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Quora Question Pairs

Business Problem

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.

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.

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.

Machine Learning Probelm

Data

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

Example Data point

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

Mapping the real world problem to an ML problem

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.

Performance Metric

Metrics:

- log-loss
- Binary Confusion Matrix

Train and Test Construction

We build train and test by randomly splitting in the ratio of 80:20.

Data Acquisition

In [51]:
```
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
import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
from fuzzywuzzy import fuzz
from sklearn.manifold import TSNE
from wordcloud import WordCloud, STOPWORDS
from os import path
from PIL import Image
from sklearn.linear_model import LogisticRegression
import pickle as pk
from datetime import datetime
from sklearn.metrics import log_loss
from sklearn.metrics import roc_curve
from prettytable import PrettyTable
from sklearn.metrics import confusion_matrix
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
from sklearn.feature_extraction import text
```

In [2]:
```
if os.path.isfile('train-2.csv'):
    train = pd.read_csv('train-2.csv')
    print(train.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404290 entries, 0 to 404289
Data columns (total 6 columns):
id              404290 non-null int64
qid1            404290 non-null int64
qid2            404290 non-null int64
question1       404289 non-null object
question2       404288 non-null object
is_duplicate    404290 non-null int64
dtypes: int64(4), object(2)
memory usage: 18.5+ MB
None
```

In [11]:
```
train.head()
```

Out[11]:

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

Data Analysis & Data Cleaning

checking duplicates

In [15]:
```
no_duplicated_data = train.drop_duplicates(subset=['question1','question2'], keep='first', inplace=False)
print("Number of similiar data points : ",train.shape[0]-no_duplicated_data.shape[0])
```

```
Number of similiar data points :  0
```

checking if any data point has same question1 and question2

In [17]:
```
count =0
for i in range(0,train.shape[0]):
    if train['question1'].iloc[i] == train['question2'].iloc[i]:
        count = count +1
print(" Number of data points with the same 'question1' and 'question2' :", count)
```

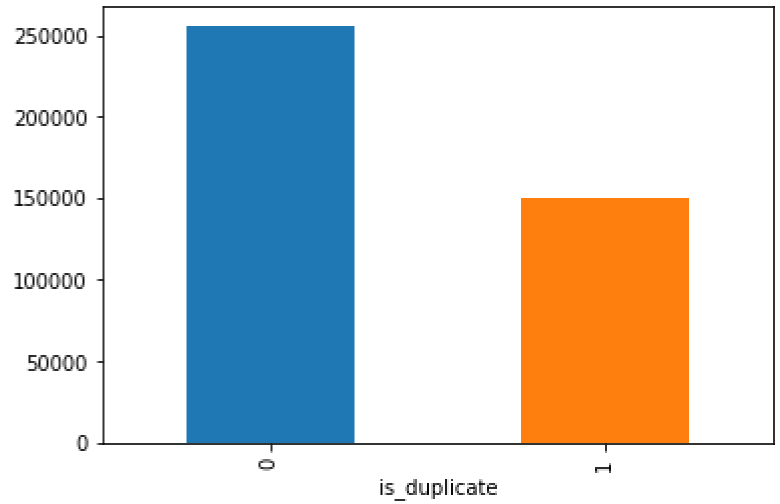
```
 Number of data points with the same 'question1' and 'question2' : 0
```

Distribution of data points among output classes

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

In [27]:
```
train.groupby("is_duplicate")['id'].count().plot.bar()
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x10607ba90>



observation:

```
* it's a slightly imbalanced data.
```

In [30]:
```
print('~> Total number of question pairs for training:  {}'.format(len(train)))
print('\n~> Question pairs are not Similar (is_duplicate = 0): {}%'.format(100 - round(train['is_duplicate'].mean()*100, 2)))
print('\n~> Question pairs are Similar (is_duplicate = 1):  {}%'.format(round(train['is_duplicate'].mean()*100, 2)))
```

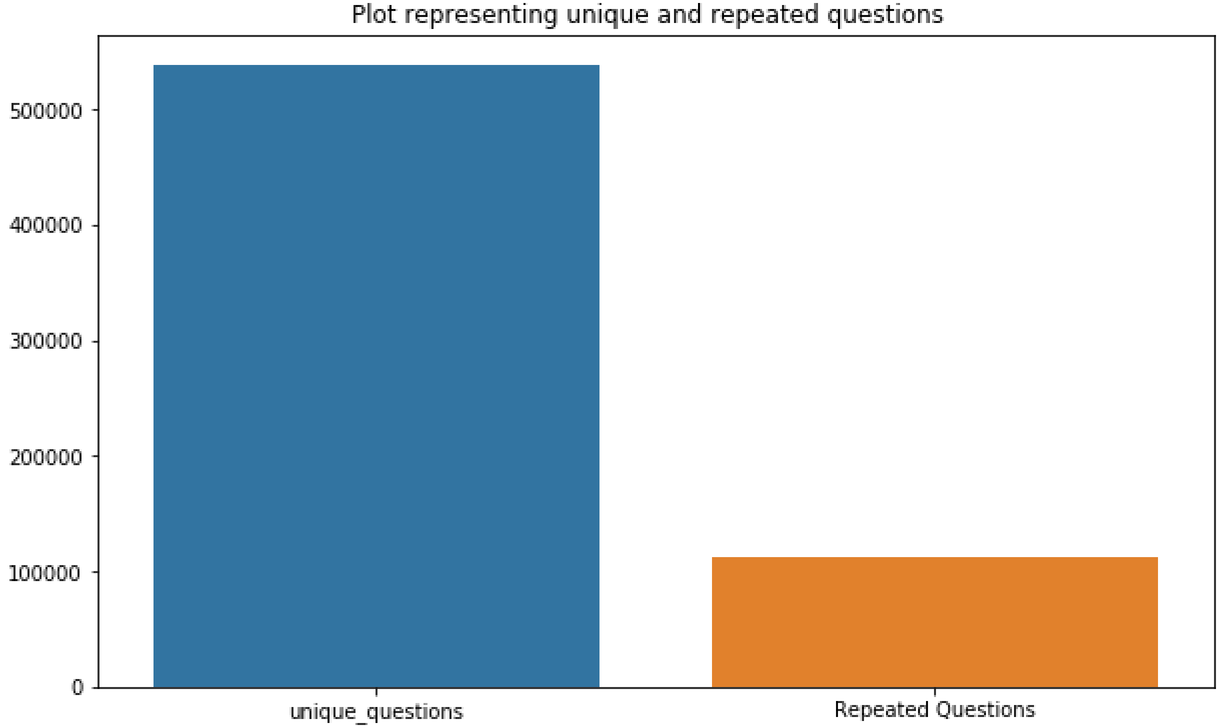
```
~> Total number of question pairs for training:  404290

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

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

Number of unique questions

In [31]:
```
qids = pd.Series(train['qid1'].tolist() + train['qid2'].tolist())
unique_qs = len(np.unique(qids))
qs_morethan_onetime = np.sum(qids.value_counts() > 1)
print ('Total number of  Unique Questions are: {}\n'.format(unique_qs))
#print len(np.unique(qids))

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

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

q_vals=qids.value_counts()

q_vals=q_vals.values
```

```
Total number of  Unique Questions are: 537933

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

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

In [32]:
```
x = ["unique_questions" , "Repeated Questions"]
y =  [unique_qs , qs_morethan_onetime]

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



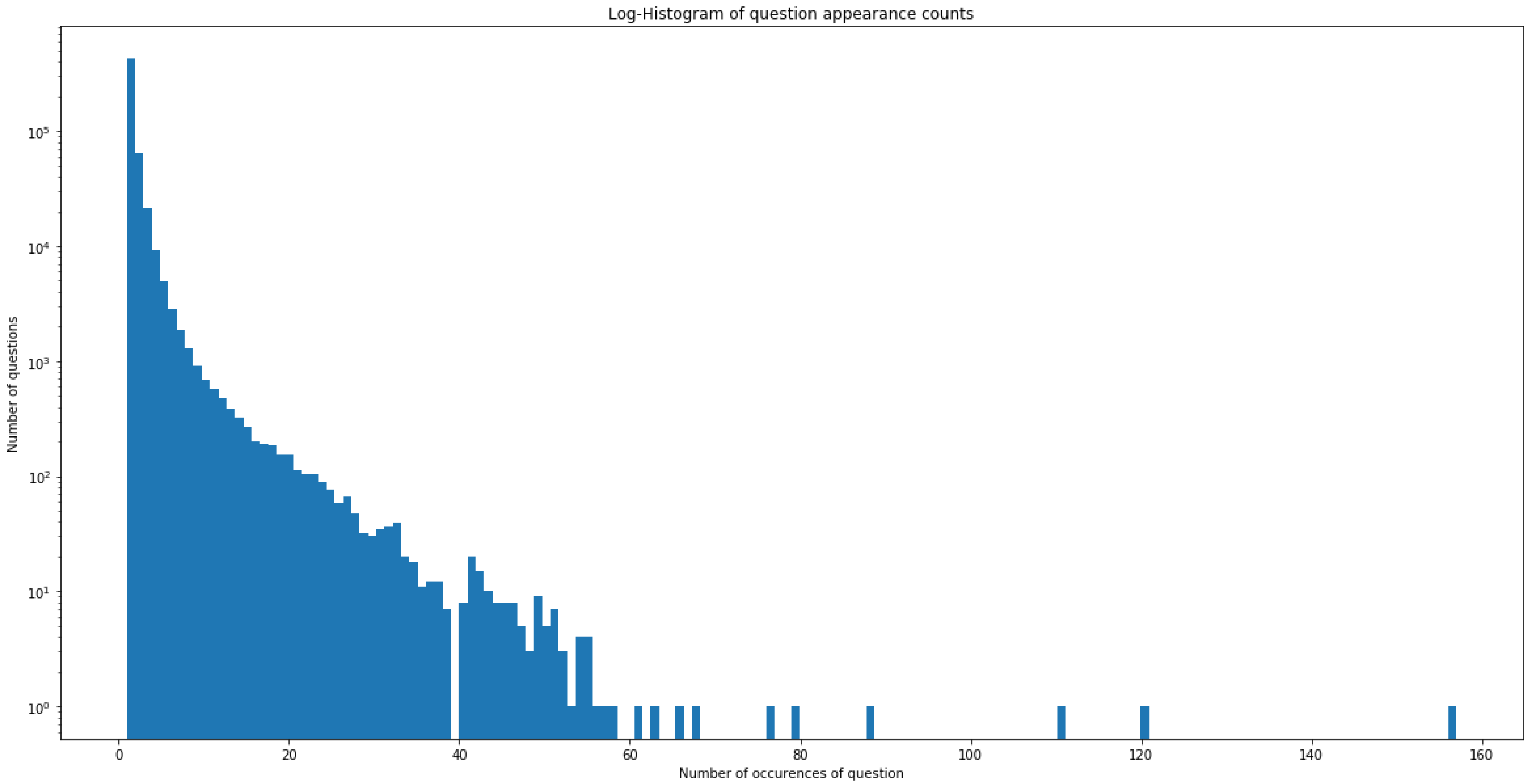
observation:

```
* most of the questions are unique.
```

