Quora Question Pairs

1. Business Problem

1.1 Description

Quora is a place to gain and share knowledge—about anything. It's a platform to ask questions and connect with people who contribute unique insights and quality answers. This empowers people to learn from each other and to better understand the world.

Over 100 million people visit Quora every month, so it's no surprise that many people ask similarly worded questions. Multiple questions with the same intent can cause seekers to spend more time finding the best answer to their question, and make writers feel they need to answer multiple versions of the same question. Quora values canonical questions because they provide a better experience to active seekers and writers, and offer more value to both of these groups in the long term.

> Credits: Kaggle __ Problem Statement __ - Identify which questions asked on Quora are duplicates of questions that have already been asked. - This could be useful to instantly provide answers to questions that have already been answered. - We are tasked with predicting whether a pair of questions are duplicates or not.

1.2 Sources/Useful Links
- Source : https://www.kaggle.com/c/quora-question-pairs

____ Useful Links ____ - Discussions : https://www.kaggle.com/anokas/data-analysis-xgboost-starter-0-35460-lb/comments - Kaggle Winning Solution and other approaches: https://www.dropbox.com/sh/93968nfnrzh8bp5/AACZdtsApc1QSTQc7X0H3QZ5a?dl=0 - Blog 1 : https://engineering.quora.com/Semantic-Question-Matching-with-Deep-Learning - Blog 2 : https://towardsdatascience.com/identifying-duplicate-questions-on-quora-top-12-on-kaggle-4c1cf93f1c30

1.3 Real world/Business Objectives and Constraints
1. The cost of a mis-classification can be very high. 2. You would want a probability of a pair of questions to be duplicates so that you can choose any threshold of choice. 3. No strict latency concerns. 4. Interpretability is partially important.

2. Machine Learning Probelm

2.1 Data

2.1.1 Data Overview

- Data will be in a file Train.csv
- Train.csv contains 5 columns : qid1, qid2, question1, question2, is_duplicate
- Size of Train.csv - 60MB
- Number of rows in Train.csv = 404,290

2.1.2 Example Data point

```
"id","qid1","qid2","question1","question2","is_duplicate"
"0","1","2","What is the step by step guide to invest in share market in india?","What is the step by step guide to invest in share market?","0"
"1","3","4","What is the story of Kohinoor (Koh-i-Noor) Diamond?","What would happen if the Indian government stole the Kohinoor (Koh-i-Noor) diamond back?","0"
"7","15","16","How can I be a good geologist?","What should I do to be a great geologist?","1"
"11","23","24","How do I read and find my YouTube comments?","How can I see all my Youtube comments?","1"
```

2.2 Mapping the real world problem to an ML problem

2.2.1 Type of Machine Leaning Problem

It is a binary classification problem, for a given pair of questions we need to predict if they are duplicate or not.

2.2.2 Performance Metric

Source: https://www.kaggle.com/c/quora-question-pairs#evaluation

Metric(s):

* log-loss : https://www.kaggle.com/wiki/LogarithmicLoss
* Binary Confusion Matrix

2.3 Train and Test Construction

We build train and test by randomly splitting in the ratio of 70:30 or 80:20 whatever we choose as we have sufficient points to work with.

3. Exploratory Data Analysis

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.tools as tls

from collections import Counter, defaultdict
import math
from subprocess import check_output
import os
import gc
import re
import nltk
nltk.download('stopwords')
import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
from datetime import datetime

import warnings
warnings.filterwarnings("ignore")
from tqdm import tqdm_notebook

# This package is used for finding longest common subsequence between two strings
# you can write your own dp code for this
from fuzzywuzzy import fuzz
from sklearn.manifold import TSNE
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

# 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

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

import time
import sqlite3
from sqlalchemy import create_engine # database connection
import csv
import datetime as dt

# Algorithms
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB, GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import SGDClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.decomposition import TruncatedSVD

from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassifier
from sklearn.calibration import CalibratedClassifierCV
from mlxtend.classifier import StackingClassifier
from sklearn import model_selection

# metrics
```

```
from sklearn.metrics import confusion_matrix, precision_recall_curve, auc, roc_curve, normalized_mutual_info_score
from sklearn.metrics.classification import accuracy_score, log_loss
from sklearn.model_selection import cross_val_score, train_test_split, GridSearchCV, StratifiedKFold, RandomizedSearchCV
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/passionateguy_bharat/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

3.1 Reading data and basic stats

In [2]:

```
# https://drive.google.com/drive/folders/1OWZoiQDvAvgOa-IUnEQ-6QKSEp_pw1XO

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

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

Number of data points: 404290

In [3]:

```
df.head()
```

Out[3]:

	id	qid1	qid2	question1	question2	is_duplicate
0	0	1	2	What is the step by step guide to invest in sh...	What is the step by step guide to invest in sh...	0
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0
2	2	5	6	How can I increase the speed of my internet co...	How can Internet speed be increased by hacking...	0
3	3	7	8	Why am I mentally very lonely? How can I solve...	Find the remainder when [math]23^{24}[/math] i...	0
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0

In [4]:

```
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

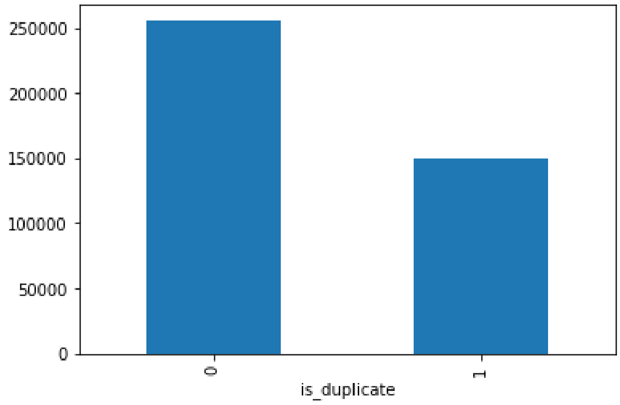
- Number of duplicate(similar) and non-duplicate(non similar) questions

In [7]:

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

Out[7]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f7140e5acf8>



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(qs_morethan_onetime,qs_morethan_onetime/unique_qs*100))

print ('Max number of times a single question is repeated: {}\n'.format(max(qids.value_counts())))

q_vals=qids.value_counts()

q_vals=q_vals.values
```

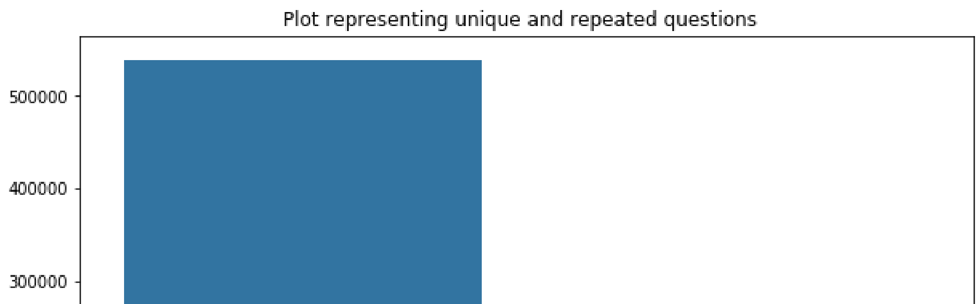
Total number of Unique Questions are: 537933

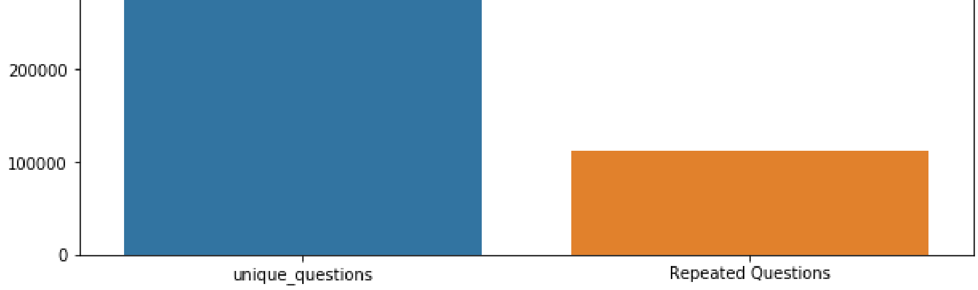
Number of unique questions that appear more than one time: 111780 (20.77953945937505%)

Max number of times a single question is repeated: 157

In [10]:

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

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





3.2.3 Checking for Duplicates

In [11]:

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

pair_duplicates = df[['qid1','qid2','is_duplicate']].groupby(['qid1','qid2']).count().reset_index()

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

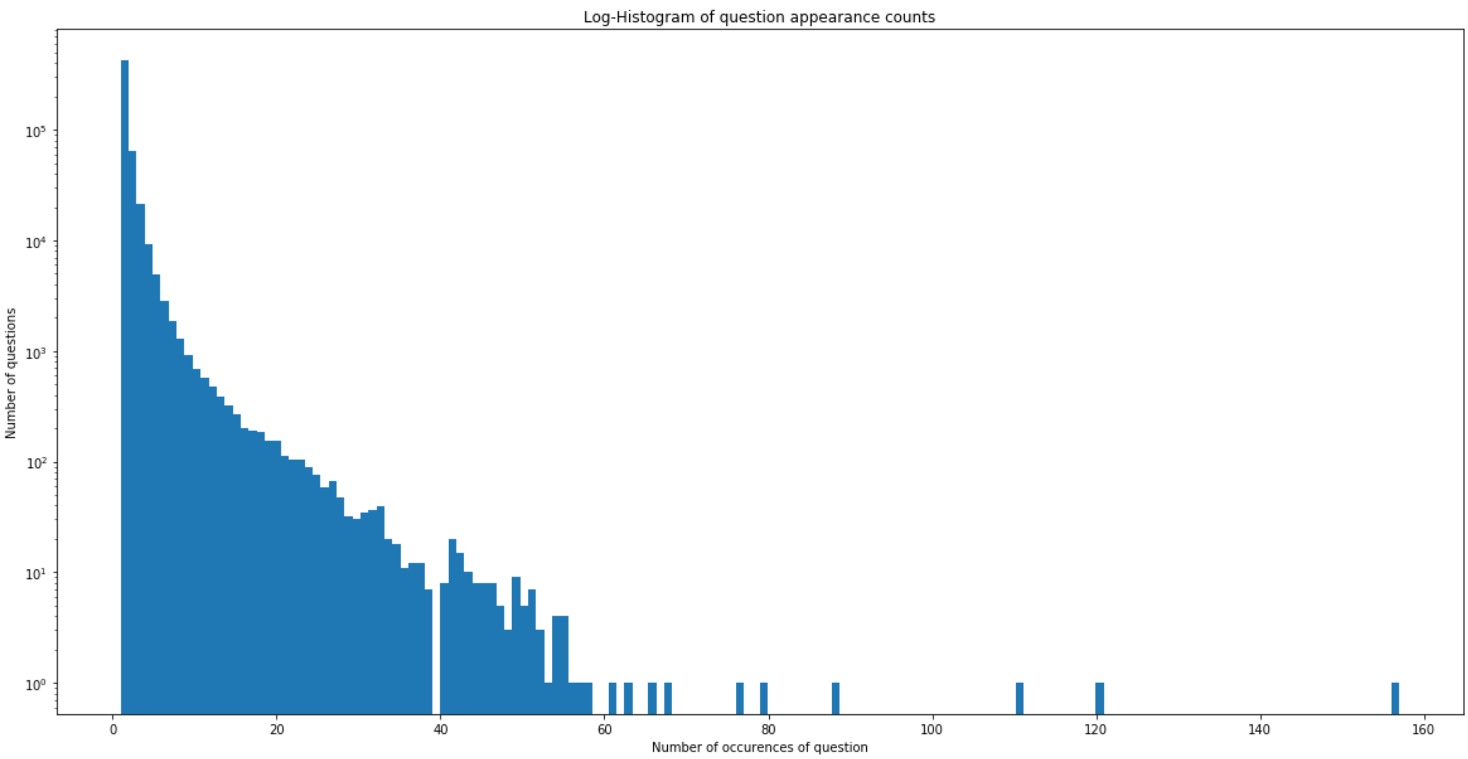
Number of duplicate questions 0

3.2.4 Number of occurrences of each question

In [12]:

```
plt.figure(figsize=(20, 10))

plt.hist(qids.value_counts(), bins=160)

plt.yscale('log', nonposy='clip')

plt.title('Log-Histogram of question appearance counts')

plt.xlabel('Number of occurences of question')

plt.ylabel('Number of questions')

print ('Maximum number of times a single question is repeated: {}\n'.format(max(qids.value_counts())))
```

Maximum number of times a single question is repeated: 157



3.2.5 Checking for NULL values

In [13]:

```
#Checking whether there are any rows with null values
nan_rows = df[df.isnull().any(1)]
print (nan_rows)
```

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

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

- There are two rows with null values in question2

In [14]:

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

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

3.3 Basic Feature Extraction (before cleaning)

Let us now construct a few features like:

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

In [15]:

```
# Train

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_new.csv", index=False)

df.head()
```

Out[15]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common	word_Total	wo
0	0	1	2	What is the step by step guide to invest in sh...	What is the step by step guide to invest in sh...	0	1	1	66	57	14	12	10.0	23.0	
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0	4	1	51	88	8	13	4.0	20.0	
2	2	5	6	How can I increase the speed of my internet co...	How can Internet speed be increased by hacking...	0	1	1	73	59	14	10	4.0	24.0	
3	3	7	8	Why am I mentally very lonely? How can I solve...	Find the remainder when [math]23^{24} [/math] i...	0	1	1	50	65	11	9	0.0	19.0	
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0	3	1	76	39	13	7	2.0	20.0	

3.3.1 Analysis of some of the extracted features

- Here are some questions have only one single words.

In [16]:

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

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

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

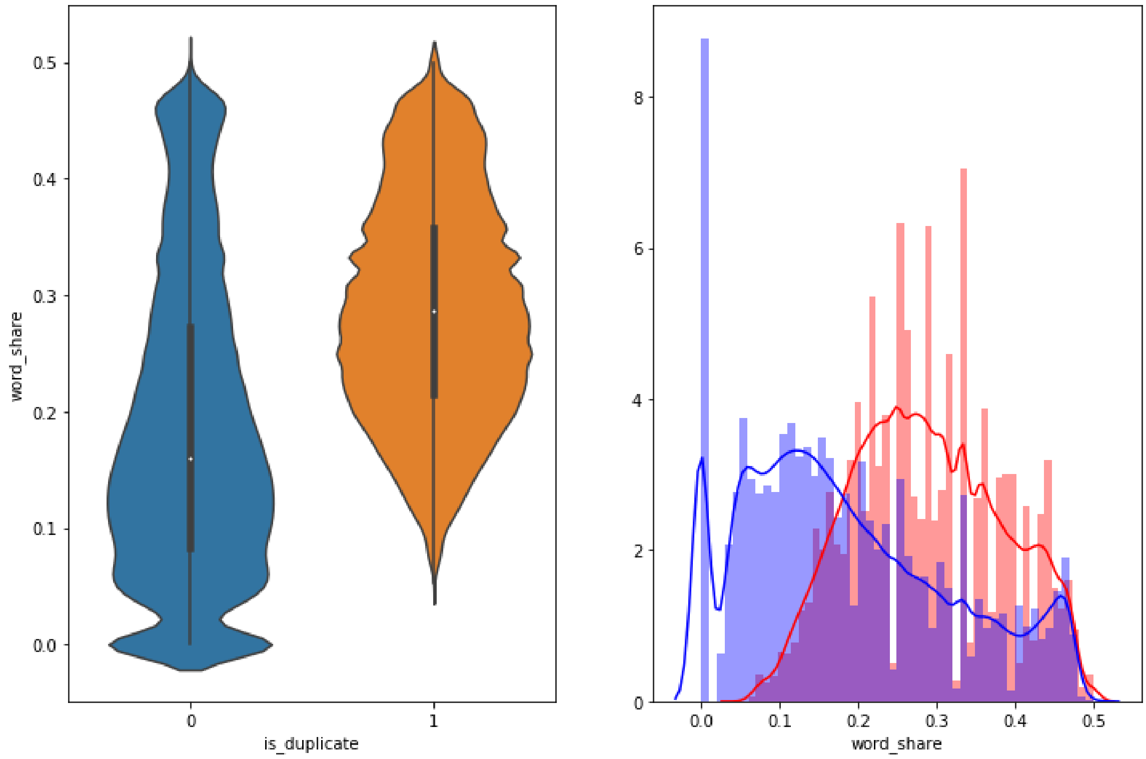
```
Minimum length of the questions in question1 :  1
Minimum length of the questions in question2 :  1
Number of Questions with minimum length [question1] : 67
Number of Questions with minimum length [question2] : 24
```

3.3.1.1 Feature: word_share

In [17]:

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

plt.subplot(1,2,1) # row, no of plots, 1st in row
sns.violinplot(x = 'is_duplicate', y = 'word_share', data = df[0:])

plt.subplot(1,2,2) # row, no of plots, 2nd in row
sns.distplot(df[df['is_duplicate'] == 1.0]['word_share'][0:] , label = "1", color = 'red')
sns.distplot(df[df['is_duplicate'] == 0.0]['word_share'][0:] , label = "0" , color = 'blue' )
```

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

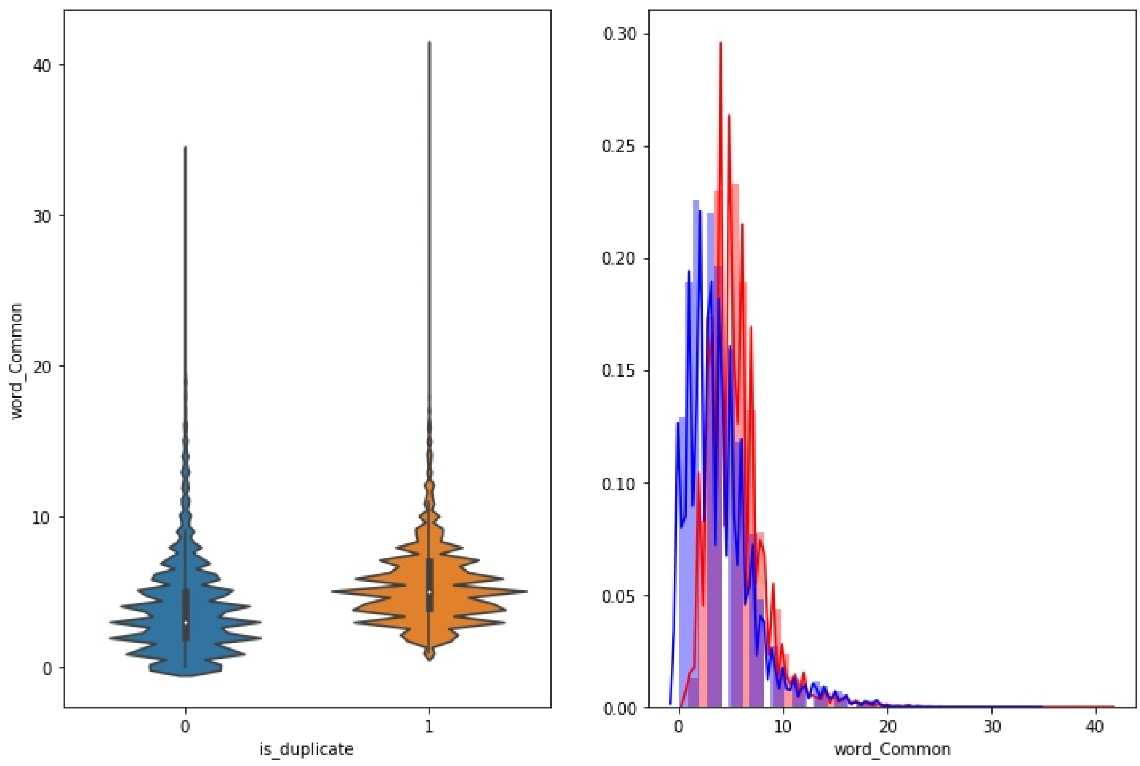


- The distributions for normalized word_share have some overlap on the far right-hand side, i.e., there are quite a lot of questions with high word similarity
- The average word share and Common no. of words of qid1 and qid2 is more when they are duplicate(Similar)

3.3.1.2 Feature: word_Common

In [18]:

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

plt.subplot(1,2,1) # row, no of plots, 1st in row
sns.violinplot(x = 'is_duplicate', y = 'word_Common', data = df[0:])

plt.subplot(1,2,2) # row, no of plots, 2nd in row
sns.distplot(df[df['is_duplicate'] == 1.0]['word_Common'][0:] , label = "1", color = 'red')
sns.distplot(df[df['is_duplicate'] == 0.0]['word_Common'][0:] , label = "0" , color = 'blue' )
plt.show()
```



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

3.4 Preprocessing of Text

- Preprocessing:
  - Removing html tags
  - Removing Punctuations
  - Performing stemming
  - Removing Stopwords (I am skipping)
  - Expanding contractions etc.

In [2]:

```
# To get the results in 4 decemal points
SAFE_DIV = 0.0001

def preprocess(x):
    x = str(x).lower()
    x = x.replace(",000,000", "m").replace(",000", "k").replace("′", "'").replace("’", "'")\
                           .replace("won't", "will not").replace("cannot", "can not").replace("can't", "can not")\
                           .replace("n't", " not").replace("what's", "what is").replace("it's", "it is")\
                           .replace("'ve", " have").replace("i'm", "i am").replace("'re", " are")\
                           .replace("he's", "he is").replace("she's", "she is").replace("'s", " own")\
                           .replace("%", " percent ").replace("₹", " rupee ").replace("$", " dollar ")\
                           .replace("€", " euro ").replace("'ll", " will")
    x = re.sub(r"([0-9]+)000000", r"\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
```

- Function to Compute and get the features: With 2 parameters of Question 1 and Question 2

3.5 Advanced Feature Extraction (NLP and Fuzzy Features)

Definition:

- **Token**: You get a token by splitting sentence a space
- **Stop_Word** : stop words as per NLTK.
- **Word** : A token that is not a stop_word

Features:

- **cwc_min** : Ratio of common_word_count to min lenghth of word count of Q1 and Q2
  cwc_min = common_word_count / (min(len(q1_words), len(q2_words))

- **cwc_max** : Ratio of common_word_count to max lenghth of word count of Q1 and Q2
  cwc_max = common_word_count / (max(len(q1_words), len(q2_words))

- **csc_min** : Ratio of common_stop_count to min lenghth of stop count of Q1 and Q2
  csc_min = common_stop_count / (min(len(q1_stops), len(q2_stops))

- **csc_max** : Ratio of common_stop_count to max lenghth of stop count of Q1 and Q2
  csc_max = common_stop_count / (max(len(q1_stops), len(q2_stops))

- **ctc_min** : Ratio of common_token_count to min lenghth of token count of Q1 and Q2
  ctc_min = common_token_count / (min(len(q1_tokens), len(q2_tokens))

- **ctc_max** : Ratio of common_token_count to max lenghth of token count of Q1 and Q2
  ctc_max = common_token_count / (max(len(q1_tokens), len(q2_tokens))

- **last_word_eq** : Check if Last word of both questions is equal or not
  last_word_eq = int(q1_tokens[-1] == q2_tokens[-1])

- **first_word_eq** : Check if First word of both questions is equal or not
  first_word_eq = int(q1_tokens[0] == q2_tokens[0])

- **abs_len_diff** : Abs. length difference
  abs_len_diff = abs(len(q1_tokens) - len(q2_tokens))

- **mean_len** : Average Token Length of both Questions
  mean_len = (len(q1_tokens) + len(q2_tokens))/2

- **fuzz_ratio** : https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/

- **fuzz_partial_ratio** : https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/

- **token_sort_ratio** : https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/

- **token_set_ratio** : https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/

- **longest_substr_ratio** : Ratio of length longest common substring to min lenghth of token count of Q1 and Q2
  longest_substr_ratio = len(longest common substring) / (min(len(q1_tokens), len(q2_tokens))

In [26]:

```python
# I have skipped using df["csc_min"], df["csc_max"]

stopwords = set(STOPWORDS)

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 stopwords.words('english')])
    q2_words = set([word for word in q2_tokens if word not in stopwords.words('english')])

    # I have skipped using this stopwords step
    '''
    #Get the stopwords in Questions
    q1_stops = set([word for word in q1_tokens if word in stopwords.words('english')])
    q2_stops = set([word for word in q2_tokens if word in stopwords.words('english')])
    '''

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

    # I have skipped using this stopwords step
    '''
    # Get the common stopwords from Question pair
    common_stop_count = len(q1_stops.intersection(q2_stops))
    '''

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


    token_features[0] = common_word_count / (min(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[1] = common_word_count / (max(len(q1_words), len(q2_words)) + SAFE_DIV)

    # I have skipped using this stopwords step
    '''
     token_features[2] = common_stop_count / (min(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[3] = common_stop_count / (max(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    '''
    token_features[2] = common_token_count / (min(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)
    token_features[3] = common_token_count / (max(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)

    # Last word of both question is same or not
```

```
    token_features[4] = int(q1_tokens[-1] == q2_tokens[-1])

    # First word of both question is same or not
    token_features[5] = int(q1_tokens[0] == q2_tokens[0])

    token_features[6] = abs(len(q1_tokens) - len(q2_tokens))

    #Average Token Length of both Questions
    token_features[7] = (len(q1_tokens) + len(q2_tokens))/2
    return token_features

# get the Longest Common sub string

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

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

    print("token features...")

    # Merging Features with dataset

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

    df["cwc_min"]       = list(map(lambda x: x[0], token_features))
    df["cwc_max"]       = list(map(lambda x: x[1], token_features))

    # I have skipped using this stopwords step
    '''
    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[2], token_features))
    df["ctc_max"]       = list(map(lambda x: x[3], token_features))
    df["last_word_eq"]  = list(map(lambda x: x[4], token_features))
    df["first_word_eq"] = list(map(lambda x: x[5], token_features))
    df["abs_len_diff"]  = list(map(lambda x: x[6], token_features))
    df["mean_len"]      = list(map(lambda x: x[7], token_features))

    #Computing Fuzzy Features and Merging with Dataset

    # do read this blog: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
    # https://stackoverflow.com/questions/31806695/when-to-use-which-fuzz-function-to-compare-2-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 tokens 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["question1"], x["question2"]), axis=1)
    df["fuzz_ratio"]            = df.apply(lambda x: fuzz.QRatio(x["question1"], x["question2"]), axis=1)
    df["fuzz_partial_ratio"]    = df.apply(lambda x: fuzz.partial_ratio(x["question1"], x["question2"]), axis=1)
    df["longest_substr_ratio"]  = df.apply(lambda x: get_longest_substr_ratio(x["question1"], x["question2"]), axis=1)

    return df
```

In [2]:

```
"""
if os.path.isfile('nlp_features_train_old.csv'):
    df = pd.read_csv("nlp_features_train_old.csv",encoding='latin-1')
    df.fillna('')
else:
    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)
"""
# As I am skipping stop words, hence using part of the code only

if not os.path.isfile('nlp_features_train.csv'):
    df = pd.read_csv("train.csv")
    df = extract_features(df)
```

```
    df.to_csv("nlp_features_train.csv", index=False)
else:
    df = pd.read_csv("nlp_features_train.csv")

df.head(2)
```

Out[2]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	abs_len_diff	mean_len
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	0.916659	0.785709	0.0	1.0	2.0	13.0
1	1	3	4	what is the story of kohinoor koh i noor dia...	what would happen if the indian government sto...	0	0.799984	0.399996	0.699993	0.466664	0.0	1.0	5.0	12.5

In [51]:

```
df.shape
```

Out[51]:

(404290, 19)

3.5.1 Analysis of extracted features

3.5.1.1 Plotting Word clouds

- Creating Word Cloud of Duplicates and Non-Duplicates Question pairs
- We can observe the most frequent occuring words

In [4]:

```
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')
np.savetxt('train_n.txt', n, delimiter=' ', fmt='%s')
```

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

In [53]:

```
d = path.dirname('.')

textp_w = open(path.join(d, 'train_p.txt')).read()
textn_w = open(path.join(d, 'train_n.txt')).read()

