Quora Question Pairs

1. Business Problem

1.1 Description

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

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

> Credits: Kaggle

Problem Statement

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

1.2 Sources/Useful Links

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

Useful Links

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

1.3 Real world/Business Objectives and Constraints

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

2. Machine Learning Probelm

2.1 Data

2.1.1 Data Overview

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

2.1.2 Example Data point

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

2.2 Mapping the real world problem to an ML problem

2.2.1 Type of Machine Leaning Problem

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

2.2.2 Performance Metric

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

Metric(s):

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

2.3 Train and Test Construction

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

3. Exploratory Data Analysis

In [4]:

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

import re
from nltk.corpus import stopwords

import warnings
warnings.filterwarnings("ignore")
```

In [5]:

```
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from sklearn.cross_validation import StratifiedKFold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
import math
from sklearn.metrics import normalized_mutual_info_score
from sklearn.ensemble import RandomForestClassifier



from sklearn.model_selection import cross_val_score
from sklearn.linear_model import SGDClassifier

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

In [0]:

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

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

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

In [0]:

```
df.head()
```

Out[0]:

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

In [0]:

```
df.info()
```

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

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

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

3.2.1 Distribution of data points among output classes

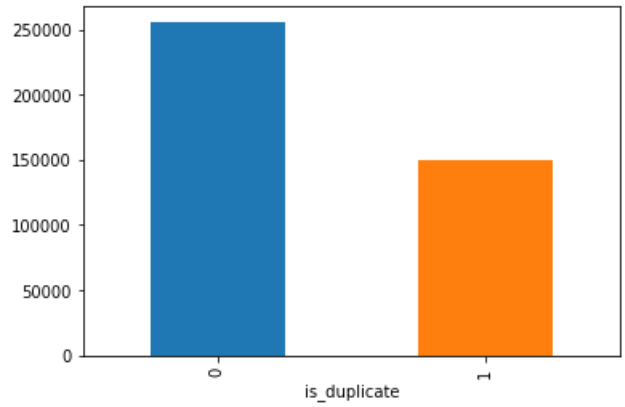
- Number of duplicate(smilar) and non-duplicate(non similar) questions

In [0]:

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

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x16d99c73550>
```



In [0]:

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

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

In [0]:

```
df['is_duplicate'].value_counts()
```

Out[0]:

```
0    255027
1    149263
Name: is_duplicate, dtype: int64
```

In [0]:

```
print('~> Question pairs are Similar (is_duplicate = 1):\n   {}%'.format(((404290-255027)/404290)*100))
print('\n~> Question pairs are not Similar (is_duplicate = 0):\n   {}%'.format(((404290-149263)/404290)*100))
```

```
~> Question pairs are Similar (is_duplicate = 1):
   36.9197853026293%

~> Question pairs are not Similar (is_duplicate = 0):
   63.08021469737069%
```

In [0]:

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

```
~> Question pairs are not Similar (is_duplicate = 0):
   63.08%

~> Question pairs are Similar (is_duplicate = 1):
   36.92%
```

3.2.2 Number of unique questions

In [0]:

```
qids = pd.Series(df['qid1'].tolist() + df['qid2'].tolist())
```

In [0]:

```
qids = pd.Series(df['qid1'].tolist())
```

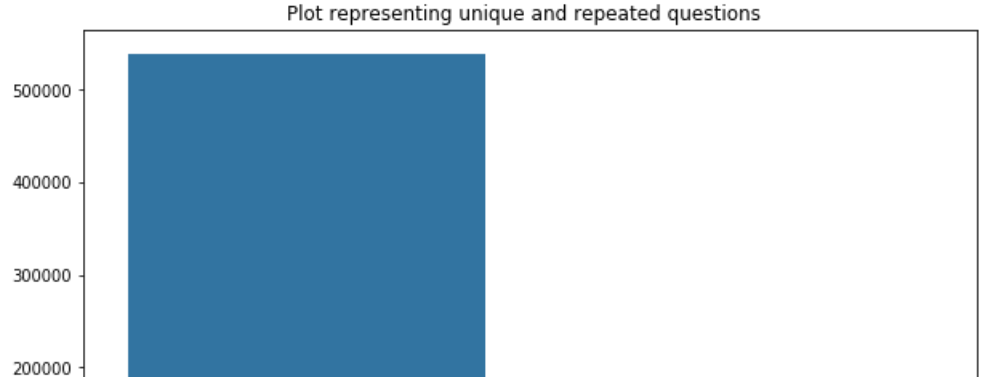
In [0]:

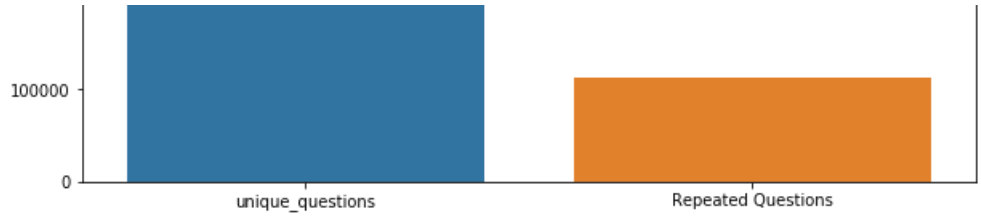
```
qids = pd.Series(df['qid1'].tolist() + df['qid2'].tolist())
unique_qs = len(np.unique(qids))
qs_morethan_onetime = np.sum(qids.value_counts() > 1)
print ('Total number of  Unique Questions are: {}\n'.format(unique_qs))
#print len(np.unique(qids))

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

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


q_vals=qids.value_counts()

q_vals=q_vals.values
```

```
Total number of  Unique Questions are: 537933

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

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

In [0]:

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

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





3.2.3 Checking for Duplicates

In [0]:

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

In [0]:

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

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

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

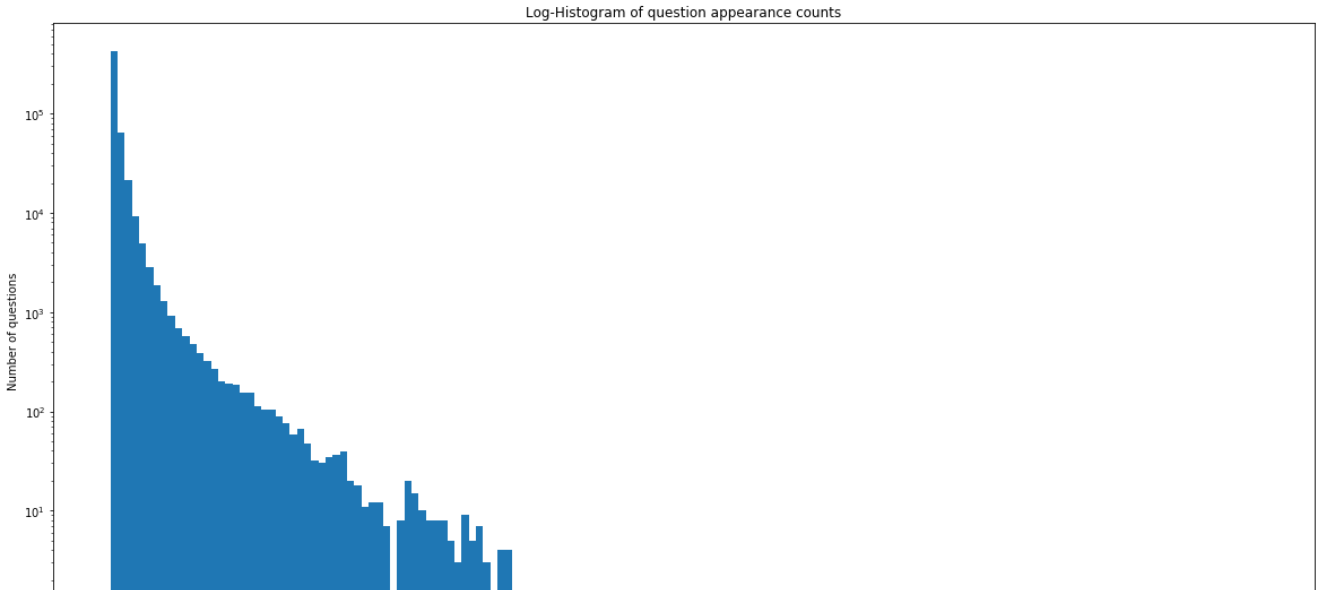
```
Number of duplicate questions 0
```

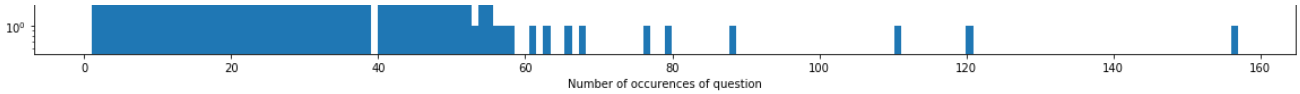
3.2.4 Number of occurrences of each question