Number of occurrences of each question

In [33]:
```
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
```



Checking for NULL values

In [37]:
```
#Checking whether there are any rows with null values
nan_rows = train[train.isnull().any(1)]
nan_rows
```

Out[37]:

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

In [39]:
```
train = train.fillna('')
```

Extracting basic features

In [3]:
```
if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    train = pd.read_csv("df_fe_without_preprocessing_train.csv",encoding='latin-1')
else:
    train['freq_qid1'] = train.groupby('qid1')['qid1'].transform('count')
    train['freq_qid2'] = train.groupby('qid2')['qid2'].transform('count')
    train['q1len'] = train['question1'].str.len()
    train['q2len'] = train['question2'].str.len()
    train['q1_n_words'] = train['question1'].apply(lambda row: len(row.split(" ")))
    train['q2_n_words'] = train['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)
    train['word_Common'] = train.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))
    train['word_Total'] = train.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))
    train['word_share'] = train.apply(normalized_word_share, axis=1)

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

    train.to_csv("df_fe_without_preprocessing_train.csv", index=False)
train.head(1)
```

Out[3]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common	worc
0	0	1	2	What is the step by step guide to invest in sh...	What is the step by step guide to invest in sh...	0	1	1	66	57	14	12	10.0	23.0

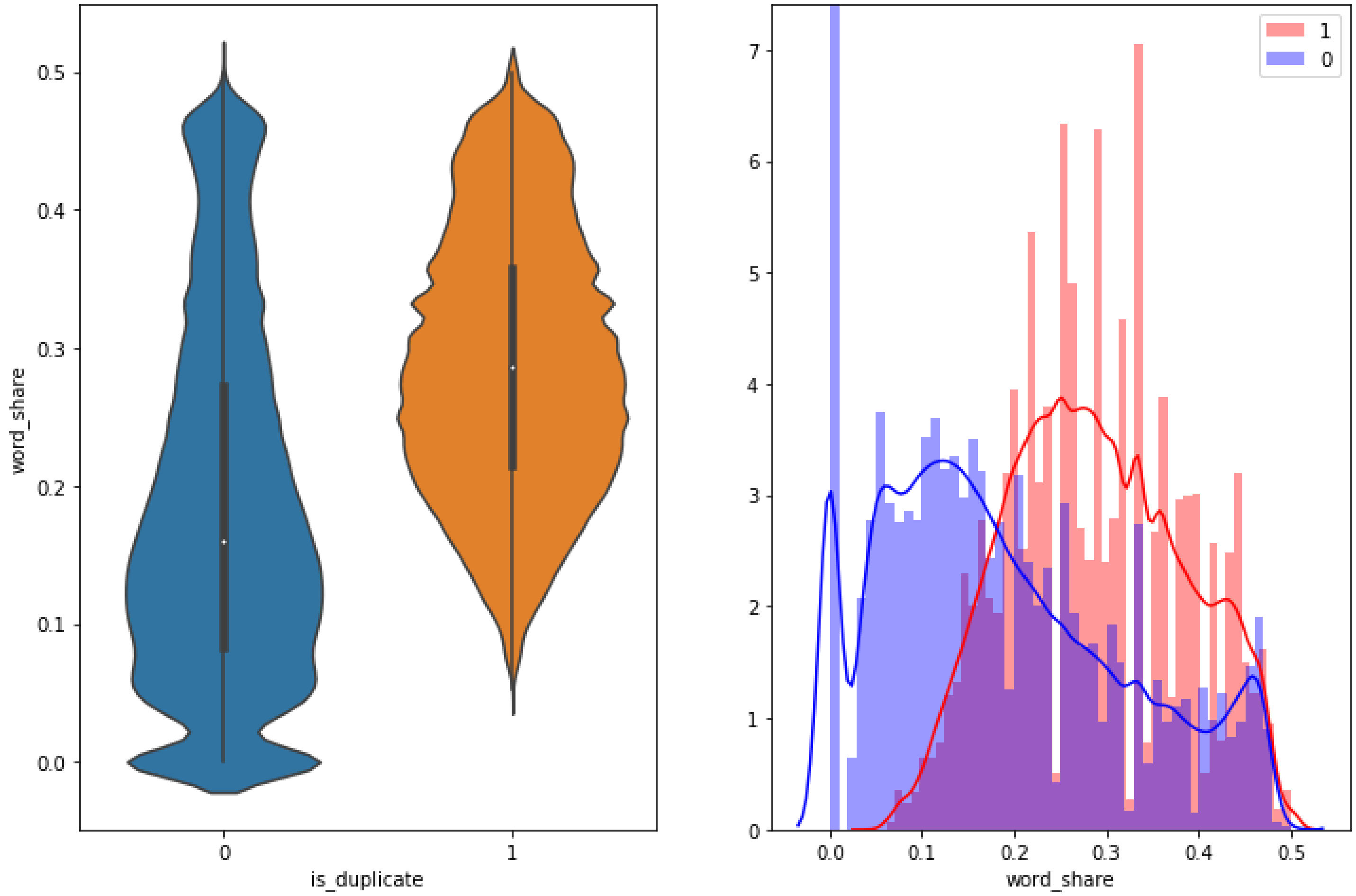
Analysis of the extracted features

In [43]:
```
print ("Minimum length of the questions in question1 : " , min(train['q1_n_words']))

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

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

Feature: word_share

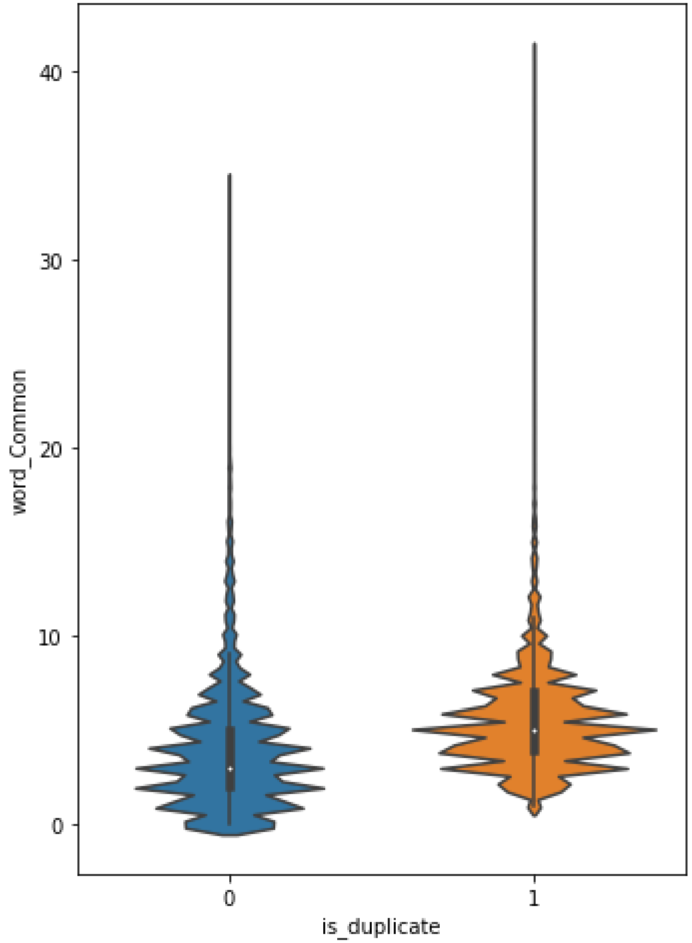
In [44]:
```
plt.figure(figsize=(12, 8))

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

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

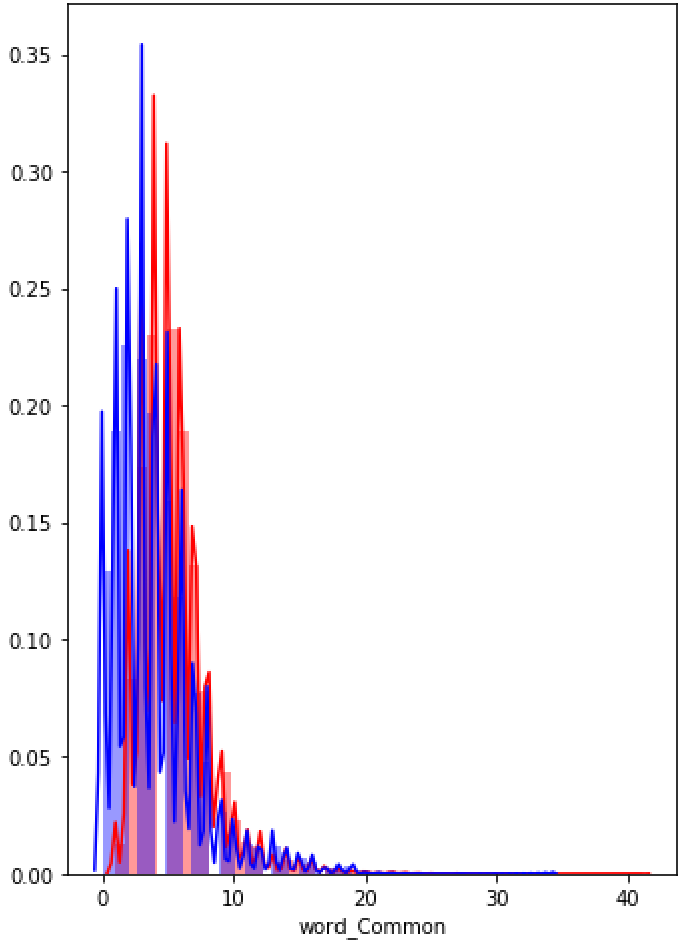


- The distributions for normalized word_share have some overlap on the far right-hand side, i.e., there are quite a lot of questions with high word similarity
- The average word share and Common no. of words of qid1 and qid2 is more when they are duplicate(Similar)

Feature: word_Common

In [46]:
```
plt.figure(figsize=(12, 8))

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

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





obsevation:

```
* word_share is comparatively important feature than word_feature
```

Analysing the duplicate question's text

In [4]:
```
train_duplicates = train[train['is_duplicate']==1]
train_not_duplicates = train[train['is_duplicate']==0]
```

In [5]:
```
index =[]
for row in range(0,train_duplicates.shape[0]):
    common = train_duplicates['word_Common'].iloc[row]
    q1= train_duplicates['q1_n_words'].iloc[row]
    q2= train_duplicates['q2_n_words'].iloc[row]
    if q1 - common < 2 or q2 - common < 2:
        if q1 - common != 0 or q2 - common != 0 :
            if (len(index) < 5):
                index.append(row)
            else:
                break
```

In [16]:
```
x = PrettyTable()
x.title = 'Duplicate questions with more number of common words'
x.field_names =['question1','question2']


for row in index:
    x.add_row([train_duplicates['question1'].iloc[row],train_duplicates['question2'].iloc[row]])
print(x)
```

```
+-------------------------------------------------------------------------------------------+
|                          Duplicate questions with more number of common words                          |
+---------------------------------------------+---------------------------------------------+
|                  question1                  |                  question2                  |
+---------------------------------------------+---------------------------------------------+
|      What can make Physics easy to learn?     |  How can you make physics easy to learn?    |
| What was your first sexual experience like?  |   What was your first sexual experience?    |
|        What does manipulation mean?          |       What does manipulation means?         |
| What is a narcissistic personality disorder? | What is narcissistic personality disorder? |
|      How I can speak English fluently?       | How can I learn to speak English fluently? |
+---------------------------------------------+---------------------------------------------+
```

observation:

```
* most of the uncommon words are stop words
```

Analysing the non-duplicate question's text

In [19]:
```
index =[]
for row in range(0,train_not_duplicates.shape[0]):
    common = train_not_duplicates['word_Common'].iloc[row]
    q1= train_not_duplicates['q1_n_words'].iloc[row]
    q2= train_not_duplicates['q2_n_words'].iloc[row]
    if q1 - common < 2 or q2 - common < 2:
        if q1 - common != 0 or q2 - common != 0 :
            if (len(index) < 5):
                index.append(row)
            else:
                break
x = PrettyTable()
x.title = 'Non-Duplicate questions with more number of common words'
x.field_names =['question1','question2']


for row in index[1:-1]:
    x.add_row([train_not_duplicates['question1'].iloc[row],train_not_duplicates['question2'].iloc[row]])
print(x)
```

```
+-------------------------------------------------------------------------------------------+
|                 Non-Duplicate questions with more number of common words                  |
+--------------------------------------------+----------------------------------------------+
|                 question1                  |                  question2                   |
+--------------------------------------------+----------------------------------------------+
|          What is web application?          |   What is the web application framework?     |
|   What is best way to make money online?   | What is best way to ask for money online?    |
| What is the best travel website in spain?  |      What is the best travel website?        |
+--------------------------------------------+----------------------------------------------+
```

observation:

```
* most of the uncommon words are nouns, proper adjectives
```

Removing symbols in the data

In [6]:
```
# To get the results in 4 decemal points
SAFE_DIV = 0.0001

STOP_WORDS = stopwords.words("english")


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



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

In [7]:
```
question1 = list(train['question1'])
question2 = list(train['question2'])
```

In [8]:
```
from tqdm import tqdm
question1_without_symbols =[]
for q in tqdm(question1):
    h = remove_symbols(q)
    question1_without_symbols.append(h)

question2_without_symbols =[]

for q in tqdm(question2):
    h = remove_symbols(q)
    question2_without_symbols.append(h)
```

```
100%|██████████| 404290/404290 [06:05<00:00, 1107.24it/s]
100%|██████████| 404290/404290 [05:32<00:00, 1217.35it/s]
```

In [9]:
```
def get_token_features(q1, q2):
    token_features = [0.0]*10

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

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

    #Get the stopwords in Questions
    q1_stops = set([word for word in q1_tokens if word in STOP_WORDS])
    q2_stops = set([word for word in q2_tokens if word in STOP_WORDS])

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

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

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


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

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

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

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

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

# get the Longest Common sub string

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

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

    print("token features...")

    # Merging Features with dataset

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

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

    #Computing Fuzzy Features and Merging with Dataset

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

```
    df["token_set_ratio"]       = df.apply(lambda x: fuzz.token_set_ratio(x["question1"], x["question2"]), ax
is=1)
    # The token sort approach involves tokenizing the string in question, sorting the tokens alphabetically,
 and
    # then joining them back into a string We then compare the transformed strings with a simple ratio().
    df["token_sort_ratio"]      = df.apply(lambda x: fuzz.token_sort_ratio(x["question1"], x["question2"]), a
xis=1)
    df["fuzz_ratio"]            = df.apply(lambda x: fuzz.QRatio(x["question1"], x["question2"]), axis=1)
    df["fuzz_partial_ratio"]    = df.apply(lambda x: fuzz.partial_ratio(x["question1"], x["question2"]), axis
=1)
    df["longest_substr_ratio"]  = df.apply(lambda x: get_longest_substr_ratio(x["question1"], x["question2"
]), axis=1)
    return df
```

In [52]:

```
if os.path.isfile('nlp_features_train.csv'):
    df = pd.read_csv("nlp_features_train.csv",encoding='latin-1')
    df.fillna('')
else:
    print("Extracting features for train:")
    df = pd.read_csv("train.csv")
    df = extract_features(df)
    df.to_csv("nlp_features_train.csv", index=False)
df.head(1)
```

Out[52]:

	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	csc_max	...	ctc_max	last_word_eq	first_word_eq
0	0	1	2	what is the step by step guide to invest in sh...	what is the step by step guide to invest in sh...	0	0.99998	0.833319	0.999983	0.999983	...	0.785709	0.0	1.0

1 rows × 21 columns

Analysis of extracted features

Plotting Word clouds

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

In [13]:
```
df_duplicate = df[df['is_duplicate'] == 1]
dfp_nonduplicate = df[df['is_duplicate'] == 0]

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

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

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

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

Word Clouds generated from duplicate pair question's text

In [27]:
```
duplicated_qns = train[train['is_duplicate']==1]
non_duplicated_qns = train[train['is_duplicate']==0]
```

In [11]:
```
stopwords = set(STOPWORDS)
stopwords.add("said")
stopwords.add("br")
stopwords.add(" ")
stopwords.remove("not")
stopwords.remove("no")
stopwords.remove("like")
```

In [38]:
```
all_duplicated_qns = np.dstack([duplicated_qns['question1'],duplicated_qns['question2']]).flatten()
```

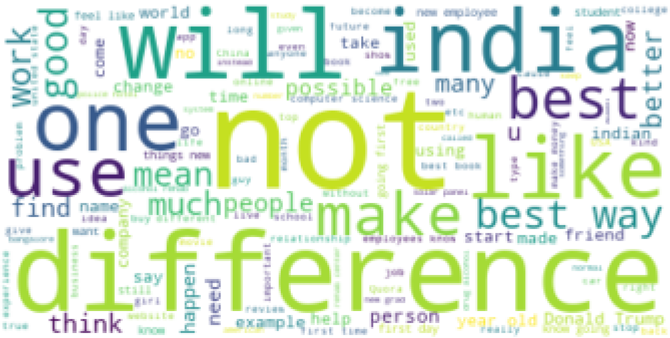
In [55]:
```
from wordcloud import WordCloud

wc = WordCloud(background_color="white",max_words=len(all_duplicated_qns) ,stopwords=stopwords,relative_scali
ng =1)
wc.generate(str(list(all_duplicated_qns)))
print ("Word Cloud for Duplicate Question pairs")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

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

In [45]:
```
all_non_duplicated_qns = np.dstack([non_duplicated_qns['question1'],non_duplicated_qns['question2']]).flatten
()
```

In [56]:
```
from wordcloud import WordCloud

wc = WordCloud(background_color="white", stopwords=stopwords,relative_scaling =1)
wc.generate(str(list(all_non_duplicated_qns)))
print ("Word Cloud for Non Duplicate Question pairs")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

