3. Exploratory Data Analysis

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from subprocess import check_output
%matplotlib inline
import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.tools as tls
import os
import gc

import re
from nltk.corpus import stopwords
import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
```

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")
from datetime 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 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
from datetime import datetime as dt
```

```
from datetime import datetime as dt
```

3.1 Reading data and basic stats

In [3]:

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

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

```
Number of data points: 404290
```

In [4]:

```
df.head()
```

Out[4]:

	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]:

```
df.info()
```

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

We are given a minimal number of data fields here, consisting of:

- id: Looks like a simple rowID
- qid{1, 2}: The unique ID of each question in the pair
- question{1, 2}: The actual textual contents of the questions.
- is_duplicate: The label that we are trying to predict - whether the two questions are duplicates of each other.

3.2.1 Distribution of data points among output classes

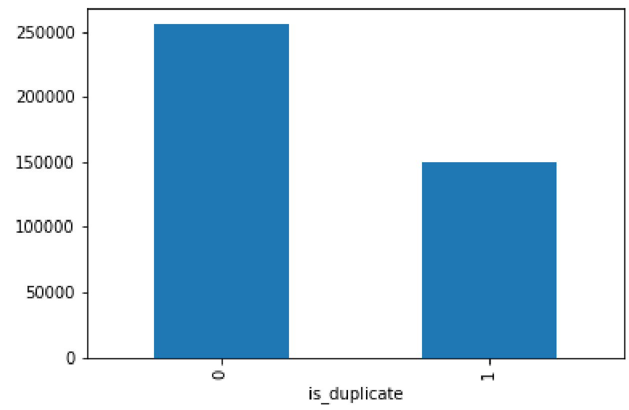
- Number of duplicate(smilar) and non-duplicate(non similar) questions

In [6]:

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

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x207cd59b128>
```



In [7]:

```python
print('~> Total number of question pairs for training:\n   {}'.format(len(df)))
```

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

In [8]:

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

3.2.2 Number of unique questions

In [9]:

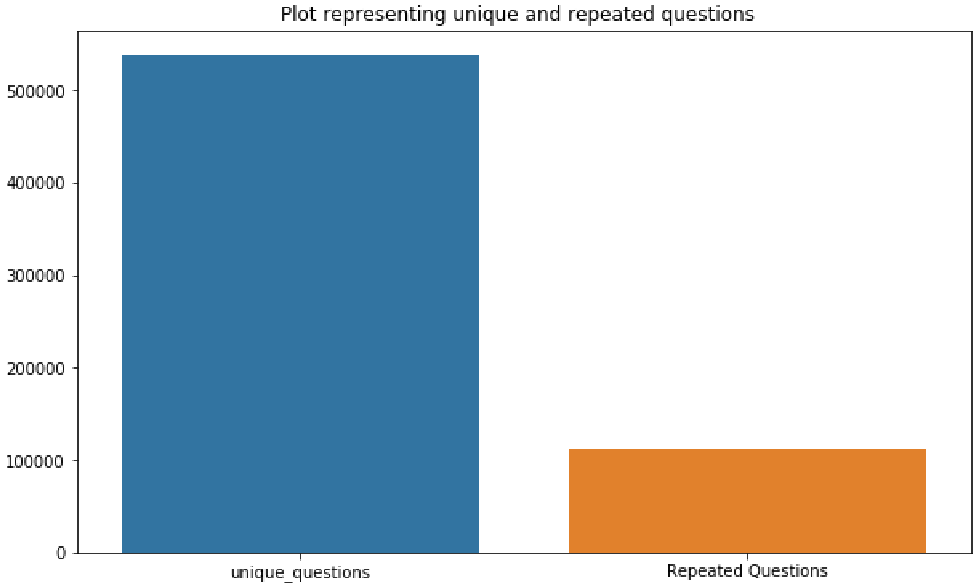
```python
qids = pd.Series(df['qid1'].tolist() + df['qid2'].tolist())
unique_qs = len(np.unique(qids))
qs_morethan_onetime = np.sum(qids.value_counts() > 1)
print ('Total number of  Unique Questions are: {}\n'.format(unique_qs))
#print len(np.unique(qids))

print ('Number of unique questions that appear more than one time: {} 
({}%)\n'.format(qs_morethan_onetime,qs_morethan_onetime/unique_qs*100))

print ('Max number of times a single question is repeated: {}\n'.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 [10]:

```python
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()
```



3.2.3 Checking for Duplicates

In [11]:

```
#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])
```

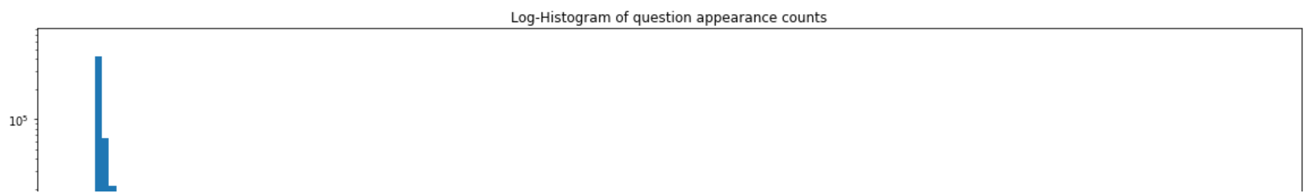
```
Number of duplicate questions 0
```

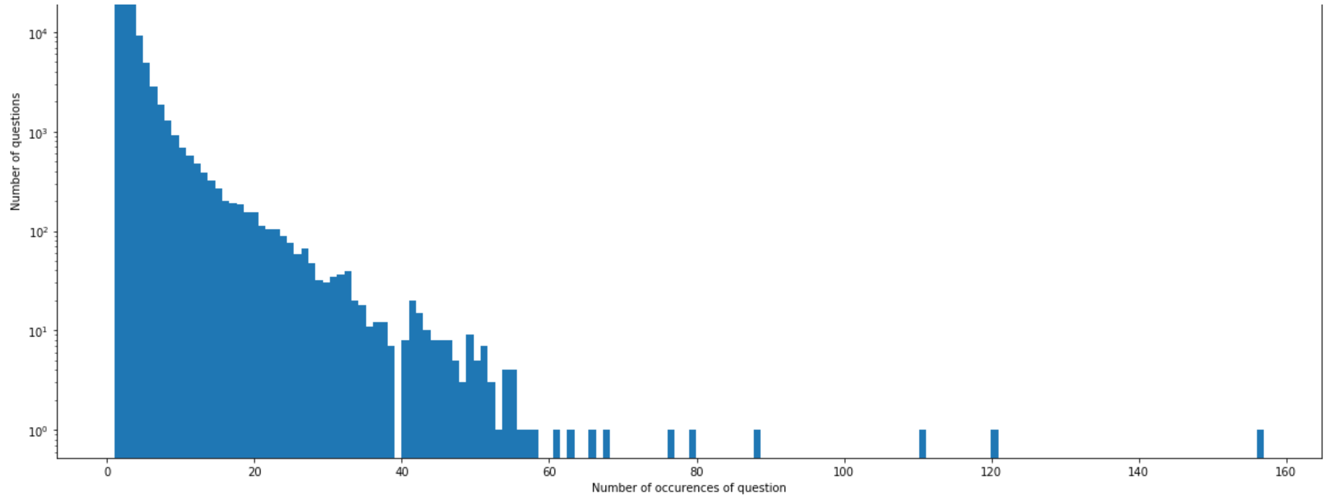
3.2.4 Number of occurrences of each question

In [12]:

```
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: {}\n'.format(max(qids.value_counts(
))))
```

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





3.2.5 Checking for NULL values

In [13]:

```
#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
```

- There are two rows with null values in question2

In [14]:

```
# 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: []
```

3.3 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 [15]:

```
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[15]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	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	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
				Which one dissolve in water	Which fish								

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_
4	4	9	10	water quikly sugar, salt...	would survive in salt water?	0	3	1	76	39	13	7	2.0

3.3.1 Analysis of some of the extracted features

- Here are some questions have only one single words.

In [16]:

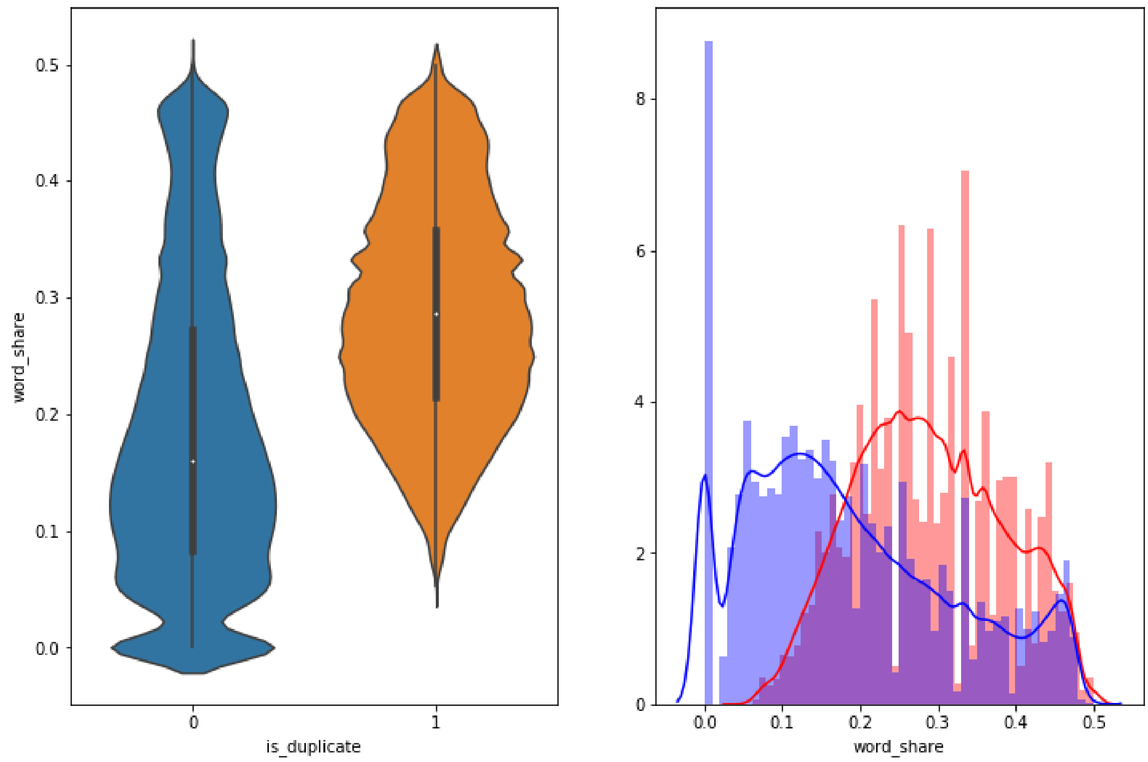
```
print ("Minimum length of the questions in question1 : " , min(df['q1_n_words']))

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
```

3.3.1.1 Feature: word_share

In [17]:

```
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()
```



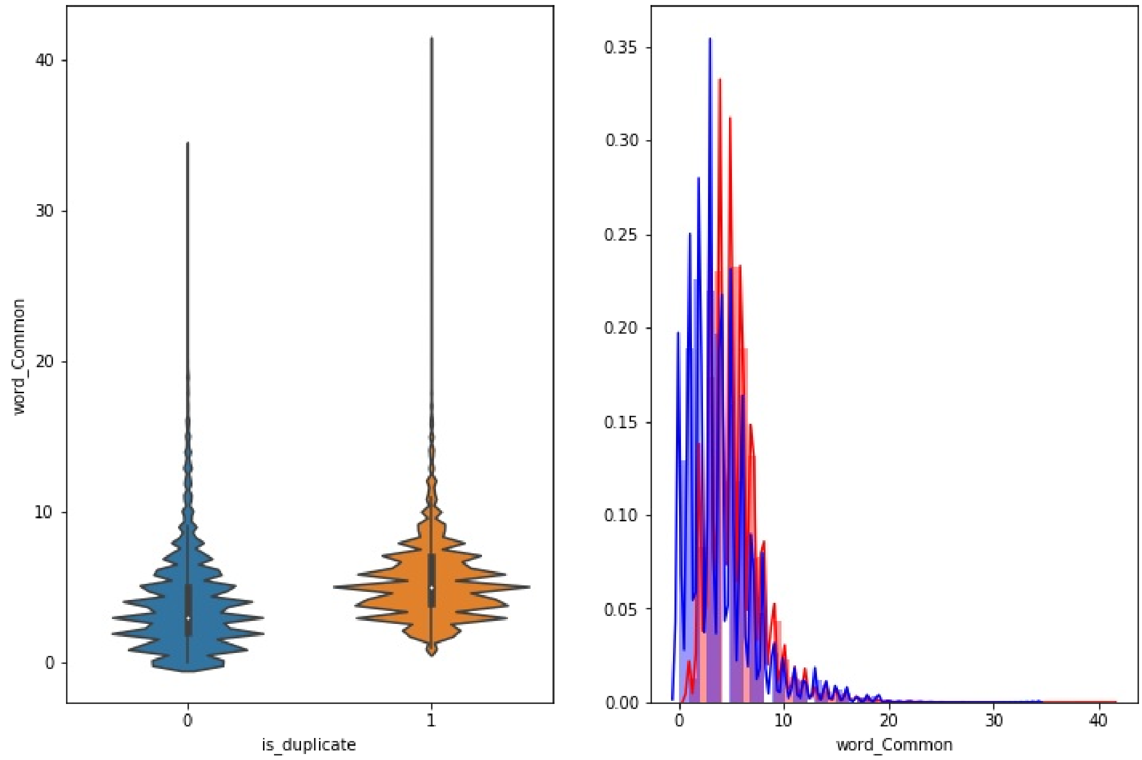
- The distributions for normalized word_share have some overlap on the far right-hand side, i.e., there are quite a lot of questions with high word similarity

- The average word share and Common no. of words of qid1 and qid2 is more when they are duplicate(Similar)

3.3.1.2 Feature: word_Common

In [18]:

```
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

3.4 Preprocessing of Text

In [19]:

```
# 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
```

3.5 Advanced Feature Extraction (NLP and Fuzzy Features)

In [20]:

```
import warnings
warnings.filterwarnings("ignore")
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from subprocess import check_output
%matplotlib inline
import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.tools as tls
import os
import gc

import re
from nltk.corpus import stopwords
#import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
import re
from nltk.corpus import stopwords
# This package is used for finding longest common subsequence between two strings
# you can write your own dp code for this
#import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
from fuzzywuzzy import fuzz
from sklearn.manifold import TSNE
# Import the Required lib packages for WORD-Cloud generation
# https://stackoverflow.com/questions/45625434/how-to-install-wordcloud-in-python3-6
from wordcloud import WordCloud, STOPWORDS
from os import path
from PIL import Image
```

In [21]:

```
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"]), axis=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["question2"]), axis=1)
    return df
```

In [22]:

```
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(2)
```

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

Out[22]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	...	ctc_max	last_word_eq	fi
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	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	1

2 rows × 21 columns

Analysis of extracted features

Plotting Word clouds

In [23]:

```
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 [24]:

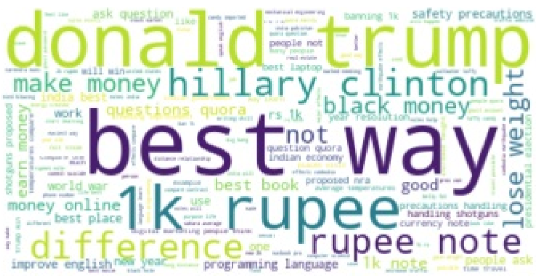
```
# reading the text files and removing the Stop Words:
from os import path
d = path.dirname('.')

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 : 16110077
Total number of words in non duplicate pair questions : 33193603
```

In [25]:

```
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
```



In [26]:

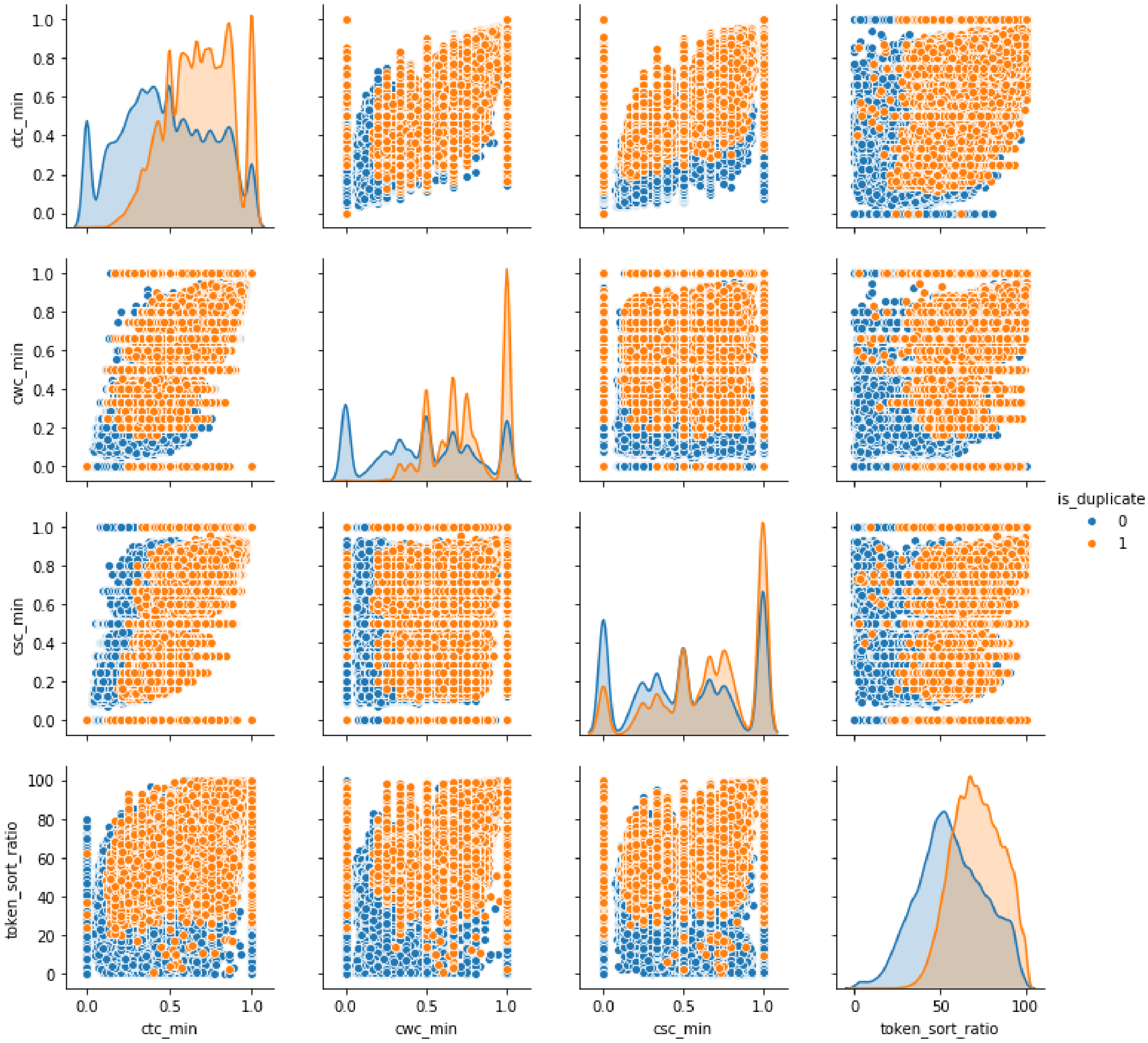
```
wc = WordCloud(background_color="white", max_words=len(textn_w),stopwords=stopwords)
# generate word cloud
wc.generate(textn_w)
print ("Word Cloud for non-Duplicate Question pairs:")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

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

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

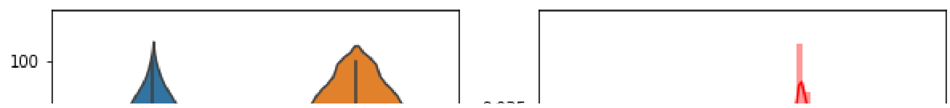
In [27]:

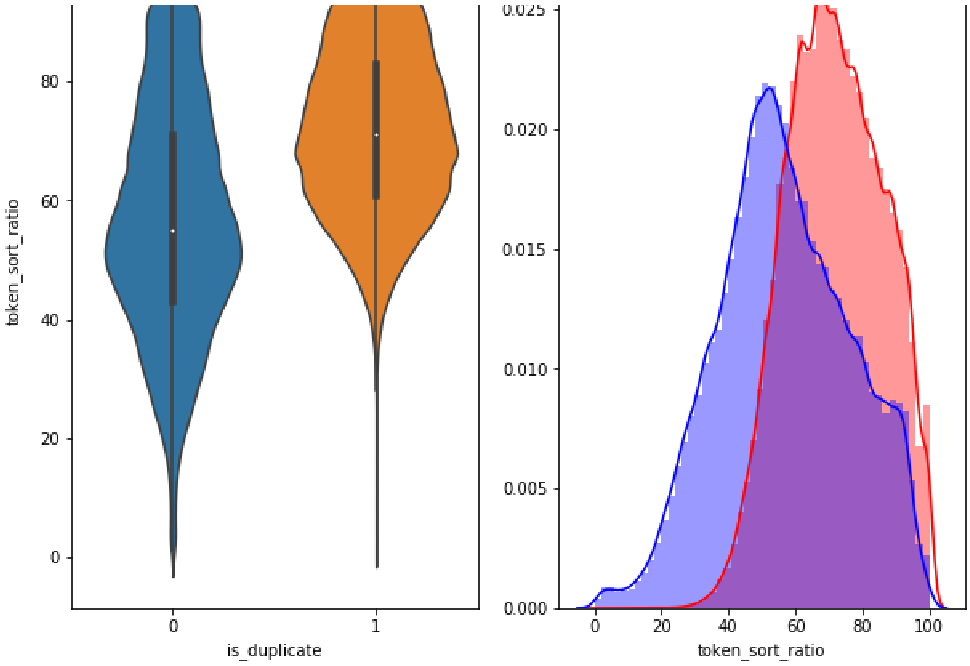
```
n = df.shape[0]
sns.pairplot(df[['ctc_min', 'cwc_min', 'csc_min', 'token_sort_ratio', 'is_duplicate']][0:n], hue='i
s_duplicate', vars=['ctc_min', 'cwc_min', 'csc_min', 'token_sort_ratio'])
plt.show()
```



In [28]:

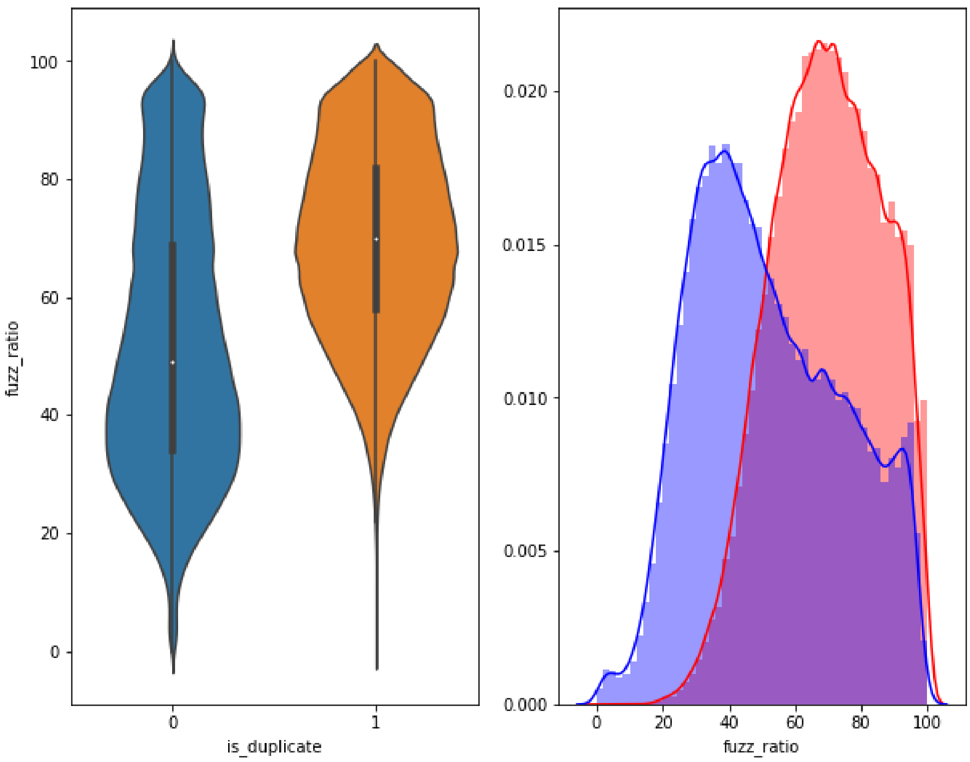
```
# Distribution of the token_sort_ratio
plt.figure(figsize=(10, 8))

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 [29]:

```
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()
```



3.5.2 Visualization

In [30]:

```
# Using TSNE for Dimentionality reduction for 15 Features(Generated after cleaning the data) to 3
dimention
```

