```
In [0]:
from google.colab import drive
drive.mount('/content/MyDrive/')
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%
b&response type=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2
www.googleapis.com%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly
ttps%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly
Enter your authorization code:
Mounted at /content/MyDrive/
In [2]:
import nltk
nltk.download('stopwords')
[nltk data] Downloading package stopwords to /home/ubuntu/nltk data...
            Package stopwords is already up-to-date!
[nltk data]
Out[2]:
True
In [3]:
#import liraries
#General
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import os
import warnings
warnings.filterwarnings('ignore')
#others
import plotly.offline as py
py.init notebook mode (connected=True)
import plotly.graph_objs as go
import plotly.tools as tls
from tqdm import tqdm
import sqlite3
from sqlalchemy import create engine
import datetime
#preprocessing
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
import distance
from wordcloud import WordCloud
from sklearn.preprocessing import MinMaxScaler
from sklearn.manifold import TSNE
import cv2
import spacy
from sklearn.feature_extraction.text import TfidfVectorizer
#Modelling
from sklearn.model selection import train test split
from sklearn.linear model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from xgboost import XGBClassifier
from sklearn.metrics import log_loss
from sklearn.model_selection import GridSearchCV
from sklearn.dummy import DummyClassifier
```

from sklearn metrics import confusion matrix

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1. Reading Data

```
In [0]:
```

```
df = pd.read_csv('/content/MyDrive/My Drive/Applied AI/Case studies/1. Quora/train.csv')
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]:

```
print(df.shape)
(404290, 6)
```

In [0]:

```
df.info()
```

<class 'pandas.core.frame.DataFrame'>

5 is_duplicate 404290 non-null int64 dtypes: int64(4), object(2) memory usage: 18.5+ MB

In [0]:

```
df.isna().sum()
```

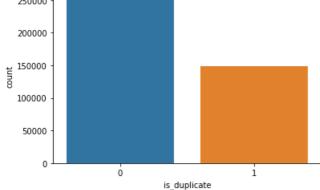
Out[0]:

2.EDA

2.1 Distribution of data points based on output variable

```
In [0]:
df.groupby('is duplicate')['id'].count()
Out[0]:
is duplicate
    255027
    149263
Name: id, dtype: int64
In [0]:
sns.countplot(x='is duplicate', data =df)
Out[0]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f362cbb9898>
```





2.2 Percentage of points where is duplicate = 0 & 1

```
In [0]:
```

```
print(len(df[df['is duplicate']==0]))
print(len(df[df['is_duplicate']==1]))
print(len(df[df['is duplicate']==0]) + len(df[df['is duplicate']==1]))
print(len(df))
255027
```

149263 404290

404290

In [0]:

```
print('Percentage of points where is_duplicate=0:',((len(df[df['is_duplicate']==0]))/ (len(df)))*10
0)
```

Percentage of points where is duplicate=0: 63.08021469737069 Percentage of points where is duplicate=1: 36.9197853026293

2.3 Number of Unique question in dataset

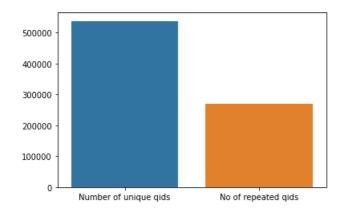
```
#take qids on both questions and combine them and use 'set' to find unique qids
print('Total number of unique questions:', len(list(set(df['qid1'].tolist() + df['qid2'].tolist()))
```

```
Out[0]:
537933
In [0]:
#unique qids that appear max than one time
print(pd.Series(df['qid1'].tolist() + df['qid2'].tolist()).value_counts())
print('Number of times a qid appears most:', max(pd.Series(df['qid1'].tolist() + df['qid2'].tolist()
).value counts()))
         157
2559
30782
          120
4044
          111
2561
          8.8
           79
14376
75109
          1
81254
            1
85352
            1
83305
            1
168274
Length: 537933, dtype: int64
Number of times a qid appears most: 157
In [0]:
print((pd.Series([1,2,3,3,4,4,5,6])).value\_counts() > 1)
#to add number of True we use sum
print(sum((pd.Series([1,2,3,3,4,4,5,6])).value_counts() > 1))
4
     True
3
     True
6
    False
     False
     False
    False
dtype: bool
2
In [0]:
#number of unique qids that appear more than one time
sum(pd.Series(df['qid1'].tolist() + df['qid2'].tolist()).value counts() > 1)
Out[0]:
111780
2.4 Count plot for unique questions and repeated question
In [0]:
total qids = len(df['qid1'].tolist() + df['qid2'].tolist())
no unique qids = len(list(set(df['qid1'].tolist() + df['qid2'].tolist())))
repeated_qids = total_qids - no_unique_qids
print(no_unique_qids)
print(repeated_qids)
537933
270647
In [0]:
x =['Number of unique qids', 'No of repeated qids']
y = [no_unique_qids, repeated_qids]
```

sns.barplot(x,y)

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f362c9d3128>



2.5 Checking for Duplicates

In [0]:

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

Out[0]:

	qid1	qid2	is_duplicate
0	1	2	1
1	3	4	1
2	3	282170	1
3	3	380197	1
4	3	488853	1
404285	537924	537925	1
404286	537926	537927	1
404287	537928	537929	1
404288	537930	537931	1
404289	537932	537933	1

404290 rows × 3 columns

In [0]:

```
print('No of duplicates=', df.shape[0] - pair_dupicates.shape[0])
```

No of duplicates= 0

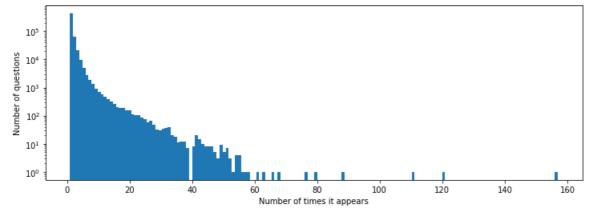
2.6 Number of occurences of each question

```
number_of_occurences_of_each_qids = pd.Series(df['qid1'].tolist()+df['qid2'].tolist()).value_counts
()
print(number_of_occurences_of_each_qids)
```

```
2559 157
30782 120
4044 111
```

```
2561 88
14376 79
...
75109 1
81254 1
85352 1
83305 1
168274 1
Length: 537933, dtype: int64
```

```
plt.figure(figsize=(12,4))
plt.hist(number_of_occurences_of_each_qids, bins=160)
plt.yscale('log')
plt.ylabel('Number of questions')
plt.xlabel('Number of times it appears')
plt.show()
```



2.7 Checking for Null values

In [0]:

qid2 0 question1 1 question2 2 is_duplicate dtype: int64

In [0]:

```
df[df.isna().any(1)]
```

Out[0]:

	id	qid1	qid2	question1	question2	is_duplicate
105780	105780	174363	174364	How can I develop android app?	NaN	0
201841	201841	303951	174364	How can I create an Android app?	NaN	0
363362	363362	493340	493341	NaN	My Chinese name is Haichao Yu. What English na	0

```
#filling it with empty string
df = df.fillna('')
```

```
#looking it again
df[df.isna().any(1)]
Out[0]:
  id qid1 qid2 question1 question2 is_duplicate
In [0]:
df.iloc[201841] # look at question2 and it fills with empty string
Out[0]:
                                          201841
id
qid1
                                          303951
qid2
                                          174364
question1
              How can I create an Android app?
question2
is_duplicate
Name: 201841, dtype: object
3. Basic Feature Extraction
In [0]:
#1. frequency of qid1
df.groupby('qid1')['qid1'].transform('count')
Out[0]:
0
          1
          4
1
          1
          1
          3
404285
         2
404286
        12
404287
          1
404288
         1
Name: qid1, Length: 404290, dtype: int64
In [0]:
# frequency of qid2
df.groupby('qid2')['qid2'].transform('count')
Out[0]:
0
         1
          1
1
3
         1
4
         1
404285
         2
404286
       1
404287
        1
404288
404289
         1
Name: qid2, Length: 404290, dtype: int64
In [0]:
\# 2. length of question1 and question2 , here length includes space and individual chars
print(df['question1'].str.len())
print('='*50)
```

```
| print(df['question2'].str.len())
0
         66
1
         51
          73
2
          50
         76
4
404285
         85
404286
         41
404287
         17
404288
         94
404289
        37
Name: question1, Length: 404290, dtype: int64
_____
          8.8
          59
2
4
          39
404285
         79
         42
404286
404287
         17
404288
       127
404289
         4.5
Name: question2, Length: 404290, dtype: int64
In [0]:
#3. number of words in each question
print(df['question1'].apply(lambda x: len(x.split(' '))))
print('='*50)
print(df['question2'].apply(lambda x: len(x.split(' '))))
0
        14
         8
1
         14
         11
         13
404285
        14
        8
404286
404287
          4
        17
404288
         8
Name: question1, Length: 404290, dtype: int64
0
1
         13
         10
2
         9
          7
4
         . .
404285
         13
404286
         9
404287
404288
       25
         1.0
404289
Name: question2, Length: 404290, dtype: int64
In [0]:
# 4. number of common words in question1 and question2 for just first row
print(set(map(lambda x:x.lower().strip(), df['question1'][0].split(' '))))
print(set(map(lambda x:x.lower().strip() , df['question2'][0].split(' '))))
print('='*25, 'Common words in ques1 and ques2 in row1', '='*25)
x:x.lower().strip() , df['question2'][0].split(' ')))
{'what', 'step', 'by', 'is', 'share', 'invest', 'guide', 'the', 'market', 'india?', 'in', 'to'} {'what', 'step', 'by', 'is', 'share', 'invest', 'guide', 'the', 'market?', 'in', 'to'}
======= Common words in ques1 and ques2 in row1 ================================
```

```
Out[0]:
{'by', 'guide', 'in', 'invest', 'is', 'share', 'step', 'the', 'to', 'what'}
In [0]:
# 5. total number of words in ques1 and ques2 for first row
print('Number of words in question1 in row1')
print(list(map(lambda x:x.lower().strip() ,df['question1'][0].split(' '))))
print(len(list(map(lambda x:x.lower().strip() ,df['question1'][0].split(' ')))))
print('='*50)
print('Number of words in question2 in row2')
print(list(map(lambda x: x.lower().strip(), df['question2'][0].split(' '))))
print(len(list(map(lambda x: x.lower().strip(), df['question2'][0].split(' ')))))
Number of words in question1 in row1
['what', 'is', 'the', 'step', 'by', 'step', 'guide', 'to', 'invest', 'in', 'share', 'market',
'in', 'india?']
_____
Number of words in question2 in row2
['what', 'is', 'the', 'step', 'by', 'step', 'guide', 'to', 'invest', 'in', 'share', 'market?']
12
In [0]:
# 6. percentage of word share in row1 ==> number of common words/number of total words in row1
len(set(map(lambda x: x.lower().strip(), df['question1'][0].split(' '))) & set(map(lambda x: x.lower
().strip(), df['question2'][0].split(' ')))) /(len(list(map(lambda x:x.lower().strip() ,df['questio
n1'][0].split(' ')))) + len(list(map(lambda x: x.lower().strip(), df['question2'][0].split(' ')))))
4
Out[0]:
0.38461538461538464
In [0]:
os.path.isfile('/content/MyDrive/My Drive/Applied AI/Case studies/1.
Quora/df fe without preprocessing train.csv')
Out[0]:
True
In [0]:
# Function to accompany all these things
if os.path.isfile('/content/MyDrive/My Drive/Applied AI/Case studies/1.
Quora/df fe without preprocessing train.csv'):
   df = pd.read_csv('/content/MyDrive/My Drive/Applied AI/Case studies/1.
Quora/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(" ")))
        \label{eq:w2} w2 = \text{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 co	How can Internet speed be increased by hacking	0	1	1	73	59	14	10	4.0
;	3	3	7	8	Why am I mentally very lonely? How can I solve	Find the remainder when [math]23^{24} [/math] i	0	1	1	50	65	11	9	0.0
,	4	4	9	10	Which one dissolve in water quikly sugar, salt	Which fish would survive in salt water?	0	3	1	76	39	13	7	2.0
4														<u>F</u>

3.1 Data Analysis in extracted features

```
In [0]:
```

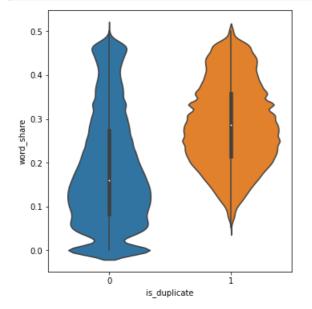
```
print('min number of words in a question1: ',min(df['q1_n_words']) )
print('min number of words in a question2: ',min(df['q2_n_words']) )
print('Number of question wiht min length [question1]: ', len(df[df['q1_n_words']==1]))
print('Number of question wiht min length [question2]: ', len(df[df['q2_n_words']==1]))
min number of words in a question1: 1
min number of words in a question2: 1
Number of question wiht min length [question1]: 67
Number of question wiht min length [question2]: 24
```

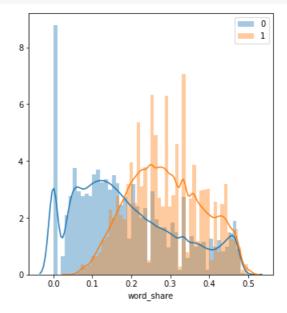
3.2 Featured word share

```
In [0]:
```

```
plt.figure(figsize=(12,6))
plt.subplot(1,2,1)
sns.violinplot(x='is_duplicate', y='word_share', data=df)
```

```
plt.subplot(1,2,2)
sns.distplot(df[df['is_duplicate']==0]['word_share'], label='0')
sns.distplot(df[df['is_duplicate']==1]['word_share'], label='1')
plt.legend()
plt.show()
```



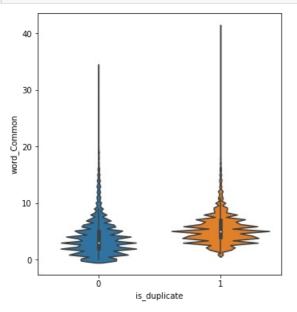


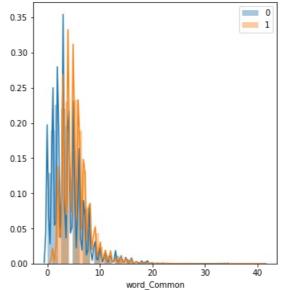
3.3 Word common

In [0]:

```
plt.figure(figsize=(12,6))
plt.subplot(1,2,1)
sns.violinplot(x='is_duplicate', y='word_Common', data=df)

plt.subplot(1,2,2)
sns.distplot(df[df['is_duplicate']==0]['word_Common'], label='0')
sns.distplot(df[df['is_duplicate']==1]['word_Common'], label='1')
plt.legend()
plt.show()
```