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

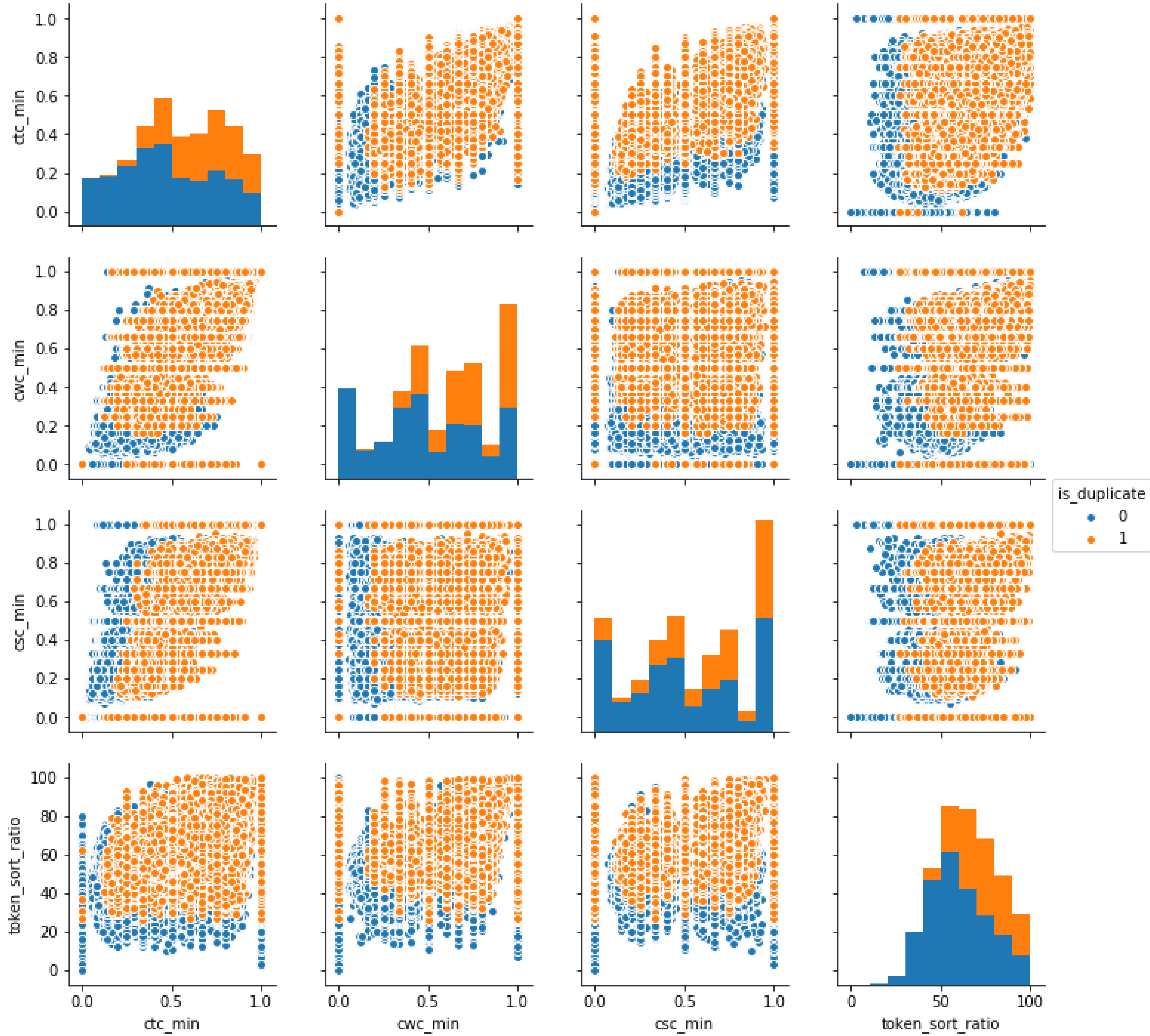


observation:

```
* few words occur frequently
```

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

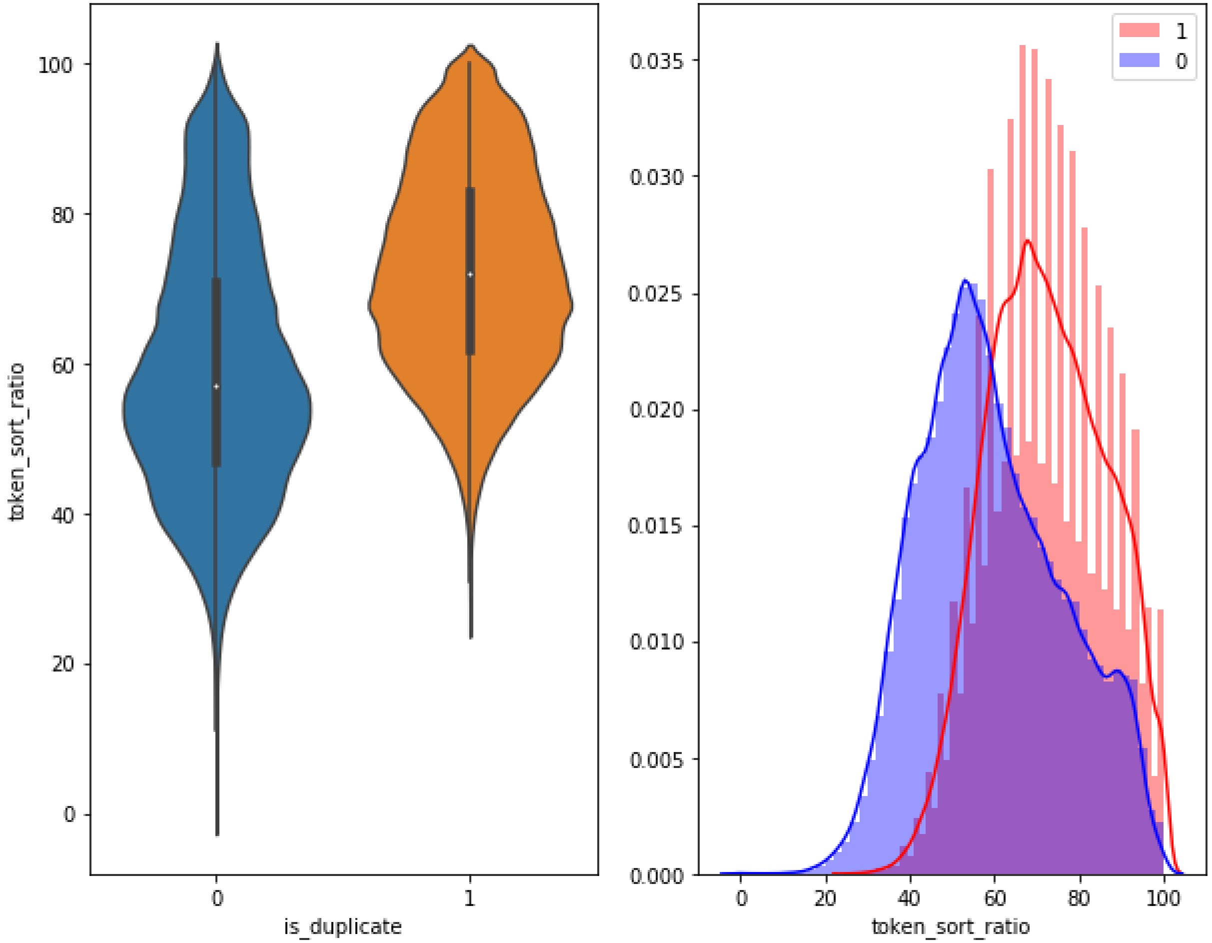
In [57]:
```
n = df.shape[0]
sns.pairplot(df[['ctc_min', 'cwc_min', 'csc_min', 'token_sort_ratio', 'is_duplicate']][0:n], hue='is_duplicat
e', vars=['ctc_min', 'cwc_min', 'csc_min', 'token_sort_ratio'])
plt.show()
```


ctc_min
cwc_min
csc_min
token_sort_ratio
is_duplicate
0
1
0.0
0.5
1.0
0
50
100

observation:

```
* all the feature seems useful as the data is partialy seperable in almost all paitplots
```

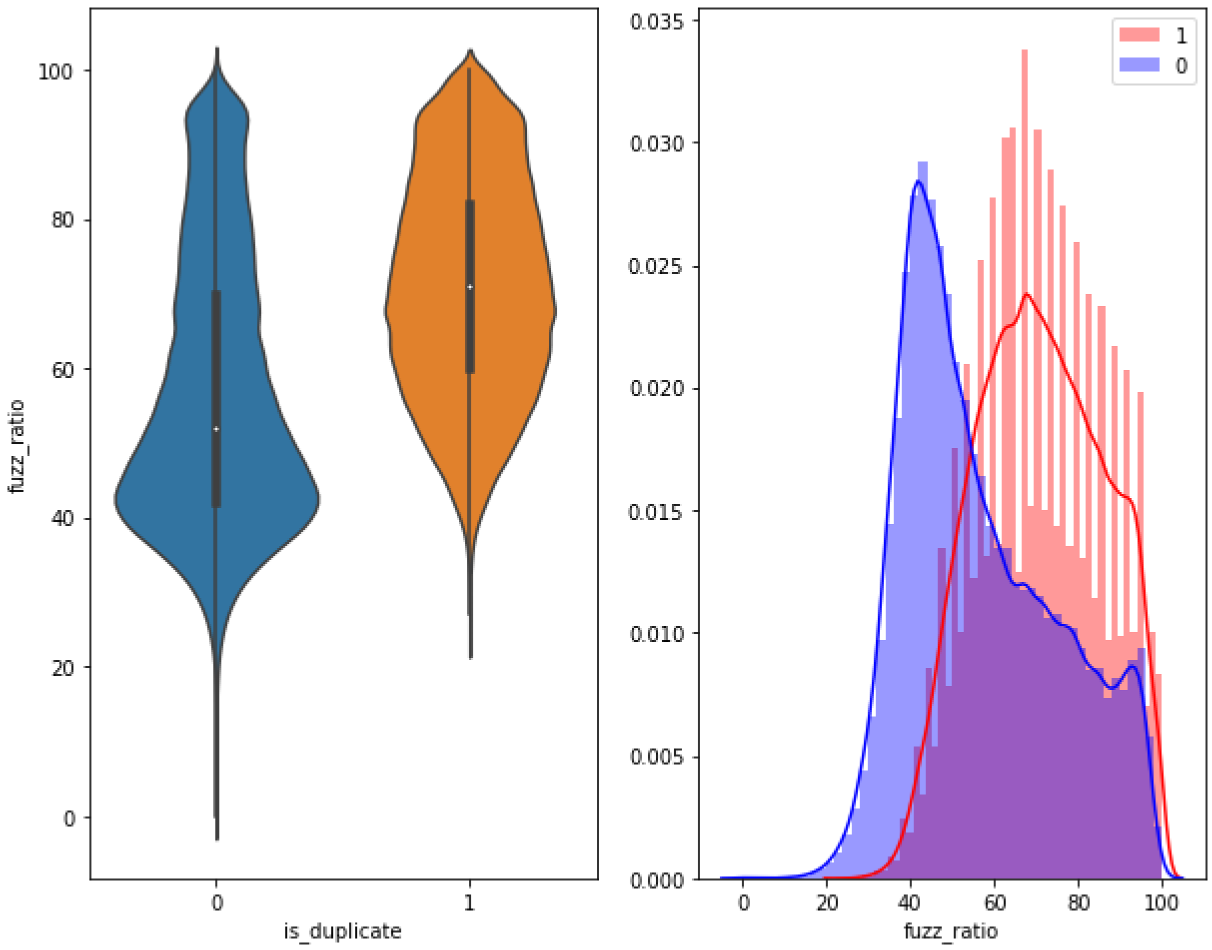
In [60]:
```
# Distribution of the token_sort_ratio
plt.figure(figsize=(10, 8))

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

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



observation:

```
* duplicate questions tend to have lesser token sort ratio.
* non-duplicate questions tend to have larger token sort ratio.
```

In [61]:
```
plt.figure(figsize=(10, 8))

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

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



observation:

```
* duplicate questions tend to have lesser fuzz ratio.
* non-duplicate questions tend to have larger fuzz ratio.
```

