap on the far right-hand side, i.e., there are quite a lot of questions with high word similarity
- The average word share and Common no. of words of qid1 and qid2 is more when they are duplicate(Similar)

Feature: word_Common

In [22]:

```
plt.figure(figsize=(12, 8))

plt.subplot(1,2,1)
```

```
sns.violinplot(x = 'is_duplicate', y = 'word_Common', data = df[0:])

plt.subplot(1,2,2)
sns.distplot(df[df['is_duplicate'] == 1.0]['word_Common'][0:] , label = "1", color = 'red')
sns.distplot(df[df['is_duplicate'] == 0.0]['word_Common'][0:] , label = "0" , color = 'blue' )
plt.show()
```



- The distributions of the word_Common feature in similar and non-similar questions are highly overlapping.

Preprocessing of Text

In [24]:

```
import nltk
nltk.download('stopwords')

# To get the results in 4 decemal points
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'
", "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"\1m", x)
    x = re.sub(r"([0-9]+)000", r"\1k", x)

    porter = PorterStemmer()
    pattern = re.compile('\W')

    if type(x) == type(''):
        x = re.sub(pattern, ' ', x)

    if type(x) == type(''):
```

```
        x = porter.stem(x)
        example1 = BeautifulSoup(x)
        x = example1.get_text()

    return x
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\HP\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping corpora\stopwords.zip.
```

Advanced Feature Extraction (NLP and Fuzzy Features)

In [25]:

```
def get_token_features(q1, q2):
    token_features = [0.0]*10

    # Converting the Sentence into Tokens:
    q1_tokens = q1.split()
    q2_tokens = q2.split()

    if len(q1_tokens) == 0 or len(q2_tokens) == 0:
        return token_features
    # Get the non-stopwords in Questions
    q1_words = set([word for word in q1_tokens if word not in STOP_WORDS])
    q2_words = set([word for word in q2_tokens if word not in STOP_WORDS])

    #Get the stopwords in Questions
    q1_stops = set([word for word in q1_tokens if word in STOP_WORDS])
    q2_stops = set([word for word in q2_tokens if word in STOP_WORDS])

    # Get the common non-stopwords from Question pair
    common_word_count = len(q1_words.intersection(q2_words))

    # Get the common stopwords from Question pair
    common_stop_count = len(q1_stops.intersection(q2_stops))

    # Get the common Tokens from Question pair
    common_token_count = len(set(q1_tokens).intersection(set(q2_tokens)))


    token_features[0] = common_word_count / (min(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[1] = common_word_count / (max(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[2] = common_stop_count / (min(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[3] = common_stop_count / (max(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[4] = common_token_count / (min(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)
    token_features[5] = common_token_count / (max(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)

    # Last word of both question is same or not
    token_features[6] = int(q1_tokens[-1] == q2_tokens[-1])

    # First word of both question is same or not
    token_features[7] = int(q1_tokens[0] == q2_tokens[0])

    token_features[8] = abs(len(q1_tokens) - len(q2_tokens))

    #Average Token Length of both Questions
    token_features[9] = (len(q1_tokens) + len(q2_tokens))/2
    return token_features

# get the Longest Common sub string

def get_longest_substr_ratio(a, b):
    strs = list(distance.lcsubstrings(a, b))
    if len(strs) == 0:
        return 0
    else:
        return len(strs[0]) / (min(len(a), len(b)) + 1)

def extract_features(df):
    # preprocessing each question
    df["question1"] = df["question1"].fillna("").apply(preprocess)
    df["question2"] = df["question2"].fillna("").apply(preprocess)
```

```
    print("token features...")

    # Merging Features with dataset

    token_features = df.apply(lambda x: get_token_features(x["question1"], x["question2"]), axis=1)

    df["cwc_min"]       = list(map(lambda x: x[0], token_features))
    df["cwc_max"]       = list(map(lambda x: x[1], token_features))
    df["csc_min"]       = list(map(lambda x: x[2], token_features))
    df["csc_max"]       = list(map(lambda x: x[3], token_features))
    df["ctc_min"]       = list(map(lambda x: x[4], token_features))
    df["ctc_max"]       = list(map(lambda x: x[5], token_features))
    df["last_word_eq"]  = list(map(lambda x: x[6], token_features))
    df["first_word_eq"] = list(map(lambda x: x[7], token_features))
    df["abs_len_diff"]  = list(map(lambda x: x[8], token_features))
    df["mean_len"]      = list(map(lambda x: x[9], token_features))

    #Computing Fuzzy Features and Merging with Dataset

    # do read this blog: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
    # https://stackoverflow.com/questions/31806695/when-to-use-which-fuzz-function-to-compare-2-st
rings
    # https://github.com/seatgeek/fuzzywuzzy
    print("fuzzy features..")

    df["token_set_ratio"]       = df.apply(lambda x: fuzz.token_set_ratio(x["question1"],
x["question2"]), axis=1)
    # The token sort approach involves tokenizing the string in question, sorting the tokens alpha
betically, and
    # then joining them back into a string We then compare the transformed strings with a simple r
atio().
    df["token_sort_ratio"]      = df.apply(lambda x: fuzz.token_sort_ratio(x["question1"],
x["question2"]), axis=1)
    df["fuzz_ratio"]            = df.apply(lambda x: fuzz.QRatio(x["question1"], x["question2"]), ax
is=1)
    df["fuzz_partial_ratio"]    = df.apply(lambda x: fuzz.partial_ratio(x["question1"],
x["question2"]), axis=1)
    df["longest_substr_ratio"]  = df.apply(lambda x: get_longest_substr_ratio(x["question1"], x["qu
estion2"]), axis=1)
    return df
```

In [28]:

```
from fuzzywuzzy import fuzz
print("Extracting features for train:")
df = pd.read_csv("train.csv")
df = extract_features(df)
df.to_csv("nlp_features_train.csv", index=False)
df.head()
```

```
Extracting features for train:
token features...
fuzzy features..
```

Out[28]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	...	ctc_max	last_word_eq	first_word_
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	0.999980	0.833319	0.999983	0.999983	...	0.785709	0.0	
1	1	3	4	what is the story of kohinoor koh i noor dia...	what would happen if the indian government sto...	0	0.799984	0.399996	0.749981	0.599988	...	0.466664	0.0	
2	2	5	6	how can i increase the speed of my internet co...	how can internet speed be increased by hacking...	0	0.399992	0.333328	0.399992	0.249997	...	0.285712	0.0	
				why am i	find the									

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	...	ctc_max	last_word_eq	first_word_
3	3	7	8	mentally very lonely how can i solve...	find the remainder when math 23 24 math i...	0	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.0	
4	4	9	10	which one dissolve in water quikly sugar salt...	which fish would survive in salt water	0	0.399992	0.199998	0.999950	0.666644	...	0.307690	0.0	

5 rows × 21 columns

Analysis of extracted features

Plotting Word clouds

In [30]:

```
df_duplicate = df[df['is_duplicate'] == 1]
dfp_nonduplicate = df[df['is_duplicate'] == 0]

# Converting 2d array of q1 and q2 and flatten the array: like {{1,2},{3,4}} to {1,2,3,4}
p = np.dstack([df_duplicate["question1"], df_duplicate["question2"]]).flatten()
n = np.dstack([dfp_nonduplicate["question1"], dfp_nonduplicate["question2"]]).flatten()

print ("Number of data points in class 1 (duplicate pairs) :", len(p))
print ("Number of data points in class 0 (non duplicate pairs) :", len(n))

#Saving the np array into a text file
np.savetxt('train_p.txt', p, delimiter=' ', fmt='%s',encoding='utf-8')
np.savetxt('train_n.txt', n, delimiter=' ', fmt='%s',encoding='utf-8')
```

```
Number of data points in class 1 (duplicate pairs) : 298526
Number of data points in class 0 (non duplicate pairs) : 510054
```

In [32]:

```
# reading the text files and removing the Stop Words:
from wordcloud import WordCloud, STOPWORDS
from os import path
d = path.dirname('.')

textp_w = open(path.join(d, 'train_p.txt'), encoding="utf-8").read()
textn_w = open(path.join(d, 'train_n.txt'), encoding="utf-8").read()



stopwords = set(STOPWORDS)
stopwords.add("said")
stopwords.add("br")
stopwords.add(" ")
stopwords.remove("not")

stopwords.remove("no")
#stopwords.remove("good")
#stopwords.remove("love")
stopwords.remove("like")
#stopwords.remove("best")
#stopwords.remove("!")
print ("Total number of words in duplicate pair questions :",len(textp_w))
print ("Total number of words in non duplicate pair questions :",len(textn_w))
```

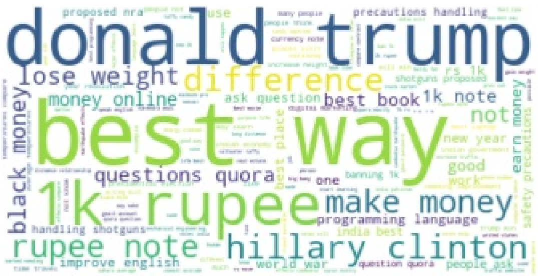
```
Total number of words in duplicate pair questions : 16109886
Total number of words in non duplicate pair questions : 33193067
```

In [33]:

```
wc = WordCloud(background_color="white", max_words=len(textp_w), stopwords=stopwords)
wc.generate(textp_w)
```

```
print ("Word Cloud for Duplicate Question pairs")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

```
Word Cloud for Duplicate Question pairs
```



Observations

- In Duplicate questions there are more occurance of words like donald, trump, best, waym rupee, etc.
- According to kaggle site this dataset was from june, 2017 and in january, 2017 trump was elected as president. So it is obvious that there may be more questions related to donald trump.

In [34]:

```
wc = WordCloud(background_color="white", max_words=len(textn_w),stopwords=stopwords)
# generate word cloud
wc.generate(textn_w)
print ("Word Cloud for non-Duplicate Question pairs:")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

```
Word Cloud for non-Duplicate Question pairs:
```

