1.2.1 : EDA: Advanced Feature Extraction.

In [1]:

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

import re
from nltk.corpus import stopwords
import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
import re
from nltk.corpus import stopwords
# This package is used for finding longest common subsequence between two strings
# you can write your own dp code for this
import distance
from nltk.stem import PorterStemmer
from bs4 import BeautifulSoup
from fuzzywuzzy import fuzz
from sklearn.manifold import TSNE
# Import the Required lib packages for WORD-Cloud generation
# https://stackoverflow.com/questions/45625434/how-to-install-wordcloud-in-python3-6
from wordcloud import WordCloud, STOPWORDS
from os import path
from PIL import Image
```

In [2]:

```
#https://stackoverflow.com/questions/12468179/unicodedecodeerror-utf8-codec-cant-decode-byte-0x9c
if os.path.isfile('df_basicfe_train.csv'):
    df = pd.read_csv("df_basicfe_train.csv",encoding='latin-1')
    df = df.fillna('')
    df.head()
else:
    print("get df_basicfe_train.csv from drive or run the previous notebook")
```

In [3]:

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

Out[3]:

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common	v
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	
				What is the story of	What would happen if									

	id	qid1	qid2	question1	question2	is_duplicate	freq_qid1	freq_qid2	q1len	q2len	q1_n_words	q2_n_words	word_Common	w
1	1	3	4	Kohinoor (Koh-i-Noor) Dia...	the Indian government sto...	0	4	1	51	88	8	13	4.0	

3.4 Preprocessing of Text

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

In [4]:

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

STOP_WORDS = stopwords.words("english")


def preprocess(x):
    # Convert into lowercase
    x = str(x).lower()
    # Replacing some the string into other string
    # For eg -> 1,000 replaced with 1k, he's replaced with he is
    x = x.replace(",000,000", "m").replace(",000", "k").replace("′", "'").replace("’", "'")\
                            .replace("won't", "will not").replace("cannot", "can not").replace("can't",
"can not")\
                            .replace("n't", " not").replace("what's", "what is").replace("it's", "it is"
)\
                            .replace("'ve", " have").replace("i'm", "i am").replace("'re", " are")\
                            .replace("he's", "he is").replace("she's", "she is").replace("'s", " own")\
                            .replace("%", " percent ").replace("₹", " rupee ").replace("$", " dollar ")\
                            .replace("€", " euro ").replace("'ll", " will")
    # If an regular expression where appear x'000000' then it replaced with xm where x is any number
    x = re.sub(r"([0-9]+)000000", r"\1m", x)
    # If an regular expression where appear x'000' then it replaced with xk where x is any number
    x = re.sub(r"([0-9]+)000", r"\1k", x)

    # Stemming algorithm with NLTK
    # Ref : https://www.geeksforgeeks.org/python-stemming-words-with-nltk/
    porter = PorterStemmer()
    # This matches any non-alphanumeric character [^a-zA-Z0-9]
    # Ref : https://scotch.io/tutorials/an-introduction-to-regex-in-python
    pattern = re.compile('\W')

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

    if type(x) == type(''):
        x = porter.stem(x)
        # Ref : https://www.crummy.com/software/BeautifulSoup/bs4/doc/
        example1 = BeautifulSoup(x)
        # New only text (rest of the part will automatically neglect)
        x = example1.get_text()

    return x
```

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

3.5 Advanced Feature Extraction (NLP and Fuzzy Features)

Definition:

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

Features:

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

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

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

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

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

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

- **last_word_eq** : Check if Last word of both questions is equal or not
  last_word_eq = int(q1_tokens[-1] == q2_tokens[-1])

- **first_word_eq** : Check if First word of both questions is equal or not
  first_word_eq = int(q1_tokens[0] == q2_tokens[0])

- **abs_len_diff** : Abs. length difference
  abs_len_diff = abs(len(q1_tokens) - len(q2_tokens))

- **mean_len** : Average Token Length of both Questions
  mean_len = (len(q1_tokens) + len(q2_tokens))/2