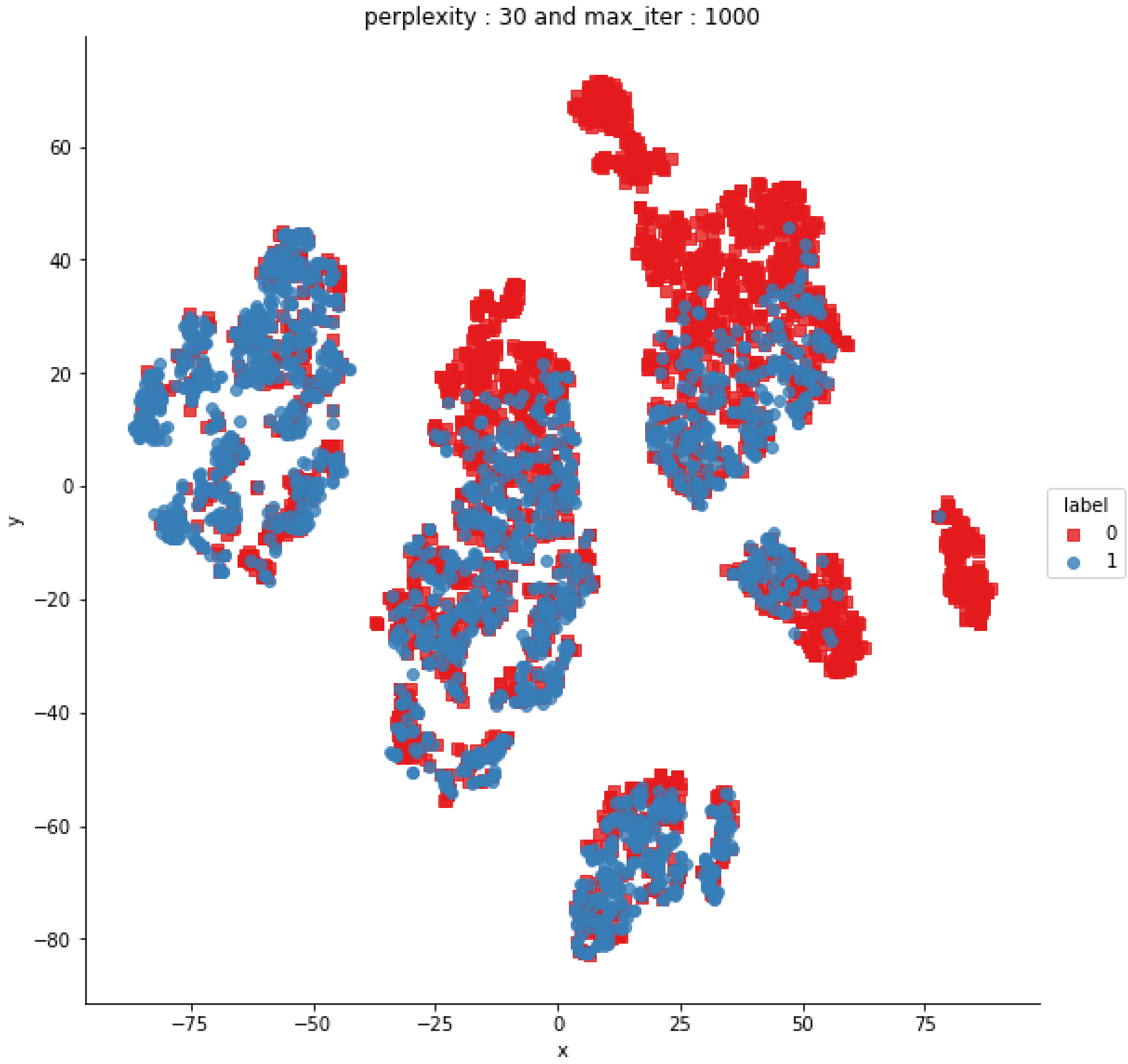
Data visualization

In [53]:
```
from sklearn.preprocessing import MinMaxScaler

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

In [72]:
```
tsne2d = TSNE(
    n_components=2,
    init='random', # pca
    random_state=101,
    method='barnes_hut',
    n_iter=1000,
    verbose=2,
    angle=0.5
).fit_transform(X)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.013s...
[t-SNE] Computed neighbors for 5000 samples in 0.443s...
[t-SNE] Computed conditional probabilities for sample 1000 / 5000
[t-SNE] Computed conditional probabilities for sample 2000 / 5000
[t-SNE] Computed conditional probabilities for sample 3000 / 5000
[t-SNE] Computed conditional probabilities for sample 4000 / 5000
[t-SNE] Computed conditional probabilities for sample 5000 / 5000
[t-SNE] Mean sigma: 0.116557
[t-SNE] Computed conditional probabilities in 0.235s
[t-SNE] Iteration 50: error = 80.8968964, gradient norm = 0.0430571 (50 iterations in 8.832s)
[t-SNE] Iteration 100: error = 70.3833160, gradient norm = 0.0099593 (50 iterations in 7.692s)
[t-SNE] Iteration 150: error = 68.6159134, gradient norm = 0.0056708 (50 iterations in 7.577s)
[t-SNE] Iteration 200: error = 67.7694321, gradient norm = 0.0040581 (50 iterations in 7.548s)
[t-SNE] Iteration 250: error = 67.2746048, gradient norm = 0.0033067 (50 iterations in 7.040s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.274605
[t-SNE] Iteration 300: error = 1.7729300, gradient norm = 0.0011900 (50 iterations in 8.123s)
[t-SNE] Iteration 350: error = 1.3714967, gradient norm = 0.0004818 (50 iterations in 7.946s)
[t-SNE] Iteration 400: error = 1.2036748, gradient norm = 0.0002779 (50 iterations in 8.154s)
[t-SNE] Iteration 450: error = 1.1132656, gradient norm = 0.0001889 (50 iterations in 8.600s)
[t-SNE] Iteration 500: error = 1.0582460, gradient norm = 0.0001434 (50 iterations in 7.657s)
[t-SNE] Iteration 550: error = 1.0222589, gradient norm = 0.0001180 (50 iterations in 8.077s)
[t-SNE] Iteration 600: error = 0.9984865, gradient norm = 0.0001015 (50 iterations in 8.070s)
[t-SNE] Iteration 650: error = 0.9830498, gradient norm = 0.0000958 (50 iterations in 7.557s)
[t-SNE] Iteration 700: error = 0.9726909, gradient norm = 0.0000877 (50 iterations in 8.105s)
[t-SNE] Iteration 750: error = 0.9647216, gradient norm = 0.0000823 (50 iterations in 7.726s)
[t-SNE] Iteration 800: error = 0.9582971, gradient norm = 0.0000755 (50 iterations in 8.045s)
[t-SNE] Iteration 850: error = 0.9531373, gradient norm = 0.0000697 (50 iterations in 8.427s)
[t-SNE] Iteration 900: error = 0.9484153, gradient norm = 0.0000696 (50 iterations in 7.202s)
[t-SNE] Iteration 950: error = 0.9445393, gradient norm = 0.0000659 (50 iterations in 7.228s)
[t-SNE] Iteration 1000: error = 0.9412127, gradient norm = 0.0000674 (50 iterations in 7.248s)
[t-SNE] Error after 1000 iterations: 0.941213
```

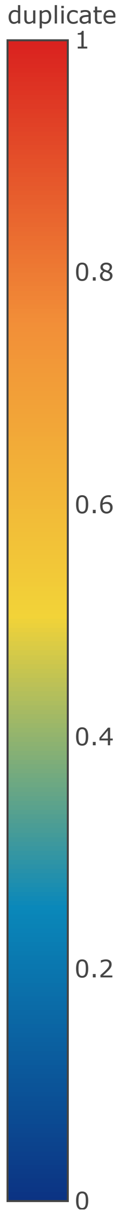
In [73]:
```
df = pd.DataFrame({'x':tsne2d[:,0], 'y':tsne2d[:,1] ,'label':y})

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



In [54]:
```
from sklearn.manifold import TSNE

tsne3d = TSNE(
    n_components=3,
    init='random', # pca
    random_state=101,
    method='barnes_hut',
    n_iter=1000,
    verbose=2,
    angle=0.5
).fit_transform(X)

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 embedding with engineered features')
fig=dict(data=data, layout=layout)
py.iplot(fig, filename='3DBubble')
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.017s...
[t-SNE] Computed neighbors for 5000 samples in 0.466s...
[t-SNE] Computed conditional probabilities for sample 1000 / 5000
[t-SNE] Computed conditional probabilities for sample 2000 / 5000
[t-SNE] Computed conditional probabilities for sample 3000 / 5000
[t-SNE] Computed conditional probabilities for sample 4000 / 5000
[t-SNE] Computed conditional probabilities for sample 5000 / 5000
[t-SNE] Mean sigma: 0.116557
[t-SNE] Computed conditional probabilities in 0.240s
[t-SNE] Iteration 50: error = 80.3592682, gradient norm = 0.0335202 (50 iterations in 15.736s)
[t-SNE] Iteration 100: error = 69.1112671, gradient norm = 0.0036575 (50 iterations in 8.584s)
[t-SNE] Iteration 150: error = 67.6171112, gradient norm = 0.0017708 (50 iterations in 8.323s)
[t-SNE] Iteration 200: error = 67.0565109, gradient norm = 0.0011567 (50 iterations in 8.767s)
[t-SNE] Iteration 250: error = 66.7296524, gradient norm = 0.0009161 (50 iterations in 8.040s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 66.729652
[t-SNE] Iteration 300: error = 1.4983541, gradient norm = 0.0006807 (50 iterations in 10.632s)
[t-SNE] Iteration 350: error = 1.1549147, gradient norm = 0.0001922 (50 iterations in 11.581s)
[t-SNE] Iteration 400: error = 1.0101781, gradient norm = 0.0000912 (50 iterations in 11.593s)
[t-SNE] Iteration 450: error = 0.9388669, gradient norm = 0.0000628 (50 iterations in 11.210s)
[t-SNE] Iteration 500: error = 0.9029322, gradient norm = 0.0000524 (50 iterations in 11.260s)
[t-SNE] Iteration 550: error = 0.8841860, gradient norm = 0.0000482 (50 iterations in 11.183s)
[t-SNE] Iteration 600: error = 0.8722453, gradient norm = 0.0000365 (50 iterations in 11.273s)
[t-SNE] Iteration 650: error = 0.8627461, gradient norm = 0.0000347 (50 iterations in 10.933s)
[t-SNE] Iteration 700: error = 0.8549610, gradient norm = 0.0000312 (50 iterations in 10.844s)
[t-SNE] Iteration 750: error = 0.8487639, gradient norm = 0.0000311 (50 iterations in 11.031s)
[t-SNE] Iteration 800: error = 0.8440317, gradient norm = 0.0000281 (50 iterations in 11.046s)
[t-SNE] Iteration 850: error = 0.8396705, gradient norm = 0.0000250 (50 iterations in 11.107s)
[t-SNE] Iteration 900: error = 0.8354425, gradient norm = 0.0000242 (50 iterations in 10.827s)
[t-SNE] Iteration 950: error = 0.8317489, gradient norm = 0.0000233 (50 iterations in 10.913s)
[t-SNE] Iteration 1000: error = 0.8288577, gradient norm = 0.0000257 (50 iterations in 10.514s)
[t-SNE] Error after 1000 iterations: 0.828858
```

3d embedding with engineered features



Export to plot.ly »

observation:

```
* we can observe few datapoints of same class being clustered together. Hence these fuzzywuzzy features plays an
 important role in classifying the datapoints.
```

Data Preprocessing

In [12]:
```
from tqdm import tqdm
stop = stopwords
sno = PorterStemmer()

def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special characters
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned

i=0
str1=' '
cleaned_question1_again=[]
s=''
for sent in tqdm(question1_without_symbols):
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)

                else:
                    continue
            else:
                continue
    str1 = b" ".join(filtered_sentence)
    cleaned_question1_again.append(str1)
    i+=1

i=0
str1=' '
cleaned_question2_again=[]
s=''
for sent in tqdm(question2_without_symbols):
    filtered_sentence=[]
```

```
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                else:
                    continue
            else:
                continue
    str1 = b" ".join(filtered_sentence)
    cleaned_question2_again.append(str1)
    i+=1
```

```
100%|██████████| 404290/404290 [01:25<00:00, 4727.96it/s]
100%|██████████| 404290/404290 [01:28<00:00, 4575.56it/s]
```

In [13]:
```
cleaned_question1_again_df = pd.DataFrame(cleaned_question1_again,columns=['CleanedText_q1'],index=train.inde
x)
```

In [14]:
```
cleaned_question2_again_df = pd.DataFrame(cleaned_question2_again,columns=['CleanedText_q2'],index=train.inde
x)
```

In [15]:
```
features = pd.concat([df,train,cleaned_question1_again_df,cleaned_question2_again_df],axis = 1)
```

In [16]:
```
#https://stackoverflow.com/questions/14984119/python-pandas-remove-duplicate-columns
features = features.loc[:,~features.columns.duplicated()]
```

In [17]:
```
features = features.fillna('')
```

In [80]:
```
from tqdm import tqdm

dissimilar_words_for_question =[]
for row in tqdm(range(0,features.shape[0])):
    q1 = features['question1'][row].split()
    q2 = features['question2'][row].split()
    dissimilar_words_1 = [x for x in q1 if x not in q2]
    dissimilar_words_2 = [x for x in q2 if x not in q1]
    if(len(dissimilar_words_1)==0):
        dissimilar_words =" ".join(dissimilar_words_2)
    if(len(dissimilar_words_2)==0):
        dissimilar_words =" ".join(dissimilar_words_1)
    if (len(dissimilar_words_1)!=0 and len(dissimilar_words_2)!=0):
        dissimilar_words = dissimilar_words_1 + dissimilar_words_2
        dissimilar_words = set(dissimilar_words)
        dissimilar_words =" ".join(dissimilar_words)
    dissimilar_words_for_question.append(dissimilar_words)
```

```
100%|██████████| 404290/404290 [00:18<00:00, 21461.37it/s]
```