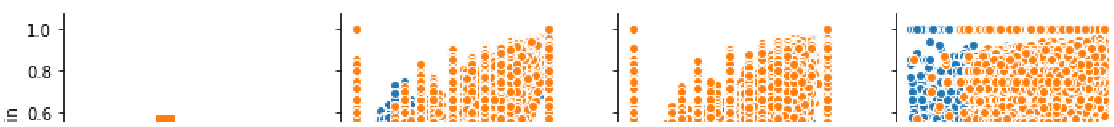
Observations

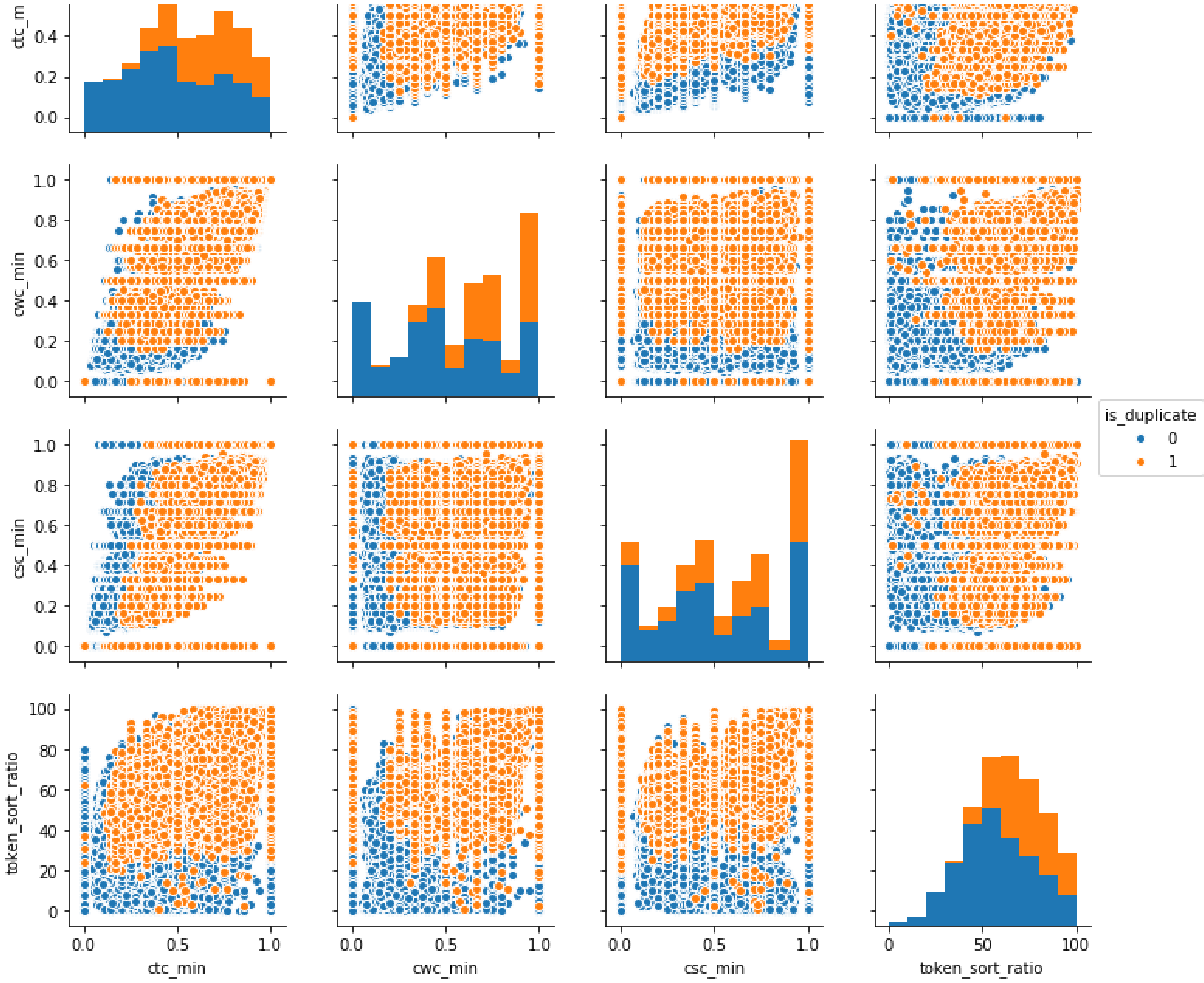
- For Non-duplicate questions thera are words like difference, not, will, india that occures more as compare to other words.

Pair plot of features ['ctc_min', 'cwc_min', 'csc_min', 'token_sort_ratio']

In [35]:

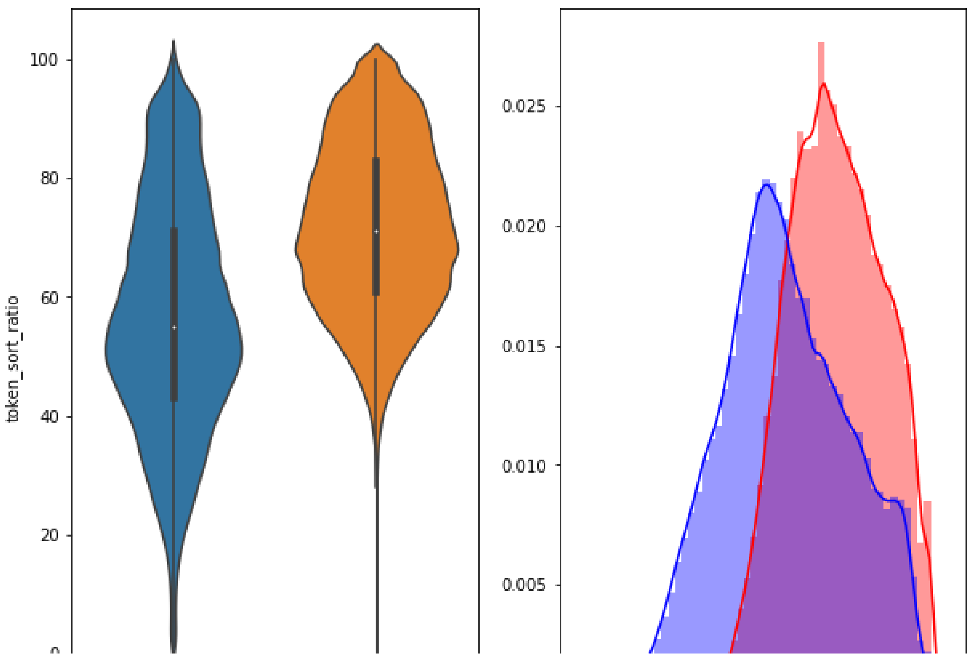
```
n = df.shape[0]
sns.pairplot(df[['ctc_min', 'cwc_min', 'csc_min', 'token_sort_ratio', 'is_duplicate']][0:n], hue='i
s_duplicate', vars=['ctc_min', 'cwc_min', 'csc_min', 'token_sort_ratio'])
plt.show()
```

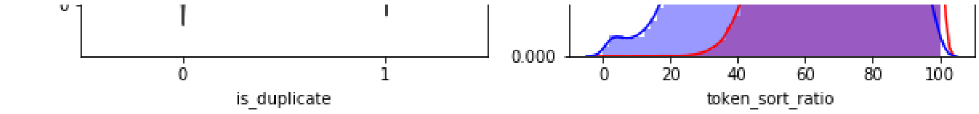




In [36]:

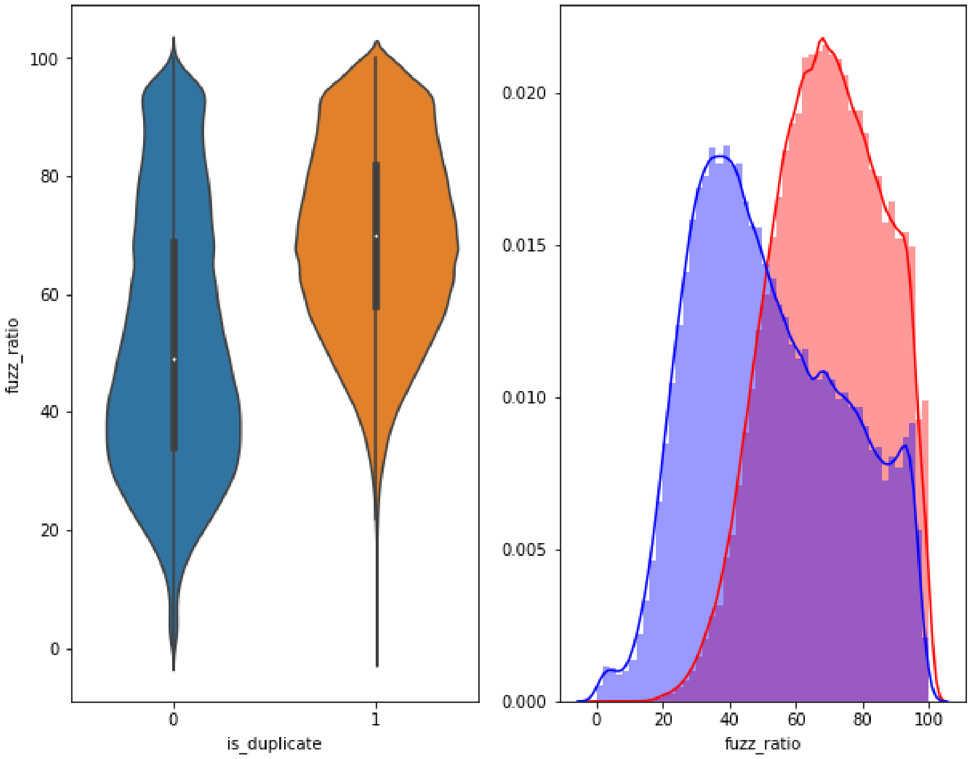
```
# Distribution of the token_sort_ratio
plt.figure(figsize=(10, 8))

plt.subplot(1,2,1)
sns.violinplot(x = 'is_duplicate', y = 'token_sort_ratio', data = df[0:] , )

plt.subplot(1,2,2)
sns.distplot(df[df['is_duplicate'] == 1.0]['token_sort_ratio'][0:] , label = "1", color = 'red')
sns.distplot(df[df['is_duplicate'] == 0.0]['token_sort_ratio'][0:] , label = "0" , color = 'blue' )
plt.show()
```





In [37]:

```
plt.figure(figsize=(10, 8))
plt.subplot(1,2,1)
sns.violinplot(x = 'is_duplicate', y = 'fuzz_ratio', data = df[0:] , )

plt.subplot(1,2,2)
sns.distplot(df[df['is_duplicate'] == 1.0]['fuzz_ratio'][0:] , label = "1", color = 'red')
sns.distplot(df[df['is_duplicate'] == 0.0]['fuzz_ratio'][0:] , label = "0" , color = 'blue' )
plt.show()
```



Visualization

In [38]:

```
from sklearn.preprocessing import MinMaxScaler

dfp_subsampled = df[0:5000]
X = MinMaxScaler().fit_transform(dfp_subsampled[['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']])
y = dfp_subsampled['is_duplicate'].values
```

In [39]:

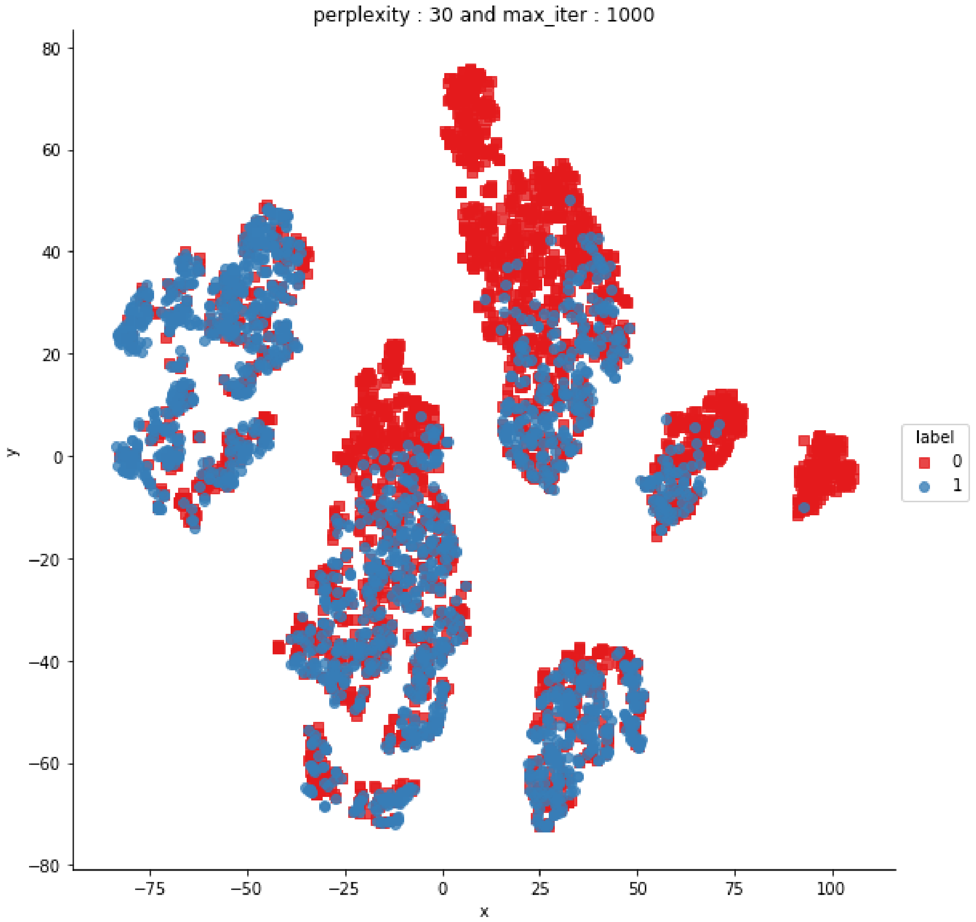
```
tsne2d = TSNE(n_components=2, init='random', random_state=101, method='barnes_hut', n_iter=1000, ve
rbose=2, angle=0.5).fit_transform(X)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.221s...
[t-SNE] Computed neighbors for 5000 samples in 0.849s...
[t-SNE] Computed conditional probabilities for sample 1000 / 5000
[t-SNE] Computed conditional probabilities for sample 2000 / 5000
[t-SNE] Computed conditional probabilities for sample 3000 / 5000
[t-SNE] Computed conditional probabilities for sample 4000 / 5000
[t-SNE] Computed conditional probabilities for sample 5000 / 5000
[t-SNE] Mean sigma: 0.130446
```

```
[t-SNE] Mean sigma: 0.150446
[t-SNE] Computed conditional probabilities in 0.623s
[t-SNE] Iteration 50: error = 81.3425446, gradient norm = 0.0466835 (50 iterations in 3.747s)
[t-SNE] Iteration 100: error = 70.6490860, gradient norm = 0.0087385 (50 iterations in 3.002s)
[t-SNE] Iteration 150: error = 68.9494553, gradient norm = 0.0055224 (50 iterations in 2.898s)
[t-SNE] Iteration 200: error = 68.1286011, gradient norm = 0.0044136 (50 iterations in 2.985s)
[t-SNE] Iteration 250: error = 67.6222382, gradient norm = 0.0040027 (50 iterations in 2.944s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.622238
[t-SNE] Iteration 300: error = 1.7932034, gradient norm = 0.0011886 (50 iterations in 3.104s)
[t-SNE] Iteration 350: error = 1.3933792, gradient norm = 0.0004814 (50 iterations in 3.061s)
[t-SNE] Iteration 400: error = 1.2277224, gradient norm = 0.0002778 (50 iterations in 3.078s)
[t-SNE] Iteration 450: error = 1.1382110, gradient norm = 0.0001874 (50 iterations in 3.041s)
[t-SNE] Iteration 500: error = 1.0834070, gradient norm = 0.0001423 (50 iterations in 3.062s)
[t-SNE] Iteration 550: error = 1.0472494, gradient norm = 0.0001143 (50 iterations in 3.111s)
[t-SNE] Iteration 600: error = 1.0229402, gradient norm = 0.0000992 (50 iterations in 3.063s)
[t-SNE] Iteration 650: error = 1.0064085, gradient norm = 0.0000887 (50 iterations in 3.096s)
[t-SNE] Iteration 700: error = 0.9950162, gradient norm = 0.0000781 (50 iterations in 3.090s)
[t-SNE] Iteration 750: error = 0.9863963, gradient norm = 0.0000739 (50 iterations in 3.105s)
[t-SNE] Iteration 800: error = 0.9797970, gradient norm = 0.0000678 (50 iterations in 3.170s)
[t-SNE] Iteration 850: error = 0.9741811, gradient norm = 0.0000626 (50 iterations in 3.107s)
[t-SNE] Iteration 900: error = 0.9692637, gradient norm = 0.0000620 (50 iterations in 3.183s)
[t-SNE] Iteration 950: error = 0.9652759, gradient norm = 0.0000559 (50 iterations in 3.113s)
[t-SNE] Iteration 1000: error = 0.9615012, gradient norm = 0.0000559 (50 iterations in 3.178s)
[t-SNE] KL divergence after 1000 iterations: 0.961501
```

In [40]:

```
df = pd.DataFrame({'x':tsne2d[:,0], 'y':tsne2d[:,1] ,'label':y})

# draw the plot in appropriate place in the grid
sns.lmplot(data=df, x='x', y='y', hue='label', fit_reg=False, size=8,palette="Set1",markers=['s','o
'])
plt.title("perplexity : {} and max_iter : {}".format(30, 1000))
plt.show()
```



In [41]:

```
tsne3d = TSNE(n_components=3, init='random', random_state=101, method='barnes_hut', n_iter=1000, ve
rbose=2, angle=0.5).fit_transform(X)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.029s...
[t-SNE] Computed neighbors for 5000 samples in 0.764s...
[t-SNE] Computed conditional probabilities for sample 1000 / 5000
[t-SNE] Computed conditional probabilities for sample 2000 / 5000
[t-SNE] Computed conditional probabilities for sample 3000 / 5000
[t-SNE] Computed conditional probabilities for sample 4000 / 5000
[t-SNE] Computed conditional probabilities for sample 5000 / 5000
[t-SNE] Mean sigma: 0.130446
[t-SNE] Computed conditional probabilities in 0.443s
[t-SNE] Iteration 50: error = 80.5739899, gradient norm = 0.0296227 (50 iterations in 9.567s)
[t-SNE] Iteration 100: error = 69.4174042, gradient norm = 0.0032491 (50 iterations in 5.637s)
[t-SNE] Iteration 150: error = 68.0031281, gradient norm = 0.0017356 (50 iterations in 5.279s)
[t-SNE] Iteration 200: error = 67.4430008, gradient norm = 0.0010772 (50 iterations in 5.410s)
[t-SNE] Iteration 250: error = 67.1309662, gradient norm = 0.0008710 (50 iterations in 5.289s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.130966
[t-SNE] Iteration 300: error = 1.5201368, gradient norm = 0.0007081 (50 iterations in 6.293s)
[t-SNE] Iteration 350: error = 1.1816182, gradient norm = 0.0002203 (50 iterations in 7.446s)
[t-SNE] Iteration 400: error = 1.0402298, gradient norm = 0.0000987 (50 iterations in 7.459s)
[t-SNE] Iteration 450: error = 0.9677289, gradient norm = 0.0000689 (50 iterations in 7.491s)
[t-SNE] Iteration 500: error = 0.9297425, gradient norm = 0.0000527 (50 iterations in 7.389s)
[t-SNE] Iteration 550: error = 0.9080616, gradient norm = 0.0000421 (50 iterations in 7.348s)
[t-SNE] Iteration 600: error = 0.8943869, gradient norm = 0.0000375 (50 iterations in 7.359s)
[t-SNE] Iteration 650: error = 0.8848615, gradient norm = 0.0000347 (50 iterations in 7.368s)
[t-SNE] Iteration 700: error = 0.8775508, gradient norm = 0.0000331 (50 iterations in 7.370s)
[t-SNE] Iteration 750: error = 0.8712236, gradient norm = 0.0000321 (50 iterations in 7.416s)
[t-SNE] Iteration 800: error = 0.8660488, gradient norm = 0.0000298 (50 iterations in 7.348s)
[t-SNE] Iteration 850: error = 0.8619837, gradient norm = 0.0000276 (50 iterations in 7.354s)
[t-SNE] Iteration 900: error = 0.8582878, gradient norm = 0.0000237 (50 iterations in 7.333s)
[t-SNE] Iteration 950: error = 0.8544908, gradient norm = 0.0000232 (50 iterations in 7.344s)
[t-SNE] Iteration 1000: error = 0.8511389, gradient norm = 0.0000222 (50 iterations in 7.316s)
[t-SNE] KL divergence after 1000 iterations: 0.851139
```

In [44]:

```
import plotly.graph_objs as go
import plotly.offline as py
trace1 = go.Scatter3d(
    x=tsne3d[:,0],
    y=tsne3d[:,1],
    z=tsne3d[:,2],
    mode='markers',
    marker=dict(
        sizemode='diameter',
        color = y,
        colorscale = 'Portland',
        colorbar = dict(title = 'duplicate'),
        line=dict(color='rgb(255, 255, 255)'),
        opacity=0.75
    )
)

data=[trace1]
layout=dict(height=800, width=800, title='3d embedding with engineered features')
fig=dict(data=data, layout=layout)
py.iplot(fig, filename='3DBubble')
```

Featurizing text data with Tf-idf W2V

In [45]:

```
df = pd.read_csv("train.csv")

df['question1'] = df['question1'].apply(lambda x: str(x))
df['question2'] = df['question2'].apply(lambda x: str(x))

df.head()
```

Out[45]:

	id	qid1	qid2	question1	question2	is_duplicate
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
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0
2	2	5	6	How can I increase the speed of my internet co...	How can Internet speed be increased by hacking...	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
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0