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

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

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

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

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

In [6]:

```
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)))

    # Apply First six features as per description in above
    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])

    # Absolute length difference
    token_features[8] = abs(len(q1_tokens) - len(q2_tokens))

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

# get the Longest Common sub string

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

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

    print("token features...")

    # Merging Features with dataset
    token_features = df.apply(lambda x: get_token_features(x["question1"], x["question2"]), axis=1)

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

    #Computing Fuzzy Features and Merging with Dataset

    # do read this blog: http://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/
    # https://stackoverflow.com/questions/31806695/when-to-use-which-fuzz-function-to-compare-2-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"
]), axis=1)
    # The token sort approach involves tokenizing the string in question, sorting the tokens alphabetic
```

```
    # The token sort approach involves tokenizing the string in question, sorting the tokens alphabetic
ally, 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
"]), axis=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["questi
on2"]), axis=1)
    return df
```

In [7]:

```
if os.path.isfile('nlp_features_train.csv'):
    df = pd.read_csv("nlp_features_train.csv",encoding='latin-1')
    df.fillna('')
else:
    print("Extracting features for train:")
    df = pd.read_csv("train.csv")
    df = extract_features(df)
    df.to_csv("nlp_features_train.csv", index=False)
df.head(2)
```

Out[7]:

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

2 rows × 21 columns

3.5.1 Analysis of extracted features

3.5.1.1 Plotting Word clouds

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

In [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', encoding='utf-8')
np.savetxt('train_n.txt', n, delimiter=' ', fmt='%s', encoding='utf-8')
```

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

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

In [14]:

```
# reading the text files and removing the Stop Words:

textp_w = open('train_p.txt').read()
textn_w = open('train_n.txt').read()
stopwords = set(STOPWORDS)
stopwords.add("said")
stopwords.add("br")
stopwords.add(" ")
stopwords.remove("not")

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

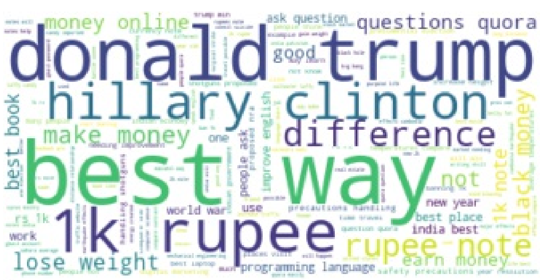
```
Total number of words in duplicate pair questions : 16110303
Total number of words in non duplicate pair questions : 33194892
```

Word Clouds generated from duplicate pair question's text

In [15]:

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

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

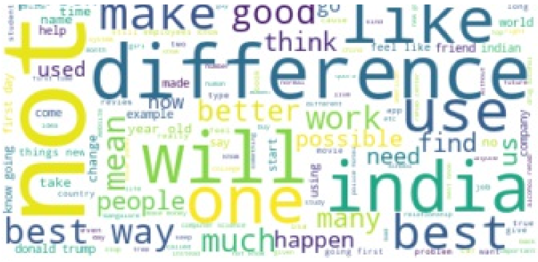


Word Clouds generated from non duplicate pair question's text

In [16]:

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

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



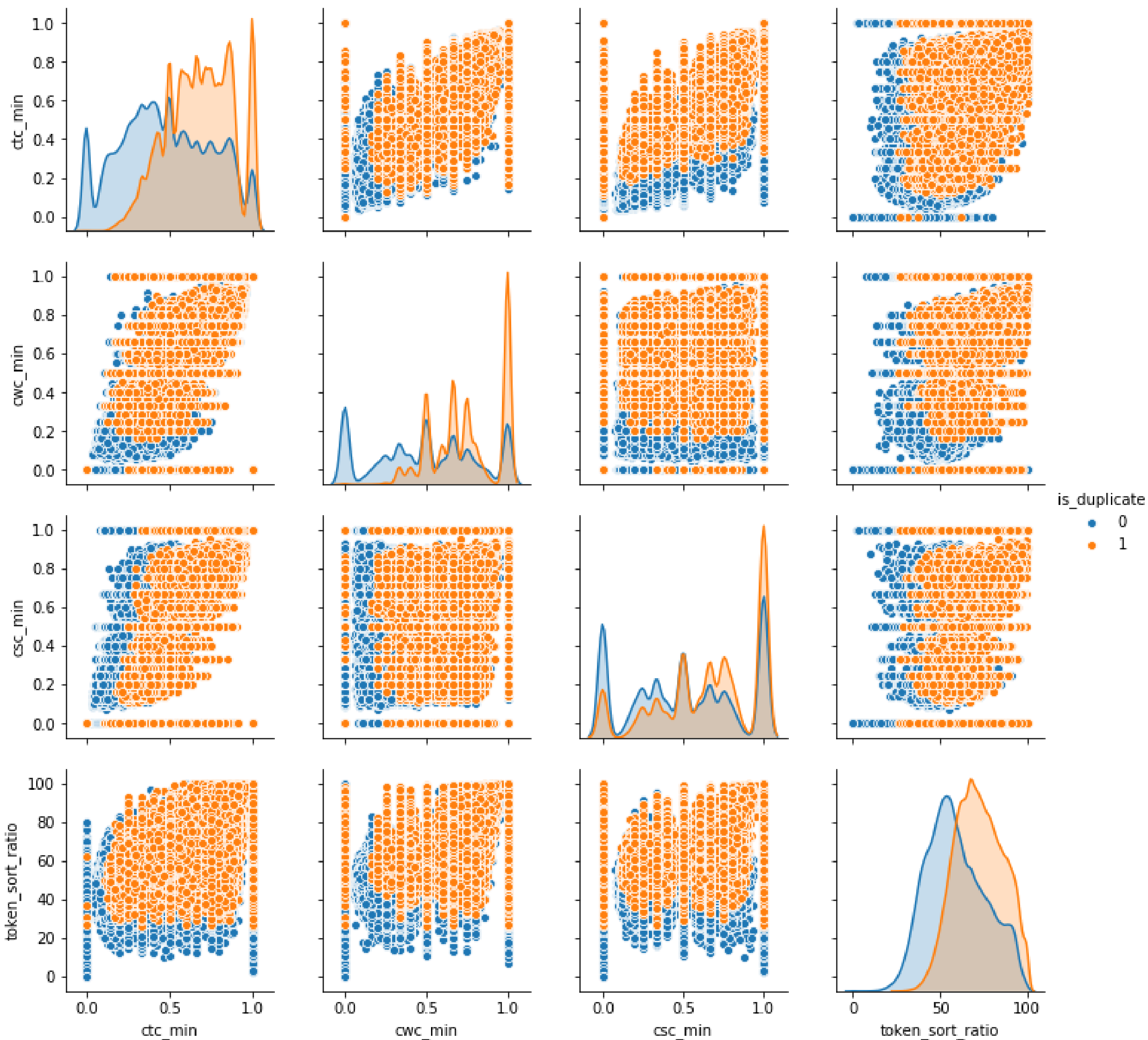
Observation

'Best way' and 'difference' word are most frequent appear on both 'duplicate' and 'not_duplicate' label.

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

In [17]:

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



Observation

1. From the four features, they all are more overlapping (not highly) except [csc,min] with others.

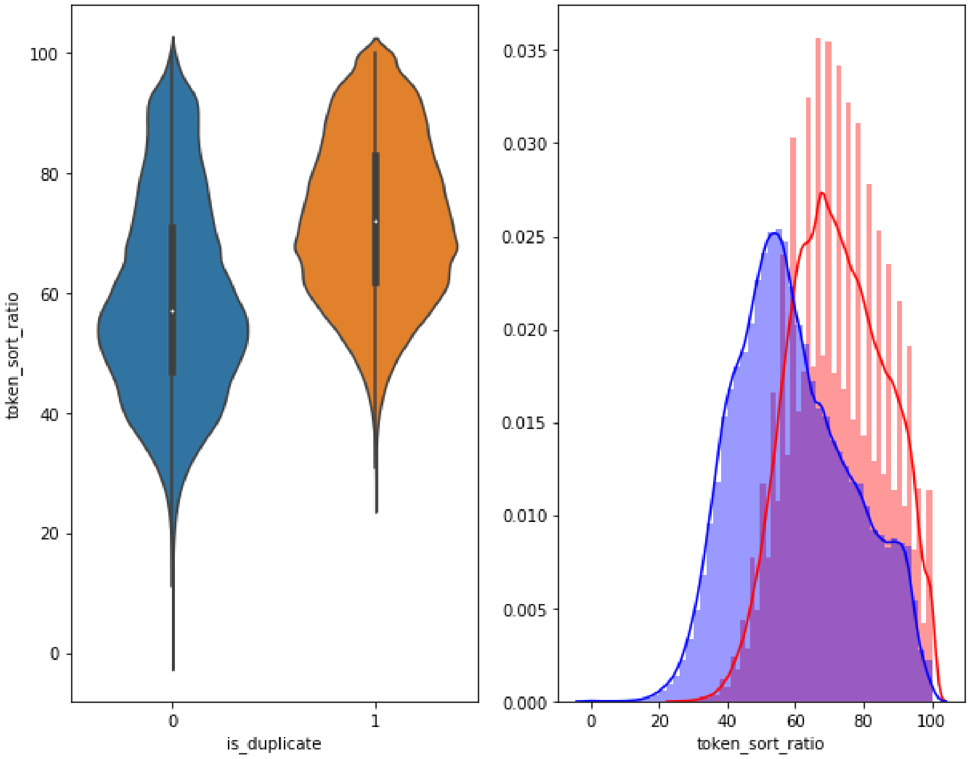
2. Since there so many points that are not visible in the graph. That means, there are points which are overlap to each other

In [18]:

```
# Distribution of the token_sort_ratio
plt.figure(figsize=(10, 8))

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

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

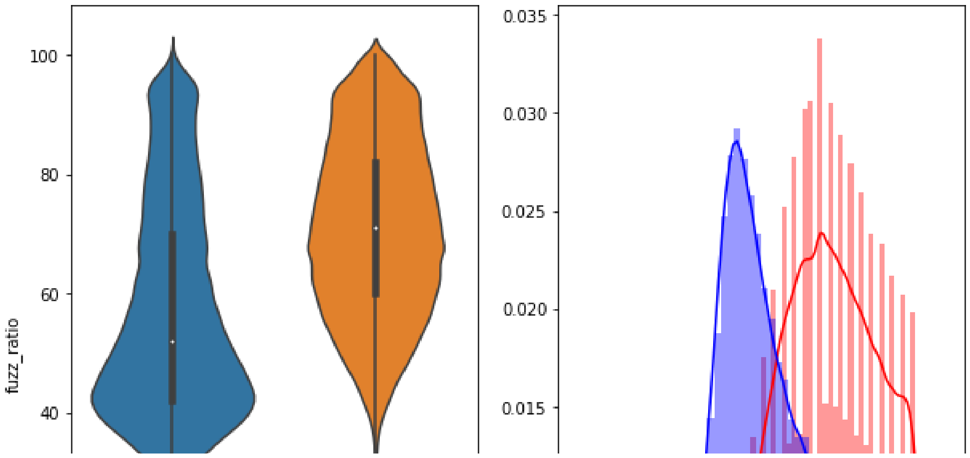


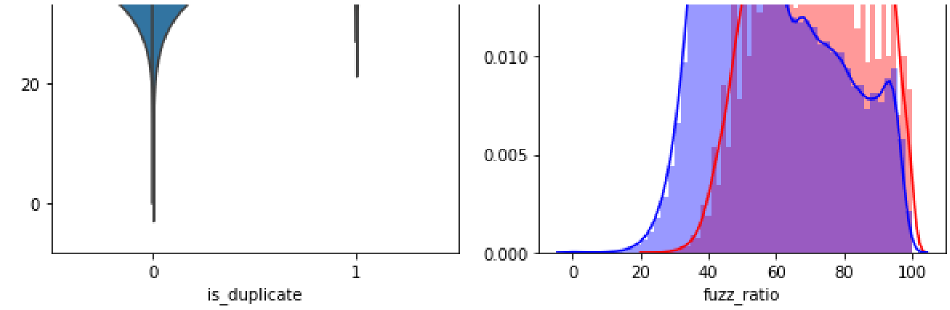
In [19]:

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

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

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





Observation

Above two features graphs (token_sort_ratio and fuzz_ratio), they are more overlap (not highly) with 'is_duplicate' label

3.5.2 Visualization

In [20]:

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

from sklearn.preprocessing import MinMaxScaler

# Taking 5k data, becoz t-SNE computation take too much time
dfp_subsampled = df[0:5000]

# Taking data with Advance NLP features only.
# With that feature, we normalize the data in range [0,1]
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' , 'toke
n_sort_ratio' ,  'fuzz_ratio' , 'fuzz_partial_ratio' , 'longest_substr_ratio']])

# Put class label value into 'y' variable
y = dfp_subsampled['is_duplicate'].values
```

In [21]:

```
# Perform t-SNE
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)
```