In [0]:

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

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

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

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

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

plt.ylabel('Number of questions')

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

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





3.2.5 Checking for NULL values

In [0]:

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

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

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

- There are two rows with null values in question2

In [0]:

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

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

3.3 Basic Feature Extraction (before cleaning)

Let us now construct a few features like:

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

In [0]:

```
if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    df = pd.read_csv("df_fe_without_preprocessing_train.csv",encoding='latin-1')
else:
    df['freq_qid1'] = df.groupby('qid1')['qid1'].transform('count')
    df['freq_qid2'] = df.groupby('qid2')['qid2'].transform('count')
    df['q1len'] = df['question1'].str.len()
    df['q2len'] = df['question2'].str.len()
    df['q1_n_words'] = df['question1'].apply(lambda row: len(row.split(" ")))
    df['q2_n_words'] = df['question2'].apply(lambda row: len(row.split(" ")))

    def normalized_word_Common(row):
        w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * len(w1 & w2)
```

```
    return 1.0 * len(w1 & w2)
df['word_Common'] = df.apply(normalized_word_Common, axis=1)

def normalized_word_Total(row):
    w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
    w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
    return 1.0 * (len(w1) + len(w2))
df['word_Total'] = df.apply(normalized_word_Total, axis=1)

def normalized_word_share(row):
    w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
    w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
    return 1.0 * len(w1 & w2)/(len(w1) + len(w2))
df['word_share'] = df.apply(normalized_word_share, axis=1)

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

df.to_csv("df_fe_without_preprocessing_train.csv", index=False)

df.head()
```

Out[0]:

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

3.3.1 Analysis of some of the extracted features

- Here are some questions have only one single words.

In [0]:

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

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

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

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

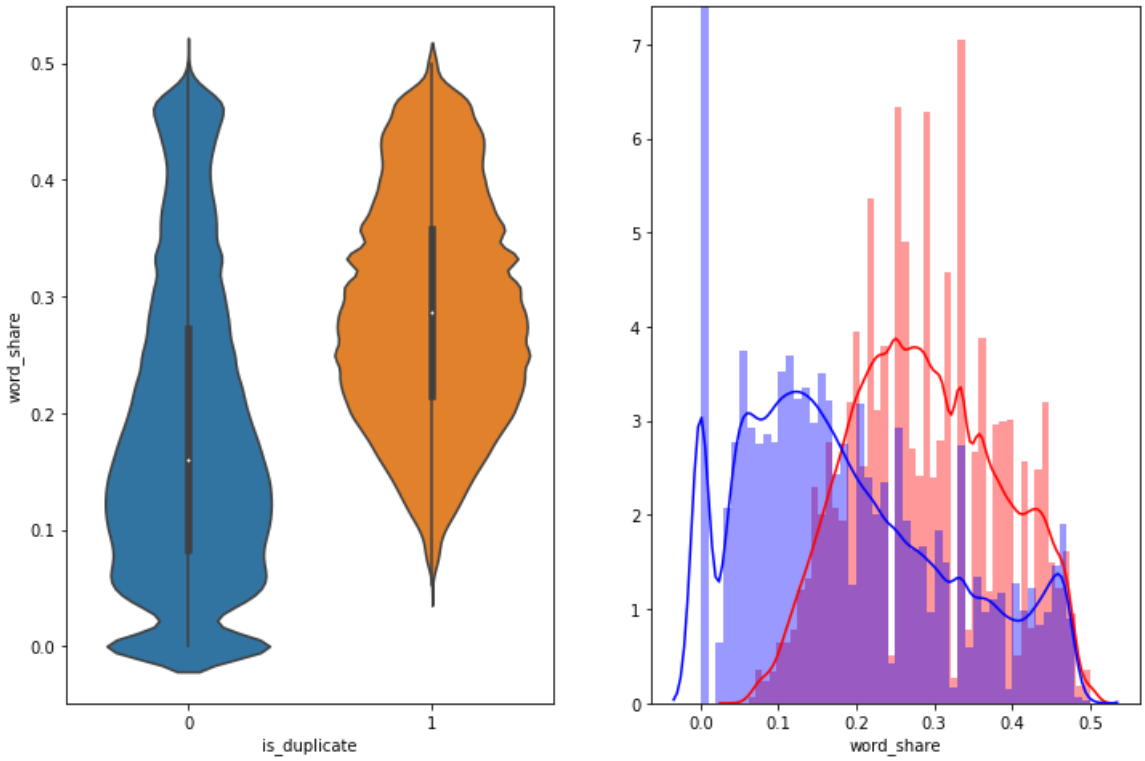
```
Minimum length of the questions in question1 :  1
Minimum length of the questions in question2 :  1
Number of Questions with minimum length [question1] : 67
Number of Questions with minimum length [question2] : 24
```

3.3.1.1 Feature: word_share

In [0]:

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

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

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

```
C:\Users\Mayur\Anaconda3\lib\site-packages\scipy\stats\stats.py:1706: FutureWarning:

Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` inst
ead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`,
which will result either in an error or a different result.
```



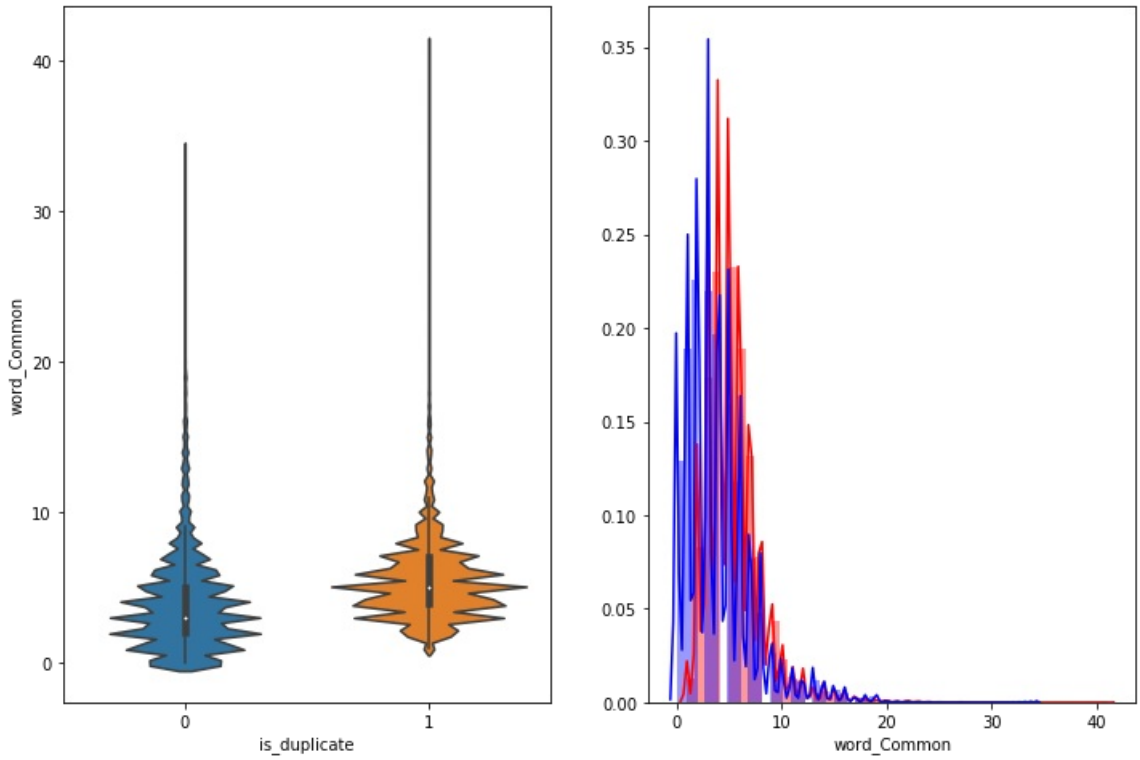
- The distributions for normalized word_share have some overlap on the far right-hand side, i.e., there are quite a lot of questions with high word similarity
- The average word share and Common no. of words of qid1 and qid2 is more when they are duplicate(Similar)

3.3.1.2 Feature: word_Common

In [0]:

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

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

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

```
C:\Users\Mayur\Anaconda3\lib\site-packages\scipy\stats\stats.py:1706: FutureWarning:

Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` inst
ead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`,
which will result either in an error or a different result.
```



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

In [0]:

```
df.head(2)
```

Out[0]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_C
0	0	1	2	What is the step by step guide to invest in sh...	What is the step by step guide to invest in sh...	0	1	1	66	57	14	12	10.0
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0	4	1	51	88	8	13	4.0

3.4 Preprocessing of Text

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

In [0]:

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

STOP_WORDS = stopwords.words("english")


def preprocess(x):
    x = str(x).lower()
    x = x.replace(",000,000", "m").replace(",000", "k").replace("’", "'").replace("‘", "'")\
                           .replace("won't", "will not").replace("cannot", "can not").replace("can'
", "can not")\
                           .replace("n't", " not").replace("what's", "what is").replace("it's", "it
is")\
                           .replace("'ve", " have").replace("i'm", "i am").replace("'re", " are")\
                           .replace("he's", "he is").replace("she's", "she is").replace("'s", " own
)\
                           .replace("%", " percent ").replace("₹", " rupee ").replace("$", " dollar
")\
                           .replace("€", " euro ").replace("'ll", " will")
    x = re.sub(r"([0-9]+)000000", r"\1m", x)
    x = re.sub(r"([0-9]+)000", r"\1k", x)


    porter = PorterStemmer()
    pattern = re.compile('\W') # any non character word

    if type(x) == type(''):
        x = re.sub(pattern, ' ', x)


    if type(x) == type(''):
        x = porter.stem(x)
        example1 = BeautifulSoup(x)
        x = example1.get_text()


    return x
```

3.5 Advanced Feature Extraction (NLP and Fuzzy Features)

Definition:

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

Features:

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

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

- **csc_min** : Ratio of common_stop_count to min lenghth of stop count of Q1 and Q2

csc_min = common_stop_count / (min(len(q1_stops), len(q2_stops))

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

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

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

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

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

In [0]:

```
from bs4 import BeautifulSoup
from fuzzywuzzy import fuzz
from sklearn.manifold import TSNE
# Import the Required lib packages for WORD-Cloud generation
# https://stackoverflow.com/questions/45625434/how-to-install-wordcloud-in-python3-6
from wordcloud import WordCloud, STOPWORDS
from os import path
from PIL import Image
```

In [0]:

```
def get_token_features(q1, q2):
    token_features = [0.0]*10

    # Converting the Sentence into Tokens:
    q1_tokens = q1.split()
    q2_tokens = q2.split()

    if len(q1_tokens) == 0 or len(q2_tokens) == 0:
        return token_features
    # Get the non-stopwords in Questions
    q1_words = set([word for word in q1_tokens if word not in STOP_WORDS])
    q2_words = set([word for word in q2_tokens if word not in STOP_WORDS])

    #Get the stopwords in Questions
    q1_stops = set([word for word in q1_tokens if word in STOP_WORDS])
```

```
    q2_stops = set([word for word in q2_tokens if word in STOP_WORDS])

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

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

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


    token_features[0] = common_word_count / (min(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[1] = common_word_count / (max(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[2] = common_stop_count / (min(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[3] = common_stop_count / (max(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[4] = common_token_count / (min(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)
    token_features[5] = common_token_count / (max(len(q1_tokens), len(q2_tokens)) + SAFE_DIV)

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

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

    token_features[8] = abs(len(q1_tokens) - len(q2_tokens))

    #Average Token Length of both Questions
    token_features[9] = (len(q1_tokens) + len(q2_tokens))/2
    return token_features

# get the Longest Common sub string

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

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

    print("token features...")

    # Merging Features with dataset

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

    df["cwc_min"]       = list(map(lambda x: x[0], token_features))
    df["cwc_max"]       = list(map(lambda x: x[1], token_features))
    df["csc_min"]       = list(map(lambda x: x[2], token_features))
    df["csc_max"]       = list(map(lambda x: x[3], token_features))
    df["ctc_min"]       = list(map(lambda x: x[4], token_features))
    df["ctc_max"]       = list(map(lambda x: x[5], token_features))
    df["last_word_eq"]  = list(map(lambda x: x[6], token_features))
    df["first_word_eq"] = list(map(lambda x: x[7], token_features))
    df["abs_len_diff"]  = list(map(lambda x: x[8], token_features))
    df["mean_len"]      = list(map(lambda x: x[9], token_features))

    #Computing Fuzzy Features and Merging with Dataset

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

    df["token_set_ratio"]       = df.apply(lambda x: fuzz.token_set_ratio(x["question1"],
x["question2"]), axis=1)
    # The token sort approach involves tokenizing the string in question, sorting the tokens alpha
betically, and
    # then joining them back into a string We then compare the transformed strings with a simple r
atio().
    df["token_sort_ratio"]      = df.apply(lambda x: fuzz.token_sort_ratio(x["question1"],
```

```
x["question2"]), axis=1)
    df["fuzz_ratio"]            = df.apply(lambda x: fuzz.QRatio(x["question1"], x["question2"]), a
is=1)
    df["fuzz_partial_ratio"]    = df.apply(lambda x: fuzz.partial_ratio(x["question1"],
x["question2"]), axis=1)
    df["longest_substr_ratio"]  = df.apply(lambda x: get_longest_substr_ratio(x["question1"], x["qu
estion2"]), axis=1)
    return df
```

In [6]:

```
if os.path.isfile('nlp_features_train.csv'):
    df = pd.read_csv("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[6]:

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

2 rows × 21 columns

3.5.1 Analysis of extracted features

3.5.1.1 Plotting Word clouds

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

In [0]:

```
df_duplicate = df[df['is_duplicate'] == 1]
dfp_nonduplicate = df[df['is_duplicate'] == 0]

# Converting 2d array of q1 and q2 and flatten the array: like {{1,2},{3,4}} to {1,2,3,4}
p = np.dstack([df_duplicate["question1"], df_duplicate["question2"]]).flatten()
n = np.dstack([dfp_nonduplicate["question1"], dfp_nonduplicate["question2"]]).flatten()

print ("Number of data points in class 1 (duplicate pairs) :",len(p))
print ("Number of data points in class 0 (non duplicate pairs) :",len(n))

#Saving the np array into a text file
np.savetxt('train_p.txt', p, delimiter=' ', fmt='%s',encoding="utf-8")
np.savetxt('train_n.txt', n, delimiter=' ', fmt='%s',encoding="utf-8")
```

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

In [0]:

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

textp_w = open(path.join(d, 'train_p.txt'),encoding="utf-8").read()
textn_w = open(path.join(d, 'train_n.txt'),encoding="utf-8").read()
stopwords = set(STOPWORDS)
stopwords.add("said")
stopwords.add("br")
stopwords.add(" ")
stopwords.remove("not")

stopwords.remove("no")
#stopwords.remove("good")
#stopwords.remove("love")
stopwords.remove("like")
#stopwords.remove("best")
#stopwords.remove("!")
print ("Total number of words in duplicate pair questions :",len(textp_w))
print ("Total number of words in non duplicate pair questions :",len(textn_w))
```

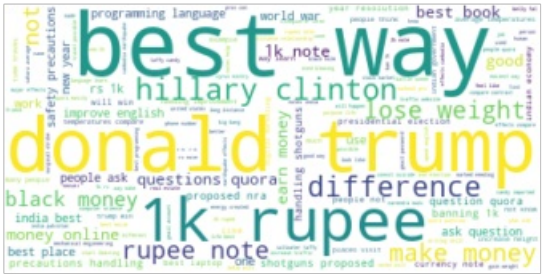
```
Total number of words in duplicate pair questions : 16109886
Total number of words in non duplicate pair questions : 33193067
```

Word Clouds generated from duplicate pair question's text

In [0]:

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

```
Word Cloud for Duplicate Question pairs
```

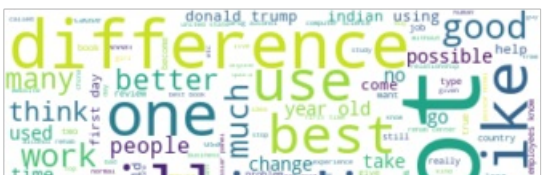


Word Clouds generated from non duplicate pair question's text

In [0]:

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

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



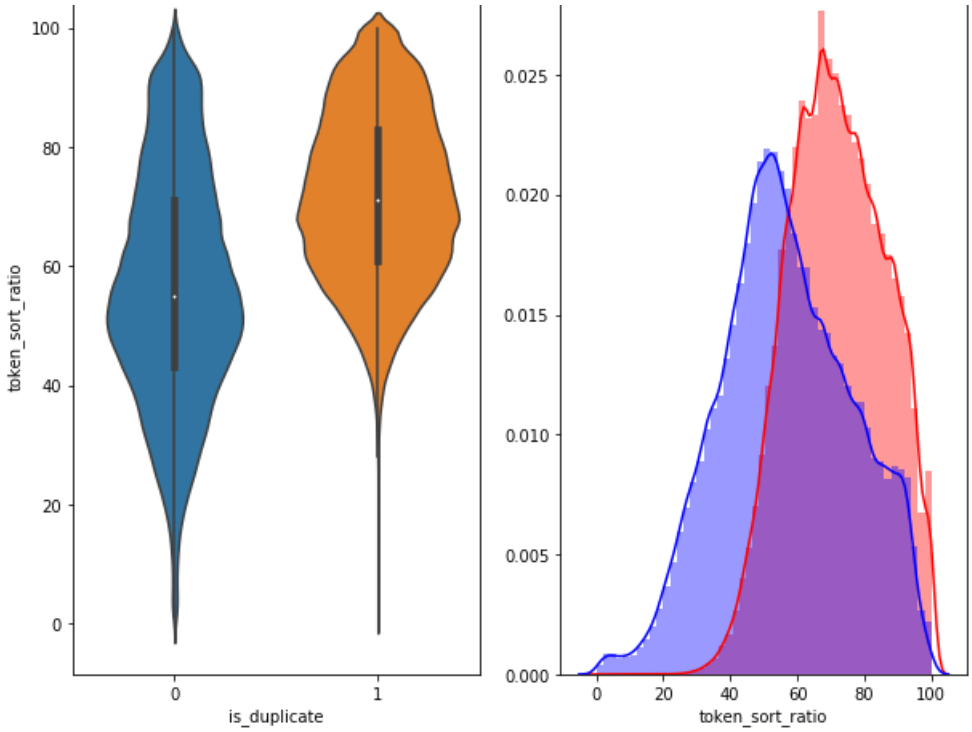
3.5.1.2 Pair plot of features ['ctc_min', 'cwc_min', 'csc_min', 'token_sort_ratio']

In [0]:

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

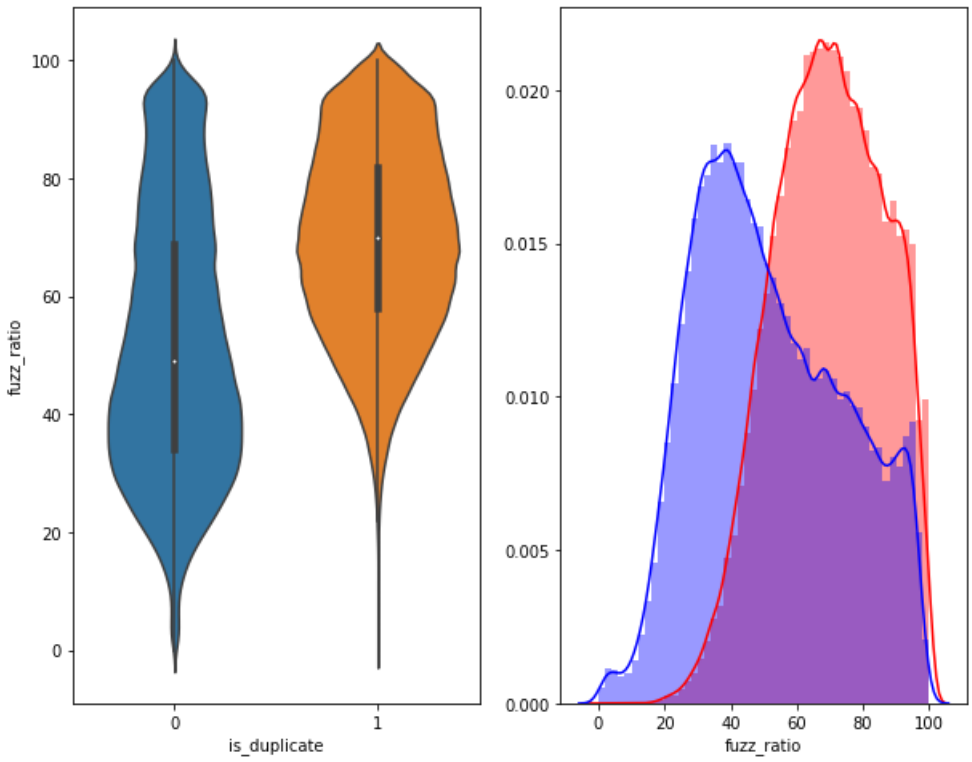
In [0]:

```
# 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()
```



In [0]:

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

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

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



3.5.2 Visualization

In [0]:

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

from sklearn.preprocessing import MinMaxScaler

dfp_subsampled = df[0:5000]
X = MinMaxScaler().fit_transform(dfp_subsampled[['cwc_min', 'cwc_max', 'csc_min', 'csc_max' , 'ctc_min' , 'ctc_max' , 'last_word_eq', 'first_word_eq' , 'abs_len_diff' , 'mean_len' , 'token_set_ratio' , 'token_sort_ratio' ,  'fuzz_ratio' , 'fuzz_partial_ratio' , 'longest_substr_ratio']])
y = dfp_subsampled['is_duplicate'].values
```

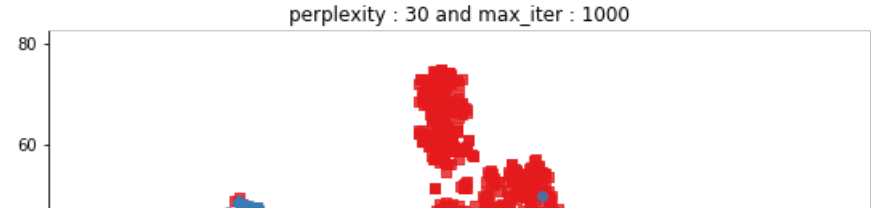
In [0]:

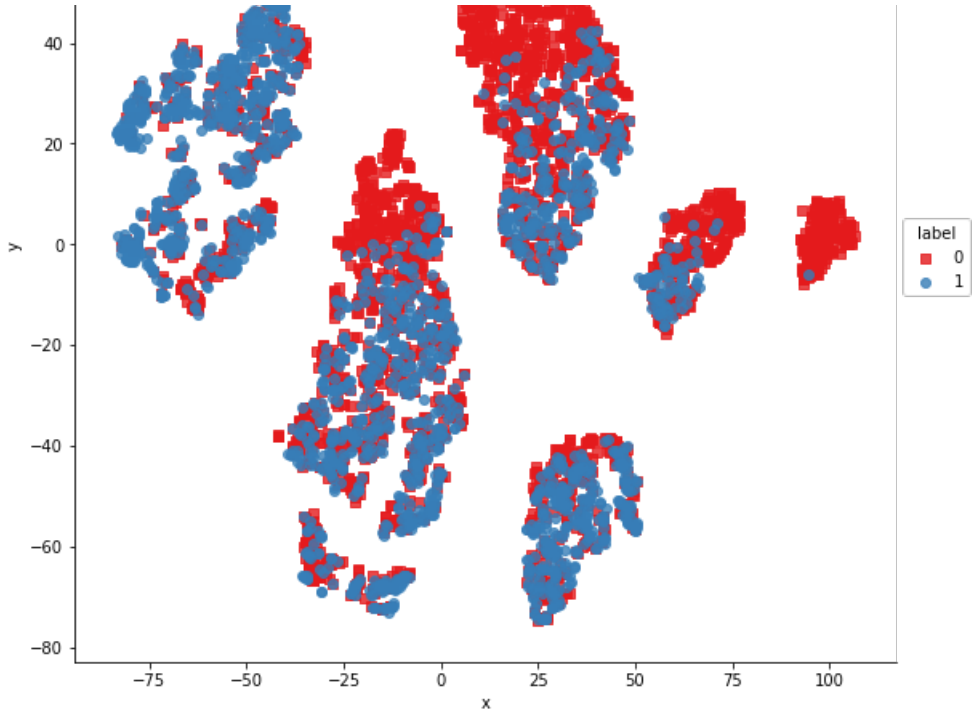
```
tsne2d = TSNE(
    n_components=2,
    init='random', # pca
    random_state=101,
    method='barnes_hut',
    n_iter=1000,
    verbose=2,
    angle=0.5
).fit_transform(X)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.116s...
[t-SNE] Computed neighbors for 5000 samples in 0.723s...
[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: 0.130446
[t-SNE] Computed conditional probabilities in 0.572s
[t-SNE] Iteration 50: error = 81.2897949, gradient norm = 0.0455700 (50 iterations in 13.148s)
[t-SNE] Iteration 100: error = 70.6164398, gradient norm = 0.0095177 (50 iterations in 9.286s)
[t-SNE] Iteration 150: error = 68.9172134, gradient norm = 0.0056736 (50 iterations in 9.234s)
[t-SNE] Iteration 200: error = 68.1004639, gradient norm = 0.0049672 (50 iterations in 9.564s)
[t-SNE] Iteration 250: error = 67.5914536, gradient norm = 0.0039700 (50 iterations in 9.703s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.591454
[t-SNE] Iteration 300: error = 1.7926962, gradient norm = 0.0011878 (50 iterations in 10.110s)
[t-SNE] Iteration 350: error = 1.3936826, gradient norm = 0.0004807 (50 iterations in 10.000s)
[t-SNE] Iteration 400: error = 1.2281071, gradient norm = 0.0002778 (50 iterations in 9.749s)
[t-SNE] Iteration 450: error = 1.1385784, gradient norm = 0.0001864 (50 iterations in 9.785s)
[t-SNE] Iteration 500: error = 1.0835493, gradient norm = 0.0001437 (50 iterations in 9.777s)
[t-SNE] Iteration 550: error = 1.0471643, gradient norm = 0.0001152 (50 iterations in 9.811s)
[t-SNE] Iteration 600: error = 1.0231258, gradient norm = 0.0001007 (50 iterations in 9.855s)
[t-SNE] Iteration 650: error = 1.0069925, gradient norm = 0.0000892 (50 iterations in 9.886s)
[t-SNE] Iteration 700: error = 0.9953420, gradient norm = 0.0000804 (50 iterations in 10.412s)
[t-SNE] Iteration 750: error = 0.9866475, gradient norm = 0.0000728 (50 iterations in 10.188s)
[t-SNE] Iteration 800: error = 0.9796536, gradient norm = 0.0000658 (50 iterations in 9.985s)
[t-SNE] Iteration 850: error = 0.9737327, gradient norm = 0.0000618 (50 iterations in 9.971s)
[t-SNE] Iteration 900: error = 0.9688665, gradient norm = 0.0000594 (50 iterations in 10.021s)
[t-SNE] Iteration 950: error = 0.9644679, gradient norm = 0.0000589 (50 iterations in 10.677s)
[t-SNE] Iteration 1000: error = 0.9610358, gradient norm = 0.0000559 (50 iterations in 10.635s)
[t-SNE] Error after 1000 iterations: 0.961036
```

In [0]:

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

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





In [0]:

```
df.head(2)
```

Out[0]:

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

2 rows × 21 columns

3.5.3 TFIDF Features Extraction and Data Preparation

In [7]:

```
from sklearn.utils import resample
df1=resample(df, n_samples=100000, random_state=30)
```

3.5.3.1 Split data into train and test

In [10]:

```
from sklearn.model_selection import train_test_split
df1_train,df1_test = train_test_split(df1, test_size=0.3)
```

3.5.3.2 Appllying and Fitting TF-IDF on Train Data

In [18]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
# merge texts
questions = list(df1_train['question1']) + list(df1_train['question2'])
questions1 = list(df1_train['question1'])
questions2 = list(df1_train['question2'])
questions=np.asarray(questions)
questions1=np.asarray(questions1)
questions2=np.asarray(questions2)

tfidf = TfidfVectorizer(lowercase=False)
df3=tfidf.fit_transform(questions.astype('U'))
df1_q1=tfidf.transform(questions1.astype('U'))
df1_q2=tfidf.transform(questions2.astype('U'))
```

3.5.3.2 Applying TF-IDF on Test Data

In [19]:

```
questions11 = list(df1_test['question1'])
questions22 = list(df1_test['question2'])
questions11=np.asarray(questions11)
questions22=np.asarray(questions22)
df1_q11=tfidf.transform(questions11.astype('U'))
df1_q22=tfidf.transform(questions22.astype('U'))
```

In [75]:

```
from scipy.sparse import coo_matrix, hstack
df3 = df1_train.drop(['id','qid1','qid2','question1','question2','is_duplicate'],axis=1)
df4=hstack([df1_q1,df1_q2])
df3=csr_matrix(df3.values)
df5=hstack([df4,df3])
```

In [82]:

```
from scipy.sparse import coo_matrix, hstack
df3 = df1_test.drop(['id','qid1','qid2','question1','question2','is_duplicate'],axis=1)
df4=hstack([df1_q11,df1_q22])
df3=csr_matrix(df3.values)
df6=hstack([df4,df3])
```

In [84]:

```
y_train=df1_train['is_duplicate']
y_test=df1_test['is_duplicate']
```

In [89]:

```
X_train=df5
X_test=df6
```

3.6 Featurizing text data with tfidf weighted word-vectors

In [0]:

```
import pandas as pd
df=pd.read_csv(r"/content/drive/My Drive/final_features.csv")
```

In [7]:

```
df.head(5)
```

Out[7]:

	Unnamed: 0	id	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	...	374_y	
0	0	0	0	0.999980	0.833319	0.999983	0.999983	0.916659	0.785709	0.0	...	16.165592	33.(
1	1	1	0	0.799984	0.399996	0.749981	0.599988	0.699993	0.466664	0.0	...	-4.901128	-4.5
2	2	2	0	0.399992	0.333328	0.399992	0.249997	0.399996	0.285712	0.0	...	8.359966	-2.1
3	3	3	0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	...	3.311411	3.7(
4	4	4	0	0.399992	0.199998	0.999950	0.666644	0.571420	0.307690	0.0	...	-2.403870	11.9

5 rows × 797 columns

In [0]:

```
from sklearn.utils import resample
df2=resample(df, n_samples=100000, random_state=30)
```

In [9]:

```
df2.shape
```

Out[9]:

```
(100000, 797)
```

In [0]:

```
y_true=df2['is_duplicate']
```

In [0]:

```
df1=df2.drop(['Unnamed: 0','id','is_duplicate'],axis=1)
```

In [12]:

```
df1.head(5)
```

Out[12]:

	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	abs_len_diff	mean_len
48045	0.666644	0.399992	0.666644	0.399992	0.666656	0.363633	0.0	1.0	5.0	8.5
360948	0.749981	0.749981	0.166664	0.124998	0.399996	0.333331	0.0	0.0	2.0	11.0
46220	0.749981	0.749981	0.999950	0.999950	0.833319	0.833319	1.0	1.0	0.0	6.0
328599	0.999900	0.499975	0.999950	0.999950	0.999967	0.749981	0.0	1.0	1.0	3.5
358197	0.444440	0.399996	0.599988	0.428565	0.499996	0.368419	1.0	1.0	5.0	16.5

5 rows × 794 columns

4. Machine Learning Model

4.1 Random train test split(70:30)

In [0]:

```
from sklearn.model_selection import train_test_split
X_train,X_test, y_train, y_test = train_test_split(df12[:,0:173058], y_true, stratify=y_true, test_
size=0.3)
```

In [90]:

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

```
Number of data points in train data : (70000, 75575)
Number of data points in test data : (30000, 75575)
```

In [91]:

```
from collections import Counter
print("-"*10, "Distribution of output variable in train data", "-"*10)
train_distr = Counter(y_train)
train_len = len(y_train)
print("Class 0: ",int(train_distr[0])/train_len,"Class 1: ", int(train_distr[1])/train_len)
print("-"*10, "Distribution of output variable in test data", "-"*10)
test_distr = Counter(y_test)
test_len = len(y_test)
print("Class 0: ",int(test_distr[1])/test_len, "Class 1: ",int(test_distr[1])/test_len)
```

```
---------- Distribution of output variable in train data ----------
Class 0:  0.6270142857142857 Class 1:  0.3729857142857143
---------- Distribution of output variable in test data ----------
Class 0:  0.36756666666666665 Class 1:  0.36756666666666665
```

In [92]:

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

    A =(((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in that column

    # C = [[1, 2],
    #     [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                           [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                           [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in that row
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                      [3/4, 4/6]]
    plt.figure(figsize=(20,4))

    labels = [1,2]
    # representing A in heatmap format
```

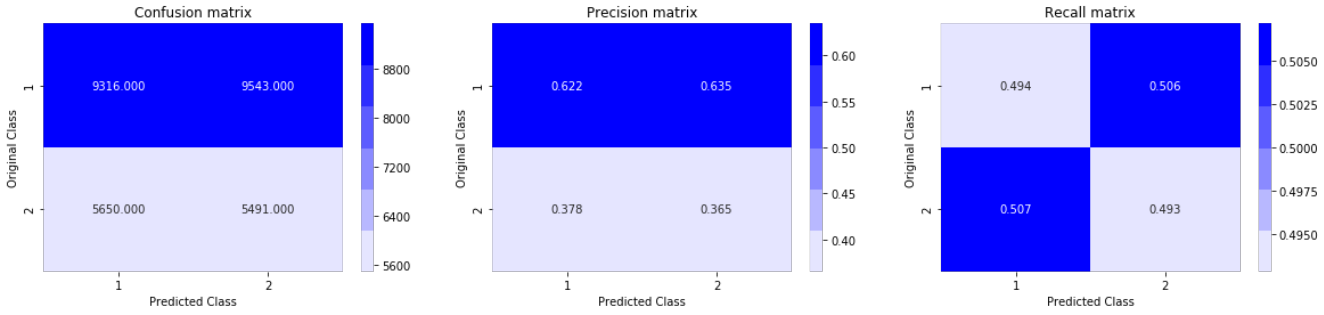
```
    cmap=sns.light_palette("blue",as_cmap=True)
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

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

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

    plt.show()
```

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

In [0]:

```
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix
predicted_y = np.zeros((test_len,2))
for i in range(test_len):
    rand_probs = np.random.rand(1,2)
    predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
print("Log loss on Test Data using Random Model",log_loss(y_test, predicted_y, eps=1e-15))

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

```
Log loss on Test Data using Random Model 0.8856214752296263
```



4.3 Logistic Regression with hyperparameter tuning

In [94]:

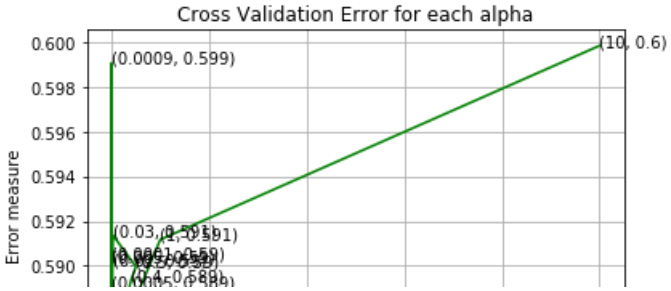
```
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix
```

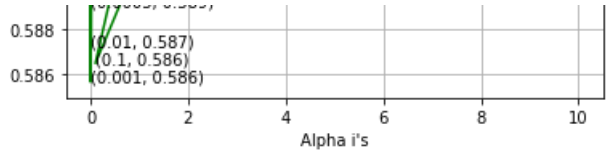
In [99]:

```
alpha = [0.0001,0.0005,0.0009,0.001,0.005,0.01,0.02,0.03,0.5,0.4,0.1,1,10] # hyperparam for SGD cla
ssifier.

# read more about SGDClassifier() at http://scikit-
learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss='hinge', penalty='l2', alpha=0.0001, l1_ratio=0.15, fit_intercept=True, max_i
ter=None, tol=None,
```

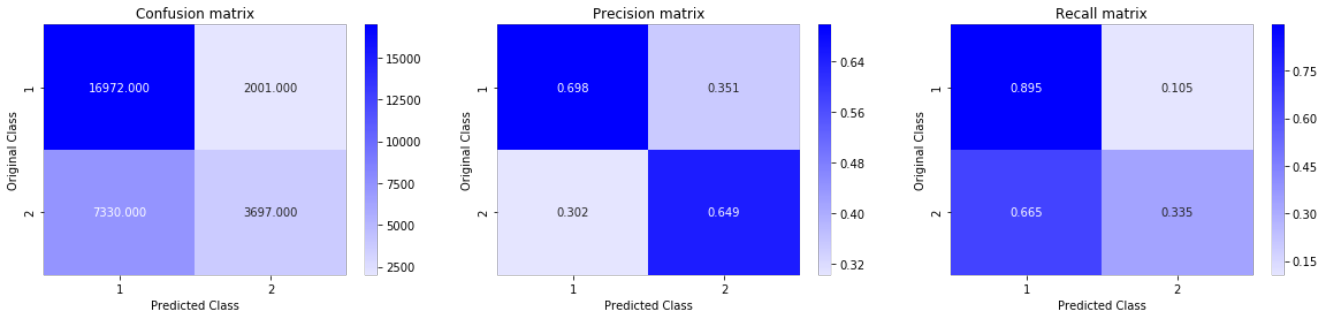
```
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None, learning_rate='optimal', eta0
=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

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

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


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

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


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

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

```
For values of alpha =  0.0001 The log loss is: 0.5903050234257222
For values of alpha =  0.0005 The log loss is: 0.5890686433383788
For values of alpha =  0.0009 The log loss is: 0.5990766686205407
For values of alpha =  0.001 The log loss is: 0.5856517786006172
For values of alpha =  0.005 The log loss is: 0.5901780549964594
For values of alpha =  0.01 The log loss is: 0.5872784466138555
For values of alpha =  0.02 The log loss is: 0.5900171775225174
For values of alpha =  0.03 The log loss is: 0.5913589947446735
For values of alpha =  0.5 The log loss is: 0.5899603773538579
For values of alpha =  0.4 The log loss is: 0.5893444039779905
For values of alpha =  0.1 The log loss is: 0.586482304191585
For values of alpha =  1 The log loss is: 0.5911690156678646
For values of alpha =  10 The log loss is: 0.599844528995524
```






```
For values of best alpha =  0.001 The train log loss is: 0.5867173818037488
For values of best alpha =  0.001 The test log loss is: 0.5856517786006172
Total number of data points : 30000
```



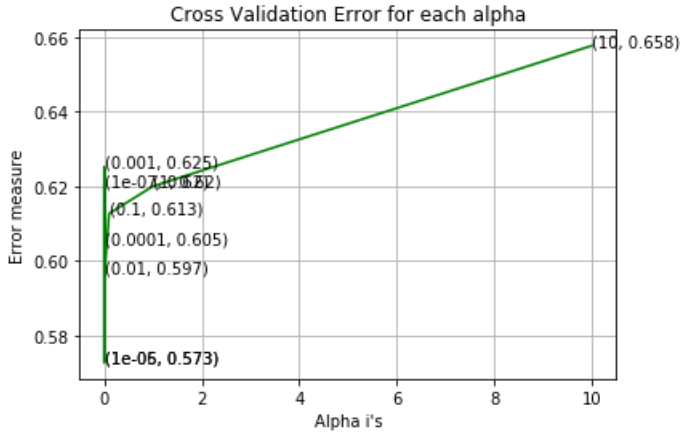
4.4 Linear SVM with hyperparameter tuning

In [100]:

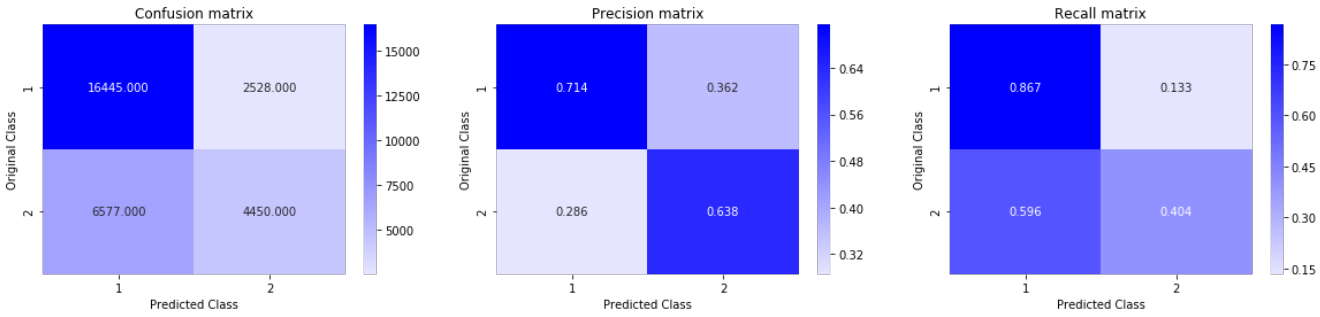
```
alpha = [10 ** x for x in range(-7, 2)] # hyperparam for SGD classifier.

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

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

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


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

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


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge', random_state=42)
clf.fit(X_train, y_train)
```

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

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

```
For values of alpha =  1e-07 The log loss is: 0.6202705052713428
For values of alpha =  1e-06 The log loss is: 0.5726428177412126
For values of alpha =  1e-05 The log loss is: 0.5726694154185484
For values of alpha =  0.0001 The log loss is: 0.6046284667570027
For values of alpha =  0.001 The log loss is: 0.625214624932709
For values of alpha =  0.01 The log loss is: 0.5967623003040731
For values of alpha =  0.1 The log loss is: 0.6126835842344087
For values of alpha =  1 The log loss is: 0.6200188471208247
For values of alpha =  10 The log loss is: 0.6577108159955123
```




```
For values of best alpha =  1e-06 The train log loss is: 0.573703627834042
For values of best alpha =  1e-06 The test log loss is: 0.5726428177412126
Total number of data points : 30000
```



4.5 XGBOOST Model for TF_IDF W2V

The data of tfidf-w2v is mentioned in section 3.6

In [0]:

```
from sklearn.model_selection import train_test_split
X_train,X_test, y_train, y_test = train_test_split(df1, y_true, stratify=y_true, test_size=0.3)
```

In [14]:

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

```
Number of data points in train data : (70000, 794)
Number of data points in test data : (30000, 794)
```

XGBOOST Hyper-Parameter Tunning-1

In [26]:

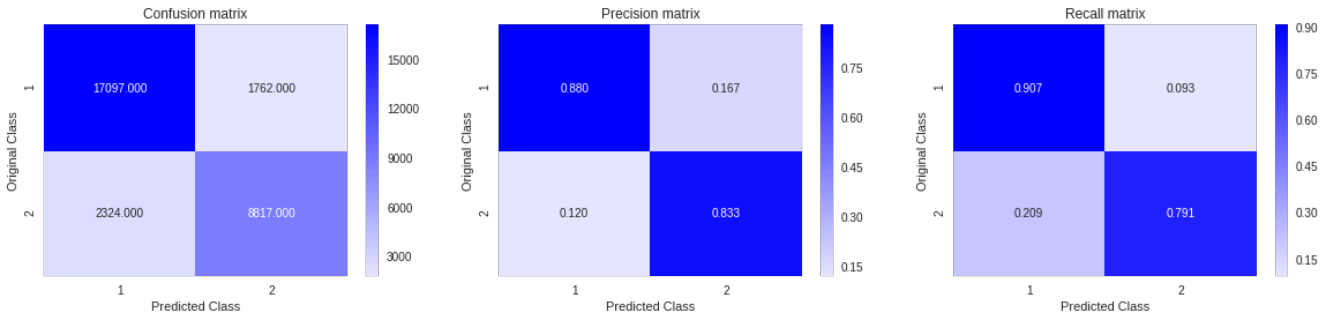
```
from sklearn.model_selection import RandomizedSearchCV
from scipy import stats
from xgboost import XGBClassifier
param_dist = {'n_estimators': stats.randint(5, 200),
              'learning_rate': stats.uniform(0.01, 0.07),
              'subsample': stats.uniform(0.3, 0.7),
              'max_depth': stats.randint(5, 30),
              'colsample_bytree': stats.uniform(0.5, 0.45),
              'min_child_weight': [1, 2, 3]
             }
model=RandomizedSearchCV(XGBClassifier(n_jobs=-1), param_distributions=param_dist, scoring = 'neg_l
og_loss', cv=3)
model.fit(X_train, y_train)
print(model.best_estimator_)
print(model.score(X_test, y_test))
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=0.8093581422813731, gamma=0,
       learning_rate=0.05221407899993648, max_delta_step=0, max_depth=17,
       min_child_weight=2, missing=None, n_estimators=194, n_jobs=-1,
       nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=0.8899023891416735)
-0.2918076129439966
```

In [45]:

```
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix
import numpy as np
from pylab import imshow, show, get_cmap
predict_y = model.predict_proba(X_train)
print('For values of best parameters', "The train log loss is:",log_loss(y_train, predict_y, label
s=model.classes_, eps=1e-15))
predict_y = model.predict_proba(X_test)
print('For values of best Parameters',"The test log loss is:",log_loss(y_test, predict_y, labels=m
odel.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of best parameters The train log loss is: 0.021194313074824094
For values of best Parameters The test log loss is: 0.2918076129439966
Total number of data points : 30000
```



XGBOOST Hyperparameter tunning-2

In [46]:

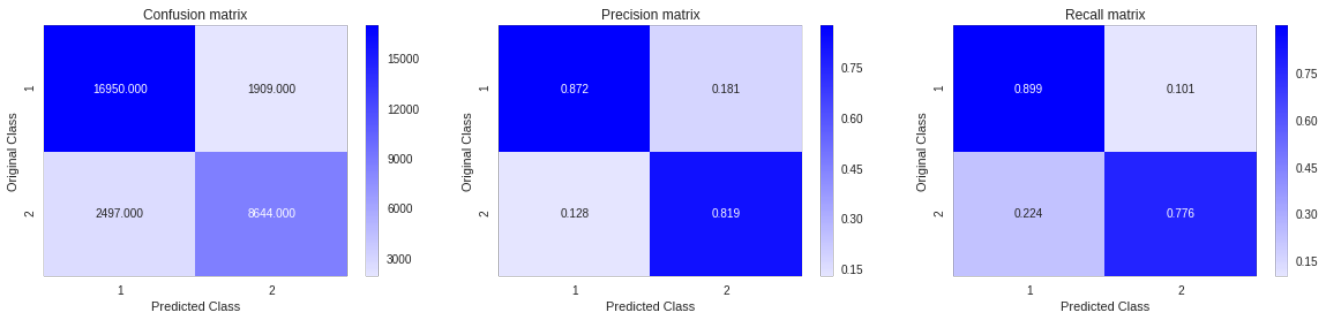
```
from sklearn.model_selection import RandomizedSearchCV
from scipy import stats
from xgboost import XGBClassifier
param_dist = {'n_estimators': stats.randint(5, 100),
              'learning_rate': stats.uniform(0.01, 0.07),
              'subsample': stats.uniform(0.3, 0.5),
              'max_depth': stats.randint(5, 30),
              'colsample_bytree': stats.uniform(0.3, 0.4),
              'min_child_weight': [1, 2]
             }
model=RandomizedSearchCV(XGBClassifier(n_jobs=-1), param_distributions=param_dist, scoring = 'log_l
oss', cv=3)
model.fit(X_train, y_train)
print(model.best_estimator_)
print(model.score(X_test, y_test))
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=0.4387334259086641, gamma=0,
       learning_rate=0.07126337089902758, max_delta_step=0, max_depth=17,
       min_child_weight=1, missing=None, n_estimators=80, n_jobs=-1,
       nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=0.38793528921378484)
-0.3080767333132758
```

In [47]:

```
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix
import numpy as np
from pylab import imshow, show, get_cmap
predict_y = model.predict_proba(X_train)
print('For values of best parameters', "The train log loss is:",log_loss(y_train, predict_y, label
s=model.classes_, eps=1e-15))
predict_y = model.predict_proba(X_test)
print('For values of best Parameters',"The test log loss is:",log_loss(y_test, predict_y, labels=m
odel.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of best parameters The train log loss is: 0.0955516838646577
For values of best Parameters The test log loss is: 0.3080767333132758
Total number of data points : 30000
```



XGBOOST Hyperparameter tunning-3

In [17]:

```
from sklearn.model_selection import RandomizedSearchCV
from scipy import stats
```

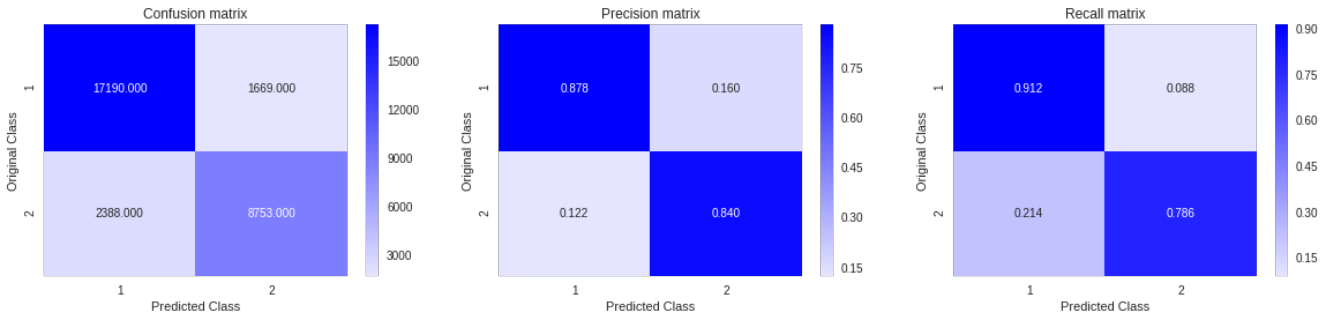
```
from xgboost import XGBClassifier
param_dist = {'n_estimators': stats.randint(200,400),
              'learning_rate': stats.uniform(0.01, 0.07),
              'subsample': stats.uniform(0.3, 0.5),
              'max_depth': stats.randint(5,20),
              'colsample_bytree': stats.uniform(0.3, 0.4),
              'reg_lambda':[0.01,0.1,1]
             }
model=RandomizedSearchCV(XGBClassifier(n_jobs=-1), param_distributions=param_dist, scoring = 'log_l
oss', cv=3)
model.fit(X_train, y_train)
print(model.best_estimator_)
print(model.score(X_test, y_test))
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=0.47188054780145805, gamma=0,
       learning_rate=0.04090559332367365, max_delta_step=0, max_depth=13,
       min_child_weight=1, missing=None, n_estimators=351, n_jobs=-1,
       nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=0.01, scale_pos_weight=1, seed=None,
       silent=True, subsample=0.39494934326108116)
-0.2863089847528737
```

In [21]:

```
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix
import numpy as np
from pylab import imshow, show, get_cmap
predict_y = model.predict_proba(X_train)
print('For values of best parameters', "The train log loss is:",log_loss(y_train, predict_y, label
s=model.classes_, eps=1e-15))
predict_y = model.predict_proba(X_test)
print('For values of best Parameters',"The test log loss is:",log_loss(y_test, predict_y, labels=m
odel.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of best parameters The train log loss is: 0.03197903703661195
For values of best Parameters The test log loss is: 0.2863089847528737
Total number of data points : 30000
```



5 Conclusion

In [103]:

```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["Model ", "Train Loss", "Test Loss"]

x.add_row(['Log Regression',0.5867,0.5856])
x.add_row(['SVM',0.5737,0.5726])

print(x)
```

```
+----------------+------------+-----------+
|     Model      | Train Loss | Test Loss |
+----------------+------------+-----------+
| Log Regression |   0.5867   |   0.5856  |
|      SVM       |   0.5737   |   0.5726  |
+----------------+------------+-----------+
```

In [27]:

```
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["Model ", "Train Loss", "Test Loss","No of Estimator","Max Depth","Learning Rate",
"reg_lambda"]

x.add_row(['XGBOOST',0.0211,0.29180,194,17,0.05221,1])
x.add_row(['XGBOOST',0.0955,0.3080,80,17,0.0712633,1])
x.add_row(['XGBOOST',0.0319,0.286,351,13,0.04090,0.01])


print(x)
```

```
+---------+------------+-----------+-----------------+-----------+---------------+------------+
|  Model  | Train Loss | Test Loss | No of Estimator | Max Depth | Learning Rate | reg_lambda |
+---------+------------+-----------+-----------------+-----------+---------------+------------+
| XGBOOST |   0.0211   |   0.2918  |       194       |     17    |    0.05221    |     1      |
| XGBOOST |   0.0955   |   0.308   |        80       |     17    |   0.0712633   |     1      |
| XGBOOST |   0.0319   |   0.286   |       351       |     13    |     0.0409    |    0.01    |
+---------+------------+-----------+-----------------+-----------+---------------+------------+
```