

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 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 quest cause seekers to spend more time finding the best answer to their question, and make writers feel they need to a Quora values canonical questions because they provide a better experience to active seekers and writers, and of term.

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

1.2 Sources/Useful Links

- Source: https://www.kaggle.com/c/quora-question-pairs
 - __ Useful Links __
- Discussions: https://www.kaggle.com/anokas/data-analysis-xgboost-starter-0-35460-lb/comments
- Kaggle Winning Solution and other approaches: https://www.dropbox.com/sh/93968nfnrzh8bp5/AACZdt
- Blog 1: https://engineering.guora.com/Semantic-Question-Matching-with-Deep-Learning
- Blog 2: https://towardsdatascience.com/identifying-duplicate-questions-on-quora-top-12-on-kaggle-4c1c

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
- 3. No strict latency concerns.
- 4. Interpretability is partially important.

```
drive.mount('/content/drive')
%cd ./drive/My Drive
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m [Errno 2] No such file or directory: './drive/My Drive' /content/drive/My Drive

2. Machine Learning Probelm

2.1 Data

2.1.1 Data Overview

- Data will be in a file Train.csv
- Train.csv contains 5 columns: qid1, qid2, question1, question2, is_duplicate
- Size of Train.csv 60MB
- Number of rows in Train.csv = 404.290

2.1.2 Example Data point

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

2.2 Mapping the real world problem to an ML problem

2.2.1 Type of Machine Leaning Problem

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

2.2.2 Performance Metric

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

Metric(s):

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

- Reading the data

```
!pip3 install fuzzywuzzy
!pip3 install distance
!pip3 install spacy
import numpy as np
import pandas as pd
from pandas import DataFrame, Series
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 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 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 cornus import stanwards
```

```
ווטווו וובנה.נטו שמש בווושטו נ שנטשטו מש
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion matrix
from sklearn.metrics.classification import accuracy score, log loss
from sklearn.feature extraction.text import TfidfVectorizer
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
#from sklearn.cross_validation import StratifiedKFold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model selection import GridSearchCV
import math
from sklearn.metrics import normalized mutual info score
from sklearn.ensemble import RandomForestClassifier
from sklearn.model selection import cross val score
from sklearn.linear_model import SGDClassifier
from mlxtend.classifier import StackingClassifier
from sklearn import model selection
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision recall curve, auc, roc curve
from fuzzywuzzy import fuzz
from sklearn.manifold import TSNE
# Import the Required lib packages for WORD-Cloud generation
# https://stackoverflow.com/questions/45625434/how-to-install-wordcloud-in-python3-6
from wordcloud import WordCloud, STOPWORDS
from os import path
from PIL import Image
import nltk
nltk.download('stopwords')
 Гэ
```

Requirement already satisfied: fuzzywuzzy in /usr/local/lib/python3.6/dist-packages (Requirement already satisfied: distance in /usr/local/lib/python3.6/dist-packages (0.

```
Requirement already satisfied: spacy in /usr/local/lib/python3.6/dist-packages (2.1.8
     Requirement already satisfied: wasabi<1.1.0,>=0.2.0 in /usr/local/lib/python3.6/dist-
     Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in /usr/local/lib/python3.6/
     Requirement already satisfied: preshed<2.1.0,>=2.0.1 in /usr/local/lib/python3.6/dist
     Requirement already satisfied: blis<0.3.0,>=0.2.2 in /usr/local/lib/python3.6/dist-pa
     Requirement already satisfied: srsly<1.1.0,>=0.0.6 in /usr/local/lib/python3.6/dist-p
     Requirement already satisfied: plac<1.0.0,>=0.9.6 in /usr/local/lib/python3.6/dist-pa
     Requirement already satisfied: thinc<7.1.0,>=7.0.8 in /usr/local/lib/python3.6/dist-p
     Requirement already satisfied: cymem<2.1.0,>=2.0.2 in /usr/local/lib/python3.6/dist-p
     Requirement already satisfied: numpy>=1.15.0 in /usr/local/lib/python3.6/dist-package
     Requirement already satisfied: requests<3.0.0,>=2.13.0 in /usr/local/lib/python3.6/di
     Requirement already satisfied: tqdm<5.0.0,>=4.10.0 in /usr/local/lib/python3.6/dist-p
     Requirement already satisfied: idna<2.9,>=2.5 in /usr/local/lib/python3.6/dist-packag
     Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-pa
     Requirement already satisfied: urllib3<1.25,>=1.21.1 in /usr/local/lib/python3.6/dist
     Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist
     [nltk_data] Downloading package stopwords to /root/nltk_data...
     [nltk data] Package stopwords is already up-to-date!
     True
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predicted
    A = (((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in that column
    \# C = [[1, 2],
          [3, 4]]
    # C.T = [[1, 3],
    #
             [2, 4]]
    # C.sum(axis = 1) axis=0 corresonds to columns and axis=1 corresponds to rows in two
    \# C.sum(axix = 1) = [[3, 7]]
    \# ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #
                                [2/3, 4/7]
    \# ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]]
                                [3/7, 4/7]]
    # sum of row elements = 1
    B = (C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in that row
    \# C = [[1, 2],
          [3, 4]]
    # C.sum(axis = 0) axis=0 corresonds to columns and axis=1 corresponds to rows in two
    \# 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
```

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```
cmap-sns.rrgnc_parecce( prue )
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=label
    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=label
    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=label
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")
    plt.show()
data = pd.read_csv("train.csv")
data=data[0:50000:5]
```

data.head()