In [46]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer

questions = list(df['question1']) + list(df['question2'])

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

word2tfidf = dict(zip(tfidf.get_feature_names(), tfidf.idf_))
```

In [50]:

```
# en_vectors_web_lg, which includes over 1 million unique vectors.
```

```python
import en_core_web_sm
nlp = en_core_web_sm.load()
#nlp = spacy.load('en_core_web_sm')

vecs1 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu1 in tqdm(list(df['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)
df['q1_feats_m'] = list(vecs1)
```

```
100%|██████████████████████████████████████████████████████████████████████| 404290/404290
[1:14:02<00:00, 91.01it/s]
```

In [52]:

```python
vecs2 = []
for qu2 in tqdm(list(df['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
        # compute final vec
        mean_vec2 += vec2 * idf
    mean_vec2 = mean_vec2.mean(axis=0)
    vecs2.append(mean_vec2)
df['q2_feats_m'] = list(vecs2)
```

```
100%|██████████████████████████████████████████████████████████████████████| 404290/404290
[1:42:52<00:00, 65.50it/s]
```

In [53]:

```python
#prepro_features_train.csv (Simple Preprocessing Feartures)
#nlp_features_train.csv (NLP Features)

if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    dfppro  = pd.read_csv("df_fe_without_preprocessing_train.csv",encoding='latin-1')

dfppro.head()
```

Out[53]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common
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	1	1	66	57	14	12	10.0

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0	4	1	51	88	8	13	4.0
2	2	5	6	How can I increase the speed of my internet co...	How can Internet speed be increased by hacking...	0	1	1	73	59	14	10	4.0
3	3	7	8	Why am I mentally very lonely? How can I solve...	Find the remainder when [math]23^{24}[/math] i...	0	1	1	50	65	11	9	0.0
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0	3	1	76	39	13	7	2.0

In [54]:

```
#nlp_features_train.csv (NLP Features)
if os.path.isfile('train.csv'):
    dfnlp = pd.read_csv("train.csv",nrows=50000,encoding='latin-1')

dfnlp.head()
```

Out[54]:

	id	qid1	qid2	question1	question2	is_duplicate
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
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0
2	2	5	6	How can I increase the speed of my internet co...	How can Internet speed be increased by hacking...	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
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0

In [55]:

```
df1 = dfnlp.drop(['qid1','qid2','question1','question2'],axis=1)
df2 = dfppro.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
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)
```

In [56]:

```
# Questions 1 tfidf weighted word2vec
print("Question 1 Tf-Idf W2V : ")
df3_q1.head()

# Questions 2 tfidf weighted word2vec
print("Question 2 Tf-Idf W2V : ")
df3_q2.head()
```

```
Question 1 Tf-Idf W2V :
Question 2 Tf-Idf W2V :
```

Out[56]:

	0	1	2	3	4	5	6	7	8	9	...	86
0	-14.616981	59.755488	-53.263745	19.514497	113.916473	101.657056	8.561499	66.232769	32.888127	210.812733	...	-72.266625

	0	1	2	3	4	5	6	7	8	9	...	86
1	-3.565742	-16.844571	-130.911785	0.320254	79.350278	23.562028	79.124551	84.119839	128.684135	279.539877	...	6.193171
2	156.833630	59.991896	-8.414311	29.251426	133.680218	112.457566	89.849781	21.613022	24.331766	171.114490	...	-26.185226
3	41.472439	56.717317	31.530616	-5.520164	33.454800	79.596179	15.508996	40.042066	21.094017	101.998116	...	-17.779019
4	-14.446975	-4.338255	-70.196208	-48.636382	18.356858	-50.807069	24.311196	60.043674	32.421993	57.148702	...	36.089472

5 rows × 96 columns

In [57]:

```
print("Number of features in nlp dataframe : ", df1.shape[1])
print("Number of features in preprocessed dataframe : ", df2.shape[1])
print("Number of features in question1 w2v  dataframe : ", df3_q1.shape[1])
print("Number of features in question2 w2v  dataframe : ", df3_q2.shape[1])
print("Number of features in final dataframe  : ", df1.shape[1] + df2.shape[1] + df3_q1.shape[1] + 
df3_q2.shape[1])
```

```
Number of features in nlp dataframe :  2
Number of features in preprocessed dataframe :  12
Number of features in question1 w2v  dataframe :  96
Number of features in question2 w2v  dataframe :  96
Number of features in final dataframe  :  206
```

In [58]:

```
# storing the final features to csv file
if not os.path.isfile('final_features.csv'):
    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')
    result.to_csv('final_features.csv')
```

Machine Learning Models

Reading data from file and storing into sql table

In [59]:

```
if os.path.isfile('final_features.csv'):
    data = pd.read_csv('final_features.csv', nrows=50000, encoding = 'utf-8')

data.head()
```

Out[59]:

	Unnamed: 0	id	is_duplicate	freq_qid1_x	freq_qid2_x	q1len_x	q2len_x	q1_n_words_x	q2_n_words_x	word_Common_x	...	freq_q
0	0	0	0	1	1	66	57	14	12	10.0	...	
1	1	1	0	4	1	51	88	8	13	4.0	...	
2	2	2	0	1	1	73	59	14	10	4.0	...	
3	3	3	0	1	1	50	65	11	9	0.0	...	
4	4	4	0	3	1	76	39	13	7	2.0	...	

5 rows × 25 columns

Random train test split

In [60]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data, data['is_duplicate'], stratify=data['is_d
uplicate'], random_state=5)
```

In [61]:

```
# Printing Shape and top datapoints

print(X_train.shape)
X_train.head()
```

```
(37500, 25)
```

Out[61]:

	Unnamed: 0	id	is_duplicate	freq_qid1_x	freq_qid2_x	q1len_x	q2len_x	q1_n_words_x	q2_n_words_x	word_Common_x	...
46084	46084	46084	1	5	1	39	46	6	6	5.0	...
31337	31337	31337	1	8	18	47	41	6	6	3.0	...
20200	20200	20200	0	1	1	94	103	15	20	5.0	...
498	498	498	0	1	1	51	44	10	9	2.0	...
39170	39170	39170	1	2	1	62	49	14	11	6.0	...

5 rows × 25 columns

In [62]:

```
# extraction  features from train  data frame
X_train = X_train.drop(['Unnamed: 0', 'id','is_duplicate'], axis=1, inplace=False)

# extraction  features from test data frame
X_test = X_test.drop(['Unnamed: 0', 'id','is_duplicate'], axis=1, inplace=False)

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 : (37500, 22)
Number of data points in test data : (12500, 22)
```

In [63]:

```
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 train data", "-"*10)
test_distr = Counter(y_test)
test_len = len(y_test)
print("Class 0: ",int(test_distr[1])/test_len, "Class 1: ",int(test_distr[1])/test_len)
```

```
---------- Distribution of output variable in train data ----------
Class 0:  0.6270133333333333 Class 1:  0.3729866666666667
---------- Distribution of output variable in train data ----------
Class 0:  0.37296 Class 1:  0.37296
```

In [64]:

```
# 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
```

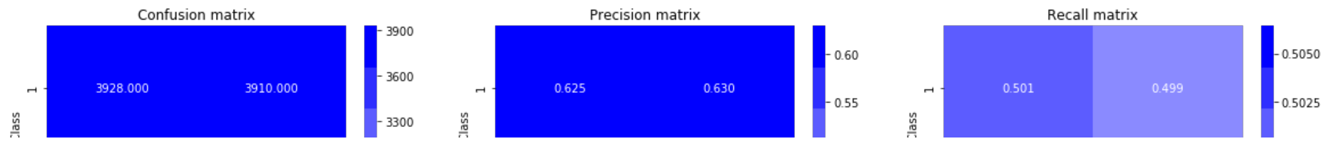
```
    # C = [[1, 2],
    #     [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in two 
diamensional array
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                            [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')
    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()
```

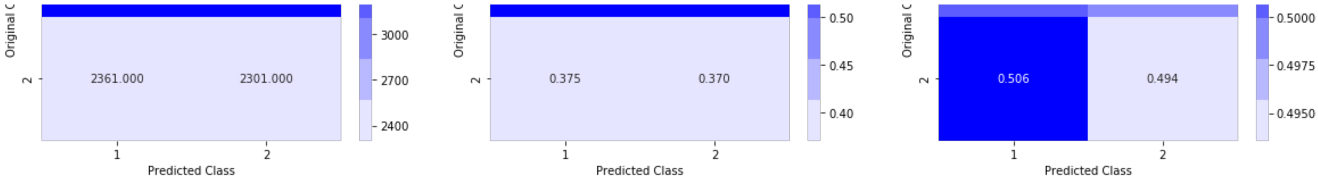
Building a random model (Finding worst-case log-loss)

In [65]:

```
# 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 0.8879535793508352
```





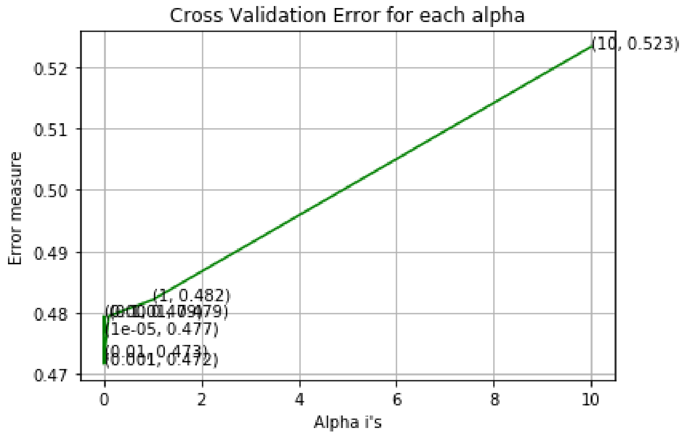
Logistic Regression with hyperparameter tuning

In [66]:

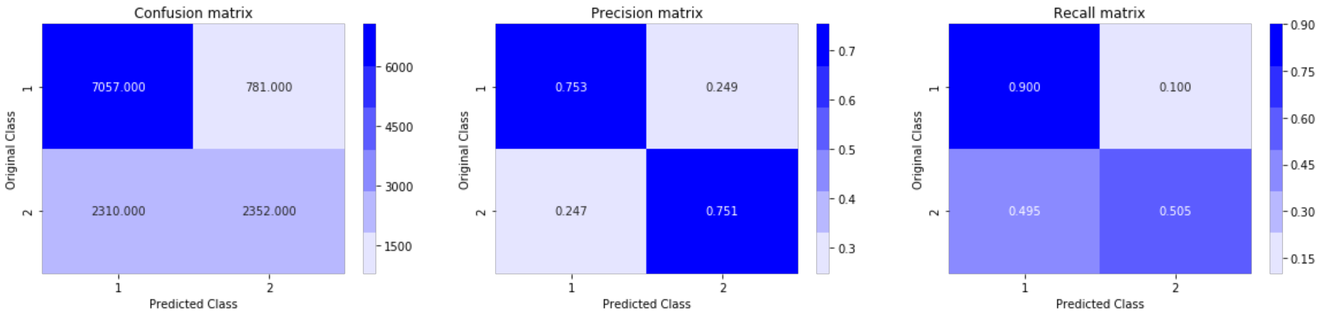
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# 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_i
ter=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.




