Predict whether the Tweet is a real Disaster or Not?

Target = 1 means Real Disaster Tweet or else Target =0 Not Real Disaster Tweet

```
!pip install category_encoders
```

```
Collecting category_encoders
  Downloading https://files.pythonhosted.org/packages/44/57/fcef41c248701ee62e8325026
     |████████████████████████████████| 81kB 3.6MB/s
Requirement already satisfied: pandas>=0.21.1 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.6/dist-pa
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.6/dist-
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.6/dis
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from pa
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages
Installing collected packages: category-encoders
Successfully installed category-encoders-2.2.2
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import re,string
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
import category_encoders as ce
import nltk
from nltk import word_tokenize
from sklearn.model_selection import train_test_split,GridSearchCV,KFold,StratifiedKFold
from sklearn.metrics import f1_score,accuracy_score,confusion_matrix
from nltk import FreqDist,bigrams
from wordcloud import STOPWORDS
from wordcloud import WordCloud
from sklearn.feature_selection import RFECV
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

```
train=pd.read_csv('train.csv')
test=pd.read_csv('test.csv')
```

```
train.head()
```

	id	keyword	location	text	target
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M...	1
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1
2	5	NaN	NaN	All residents asked to 'shelter in place' are ...	1
3	6	NaN	NaN	13,000 people receive #wildfires evacuation or...	1
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as ...	1

```
test.head()
```

	id	keyword	location	text
0	0	NaN	NaN	Just happened a terrible car crash
1	2	NaN	NaN	Heard about #earthquake is different cities, s...
2	3	NaN	NaN	there is a forest fire at spot pond, geese are...
3	9	NaN	NaN	Apocalypse lighting. #Spokane #wildfires
4	11	NaN	NaN	Typhoon Soudelor kills 28 in China and Taiwan

```
(train.isna().mean()*100)
```

```
id           0.000000
keyword      0.801261
location    33.272035
text         0.000000
target       0.000000
dtype: float64
```

```
test.isna().mean()*100
```

```
id           0.000000
keyword      0.796813
location    33.864542
text         0.000000
dtype: float64
```

- so 33% of location values and around 8% of keyword values are missing in both test and train

```
train.target.value_counts()
```

```
0    4342
1    3271
Name: target, dtype: int64
```

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   id        7613 non-null   int64
 1   keyword   7552 non-null   object
 2   location  5080 non-null   object
 3   text      7613 non-null   object
 4   target    7613 non-null   int64
dtypes: int64(2), object(3)
memory usage: 297.5+ KB
```

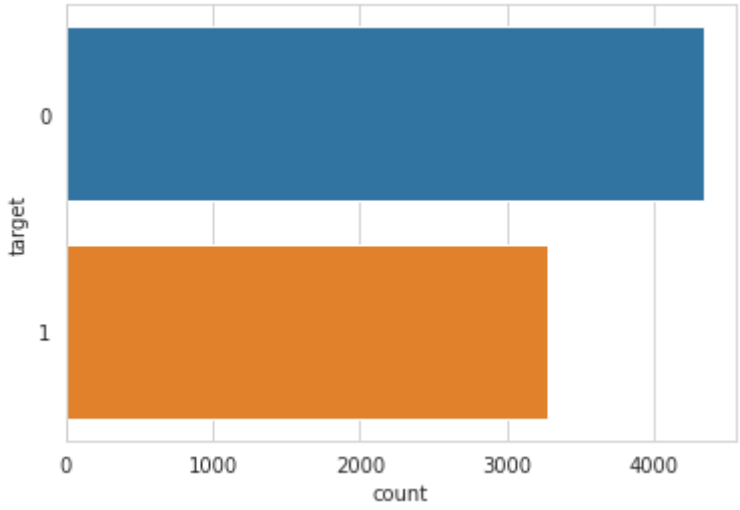
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3263 entries, 0 to 3262
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   id        3263 non-null   int64
 1   keyword   3237 non-null   object
 2   location  2158 non-null   object
 3   text      3263 non-null   object
dtypes: int64(1), object(3)
memory usage: 102.1+ KB
```

```
train.duplicated().sum()
```

```
0
```

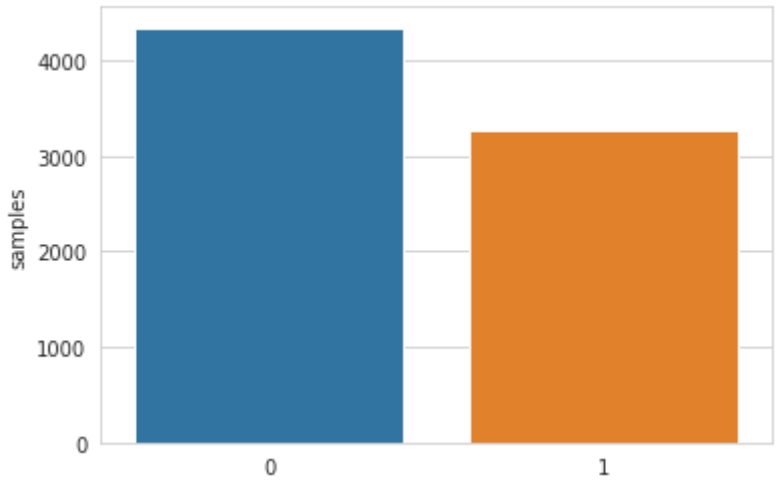
```
sns.countplot(y=train.target)
plt.show()
```




```
train[~train.keyword.isnull()]
```

	id	keyword	location	text	target
31	48	ablaze	Birmingham	@bbcmtd Wholesale Markets ablaze http://t.co/l...	1
32	49	ablaze	Est. September 2012 - Bristol	We always try to bring the heavy. #metal #RT h...	0
33	50	ablaze	AFRICA	#AFRICANBAZE: Breaking news:Nigeria flag set a...	1
34	52	ablaze	Philadelphia, PA	Crying out for more! Set me ablaze	0
35	53	ablaze	London, UK	On plus side LOOK AT THE SKY LAST NIGHT IT WAS...	0
...	...	...	...	...	...
				@it_ruff23 @cameronhacker and I	

```
x=train.target.value_counts()
sns.barplot(x.index,x)
plt.gca().set_ylabel('samples')
plt.show()
```




```
train.keyword.nunique()-test.keyword.nunique()
```

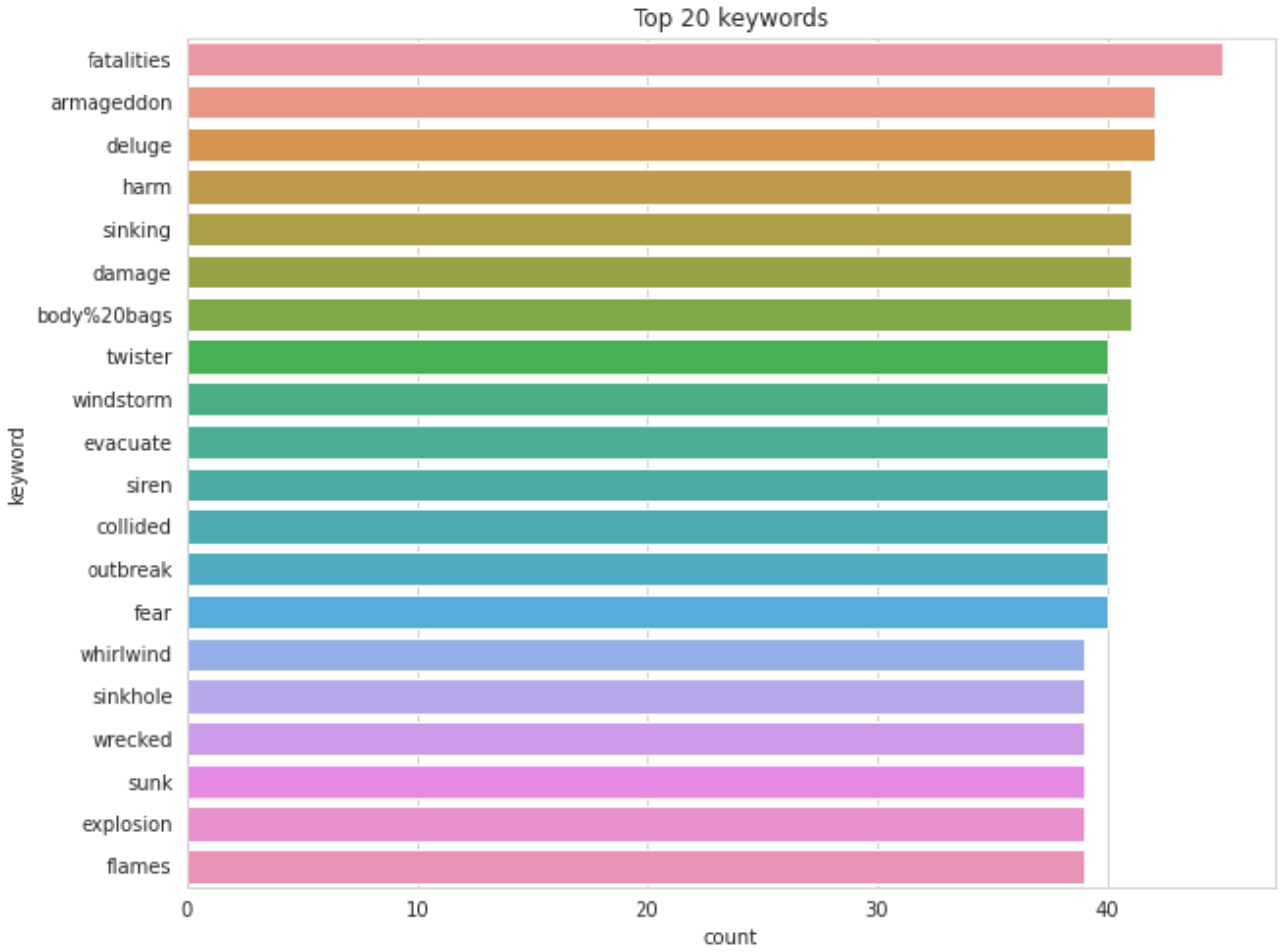
```
0
```

```
kw=train.keyword.value_counts()[:20]
kw
```

```
fatalities     45
armageddon     42
deluge         42
harm           41
sinking        41
damage         41
body%20bags    41
twister        40
windstorm      40
evacuate       40
siren          40
collided       40
```