```
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
```

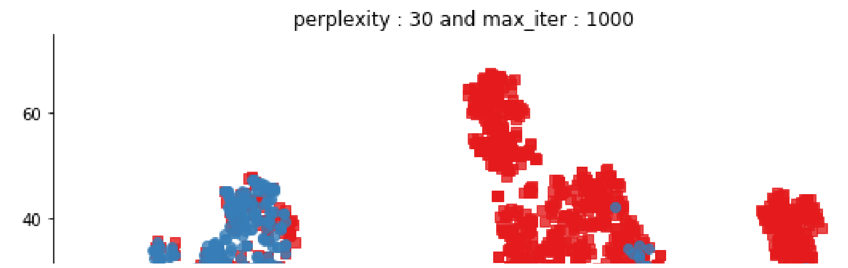
In [31]:

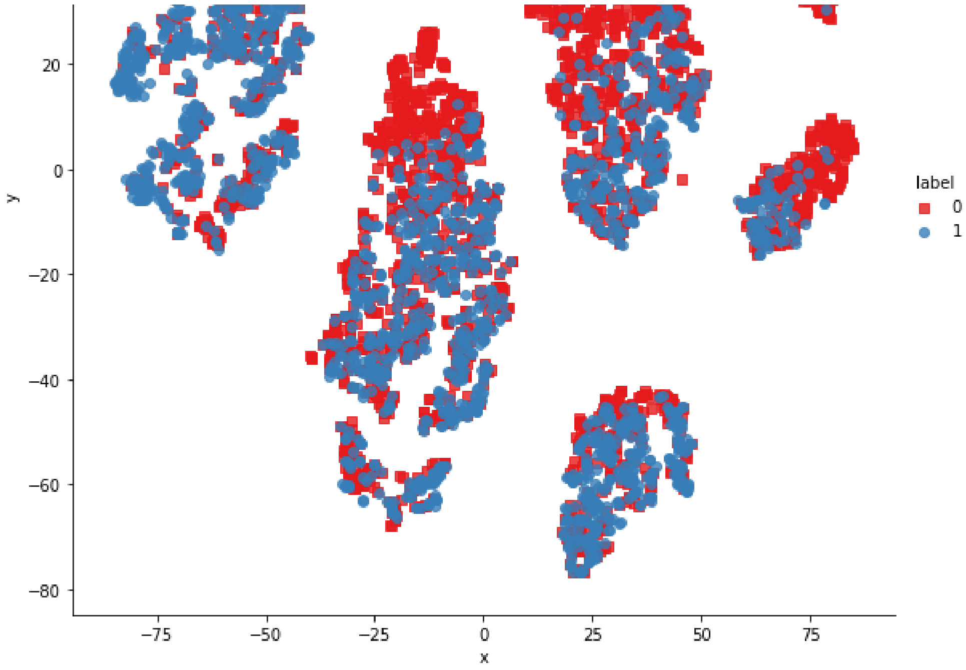
```
tsne2d = TSNE(
    n_components=2,
    init='random', # pca
    random_state=101,
    method='barnes_hut',
    n_iter=1000,
    verbose=2,
    angle=0.5
).fit_transform(X)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.018s...
[t-SNE] Computed neighbors for 5000 samples in 0.778s...
[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: 0.131928
[t-SNE] Computed conditional probabilities in 0.444s
[t-SNE] Iteration 50: error = 81.2975616, gradient norm = 0.0496455 (50 iterations in 6.219s)
[t-SNE] Iteration 100: error = 70.6435165, gradient norm = 0.0094614 (50 iterations in 4.245s)
[t-SNE] Iteration 150: error = 68.9952850, gradient norm = 0.0056374 (50 iterations in 4.003s)
[t-SNE] Iteration 200: error = 68.2175980, gradient norm = 0.0044332 (50 iterations in 4.286s)
[t-SNE] Iteration 250: error = 67.7385254, gradient norm = 0.0034321 (50 iterations in 4.381s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.738525
[t-SNE] Iteration 300: error = 1.7930490, gradient norm = 0.0011818 (50 iterations in 4.481s)
[t-SNE] Iteration 350: error = 1.3966638, gradient norm = 0.0004836 (50 iterations in 4.249s)
[t-SNE] Iteration 400: error = 1.2328721, gradient norm = 0.0002750 (50 iterations in 4.227s)
[t-SNE] Iteration 450: error = 1.1440563, gradient norm = 0.0001877 (50 iterations in 4.346s)
[t-SNE] Iteration 500: error = 1.0895753, gradient norm = 0.0001404 (50 iterations in 4.348s)
[t-SNE] Iteration 550: error = 1.0542322, gradient norm = 0.0001145 (50 iterations in 4.334s)
[t-SNE] Iteration 600: error = 1.0302582, gradient norm = 0.0001017 (50 iterations in 4.468s)
[t-SNE] Iteration 650: error = 1.0142238, gradient norm = 0.0000900 (50 iterations in 4.393s)
[t-SNE] Iteration 700: error = 1.0029600, gradient norm = 0.0000806 (50 iterations in 4.305s)
[t-SNE] Iteration 750: error = 0.9942252, gradient norm = 0.0000781 (50 iterations in 4.357s)
[t-SNE] Iteration 800: error = 0.9875125, gradient norm = 0.0000736 (50 iterations in 4.360s)
[t-SNE] Iteration 850: error = 0.9824185, gradient norm = 0.0000673 (50 iterations in 4.376s)
[t-SNE] Iteration 900: error = 0.9780059, gradient norm = 0.0000659 (50 iterations in 4.469s)
[t-SNE] Iteration 950: error = 0.9744161, gradient norm = 0.0000617 (50 iterations in 4.448s)
[t-SNE] Iteration 1000: error = 0.9713724, gradient norm = 0.0000583 (50 iterations in 4.413s)
[t-SNE] KL divergence after 1000 iterations: 0.971372
```

In [32]:

```
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 [33]:

```
from sklearn.manifold import TSNE
tsne3d = TSNE(
    n_components=3,
    init='random', # pca
    random_state=101,
    method='barnes_hut',
    n_iter=1000,
    verbose=2,
    angle=0.5
).fit_transform(X)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.021s...
[t-SNE] Computed neighbors for 5000 samples in 0.779s...
[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: 0.131928
[t-SNE] Computed conditional probabilities in 0.399s
[t-SNE] Iteration 50: error = 80.5249557, gradient norm = 0.0319611 (50 iterations in 20.978s)
[t-SNE] Iteration 100: error = 69.4158859, gradient norm = 0.0033386 (50 iterations in 10.925s)
[t-SNE] Iteration 150: error = 68.0448608, gradient norm = 0.0019634 (50 iterations in 9.936s)
[t-SNE] Iteration 200: error = 67.4930801, gradient norm = 0.0011609 (50 iterations in 10.030s)
[t-SNE] Iteration 250: error = 67.1813202, gradient norm = 0.0008686 (50 iterations in 9.898s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.181320
[t-SNE] Iteration 300: error = 1.5266187, gradient norm = 0.0007106 (50 iterations in 12.759s)
[t-SNE] Iteration 350: error = 1.1894693, gradient norm = 0.0001963 (50 iterations in 16.028s)
[t-SNE] Iteration 400: error = 1.0453291, gradient norm = 0.0000995 (50 iterations in 16.134s)
[t-SNE] Iteration 450: error = 0.9735472, gradient norm = 0.0000740 (50 iterations in 15.855s)
[t-SNE] Iteration 500: error = 0.9391118, gradient norm = 0.0000586 (50 iterations in 15.307s)
[t-SNE] Iteration 550: error = 0.9216439, gradient norm = 0.0000491 (50 iterations in 15.245s)
[t-SNE] Iteration 600: error = 0.9106981, gradient norm = 0.0000487 (50 iterations in 15.564s)
[t-SNE] Iteration 650: error = 0.9030094, gradient norm = 0.0000377 (50 iterations in 15.861s)
[t-SNE] Iteration 700: error = 0.8947795, gradient norm = 0.0000328 (50 iterations in 16.001s)
[t-SNE] Iteration 750: error = 0.8864105, gradient norm = 0.0000338 (50 iterations in 16.013s)
[t-SNE] Iteration 800: error = 0.8798748, gradient norm = 0.0000314 (50 iterations in 15.723s)
[t-SNE] Iteration 850: error = 0.8745480, gradient norm = 0.0000292 (50 iterations in 15.767s)
[t-SNE] Iteration 900: error = 0.8701542, gradient norm = 0.0000287 (50 iterations in 15.907s)
[t-SNE] Iteration 950: error = 0.8666047, gradient norm = 0.0000262 (50 iterations in 15.912s)
[t-SNE] Iteration 1000: error = 0.8636045, gradient norm = 0.0000248 (50 iterations in 16.175s)
[t-SNE] KL divergence after 1000 iterations: 0.863604
```

In [34]:

```
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 tfidf weighted word-vectors

In [35]:

```
import pandas as pd
import matplotlib.pyplot as plt
```

```
import re
import time
import warnings
import numpy as npx
from nltk.corpus import stopwords
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
warnings.filterwarnings("ignore")
import sys
import os
import pandas as pd
import numpy as np
from tqdm import tqdm

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

In [36]:

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

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

In [37]:

```
df.head()
```

Out[37]:

	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 [38]:

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

After we find TF-IDF scores, we convert each question to a weighted average of word2vec vectors by these scores. here we use a pre-trained GLOVE model which comes free with "Spacy". https://spacy.io/usage/vectors-similarity It is trained on Wikipedia and therefore, it is stronger in terms of word semantics.

In [39]:

```
# en_vectors_web_lg, which includes over 1 million unique vectors.
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
[1:45:30<00:00, 63.87it/s]
```

In [40]:

```
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
[49:51<00:00, 135.16it/s]
```

In [41]:

```
#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')
```

In [42]:

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

In [43]:

```
# dataframe of nlp features
dfnlp.head(2)
```

Out[43]:

	id	qid1	qid2	question1	question2	is_duplicate

	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

In [44]:

```
# data before preprocessing
dfppro.head(2)
```

Out[44]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_C
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

In [45]:

```
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 [46]:

```
# Questions 1 tfidf weighted word2vec
df3_q1.head()
```

Out[46]:

	0	1	2	3	4	5	6	7	8	
0	211.129864	-144.683059	-68.811247	-153.662141	-89.931593	2.311301	136.743747	50.449112	-64.150964	56.62752
1	144.124685	-114.012484	-111.716694	-104.885038	-88.238478	16.441834	58.238013	102.095138	6.026966	178.4984
2	81.757898	-142.184507	0.559867	-104.660084	-84.156631	22.515110	115.521661	50.436953	-111.740923	51.71331
3	-126.651922	-59.747160	-67.763201	-138.114731	-101.038699	88.148523	-22.912261	85.941426	27.784233	50.81065
4	299.444044	-188.632001	-22.946291	-273.683355	-188.480395	107.123044	174.946302	-72.042341	-98.290527	137.43997

5 rows × 96 columns

In [47]:

```
# Questions 2 tfidf weighted word2vec
df3_q2.head()
```

```
df3_q1.head()
```

Out[47]:

	0	1	2	3	4	5	6	7	8	9	...
0	151.268526	-127.013168	-31.546286	-142.905807	-97.249094	9.485758	106.682259	36.754201	-36.541905	53.162199	...
1	152.023095	-44.955390	-103.559249	-128.467601	-118.567610	44.577916	137.906144	26.984746	-78.328355	86.576880	...
2	4.930220	-29.029581	-117.808812	-98.332275	-19.064096	-9.867805	141.808202	91.269564	50.727205	12.816846	...
3	-6.951929	-44.951731	-17.343082	-61.444452	-7.469152	16.942014	95.049250	-2.631600	-13.050916	-28.038393	...
4	96.174524	-71.613948	21.584882	-92.742468	-106.643129	10.646790	92.190157	-40.565982	-34.739525	56.340519	...

5 rows × 96 columns

In [48]:

```
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 [49]:

```
# 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')
```

4. Machine Learning Models

4.1 Reading data from file and storing into sql table

In [50]:

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

In [51]:

```
data.head(3)
```

Out[51]:

	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_

	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
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 rows × 47 columns

4.3 Random train test split

In [52]:

```
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_dup
licate'], random_state=32)
```

In [53]:

```
X_train.shape
```

Out[53]:

```
(37500, 47)
```

In [54]:

```
X_train.head(2)
```

Out[54]:

	Unnamed: 0	id	is_duplicate	freq_qid1_x	freq_qid2_x	q1len_x	q2len_x	q1_n_words_x	q2_n_words_x	word_Co
23561	23561	23561	0	1	1	33	50	7	10	4.0
3536	3536	3536	0	1	1	46	58	10	12	1.0

2 rows × 47 columns

In [55]:

```
# 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, 44)
Number of data points in test data : (12500, 44)
```

In [56]:

```
y_train.shape
```

Out[56]:

```
(37500,)
```

In [57]:

```
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 [58]:

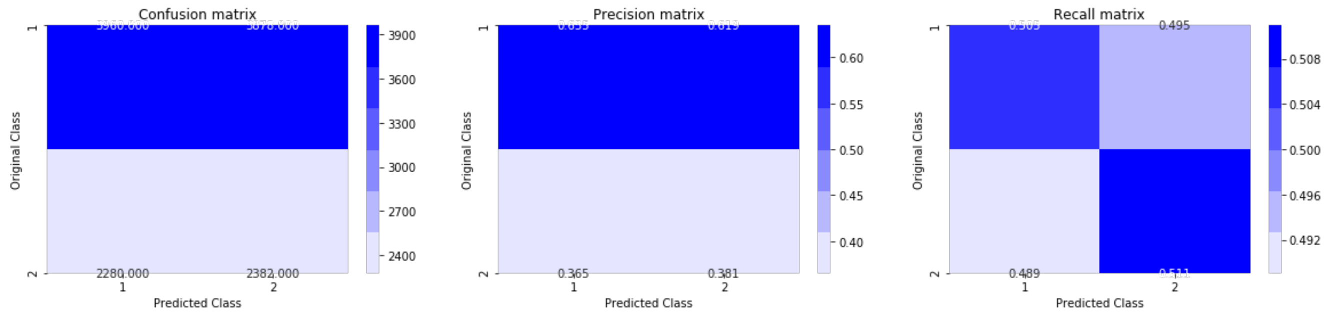
```
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predicted class j

    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()
```

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

In [59]:

```
# 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 0.8746716989316823
```



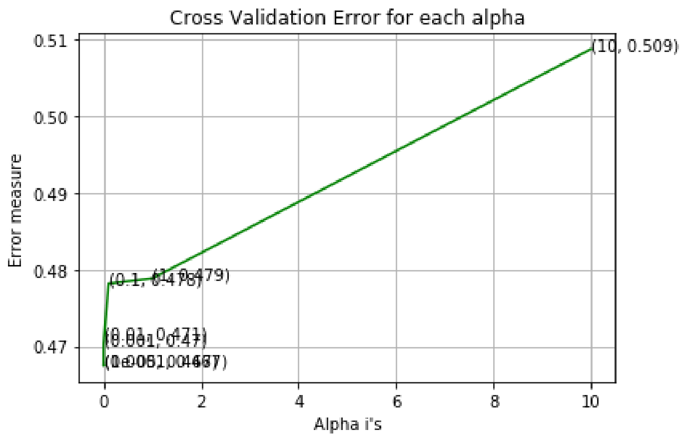
4.4 Logistic Regression with hyperparameter tuning </h2>

In [60]:

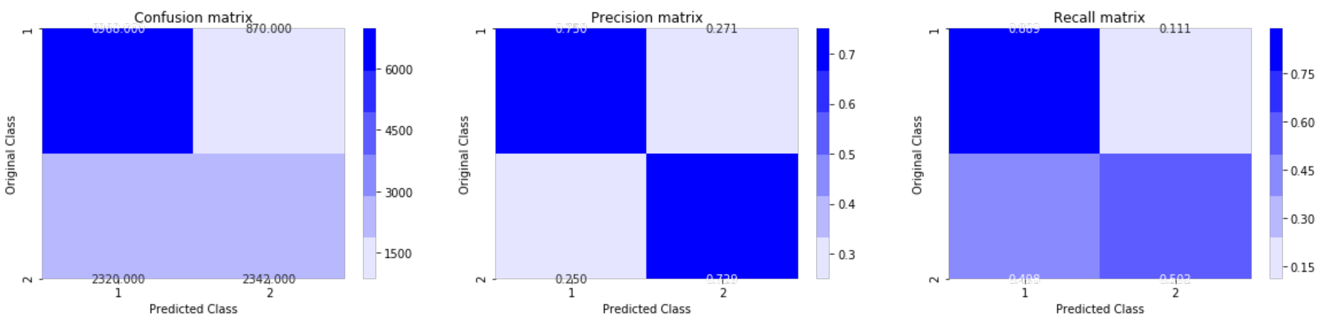
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# 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)
```

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

predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha =  1e-05 The log loss is: 0.46748950473787415
For values of alpha =  0.0001 The log loss is: 0.467411411795257
For values of alpha =  0.001 The log loss is: 0.4702043503620991
For values of alpha =  0.01 The log loss is: 0.47095651464973903
For values of alpha =  0.1 The log loss is: 0.47815931432174075
For values of alpha =  1 The log loss is: 0.47883932764652315
For values of alpha =  10 The log loss is: 0.5087726243467064
```




```
For values of best alpha =  0.0001 The train log loss is: 0.4658529781704176
For values of best alpha =  0.0001 The test log loss is: 0.467411411795257
Total number of data points : 12500
```



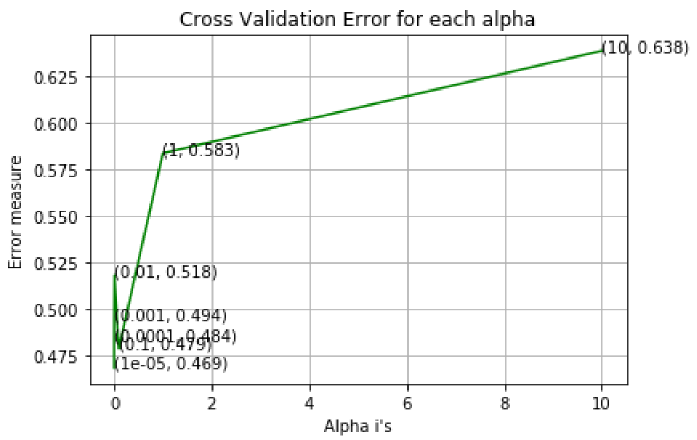
4.5 Linear SVM with hyperparameter tuning

In [61]:

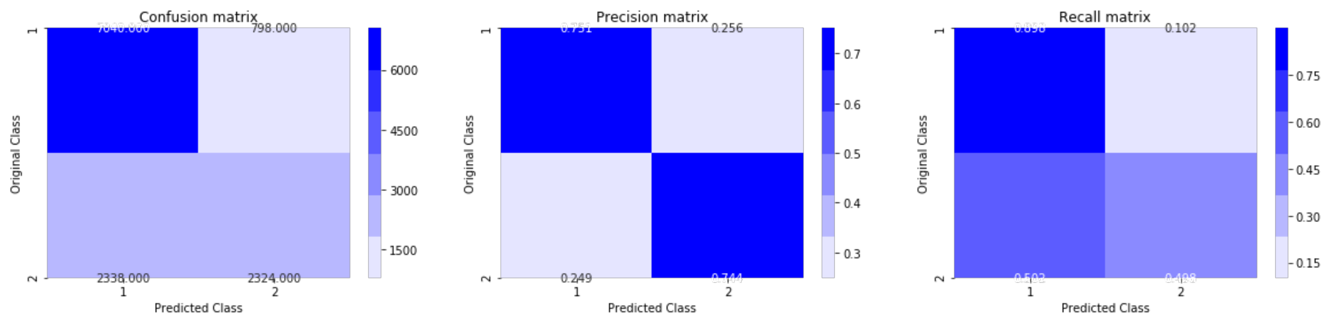
```python
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# 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)
```

```
# 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, 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: 0.468568715140383
For values of alpha =  0.0001 The log loss is: 0.4836764509430551
For values of alpha =  0.001 The log loss is: 0.49419792841068927
For values of alpha =  0.01 The log loss is: 0.5181667966968087
For values of alpha =  0.1 The log loss is: 0.47892462615236553
For values of alpha =  1 The log loss is: 0.583450288631332
For values of alpha =  10 The log loss is: 0.6384048153029616
```




```
For values of best alpha =  1e-05 The train log loss is: 0.46792983199906313
For values of best alpha =  1e-05 The test log loss is: 0.468568715140383
Total number of data points : 12500
```



4.6 XGBoost

In [62]:

```
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))
```

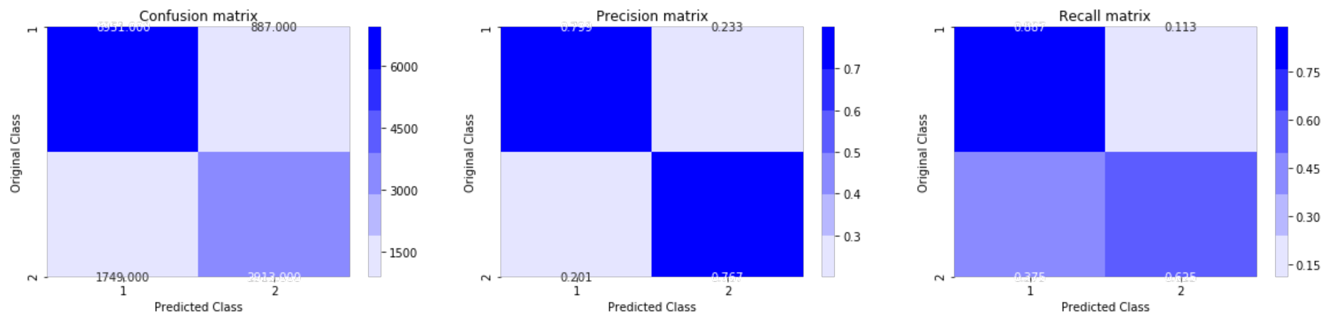
```
[0] train-logloss:0.685301 valid-logloss:0.685242
Multiple eval metrics have been passed: 'valid-logloss' will be used for early stopping.

Will train until valid-logloss hasn't improved in 20 rounds.
[10] train-logloss:0.620617 valid-logloss:0.620098
[20] train-logloss:0.573226 valid-logloss:0.572814
[30] train-logloss:0.537786 valid-logloss:0.537428
[40] train-logloss:0.511344 valid-logloss:0.51081
[50] train-logloss:0.490437 valid-logloss:0.489951
[60] train-logloss:0.475004 valid-logloss:0.47453
[70] train-logloss:0.462591 valid-logloss:0.462188
[80] train-logloss:0.452563 valid-logloss:0.452189
[90] train-logloss:0.4443 valid-logloss:0.443862
[100] train-logloss:0.437586 valid-logloss:0.437173
[110] train-logloss:0.432111 valid-logloss:0.431734
[120] train-logloss:0.427581 valid-logloss:0.427275
[130] train-logloss:0.423936 valid-logloss:0.423784
[140] train-logloss:0.420928 valid-logloss:0.420948
[150] train-logloss:0.418488 valid-logloss:0.418605
[160] train-logloss:0.416269 valid-logloss:0.416503
[170] train-logloss:0.414331 valid-logloss:0.414624
[180] train-logloss:0.412715 valid-logloss:0.413083
[190] train-logloss:0.411387 valid-logloss:0.411845
[200] train-logloss:0.409991 valid-logloss:0.410484
[210] train-logloss:0.408918 valid-logloss:0.409456
[220] train-logloss:0.407908 valid-logloss:0.408576
[230] train-logloss:0.406951 valid-logloss:0.407746
[240] train-logloss:0.406023 valid-logloss:0.406964
[250] train-logloss:0.405104 valid-logloss:0.40621
[260] train-logloss:0.404181 valid-logloss:0.405476
[270] train-logloss:0.403293 valid-logloss:0.404614
[280] train-logloss:0.402551 valid-logloss:0.40399
[290] train-logloss:0.401995 valid-logloss:0.403561
[300] train-logloss:0.401437 valid-logloss:0.403178
[310] train-logloss:0.4008 valid-logloss:0.402659
[320] train-logloss:0.400363 valid-logloss:0.402358
[330] train-logloss:0.399898 valid-logloss:0.402057
[340] train-logloss:0.399432 valid-logloss:0.401745
```

```
[350] train-logloss:0.39891 valid-logloss:0.401362
[360] train-logloss:0.398474 valid-logloss:0.40103
[370] train-logloss:0.398037 valid-logloss:0.400724
[380] train-logloss:0.397639 valid-logloss:0.400436
[390] train-logloss:0.397208 valid-logloss:0.400196
[399] train-logloss:0.396794 valid-logloss:0.399874
The test log loss is: 0.399874138790532
```

In [63]:

```
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
```



1. Let us 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.

5.1 Reading data from file

In [64]:

```
if os.path.isfile('nlp_features_train.csv'):
    df1 = pd.read_csv("nlp_features_train.csv",nrows=50000,encoding='latin-1')

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

In [65]:

```
df1.head(2)
```

Out[65]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	...	ctc_max	last_word_eq	fi
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	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	1

2 rows × 21 columns

In [66]:

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

In [67]:

```
dfnlp.head(2)
```

Out[67]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	...	freq_qid2	q1len	q2len	q
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	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	8

2 rows × 32 columns

In [68]:

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

```
Empty DataFrame
Columns: [id, qid1, qid2, question1, question2, is_duplicate, cwc_min, cwc_max, csc_min, csc_max,
ctc_min, ctc_max, last_word_eq, first_word_eq, abs_len_diff, mean_len, token_set_ratio,
token_sort_ratio, fuzz_ratio, fuzz_partial_ratio, longest_substr_ratio, freq_qid1, freq_qid2, q1le
n, q2len, q1_n_words, q2_n_words, word_Common, word_Total, word_share, freq_q1+q2, freq_q1-q2]
Index: []

[0 rows x 32 columns]
```

In [69]:

```
# Filling the null values with ' '
dfnlp = dfnlp.fillna('')
nan_rows = dfnlp[dfnlp.isnull().any(1)]
print (nan_rows)
```

```
Empty DataFrame
Columns: [id, qid1, qid2, question1, question2, is_duplicate, cwc_min, cwc_max, csc_min, csc_max,
ctc_min, ctc_max, last_word_eq, first_word_eq, abs_len_diff, mean_len, token_set_ratio,
token_sort_ratio, fuzz_ratio, fuzz_partial_ratio, longest_substr_ratio, freq_qid1, freq_qid2, q1le
n, q2len, q1_n_words, q2_n_words, word_Common, word_Total, word_share, freq_q1+q2, freq_q1-q2]
Index: []

[0 rows x 32 columns]
```

5.2 Splitting data into Train and cross validation(or test): Stratified Sampling

In [70]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(dfnlp,dfnlp['is_duplicate'],stratify=dfnlp['is
```

```
duplicate'], random_state=32)
```

In [71]:

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

Out[71]:

```
(37500, 31)
```

In [72]:

```
y_train.shape
```

Out[72]:

```
(37500,)
```

In [73]:

```
y_test.shape
```

Out[73]:

```
(12500,)
```

In [74]:

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

Out[74]:

```
(12500, 31)
```

In [75]:

```
X_train.head()
```

Out[75]:

	id	qid1	qid2	question1	question2	cwc_min	cwc_max	csc_min	csc_max	ctc_min	...	freq_qid2	q1len
23561	23561	44124	44125	how do i learn geography for nda	how do i learn to accept myself and my appeara...	0.333322	0.333322	0.749981	0.428565	0.571420	...	1	33
3536	3536	7006	7007	what happens when 0 gb disk space is reached	is there a pokemon fan game or romhack set dur...	0.000000	0.000000	0.333322	0.166664	0.111110	...	1	46
33192	33192	61018	19621	why do people ask so many googleable questions...	why do some people ask questions on quora that...	0.666656	0.399996	0.749981	0.374995	0.699993	...	23	56
				what is									

	id	qid1	qid2	question1	question2	cwc_min	cwc_max	csc_min	csc_max	ctc_min	...	freq_qid2	q1len
35725	35725	65244	65245	china doing to help nepal	how can we help nepal	0.999950	0.666644	0.000000	0.000000	0.399992	...	1	34
6320	6320	12389	12390	what are the best education portals in india	which are the best sites for free education in...	0.749981	0.599988	0.749981	0.599988	0.749991	...	1	45

5 rows × 31 columns

5.3 TFIDF vectorizer on Questions Text Data

In [76]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(ngram_range=(1,2), min_df=10)

# merge texts
questions = list(X_train['question1']) + list(X_train['question2'])
#questions = list(df['question1']) + list(df['question2'])


vectorizer.fit(questions)
```

Out[76]:

```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
                dtype=<class 'numpy.float64'>, encoding='utf-8',
                input='content', lowercase=True, max_df=1.0, max_features=None,
                min_df=10, ngram_range=(1, 2), norm='l2', preprocessor=None,
                smooth_idf=True, stop_words=None, strip_accents=None,
                sublinear_tf=False, token_pattern='(?u)\\b\\w\\w+\\b',
                tokenizer=None, use_idf=True, vocabulary=None)
```

Train Data

In [77]:

```
tfidf_train_ques1= vectorizer.transform(X_train['question1'])
print("Shape of matrix after one hot encodig ",tfidf_train_ques1.shape)

print("the number of unique words ", tfidf_train_ques1.get_shape()[1])
```

```
Shape of matrix after one hot encodig  (37500, 13369)
the number of unique words  13369
```

In [78]:

```
tfidf_train_ques2= vectorizer.transform(X_train['question2'])
print("Shape of matrix after one hot encodig ",tfidf_train_ques2.shape)
print("the number of unique words ", tfidf_train_ques2.get_shape()[1])
```

```
Shape of matrix after one hot encodig  (37500, 13369)
the number of unique words  13369
```

In [79]:

```
# extraction  features from train  data frame
X_train_feature_df = X_train.drop(['id','qid1','qid2','question1','question2'], axis=1, inplace=Fal
se)
```

In [80]:

```
X_train_feature_df.head(2)
```

Out[80]:

	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	abs_len_diff	mean_len	...
23561	0.333322	0.333322	0.749981	0.428565	0.57142	0.399996	0.0	1.0	3.0	8.5	...
3536	0.000000	0.000000	0.333322	0.166664	0.11111	0.083333	0.0	0.0	3.0	10.5	...

2 rows × 26 columns

In [81]:

```
import scipy
# X_train.head()
print("train Shape Before -> ",X_train_feature_df.shape," Type",type(X_train_feature_df))

#so we need to convert our feature data into sparse matrix so that we will combine our feature and
and tfidf vec
train_feat_sparse = scipy.sparse.csr_matrix(X_train_feature_df)

print("train Shape After-> ",train_feat_sparse.shape," Type",type(train_feat_sparse))
```

```
train Shape Before ->  (37500, 26)  Type <class 'pandas.core.frame.DataFrame'>
train Shape After->  (37500, 26)  Type <class 'scipy.sparse.csr.csr_matrix'>
```

TEST Data

In [82]:

```
tfidf_test_ques1= vectorizer.transform(X_test['question1'])
print("Shape of matrix after one hot encodig ",tfidf_test_ques1.shape)
print("the number of unique words ", tfidf_test_ques1.get_shape()[1])


tfidf_test_ques2= vectorizer.transform(X_test['question2'])
print("Shape of matrix after one hot encodig ",tfidf_test_ques2.shape)
print("the number of unique words ", tfidf_test_ques2.get_shape()[1])
```

```
Shape of matrix after one hot encodig  (12500, 13369)
the number of unique words  13369
Shape of matrix after one hot encodig  (12500, 13369)
the number of unique words  13369
```

In [83]:

```
# extraction  features from test  data frame
X_test_feature_df = X_test.drop(['id','qid1','qid2','question1','question2'], axis=1, inplace=False
)


print("test Shape Before -> ",X_test_feature_df.shape," Type",type(X_test_feature_df))

#so we need to convert our feature data into sparse matrix so that we will combine our feature and
and tfidf vec
test_feat_sparse = scipy.sparse.csr_matrix(X_test_feature_df)

print("test Shape After-> ",test_feat_sparse.shape," Type",type(test_feat_sparse))
```

```
test Shape Before ->  (12500, 26)  Type <class 'pandas.core.frame.DataFrame'>
test Shape After->  (12500, 26)  Type <class 'scipy.sparse.csr.csr_matrix'>
```

In [84]:

```
# combining our tfidf and features into one
```

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack


tfidf_train = hstack((tfidf_train_ques1,tfidf_train_ques2))

# test features(feat + tfidfvec)
tfidf_test = hstack((tfidf_test_ques1,tfidf_test_ques2))

#final train and test data shape
print("train data shape",tfidf_train.shape)

print("Test data shape ",tfidf_test.shape)
```

```
train data shape (37500, 26738)
Test data shape  (12500, 26738)
```

In [85]:

```
tfidf_train.shape
```

Out[85]:

```
(37500, 26738)
```

In [86]:

```
from scipy.sparse import hstack

tfidf_train = hstack((train_feat_sparse,tfidf_train_ques1,tfidf_train_ques2))

# test features(feat + tfidfvec)
tfidf_test = hstack((test_feat_sparse,tfidf_test_ques1,tfidf_test_ques2))

#final train and test data shape
print("train data shape",tfidf_train.shape)

print("Test data shape ",tfidf_test.shape)
```

```
train data shape (37500, 26764)
Test data shape  (12500, 26764)
```

In [87]:

```
print("Final Shape of the Data matrix")
print(tfidf_train.shape, y_train.shape)

print(tfidf_test.shape, y_test.shape)
```

```
Final Shape of the Data matrix
(37500, 26764) (37500,)
(12500, 26764) (12500,)
```

In [88]:

```
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
```

5.4 Function For Confusion Matrix

In [89]:

```
# 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()
```

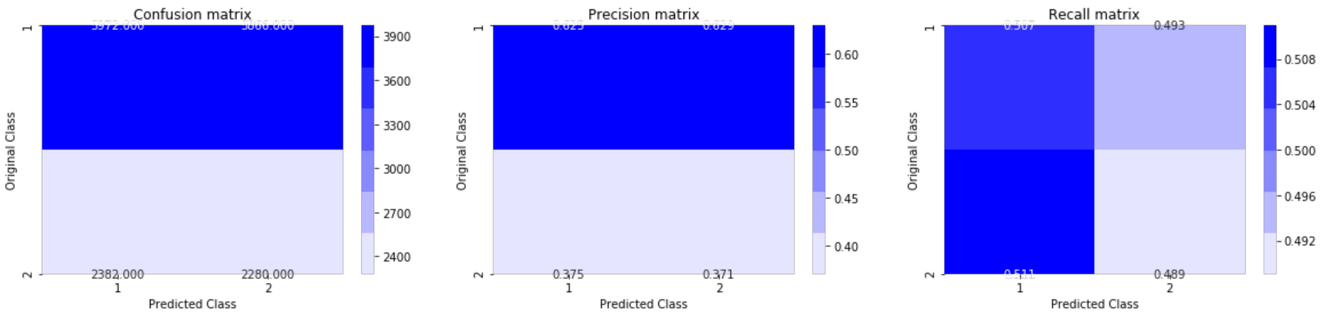
5.5 Building a random model (Finding worst-case log-loss)

In [90]:

```
# 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 0.8878177387261336
```



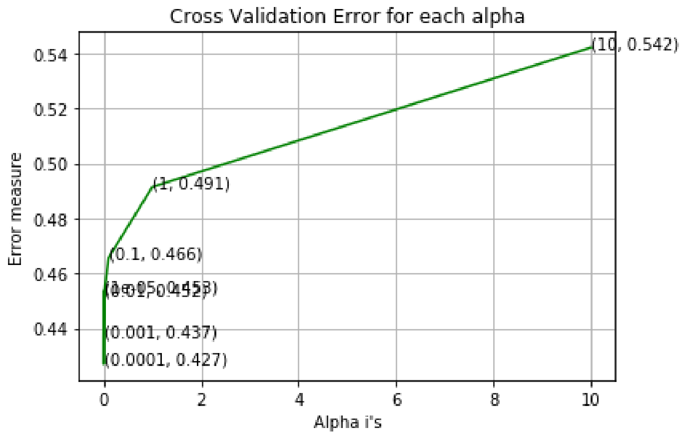
5.6 Logistic Regression with hyperparameter tuning

In [91]:

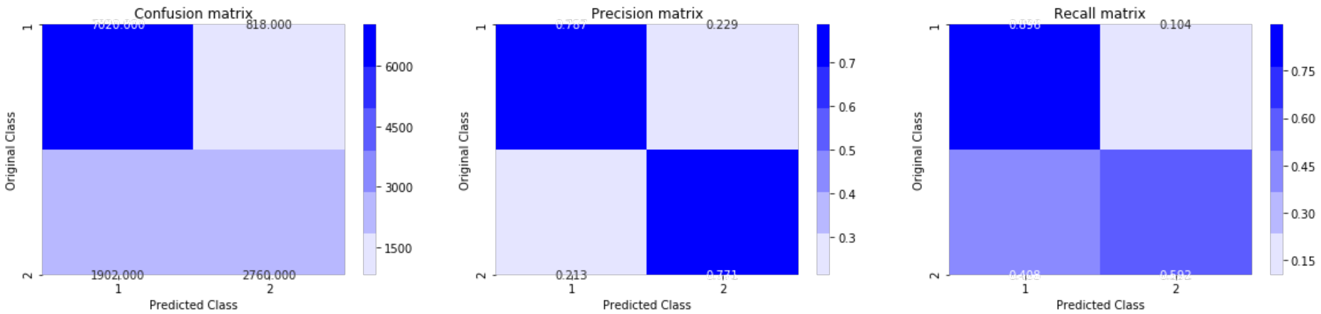
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# 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(tfidf_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(tfidf_train, y_train)
    predict_y = sig_clf.predict_proba(tfidf_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(tfidf_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(tfidf_train, y_train)

predict_y = sig_clf.predict_proba(tfidf_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(tfidf_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: 0.4534364133470595
For values of alpha =  0.0001 The log loss is: 0.427024623201395
For values of alpha =  0.001 The log loss is: 0.43679236027990154
For values of alpha =  0.01 The log loss is: 0.45224537554092165
For values of alpha =  0.1 The log loss is: 0.46560955951780664
For values of alpha =  1 The log loss is: 0.4914680785258957
For values of alpha =  10 The log loss is: 0.5421455955505056
```




```
For values of best alpha =  0.0001 The train log loss is: 0.41523107644180174
For values of best alpha =  0.0001 The test log loss is: 0.427024623201395
Total number of data points : 12500
```



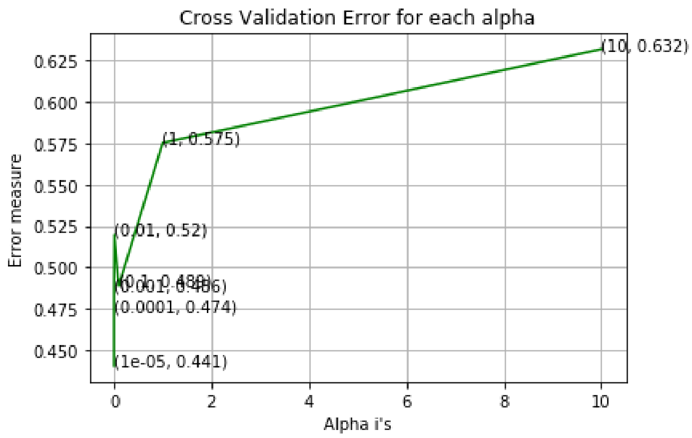
5.7 Linear SVM with hyperparameter tuning

In [92]:

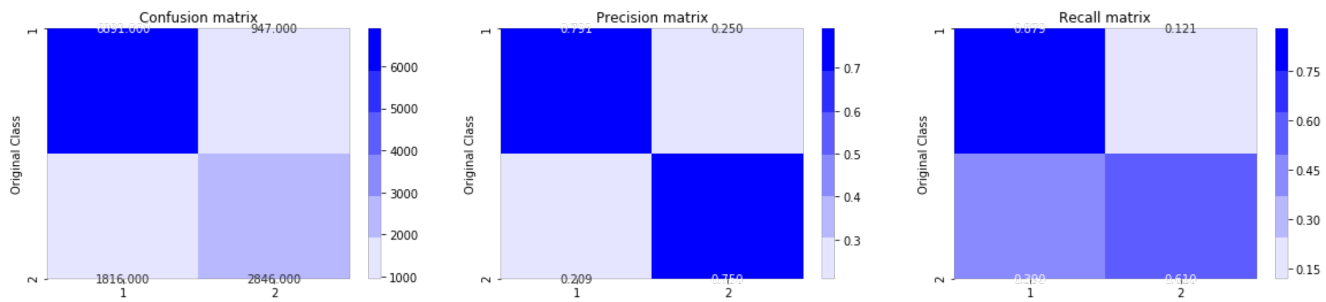
```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# 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(tfidf_train, y_train)
```

```
    clf.fit(tfidf_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(tfidf_train, y_train)
    predict_y = sig_clf.predict_proba(tfidf_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(tfidf_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(tfidf_train, y_train)

predict_y = sig_clf.predict_proba(tfidf_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(tfidf_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: 0.44055060308003713
For values of alpha =  0.0001 The log loss is: 0.4739964863198457
For values of alpha =  0.001 The log loss is: 0.4861788835774691
For values of alpha =  0.01 The log loss is: 0.5196767681537059
For values of alpha =  0.1 The log loss is: 0.48887010386648644
For values of alpha =  1 The log loss is: 0.5751288906659099
For values of alpha =  10 The log loss is: 0.6316597464583033
```




```
For values of best alpha =  1e-05 The train log loss is: 0.42745588054917155
For values of best alpha =  1e-05 The test log loss is: 0.44055060308003713
Total number of data points : 12500
```



Predicted Class Predicted Class Predicted Class

5.8 XGBoost

A. Hyperparameter Tuning

In [93]:

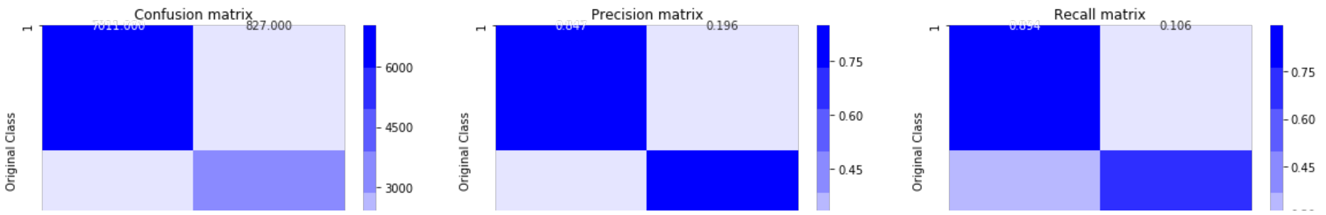
```
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
import scipy.stats as sc




params = {

        "learning_rate":sc.uniform(0.05,0.3),
        'max_depth': sc.randint(3,15),
        'n_estimators' : sc.randint(10,200),
        "min_child_weight" : [ 1, 3, 5, 7 ],
        'gamma': sc.uniform(0.0,0.5)
        }
x_model = xgb.XGBClassifier(objective='binary:logistic', eval_metric='logloss',n_jobs=-1)

xgb_random_search = RandomizedSearchCV(x_model, param_distributions = params,n_iter=30,
                         scoring = 'neg_log_loss', n_jobs = -1,cv=3)

#xgb_random_search.fit(X_train, y_train)


#print("Score : ",xgb_random_search.best_score_)
#print("Best Params",xgb_random_search.best_params_)
```

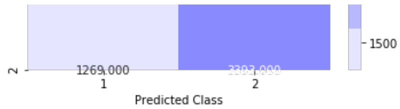
B. With Best Params

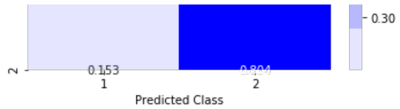
In [94]:

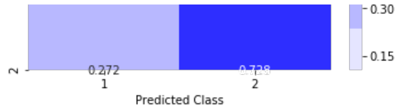
```
bst =
xgb.XGBClassifier(max_depth=10,learning_rate=0.1042,objective='binary:logistic',gamma=0.35,n_estima
tors=187,min_child_weight=7,n_jobs=-1)
bst.fit(tfidf_train, y_train)


clf_calib = CalibratedClassifierCV(bst, method="sigmoid")
clf_calib.fit(tfidf_train, y_train)

predict_y = clf_calib.predict_proba(tfidf_train)

print("The train log loss is: ",log_loss(y_train, predict_y,labels=bst.classes_, eps=1e-15))

predict_y = clf_calib.predict_proba(tfidf_test)
print("The test log loss is : ",log_loss(y_test, predict_y,labels=bst.classes_, eps=1e-15))


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

```
The train log loss is:  0.2499683753545042
The test log loss is :  0.3461761557838114
```









TFIDF Weighted Word2Vec

In [167]:

```
# Load Basic Features
dftw_50k = pd.read_csv("df_fe_without_preprocessing_train.csv",encoding='latin-1')
#Taking samples of 50k
# Creating duplicate of df_50k for TFIDF Weighted Word2Vec
dftw_50k = dftw_50k.sample(n = 50000)
print("Columns in dftw_50k dataframe:\n")
print(dftw_50k.columns)

dftw_50k.head()
```

```
Columns in dftw_50k dataframe:

Index(['id', 'qid1', 'qid2', 'question1', 'question2', 'is_duplicate',
       'freq_qid1', 'freq_qid2', 'q1len', 'q2len', 'q1_n_words', 'q2_n_words',
       'word_Common', 'word_Total', 'word_share', 'freq_q1+q2', 'freq_q1-q2'],
      dtype='object')
```

Out[167]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q
178300	178300	221393	273887	Is Quora degrading itself?	Why is the quality of Quora degrading?	0	1	1	26	38	4	7
24373	24373	12916	45545	What is the best time for studying? Why?	What is the best time of the day to learn or s...	0	3	1	40	51	8	1
65759	65759	114071	114072	As an international student in the United Stat...	Are international students on an F-1 Visa elig...	0	1	1	174	71	32	1
11495	11495	22194	18788	How can one learn to scrap web data using Python?	What are some good resources to learn web scra...	1	3	3	49	63	10	1
13576	13576	26055	26056	Why it is diffulcut to get jobs in upwork.com?	Why am I not getting any freelance jobs on Upw...	0	1	2	46	50	9	1

In [192]:

```
dftw_50k['question1'] = dftw_50k['question1'].apply(lambda x: str(x))
dftw_50k['question2'] = dftw_50k['question2'].apply(lambda x: str(x))
```

In [194]:

```
x_tw = dftw_50k.drop(['is_duplicate', 'id'], axis = 1)
```

```
y_tw = dftw_50k['is_duplicate']
```

In [196]:

```
#Train Test Split
from sklearn.model_selection import train_test_split

x_train_tw, x_test_tw, y_train_tw, y_test_tw = train_test_split(x_tw, y_tw, test_size = 0.3, random
_state = 0, shuffle = False)
```

In [197]:

```
print("Shape of x train data:", x_train_tw.shape)
print("Shape of x test data:", x_test_tw.shape)
print("Shape of y train data:", y_train_tw.shape)
print("Shape of y test data:", y_test_tw.shape)
```

```
Shape of x train data: (35000, 15)
Shape of x test data: (15000, 15)
Shape of y train data: (35000,)
Shape of y test data: (15000,)
```

In [198]:

```
# With train data, creating list of questions, dictionary of feature names and idf values

# Importing library
from sklearn.feature_extraction.text import TfidfVectorizer

# Merge texts
questions = list(x_train_tw['question1']) + list(x_train_tw['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 [199]:

```
# Defining a function 'vec' to create TF-IDF Weighted Word2Vec

# Importing libraries
import os
import spacy
from tqdm import tqdm

def vec(xtw):

    # en_vectors_web_lg, which includes over 1 million unique vectors.
    nlp = spacy.load('en_core_web_sm')

    vecs = []

    # https://github.com/noamraph/tqdm
    # tqdm is used to print the progress bar
    for qu in tqdm(list(xtw)):

        doc = nlp(qu)
        # 96 is the number of dimensions of vectors
        mean_vec = np.zeros([len(doc), 96])

        for word in doc:
            # word2vec
            vec = word.vector
            # fetch df score

            try:
                idf = word2tfidf[str(word)]

            except:
                idf = 0
```

```
            # compute final vec
            mean_vec += vec * idf

        mean_vec = mean_vec.mean(axis = 0)
        vecs.append(mean_vec)
    #dftw_100k['q1_feats_m'] = list(vecs1)

    return vecs
```

In [201]:

```
# Calling 'vec' function for train question1

x_train_tw['que1_tw'] = vec(x_train_tw['question1'])
```

```
100%|████████████████████████████████████████████████████████████████████████████| 35000/35000 [04:
48<00:00, 121.50it/s]
```

In [202]:

```
# Calling 'vec' function for train question2

x_train_tw['que2_tw'] = vec(x_train_tw['question2'])
```

```
100%|████████████████████████████████████████████████████████████████████████████| 35000/35000 [05:
18<00:00, 109.79it/s]
```

In [203]:

```
# Calling 'vec' function for test question1

x_test_tw['que1_tw'] = vec(x_test_tw['question1'])
```

```
100%|████████████████████████████████████████████████████████████████████████████| 15000/15000 [02:
04<00:00, 120.26it/s]
```

In [204]:

```
# Calling 'vec' function for test question2

x_test_tw['que2_tw'] = vec(x_test_tw['question2'])
```

```
100%|████████████████████████████████████████████████████████████████████████████| 15000/15000 [02:
06<00:00, 118.24it/s]
```

In [205]:

```
print("Type of x_train_tw['que1_tw']:", type(x_train_tw['que1_tw']))
print("Type of x_train_tw['que2_tw']:", type(x_train_tw['que2_tw']), '\n')
print("Type of x_test_tw['que1_tw']:", type(x_test_tw['que1_tw']))
print("Type of x_test_tw['que2_tw']:", type(x_test_tw['que2_tw']), '\n')

print("Shape of x train question1:", x_train_tw['que1_tw'].shape)
print("Shape of x test question1 data:", x_test_tw['que1_tw'].shape, '\n')


print("Shape of x train question2:", x_train_tw['que2_tw'].shape)
print("Shape of x test question2 data:", x_test_tw['que1_tw'].shape, '\n')
```

```
Type of x_train_tw['que1_tw']: <class 'pandas.core.series.Series'>
Type of x_train_tw['que2_tw']: <class 'pandas.core.series.Series'>

Type of x_test_tw['que1_tw']: <class 'pandas.core.series.Series'>
Type of x_test_tw['que2_tw']: <class 'pandas.core.series.Series'>

Shape of x train question1: (35000,)
Shape of x test question1 data: (15000,)

Shape of x train question2: (35000,)
```

```
Shape of x train question2: (35000,)
Shape of x test question2 data: (15000,)
```

In [206]:

```
# Train dataframe

x_tr_tw1 = pd.DataFrame(x_train_tw['que1_tw'].values.tolist(), index = x_train_tw.index)

x_tr_tw2 = pd.DataFrame(x_train_tw['que2_tw'].values.tolist(), index = x_train_tw.index,
                        columns = np.arange(x_tr_tw1.shape[1], x_tr_tw1.shape[1] * 2))


# Test dataframe

x_te_tw1 = pd.DataFrame(x_test_tw['que1_tw'].values.tolist(), index = x_test_tw.index)

x_te_tw2 = pd.DataFrame(x_test_tw['que2_tw'].values.tolist(), index = x_test_tw.index,
                        columns = np.arange(x_te_tw1.shape[1], x_te_tw1.shape[1] * 2))
```

In [207]:

```
 #Concatinating train question1 and train question2 vectors with dataframe

final_tr_tw = pd.concat([x_train_tw, x_tr_tw1, x_tr_tw2], axis = 1)

# Dropping question1 and question2 columns from final_test dataframe

final_te_tw = pd.concat([x_test_tw, x_te_tw1, x_te_tw2], axis = 1)
```

In [208]:

```
# Filling train dataframe
final_tr_tw = final_tr_tw.fillna(0)

# Filling test dataframe
final_te_tw = final_te_tw.fillna(0)
```

In [209]:

```
# Dropping question1 and question2 columns from final_train dataframe

final_tr_tw = final_tr_tw.drop(['question1', 'question2', 'que1_tw', 'que2_tw'], axis = 1)

# Dropping question1 and question2 columns from final_test dataframe

final_te_tw = final_te_tw.drop(['question1', 'question2', 'que1_tw', 'que2_tw'], axis = 1)
```

In [210]:

```
print("Shape of final_tr_tw dataframe:", final_tr_tw.shape, '\n')

print("Shape of final_te_tw dataframe:", final_te_tw.shape, '\n')
```

```
Shape of final_tr_tw dataframe: (35000, 205)

Shape of final_te_tw dataframe: (15000, 205)
```

In [211]:

```
# Saving final train data
final_tr_tw.to_csv("quora_final_tr_tw.csv")

# Saving final test data
final_te_tw.to_csv("quora_final_te_tw.csv")
```

In [212]:

```
# Import libraries
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
from sklearn.metrics import log_loss

start = dt.now()

# Parameters we need to try are
param_grid = {'n_estimators' : [5, 10, 100, 500], 'max_depth' : [2, 5, 8, 10]}

rs_k = RandomizedSearchCV(estimator = XGBClassifier(objective = 'binary:logistic', eval_metric = 'l
ogloss', eta = 0.02),
                          param_distributions = param_grid)

# fit train sets
rs_k.fit(final_tr_tw, y_train_tw)

# Prediction
predict_tw = rs_k.predict(final_te_tw)

print("Time taken to run this cell:", dt.now() - start)
```

```
Time taken to run this cell: 0:22:35.269475
```