In [82]:
```
dissimilar_words_for_cleaned_question =[]
for row in tqdm(range(0,features.shape[0])):
    q1 = features['CleanedText_q1'][row].split()
    q2 = features['CleanedText_q2'][row].split()
    dissimilar_words_1 = [x for x in q1 if x not in q2]
    dissimilar_words_2 = [x for x in q2 if x not in q1]
    if(len(dissimilar_words_1)==0):
        dissimilar_words =b" ".join(dissimilar_words_2)
    if(len(dissimilar_words_2)==0):
        dissimilar_words =b" ".join(dissimilar_words_1)
    if (len(dissimilar_words_1)!=0 and len(dissimilar_words_2)!=0):
        dissimilar_words = dissimilar_words_1 + dissimilar_words_2
        dissimilar_words = set(dissimilar_words)
        dissimilar_words =b" ".join(dissimilar_words)
    dissimilar_words_for_cleaned_question.append(dissimilar_words)
```

```
100%|██████████| 404290/404290 [00:16<00:00, 24645.60it/s]
```

In [83]:
```
features_final = pd.concat([features,pd.DataFrame(dissimilar_words_for_question,columns=["dissimilar_words_fo
r_question"]) \
                            , pd.DataFrame(dissimilar_words_for_cleaned_question,columns=["dissimilar_words_f
or_cleaned_question"])],axis=1)
```

In [84]:
```
features_final.to_csv("features_final.csv")
```

Featurization

In [20]:
```
features_final = pd.read_csv("features_final.csv")
```

In [21]:
```
features_final.head(1)
```

Out[21]:

	Unnamed: 0	id	qid1	qid2	question1	question2	is_duplicate	cwc_min	cwc_max	csc_min	...	q2_n_words	word_Common	word_T
0	0	0	1	2	what is the step by step guide to invest in sh...	what is the step by step guide to invest in sh...	0	0.99998	0.833319	0.999983	...	12	10.0	23.0

1 rows × 37 columns

In [4]:
```
tfidf_glove_instance = text.TfidfVectorizer(lowercase=False,)
tfidf_glove_instance.fit_transform(features_final['dissimilar_words_for_cleaned_question'])

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

In [5]:
```
#https://github.com/explosion/spaCy/issues/1721
import spacy
nlp = spacy.load('en')
```

In [6]:
```
vecs1 = []
for qu1 in tqdm(list(features_final['dissimilar_words_for_cleaned_question'])):
    qu1 = qu1[2:-1]
    doc1 = nlp(qu1)
    # 384 is the number of dimensions of vectors
    mean_vec1 = np.zeros([len(doc1), 384])
    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)
```

```
100%|██████████| 404290/404290 [1:21:40<00:00, 82.97it/s]
```

In [7]:
```
features_final['glove_feat'] = list(vecs1)
```

In [22]:
```
from sklearn.model_selection import train_test_split

train_features,test_features = train_test_split(features_final,train_size=0.8,test_size=0.2)
```

In [23]:
```
train_score = train_features['is_duplicate']
test_score = test_features['is_duplicate']
```

In [24]:
```
train_features = train_features.drop(["is_duplicate"],axis =1)
test_features = test_features.drop(["is_duplicate"],axis =1)
```

In [11]:
```
train_features.head(1)
```

Out[11]:

	Unnamed: 0	id	qid1	qid2	question1	question2	cwc_min	cwc_max	csc_min	csc_max	...	word_Common	word_Tota
381910	381910	381910	13650	23718	is time travel possible in next 5 years	will time travel be possible in the next 10 ye...	0.833319	0.833319	0.499975	0.249994	...	6.0	18.0

1 rows × 37 columns

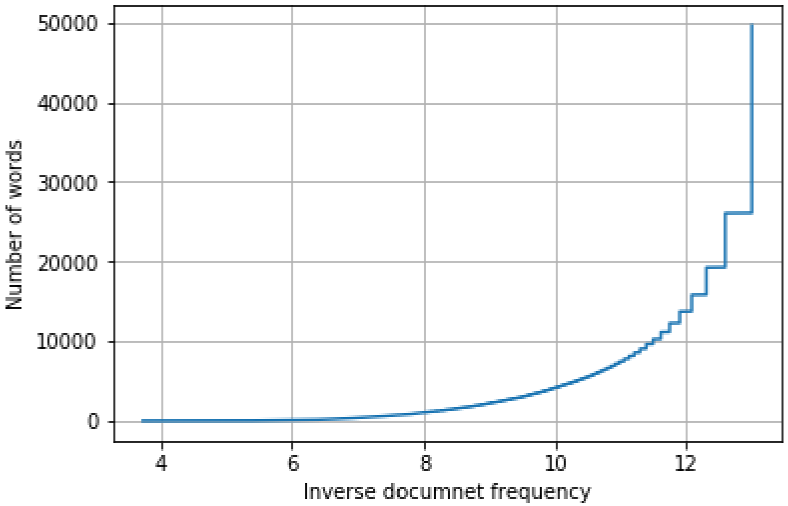
In [12]:
```
train_glove_features = train_features['glove_feat'].values
test_glove_features = test_features['glove_feat'].values
```

In [25]:
```
from sklearn.feature_extraction import text

tfidf_instance = text.TfidfVectorizer(ngram_range=(1,1))

train_features_tfidf = tfidf_instance.fit_transform(train_features['dissimilar_words_for_cleaned_question'].v
alues.astype(str))
test_features_tfidf = tfidf_instance.transform(test_features['dissimilar_words_for_cleaned_question'].values.
astype(str))
```

In [26]:
```
unique_words = tfidf_instance.get_feature_names()
idf_values = tfidf_instance.idf_
word_idf_df = pd.concat([pd.DataFrame(unique_words,columns =['word']),pd.DataFrame(idf_values,columns=['idf'
])],axis =1)
sorted_word_idf_df = word_idf_df.sort_values(by=['idf'])
```

In [27]:
```
sorted_word_idf_df = sorted_word_idf_df.reset_index()
```

In [28]:
```
plt.plot(sorted_word_idf_df['idf'],sorted_word_idf_df.index)
plt.ylabel("Number of words")
plt.xlabel("Inverse documnet frequency")
plt.grid()
plt.show()
```



observation:

```
* almost half number of words occurred very rare in the dataset.
```

In [16]:
```
train_features = train_features.drop(['Unnamed: 0','CleanedText_q1','CleanedText_q2','id','qid1','qid2','ques
tion1','question2','dissimilar_words_for_question','dissimilar_words_for_cleaned_question','glove_feat'],axis
 =1)
test_features = test_features.drop(['Unnamed: 0','CleanedText_q1','CleanedText_q2','id','qid1','qid2','questi
on1','question2','dissimilar_words_for_question','dissimilar_words_for_cleaned_question','glove_feat'],axis =
1)
```

In [17]:
```
train_features.head(1)
```

Out[17]:

	cwc_min	cwc_max	csc_min	csc_max	ctc_min	ctc_max	last_word_eq	first_word_eq	abs_len_diff	mean_len	...	freq_qid2
165137	0.99995	0.399992	0.0	0.0	0.333328	0.199998	1.0	0.0	4.0	8.0	...	2

1 rows × 26 columns

In [18]:
```
train_features = np.array(train_features)
test_features = np.array(test_features)
```

In [17]:
```
train_glove_features_list = train_glove_features.tolist()
```

In [18]:
```
test_glove_features_list = test_glove_features.tolist()
```

In [19]:
```
for row in train_glove_features_list:
    row = row.tolist()
```

In [20]:
```
for row in test_glove_features_list:
    row = row.tolist()
```

In [21]:
```
train_glove_features_numpy = np.array(train_glove_features_list)
test_glove_features_numpy = np.array(test_glove_features_list)
```

In [22]:
```
from scipy.sparse import hstack

train_features_glove_final = np.hstack((train_features,train_glove_features_numpy))
test_features_glove_final = np.hstack((test_features,test_glove_features_numpy))
```

In [23]:
```
from sklearn.preprocessing import scale

train_features_glove_final = scale(train_features_glove_final,with_mean=False)
test_features_glove_final = scale(test_features_glove_final,with_mean=False)
```

In [21]:
```
from scipy.sparse import hstack

train_features_tfidf = hstack((train_features,train_features_tfidf))
test_features_tfidf = hstack((test_features,test_features_tfidf))
```

In [23]:
```
from sklearn.preprocessing import scale

train_features_tfidf = scale(train_features_tfidf,with_mean=False)
test_features_tfidf = scale(test_features_tfidf,with_mean=False)
```

In [26]:
```
import pickle as pk

with open('quora_objs.pkl', 'wb') as f:
    pk.dump([train_score,test_score,train_features_glove_final, test_features_glove_final, train_features,tes
t_features,train_features_tfidf,test_features_tfidf], f)
```

In [27]:
```
import pickle as pk

with open('quora_objs_copy.pkl', 'wb') as f:
    pk.dump([train_score,test_score,train_features_glove_final, test_features_glove_final, train_features,tes
t_features,train_features_tfidf,test_features_tfidf], f)
```

Modeling

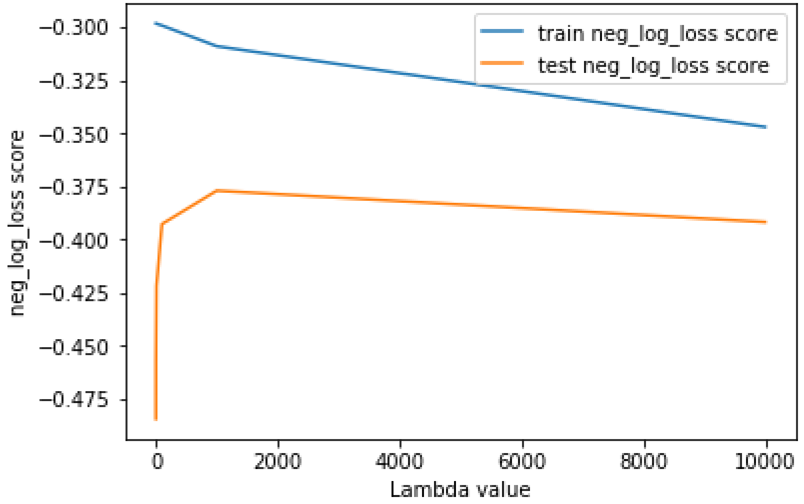
In [27]:
```
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)

    A =(((C.T)/(C.sum(axis=1))).T)

    B =(C/C.sum(axis=0))

    plt.figure(figsize=(20,4))

    labels = [1,2]
    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)
    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()
```

Applying Logestic Regression for TF-IDF Representation.

In [34]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

tuned_parameters = [{'C': [10**-4,10**-3,10**-2,10**-1,1,10**1]}]

model = GridSearchCV(LogisticRegression(max_iter=1000,solver='lbfgs'), tuned_parameters, scoring = 'neg_log_l
oss', cv=4,n_jobs=-1,return_train_score=True)
model.fit(train_features,train_score)

print(model.best_estimator_)
```

```
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=1000, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='lbfgs',
          tol=0.0001, verbose=0, warm_start=False)
```

In [35]:
```
cv_scores = pd.DataFrame(model.cv_results_)
cv_scores = cv_scores.sort_values(by =['param_C'])

plt.plot(1/cv_scores['param_C'],cv_scores['mean_train_score'],label='train neg_log_loss score')
plt.plot(1/cv_scores['param_C'],cv_scores['mean_test_score'],label='test neg_log_loss score')

plt.xlabel('Lambda value')
plt.ylabel('neg_log_loss score')
plt.legend()
plt.show()
```

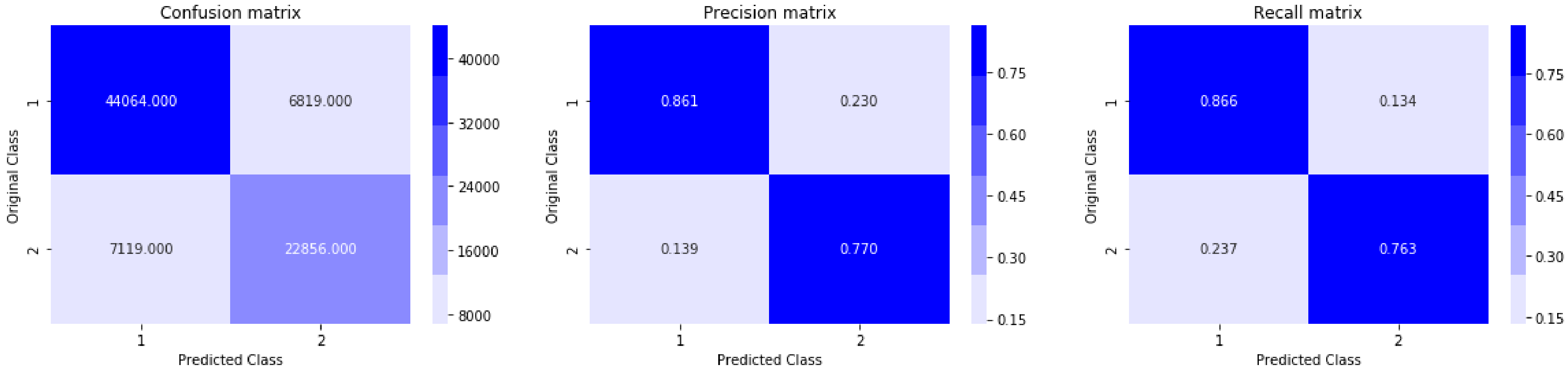


In [53]:
```
y_prob = model.best_estimator_.predict_proba(test_features)
y_prob = y_prob.transpose()
predict_y = y_prob[1]

score = log_loss(test_score,predict_y)
print("test log loss",score)
```

```
test log loss 0.3648848509555236
```

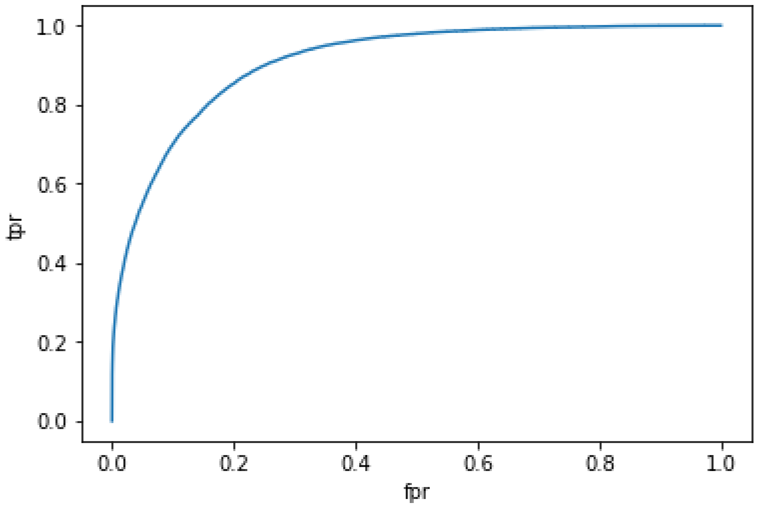
In [54]:
```
from sklearn.metrics import confusion_matrix

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

```
Total number of data points : 80858
```



In [61]:
```
from sklearn.metrics import roc_curve

fpr , tpr , thresholds = roc_curve(test_score, y_prob[1])
print("--------------------roc curve--------------------")
plt.plot(fpr, tpr)
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.show()
```

```
--------------------roc curve--------------------
```



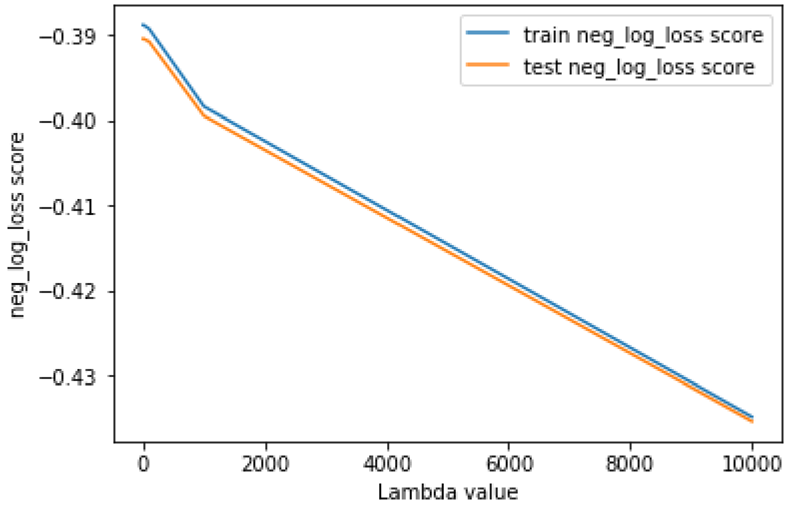
Applying Logestic Regression for TF-IDF weighted GLOVE Representation.

In [67]:
```
train_features_glove_final_no_nan = np.nan_to_num(train_features_glove_final)
test_features_glove_final_no_nan = np.nan_to_num(test_features_glove_final)
```

In [68]:
```
tuned_parameters = [{'C': [10**-4,10**-3,10**-2,10**-1,1,10**1]}]

model = GridSearchCV(LogisticRegression(max_iter=1000,solver='lbfgs'), tuned_parameters, scoring = 'neg_log_l
oss', cv=4,n_jobs=-1,return_train_score=True)
model.fit(train_features_glove_final_no_nan,train_score)

print(model.best_estimator_)
```

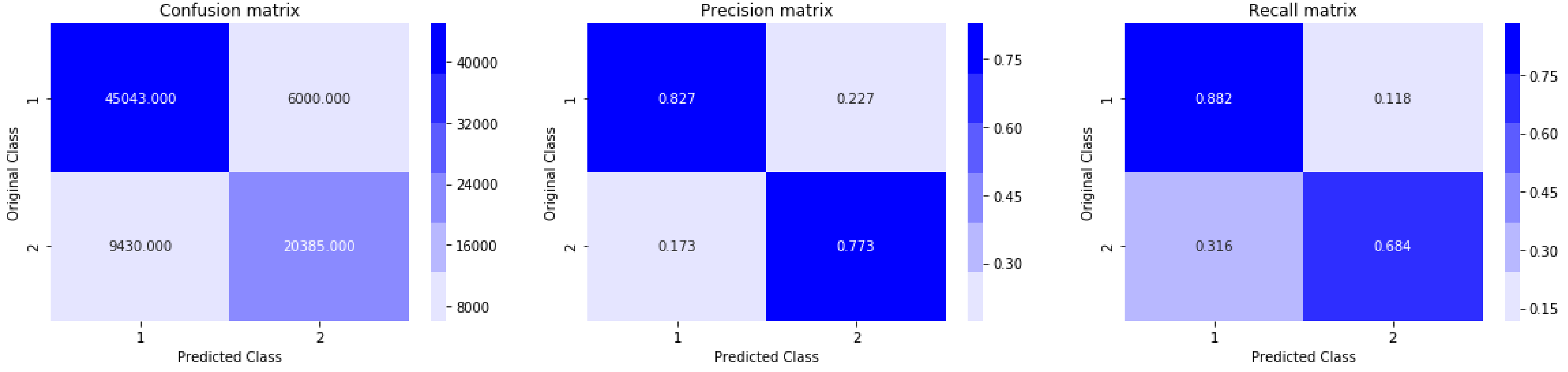
```
LogisticRegression(C=0.1, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=1000, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='lbfgs',
          tol=0.0001, verbose=0, warm_start=False)
```

In [69]:
```
cv_scores = pd.DataFrame(model.cv_results_)
cv_scores = cv_scores.sort_values(by =['param_C'])

plt.plot(1/cv_scores['param_C'],cv_scores['mean_train_score'],label='train neg_log_loss score')
plt.plot(1/cv_scores['param_C'],cv_scores['mean_test_score'],label='test neg_log_loss score')

plt.xlabel('Lambda value')
plt.ylabel('neg_log_loss score')
plt.legend()
plt.show()
```

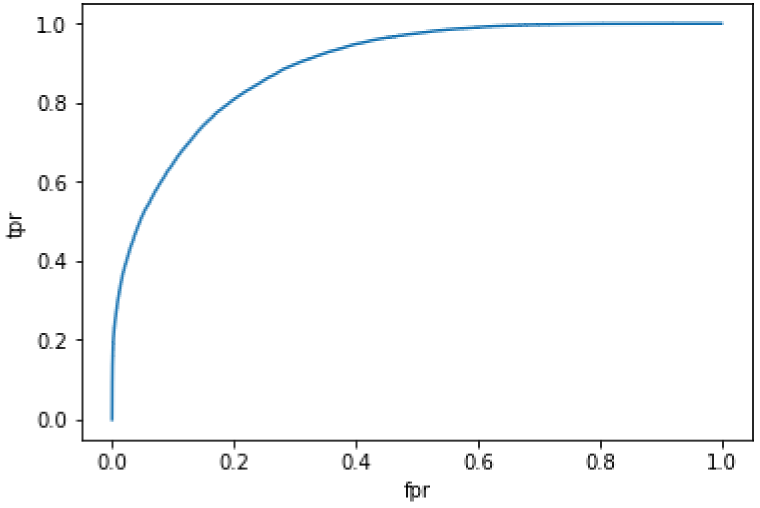


In [79]:
```
from sklearn.metrics import log_loss

y_prob = model.best_estimator_.predict_proba(train_features_glove_final_no_nan)
y_prob = y_prob.transpose()
predict_y = y_prob[1]

score = log_loss(train_score,predict_y)
print("Train log loss :",np.round(score,decimals=4))

y_prob = model.best_estimator_.predict_proba(test_features_glove_final_no_nan)
y_prob = y_prob.transpose()
predict_y = y_prob[1]

score = log_loss(test_score,predict_y)
print("Test log loss :",np.round(score,decimals=4))


from sklearn.metrics import confusion_matrix

predicted_y =np.argmax(y_prob.T,axis=1)
print("Total number of Test data points :", len(predicted_y))
plot_confusion_matrix(test_score, predicted_y)

from sklearn.metrics import roc_curve

fpr , tpr , thresholds = roc_curve(test_score, y_prob[1])
print("--------------------roc curve--------------------")
plt.plot(fpr, tpr)
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.show()
```

```
Train log loss : 0.389
Test log loss : 0.391
Total number of Test data points : 80858
```