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.cl
asses_, 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, p
redict_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: 0.4767806610875794
For values of alpha =  0.0001 The log loss is: 0.4794587001597146
For values of alpha =  0.001 The log loss is: 0.47167497782904216
For values of alpha =  0.01 The log loss is: 0.47308761367642094
For values of alpha =  0.1 The log loss is: 0.47945620818593515
```

```
For values of alpha =  1 The log loss is: 0.48210605709028576
For values of alpha =  10 The log loss is: 0.5233189937953077
```




```
For values of best alpha =  0.001 The train log loss is: 0.46583289810755885
For values of best alpha =  0.001 The test log loss is: 0.47167497782904216
Total number of data points : 12500
```



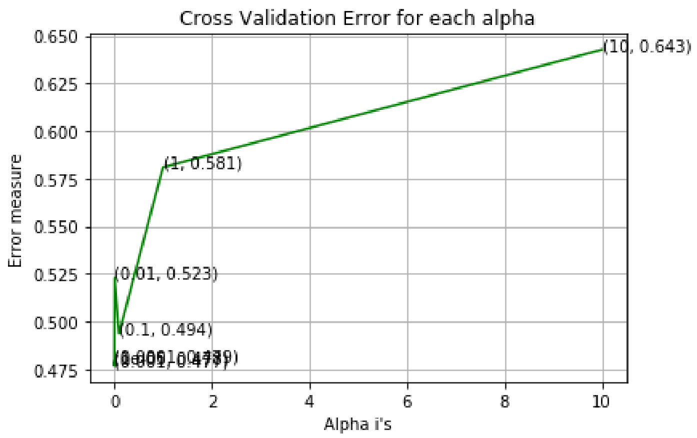
Linear SVM with hyperparameter tuning

In [67]:

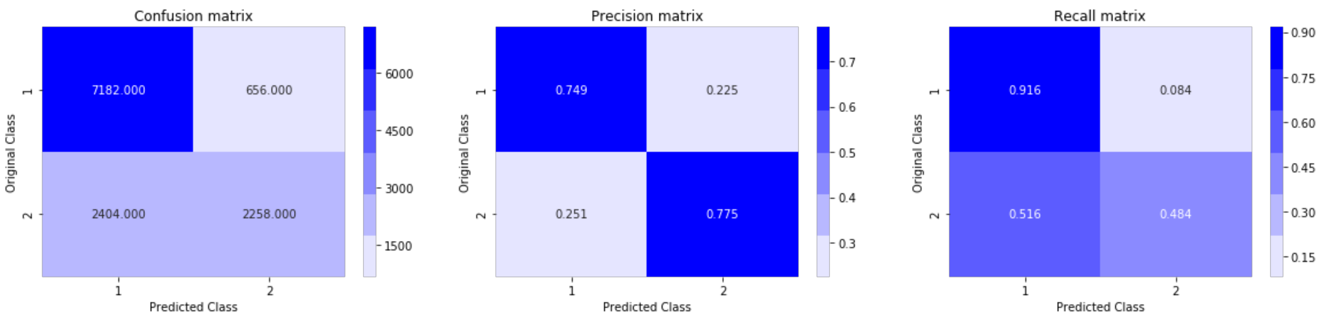
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# 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_i
ter=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.



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.cl
asses_, 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: 0.478400248542998
For values of alpha =  0.0001 The log loss is: 0.47900869710685606
For values of alpha =  0.001 The log loss is: 0.4765817779308944
For values of alpha =  0.01 The log loss is: 0.5229824110049747
For values of alpha =  0.1 The log loss is: 0.4936434387231388
For values of alpha =  1 The log loss is: 0.5809380979910945
For values of alpha =  10 The log loss is: 0.6427164188857588
```




```
For values of best alpha =  0.001 The train log loss is: 0.4706994417690217
For values of best alpha =  0.001 The test log loss is: 0.4765817779308944
Total number of data points : 12500
```



XGBoost

In [68]:

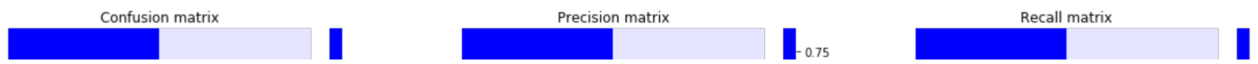
```
import xgboost as xgb
params = {}
params['objective'] = 'binary:logistic'
params['eval_metric'] = 'logloss'
params['eta'] = 0.02
params['max_depth'] = 4

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, labels=clf.classes_, eps=1e-15))
```

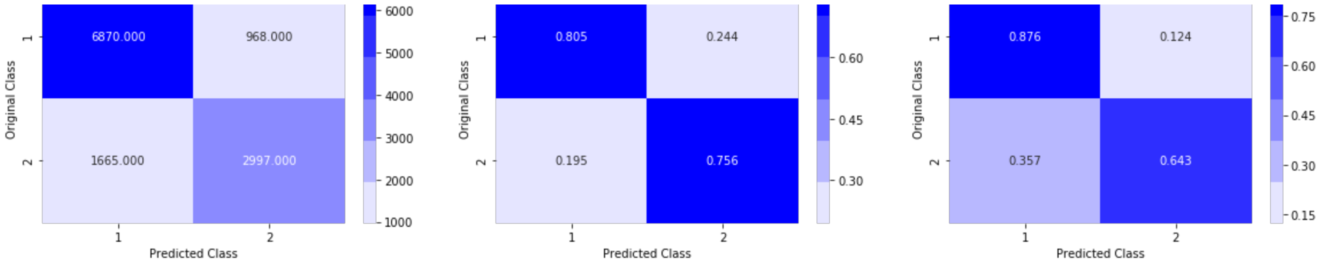
```
[0] train-logloss:0.68523 valid-logloss:0.68532
Multiple eval metrics have been passed: 'valid-logloss' will be used for early stopping.

Will train until valid-logloss hasn't improved in 20 rounds.
[10] train-logloss:0.61993 valid-logloss:0.62095
[20] train-logloss:0.57305 valid-logloss:0.57494
[30] train-logloss:0.53787 valid-logloss:0.54027
[40] train-logloss:0.51154 valid-logloss:0.51434
[50] train-logloss:0.49091 valid-logloss:0.49411
[60] train-logloss:0.47503 valid-logloss:0.47863
[70] train-logloss:0.46224 valid-logloss:0.46623
[80] train-logloss:0.45166 valid-logloss:0.45606
[90] train-logloss:0.44313 valid-logloss:0.44789
[100] train-logloss:0.43628 valid-logloss:0.44129
[110] train-logloss:0.43056 valid-logloss:0.43582
[120] train-logloss:0.42584 valid-logloss:0.43139
[130] train-logloss:0.42210 valid-logloss:0.42790
[140] train-logloss:0.41885 valid-logloss:0.42495
[150] train-logloss:0.41621 valid-logloss:0.42248
[160] train-logloss:0.41401 valid-logloss:0.42046
[170] train-logloss:0.41203 valid-logloss:0.41867
[180] train-logloss:0.41038 valid-logloss:0.41718
[190] train-logloss:0.40889 valid-logloss:0.41581
[200] train-logloss:0.40763 valid-logloss:0.41468
[210] train-logloss:0.40657 valid-logloss:0.41375
[220] train-logloss:0.40563 valid-logloss:0.41290
[230] train-logloss:0.40471 valid-logloss:0.41216
[240] train-logloss:0.40382 valid-logloss:0.41143
[250] train-logloss:0.40297 valid-logloss:0.41073
[260] train-logloss:0.40202 valid-logloss:0.41002
[270] train-logloss:0.40127 valid-logloss:0.40943
[280] train-logloss:0.40051 valid-logloss:0.40886
[290] train-logloss:0.39980 valid-logloss:0.40830
[300] train-logloss:0.39927 valid-logloss:0.40792
[310] train-logloss:0.39872 valid-logloss:0.40755
[320] train-logloss:0.39821 valid-logloss:0.40721
[330] train-logloss:0.39776 valid-logloss:0.40690
[340] train-logloss:0.39720 valid-logloss:0.40648
[350] train-logloss:0.39670 valid-logloss:0.40610
[360] train-logloss:0.39618 valid-logloss:0.40572
[370] train-logloss:0.39580 valid-logloss:0.40551
[380] train-logloss:0.39543 valid-logloss:0.40526
[390] train-logloss:0.39503 valid-logloss:0.40501
[399] train-logloss:0.39470 valid-logloss:0.40479
The test log loss is: 0.40479052844369784
```

In [69]:

```
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 : 12500
```





Applying Tf-Idf vector instead of Tf-Idf W2V

In [72]:

```
# Selecting 60k points

if os.path.isfile('nlp_features_train.csv'):
    nlp = pd.read_csv("nlp_features_train.csv", nrows = 60000, encoding='latin-1')

if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    pre_pro = pd.read_csv("df_fe_without_preprocessing_train.csv", encoding='latin-1')

pre_pro2 = pre_pro.drop(['qid1', 'qid2', 'question1', 'question2', 'is_duplicate'], axis=1)
nlp2 = nlp.merge(pre_pro2, on='id', how='left')
```

In [73]:

```
# Printing top values of nlp2

nlp2.head()
```

Out[73]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	...	freq_qid2	q1len	q2len	q1_n_word
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	0.999980	0.833319	0.999983	0.999983	...	1	66	57	
1	1	3	4	what is the story of kohinoor koh i noor dia...	what would happen if the indian government sto...	0	0.799984	0.399996	0.749981	0.599988	...	1	51	88	
2	2	5	6	how can i increase the speed of my internet co...	how can internet speed be increased by hacking...	0	0.399992	0.333328	0.399992	0.249997	...	1	73	59	
3	3	7	8	why am i mentally very lonely how can i solve...	find the remainder when math 23 24 math i...	0	0.000000	0.000000	0.000000	0.000000	...	1	50	65	
4	4	9	10	which one dissolve in water quikly sugar salt...	which fish would survive in salt water	0	0.399992	0.199998	0.999950	0.666644	...	1	76	39	