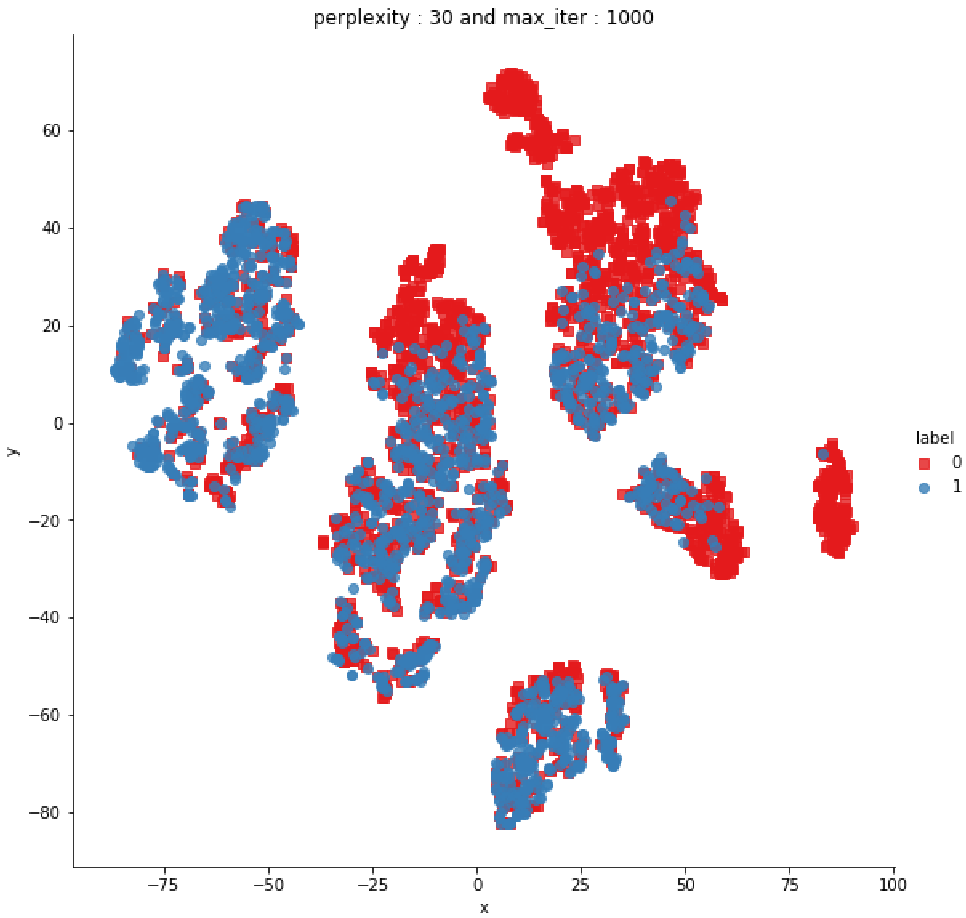
```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.011s...
[t-SNE] Computed neighbors for 5000 samples in 0.309s...
[t-SNE] Computed conditional probabilities for sample 1000 / 5000
[t-SNE] Computed conditional probabilities for sample 2000 / 5000
[t-SNE] Computed conditional 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 0.164s
[t-SNE] Iteration 50: error = 80.9162369, gradient norm = 0.0427600 (50 iterations in 2.194s)
[t-SNE] Iteration 100: error = 70.3915100, gradient norm = 0.0108003 (50 iterations in 1.665s)
[t-SNE] Iteration 150: error = 68.6126938, gradient norm = 0.0054721 (50 iterations in 1.667s)
[t-SNE] Iteration 200: error = 67.7680206, gradient norm = 0.0042246 (50 iterations in 1.718s)
[t-SNE] Iteration 250: error = 67.2733459, gradient norm = 0.0037275 (50 iterations in 1.715s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 67.273346
[t-SNE] Iteration 300: error = 1.7734827, gradient norm = 0.0011933 (50 iterations in 1.805s)
[t-SNE] Iteration 350: error = 1.3717980, gradient norm = 0.0004826 (50 iterations in 1.608s)
[t-SNE] Iteration 400: error = 1.2037998, gradient norm = 0.0002772 (50 iterations in 1.616s)
[t-SNE] Iteration 450: error = 1.1133003, gradient norm = 0.0001877 (50 iterations in 1.628s)
[t-SNE] Iteration 500: error = 1.0579894, gradient norm = 0.0001429 (50 iterations in 1.630s)
```

```
[t-SNE] Iteration 550: error = 1.0220573, gradient norm = 0.0001178 (50 iterations in 1.644s)
[t-SNE] Iteration 600: error = 0.9990303, gradient norm = 0.0001036 (50 iterations in 1.642s)
[t-SNE] Iteration 650: error = 0.9836842, gradient norm = 0.0000951 (50 iterations in 1.645s)
[t-SNE] Iteration 700: error = 0.9732341, gradient norm = 0.0000860 (50 iterations in 1.656s)
[t-SNE] Iteration 750: error = 0.9649901, gradient norm = 0.0000789 (50 iterations in 1.654s)
[t-SNE] Iteration 800: error = 0.9582695, gradient norm = 0.0000745 (50 iterations in 1.648s)
[t-SNE] Iteration 850: error = 0.9525222, gradient norm = 0.0000732 (50 iterations in 1.664s)
[t-SNE] Iteration 900: error = 0.9479918, gradient norm = 0.0000689 (50 iterations in 1.678s)
[t-SNE] Iteration 950: error = 0.9442031, gradient norm = 0.0000651 (50 iterations in 1.665s)
[t-SNE] Iteration 1000: error = 0.9408465, gradient norm = 0.0000590 (50 iterations in 1.668s)
[t-SNE] KL divergence after 1000 iterations: 0.940847
```

In [22]:

```
# Put the result into panda DataFrame
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()
```



Observation

Some of the points are overlapping, but some of the red region ('not_duplicate' label) are not overlapping with other. It might useful for model to recognized with this feature.

In [23]:

```
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)
```

```
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Indexed 5000 samples in 0.008s...
[t-SNE] Computed neighbors for 5000 samples in 0.314s...
[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 0.166s
[t-SNE] Iteration 50: error = 80.3552017, gradient norm = 0.0329941 (50 iterations in 7.687s)
[t-SNE] Iteration 100: error = 69.1100388, gradient norm = 0.0034323 (50 iterations in 4.265s)
[t-SNE] Iteration 150: error = 67.6163483, gradient norm = 0.0017810 (50 iterations in 3.729s)
[t-SNE] Iteration 200: error = 67.0578613, gradient norm = 0.0011246 (50 iterations in 3.787s)
[t-SNE] Iteration 250: error = 66.7297821, gradient norm = 0.0009272 (50 iterations in 3.756s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 66.729782
[t-SNE] Iteration 300: error = 1.4978341, gradient norm = 0.0006938 (50 iterations in 4.738s)
[t-SNE] Iteration 350: error = 1.1559117, gradient norm = 0.0001985 (50 iterations in 6.097s)
[t-SNE] Iteration 400: error = 1.0108488, gradient norm = 0.0000976 (50 iterations in 6.138s)
[t-SNE] Iteration 450: error = 0.9391674, gradient norm = 0.0000627 (50 iterations in 6.161s)
[t-SNE] Iteration 500: error = 0.9015961, gradient norm = 0.0000508 (50 iterations in 6.049s)
[t-SNE] Iteration 550: error = 0.8815936, gradient norm = 0.0000433 (50 iterations in 5.899s)
[t-SNE] Iteration 600: error = 0.8682337, gradient norm = 0.0000373 (50 iterations in 5.875s)
[t-SNE] Iteration 650: error = 0.8589998, gradient norm = 0.0000360 (50 iterations in 6.041s)
[t-SNE] Iteration 700: error = 0.8518325, gradient norm = 0.0000281 (50 iterations in 6.082s)
[t-SNE] Iteration 750: error = 0.8455728, gradient norm = 0.0000284 (50 iterations in 6.065s)
[t-SNE] Iteration 800: error = 0.8401663, gradient norm = 0.0000264 (50 iterations in 6.010s)
[t-SNE] Iteration 850: error = 0.8351609, gradient norm = 0.0000265 (50 iterations in 6.022s)
[t-SNE] Iteration 900: error = 0.8312420, gradient norm = 0.0000225 (50 iterations in 6.030s)
[t-SNE] Iteration 950: error = 0.8273517, gradient norm = 0.0000231 (50 iterations in 6.055s)
[t-SNE] Iteration 1000: error = 0.8240154, gradient norm = 0.0000213 (50 iterations in 6.240s)
[t-SNE] KL divergence after 1000 iterations: 0.824015
```

In [25]:

```
# Plot in 3D space
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='t-SNE with perplexity : {} and max_iter : {}'.format(30,1000)
)
fig=dict(data=data, layout=layout)
py.iplot(fig, filename='3DBubble')
```

Observation

From the t-SNE with n=3 component, we found some blue points ('duplicate' label) in 3D space which are not overlapping with red ones.

In [ ]:

```

```