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 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

Columns available in the dataset --> ["id", "qid1", "qid2", "question1", "question2", "is duplicate"]

Negative Data Points Examples

- 1. "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"
- 2. "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"

Positive Data PointsExamples

- 1. "7","15","16","How can I be a good geologist?","What should I do to be a great geologist?","1"
- 2. "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.

Mounting Drive

```
In [0]:
   !kill -9 -1
  In [0]:
   from google.colab import drive
   drive.mount('/content/drive')
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client id=947318989803-6bn6
 qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%
\texttt{b\&scope=email} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$20 \texttt{https} \$3 \texttt{A} \$2 \texttt{F} \$2 \texttt{Fwww.googleapis.com} \$2 \texttt{Fauth} \$2 \texttt{Fdocs.test} \$2 \texttt{Futh} \$2 \texttt{Fdocs.test} \$2 \texttt{Fdocs.test} \$2 \texttt{Futh} \$2 \texttt{Fdocs.test} \$2 \texttt{Futh} \$2 \texttt{Fdocs.test} \$2 \texttt{Fdocs.tes
 2 Fauth \$2 Fdrive \$20 https \$3A \$2F \$2Fwww.googleap is.com \$2Fauth \$2Fdrive.photos.readonly \$20 https \$3A \$2F \$2Fwww.googleap is.com \$2Fauth \$
 ogleapis.com%2Fauth%2Fpeopleapi.readonly&response type=code
 Enter your authorization code:
Mounted at /content/drive
 In [1]:
  !pwd
   !ls
 drive sample data
  In [2]:
   import os
  PATH = os.getcwd()
  print (PATH)
```

```
/content
```

In [3]:

```
data_path = PATH + '/drive/My Drive/AAIC/Case Studies/Quora Case Study/'
data_path
```

Out[3]:

'/content/drive/My Drive/AAIC/Case Studies/Quora Case Study/'

3. Exploratory Data Analysis

· Installing some Modules

```
In [0]:
```

```
pip install fuzzywuzzy
Collecting fuzzywuzzy
     Downloading
\verb|https://files.pythonhosted.org/packages/d8/f1/5a267addb30ab7eaa1beab2b9323073815da4551076554ecc890ard and a substitution of the substitution o
ec9/fuzzywuzzy-0.17.0-py2.py3-none-any.whl
 Installing collected packages: fuzzywuzzy
 Successfully installed fuzzywuzzy-0.17.0
 In [0]:
 pip install Distance
Collecting Distance
     Downloading
https://files.pythonhosted.org/packages/5c/1a/883e47df323437aefa0d0a92ccfb38895d9416bd0b56262c2e46a
7b8/Distance-0.1.3.tar.gz (180kB)
                                                                                                                                   | 184kB 3.4MB/s
Building wheels for collected packages: Distance
      Building wheel for Distance (setup.py) ... done
       Stored in directory:
 /root/.cache/pip/wheels/d5/aa/e1/dbba9e7b6d397d645d0f12db1c66dbae9c5442b39b001db18e
 Successfully built Distance
 Installing collected packages: Distance
 Successfully installed Distance-0.1.3
 4
```

• Importing Important modules

In [4]:

```
import warnings
warnings.filterwarnings("ignore")
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from subprocess import check_output
%matplotlib inline
import plotly.offline as py
py.init notebook mode(connected=True)
import plotly.graph objs as go
import plotly.tools as tls
import os
import gc
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
```

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

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

3.1 Reading data and basic stats

```
In [0]:
```

```
df = pd.read_csv(data_path + "train.csv")
print("Number of data points:",df.shape[0])
```

Number of data points: 404290

In [0]:

```
df.head()
```

Out[0]:

	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 [0]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404290 entries, 0 to 404289
Data columns (total 6 columns):
id
               404290 non-null int64
               404290 non-null int64
gid1
               404290 non-null int64
qid2
              404289 non-null object
question1
question2
              404288 non-null object
              404290 non-null int64
is duplicate
dtypes: int64(4), object(2)
memory usage: 18.5+ MB
```

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

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

3.2.1 Distribution of data points among output classes

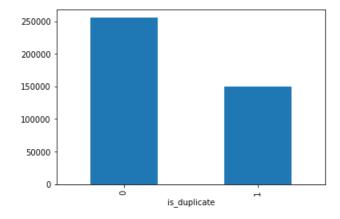
• Number of duplicate(smilar) and non-duplicate(non similar) questions

In [0]:

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

Out[0]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f452f132ef0>



In [0]:

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

 $\sim>$ Total number of question pairs for training: 404290

In [0]:

- ~> 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

```
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

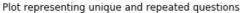
Number of unique questions that appear more than one time: 111780 (20.77953945937505 %)

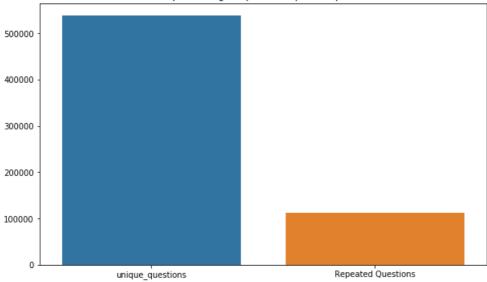
Max number of times a single question is repeated: 157

In [0]:

```
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 [0]:

```
#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])
```

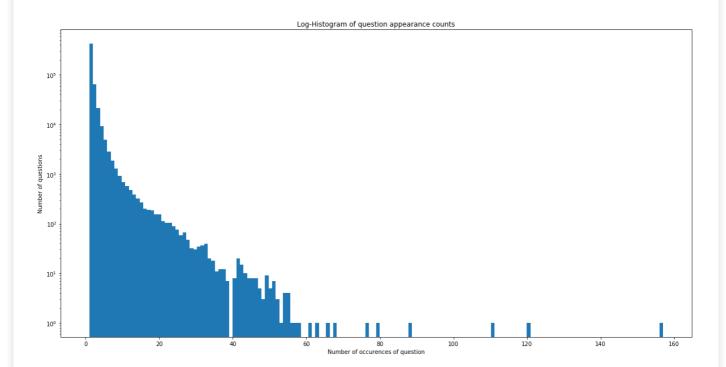
Number of duplicate questions 0

3.2.4 Number of occurrences of each question

```
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 [0]:

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

id ... is_duplicate
```

```
id ... is_duplicate
105780 105780 ... 0
201841 201841 ... 0
363362 363362 ... 0
```

[3 rows x 6 columns]

• There are two rows with null values in question2

In [0]:

```
# 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 [0]:

```
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['qllen'] = df['question1'].str.len()
    df['q2len'] = df['question2'].str.len()
    df['q1 n words'] = df['question1'].apply(lambda row: len(row.split(" ")))
    df['q2 n words'] = df['question2'].apply(lambda row: len(row.split(" ")))
    def normalized word Common(row):
       w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * len(w1 & w2)
    df['word Common'] = df.apply(normalized word Common, axis=1)
    def normalized word Total(row):
        w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * (len(w1) + len(w2))
    df['word Total'] = df.apply(normalized word Total, axis=1)
    def normalized word share(row):
       w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
       return 1.0 * len(w1 & w2)/(len(w1) + len(w2))
    df['word share'] = df.apply(normalized word share, axis=1)
    df['freq q1+q2'] = df['freq qid1']+df['freq qid2']
    df['freq q1-q2'] = abs(df['freq qid1']-df['freq qid2'])
    df.to csv("df fe without preprocessing train.csv", index=False)
df.head()
```

Out[0]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common
0	0	1	2	What is the step by step guide to invest in sh	What is the step by step guide to invest in sh	0	1	1	66	57	14	12	10.0
1	1	3	4	What is the story of Kohinoor (Koh-i- Noor) Dia	What would happen if the Indian government sto	0	4	1	51	88	8	13	4.0
2	2	5	6	How can I increase the speed of my internet	How can Internet speed be increased by hacking	0	1	1	73	59	14	10	4.0

3	id 3	qid1	qid2	question 1 Why am 1 mentally very lonely? How can I solve	question2 Find the remainder when [math]23^{24} [/math] i	is_duplicate	freq_qid1	freq_qid2	q1len 50	q2len	q1_n_words	q2_n_words	word_Common
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
4													Þ

3.3.1 Analysis of some of the extracted features

• Here are some questions have only one single words.

In [0]:

```
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])

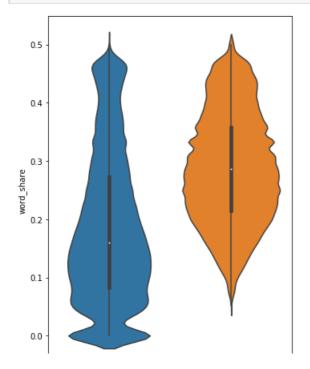
Minimum length of the questions in question1 : 1
Minimum length of the questions in question2 : 1
Number of Questions with minimum length [question1] : 67
Number of Questions with minimum length [question2] : 24
```

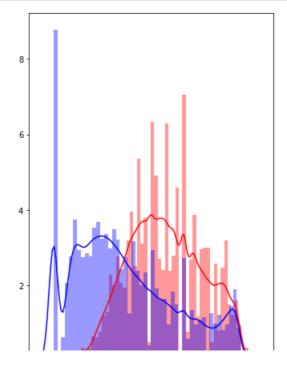
3.3.1.1 Feature: word_share

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

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

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







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

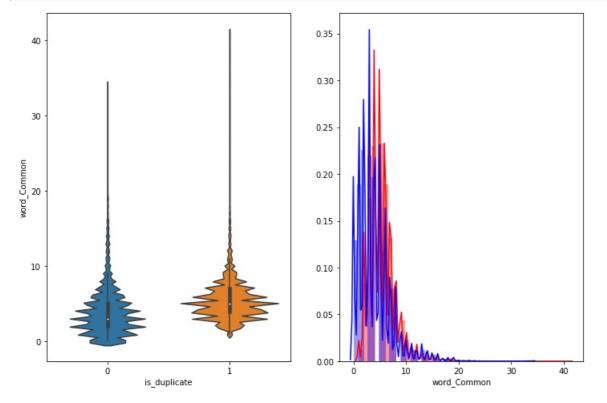
3.3.1.2 Feature: word_Common

In [0]:

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

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

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



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

3.4 Preprocessing of Text

- · Preprocessing:
 - Removing html tags
 - Removing Punctuations
 - Performing stemming
 - Removing Stopwords
 - Expanding contractions etc.