In [213]:

```
bp = rs_k.best_params_
bs = rs_k.best_score_

print("Optimal hyperParameter:", bp, '\n')
print("Maximum accuracy:", bs * 100)
```

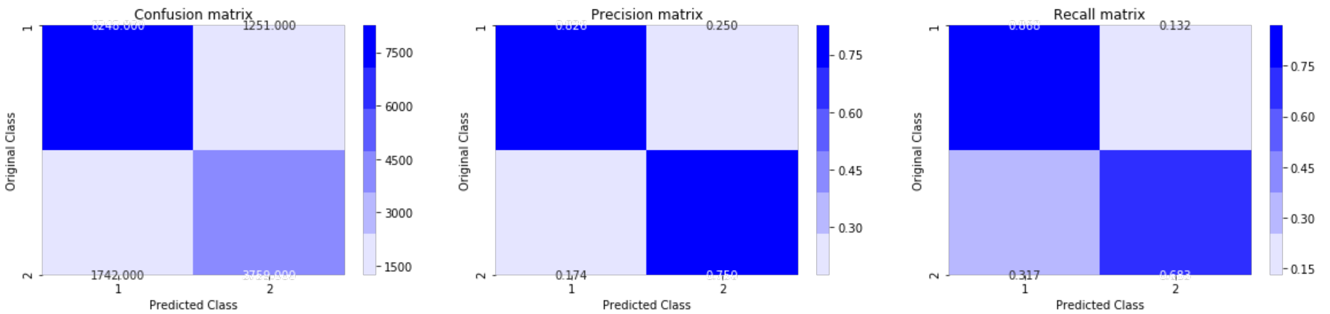
```
Optimal hyperParameter: {'n_estimators': 500, 'max_depth': 5}

Maximum accuracy: 79.9057142857143
```

Confusion Matrix

In [214]:

```
predicted_y = np.array(predict_tw > 0.5, dtype = int)

print("Total number of data points :", len(predicted_y))

plot_confusion_matrix(y_test_tw, predicted_y)
```

```
Total number of data points : 15000
```



Hyperparameters

max_depth: 10

n_estimators: 100

In [215]:

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

d_train = xgb.DMatrix(final_tr_tw, label= y_train_tw)
d_test = xgb.DMatrix(final_te_tw, label = y_test_tw)

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

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

xgdmat = xgb.DMatrix(final_tr_tw,y_train_tw)
predict_y = bst.predict(d_test)
print("The test log loss is:",log_loss(y_test_tw, predict_y, eps=1e-15))
```

```
[0] train-logloss:0.682685 valid-logloss:0.684053
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:0.67253 valid-logloss:0.675285
[2] train-logloss:0.662892 valid-logloss:0.666873
[3] train-logloss:0.653559 valid-logloss:0.658784
[4] train-logloss:0.644464 valid-logloss:0.651093
[5] train-logloss:0.635684 valid-logloss:0.643558
[6] train-logloss:0.627259 valid-logloss:0.636413
[7] train-logloss:0.619013 valid-logloss:0.629573
[8] train-logloss:0.611035 valid-logloss:0.622898
[9] train-logloss:0.603278 valid-logloss:0.616472
[10] train-logloss:0.595753 valid-logloss:0.61029
[11] train-logloss:0.588505 valid-logloss:0.604363
[12] train-logloss:0.581432 valid-logloss:0.598615
[13] train-logloss:0.574594 valid-logloss:0.593007
[14] train-logloss:0.567993 valid-logloss:0.587659
[15] train-logloss:0.561445 valid-logloss:0.582469
[16] train-logloss:0.555151 valid-logloss:0.577451
[17] train-logloss:0.549024 valid-logloss:0.572565
[18] train-logloss:0.543019 valid-logloss:0.567842
[19] train-logloss:0.537064 valid-logloss:0.56314
[20] train-logloss:0.531377 valid-logloss:0.55863
[21] train-logloss:0.525739 valid-logloss:0.554304
[22] train-logloss:0.52028 valid-logloss:0.550101
[23] train-logloss:0.514974 valid-logloss:0.545981
[24] train-logloss:0.509765 valid-logloss:0.542011
[25] train-logloss:0.50476 valid-logloss:0.538137
[26] train-logloss:0.499839 valid-logloss:0.534365
[27] train-logloss:0.495086 valid-logloss:0.530792
[28] train-logloss:0.490457 valid-logloss:0.527273
[29] train-logloss:0.485944 valid-logloss:0.523819
[30] train-logloss:0.481496 valid-logloss:0.520523
[31] train-logloss:0.477217 valid-logloss:0.517267
[32] train-logloss:0.473 valid-logloss:0.51418
[33] train-logloss:0.468961 valid-logloss:0.51119
[34] train-logloss:0.464915 valid-logloss:0.508262
[35] train-logloss:0.460966 valid-logloss:0.505378
[36] train-logloss:0.457182 valid-logloss:0.502618
[37] train-logloss:0.453382 valid-logloss:0.499851
[38] train-logloss:0.449714 valid-logloss:0.497267
[39] train-logloss:0.44608 valid-logloss:0.494721
[40] train-logloss:0.442572 valid-logloss:0.492224
[41] train-logloss:0.439085 valid-logloss:0.489819
[42] train-logloss:0.43565 valid-logloss:0.487432
[43] train-logloss:0.432245 valid-logloss:0.485088
[44] train-logloss:0.428874 valid-logloss:0.482701
[45] train-logloss:0.425653 valid-logloss:0.480604
[46] train-logloss:0.422496 valid-logloss:0.478283
[47] train-logloss:0.419389 valid-logloss:0.476099
[48] train-logloss:0.416354 valid-logloss:0.474079
[49] train-logloss:0.413382 valid-logloss:0.472049
[50] train-logloss:0.410398 valid-logloss:0.470139
[51] train-logloss:0.407533 valid-logloss:0.468284
[52] train-logloss:0.404719 valid-logloss:0.466486
[53] train-logloss:0.401996 valid-logloss:0.46472
```

```
[54] train-logloss:0.399303 valid-logloss:0.462962
[55] train-logloss:0.396646 valid-logloss:0.461283
[56] train-logloss:0.394059 valid-logloss:0.45962
[57] train-logloss:0.391522 valid-logloss:0.45803
[58] train-logloss:0.389056 valid-logloss:0.45644
[59] train-logloss:0.386633 valid-logloss:0.454882
[60] train-logloss:0.384297 valid-logloss:0.453363
[61] train-logloss:0.382015 valid-logloss:0.451887
[62] train-logloss:0.379661 valid-logloss:0.450474
[63] train-logloss:0.377392 valid-logloss:0.449074
[64] train-logloss:0.375168 valid-logloss:0.447711
[65] train-logloss:0.372913 valid-logloss:0.446429
[66] train-logloss:0.370701 valid-logloss:0.445206
[67] train-logloss:0.368554 valid-logloss:0.444023
[68] train-logloss:0.366584 valid-logloss:0.442838
[69] train-logloss:0.36458 valid-logloss:0.441667
[70] train-logloss:0.362554 valid-logloss:0.440584
[71] train-logloss:0.360748 valid-logloss:0.439392
[72] train-logloss:0.358862 valid-logloss:0.438399
[73] train-logloss:0.356994 valid-logloss:0.437302
[74] train-logloss:0.355162 valid-logloss:0.436234
[75] train-logloss:0.353305 valid-logloss:0.435263
[76] train-logloss:0.351425 valid-logloss:0.434247
[77] train-logloss:0.349686 valid-logloss:0.433214
[78] train-logloss:0.348096 valid-logloss:0.432245
[79] train-logloss:0.346424 valid-logloss:0.431233
[80] train-logloss:0.34479 valid-logloss:0.430294
[81] train-logloss:0.343125 valid-logloss:0.429348
[82] train-logloss:0.341546 valid-logloss:0.428472
[83] train-logloss:0.339961 valid-logloss:0.427578
[84] train-logloss:0.338388 valid-logloss:0.42669
[85] train-logloss:0.336835 valid-logloss:0.425833
[86] train-logloss:0.335318 valid-logloss:0.425011
[87] train-logloss:0.333825 valid-logloss:0.424196
[88] train-logloss:0.332336 valid-logloss:0.423408
[89] train-logloss:0.330863 valid-logloss:0.422686
[90] train-logloss:0.329486 valid-logloss:0.421926
[91] train-logloss:0.328064 valid-logloss:0.421188
[92] train-logloss:0.326771 valid-logloss:0.420464
[93] train-logloss:0.325344 valid-logloss:0.419783
[94] train-logloss:0.324076 valid-logloss:0.419093
[95] train-logloss:0.322823 valid-logloss:0.418508
[96] train-logloss:0.321539 valid-logloss:0.4179
[97] train-logloss:0.320303 valid-logloss:0.417309
[98] train-logloss:0.319071 valid-logloss:0.41672
[99] train-logloss:0.317833 valid-logloss:0.416177
[100] train-logloss:0.316595 valid-logloss:0.415587
[101] train-logloss:0.315349 valid-logloss:0.414976
[102] train-logloss:0.314238 valid-logloss:0.414469
[103] train-logloss:0.313016 valid-logloss:0.413891
[104] train-logloss:0.31181 valid-logloss:0.41331
[105] train-logloss:0.310747 valid-logloss:0.412749
[106] train-logloss:0.309699 valid-logloss:0.412272
[107] train-logloss:0.308621 valid-logloss:0.411723
[108] train-logloss:0.307509 valid-logloss:0.411274
[109] train-logloss:0.30646 valid-logloss:0.410735
[110] train-logloss:0.305382 valid-logloss:0.410273
[111] train-logloss:0.304272 valid-logloss:0.409703
[112] train-logloss:0.30335 valid-logloss:0.409228
[113] train-logloss:0.302329 valid-logloss:0.408854
[114] train-logloss:0.301327 valid-logloss:0.408423
[115] train-logloss:0.300303 valid-logloss:0.407959
[116] train-logloss:0.299282 valid-logloss:0.407586
[117] train-logloss:0.298301 valid-logloss:0.40721
[118] train-logloss:0.297421 valid-logloss:0.406785
[119] train-logloss:0.296551 valid-logloss:0.406378
[120] train-logloss:0.295745 valid-logloss:0.405988
[121] train-logloss:0.294934 valid-logloss:0.405606
[122] train-logloss:0.294109 valid-logloss:0.405217
[123] train-logloss:0.293231 valid-logloss:0.404829
[124] train-logloss:0.292456 valid-logloss:0.404471
[125] train-logloss:0.291625 valid-logloss:0.404104
[126] train-logloss:0.290871 valid-logloss:0.403776
[127] train-logloss:0.29004 valid-logloss:0.403414
[128] train-logloss:0.289087 valid-logloss:0.40303
[129] train-logloss:0.288224 valid-logloss:0.402676
[130] train-logloss:0.287363 valid-logloss:0.402354
```