```
outbreak       40
fear           40
whirlwind      39
sinkhole       39
wrecked        39
sunk           39
explosion      39
flames         39
Name: keyword, dtype: int64
```

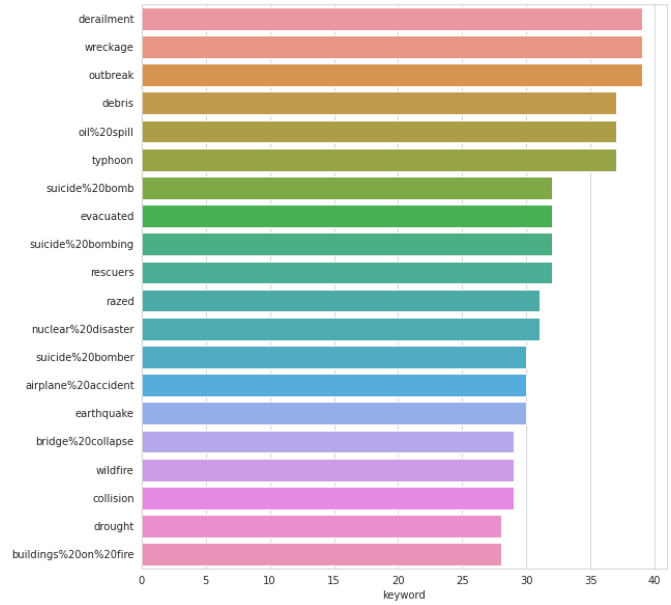
```
plt.figure(figsize=(10,8))
sns.countplot(y=train.keyword,order=kw.index)
plt.title('Top 20 keywords')
plt.show()
```

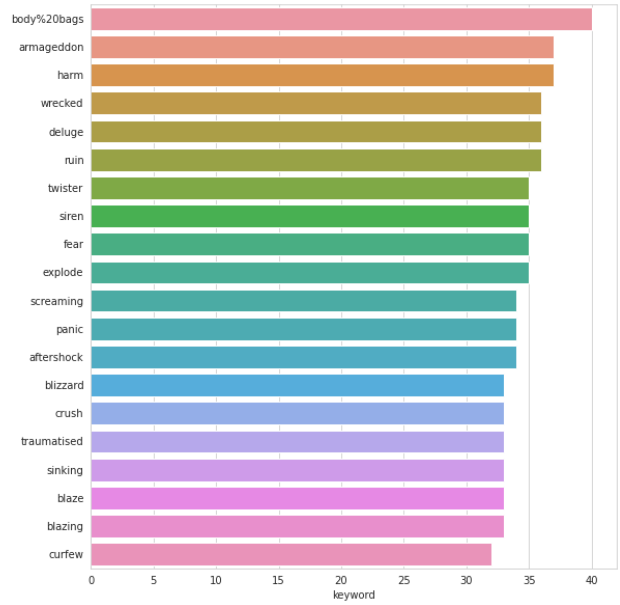



```
disaster_keyword=train[train.target==1]['keyword'].value_counts()[:20]
nonDisaster_keyword=train[train.target==0].keyword.value_counts()[:20]
```

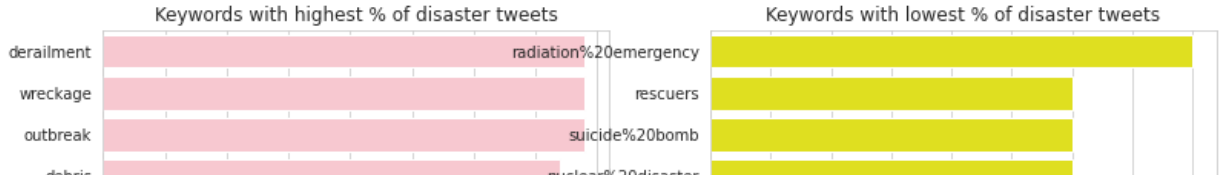
```
plt.figure(figsize=(20,10))
plt.subplot(121)
sns.barplot(disaster_keyword,disaster_keyword.index)
plt.subplot(122)
sns.barplot(nonDisaster_keyword,nonDisaster_keyword.index)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f41c0344550>
```






```
top_d=train[train.target==1]['keyword'].value_counts()[:10]
top_nd=train[train.target==0].keyword.value_counts()[-10:]
plt.figure(figsize=(13,5))
plt.subplot(121)
sns.barplot(top_d, top_d.index, color='pink')
plt.title('Keywords with highest % of disaster tweets')
plt.subplot(122)
sns.barplot(top_nd, top_nd.index, color='yellow')
plt.title('Keywords with lowest % of disaster tweets')
plt.show()
```



Data Cleaning & Creating Seperate Hashtags , Mentions and Links


```
def clean_text(text):
  text=re.sub(r'\n',' ',text)
  text=re.sub(r'\s+',' ',text)
  text=re.sub(r'https?://\S+','',text)
  return text

def get_mentions(text):
  return ' '.join([match.group(0)[1:] for match in re.finditer(r'@\w+',text)]) or 'none'
def get_hashtags(text):
  return ' '.join([match.group(0)[1:] for match in re.finditer(r'#\w+',text)]) or 'none'
def get_links(text):
  return ' '.join([match.group(0) for match in re.finditer(r'https?://\S+',text)]) or 'non
```

Double-click (or enter) to edit

```
def process_df(df):
  df['mentions']=df.text.apply(get_mentions)
  df['hashtags']=df.text.apply(get_hashtags)
  df['links']=df.text.apply(get_links)
  df['clean_text']=df.text.apply(clean_text)
  return df


train=process_df(train)
test=process_df(test)


train.head()
```

	id	keyword	location	text	target	mentions	hashtags	links	clean_text
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M... Forest fire near La	1	none	earthquake	none	Our Deeds are the Reason of this #earthquake M... Forest fire near La

```
# https://stackoverflow.com/a/47091490/4084039
def decontracted(phrase):
 phrase = re.sub(r"won't", "will not", phrase)
 phrase = re.sub(r"can\'t", "can not", phrase)
 # general
```

```
 # general
 phrase = re.sub(r"n\'t", " not", phrase)
 phrase = re.sub(r"\'re", " are", phrase)
 phrase = re.sub(r"\'s", " is", phrase)
 phrase = re.sub(r"\'d", " would", phrase)
 phrase = re.sub(r"\'ll", " will", phrase)
 phrase = re.sub(r"\'t", " not", phrase)
 phrase = re.sub(r"\'ve", " have", phrase)
 phrase = re.sub(r"\'m", " am", phrase)
 return phrase
def preprocess(Input_Text):
  Input_Text=Input_Text.lower()
  Input_Text=re.sub(r"<[^>]*>",' ',Input_Text) #any html tags
  Input_Text=re.sub(r'(\().*?(\))',' ',Input_Text) #brackets removal
  Input_Text= re.sub('[^A-Za-z0-9]+', ' ', Input_Text) #punctuation removal
  Input_Text=decontracted(Input_Text)
  Input_Text =''.join([i for i in Input_Text if not i.isdigit()])
  Input_Text=' '.join([i for i in Input_Text.split() if i.isalpha()])

  return Input_Text


preprocess(train.clean_text.iloc[1])
```

```
'forest fire near la ronge sask canada'
```

```
train['fully_cleaned']=train.clean_text.apply(lambda x: preprocess(x))
```

```
test['fully_cleaned']=test.clean_text.apply(lambda x: preprocess(x))
```

```
train.head()
```

	id	keyword	location	text	target	mentions	hashtags	links	clean_text
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M...	1	none	earthquake	none	Our Deeds are the Reason of this #earthquake M...
				Forest fire near La					Forest fire near La

Feature Engineering

```
def create_stat(df):
    # Tweet length
    df['text_len']=df.clean_text.apply(len)
    df['word_count']=df.clean_text.apply(lambda x:len(x.split()))
    df['stopword_count']=df.clean_text.apply(lambda x:len([i for i in str(x).lower().split
    df['hashtag_count']=df.hashtags.apply(lambda x:len(x.split()))
```

```
    df['mention_count'] = df['mentions'].apply(lambda x: len(str(x).split()))
    # Punctuation count
    df['punctuation_count'] = df['clean_text'].apply(lambda x: len([i for i in x if i in s
    df['link_count'] = df['links'].apply(lambda x: len(str(x).split()))
    df['caps_count']=df.clean_text.apply(lambda x: len([i for i in x if i.isupper()]))
    # Ratio of uppercase letters
    df['caps_ratio']=df['caps_count'] / df['text_len']

    return df


train_data = create_stat(train)
test_data = create_stat(test)

print(train_data.shape, test_data.shape)
```

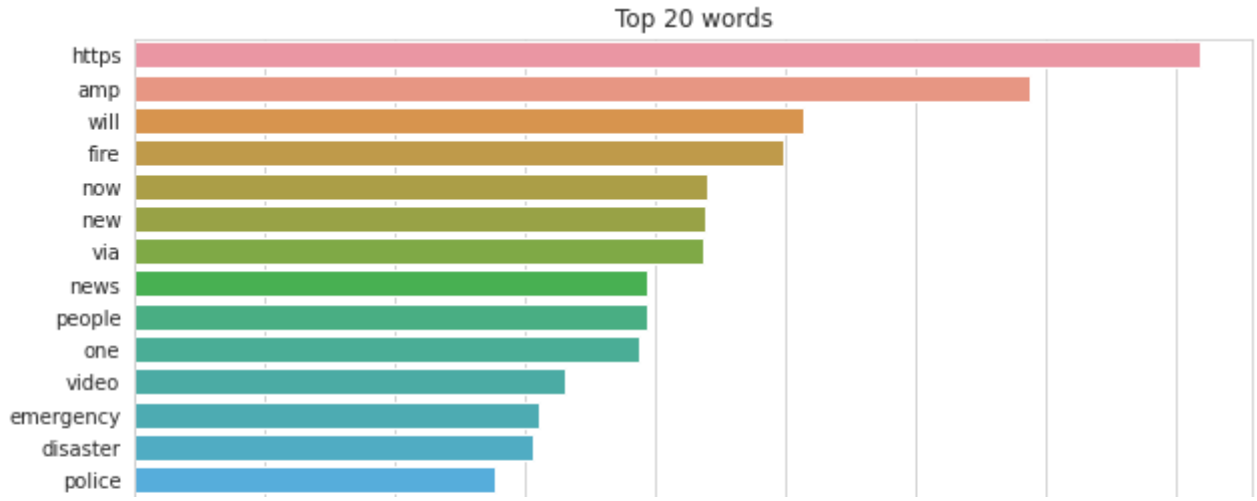
```
(7613, 19) (3263, 18)
```

```
train_data.corr()['target'].sort_values()
```

```
mention_count       -0.049654
caps_ratio          -0.015365
punctuation_count   -0.012535
word_count           0.017081
link_count           0.020244
caps_count           0.027808
hashtag_count        0.032853
id                   0.060781
text_len             0.100721
target               1.000000
stopword_count            NaN
Name: target, dtype: float64
```

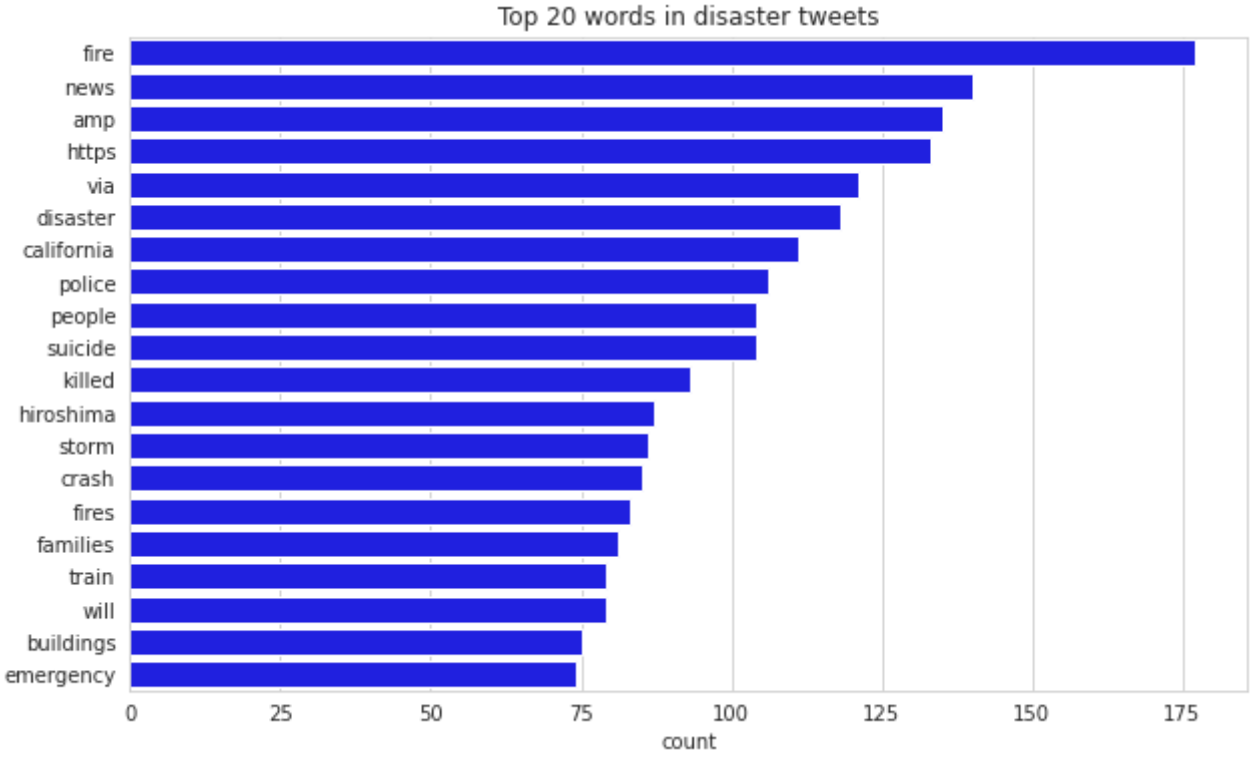
```
"""
Most Frequent Words amnd Bigrams
"""
nltk.download('punkt')
stopwords=set(STOPWORDS)
word_freq=FreqDist(w for w in word_tokenize(' '.join(train.text).lower() )if w not in stop
df_word_freq=pd.DataFrame.from_dict(word_freq,columns=['count'],orient='index')
top20words=df_word_freq.sort_values('count',ascending=False).head(20)
plt.figure(figsize=(10,6))
sns.barplot(top20words['count'],top20words.index)
plt.title('Top 20 words')
plt.show()
```

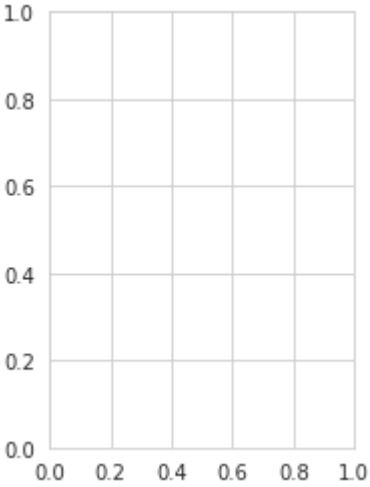
```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

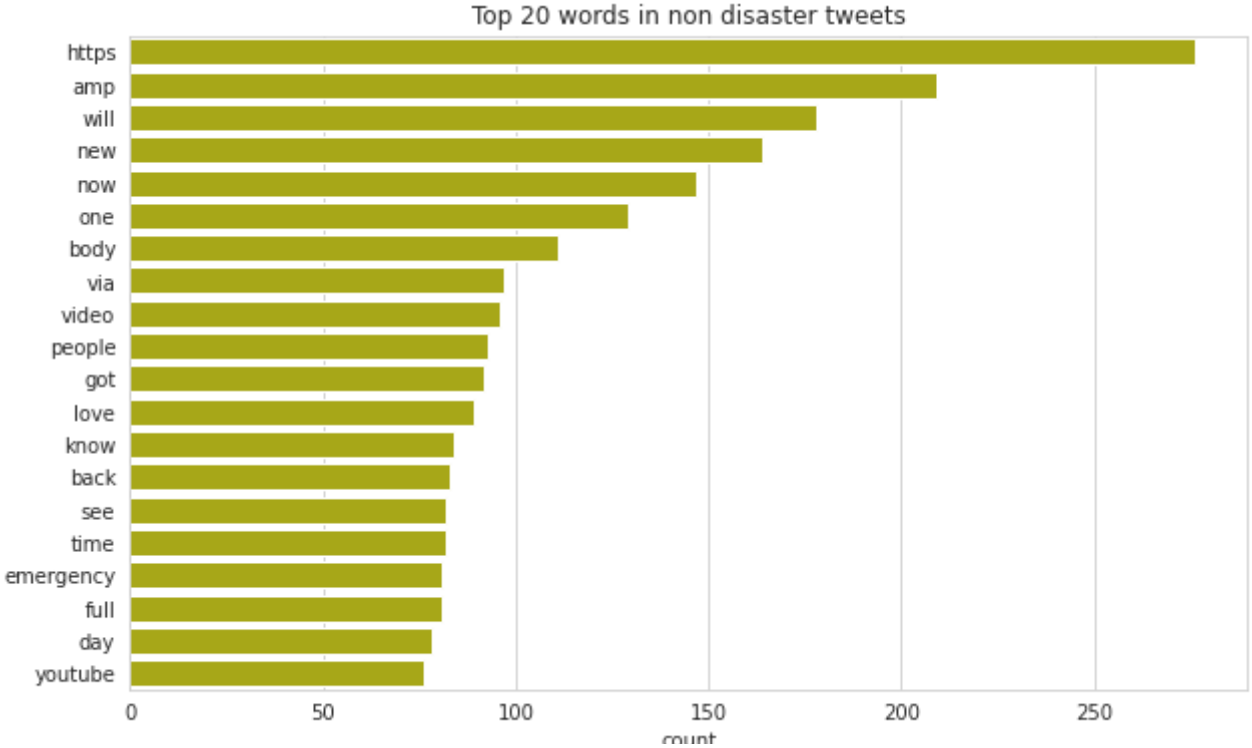



```
"""
Most Frequent Words amnd Bigrams
"""
plt.figure(figsize=(10,6))
plt.tight_layout()
plt.subplot(1,2,1)
freq_pos=FreqDist(w for w in word_tokenize(' '.join(train.loc[train.target==1,'text']).low
df_freq_pos=pd.DataFrame.from_dict(freq_pos,columns=['count'],orient='index')
top20words=df_freq_pos.sort_values('count',ascending=False).head(20)
plt.figure(figsize=(10,6))
sns.barplot(top20words['count'],top20words.index,color='b')
plt.title('Top 20 words in disaster tweets')
plt.show()
plt.tight_layout()
plt.subplot(1,2,2)
freq_neg=FreqDist(w for w in word_tokenize(' '.join(train.loc[train.target==0,'text']).low
df_freq_neg=pd.DataFrame.from_dict(freq_neg,columns=['count'],orient='index')
top20words=df_freq_neg.sort_values('count',ascending=False).head(20)
plt.figure(figsize=(10,6))
sns.barplot(top20words['count'],top20words.index,color='y')
plt.title('Top 20 words in non disaster tweets')
plt.show()
```

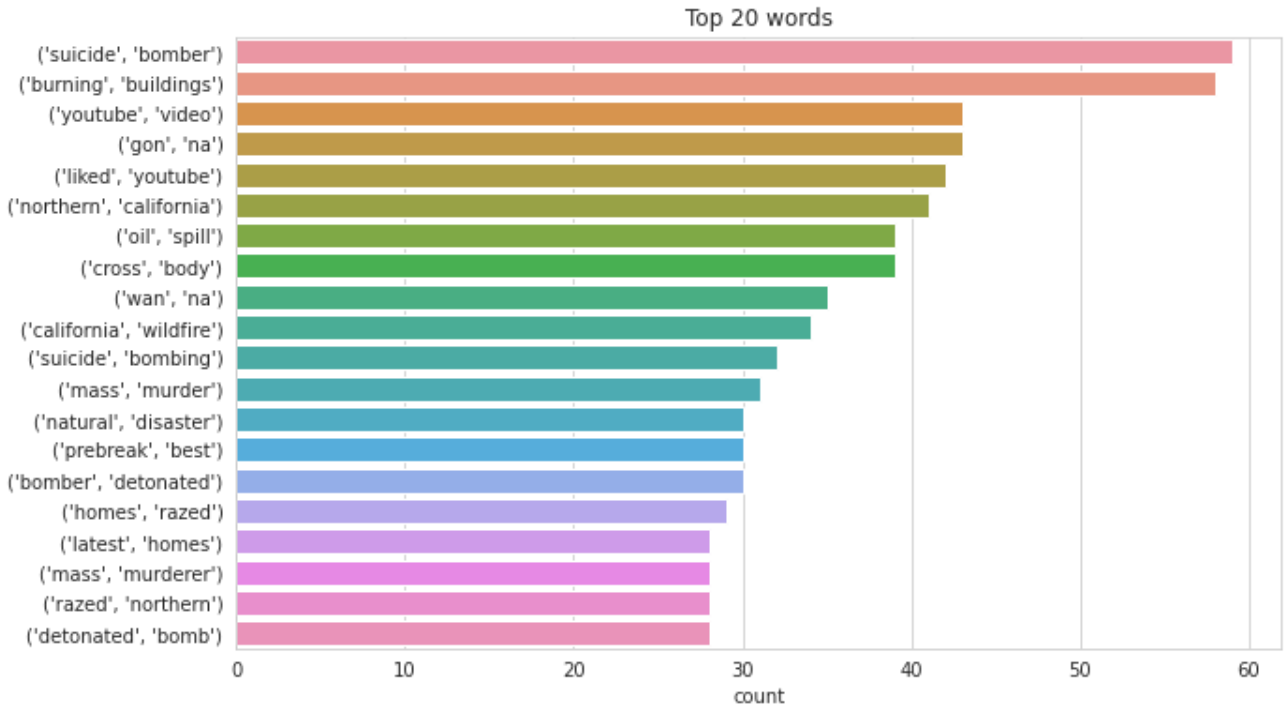

0.0
0.0
0.2
0.4
0.6
0.8
1.0


Top 20 words in disaster tweets
fire
news
amp
https
via
disaster
california
police
people
suicide
killed
hiroshima
storm
crash
fires
families
train
will
buildings
emergency
0
25
50
75
100
125
150
175
count


1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

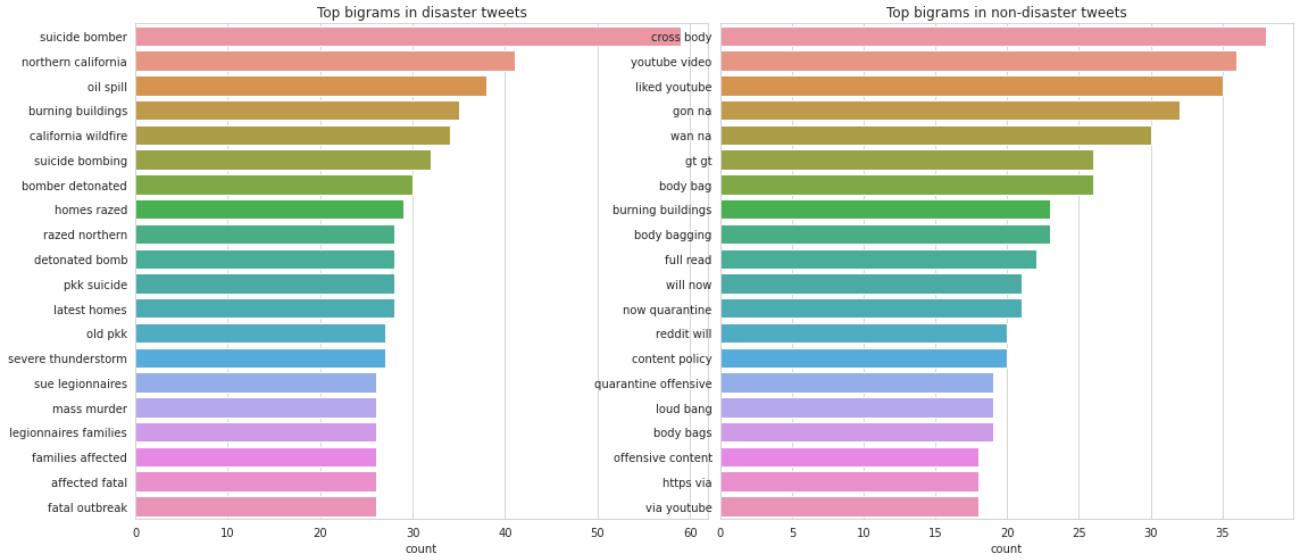

Top 20 words in non disaster tweets
https
amp
will
new
now
one
body
via
video
people
got
love
know
back
see
time
emergency
full
day
youtube
0
50
100
150
200
250
count

```
#bigrams
bigrams1=bigrams(w for w in word_tokenize(' '.join(train.text).lower() )if w not in stopwo
word_freq=FreqDist([b for b in bigrams1])
df_word_freq=pd.DataFrame.from_dict(word_freq,columns=['count'],orient='index')
top20words=df_word_freq.sort_values('count',ascending=False).head(20)
plt.figure(figsize=(10,6))
sns.barplot(top20words['count'],top20words.index)
plt.title('Top 20 words')
plt.show()
```




```
# Bigrams

plt.figure(figsize=(16,7))
plt.tight_layout()
plt.subplot(1,2,1)
bigram_d = list(bigrams([w for w in word_tokenize(' '.join(train.loc[train.target==1, 'tex
              (w not in stopwords) & (w.isalpha())]))
d_fq = FreqDist(bg for bg in bigram_d)
bgdf_d = pd.DataFrame.from_dict(d_fq, orient='index', columns=['count'])
bgdf_d.index = bgdf_d.index.map(lambda x: ' '.join(x))
bgdf_d = bgdf_d.sort_values('count',ascending=False)
sns.barplot(bgdf_d.head(20)['count'], bgdf_d.index[:20])
plt.title('Top bigrams in disaster tweets')

plt.tight_layout()
plt.subplot(1,2,2)
```

```
plt.subplot(1,2,2)
bigram_nd = list(bigrams([w for w in word_tokenize(' '.join(train.loc[train.target==0, 'te
             (w not in stopwords) & (w.isalpha())]))
nd_fq = FreqDist(bg for bg in bigram_nd)
bgdf_nd = pd.DataFrame.from_dict(nd_fq, orient='index', columns=['count'])
bgdf_nd.index = bgdf_nd.index.map(lambda x: ' '.join(x))
bgdf_nd = bgdf_nd.sort_values('count',ascending=False)
sns.barplot(bgdf_nd.head(20)['count'], bgdf_nd.index[:20])
plt.title('Top bigrams in non-disaster tweets')
plt.show()
```



Analyse Missing values

```
train.isna().sum()
```

```
id                0
keyword          61
location       2533
text              0
target            0
mentions          0
hashtags          0
links             0
clean_text        0
fully_cleaned     0
text_len          0
word_count        0
```

```
stopword_count          0
hashtag_count           0
mention_count           0
punctuation_count       0
link_count              0
caps_count              0
caps_ratio              0
dtype: int64
```

```
train.keyword.value_counts()
```

```
fatalities               45
armageddon               42
deluge                   42
harm                     41
sinking                  41
                         ..
forest%20fire            19
epicentre                12
threat                   11
inundation               10
radiation%20emergency     9
Name: keyword, Length: 221, dtype: int64
```

```
train.keyword.unique()
```

```
array([nan, 'ablaze', 'accident', 'aftershock', 'airplane%20accident',
       'ambulance', 'annihilated', 'annihilation', 'apocalypse',
       'armageddon', 'army', 'arson', 'arsonist', 'attack', 'attacked',
       'avalanche', 'battle', 'bioterror', 'bioterrorism', 'blaze',
       'blazing', 'bleeding', 'blew%20up', 'blight', 'blizzard', 'blood',
       'bloody', 'blown%20up', 'body%20bag', 'body%20bagging',
       'body%20bags', 'bomb', 'bombed', 'bombing', 'bridge%20collapse',
       'buildings%20burning', 'buildings%20on%20fire', 'burned',
       'burning', 'burning%20buildings', 'bush%20fires', 'casualties',
       'casualty', 'catastrophe', 'catastrophic', 'chemical%20emergency',
       'cliff%20fall', 'collapse', 'collapsed', 'collide', 'collided',
       'collision', 'crash', 'crashed', 'crush', 'crushed', 'curfew',
       'cyclone', 'damage', 'danger', 'dead', 'death', 'deaths', 'debris',
       'deluge', 'deluged', 'demolish', 'demolished', 'demolition',
       'derail', 'derailed', 'derailment', 'desolate', 'desolation',
       'destroy', 'destroyed', 'destruction', 'detonate', 'detonation',
       'devastated', 'devastation', 'disaster', 'displaced', 'drought',
       'drown', 'drowned', 'drowning', 'dust%20storm', 'earthquake',
       'electrocute', 'electrocuted', 'emergency', 'emergency%20plan',
       'emergency%20services', 'engulfed', 'epicentre', 'evacuate',
       'evacuated', 'evacuation', 'explode', 'exploded', 'explosion',
       'eyewitness', 'famine', 'fatal', 'fatalities', 'fatality', 'fear',
       'fire', 'fire%20truck', 'first%20responders', 'flames',
       'flattened', 'flood', 'flooding', 'floods', 'forest%20fire',
       'forest%20fires', 'hail', 'hailstorm', 'harm', 'hazard',
       'hazardous', 'heat%20wave', 'hellfire', 'hijack', 'hijacker',
       'hijacking', 'hostage', 'hostages', 'hurricane', 'injured',
       'injuries', 'injury', 'inundated', 'inundation', 'landslide',
       'lava', 'lightning', 'loud%20bang', 'mass%20murder',
       'mass%20murderer', 'massacre', 'mayhem', 'meltdown', 'military',
       'mudslide', 'natural%20disaster', 'nuclear%20disaster',
       'nuclear%20reactor', 'obliterate', 'obliterated', 'obliteration',
       'oil%20spill', 'outbreak', 'pandemonium', 'panic', 'panicking',
```

```
       'police', 'quarantine', 'quarantined', 'radiation%20emergency',
       'rainstorm', 'razed', 'refugees', 'rescue', 'rescued', 'rescuers',
       'riot', 'rioting', 'rubble', 'ruin', 'sandstorm', 'screamed',
       'screaming', 'screams', 'seismic', 'sinkhole', 'sinking', 'siren',
       'sirens', 'smoke', 'snowstorm', 'storm', 'stretcher',
       'structural%20failure', 'suicide%20bomb', 'suicide%20bomber',
       'suicide%20bombing', 'sunk', 'survive', 'survived', 'survivors',
       'terrorism', 'terrorist', 'threat', 'thunder', 'thunderstorm',
       'tornado', 'tragedy', 'trapped', 'trauma', 'traumatised',
       'trouble', 'tsunami', 'twister', 'typhoon', 'upheaval',
       'violent%20storm', 'volcano', 'war%20zone', 'weapon', 'weapons',
       'whirlwind', 'wild%20fires', 'wildfire', 'windstorm', 'wounded',
       'wounds', 'wreck', 'wreckage', 'wrecked'], dtype=object)
```

There is '%20' in some keywords .let us remove it

```
train.keyword=train.keyword.str.replace('%20','_')
```

```
train.keyword.unique()
```

```
array([nan, 'ablaze', 'accident', 'aftershock', 'airplane_accident',
       'ambulance', 'annihilated', 'annihilation', 'apocalypse',
       'armageddon', 'army', 'arson', 'arsonist', 'attack', 'attacked',
       'avalanche', 'battle', 'bioterror', 'bioterrorism', 'blaze',
       'blazing', 'bleeding', 'blew_up', 'blight', 'blizzard', 'blood',
       'bloody', 'blown_up', 'body_bag', 'body_bagging', 'body_bags',
       'bomb', 'bombed', 'bombing', 'bridge_collapse',
       'buildings_burning', 'buildings_on_fire', 'burned', 'burning',
       'burning_buildings', 'bush_fires', 'casualties', 'casualty',
       'catastrophe', 'catastrophic', 'chemical_emergency', 'cliff_fall',
       'collapse', 'collapsed', 'collide', 'collided', 'collision',
       'crash', 'crashed', 'crush', 'crushed', 'curfew', 'cyclone',
       'damage', 'danger', 'dead', 'death', 'deaths', 'debris', 'deluge',
       'deluged', 'demolish', 'demolished', 'demolition', 'derail',
       'derailed', 'derailment', 'desolate', 'desolation', 'destroy',
       'destroyed', 'destruction', 'detonate', 'detonation', 'devastated',
       'devastation', 'disaster', 'displaced', 'drought', 'drown',
       'drowned', 'drowning', 'dust_storm', 'earthquake', 'electrocute',
       'electrocuted', 'emergency', 'emergency_plan',
       'emergency_services', 'engulfed', 'epicentre', 'evacuate',
       'evacuated', 'evacuation', 'explode', 'exploded', 'explosion',
       'eyewitness', 'famine', 'fatal', 'fatalities', 'fatality', 'fear',
       'fire', 'fire_truck', 'first_responders', 'flames', 'flattened',
       'flood', 'flooding', 'floods', 'forest_fire', 'forest_fires',
       'hail', 'hailstorm', 'harm', 'hazard', 'hazardous', 'heat_wave',
       'hellfire', 'hijack', 'hijacker', 'hijacking', 'hostage',
       'hostages', 'hurricane', 'injured', 'injuries', 'injury',
       'inundated', 'inundation', 'landslide', 'lava', 'lightning',
       'loud_bang', 'mass_murder', 'mass_murderer', 'massacre', 'mayhem',
       'meltdown', 'military', 'mudslide', 'natural_disaster',
       'nuclear_disaster', 'nuclear_reactor', 'obliterate', 'obliterated',
       'obliteration', 'oil_spill', 'outbreak', 'pandemonium', 'panic',
       'panicking', 'police', 'quarantine', 'quarantined',
       'radiation_emergency', 'rainstorm', 'razed', 'refugees', 'rescue',
       'rescued', 'rescuers', 'riot', 'rioting', 'rubble', 'ruin',
       'sandstorm', 'screamed', 'screaming', 'screams', 'seismic',
       'sinkhole', 'sinking', 'siren', 'sirens', 'smoke', 'snowstorm',
       'storm', 'stretcher', 'structural_failure', 'suicide_bomb',
       'suicide_bomber', 'suicide_bombing', 'sunk', 'survive', 'survived',
```

```
            'survivors', 'terrorism', 'terrorist', 'threat', 'thunder',
            'thunderstorm', 'tornado', 'tragedy', 'trapped', 'trauma',
            'traumatised', 'trouble', 'tsunami', 'twister', 'typhoon',
            'upheaval', 'violent_storm', 'volcano', 'war_zone', 'weapon',
            'weapons', 'whirlwind', 'wild_fires', 'wildfire', 'windstorm',
            'wounded', 'wounds', 'wreck', 'wreckage', 'wrecked'], dtype=object)
```

```
test.keyword=test.keyword.str.replace('%20','_')
```

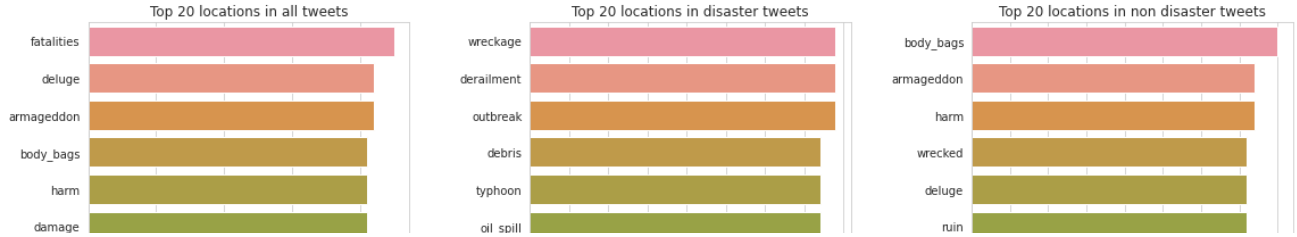
```
train.location.value_counts()
```

```
     USA                                104
     New York                            71
     United States                       50
     London                              45
     Canada                              29
                                        ...
     Reading UK                           1
     #EngleWood CHICAGO                   1
     Salt Lake City, Utah                 1
     Bandar Lampung, Indonesia            1
     Center for Domestic Preparedness     1
     Name: location, Length: 3341, dtype: int64
```

Since some of the locations are repeated, this will require some bit of cleaning.

```
# Replacing the ambigious locations name with Standard names
for i in [train,test]:
  i['location'].replace({'United States':'USA',
                         'New York':'USA',
                          "London":'UK',
                          "Los Angeles, CA":'USA',
                          "Washington, D.C.":'USA',
                          "California":'USA',
                           "Chicago, IL":'USA',
                           "Chicago":'USA',
                          "New York, NY":'USA',
                          "California, USA":'USA',
                          "FLorida":'USA',
                          "Nigeria":'Africa',
                          "Kenya":'Africa',
                          "Everywhere":'Worldwide',
                          "San Francisco":'USA',
                          "Florida":'USA',
                          "United Kingdom":'UK',
                          "Los Angeles":'USA',
                          "Toronto":'Canada',
                          "San Francisco, CA":'USA',
                          "NYC":'USA',
                          "Seattle":'USA',
                          "Earth":'Worldwide',
                          "Ireland":'UK',
                          "London, England":'UK'
```

```
                                    "London, England":'UK',
                                    "New York City":'USA',
                                    "Texas":'USA',
                                    "London, UK":'UK',
                                    "Atlanta, GA":'USA',
                                    "Mumbai":"India",
                                    "304":"US"},inplace=True)


plt.figure(figsize=(16,10))
plt.tight_layout()
plt.subplot(1,3,1)
plt.title("Top 20 locations in all tweets")
sns.barplot(y=train.keyword.value_counts()[:20].index,x=train.keyword.value_counts()[:20],
plt.tight_layout()
plt.subplot(1,3,2)
plt.title("Top 20 locations in disaster tweets")
sns.barplot(y=train[train.target==1].keyword.value_counts()[:20].index,x=train[train.targe
plt.tight_layout()
plt.subplot(1,3,3)
plt.title("Top 20 locations in non disaster tweets")
sns.barplot(y=train[train.target==0].keyword.value_counts()[:20].index,x=train[train.targe
plt.show()
```



Observations

1) In whole training data 'fatalities' keyword is highly seen.

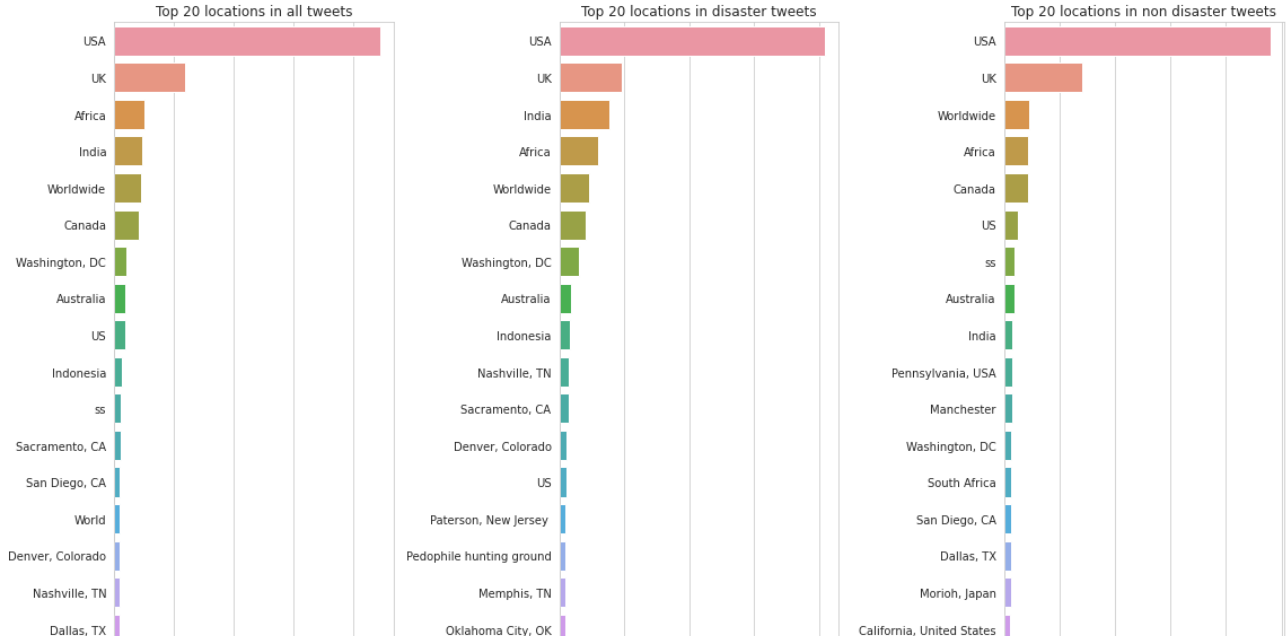
2) In disaster tweets,outbreak, wreckage,derailment these are most repeated keywords.

3) In non-disaster tweets,body%20bags is the most repeated keyword.

4) In disaster tweets, missing value will be filled by 'derailment' keyword.

5)In non-disaster tweets, missing value will be filled by 'body_bags' keyword.


```
plt.figure(figsize=(16,10))
plt.tight_layout()
plt.subplot(1,3,1)
plt.title("Top 20 locations in all tweets")
sns.barplot(y=train.location.value_counts()[:20].index,x=train.location.value_counts()[:20
plt.tight_layout()
plt.subplot(1,3,2)
plt.title("Top 20 locations in disaster tweets")
sns.barplot(y=train[train.target==1].location.value_counts()[:20].index,x=train[train.targ
plt.tight_layout()
plt.subplot(1,3,3)
plt.title("Top 20 locations in non disaster tweets")
sns.barplot(y=train[train.target==0].location.value_counts()[:20].index,x=train[train.targ
plt.show()
```



- In whole training data, Highly repeated locations are USA and UK where USA is repeated more than 400 times and UK is repeated more than 100 times in train dataset.
- In disaster and non-disaster tweets,USA is repeated more than 200 times.
- In disaster and non-disaster tweets, missing values will be filled by 'USA' location.

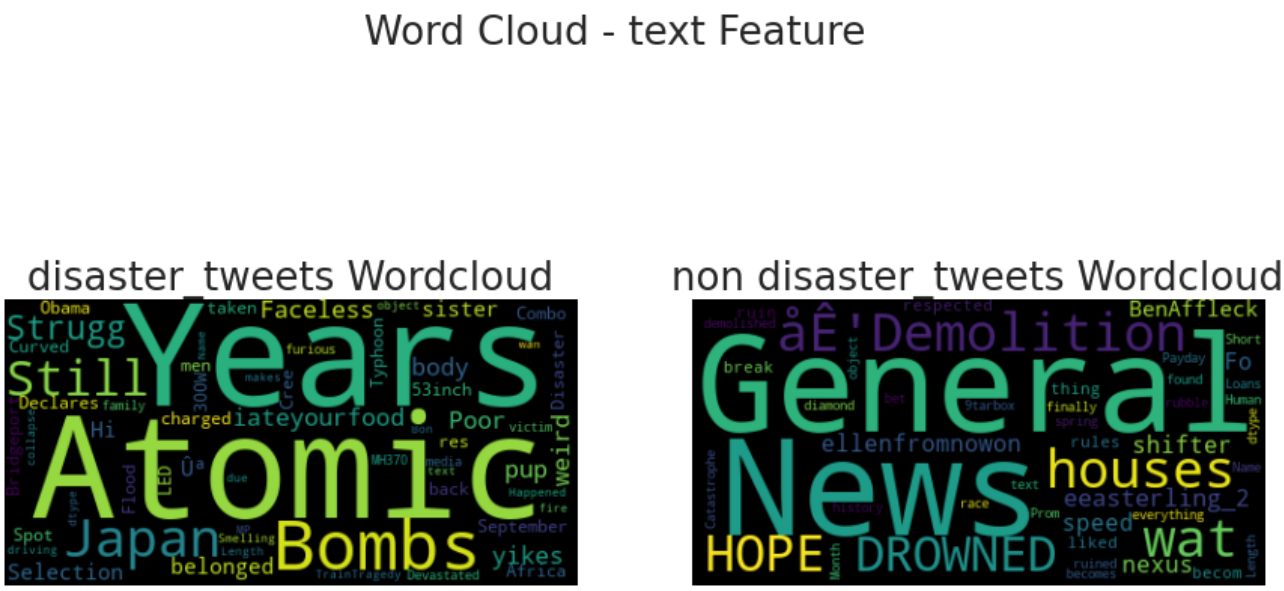
```
dis_tweets=train[train.target==1]
non_dis_tweets=train[train.target==0]
dis_tweets.keyword.fillna('wreckage',inplace=True)
non_dis_tweets.keyword.fillna('body_bags',inplace=True)


test.keyword.fillna('body_bags',inplace=True)


train=pd.concat([dis_tweets,non_dis_tweets])


train['location'].fillna('USA',inplace = True)
test['location'].fillna('USA',inplace = True)
```

Exploring the 'text' column

```
#https://www.kaggle.com/ekhtiar/unintended-eda-with-tutorial-notes
from wordcloud import WordCloud
def generate_word_cloud(identity, disaster_tweets, non_disaster_tweets):
  # convert stop words to sets as required by the wordcloud library

  wc_toxic=WordCloud(stopwords=stopwords,max_font_size=100,max_words=100,background_color=
  wc_nontoxic=WordCloud(stopwords=stopwords,max_font_size=100,max_words=100,background_col
  # draw the two wordclouds side by side using subplot
  fig = plt.figure(figsize=[15,8])
  fig.add_subplot(1,2,1).set_title("disaster_tweets Wordcloud", fontsize=26)
  plt.imshow(wc_toxic,interpolation='bilinear')
```

```
  plt.axis('off')
  fig.add_subplot(1,2,2).set_title("non disaster_tweets Wordcloud", fontsize=26)
  plt.imshow(wc_nontoxic,interpolation='bilinear')
  plt.axis('off')
  plt.subplots_adjust(top=0.85)
  plt.suptitle('Word Cloud - {} Feature'.format(identity), size = 26)
  plt.show()
```

```
generate_word_cloud('text',train[train.target==1]['text'].sample(3000),train[train.target=
```



Observations:

- In disaster text,more frequent words are accident ,Latest
- In non_disaster text,more frequent words are Burned,sister

Count number of positive and negative words in each comment

https://gist.github.com/mkulakowski2/4289441

https://gist.github.com/mkulakowski2/4289437

```
from tqdm.notebook import tqdm
tqdm.pandas()
from textblob import TextBlob, Word, Blobber
```

```
pos_path='./positive-words.txt'
neg_path='./negative-words.txt'
def load_file(path):
  fp=open(path,'r')
  all_lines=fp.readlines()
```

```
  words_list=[]
  for line in all_lines:
    words_list.append(line.strip())
  fp.close()
  return words_list

pos_words=load_file(pos_path)
neg_words=load_file(neg_path)

#count  number of positive and negative words in each tweet
def pos_word_count(comment):
  count=0
  for i in comment.split():
    if i in pos_words:
      count+=1
  return count
def neg_word_count(comment):
  count=0
  for i in comment.split():
    if i in neg_words:
      count+=1
  return count


train['pos_word_count']=train.clean_text.apply(pos_word_count)
train['neg_word_count']=train.clean_text.apply(neg_word_count)
test['pos_word_count']=test.clean_text.apply(pos_word_count)
test['neg_word_count']=test.clean_text.apply(neg_word_count)
```

Find the sentiment of each comment

```
TextBlob(train.clean_text.iloc[1]).sentiment[0]
```

```
0.1
```

```
#https://www.pluralsight.com/guides/natural-language-processing-extracting-sentiment-from-
```

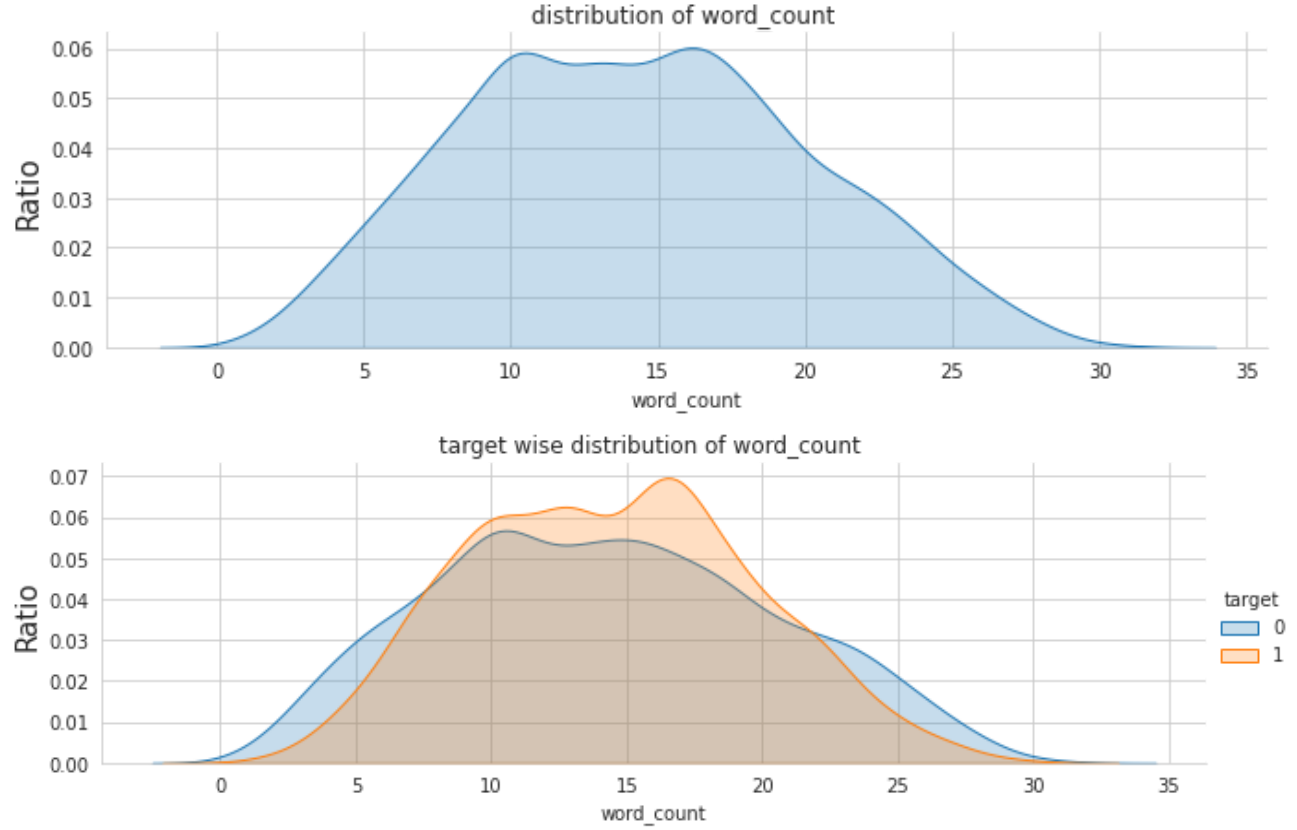
```
%%time
sentiment_count=[]
for i in train.clean_text.values:
  sentiment_count.append(TextBlob(i).sentiment[0])
train['sentiment']=sentiment_count
sentiment_count=[]
for i in test.clean_text.values:
  sentiment_count.append(TextBlob(i).sentiment[0])
test['sentiment']=sentiment_count
```

```
CPU times: user 4.59 s, sys: 1.07 ms, total: 4.59 s
Wall time: 4.59 s
```

Univariate Analysis: word_count feature

```
plt.figure(figsize=(13,8))
sns.FacetGrid(train,aspect=3).map(sns.kdeplot,'word_count',shade=True).add_legend()
plt.title('distribution of word_count ')
plt.ylabel('Ratio',fontsize=15)
sns.FacetGrid(train,hue='target',aspect=3).map(sns.kdeplot,'word_count',shade=True).add_le
plt.title('target wise distribution of word_count ')
plt.ylabel('Ratio',fontsize=15)
plt.show()
```

```
<Figure size 936x576 with 0 Axes>
```



Observation :

1)Many tweets are with word count of 8-13.

2) Distribution of disaster tweets is peaked than distribution of non-disaster tweets.

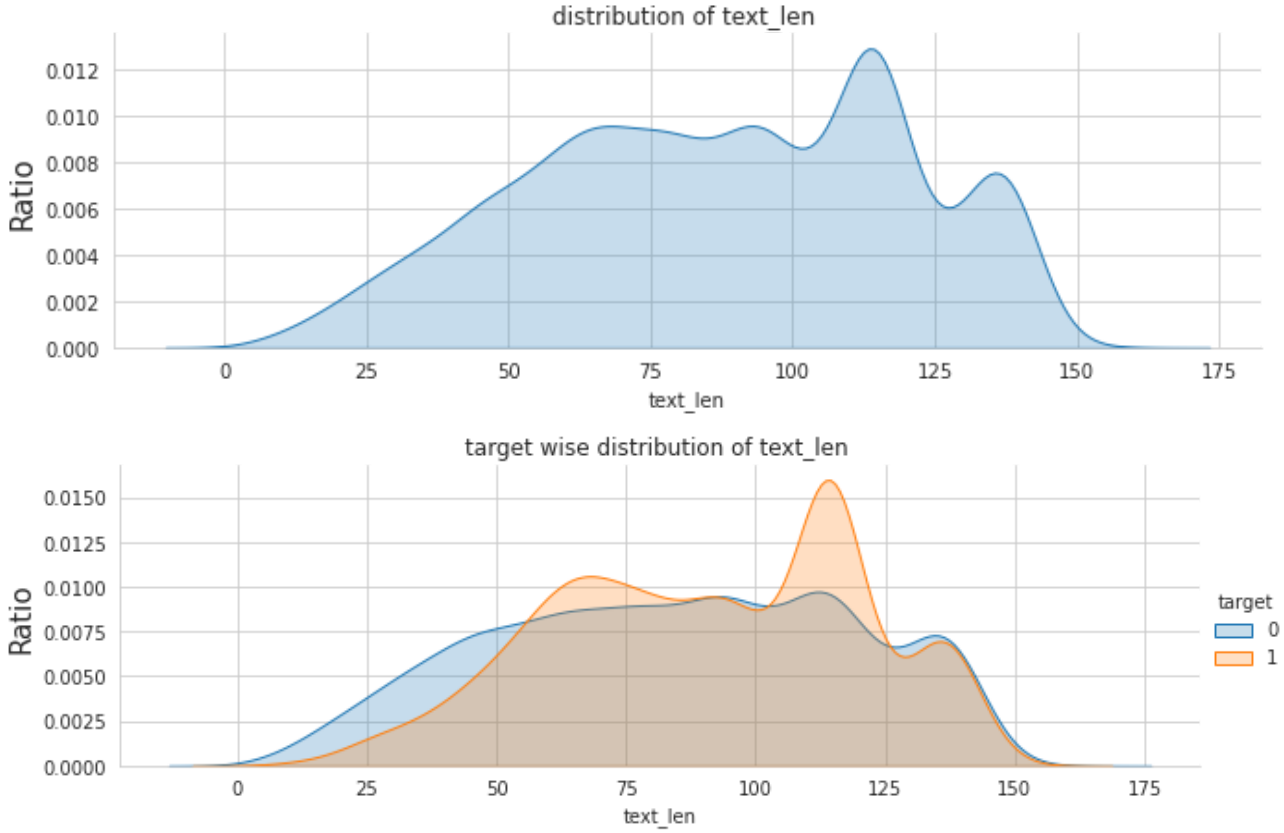
3)Distribution of both classes is overlapping.

Univariate Analysis: text_len feature

```
plt.figure(figsize=(13,8))
sns.FacetGrid(train,aspect=3).map(sns.kdeplot,'text_len',shade=True).add_legend()
plt.title('distribution of text_len ')
plt.ylabel('Ratio',fontsize=15)
sns.FacetGrid(train,hue='target',aspect=3).map(sns.kdeplot,'text_len',shade=True).add_lege
plt.title('target wise distribution of text_len ')
```

```
plt.ylabel('Ratio',fontsize=15)
plt.show()
```

```
<Figure size 936x576 with 0 Axes>
```



Observation :

1)Many tweets are with char count of 75-85.

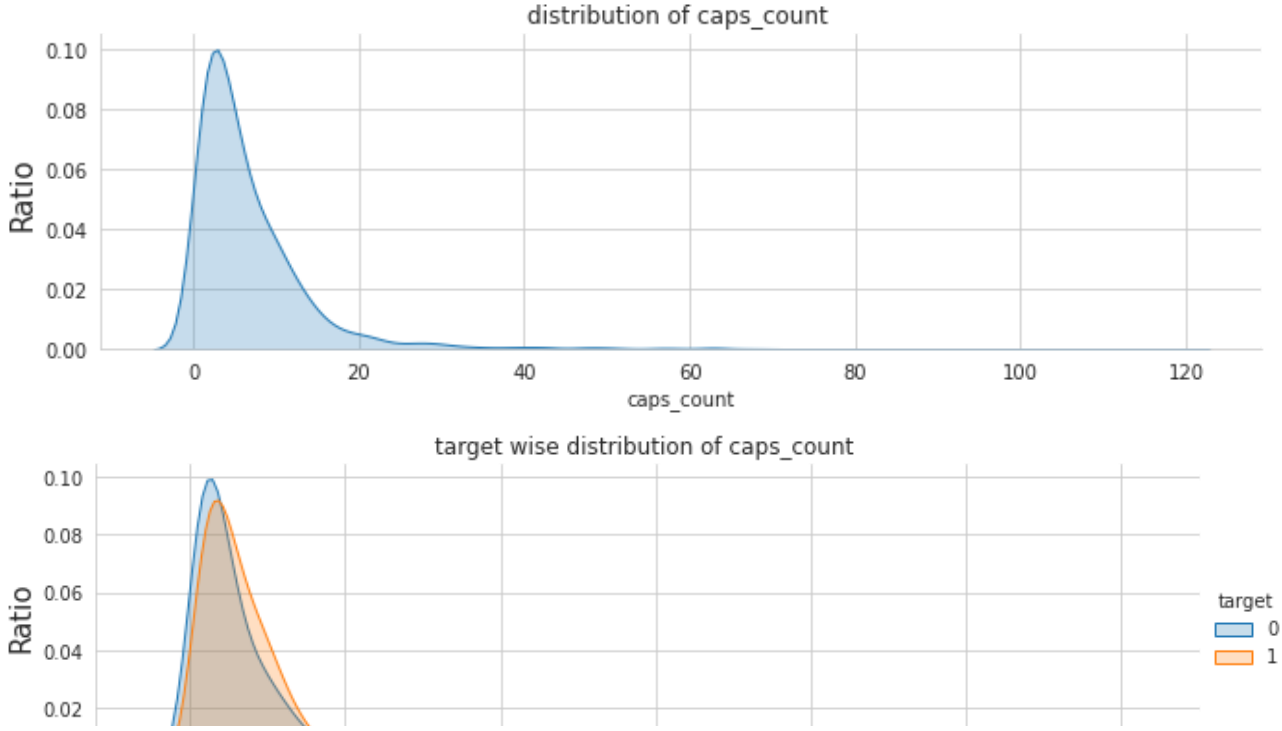
2) Distribution of disaster tweets is peaked than distribution of non-disaster tweets.

3)Distribution of both classes is overlapping.

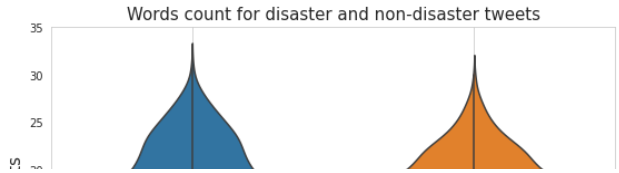
Univariate Analysis: caps_count feature

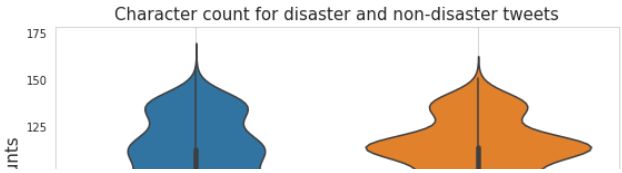
```
plt.figure(figsize=(13,8))
sns.FacetGrid(train,aspect=3).map(sns.kdeplot,'caps_count',shade=True).add_legend()
plt.title('distribution of caps_count ')
plt.ylabel('Ratio',fontsize=15)
sns.FacetGrid(train,hue='target',aspect=3).map(sns.kdeplot,'caps_count',shade=True).add_le
plt.title('target wise distribution of caps_count ')
plt.ylabel('Ratio',fontsize=15)
plt.show()
```

```
<Figure size 936x576 with 0 Axes>
```




```
#getting violin plot on train data with word_count feature
plt.figure(figsize=(20,6))
plt.subplot(1,2,1)
sns.violinplot(x = 'target', y = 'word_count', data = train[0:])
plt.xticks([0,1],('disaster tweets  ','non-disaster tweets'), fontsize=15)
plt.ylabel('Word counts', fontsize=15)
plt.title('Words count for disaster and non-disaster tweets', fontsize=15)
plt.grid()

plt.subplot(1,2,2)
sns.violinplot(x = 'target', y = 'text_len', data = train[0:])
plt.xticks([0,1],('disaster tweets  ','non-disaster tweets'), fontsize=15)
plt.ylabel('Character counts',fontsize=15)
plt.title('Character count for disaster and non-disaster tweets', fontsize=15)
plt.grid()
```





Observation

This plot giving more clear picture than distribution plot. For Disaster tweets word count distribution is flattened at count 9-13 and In character count distribution is flattened at count 75-90.

For non-disaster tweets word count distribution is peaked at count 12 and In character count distribution is flattened at count 85.

Average word count of disaster tweets is 10 and for non-disaster tweets its 12.

Average char count of disaster tweets is 65 and for non-disaster tweets its 75.

Distributions of disaster and non-disaster tweets are almost same

```
plt.figure(figsize=(13,8))
sns.FacetGrid(train,aspect=3).map(sns.kdeplot,'sentiment',shade=True).add_legend()
plt.title('distribution of sentiment ')
plt.ylabel('Ratio',fontsize=15)
sns.FacetGrid(train,hue='target',aspect=3).map(sns.kdeplot,'sentiment',shade=True).add_leg
plt.title('target wise distribution of sentiment ')
plt.ylabel('Ratio',fontsize=15)
plt.show()
```

```
<Figure size 936x576 with 0 Axes>
```

Observation:

1) More than 90% data is neutral.

2) Most of the neutral tweets are from disaster category.

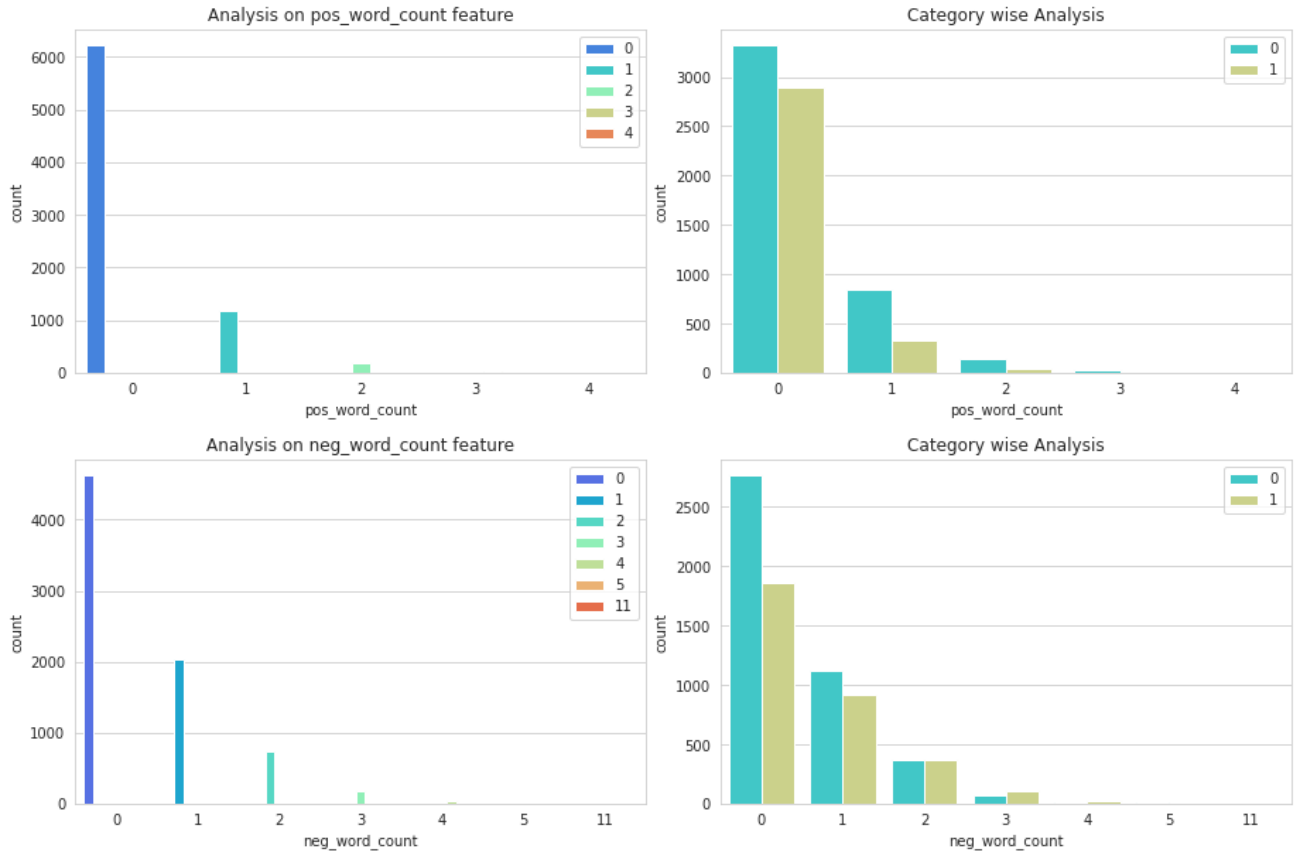
3)Neutrality ratio of non-disaster tweets are half of the disaster tweets.

Univariate Analysis: positive and negative words count of each comment

```
train.pos_word_count.value_counts()
```

```
0    6218
1    1170
2     190
3      30
4       5
Name: pos_word_count, dtype: int64
```

```
cat_cols=['pos_word_count','neg_word_count']
for col in cat_cols:
  plt.figure(figsize=(13,8))
  plt.tight_layout(h_pad=2,w_pad=3)
  plt.subplot(2,2,1)
  plt.tight_layout(h_pad=2,w_pad=3)
  sns.set_style('whitegrid')
  plt.title("Analysis on {0} feature".format(col))
  sns.countplot(x=col,hue=col,data=train,palette='rainbow')
  plt.legend(loc=1)

  plt.subplot(2,2,2)
  plt.tight_layout(h_pad=2,w_pad=3)
  sns.set_style('whitegrid')
  plt.title("Category wise Analysis".format(col))
  sns.countplot(x=col,hue='target',data=train,palette='rainbow')
  plt.legend(loc=1)
```



Observation:

pos_word_count Feature:

1)Here tweets with 0 positive words are more and some tweets included with 1 or 2 positive words. neg_word_count Feature:

1)Here tweets with 0 or 1 negative words are more and some tweets included with 2-4 negative words.

Encoding categorical feature : keyword

```
vec=CountVectorizer(min_df=5)
key_vec=vec.fit_transform(train.keyword)
X_train_key=pd.DataFrame(key_vec.toarray(),columns=vec.get_feature_names())
key_vec_t=vec.transform(test.keyword)
X_test_key=pd.DataFrame(key_vec_t.toarray(),columns=vec.get_feature_names())
X_train_key.head()
```

	ablaze	accident	aftershock	airplane_accident	ambulance	annihilated	annihilat
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	

```
vec=CountVectorizer(min_df=5)
men_vec=vec.fit_transform(train.mentions)
X_train_men=pd.DataFrame(men_vec.toarray(),columns=vec.get_feature_names())
men_vec_t=vec.transform(test.mentions)
X_test_men=pd.DataFrame(men_vec_t.toarray(),columns=vec.get_feature_names())
X_train_men.head()
```

	ap	arianagrande	change	djicemoon	emmerdale	foxnews	invalid	justinbieber	m
0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	

```
vec=CountVectorizer(min_df=5)
hash_vec=vec.fit_transform(train.hashtags)
X_train_hash=pd.DataFrame(hash_vec.toarray(),columns=vec.get_feature_names())
hash_vec_t=vec.transform(test.hashtags)
X_test_hash=pd.DataFrame(hash_vec_t.toarray(),columns=vec.get_feature_names())
X_train_hash.head()
```

	abstorm	africa	afterlife	allah	animalrescue	antioch	armageddon	art	bb17	b
0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	

5 rows × 107 columns

```
vec=CountVectorizer(min_df=5,analyzer='word',token_pattern=r'https?://\S+')
links_vec=vec.fit_transform(train.links)
X_train_link=pd.DataFrame(links_vec.toarray(),columns=vec.get_feature_names())
links_vec_t=vec.transform(test.links)
X_test_link=pd.DataFrame(links_vec_t.toarray(),columns=vec.get_feature_names())
X_train_link.head()
```

	http://t.co/cybksxhf7d	http://t.co/encmhz6y34	http://t.co/ksawlyux02	http://t.
0	0	0	0	
1	0	0	0	
2	0	0	0	

```
train.head()
```

	id	keyword	location	text	target	mentions	hashtags	links	clean_text
0	1	wreckage	USA	Our Deeds are the Reason of this #earthquake M...	1	none	earthquake	none	Our Deeds are the Reason o this #earthquake M..
1	4	wreckage	USA	Forest fire near La Ronge Sask. Canada	1	none	none	none	Forest fire near La Ronge Sask Canada
2	5	wreckage	USA	All residents asked to 'shelter in place' are ...	1	none	none	none	All residents asked to 'shelter in place' are ..
3	6	wreckage	USA	13,000 people receive #wildfires evacuation or...	1	none	wildfires	none	13,000 people receive #wildfires evacuation or..
4	7	wreckage	USA	Just got sent this photo from Ruby #Alaska as ...	1	none	Alaska wildfires	none	Just go sent this photo from Ruby #Alaska as ..

TF-IDF Vectoriser

```
tfidf=TfidfVectorizer(min_df=10,ngram_range=(1,2),stop_words='english')
# Only include >=10 occurrences
# Have unigrams , bigrams,trigrams
text_vec=tfidf.fit_transform(train.clean_text)
X_train_text=pd.DataFrame(text_vec.toarray(),columns=tfidf.get_feature_names())
key_vec_t=tfidf.transform(test.clean_text)
X_test_text=pd.DataFrame(text_vec.toarray(),columns=tfidf.get_feature_names())
X_train_text.head()
```

	00	01	04	05	06	07	08	08 05	08 06	10	100	11	11 year	12	12000	12000 nigerian
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 1691 columns

```
train=train.join(X_train_hash,rsuffix='_hashtag')
train=train.join(X_train_link,rsuffix='_link')
train=train.join(X_train_key,rsuffix='_key')
train=train.join(X_train_men,rsuffix='_men')
train=train.join(X_train_text,rsuffix='_text')
test=test.join(X_test_hash,rsuffix='_hashtag')
test=test.join(X_test_link,rsuffix='_link')
test=test.join(X_test_key,rsuffix='_key')
test=test.join(X_test_men,rsuffix='_men')
test=test.join(X_test_text,rsuffix='_text')
```

```
train.shape,test.shape
```

```
((7613, 2065), (3263, 2064))
```

```
train.head()
```

	id	keyword	location	text	target	mentions	hashtags	links	clean_text
0	1	wreckage	USA	Our Deeds are the Reason of this #earthquake M... Forest fire near La	1	none	earthquake	none	Our Deeds are the Reason o this #earthquake M.. Forest fire near La

```
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
features_to_drop = ['id', 'keyword','location','text','clean_text', 'hashtags','fully_clea
scaler=MinMaxScaler()
X_train=train.drop(columns=features_to_drop+['target'],axis=1)
X_test=test.drop(columns=features_to_drop,axis=1)
y_train=train.target
lr=LogisticRegression(solver='liblinear',random_state=95)# Other solvers have failure to c

pipeline=Pipeline([('scaler',scaler),('lr',lr),])
pipeline.fit(X_train,y_train)
```

```
Pipeline(memory=None,
         steps=[('scaler', MinMaxScaler(copy=True, feature_range=(0, 1))),
                ('lr',
                 LogisticRegression(C=1.0, class_weight=None, dual=False,
                                    fit_intercept=True, intercept_scaling=1,
                                    l1_ratio=None, max_iter=100,
                                    multi_class='auto', n_jobs=None,
                                    penalty='l2', random_state=95,
                                    solver='liblinear', tol=0.0001, verbose=0,
                                    warm_start=False))],
         verbose=False)
```

```
y_test = pipeline.predict(X_test)
submission=pd.read_csv('sample_submission.csv')
submit = submission.copy()
submit.target = y_test
submit.to_csv('submit_lr.csv',index=False)
```

```
print('training accuacy',pipeline.score(X_train,y_train))
```

```
training accuacy 0.7791934848285826
```

```
print('train f1 score',f1_score(y_train,pipeline.predict(X_train)))
```

```
train f1 score 0.72599837000815
```

```
pd.DataFrame(confusion_matrix(y_train,pipeline.predict(X_train)))
```

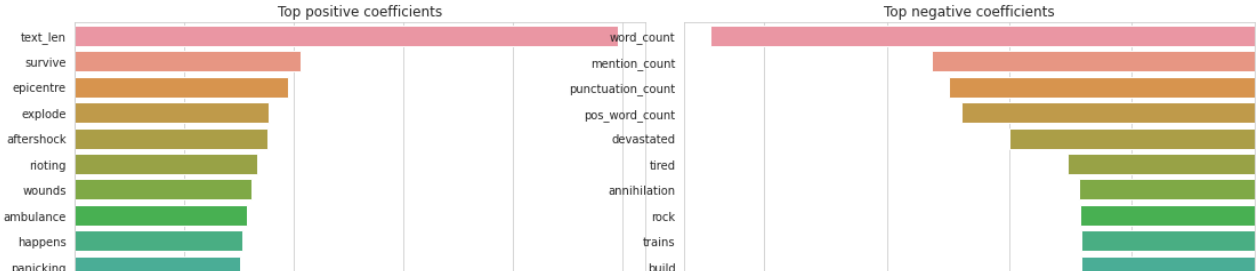
	0	1
0	3705	637
1	1044	2227

Model Evaluation

```
#https://stackoverflow.com/questions/34731421/whats-the-difference-between-kfold-and-shuff
from sklearn.model_selection import cross_val_score,ShuffleSplit
cv=ShuffleSplit(n_splits=5,test_size=0.2,random_state=95)
cv_score=cross_val_score(pipeline,X_train,y_train,scoring='f1',cv=cv)
print('Cross validation F-1 score: %.3f' %np.mean(cv_score))
```

```
Cross validation F-1 score: 0.600
```

```
"""
Feature Selection - Identifying the Top Features
"""
plt.figure(figsize=(16,7))
s1=pd.Series(np.transpose(lr.coef_[0]),index=X_train.columns).sort_values(ascending=False)
s2=pd.Series(np.transpose(lr.coef_[0]),index=X_train.columns).sort_values()[:20]
plt.subplot(121)
plt.tight_layout()
sns.barplot(y=s1.index,x=s1)
plt.title('Top positive coefficients')
plt.subplot(122)
plt.tight_layout()
sns.barplot(y=s2.index,x=s2)
plt.title('Top negative coefficients')
plt.show()
```



Findings: 'text_len' is the top positive coefficient, meaning the keyword column made a good feature hiroshima both as text and hashtag made the top 20 positive coefficients Punctuation count and word_count are among top 20 negative coefficients None of the bigrams made the top features

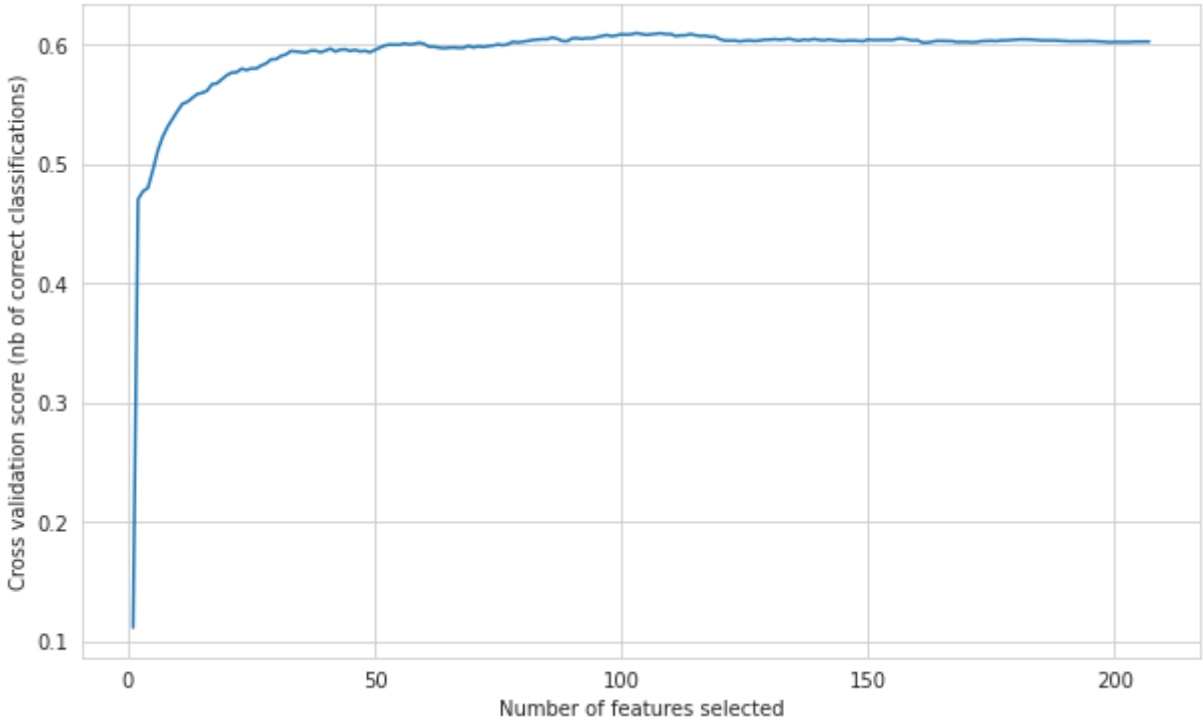

```
"""
step parameter in RFECV corresponds to the (integer) number of features to remove at each
"""

steps=10
rfecv=RFECV(lr,steps,scoring='f1',cv=cv)
p2=Pipeline([('scale',scaler),('rfecv',rfecv),])
p2.fit(X_train,y_train)
```

```
Pipeline(memory=None,
         steps=[('scale', MinMaxScaler(copy=True, feature_range=(0, 1))),
                ('rfecv',
                 RFECV(cv=ShuffleSplit(n_splits=5, random_state=95, test_size=0.2, tr
                       estimator=LogisticRegression(C=1.0, class_weight=None,
                                                    dual=False,
                                                    fit_intercept=True,
                                                    intercept_scaling=1,
                                                    l1_ratio=None, max_iter=100,
                                                    multi_class='auto',
                                                    n_jobs=None, penalty='l2',
                                                    random_state=95,
                                                    solver='liblinear',
                                                    tol=0.0001, verbose=0,
                                                    warm_start=False),
                       min_features_to_select=1, n_jobs=None, scoring='f1',
                       step=10, verbose=0))],
         verbose=False)
```

```
"""
RFECV exposes support_ which is another attribute to find out the features which contribut
In order to find out which features are selected we can use the following code.
"""
selected_features=X_train.columns[rfecv.support_==True]
X1=X_train[selected_features]
X2=X_test[selected_features]
X1.shape
```

```
(7613, 1015)
```

```
plt.figure(figsize=(10,6))
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
plt.show()
```




```
"""
Grid Search CV - Hyperparamater Tuning
"""

grid={"C":np.logspace(-2,2,5), "penalty":["l1","l2"]}
lr_cv = GridSearchCV(LogisticRegression(solver='liblinear', random_state=20), grid, cv=cv,

pipeline_grid = Pipeline([('scale',scaler), ('gridsearch', lr_cv),])

pipeline_grid.fit(X1, y_train)

print("Best parameter: ", lr_cv.best_params_)
print("F-1 score: %.3f" %lr_cv.best_score_)
```

```
     Best parameter:  {'C': 1.0, 'penalty': 'l2'}
     F-1 score: 0.655
```

```
y_test2 = pipeline_grid.predict(X2)
submit2 = submission.copy()
submit2.target = y_test2
submit2.to_csv('submit_lr2.csv',index=False)


from sklearn.naive_bayes import GaussianNB
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

```
scaler=StandardScaler()


nb=GaussianNB()# Other solvers have failure to converge problem

pipeline3=Pipeline([('scaler',scaler),('nb',nb),])
pipeline3.fit(X_train,y_train)
```

```
     Pipeline(memory=None,
              steps=[('scaler',
                      StandardScaler(copy=True, with_mean=True, with_std=True)),
                     ('nb', GaussianNB(priors=None, var_smoothing=1e-09))],
              verbose=False)
```

```
y_test2 = pipeline3.predict(X_test)

submit2 = submission.copy()
submit2.target = y_test2
submit2.to_csv('submit_nb.csv',index=False)


print('train f1 score',f1_score(y_train,pipeline3.predict(X_train)))
print('training accuacy',pipeline3.score(X_train,y_train))
```

```
     train f1 score 0.680184331797235
     training accuacy 0.6353605674504138
```

```
#https://stackoverflow.com/questions/34731421/whats-the-difference-between-kfold-and-shuff
from sklearn.model_selection import cross_val_score,ShuffleSplit
cv=ShuffleSplit(n_splits=10,test_size=0.2,random_state=95)
cv_score2=cross_val_score(pipeline3,X_train,y_train,scoring='f1',cv=cv)
print('Cross validation F-1 score: %.3f' %np.mean(cv_score2))
```

```
     Cross validation F-1 score: 0.612
```