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

```
STOP WORDS = stopwords.words("english")
def preprocess(x):
    x = str(x).lower()
    x = x.replace(",000,000", "m").replace(",000", "k").replace("'", "'").replace("'", "'")
                            .replace("won't", "will not").replace("cannot", "can not").replace("can'
", "can not")\
                            .replace("n't", " not").replace("what's", "what is").replace("it's", "it
is")\
                            .replace("'ve", " have").replace("i'm", "i am").replace("'re", " are")\
                            .replace("he's", "he is").replace("she's", "she is").replace("'s", " own
) \
                            .replace("%", " percent ").replace("₹", " rupee ").replace("$", " dollar
")\
                            .replace("€", " euro ").replace("'ll", " will")
    x = re.sub(r''([0-9]+)000000'', r'' \setminus 1m'', x)
    x = re.sub(r''([0-9]+)000'', r''\setminus 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 length 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 length 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 length 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 length 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 length 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 length of token count of Q1 and Q2 ctc_max = common_token_count / (max(len(q1_tokens), len(q2_tokens))
- last_word_eq: Check if First 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: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
- fuzz_partial_ratio: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
- token_sort_ratio: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
- token_set_ratio: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
- longest_substr_ratio: Ratio of length longest common substring to min lengthh of token count of Q1 and Q2 longest substr ratio = len(longest common substring) / (min(len(q1 tokens), len(q2 tokens))

```
def get token features(q1, q2):
   token features = [0.0]*10
   # Converting the Sentence into Tokens:
   q1 tokens = q1.split()
   q2 tokens = q2.split()
   if len(q1_tokens) == 0 or len(q2_tokens) == 0:
       return token features
    # Get the non-stopwords in Questions
   q1_words = set([word for word in q1_tokens if word not in STOP WORDS])
   q2 words = set([word for word in q2 tokens if word not in STOP WORDS])
   #Get the stopwords in Questions
   q1 stops = set([word for word in q1 tokens if word in STOP WORDS])
   q2 stops = set([word for word in q2 tokens if word in STOP WORDS])
    # Get the common non-stopwords from Question pair
   common_word_count = len(q1_words.intersection(q2_words))
    # Get the common stopwords from Question pair
   common_stop_count = len(q1_stops.intersection(q2_stops))
    # Get the common Tokens from Question pair
   common_token_count = len(set(q1_tokens).intersection(set(q2_tokens)))
   token_features[0] = common_word_count / (min(len(q1_words), len(q2_words)) + SAFE_DIV)
   token features[1] = common word count / (max(len(q1 words), len(q2 words)) + SAFE DIV)
   token features[2] = common stop count / (min(len(q1 stops), len(q2 stops)) + SAFE DIV)
   token features[3] = common stop count / (max(len(q1 stops), len(q2 stops)) + SAFE DIV)
   token_features[4] = common_token_count / (min(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)
   token_features[5] = common_token_count / (max(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)
    # Last word of both question is same or not
   token_features[6] = int(q1_tokens[-1] == q2_tokens[-1])
    # First word of both question is same or not
   token_features[7] = int(q1_tokens[0] == q2_tokens[0])
   token_features[8] = abs(len(q1_tokens) - len(q2_tokens))
    #Average Token Length of both Ouestions
```

```
token_features[9] = (len(q1_tokens) + len(q2_tokens))/2
    return token_features
# get the Longest Common sub string
def get longest substr ratio(a, b):
    strs = list(distance.lcsubstrings(a, b))
    if len(strs) == 0:
        return 0
    else:
        return len(strs[0]) / (min(len(a), len(b)) + 1)
def extract_features(df):
    # preprocessing each question
    df["question1"] = df["question1"].fillna("").apply(preprocess)
    df["question2"] = df["question2"].fillna("").apply(preprocess)
    print("token features...")
    # Merging Features with dataset
    token features = df.apply(lambda x: get token features(x["question1"], x["question2"]), axis=1)
                        = list(map(lambda x: x[0], token_features))
    df["cwc min"]
    df["cwc max"]
                        = list(map(lambda x: x[1], token_features))
    df["csc min"]
                        = list(map(lambda x: x[2], token_features))
    df["csc max"]
                       = list(map(lambda x: x[3], token features))
    df["ctc min"]
                       = list(map(lambda x: x[4], token_features))
    df["ctc_max"]
                        = list(map(lambda x: x[5], token_features))
    df["last_word_eq"] = list(map(lambda x: x[6], token_features))
    df["first_word_eq"] = list(map(lambda x: x[7], token_features))
    df["abs len diff"] = list(map(lambda x: x[8], token features))
    df["mean len"]
                      = list(map(lambda x: x[9], token features))
    #Computing Fuzzy Features and Merging with Dataset
    # do read this blog: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
    # https://stackoverflow.com/questions/31806695/when-to-use-which-fuzz-function-to-compare-2-st
    # https://github.com/seatgeek/fuzzywuzzy
    print("fuzzy features..")
    df["token set ratio"]
                                = df.apply(lambda x: fuzz.token_set_ratio(x["question1"],
x["question2"]), axis=1)
    # The token sort approach involves tokenizing the string in question, sorting the tokens alpha
betically, and
    # then joining them back into a string We then compare the transformed strings with a simple r
atio().
   df["token sort ratio"]
                                = df.apply(lambda x: fuzz.token sort ratio(x["question1"],
x["question2"]), axis=1)
    df["fuzz_ratio"]
                                = df.apply(lambda x: fuzz.QRatio(x["question1"], x["question2"]), a:
is=1)
    df["fuzz partial ratio"]
                                = df.apply(lambda x: fuzz.partial ratio(x["question1"],
x["question2"]), axis=1)
    df["longest substr ratio"] = df.apply(lambda x: get longest substr ratio(x["question1"], x["qu
estion2"]), axis=1)
    return df
In [0]:
if os.path.isfile(data_path + 'nlp_features_train.csv'):
    df = pd.read csv(data path + "nlp features train.csv",encoding='latin-1')
    df.fillna('')
else:
    print("Extracting features for train:")
    df = pd.read csv(data path + "train.csv")
    df = extract features(df)
    df.to csv(data path + "nlp features train.csv", index=False)
df.head(2)
Out[0]:
```

id qid1 qid2 question1 question2 is_duplicate cwc_min cwc_max csc_min csc_max ctc_min ctc_max last_word_eq first

```
id qid1
                                        is_duplicate cwc_min cwc_max resemin csc_max octcomin ctc_max last_word_eg
                  to invest
                            to invest in
                   in sh...
                                  sh...
                what is the
                            what would
                   story of
                             happen if
                                                  0 0.799984 0.399996 0.749981 0.599988 0.699993 0.466664
      3
                  kohinoor
                             the indian
                                                                                                                              0.0
                 koh i noor
                           government
                     dia...
                                 sto...
```

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 [0]:

```
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 [0]:

```
# reading the text files and removing the Stop Words:
d = path.dirname('.')
textp_w = open(path.join(d, 'train_p.txt')).read()
textn_w = open(path.join(d, 'train_n.txt')).read()
stopwords = set(STOPWORDS)
stopwords.add("said")
stopwords.add("br")
stopwords.add(" ")
stopwords.remove("not")
stopwords.remove("no")
#stopwords.remove("good")
#stopwords.remove("love")
stopwords.remove("like")
#stopwords.remove("best")
#stopwords.remove("!")
print ("Total number of words in duplicate pair questions :",len(textp w))
print ("Total number of words in non duplicate pair questions :",len(textn_w))
```

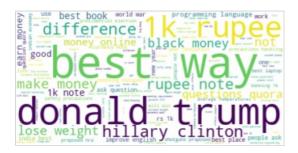
Total number of words in duplicate pair questions : 16109886 Total number of words in non duplicate pair questions : 33193130

Word Clouds generated from duplicate pair question's text

```
wc = WordCloud(background_color="white", max_words=len(textp_w), stopwords=stopwords)
wc.generate(textp_w)
print ("Word Cloud for Duplicate Question pairs")
plt.imshow(wc, interpolation='bilinear')
```

```
plt.axis("off")
plt.show()
```

Word Cloud for Duplicate Question pairs



Word Clouds generated from non duplicate pair question's text

In [0]:

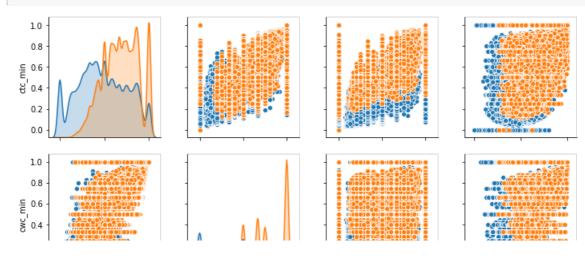
```
wc = WordCloud(background_color="white", max_words=len(textn_w), stopwords=stopwords)
# generate word cloud
wc.generate(textn_w)
print ("Word Cloud for non-Duplicate Question pairs:")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

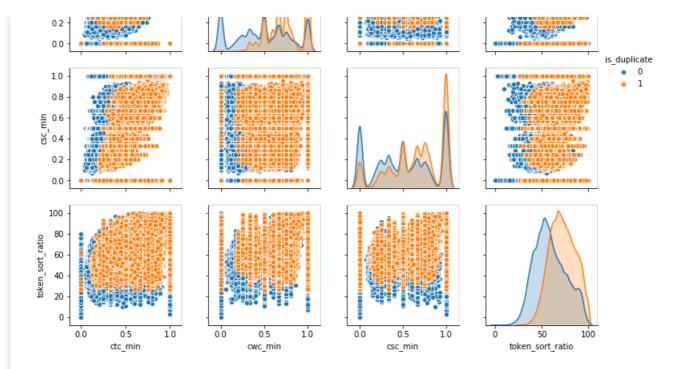
Word Cloud for non-Duplicate Question pairs:



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

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

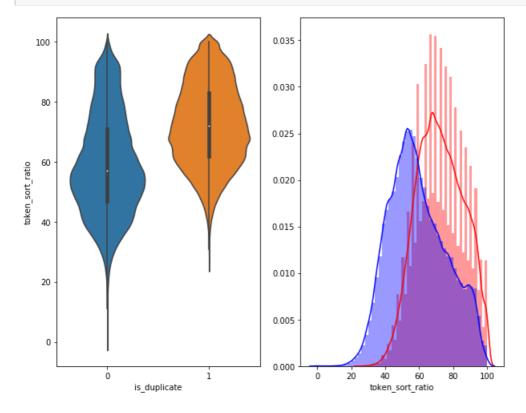




```
# Distribution of the token_sort_ratio
plt.figure(figsize=(10, 8))

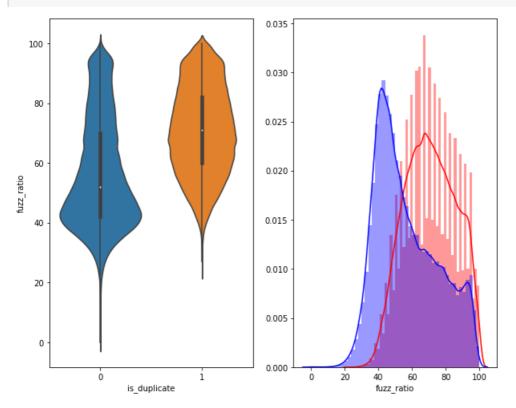
plt.subplot(1,2,1)
sns.violinplot(x = 'is_duplicate', y = 'token_sort_ratio', data = df[0:] , )

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()
```



```
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 [0]:

```
\# Using TSNE for Dimentionality reduction for 15 Features(Generated after cleaning the data) to 3
dimention
from sklearn.preprocessing import MinMaxScaler
dfp_subsampled = df[0:5000]
X = MinMaxScaler().fit_transform(dfp_subsampled[['cwc_min', 'cwc_max', 'csc_min', 'csc_max' ,
'ctc_min' , 'ctc_max' , 'last_word_eq', 'first_word_eq' , 'abs_len_diff' , 'mean_len' , 'token_set_
ratio', 'token_sort_ratio', 'fuzz_ratio', 'fuzz_partial_ratio', 'longest_substr_ratio']])
y = dfp subsampled['is duplicate'].values
```

In [0]:

```
tsne2d = TSNE(
   n components=2,
   init='random', # pca
   random_state=101,
   method='barnes hut',
   n iter=1000,
   verbose=2,
    angle=0.5
).fit transform(X)
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.013s...
[t-SNE] Computed neighbors for 5000 samples in 0.329s...
[t-SNE] Computed conditional probabilities for sample 1000 / 5000
[t-SNE] Computed conditional probabilities for sample 2000 / 5000
```

[t-SNE] Computed conditional probabilities for sample 5000 / 5000[t-SNE] Mean sigma: 0.116557

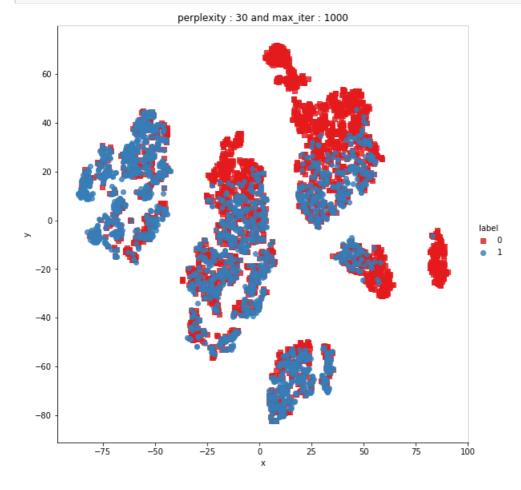
[t-SNE] Computed conditional probabilities in 0.284s

[t-SNE] Computed conditional probabilities for sample 3000 / 5000 [t-SNE] Computed conditional probabilities for sample 4000 / 5000

```
[t-SNE] Iteration 50: error = 80.9162369, gradient norm = 0.0427600 (50 iterations in 2.241s)
[t-SNE] Iteration 100: error = 70.3915100, gradient norm = 0.0108003 (50 iterations in 1.683s)
[t-SNE] Iteration 150: error = 68.6126938, gradient norm = 0.0054721 (50 iterations in 1.703s)
[t-SNE] Iteration 200: error = 67.7680206, gradient norm = 0.0042246 (50 iterations in 1.737s)
[t-SNE] Iteration 250: error = 67.2733459, gradient norm = 0.0037275 (50 iterations in 1.794s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.273346
[t-SNE] Iteration 300: error = 1.7734827, gradient norm = 0.0011933 (50 iterations in 1.830s)
[t-SNE] Iteration 350: error = 1.3717980, gradient norm = 0.0004826 (50 iterations in 1.723s)
[t-SNE] Iteration 400: error = 1.2037998, gradient norm = 0.0002772 (50 iterations in 1.744s)
[t-SNE] Iteration 450: error = 1.1133003, gradient norm = 0.0001877 (50 iterations in 1.764s)
[t-SNE] Iteration 500: error = 1.0579894, gradient norm = 0.0001429 (50 iterations in 1.754s)
       Iteration 550: error = 1.0220573, gradient norm = 0.0001178 (50 iterations in 1.755s)
[t-SNE] Iteration 600: error = 0.9990303, gradient norm = 0.0001036 (50 iterations in 1.737s)
[t-SNE] Iteration 650: error = 0.9836842, gradient norm = 0.0000951 (50 iterations in 1.722s)
[t-SNE] Iteration 700: error = 0.9732341, gradient norm = 0.0000860 (50 iterations in 1.735s)
[t-SNE] Iteration 750: error = 0.9649901, gradient norm = 0.0000789 (50 iterations in 1.747s)
       Iteration 800: error = 0.9582695, gradient norm = 0.0000745 (50 iterations in 1.718s)
[t-SNE]
[t-SNE] Iteration 850: error = 0.9525222, gradient norm = 0.0000732 (50 iterations in 1.726s)
[t-SNE] Iteration 900: error = 0.9479918, gradient norm = 0.0000689 (50 iterations in 1.721s)
[t-SNE] Iteration 950: error = 0.9442031, gradient norm = 0.0000651 (50 iterations in 1.738s)
[t-SNE] Iteration 1000: error = 0.9408465, gradient norm = 0.0000590 (50 iterations in 1.754s)
[t-SNE] KL divergence after 1000 iterations: 0.940847
```

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

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



3.6 Featurizing text data with tfidf weighted word-vectors

```
from nltk.corpus import stopwords
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from tqdm import tqdm
# exctract word2vec vectors
# https://github.com/explosion/spaCy/issues/1721
# http://landinghub.visualstudio.com/visual-cpp-build-tools
import spacy
```

In [0]:

```
df.head()
```

Out[0]:

	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 [0]:

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

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

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

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

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

vecs1 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qul in tqdm(list(df['question1'])):
    doc1 = nlp(qu1)
    # 384 is the number of dimensions of vectors
```

```
mean_vec1 = np.zeros([len(doc1), len(doc1[U].vector)])
    for word1 in doc1:
        # word2vec
       vec1 = word1.vector
       # fetch df score
          idf = word2tfidf[str(word1)]
       except:
           idf = 0
       # compute final vec
       mean vec1 += vec1 * idf
    mean vec1 = mean vec1.mean(axis=0)
    vecs1.append(mean_vec1)
df['q1 feats m'] = list(vecs1)
100%| 404290/404290 [53:12<00:00, 126.65it/s]
In [0]:
vecs2 = []
```

```
for qu2 in tqdm(list(df['question2'])):
   doc2 = nlp(qu2)
   mean vec2 = np.zeros([len(doc1), len(doc2[0].vector)])
   for word2 in doc2:
        # word2vec
       vec2 = word2.vector
        # fetch df score
            idf = word2tfidf[str(word2)]
        except:
            #print word
           idf = 0
        # compute final vec
       mean vec2 += vec2 * idf
    mean_vec2 = mean_vec2.mean(axis=0)
    vecs2.append(mean vec2)
df['q2 feats_m'] = list(vecs2)
100%| 404290/404290 [53:10<00:00, 126.73it/s]
```