```
[131] train-logloss:0.286479 valid-logloss:0.402083
[132] train-logloss:0.285495 valid-logloss:0.40178
[133] train-logloss:0.284837 valid-logloss:0.401517
[134] train-logloss:0.284067 valid-logloss:0.401212
[135] train-logloss:0.283391 valid-logloss:0.40096
[136] train-logloss:0.282617 valid-logloss:0.400671
[137] train-logloss:0.282022 valid-logloss:0.400446
[138] train-logloss:0.281146 valid-logloss:0.400242
[139] train-logloss:0.280459 valid-logloss:0.399963
[140] train-logloss:0.279844 valid-logloss:0.399714
[141] train-logloss:0.279051 valid-logloss:0.399477
[142] train-logloss:0.278507 valid-logloss:0.399266
[143] train-logloss:0.277839 valid-logloss:0.398971
[144] train-logloss:0.277079 valid-logloss:0.398646
[145] train-logloss:0.276369 valid-logloss:0.39843
[146] train-logloss:0.275612 valid-logloss:0.398246
[147] train-logloss:0.274823 valid-logloss:0.398057
[148] train-logloss:0.274298 valid-logloss:0.397866
[149] train-logloss:0.273709 valid-logloss:0.397681
[150] train-logloss:0.27293 valid-logloss:0.397517
[151] train-logloss:0.272151 valid-logloss:0.397261
[152] train-logloss:0.271426 valid-logloss:0.397066
[153] train-logloss:0.270865 valid-logloss:0.396843
[154] train-logloss:0.270118 valid-logloss:0.396683
[155] train-logloss:0.269527 valid-logloss:0.396535
[156] train-logloss:0.269075 valid-logloss:0.396387
[157] train-logloss:0.268439 valid-logloss:0.396195
[158] train-logloss:0.267721 valid-logloss:0.396002
[159] train-logloss:0.267266 valid-logloss:0.39584
[160] train-logloss:0.266538 valid-logloss:0.395623
[161] train-logloss:0.26613 valid-logloss:0.395518
[162] train-logloss:0.265552 valid-logloss:0.395356
[163] train-logloss:0.264821 valid-logloss:0.39523
[164] train-logloss:0.263946 valid-logloss:0.395119
[165] train-logloss:0.263408 valid-logloss:0.394924
[166] train-logloss:0.262751 valid-logloss:0.394793
[167] train-logloss:0.261787 valid-logloss:0.394592
[168] train-logloss:0.261166 valid-logloss:0.394473
[169] train-logloss:0.260364 valid-logloss:0.394318
[170] train-logloss:0.259771 valid-logloss:0.394232
[171] train-logloss:0.25894 valid-logloss:0.394044
[172] train-logloss:0.258359 valid-logloss:0.39388
[173] train-logloss:0.257789 valid-logloss:0.393816
[174] train-logloss:0.257203 valid-logloss:0.393706
[175] train-logloss:0.256653 valid-logloss:0.393558
[176] train-logloss:0.255742 valid-logloss:0.393369
[177] train-logloss:0.255265 valid-logloss:0.393276
[178] train-logloss:0.2547 valid-logloss:0.393142
[179] train-logloss:0.25424 valid-logloss:0.392989
[180] train-logloss:0.253489 valid-logloss:0.392862
[181] train-logloss:0.253043 valid-logloss:0.392781
[182] train-logloss:0.25226 valid-logloss:0.392578
[183] train-logloss:0.251731 valid-logloss:0.392486
[184] train-logloss:0.251193 valid-logloss:0.392401
[185] train-logloss:0.250919 valid-logloss:0.392292
[186] train-logloss:0.250406 valid-logloss:0.392209
[187] train-logloss:0.24965 valid-logloss:0.392025
[188] train-logloss:0.249096 valid-logloss:0.391948
[189] train-logloss:0.248622 valid-logloss:0.391836
[190] train-logloss:0.248228 valid-logloss:0.391776
[191] train-logloss:0.247433 valid-logloss:0.391612
[192] train-logloss:0.247065 valid-logloss:0.391523
[193] train-logloss:0.246409 valid-logloss:0.391372
[194] train-logloss:0.245999 valid-logloss:0.391286
[195] train-logloss:0.245306 valid-logloss:0.391145
[196] train-logloss:0.244666 valid-logloss:0.391036
[197] train-logloss:0.24425 valid-logloss:0.390999
[198] train-logloss:0.243512 valid-logloss:0.390908
[199] train-logloss:0.243093 valid-logloss:0.390873
[200] train-logloss:0.242677 valid-logloss:0.390768
[201] train-logloss:0.242291 valid-logloss:0.390708
[202] train-logloss:0.241887 valid-logloss:0.390643
[203] train-logloss:0.24118 valid-logloss:0.390538
[204] train-logloss:0.240722 valid-logloss:0.390456
[205] train-logloss:0.239998 valid-logloss:0.390349
[206] train-logloss:0.239611 valid-logloss:0.390276
[207] train-logloss:0.239126 valid-logloss:0.390215
```

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[208] train-logloss:0.238727 valid-logloss:0.39017
[209] train-logloss:0.237982 valid-logloss:0.390045
[210] train-logloss:0.237634 valid-logloss:0.389966
[211] train-logloss:0.236992 valid-logloss:0.389863
[212] train-logloss:0.236288 valid-logloss:0.3898
[213] train-logloss:0.235841 valid-logloss:0.389745
[214] train-logloss:0.235549 valid-logloss:0.389702
[215] train-logloss:0.234823 valid-logloss:0.389598
[216] train-logloss:0.234442 valid-logloss:0.389566
[217] train-logloss:0.234119 valid-logloss:0.389555
[218] train-logloss:0.233409 valid-logloss:0.389488
[219] train-logloss:0.233144 valid-logloss:0.389484
[220] train-logloss:0.232622 valid-logloss:0.389442
[221] train-logloss:0.23212 valid-logloss:0.389391
[222] train-logloss:0.231483 valid-logloss:0.389297
[223] train-logloss:0.231096 valid-logloss:0.389242
[224] train-logloss:0.230586 valid-logloss:0.38922
[225] train-logloss:0.22995 valid-logloss:0.389138
[226] train-logloss:0.229366 valid-logloss:0.389024
[227] train-logloss:0.228741 valid-logloss:0.388969
[228] train-logloss:0.228398 valid-logloss:0.38896
[229] train-logloss:0.227902 valid-logloss:0.388923
[230] train-logloss:0.227445 valid-logloss:0.388833
[231] train-logloss:0.22695 valid-logloss:0.388815
[232] train-logloss:0.226408 valid-logloss:0.388734
[233] train-logloss:0.225778 valid-logloss:0.388676
[234] train-logloss:0.225258 valid-logloss:0.388663
[235] train-logloss:0.224727 valid-logloss:0.388646
[236] train-logloss:0.224374 valid-logloss:0.388638
[237] train-logloss:0.223593 valid-logloss:0.388575
[238] train-logloss:0.223021 valid-logloss:0.38854
[239] train-logloss:0.222505 valid-logloss:0.388518
[240] train-logloss:0.222035 valid-logloss:0.388484
[241] train-logloss:0.221485 valid-logloss:0.388453
[242] train-logloss:0.221255 valid-logloss:0.388428
[243] train-logloss:0.220813 valid-logloss:0.388405
[244] train-logloss:0.22055 valid-logloss:0.388366
[245] train-logloss:0.220265 valid-logloss:0.388314
[246] train-logloss:0.220081 valid-logloss:0.388312
[247] train-logloss:0.21961 valid-logloss:0.388281
[248] train-logloss:0.21924 valid-logloss:0.38826
[249] train-logloss:0.218881 valid-logloss:0.388246
[250] train-logloss:0.218606 valid-logloss:0.388202
[251] train-logloss:0.218284 valid-logloss:0.388155
[252] train-logloss:0.217865 valid-logloss:0.388161
[253] train-logloss:0.217197 valid-logloss:0.388075
[254] train-logloss:0.216612 valid-logloss:0.388042
[255] train-logloss:0.216463 valid-logloss:0.38804
[256] train-logloss:0.215803 valid-logloss:0.387966
[257] train-logloss:0.215263 valid-logloss:0.387881
[258] train-logloss:0.214994 valid-logloss:0.387868
[259] train-logloss:0.214419 valid-logloss:0.387839
[260] train-logloss:0.214045 valid-logloss:0.387815
[261] train-logloss:0.213791 valid-logloss:0.387806
[262] train-logloss:0.21316 valid-logloss:0.387725
[263] train-logloss:0.212793 valid-logloss:0.387721
[264] train-logloss:0.212604 valid-logloss:0.387699
[265] train-logloss:0.211988 valid-logloss:0.387662
[266] train-logloss:0.211469 valid-logloss:0.387623
[267] train-logloss:0.211279 valid-logloss:0.387617
[268] train-logloss:0.210935 valid-logloss:0.38757
[269] train-logloss:0.210313 valid-logloss:0.3875
[270] train-logloss:0.209839 valid-logloss:0.387475
[271] train-logloss:0.209561 valid-logloss:0.387474
[272] train-logloss:0.209172 valid-logloss:0.38743
[273] train-logloss:0.208657 valid-logloss:0.387419
[274] train-logloss:0.208407 valid-logloss:0.387401
[275] train-logloss:0.20804 valid-logloss:0.387429
[276] train-logloss:0.207741 valid-logloss:0.387376
[277] train-logloss:0.207496 valid-logloss:0.387351
[278] train-logloss:0.20717 valid-logloss:0.387348
[279] train-logloss:0.206927 valid-logloss:0.38731
[280] train-logloss:0.2067 valid-logloss:0.387268
[281] train-logloss:0.206364 valid-logloss:0.387248
[282] train-logloss:0.205642 valid-logloss:0.387232
[283] train-logloss:0.20529 valid-logloss:0.387201
[284] train-logloss:0.204483 valid-logloss:0.387178
```

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[285] train-logloss:0.204336 valid-logloss:0.387119
[286] train-logloss:0.203894 valid-logloss:0.387031
[287] train-logloss:0.203482 valid-logloss:0.387013
[288] train-logloss:0.202893 valid-logloss:0.386976
[289] train-logloss:0.202615 valid-logloss:0.386968
[290] train-logloss:0.202126 valid-logloss:0.387012
[291] train-logloss:0.201267 valid-logloss:0.38702
[292] train-logloss:0.200807 valid-logloss:0.38704
[293] train-logloss:0.200076 valid-logloss:0.387035
[294] train-logloss:0.199932 valid-logloss:0.387012
[295] train-logloss:0.199435 valid-logloss:0.387015
[296] train-logloss:0.198653 valid-logloss:0.387016
[297] train-logloss:0.197922 valid-logloss:0.386999
[298] train-logloss:0.197461 valid-logloss:0.386982
[299] train-logloss:0.196791 valid-logloss:0.387029
[300] train-logloss:0.196508 valid-logloss:0.386996
[301] train-logloss:0.195926 valid-logloss:0.386994
[302] train-logloss:0.195483 valid-logloss:0.386987
[303] train-logloss:0.195214 valid-logloss:0.386971
[304] train-logloss:0.194889 valid-logloss:0.386958
[305] train-logloss:0.194451 valid-logloss:0.386978
[306] train-logloss:0.194385 valid-logloss:0.386971
[307] train-logloss:0.193693 valid-logloss:0.386942
[308] train-logloss:0.193299 valid-logloss:0.386925
[309] train-logloss:0.192569 valid-logloss:0.386918
[310] train-logloss:0.192235 valid-logloss:0.386934
[311] train-logloss:0.192109 valid-logloss:0.386913
[312] train-logloss:0.192007 valid-logloss:0.386907
[313] train-logloss:0.191657 valid-logloss:0.3869
[314] train-logloss:0.19108 valid-logloss:0.3869
[315] train-logloss:0.19051 valid-logloss:0.386926
[316] train-logloss:0.189884 valid-logloss:0.386876
[317] train-logloss:0.189505 valid-logloss:0.386886
[318] train-logloss:0.189045 valid-logloss:0.386854
[319] train-logloss:0.188499 valid-logloss:0.38686
[320] train-logloss:0.187904 valid-logloss:0.38679
[321] train-logloss:0.187308 valid-logloss:0.386827
[322] train-logloss:0.186952 valid-logloss:0.386855
[323] train-logloss:0.186707 valid-logloss:0.386864
[324] train-logloss:0.186333 valid-logloss:0.386886
[325] train-logloss:0.186066 valid-logloss:0.386881
[326] train-logloss:0.185608 valid-logloss:0.386896
[327] train-logloss:0.185189 valid-logloss:0.386866
[328] train-logloss:0.184989 valid-logloss:0.386824
[329] train-logloss:0.184276 valid-logloss:0.386828
[330] train-logloss:0.183739 valid-logloss:0.386869
[331] train-logloss:0.182995 valid-logloss:0.386823
[332] train-logloss:0.182684 valid-logloss:0.386847
[333] train-logloss:0.182446 valid-logloss:0.386866
[334] train-logloss:0.181919 valid-logloss:0.386883
[335] train-logloss:0.181303 valid-logloss:0.386835
[336] train-logloss:0.180737 valid-logloss:0.386827
[337] train-logloss:0.180163 valid-logloss:0.386837
[338] train-logloss:0.179961 valid-logloss:0.38684
[339] train-logloss:0.179548 valid-logloss:0.386807
[340] train-logloss:0.179007 valid-logloss:0.386863
Stopping. Best iteration:
[320] train-logloss:0.187904 valid-logloss:0.38679

The test log loss is: 0.38686106475459336
```

CONCLUSION:

In [218]:

```
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model Comparision "
ptable.field_names = ['Serial No.', 'Model Name', 'Tokenizer','Hyperparameter Tunning', 'Test Log L
oss']
ptable.add_row(["1","Random","TFIDF Weighted W2V","-","0.89"])
ptable.add_row(["2","Logistic Regression","TFIDF Weighted W2V","Done","0.46"])
ptable.add_row(["3","Linear SVM","TFIDF Weighted W2V","Done","0.46"])
ptable.add_row(["4","XGBoost","TFIDF Weighted W2V","-","0.399"])
```

```python
ptable.add_row(["\n","\n","\n","\n","\n"])
ptable.add_row(["1","Random","TFIDF","-","0.89"])
ptable.add_row(["2","Logistic Regression","TFIDF","Done","0.42"])
ptable.add_row(["3","Linear SVM","TFIDF","Done","0.439"])
ptable.add_row(["4","XGBoost","TFIDF","Done","0.386"])
print(ptable)
```

```
+------------+---------------------+--------------------+-------------------------+---------------+
| Serial No. |      Model Name     |     Tokenizer      | Hyperparameter Tunning  | Test Log Loss |
+------------+---------------------+--------------------+-------------------------+---------------+
|     1      |        Random       | TFIDF Weighted W2V |            -            |      0.89     |
|     2      | Logistic Regression | TFIDF Weighted W2V |           Done          |      0.46     |
|     3      |      Linear SVM     | TFIDF Weighted W2V |           Done          |      0.46     |
|     4      |       XGBoost       | TFIDF Weighted W2V |            -            |     0.399     |
|            |                     |                    |                         |               |
|            |                     |                    |                         |               |
|     1      |        Random       |       TFIDF        |            -            |      0.89     |
|     2      | Logistic Regression |       TFIDF        |           Done          |      0.42     |
|     3      |      Linear SVM     |       TFIDF        |           Done          |     0.439     |
|     4      |       XGBoost       |       TFIDF        |           Done          |     0.386     |
+------------+---------------------+--------------------+-------------------------+---------------+
```