# reading the text files and removing the Stop Words:

"""
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))
"""
```

Out[53]:

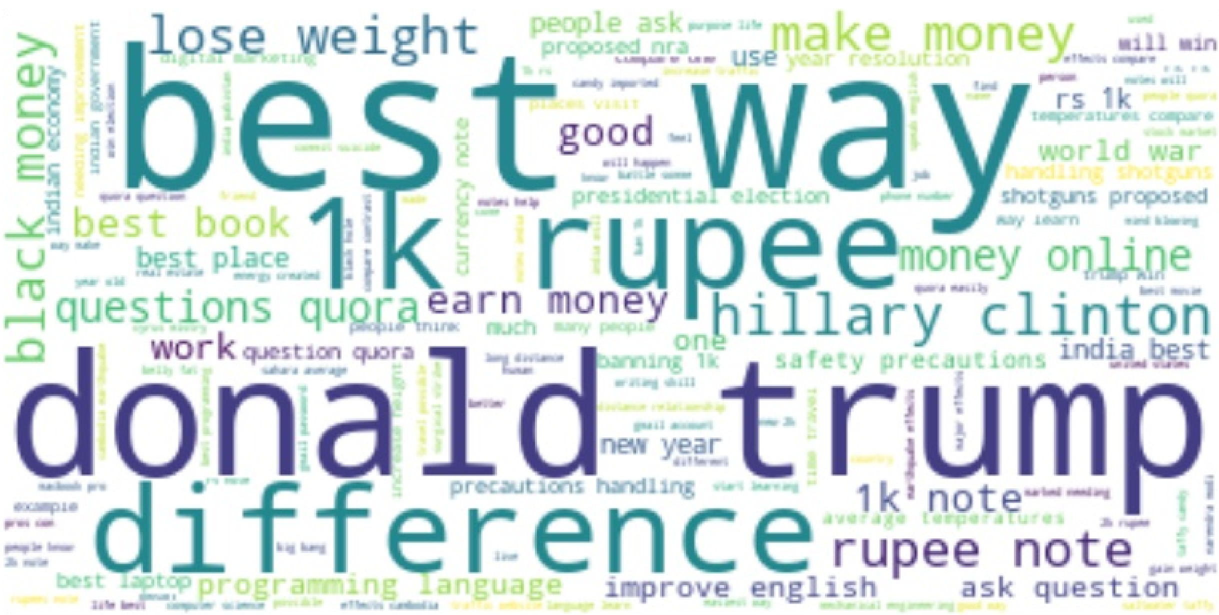
'\nstopwords = set(STOPWORDS)\nstopwords.add("said")\nstopwords.add("br")\nstopwords.add(" ")\nstopwords.remove("not")\n\nstopwords.remove("no")\n#stopwords.remove("good")\n#stopwords.remove("love")\nstopwords.remove("like")\n#stopwords.remove("best")\n#stopwords.remove("!")\nprint ("Total number of words in duplicate pair questions :",len(textp_w))\nprint ("Total number of words in non duplicate pair questions :",len(textn_w))\n'

Word Clouds generated from duplicate pair question's text

In [54]:

```
# we use this for stop words
# wc = WordCloud(background_color="white", max_words=len(textp_w), stopwords=stopwords)

wc = WordCloud(background_color="white", max_words=len(textp_w))
wc.generate(textp_w)
print ("Word Cloud for Duplicate Question pairs")
plt.figure(figsize=(15,7))
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

Word Cloud for Duplicate Question pairs



Word Clouds generated from non duplicate pair question's text

In [55]:

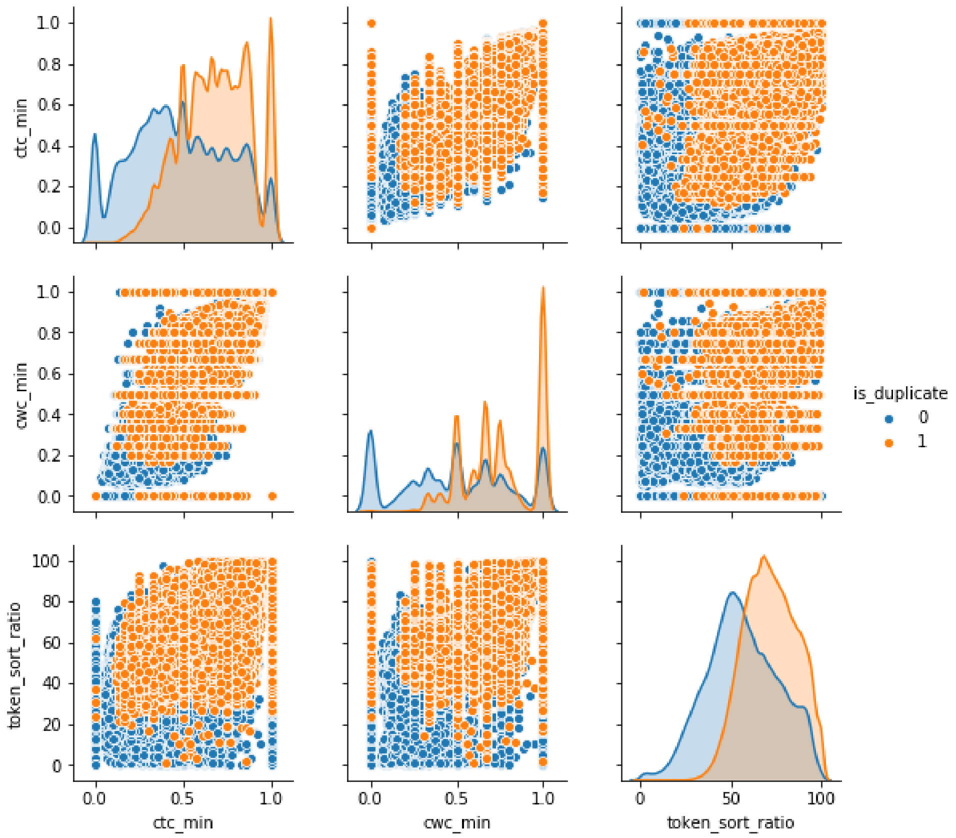
```
# we use this for stop words
# wc = WordCloud(background_color="white", max_words=len(textn_w), stopwords=stopwords)

wc = WordCloud(background_color="white", max_words=len(textn_w))
# generate word cloud
wc.generate(textn_w)
print ("Word Cloud for non-Duplicate Question pairs:")
plt.figure(figsize=(15,7))
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', 'token_sort_ratio']

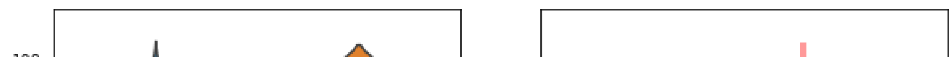
In [56]:

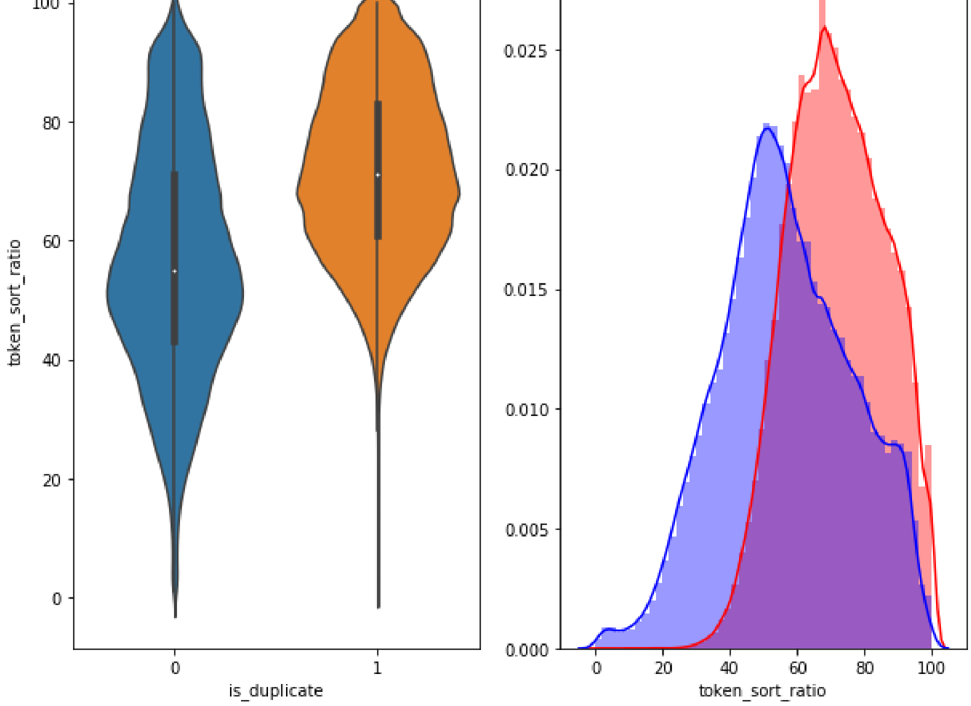
```
# we dont use 'csc_min'

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



In [57]:

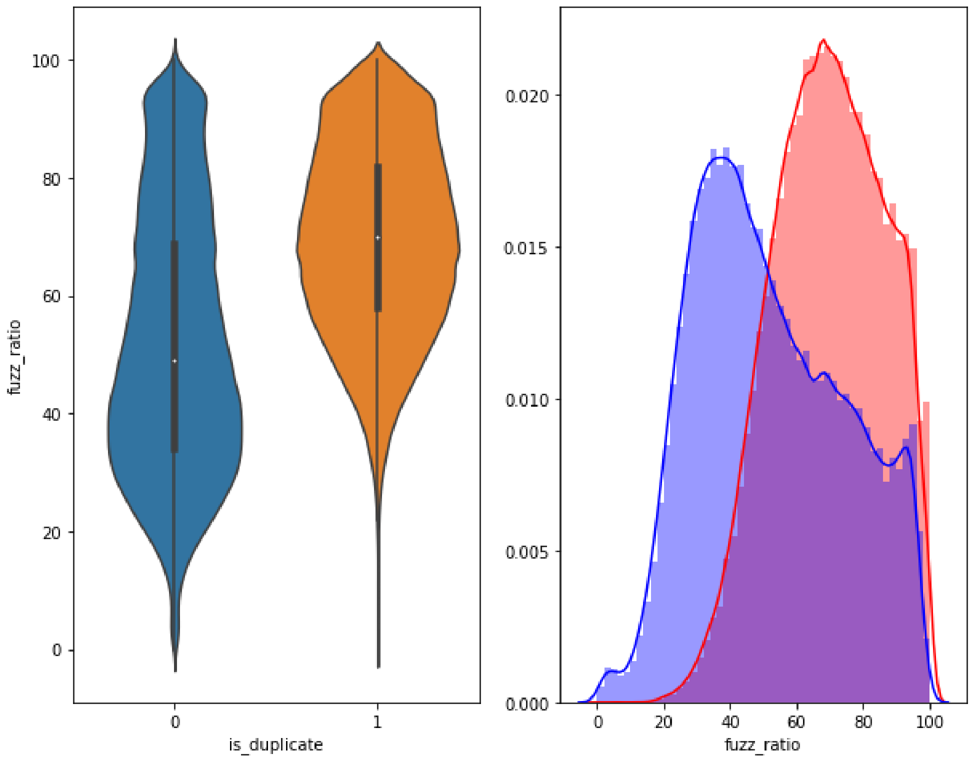
```
# Distribution of the token_sort_ratio
plt.figure(figsize=(10, 8))

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

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





In [58]:

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

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

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



3.5.2 Visualization

In [3]:

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

from sklearn.preprocessing import MinMaxScaler

# Considering all 300k datapoints.
```

```
dfp_subsampled = df[:300000]

# skipping  'csc_min', 'csc_max'
X = MinMaxScaler().fit_transform(dfp_subsampled[['cwc_min', 'cwc_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 [4]:

```
start = datetime.now()

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)

print('Time to complete: ', datetime.now() - start)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 300000 samples in 77.293s...
[t-SNE] Computed neighbors for 300000 samples in 228.109s...
[t-SNE] Computed conditional probabilities for sample 1000 / 300000
[t-SNE] Computed conditional probabilities for sample 2000 / 300000
[t-SNE] Computed conditional probabilities for sample 3000 / 300000
[t-SNE] Computed conditional probabilities for sample 4000 / 300000
[t-SNE] Computed conditional probabilities for sample 5000 / 300000
[t-SNE] Computed conditional probabilities for sample 6000 / 300000
[t-SNE] Computed conditional probabilities for sample 7000 / 300000
[t-SNE] Computed conditional probabilities for sample 8000 / 300000
[t-SNE] Computed conditional probabilities for sample 9000 / 300000
[t-SNE] Computed conditional probabilities for sample 10000 / 300000
[t-SNE] Computed conditional probabilities for sample 11000 / 300000
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[t-SNE] Computed conditional probabilities for sample 203000 / 300000
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[t-SNE] Computed conditional probabilities for sample 205000 / 300000
[t-SNE] Computed conditional probabilities for sample 206000 / 300000
[t-SNE] Computed conditional probabilities for sample 207000 / 300000
[t-SNE] Computed conditional probabilities for sample 208000 / 300000
[t-SNE] Computed conditional probabilities for sample 209000 / 300000
[t-SNE] Computed conditional probabilities for sample 210000 / 300000
[t-SNE] Computed conditional probabilities for sample 211000 / 300000
[t-SNE] Computed conditional probabilities for sample 212000 / 300000
[t-SNE] Computed conditional probabilities for sample 213000 / 300000
[t-SNE] Computed conditional probabilities for sample 214000 / 300000
[t-SNE] Computed conditional probabilities for sample 215000 / 300000
[t-SNE] Computed conditional probabilities for sample 216000 / 300000
[t-SNE] Computed conditional probabilities for sample 217000 / 300000
[t-SNE] Computed conditional probabilities for sample 218000 / 300000
[t-SNE] Computed conditional probabilities for sample 219000 / 300000
[t-SNE] Computed conditional probabilities for sample 220000 / 300000
[t-SNE] Computed conditional probabilities for sample 221000 / 300000
```
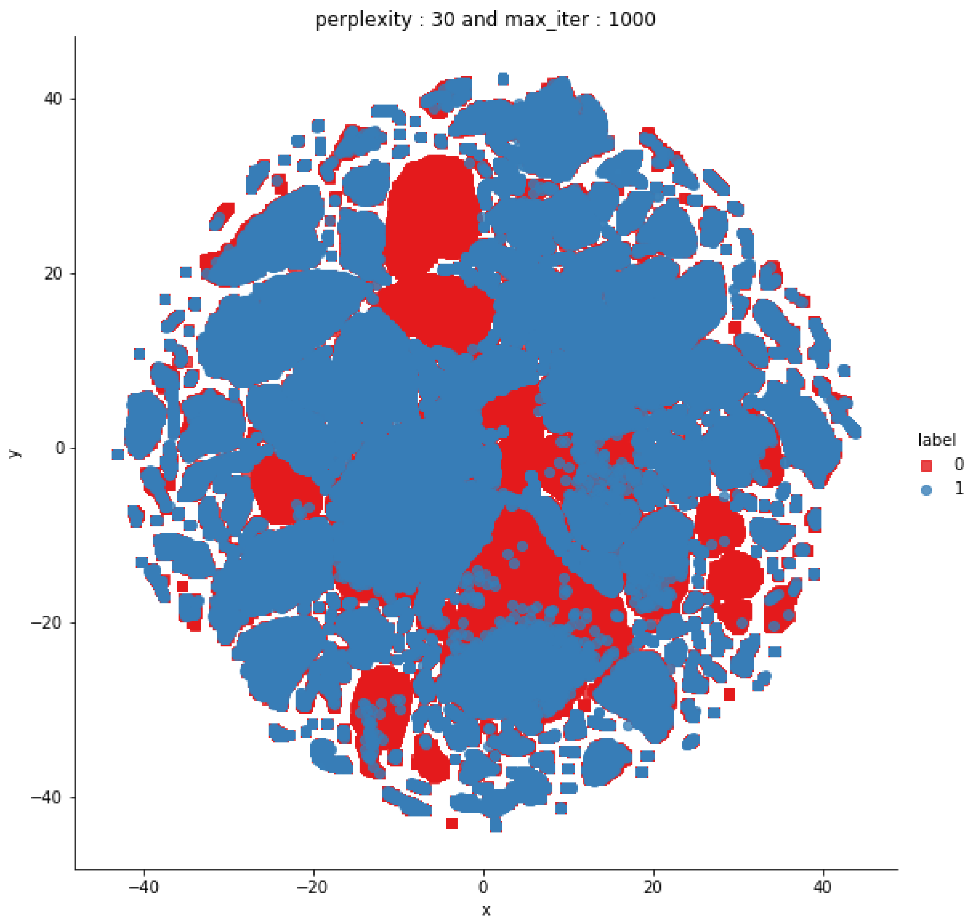