₽		id	qid1	qid2	question1	
	0	0	1	2	What is the step by step guide to invest in sh	What is the step by step
	5	5	11	12	Astrology: I am a Capricorn Sun Cap moon and c	I'm a triple Capricorn (Sun
	10	10	21	22	Method to find separation of slits using fresn	What are some of the thin
	15	15	31	32	What would a Trump presidency mean for current	How will a Trump preside
	20	20	41	42	Why do rockets look white?	Why are rockets and t

```
data.shape[0],data.shape[1]
```

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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 suffic

```
from sklearn.model_selection import train_test_split

df_train,df_test=train_test_split(data,test_size=0.25)
```

df_train.head()

```
С⇒
                id
                      qid1
                             qid2
                                                                       question1
      6075
              6075 11913 11914
                                                      What is Artificial Intelligence?
                                                                                        What all doe
      1205
              1205
                     2402
                                                                                    Which one is a be
                             2403
                                      Which processor is faster and better for batte...
     16030 16030 30586 25457 What should be the most important thing in you... Life Advice: What a
     37040 37040 67461 67462
                                      What are the largest veins and arteries in the... What are the maj
     44110 44110 79241 79242
                                                      How do bladeless fans work?
                                                                                                   F
```

```
#Checking whether there are any rows with null values
nan rows = df train[df train.isnull().any(1)]
print (nan rows)
# Filling the null values with ' '
df train = df train.fillna('')
nan_rows = df_train[df_train.isnull().any(1)]
print (nan_rows)
     Empty DataFrame
     Columns: [id, qid1, qid2, question1, question2, is_duplicate]
     Index: []
     Empty DataFrame
     Columns: [id, qid1, qid2, question1, question2, is_duplicate]
     Index: []
#Test
#Checking whether there are any rows with null values
nan_rows = df_test[df_test.isnull().any(1)]
print (nan rows)
# Filling the null values with ' '
df_test = df_test.fillna('')
nan rows = df test[df test.isnull().any(1)]
print (nan_rows)
     Empty DataFrame
     Columns: [id, qid1, qid2, question1, question2, is duplicate]
     Index: []
     Empty DataFrame
     Columns: [id, qid1, qid2, question1, question2, is_duplicate]
     Index: []
```

2 2 Racio Egatura Extraction (hafara clasning)

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

3.4 Preprocessing of Text

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

```
# To get the results in 4 decemal points
SAFE DIV = 0.0001
STOP_WORDS = stopwords.words("english")
def preprocess(x):
    x = str(x).lower()
    x = x.replace(",000,000", "m").replace(",000", "k").replace("'", "'").replace("'", "'")
                            .replace("won't", "will not").replace("cannot", "can not").repl
                            .replace("n't", " not").replace("what's", "what is").replace("i
                            .replace("'ve", " have").replace("i'm", "i am").replace("'re",
                            .replace("he's", "he is").replace("she's", "she is").replace("'
                            .replace("%", " percent ").replace("₹", " rupee ").replace("$",
                            .replace("€", " euro ").replace("'ll", " will")
    x = re.sub(r''([0-9]+)000000'', r''\setminus 1m'', x)
    x = re.sub(r''([0-9]+)000'', r''\setminus 1k'', x)
    porter = PorterStemmer()
    pattern = re.compile('\W')
    if type(x) == type(''):
        x = re.sub(pattern, ' ', x)
    if type(x) == type(''):
```

```
x = porter.stem(x)
example1 = BeautifulSoup(x)
x = example1.get_text()
```

return x

3.5 Advanced Feature Extraction (NLP and Fuzzy Features)

Definition:

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

Features:

- cwc_min: Ratio of common_word_count to min length of word count of Q1 and Q2
 cwc_min = common_word_count / (min(len(q1_words), len(q2_words))
- cwc_max: Ratio of common_word_count to max length of word count of Q1 and Q2 cwc_max = common_word_count / (max(len(q1_words), len(q2_words))
- csc_min: Ratio of common_stop_count to min length of stop count of Q1 and Q2
 csc_min = common_stop_count / (min(len(q1_stops), len(q2_stops))
- csc_max: Ratio of common_stop_count to max length of stop count of Q1 and Q2
 csc_max = common_stop_count / (max(len(q1_stops), len(q2_stops))
- ctc_min: Ratio of common_token_count to min length of token count of Q1 and Q2
 ctc_min = common_token_count / (min(len(q1_tokens), len(q2_tokens))
- ctc_max: Ratio of common_token_count to max length of token count of Q1 and Q2 ctc_max = common_token_count / (max(len(q1_tokens), len(q2_tokens))
- last_word_eq: Check if First word of both questions is equal or not last_word_eq = int(q1_tokens[-1] == q2_tokens[-1])