```
--------------------roc curve--------------------
```



Applying XG BOOST for TF-IDF weighted GLOVE Representation.

In [1]:
```
with open('quora_objs.pkl','rb') as f:
    train_score,test_score,train_features_glove_final, test_features_glove_final, train_features,test_feature
s,train_features_tfidf,test_features_tfidf = pk.load(f)
```

In [4]:
```
train_features_glove_final_no_nan = np.nan_to_num(train_features_glove_final)
test_features_glove_final_no_nan = np.nan_to_num(test_features_glove_final)
```

In [6]:
```
start = datetime.now()
tuned_parameters={
    'max_depth' : [2,3,4],
    'n_estimators': [25,55,75],
    'learning_rate':[1,0.1],
    'colsample_bytree':[0.25,0.5,1],
    'colsample_bylevel':[0.5,1],
    'reg_alpha':[1,10],
    'objective':['binary:logistic'],
    'eval_metric':['logloss'],
    'booster':['gbtree'],

}

xgb_model = xgb.XGBClassifier()

model = GridSearchCV(xgb_model, tuned_parameters, scoring = 'neg_log_loss', cv=3,n_jobs=-1,return_train_score
=True)
model.fit(train_features_glove_final_no_nan,train_score)

print(model.best_estimator_)
print("Time taken to train :",datetime.now() - start)
```

```
/home/hanishsidhu/.local/lib/python3.5/site-packages/sklearn/model_selection/_search.py:841: DeprecationWarn
ing: The default of the `iid` parameter will change from True to False in version 0.22 and will be removed i
n 0.24. This will change numeric results when test-set sizes are unequal.
  DeprecationWarning)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, eval_metric='logloss', gamma=0, learning_rate=1,
       max_delta_step=0, max_depth=3, min_child_weight=1, missing=None,
       n_estimators=75, n_jobs=1, nthread=None,
       objective='binary:logistic', random_state=0, reg_alpha=10,
       reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
       subsample=1)
Time taken to train : 2:29:01.410957
```

In [18]:
```
cv_scores = pd.DataFrame(model.cv_results_)
```

In [21]:
```
cv_scores_best_models = cv_scores.sort_values(by=['rank_test_score'],axis=0)
```

In [42]:
```
print(" Top 5 BEST estimators ")
cv_scores_best_models[['mean_score_time','mean_test_score','mean_train_score','param_n_estimators','param_max_depth','param_learning_rate','param_colsample_bylevel','param_colsample_bytree','param_reg_alpha']].head(5)
```

```
 Top 5 BEST estimators
```

Out[42]:

	mean_score_time	mean_test_score	mean_train_score	param_n_estimators	param_max_depth	param_learning_rate	param_col
191	1.300309	-0.340046	-0.321079	75	3	1	1
190	1.380963	-0.341347	-0.320462	75	3	1	1
195	1.250852	-0.341570	-0.309138	55	4	1	1
155	1.299649	-0.341869	-0.323273	75	3	1	1
189	1.282317	-0.342011	-0.328131	55	3	1	1

In [46]:
```
print(" 5 WORST estimators ")
cv_scores_best_models = cv_scores.sort_values(by=['rank_test_score'],axis=0,ascending=False)
cv_scores_best_models[['mean_score_time','mean_test_score','mean_train_score','param_n_estimators','param_max_depth','param_learning_rate','param_colsample_bylevel','param_colsample_bytree','param_reg_alpha']].head(5)
```

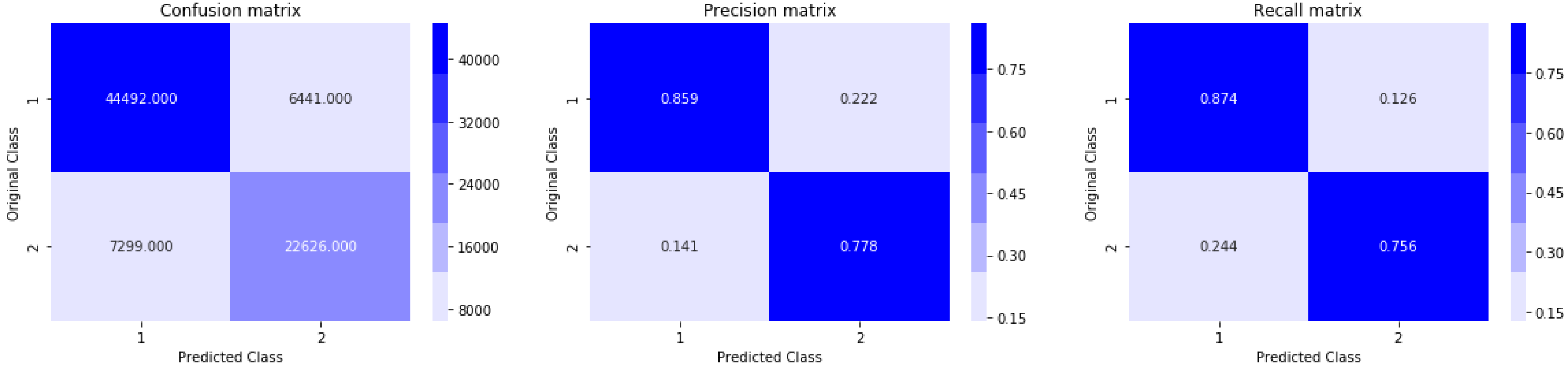
```
 5 WORST estimators
```

Out[46]:

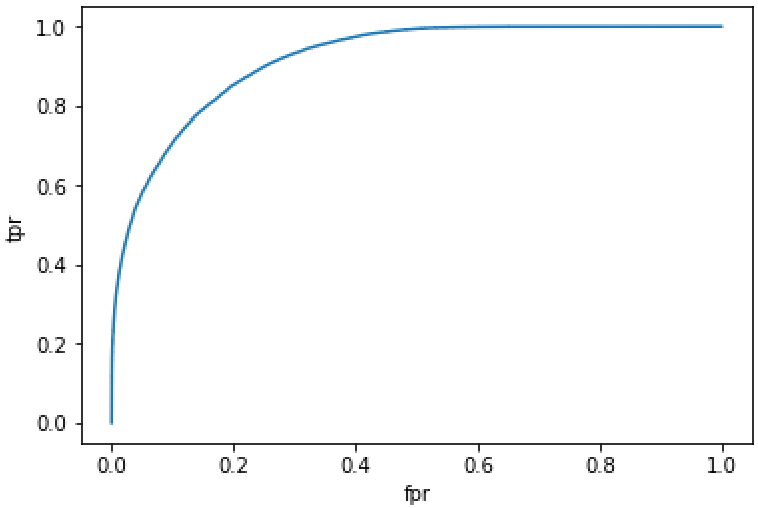
	mean_score_time	mean_test_score	mean_train_score	param_n_estimators	param_max_depth	param_learning_rate	param_col
122	1.273173	NaN	NaN	55	4	1	1
124	1.387473	NaN	NaN	75	4	1	1
120	1.076203	-inf	-inf	25	4	1	1
19	1.001440	-0.460614	-0.460319	25	2	0.1	0.5
18	0.973360	-0.460408	-0.460172	25	2	0.1	0.5

In [47]:
```
y_prob = model.best_estimator_.predict_proba(train_features_glove_final_no_nan)
y_prob = y_prob.transpose()
predict_y = y_prob[1]

score = log_loss(train_score,predict_y)
print("Train log loss :",np.round(score,decimals=4))

y_prob = model.best_estimator_.predict_proba(test_features_glove_final_no_nan)
y_prob = y_prob.transpose()
predict_y = y_prob[1]

score = log_loss(test_score,predict_y)
print("Test log loss :",np.round(score,decimals=4))


predicted_y =np.argmax(y_prob.T,axis=1)
print("Total number of Test data points :", len(predicted_y))
plot_confusion_matrix(test_score, predicted_y)


fpr , tpr , thresholds = roc_curve(test_score, y_prob[1])
print("--------------------roc curve--------------------")
plt.plot(fpr, tpr)
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.show()
```

```
Train log loss : 0.3254
Test log loss : 0.3477
Total number of Test data points : 80858
```




```
--------------------roc curve--------------------
```



In [51]:
```
cv_scores.to_csv("XGBOOST_CV_SCORES.csv")
```

Conclusion

In [46]:
```
x = PrettyTable()
x.field_names = ["Vectorizer",'Model',"Hyper-Parameters","log loss"]
x.add_row(['Tfidf\n','Logistic Regression','C = 0.001','0.364'])
x.add_row(['Tfidf weighted GLOVE\n\n','Logistic Regression ','C = 0.1','0.391'])
x.add_row(['Tfidf weighted GLOVE\n','XG BOOST','n_estimators =75\n max_depth=3 \n learning rate =1\ncolsample_bylevel =1\ncolsample_bytree =1\nreg_alpha=10\n','0.347'])
print(x)
```

```
+----------------------+----------------------+----------------------+----------+
|      Vectorizer      |        Model         |   Hyper-Parameters   | log loss |
+----------------------+----------------------+----------------------+----------+
|        Tfidf         | Logistic Regression  |      C = 0.001       |  0.364   |
|                      |                      |                      |          |
| Tfidf weighted GLOVE | Logistic Regression  |       C = 0.1        |  0.391   |
|                      |                      |                      |          |
|                      |                      |                      |          |
| Tfidf weighted GLOVE |       XG BOOST       |   n_estimators =75   |  0.347   |
|                      |                      |     max_depth=3      |          |
|                      |                      |   learning rate =1   |          |
|                      |                      | colsample_bylevel =1 |          |
|                      |                      | colsample_bytree =1  |          |
|                      |                      |     reg_alpha=10     |          |
|                      |                      |                      |          |
+----------------------+----------------------+----------------------+----------+
```

Procedure

- It was clear that the main objective for this bussiness problem was to predict if the questions are similar or not.
- Since the train.csv file was small, I had loaded the data without using Sqlite
- Cleaned data and basic data analysis on the csv file.
- Basic featurization like calculating number of common words, number of common stop words, etc. in the quesions
- Analysed the basic features.
- Analysed duplicate question's text and non-duplicate question's text.
- Extracted and analysed Fuzzywuzzy features.
- visualised the Fuzzywuzzy features using T-SNE
- Cleaned and preprocessed the text data of the questions.
- As the dissimilar words of two questions decides whether those questions are duplicate or not, I had vectorized only the dissimilar words of the two questions by using TF-IDF vectorizer and TF-IDF weighted GLOVE representation.
- Two main reasons of vectorizing only dissimilar words of the two questions are:
  - this will decrease overall dimensions of a tf-idf vector representation, as the corpus size of dissimilar words is less when compared with the text of two questions.
  - this will also help the model to understand only the dissimilar words of two questions are causing a datapoint to be duplicate, which is very important as nearly 80% of questions in the dataset are unique.
- As most of the dissimilar words were less frequent in the dataset, I had used Tf-idf vector representation over count vector representation(Bag of Words) for featurizing the dissimilar words.
- Applied logistic regression, As it performs very well with large set of features and also with large number of datapoints
- I had not applied Linear-SVC, as the fit time complexity is more than quadratic with the number of datapoints
- Applied XG Boost on TF-IDF Weighted GLOVE representation, which performed very well than logistic regression
- Compared all the models using pretty table.

--THE END---