```
[t-SNE] Computed conditional probabilities for sample 222000 / 300000
[t-SNE] Computed conditional probabilities for sample 223000 / 300000
[t-SNE] Computed conditional probabilities for sample 224000 / 300000
[t-SNE] Computed conditional probabilities for sample 225000 / 300000
[t-SNE] Computed conditional probabilities for sample 226000 / 300000
[t-SNE] Computed conditional probabilities for sample 227000 / 300000
[t-SNE] Computed conditional probabilities for sample 228000 / 300000
[t-SNE] Computed conditional probabilities for sample 229000 / 300000
[t-SNE] Computed conditional probabilities for sample 230000 / 300000
[t-SNE] Computed conditional probabilities for sample 231000 / 300000
[t-SNE] Computed conditional probabilities for sample 232000 / 300000
[t-SNE] Computed conditional probabilities for sample 233000 / 300000
[t-SNE] Computed conditional probabilities for sample 234000 / 300000
[t-SNE] Computed conditional probabilities for sample 235000 / 300000
[t-SNE] Computed conditional probabilities for sample 236000 / 300000
[t-SNE] Computed conditional probabilities for sample 237000 / 300000
[t-SNE] Computed conditional probabilities for sample 238000 / 300000
[t-SNE] Computed conditional probabilities for sample 239000 / 300000
[t-SNE] Computed conditional probabilities for sample 240000 / 300000
[t-SNE] Computed conditional probabilities for sample 241000 / 300000
[t-SNE] Computed conditional probabilities for sample 242000 / 300000
[t-SNE] Computed conditional probabilities for sample 243000 / 300000
[t-SNE] Computed conditional probabilities for sample 244000 / 300000
[t-SNE] Computed conditional probabilities for sample 245000 / 300000
[t-SNE] Computed conditional probabilities for sample 246000 / 300000
[t-SNE] Computed conditional probabilities for sample 247000 / 300000
[t-SNE] Computed conditional probabilities for sample 248000 / 300000
[t-SNE] Computed conditional probabilities for sample 249000 / 300000
[t-SNE] Computed conditional probabilities for sample 250000 / 300000
[t-SNE] Computed conditional probabilities for sample 251000 / 300000
[t-SNE] Computed conditional probabilities for sample 252000 / 300000
[t-SNE] Computed conditional probabilities for sample 253000 / 300000
[t-SNE] Computed conditional probabilities for sample 254000 / 300000
[t-SNE] Computed conditional probabilities for sample 255000 / 300000
[t-SNE] Computed conditional probabilities for sample 256000 / 300000
[t-SNE] Computed conditional probabilities for sample 257000 / 300000
[t-SNE] Computed conditional probabilities for sample 258000 / 300000
[t-SNE] Computed conditional probabilities for sample 259000 / 300000
[t-SNE] Computed conditional probabilities for sample 260000 / 300000
[t-SNE] Computed conditional probabilities for sample 261000 / 300000
[t-SNE] Computed conditional probabilities for sample 262000 / 300000
[t-SNE] Computed conditional probabilities for sample 263000 / 300000
[t-SNE] Computed conditional probabilities for sample 264000 / 300000
[t-SNE] Computed conditional probabilities for sample 265000 / 300000
[t-SNE] Computed conditional probabilities for sample 266000 / 300000
[t-SNE] Computed conditional probabilities for sample 267000 / 300000
[t-SNE] Computed conditional probabilities for sample 268000 / 300000
[t-SNE] Computed conditional probabilities for sample 269000 / 300000
[t-SNE] Computed conditional probabilities for sample 270000 / 300000
[t-SNE] Computed conditional probabilities for sample 271000 / 300000
[t-SNE] Computed conditional probabilities for sample 272000 / 300000
[t-SNE] Computed conditional probabilities for sample 273000 / 300000
[t-SNE] Computed conditional probabilities for sample 274000 / 300000
[t-SNE] Computed conditional probabilities for sample 275000 / 300000
[t-SNE] Computed conditional probabilities for sample 276000 / 300000
[t-SNE] Computed conditional probabilities for sample 277000 / 300000
[t-SNE] Computed conditional probabilities for sample 278000 / 300000
[t-SNE] Computed conditional probabilities for sample 279000 / 300000
[t-SNE] Computed conditional probabilities for sample 280000 / 300000
[t-SNE] Computed conditional probabilities for sample 281000 / 300000
[t-SNE] Computed conditional probabilities for sample 282000 / 300000
[t-SNE] Computed conditional probabilities for sample 283000 / 300000
[t-SNE] Computed conditional probabilities for sample 284000 / 300000
[t-SNE] Computed conditional probabilities for sample 285000 / 300000
[t-SNE] Computed conditional probabilities for sample 286000 / 300000
[t-SNE] Computed conditional probabilities for sample 287000 / 300000
[t-SNE] Computed conditional probabilities for sample 288000 / 300000
[t-SNE] Computed conditional probabilities for sample 289000 / 300000
[t-SNE] Computed conditional probabilities for sample 290000 / 300000
[t-SNE] Computed conditional probabilities for sample 291000 / 300000
[t-SNE] Computed conditional probabilities for sample 292000 / 300000
[t-SNE] Computed conditional probabilities for sample 293000 / 300000
[t-SNE] Computed conditional probabilities for sample 294000 / 300000
[t-SNE] Computed conditional probabilities for sample 295000 / 300000
[t-SNE] Computed conditional probabilities for sample 296000 / 300000
[t-SNE] Computed conditional probabilities for sample 297000 / 300000
[t-SNE] Computed conditional probabilities for sample 298000 / 300000
[t-SNE] Computed conditional probabilities for sample 299000 / 300000
[t-SNE] Computed conditional probabilities for sample 300000 / 300000
[t-SNE] Mean sigma: 0.000000
[t-SNE] Computed conditional probabilities in 24.386s
[t-SNE] Iteration 50: error = 125.7099686, gradient norm = 0.0000001 (50 iterations in 341.455s)
[t-SNE] Iteration 50: gradient norm 0.000000. Finished
```

```
[t-SNE] Iteration 50: gradient norm 0.000000. Finished.
[t-SNE] KL divergence after 50 iterations with early exaggeration: 125.709969
[t-SNE] Iteration 100: error = 8.2490549, gradient norm = 0.0000009 (50 iterations in 354.165s)
[t-SNE] Iteration 150: error = 8.2428894, gradient norm = 0.0004239 (50 iterations in 387.354s)
[t-SNE] Iteration 200: error = 6.7796559, gradient norm = 0.0007852 (50 iterations in 318.050s)
[t-SNE] Iteration 250: error = 6.1827765, gradient norm = 0.0005051 (50 iterations in 296.216s)
[t-SNE] Iteration 300: error = 5.8126183, gradient norm = 0.0003936 (50 iterations in 297.431s)
[t-SNE] Iteration 350: error = 5.5274935, gradient norm = 0.0003265 (50 iterations in 299.707s)
[t-SNE] Iteration 400: error = 5.2934322, gradient norm = 0.0002772 (50 iterations in 300.269s)
[t-SNE] Iteration 450: error = 5.0988846, gradient norm = 0.0002368 (50 iterations in 302.404s)
[t-SNE] Iteration 500: error = 4.9375992, gradient norm = 0.0002052 (50 iterations in 304.982s)
[t-SNE] Iteration 550: error = 4.8009281, gradient norm = 0.0001808 (50 iterations in 303.392s)
[t-SNE] Iteration 600: error = 4.6820831, gradient norm = 0.0001611 (50 iterations in 301.230s)
[t-SNE] Iteration 650: error = 4.5779867, gradient norm = 0.0001443 (50 iterations in 301.915s)
[t-SNE] Iteration 700: error = 4.4857368, gradient norm = 0.0001302 (50 iterations in 301.606s)
[t-SNE] Iteration 750: error = 4.4029298, gradient norm = 0.0001190 (50 iterations in 302.003s)
[t-SNE] Iteration 800: error = 4.3283806, gradient norm = 0.0001096 (50 iterations in 299.207s)
[t-SNE] Iteration 850: error = 4.2605305, gradient norm = 0.0001015 (50 iterations in 301.823s)
[t-SNE] Iteration 900: error = 4.1982131, gradient norm = 0.0000941 (50 iterations in 299.423s)
[t-SNE] Iteration 950: error = 4.1407647, gradient norm = 0.0000878 (50 iterations in 301.399s)
[t-SNE] Iteration 1000: error = 4.0878043, gradient norm = 0.0000822 (50 iterations in 301.139s)
[t-SNE] KL divergence after 1000 iterations: 4.087804
Time to complete:  1:49:05.106164
```

In [5]:

```
df1 = pd.DataFrame({'x':tsne2d[:,0], 'y':tsne2d[:,1] ,'label':y})

# draw the plot in appropriate place in the grid
sns.lmplot(data=df1, x='x', y='y', hue='label', fit_reg=False, size=8,palette="Set1",markers=['s','o'])
plt.title("perplexity : {} and max_iter : {}".format(30, 1000))
plt.show()
```



Splitting the data

In [4]:

```
# avoid decoding problems
df = pd.read_csv("train.csv")

# encode questions to unicode
# https://stackoverflow.com/a/6812069
# ---------------- python 2 --------------------
# df['question1'] = df['question1'].apply(lambda x: unicode(str(x),"utf-8"))
```

```
# df['question2'] = df['question2'].apply(lambda x: unicode(str(x),"utf-8"))
# ----------------- python 3 ---------------------
df['question1'] = df['question1'].apply(lambda x: str(x))
df['question2'] = df['question2'].apply(lambda x: str(x))
```

In [5]:

```
df.head()
```

Out[5]:

	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 [4]:

```
df.shape
```

Out[4]:

(404290, 6)

In [6]:

```
# considering 1L datapoints for our case study
df1 = df[:100000]
```

In [7]:

```
# Creating y label
y_true = df1['is_duplicate']

# dropping y-label from data thereby remaining data considered as x-label
df1.drop(['is_duplicate'],axis=1, inplace= True)
```

In [8]:

```
X_train, X_test, y_train, y_test = train_test_split(df1, y_true, stratify=y_true, test_size=0.3)
```

In [6]:

```
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 : (70000, 5)
Number of data points in test data : (30000, 5)
```

In [7]:

```
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:  0.6274571428571428 Class 1:  0.3725428571428571
---------- Distribution of output variable in train data ----------
Class 0:  0.3725333333333333 Class 1:  0.3725333333333333
```

Part - I

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 [6]:

```
# Train data

X_train['freq_qid1']  = X_train.groupby('qid1')['qid1'].transform('count')
X_train['freq_qid2']  = X_train.groupby('qid2')['qid2'].transform('count')
X_train['q1len']      = X_train['question1'].str.len()
X_train['q2len']      = X_train['question2'].str.len()
X_train['q1_n_words'] = X_train['question1'].apply(lambda row: len(row.split(" ")))
X_train['q2_n_words'] = X_train['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)
X_train['word_Common'] = X_train.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))
X_train['word_Total'] = X_train.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))
X_train['word_share'] = X_train.apply(normalized_word_share, axis=1)

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

In [7]:

```
# Test data

X_test['freq_qid1']  = X_test.groupby('qid1')['qid1'].transform('count')
X_test['freq_qid2']  = X_test.groupby('qid2')['qid2'].transform('count')
X_test['q1len']      = X_test['question1'].str.len()
X_test['q2len']      = X_test['question2'].str.len()
X_test['q1_n_words'] = X_test['question1'].apply(lambda row: len(row.split(" ")))
X_test['q2_n_words'] = X_test['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)
X_test['word_Common'] = X_test.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))
X_test['word_Total'] = X_test.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))
X_test['word_share'] = X_test.apply(normalized_word_share, axis=1)

X_test['freq_q1+q2'] = X_test['freq_qid1'] + X_test['freq_qid2']
```

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

Tf-Idf

In [9]:

```
# Tfidf Vectorizer for linear models ()
# merging together under one column
X_train['questions'] = X_train['question1'].map(str) + X_train['question2'].map(str)
X_test['questions'] = X_test['question1'].map(str) + X_test['question2'].map(str)

# Train
tfidf = TfidfVectorizer(min_df = 10, ngram_range = (1,2))
tfidf_tr = tfidf.fit_transform(X_train['questions'])        # fit and transform

# Test
tfidf_ts = tfidf.transform(X_test['questions'])           # transform
```