- first_word_eq: Check if First word of both questions is equal or not first_word_eq = int(q1_tokens[0] == q2_tokens[0])
- abs_len_diff: Abs. length difference
 abs_len_diff = abs(len(q1_tokens) len(q2_tokens))
- mean_len: Average Token Length of both Questions mean_len = (len(q1_tokens) + len(q2_tokens))/2
- fuzz_ratio : https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywuzzy-f
- fuzz_partial_ratio: http://chairnerd.seatgeek.com/fuzzy
- token_sort_ratio: https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzyw
- token_set_ratio: https://github.com/seatgeek/fuzzywuzzy#usage http://chairnerd.seatgeek.com/fuzzywu
- longest_substr_ratio: Ratio of length longest common substring to min lengthh of token count of Q1 and

```
def get_token_features(q1, q2):
   token_features = [0.0]*10
   # Converting the Sentence into Tokens:
   q1 tokens = q1.split()
   q2_tokens = q2.split()
   if len(q1 tokens) == 0 or len(q2 tokens) == 0:
        return token features
   # Get the non-stopwords in Questions
   q1 words = set([word for word in q1 tokens if word not in STOP WORDS])
   q2_words = set([word for word in q2_tokens if word not in STOP_WORDS])
   #Get the stopwords in Questions
   q1_stops = set([word for word in q1_tokens if word in STOP_WORDS])
   q2_stops = set([word for word in q2_tokens if word in STOP_WORDS])
   # Get the common non-stopwords from Question pair
   common_word_count = len(q1_words.intersection(q2_words))
   # Get the common stopwords from Question pair
   common_stop_count = len(q1_stops.intersection(q2_stops))
   # Get the common Tokens from Question pair
   common_token_count = len(set(q1_tokens).intersection(set(q2_tokens)))
```

```
token_features[0] = common_word_count / (min(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[1] = common_word_count / (max(len(q1_words), len(q2_words)) + SAFE_DIV)
    token_features[2] = common_stop_count / (min(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[3] = common_stop_count / (max(len(q1_stops), len(q2_stops)) + SAFE_DIV)
    token_features[4] = common_token_count / (min(len(q1_tokens), len(q2_tokens)) + SAFE_D
    token_features[5] = common_token_count / (max(len(q1_tokens), len(q2_tokens)) + SAFE_D
    # Last word of both question is same or not
    token_features[6] = int(q1_tokens[-1] == q2_tokens[-1])
    # First word of both question is same or not
    token_features[7] = int(q1_tokens[0] == q2_tokens[0])
    token_features[8] = abs(len(q1_tokens) - len(q2_tokens))
    #Average Token Length of both Questions
    token_features[9] = (len(q1_tokens) + len(q2_tokens))/2
    return token_features
# get the Longest Common sub string
def get_longest_substr_ratio(a, b):
    strs = list(distance.lcsubstrings(a, b))
    if len(strs) == 0:
        return 0
    else:
        return len(strs[0]) / (min(len(a), len(b)) + 1)
def extract_features(df):
    df['freq_qid1'] = df.groupby('qid1')['qid1'].transform('count')
    df['freq_qid2'] = df.groupby('qid2')['qid2'].transform('count')
    df['q1len'] = df['question1'].str.len()
    df['q2len'] = df['question2'].str.len()
    df['q1_n_words'] = df['question1'].apply(lambda row: len(row.split(" ")))
    df['q2_n_words'] = df['question2'].apply(lambda row: len(row.split(" ")))
    def normalized_word_Common(row):
        w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * len(w1 & w2)
    df['word_Common'] = df.apply(normalized_word_Common, axis=1)
    def normalized_word_Total(row):
        w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * (len(w1) + len(w2))
    df['word_Total'] = df.apply(normalized_word_Total, axis=1)
    def normalized_word_share(row):
        w1 = set(map(lambda word: word.lower().strip(), row['question1'].split(" ")))
        w2 = set(map(lambda word: word.lower().strip(), row['question2'].split(" ")))
        return 1.0 * len(w1 & w2)/(len(w1) + len(w2))
    df['word_share'] = df.apply(normalized_word_share, axis=1)
```

```
df['freq_q1+q2'] = df['freq_qid1']+df['freq_qid2']
   df['freq_q1-q2'] = abs(df['freq_qid1']-df['freq_qid2'])
   # preprocessing each question
   df["question1"] = df["question1"].fillna("").apply(preprocess)
   df["question2"] = df["question2"].fillna("").apply(preprocess)
   print("token features...")
   # Merging Features with dataset
   token_features = df.apply(lambda x: get_token_features(x["question1"], x["question2"])
                       = list(map(lambda x: x[0], token_features))
   df["cwc_min"]
                       = list(map(lambda x: x[1], token_features))
   df["cwc_max"]
   df["csc_min"]
                       = list(map(lambda x: x[2], token_features))
                       = list(map(lambda x: x[3], token_features))
   df["csc_max"]
   df["ctc_min"]
                      = list(map(lambda x: x[4], token_features))
                      = list(map(lambda x: x[5], token_features))
   df["ctc_max"]
   df["last_word_eq"] = list(map(lambda x: x[6], token_features))
   df["first_word_eq"] = list(map(lambda x: x[7], token_features))
   df["abs_len_diff"] = list(map(lambda x: x[8], token_features))
   df["mean_len"]
                       = list(map(lambda x: x[9], token_features))
   #Computing Fuzzy Features and Merging with Dataset
   # do read this blog: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in
   # https://stackoverflow.com/questions/31806695/when-to-use-which-fuzz-function-to-comp
   # https://github.com/seatgeek/fuzzywuzzy
   print("fuzzy features..")
   df["token_set_ratio"]
                               = df.apply(lambda x: fuzz.token_set_ratio(x["question1"],
   # The token sort approach involves tokenizing the string in question, sorting the toke
   # then joining them back into a string We then compare the transformed strings with a
   df["token_sort_ratio"]
                               = df.apply(lambda x: fuzz.token_sort_ratio(x["question1"],
                               = df.apply(lambda x: fuzz.QRatio(x["question1"], x["questi
   df["fuzz ratio"]
   df["fuzz_partial_ratio"] = df.apply(lambda x: fuzz.partial_ratio(x["question1"], x[
   df["longest substr ratio"] = df.apply(lambda x: get longest substr ratio(x["question1
   return df
df_train_afe = extract_features(df_train)
df_test_afe=extract_features(df_test)

    token features...

    fuzzy features..
     token features...
     fuzzy features..
df_train_afe.shape
```