```
#prepro_features_train.csv (Simple Preprocessing Feartures)
#nlp_features_train.csv (NLP Features)
if os.path.isfile(data_path + 'nlp_features_train.csv'):
    dfnlp = pd.read_csv(data_path + "nlp_features_train.csv",encoding='latin-1')
else:
    print("download nlp_features_train.csv from drive or run previous notebook")

if os.path.isfile(data_path + 'df_fe_without_preprocessing_train.csv'):
    dfppro = pd.read_csv(data_path + "df_fe_without_preprocessing_train.csv",encoding='latin-1')
else:
    print("download df_fe_without_preprocessing_train.csv from drive or run previous notebook")
```

download df_fe_without_preprocessing_train.csv from drive or run previous notebook

In [0]:

```
df1 = dfnlp.drop(['qid1','qid2','question1','question2'],axis=1)
df2 = dfppro.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
df3 = df.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
df3_q1 = pd.DataFrame(df3.q1_feats_m.values.tolist(), index= df3.index)
df3_q2 = pd.DataFrame(df3.q2_feats_m.values.tolist(), index= df3.index)
```

In [0]:

```
# dataframe of nlp features
dfl.head()
```

Out[0]:

	id	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	abs_len_diff	mean_len
0	0	0	0.999980	0.833319	0.999983	0.999983	0.916659	0.785709	0.0	1.0	2.0	13.0
1	1	0	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	1.0	5.0	12.5
2	2	0	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	1.0	4.0	12.0
3	3	0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	2.0	12.0
4	4	0	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	1.0	6.0	10.0
4												<u> </u>

data before preprocessing
df2.head()

Out[0]:

	id	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	$\mathbf{word}_\mathbf{Common}$	word_Total	word_share	freq_q1+q2	freq_q1-q2
0	0	1	1	66	57	14	12	10.0	23.0	0.434783	2	0
1	1	4	1	51	88	8	13	4.0	20.0	0.200000	5	3
2	2	1	1	73	59	14	10	4.0	24.0	0.166667	2	0
3	3	1	1	50	65	11	9	0.0	19.0	0.000000	2	0
4	4	3	1	76	39	13	7	2.0	20.0	0.100000	4	2

In [0]:

Questions 1 tfidf weighted word2vec
df3_q1.head()

Out[0]:

	0	1	2	3	4	5	6	7	8	9	10
0	211.129864	144.683059	-68.811247	153.662141	-89.931593	2.311301	136.743747	50.449112	-64.150964	56.627526	70.148884
1	144.124685	- 114.012484	- 111.716694	104.885038	-88.238478	16.441834	58.238013	102.095138	6.026966	178.498497	22.003573
2	81.757898	- 142.184507	0.559867	104.660084	-84.156631	22.515110	115.521661	50.436953	111.740923	51.713310	50.512388
3	126.651922	-59.747160	-67.763201	138.114731	101.038699	88.148523	-22.912261	85.941426	27.784233	50.810650	64.085183
4	299.444044	188.632001	-22.946291	273.683355	188.480395	107.123044	174.946302	-72.042341	-98.290527	137.439973	72.358986

5 rows × 96 columns

•

In [0]:

Questions 2 tfidf weighted word2vec
df3_q2.head()

Out[0]:

	0	1	2	3	4	5	6	7	8	9	10	
0	151.268526	127.013168	-31.546286	142.905807	-97.249094	9.485758	106.682259	36.754201	36.541905	53.162199	57.798781	34
1	152.023095	-44.955390	103.559249	- 128.467601	- 118.567610	44.577916	137.906144	26.984746	- 78.328355	86.576880	38.312126	82
2	4.930220	-29.029581	- 117.808812	-98.332275	-19.064096	-9.867805	141.808202	91.269564	50.727205	12.816846	22.755020	61
3	-6.951929	-44.951731	-17.343082	-61.444452	-7.469152	16.942014	95.049250	-2.631600	13.050916	28.038393	28.901785	37
4	96.174524	-71.613948	21.584882	-92.742468	106.643129	10.646790	92.190157	40.565982	34.739525	56.340519	- 25.369210	36

```
10
5 rows × 96 columns
In [0]:
print("Number of features in nlp dataframe :", dfl.shape[1])
print("Number of features in preprocessed dataframe: ", df2.shape[1])
print("Number of features in question1 w2v dataframe :", df3_q1.shape[1])
print("Number of features in question2 w2v dataframe :", df3_q2.shape[1])
print("Number of features in final dataframe :", dfl.shape[1]+df2.shape[1]+df3 ql.shape[1]+df3 q2.
shape[1])
Number of features in nlp dataframe : 17
Number of features in preprocessed dataframe: 12
Number of features in question1 w2v dataframe: 96
Number of features in question2 w2v dataframe: 96
Number of features in final dataframe : 221
In [0]:
# storing the final features to csv file
if not os.path.isfile(data path + 'final features.csv'):
    df3 q1['id']=df1['id']
    df3 q2['id']=df1['id']
        = df1.merge(df2, on='id',how='left')
    df1
    df2 = df3 q1.merge(df3_q2, on='id',how='left')
    result = df1.merge(df2, on='id', how='left')
    result.to_csv(data_path + 'final_features.csv')
```

4. Machine Learning Models Applying models on TFIDF weighted W2V

4.1 Reading data from file and storing into sql table

```
In [0]:
```

```
import pandas as pd
import matplotlib.pyplot as plt
import re
import time
import warnings
import sqlite3
from sqlalchemy import create engine # database connection
import csv
import os
warnings.filterwarnings("ignore")
import datetime as dt
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion matrix
from sklearn.metrics.classification import accuracy score, log loss
from sklearn.feature extraction.text import TfidfVectorizer
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model selection import GridSearchCV
import math
from sklearn.metrics import normalized mutual info score
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import SGDClassifier
from mlxtend.classifier import StackingClassifier

from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_curve, auc, roc_curve
```

```
#Creating db file from csv
if not os.path.isfile(data_path + 'train.db'):
        disk engine = create engine('sqlite:///train.db')
        start = dt.datetime.now()
       chunksize = 180000
        \dot{1} = 0
        index start = 1
        for df in pd.read csv(data path + 'final features.csv', names=['Unnamed: 0','id','is duplicate'
,'cwc_min','cwc_max','csc_min','csc_max','ctc_min','ctc_max','last_word_eq','first_word_eq','abs_l
en_diff','mean_len','token_set_ratio','token_sort_ratio','fuzz_ratio','fuzz_partial_ratio','longest
 substr_ratio','freq_qid1','freq_qid2','q1len','q2len','q1_n_words','q2_n_words','word_Common','wor_
d_Total','word_share','freq_q1+q2','freq_q1-
q2','0_x','1_x','2_x','3_x','4_x','5_x','6_x','7_x','8_x','9_x','10_x','11_x','12_x','13_x','14_x',
'15_x','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','4
3_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<sup>'</sup>,'113 x<sup>'</sup>,'114 x<sup>'</sup>,'115 x<sup>'</sup>,'116 x<sup>'</sup>,'117 x<sup>'</sup>,'118 x<sup>'</sup>,'119 x<sup>'</sup>,'120 x<sup>'</sup>,'121 x<sup>'</sup>,'122 x<sup>'</sup>,'123 x<sup>'</sup>,'12
4 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^{T}, '186 x^{T}, '187 x^{T}, '188 x^{T}, '189 x^{T}, '190 x^{T}, '191 x^{T}, '192 x^{T}, '193 x^{T}, '194 x^{T}, '195 x^{T}, '196 x^{T}, '197 x^{T}
,'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','22
2 x','223 x<sup>1</sup>,'224 x<sup>1</sup>,'225 x','226 x<sup>1</sup>,'227 x<sup>1</sup>,'228 x<sup>1</sup>,'229 x','230 x<sup>1</sup>,'231 x<sup>1</sup>,'232 x','233 x<sup>1</sup>,'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<sup>7</sup>,'248 x<sup>7</sup>,'249 x<sup>7</sup>,'250 x<sup>7</sup>,'251 x<sup>7</sup>,'252 x<sup>7</sup>,'253 x<sup>7</sup>,'254 x<sup>7</sup>,'255 x<sup>7</sup>,'256 x<sup>7</sup>,'257 x<sup>7</sup>,'258 x<sup>7</sup>,'
259 x','260 x','261 x','262 x','263 x','264 x','265 x','266 x','267 x','268 x','269 x','270 x','27
1 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<sup>'</sup>,'284 x<sup>'</sup>,'285 x<sup>'</sup>,'286 x<sup>'</sup>,'287 x','288 x<sup>'</sup>,'289 x<sup>'</sup>,'290 x','291 x<sup>'</sup>,'292 x<sup>'</sup>,'293 x','294 x<sup>'</sup>,'295 x<sup>'</sup>
,'296_x','297_x','298_x','299_x','300_x','301_x','302_x','303_x','304_x','305_x','306_x','307_x','
308 x<sup>'</sup>, '309 x<sup>'</sup>, '310 x<sup>'</sup>, '311 x<sup>'</sup>, '312 x<sup>'</sup>, '313 x<sup>'</sup>, '314 x<sup>'</sup>, '315 x<sup>'</sup>, '316 x<sup>'</sup>, '317 x<sup>'</sup>, '318 x<sup>'</sup>, '319 x<sup>'</sup>, '32
0 \times \overline{\text{v}}, 321 \times \overline{\text{v}}, 322 \times \overline{\text{v}}, 323 \times \overline{\text{v}}, 324 \times \overline{\text{v}}, 325 \times \overline{\text{v}}, 326 \times \overline{\text{v}}, 327 \times \overline{\text{v}}, 328 \times \overline{\text{v}}, 329 \times \overline{\text{v}}, 330 \times \overline{\text{v}}, 331 \times \overline{\text{v}}, 332 \times \overline{\text{v}}, 331 \times \overline{\text{v}}, 332 \times \overline{\text{v}}, 331 \times \overline{\text{v}}, 332 \times \overline{\text{v}}, 331 \times \overline{\text{v}}, 331 \times \overline{\text{v}}, 332 \times \overline{\text{v}}, 331 \times \overline{\text{v}}, 331 \times \overline{\text{v}}, 332 \times \overline{\text{v}}, 331 \times \overline{\text{v}}, 332 \times \overline{\text{v}}, 331 \times 
x<sup>-</sup>, '333_x<sup>-</sup>, '334_x<sup>-</sup>, '335_x<sup>-</sup>, '336_x<sup>-</sup>, '337_x<sup>-</sup>, '338_x<sup>-</sup>, '339_x<sup>-</sup>, '340_x<sup>-</sup>, '341_x<sup>-</sup>, '342_x<sup>-</sup>, '343_x<sup>-</sup>, '344_x<sup>-</sup>
,'345 x<sup>-</sup>,'346 x<sup>-</sup>,'347 x<sup>-</sup>,'348 x<sup>-</sup>,'349 x<sup>-</sup>,'350 x<sup>-</sup>,'351 x<sup>-</sup>,'352 x<sup>-</sup>,'353 x<sup>-</sup>,'354 x<sup>-</sup>,'355 x<sup>-</sup>,'356 x<sup>-</sup>,'
357_x','358_x','359_x','360_x','361_x','362_x','363_x','364_x','365_x','366_x','367_x','368_x','36
9 x','370_x','371_x','372_x','373_x','374_x','375_x','376_x','377_x','378_x','379_x','380_x','381
x','382_x','383_x','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','5
5_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_
','98_y','99_y','100_y','101_y','102_y','103_y','104_y','105_y','106_y','107_y','108_y','109_y','11
0 y','111 y','112 y','113 y','114 y','115 y','116 y','117 y','118 y','119 y','120 y','121 y','121
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','15
9_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','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','25
7 y','258 y<sup>'</sup>,'259 y<sup>'</sup>,'260 y','261 y','262 y<sup>'</sup>,'263 y<sup>'</sup>,'264 y','265 y<sup>'</sup>,'266 y<sup>'</sup>,'267 y<sup>'</sup>,'268 y','269
      '270_y','271_y','272_y','273_y','274_y','275_y','276_y','277_y','278_y','279_y','280_y','281_y'
```