In [10]:

```
print("Number of data points in Tfidf train data :",tfidf_tr.shape)
print("Number of data points in Tfidf test data :",tfidf_ts.shape)
```

```
Number of data points in Tfidf train data : (70000, 21006)
Number of data points in Tfidf test data : (30000, 21006)
```

In [11]:

```
# merge texts

# Train
questions_train = list(X_train['question1']) + list(X_train['question2'])

# Test
questions_test = list(X_test['question1']) + list(X_test['question2'])
```

Tf-Idf W2V

In [12]:

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

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

In [13]:

```
# en_vectors_web_lg, which includes over 1 million unique vectors.
# ! python3 -m spacy download en_core_web_sm --user (doesnt work) hence we use below code
# https://github.com/explosion/spaCy/issues/4577

'''
! pip3 install https://github.com/explosion/spacy-models/releases/download/en_core_web_sm-2.2.0/en_core_web_sm-2.2.0.tar.gz
--user
'''

# https://stackoverflow.com/a/50487792/10219869

import en_core_web_lg
nlp = spacy.load('en_core_web_lg')
```

In [14]:

```
# Train question1

vecs1_train = []
# https://github.com/noamraph/tqdm
# tqdm_notebook is used to print the progress bar
for qu1 in tqdm_notebook(list(X_train['question1'])):
```

```
    doc1 = nlp(qu1)
    # 96 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 idf score
        try:
            idf = word2tfidf[str(word1)]
        except:
            idf = 0
        # compute final vec
        mean_vec1 += vec1 * idf
    mean_vec1 = mean_vec1.mean(axis=0)
    vecs1_train.append(mean_vec1)
X_train['q1_feats_m_train'] = vecs1_train
```

In [15]:

```
len(X_train['q1_feats_m_train'][0])
```

Out[15]:

300

In [16]:

```
# Test question1

vecs1_test = []
# https://github.com/noamraph/tqdm
# tqdm_notebook is used to print the progress bar
for qu1 in tqdm_notebook(list(X_test['question1'])):
    doc1 = nlp(qu1)
    # 96 is the number of dimensions of vectors
    mean_vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
    for word1 in doc1:
        # word2vec
        vec1 = word1.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word1)]
        except:
            idf = 0
        # compute final vec
        mean_vec1 += vec1 * idf
    mean_vec1 = mean_vec1.mean(axis=0)
    vecs1_test.append(mean_vec1)
X_test['q1_feats_m_test'] = vecs1_test
```

In [17]:

```
# Train question2

vecs2_train = []
for qu2 in tqdm_notebook(list(X_train['question2'])):
    doc2 = nlp(qu2)
    # 96 is the number of dimensions of vectors
    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_train.append(mean_vec2)
X_train['q2_feats_m_train'] = vecs2_train
```

In [18]:

```
# Test question2

vecs2_test = []
for qu2 in tqdm_notebook(list(X_test['question2'])):
    doc2 = nlp(qu2)
    # 96 is the number of dimensions of vectors
    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_test.append(mean_vec2)
X_test['q2_feats_m_test'] = vecs2_test
```

Part II

In [19]:

```
# 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)

# Train

# I have skipped using df["csc_min"], df["csc_max"], ["cwc_min"], ["cwc_max"]

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

    # I have skipped using this stopwords step

    '''
    # Get the non-stopwords in Questions
    q1_words = set([word for word in q1_tokens if word not in stopwords.words('english')])
    q2_words = set([word for word in q2_tokens if word not in stopwords.words('english')])

    #Get the stopwords in Questions
    q1_stops = set([word for word in q1_tokens if word in stopwords.words('english')])
    q2_stops = set([word for word in q2_tokens if word in stopwords.words('english')])


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

    # I have skipped using this stopwords step
    # Get the common stopwords from Question pair
    common_stop_count = len(q1_stops.intersection(q2_stops))
    '''

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

    '''
```

```
    token_features[0] = common_word_count / (min(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[1] = common_word_count / (max(len(q1_words), len(q2_words)) + SAFE_DIV)

     token_features[2] = common_stop_count / (min(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[3] = common_stop_count / (max(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    '''
    token_features[0] = common_token_count / (min(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)
    token_features[1] = common_token_count / (max(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)

    # Last word of both question is same or not
    token_features[2] = int(q1_tokens[-1] == q2_tokens[-1])

    # First word of both question is same or not
    token_features[3] = int(q1_tokens[0] == q2_tokens[0])

    token_features[4] = abs(len(q1_tokens) - len(q2_tokens))

    #Average Token Length of both Questions
    token_features[5] = (len(q1_tokens) + len(q2_tokens))/2

    return token_features

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

    print("token features...")

    # Merging Features with dataset

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

    # I have skipped using this stopwords step
    '''
    X_train["cwc_min"]       = list(map(lambda x: x[0], token_features))
    X_train["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))
    '''

    X_train["ctc_min"]       = list(map(lambda x: x[0], token_features))
    X_train["ctc_max"]       = list(map(lambda x: x[1], token_features))
    X_train["last_word_eq"]  = list(map(lambda x: x[2], token_features))
    X_train["first_word_eq"] = list(map(lambda x: x[3], token_features))
    X_train["abs_len_diff"]  = list(map(lambda x: x[4], token_features))
    X_train["mean_len"]      = list(map(lambda x: x[5], token_features))

    #Computing Fuzzy Features and Merging with Dataset

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

    print("fuzzy features..")

    X_train["token_set_ratio"]       = X_train.apply(lambda x: fuzz.token_set_ratio(x["question1"], x["question2"]), axis=1)

    """
    The token sort approach involves tokenizing the string in question, sorting the tokens alphabetically, and then joining
    them back into a string We then compare the transformed strings with a simple ratio().
    """

    X_train["token_sort_ratio"]      = X_train.apply(lambda x: fuzz.token_sort_ratio(x["question1"], x["question2"]), axis=1)
    X_train["fuzz_ratio"]            = X_train.apply(lambda x: fuzz.QRatio(x["question1"], x["question2"]), axis=1)
    X_train["fuzz_partial_ratio"]    = X_train.apply(lambda x: fuzz.partial_ratio(x["question1"], x["question2"]), axis=1)
    X_train["longest_substr_ratio"]  = X_train.apply(lambda x: get_longest_substr_ratio(x["question1"], x["question2"]),
                                        axis=1)

    return X_train
```

In [21]:

```
# Train
start = datetime.now()
X_train_fuzz = extract_features(X_train)
print('Time taken to complete: ', datetime.now()-start)
```

```
token features...
fuzzy features..
```

Time taken to complete: 0:06:08.826427

In [22]:

```
# Test

# I have skipped using df["csc_min"], df["csc_max"]

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

    # I have skipped using this stopwords step

    '''
    # Get the non-stopwords in Questions
    q1_words = set([word for word in q1_tokens if word not in stopwords.words('english')])
    q2_words = set([word for word in q2_tokens if word not in stopwords.words('english')])

    #Get the stopwords in Questions
    q1_stops = set([word for word in q1_tokens if word in stopwords.words('english')])
    q2_stops = set([word for word in q2_tokens if word in stopwords.words('english')])

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

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

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

    '''
    token_features[0] = common_word_count / (min(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[1] = common_word_count / (max(len(q1_words), len(q2_words)) + SAFE_DIV)

     token_features[2] = common_stop_count / (min(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[3] = common_stop_count / (max(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    '''

    token_features[0] = common_token_count / (min(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)
    token_features[1] = common_token_count / (max(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)

    # Last word of both question is same or not
    token_features[2] = int(q1_tokens[-1] == q2_tokens[-1])

    # First word of both question is same or not
    token_features[3] = int(q1_tokens[0] == q2_tokens[0])

    token_features[4] = abs(len(q1_tokens) - len(q2_tokens))

    #Average Token Length of both Questions
    token_features[5] = (len(q1_tokens) + len(q2_tokens))/2

    return token_features

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

    print("token features...")

    # Merging Features with dataset

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

    # I have skipped using this stopwords step
    '''
    X_test["cwc_min"]       = list(map(lambda x: x[0], token_features))
    X_test["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))
    '''
```

```
    X_test["ctc_min"]      = list(map(lambda x: x[0], token_features))
    X_test["ctc_max"]      = list(map(lambda x: x[1], token_features))
    X_test["last_word_eq"]  = list(map(lambda x: x[2], token_features))
    X_test["first_word_eq"] = list(map(lambda x: x[3], token_features))
    X_test["abs_len_diff"]  = list(map(lambda x: x[4], token_features))
    X_test["mean_len"]     = list(map(lambda x: x[5], token_features))

    #Computing Fuzzy Features and Merging with Dataset

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

    print("fuzzy features..")

    X_test["token_set_ratio"]      = X_test.apply(lambda x: fuzz.token_set_ratio(x["question1"], x["question2"]), axis=1)

    """
    The token sort approach involves tokenizing the string in question, sorting the tokens alphabetically, and then joining
    them back into a string We then compare the transformed strings with a simple ratio().
    """

    X_test["token_sort_ratio"]     = X_test.apply(lambda x: fuzz.token_sort_ratio(x["question1"], x["question2"]), axis=1)
    X_test["fuzz_ratio"]           = X_test.apply(lambda x: fuzz.QRatio(x["question1"], x["question2"]), axis=1)
    X_test["fuzz_partial_ratio"]   = X_test.apply(lambda x: fuzz.partial_ratio(x["question1"], x["question2"]), axis=1)
    X_test["longest_substr_ratio"]  = X_test.apply(lambda x: get_longest_substr_ratio(x["question1"], x["question2"]),
                                    axis=1)

    return X_test
```

In [23]:

```
# Test
start=datetime.now()
X_test_fuzz = extract_features(X_test)
print('Time taken to complete: ', datetime.now()-start)
```

token features...
fuzzy features..
Time taken to complete: 0:02:38.153609

In [24]:

```
print("Number of data points in train data :", X_train_fuzz.shape)
print("Number of data points in test data :", X_test_fuzz.shape)
```

Number of data points in train data : (70000, 30)
Number of data points in test data : (30000, 30)

In [25]:

```
X_train_fuzz.head(2)
```

Out[25]:

	id	qid1	qid2	question1	question2	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	...	ctc_max	last_word_eq	first_word_eq	abs_
19318	19318	36506	36507	could anyone write a c program to display a bi...	what is the difference between a avl tree and ...	1	1	96	67	18	...	0.277776	0.0	0.0	
83141	83141	140825	140826	in today own society what is considered dating	what salary range do you need to make to be co...	1	1	46	78	7	...	0.266665	0.0	0.0	

2 rows × 30 columns

In [28]:

```
# converting the w2v (300 vectors) to dataframe
# Train
```

```
X_train_q1 = pd.DataFrame(X_train['q1_feats_m_train'].values.tolist(), index= X_train.index, columns= ['0_x','1_x','2_x','3_x','4_x','5_x','6_x','7_x','8_x','9_x','10_x','11_x','12_x','13_x','14_x','15_x','16_x','17_x','18_x','19_x','20_x','21_x','22_x','23_x','24_x','25_x','26_x','27_x','28_x','29_x','30_x','31_x','32_x','33_x','34_x','35_x','36_x','37_x','38_x','39_x','40_x','41_x','42_x','43_x','44_x','45_x','46_x','47_x','48_x','49_x','50_x','51_x','52_x','53_x','54_x','55_x','56_x','57_x','58_x','59_x','60_x','61_x','62_x','63_x','64_x','65_x','66_x','67_x','68_x','69_x','70_x','71_x','72_x','73_x','74_x','75_x','76_x','77_x','78_x','79_x','80_x','81_x','82_x','83_x','84_x','85_x','86_x','87_x','88_x','89_x','90_x','91_x','92_x','93_x','94_x','95_x','96_x','97_x','98_x','99_x','100_x','101_x','102_x','103_x','104_x','105_x','106_x','107_x','108_x','109_x','110_x','111_x','112_x','113_x','114_x','115_x','116_x','117_x','118_x','119_x','120_x','121_x','122_x','123_x','124_x','125_x','126_x','127_x','128_x','129_x','130_x','131_x','132_x','133_x','134_x','135_x','136_x','137_x','138_x','139_x','140_x','141_x','142_x','143_x','144_x','145_x','146_x','147_x','148_x','149_x','150_x','151_x','152_x','153_x','154_x','155_x','156_x','157_x','158_x','159_x','160_x','161_x','162_x','163_x','164_x','165_x','166_x','167_x','168_x','169_x','170_x','171_x','172_x','173_x','174_x','175_x','176_x','177_x','178_x','179_x','180_x','181_x','182_x','183_x','184_x','185_x','186_x','187_x','188_x','189_x','190_x','191_x','192_x','193_x','194_x','195_x','196_x','197_x','198_x','199_x','200_x','201_x','202_x','203_x','204_x','205_x','206_x','207_x','208_x','209_x','210_x','211_x','212_x','213_x','214_x','215_x','216_x','217_x','218_x','219_x','220_x','221_x','222_x','223_x','224_x','225_x','226_x','227_x','228_x','229_x','230_x','231_x','232_x','233_x','234_x','235_x','236_x','237_x','238_x','239_x','240_x','241_x','242_x','243_x','244_x','245_x','246_x','247_x','248_x','249_x','250_x','251_x','252_x','253_x','254_x','255_x','256_x','257_x','258_x','259_x','260_x','261_x','262_x','263_x','264_x','265_x','266_x','267_x','268_x','269_x','270_x','271_x','272_x','273_x','274_x','275_x','276_x','277_x','278_x','279_x','280_x','281_x','282_x','283_x','284_x','285_x','286_x','287_x','288_x','289_x','290_x','291_x','292_x','293_x','294_x','295_x','296_x','297_x','298_x','299_x'])
X_train_q2 = pd.DataFrame(X_train['q2_feats_m_train'].values.tolist(), index= X_train.index, columns= ['0_y','1_y','2_y','3_y','4_y','5_y','6_y','7_y','8_y','9_y','10_y','11_y','12_y','13_y','14_y','15_y','16_y','17_y','18_y','19_y','20_y','21_y','22_y','23_y','24_y','25_y','26_y','27_y','28_y','29_y','30_y','31_y','32_y','33_y','34_y','35_y','36_y','37_y','38_y','39_y','40_y','41_y','42_y','43_y','44_y','45_y','46_y','47_y','48_y','49_y','50_y','51_y','52_y','53_y','54_y','55_y','56_y','57_y','58_y','59_y','60_y','61_y','62_y','63_y','64_y','65_y','66_y','67_y','68_y','69_y','70_y','71_y','72_y','73_y','74_y','75_y','76_y','77_y','78_y','79_y','80_y','81_y','82_y','83_y','84_y','85_y','86_y','87_y','88_y','89_y','90_y','91_y','92_y','93_y','94_y','95_y','96_y','97_y','98_y','99_y','100_y','101_y','102_y','103_y','104_y','105_y','106_y','107_y','108_y','109_y','110_y','111_y','112_y','113_y','114_y','115_y','116_y','117_y','118_y','119_y','120_y','121_y','122_y','123_y','124_y','125_y','126_y','127_y','128_y','129_y','130_y','131_y','132_y','133_y','134_y','135_y','136_y','137_y','138_y','139_y','140_y','141_y','142_y','143_y','144_y','145_y','146_y','147_y','148_y','149_y','150_y','151_y','152_y','153_y','154_y','155_y','156_y','157_y','158_y','159_y','160_y','161_y','162_y','163_y','164_y','165_y','166_y','167_y','168_y','169_y','170_y','171_y','172_y','173_y','174_y','175_y','176_y','177_y','178_y','179_y','180_y','181_y','182_y','183_y','184_y','185_y','186_y','187_y','188_y','189_y','190_y','191_y','192_y','193_y','194_y','195_y','196_y','197_y','198_y','199_y','200_y','201_y','202_y','203_y','204_y','205_y','206_y','207_y','208_y','209_y','210_y','211_y','212_y','213_y','214_y','215_y','216_y','217_y','218_y','219_y','220_y','221_y','222_y','223_y','224_y','225_y','226_y','227_y','228_y','229_y','230_y','231_y','232_y','233_y','234_y','235_y','236_y','237_y','238_y','239_y','240_y','241_y','242_y','243_y','244_y','245_y','246_y','247_y','248_y','249_y','250_y','251_y','252_y','253_y','254_y','255_y','256_y','257_y','258_y','259_y','260_y','261_y','262_y','263_y','264_y','265_y','266_y','267_y','268_y','269_y','270_y','271_y','272_y','273_y','274_y','275_y','276_y','277_y','278_y','279_y','280_y','281_y','282_y','283_y','284_y','285_y','286_y','287_y','288_y','289_y','290_y','291_y','292_y','293_y','294_y','295_y','296_y','297_y','298_y','299_y'])
```