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3.6 Featurizing text data with tfidf word-vectors

```
df_train_afe['question1'] = df_train_afe['question1']
df_train_afe['question2'] = df_train_afe['question2']
df_test_afe['question1'] = df_test_afe['question1']
df_test_afe['question2'] = df_test_afe['question2']
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
# merge texts
questions_train = list(df_train_afe['question1']+df_train_afe['question2'])
tfidf = TfidfVectorizer(lowercase=False )
tfidf.fit(questions_train)
word2tfidf = dict(zip(tfidf.get feature names(), tfidf.idf ))
df_train_vec=DataFrame()
df_test_vec=DataFrame()
# en vectors web lg, which includes over 1 million unique vectors.
import spacy
nlp=spacy.load('en_core_web_sm')
from spacy.lang.en import English
from tqdm import tqdm
vecs1 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu1 in tqdm(list(df_train_afe['question1'])):
    doc1 = nlp(qu1)
    # 384 is the number of dimensions of vectors
    mean_vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
    for word1 in doc1:
        # word2vec
        vec1 = word1.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word1)]
        except:
            idf = 0
        # compute final vec
        mean vec1 += vec1 * idf
    mean vec1 = mean vec1.mean(axis=0)
    vecs1.append(mean vec1)
df_train_vec['feats_1'] = list(vecs1)
```

```
vecs1 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu1 in tqdm(list(df_train_afe['question2'])):
    doc1 = nlp(qu1)
    # 384 is the number of dimensions of vectors
    mean_vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
    for word1 in doc1:
        # word2vec
        vec1 = word1.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word1)]
        except:
            idf = 0
        # compute final vec
        mean_vec1 += vec1 * idf
    mean_vec1 = mean_vec1.mean(axis=0)
    vecs1.append(mean_vec1)
df_train_vec['feats_2'] = list(vecs1)
df_train_vec.head
df_train_ave = pd.DataFrame(df_train_vec.feats_1.values.tolist())
df_train_ave2 = pd.DataFrame(df_train_vec.feats_2.values.tolist())
df_train_ave2.shape
 「→ (7500, 96)
# en vectors web lg, which includes over 1 million unique vectors.
import spacy
nlp=spacy.load('en_core_web_sm')
from spacy.lang.en import English
from tqdm import tqdm
vecs1 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu1 in tqdm(list(df_test_afe['question1'])):
    doc1 = nlp(qu1)
    # 384 is the number of dimensions of vectors
    mean_vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
    for word1 in doc1:
        # word2vec
        vec1 = word1.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word1)]
        except:
```

```
idf = 0
        # compute final vec
        mean vec1 += vec1 * idf
    mean vec1 = mean vec1.mean(axis=0)
    vecs1.append(mean_vec1)
df_test_vec['feats_1'] = list(vecs1)
# en vectors web lg, which includes over 1 million unique vectors.
import spacy
nlp=spacy.load('en_core_web_sm')
from spacy.lang.en import English
from tqdm import tqdm
vecs1 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu1 in tqdm(list(df_test_afe['question2'])):
    doc1 = nlp(qu1)
    # 384 is the number of dimensions of vectors
    mean_vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
    for word1 in doc1:
        # word2vec
        vec1 = word1.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word1)]
        except:
            idf = 0
        # compute final vec
        mean_vec1 += vec1 * idf
    mean_vec1 = mean_vec1.mean(axis=0)
    vecs1.append(mean_vec1)
df_test_vec['feats_2'] = list(vecs1)
df_test_ave = pd.DataFrame(df_test_vec.feats_1.values.tolist())
df test ave2 = pd.DataFrame(df test vec.feats 2.values.tolist())
df_test_ave.head
 C→
```

```
<bound method NDFrame.head of</pre>
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        16.430224
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                                                      22.563435
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2488
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2494
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2495
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2496
        49.035355
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2497
        91.952072
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                                                                  -61.371228
                                                                                 71.622765
2498
        72.003094
                    -57.647030
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                                  -66.112287
```