4.Preprocessing

- · Removing html tags
- Removing Punctuations
- · Performing stemming

- · Removing Stopwords
- · Expanding contractions etc.

```
def preprocess(x):
    x = x.str.lower()
    #expanding contradictions
    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)
    #matches any non-alpha numeric a d substitue them with space ie ' '
    pattern = re.compile('\W')
    if type(x) ==type(''):
     x = re.sub(pattern, '', x)
    #stemming the words
    porter = PorterStemmer()
    if type(x) == type(''):
     x = porter.stem(x)
     example = BeautifulSoup(x)
     x = example.get_text()
    return x
```

5. Extracting 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 lengthh 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: https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
- fuzz_partial_ratio: https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
- token_sort_ratio: https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
- token_set_ratio: 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))

```
print(len(set(['a','b','c']) & (set(['b','c', 'd']))))
```

In [0]:

2

```
Stop Words = stopwords.words('english')
SAFE DIV = 0.0001
def get token features(q1, q2):
    token featues = [0.0]*10
    #split the questions into tokens
    q1\_tokens = q1.split()
    q2 \text{ tokens} = q2.\text{split()}
    if (q1 \text{ tokens}==0) or (q2 \text{ tokens}==0):
        return get token features
    #remove stop words in question
    q1 words = set([i for i in q1 tokens if i not in Stop Words])
    q2 words = set([i for i in q2 tokens if i not in Stop Words])
    #get the stop words in question
    \verb|q1_stop_words| = \verb|set([i for i in q1_tokens if i in Stop_Words])| \\
    q2 stop words = set([i for i in q2 tokens if i in Stop Words])
    #get the common non stop word from question
    common word count = len(q1 words & q2 words)
    #get the common stopword from question
    common stop word count = len(q1 stop words & q2 stop words)
    #get the common token (ie before removing stop words)
    common_token_count = len(set(q1_tokens) & set(q2_tokens))
    token feature[0] = common word count/(min(len(q1 words)&len(q2 words))+SAFE DIV)
    token feature[1] = common word count/max((len(q1 words)&len(q2 words))+SAFE DIV)
    token_feature[2] = common_stop_word_count/(min(len(q1_stop_words)&len(q2_stop_words))+SAFE_DIV)
```

```
token_feature[3] = common_stop_word_count/(max(len(q1_stop_words)&len(q2_stop_words))+SAFE_DIV)
token_feature[4] = common_token_count/(min(len(q1_tokens)&len(q2_tokens))+SAFE_DIV)
token_feature[5] = common_token_count/(max(len(q1_tokens)&len(q2_tokens))+SAFE_DIV)

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

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

#difference bw length of two questions
token_feature[8] = abs(len(q1_tokens) - len(q2_tokens))

#average of length of two questions
token_feature[9] = (len(q1_tokens) + len(q2_tokens))/2

return token_feature
```

```
#check what distance.lcsubstrings return
print(list(distance.lcsubstrings('Kevin peterson', 'Alviron peterson'))[0])
print(len(list(distance.lcsubstrings('Kevin peterson', 'Alviron peterson'))[0]))
```

n peterson

In [0]:

```
#get the substring ratio
def get_longest_substring_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 get_token_features(q1, q2):
    token features = [0.0]*10
    # Converting the Sentence into Tokens:
    q1_tokens = q1.split()
    q2 \text{ tokens} = q2.\text{split()}
    if len(q1 tokens) == 0 or <math>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)
```

```
COMEN TESTUTES[0] - CONNICON COMEN CONTROL / (MSA/TEN/AT COMENS), TEN/AS COMENS)) + DATE DIV)
       # Last word of both question is same or not
       token features[6] = int(q1 tokens[-1] == q2 tokens[-1])
       # First word of both question is same or not
       token features[7] = int(q1 tokens[0] == q2 tokens[0])
       token features[8] = abs(len(q1 tokens) - len(q2 tokens))
       #Average Token Length of both Questions
       token features[9] = (len(q1 tokens) + len(q2 tokens))/2
       return token features
# get the Longest Common sub string
def get_longest_substr_ratio(a, b):
       strs = list(distance.lcsubstrings(a, b))
       if len(strs) == 0:
             return 0
       else:
             return len(strs[0]) / (min(len(a), len(b)) + 1)
def extract features(df):
       # preprocessing each question
       df["question1"] = df["question1"].fillna("").apply(preprocess)
       df["question2"] = df["question2"].fillna("").apply(preprocess)
       print("token features...")
       # Merging Features with dataset
       token_features = df.apply(lambda x: get_token_features(x["question1"], x["question2"]), axis=1)
       df["cwc min"]
                                          = list(map(lambda x: x[0], token_features))
       df["cwc max"]
                                          = list(map(lambda x: x[1], token features))
       df["csc min"]
                                          = list(map(lambda x: x[2], token features))
       df["csc max"]
                                          = list(map(lambda x: x[3], token_features))
       df["ctc_min"]
                                          = list(map(lambda x: x[4], token_features))
                                           = list(map(lambda x: x[5], token_features))
       df["ctc max"]
       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
       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)
       \label{eq:condition} $$ df["longest_substr_ratio"] = df.apply(lambda x: get_longest_substr_ratio(x["question1"], x["question1"], x["question
estion2"]), axis=1)
       return df
In [0]:
os.path.exists('/content/MyDrive/My Drive/Applied AI/Case studies/1. Quora/nlp features train.csv'
Out[0]:
True
```

```
if os.path.isfile('/content/MyDrive/My Drive/Applied AI/Case studies/1.
Quora/nlp_features_train.csv'):
    df = pd.read_csv('/content/MyDrive/My Drive/Applied AI/Case studies/1.
Quora/nlp_features_train.csv',encoding='latin-1')
    df.fillna('')
else:
    print("Extracting features for train:")
    df = pd.read_csv("train.csv")
    df = extract_features(df)
    df.to_csv("nlp_features_train.csv", index=False)
df.head(2)
```

Out[0]:

	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														Þ

6. Analysis of extracted Fuzzy features

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

```
In [0]:
```

```
print((np.dstack([['i am prem kumar'], ['i am a data scientist']]).flatten()))
print(len(np.dstack([['i am prem kumar'], ['i am a data scientist']]).flatten()))

['i am prem kumar' 'i am a data scientist']

In [0]:

df_duplicate = df[df['is_duplicate']==0]
df_nonduplicate = df[df['is_duplicate']==1]

# 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([df_nonduplicate['question1'], df_nonduplicate['question2']]).flatten()

#no of data points in duplicate and non-duplicate
print ("Number of data points in class 1 (duplicate pairs) :",len(p))
print ("Number of data points in class 1 (duplicate pairs) : 510054
Number of data points in class 0 (non duplicate pairs) : 298526
```

In [0]:

```
#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')
```

```
# reading the text files and removing the Stop Words:
textp_w = open('/content/MyDrive/My Drive/Applied AI/Case studies/1. Quora/train_p.txt', encoding=
'latin-1').read()
textn_w = open('/content/MyDrive/My Drive/Applied AI/Case studies/1. Quora/train_n.txt', encoding=
'latin-1') read()
```

```
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

6.1Word cloud

```
In [0]:
```

```
stop_words = set(Stop_Words)
stop_words.add("said")
stop_words.add("br")
stop_words.add(" ")

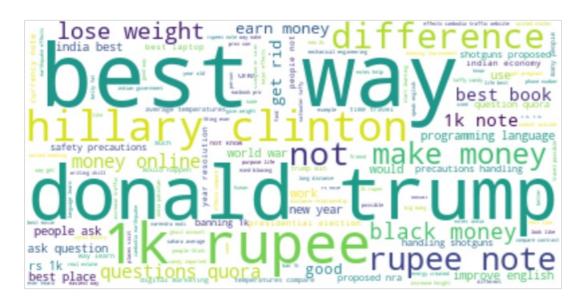
stop_words.remove("not")
stop_words.remove("no")
```

In [0]:

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

plt.figure(figsize=(12,8))
print ("Word Cloud for Duplicate Question pairs")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

Word Cloud for Duplicate Question pairs



In [0]:

```
wc = WordCloud(background_color='white', max_words=len(textn_w), stopwords=stop_words)
wc.generate(textn_w)

plt.figure(figsize=(12,8))
print ("Word Cloud for Non Duplicate Question pairs")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

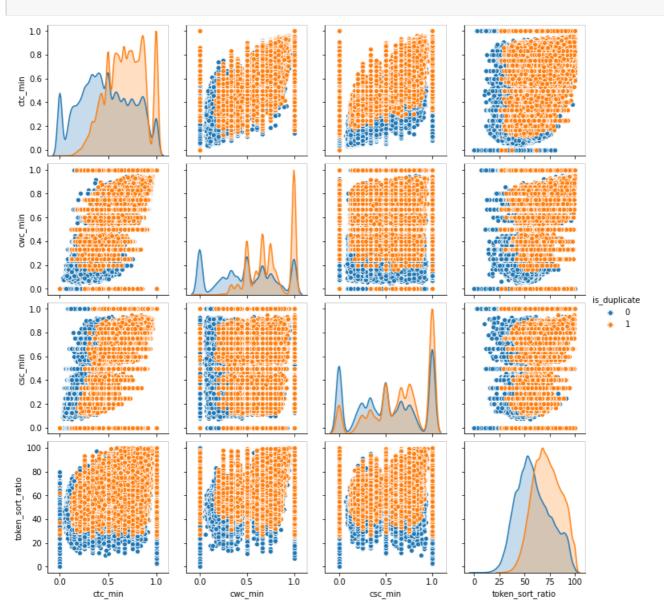
Word Cloud for Non Duplicate Question pairs





6.2 Pair plot

```
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()
```



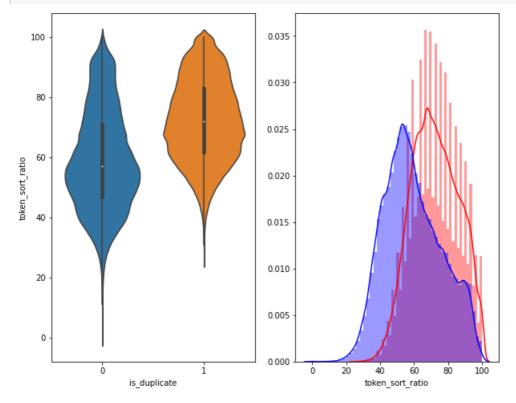
6.3 Violin Plot

In [0]:

```
# 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:] ,)

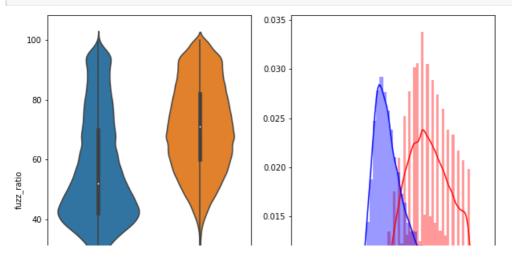
plt.subplot(1,2,2)
sns.distplot(df[df['is_duplicate'] == 1.0]['token_sort_ratio'][0:] , label = "1", color = 'red')
sns.distplot(df[df['is_duplicate'] == 0.0]['token_sort_ratio'][0:] , label = "0" , color = 'blue' )
plt.show()
```

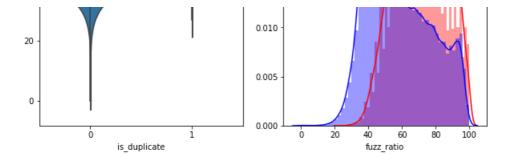


```
plt.figure(figsize=(10, 8))

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()
```





7. Visualisation of features using t-SNE

In [0]:

```
#taking only sample of 5000 to visualize it
df_sampled = df[0:5000]
df.head()
```

Out[0]:

	ic	d	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	firs
•) (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	
,	I 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	
:	2 2	2	5	6	how can i increase the speed of my internet co	how can internet speed be increased by hacking	0	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	
;	3 3	3	7	8	why am i mentally very lonely how can i solve	find the remainder when math 23 24 math i	0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	
	1 4	4	9	10	which one dissolve in water quikly sugar salt	which fish would survive in salt water	0	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	
4															Þ

In [0]:

```
X = MinMaxScaler().fit_transform(df_sampled[['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 = df_sampled['is_duplicate'].values
```

7.1 t-SNE - 2D

```
tsne_2d = TSNE(n_components=2, init='random', random_state=42, method='barnes_hut', n_iter=1000, ve
rbose=2, angle=0.5).fit_transform(X)

[t-SNE] Computing 91 nearest neighbors...
```