In [29]:

```
# Test

X_test_q1 = pd.DataFrame(X_test['q1_feats_m_test'].values.tolist(), index= X_test.index, columns= ['0_x','1_x','2_x','3_x','4_x','5_x','6_x','7_x','8_x','9_x','10_x','11_x','12_x','13_x','14_x','15_x','16_x','17_x','18_x','19_x','20_x','21_x','22_x','23_x','24_x','25_x','26_x','27_x','28_x','29_x','30_x','31_x','32_x','33_x','34_x','35_x','36_x','37_x','38_x','39_x','40_x','41_x','42_x','43_x','44_x','45_x','46_x','47_x','48_x','49_x','50_x','51_x','52_x','53_x','54_x','55_x','56_x','57_x','58_x','59_x','60_x','61_x','62_x','63_x','64_x','65_x','66_x','67_x','68_x','69_x','70_x','71_x','72_x','73_x','74_x','75_x','76_x','77_x','78_x','79_x','80_x','81_x','82_x','83_x','84_x','85_x','86_x','87_x','88_x','89_x','90_x','91_x','92_x','93_x','94_x','95_x','96_x','97_x','98_x','99_x','100_x','101_x','102_x','103_x','104_x','105_x','106_x','107_x','108_x','109_x','110_x','111_x','112_x','113_x','114_x','115_x','116_x','117_x','118_x','119_x','120_x','121_x','122_x','123_x','124_x','125_x','126_x','127_x','128_x','129_x','130_x','131_x','132_x','133_x','134_x','135_x','136_x','137_x','138_x','139_x','140_x','141_x','142_x','143_x','144_x','145_x','146_x','147_x','148_x','149_x','150_x','151_x','152_x','153_x','154_x','155_x','156_x','157_x','158_x','159_x','160_x','161_x','162_x','163_x','164_x','165_x','166_x','167_x','168_x','169_x','170_x','171_x','172_x','173_x','174_x','175_x','176_x','177_x','178_x','179_x','180_x','181_x','182_x','183_x','184_x','185_x','186_x','187_x','188_x','189_x','190_x','191_x','192_x','193_x','194_x','195_x','196_x','197_x','198_x','199_x','200_x','201_x','202_x','203_x','204_x','205_x','206_x','207_x','208_x','209_x','210_x','211_x','212_x','213_x','214_x','215_x','216_x','217_x','218_x','219_x','220_x','221_x','222_x','223_x','224_x','225_x','226_x','227_x','228_x','229_x','230_x','231_x','232_x','233_x','234_x','235_x','236_x','237_x','238_x','239_x','240_x','241_x','242_x','243_x','244_x','245_x','246_x','247_x','248_x','249_x','250_x','251_x','252_x','253_x','254_x','255_x','256_x','257_x','258_x','259_x','260_x','261_x','262_x','263_x','264_x','265_x','266_x','267_x','268_x','269_x','270_x','271_x','272_x','273_x','274_x','275_x','276_x','277_x','278_x','279_x','280_x','281_x','282_x','283_x','284_x','285_x','286_x','287_x','288_x','289_x','290_x','291_x','292_x','293_x','294_x','295_x','296_x','297_x','298_x','299_x'])
X_test_q2 = pd.DataFrame(X_test['q2_feats_m_test'].values.tolist(), index= X_test.index, columns= ['0_y','1_y','2_y','3_y','4_y','5_y','6_y','7_y','8_y','9_y','10_y','11_y','12_y','13_y','14_y','15_y','16_y','17_y','18_y','19_y','20_y','21_y','22_y','23_y','24_y','25_y','26_y','27_y','28_y','29_y','30_y','31_y','32_y','33_y','34_y','35_y','36_y','37_y','38_y','39_y','40_y','41_y','42_y','43_y','44_y','45_y','46_y','47_y','48_y','49_y','50_y','51_y','52_y','53_y','54_y','55_y','56_y','57_y','58_y','59_y','60_y','61_y','62_y','63_y','64_y','65_y','66_y','67_y','68_y','69_y','70_y','71_y','72_y','73_y','74_y','75_y','76_y','77_y','78_y','79_y','80_y','81_y','82_y','83_y','84_y','85_y','86_y','87_y','88_y','89_y','90_y','91_y','92_y','93_y','94_y','95_y','96_y','97_y','98_y','99_y','100_y','101_y','102_y','103_y','104_y','105_y','106_y','107_y','108_y','109_y','110_y','111_y','112_y','113_y','114_y','115_y','116_y','117_y','118_y','119_y','120_y','121_y','122_y','123_y','124_y','125_y','126_y','127_y','128_y','129_y','130_y','131_y','132_y','133_y','134_y','135_y','136_y','137_y','138_y','139_y','140_y','141_y','142_y','143_y','144_y','145_y','146_y','147_y','148_y','149_y','150_y','151_y','152_y','153_y','154_y','155_y','156_y','157_y','158_y','159_y','160_y','161_y','162_y','163_y','164_y','165_y','166_y','167_y','168_y','169_y','170_y','171_y','172_y','173_y','174_y','175_y','176_y','177_y','178_y','179_y','180_y','181_y','182_y','183_y','184_y','185_y','186_y','187_y','188_y','189_y','190_y','191_y','192_y','193_y','194_y','195_y','196_y','197_y','198_y','199_y','200_y','201_y','202_y','203_y','204_y','205_y','206_y','207_y','208_y','209_y','210_y','211_y','212_y','213_y','214_y','215_y','216_y','217_y','218_y','219_y','220_y','221_y','222_y','223_y','224_y','225_y','226_y','227_y','228_y','229_y','230_y','231_y','232_y','233_y','234_y','235_y','236_y','237_y','238_y','239_y','240_y','241_y','242_y','243_y','244_y','245_y','246_y','247_y','248_y','249_y','250_y','251_y','252_y','253_y','254_y','255_y','256_y','257_y','258_y','259_y','260_y','261_y','262_y','263_y','264_y','265_y','266_y','267_y','268_y','269_y','270_y','271_y','272_y','273_y','274_y','275_y','276_y','277_y','278_y','279_y','280_y','281_y','282_y','283_y','284_y','285_y','286_y','287_y','288_y','289_y','290_y','291_y','292_y','293_y','294_y','295_y','296_y','297_y','298_y','299_y'])
```

In [30]:

```
# must be 300 features
print("Number of data points in train q1 data :",X_train_q1.shape)
print("Number of data points in train q2 data :",X_train_q2.shape)
print("Number of data points in test q1 data :",X_test_q1.shape)
print("Number of data points in test q2 data :",X_test_q2.shape)
```

```
Number of data points in train q1 data : (70000, 300)
```

Number of data points in train q2 data : (70000, 300)
Number of data points in test q1 data : (30000, 300)
Number of data points in test q2 data : (30000, 300)

In [31]:

```
# https://stackoverflow.com/a/43580536/10219869

# Train
X_train_fuzz.drop(['id', 'q1_feats_m_train', 'q2_feats_m_train', 'question1', 'question2', 'questions', 'qid1', 'qid2'], axis=1, inplace=True)

# Test
X_test_fuzz.drop(['id', 'q1_feats_m_test', 'q2_feats_m_test', 'question1', 'question2', 'questions', 'qid1', 'qid2'], axis=1, inplace=True)
```

In [32]:

```
pd.set_option('display.max_columns', 500)
# After removal of w2v
X_train_fuzz.head(2)
```

Out[32]:

	id	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common	word_Total	word_share	freq_q1+q2	freq_q1-q2	ctc_min
19318	19318	1	1	96	67	18	13	5.0	29.0	0.172414	2	0	0.384612
83141	83141	1	1	46	78	7	15	3.0	21.0	0.142857	2	0	0.499994

In [33]:

```
X_train_fuzz.columns
```

Out[33]:

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

Part III

X_train_fuzz with 28 NLP features are common for the XGB dataframe and Linear dataframe

In [34]:

```
# Train XGB
X_train_xgb = pd.concat([X_train_fuzz, X_train_q1, X_train_q2], axis=1)

# Test XGB
X_test_xgb = pd.concat([X_test_fuzz, X_test_q1, X_test_q2], axis=1)
```

In [35]:

```
print("Number of data points in train data :",X_train_xgb.shape)
print("Number of data points in test data :",X_test_xgb.shape)
```

Number of data points in train data : (70000, 623)
Number of data points in test data : (30000, 623)

In [37]:

```
# Exporting to csv
X_train_xgb.to_csv('X_train_xgb_new300.csv')
X_test_xgb.to_csv('X_test_xgb_new300.csv')
```

In [55]:

```
X_train_xgb = pd.read_csv('X_train_xgb_new300.csv')
X_test_xgb = pd.read_csv('X_test_xgb_new300.csv')
```

```
X_test_xgb = pd.read_csv('X_test_xgb_new300.csv')
```

In [56]:

```
X_train_xgb.drop(['Unnamed: 0'], axis=1, inplace=True)
X_test_xgb.drop(['Unnamed: 0'], axis=1, inplace=True)
```

In [13]:

```
X_train_fuzz_linear = pd.read_csv('X_train_xgb_new300.csv')
X_train_fuzz_linear = X_train_fuzz_linear[['freq_qid1', 'freq_qid2', 'q1len', 'q2len', 'q1_n_words','q2_n_words', 'word_Common',
                                           'word_Total', 'word_share', 'freq_q1+q2', 'freq_q1-q2', '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']]
```

In [30]:

```
# https://stackoverflow.com/a/51701528/10219869

from scipy.sparse import coo_matrix, hstack
(coo_matrix(tfidf_tr)).shape
```

Out[30]:

```
(70000, 21006)
```

In [31]:

```
X_train_linear1 = hstack((X_train_fuzz_linear, (coo_matrix(tfidf_tr))))
```

In [32]:

```
X_test_fuzz = pd.read_csv('X_test_xgb_new300.csv')
X_test_fuzz = X_test_fuzz[['freq_qid1', 'freq_qid2', 'q1len', 'q2len', 'q1_n_words','q2_n_words', 'word_Common',
                           'word_Total', 'word_share', 'freq_q1+q2', 'freq_q1-q2', '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']]
```

In [36]:

```
X_test_linear1 = hstack((X_test_fuzz, coo_matrix(tfidf_ts)))
```

In [37]:

```
print("Number of data points in train data :",X_train_linear1.shape)
print("Number of data points in test data :",X_test_linear1.shape)
```

```
Number of data points in train data : (70000, 21028)
Number of data points in test data : (30000, 21028)
```

4. Machine Learning Models

In [38]:

```
# Created my own function with slight changes

def confusionmatrix(test_y, predict_y):
    c_m = confusion_matrix(y_test, predict_y)

    precision = (c_m / c_m.sum(axis=0))
    recall = (c_m.T / c_m.sum(axis=0)).T

    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_m, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")
```

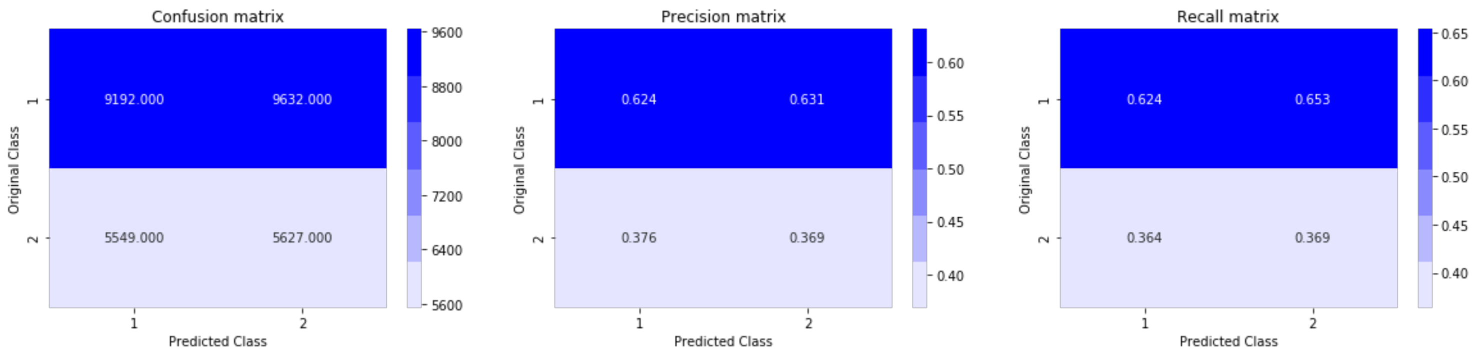
```
plt.subplot(1, 3, 2)
sns.heatmap(precision, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.title("Precision matrix")

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

plt.show()
```