2499 15.237106 -9.080193 -89.208226 ... -10.946389 34.018420 -39.885777

[2500 rows x 96 columns]>

df_train_afe

₽

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq
6075	6075	11913	11914	what is artificial intelligence	what all does artificial intelligence include	0	1	
1205	1205	2402	2403	which processor is faster and better for batte	which one is a better processor 1 8 ghz intel	0	1	
16030	16030	30586	25457	what should be the most important thing in you	life advice what are some of the most importa	0	1	
37040	37040	67461	67462	what are the largest veins and arteries in the	what are the major arteries of the human body	0	1	
44110	44110	79241	79242	how do bladeless fans work	how does bladeless fan works	1	1	
29645	29645	39425	54825	what is meant by surgical strike	what is the meaning of surgical strike	1	1	
23200	23200	43491	43492	i leveraged 100k to secure a loan for a startu	does amalgam filing dangerous	0	1	
6875	6875	13455	13456	does china has prime minister	is there prime minister in china	1	1	
3855	3855	7635	7636	what is travis kalanick like on investor confe	what ethnicity is travis kalanick	0	1	
45765	45765	49437	1215	is world war 3 coming	is world war 3 more imminent than expected	1	1	
39590	39590	46356	19540	how can you cope with loneliness	what are the ways to end loneliness	1	1	
17900	17900	33951	33952	why will not richard muller answer my question	how do i get richard muller answer my questions	0	1	
47020	47020	84007	84008 ledsYHALI7	what does iq	what does actually iq	1 /eULWH&printMode=tr	1	18/3

mean

17660	33522	33523	are there any substantial way to quit meth	what is the best way to quit meth	1	I 1
23675	44319	44320	what are the future methodology changes in the	what are the examinations i can appear for aft	C) 1
20610	38870	38871	what kind of jobs are byu computer science bi	is quora a better realization of google own vi	C) 1
41995	75736	75737	what can we study after pursuing graduation in	what are the fields of study after graduating	1	1 1
32365	59595	59596	why does my wrist hurt when i cry	why do my wrist hurt when squatting	C) 1
6125	12008	12009	how do i make green tea	what is the right procedure to make green tea	1	1 1
32145	59207	59208	does electricity travel at the speed of light	is the speed of electricity a synonym for the	1	1 1
42100	75910	75911	what is the best strategy to prepare for cat i	how do i prepare for cat in one month	1	l 1
42330	23143	76297	i am financially stuck in a half baked relatio	i am looking for a job change but i am unable	C) 2
42200	76080	76081	what is the difference between pitch and tar	what are the best react is repositories that f	C) 1
10805	20905	20906	which is the best institute in mumbai for doin	which is the best institute in mumbai from whe	1	I 1
	23675 20610 41995 32365 6125 42100 42330	23675 44319 20610 38870 41995 75736 6125 12008 32145 59207 42100 75910 42330 23143 42200 76080	23675 44319 44320 20610 38870 38871 41995 75736 75737 59595 59596 6125 12008 12009 42100 75910 75911 42330 23143 76297 42200 76080 76081	176603352233523substantial way to quit meth236754431944320what are the future methodology changes in the206103887038871what kind of jobs are byu computer science bi419957573675737what can we study after pursuing graduation in323655959559596why does my wrist hurt when i cry61251200812009how do i make green tea321455920759208electricity travel at the speed of light421007591075911what is the best strategy to prepare for cat i423302314376297what is the baked relatio422007608076081what is the difference between pitch and tar108052090520906which is the best institute in mumbai for	17660 33522 33523 substantial way to quit meth What are the future methodology changes in the what are the future methodology changes in the what are the future methodology changes in the what kind of jobs are byu computer science bi is quora a better realization of google own vi 41995 75736 75737 what can we study after pursuing graduation in what are the fields of study after graduating 32365 59595 59596 why does my wrist hurt when i cry why do my wrist hurt when i cry 6125 12008 12009 make green tea what is the best irategy to prepare for cat in what is the best strategy to prepare for cat in i am looking for a job change but i am unable 42330 23143 76297 what is the difference between pitch and tar the best react js repositories that f which is the best institute in mumbai for in mumbai	substantial way to quit meth What are the future methodology changes in the 23675 44319 44320 What kind of jobs are byu computer science bi 20610 38870 38871 What kind of jobs are byu computer science bi 41995 75736 75737 What can we study after pursuing graduation in 32365 59595 59596 Why does my wrist hurt when i cry when i cry what is the right procedure to make green tea 32145 59207 59208 Computer science bi 42100 75910 75911 What is the best institute in mumbai of mumbai for all mumbai of mumbai for in mumbai in m