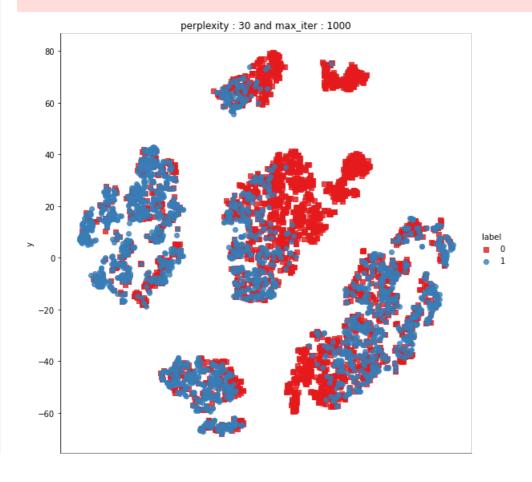
```
[t-SNE] Indexed 5000 samples in 0.021s...
[t-SNE] Computed neighbors for 5000 samples in 0.391s...
[t-SNE] Computed conditional probabilities for sample 1000 / 5000
[t-SNE] Computed conditional probabilities for sample 2000 / 5000
```

```
[L-SME] COMPUTED CONDITIONAL PROBABILITIES FOR SAMPLE 2000 / SUUD
[t-SNE] Computed conditional probabilities for sample 3000 / 5000
[t-SNE] Computed conditional probabilities for sample 4000 / 5000
[t-SNE] Computed conditional probabilities for sample 5000 / 5000
[t-SNE] Mean sigma: 0.116557
[t-SNE] Computed conditional probabilities in 0.315s
[t-SNE] Iteration 50: error = 82.2403336, gradient norm = 0.0485435 (50 iterations in 2.200s)
       Iteration 100: error = 70.3681030, gradient norm = 0.0092659 (50 iterations in 1.621s)
[t-SNE] Iteration 150: error = 68.5769806, gradient norm = 0.0058538 (50 iterations in 1.520s)
[t-SNE] Iteration 200: error = 67.7360840, gradient norm = 0.0040857 (50 iterations in 1.573s)
[t-SNE] Iteration 250: error = 67.2339020, gradient norm = 0.0052474 (50 iterations in 1.577s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.233902
[t-SNE] Iteration 300: error = 1.7625930, gradient norm = 0.0011850 (50 iterations in 1.706s)
[t-SNE] Iteration 350: error = 1.3605168, gradient norm = 0.0004797 (50 iterations in 1.684s)
[t-SNE] Iteration 400: error = 1.1939461, gradient norm = 0.0002759 (50 iterations in 1.691s)
[t-SNE] Iteration 450: error = 1.1049948, gradient norm = 0.0001849 (50 iterations in 1.724s)
[t-SNE] Iteration 500: error = 1.0508957, gradient norm = 0.0001383 (50 iterations in 1.700s)
[t-SNE] Iteration 550: error = 1.0155830, gradient norm = 0.0001115 (50 iterations in 1.698s)
[t-SNE] Iteration 600: error = 0.9920100, gradient norm = 0.0000971 (50 iterations in 1.714s)
[t-SNE] Iteration 650: error = 0.9761610, gradient norm = 0.0000874 (50 iterations in 1.707s)
[t-SNE] Iteration 700: error = 0.9652733, gradient norm = 0.0000820 (50 iterations in 1.732s)
[t-SNE] Iteration 750: error = 0.9575369, gradient norm = 0.0000762 (50 iterations in 1.690s)
[t-SNE] Iteration 800: error = 0.9517581, gradient norm = 0.0000729 (50 iterations in 1.714s)
[t-SNE] Iteration 850: error = 0.9465392, gradient norm = 0.0000655 (50 iterations in 1.684s)
[t-SNE] Iteration 900: error = 0.9419289, gradient norm = 0.0000655 (50 iterations in 1.697s)
[t-SNE] Iteration 950: error = 0.9379401, gradient norm = 0.0000598 (50 iterations in 1.696s)
[t-SNE] Iteration 1000: error = 0.9343591, gradient norm = 0.0000603 (50 iterations in 1.684s)
[t-SNE] KL divergence after 1000 iterations: 0.934359
```

```
df_2d = pd.DataFrame({'x':tsne_2d[:,0], 'y':tsne_2d[:,1],'label':y})

# draw the plot in appropriate place in the grid
sns.lmplot(data=df_2d, 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()

/usr/local/lib/python3.6/dist-packages/seaborn/regression.py:573: UserWarning: The `size`
parameter has been renamed to `height`; please update your code.
warnings.warn(msg, UserWarning)
```



```
-80
          -60
                    -40
                               -20
                                          0
                                                     20
                                                               40
                                                                          60
                                                                                    80
```

7.2 t-SNE - 3D

```
In [0]:
```

```
tsne 3d = TSNE(
   n components=3,
   init='random', # pca
   random state=101,
   method='barnes hut',
   n iter=1000,
   verbose=2,
   angle=0.5
).fit_transform(X)
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.017s...
[t-SNE] Computed neighbors for 5000 samples in 0.378s...
[t-SNE] Computed conditional probabilities for sample 1000 / 5000
[t-SNE] Computed conditional probabilities for sample 2000 / 5000
[t-SNE] Computed conditional probabilities for sample 3000 / 5000
[t-SNE] Computed conditional probabilities for sample 4000 / 5000
[t-SNE] Computed conditional probabilities for sample 5000 / 5000
[t-SNE] Mean sigma: 0.116557
[t-SNE] Computed conditional probabilities in 0.310s
[t-SNE] Iteration 50: error = 80.3825836, gradient norm = 0.0316220 (50 iterations in 9.710s)
[t-SNE] Iteration 100: error = 69.1291580, gradient norm = 0.0034171 (50 iterations in 4.833s)
[t-SNE] Iteration 150: error = 67.6390839, gradient norm = 0.0017523 (50 iterations in 4.328s)
[t-SNE] Iteration 200: error = 67.0798187, gradient norm = 0.0011316 (50 iterations in 4.2868)
[t-SNE] Iteration 250: error = 66.7545319, gradient norm = 0.0010951 (50 iterations in 4.253s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 66.754532
[t-SNE] Iteration 300: error = 1.4973605, gradient norm = 0.0006769 (50 iterations in 5.712s)
[t-SNE] Iteration 350: error = 1.1548493, gradient norm = 0.0001913 (50 iterations in 7.629s)
[t-SNE] Iteration 400: error = 1.0096524, gradient norm = 0.0000907 (50 iterations in 7.676s)
[t-SNE] Iteration 450: error = 0.9380181, gradient norm = 0.0000588 (50 iterations in 7.538s)
[t-SNE] Iteration 500: error = 0.8995014, gradient norm = 0.0000524 (50 iterations in 7.472s)
[t-SNE] Iteration 550: error = 0.8804497, gradient norm = 0.0000466 (50 iterations in 7.407s)
[t-SNE] Iteration 600: error = 0.8691350, gradient norm = 0.0000411 (50 iterations in 7.322s)
[t-SNE] Iteration 650: error = 0.8599784, gradient norm = 0.0000348 (50 iterations in 7.240s)
[t-SNE] Iteration 700: error = 0.8518915, gradient norm = 0.0000336 (50 iterations in 7.289s)
[t-SNE] Iteration 750: error = 0.8449173, gradient norm = 0.0000285 (50 iterations in 7.308s)
[t-SNE] Iteration 800: error = 0.8392022, gradient norm = 0.0000273 (50 iterations in 7.289s)
[t-SNE] Iteration 850: error = 0.8342683, gradient norm = 0.0000274 (50 iterations in 7.265s)
[t-SNE] Iteration 900: error = 0.8303084, gradient norm = 0.0000280 (50 iterations in 7.222s)
[t-SNE] Iteration 950: error = 0.8269118, gradient norm = 0.0000239 (50 iterations in 7.204s)
[t-SNE] Iteration 1000: error = 0.8239461, gradient norm = 0.0000245 (50 iterations in 7.211s)
[t-SNE] KL divergence after 1000 iterations: 0.823946
```

```
def configure plotly browser state():
 import IPython
 display(IPython.core.display.HTML('''
        <script src="/static/components/requirejs/require.js"></script>
        <script>
          requirejs.config({
              base: '/static/base',
              plotly: 'https://cdn.plot.ly/plotly-latest.min.js?noext',
          });
        </script>
        '''))
```

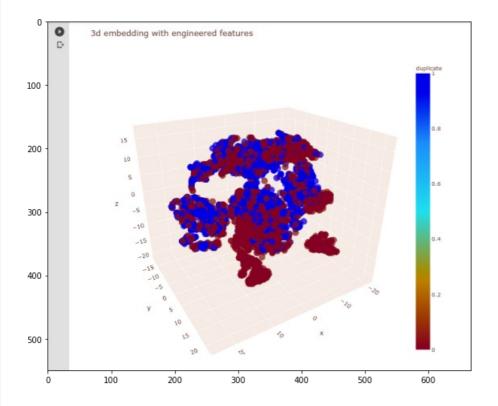
```
configure plotly browser state()
trace1 = go.Scatter3d(
  x=tsne 3d[:,0],
```

```
y=tsne_3d[:,1],
z=tsne_3d[:,2],
mode='markers',
marker=dict(
    sizemode='diameter',
    color = y,
    colorscale = 'Portland',
    colorbar = dict(title = 'duplicate'),
    line=dict(color='rgb(255, 255, 255)'),
    opacity=0.75
)
)

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

```
In [0]:
```

```
img = cv2.imread('/content/MyDrive/My Drive/Applied AI/Case studies/1. Quora/plotly-fig.png')
plt.figure(figsize=(12,8))
plt.imshow(img)
```



8. TFIDF-W2V

In [4]:

df = pd.read_csv('/home/ubuntu/Quora/*Assign 22 -Quora/nlp_features_train.csv', encoding='latin-1'
)
df.head()

Out[4]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	 ctc_max	last_word_eq	first_word_
0	0	1	2	what is the step by step guide to invest in sh	what is the step by step guide to invest in sh	0	0.999980	0.833319	0.999983	0.999983	 0.785709	0.0	
1	1	3	4	what is the story of kohinoor koh i noor dia	what would happen if the indian government sto	0	0.799984	0.399996	0.749981	0.599988	 0.466664	0.0	
2	2	5	6	how can i increase the speed of my internet co	how can internet speed be increased by hacking	0	0.399992	0.333328	0.399992	0.249997	 0.285712	0.0	
3	3	7	8	why am i mentally very lonely how can i solve	find the remainder when math 23 24 math i	0	0.000000	0.000000	0.000000	0.000000	 0.000000	0.0	
4	4	9	10	which one dissolve in water quikly sugar salt	which fish would survive in salt water	0	0.399992	0.199998	0.999950	0.666644	 0.307690	0.0	

5 rows × 21 columns

```
In [5]:

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

Note:

- We need to apply tfidf weightedW2V on cleaned data (nlp_features_train.csv) rather than train.csv.
- Also we need to split the data before applying tf-idf weighted W2V

In [6]:

```
#we need only questions1 and question2 and id to merge using it
df = df[['id', 'question1', 'question2', 'is_duplicate']]
df.head()
```

Out[6]:

	id	question1	question2	is_duplicate
0	0	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	what is the story of kohinoor koh i noor dia	what would happen if the indian government sto	0
2	2	how can i increase the speed of my internet co	how can internet speed be increased by hacking	0
3	3	why am i mentally very lonely how can i solve	find the remainder when math 23 24 math i	0
4	4	which one dissolve in water quikly sugar salt	which fish would survive in salt water	0

8.1 Splitting the data

```
In [7]:
```

```
print(df.shape)
print(df.iloc[:,-1:].shape)

(404290, 4)
(404290, 1)
```

In [8]:

```
df_train, df_val, y_train, y_val = train_test_split(df, df.iloc[:, -1:], test_size = 0.3, random_st
ate=0 , stratify = df.iloc[:,-1:])
df_train, df_test, y_train, y_test = train_test_split(df_train, y_train, test_size= 0.3, random_sta
te=0, stratify = y_train)
```

In [9]:

```
print(df_train.shape)
print(df_val.shape)
print(df_test.shape)

print(y_train.shape)
print(y_val.shape)
print(y_test.shape)

(198102, 4)
(121287, 4)
(84901, 4)
(198102, 1)
(121287, 1)
(84901, 1)
```

In [16]:

```
df train.head()
```

Out[16]:

	id	question1	question2	is_duplicate
209577	209577	how do i use shall and should will and would	how do i use will and would in a sentence	0
17392	17392	is writing a good profession	can writing be a good profession	1
14251	14251	were there atheists in ancient mesopotamian ci	were there atheists in ancient persia	0
265830	265830	has india really isolated pakistan globally i	what do you think of russian troops arriving i	0
123216	123216	which are the most visited temples of chhattis	which are the most visited temples in chhattis	1

In [17]:

```
df_val.head()
```

Out[17]:

	id	question1	question2	is_duplicate
40373	40373	what is the name of the italian song goes some	what is the title of the slow song that goes I	0
218089	218089	what are some ways for you to lose 40 pounds i	is it safe to lose 40 pounds in 2 weeks	1
184729	184729	what are some good ways to detoxify one own body	what are the most effective ways to detoxify y	1
218907	218907	how many hours of deep sleep delta wave porti	what is the ideal amount of sleep time that a \dots	0
224215	224215	what are some important lesson you learn from	what are some important lessons you learned ou	0

In [18]:

```
df_test.head()
```

Out[18]:

	id	question1	question2	is_duplicate
372980	372980	how can i increase the traffic on my blog www	how do i increase traffic on my site	1
14252	14252	what is the difference between pu leather and	are leather vans shoes made of real leather	0
102303	102303	which is correct 2 dozen of eggs cost 30 rup	which one is correct 1 look out of the windo	0
274316	274316	what are the best one liners	what are the best one liners in hindi	0
370597	370597	how can i start making money using internet	what is the easiest way to earn money using in	1

8.2 IDF of words in questions

In [10]:

```
train_questions = df_train['question1'] + df_train['question2']
train_questions.head()
```

Out[10]:

```
209577 how do i use shall and should will and would ...
17392 is writing a good profession can writing be a ...
14251 were there atheists in ancient mesopotamian ci...
265830 has india really isolated pakistan globally i...
123216 which are the most visited temples of chhattis...
dtype: object
```

```
vec = TfidfVectorizer(min df = 25)
 vec.fit transform(train questions)
 #zip of (word, idf values of word) and then dict it
 word2tfidf = dict(zip(vec.get feature names(), vec.idf ))
 In [20]:
 len(word2tfidf)
Out[20]:
7316
Note:
     • As said in email, i tried different min df values of 10, 20, 25 and it gives 12.8k, 8.5k, and 7.3k respectively. I am using min df =
            25 for 2 reasons. First one is it reduces the dimension and the second one, the questions are almost similar to each other and
            the words in questions repeating again and again
 In [21]:
 #sum of all idf values which will be useful to find weighted tfidf w2v ==> ((idf w1*vec w1) + (idf w2*vec w1)) + (idf w2*vec w1)) + (idf w2*vec w1) + (idf w2*vec w1)) + (idf w2*vec w
  f w2*vec w2) +...+(idf wn*vec wn))/(idf w1+idf w2+...+idf wn)
 #https://kite.com/python/answers/how-to-sum-the-values-in-a-dictionary-in-
 python#:~:text=Use%20sum()%20to%20sum,values%20from%20the%20previous%20step.
 sum idf = sum(word2tfidf.values())
 print(sum idf)
 63219.72464508459
```

8.3 Loading glove in spacy

```
In [2]:
```

```
glove = spacy.load('en_core_web_sm')
print(glove)
```

<spacy.lang.en.English object at 0x7f31f0a816a0>

```
In [16]:
```

```
#see what glove return when we given a sentence and its type
print(glove(df_train['question1'].iloc[0]))
print(type(glove(df_train['question1'].iloc[0])))
```

how do i use shall and should will and would can and could in a sentence <class 'spacy.tokens.doc.Doc'> $\$

