```
In [1]: ![Quora-1.png] (attachment:Quora-1.png)
```

```
/bin/bash: -c: line 0: syntax error near unexpected token `attachment:Quora-1.png' /bin/bash: -c: line 0: `[Quora-1.png] (attachment:Quora-1.png)'
```

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 has

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/dataanalysis-xgboost-starter-0-35460lb/comments
- Kaggle Winning Solution and other approaches: https://www.dropbox.com/sh/93968nfnrzh8bp5//dl=0
- Blog 1:
 https://engineering.quora.com/Semantic-Question-Matching-with-Deep-Learning
- Blog 2: https://towardsdatascience.com/identifying-

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", "question 2", "is duplicate" "0", "1", "2", "What is the step by step gu ide to invest in share market in indi a?", "What is the step by step guide to i nvest in share market?","0" "1", "3", "4", "What is the story of Kohino or (Koh-i-Noor) Diamond?","What would ha ppen if the Indian government stole the Kohinoor (Koh-i-Noor) diamond back?", "0" "7", "15", "16", "How can I be a good geolo gist?", "What should I do to be a great g eologist?","1" "11", "23", "24", "How do I read and find m y 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: <u>https://www.kaggle.com/wiki/LogarithmicLoss</u>
- 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.

Approch method

https://classroom.appliedcourse.com/classrooms/e69

https://github.com/krpiyush5/Quora-Question-Pair-Similarity-Problem-/blob/master/final_update_QuoraQuestionPair.ipynb

https://www.appliedaicourse.com/

Procedure

1) First we have to perform Exploratory Data Analysis on Quora Question Pair data in which we going perform such as finding number of different questions, checking for duplicates, number of occurence of questions etc.

- 2) Then we will perform some feature extraction like fuzz ratio, fuzz partial ration, longest common substring etc.
- 3) After performing feature extraction we will apply some visualisation techniques such as pair-plot, violin plot, TSNE etc.
- 4) Then we going to perform the tridf-w2vec vectorizer on pair of questions dataset and then we merge each the tridf-w2vec vectors to our advanced featured vectors.
- 5) In the next step we will apply some machine learning algorithm such as logistic regression, support vector machines etc and found log-loss for both train and test dataset.
- 6) After choosing best parameters we then plot confusion matrix, precision matrix and recall matrix for each one.
- 7) we will perform same process for tfidf vectorizer at the end of this project

3. Exploratory Data Analysis

```
In [0]: from google.colab import drive
    drive.mount('/content/drive')
```

Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=9 47318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response type=code&scope=email%20https%3a%2

f%2fwww.googleapis.com%2fauth%2fdocs.tes t%20https%3a%2f%2fwww.googleapis.com%2fau th%2fdrive%20https%3a%2f%2fwww.googleapi s.com%2fauth%2fdrive.photos.readonly%20ht tps%3a%2f%2fwww.googleapis.com%2fauth%2fp eopleapi.readonly

Enter your authorization code:
.....

Mounted at /content/drive

In [0]:

pip install distance

Collecting distance

Downloading https://files.pythonhosted.org/packages/5c/la/883e47df323437aefa0d0a92ccfb38895d9416bd0b56262c2e46a47767b8/Distance-0.1.3.tar.gz (180kB)

Building wheels for collected packages: d istance

Building wheel for distance (setup.py)
... done

Created wheel for distance: filename=Distance-0.1.3-cp36-none-any.whl size=16261 sha256=67572c781d95994d908ca9ff7741f419be clecf37ac59920d5bf54401f2d7b50

Stored in directory: /root/.cache/pip/w heels/d5/aa/e1/dbba9e7b6d397d645d0f12db1c 66dbae9c5442b39b001db18e

Successfully built distance

Installing collected packages: distance Successfully installed distance-0.1.3

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from subprocess import check output
%matplotlib inline
import plotly.offline as py
py.init notebook mode(connected=True)
import plotly.graph objs as go
import plotly.tools as tls
import os
import gc
import re
from nltk.corpus import stopwords
import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
```

3.1 Reading data and basic stats

	id	qid1	qid2	question1	question2	is
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

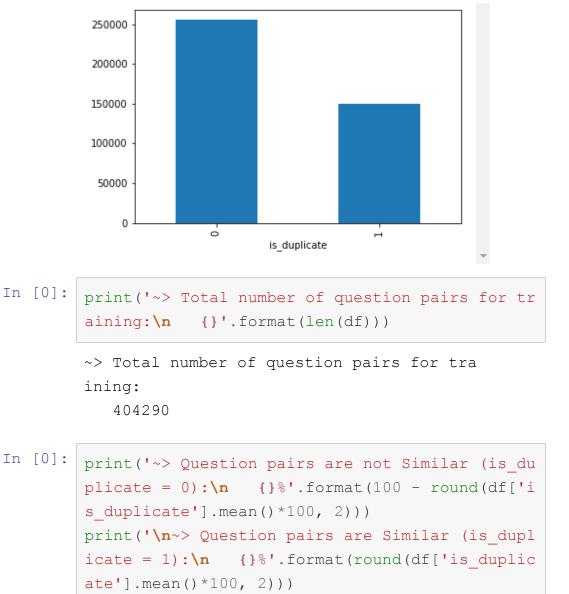
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404290 entries, 0 to 404289
Data columns (total 6 columns):
id
               404290 non-null int64
gid1
               404290 non-null int64
qid2
               404290 non-null int64
question1
            404289 non-null object
question2
               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 nonduplicate(non similar) questions



```
63.08%

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

~> Question pairs are not Similar (is dup

licate = 0):

3.2.2 Number of unique questions

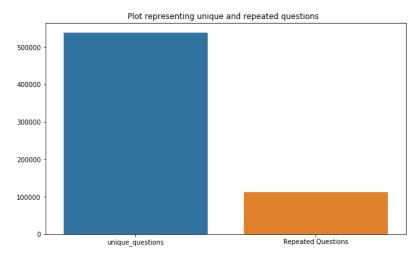
```
In [0]: | qids = pd.Series(df['qid1'].tolist() + df['qid
        2'].tolist())
        unique qs = len(np.unique(qids))
        qs morethan onetime = np.sum(qids.value counts
        () > 1)
        print ('Total number of Unique Questions are:
        {}\n'.format(unique qs))
        #print len(np.unique(qids))
        print ('Number of unique questions that appear
         more than one time: {} ({}%)\n'.format(qs more
        than onetime, qs morethan onetime/unique qs*100
        ) )
        print ('Max number of times a single question i
        s repeated: {}\n'.format(max(qids.value counts))
        ())))
        q vals=qids.value counts()
        q vals=q vals.values
        Total number of Unique Questions are: 53
        7933
        Number of unique questions that appear mo
        re than one time: 111780 (20.779539459375
        05%)
        Max number of times a single question is
        repeated: 157
```

x = ["unique questions" , "Repeated Questions"]

In [0]:

```
y = [unique_qs , qs_morethan_onetime]

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



3.2.3 Checking for Duplicates

```
In [0]: #checking whether there are any repeated pair o
    f questions

pair_duplicates = df[['qid1','qid2','is_duplica
    te']].groupby(['qid1','qid2']).count().reset_in
    dex()

print ("Number of duplicate questions", (pair_du
    plicates).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')

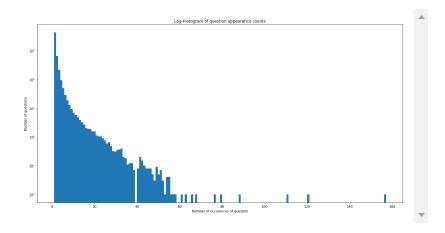
plt.title('Log-Histogram of question appearance counts')

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

 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 gid1 and gid2
- freq_q1-freq_q2 = absolute difference of frequency of qid1 and qid2

```
mbda 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 wor
d 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) + le
n (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 trai
```

```
n.csv", index=False)

df.head()
```

Out[0]:

	id	qid1	qid2	question1	question2	is
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

	id	qid1	qid2	question1	question2	is
4	4	9	10	Which one dissolve in water quikly sugar, salt	Which fish would survive in salt water?	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 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

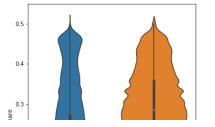
Number of Questions with minimum length
[question1] : 67
Number of Questions with minimum length
[question2] : 24

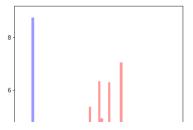
3.3.1.1 Feature: word_share

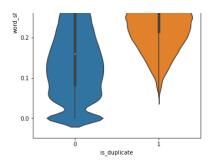
```
In [0]: plt.figure(figsize=(12, 8))

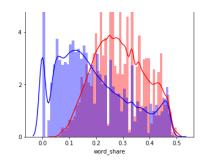
plt.subplot(1,2,1)
sns.violinplot(x = 'is_duplicate', y = 'word_sh
are', data = df[0:])

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









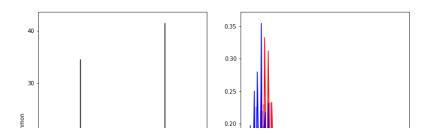
- The distributions for normalized word_share have some overlap on the far right-hand side, i.e., there are quite a lot of questions with high word similarity
- The average word share and Common no. of words of qid1 and qid2 is more when they are duplicate(Similar)

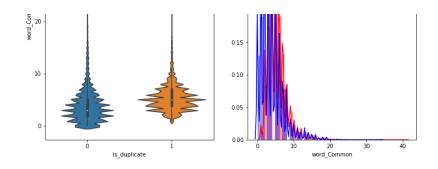
3.3.1.2 Feature: word_Common

```
In [0]: plt.figure(figsize=(12, 8))

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

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





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

1.2.1 : EDA: Advanced Feature Extraction.

```
In [0]: pip install fuzzywuzzy
```

Collecting fuzzywuzzy

Downloading https://files.pythonhosted.org/packages/d8/f1/5a267addb30ab7eaa1beab2b9323073815da4551076554ecc890a3595ec9/fuzzywuzzy-0.17.0-py2.py3-none-any.whl
Installing collected packages: fuzzywuzzySuccessfully installed fuzzywuzzy-0.17.0

```
In [0]: import warnings
    warnings.filterwarnings("ignore")
    import numpy as np
    import pandas as pd
    import seaborn as sns
    import matplotlib.pyplot as plt
    from subprocess import check_output
    %matplotlib inline
    import plotly.offline as py
    py.init_notebook_mode(connected=True)
```

```
import plotly.graph objs as go
import plotly.tools as tls
import os
import gc
import re
from nltk.corpus import stopwords
import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
import re
from nltk.corpus import stopwords
# This package is used for finding longest comm
on subsequence between two strings
# you can write your own dp code for this
import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
from fuzzywuzzy import fuzz
from sklearn.manifold import TSNE
# Import the Required lib packages for WORD-Clo
ud 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]: #https://stackoverflow.com/questions/12468179/u
    nicodedecodeerror-utf8-codec-cant-decode-byte-0
    x9c
    if os.path.isfile('df_fe_without_preprocessing_
        train.csv'):
        df = pd.read_csv("df_fe_without_preprocessi
        ng_train.csv",encoding='latin-1')
```

```
df = df.fillna('')
    df.head()
else:
   print("get df_fe_without_preprocessing_trai
n.csv from drive or run the previous notebook")
```

In [0]: df.head(2)

Out[0]:

	id	qid1	qid2	question1	question2	is_(
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

3.4 Preprocessing of Text

- Preprocessing:
 - Removing html tags
 - Removing PunctuationsPerforming stemming

 - Removing Stopwords
 - Expanding contractions etc.

```
In [0]: import nltk
        nltk.download('stopwords')
        [nltk data] Downloading package stopwords
        to /root/nltk data...
        [nltk data] Unzipping corpora/stopword
        s.zip.
Out[0]: True
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(",00
        0", "k").replace("'", "'").replace("'", "'")\
                                    .replace("won't", "w
        ill not").replace("cannot", "can not").replace(
        "can't", "can not") \
                                    .replace("n't", " no
        t").replace("what's", "what is").replace("it's"
        , "it is")\
                                    .replace("'ve", " ha
        ve").replace("i'm", "i am").replace("'re", " ar
        e")\
                                    .replace("he's", "he
        is").replace("she's", "she is").replace("'s", "
        own") \
                                    .replace("%", " perc
        ent ").replace("₹", " rupee ").replace("$", " d
        ollar ") \
                                    .replace("€", " euro
```

```
").replace("'ll", " will")
    x = re.sub(r"([0-9]+)000000", r"\lm", x)
    x = re.sub(r"([0-9]+)000", r"\lk", x)

porter = PorterStemmer()
    pattern = re.compile('\W')

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

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

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

3.5 Advanced Feature Extraction (NLP and Fuzzy Features)

Definition:

 Token: You get a token by splitting sentence a space

- Stop_Word : stop words as per NLTK.
- Word : A token that is not a stop_word

Features:

cwc_min: Ratio of common_word_count to min length of word count of Q1 and Q2
 cwc_min = common_word_count / (min(len(q1 words), len(q2 words))

cwc_max: Ratio of common_word_count to max length of word count of Q1 and Q2
 cwc_max = common_word_count / (max(len(q1 words), len(q2 words))

- csc_min: Ratio of common_stop_count to min 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 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 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/fuzzywuzzyfuzzy-string-matching-in-python/

• fuzz partial ratio :

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

• token sort ratio:

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

• token_set_ratio :

https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzyfuzzy-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))

```
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 Questio
        n pair
            common word count = len(q1 words.intersecti
        on(q2 words))
             # Get the common stopwords from Question pa
        ir
            common stop count = len(q1 stops.intersecti
        on(q2 stops))
```

```
# Get the common Tokens from Question pair
    common token count = len(set(q1 tokens).int
ersection(set(q2 tokens)))
    token features[0] = common word count / (mi
n(len(q1 words), len(q2 words)) + SAFE DIV)
    token features[1] = common word count / (ma
x(len(q1 words), len(q2 words)) + SAFE DIV)
    token features[2] = common stop count / (mi
n(len(q1 stops), len(q2 stops)) + SAFE DIV)
    token features[3] = common stop count / (ma
x(len(q1 stops), len(q2 stops)) + SAFE DIV)
    token features[4] = common token count / (m
in(len(q1 tokens), len(q2 tokens)) + SAFE DIV)
    token features[5] = common token count / (m
ax(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 no
t
    token features[7] = int(q1 tokens[0] == q2
tokens[0])
    token features[8] = abs(len(q1 tokens) - le
n(q2 tokens))
    #Average Token Length of both Questions
    token features[9] = (len(q1 tokens) + len(q
2 \text{ 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 tok
en features(x["question1"], x["question2"]), ax
is=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.seatg
eek.com/fuzzywuzzy-fuzzy-string-matching-in-pyt
hon/
    # https://stackoverflow.com/questions/31806
695/when-to-use-which-fuzz-function-to-compare-
2-strings
    # https://github.com/seatgeek/fuzzywuzzy
   print("fuzzy features..")
    df["token set ratio"] = df.apply(lamb
da x: fuzz.token set ratio(x["question1"], x["q
uestion2"]), axis=1)
    # The token sort approach involves tokenizi
ng the string in question, sorting the tokens a
Iphabetically, and
    # then joining them back into a string We t
hen compare the transformed strings with a simp
le ratio().
    df["token sort ratio"] = df.apply(lamb
da x: fuzz.token sort ratio(x["question1"], x[
"question2"]), axis=1)
    df["fuzz ratio"] = df.apply(lamb
da x: fuzz.QRatio(x["question1"], x["question2"
```

```
]), axis=1)
    df["fuzz_partial_ratio"] = df.apply(lamb
da x: fuzz.partial_ratio(x["question1"], x["que
stion2"]), axis=1)
    df["longest_substr_ratio"] = df.apply(lamb
da x: get_longest_substr_ratio(x["question1"],
    x["question2"]), axis=1)
    return df
```

```
In [0]:
    if os.path.isfile('nlp_features_train.csv'):
        df = pd.read_csv("/content/drive/My Drive/Q
        uora/nlp_features_train.csv",encoding='latin-1'
    )
        df.fillna('')
    else:
        print("Extracting features for train:")
        df = pd.read_csv("/content/drive/My Drive/Q
        uora/train.csv")
        df = extract_features(df)
        df.to_csv("nlp_features_train.csv", index=F
        alse)
```

Extracting features for train: token features...
fuzzy features..

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 du
        plicate["question2"]]).flatten()
        n = np.dstack([dfp nonduplicate["question1"], d
        fp nonduplicate["question2"]]).flatten()
        print ("Number of data points in class 1 (dupli
        cate pairs) :",len(p))
        print ("Number of data points in class 0 (non d
        uplicate pairs) :",len(n))
        #Saving the np array into a text file
        np.savetxt('train p.txt', p, delimiter=' ', fmt
        = ' %s')
        np.savetxt('train n.txt', n, delimiter=' ', fmt
        = '%s')
```

Number of data points in class 1 (duplica te pairs): 298526 Number of data points in class 0 (non dup licate pairs): 510054

```
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))
```

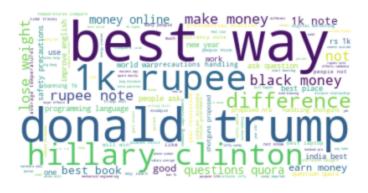
Total number of words in duplicate pair questions: 16109886

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_wo
    rds=len(textp_w), stopwords=stopwords)
    wc.generate(textp_w)
    print ("Word Cloud for Duplicate Question pair
    s")
    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

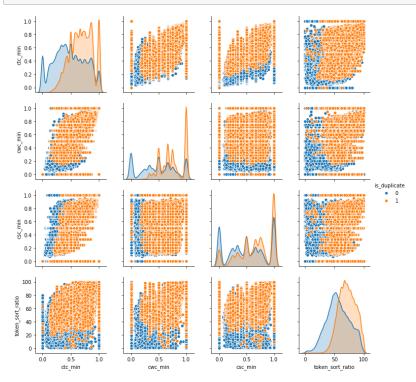
```
In [0]: wc = WordCloud(background_color="white", max_wo
    rds=len(textn_w), stopwords=stopwords)
# generate word cloud
wc.generate(textn_w)
print ("Word Cloud for non-Duplicate Question p
    airs:")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

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

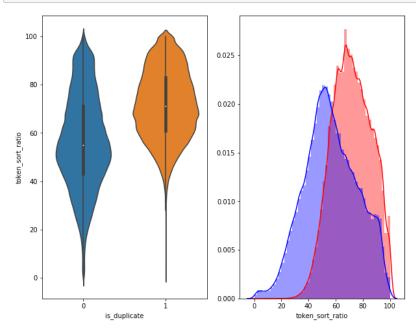


```
In [0]: # Distribution of the token_sort_ratio
    plt.figure(figsize=(10, 8))

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

plt.subplot(1,2,2)
    sns.distplot(df[df['is_duplicate'] == 1.0]['tok
    en_sort_ratio'][0:], label = "1", color = 're
    d')
    sns.distplot(df[df['is_duplicate'] == 0.0]['tok
    en_sort_ratio'][0:], label = "0", color = 'bl
```

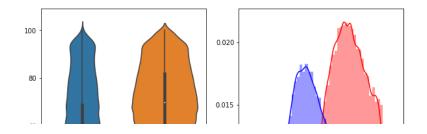
```
ue' )
plt.show()
```

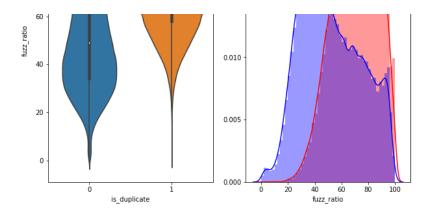


```
In [0]: plt.figure(figsize=(10, 8))

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

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





3.5.2 Visualization

```
In [0]: # Using TSNE for Dimentionality reduction for 1
    5 Features(Generated after cleaning the data) t
    o 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_rati
    o', 'fuzz_partial_ratio', 'longest_substr_rat
    io']])
    y = dfp_subsampled['is_duplicate'].values
```

```
angle=0.5
).fit transform(X)
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.015s...
[t-SNE] Computed neighbors for 5000 sampl
es in 0.382s...
[t-SNE] Computed conditional probabilitie
s for sample 1000 / 5000
[t-SNE] Computed conditional probabilitie
s for sample 2000 / 5000
[t-SNE] Computed conditional probabilitie
s for sample 3000 / 5000
[t-SNE] Computed conditional probabilitie
s for sample 4000 / 5000
[t-SNE] Computed conditional probabilitie
s for sample 5000 / 5000
[t-SNE] Mean sigma: 0.130446
[t-SNE] Computed conditional probabilitie
s in 0.300s
[t-SNE] Iteration 50: error = 81.2911148,
gradient norm = 0.0457501 (50 iterations
in 2.775s)
[t-SNE] Iteration 100: error = 70.604415
9, gradient norm = 0.0086692 (50 iteratio
ns in 1.918s)
[t-SNE] Iteration 150: error = 68.912490
8, gradient norm = 0.0056016 (50 iteratio
ns in 1.798s)
[t-SNE] Iteration 200: error = 68.101074
2, gradient norm = 0.0047585 (50 iteratio
ns in 1.872s)
[t-SNE] Iteration 250: error = 67.590797
4, gradient norm = 0.0033576 (50 iteratio
ns in 1.950s)
[t-SNE] KL divergence after 250 iteration
```

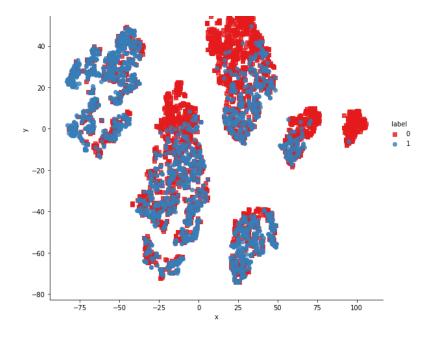
s with early exaggeration: 67.590797 [t-SNE] Iteration 300: error = 1.7929677, gradient norm = 0.0011899 (50 iterations)in 2.001s)[t-SNE] Iteration 350: error = 1.3937442, gradient norm = 0.0004817 (50 iterations in 1.933s)[t-SNE] Iteration 400: error = 1.2280033, gradient norm = 0.0002773 (50 iterations)in 1.936s) [t-SNE] Iteration 450: error = 1.1383208, gradient norm = 0.0001865 (50 iterations)in 1.960s)[t-SNE] Iteration 500: error = 1.0834006, gradient norm = 0.0001423 (50 iterations)in 1.960s)[t-SNE] Iteration 550: error = 1.0474092, gradient norm = 0.0001144 (50 iterations in 1.971s) [t-SNE] Iteration 600: error = 1.0231259, gradient norm = 0.0000995 (50 iterations in 1.985s)[t-SNE] Iteration 650: error = 1.0066353, gradient norm = 0.0000895 (50 iterations)in 1.996s) [t-SNE] Iteration 700: error = 0.9954656, gradient norm = 0.0000805 (50 iterations)in 2.012s) [t-SNE] Iteration 750: error = 0.9871529, gradient norm = 0.0000719 (50 iterations in 2.035s)[t-SNE] Iteration 800: error = 0.9801921, gradient norm = 0.0000657 (50 iterations)in 2.043s) [t-SNE] Iteration 850: error = 0.9743395,

gradient norm = 0.0000631 (50 iterations)

```
in 2.041s)
[t-SNE] Iteration 900: error = 0.9693972,
gradient norm = 0.0000606 (50 iterations
in 2.025s)
[t-SNE] Iteration 950: error = 0.9654404,
gradient norm = 0.0000594 (50 iterations
in 2.049s)
[t-SNE] Iteration 1000: error = 0.962230
2, gradient norm = 0.0000565 (50 iterations
in 2.037s)
[t-SNE] KL divergence after 1000 iterations: 0.962230
```

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

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




```
[t-SNE] Indexed 5000 samples in 0.008s...
[t-SNE] Computed neighbors for 5000 sampl
es in 0.376s...
[t-SNE] Computed conditional probabilitie
s for sample 1000 / 5000
[t-SNE] Computed conditional probabilitie
s for sample 2000 / 5000
[t-SNE] Computed conditional probabilitie
s for sample 3000 / 5000
[t-SNE] Computed conditional probabilitie
```

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

```
s for sample 4000 / 5000
[t-SNE] Computed conditional probabilitie
s for sample 5000 / 5000
[t-SNE] Mean sigma: 0.130446
[t-SNE] Computed conditional probabilitie
s in 0.285s
[t-SNE] Iteration 50: error = 80.5316772,
gradient norm = 0.0296611 (50 iterations
in 12.905s)
[t-SNE] Iteration 100: error = 69.382316
6, gradient norm = 0.0032796 (50 iteratio
ns in 6.122s)
[t-SNE] Iteration 150: error = 67.972602
8, gradient norm = 0.0016793 (50 iteratio
ns in 5.572s)
[t-SNE] Iteration 200: error = 67.417617
8, gradient norm = 0.0010922 (50 iteratio
ns in 5.594s)
[t-SNE] Iteration 250: error = 67.103363
0, gradient norm = 0.0008839 (50 iteratio
ns in 5.561s)
[t-SNE] KL divergence after 250 iteration
s with early exaggeration: 67.103363
[t-SNE] Iteration 300: error = 1.5262967,
gradient norm = 0.0007234 (50 iterations)
in 7.581s)
[t-SNE] Iteration 350: error = 1.1826925,
gradient norm = 0.0002056 (50 iterations)
in 9.884s)
[t-SNE] Iteration 400: error = 1.0364963,
gradient norm = 0.0000999 (50 iterations)
in 9.503s)
[t-SNE] Iteration 450: error = 0.9654390,
gradient norm = 0.0000914 (50 iterations)
in 9.483s)
[t-SNE] Iteration 500: error = 0.9289201,
```

gradient norm = 0.0000634 (50 iterations in 9.358s)[t-SNE] Iteration 550: error = 0.9090494, gradient norm = 0.0000504 (50 iterations in 9.167s) [t-SNE] Iteration 600: error = 0.8954713, gradient norm = 0.0000525 (50 iterations)in 8.841s) [t-SNE] Iteration 650: error = 0.8866501, gradient norm = 0.0000497 (50 iterations in 8.900s) [t-SNE] Iteration 700: error = 0.8820391, gradient norm = 0.0000369 (50 iterations)in 9.120s) [t-SNE] Iteration 750: error = 0.8775222, gradient norm = 0.0000342 (50 iterations in 9.106s) [t-SNE] Iteration 800: error = 0.8723416, gradient norm = 0.0000288 (50 iterations in 9.160s) [t-SNE] Iteration 850: error = 0.8663230, gradient norm = 0.0000297 (50 iterations in 9.217s) [t-SNE] Iteration 900: error = 0.8605922, gradient norm = 0.0000286 (50 iterations in 9.248s) [t-SNE] Iteration 950: error = 0.8555549, gradient norm = 0.0000312 (50 iterationsin 9.236s)

[t-SNE] KL divergence after 1000 iteratio
ns: 0.852175

[t-SNE] Iteration 1000: error = 0.852174
5, gradient norm = 0.0000278 (50 iteratio

ns in 9.152s)

```
trace1 = go.Scatter3d(
    x=tsne3d[:,0],
    y=tsne3d[:,1],
    z=tsne3d[:,2],
    mode='markers',
    marker=dict(
        sizemode='diameter',
        color = y,
        colorscale = 'Portland',
        colorbar = dict(title = 'duplicate'),
        line=dict(color='rgb(255, 255, 255)'),
        opacity=0.75
)
data=[trace1]
layout=dict(height=800, width=800, title='3d em
bedding with engineered features')
fig=dict(data=data, layout=layout)
py.iplot(fig, filename='3DBubble')
```

3.6 Featurizing text data with tfidf weighted word-vectors

```
In [0]: import pandas as pd
  import matplotlib.pyplot as plt
  import re
  import time
  import warnings
  import numpy as np
  from nltk.corpus import stopwords
  from sklearn.preprocessing import normalize
  from sklearn.feature_extraction.text import Cou
```

```
ntVectorizer
from sklearn.feature_extraction.text import Tfi
dfVectorizer
warnings.filterwarnings("ignore")
import sys
import os
import pandas as pd
import numpy as np
from tqdm import tqdm

# exctract word2vec vectors
# https://github.com/explosion/spaCy/issues/172
1
# http://landinghub.visualstudio.com/visual-cpp
-build-tools
import spacy
```

```
In [0]:
       # avoid decoding problems
        df = pd.read csv("/content/drive/My Drive/Quor
        a/train.csv")
        # encode questions to unicode
        # https://stackoverflow.com/a/6812069
        # ----- python 2 -----
        # df['question1'] = df['question1'].apply(lambd
        a x: unicode(str(x),"utf-8"))
        # df['question2'] = df['question2'].apply(lambd
        a x: unicode(str(x),"utf-8"))
        # ----- python 3 -----
        df['question1'] = df['question1'].apply(lambda
        x: str(x)
       df['question2'] = df['question2'].apply(lambda
        x: str(x)
```

In [0]: | df.head()

Out[0]:

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

In [0]:
 from sklearn.feature_extraction.text import Tfi
 dfVectorizer
 from sklearn.feature_extraction.text import Cou
 ntVectorizer
 # merge texts
 questions = list(df['question1']) + list(df['question2'])

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

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

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

```
In [0]: # en_vectors_web_lg, which includes over 1 mill
    ion unique vectors.
    nlp = spacy.load('en_core_web_sm')

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

```
mean vec1 = np.zeros([len(doc1), len(doc1[0
        1.vector)])
            for word1 in doc1:
                # word2vec
                vec1 = word1.vector
                # fetch df score
                try:
                    idf = word2tfidf[str(word1)]
                except:
                    idf = 0
                # compute final vec
                mean vec1 += vec1 * idf
            mean vec1 = mean vec1.mean(axis=0)
            vecs1.append(mean vec1)
        df['q1 feats m'] = list(vecs1)
              404290/404290 [59:15<00:
        100%|
        00, 113.71it/s]
In [0]:
        # en vectors web lg, which includes over 1 mill
        ion unique vectors.
        nlp = spacy.load('en core web sm')
        vecs2 = []
        for qu2 in tqdm(list(df['question2'])):
            doc2 = nlp(qu2)
            mean vec2 = np.zeros([len(doc1), len(doc2[0
        1.vector)1)
            for word2 in doc2:
                # word2vec
                vec2 = word2.vector
                # fetch df score
                try:
                    idf = word2tfidf[str(word2)]
                except:
                     #print word
```

```
idf = 0
                # compute final vec
                mean vec2 += vec2 * idf
            mean vec2 = mean vec2.mean(axis=0)
            vecs2.append(mean vec2)
        df['q2 feats m'] = list(vecs2)
              404290/404290 [1:00:11<0
        100%|
        0:00, 111.95it/s]
In [0]:
        #prepro features train.csv (Simple Preprocessin
        g Feartures)
        #nlp features train.csv (NLP Features)
        if os.path.isfile('nlp features train.csv'):
            dfnlp = pd.read csv("/content/drive/My Driv
        e/Quora/nlp features train.csv", encoding='latin
        -1')
        else:
            print("download nlp features train.csv from
        drive or run previous notebook")
        if os.path.isfile('df fe without preprocessing
        train.csv'):
            dfppro = pd.read csv("/content/drive/My Dri
        ve/Quora/df fe without preprocessing train.csv"
        , encoding='latin-1')
        else:
            print("download df fe without preprocessing
        train.csv from drive or run previous notebook"
In [0]:
        df1 = dfnlp.drop(['qid1','qid2','question1','qu
        estion2'],axis=1)
        df2 = dfppro.drop(['qid1','qid2','question1','q
        uestion2','is duplicate'],axis=1)
```

```
df3 = df.drop(['qid1','qid2','question1','quest
ion2','is_duplicate'],axis=1)
df3_q1 = pd.DataFrame(df3.q1_feats_m.values.tol
ist(), index= df3.index)
df3_q2 = pd.DataFrame(df3.q2_feats_m.values.tol
ist(), index= df3.index)
```

Out[0]:

	id	is_duplicate	cwc_min	cwc_max	csc
0	0	0	0.999980	0.833319	0.99
1	1	0	0.799984	0.399996	0.74
2	2	0	0.399992	0.333328	0.39
3	3	0	0.000000	0.000000	0.00
4	4	0	0.399992	0.199998	0.99

Out[0]:

	id	freq_qid1	freq_qid2	q1len	q2len	q1_
0	0	1	1	66	57	14
1	1	4	1	51	88	8
2	2	1	1	73	59	14
3	3	1	1	50	65	11
4	4	3	1	76	39	13

In [0]:

```
# Questions 1 tfidf weighted word2vec
df3_q1.head()
```

Out[0]:

	0	1	2	
0	211.129864	-144.683059	-68.811247	-1
1	144.124685	-114.012484	-111.716694	-1
2	81.757898	-142.184507	0.559867	-1
3	-126.651922	-59.747160	-67.763201	-1
4	299.444044	-188.632001	-22.946291	-2

5 rows × 96 columns

```
In [0]: # Questions 2 tfidf weighted word2vec
df3_q2.head()
```

Out[0]:

	0	1	2	
0	151.268526	-127.013168	-31.546286	-14
1	152.023095	-44.955390	-103.559249	-12
2	4.930220	-29.029581	-117.808812	-98
3	-6.951929	-44.951731	-17.343082	-6
4	96.174524	-71.613948	21.584882	-92

5 rows × 96 columns

```
In [0]: print("Number of features in nlp dataframe :",
    df1.shape[1])
    print("Number of features in preprocessed dataf
    rame :", df2.shape[1])
    print("Number of features in question1 w2v dat
```

```
aframe :", df3 q1.shape[1])
        print("Number of features in question2 w2v dat
        aframe :", df3 q2.shape[1])
        print("Number of features in final dataframe
         :", df1.shape[1]+df2.shape[1]+df3 q1.shape[1]+
        df3 q2.shape[1])
        Number of features in nlp dataframe: 17
        Number of features in preprocessed datafr
        ame : 12
        Number of features in question1 w2v
        frame: 96
        Number of features in question2 w2v
        frame: 96
        Number of features in final dataframe
        221
In [0]:
        # storing the final features to csv file
        if not os.path.isfile('final features.csv'):
            df3 q1['id']=df1['id']
            df3 q2['id']=df1['id']
            df1 = df1.merge(df2, on='id',how='left')
            df2 = df3 q1.merge(df3 q2, on='id', how='le
        ft')
            result = df1.merge(df2, on='id', how='left'
        )
            result.to csv('final features.csv')
In [0]:
        import pandas as pd
        import matplotlib.pyplot as plt
        import re
        import time
        import warnings
        import sqlite3
        from sqlalchemy import create engine # database
```

```
connection
import csv
import os
warnings.filterwarnings("ignore")
import datetime as dt
import numpy as np
from nltk.corpus import stopwords
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature extraction.text import Cou
ntVectorizer
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassif
ier
from sklearn.metrics import confusion matrix
from sklearn.metrics.classification import accu
racy score, log loss
from sklearn.feature extraction.text import Tfi
dfVectorizer
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassif
ier
from sklearn.svm import SVC
from sklearn.model selection import StratifiedK
Fold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClass
ifierCV
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 GridSearchC
```

```
import math
from sklearn.metrics import normalized_mutual_i
nfo_score
from sklearn.ensemble import RandomForestClassi
fier

from sklearn.model_selection import cross_val_s
core
from sklearn.linear_model import SGDClassifier
from mlxtend.classifier import StackingClassifi
er

from sklearn import model_selection
from sklearn.linear_model import LogisticRegres
sion
from sklearn.metrics import precision_recall_cu
rve, auc, roc_curve
```

```
/usr/local/lib/python3.6/dist-packages/sk learn/externals/six.py:31: DeprecationWar ning: The module is deprecated in version 0.21 and will be removed in version 0.23 since we've dropped support for Python 2.
7. Please rely on the official version of six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", DeprecationWarning)
```

4. Machine Learning Models

4.1 Reading data from file and storing into sql table

```
In [0]:
        #Creating db file from csv
        if not os.path.isfile('train.db'):
            disk engine = create engine('sqlite:///trai
        n.db')
            start = dt.datetime.now()
            chunksize = 180000
            \dot{1} = 0
            index start = 1
            for df in pd.read csv('/content/drive/My Dr
        ive/Quora/final features.csv', names=['Unnamed:
        0','id','is duplicate','cwc min','cwc max','csc
        min','csc max','ctc min','ctc max','last word
        eq','first word eq','abs len diff','mean len',
        'token set ratio', 'token sort ratio', 'fuzz rati
        o','fuzz partial ratio','longest substr ratio',
        'freq qid1', 'freq qid2', 'q1len', 'q2len', 'q1 n w
        ords','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','2
        9 x','30 x','31 x','32 x','33 x','34 x','35 x',
        '36 x','37 x','38 x','39 x','40 x','41 x','42
        x','43 x','44 x','45 x','46 x','47 x','48 x','4
        9 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','6
        9 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','8
```

9 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','10 2 x','103 x','104 x','105 x','106 x','107 x','1 08 x','109 x','110 x','111 x','112 x','113 x', '114 x','115 x','116 x','117 x','118 x','119 x' ,'120 x','121 x','122 x','123 x','124 x','125 x','126 x','127 x','128 x','129 x','130 x','131 x','132 x','133 x','134 x','135 x','136 x','13 7 x','138 x','139 x','140 x','141 x','142 x','1 43 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','17 2 x','173 x','174 x','175 x','176 x','177 x','1 78 x','179 x','180 x','181 x','182 x','183 x', '184 x','185 x','186 x','187 x','188 x','189 x' ,'190 x','191 x','192 x','193 x','194 x','195 x','196 x','197 x','198 x','199 x','200 x','201 x','202 x','203 x','204 x','205 x','206 x','20 7 x','208 x','209 x','210 x','211 x','212 x','2 13 x','214 x','215 x','216 x','217 x','218 x', '219 x','220 x','221 x','222 x','223 x','224 x' ,'225 x','226 x','227 x','228 x','229 x','230 x','231 x','232 x','233 x','234 x','235 x','236 x','237 x','238 x','239 x','240 x','241 x','24 2 x','243 x','244 x','245 x','246 x','247 x','2 48 x','249 x','250 x','251 x','252 x','253 x', '254 x','255 x','256 x','257 x','258 x','259 x' ,'260 x','261 x','262 x','263 x','264 x','265 x','266 x','267 x','268 x','269 x','270 x','271 x','272 x','273 x','274 x','275 x','276 x','27 7_x','278_x','279_x','280 x','281 x','282 x','2 83 x','284 x','285 x','286 x','287 x','288 x', '289 x','290 x','291 x','292 x','293 x','294 x' ,'295 x','296 x','297 x','298 x','299 x','300

x','301 x','302 x','303 x','304 x','305 x','306 x','307 x','308 x','309 x','310 x','311 x','31 2 x','313 x','314 x','315 x','316 x','317 x','3 18 x', '319 x', '320 x', '321 x', '322 x', '323 x', '324_x','325_x','326_x','327 x','328 x','329 x' ,'330 x','331 x','332 x','333 x','334 x','335 x','336 x','337 x','338 x','339 x','340 x','341 x','342 x','343 x','344 x','345 x','346 x','34 7 x','348 x','349 x','350 x','351 x','352 x','3 53 x','354 x','355 x','356 x','357 x','358 x', '359 x','360 x','361 x','362 x','363 x','364 x' ,'365_x','366_x','367_x','368_x','369_x','370_ x','371 x','372 x','373 x','374 x','375 x','376 x','377 x','378 x','379 x','380_x','381_x','38 2 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','2 6 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','4 6_y','47_y','48_y','49_y','50_y','51_y','52_y', '53 y','54 y','55 y','56 y','57 y','58 y','59 y','60 y','61 y','62 y','63 y','64 y','65 y','6 6 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','8 6 y','87 y','88 y','89 y','90 y','91 y','92 y', '93_y','94_y','95_y','96_y','97_y','98_y','99_ y','100 y','101 y','102 y','103 y','104 y','105 y','106 y','107 y','108 y','109 y','110 y','11 1 y','112 y','113 y','114 y','115 y','116 y','1 17 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','14 6 y','147 y','148 y','149 y','150 y','151 y','1 52 y','153 y','154 y','155 y','156 y','157 y', '158 y','159 y','160 y','161 y','162 y','163 y' ,'164_y','165_y','166_y','167_y','168_y','169_ y','170 y','171 y','172 y','173 y','174 y','175 y','176 y','177 y','178 y','179 y','180 y','18 1 y','182 y','183 y','184 y','185 y','186 y','1 87 y','188 y','189 y','190 y','191 y','192 y', '193 y','194 y','195 y','196 y','197 y','198 y' ,'199 y','200 y','201 y','202 y','203 y','204 y','205_y','206_y','207_y','208_y','209_y','210 y','211 y','212 y','213 y','214 y','215 y','21 6 y','217 y','218 y','219 y','220 y','221 y','2 22 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','25 1 y','252 y','253 y','254 y','255 y','256 y','2 57 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','28 6 y','287 y','288 y','289 y','290 y','291 y','2 92 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','306_y','307_y','308_y','309_ y','310 y','311 y','312 y','313 y','314 y','315 y','316 y','317 y','318 y','319 y','320 y','32 1 y','322 y','323 y','324 y','325 y','326 y','3 27 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','355 y','35
        6 y','357 y','358 y','359 y','360 y','361 y','3
        62 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
                 i += 1
                print('{} rows'.format(j*chunksize))
                 df.to sql('data', disk engine, if exist
        s='append')
                 index start = df.index[-1] + 1
        180000 rows
        360000 rows
        540000 rows
In [0]:
        #http://www.sqlitetutorial.net/sqlite-python/cr
        eate-tables/
        def create connection(db file):
             """ create a database connection to the SQL
        ite database
                 specified by db file
             :param db file: database file
             :return: Connection object or None
             11 II II
             try:
                 conn = sqlite3.connect(db file)
                 return conn
            except Error as e:
                print(e)
```

return None

```
def checkTableExists(dbcon):
            cursr = dbcon.cursor()
            str = "select name from sqlite master where
        type='table'"
            table names = cursr.execute(str)
            print("Tables in the databse:")
            tables =table names.fetchall()
            print(tables[0][0])
            return(len(tables))
In [0]: read_db = 'train.db'
        conn r = create connection(read db)
        checkTableExists(conn r)
        conn r.close()
        Tables in the databse:
        data
In [0]:
        # try to sample data according to the computing
        power you have
        if os.path.isfile(read db):
            conn r = create connection(read db)
            if conn r is not None:
                 # for selecting first 1M rows
                 # data = pd.read sql query("""SELECT *
         FROM data LIMIT 100001;""", conn r)
                 # for selecting random points
                data = pd.read sql query("SELECT * From
        data ORDER BY RANDOM() LIMIT 100001;", conn r)
                conn r.commit()
                conn r.close()
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_dupli
cate'], axis=1, inplace=True)
```

```
In [0]: data.head()
```

Out[0]:

	cwc_min	cwc_max
1	0.333327777870369	0.222219753113854
2	0.285710204139941	0.249996875039062
3	0.199996000079998	0.14285510206997
4	0.999975000624984	0.799984000319994
5	0.0	0.0

5 rows × 794 columns

4.2 Converting strings to numerics

```
In [0]: # after we read from sql table each entry was r
    ead it as a string
    # we convert all the features into numaric befo
    re we apply any model
    cols = list(data.columns)
    for i in cols:
        data[i] = data[i].apply(pd.to_numeric)
        print(i)
```

```
cwc_min
cwc_max
csc min
```

```
csc_max
ctc min
ctc max
last_word_eq
first_word_eq
abs len diff
mean len
token set ratio
token_sort_ratio
fuzz ratio
fuzz_partial_ratio
longest_substr_ratio
freq qid1
freq_qid2
q1len
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
```

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- 382_y
- 383 у

```
In [0]: # after we read from sql table each entry was r
        ead it as a string
        # we convert all the features into numaric befo
        re we apply any model
        cols = list(data.columns)
        data = pd.DataFrame(np.array(data.values,dtype=
        np.float64),columns=cols)
In [0]:
        # https://stackoverflow.com/questions/7368789/c
        onvert-all-strings-in-a-list-to-int
        y true = list(map(int, y true.values))
        4.3 Random train test split(
        70:30)
In [0]:
       X train, X test, y train, y test = train test sp
        lit(data, y true, stratify=y true, test_size=0.
        3)
In [0]:
        print("Number of data points in train data :",X
        train.shape)
        print("Number of data points in test data :", X
        test.shape)
        Number of data points in train data: (70
        000, 794)
        Number of data points in test data: (300
        00, 794)
In [0]:
        print("-"*10, "Distribution of output variable
         in train data", "-"*10)
        train distr = Counter(y train)
        train len = len(y train)
```

```
print("Class 0: ",int(train distr[0])/train len
        ,"Class 1: ", int(train distr[1])/train len)
        print("-"*10, "Distribution of output variable
        in train data", "-"*10)
        test distr = Counter(y test)
        test len = len(y test)
        print("Class 0: ",int(test distr[1])/test len,
        "Class 1: ",int(test distr[1])/test len)
        ----- Distribution of output variabl
        e in train data -----
        Class 0: 0.6319 Class 1: 0.3681
        ----- Distribution of output variabl
        e in train data -----
        Class 0: 0.3681 Class 1: 0.3681
In [0]:
        # This function plots the confusion matrices gi
        ven y i, y i hat.
        def plot confusion matrix(test y, predict y):
            C = confusion matrix(test y, predict y)
            \# C = 9,9 \text{ matrix, each cell (i,j) represent}
        s number of points of class i are predicted cla
        ss i
            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 col
        umns and axis=1 corresponds to rows in two diam
        ensional 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 col
umns and axis=1 corresponds to rows in two diam
ensional array
    \# C.sum(axix = 0) = [[4, 6]]
    \# (C/C.sum(axis=0)) = [[1/4, 2/6],
                           [3/4, 4/6]]
   plt.figure(figsize=(20,4))
   labels = [1,2]
   # representing A in heatmap format
   cmap=sns.light palette("blue")
   plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=
".3f", xticklabels=labels, yticklabels=labels)
   plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
   plt.title("Confusion matrix")
   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")
```

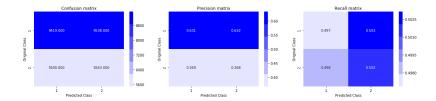
```
plt.subplot(1, 3, 3)
# representing B in heatmap format
sns.heatmap(A, annot=True, cmap=cmap, fmt=
".3f", xticklabels=labels, yticklabels=labels)
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.title("Recall matrix")
```

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

```
In [0]:
        # we need to generate 9 numbers and the sum of
        numbers should be 1
        # one solution is to genarate 9 numbers and div
        ide each of the numbers by their sum
        # ref: https://stackoverflow.com/a/18662466/408
        40.39
        # we create a output array that has exactly sam
        e size as the CV data
        predicted y = np.zeros((test len,2))
        for i in range(test len):
            rand probs = np.random.rand(1,2)
            predicted y[i] = ((rand probs/sum(sum(rand
        probs)))[0])
        print("Log loss on Test Data using Random Mode
        l",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

0.8884007769125581



4.4 Logistic Regression with hyperparameter tuning

```
In [0]: nan_rows = X_train[X_train.isnull().any(1)]
    print (nan_rows)
```

Empty DataFrame

Columns: [cwc min, cwc max, csc min, csc max, ctc min, ctc max, last word eq, firs t 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 Tota 1, 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, 2 9 x, 30_x, 31_x, 32_x, 33_x, 34_x, 35_x, 36 x, 37 x, 38 x, 39 x, 40 x, 41 x, 42 x, 43 x, 44 x, 45 x, 46 x, 47 x, 48 x, 49 x, 50 x, 51 x, 52 x, 53 x, 54 x, 55 x, 56 x, 57 x, 58 x, 59 x, 60 x, 61 x, 62 x, 63 x, 64 x, 65 x, 66 x, 67 x, 68 x, 69 x, 70 x, 71 x, 72 x, 73 x, ...]

Index: []

```
In [0]: nan_rows = X_train[X_train.isnull().any(1)]
    print (nan_rows)
```

Empty DataFrame

Columns: [cwc min, cwc max, csc_min, csc_ max, ctc min, ctc max, last word eq, firs t 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 Tota 1, 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, 2 9_x, 30_x, 31_x, 32_x, 33_x, 34_x, 35_x, 36 x, 37 x, 38 x, 39 x, 40 x, 41 x, 42 x, 43 x, 44 x, 45 x, 46 x, 47 x, 48 x, 49 x, 50 x, 51 x, 52 x, 53 x, 54 x, 55 x, 56 x, 57 x, 58 x, 59 x, 60 x, 61 x, 62 x, 63 x, 64 x, 65 x, 66 x, 67 x, 68 x, 69 x, 70 x, 71 x, 72 x, 73 x, ...] Index: []

[0 rows x 794 columns]

```
In [0]: # Filling the null values with ' '
X_train = X_train.fillna('')
nan_rows = X_train[X_train.isnull().any(1)]
print (nan_rows)
```

Empty DataFrame

Columns: [cwc min, cwc max, csc min, csc max, ctc min, ctc max, last word eq, firs t 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 Tota 1, 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, 2 9 x, 30 x, 31 x, 32 x, 33 x, 34 x, 35 x, 36 x, 37 x, 38 x, 39 x, 40 x, 41 x, 42 x, 43 x, 44 x, 45 x, 46_x, 47_x, 48_x, 49_x, 50 x, 51 x, 52 x, 53 x, 54 x, 55 x, 56 x, 57 x, 58 x, 59 x, 60 x, 61 x, 62 x, 63 x, 64 x, 65 x, 66 x, 67 x, 68 x, 69 x, 70 x, 71 x, 72 x, 73 x, ...] Index: []

[0 rows x 794 columns]

```
In [0]: alpha = [10 ** x for x in range(-5, 2)] # hyper
    param for SGD classifier.

# read more about SGDClassifier() at http://sci
    kit-learn.org/stable/modules/generated/sklearn.
    linear_model.SGDClassifier.html
# ------
# default parameters
# SGDClassifier(loss='hinge', penalty='12', alp
    ha=0.0001, l1_ratio=0.15, fit_intercept=True, m
    ax_iter=None, tol=None,
    # shuffle=True, verbose=0, epsilon=0.1, n_jobs=
```

```
1, random state=None, learning rate='optimal',
eta0=0.0, power t=0.5,
# class weight=None, warm start=False, average=
False, n iter=None)
# some of methods
# fit(X, y[, coef init, intercept init, ...])
Fit linear model with Stochastic Gradient Desce
nt.
# predict(X) Predict class labels for sample
s in X.
# video link:
#-----
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, metho
d="sigmoid")
    sig clf.fit(X train, y train)
   predict y = sig clf.predict proba(X test)
   log error array.append(log loss(y test, pre
dict y, labels=clf.classes , eps=1e-15))
   print('For values of alpha = ', i, "The log
loss is:",log loss(y test, predict y, labels=cl
f.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 arra
y, 3)):
```

```
ax.annotate((alpha[i], np.round(txt, 3)), (al
pha[i],log error array[i]))
plt.grid()
plt.title("Cross Validation Error for each alph
a")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
best alpha = np.argmin(log error array)
clf = SGDClassifier(alpha=alpha[best alpha], pe
nalty='12', loss='log', random state=42)
clf.fit(X train, y train)
sig clf = CalibratedClassifierCV(clf, method="s
igmoid")
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 tr
ain, 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 tes
t, predict y, labels=clf.classes , eps=1e-15))
predicted y =np.argmax(predict y,axis=1)
print("Total number of data points :", len(pred
icted y))
plot confusion matrix(y test, predicted y)
```

```
For values of alpha = 1e-05 The log loss is: 0.5725280378306258
For values of alpha = 0.0001 The log los s is: 0.4552477552698689
```

For values of alpha = 0.001 The log loss

is: 0.4502130190534189

For values of alpha = 0.01 The log loss

is: 0.459910473927018

For values of alpha = 0.1 The log loss i

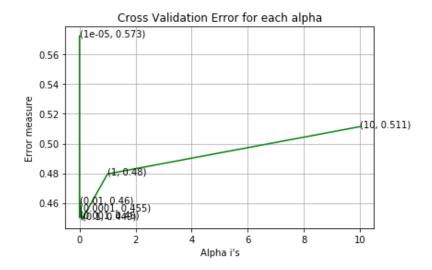
s: 0.44922600318403383

For values of alpha = 1 The log loss is:

0.47955708651426576

For values of alpha = 10 The log loss i

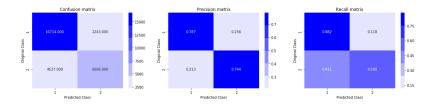
s: 0.5113949951147514



For values of best alpha = 0.1 The train log loss is: 0.4399629073595153

For values of best alpha = 0.1 The test log loss is: 0.44922600318403383

Total number of data points: 30000



4.5 Linear SVM with hyperparameter tuning

```
In [0]:
       %%time
        alpha = [10 ** x for x in range(-5, 2)] # hyper
        param for SGD classifier.
        # read more about SGDClassifier() at http://sci
        kit-learn.org/stable/modules/generated/sklearn.
        linear model.SGDClassifier.html
        # -----
        # default parameters
        # SGDClassifier(loss='hinge', penalty='12', alp
        ha=0.0001, l1 ratio=0.15, fit intercept=True, m
        ax iter=None, tol=None,
        # shuffle=True, verbose=0, epsilon=0.1, n jobs=
        1, random state=None, learning rate='optimal',
        eta0=0.0, power t=0.5,
        # class weight=None, warm start=False, average=
        False, n iter=None)
        # some of methods
        # fit(X, y[, coef init, intercept init, ...])
        Fit linear model with Stochastic Gradient Desce
        nt.
        # predict(X) Predict class labels for sample
        s in X.
        #-----
        # video link:
        log error array=[]
```

```
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='11',
 loss='hinge', random state=42)
    clf.fit(X train, y train)
    sig clf = CalibratedClassifierCV(clf, metho
d="sigmoid")
    sig clf.fit(X train, y train)
    predict y = sig clf.predict proba(X test)
    log error array.append(log loss(y test, pre
dict y, labels=clf.classes , eps=1e-15))
    print('For values of alpha = ', i, "The log
loss is:",log loss(y test, predict y, labels=cl
f.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 arra
v, 3)):
    ax.annotate((alpha[i], np.round(txt, 3)), (al
pha[i],log error array[i]))
plt.grid()
plt.title("Cross Validation Error for each alph
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
best alpha = np.argmin(log error array)
clf = SGDClassifier(alpha=alpha[best alpha], pe
nalty='11', loss='hinge', random state=42)
clf.fit(X train, y train)
sig clf = CalibratedClassifierCV(clf, method="s
igmoid")
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_tr
ain, predict_y, labels=clf.classes_, eps=1e-1
5))
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, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y = np.argmax(predict_y, axis=1)
print("Total number of data points:", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
```

```
For values of alpha = 1e-05 The log loss is: 0.6579367200579354

For values of alpha = 0.0001 The log los s is: 0.6579367200579354

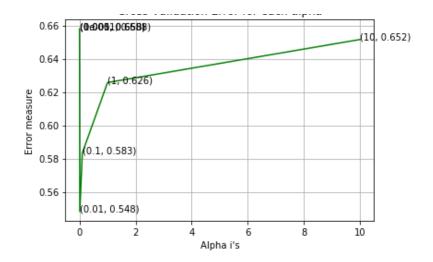
For values of alpha = 0.001 The log loss is: 0.6579367200579354

For values of alpha = 0.01 The log loss is: 0.5481499979750184

For values of alpha = 0.1 The log loss is: 0.5832984756289242

For values of alpha = 1 The log loss is: 0.6256469625313519

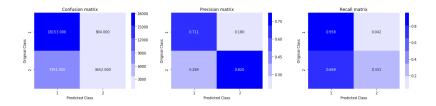
For values of alpha = 10 The log loss is: s: 0.6515001183736375
```



For values of best alpha = 0.01 The train log loss is: 0.545125304525286

For values of best alpha = 0.01 The test log loss is: 0.5481499979750184

Total number of data points: 30000



CPU times: user 2h 29min 53s, sys: 3min 1

8s, total: 2h 33min 11s Wall time: 2h 29min 12s

Parser : 135 ms

4.6 XGBoost

```
In [0]: %%time
    import xgboost as xgb
    params = {}
    params['objective'] = 'binary:logistic'
```

```
params['eval metric'] = 'logloss'
params['eta'] = 0.02
params['max depth'] = 4
d train = xgb.DMatrix(X train, label=y train)
d test = xgb.DMatrix(X test, label=y test)
watchlist = [(d train, 'train'), (d test, 'vali
d')]
bst = xgb.train(params, d train, 400, watchlis
t, early stopping rounds=20, verbose eval=10)
xgdmat = xgb.DMatrix(X train, y train)
predict y = bst.predict(d test)
print("The test log loss is:", log loss(y test,
 predict y, labels=clf.classes , eps=1e-15))
ΓΟ1
       train-logloss:0.684854 valid-log
loss:0.684817
Multiple eval metrics have been passed:
'valid-logloss' will be used for early st
opping.
Will train until valid-logloss hasn't imp
roved in 20 rounds.
       train-logloss:0.615155 valid-log
loss:0.615065
[20] train-logloss:0.563704 valid-log
loss:0.563578
[30] train-logloss:0.525997 valid-log
loss:0.525726
[40] train-logloss:0.496892 valid-log
loss:0.496527
[50] train-logloss:0.473233 valid-log
```

loss:0.472884

```
[60] train-logloss:0.454724 valid-log
loss:0.454407
[70] train-logloss:0.43984 valid-log
loss:0.439597
[80] train-logloss:0.427771 valid-log
loss:0.427637
     train-logloss:0.417995 valid-log
[90]
loss:0.417895
[100] train-logloss:0.409728 valid-log
loss:0.409714
[110] train-logloss:0.402778 valid-log
loss:0.402847
[120] train-logloss:0.396942 valid-log
loss:0.397114
[130] train-logloss:0.392061 valid-log
loss:0.392382
[140] train-logloss:0.387872 valid-log
loss:0.388373
[150] train-logloss:0.384392 valid-log
loss:0.385178
[160] train-logloss:0.381274 valid-log
loss:0.382299
[170] train-logloss:0.378437 valid-log
loss:0.379793
[180] train-logloss:0.375854 valid-log
loss:0.37747
[190] train-logloss:0.373571 valid-log
loss:0.375462
[200] train-logloss:0.371199 valid-log
loss:0.373368
[210] train-logloss:0.368932 valid-log
loss:0.371358
```

[220] train-logloss:0.367146 valid-log

[230] train-logloss:0.365382 valid-log

loss:0.369816

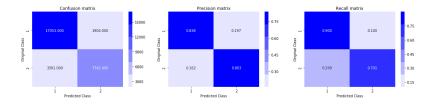
loss:0.368348

```
[240] train-logloss:0.363378 valid-log
loss:0.366641
[250] train-logloss:0.361745 valid-log
loss:0.365325
[260] train-logloss:0.36017 valid-log
loss:0.364083
[270] train-logloss:0.358561 valid-log
loss:0.36283
[280] train-logloss:0.357068 valid-log
loss:0.361743
[290] train-logloss:0.355691 valid-log
loss:0.360688
[300] train-logloss:0.354336 valid-log
loss:0.359735
[310] train-logloss:0.35309 valid-log
loss:0.35884
[320] train-logloss:0.351938 valid-log
loss:0.358094
[330] train-logloss:0.35075 valid-log
loss:0.357309
[340] train-logloss:0.349477 valid-log
loss:0.356474
[350] train-logloss:0.348308 valid-log
loss:0.355684
[360] train-logloss:0.347177 valid-log
loss:0.355021
[370] train-logloss:0.346093 valid-log
loss:0.354314
[380] train-logloss:0.344985 valid-log
loss:0.353589
[390] train-logloss:0.343936 valid-log
loss:0.352981
[399] train-logloss:0.342996 valid-log
loss:0.352343
The test log loss is: 0.3523431428180212
CPU times: user 1h 1min 14s, sys: 288 ms,
```

total: 1h 1min 14s Wall time: 1min 35s

In [0]: predicted_y =np.array(predict_y>0.5,dtype=int)
 print("Total number of data points :", len(pred
 icted_y))
 plot_confusion_matrix(y_test, predicted_y)

Total number of data points : 30000



5. Assignments

- 1. Try out models (Logistic regression, Linear-SVM) with simple TF-IDF vectors instead of TD IDF weighted word2Vec.
- Perform hyperparameter tuning of XgBoost models using RandomsearchCV with vectorizer as TF-IDF W2V to reduce the log-loss.

```
In [3]: import pandas as pd
   import matplotlib.pyplot as plt
   import re
   import time
   import warnings
   import sqlite3
   from sqlalchemy import create_engine # database
   connection
   import csv
   import os
```

```
warnings.filterwarnings("ignore")
import datetime as dt
import numpy as np
from nltk.corpus import stopwords
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature extraction.text import Cou
ntVectorizer
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassif
ier
from sklearn.metrics import confusion matrix
from sklearn.metrics.classification import accu
racy score, log loss
from sklearn.feature extraction.text import Tfi
dfVectorizer
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassif
ier
from sklearn.svm import SVC
from sklearn.model selection import StratifiedK
Fold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClass
ifierCV
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 GridSearchC
import math
from sklearn.metrics import normalized mutual i
nfo score
```

```
from sklearn.ensemble import RandomForestClassi
fier

from sklearn.model_selection import cross_val_s
core
from sklearn.linear_model import SGDClassifier
from mlxtend.classifier import StackingClassifi
er

from sklearn import model_selection
from sklearn.linear_model import LogisticRegres
sion
from sklearn.metrics import precision_recall_cu
rve, auc, roc_curve

/usr/local/lib/python3.6/dist-packages/sk
learn/externals/six.py:31: DeprecationWar
```

```
/usr/local/lib/python3.6/dist-packages/sk
learn/externals/six.py:31: DeprecationWar
ning: The module is deprecated in version
0.21 and will be removed in version 0.23
since we've dropped support for Python 2.
7. Please rely on the official version of
six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", Dep
recationWarning)
```

Perfom Modeling on complete dataset with TF-IDF Features

```
ven y i, y i hat.
def plot confusion matrix(test y, predict y):
    C = confusion matrix(test y, predict y)
    \# C = 9,9 \text{ matrix, each cell (i,j) represent}
s number of points of class i are predicted cla
ss 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 col
umns and axis=1 corresponds to rows in two diam
ensional 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, 411
    # C.sum(axis = 0) axis=0 corresonds to col
umns and axis=1 corresponds to rows in two diam
ensional array
   \# C.sum(axix = 0) = [[4, 6]]
   \# (C/C.sum(axis=0)) = [[1/4, 2/6],
```

```
[3/4, 4/6]]
   plt.figure(figsize=(20,4))
    labels = [1,2]
    # representing A in heatmap format
    cmap=sns.light palette("blue")
   plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=
".3f", xticklabels=labels, yticklabels=labels)
   plt.xlabel('Predicted Class')
   plt.ylabel('Original Class')
   plt.title("Confusion matrix")
   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()
```

```
import matplotlib.pyplot as plt
import re
import time
import warnings
import sqlite3
```

```
from sqlalchemy import create engine # database
connection
import csv
import os
warnings.filterwarnings("ignore")
import datetime as dt
import numpy as np
from nltk.corpus import stopwords
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature extraction.text import Cou
ntVectorizer
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassif
ier
from sklearn.metrics import confusion matrix
from sklearn.metrics.classification import accu
racy score, log loss
from sklearn.feature extraction.text import Tfi
dfVectorizer
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassif
ier
from sklearn.svm import SVC
from sklearn.model selection import StratifiedK
Fold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClass
ifierCV
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 GridSearchC
```

```
import math
from sklearn.metrics import normalized_mutual_i
nfo_score
from sklearn.ensemble import RandomForestClassi
fier

from sklearn.model_selection import cross_val_s
core
from sklearn.linear_model import SGDClassifier
from mlxtend.classifier import StackingClassifi
er

from sklearn import model_selection
from sklearn.linear_model import LogisticRegres
sion
from sklearn.metrics import precision_recall_cu
rve, auc, roc_curve
```

```
In [0]: dfnlp = pd.read_csv("/content/drive/My Drive/Qu
    ora/nlp_features_train.csv",encoding='latin-1')
    dfppro = pd.read_csv("/content/drive/My Drive/Q
    uora/df_fe_without_preprocessing_train.csv",enc
    oding='latin-1')
    df1 = dfnlp.drop(['qid1','qid2','question1','qu
    estion2','is_duplicate'],axis=1)
    df2 = dfppro.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
    df3 = dfnlp[['id','question1','question2']]
    duplicate = dfnlp.is_duplicate
```

```
In [0]: df3 = df3.fillna(' ')
    #assigning new dataframe with columns question
```

```
(q1+q2) and id same as df3
        new df = pd.DataFrame()
        new df['questions'] = df3.question1 + ' ' + df3
        .question2
        new df['id'] = df3.id
        df2['id']=df1['id']
        new df['id']=df1['id']
        final df = df1.merge(df2, on='id',how='left') #
        merging dfl and df2
        X = final df.merge(new df, on='id',how='left')
        #merging final df and new df
In [8]:
        #removing id from X
        X=X.drop('id',axis=1)
        X.columns
Out[8]: Index(['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 rat
        io', 'fuzz ratio',
                'fuzz partial ratio', 'longest sub
        str ratio', 'freq qid1', 'freq qid2',
                'qllen', 'q2len', 'q1 n words', 'q
        2 n words', 'word Common',
                'word Total', 'word share', 'freq
        q1+q2', 'freq q1-q2', 'questions'],
              dtype='object')
In [0]: | y=np.array(duplicate)
In [0]:
        #splitting data into train and test
        X train, X test, y train, y test=train test split(
        X,y,random state=3,test size=0.3)
```

```
In [11]:
         print(X train.shape)
         print(y train.shape)
         print(X test.shape)
         print(y test.shape)
         (283003, 27)
         (283003,)
         (121287, 27)
         (121287,)
In [0]:
        #seperating questions for tfidf vectorizer
         X train ques=X train['questions']
         X test ques=X test['questions']
         X train=X train.drop('questions',axis=1)
         X_test=X_test.drop('questions',axis=1)
In [0]:
         #tfidf vectorizer
         tf idf vect = TfidfVectorizer(ngram range=(1,4
         ), min df=10)
         X train tfidf=tf idf vect.fit transform(X train
         ques)
         X test tfidf=tf idf vect.transform(X test ques)
In [14]:
         #adding tfidf features to our train and test da
         ta using hstack
         X train = hstack((X train.values, X train tfidf
         X test= hstack((X test.values, X test tfidf))
         print(X train.shape)
         print(X test.shape)
         (283003, 156393)
         (121287, 156393)
```

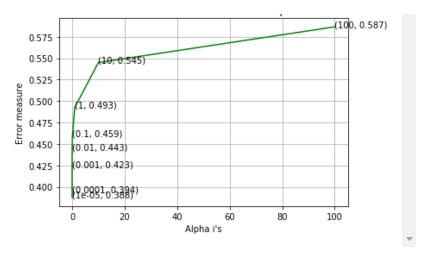
```
In [0]: # #standardising data
    # from sklearn import preprocessing
    # scaler = preprocessing.StandardScaler(with_me
    an=False)
    # X_train = scaler.fit_transform(X_train)
    # X_test = scaler.transform(X_test)
```

Applying Logistic Regression

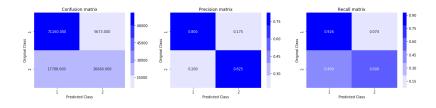
```
In [0]:
        alpha = [10 ** x for x in range(-5, 3)] # hyper
        param for SGD classifier.
        # read more about SGDClassifier() at http://sci
        kit-learn.org/stable/modules/generated/sklearn.
        linear model.SGDClassifier.html
        # default parameters
        # SGDClassifier(loss='hinge', penalty='12', alp
        ha=0.0001, 11 ratio=0.15, fit intercept=True, m
        ax iter=None, tol=None,
        # shuffle=True, verbose=0, epsilon=0.1, n jobs=
        1, random state=None, learning rate='optimal',
        eta0=0.0, power t=0.5,
        # class weight=None, warm start=False, average=
        False, n iter=None)
        # some of methods
        # fit(X, y[, coef init, intercept init, ...])
        Fit linear model with Stochastic Gradient Desce
        nt.
        # predict(X) Predict class labels for sample
        s in X.
```

```
# video link:
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, metho
d="sigmoid")
    sig clf.fit(X train, y train)
   predict y = sig clf.predict proba(X test)
    log error array.append(log loss(y test, pre
dict y, labels=clf.classes , eps=1e-15))
    print('For values of alpha = ', i, "The log
loss is:",log loss(y test, predict y, labels=cl
f.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 arra
y, 3)):
    ax.annotate((alpha[i], np.round(txt, 3)), (al
pha[i],log error array[i]))
plt.grid()
plt.title("Cross Validation Error for each alph
a")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
best alpha = np.argmin(log error array)
clf = SGDClassifier(alpha=alpha[best alpha], pe
nalty='12', loss='log', random state=42)
```

```
clf.fit(X train, y train)
sig clf = CalibratedClassifierCV(clf, method="s
igmoid")
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 tr
ain, 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 tes
t, predict y, labels=clf.classes , eps=1e-15))
predicted y =np.argmax(predict y,axis=1)
print("Total number of data points :", len(pred
icted y))
plot confusion matrix(y test, predicted y)
For values of alpha = 1e-05 The log loss
is: 0.3876589202822967
For values of alpha = 0.0001 The log los
s is: 0.3937861342051053
For values of alpha = 0.001 The log loss
is: 0.4233023910050718
For values of alpha = 0.01 The log loss
is: 0.4434536788024677
For values of alpha = 0.1 The log loss i
s: 0.4591654650352666
For values of alpha = 1 The log loss is:
0.4926263271528424
For values of alpha = 10 The log loss i
s: 0.5448710637409396
For values of alpha = 100 The log loss i
s: 0.5865222819503731
```



For values of best alpha = 1e-05 The tra in log loss is: 0.3849777035821042 For values of best alpha = 1e-05 The tes t log loss is: 0.3876589202822967 Total number of data points: 121287



Applying Linear SVM

```
In [0]: %%time
    alpha = [10 ** x for x in range(-5, 4)] # hyper
    param for SGD classifier.

# read more about SGDClassifier() at http://sci
    kit-learn.org/stable/modules/generated/sklearn.
    linear_model.SGDClassifier.html
    # -------
# default parameters
# SGDClassifier(loss='hinge', penalty='12', alp
```

```
ha=0.0001, l1 ratio=0.15, fit intercept=True, m
ax iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n jobs=
1, random state=None, learning rate='optimal',
eta0=0.0, power t=0.5,
# class weight=None, warm start=False, average=
False, n iter=None)
# some of methods
# fit(X, y[, coef init, intercept init, ...])
Fit linear model with Stochastic Gradient Desce
nt.
# predict(X) Predict class labels for sample
s in X.
#-----
# video link:
log error array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='11',
 loss='hinge', random state=42)
    clf.fit(X train, y train)
    sig clf = CalibratedClassifierCV(clf, metho
d="sigmoid")
    sig clf.fit(X train, y train)
   predict y = sig clf.predict proba(X test)
    log error array.append(log loss(y test, pre
dict y, labels=clf.classes , eps=1e-15))
    print('For values of alpha = ', i, "The log
loss is:",log loss(y test, predict y, labels=cl
f.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 arra
y, 3)):
    ax.annotate((alpha[i], np.round(txt, 3)), (al
pha[i],log error array[i]))
plt.grid()
plt.title("Cross Validation Error for each alph
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
best alpha = np.argmin(log error array)
clf = SGDClassifier(alpha=alpha[best alpha], pe
nalty='11', loss='hinge', random state=42)
clf.fit(X train, y train)
sig clf = CalibratedClassifierCV(clf, method="s
igmoid")
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 tr
ain, predict y, labels=clf.classes , eps=1e-1
5))
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 tes
t, predict y, labels=clf.classes , eps=1e-15))
predicted y =np.argmax(predict y,axis=1)
print("Total number of data points :", len(pred
icted y))
plot confusion matrix(y test, predicted y)
```

For values of alpha = 1e-0.5 The log loss

--- . ---- -- --- --- --- --- ---

is: 0.4187868285636254

For values of alpha = 0.0001 The log los

s is: 0.4494938960115246

For values of alpha = 0.001 The log loss

is: 0.4590994398298589

For values of alpha = 0.01 The log loss

is: 0.507502478793165

For values of alpha = 0.1 The log loss i

s: 0.49495228963091503

For values of alpha = 1 The log loss is:

0.5790224258771397

For values of alpha = 10 The log loss i

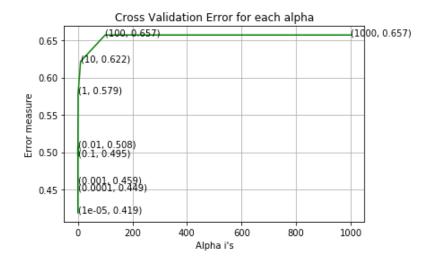
s: 0.6216484120064324

For values of alpha = 100 The log loss i

s: 0.6571084989895938

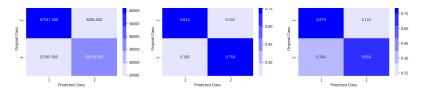
For values of alpha = 1000 The log loss

is: 0.6571084989603588



For values of best alpha = 1e-05 The tra in log loss is: 0.4170704354727345 For values of best alpha = 1e-05 The tes t log loss is: 0.4187868285636254 Total number of data points: 121287

Confusion matrix Precision matrix Recall matrix



CPU times: user 37min 4s, sys: 16min 14

s, total: 53min 18s Wall time: 34min 7s

XGBOOST

```
In [0]: import xgboost as xgb
```

```
In [0]:
         88 time
        n estimators = [50, 100, 150, 200, 300, 400, 500]
        test scores = []
        train scores = []
         for i in n estimators:
             clf = xgb.XGBClassifier(learning rate=0.1, n
         estimators=i,n jobs=-1)
             clf.fit(X train, y train)
             y pred = clf.predict proba(X train)
             log loss train = log loss(y train, y pred,
          eps=1e-15)
            train scores.append(log loss train)
             y pred = clf.predict proba(X test)
            log loss test = log loss(y test, y pred, ep
         s=1e-15)
            test scores.append(log loss test)
            print('For n estimators = ',i,'Train Log Lo
        ss ',log loss train, 'Test Log Loss ',log_loss_t
        est)
```

For n_estimators = 50 Train Log Loss 0. 3802022451846393 Test Log Loss 0.3815880

153715477

For n estimators = 100 Train Log Loss 0.3601035226913487 Test Log Loss 0.36236 71979711734

For $n_{estimators} = 150$ Train Log Loss 0.3506867034074368 Test Log Loss 0.35379 625301920425

For n estimators = 200 Train Log Loss 0.3428548466945084 Test Log Loss 0.34656 819162382024

For n estimators = 300 Train Log Loss 0.33327452415665726 Test Log Loss 0.3382 9663616353656

For n estimators = 400 Train Log Loss 0.3269292490820392 Test Log Loss 0.33304 25109036889

For n estimators = 500 Train Log Loss 0.32188343164123673 Test Log Loss 0.3291 1847991728505

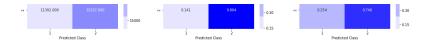
CPU times: user 3h 23min 11s, sys: 6.24

s, total: 3h 23min 18s Wall time: 11min 57s

In [0]: clf=xgb.XGBClassifier(learning_rate=0.1,n_estim ators=500, n jobs=-1) clf.fit(X train, y train) y pred=clf.predict proba(X test) print("The test log loss is:",log loss(y test, y pred, eps=1e-15)) predicted y =np.argmax(y pred,axis=1) plot confusion matrix(y test, predicted y)

The test log loss is: 0.32911847991728505



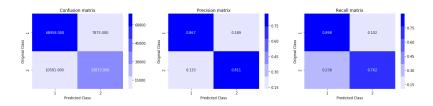


Hyperparameter tunning using RandomSearch

```
In [0]:
         import xgboost as xgb
In [18]:
         %%time
          from sklearn.model selection import RandomizedS
          earchCV
          param grid = \{\text{"max depth"}: [2, 5, 8, 10],
                        "n_estimators":[5, 10, 50, 100]}
         model = RandomizedSearchCV(xgb.XGBClassifier(n
          jobs=-1,random state=25), param distributions=p
          aram grid, n iter=30, scoring='neg log loss', cv=
          3, n \text{ jobs}=-1)
         model.fit(X train, y train)
          model.best params
         CPU times: user 1h 31min 26s, sys: 2.64
          s, total: 1h 31min 29s
         Wall time: 13min 2s
In [20]:
         %%time
          clf=xqb.XGBClassifier(n jobs=-1, random state=2
          5, max depth=10, n estimators=100)
          clf.fit(X train, y train)
          y pred test=clf.predict proba(X test)
          y pred train=clf.predict proba(X train)
          log loss train = log loss(y train, y pred trai
```

```
n, eps=1e-15)
log_loss_test=log_loss(y_test,y_pred_test,eps=1
e-15)
print('Train log loss = ',log_loss_train,' Test
log loss = ',log_loss_test)
predicted_y=np.argmax(y_pred_test,axis=1)
plot_confusion_matrix(y_test,predicted_y)
```

Train log loss = 0.2793043393157809 Tes t log loss = 0.3143578907429847



CPU times: user 35min 32s, sys: 1.35 s, t

otal: 35min 33s

Wall time: 2min 25s

```
In [0]: from prettytable import PrettyTable
    x = PrettyTable()
    x.field_names = ["Model","vectorizer","log los
    s"]
    x.add_row(['Logistic regression','TFIDF w2vec',
    '0.4492'])
    x.add_row(['Linear SVM','TFIDF w2vec',' 0.5481'])
    x.add_row(['XGBOOST','TFIDF w2vec','0.3523'])
    x.add_row(['Logistic regression','TFIDF ',' 0.3
    876'])
    x.add_row(['Linear SVM','TFIDF','0.4187'])
    x.add_row(['XGBOOST','TFIDF','0.3143'])
    print(x)
```

STEP BY STEP PROCEDURE:

- 1.As we know, we have a data set containing Number of rows 404,290, containing 5 columns: qid1, qid2, question1, question2, is duplicate from which ' is duplicate ' is a class label specifying that Question 1 and Question 2 are similar or not, and this is a binary classification problem, and we need to predict whether or not they are duplicate.
- 2.Firstly we preprocessed our data, did feature engineering to create new features which might help us and created our dataframes, then we merged dataframes and got out final matrix. Now after doing simple EDA on dataset we will try some Basic Feature Extraction (before cleaning) the datset like Frequency of qid1's ,word_Common and etc. and using this featured datset we will do some EDA on it so that we will able to rectify which features are most useful features our of all features i.e(wich feature is helpful for classification)
- 3.We will try some Advanced Feature Extraction using NLP and Fuzzy Features after doing basic Basic Feature Extractions, but before we do this we will do Text Preprocessing and then we will do Advanced Feature Extraction and try to show our Advanced Feature using EDA, PCA and word clouds.
- 4. Then we randomly split data. We could also have splitted time-based, as the model could also forecast unknown information for the future. But, no timestamp column was provided, so the only option was to randomly split it.
- 5. Now that we know we have columns of two questions i.e. Question 1 and Question 2 and we will vector that col using tfidf weighted wordvectors so that we can apply models on it and after

doing all these we will merge all the features i.e. besic features + advance features + Question 1 tfidf w2v + and Question 2 tfidf w2v together. And now we're going to apply models to it after doing all of it.

6.In this case study, as we know, we use two main performance matrix, i.e. log-loss and confusion matrix, and we'll get our performance of the models there.

7.Let's start: here's a model i.e. Logistic Regression linear svm and XgBoost and a random model where the worst-case log-loss is found and then we're trying to compare it.

8.In the next step we will test our models with other vectorizers i.e. tfidf instead of tfidf weighted w2v and seek some hyperparameter tuning to improve the performance of the model.

9.We used a simple Random / Dumb model now. It gave 0.88 log loss. That's the worst log-loss scenario. This will serve as a foundation and any system that we build should have a lower log-loss than this dumb model.

10.After that we have applied Logistic Regression with hyperparameter tuning. It gave a log-loss of 0.38, which is lower than Random Model. We can also see that there is no Overfitting problem, since, Train log-loss and Test log-loss and very close.

11.After that we have applied Linear SVM with hyperparameter tuning. It gave the log-loss of 0.41, which is lower than Random Model. We can also see that there is no Overfitting problem, since, Train log-loss and Test log-loss and very close.

12. After that we have applied Xgboost with hyperparameter tuning. It gave the log-loss of