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				quoia_xgb.	wind are the		
28775	28775	53318	53319	keyboardist on bits pilani ca	best pop punk bands	C	1
19985	19985	37741	37742	what is the difference between hardware techno	what is the difference between software and ha	C	1
15460	15460	29534	29535	which type of css js framework used paytm	what js framework should i use on a site with 	C	1
4070	4070	8056	8057	what do you do when you are upset	what you do when you get upset	1	1
27515	27515	51113	49664	does house baratheon have any future	is house baratheon extinct	1	1
29685	29685	54892	54893	what is the coolest thing or task that you hav	what were the coolest things you have automated	1	1
37395	37395	68055	68056	what are the most common barriers that affect	what are the most common barriers that affect	O	1
22640	22640	42469	42470	what are the best ways to fake your own death	what are the worst ways to fake one own own de	C	1
37365	37365	67999	68000	what were the books studied by aiims topper 2016	what books should i study for my pg entrance i	C	1
17720	17720	33624	28584	what happen actually after we die where does	what will happen after we die does nothing ha	1	1
39365	39365	71368	71369	how is the march 2 success asvab practice test	my kaplan own practice tests average score is	C	1
8455	8455	16483	16484	how do i wear red lipstick without sending a	how should i convince my son to not wear lipst	C	1

					ipynb - Colaboratory		
39275	39275	71223	71224	what advice would you give to someone that giv	what kind of a person is someone who does not	0	1
7450	7450	14555	14556	what has been the economic impact from brexit	what have been the economic effects of brexit	1	1
17380	17380	33031	33032	what are some successful ways to quit smoking	how do you quit smoking	1	1
33075	33075	60815	60816	will deafness or blindness be cured	will blindness and deafness be cured	1	1
6000	6000	5534	11770	does masturbation cause infertility	does masturbation in males lead to sexual infe	1	1
33035	33035	60746	60747	which is the best and reasonable web hosting s	which is the best web hosting service provider	1	1
9310	9310	18094	18095	who would win in a fight goku or the hulk	who would win in a fight the hulk or the marv	0	1
14590	14590	27929	27930	why do people want to earn more money	why do people want to earn more money	1	1
1320	1320	2632	2633	presently 2015 how many articles parts and	how many pages are there in the indian constit	0	1
32720	32720	5297	38545	how do you control your anger	how do i control my anger and have patience	1	2
45970	45970	82285	82286	why do women have so much sex	why do women have sex with men	0	1
43525	43525	78275	78276	how do i find out someone location through mob	is there any mobile app through which i can do	0	1

37330	37330	67946	67947	what is the atomic mass of methane how is it	what is relative atomic mass and how is it det	C) 1
18955	18955	35862	35863	what is the relationship between power and the	what is the relationship between power and time	C) 1
27675	27675	51389	51390	what is the scope for mba operations managemen	how good is the future of operations managemen	1	1 1
7375	7375	14410	14411	were any major party candidates as problematic	i am now 7 sem be mech can i crack gate exam	() 1
10705	10705	20715	20716	is deep web really that dangerous	how unsafe the deep web is	1	1 1
27765	27765	51552	51553	what is best average worst case time complex	what is best algorithm run time complexity	() 1
38185	38185	69390	69391	can i use html5 video for backgrounds with the	how do i use a child theme in wordpress	C) 1
35485	35485	64833	64834	ball mill ball mill manufacture	do you know ball mill	C) 1
25495	25495	47518	47519	what is the current ongoing research related t	what kind of studies are currently ongoing wit	C) 1
15220	15220	29094	29095	what is it like to switch to a macbook after 	why do some people still use windows laptops w	C) 1
21775	21775	40957	40958	how big can the iss get	how big is the iss	() 1
36935	36935	37176	67284	what is the best perfume under rs 500 for men	what are the best perfumes for men that are av	() 1

7500 rows × 32 columns

```
df_train_afe=df_train_afe.reset_index(drop=True)
df_test_afe=df_test_afe.reset_index(drop=True)

df_train_afe
```

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_
0	6075	11913	11914	what is artificial intelligence	what all does artificial intelligence include	0	1	
1	1205	2402	2403	which processor is faster and better for batte	which one is a better processor 1 8 ghz intel	0	1	
2	16030	30586	25457	what should be the most important thing in you	life advice what are some of the most importa	0	1	
3	37040	67461	67462	what are the largest veins and arteries in the	what are the major arteries of the human body	0	1	
4	44110	79241	79242	how do bladeless fans work	how does bladeless fan works	1	1	
5	29645	39425	54825	what is meant by surgical strike	what is the meaning of surgical strike	1	1	
6	23200	43491	43492	i leveraged 100k to secure a loan for a startu	does amalgam filing dangerous	0	1	
7	6875	13455	13456	does china has prime minister	is there prime minister in china	1	1	
8	3855	7635	7636	what is travis kalanick like on investor confe	what ethnicity is travis kalanick	0	1	
9	45765	49437	1215	is world war 3 coming	is world war 3 more imminent than expected	1	1	
10	39590	46356	19540	how can you cope with loneliness	what are the ways to end loneliness	1	1	
11	17900	33951	33952	why will not richard muller answer my question	how do i get richard muller answer my questions	0	1	
12	47020	84007	84008	what does iq	what does actually iq	1 GVeULWH&printMode=	1	24/3