In [17]:

```
for i in glove(df_train['question1'].iloc[0]): #we dont need to split it and i.vector gives the
vecotr representation of the word
    print((i, i.vector))
    print(len(i.vector)) #which gives dimension of each word
```

```
(how, array([-0.25642753, -1.651585], -2.1492958], -2.841151], -0.38527584, 2.9442854], 1.1803646], 0.25771916, 4.2077155], -3.7638094], 0.8159517], -1.179973], -1.6908273], -0.77429676, -1.0198613], 0.25888532], 2.2379441], -2.775265], 2.6454005], -3.402844], -0.8123921], 0.3909678], 1.4348501], 0.06442726, -0.08965635, 0.06323573], 1.1758895], -1.3840092], 1.2733849], -0.3706682], 8.229353], -3.9226766], 3.9517229], 1.2850422], -1.9552982].
```

```
-3.0285926 , 0.51044536, 1.8431818 , 0.16051283, 5.5677285 ,
         -2.5549846 , 2.0888383 , -4.9345465 , 2.7583025 , -2.8520746 ,
         0.67331225, -1.9051372 , -1.1828032 , -3.6110253 , 0.7943965 ,
        -1.1050334 , 0.7351209 , 7.117074 , 0.3570062 , 6.0055594 , 0.6539494 , -2.1824207 , -0.97305405 , 0.886073 , 0.5186693 , -2.7837663 , -1.7447785 , -2.0322268 , 2.2677383 , 1.1464663 ,
         -0.67210156, -2.8589587 , -2.7366796 , -1.2349586 , -1.2178357 ,
        -0.86662954, 2.3929112, -3.6356106, 0.84763104, -3.2111478,
        1.2897842 , -0.14211886, 2.671087 , -0.1927194 , 0.95919174, -1.9453676 , 2.4562008 , -1.5821563 , -1.7843827 , 1.3448919 , 0.17707098, 2.9111865 , -0.8712585 , -2.3777854 , -1.6727947 , -1.1056525 , -0.16875213, 1.3103461 , 0.54000896, 0.67570496,
          4.0727477 ], dtype=float32))
96
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         -0.1344763 , 1.6927705 , 0.6454431 , -0.81977314, 1.7133493 ,
         -1.2242761 , -1.5546625 , -0.33322573, -0.38228086, 3.5537271 ,
         3.579337 , -4.769132 , -3.966068 , 2.0802655 , -0.25107455,
        -1.3138151 , 1.1911623 , 0.2777772 , 2.3845375 , 0.7138606 , 0.98208255, -1.1053947 , 0.1980946 , 1.0509872 , -3.2584171 ,
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         -3.9811914 , 1.0234544 , -1.1655209 , 1.6853355 , -1.1085854 ,
         -3.9195406 \ , \ -1.3738762 \ , \ 0.31924742, \ 0.83503556, \ -0.9004183 \ ,
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         1.0614992 , -3.9281464 , -1.0820308 , -3.65922 , 0.31834733,
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        4.7620025 , 2.4852495 , -0.68872845 , 1.1090326 , -1.8962581 , 3.349251 , 1.6775932 , 0.02843451 , 0.06870532 , 3.410138 , -0.918211 , 2.4596777 , -0.6254596 , -7.150746 , -2.7112927 ,
         -1.0749812 ], dtype=float32))
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        -5.92462301e-01, 2.27682501e-01, -1.23571134e+00, -1.10804915e-01,
         5.28477144e+00, -4.66782242e-01, 1.65800393e-01, -1.69914269e+00,
        -2.26735210e+00, -6.22627914e-01, -4.31932831e+00, 1.43344069e+00,
        1.85943019e+00, 7.39773846e+00, -1.94502378e+00, -9.73612070e-04, -5.05453777e+00, -8.20800245e-01, -1.06380332e+00, 2.42890906e+00, -2.19072151e+00, -1.70662570e+00, 7.29388297e-01, 5.30261397e-01,
        -4.06706762e+00, 6.11344433e+00, 1.18741345e+00, 7.60611892e-01,
         -1.19192529e+00, -3.38866568e+00, 1.05509186e+00, -2.08307362e+00,
         2.08184624e+00, -1.95567250e+00, 2.03372574e+00, 3.80959392e+00,
        -1.90612447e+00, -1.76105595e+00, -1.87076545e+00, 2.46954107e+00, 5.67326903e-01, -2.68147302e+00, -3.10673785e+00, 3.77704453e+00, -2.85054803e-01, 2.48266816e-01, -2.91387582e+00, 7.89763153e-01,
          5.76890039e+00, 6.27124739e+00, 1.27420485e-01, -5.99805117e-01,
         -1.29484272e+00, -1.64279795e+00, -1.27427125e+00, -5.41530561e+00,
        -8.28331113e-01, 1.09653616e+00, -2.38027692e-01, -1.62775412e-01, 2.59898067e-01, 1.85842490e+00, -2.41807365e+00, 3.96174192e-02, 2.27299166e+00, 2.86062384e+00, 2.01246691e+00, 1.11632562e+00,
          9.46908057e-01, -3.02326649e-01, -2.02290797e+00, -6.70594454e-01,
          6.18272483e-01, 3.09108925e+00, 1.63820696e+00, -3.06159377e-01,
          3.86954069e+00, 3.48318505e+00, -7.98989654e-01, -2.45954418e+00,
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         -2.0806403 , 2.1253698 , 3.5897965 , -0.09307623, 1.0125511 , 0.02710414, 2.7443326 , -0.98280233, 2.572997 , 3.490713 ,
          3.0911255 , -3.3607087 , -0.5239498 , -0.04480743, 0.03356773,
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          0.0440208 , 4.351934 , -3.2287283 , -0.2567569 , -0.2235949 ,
         -2.2217908 , 1.2189921 , -1.7828828 , -3.6545582 , 1.8776078 ,
         -4.468121 , -2.0717325 , -1.1232454 , -0.16662705, -0.9959103 ,
         1.1080636 , 0.7803321 , 0.61057276, 0.8831149 , -0.6006123 ,
         3.197847 , 6.432417 , 0.7935058 , 2.8843098 , -1.3444579 ,
         -1.1025096 , 3.453412 , 1.939812 , -0.8211528 , 1.3005093 ,
```

```
2.155103 , -2.2803574 , -0.821892 , 4.580947 , -4.2441573 ,
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         -0.97301096, -1.8893895 , 2.4958305 , -4.4917374 , -0.81330055,
         -0.03684807], dtype=float32))
96
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          -0.5275141 \ , \ -0.95231676, \ -3.1807559 \ , \ -0.01380289, \ -0.9311544 \ , \\
         -1.2969286 , 0.30910328, 0.69077057, 0.43853864, -1.4694015 ,
         -1.6640726 , 4.3107023 , 1.4078577 , -3.0032415 , 1.2277792 ,
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         2.834002 , -1.8379993 , 0.8137278 , 2.0027342 , -0.3276403 , -0.14186215, 2.5559177 , 1.9241382 , 0.38220072, -0.15598056, -1.272683 , 1.4823936 , -0.20603439 , -2.6638765 , -0.46880865 , -0.61137 , -2.4376752 , -2.3403718 , 0.3913221 , 3.9619288 ,
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         -2.0404482 , 4.0485687 , -0.16821426, 2.877113 , 3.4919543 ,
          3.9471493 , -2.6206865 , -5.4289236 , -0.7024258 , -1.1976585 ,
         -1.7865458 , -3.1823862 , 0.18244746, 0.3150241 , 0.8171015 ,
           4.0061536 , 1.4125323 , -0.8460728 , -2.0482717 , 0.18916392,
         3.1090589 , 0.4750973 , -1.9381555 , -2.1245928 , -0.53330255, -0.7507608 , -2.902802 , 1.1151662 , 1.6742994 , 1.0107236 ,
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96
(should, array([ 5.55123568e-01, -2.47891158e-01, -2.50211883e+00, -1.09389138e+00,
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          -1.34903252e+00, -4.14042521e+00, -3.58748794e-01, 3.31533670e-01,
           3.40512371e+00, 8.76843810e-01, -1.41649199e+00, -2.69891691e+00,
          1.65419984e+00, 2.03910375e+00, -2.25035191e+00, 1.36553872e+00,
         -1.53225577e+00, 2.43189549e+00, -2.92043686e+00, 1.80630052e+00, 1.27025807e+00, 7.90006161e-01, 3.59393644e+00, 1.41492295e+00, 1.37325525e-02, -3.35233712e+00, -8.33713055e-01, -5.90884089e-02,
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          3.31145048e+00, 4.93912506e+00, -4.35134268e+00, 1.53379428e+00,
          4.77122188e-01, 3.41002154e+00, -2.34708834e+00, -1.00840151e+00,
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         -1.77582026e+00, 4.39793158e+00, -7.68976569e-01, 3.54227066e-01,
          1.06844890e+00, 2.55257869e+00, 3.79814005e+00, -4.47737408e+00,
         -1.27869022e+00, 5.37174273e+00, -1.47825503e+00, -1.08680740e-01, 2.09526038e+00, 5.02430558e-01, 1.49691737e+00, -2.71526903e-01, 4.26632315e-01, -5.54847717e-03, -1.67395914e+00, -1.14735389e+00,
         -1.65670723e-01, -1.20930374e+00, -2.97780919e+00, -3.99214745e+00,
         -3.22391939e+00, 1.05087018e+00, -2.29342389e+00, -1.52229452e+00,
         -2.43692803e+00, 5.83139849e+00, -3.01274896e-01, 3.21656299e+00, 4.72599173e+00, -1.96540737e+00, -1.42795658e+00, 5.59607744e-01],
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96
(, array([-1.02923608e+00, -1.69119155e+00, -1.15366387e+00, -1.25511348e-01,
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```

```
1.0J1J4ZZOE-U1, -Z.0JZZJUJ/ETUU,
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```

```
8.4 Tfidf-W2V of training data
In [22]:
glove = spacy.load('en core web sm')
X train question1 TfidfW2V = []
for row in tqdm(list(df train['question1'].values)):
   doc1 = glove(row)
                           # it will return <class spacy.tokens.doc.Doc> which inclues word and it
s vector representation
    tfidf vec = np.zeros((len(doc1), len(doc1[0].vector))) # it returns the shape of length of th
e question we have(len(df train['question1'].iloc[0])), shape of vector representation of each wo
rd)
    for word in doc1:
       vec1 = word.vector
            idf = word2tfidf[str(word)] # we are getting the idf value of word from word2tfidf v
hich we found before
        except:
            idf = 0
                                          # if there is no such word found in word2tfidf put idf =
        tfidf vec += vec1 * idf
    tfidf_vec = tfidf_vec.mean(axis=0)
    X train question1 TfidfW2V.append(tfidf vec/sum idf)
# For question2
X train question2 TfidfW2V = []
for row in tqdm(df_train['question2'].values):
    doc1 = glove(row)
    tfidf vec = np.zeros((len(doc1), len(doc1[0].vector)))
    for word in doc1:
       vec1 = word.vector
           idf = word2tfidf[str(word)]
        except:
           idf = 0
        tfidf vec += vec1 * idf
    tfidf vec = tfidf vec.mean(axis=0)
    X train question2 TfidfW2V.append(tfidf vec/sum idf)
100%| 198102/198102 [22:27<00:00, 147.05it/s]
              | 198102/198102 [22:21<00:00, 147.72it/s]
In [231:
(pd.DataFrame(list(X_train_question1_TfidfW2V), index=df_train.index)).head()
Out[23]:
                                                        6
                                                                               9 ...
                                                                                                87
                                                                                        86
```

209577 0.001408 0.000327 0.000356 0.000416 0.001152 0.000225 0.001099 0.000287 0.000180 ... 0.000180 ... 0.000187 0.001495 0.001495 0.001495 0.001495 0.001495 0.001495 0.001495 0.001498 0.00

17392 0.000516 0.00057 0.000124 0.000089 0.00012 0.000848 0.000239 0.000039 0.000056 0.000125 0.000056

```
0.000218
4 5
                           0.000344
     14251 0.000334 0.000510 0.000159 0.000220 0.000479 0.000201 0.000521 0.000392 0.000214 0.000038 ... 0.000050 0.000384
  265830 0.000964 0.000363 0.000142 0.001105 0.000086 0.000750 0.002265 0.000686 0.001093 0.002652 ... 0.000203 0.000720 0.
   123216 0.000499 0.000644 0.000045 0.000645 0.000056 0.000088 0.000884 0.000917 0.000086 0.000066 ... 0.000612 0.001536 0.
5 rows × 96 columns
In [24]:
 \#creating \ a \ new\_df \ and \ store \ the \ values \ pf \ X\_train\_question1\_TfidfW2V, \ X\_train\_question2\_TfidfW2V \ A_train\_question2\_TfidfW2V \ A_train\_question3\_TfidfW2V \ A_train\_ques
 \label{eq:dfl_train_ql} \texttt{dfl\_train\_ql} = \texttt{pd.DataFrame} (\texttt{list}(\texttt{X\_train\_question1\_TfidfW2V}) \text{, index=df\_train.index})
                train q2 = pd.DataFrame(list(X train question2 TfidfW2V), index=df train.index)
dfl_train_ql['id'] = df_train['id']
df1 train q2['id'] = df train['id']
In [25]:
dfl_train_ql.head()
Out[25]:
  209577 0.001408 0.000327 0.000356 0.000416 0.001152 0.000225 0.001099 0.000287 0.000768 0.000180 ... 0.001495 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674 0.000674
     17392 0.000344 0.000516 0.000370 0.000124 0.000089 0.000218 0.000848 0.000239 0.000233 0.000029 ... 0.000107 0.000330 0.000239
      14251 0.000334 0.000510 0.000159 0.000220 0.000479 0.000201 0.000521 0.000392 0.000214 0.000038 ... 0.000384 0.000271 0.
  265830 0.000964 0.000363 0.000142 0.001105 0.000086 0.000750 0.002265 0.000686 0.001093 0.002652 ... 0.000720 0.000117 0.
  5 rows × 97 columns
In [26]:
 import pickle
 with open('/home/ubuntu/Quora/*Assign 22 -Quora/df1 train q1', 'wb') as f:
             pickle.dump(df1_train_q1, f)
In [27]:
import pickle
 with open('/home/ubuntu/Quora/*Assign 22 -Quora/df1_train_q2', 'wb') as f:
              pickle.dump(df1 train q2, f)
```