```
#http://www.sqlitetutorial.net/sqlite-python/create-tables/
def create connection(db file):
    """ create a database connection to the SQLite database
       specified by db file
    :param db_file: database file
   :return: Connection object or None
   try:
       conn = sqlite3.connect(db file)
       return conn
   except Error as e:
       print(e)
   return None
def checkTableExists(dbcon):
   cursr = dbcon.cursor()
   str = "select name from sqlite_master where type='table'"
   table names = cursr.execute(str)
   print("Tables in the databse:")
   tables =table names.fetchall()
   print(tables[0][0])
   return (len (tables))
```

In [0]:

```
import sqlite3
read_db = data_path + 'train.db'
conn_r = create_connection(read_db)
checkTableExists(conn_r)
conn_r.close()
```

Tables in the databse: data

In [0]:

```
# try to sample data according to the computing power you have
if os.path.isfile(read_db):
    conn_r = create_connection(read_db)
    if conn_r is not None:
        # for selecting first 1M rows
        # data = pd.read_sql_query("""SELECT * FROM data LIMIT 100001;""", conn_r)

# for selecting random points
        data = pd.read_sql_query("SELECT * From data ORDER BY RANDOM() LIMIT 100001;", conn_r)
        conn_r.commit()
        conn_r.close()
```

```
# remove the first row
data.drop(data.index[0], inplace=True)
y_true = data['is_duplicate']

data_drop(data.index[0], inplace=True)
```

```
aata.arop(['Unnamea: U', 'la','lndex','ls_aupilcate'], axis=1, inplace=True)
In [0]:
data.head()
Out[0]:
```

	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_
1	0.749981250468738	0.374995312558593	0.0	0.0	0.374995312558593	0.230767455634957	(
2	0.66664444518516	0.249996875039062	0.33332222259258	0.111109876556927	0.499991666805553	0.157893905821548	(
3	0.499991666805553	0.199998666675556	0.599988000239995	0.333329629670781	0.545449586821938	0.23999904000384	
4	0.399992000159997	0.399992000159997	0.499987500312492	0.499987500312492	0.444439506227709	0.39999600004	(
5	0.0	0.0	0.249993750156246	0.166663888935184	0.0555552469152949	0.0416664930562789	(
5 ro	ows × 794 columns						

4.2 Converting strings to numerics

```
In [0]:
# after we read from sql table each entry was read it as a string
\# we convert all the features into numaric before we apply any model
cols = list(data.columns)
for i in cols:
   data[i] = data[i].apply(pd.to_numeric)
   print(i)
cwc_min
cwc_max
csc_min
csc_max
ctc min
ctc_max
last_word_eq
first word eq
abs_len_diff
mean len
token_set_ratio
token_sort_ratio
fuzz_ratio
fuzz_partial_ratio
longest_substr_ratio
freq qid1
freq_qid2
q1len
q21en
q1_n_words
q2 n words
word Common
word_Total
word_share
freq q1+q2
freq_q1-q2
0 x
1_x
2_x
3_x
4_x
5_x
6 x
7_x
8_x
9_x
```

10_x 11_x 12_x 13_x 14_x 15_x 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 300_x 301_x 302_x 303_x 304_x 305_x 306_x 307_x 308_x 309_x 310_x 311_x 312_x 313_x 314_x 315_x 316_x 317 x

318_x 319_x 320_x 321_x 322_x 323_x 324_x 325_x 326_x 327 x 328_x 329_x 330_x 331_x 332_x 333_x 334_x 335_x 336_x 337_x 338_x 339_x 340_x 341_x 342_x 343_x 344_x 345_x 346_x 347_x 348_x 349_x 350_x 351_x 352_x 353_x 354_x 355 x 356_x 357_x 358_x 359_x 360_x 361_x 362_x 363_x 364_x 365_x 366_x 367_x 368_x 369_x 370_x 371_x 372_x 373_x 374_x 375_x 376_x 377_x 378_x 379_x 380_x 381_x 382_x 383_x 0_y 1_y 2_y 3_y 4_y 5_y 6_у 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_у 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 v

88_y 89_y 90_y 91_y 92_y 93_y 94_y 95_y 96_y 97_y 98_y 99 у 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 v

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 v

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<u>y</u> 257_y 258_y 259_у 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 у 299<u>y</u> 300_y 301_y 302_y 303_y 304_y 305_y 306_y 307_y 308_y 309_y 310_y 311_y 312_y 313_y 314_y 315_y 316_y 317_y 318 v

```
319_y
320<u>y</u>
321_y
322_y
323_y
324_y
325_y
326_y
327_y
328_y
329_y
330_y
331_y
332 y
333_y
334_y
335_y
336_y
337_y
338_y
339_у
340_y
341_y
342_y
343 у
344_y
345_y
346 у
347_y
348_y
349_y
350_y
351_y
352_y
353_y
354_y
355_y
356_y
357_y
358_y
359 у
360_y
361_y
362 y
363_y
364<u>y</u>
365_y
366_у
367_y
368_y
369<u>y</u>
370_y
371_y
372_y
373_y
374_y
375_y
376 у
377_y
378_y
379_y
380_y
381_y
382_y
383_y
In [0]:
# https://stackoverflow.com/questions/7368789/convert-all-strings-in-a-list-to-int
y_true = list(map(int, y_true.values))
```

4.3 Random train test split(70:30)

```
In [0]:
X train, X test, y train, y test = train test split(data, y true, stratify=y true, test size=0.3)
In [0]:
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, 794)
Number of data points in test data: (30000, 794)
In [0]:
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: 0.6302428571428571 Class 1: 0.36975714285714284
----- Distribution of output variable in train data -----
Class 0: 0.3697333333333333 Class 1: 0.3697333333333333
In [0]:
# This function plots the confusion matrices given y i, y i hat.
def plot confusion matrix(test y, predict y):
   C = confusion_matrix(test_y, predict_y)
    \# C = 9,9 matrix, each cell (i,j) represents number of points of class i are predicted class j
    A = (((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in that column
    \# C = [[1, 2],
         [3, 4]]
    # C.T = [[1, 3],
            [2, 4]]
    \# C.sum(axis = 1)
                       axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
    \# C.sum(axix = 1) = [[3, 7]]
    \# ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
                                [2/3, 4/7]]
    \# ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
                                [3/7, 4/7]]
    # sum of row elements = 1
    B = (C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in that row
    \# C = [[1, 2],
          [3, 4]]
    # C.sum(axis = 0) axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
    \# C.sum(axix = 0) = [[4, 6]]
    \# (C/C.sum(axis=0)) = [[1/4, 2/6],
                           [3/4, 4/6]]
    plt.figure(figsize=(20,4))
    labels = [1,2]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")
    nlt subplot (1 3 2)
```

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

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

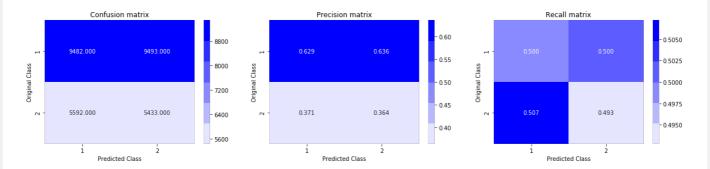
4.4 Building a random model (Finding worst-case log-loss)

```
In [0]:
```

```
# we need to generate 9 numbers and the sum of numbers should be 1
# one solution is to genarate 9 numbers and divide each of the numbers by their sum
# ref: https://stackoverflow.com/a/18662466/4084039
# we create a output array that has exactly same size as the CV data
predicted_y = np.zeros((test_len,2))
for i in range(test_len):
    rand_probs = np.random.rand(1,2)
    predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
print("Log loss on Test Data using Random Model",log_loss(y_test, predicted_y, eps=1e-15))

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

Log loss on Test Data using Random Model 0.887242646958



4.4 Logistic Regression with hyperparameter tuning on TFIDF weighted W2V based vectorization

```
In [0]:
```

```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
log error array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='12', loss='log', random state=42 , class weight='balanced
    clf.fit(X_train, y_train)
    sig clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_test)
    \label{log_error_array.append} $$\log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))$$
    print('For values of alpha = ', i, "The log loss is:",log loss(y test, predict y, labels=clf.cl
asses_, eps=1e-15))
fig, ax = plt.subplots()
ax.plot(alpha, log error array,c='g')
for i, txt in enumerate(np.round(log error array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
```

```
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='12', loss='log', random_state=42 , class_weig
ht='balanced')
clf.fit(X_train, y_train)
sig clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train, y_train)
predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train,
predict y, labels=clf.classes , eps=1e-15))
predict y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best alpha], "The test log loss is:",log loss(y test, p
redict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha = 1e-05 The log loss is: 0.6589734189474593

For values of alpha = 0.0001 The log loss is: 0.4596576080712704

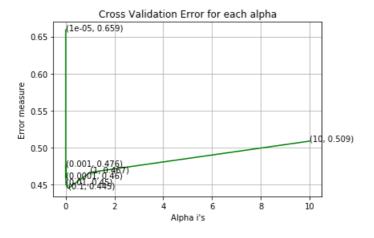
For values of alpha = 0.001 The log loss is: 0.47598914345811755

For values of alpha = 0.01 The log loss is: 0.4504643129769408

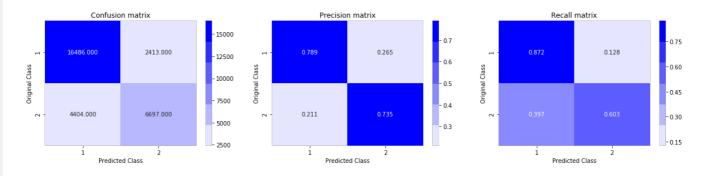
For values of alpha = 0.1 The log loss is: 0.44514274763570344

For values of alpha = 1 The log loss is: 0.4668107459743148

For values of alpha = 10 The log loss is: 0.5089490456091396
```



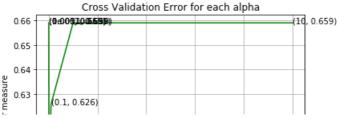
For values of best alpha = 0.1 The train log loss is: 0.44207416978281233 For values of best alpha = 0.1 The test log loss is: 0.4502394595299378 Total number of data points : 30000

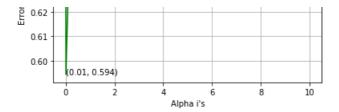


4.5 Linear SVM with hyperparameter tuning on TFIDF weighted W2V based vectorization

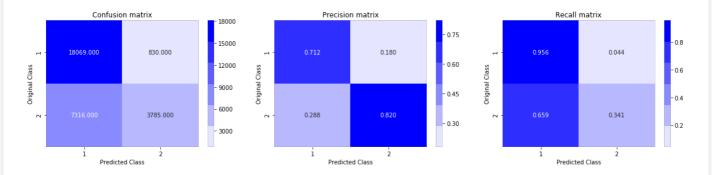
```
In [0]:
```

```
# read more about SGDClassifier() at http://scikit-
learn.org/stable/modules/generated/sklearn.linear\_model.SGDClassifier.html
# default parameters
# SGDClassifier(loss='hinge', penalty='12', alpha=0.0001, 11 ratio=0.15, fit intercept=True, max i
ter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n jobs=1, random state=None, learning rate='optimal', eta0
=0.0, power t=0.5,
# class weight=None, warm start=False, average=False, n iter=None)
# some of methods
# fit(X, y[, coef_init, intercept_init, ...]) Fit linear model with Stochastic Gradient Descent.
# predict(X) Predict class labels for samples in X.
# video link:
log error array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='11', loss='hinge', random state=42 , class weight='balanc
    clf.fit(X train, y train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig clf.fit(X_train, y_train)
   predict_y = sig_clf.predict_proba(X_test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log loss(y test, predict y, labels=clf.cl
asses , eps=1e-15))
fig, ax = plt.subplots()
ax.plot(alpha, log error array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log error array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
best alpha = np.argmin(log error array)
clf = SGDClassifier(alpha=alpha[best alpha], penalty='ll', loss='hinge', random state=42, class we
ight='balanced')
clf.fit(X train, y train)
sig clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train, y_train)
predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best alpha], "The train log loss is:",log loss(y train,
predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best alpha], "The test log loss is: ", log loss (y test, p
redict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted y))
plot_confusion_matrix(y_test, predicted_y)
For values of alpha = 1e-05 The log loss is: 0.6589734189474593
For values of alpha = 0.0001 The log loss is: 0.6589734189474593
For values of alpha = 0.001 The log loss is: 0.6589734189474593
For values of alpha = 0.01 The log loss is: 0.5944656394362929
For values of alpha = 0.1 The log loss is: 0.625927058211714
For values of alpha = 1 The log loss is: 0.6589734189474593
For values of alpha = 10 The log loss is: 0.6589734189474593
```





For values of best alpha = 0.01 The train log loss is: 0.5449069649156968 For values of best alpha = 0.01 The test log loss is: 0.5457181186452043 Total number of data points : 30000



4.6 XGBoost on TFIDF weighted W2V based vectorization

In [0]:

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

d_train = xgb.DMatrix(X_train, label=y_train)
d_test = xgb.DMatrix(X_test, label=y_test)

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

bst = xgb.train(params, d_train, 400, watchlist, early_stopping_rounds=20, verbose_eval=10)

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

[0] train-logloss:0.684819 valid-logloss:0.684845
Multiple eval metrics have been passed: 'valid-logloss' will be used for early stopping.

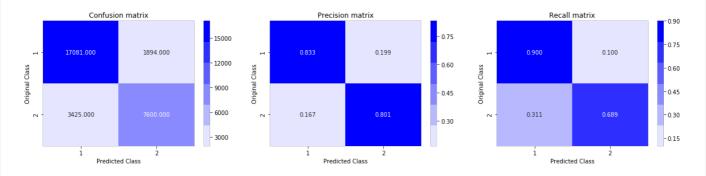
```
Will train until valid-logloss hasn't improved in 20 rounds.
[10] train-logloss:0.61583 valid-logloss:0.616104
[20] train-logloss:0.564616 valid-logloss:0.565273
[30] train-logloss:0.525758 valid-logloss:0.52679
[40] train-logloss:0.496661 valid-logloss:0.498021
[50] train-logloss:0.473563 valid-logloss:0.475182
[60] train-logloss:0.455315 valid-logloss:0.457186
[70] train-logloss:0.440442 valid-logloss:0.442482
[80] train-logloss:0.428424 valid-logloss:0.430795
[90] train-logloss:0.418803 valid-logloss:0.421447
[100] train-logloss:0.41069 valid-logloss:0.413583
[110] train-logloss:0.403831 valid-logloss:0.40693
[120] train-logloss:0.398076 valid-logloss:0.401402
[130] train-logloss:0.393305 valid-logloss:0.396851
[140] train-logloss:0.38913 valid-logloss:0.392952
[150] train-logloss:0.385469 valid-logloss:0.389521
[160] train-logloss:0.382327 valid-logloss:0.386667
[170] train-logloss:0.379541 valid-logloss:0.384148
[180] train-logloss:0.377014 valid-logloss:0.381932
[190] train-logloss:0.374687 valid-logloss:0.379883
[200] train-logloss:0.372585 valid-logloss:0.378068
[210] train-logloss:0.370615 valid-logloss:0.376367
```

```
[220] train-logloss:0.368559 valid-logloss:0.374595
[230] train-logloss:0.366545 valid-logloss:0.372847
[240] train-logloss:0.364708 valid-logloss:0.371311
[250] train-logloss:0.363021 valid-logloss:0.369886
[260] train-logloss:0.36144 valid-logloss:0.368673
[270] train-logloss:0.359899 valid-logloss:0.367421
[280] train-logloss:0.358465 valid-logloss:0.366395
[290] train-logloss:0.357128 valid-logloss:0.365361
[300] train-logloss:0.355716 valid-logloss:0.364315
[310] train-logloss:0.354425 valid-logloss:0.363403
[320] train-logloss:0.353276 valid-logloss:0.362595
[330] train-logloss:0.352084 valid-logloss:0.361823
[340] train-logloss:0.351051 valid-logloss:0.361167
[350] train-logloss:0.349867 valid-logloss:0.36043
[360] train-logloss:0.348829 valid-logloss:0.359773
[370] train-logloss:0.347689 valid-logloss:0.359019
[380] train-logloss:0.346607 valid-logloss:0.358311
[390] train-logloss:0.345568 valid-logloss:0.357674
The test log loss is: 0.357054433715
```

In [0]:

```
predicted_y =np.array(predict_y>0.5,dtype=int)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

Total number of data points : 30000



5. Assignments

In [12]:

```
df = pd.read_csv(data_path + "nlp_features_train.csv", encoding='latin-1')
df.head(2)
```

Out[12]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	firs
0	0	1	2	what is the step by step guide to invest in sh	what is the step by step guide to invest in sh	0	0.999980	0.833319	0.999983	0.999983	0.916659	0.785709	0.0	
1	1	3	4	what is the story of kohinoor koh i noor dia	what would happen if the indian government sto	0	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	
4														· •

In [13]:

```
len(df)
df = df.fillna('')
df=df[:100000]
len(df)
```

```
100000
In [14]:
df train = df[:70000]
print(len(df_train))
df test = df[70000:]
print(len(df_test))
70000
30000
In [15]:
vectorizer = TfidfVectorizer(min df=10)
text1_tfidf_train = vectorizer.fit_transform(df_train['question1'])
text1_tfidf_test = vectorizer.transform(df_test['question1'])
print("Shape of matrix after one hot encodig ",text1_tfidf_train.shape)
Shape of matrix after one hot encodig (70000, 5204)
In [16]:
vectorizer = TfidfVectorizer(min df=10)
text2_tfidf_train = vectorizer.fit_transform(df_train['question2'])
text2_tfidf_test = vectorizer.transform(df_test['question2'])
print("Shape of matrix after one hot encodig ",text2 tfidf train.shape)
Shape of matrix after one hot encodig (70000, 5167)
In [0]:
from scipy.sparse import hstack
In [18]:
X train = hstack((np.array(df train[['id','qid1','qid2','cwc min','cwc max','csc min','csc max','c
tc_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']]) , text1_tfidf_train , tex
t2 tfidf train))
X_test =
hstack((np.array(df_test[['id','qid1','qid2','cwc_min','cwc_max','csc_min','csc_max','ctc_min','ct
c_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']]) , text1 tfidf test ,
text2_tfidf_test))
X1_train=X_train.tocsr()
X1_test=X_test.tocsr()
print(X1_train.shape)
print(X1 test.shape)
4
(70000, 10389)
(30000, 10389)
In [19]:
y train = df train['is duplicate']
y_test = df_test['is_duplicate']
print(y_train.shape)
print(y_test.shape)
(70000.)
(30000,)
```

5.1 Logistic Regression with hyperparameter tuning on TFIDF based

vectorization

5.1.1 With Class weight as Balanced

```
In [28]:
```

```
alpha = [10 ** x for x in range(-4, 3)] # hyperparam for SGD classifier.
log error array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='12', loss='log', class weight='balanced')
    clf.fit(X1_train, y_train)
    sig clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig clf.fit(X1 train, y train)
    predict y = sig clf.predict proba(X1 test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test, predict_y, labels=clf.cl
asses_, eps=1e-15))
fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log error array, 3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log error array[i]))
plt.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='12', loss='log', class_weight='balanced')
clf.fit(X1 train, y train)
sig clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X1_train, y_train)
predict_y = sig_clf.predict_proba(X1_train)
print('For values of best alpha = ', alpha[best alpha], "The train log loss is:",log loss(y train,
predict y, labels=clf.classes , eps=1e-15))
predict_y = sig_clf.predict_proba(X1_test)
print('For values of best alpha = ', alpha[best alpha], "The test log loss is: ", log loss (y test, p
redict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted y))
plot confusion matrix(y test, predicted y)
For values of alpha = 0.0001 The log loss is: 0.6603945477700923
```

```
For values of alpha = 0.0001 The log loss is: 0.6603945477700923

For values of alpha = 0.001 The log loss is: 0.6603945477700923

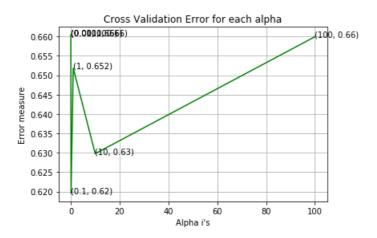
For values of alpha = 0.01 The log loss is: 0.6603945477700923

For values of alpha = 0.1 The log loss is: 0.6195181544644561

For values of alpha = 1 The log loss is: 0.6517943474881931

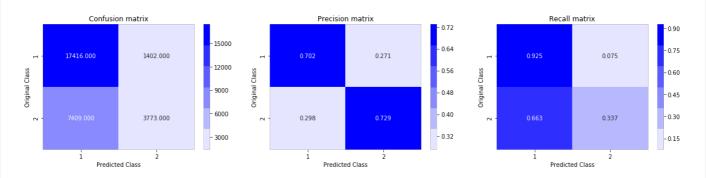
For values of alpha = 10 The log loss is: 0.6297789784714061

For values of alpha = 100 The log loss is: 0.659900447466102
```



```
For values of best alpha = 0.1 The train log loss is: 0.6296961919480639 For values of best alpha = 0.1 The test log loss is: 0.6038942850134336
```

Total number of data points : 30000



5.1.2 Without Class weight as Balanced

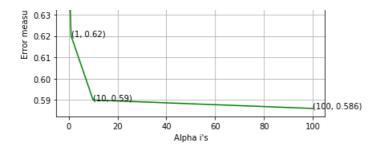
In [29]:

```
alpha = [10 ** x for x in range(-4, 3)] # hyperparam for SGD classifier.
log error array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='12', loss='log', random state=42)
    clf.fit(X1 train, y train)
    sig clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X1_train, y_train)
    predict_y = sig_clf.predict_proba(X1_test)
    \label{log_error_array.append} $$\log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))$$
    print ('For values of alpha = ', i, "The log loss is:", log loss (y test, predict y, labels=clf.cl
asses , eps=1e-15))
fig, ax = plt.subplots()
ax.plot(alpha, log error array,c='g')
for i, txt in enumerate(np.round(log error array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log error array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
best alpha = np.argmin(log error array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='12', loss='log', random_state=42)
clf.fit(X1_train, y_train)
sig clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X1_train, y_train)
predict_y = sig_clf.predict_proba(X1_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train,
predict y, labels=clf.classes , eps=1e-15))
predict y = sig clf.predict proba(X1 test)
print('For values of best alpha = ', alpha[best alpha], "The test log loss is: ",log loss(y test, p
redict y, labels=clf.classes , eps=1e-15))
predicted y =np.argmax(predict y,axis=1)
print("Total number of data points :", len(predicted y))
plot_confusion_matrix(y_test, predicted_y)
For values of alpha = 0.0001 The log loss is: 0.6603945477700923
For values of alpha = 0.001 The log loss is: 0.6603945477700923
For values of alpha = 0.01 The log loss is: 0.6603945477700923
For values of alpha = 0.1 The log loss is: 0.6509167359319714
For values of alpha =
                       1 The log loss is: 0.6200529705909165
For values of alpha = 10 The log loss is: 0.5899721593642986
```

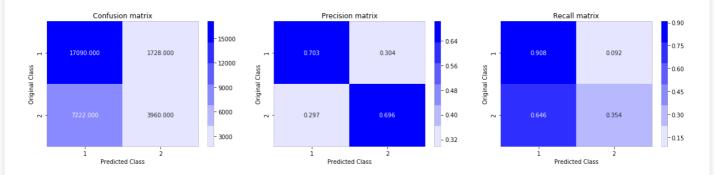
Cross Validation Error for each alpha

For values of alpha = 100 The log loss is: 0.5860248750661626

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	0.00	, , ,		
		(0.1, 0.651)		
	0.65 -	,		
	0.64 -			
ø				



For values of best alpha = 100 The train log loss is: 0.6371126567390029 For values of best alpha = 100 The test log loss is: 0.5860248750661626 Total number of data points : 30000



5.2 Linear SVM with hyperparameter tuning on TFIDF based vectorization

5.1.1 With Class weight as Balanced

```
In [30]:
```

```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
log error array=[]
for i in alpha:
   clf = SGDClassifier(alpha=i, penalty='11', loss='hinge', random state=42 , class weight='balanc
    clf.fit(X1 train, y train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X1_train, y_train)
    predict y = sig clf.predict proba(X1 test)
   log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log loss(y test, predict y, labels=clf.cl
asses_, eps=1e-15))
fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log error array,3)):
   ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log error array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
best alpha = np.argmin(log error array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='11', loss='hinge', random_state=42 , class_we
ight='balanced')
clf.fit(X1_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig clf.fit(X1_train, y_train)
predict_y = sig_clf.predict_proba(X1_train)
print('For values of best alpha = ', alpha[best alpha], "The train log loss is:",log loss(y train,
predict y, labels=clf.classes , eps=1e-15))
predict_y = sig_clf.predict_proba(X1_test)
print('For values of best alpha = ', alpha[best alpha], "The test log loss is:",log loss(y test, p
redict y, labels=clf.classes , eps=1e-15))
```

```
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha = 1e-05 The log loss is: 0.6603945477700923

For values of alpha = 0.0001 The log loss is: 0.6603945477700923

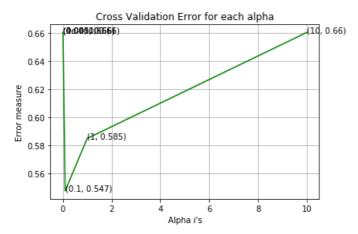
For values of alpha = 0.001 The log loss is: 0.6603945477700923

For values of alpha = 0.01 The log loss is: 0.6603945477700923

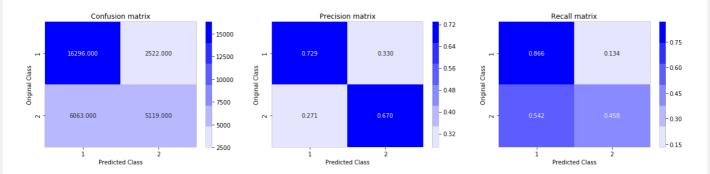
For values of alpha = 0.1 The log loss is: 0.5474040222598306

For values of alpha = 1 The log loss is: 0.584768669817024

For values of alpha = 10 The log loss is: 0.6603945477700923
```



For values of best alpha = 0.1 The train log loss is: 0.5741202810503914 For values of best alpha = 0.1 The test log loss is: 0.5474040222598306 Total number of data points : 30000



5.1.1 Without Class weight as Balanced

In [31]:

```
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.
log error array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='11', loss='hinge', random state=42)
    clf.fit(X1_train, y_train)
    sig clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig clf.fit(X1 train, y train)
    predict y = sig clf.predict proba(X1 test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log loss(y test, predict y, labels=clf.cl
asses , eps=1e-15))
fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log error array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
```

```
best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='ll', loss='hinge', random_state=42)
clf.fit(X1_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X1_train, y_train)

predict_y = sig_clf.predict_proba(X1_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X1_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:",log_loss(y_test, p redict_y, labels=clf.classes_, eps=1e-15))
predicted_y = np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha = 1e-05 The log loss is: 0.6603945477700923

For values of alpha = 0.0001 The log loss is: 0.6603945477700923

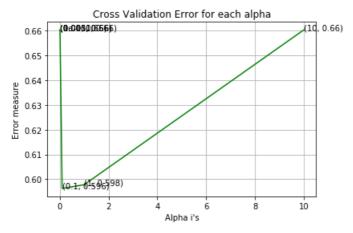
For values of alpha = 0.001 The log loss is: 0.6603945477700923

For values of alpha = 0.01 The log loss is: 0.6603945477700923

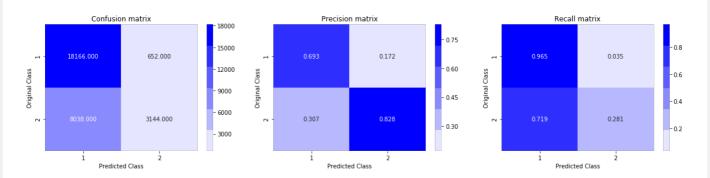
For values of alpha = 0.1 The log loss is: 0.5962508713682829

For values of alpha = 1 The log loss is: 0.5977519147303617

For values of alpha = 10 The log loss is: 0.6603945477700923
```



For values of best alpha = 0.1 The train log loss is: 0.6266487755781842 For values of best alpha = 0.1 The test log loss is: 0.5962508713682829 Total number of data points : 30000



5.3 XGBoost with Hyperparameter Tuning on TFIDF based vectorization

In [0]:

```
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
from datetime import datetime
xgb = XGBClassifier()
clf = RandomizedSearchCV(xgb, params, cv=5)
start_time = timer(None) # timing starts from this point for "start_time" variable
clf.fit(X1_train, y_train)
timer(start_time) # timing ends here for "start_time" variable
```

Time taken: 0 hours 51 minutes and 24.76 seconds.

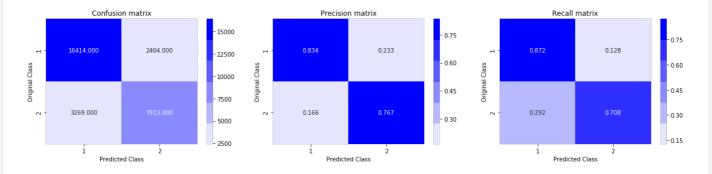
```
In [0]:
```

```
clf.best params
{'learning rate': 0.1,
 'max depth': 7,}
In [0]:
import xgboost as xgb
params = {}
params['objective'] = 'binary:logistic'
params['eval metric'] = 'logloss'
params['eta'] = 0.1
params['max_depth'] = 7
d_train = xgb.DMatrix(X1_train, label=y_train)
d_test = xgb.DMatrix(X1_test, label=y_test)
watchlist = [(d train, 'train'), (d test, 'valid')]
bst = xgb.train(params, d train, 400, watchlist, early stopping rounds=20, verbose eval=10)
xgdmat = xgb.DMatrix(X train,y train)
predict y = bst.predict(d test)
print("The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
[0] train-logloss:0.656874 valid-logloss:0.656017
Multiple eval metrics have been passed: 'valid-logloss' will be used for early stopping.
Will train until valid-logloss hasn't improved in 20 rounds.
[10] train-logloss:0.493699 valid-logloss:0.492732
[20] train-logloss: 0.441675 valid-logloss: 0.445827
[30] train-logloss:0.419565 valid-logloss:0.42762
[40] train-logloss:0.406935 valid-logloss:0.417782
[50] train-logloss:0.39803 valid-logloss:0.41141
[60] train-logloss:0.390751 valid-logloss:0.40802
[70] train-logloss:0.385838 valid-logloss:0.405492
[80] train-logloss:0.380294 valid-logloss:0.40285
[90] train-logloss:0.376155 valid-logloss:0.400955
[100] train-logloss:0.372537 valid-logloss:0.398314
[110] train-logloss:0.36878 valid-logloss:0.396632
[120] train-logloss:0.365682 valid-logloss:0.395615
[130] train-logloss:0.362759 valid-logloss:0.394406
[140] train-logloss:0.360011 valid-logloss:0.3935
[150] train-logloss:0.357383 valid-logloss:0.392486
[160] train-logloss:0.354643 valid-logloss:0.391496
[170] train-logloss:0.351753 valid-logloss:0.389005
[180] train-logloss:0.349142 valid-logloss:0.388219
[190] train-logloss:0.347176 valid-logloss:0.387547
[200] train-logloss:0.345148 valid-logloss:0.386932
[210] train-logloss:0.343052 valid-logloss:0.386377
[220] train-logloss:0.34147 valid-logloss:0.385705
[230] train-logloss:0.339635 valid-logloss:0.385283
[240] train-logloss:0.337196 valid-logloss:0.383486
[250] train-logloss:0.334793 valid-logloss:0.382723
[260] train-logloss:0.333202 valid-logloss:0.382337
[270] train-logloss:0.331062 valid-logloss:0.381668
[280] train-logloss:0.329744 valid-logloss:0.381325
[290] train-logloss:0.328071 valid-logloss:0.380876
[300] train-logloss:0.326183 valid-logloss:0.380512
[310] train-logloss:0.324586 valid-logloss:0.380007
[320] train-logloss:0.322927 valid-logloss:0.379676
[330] train-logloss:0.321289 valid-logloss:0.379057
[340] train-logloss:0.320157 valid-logloss:0.378755
[350] train-logloss:0.318757 valid-logloss:0.378562
[360] train-logloss:0.317639 valid-logloss:0.378362
[370] train-logloss:0.316354 valid-logloss:0.378032
[380] train-logloss:0.315156 valid-logloss:0.377823
[390] train-logloss:0.313446 valid-logloss:0.377353
[399] train-logloss:0.312387 valid-logloss:0.377094
The test log loss is: 0.3770938920243238
```

In [0]:

```
predicted_y =np.array(predict_y>0.5,dtype=int)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

Total number of data points : 30000



6. Conclusion

In [0]:

```
from prettytable import PrettyTable
```

In [0]:

```
x = PrettyTable()
x.field_names = ["Algorithm", "Vectorizer", "Model", "Hyper Parameters", "Log-Loss"]
```

In [0]:

```
x.add_row(["Logistic Regression + class balancing", "Tfidf W2V", "Brute", "alpha=0.1", 0.450])
x.add_row(["Linear SVM + class balancing", "Tfidf W2V", "Brute", "alpha=0.01", 0.545])
x.add_row(["XGBoost", "Tfidf W2V", "Brute", "eta=0.02 , max_depth=4", 0.357])
x.add_row(["Logistic Regression", "Tfidf", "Brute", "alpha=100", 0.586])
x.add_row(["Linear SVM", "Tfidf", "Brute", "alpha=0.1", 0.596])
x.add_row(["Logistic Regression + class balancing", "Tfidf", "Brute", "alpha=0.1", 0.603])
x.add_row(["Linear SVM + class balancing", "Tfidf", "Brute", "alpha=0.1", 0.547])
x.add_row(["XGBoost", "Tfidf", "Brute", "eta=0.1 , max_depth=7", 0.377])
```

In [43]:

```
print(x)
```

Algorithm	Vectorizer	Model	+ Hyper Parameters +	Log-Loss	3
Logistic Regression + class balancing	Tfidf W2V	Brute	alpha=0.1	0.45	
Linear SVM + class balancing XGBoost	Tfidf W2V Tfidf W2V	Brute Brute	alpha=0.01 eta=0.02 , max_depth=4	0.545	
Logistic Regression	Tfidf	Brute	alpha=100	0.586	
Linear SVM Logistic Regression + class balancing	Tfidf Tfidf	Brute Brute		0.596	
Linear SVM + class balancing	Tfidf	Brute	alpha=0.1	0.547	- [
XGBoost	Tfidf	Brute +	eta=0.1 , max_depth=7 +	0.377 +	 -+

Steps that were followed during this case study

- 1. Initially to understand the data better Exploratory data analysis was performed and the results were taken into account.
- 2. There was a need for feature engineering in this task therefore after going through various blogs regarding this problem and discussions that happened on kaggle certain important and very elegant features were added to the dataset to make it information rich.
- 3. The new features are then analysed to see if they are actually important and do they really help in classification of data.
- 4. All the data is then compiled and models are applied on top of it. The data features are taken in two ways TFIDF and TFIDF

weighted W2V.

- 5. Three models are implied on top of it Linear SVM, Logistic Regression, XGBoost.
- 6. The Logerithmic loss for all the three models for different vectorizers is compiled in the above table which clearly shows that XGBoost with TFIDF W2V vectorizer performs the best(considering the log-loss metric) with just 0.357 log loss.