mean mean

13	17660	33522	33523	are there any substantial way to quit meth	what is the best way to quit meth	1	1
14	23675	44319	44320	what are the future methodology changes in the	what are the examinations i can appear for aft	0	1
15	20610	38870	38871	what kind of jobs are byu computer science bi	is quora a better realization of google own vi	0	1
16	41995	75736	75737	what can we study after pursuing graduation in	what are the fields of study after graduating	1	1
17	32365	59595	59596	why does my wrist hurt when i cry	why do my wrist hurt when squatting	0	1
18	6125	12008	12009	how do i make green tea	what is the right procedure to make green tea	1	1
19	32145	59207	59208	does electricity travel at the speed of light	is the speed of electricity a synonym for the	1	1
20	42100	75910	75911	what is the best strategy to prepare for cat i	how do i prepare for cat in one month	1	1
21	42330	23143	76297	i am financially stuck in a half baked relatio	i am looking for a job change but i am unable	0	2
22	42200	76080	76081	what is the difference between pitch and tar	what are the best react is repositories that f	0	1
23	10805	20905	20906	which is the best institute in mumbai for doin	which is the best institute in mumbai from whe	1	1

who is the

hest what are the

24	28775	53318	53319	keyboardist on bits pilani ca	best pop punk bands	0	1
25	19985	37741	37742	what is the difference between hardware techno	what is the difference between software and ha	0	1
26	15460	29534	29535	which type of css js framework used paytm	what js framework should i use on a site with 	0	1
27	4070	8056	8057	what do you do when you are upset	what you do when you get upset	1	1
28	27515	51113	49664	does house baratheon have any future	is house baratheon extinct	1	1
29	29685	54892	54893	what is the coolest thing or task that you hav	what were the coolest things you have automated	1	1
•••							
7470	37395	68055	68056	what are the most common barriers that affect	what are the most common barriers that affect	0	1
7471	22640	42469	42470	what are the best ways to fake your own death	what are the worst ways to fake one own own de	0	1
7472	37365	67999	68000	what were the books studied by aiims topper 2016	what books should i study for my pg entrance i	0	1
7473	17720	33624	28584	what happen actually after we die where does	what will happen after we die does nothing ha	1	1
7474	39365	71368	71369	how is the march 2 success asvab practice test	my kaplan own practice tests average score is	0	1
7475	8455	16483	16484	how do i wear red lipstick without sending a	how should i convince my son to not wear lipst	0	1

7476	39275	71223	71224	quora_xg wnat advice would you give to	what kind of a person is	() 1
				someone that giv	someone who does not		
7477	7450	14555	14556	what has been the economic impact from brexit	what have been the economic effects of brexit	1	1 1
7478	17380	33031	33032	what are some successful ways to quit smoking	how do you quit smoking	•	1 1
7479	33075	60815	60816	will deafness or blindness be cured	will blindness and deafness be cured		1 1
7480	6000	5534	11770	does masturbation cause infertility	does masturbation in males lead to sexual infe	•	1 1
7481	33035	60746	60747	which is the best and reasonable web hosting s	which is the best web hosting service provider		1 1
7482	9310	18094	18095	who would win in a fight goku or the hulk	who would win in a fight the hulk or the marv	() 1
7483	14590	27929	27930	why do people want to earn more money	why do people want to earn more money	•	1 1
7484	1320	2632	2633	presently 2015 how many articles parts and	how many pages are there in the indian constit	() 1
7485	32720	5297	38545	how do you control your anger	how do i control my anger and have patience		1 2
7486	45970	82285	82286	why do women have so much sex	why do women have sex with men	() 1
7487	43525	78275	78276	how do i find out someone location through mob	is there any mobile app through which i can do	() 1

7488	37330	67946	67947	what is the atomic mass of methane how is it	what is relative atomic mass and how is it det	(0	1
7489	18955	35862	35863	what is the relationship between power and the	what is the relationship between power and time	(0	1
7490	27675	51389	51390	what is the scope for mba operations managemen	how good is the future of operations managemen		1	1
7491	7375	14410	14411	were any major party candidates as problematic	i am now 7 sem be mech can i crack gate exam	(0	1
7492	10705	20715	20716	is deep web really that dangerous	how unsafe the deep web is		1	1
7493	27765	51552	51553	what is best average worst case time complex	what is best algorithm run time complexity	(0	1
7494	38185	69390	69391	can i use html5 video for backgrounds with the	how do i use a child theme in wordpress	(0	1
7495	35485	64833	64834	ball mill ball mill manufacture	do you know ball mill	(0	1
7496	25495	47518	47519	what is the current ongoing research related t	what kind of studies are currently ongoing wit	(0	1
7497	15220	29094	29095	what is it like to switch to a macbook after 	why do some people still use windows laptops w	(0	1
7498	21775	40957	40958	how big can the iss get	how big is the iss	(0	1
7499	36935	37176	67284	what is the best perfume under rs 500 for men	what are the best perfumes for men that are av	(0	1