8.4 Tfidf-W2V of Validation data

```
In [28]:
```

```
X_val_question1_TfidfW2V = []

for row in tqdm(df_val['question1'].values):
    doc1 = glove(row)

    tfidf_vec = np.zeros((len(doc1), len(doc1[0].vector)))
    for word in doc1:
        vec1 = word.vector

    try:
        idf = word2tfidf[str(word)]
```

```
eacept.
             idf = 0
        tfidf vec += vec1*idf
    tfidf vec = tfidf vec.mean(axis=0)
    X_val_question1_TfidfW2V.append(tfidf_vec/sum_idf)
#for question2
X val question2 TfidfW2V = []
for row in tqdm(df val['question2'].values):
    doc1 = glove(row)
    tfidf vec = np.zeros((len(doc1), len(doc1[0].vector)))
    for word in doc1:
        vec1 = word.vector
        try:
            idf = word2tfidf[str(word)]
        except:
            idf = 0
        tfidf_vec += vec1*idf
    tfidf vec = tfidf vec.mean(axis=0)
    X_val_question2_TfidfW2V.append(tfidf_vec/sum_idf)
100%∣
               | 121287/121287 [13:41<00:00, 147.68it/s]
                | 121287/121287 [13:41<00:00, 147.69it/s]
In [0]:
#df val['q1 feat m'] = list(X val question1 TfidfW2V)
#df val['q2 feat m'] = list(X val question2 TfidfW2V)
In [29]:
#creating a new df and store the values pf X train question1 TfidfW2V, X train question2 TfidfW2V
dfl_val_ql = pd.DataFrame(list(X_val_question1_TfidfW2V), index=df_val.index)
df1 val q2 = pd.DataFrame(list(X val question2 TfidfW2V), index=df val.index)
df1_val_q1['id'] = df_val['id']
df1_val_q2['id'] = df_val['id']
In [30]:
df1 val q1.head()
Out[30]:
 40373 0.000159 0.000458 0.000402 0.000483 0.000130 0.000119 0.001170 0.001561 0.000635 0.000450 ... 0.000481 0.000330 0.
218089 0.000898 0.000156 0.000911 0.000556 0.000303 0.000870 0.001503 0.002291 0.000382 0.001005 ... 0.001964 0.000057 0.
184729 0.000133 0.000457 0.000055 0.000310 0.000429 0.000365 0.000877 0.001336 0.000402 0.000686 ... 0.000902 0.000764 0.
218907 0.000462 0.002448 0.001263 0.001688 0.002052 0.001278 0.001801 0.000822 0.000178 0.000191 ... 0.003103 0.002005 0.
224215 0.000054 0.000435 0.000574 0.000348 0.001170 0.000409 0.001567 0.001446 0.001041 0.000295 ... 0.001201 0.000728 0.0001728
5 rows × 97 columns
In [31]:
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/df1_val_q1', 'wb') as f:
pickle.dump(df1 val d1. f)
```

```
provide aump (arr_var_qr, r,
```

```
In [32]:
```

```
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/df1_val_q2', 'wb') as f:
    pickle.dump(df1_val_q2, f)
```

8.5 Tfidf-W2V of test data

```
In [33]:
```

```
X test question1 TfidfW2V = []
for row in tqdm(df test['question1'].values):
   doc1 = glove(row)
    tfidf_vec = np.zeros((len(doc1), len(doc1[0].vector)))
    for word in doc1:
       vec1 = word.vector
        try:
           idf = word2tfidf[str(word)]
        except:
           idf = 0
       tfidf vec += vec1*idf
    tfidf vec = tfidf_vec.mean(axis=0)
    X test question1 TfidfW2V.append(tfidf vec/sum idf)
#for question2
X \text{ test question2 TfidfW2V} = []
for row in tqdm(df test['question2'].values):
   doc1 = glove(row)
    tfidf vec = np.zeros((len(doc1), len(doc1[0].vector)))
    for word in doc1:
       vec1 = word.vector
            idf = word2tfidf[str(word)]
        except:
           idf = 0
       tfidf_vec += vec1*idf
    tfidf vec = tfidf vec.mean(axis=0)
    X_test_question2_TfidfW2V.append(tfidf_vec/sum_idf)
100%| 84901/84901 [09:40<00:00, 146.15it/s]
        | 84901/84901 [09:38<00:00, 146.78it/s]
```

In [0]:

```
#df_test['q1_feat_m'] = list(X_test_question1_TfidfW2V)
#df_test['q2_feat_m'] = list(X_test_question2_TfidfW2V)
```

In [34]:

```
#creating a new_df and store the values pf X_test_question1_TfidfW2V, X_test_question2_TfidfW2V
df1_test_q1 = pd.DataFrame(list(X_test_question1_TfidfW2V), index=df_test.index)
df1_test_q2 = pd.DataFrame(list(X_test_question2_TfidfW2V), index=df_test.index)
df1_test_q1['id'] = df_test['id']
df1_test_q2['id'] = df_test['id']
```

```
df1_test_q1.head()
Out[35]:
                      1
                               2
                                         3
                                                  4
                                                          5
                                                                           7
                                                                                             9 ...
                                                                                                       87
                                                                                                                88
 372980 0.000377 0.001172 0.000138 4.555279e- 0.000465 0.001193 0.001572 0.000303 0.000256 0.000120 ... 0.001498 0.000906
  14252 0.000528 0.002283 0.001105 4.036084e- 0.000775 0.000185 0.000425 0.001776 0.000436 0.000561 ... 0.000986 0.001245
 102303 0.000677 0.001573 0.000833 9.117768e- 0.000431 0.000549 0.00038 0.001381 0.000317 0.001411 ... 0.002414 0.000285
 274316 0.000050 0.000015 0.000009 1.674369e-
                                            0.000129
                                                    0.000316 0.000146 0.000182 0.000002 0.000020 ... 0.000116 0.000231
 370597 0.000573 0.000716 0.000578 3.668037e- 0.000186 0.000074 0.001728 0.000995 0.000444 0.000115 ... 0.001228 0.000281
5 rows × 97 columns
4
                                                                                                                 F
In [36]:
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/df1 test q1', 'wb') as f:
     pickle.dump(df1 test q1, f)
In [37]:
with open('/home/ubuntu/Quora/*Assign 22 -Quora/df1_test_q2', 'wb') as f:
     pickle.dump(df1 test q2, f)
In [39]:
print(df1_train_q1.shape)
print(df1 train q2.shape)
print(df1_val_q1.shape)
print (df1_val_q2.shape)
print (df1_test_q1.shape)
print(df1 test q2.shape)
print(y train.shape)
print(y_val.shape)
print(y_test.shape)
(198102, 97)
(198102, 97)
(121287, 97)
(121287, 97)
(84901, 97)
(84901, 97)
 (198102, 1)
(121287, 1)
(84901, 1)
```

8.6 Adding all the features to make the final dataframe

- df1 ==>tfidf_w2v_q1, tfidf_w2v_q2
- df2 ==> df_fe_without_preprocessing
- df3 ==>nlp_preprocessed

8.6.1 df_fe_without_preprocessing

```
# 1. importing the df_fe_without_preprocessing
df2 = pd.read_csv('df_fe_without_preprocessing_train.csv', encoding='latin-1')
df2.head()
```

Out[38]:

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

In [40]:

```
df2.drop(labels=['qid1', 'qid2', 'question1', 'question2'], axis=1, inplace=True)
df2.head()
```

Out[40]:

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

In [41]:

```
#Splitting it
df2_train, df2_val, y_train, y_val = train_test_split(df2, df.iloc[:, -1:], test_size=0.3, random_s
tate=0, stratify = df.iloc[:, -1:])
df2_train, df2_test, y_train, y_test = train_test_split(df2_train, y_train, test_size=0.3, random_s
tate=0, stratify = y_train)
```

In [42]:

```
print(df2_train.shape)
print(df2_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(198102, 13)
(84901, 13)
(198102, 1)
(84901, 1)
```

In [43]:

```
df2_train.head()
```

Out[43]:

	id	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common	word_Total	word_share	fı
209577	209577	0	4	2	75	46	16	10	8.0	24.0	0.333333	
17392	17392	1	1	1	29	33	5	6	4.0	11.0	0.363636	
14251	14251	0	1	1	58	38	7	6	5.0	13.0	0.384615	
265830	265830	0	1	5	124	136	20	24	5.0	42.0	0.119048	
123216	123216	1	1	1	51	51	8	8	7.0	16.0	0.437500	
4												▶

8.6.2 NLP_features

In [47]:

```
# 2. importing nlp_features
df3 = pd.read_csv('nlp_features_train.csv', encoding='latin-1')
df3.head()
```

Out[47]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	 ctc_max	last_word_eq	first_word_
0	0	1	2	what is the step by step guide to invest in sh	what is the step by step guide to invest in sh	0	0.999980	0.833319	0.999983	0.999983	 0.785709	0.0	
1	1	3	4	what is the story of kohinoor koh i noor dia	what would happen if the indian government sto	0	0.799984	0.399996	0.749981	0.599988	 0.466664	0.0	
2	2	5	6	how can i increase the speed of my internet co	how can internet speed be increased by hacking	0	0.399992	0.333328	0.399992	0.249997	 0.285712	0.0	
3	3	7	8	why am i mentally very lonely how can i solve	find the remainder when math 23 24 math i	0	0.000000	0.000000	0.000000	0.000000	 0.000000	0.0	
4	4	9	10	which one dissolve in water quikly sugar salt	which fish would survive in salt water	0	0.399992	0.199998	0.999950	0.666644	 0.307690	0.0	

5 rows × 21 columns

In [48]:

```
df3.drop(labels=['qid1', 'qid2', 'question1', 'question2', 'is_duplicate'], axis=1, inplace=True)
df3.head()
```

Out[48]:

	id	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_rat
0	0	0.999980	0.833319	0.999983	0.999983	0.916659	0.785709	0.0	1.0	2.0	13.0	10
1	1	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	1.0	5.0	12.5	}
2	2	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	1.0	4.0	12.0	(
3	3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	2.0	12.0	:
4	4	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	1.0	6.0	10.0	(
4												Þ

In [49]:

```
#Splitting it
df3_train, df3_val, y_train, y_val = train_test_split(df3, df.iloc[:, -1:], test_size=0.3, random_s
tate=0, stratify=df.iloc[:, -1:])
df3_train, df3_test, y_train, y_test = train_test_split(df3_train, y_train, test_size=0.3, random_s
tate=0, stratify=y_train)
```

In [50]:

```
print(df3_train.shape)
print(df3_test.shape)
print(y_train.shape)
print(y_test.shape)
```

(198102, 16) (84901, 16) (198102, 1) (84901, 1)

In [51]:

```
df3_train.head()
```

Out[51]:

	id	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	abs_len_diff	mean_len	tok
209577	209577	0.999967	0.599988	0.999986	0.777769	0.999990	0.624996	1.0	1.0	6.0	13.0	
17392	17392	0.999967	0.999967	0.499975	0.333322	0.799984	0.666656	1.0	0.0	1.0	5.5	
14251	14251	0.666644	0.499988	0.999967	0.999967	0.833319	0.714276	0.0	1.0	1.0	6.5	
265830	265830	0.272725	0.249998	0.249997	0.199998	0.249999	0.208332	0.0	0.0	4.0	22.0	
123216	123216	0.999967	0.999967	0.799984	0.799984	0.874989	0.874989	1.0	1.0	0.0	8.0	
4												Þ

8.7 Merging all the features to make it one

In [52]:

```
df1_train_q1.head()
```

Out[52]:

	0	1	2	3	4	5	6	7	8	9	 87	88	
209577	0.001408	0.000327	0.000356	0.000416	0.001152	0.000225	0.001099	0.000287	0.000768	0.000180	 0.001495	0.000674	0.
17392	0.000344	0.000516	0.000370	0.000124	0.000089	0.000218	0.000848	0.000239	0.000233	0.000029	 0.000107	0.000330	0.
14251	0.000334	0.000510	0.000159	0.000220	0.000479	0.000201	0.000521	0.000392	0.000214	0.000038	 0.000384	0.000271	0.
265830	0.000964	0.000363	0.000142	0.001105	0.000086	0.000750	0.002265	0.000686	0.001093	0.002652	 0.000720	0.000117	0.
123216	0.000499	0.000644	0.000045	0.000645	0.000056	0.000088	0.000884	0.000917	0.000086	0.000066	 0.001536	0.000459	0.

```
5 rows × 97 columns
4
 In [53]:
 df1 train q2.head()
Out[53]:
                                                              2
                                                                                                                                                                                      9 ...
                                                                                                                                                                                                                             88
  209577 0.000420 0.000732 0.000223 0.000098 0.000457 0.000188 0.000593 0.000071 0.000114 0.000216 ··· 0.001276 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195 0.000195
    17392 0.000241 0.000540 0.000648 0.000138 0.000073 0.000196 0.000974 0.000221 0.000201 0.000083 ... 0.000613 0.000766 0.
    14251 0.000454 0.000364 0.000215 0.000243 0.000016 0.000652 0.000399 0.000200 0.000213 ... 0.000569 0.000327 0.
  265830 0.000921 0.001301 0.001301 0.001595 0.001618 0.000932 0.001984 0.001619 0.000762 0.000165 ... 0.001595 0.001627 0.001627
  123216 0.000330 0.000452 0.000152 0.000489 0.000366 0.000410 0.000901 0.000759 0.000181 0.000383 ... 0.001200 0.000771 0.000771
5 rows × 97 columns
4
 In [54]:
 df2 train.head()
Out[54]:
                        id is_duplicate freq_qid1 freq_qid2 q1len q2len q1_n_words q2_n_words word_Common word_Total word_share fi
  209577 209577
                                                0
                                                                                     2
                                                                                               75
                                                                                                                                                                                                      24.0
                                                                                                                                                                                                                    0.333333
                                                                                                          46
                                                                                                                                 16
                                                                                                                                                        10
                                                                                                                                                                                  8.0
    17392 17392
                                                1
                                                                   1
                                                                                     1
                                                                                               29
                                                                                                           33
                                                                                                                                   5
                                                                                                                                                          6
                                                                                                                                                                                  4.0
                                                                                                                                                                                                      11.0
                                                                                                                                                                                                                    0.363636
                                                                                                                                   7
   14251 14251
                                                0
                                                                                                           38
                                                                                                                                                         6
                                                                                                                                                                                  5.0
                                                                                                                                                                                                      13.0
                                                                                                                                                                                                                    0.384615
                                                                                     1
                                                                                               58
  265830 265830
                                                0
                                                                   1
                                                                                     5
                                                                                             124
                                                                                                         136
                                                                                                                                 20
                                                                                                                                                        24
                                                                                                                                                                                  5.0
                                                                                                                                                                                                      42.0
                                                                                                                                                                                                                    0.119048
                                                                                                                                                                                                                    0.437500
  123216 123216
                                                                  1
                                                                                     1
                                                                                               51
                                                                                                          51
                                                                                                                                   8
                                                                                                                                                         8
                                                                                                                                                                                  7.0
                                                                                                                                                                                                      16.0
4
 In [44]:
 df3 train.head()
Out[44]:
                        id cwc_min cwc_max csc_min csc_max ctc_min ctc_max last_word_eq first_word_eq abs_len_diff mean_len tok
  209577 209577 0.999967
                                                0.599988 0.999986
                                                                                   0.777769 0.999990 0.624996
                                                                                                                                                        1.0
                                                                                                                                                                                 1.0
                                                                                                                                                                                                                         13.0
                                                                                                                                                                                                       6.0
   17392 17392 0.999967
                                                0.999967 0.499975 0.333322 0.799984 0.666656
                                                                                                                                                                                0.0
                                                                                                                                                                                                        1.0
                                                                                                                                                        1.0
                                                                                                                                                                                                                          5.5
    14251
                 14251 0.666644
                                                 0.499988 0.999967
                                                                                   0.999967 0.833319 0.714276
                                                                                                                                                        0.0
                                                                                                                                                                                 1.0
                                                                                                                                                                                                        1.0
                                                                                                                                                                                                                          6.5
  265830 265830 0.272725
                                                0.249998 0.249997
                                                                                   0.199998 0.249999 0.208332
                                                                                                                                                        0.0
                                                                                                                                                                                 0.0
                                                                                                                                                                                                       4.0
                                                                                                                                                                                                                         22.0
  123216 123216 0.999967 0.999967 0.799984 0.799984 0.874989 0.874989
                                                                                                                                                        1.0
                                                                                                                                                                                 1.0
                                                                                                                                                                                                       0.0
                                                                                                                                                                                                                          8.0
4
 In [55]:
 #merging all by id
 df3_train = df3_train.merge(df2_train, on='id', how='left')
 df3_train = df3_train.merge(df1_train_q1, on='id', how='left')
 result train = df3 train.merge(df1 train q2, on='id', how='left')
 df3 val = df3 val.merge(df2 val, on='id', how='left')
 df3 val = df3 val.merge(df1 val q1, on='id', how='left')
 result_val = df3_val.merge(df1_val_q2, on='id', how='left')
```

```
df3 test = df3 test.merge(df2 test, on='id', how='left')
df3 test = df3_test.merge(df1_test_q1, on='id', how='left')
result_test = df3_test.merge(df1_test_q2, on='id', how='left')
In [56]:
result train.head()
Out[56]:
                                             ctc_min ctc_max last_word_eq first_word_eq abs_len_diff ...
                                                                                                       86 v
                                                                                                               87
       id cwc min cwc max csc min csc max
                                                                                             6.0 ... 0.000075 0.0012
  209577 0.999967
                   0.599988 0.999986 0.777769 0.999990 0.624996
                                                                     1.0
                                                                                  1.0
    17392 0.999967 0.999967 0.499975 0.333322 0.799984 0.666656
                                                                     1.0
                                                                                  0.0
                                                                                             1.0 ... 0.000448
                                                                                                            0.0006
                                                                                             1.0 ... 0.000174 0.0008
    14251 0.666644
                   0.499988 0.999967 0.999967 0.833319 0.714276
                                                                     0.0
                                                                                  1 0
                                                                                             4.0 ... 0.000124 0.0015
  265830 0.272725 0.249998 0.249997 0.199998 0.249999 0.208332
                                                                     0.0
                                                                                 0.0
                                                                                             0.0 ... 0.000776 0.0012
  123216  0.999967  0.999967  0.799984  0.799984  0.874989  0.874989
                                                                     1.0
                                                                                  1.0
5 rows × 220 columns
                                                                                                               Þ
In [57]:
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/final features train', 'wb') as f:
    pickle.dump(result train, f)
In [58]:
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/final_features val', 'wb') as f:
    pickle.dump(result val, f)
In [59]:
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/final features test', 'wb') as f:
    pickle.dump (result test, f)
```