5 rows × 32 columns

In [74]:

```
# Checking if we have any null values in nlp2

null_values = nlp2[nlp2.isnull().any(1)]
print(null_values)
```

```
             id   qid1   qid2                                           question1  \
3306       3306   6553   6554                                                 NaN
13016     13016  25026  25027                                                 NaN
20072     20072  37898  37899                               how could i solve this
20794     20794  39204  39205                                                 NaN
47056     47056  84067  84068  is there anywhere in the world offering pain m...

                                             question2  is_duplicate  \
3306   why is cornell own endowment the lowest in the...             0
13016               why should one not work at google             0
20072                                                NaN             0
20794  what is the gmail tech support help phone number             0
47056                                                NaN             0

       cwc_min  cwc_max  csc_min  csc_max  ...  freq_qid2  q1len  q2len  \
3306       0.0      0.0      0.0      0.0  ...          1      1     56
13016      0.0      0.0      0.0      0.0  ...          2      1     34
20072      0.0      0.0      0.0      0.0  ...          2     23      6
20794      0.0      0.0      0.0      0.0  ...          1      1     49
47056      0.0      0.0      0.0      0.0  ...          1    117      1

       q1_n_words  q2_n_words  word_Common  word_Total  word_share  \
3306            1          10          0.0        10.0         0.0
13016           1           7          0.0         8.0         0.0
20072           5           1          0.0         6.0         0.0
20794           1           9          0.0        10.0         0.0
47056          19           1          0.0        19.0         0.0

       freq_q1+q2  freq_q1-q2
3306            2           0
13016           4           0
20072           4           0
20794           2           0
47056           4           2

[5 rows x 32 columns]
```

In [75]:

```
# Since our nlp2 has some null values we are filling all the null values with ' '

nlp2 = nlp2.fillna('')
null_values = nlp2[nlp2.isnull().any(1)]
```

Splitting Data into Train, Test and CV Data

In [76]:

```
X_train, X_test, y_train, y_test = train_test_split(nlp2, nlp2['is_duplicate'], stratify = nlp2['is
_duplicate'], random_state = 5)
```

In [77]:

```
# Printing shape of train and test data

print("Shape of Train data : ", X_train.shape, y_train.shape)
print("Shape of Test data : ", X_test.shape, y_test.shape)
```

```
Shape of Train data :  (45000, 32) (45000,)
Shape of Test data :  (15000, 32) (15000,)
```

In [78]:

```
# Removing target feature from train and test data

X_train = X_train.drop(('is_duplicate'), axis=1)
X_test = X_test.drop(('is_duplicate'), axis=1)
```

Applying Tf-Idf Vectorizer on the Text data

In [84]:

```
vectorizer = TfidfVectorizer(min_df = 10, ngram_range = (1,2))

# Before fitting Tf-Idf Vectorizer we need to combine both question1 and question 2
Combined_que = list(X_train['question1']) + list(X_train['question2'])
vectorizer.fit(Combined_que)

# Applying Tf-Idf Vectorizer on Question-1
train_tfidf_q1 = vectorizer.transform(X_train['question1'])
test_tfidf_q1 =  vectorizer.transform(X_test['question1'])

# Applying Tf-Idf Vectorizer on Question-2
train_tfidf_q2 = vectorizer.transform(X_train['question2'])
test_tfidf_q2 = vectorizer.transform(X_test['question2'])

# Extracting Features
X_train_features = X_train.drop(['id','qid1','qid2','question1','question2'], axis = 1, inplace = F
alse)
X_test_features = X_test.drop(['id','qid1','qid2','question1','question2'], axis = 1, inplace = Fal
se)
```

In [85]:

```
# Printing Shape of text Train and test data after Vectorizing

print("Shape of Train Question-1 matrix after Vectorizing : ", train_tfidf_q1.shape)
print("Shape of Train Question-2 matrix after Vectorizing : ", train_tfidf_q2.shape)

print("Shape of Test Question-1 matrix after Vectorizing : ", test_tfidf_q1.shape)
print("Shape of Test Question-2 matrix after Vectorizing : ", test_tfidf_q2.shape)
```

```
Shape of Train Question-1 matrix after Vectorizing :  (45000, 15683)
Shape of Train Question-2 matrix after Vectorizing :  (45000, 15683)
Shape of Test Question-1 matrix after Vectorizing :  (15000, 15683)
Shape of Test Question-2 matrix after Vectorizing :  (15000, 15683)
```

Merging All the Features

In [91]:

```
from scipy.sparse import hstack
from scipy.sparse import csr_matrix

X_train_s1 = hstack((csr_matrix(X_train_features), train_tfidf_q1, train_tfidf_q2))
X_test_s1 = hstack((csr_matrix(X_test_features), test_tfidf_q1, test_tfidf_q2))

# Printing Shape of both Train and Test data after merging Features
print("Shape of Training Data : ", X_train_s1.shape, y_train.shape)
print("Shape of Test Data : ", X_test_s1.shape, y_test.shape)
```

```
Shape of Training Data :  (45000, 31392) (45000,)
Shape of Test Data :  (15000, 31392) (15000,)
```

In [92]:

```
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 train data", "-"*10)
test_distr = Counter(y_test)
test_len = len(y_test)
print("Class 0: ",int(test_distr[1])/test_len, "Class 1: ",int(test_distr[1])/test_len)
```

```
---------- Distribution of output variable in train data ----------
```

```
Class 0:  0.6266666666666667 Class 1:  0.37333333333333335
---------- Distribution of output variable in train data ----------
Class 0:  0.37333333333333335 Class 1:  0.37333333333333335
```

Confusion Matrix function

In [93]:

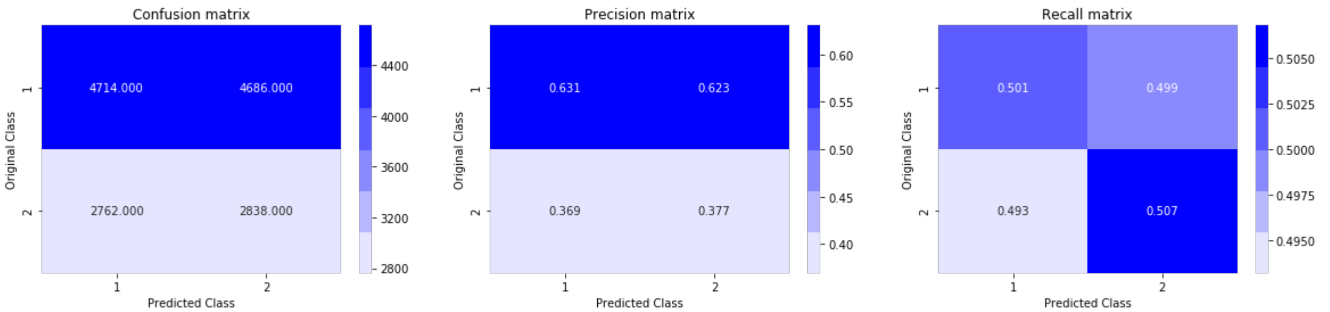
```python
def plot_confusion_matrix(t_y, p_y):

    C = confusion_matrix(t_y, p_y)
    A = (((C.T) / (C.sum(axis=1))).T)
    B = (C/C.sum(axis=0))

    plt.figure(figsize=(20,4))
    labels = [1,2]

    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)
    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()
```

Finding Worst case Log-loss by Building a Random model

In [94]:

```python
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 0.882555878819354
```



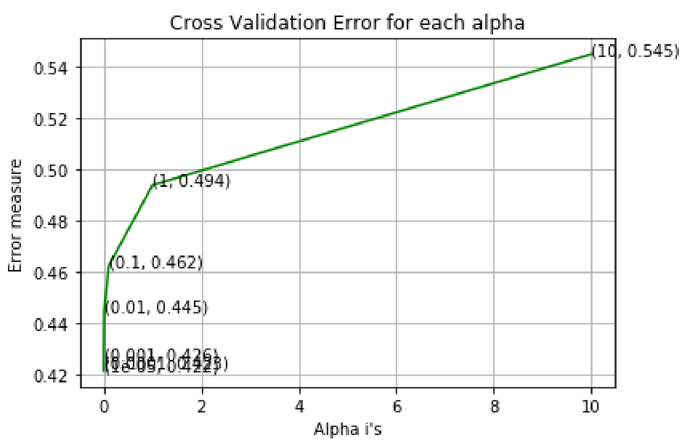
Logistic Regression with Hyperparameter Tuning

Logistic Regression with Hyperparameter Tuning

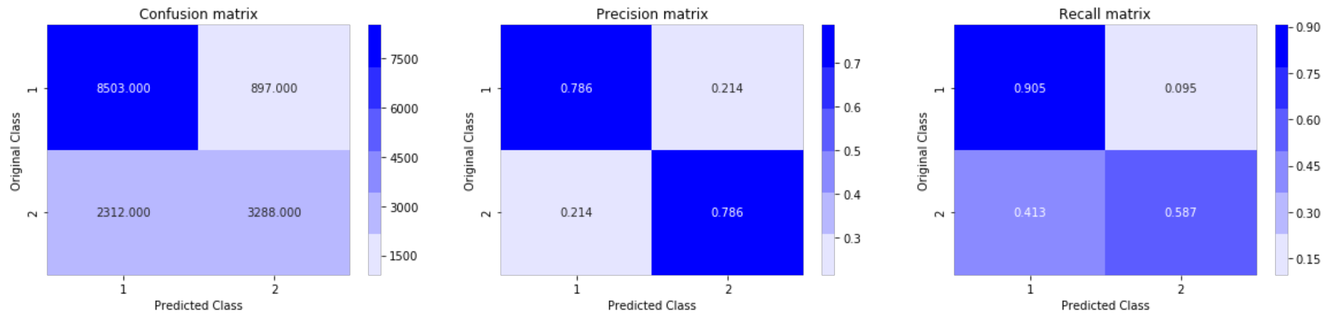
In [95]:

```
alpha = [10 ** x for x in range(-5, 2)]

log_error_array=[]

for i in alpha:
    clf = SGDClassifier(alpha = i, penalty='l2', loss='log', random_state = 5)
    clf.fit(X_train_s1, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train_s1, y_train)
    predict_y = sig_clf.predict_proba(X_test_s1)
    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 = 5)
clf.fit(X_train_s1, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_s1, y_train)

predict_y = sig_clf.predict_proba(X_train_s1)
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_s1)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, p
redict_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: 0.42150882312976923
For values of alpha =  0.0001 The log loss is: 0.4227130968358387
For values of alpha =  0.001 The log loss is: 0.42591685127960466
For values of alpha =  0.01 The log loss is: 0.44480068919435606
For values of alpha =  0.1 The log loss is: 0.46234921158677555
For values of alpha =  1 The log loss is: 0.4938235946324831
For values of alpha =  10 The log loss is: 0.5447677661757477
```




```
For values of best alpha =  1e-05 The train log loss is: 0.4121890377696049
For values of best alpha =  1e-05 The test log loss is: 0.42150882312976923
Total number of data points :  15000
```

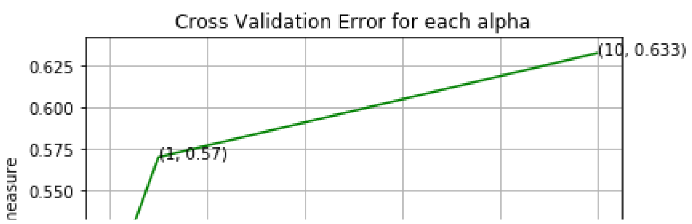


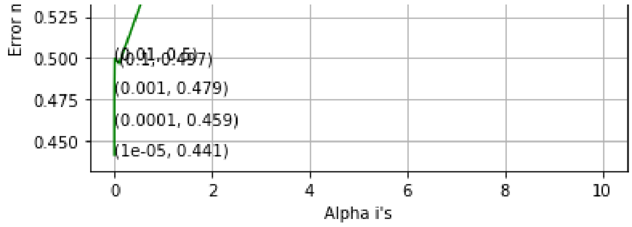
Linear SVM with Hyperparameter Tuning

In [96]:

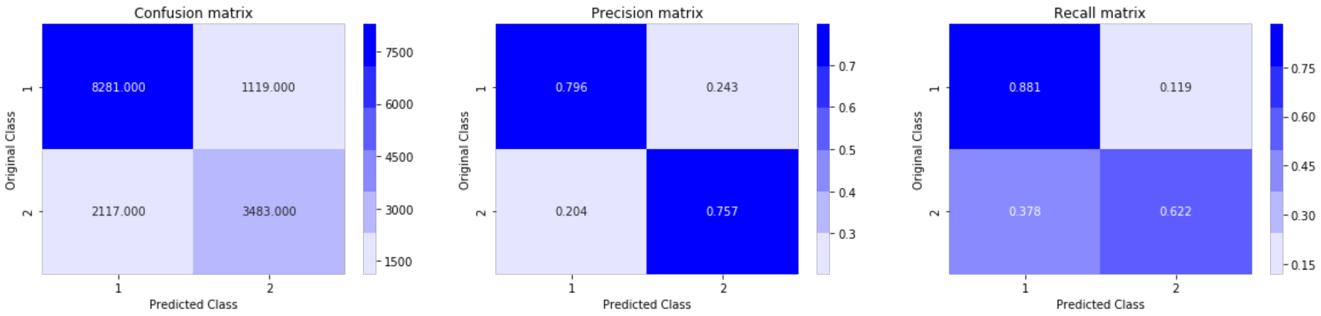
```
alpha = [10 ** x for x in range(-5, 2)]

log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha = i, penalty='l1', loss = 'hinge', random_state = 5)
    clf.fit(X_train_s1, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train_s1, y_train)
    predict_y = sig_clf.predict_proba(X_test_s1)
    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.cl
asses_, 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 = 5)
clf.fit(X_train_s1, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_s1, y_train)

predict_y = sig_clf.predict_proba(X_train_s1)
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_s1)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, p
redict_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: 0.44122426606865445
For values of alpha =  0.0001 The log loss is: 0.4594414147876107
For values of alpha =  0.001 The log loss is: 0.47937219149563715
For values of alpha =  0.01 The log loss is: 0.49964642247254404
For values of alpha =  0.1 The log loss is: 0.49654406568727366
For values of alpha =  1 The log loss is: 0.5697232319961436
For values of alpha =  10 The log loss is: 0.6329082675889889
```






```
For values of best alpha =  1e-05 The train log loss is: 0.4264999048498056
For values of best alpha =  1e-05 The test log loss is: 0.44122426606865445
Total number of data points : 15000
```



XGBoost Model

In [99]:

```
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
from sklearn.metrics import log_loss

param_grid = {'n_estimators' : [5, 10, 100, 500], 'max_depth' : [2, 5, 8, 10]}

rs = RandomizedSearchCV(estimator = XGBClassifier(objective = 'binary:logistic', eval_metric = 'log
loss', eta = 0.02), param_distributions = param_grid)

# fit train sets
rs.fit(X_train_s1, y_train)

# Prediction
predict = rs.predict(X_test_s1)
```

In [100]:

```
b_para = rs.best_params_
b_score = rs.best_score_

print("Optimal hyperParameter:", b_para)
print("Maximum accuracy:", b_score * 100)
```

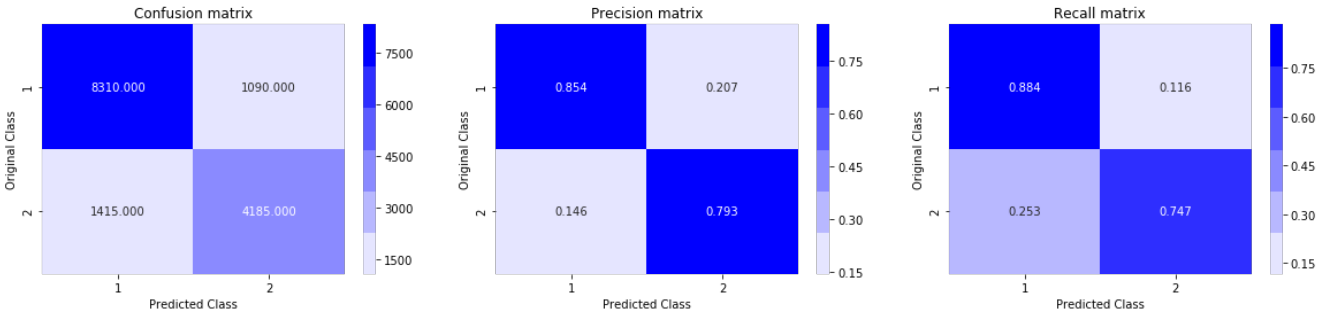
```
Optimal hyperParameter: {'n_estimators': 500, 'max_depth': 10}
Maximum accuracy: 83.53777777777779
```

Confusion Matrix

In [101]:

```
predicted_y = np.array(predict > 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 :  15000
```