7500 rows × 32 columns

```
df_train_ave_final=pd.concat([df_train_ave,df_train_ave2],axis=1)
df_test_ave_final=pd.concat([df_test_ave,df_test_ave2],axis=1)
X_train=pd.concat([df_train_afe,df_train_ave_final],axis=1)
X_test=pd.concat([df_test_afe,df_test_ave_final],axis=1)
print(X_train.shape)
print(X_test.shape)
     (7500, 224)
     (2500, 224)
y_train= X_train['is_duplicate']
y_test=X_test['is_duplicate']
X_train.drop([ 'id','qid1','qid2','question1','question2','is_duplicate'], axis=1, inplace
X_test.drop([ 'id', 'qid1', 'qid2', 'question1', 'question2', 'is_duplicate'], axis=1, inplace=
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
    (7500, 218)
     (7500,)
     (2500, 218)
     (2500,)
print(X train.columns)
                             'freq_qid2',
                                                 'q1len',
                                                                'q2len',
              'freq_qid1',
     Index([
             'q1_n_words',
                            'q2_n_words', 'word_Common',
                                                           'word_Total',
                            'freq_q1+q2',
             'word_share',
                       86,
                                       87,
                                                      88,
                                                                     89,
                                      91,
                       90,
                                                      92,
                                                                     93,
                       94,
                                      95],
           dtype='object', length=218)
   X_train.columns =([ 'freq_qid1','freq_qid2','q1len','q2len','q1_n_words','q2_n_words','
'cwc_min','cwc_max','csc_min','csc_max','ctc_min','ctc_max','last_word_eq','first_word_eq'
      'mean_len','token_set_ratio','token_sort_ratio','fuzz_ratio','fuzz_partial_ratio','l
      '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
      '21_x','22_x','23_x','24_x','25_x','26_x','27_x','28_x','29_x','30_x','31_x','32_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',
      '61_x','62_x','63_x','64_x','65_x','66_x','67_x','68_x','69_x','70_x','71_x','72_x',
      '81_x','82_x','83_x','84_x','85_x','86_x','87_x','88_x','89_x','90_x','91_x','92_x',
      '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
      '19_y','20_y','21_y','22_y','23_y','24_y','25_y','26_y','27_y','28_y','29_y','30_y',
```

'37_y','38_y','39_y','40_y','41_y','42_y','43_y','44_y','45_y','46_y','47_y','48_y',

```
'55_y','56_y','57_y','58_y','59_y','60_y','61_y','62_y','63_y','64_y','65_y','66_y',
'73_y','74_y','75_y','76_y','78_y','79_y','80_y','81_y','82_y','83_y','84_y',
'91_y','92_y','93_y','94_y','95_y'])
```

- XGBOOST

```
#https://www.kaggle.com/tilii7/hyperparameter-grid-search-with-xgboost
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
xgb = XGBClassifier(learning_rate=0.02, n_estimators=600, objective='binary:logistic')
params = {
    'min_child_weight': [1, 5, 10],
    'gamma': [0.5, 1, 1.5, 2, 5],
    'subsample': [0.6, 0.8, 1.0],
    'colsample_bytree': [0.6, 0.8, 1.0],
    'max_depth': [3, 4, 5]
}
random_search = RandomizedSearchCV(xgb, param_distributions=params, scoring='roc_auc', n_j
random_search.fit(X_train, y_train)

$\subseteq$
\[
\begin{align*}
\text{Tain}
\text{Train}
\text{Train}
\text{Train}
\text{Train}
\text{Train}
\text{Train}
\end{align*}
\]
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
     [Parallel(n jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
     [Parallel(n jobs=-1)]: Done 28 tasks
                                              elapsed: 20.5min
     [Parallel(n_jobs=-1)]: Done 50 out of 50 | elapsed: 33.3min finished
     RandomizedSearchCV(cv=5, error_score='raise-deprecating',
                       estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                               colsample bylevel=1,
                                               colsample_bynode=1,
                                               colsample_bytree=1, gamma=0,
                                               learning_rate=0.02, max_delta_step=0,
                                               max_depth=3, min_child_weight=1,
                                               missing=None, n_estimators=600,
                                               n jobs=1, nthread=None,
                                               objective='binary:logistic',
                                               random_state=0, reg_alpha=0,
                                               reg_lambda=1, scale_pos_weight=1,
                                               seed=None, silent=None, subsample=1,
                                               verbosity=1),
                       iid='warn', n_iter=10, n_jobs=-1,
                       param_distributions={'colsample_bytree': [0.6, 0.8, 1.0],
                                            gamma': [0.5, 1, 1.5, 2, 5],
                                            'max_depth': [3, 4, 5],
                                            'min_child_weight': [1, 5, 10],
                                            'subsample': [0.6, 0.8, 1.0]},
                       pre_dispatch='2*n_jobs', random_state=1001, refit=True,
                       return_train_score=False, scoring='roc_auc', verbose=3)
print(random_search.best_estimator_)
 colsample_bynode=1, colsample_bytree=0.8, gamma=1,
                  learning_rate=0.02, max_delta_step=0, max_depth=5,
                  min_child_weight=5, missing=None, n_estimators=600, n_jobs=1,
                  nthread=None, objective='binary:logistic', random_state=0,
                  reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                  silent=None, subsample=0.8, verbosity=1)
xgb = XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.8, gamma=1,
             learning rate=0.02, max delta step=0, max depth=5,
             min_child_weight=5, missing=None, n_estimators=600, n_jobs=1,
             nthread=None, objective='binary:logistic', random_state=0,
             reg alpha=0, reg lambda=1, scale pos weight=1, seed=None,
             silent=None, subsample=0.8, verbosity=1)
xgb.fit(X train, y train)
predict_y = xgb.predict(X_test)
predicted y =np.array(predict y>0.5,dtype=int)
print("Total number of data points :", len(predicted y))
plot_confusion_matrix(y_test, predicted_y)
```

Total number of data points : 2500

