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
```

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

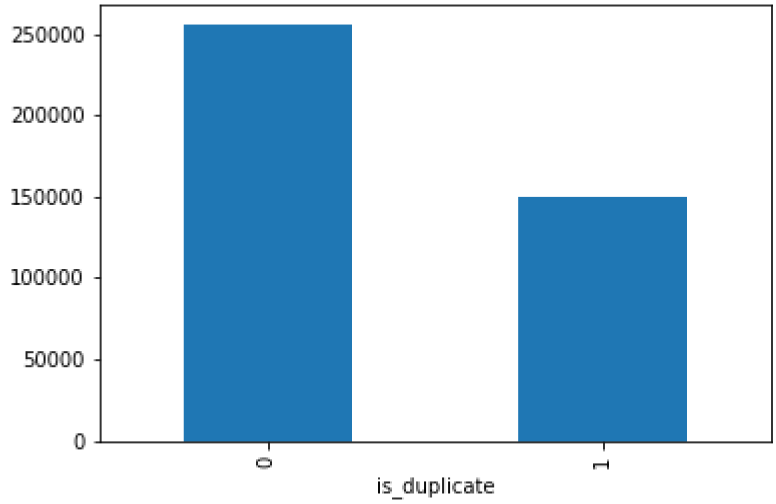
- Number of duplicate(smilar) and non-duplicate(non similar) questions

In [6]:

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

Out[6]:

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



In [7]:

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

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

In [8]:

```
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

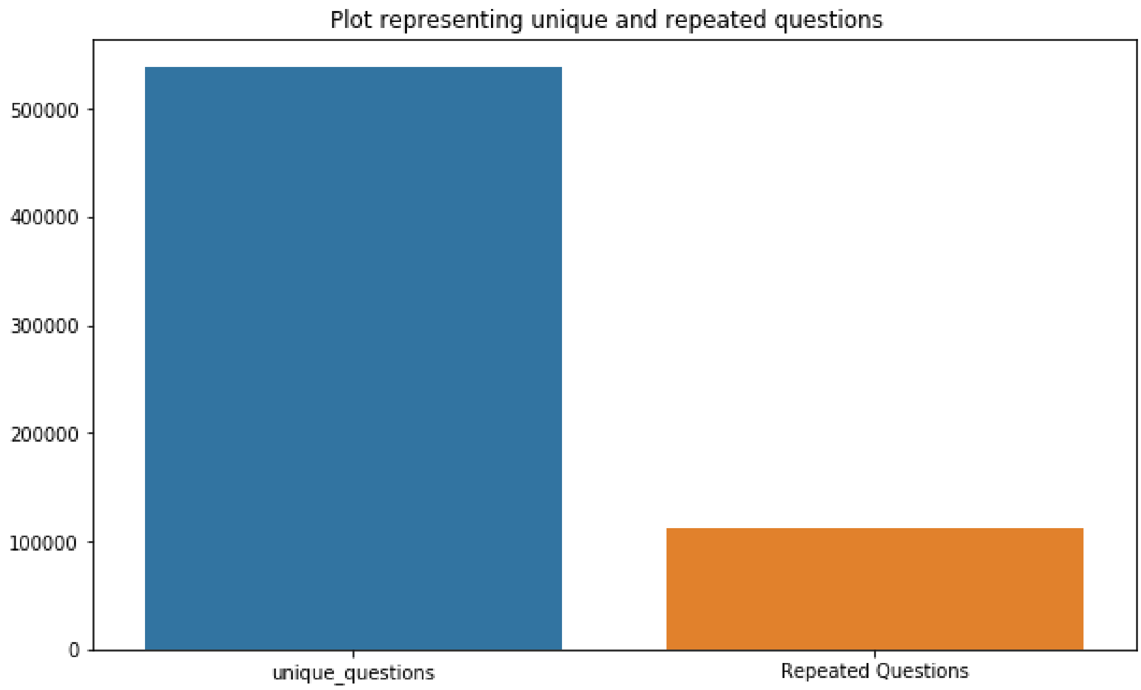
In [9]:

```
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(q
s_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 (20.7795
3945937505%)

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

In [10]:

```
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().r
eset_index()

print ("Number of duplicate questions",(pair_duplicates).shape[0] - df.shape[0])
```

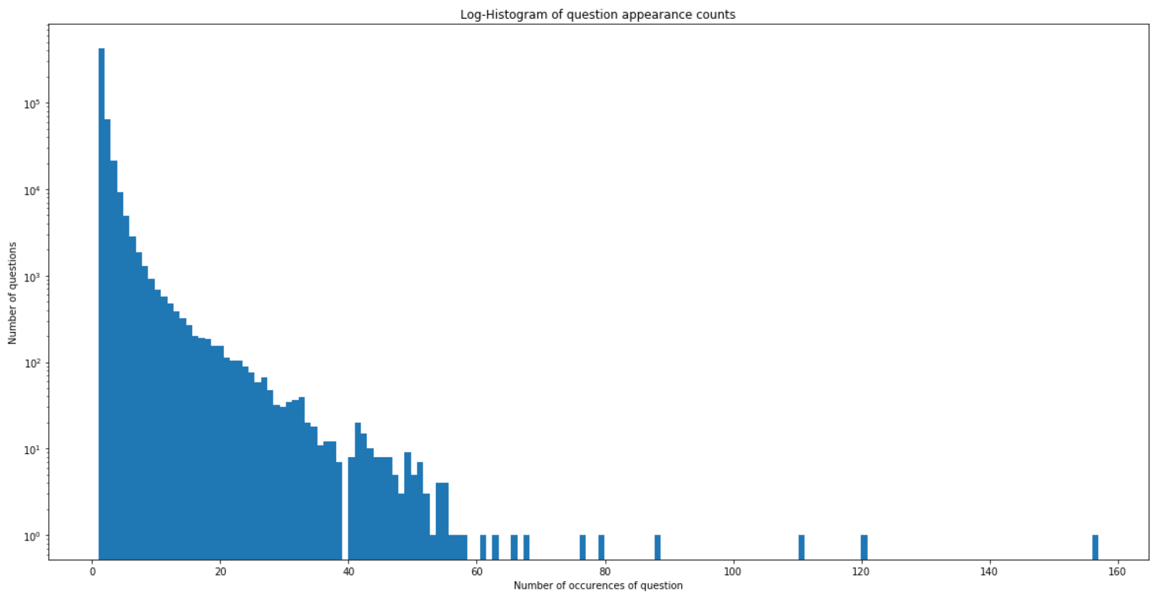
```
Number of duplicate questions 0
```

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.va
lue_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
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
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
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
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
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0	3	1	76	39

3.3.1 Analysis of some of the extracted features

- Here are some questions have only one single words.

In [16]:

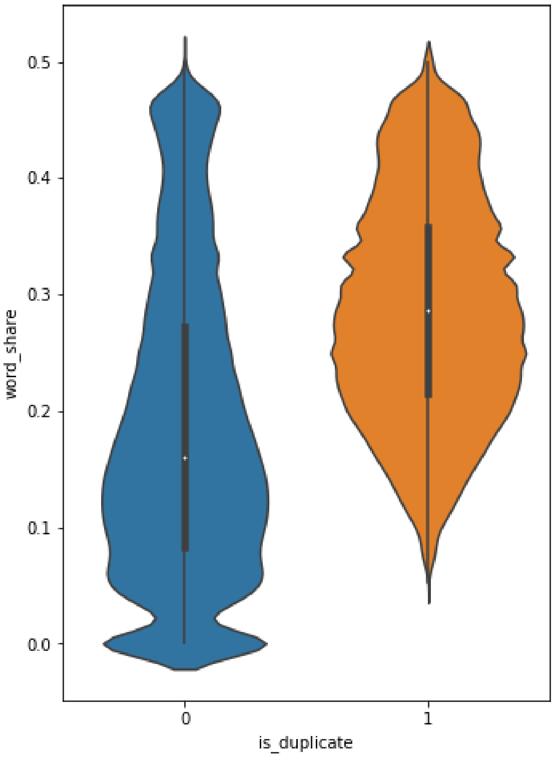
```
print ("Minimum length of the questions in question1 : " , min(df['q1_n_words']))