In [103]:

```
import xgboost as xg
params = {}
params['objective'] = 'binary:logistic'
params['eval_metric'] = 'logloss'
params['eta'] = 0.02
params['max_depth'] = 10
params['n_estimators'] = 100

d_train = xg.DMatrix(X_train_s1, label= y_train)
d_test = xg.DMatrix(X_test_s1, label = y_test)

watchlist = [(d_train, 'train'), (d_test, 'valid')]

bst = xg.train(params, d_train, 400, watchlist, early_stopping_rounds=20)

xgdmat = xg.DMatrix(X_train_s1, y_train)
predict_y = bst.predict(d_test)
print("The test log loss is:",log_loss(y_test, predict_y, eps=1e-15))
```

```
[10:04:51] WARNING: C:\Users\Administrator\workspace\xgboost-
win64_release_1.0.0\src\learner.cc:328:
Parameters: { n_estimators } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


[0] train-logloss:0.68217 valid-logloss:0.68294
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.
[1] train-logloss:0.67166 valid-logloss:0.67313
[2] train-logloss:0.66157 valid-logloss:0.66370
[3] train-logloss:0.65183 valid-logloss:0.65463
[4] train-logloss:0.64242 valid-logloss:0.64592
[5] train-logloss:0.63330 valid-logloss:0.63748
[6] train-logloss:0.62457 valid-logloss:0.62938
[7] train-logloss:0.61615 valid-logloss:0.62168
[8] train-logloss:0.60797 valid-logloss:0.61417
[9] train-logloss:0.60007 valid-logloss:0.60689
[10] train-logloss:0.59242 valid-logloss:0.59994
[11] train-logloss:0.58500 valid-logloss:0.59320
[12] train-logloss:0.57785 valid-logloss:0.58669
[13] train-logloss:0.57085 valid-logloss:0.58038
[14] train-logloss:0.56404 valid-logloss:0.57433
[15] train-logloss:0.55755 valid-logloss:0.56847
[16] train-logloss:0.55114 valid-logloss:0.56279
[17] train-logloss:0.54497 valid-logloss:0.55729
[18] train-logloss:0.53893 valid-logloss:0.55197
[19] train-logloss:0.53314 valid-logloss:0.54681
[20] train-logloss:0.52741 valid-logloss:0.54176
[21] train-logloss:0.52190 valid-logloss:0.53686
[22] train-logloss:0.51656 valid-logloss:0.53212
[23] train-logloss:0.51135 valid-logloss:0.52753
[24] train-logloss:0.50626 valid-logloss:0.52298
[25] train-logloss:0.50126 valid-logloss:0.51865
[26] train-logloss:0.49649 valid-logloss:0.51446
[27] train-logloss:0.49177 valid-logloss:0.51037
[28] train-logloss:0.48724 valid-logloss:0.50636
```

```
[29] train-logloss:0.48271 valid-logloss:0.50249
[30] train-logloss:0.47842 valid-logloss:0.49872
[31] train-logloss:0.47425 valid-logloss:0.49508
[32] train-logloss:0.47004 valid-logloss:0.49152
[33] train-logloss:0.46597 valid-logloss:0.48802
[34] train-logloss:0.46205 valid-logloss:0.48463
[35] train-logloss:0.45814 valid-logloss:0.48127
[36] train-logloss:0.45435 valid-logloss:0.47802
[37] train-logloss:0.45070 valid-logloss:0.47491
[38] train-logloss:0.44713 valid-logloss:0.47186
[39] train-logloss:0.44357 valid-logloss:0.46885
[40] train-logloss:0.44021 valid-logloss:0.46596
[41] train-logloss:0.43690 valid-logloss:0.46318
[42] train-logloss:0.43365 valid-logloss:0.46045
[43] train-logloss:0.43048 valid-logloss:0.45781
[44] train-logloss:0.42734 valid-logloss:0.45524
[45] train-logloss:0.42426 valid-logloss:0.45267
[46] train-logloss:0.42133 valid-logloss:0.45017
[47] train-logloss:0.41850 valid-logloss:0.44782
[48] train-logloss:0.41570 valid-logloss:0.44555
[49] train-logloss:0.41283 valid-logloss:0.44315
[50] train-logloss:0.41013 valid-logloss:0.44088
[51] train-logloss:0.40751 valid-logloss:0.43874
[52] train-logloss:0.40492 valid-logloss:0.43665
[53] train-logloss:0.40231 valid-logloss:0.43460
[54] train-logloss:0.39986 valid-logloss:0.43263
[55] train-logloss:0.39742 valid-logloss:0.43068
[56] train-logloss:0.39504 valid-logloss:0.42881
[57] train-logloss:0.39262 valid-logloss:0.42685
[58] train-logloss:0.39025 valid-logloss:0.42492
[59] train-logloss:0.38794 valid-logloss:0.42308
[60] train-logloss:0.38568 valid-logloss:0.42130
[61] train-logloss:0.38353 valid-logloss:0.41958
[62] train-logloss:0.38139 valid-logloss:0.41786
[63] train-logloss:0.37934 valid-logloss:0.41619
[64] train-logloss:0.37735 valid-logloss:0.41460
[65] train-logloss:0.37533 valid-logloss:0.41304
[66] train-logloss:0.37340 valid-logloss:0.41155
[67] train-logloss:0.37153 valid-logloss:0.41007
[68] train-logloss:0.36969 valid-logloss:0.40862
[69] train-logloss:0.36787 valid-logloss:0.40723
[70] train-logloss:0.36615 valid-logloss:0.40591
[71] train-logloss:0.36439 valid-logloss:0.40457
[72] train-logloss:0.36260 valid-logloss:0.40326
[73] train-logloss:0.36103 valid-logloss:0.40204
[74] train-logloss:0.35936 valid-logloss:0.40083
[75] train-logloss:0.35781 valid-logloss:0.39969
[76] train-logloss:0.35617 valid-logloss:0.39845
[77] train-logloss:0.35465 valid-logloss:0.39733
[78] train-logloss:0.35295 valid-logloss:0.39612
[79] train-logloss:0.35136 valid-logloss:0.39498
[80] train-logloss:0.34992 valid-logloss:0.39390
[81] train-logloss:0.34834 valid-logloss:0.39282
[82] train-logloss:0.34680 valid-logloss:0.39170
[83] train-logloss:0.34547 valid-logloss:0.39072
[84] train-logloss:0.34400 valid-logloss:0.38968
[85] train-logloss:0.34254 valid-logloss:0.38866
[86] train-logloss:0.34128 valid-logloss:0.38773
[87] train-logloss:0.33990 valid-logloss:0.38675
[88] train-logloss:0.33859 valid-logloss:0.38581
[89] train-logloss:0.33734 valid-logloss:0.38492
[90] train-logloss:0.33613 valid-logloss:0.38403
[91] train-logloss:0.33487 valid-logloss:0.38315
[92] train-logloss:0.33372 valid-logloss:0.38230
[93] train-logloss:0.33258 valid-logloss:0.38152
[94] train-logloss:0.33145 valid-logloss:0.38074
[95] train-logloss:0.33027 valid-logloss:0.37992
[96] train-logloss:0.32916 valid-logloss:0.37917
[97] train-logloss:0.32812 valid-logloss:0.37844
[98] train-logloss:0.32709 valid-logloss:0.37769
[99] train-logloss:0.32612 valid-logloss:0.37696
[100] train-logloss:0.32510 valid-logloss:0.37627
[101] train-logloss:0.32406 valid-logloss:0.37557
[102] train-logloss:0.32313 valid-logloss:0.37493
[103] train-logloss:0.32212 valid-logloss:0.37425
[104] train-logloss:0.32123 valid-logloss:0.37362
[105] train-logloss:0.32024 valid-logloss:0.37301
```

```
[106] train-logloss:0.31935 valid-logloss:0.37238
[107] train-logloss:0.31848 valid-logloss:0.37179
[108] train-logloss:0.31752 valid-logloss:0.37118
[109] train-logloss:0.31668 valid-logloss:0.37061
[110] train-logloss:0.31580 valid-logloss:0.37010
[111] train-logloss:0.31490 valid-logloss:0.36951
[112] train-logloss:0.31411 valid-logloss:0.36899
[113] train-logloss:0.31327 valid-logloss:0.36841
[114] train-logloss:0.31252 valid-logloss:0.36790
[115] train-logloss:0.31173 valid-logloss:0.36737
[116] train-logloss:0.31101 valid-logloss:0.36689
[117] train-logloss:0.31020 valid-logloss:0.36641
[118] train-logloss:0.30933 valid-logloss:0.36590
[119] train-logloss:0.30860 valid-logloss:0.36545
[120] train-logloss:0.30792 valid-logloss:0.36498
[121] train-logloss:0.30722 valid-logloss:0.36453
[122] train-logloss:0.30649 valid-logloss:0.36411
[123] train-logloss:0.30578 valid-logloss:0.36362
[124] train-logloss:0.30513 valid-logloss:0.36322
[125] train-logloss:0.30441 valid-logloss:0.36284
[126] train-logloss:0.30373 valid-logloss:0.36237
[127] train-logloss:0.30289 valid-logloss:0.36189
[128] train-logloss:0.30209 valid-logloss:0.36145
[129] train-logloss:0.30141 valid-logloss:0.36101
[130] train-logloss:0.30071 valid-logloss:0.36059
[131] train-logloss:0.30003 valid-logloss:0.36024
[132] train-logloss:0.29947 valid-logloss:0.35986
[133] train-logloss:0.29879 valid-logloss:0.35948
[134] train-logloss:0.29831 valid-logloss:0.35914
[135] train-logloss:0.29764 valid-logloss:0.35877
[136] train-logloss:0.29709 valid-logloss:0.35841
[137] train-logloss:0.29660 valid-logloss:0.35811
[138] train-logloss:0.29600 valid-logloss:0.35776
[139] train-logloss:0.29555 valid-logloss:0.35746
[140] train-logloss:0.29510 valid-logloss:0.35717
[141] train-logloss:0.29467 valid-logloss:0.35691
[142] train-logloss:0.29417 valid-logloss:0.35662
[143] train-logloss:0.29373 valid-logloss:0.35632
[144] train-logloss:0.29326 valid-logloss:0.35606
[145] train-logloss:0.29281 valid-logloss:0.35576
[146] train-logloss:0.29239 valid-logloss:0.35549
[147] train-logloss:0.29201 valid-logloss:0.35524
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The test log loss is: 0.33648131023853006
```

In [107]:

```python
from prettytable import PrettyTable

pt = PrettyTable()
pt.field_names = ['No.', 'Model Name', 'Hyperparameter Tunning', 'Test Log-Loss']
pt.add_row(["1","Random (Tf-Idf W2V)", "No", "0.887"])
pt.add_row(["2","Logistic Regression (Tf-Idf W2V)", "Yes", "0.471"])
pt.add_row(["3","Linear SVM (Tf-Idf W2V)", "Yes", "0.476"])
pt.add_row(["4","XGBoost (Tf-Idf W2V)", "No", "0.404"])
pt.add_row(["\n","\n","\n","\n"])
```

```
pt.add_row(["","","",""])
pt.add_row(["1","Random (Tf-Idf)", "No", "0.882"])
pt.add_row(["2","Logistic Regression (Tf-Idf)", "Yes", "0.421"])
pt.add_row(["3","Linear SVM (Tf-Idf)", "Yes", "0.441"])
pt.add_row(["4","XGBoost (Tf-Idf)", "Yes", "0.336"])

print(pt)
```

```
+-----+---------------------------------+-----------------------+---------------+
| No. |            Model Name           | Hyperparameter Tunning | Test Log-Loss |
+-----+---------------------------------+-----------------------+---------------+
|  1  |       Random (Tf-Idf W2V)       |           No          |     0.887     |
|  2  | Logistic Regression (Tf-Idf W2V) |          Yes          |     0.471     |
|  3  |     Linear SVM (Tf-Idf W2V)     |          Yes          |     0.476     |
|  4  |       XGBoost (Tf-Idf W2V)      |           No          |     0.404     |
|     |                                 |                       |               |
|     |                                 |                       |               |
|  1  |         Random (Tf-Idf)         |           No          |     0.882     |
|  2  |   Logistic Regression (Tf-Idf)  |          Yes          |     0.421     |
|  3  |       Linear SVM (Tf-Idf)       |          Yes          |     0.441     |
|  4  |        XGBoost (Tf-Idf)         |          Yes          |     0.336     |
+-----+---------------------------------+-----------------------+---------------+
```

Procedure Followed

PROBLEM STATEMENT : We have given a Dataset from Quora in which they have given 5 features (id of question1, id of question 2, question 1, question 2, is duplicate). Based on these features (excluding is_duplicate feature) we need to predict whether the given pair of question is duplicate or not.

STEP 1 : We have total 404290 number of datapoints. First we have check the distribution that how many datapoints says that the pair is duplicate and how many datapoints say that the pair is not duplicate. Knowing Distribution of our datapoints helps us a lot.

STEP 2 : After knowing the distribution of datapoints we just checked in our dataset how many question are unique, how many questions repeated, is there any question pair which is duplicate?. These will give us the insight of our dataset and helps us to know our dataset better.

STEP 3 : Then we did some basic feature engineering so that we can get some features that represent the underlying problem better to the model. We just included some basic features like Frequency of questions, length of questions, total number of words in questions, etc. And after Basic feature extraction we performed EDA on that. By doing EDA we can do thorough analysis of features.

STEP 4 : After Preprocessing our data we did some advance Feature engineering using Fussy features and plot word clouds, pair plot, etc. And we have visualize advance features using PCA.

STEP 5 : In provided notebooks there was a PROBLEM OF DATA LEAKAGE . So to avoid data leakage problem we need to split our data first into train, test data and then vectorize text data for both train and test data. So we randomly split our data.

STEP 6 : Now after splitting our data we will vectorize our text data (Question 1 and Question 2) using Tf-Idf vectorizer. Then we will merge all the features (Basic features, advance features, Tf-Idf vectorized question 1 and question 2). Since now we have merged all our features so we apply models on it.

STEP 7 : Since we are also using the probabily values we will consider log-loss as a performace matrix. Along with log-loss we will also use Binary confusion matrix.

STEP 8 : Before applying any other model we need to understand the worst case log-loss. And we can know the worst case log-loss by building a random model in which we randomly allocate label. It can also act as a baseline model. We got the worst case log-loss of 0.88 on the dumb model. Now any other model that we use have the log-loss less than this dumb model.

STEP 9 : Now we will apply Logistic regression model on our training data. And then we will perform hyper parameter tuning to reduce the log-loss. The log-loss we have got after hyperparameter tuning on test data is 0.421, which is less than the worst-case log-loss.

STEP 10 : Now we have applied Linear SVM model with hyperparameter tuning. By Linear SVM we got the log-loss of 0.441 which is less than the loss loss of random model.

STEP 11 : After this we have applied XGBoost Model. We also perform hyperparameter tuning so that we can get low log-loss. The log-loss we got is 0.336. The log-loss that we have achieved on XGBoost is much low than the log-loss we have achieved on Logistic Regression and Linear SVM.

Conclusion Since log-loss achieved on XGBoost is much lower than other models so we can conclude that we can use XGBoost model to find the duplicate questions on Quora.