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

In [32]:

```
# 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))

pred_y = np.argmax(predicted_y, axis=1)
confusionmatrix(y_true, pred_y)
```

Log loss on Test Data using Random Model 0.8884684277744512



4.4 Logistic Regression with hyperparameter tuning

Class Balanced

In [49]:

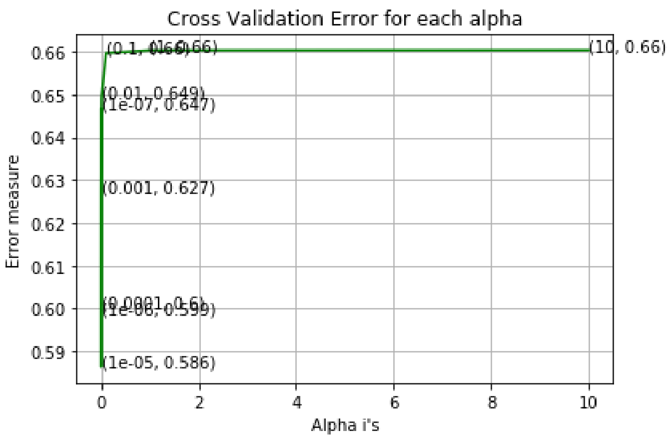
```
start = datetime.now()
alpha = [10 ** x for x in range(-7, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate='optimal', eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, …]) Fit linear model with Stochastic Gradient Descent.
# predict(X) Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
```

```
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42, class_weight= 'balanced')
    clf.fit(X_train_linear1, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train_linear1, y_train)
    predict_y = sig_clf.predict_proba(X_test_linear)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))

print('time taken: ', datetime.now()-start)
```

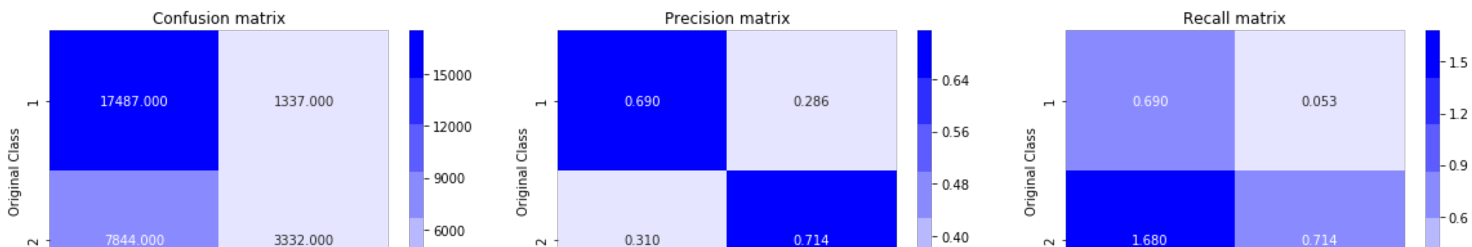
```
For values of alpha =  1e-07 The log loss is: 0.6465338571653076
For values of alpha =  1e-06 The log loss is: 0.5987604129245311
For values of alpha =  1e-05 The log loss is: 0.5863631702627327
For values of alpha =  0.0001 The log loss is: 0.6002078093086859
For values of alpha =  0.001 The log loss is: 0.6273421951901534
For values of alpha =  0.01 The log loss is: 0.6492226059548123
For values of alpha =  0.1 The log loss is: 0.6596394463178066
For values of alpha =  1 The log loss is: 0.6602836598503838
For values of alpha =  10 The log loss is: 0.6603253104808529
time taken:  0:09:12.829812
```

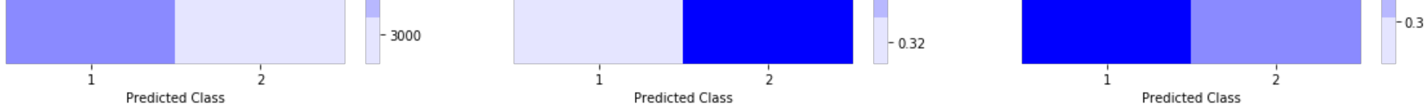
In [50]:

```
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, class_weight= 'balanced')
clf.fit(X_train_linear1, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_linear1, y_train)

predict_y = sig_clf.predict_proba(X_train_linear1)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test_linear1)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
confusionmatrix(y_test, predicted_y)
```




```
For values of best alpha =  1e-05 The train log loss is: 0.5840872241299851
For values of best alpha =  1e-05 The test log loss is: 0.5863631702627327
Total number of data points : 30000
```





Class Unbalanced

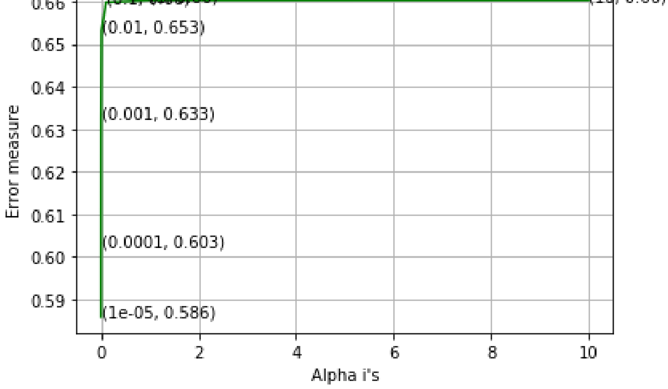
In [40]:

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

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate='optimal', eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, …]) Fit linear model with Stochastic Gradient Descent.
# predict(X) Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(X_train_linear1, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train_linear1, y_train)
    predict_y = sig_clf.predict_proba(X_test_linear)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))

print('time taken: ', datetime.now()-start)
```

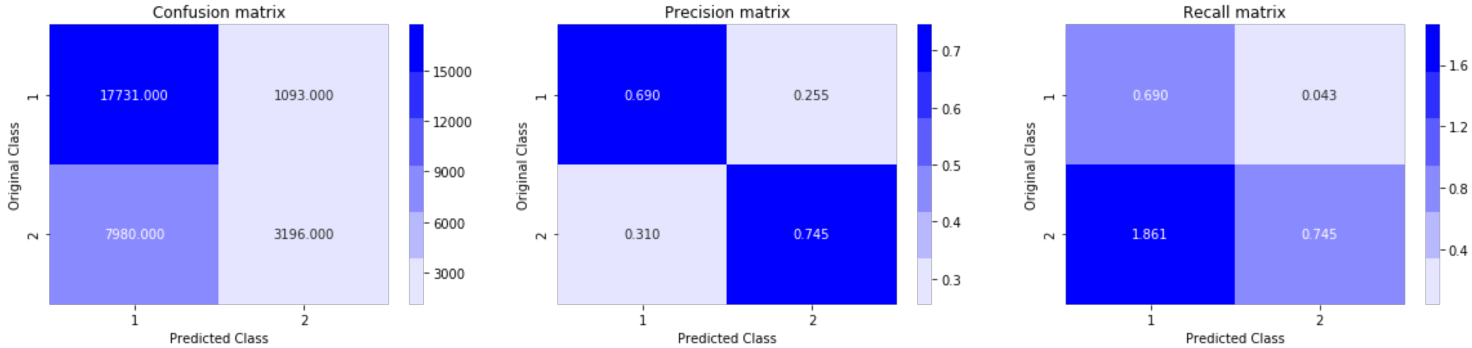
```
For values of alpha =  1e-05 The log loss is: 0.585846300666967
For values of alpha =  0.0001 The log loss is: 0.6025522166121051
For values of alpha =  0.001 The log loss is: 0.6325275683808731
For values of alpha =  0.01 The log loss is: 0.653083913388061
For values of alpha =  0.1 The log loss is: 0.6597885530880846
For values of alpha =  1 The log loss is: 0.660263141010859
For values of alpha =  10 The log loss is: 0.6602819625141958
time taken:  0:06:56.491708
```

In [41]:

```
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_linear1, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_linear1, y_train)

predict_y = sig_clf.predict_proba(X_train_linear1)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test_linear1)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
confusionmatrix(y_test, predicted_y)
```



For values of best alpha = 1e-05 The train log loss is: 0.584288620485855
For values of best alpha = 1e-05 The test log loss is: 0.585846300666967
Total number of data points : 30000



4.5 Linear SVM with hyperparameter tuning

Class Balanced

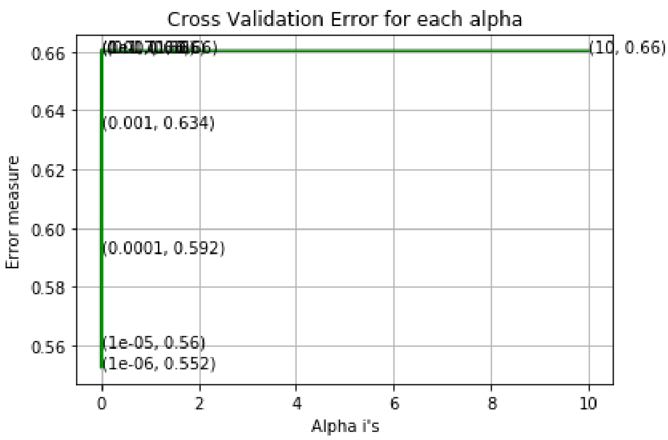
In [51]:

```
alpha = [10 ** x for x in range(-7, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate='optimal', eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, …]) Fit linear model with Stochastic Gradient Descent.
# predict(X) Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l1', loss='hinge', random_state=42, class_weight= 'balanced')
    clf.fit(X_train_linear1, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train_linear1, y_train)
    predict_y = sig_clf.predict_proba(X_test_linear1)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

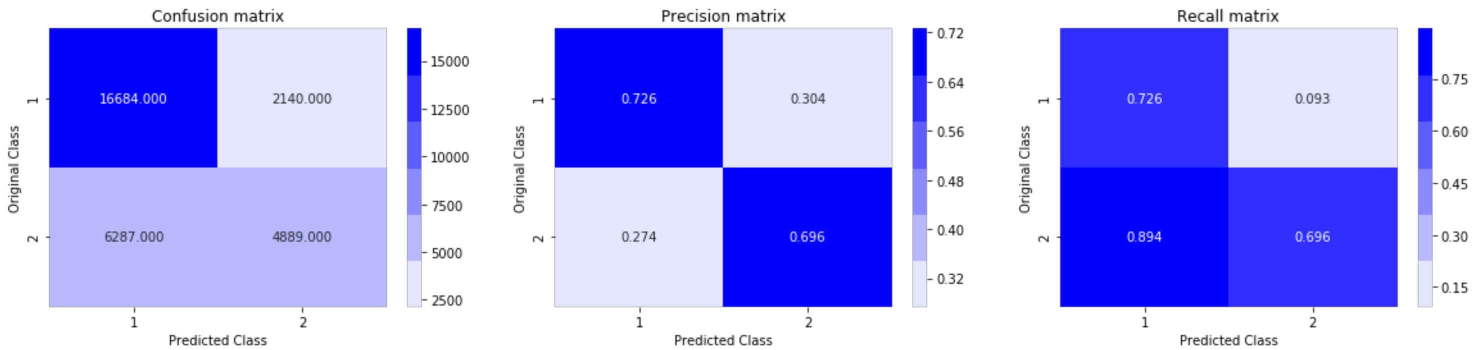
For values of alpha = 1e-07 The log loss is: 0.6602902109101162
For values of alpha = 1e-06 The log loss is: 0.5524478249145085
For values of alpha = 1e-05 The log loss is: 0.559597635154904
For values of alpha = 0.0001 The log loss is: 0.5919918545097376
For values of alpha = 0.001 The log loss is: 0.6342428168924167
For values of alpha = 0.01 The log loss is: 0.660290210209969
For values of alpha = 0.1 The log loss is: 0.660290210209969
For values of alpha = 1 The log loss is: 0.660290210209969
For values of alpha = 10 The log loss is: 0.660290210209969

In [52]:

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


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge', random_state=42, class_weight= 'balanced')
clf.fit(X_train_linear1, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_linear1, y_train)

predict_y = sig_clf.predict_proba(X_train_linear1)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test_linear1)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
confusionmatrix(y_test, predicted_y)
```



For values of best alpha = 1e-06 The train log loss is: 0.5481887889186696
For values of best alpha = 1e-06 The test log loss is: 0.5524478249145085
Total number of data points : 30000



Class Unbalanced

In [45]:

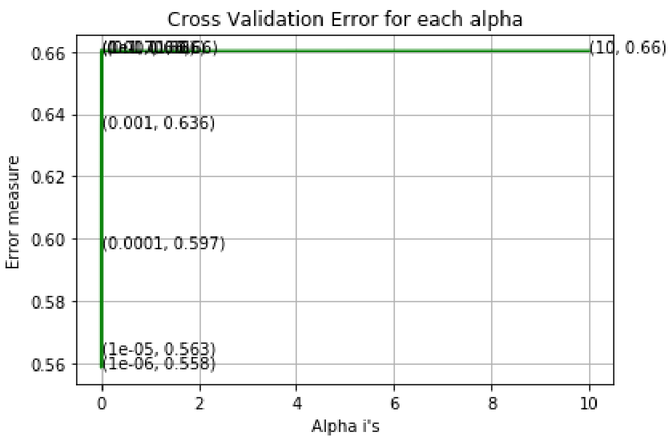
```
alpha = [10 ** x for x in range(-7, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate='optimal', eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, …]) Fit linear model with Stochastic Gradient Descent.
```