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])
```

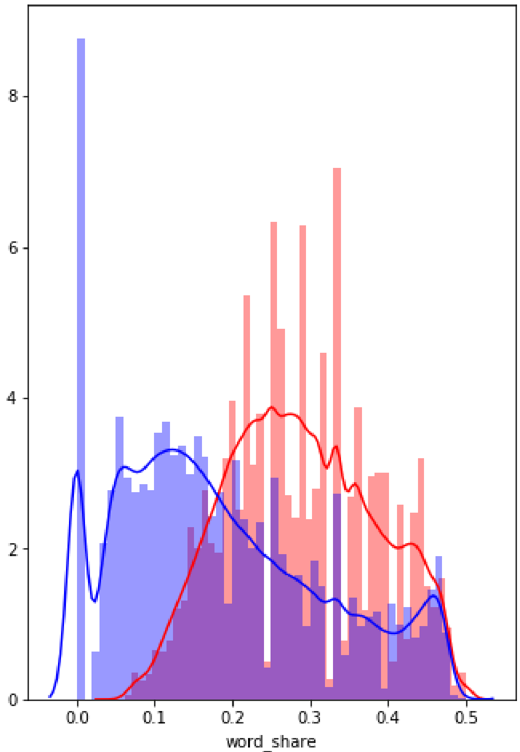
```
Minimum length of the questions in question1 :  1
Minimum length of the questions in question2 :  1
Number of Questions with minimum length [question1] : 67
Number of Questions with minimum length [question2] : 24
```

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 = 're
d')
sns.distplot(df[df['is_duplicate'] == 0.0]['word_share'][0:] , label = "0" , color = 'b
lue' )
plt.show()
```



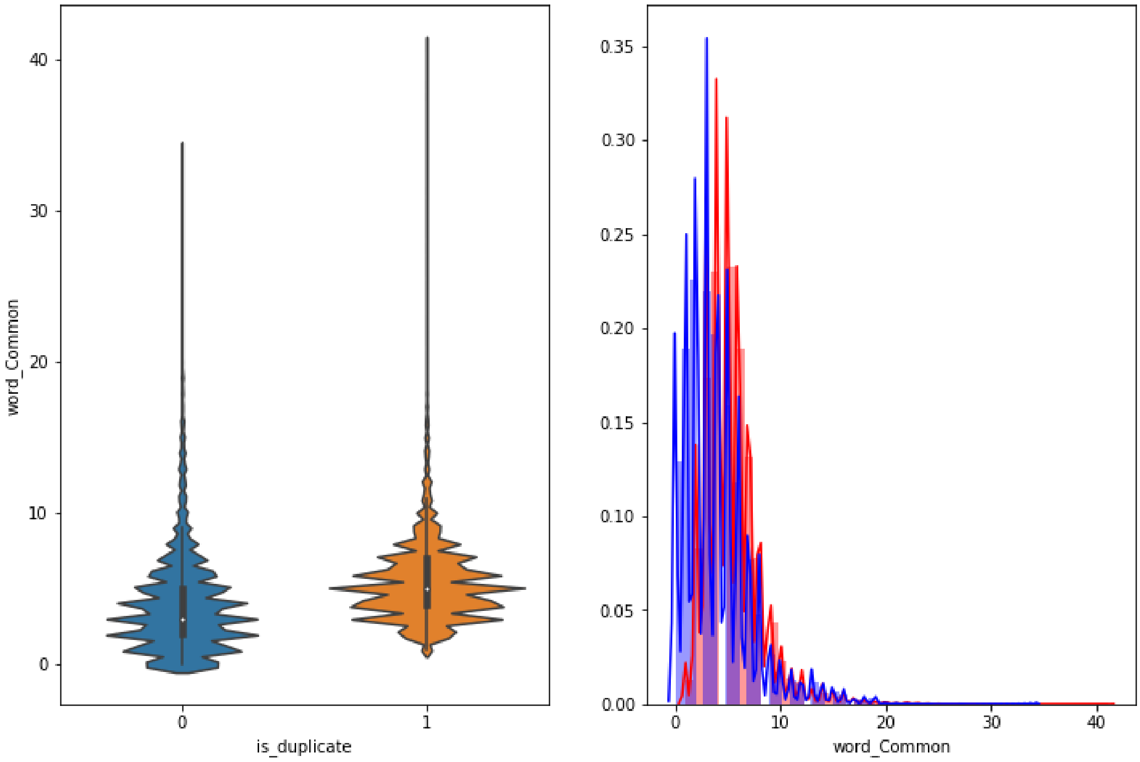


- The distributions for normalized word_share have some overlap on the far right-hand side, i.e., there are quite a lot of questions with high word similarity
- The average word share and Common no. of words of qid1 and qid2 is more when they are duplicate(Similar)

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 = 'r
ed')
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").r
eplace("can't", "can not")\
                           .replace("n't", " not").replace("what's", "what is").replace
("it's", "it is")\
                           .replace("'ve", " have").replace("i'm", "i am").replace("'r
e", " 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_D
IV)
    token_features[1] = common_word_count / (max(len(q1_words), len(q2_words)) + SAFE_D
IV)
    token_features[2] = common_stop_count / (min(len(q1_stops), len(q2_stops)) + SAFE_D
IV)
    token_features[3] = common_stop_count / (max(len(q1_stops), len(q2_stops)) + SAFE_D
IV)
    token_features[4] = common_token_count / (min(len(q1_tokens), len(q2_tokens)) + SAF
E_DIV)
    token_features[5] = common_token_count / (max(len(q1_tokens), len(q2_tokens)) + SAF
E_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["question
2"]), 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-c
ompare-2-strings
    # 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 t
okens alphabetically, and
    # then joining them back into a string We then compare the transformed strings with
a simple ratio().
    df["token_sort_ratio"]      = df.apply(lambda x: fuzz.token_sort_ratio(x["question
1"], x["question2"]), axis=1)
    df["fuzz_ratio"]            = df.apply(lambda x: fuzz.QRatio(x["question1"], x["que
stion2"]), 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["questi
on1"], 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_ma
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	0.99998
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	0.59998

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]:

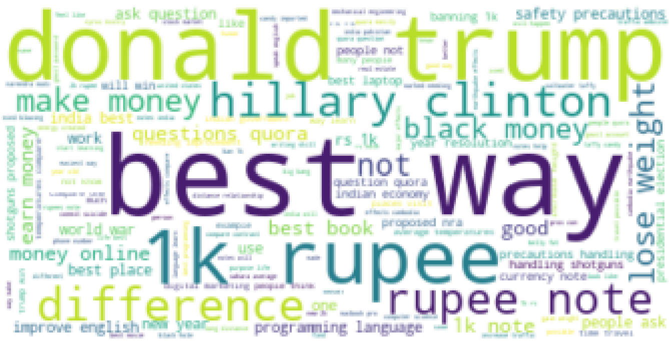
```
# reading the text files and removing the Stop Words:
from os import path
d = path.dirname('.')

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]:

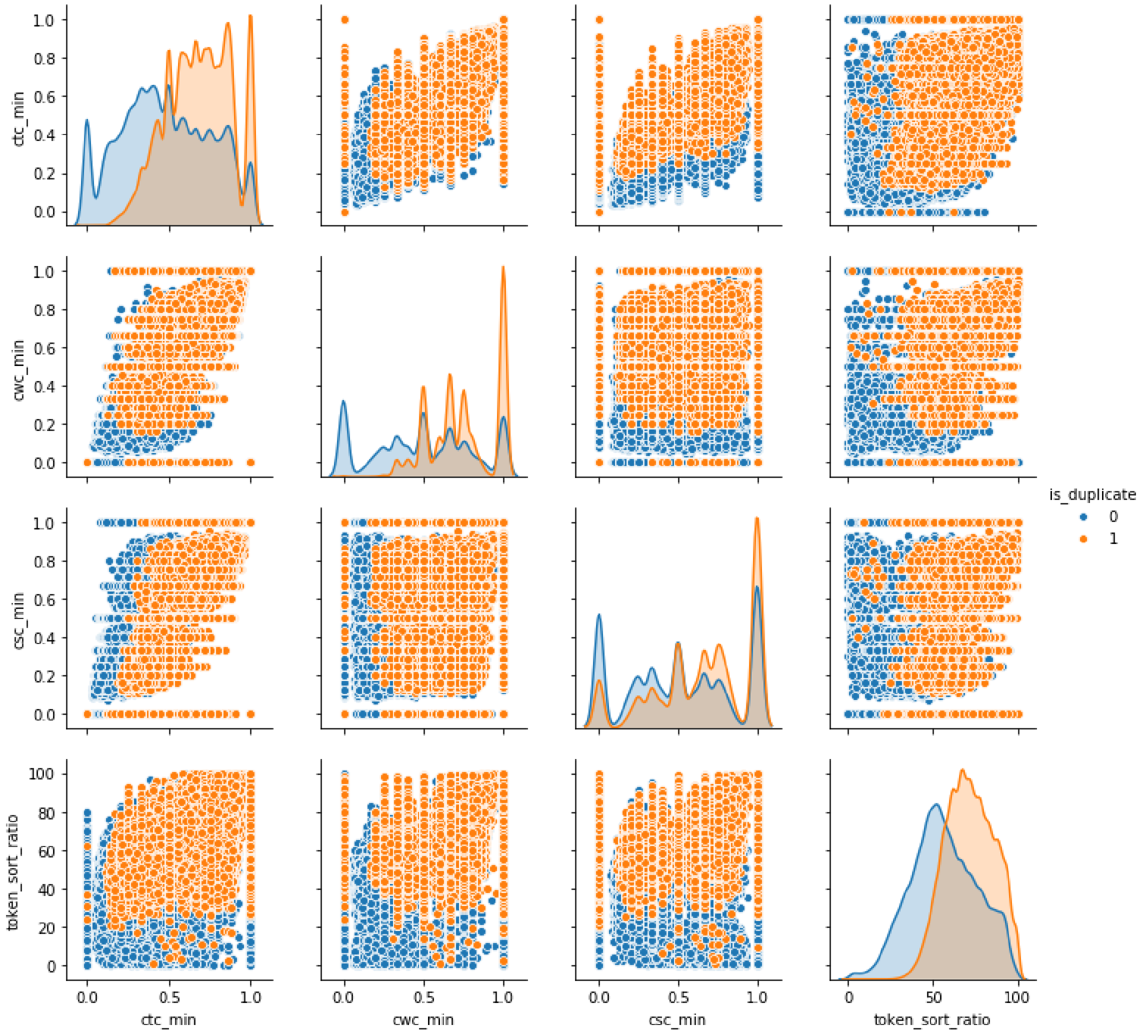
```
wc = WordCloud(background_color="white", max_words=len(textn_w),stopwords=stopwords)
# generate word cloud
wc.generate(textn_w)
print ("Word Cloud for non-Duplicate Question pairs:")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

Word Cloud for non-Duplicate Question pairs:

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

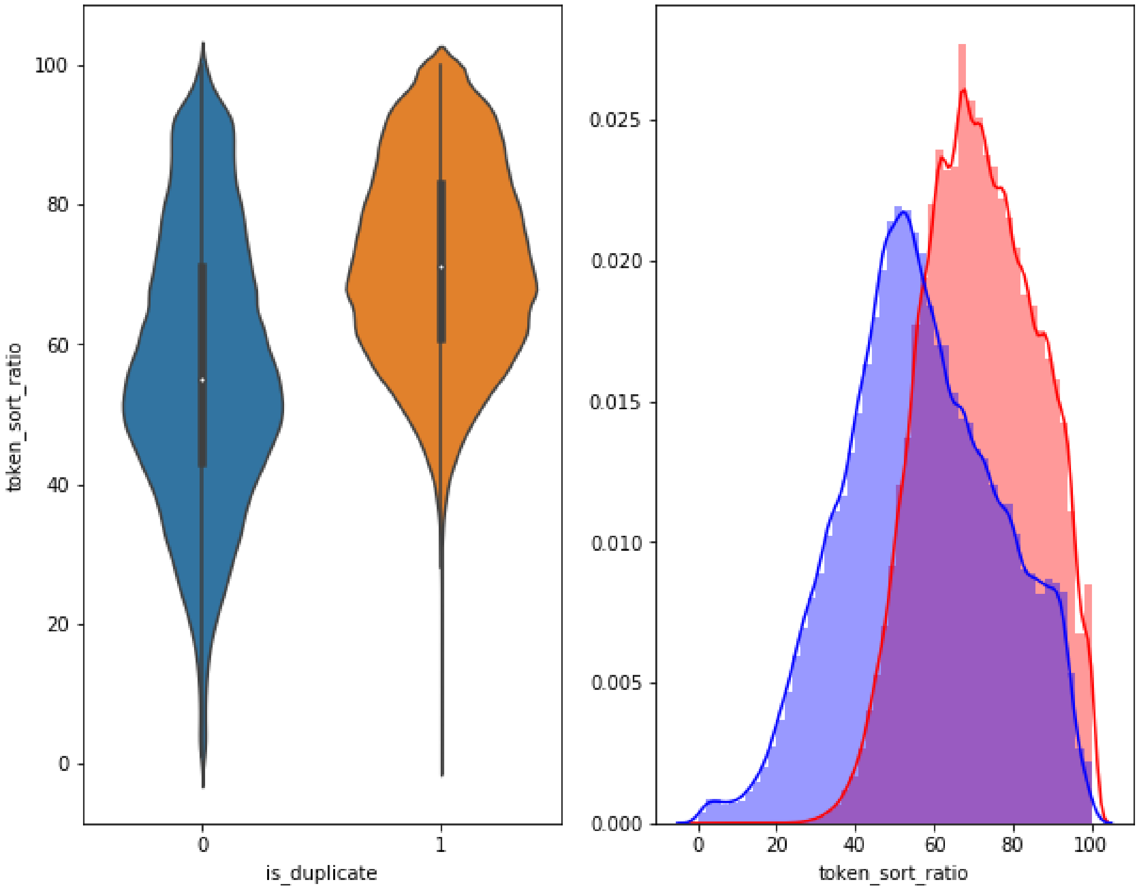
In [27]:

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



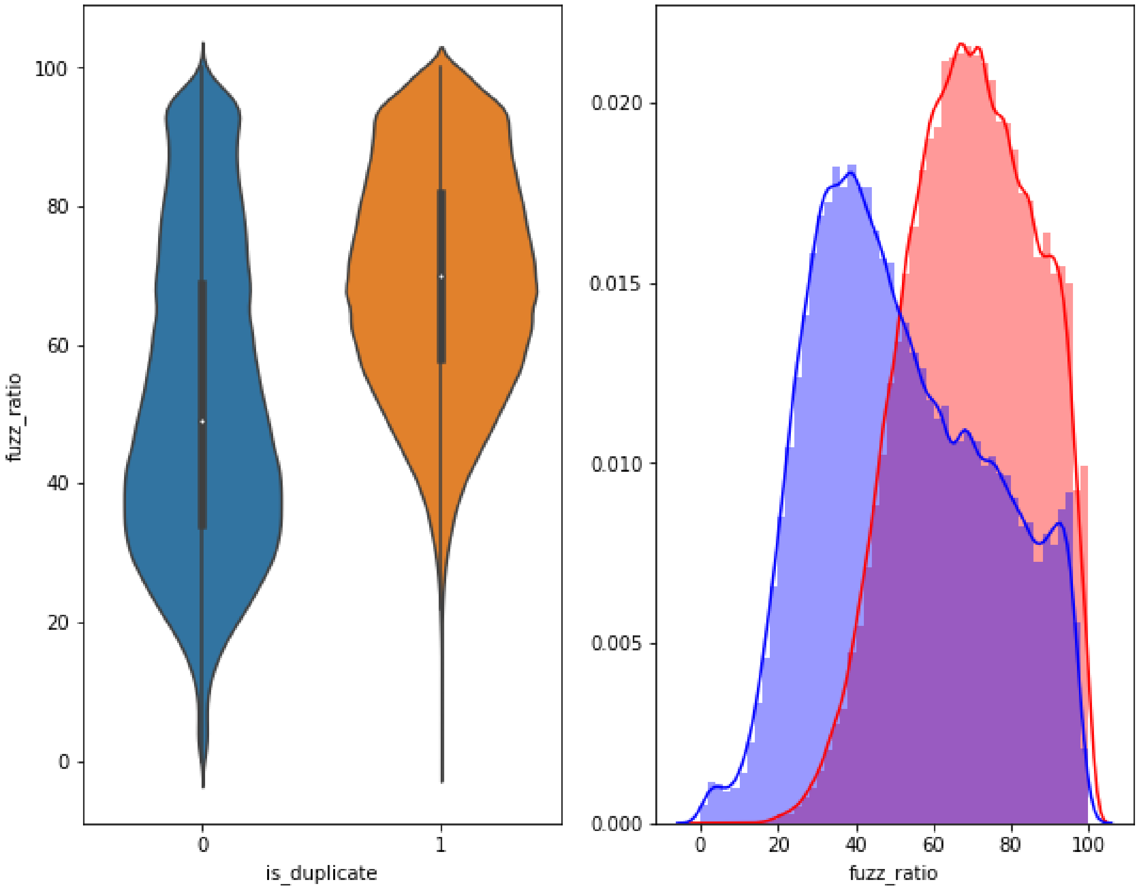
In [28]:

```
# 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" , colo
r = '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 = 're
d')
sns.distplot(df[df['is_duplicate'] == 0.0]['fuzz_ratio'][0:] , label = "0" , color = 'b
lue' )
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
```

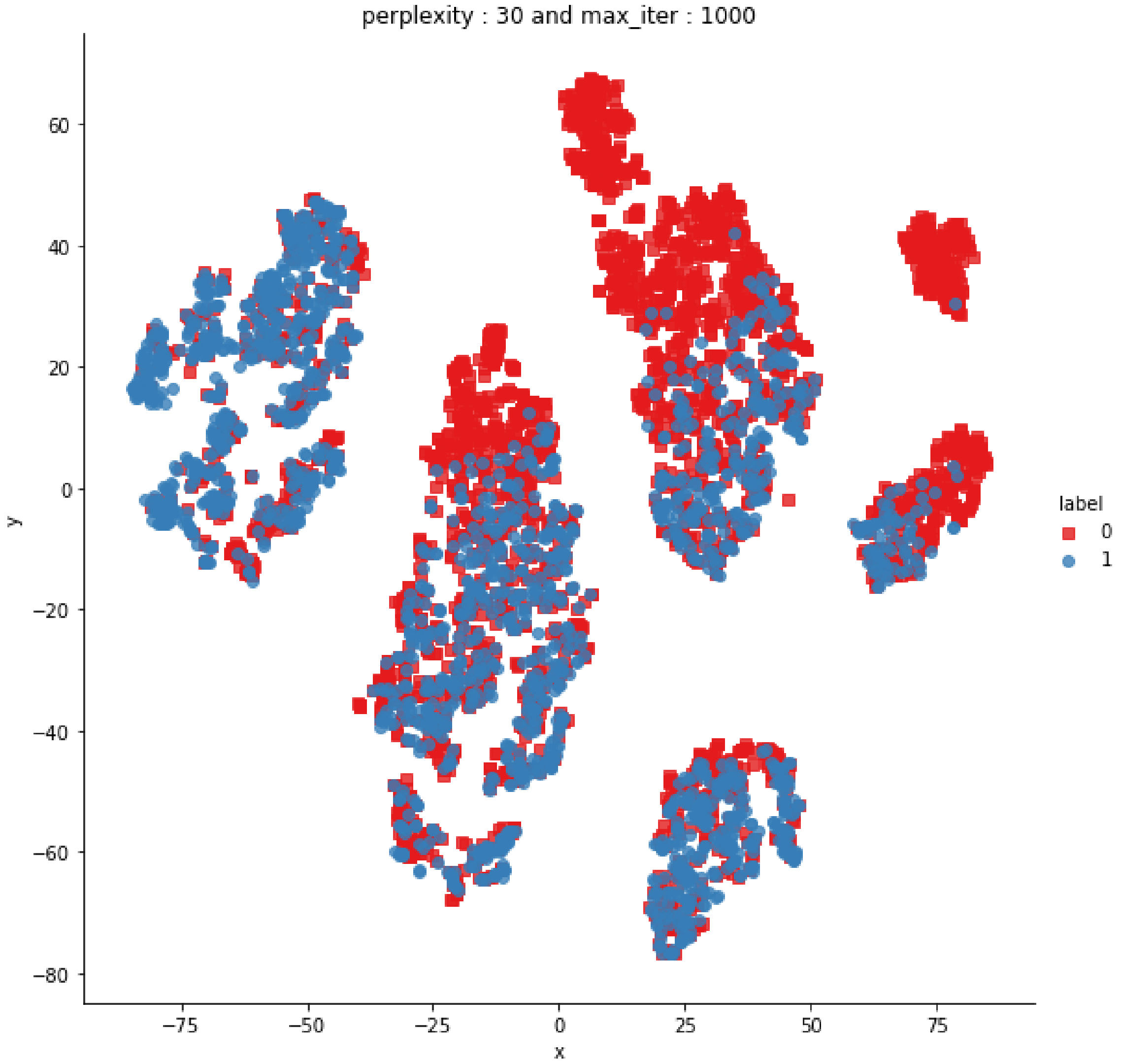
In [31]:

```
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 it
erations in 6.219s)
[t-SNE] Iteration 100: error = 70.6435165, gradient norm = 0.0094614 (50 i
terations in 4.245s)
[t-SNE] Iteration 150: error = 68.9952850, gradient norm = 0.0056374 (50 i
terations in 4.003s)
[t-SNE] Iteration 200: error = 68.2175980, gradient norm = 0.0044332 (50 i
terations in 4.286s)
[t-SNE] Iteration 250: error = 67.7385254, gradient norm = 0.0034321 (50 i
terations in 4.381s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.738
525
[t-SNE] Iteration 300: error = 1.7930490, gradient norm = 0.0011818 (50 it
erations in 4.481s)
[t-SNE] Iteration 350: error = 1.3966638, gradient norm = 0.0004836 (50 it
erations in 4.249s)
[t-SNE] Iteration 400: error = 1.2328721, gradient norm = 0.0002750 (50 it
erations in 4.227s)
[t-SNE] Iteration 450: error = 1.1440563, gradient norm = 0.0001877 (50 it
erations in 4.346s)
[t-SNE] Iteration 500: error = 1.0895753, gradient norm = 0.0001404 (50 it
erations in 4.348s)
[t-SNE] Iteration 550: error = 1.0542322, gradient norm = 0.0001145 (50 it
erations in 4.334s)
[t-SNE] Iteration 600: error = 1.0302582, gradient norm = 0.0001017 (50 it
erations in 4.468s)
[t-SNE] Iteration 650: error = 1.0142238, gradient norm = 0.0000900 (50 it
erations in 4.393s)
[t-SNE] Iteration 700: error = 1.0029600, gradient norm = 0.0000806 (50 it
erations in 4.305s)
[t-SNE] Iteration 750: error = 0.9942252, gradient norm = 0.0000781 (50 it
erations in 4.357s)
[t-SNE] Iteration 800: error = 0.9875125, gradient norm = 0.0000736 (50 it
erations in 4.360s)
[t-SNE] Iteration 850: error = 0.9824185, gradient norm = 0.0000673 (50 it
erations in 4.376s)
[t-SNE] Iteration 900: error = 0.9780059, gradient norm = 0.0000659 (50 it
erations in 4.469s)
[t-SNE] Iteration 950: error = 0.9744161, gradient norm = 0.0000617 (50 it
erations in 4.448s)
[t-SNE] Iteration 1000: error = 0.9713724, gradient norm = 0.0000583 (50 i
terations 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",mar
kers=['s','o'])
plt.title("perplexity : {} and max_iter : {}".format(30, 1000))
plt.show()
```



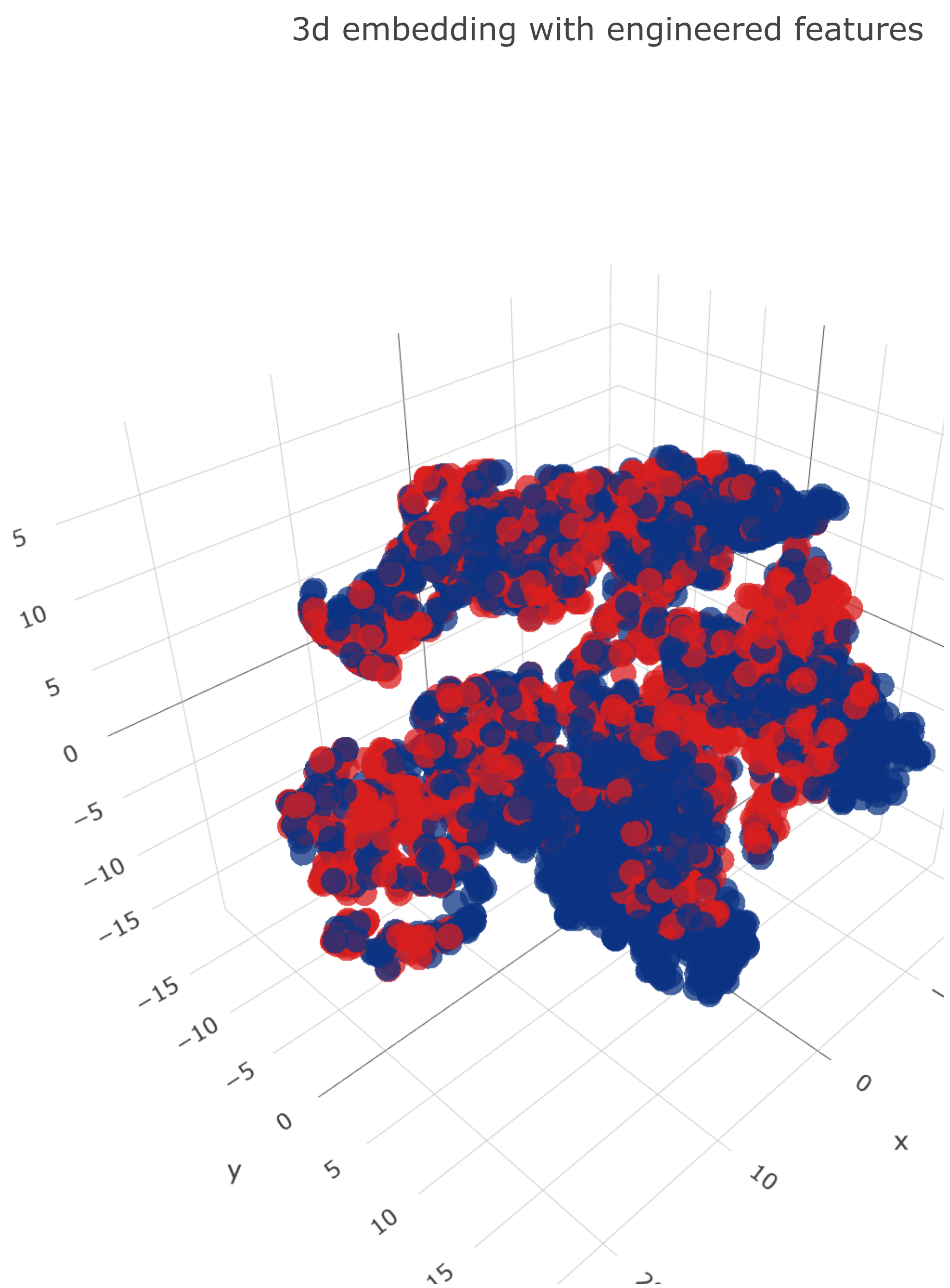
In [33]:

```
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 it
erations in 20.978s)
[t-SNE] Iteration 100: error = 69.4158859, gradient norm = 0.0033386 (50 i
terations in 10.925s)
[t-SNE] Iteration 150: error = 68.0448608, gradient norm = 0.0019634 (50 i
terations in 9.936s)
[t-SNE] Iteration 200: error = 67.4930801, gradient norm = 0.0011609 (50 i
terations in 10.030s)
[t-SNE] Iteration 250: error = 67.1813202, gradient norm = 0.0008686 (50 i
terations in 9.898s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.181
320
[t-SNE] Iteration 300: error = 1.5266187, gradient norm = 0.0007106 (50 it
erations in 12.759s)
[t-SNE] Iteration 350: error = 1.1894693, gradient norm = 0.0001963 (50 it
erations in 16.028s)
[t-SNE] Iteration 400: error = 1.0453291, gradient norm = 0.0000995 (50 it
erations in 16.134s)
[t-SNE] Iteration 450: error = 0.9735472, gradient norm = 0.0000740 (50 it
erations in 15.855s)
[t-SNE] Iteration 500: error = 0.9391118, gradient norm = 0.0000586 (50 it
erations in 15.307s)
[t-SNE] Iteration 550: error = 0.9216439, gradient norm = 0.0000491 (50 it
erations in 15.245s)
[t-SNE] Iteration 600: error = 0.9106981, gradient norm = 0.0000487 (50 it
erations in 15.564s)
[t-SNE] Iteration 650: error = 0.9030094, gradient norm = 0.0000377 (50 it
erations in 15.861s)
[t-SNE] Iteration 700: error = 0.8947795, gradient norm = 0.0000328 (50 it
erations in 16.001s)
[t-SNE] Iteration 750: error = 0.8864105, gradient norm = 0.0000338 (50 it
erations in 16.013s)
[t-SNE] Iteration 800: error = 0.8798748, gradient norm = 0.0000314 (50 it
erations in 15.723s)
[t-SNE] Iteration 850: error = 0.8745480, gradient norm = 0.0000292 (50 it
erations in 15.767s)
[t-SNE] Iteration 900: error = 0.8701542, gradient norm = 0.0000287 (50 it
erations in 15.907s)
[t-SNE] Iteration 950: error = 0.8666047, gradient norm = 0.0000262 (50 it
erations in 15.912s)
[t-SNE] Iteration 1000: error = 0.8636045, gradient norm = 0.0000248 (50 i
terations 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 (https://spacy.io/usage/vectors-similarity)](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
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	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	1	1	66	57	
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0	4	1	51	88	

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	
0	211.129864	-144.683059	-68.811247	-153.662141	-89.931593	2.311301	136.743747	
1	144.124685	-114.012484	-111.716694	-104.885038	-88.238478	16.441834	58.238013	1
2	81.757898	-142.184507	0.559867	-104.660084	-84.156631	22.515110	115.521661	
3	-126.651922	-59.747160	-67.763201	-138.114731	-101.038699	88.148523	-22.912261	
4	299.444044	-188.632001	-22.946291	-273.683355	-188.480395	107.123044	174.946302	-

5 rows × 96 columns

In [47]:

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

Out[47]:

	0	1	2	3	4	5	6	
0	151.268526	-127.013168	-31.546286	-142.905807	-97.249094	9.485758	106.682259	36
1	152.023095	-44.955390	-103.559249	-128.467601	-118.567610	44.577916	137.906144	26
2	4.930220	-29.029581	-117.808812	-98.332275	-19.064096	-9.867805	141.808202	91
3	-6.951929	-44.951731	-17.343082	-61.444452	-7.469152	16.942014	95.049250	-2
4	96.174524	-71.613948	21.584882	-92.742468	-106.643129	10.646790	92.190157	-40

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.shap
e[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	q:
0	0	0	0	1	1	66	57	14	
1	1	1	0	4	1	51	88	8	
2	2	2	0	1	1	73	59	14	

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_duplicate'], 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_wor
23561	23561	23561	0	1	1	33	50	
3536	3536	3536	0	1	1	46	58	

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 predic
ted 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 t
wo 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 t
wo 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=la
bels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=la
bels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=la
bels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")
```

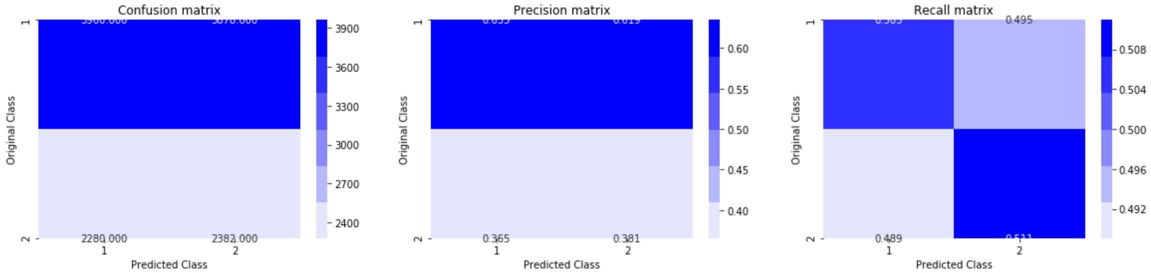
```
    plt.show()
```

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
```

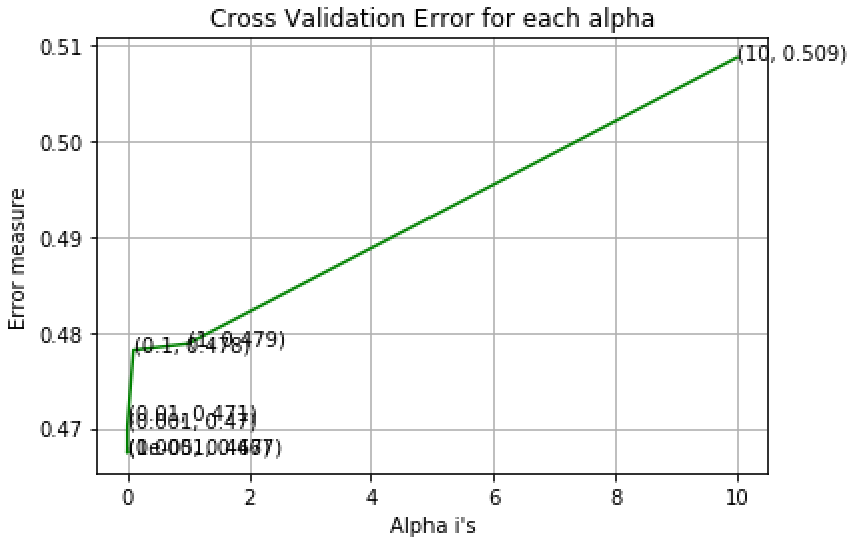


4.4 Logistic Regression with hyperparameter tuning </h2>

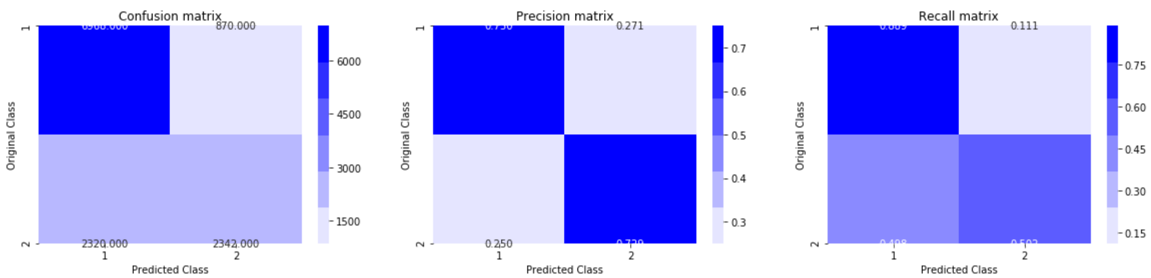
In [60]:

```
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/s
klearn.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='opt
imal', 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 Gradie
nt 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, l
abels=clf.classes_, eps=1e-15))

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


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

predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_lo
ss(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_los
s(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: 0.46585297817041
76
For values of best alpha =  0.0001 The test log loss is: 0.467411411795257
Total number of data points : 12500
```

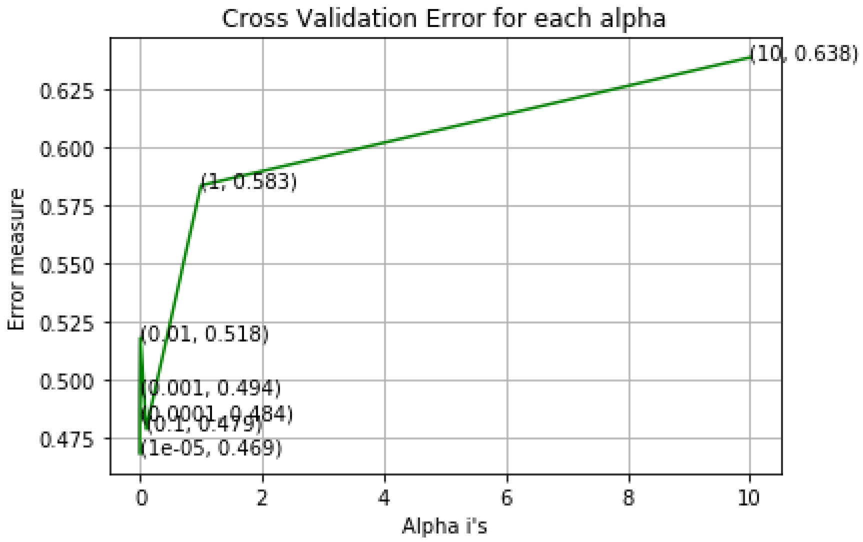


4.5 Linear SVM with hyperparameter tuning

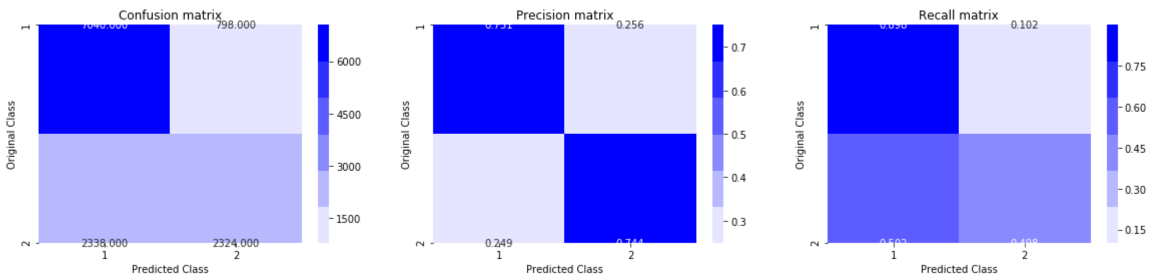
In [61]:

```
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/s
klearn.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='opt
imal', 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 Gradie
nt 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, l
abels=clf.classes_, eps=1e-15))

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


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge', random_state=4
2)
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_lo
ss(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_los
s(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: 0.468568715140383
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: 0.467929831999063
13
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]:

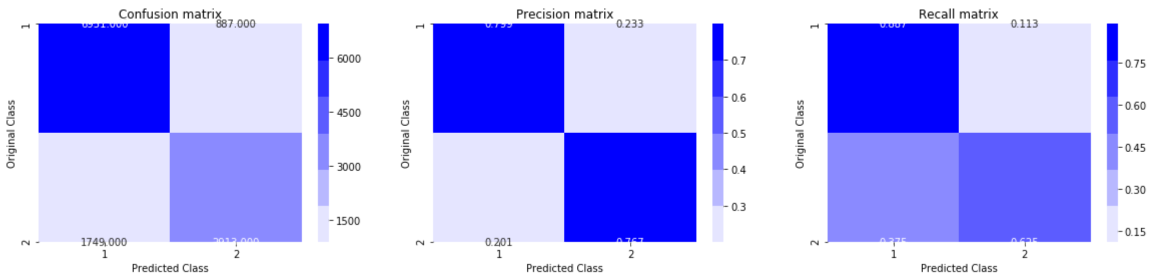
```
import xgboost as xgb
params = {}
params['objective'] = 'binary:logistic'
params['eval_metric'] = 'logloss'
params['eta'] = 0.02
params['max_depth'] = 4

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-1
5))
```

```
[0]     train-logloss:0.685301  valid-logloss:0.685242
Multiple eval metrics have been passed: 'valid-logloss' will be used for e
arly 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_ma
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	0.99998
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	0.59998

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_ma
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	0.99998
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	0.59998

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_p
artial_ratio, longest_substr_ratio, freq_qid1, freq_qid2, q1len, q2len, q1
_n_words, q2_n_words, word_Common, word_Total, word_share, freq_q1+q2, fre
q_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_p
artial_ratio, longest_substr_ratio, freq_qid1, freq_qid2, q1len, q2len, q1
_n_words, q2_n_words, word_Common, word_Total, word_share, freq_q1+q2, fre
q_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'],stratif
y=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
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
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
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
35725	35725	65244	65245	what is china doing to help nepal	how can we help nepal	0.999950	0.666644	0.000000	0.000000
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

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=Non
e,
                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=False)
```

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_
23561	0.333322	0.333322	0.749981	0.428565	0.57142	0.399996	0.0	
3536	0.000000	0.000000	0.333322	0.166664	0.11111	0.083333	0.0	(

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.DataFra
me'>
train Shape After->  (37500, 26)  Type <class 'scipy.sparse.csr.csr_matri
x'>
```

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, i
nplace=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.DataFram
e'>
test Shape After->  (12500, 26)  Type <class 'scipy.sparse.csr.csr_matri
x'>
```

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]:

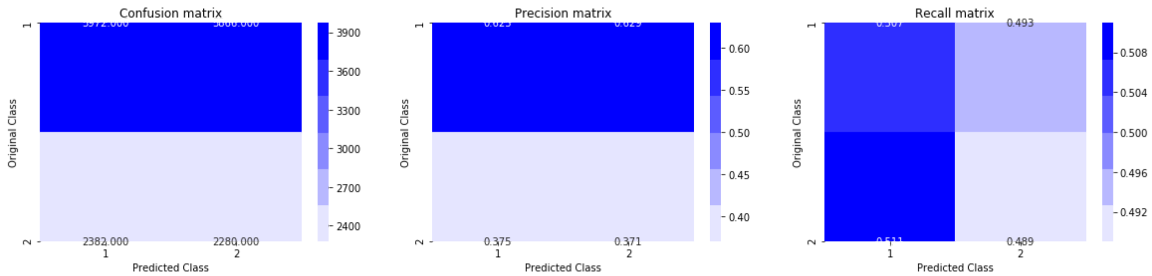
```
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predic
ted class j

    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 t
wo 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 t
wo 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=la
bels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")
    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=la
bels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=la
bels)
    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-1
5))

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
```

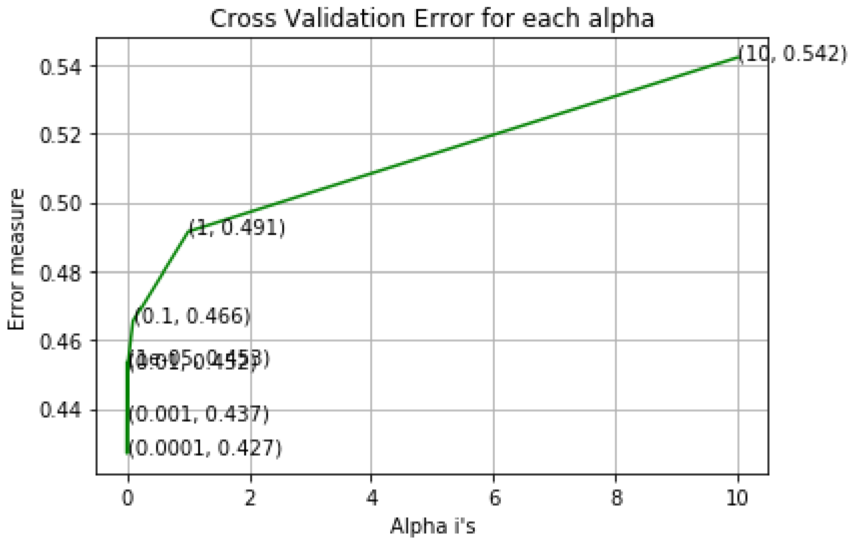


5.6 Logistic Regression with hyperparameter tuning

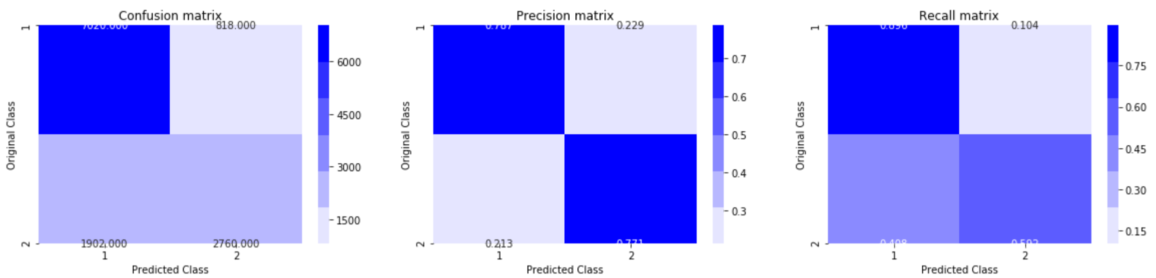
In [91]:

```
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/s
klearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss=�hinge�, penalty=�l2�, alpha=0.0001, l1_ratio=0.15, fit_intercep
t=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate=�opt
imal�, 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 Gradie
nt 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, l
abels=clf.classes_, eps=1e-15))

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


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log', random_state=42)
clf.fit(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_lo
ss(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_los
s(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: 0.4534364133470595
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: 0.41523107644180
174
For values of best alpha =  0.0001 The test log loss is: 0.427024623201395
Total number of data points : 12500
```

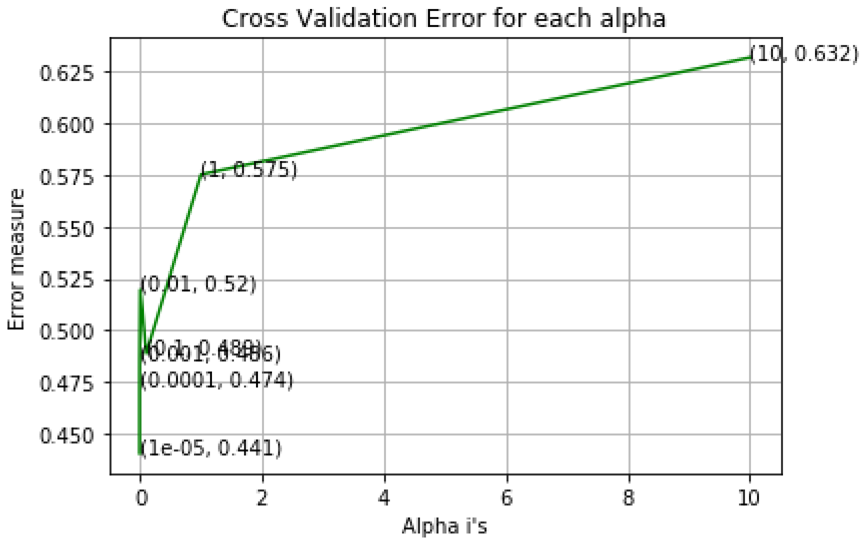


5.7 Linear SVM with hyperparameter tuning

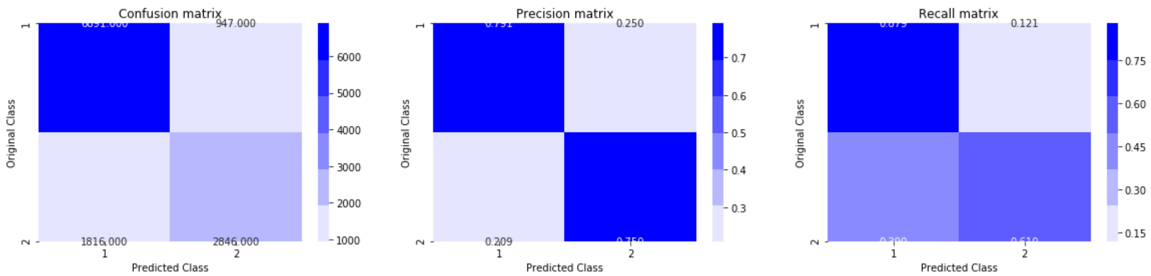
In [92]:

```
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/s
klearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss=�hinge�, penalty=�l2�, alpha=0.0001, l1_ratio=0.15, fit_intercep
t=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate=�opt
imal�, 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 Gradie
nt 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)
    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, l
abels=clf.classes_, eps=1e-15))

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


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge', random_state=4
2)
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_lo
ss(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_los
s(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: 0.44055060308003713
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: 0.427455880549171
55
For values of best alpha =  1e-05 The test log loss is: 0.4405506030800371
3
Total number of data points : 12500
```



5.8 XGBoost

A. Hyperparameter Tuning

In [93]:

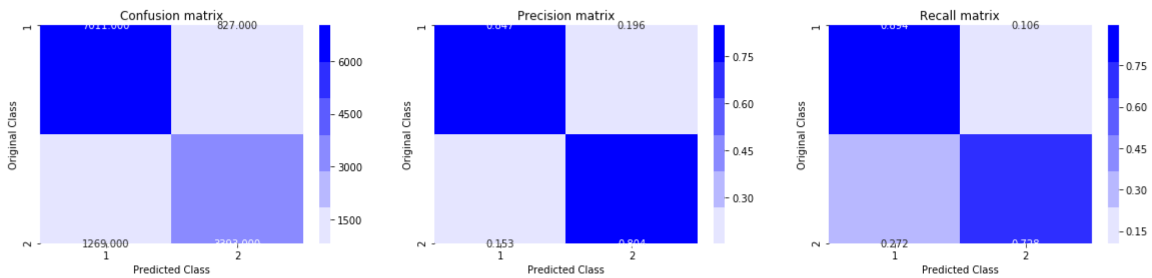
```
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
import scipy.stats as sc




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',g
amma=0.35,n_estimators=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_wor
ds',
       'word_Common', 'word_Total', 'word_share', 'freq_q1+q2', 'freq_q1-q
2'],
      dtype='object')
```

Out[167]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2
178300	178300	221393	273887	Is Quora degrading itself?	Why is the quality of Quora degrading?	0	1	1
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
65759	65759	114071	114072	As an international student in the United Stat...	Are international students on an F-1 Visa elig...	0	1	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
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

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 valu
es

# 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 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 = 'logloss', 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)
```

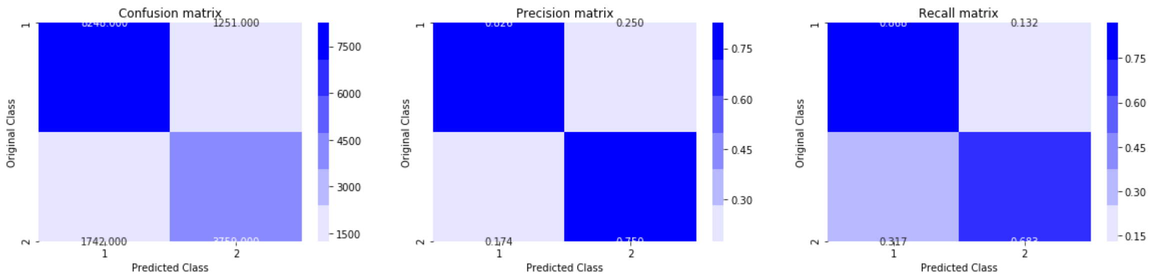
```
Optimal hyperParameter: {'n_estimators': 500, 'max_depth': 5}

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]:

```
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 e
arly 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
[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
```

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[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
[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
```

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[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 Loss']
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"])
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 T
unning | 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      |
+------------+---------------------+--------------------+-----------------
-------+---------------+
```

STEP BY STEP PROCEDURE:

1.As we know we have data set which contains Number of rows 404,290, which contains 5 columns : qid1, qid2, question1, question2, is_duplicate from which 'is_duplicate' is a class lable which specify that the question 1 and question 2 is similar or not and this is a binary classification problem, for a given pair of questions we need to predict if they are duplicate or not.

2.Firstly we preprocessed our data,did feature engineering to create new features which might help us and created our dataframes, then we merged dataframes and got out final matrix.Now after doing simple EDA on dataset we will try some Basic Feature Extraction (before cleaning) the datset like Frequency of qid1's ,word_Common and etc. and using this featured datset we will do some EDA on it so that we will able to rectify which features are most useful features our of all features i.e(wich feature is helpful for classification)

3.After doing basic Basic feature extractions we will try some Advanced Feature Extraction using NLP and Fuzzy Features but before doing this we will do Preprocessing of Text and then we will do Advanced Feature Extraction and try to visualise our Advanced Feature using EDA, PCA and word clouds.

4.Then we Splitted out data randomly . We could also have done time based splitting, since the model could predict for future unseen data too. But, there was no timestamp column provided, so the only option was to split it randomly.

5.Now as we know we have columns of two questions i.e question 1 and question 2 and we will vectorize that both col using tfidf weighted word-vectors so that we will able to apply models on it and after doing all these we will merge all the features i.e besic features + advance features + question1 tfidf w2v + and question 2 tfidf w2v. and Now after doing all of there we will apply models on it.

6.Here as we know here we are using two main performance matrix in this case study i.e log-loss and confusion matrix and using there we will get our performsnce of the models

7.Lets start: here we are there model i.e Logistic Regression linear svm and XgBoost and a random model which Finding worst-case log-loss and then we try to comparse all

8.In next step we will try our models with other vectorizer i.e tfidf instead of tfidf weighted w2v and try to do some hyperparameter tuning in order to improve the model performance.

9.Now, we have applied simple Random/Dumb Model. It gave a log loss of 0.89. This is the worst case log-loss. This will act as a base and any model we design should have a log-loss lesser than this dumb model.

10.After that we have applied Logistic Regression with hyperparameter tuning. It gave a log-loss of 0.44, which is lower than Random Model. We can also see that there is no Overfitting problem , since, Train log-loss and Test log-loss and very close.

11.After that we have applied Linear SVM with hyperparameter tuning. It gave the log-loss of 0.539,which is lower than Random Model. We can also see that there is no Overfitting problem , since, Train log-loss and Test log-loss and very close.

12.After that we have applied Xgboost with hyperparameter tuning. It gave the log-loss of 0.34,which is lower than Random Model. We can also see that there is no Overfitting problem , since, Train log-loss and Test log-loss and very close.

Looks like among all the models that we tried Xgboost seems to perform well and hence can be used to Identify which questions asked on Quora are duplicates of questions that have already been asked.