9. Saving it in sqlite db

• Since i have already finished the assignment of stackoverflow tag predictor and i worked with sqlite db there, i am here just saving it in db and i will only use the above final features train.csv, final features val.csv and final features test.csv

```
In [0]:
```

```
#creating train db using final_feature_train and storing those values in train_data table
if not os.path.isfile('train.db'):
    disk_engine = create_engine('sqlite:///train.db')
    start = datetime.datetime.now()
    chunk_size = 180000
    j = 0
    index_start = 1

    for df in pd.read_csv('final_features_train.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_len_difi','mean_len','token_set_ratio','token_sort_ratio','fuzz_ratio','fuzz_partial_ratio','longest_substr_ratio','freq_qid1','freq_qid2','qllen','q2len','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','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','41_x','31_x','32_x','33_x','33_x','34_x','35_x','36_x','37_x','38_x','39_x','40_x','41_x','42_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x','41_x
```

```
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','113 x<sup>-</sup>,'114 x<sup>-</sup>,'115 x','116 x<sup>-</sup>,'117 x<sup>-</sup>,'118 x','119 x<sup>-</sup>,'120 x<sup>-</sup>,'121 x','122 x<sup>-</sup>,'123 x<sup>-</sup>,'12
4 x<sup>'</sup>,'125 x<sup>'</sup>,'126 x<sup>'</sup>,'127 x<sup>'</sup>,'128 x<sup>'</sup>,'129 x<sup>'</sup>,'130 x<sup>'</sup>,'131 x<sup>'</sup>,'132 x<sup>'</sup>,'133 x<sup>'</sup>,'134 x<sup>'</sup>,'135 x<sup>'</sup>,'136
x<sup>'</sup>,'137 x<sup>'</sup>,'138 x<sup>'</sup>,'139 x<sup>'</sup>,'140 x<sup>'</sup>,'141 x<sup>'</sup>,'142 x<sup>'</sup>,'143 x<sup>'</sup>,'144 x<sup>'</sup>,'145 x<sup>'</sup>,'146 x<sup>'</sup>,'147 x<sup>'</sup>,'148 x<sup>'</sup>
,'149 \times,''150 \times,''151 \times,''152 \times,''153 \times,''154 \times,''155 \times,''156 \times,''157 \times,''158 \times,''159 \times,''160 \times,''
161 x','162 x','163 x','164 x','165 x','166 x','167 x','168 x','169 x','170 x','171 x','172 x','17
3 x','174 x','175 x','176 x','177 x','178 x','179 x','180 x','181 x','182 x','183 x','184 x','185
\vec{x'}, '186 \vec{x'}, '187 \vec{x'}, '188 \vec{x'}, '189 \vec{x'}, '190 \vec{x'}, '191 \vec{x'}, '192 \vec{x'}, '193 \vec{x'}, '194 \vec{x'}, '195 \vec{x'}, '196 \vec{x'}, '197 \vec{x'}
,'198_x<sup>-</sup>,'199_x<sup>-</sup>,'200_x<sup>-</sup>,'201_x<sup>-</sup>,'202_x<sup>-</sup>,'203_x<sup>-</sup>,'204_x<sup>-</sup>,'205_x<sup>-</sup>,'206_x<sup>-</sup>,'207_x<sup>-</sup>,'208_x<sup>-</sup>,'209_x<sup>-</sup>,'
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','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<sup>7</sup>,'248 x<sup>7</sup>,'249 x','250 x<sup>7</sup>,'251 x<sup>7</sup>,'252 x','253 x<sup>7</sup>,'254 x<sup>7</sup>,'255 x','256 x<sup>7</sup>,'257 x<sup>7</sup>,'258 x','
259_x<sup>-</sup>, '260_x<sup>-</sup>, '261_x<sup>-</sup>, '262_x<sup>-</sup>, '263_x<sup>-</sup>, '264_x<sup>-</sup>, '265_x<sup>-</sup>, '266_x<sup>-</sup>, '267_x<sup>-</sup>, '268_x<sup>-</sup>, '269_x<sup>-</sup>, '270_x<sup>-</sup>, '
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','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<sup>'</sup>,'297 x<sup>'</sup>,'298 x<sup>'</sup>,'299 x<sup>'</sup>,'300 x<sup>'</sup>,'301 x<sup>'</sup>,'302 x<sup>'</sup>,'303 x<sup>'</sup>,'304 x<sup>'</sup>,'305 x<sup>'</sup>,'305 x<sup>'</sup>,'307 x<sup>'</sup>,'
308 x','309 x<sup>T</sup>,'310 x<sup>T</sup>,'311 x','312 x<sup>T</sup>,'313 x<sup>T</sup>,'314 x','315 x<sup>T</sup>,'316 x<sup>T</sup>,'317 x','318 x<sup>T</sup>,'319 x<sup>T</sup>,'32
0 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<sup>†</sup>,'333_x<sup>†</sup>,'334_x<sup>†</sup>,'335_x<sup>†</sup>,'336_x','337_x<sup>†</sup>,'338_x<sup>†</sup>,'339_x','340_x<sup>†</sup>,'341_x<sup>†</sup>,'342_x','342_x<sup>†</sup>,'344_x<sup>†</sup>
  '345_x','346_x\,'347_x\,'348_x\,'349_x','350_x\,'351_x\,'352_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','36
9_x<sup>'</sup>,'370_x<sup>'</sup>,'371_x<sup>'</sup>,'372_x<sup>'</sup>,'373_x<sup>'</sup>,'374_x<sup>'</sup>,'375_x<sup>'</sup>,'376_x<sup>'</sup>,'377_x<sup>'</sup>,'378_x<sup>'</sup>,'378_x<sup>'</sup>,'380_x<sup>'</sup>,'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','122
    ,'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'
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','20
8_y','209_y','210_y','211_y','212_y','213_y','214_y','215_y','216_y','217_y','218_y','219_y','220_
y','221_y','222_y','223_y','224_y','225_y','226_y','227_y','228_y','229_y','230_y','231_y','232_y'
,'233_y','234_y','235_y','236_y','237_y','238_y','239_y','240_y','241_y','242_y','243_y','244_y','
245_y','246_y','247_y','248_y','249_y','250_y','251_y','252_y','253_y','254_y','255_y','256_y','25
7_y','258_y','259_y','260_y','261_y','262_y','263_y','264_y','265_y','266_y','267_y','268_y','269
y','270_y','271_y','272_y','273_y','274_y','275_y','276_y','277_y','278_y','279_y','280_y','281_y'
,'282_y','283_y','284_y','285_y','286_y','287_y','288_y','289_y','290_y','291_y','292_y','293_y','
294_y','295_y','296_y','297_y','298_y','299_y','300_y','301_y','302_y','303_y','304_y','305_y','30
6_y','307_y','308_y','310_y','311_y','312_y','313_y','314_y','315_y','316_y','317_y','318_
    ,'319 y','320 y','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_y','340_y','341_y','342_y'
343 y','344 y','345 y','346 y','347 y','348 y','349 y','350 y','351 y','352 y','353 y','354 y'
5_y','356_y','357_y','358_y','359_y','360_y','361_y','362_y','363_y','364_y','365_y','366_y','367_
y','368_y','369_y','370_y','371_y','372_y','373_y','374_y','375_y','376_y','377_y','378_y','379_y'
,'380 y','381 y','382 y','383 y'], chunksize=chunksize, iterator=True, encoding='utf-8'):
              df.index += index_start
               j += 1
              print('{] rows'.format(j*chunksize))
               df.tosql('train_data', disk_engine, if_exists='append')
               index start = df.index[-1]+1
4
```

In [0]:

```
#creating val db using final_feature_val and storing thoswe values in val_data table
if not os.path.isfile('val.db'):
    disk_engine = create_engine('sqlite:///val.db')
    start = datetime.datetime.now()
    chunk_size = 180000
    j = 0
    index_start = 1

for df in pd.read_csv('final_features_val.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_len_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','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','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','113 x','114 x','115 x','116 x','117 x','118 x','119 x','120 x','121 x','122 x','123 x'
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','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','136_x','
x<sup>-</sup>,'137_x<sup>-</sup>,'138_x<sup>-</sup>,'139_x<sup>-</sup>,'140_x','141_x<sup>-</sup>,'142_x<sup>-</sup>,'143_x','144_x<sup>-</sup>,'145_x<sup>-</sup>,'146_x','146_x<sup>-</sup>,'148_x<sup>-</sup>
   '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','17
3 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<sup>'</sup>,'199 x<sup>'</sup>,'200 x','201 x<sup>'</sup>,'202 x<sup>'</sup>,'203 x','204 x<sup>'</sup>,'205 x<sup>'</sup>,'206 x','207 x<sup>'</sup>,'208 x<sup>'</sup>,'209 x<sup>'</sup>,'
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','224_x','225_x','226_x','227_x','228_x','229_x','230_x','231_x','232_x','233_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','234_x','
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<sup>-</sup>, '260 x<sup>-</sup>, '261 x<sup>-</sup>, '262 x<sup>-</sup>, '263 x<sup>-</sup>, '264 x<sup>-</sup>, '265 x<sup>-</sup>, '266 x<sup>-</sup>, '267 x<sup>-</sup>, '268 x<sup>-</sup>, '269 x<sup>-</sup>, '270 x<sup>-</sup>, '
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_
      ,'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<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 \ \vec{x'}, '321 \ \vec{x'}, '322 \ \vec{x'}, '323 \ \vec{x'}, '324 \ \vec{x'}, '325 \ \vec{x'}, '326 \ \vec{x'}, '327 \ \vec{x'}, '328 \ \vec{x'}, '329 \ \vec{x'}, '330 \ \vec{x'}, '331 \ \vec{x'}, '332 \ \vec{x'}, '332 \ \vec{x'}, '332 \ \vec{x'}, '331 \ \vec{x'}, '332 \ \vec{x'}, '332 \ \vec{x'}, '331 \ \vec{x'}, '332 \ \vec{x'}, '33
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','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_y','56_y','57_y','58_y','59_y','60_y','61_y','62_y','63_y','64_y','65_y','66_y','67_y','68_y','69
_y','70_y','71_y','72_y','73_y','74_y','75_y','76_y','77_y','78_y','79_y','80_y','81_y','82_y','83
y','84_y','85_y','86_y','87_y','88_y','89_y','90_y','91_y','92_y','93_y','94_y','95_y','96_y','97_y
  ','98_y','99_y','100_y','101_y','102_y','103_y','104_y','105_y','106_y','107_y','108_y','109_y','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','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'
9_y','160_y','161_y','162_y','163_y','164_y','165_y','166_y','167_y','168_y','168_y','170_y','171_
y<sup>¯</sup>,'172_y','173_y<sup>¯</sup>,'174_y<sup>¯</sup>,'175_y','176_y<sup>¯</sup>,'177_y<sup>¯</sup>,'178_y<sup>¯</sup>,'179_y','180_y<sup>¯</sup>,'181_y<sup>¯</sup>,'182_y<sup>¯</sup>,'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'
8_y','209_y','210_y','211_y','212_y','213_y','214_y','215_y','216_y','217_y','218_y','219_
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','259_y','260_y','261_y','262_y','263_y','264_y','265_y','266_y','267_y','268_y','269
y','270_y','271_y','272_y','273_y','274_y','275_y','276_y','277_y','278_y','279_y','280_y','281_y'
  '282 y','283_y','284_y','285_y','286_y','287_y','288_y','289_y','290_y','291_y','292_y'
294 y','295 y','296 y','297 y','298 y','299 y','300 y','301 y','302 y','303 y','304 y','305 y','30
6_y','307_y','308_y','309_y','310_y','311_y','312_y','313_y','314_y','315_y','316_y','317_y','318_
y','319_y','320_y','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_y','340_y','341_y','342_y','
343_y','344_y','345_y','346_y','347_y','348_y','349_y','350_y','351_y','352_y','353_y','354_y'
5_y','356_y','357_y','358_y','359_y','360_y','361_y','362_y','363_y','364_y','365_y','366_y','367
y','368_y','369_y','370_y','371_y','372_y','373_y','374_y','375_y','376_y','377_y','378_y','379_y'
,'380 y','381_y','382_y','383_y'], chunksize=chunksize, iterator=True, encoding='utf-8'):
                      df.index += index start
                      j += 1
                      print('{] rows'.format(j*chunksize))
                      df.tosql('val data', disk engine, if exists='append')
                      index start = df.index[-1]+1
```

```
chunk size = 180000
      j = 0
      index_start = 1
      for df in pd.read_csv('final_features_test.csv', names=['Unnamed: 0','id','is_duplicate','cwc_m
in','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','q2len','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','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','113 x','114 x','115 x','116 x','117 x','118 x','119 x','120 x','121 x','122 x','123 x','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','17
3 x','174 x','175 x','176 x','177 x','178 x','179 x','180 x','181 x','182 x','183 x','183 x','184 x','185
x<sup>'</sup>,'186 x<sup>'</sup>,'187 x<sup>'</sup>,'188 x<sup>'</sup>,'189 x<sup>'</sup>,'190 x<sup>'</sup>,'191 x','192 x<sup>'</sup>,'193 x<sup>'</sup>,'194 x','195 x<sup>'</sup>,'196 x<sup>'</sup>,'197 x'
,'198 x<sup>-</sup>,'199 x<sup>-</sup>,'200 x<sup>-</sup>,'201 x<sup>-</sup>,'202 x<sup>-</sup>,'203 x<sup>-</sup>,'204 x<sup>-</sup>,'205 x<sup>-</sup>,'206 x<sup>-</sup>,'207 x<sup>-</sup>,'208 x<sup>-</sup>,'209 x<sup>-</sup>,'
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','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<sup>T</sup>,'249 x<sup>T</sup>,'250 x','251 x<sup>T</sup>,'252 x<sup>T</sup>,'253 x','254 x<sup>T</sup>,'255 x<sup>T</sup>,'256 x','257 x<sup>T</sup>,'258 x<sup>T</sup>,'
259_x<sup>'</sup>,'260_x<sup>'</sup>,'261_x<sup>'</sup>,'262_x<sup>'</sup>,'263_x<sup>'</sup>,'264_x<sup>'</sup>,'265_x<sup>'</sup>,'266_x<sup>'</sup>,'267_x<sup>'</sup>,'268_x<sup>'</sup>,'269_x<sup>'</sup>,'270_x<sup>'</sup>,'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','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<sup>-</sup>,'297_x<sup>-</sup>,'298_x<sup>-</sup>,'299_x<sup>-</sup>,'300_x<sup>-</sup>,'301_x<sup>-</sup>,'302_x<sup>-</sup>,'303_x<sup>-</sup>,'304_x<sup>-</sup>,'305_x<sup>-</sup>,'306_x<sup>-</sup>,'307_x<sup>-</sup>,'
308 x', '309 x^{-}, '310 x^{-}, '311 x', '312 x^{-}, '313 x^{-}, '314 x', '315 x^{-}, '316 x^{-}, '317 x', '318 x^{-}, '319 x^{-}, '32
0_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'
x^{T}, '333 x^{T}, '334 x^{T}, '335 x^{T}, '336 x^{T}, '337 x^{T}, '338 x^{T}, '339 x^{T}, '340 x^{T}, '341 x^{T}, '342 x^{T}, '343 x^{T}, '344 x^{T}
,'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','366_x','368_x'
9_x<sup>'</sup>,'370_x<sup>'</sup>,'371_x<sup>'</sup>,'372_x<sup>'</sup>,'373_x<sup>'</sup>,'374_x<sup>'</sup>,'375_x<sup>'</sup>,'376_x<sup>'</sup>,'377_x<sup>'</sup>,'378_x<sup>'</sup>,'379_x<sup>'</sup>,'380_x<sup>'</sup>,'381_
x<sup>7</sup>,'382_x<sup>7</sup>,'383_x<sup>7</sup>,'0_y',<sup>7</sup>1_y','2_y','3_y<sup>7</sup>,'4_y',<sup>7</sup>5_y','6_y','7_y<sup>7</sup>,'8_y',<sup>9</sup>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_
y','84_y','85_y','86_y','87_y','88_y','89_y','90_y','91_y','92_y','93_y','94_y','95_y','96_y','97_y
 ','98_y','99_y','100_y','101_y','102_y','103_y','104_y','105_y','106_y','107_y','108_y','109_y','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','122
    ,'123_y','124_y','125_y','126_y','127_y','128_y','129_y','130_y','131_y','132_y','133_y','134
,'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','168_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','20
8_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<sup>-</sup>,'234_y<sup>-</sup>,'235_y<sup>-</sup>,'236_y<sup>-</sup>,'237_y<sup>-</sup>,'238_y<sup>-</sup>,'239_y<sup>-</sup>,'240_y<sup>-</sup>,'241_y<sup>-</sup>,'242_y<sup>-</sup>,'243_y<sup>-</sup>,'244_y<sup>-</sup>,'
245_y','246_y<sup>†</sup>,'247_y<sup>†</sup>,'248_y','249_y<sup>†</sup>,'250_y<sup>†</sup>,'251_y','252_y<sup>†</sup>,'253_y<sup>†</sup>,'254_y','255_y<sup>†</sup>,'256_y<sup>†</sup>,'25
7_y','258_y','259_y','260_y','261_y','262_y','263_y','264_y','265_y','266_y','267_y','268_y','269
y','270_y','271_y','272_y','273_y','274_y','275_y','276_y','277_y','278_y','279_y','280_y','281_y'
,'282_y','283_y','284_y','285_y','286_y','287_y','288_y','289_y','290_y','291_y','292_y','293_y','
294_y','295_y','296_y','297_y','298_y','299_y','300_y','301_y','302_y','303_y','304_y','305_y','30
6\_y', '307\_y', '308\_y', '310\_y', '311\_y', '311\_y', '313\_y', '314\_y', '315\_y', '316\_y', '317\_y', '318\_y', '318_y', '318
y','319_y','320_y','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_y','340_y','341_y','342_y'
         ,'344_y','345_y','346_y','347_y','348_y','349_y','350_y','351_y','352_y','353_y','354_y'
5_y','356_y','357_y','358_y','359_y','360_y','361_y','362_y','363_y','364_y','365_y','366_y','367_
y','368_y','369_y','370_y','371_y','372_y','373_y','374_y','375_y','376_y','377_y','378_y','379_y'
,'380 y','381 y','382 y','383 y'], chunksize=chunksize, iterator=True, encoding='utf-8'):
            df.index += index start
            print('{] rows'.format(j*chunksize))
            df.tosql('test_data', disk_engine, if_exists='append')
            index start = df.index[-1]+1
```

```
In [0]:
```

```
#creating a connection
def create_connection(db):
    conn = sqlite3.connect(db)
    return conn

def check_table_exists(conn):
    cursr = conn.cursor()
    str = 'SELECT name FROM sqlite_master WHERE type="table"'
    table_names = cursr.execute(str)
    tables = table_names.fetchall()
    print(tables)
```

In [0]:

```
#read the train.db
read_train_db = 'train.db'
conn_r = create_connection(read_train_db)
check_table_exists(conn_r)
conn_r.close()

#read the val.db
read_val_db = 'val.db'
conn_r = create_connection(read_val_db)
check_table_exists(conn_r)
conn_r.close()

#read the test.db
read_test_db = 'test.db'
conn_r = create_connection(read_test_db)
check_table_exists(conn_r)
conn_r.close()
```

In [0]:

```
#sampling only 700000 in train and 300000 in val as we already split it
def create_df(db, number)
   if os.path.isfile(db):
        conn_r = create_connection(db)

    if conn_r is not None:
        data = pd.read_sql_query('SELECT * FROM train_data LIMIT {}'.format(number), conn_r)
        conn_r.commit()
        conn_r.close()
```

In [0]:

```
#trainin_df
final_df_train = create_df(read_train_db, 700001)
final_df_val = create_df(read_val_db, 300001)
final_df_test = create_df(read_test_db, 50001)
```

In [0]:

```
final_df_train.head()
```

In [0]:

```
# remove the first row
data.drop(data.index[0], inplace=True)
y_true = data['is_duplicate']
data.drop(['Unnamed: 0', 'id', 'index', 'is_duplicate'], axis=1, inplace=True)
```

In [0]:

```
final_df_val.head()
```

```
# remove the first row
data.drop(data.index[0], inplace=True)
y_true = data['is_duplicate']
data.drop(['Unnamed: 0', 'id','index','is_duplicate'], axis=1, inplace=True)

In [0]:
final_df_test.head()

In [0]:
# remove the first row
data.drop(data.index[0], inplace=True)
y_true = data['is_duplicate']
data.drop(['Unnamed: 0', 'id','index','is_duplicate'], axis=1, inplace=True)
```

8.8 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

def strings_to_numeric(df):
    cols = list(df.columns)
    for i in cols:
        df[i] = data[i].apply(pd.to_numeric)
        print(i)
```

```
In [0]:
final_train_df = strings_to_numeric(final_train_df)
final_var_df = strings_to_numeric(final_val_df)
final_test_df = strings_to_numeric(final_test_df)
```

10. Modelling

10.1 Creating confusion matrix

In [60]:

```
# 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]
   # 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
    {\tt cmap=sns.light\_palette("blue")}
    plt.subplot(1, 3, 1)
sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")
    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")
    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")
    plt.show()
```

10.2 Building a Random model

```
In [61]:
```

```
y_train = result_train['is_duplicate']
y_val = result_val['is_duplicate']
y_test = result_test['is_duplicate']
```

In [62]:

```
X_train = result_train.drop(labels='is_duplicate', axis=1, )
X_val = result_val.drop(labels='is_duplicate', axis=1)
X_test = result_test.drop(labels='is_duplicate', axis=1)
```

In [63]:

```
print(X_train.shape)
print(X_val.shape)
print(X_test.shape)

(198102, 219)
(121287, 219)
(84901, 219)
```

In [64]:

```
X_train.head()
```

Out[64]:

	id	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	abs_len_diff	 86_y	87
0	209577	0.999967	0.599988	0.999986	0.777769	0.999990	0.624996	1.0	1.0	6.0	 0.000075	0.0012
1	17392	0.999967	0.999967	0.499975	0.333322	0.799984	0.666656	1.0	0.0	1.0	 0.000448	0.0006
2	14251	0.666644	0.499988	0.999967	0.999967	0.833319	0.714276	0.0	1.0	1.0	 0.000174	0.0005

```
3 265830 6.272725 6.249998 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.249999 6.24999 6.249999 6.24999 6.24999 6.24999 6.24999 6.24999 6.24999 6.24999 6.24999 6.24999 6.24999 6.24999 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.2499 6.24
```

Note:

• We are going to consider only 70k points for training and 30k points for validation bcoz of lack of computational power

In [65]:

```
X_train = X_train.iloc[0:70000,:]
y_train = y_train[0:70000]

X_val = X_val.iloc[0:30000,:]
y_val = y_val[0:30000]
```

In [66]:

```
print(X_train.shape)
print(y_train.shape)

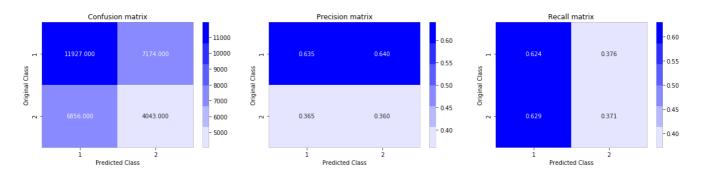
(70000, 219)
(70000,)
```

In [67]:

```
dummy_clf = DummyClassifier(strategy='stratified')
dummy_clf.fit(X_train, y_train)
y_pred = dummy_clf.predict(X_val)

print('Log loss for the random dummy model', log_loss(y_val, y_pred))
plot_confusion_matrix(y_val, y_pred)
```

Log loss for the random dummy model 16.152825637752038



10.3 Logistic Regression

In [69]:

```
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)
    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_val)
    log_error_array.append(log_loss(y_val, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_val, predict_y, labels=clf.classes_, eps=1e-15))
```

```
fig, ax = plt.subplots()
ax.plot(alpha, log error array,c='g')
for i, txt in enumerate(np.round(log error array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.xscale('log')
plt.show()
best_alpha = alpha[np.argmin(log_error_array)]
clf = SGDClassifier(alpha=best alpha, penalty='12', loss='log', random state=42)
clf.fit(X_train, y_train)
sig clf = CalibratedClassifierCV(clf, method="sigmoid")
sig clf.fit(X train, y train)
predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', 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 val)
print('For values of best alpha = ', best alpha, "The test log loss is:", log loss(y val, predict y
, labels=clf.classes_, eps=1e-15))
predicted y =np.argmax(predict y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_val, predicted_y)
```

For values of alpha = 1e-05 The log loss is: 0.6554000609637015

For values of alpha = 0.0001 The log loss is: 0.6554000609637015

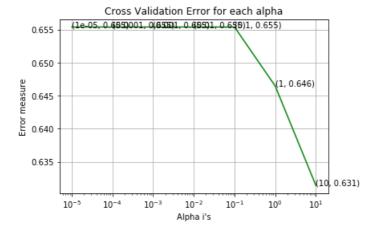
For values of alpha = 0.001 The log loss is: 0.6554000609637015

For values of alpha = 0.01 The log loss is: 0.6554000609637015

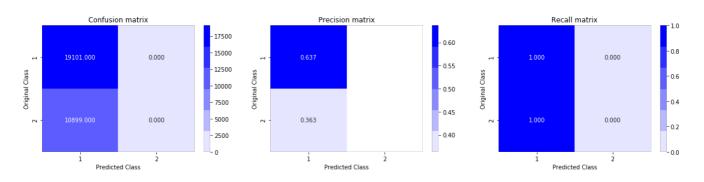
For values of alpha = 0.1 The log loss is: 0.6554000609637015

For values of alpha = 1 The log loss is: 0.6464775961647082

For values of alpha = 10 The log loss is: 0.6314334520562241



For values of best alpha = 10 The train log loss is: 0.6354490856754549 For values of best alpha = 10 The test log loss is: 0.6314334520562241 Total number of data points : 30000



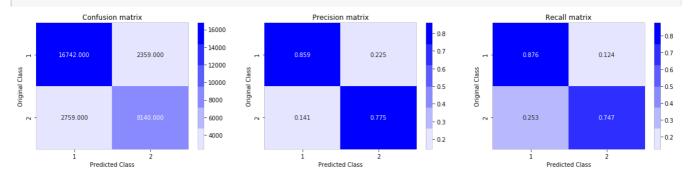
In [70]:

```
from xgboost import XGBClassifier
xqb clf = XGBClassifier()
xgb clf.fit(X train,y train)
y pred = xgb clf.predict(X val)
print('Log loss:', log_loss(y_val, y_pred, labels=xgb_clf.classes_, eps=1e-15))
```

Log loss: 5.892378127983023

In [71]:

```
plot confusion matrix(y val, y pred)
```



12. TASK -2:

• Hyperparameter tuning of XGBOOST - Since it is computationally expensive i take only this three hyperparameters. https://blog.cambridgespark.com/hyperparameter-tuning-in-xgboost-4ff9100a3b2f

In [72]:

```
from sklearn.model_selection import RandomizedSearchCV
```

In [73]:

```
XGB clf = XGBClassifier()
params = {
          'learning_rate' : [0.01, 0.05, 0.1, 0.2],
          'n_estimators' : [100, 300, 500, 1000, 2000],
          'max_depth' : [3, 5, 10],
          'subsample' : [0.1, 0.3, 0.5, 1]
random search = RandomizedSearchCV(estimator=xgb clf, param distributions=params,
scoring='neg_log_loss', cv=2, return_train_score=True, n_jobs=-1 )
```

In [74]:

```
X_train.shape
Out[74]:
```

(70000, 219)

In [75]:

```
random search = random search.fit(X train, y train)
```

In [76]:

```
random_search.best_params_
```

```
Out[76]:
{'subsample': 1, 'n_estimators': 500, 'max_depth': 5, 'learning_rate': 0.05}
In [77]:
random_search.best_params_['n_estimators']
Out[77]:
500
```

Summary:

```
In [78]:
```

```
from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ['Model', 'Best learning rate', 'Best n_estimators', 'Best max_depth', 'Best subsam
ple']
x.add_row(['XGBoost', random_search.best_params_['learning_rate'], random_search.best_params_['n_e
stimators'], random_search.best_params_['max_depth'], random_search.best_params_['subsample']])
print(x)
```

Model	Best learning rate	Best n_estimators	Best max_depth	Best subsample
XGBoost	0.05	500	5	1

11. TASK -1

- Applying tfidf instead of tfidfw2v
- df2 train q1 tfidf for q1
- df2_train_q2 tfidf for q2
- df2 ==> df_fe_without_preprocessing
- df3 ==>nlp preprocessed

11.1 SPlittingt the dataset

```
In [ ]:
```

```
df_train, df_val, y_train, y_val = train_test_split(df, df.iloc[:, -1:], test_size = 0.3, random_st
ate=0 , stratify = df.iloc[:,-1:])
df_train, df_test, y_train, y_test = train_test_split(df_train, y_train, test_size= 0.3, random_sta
te=0, stratify = y_train)
```

11.2 Get the training questions

```
In [0]:
```

```
train_questions = df_train['question1'] + df_train['question2']
train_questions.head()
```

Out[0]:

```
what is the step by step guide to invest in sh...
what is the story of kohinoor koh i noor dia...
how can i increase the speed of my internet co...
why am i mentally very lonely how can i solve...
which one dissolve in water quikly sugar salt...
dtype: object
```

11.3 TFIDF

In [84]:

```
vec = TfidfVectorizer(min_df=25)
vec.fit_transform(train_questions.values)
```

Out[84]:

<198102x7316 sparse matrix of type '<class 'numpy.float64'>' with 2863942 stored elements in Compressed Sparse Row format>

In [85]:

pd.DataFrame.sparse.from_spmatrix(vec.transform(df_train['question1'].values), index = df_train.ind ex)

Out[85]:

	0	1	2	3	4	5	6	7	8	9	 7306	7307	7308	7309	7310	7311	7312	7313	7314	7315
209577	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17392	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14251	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
265830	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
123216	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
181830	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
183325	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
346248	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
342627	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21773	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

198102 rows × 7316 columns

In [86]:

```
df2_train_q1 = pd.DataFrame.sparse.from_spmatrix(vec.transform(df_train['question1'].values), index
= df_train.index)
df2_train_q2 = pd.DataFrame.sparse.from_spmatrix(vec.transform(df_train['question2'].values), index
= df_train.index)
```

In [87]:

```
df2_train_q1['id'] = df_train['id']
df2_train_q2['id'] = df_train['id']
df2_train_q1.head()
```

Out[87]:

	0	1	2	3	4	5	6	7	8	9	 7307	7308	7309	7310	7311	7312	7313	7314	7315	id
209577	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	209577
17392	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	17392
14251	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	14251
265830	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	265830
123216	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	123216

5 rows × 7317 columns

```
df2_val_q1 = pd.DataFrame.sparse.from_spmatrix(vec.transform(df_val['question1'].values), index=df_
val.index)
df2_val_q2 = pd.DataFrame.sparse.from_spmatrix(vec.transform(df_val['question2'].values), index=df_
val.index)
```

In [89]:

```
df2_val_q1['id'] = df_val['id']
df2_val_q2['id'] = df_val['id']
df2_val_q2.head()
```

Out[89]:

	0	1	2	3	4	5	6	7	8	9	 7307	7308	7309	7310	7311	7312	7313	7314	7315	id
40373	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	40373
218089	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	218089
184729	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	184729
218907	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	218907
224215	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	224215

5 rows × 7317 columns

In [90]:

```
df2_test_q1 = pd.DataFrame.sparse.from_spmatrix(vec.transform(df_test['question1'].values), index=d
f_test.index)
df2_test_q2 = pd.DataFrame.sparse.from_spmatrix(vec.transform(df_test['question2'].values), index=d
f_test.index)
```

In [91]:

```
df2_test_q1['id'] = df_test['id']
df2_test_q2['id'] = df_test['id']
df2_test_q2.head()
```

Out[91]:

	0	1	2	3	4	5	6	7	8	9	 7307	7308	7309	7310	7311	7312	7313	7314	7315	id
372980	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	372980
14252	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	14252
102303	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	102303
274316	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	274316
370597	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	370597

5 rows × 7317 columns

11.4 Importing other dataframes

11.4.1 Importing df_fe_without_preprocessing

```
In [92]:
```

```
# 1. importing the df_fe_without_preprocessing
df2 = pd.read_csv('df_fe_without_preprocessing_train.csv', encoding='latin-1')
df2.head()
```

Out[92]:

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

In [93]:

```
df2.drop(labels=['qid1', 'qid2', 'question1', 'question2'], axis=1, inplace=True)
df2.head()
```

Out[93]:

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

In [94]:

```
#Splitting it
df2_train, df2_val, y_train, y_val = train_test_split(df2, df.iloc[:, -1:], test_size=0.3, random_s
tate=0, stratify = df.iloc[:, -1:])
df2_train, df2_test, y_train, y_test = train_test_split(df2_train, y_train, test_size=0.3, random_s
tate=0, stratify = y_train)
```

In [95]:

```
print(df2_train.shape)
print(df2_test.shape)
print(y_train.shape)
print(y_test.shape)
```

(198102, 13) (84901, 13) (198102, 1) (84901, 1)

In [96]:

```
df2 train.head()
```

Out[96]:

	id	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common	word_Total	word_share	fı
209577	209577	0	4	2	75	46	16	10	8.0	24.0	0.333333	
17392	17392	1	1	1	29	33	5	6	4.0	11.0	0.363636	
14251	14251	0	1	1	58	38	7	6	5.0	13.0	0.384615	
265830	265830	0	1	5	124	136	20	24	5.0	42.0	0.119048	
123216	123216	1	1	1	51	51	8	8	7.0	16.0	0.437500	
4												F

11.4.2 NLP_features

In [97]:

```
# 2. importing nlp_features
df3 = pd.read_csv('nlp_features_train.csv', encoding='latin-1')
df3.head()
```

Out[97]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	 ctc_max	last_word_eq	first_word
0	0	1	2	what is the step by step guide to invest in sh	what is the step by step guide to invest in sh	0	0.999980	0.833319	0.999983	0.999983	 0.785709	0.0	
1	1	3	4	what is the story of kohinoor koh i noor dia	what would happen if the indian government sto	0	0.799984	0.399996	0.749981	0.599988	 0.466664	0.0	
2	2	5	6	how can i increase the speed of my internet co	how can internet speed be increased by hacking	0	0.399992	0.333328	0.399992	0.249997	 0.285712	0.0	
3	3	7	8	why am i mentally very lonely how can i solve	find the remainder when math 23 24 math i	0	0.000000	0.000000	0.000000	0.000000	 0.000000	0.0	
4	4	9	10	which one dissolve in water quikly sugar salt	which fish would survive in salt water	0	0.399992	0.199998	0.999950	0.666644	 0.307690	0.0	

5 rows × 21 columns

In [98]:

```
df3.drop(labels=['qid1', 'qid2', 'question1', 'question2', 'is_duplicate'], axis=1, inplace=True)
df3.head()
```

Out[98]:

	id	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_rati
0	0	0.999980	0.833319	0.999983	0.999983	0.916659	0.785709	0.0	1.0	2.0	13.0	10
1	1	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	1.0	5.0	12.5	}
2	2	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	1.0	4.0	12.0	ť
3	3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	2.0	12.0	:
4	4	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	1.0	6.0	10.0	ť

```
In [99]:
#Splitting it
df3_train, df3_val, y_train, y_val = train_test_split(df3, df.iloc[:, -1:], test_size=0.3, random_s
tate=0, stratify=df.iloc[:, -1:])
df3_train, df3_test, y_train, y_test = train_test_split(df3_train, y_train, test_size=0.3, random_s
tate=0, stratify=y_train)
In [100]:
print(df3_train.shape)
print(df3_test.shape)
print(y train.shape)
print(y_test.shape)
(198102, 16)
(84901, 16)
(198102, 1)
(84901, 1)
In [101]:
df3 train.head()
Out[101]:
           id cwc_min cwc_max csc_min csc_max ctc_min ctc_max last_word_eq first_word_eq abs_len_diff mean_len tok
209577 209577 0.999967
                      0.599988 0.999986 0.777769 0.999990 0.624996
                                                                       1.0
                                                                                   1.0
                                                                                              6.0
                                                                                                      13.0
 17392 17392 0.999967
                      0.999967  0.499975  0.333322  0.799984  0.666656
                                                                       1.0
                                                                                   0.0
                                                                                              1.0
                                                                                                      5.5
 14251
        14251 0.666644
                      0.499988
                              0.999967
                                       0.999967 0.833319 0.714276
                                                                       0.0
                                                                                   1.0
                                                                                              1.0
                                                                                                      6.5
265830 265830 0.272725 0.249998 0.249997 0.199998 0.249999 0.208332
                                                                       0.0
                                                                                   0.0
                                                                                              4.0
                                                                                                      22.0
123216 123216 0.999967 0.999967 0.799984 0.799984 0.874989 0.874989
                                                                       1.0
                                                                                   1.0
                                                                                              0.0
                                                                                                      8.0
In [102]:
print(df2 train q1.shape)
print(df2_train_q2.shape)
print(df2 train.shape)
print(df3_train.shape)
print('='*50)
print(df2 val q1.shape)
print(df2_val_q2.shape)
print(df2 val.shape)
print(df3 val.shape)
(198102, 7317)
(198102, 7317)
(198102, 13)
(198102, 16)
_____
(121287, 7317)
(121287, 7317)
(121287, 13)
(121287, 16)
In [103]:
#merging all by id
df3 train = df3_train.merge(df2_train, on='id', how='left')
df3 train = df3 train.merge(df2 train q1, on='id', how='left')
assign_train = df3_train.merge(df2_train_q2, on='id', how='left')
df3 val = df3 val.merge(df2 val, on='id', how='left')
df3_val = df3_val.merge(df2_val_q1, on='id', how='left')
assign val = df3 val.merge(df2 val q2, on='id', how='left')
```

```
df3_test = df3_test.merge(df2_test, on='id', how='left')
df3_test = df3_test.merge(df2_test_q1, on='id', how='left')
assign test = df3 test.merge(df2 test q2, on='id', how='left')
In [104]:
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/assign train', 'wb') as f:
    pickle.dump(assign train, f)
In [105]:
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/assign val', 'wb') as f:
    pickle.dump (assign val, f)
In [106]:
import pickle
with open('/home/ubuntu/Quora/*Assign 22 -Quora/assign test', 'wb') as f:
   pickle.dump(assign_test, f)
In [107]:
X_train = assign_train.iloc[0:70000,:]
X_val = assign_val.iloc[0:30000,:]
In [108]:
y_train = y_train[0:70000]
y_val = y_val[0:30000]
In [109]:
print(X train.shape)
print(y_train.shape)
print(X_val.shape)
print(y val.shape)
print()
(70000, 14660)
(70000, 1)
(30000, 14660)
(30000, 1)
```

11.5 Modelling - Logistgic Regression

```
In [80]:
```

```
alpha = [10 ** i for i in range(-5, 4)]

log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='12', loss='log', random_state=0)
    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_val)
    log_error_array.append(log_loss(y_val, predict_y, labels=clf.classes_, eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_val, predict_y, labels=clf.classes_, eps=1e-15))

For values of alpha = 1e-05 The log loss is: 0.6554000609637015
For values of alpha = 0.0001 The log loss is: 0.6554000609637015
For values of alpha = 0.001 The log loss is: 0.6554000609637015
For values of alpha = 0.001 The log loss is: 0.6554000609637015
```

```
For values of alpha = 0.1 The log loss is: 0.6554000609637015

For values of alpha = 1 The log loss is: 0.6248822103768743

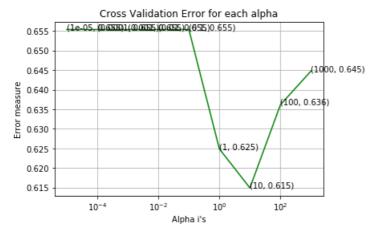
For values of alpha = 10 The log loss is: 0.6149182450360078

For values of alpha = 100 The log loss is: 0.6361725621636402

For values of alpha = 1000 The log loss is: 0.6447644179190515
```

In [81]:

```
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.xscale('log')
plt.show()
```

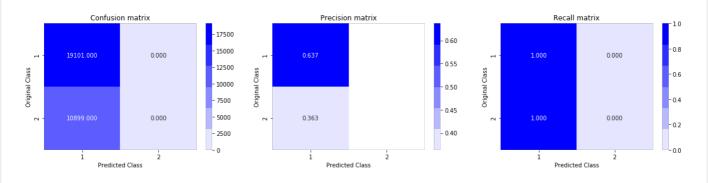


In [82]:

```
best_alpha = alpha[np.argmin(log_error_array)]
clf = SGDClassifier(alpha=best_alpha, penalty='12', loss='log', random_state=42)
clf.fit(X_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train, y_train)

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

For values of best alpha = 10 The train log loss is: 0.6354490856754549 For values of best alpha = 10 The test log loss is: 0.6314334520562241 Total number of data points : 30000



Summary

```
In [83]:
```

```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ['Model', 'vectorizer','Best Alpha', 'Best Log loss']
x.add_row(['Logistic Regression', 'tfidf', best_alpha, 0.63078])
print(x)
```

Model	vectorizer	Best Alpha	Best Log loss
Logistic Regression	tfidf +	10 +	0.63078