```
# fit(X, y[, coef_init, intercept_init, …]) Fit linear model with Stochastic Gradient Descent.
# predict(X) Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l1', loss='hinge', random_state=42)
    clf.fit(X_train_linear1, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train_linear1, y_train)
    predict_y = sig_clf.predict_proba(X_test_linear1)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
```

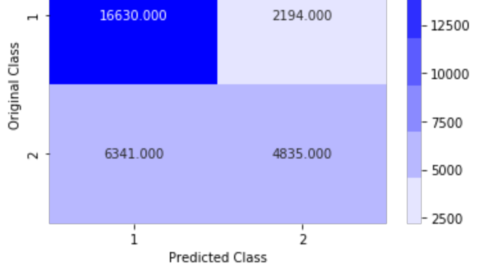
```
For values of alpha =  1e-07 The log loss is: 0.6602902109101162
For values of alpha =  1e-06 The log loss is: 0.5584227358352738
For values of alpha =  1e-05 The log loss is: 0.5630698752317267
For values of alpha =  0.0001 The log loss is: 0.59723346864655
For values of alpha =  0.001 The log loss is: 0.6358338127455307
For values of alpha =  0.01 The log loss is: 0.6603045033269931
For values of alpha =  0.1 The log loss is: 0.6602858638229934
For values of alpha =  1 The log loss is: 0.6602615784104585
For values of alpha =  10 The log loss is: 0.6602800065227967
```

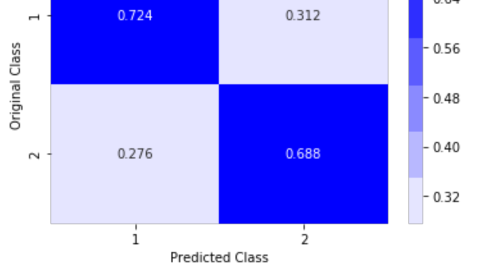
In [46]:

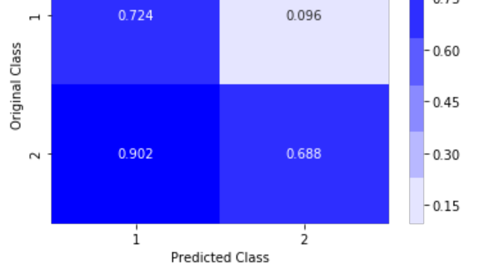
```
fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")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


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge', random_state=42)
clf.fit(X_train_linear1, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_linear1, y_train)

predict_y = sig_clf.predict_proba(X_train_linear1)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test_linear1)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
confusionmatrix(y_test, predicted_y)
```




```
For values of best alpha =  1e-06 The train log loss is: 0.5545123661381038
For values of best alpha =  1e-06 The test log loss is: 0.5584227358352738
Total number of data points : 30000
```







4.6 XGBoost

Class Balanced

In [41]:

```
count0=0
for i in y_train:
    if i == 0:
        count0 += 1
print(count0)
```

43922

In [42]:

```
count1=0
for i in y_train:
    if i == 1:
        count1 += 1
print(count1)
```

26078

In [43]:

```
# sum(negative instances) / sum(positive instances)
scale_pos_weight = count1 / count0
scale_pos_weight
```

Out[43]:

0.5937343472519466

In [44]:

```
# https://xgboost.readthedocs.io/en/latest/parameter.html

start = datetime.now()
parameters = {'n_estimators'    : [500, 1000, 2000],
              'objective'       : ['binary:logistic', 'binary:hinge', 'reg:squarederror'],
              'eval_metric'     : ['logloss', 'error'],
              'max_depth'       : [4, 6, 8],
              'eta'             : [0.001, 0.02, 0.3],
              'gamma'           : [0, 0.1, 5, 10, 15],
              'min_child_weight': [3, 5, 7],
              'reg_alpha'       : [0.005, 0.01, 0],
              'reg_lambda'      : [0.005, 0.01, 1]}

rscv = RandomizedSearchCV(estimator = xgb.XGBClassifier(n_jobs= -1, scale_pos_weight = scale_pos_weight),
                          param_distributions = parameters, n_jobs= -1, return_train_score=True, scoring = 'roc_auc')
rscv.fit(X_train_xgb, y_train)
print('Time taken to complete train linear data: ', datetime.now()-start)
```

Time taken to complete train linear data: 9:17:27.325887

In [45]:

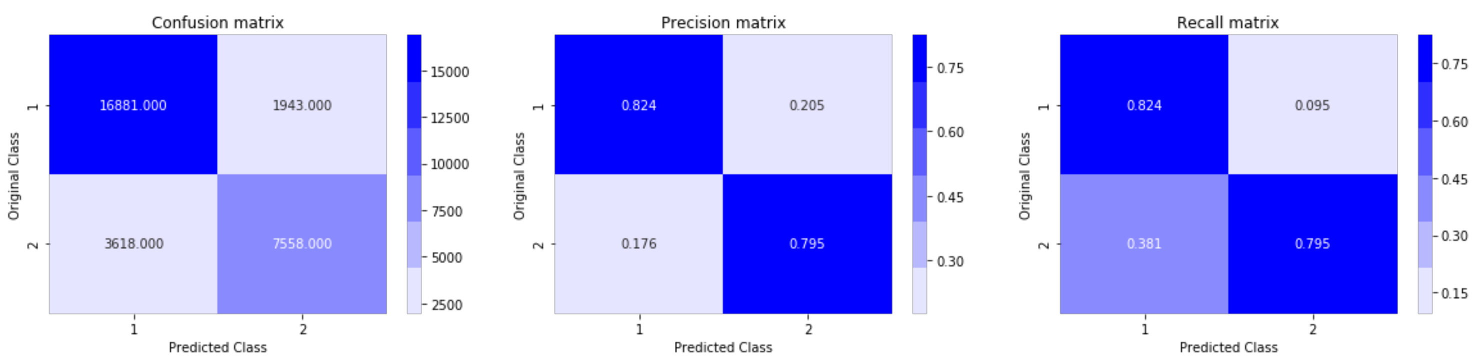
```
print('Best parameters: \n',rscv.best_estimator_)
print()
print('ROC AUC Score: ',rscv.score(X_test_xgb, y_test))
```

```
Best parameters:
 XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eta=0.3,
              eval_metric='logloss', gamma=0.1, learning_rate=0.1,
              max_delta_step=0, max_depth=6, min_child_weight=7, missing=None,
              n_estimators=2000, n_jobs=-1, nthread=None,
              objective='binary:logistic', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=0.5937343472519466, seed=None,
              silent=None, subsample=1, verbosity=1)

ROC AUC Score:  0.9048428929197134
```

In [46]:

```
start = datetime.now()

clf = xgb.XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
                        eta=0.3, eval_metric='logloss', gamma=0.1, learning_rate=0.1, max_delta_step=0, max_depth=6,
                        min_child_weight=7, missing=None, n_estimators=2000, n_jobs=-1, nthread=None, random_state=0,
                        objective='binary:logistic', reg_alpha=0, reg_lambda=1, scale_pos_weight=0.5937343472519466,
                        seed=None, silent=None, subsample=1, verbosity=1)

clf.fit(X_train_xgb, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_xgb, y_train)

predict_y = sig_clf.predict_proba(X_train_xgb)
print("The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test_xgb)
print("The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y, axis=1)
print("Total number of data points :", len(predicted_y))
confusionmatrix(y_test, predicted_y)

print('Time taken to complete train linear data: ', datetime.now()-start)
```

```
The train log loss is: 0.17649529552819543
The test log loss is: 0.4095087231363952
Total number of data points : 30000
```




```
Time taken to complete train linear data:  2:14:24.851044
```

class not balanced

In [12]:

```
# https://xgboost.readthedocs.io/en/latest/parameter.html

start= datetime.now()
parameters = {'n_estimators'    : [500, 1000, 2000],
              'objective'       : ['binary:logistic', 'binary:hinge', 'reg:squarederror'],
              'eval_metric'     : ['logloss', 'error'],
              'max_depth'       : [4, 6, 8],
              'eta'             : [0.001, 0.02, 0.3],
              'gamma'           : [0, 0.001, 0.1, 10, 15],
              'min_child_weight': [3, 5, 7],
              'reg_alpha'       : [0.005, 0.01, 0],
              'reg_lambda'      : [0.005, 0.01, 1]}

rscv_nb = RandomizedSearchCV(estimator = xgb.XGBClassifier(n_jobs= -1,), param_distributions = parameters, cv=2, n_jobs= -1,
                             return_train_score=True, scoring = 'roc_auc')

# nb = not balanced
```

```
rscv_nb.fit(X_train_xgb, y_train)

print('Time taken to complete train linear data: ', datetime.now()-start)
```

Time taken to complete train linear data: 4:08:27.061800

In [13]:

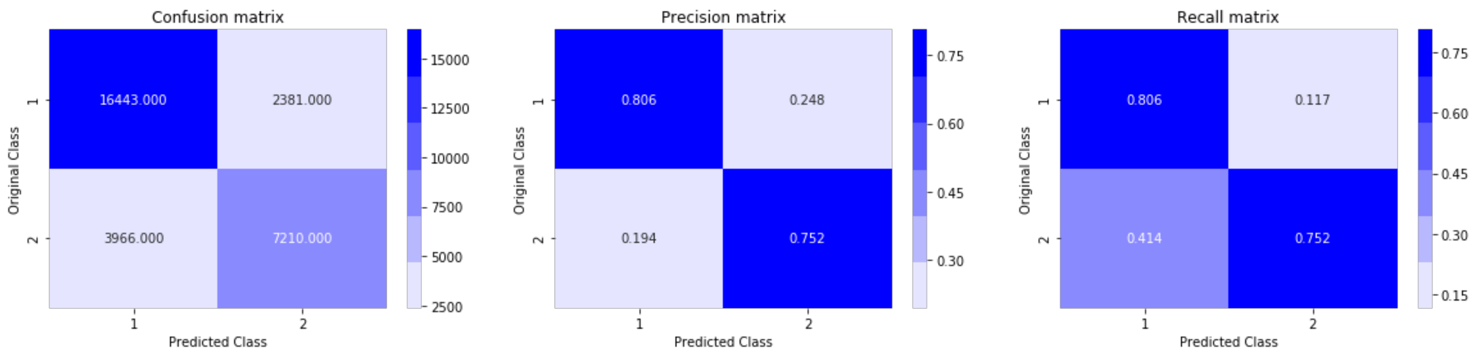
```
print('Best parameters: \n',rscv_nb.best_estimator_)
print()
print('ROC AUC Score: ',rscv_nb.score(X_test_xgb, y_test))
```

```
Best parameters:
 XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eta=0.001,
              eval_metric='logloss', gamma=0.001, learning_rate=0.1,
              max_delta_step=0, max_depth=8, min_child_weight=5, missing=None,
              n_estimators=500, n_jobs=-1, nthread=None,
              objective='binary:hinge', random_state=0, reg_alpha=0.01,
              reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
              subsample=1, verbosity=1)

ROC AUC Score:  0.49845646642477465
```

In [40]:

```
clf = xgb.XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
                        eta=0.02, eval_metric='logloss', gamma=15, learning_rate=0.1, max_delta_step=0, max_depth=8,
                        min_child_weight=5, missing=None, n_estimators=2000, n_jobs=-1, nthread=None, random_state=0,
                        objective='binary:logistic', reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
                        subsample=1, verbosity=1)

clf.fit(X_train_xgb, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train_xgb, y_train)

predict_y = sig_clf.predict_proba(X_train_xgb)
print("The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test_xgb)
print("The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
confusionmatrix(y_test, predicted_y)
```

The train log loss is: 0.3311242344470857
The test log loss is: 0.4200542157574379
Total number of data points : 30000



Observations

- With Class not balanced we get less Precision and Recall than with Class balanced (Scale_pos_weight)

Conclusions

In [62]:

```
from prettytable import PrettyTable

x = PrettyTable()
```

```
x.field_names = ["Rank", "Model", 'Type of Vector','Parameter', 'Class Weight', 'Train Log Loss', 'Test Log Loss']
x.add_row([1, "XGBC", 'Gamma = 0.1', 'Tf-idf W W2V', 'Balanced', '0.17', '0.41'])
x.add_row([2, "XGBC", 'Gamma = 15', 'Tf-idf W W2V', 'Unbalanced', '0.33', '0.42'])
x.add_row([3, "SGDC(Hinge Loss)", 'Alpha = 1e-6', 'Simple Tf-idf', 'Balanced', '0.548', '0.552'])
x.add_row([4, "SGDC(Hinge Loss)", 'Alpha = 1e-6', 'Simple Tf-idf', 'Unalanced', '0.554', '0.558'])
x.add_row([5, "SGDC(Log Loss)", 'Alpha = 1e-5', 'Simple Tf-idf', 'Balanced', '0.584', '0.586'])
x.add_row([6, "SGDC(Log Loss)", 'Alpha = 1e-5', 'Simple Tf-idf', 'Unalanced', '0.584', '0.586'])
x.add_row([7, 'Random Model', '-','-', '-', '-', '0.88'])

print(x)
```

```
+------+------------------+----------------+---------------+--------------+----------------+---------------+
| Rank |      Model       | Type of Vector |   Parameter   | Class Weight | Train Log Loss | Test Log Loss |
+------+------------------+----------------+---------------+--------------+----------------+---------------+
|  1   |       XGBC       |  Gamma = 0.1   |  Tf-idf W W2V |   Balanced   |      0.17      |      0.41     |
|  2   |       XGBC       |   Gamma = 15   |  Tf-idf W W2V |  Unbalanced  |      0.33      |      0.42     |
|  3   | SGDC(Hinge Loss) |  Alpha = 1e-6  | Simple Tf-idf |   Balanced   |     0.548      |     0.552     |
|  4   | SGDC(Hinge Loss) |  Alpha = 1e-6  | Simple Tf-idf |  Unalanced   |     0.554      |     0.558     |
|  5   |  SGDC(Log Loss)  |  Alpha = 1e-5  | Simple Tf-idf |   Balanced   |     0.584      |     0.586     |
|  6   |  SGDC(Log Loss)  |  Alpha = 1e-5  | Simple Tf-idf |  Unalanced   |     0.584      |     0.586     |
|  7   |   Random Model   |       -        |       -       |      -       |       -        |      0.88     |
+------+------------------+----------------+---------------+--------------+----------------+---------------+
```

In [ ]: