

DTSA-5511 Week 4 - NLP Disaster Tweets Kaggle Mini-Project

A Jupyter notebook with a description of the problem/data, exploratory data analysis (EDA) procedure, analysis (model building and training), result, and discussion/conclusion.

What is NLP?

NLP (Neuro-Linguistic Programming) is the science or art that boasts a unique approach to the enhancement of your communications skills, personal development, as well as psychotherapy. NLP is a powerful method that influences the behavior of the brain using language, among other forms of communication to allow one person to 're-code' the brain's response to stimuli (or its programming).

Problem



Twitter has become an important communication channel in times of emergency. The ubiquitousness of smartphones enables people to announce an emergency they're observing in real-time. Because of this, more agencies are interested in programmatically monitoring Twitter (i.e. disaster relief organizations and news agencies). The challenge of this Kaggle Mini-project is to use NLP (Natural Language Processing) to predict which Tweets are about real disasters and which ones aren't.

Dataset

The dataset was created by the company figure-eight and originally shared on their '[Data For Everyone](#)' Tweet source: <https://twitter.com/AnyOtherAnnaK/status/629195955506708480>

Each sample in the train and test set has the following information:

- The text of a tweet.
- A keyword from that tweet (although this may be blank!).
- The location the tweet was sent from (may also be blank).

1. Exploratory Data Analysis (EDA)

1.1. Importing libraries

Loading libraries required this mini-project

In [44]:

```
# Utility
import pandas as pd
import numpy as np

# Plots
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.ticker import MaxNLocator
import matplotlib.gridspec as gridspec
import matplotlib.patches as mpatches
import plotly.express as px
import seaborn as sns

# EDA
import re
import missingno as msno
from wordcloud import WordCloud
import nltk
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize

# modeling and training
import tensorflow as tf
from keras.preprocessing.text import Tokenizer
from tensorflow.keras.layers import Embedding
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from sklearn.model_selection import train_test_split
from tensorflow.keras import optimizers
from keras.callbacks import ReduceLROnPlateau, EarlyStopping, ModelCheckpoint

import warnings
warnings.filterwarnings("ignore")
```

1.2. Reading data

1.2.1. Train data

Loading train dataset from train.csv file.

In [3]:

```
train_df = pd.read_csv("./data/npl/train.csv")
display(train_df.head(), train_df.describe(include='all'))
```

	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

	id	keyword	location		text	target
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	
	id	keyword	location		text	target
count	7613.000000		7552	5080	7613	7613.000000
unique		NaN	221	3341	7503	NaN
top		NaN	fatalities	USA 11-Year-Old Boy Charged With Manslaughter of T...		NaN
freq		NaN	45	104	10	NaN
mean	5441.934848		NaN	NaN	NaN	0.42966
std	3137.116090		NaN	NaN	NaN	0.49506
min	1.000000		NaN	NaN	NaN	0.00000
25%	2734.000000		NaN	NaN	NaN	0.00000
50%	5408.000000		NaN	NaN	NaN	0.00000
75%	8146.000000		NaN	NaN	NaN	1.00000
max	10873.000000		NaN	NaN	NaN	1.00000

```
In [4]: print('Train dataset contains %d columns and %d rows' %(train_df.shape[0], train_df.sha
Train dataset contains 7613 columns and 5 rows
```

1.2.2. Test data

Loading the test dataset from test.csv file.

```
In [5]: test_df = pd.read_csv("./data/npl/test.csv")
display(test_df.head(), test_df.describe(include='all'))
```

	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

	id	keyword	location	text
count	3263.000000		3237	2158
unique		NaN	221	1602
top		NaN	deluged New York	11-Year-Old Boy Charged With Manslaughter of T...

	id	keyword	location	text
freq	NaN	23	38	3
mean	5427.152927	NaN	NaN	NaN
std	3146.427221	NaN	NaN	NaN
min	0.000000	NaN	NaN	NaN
25%	2683.000000	NaN	NaN	NaN
50%	5500.000000	NaN	NaN	NaN
75%	8176.000000	NaN	NaN	NaN
max	10875.000000	NaN	NaN	NaN

In [6]:

```
print('Test dataset contains %d columns and %d rows' %(test_df.shape[0], test_df.shape[1]))
```

Test dataset contains 3263 columns and 4 rows

1.2.3 Submission data

Loading the submission data from sample_submission.csv file.

In [7]:

```
submission_df = pd.read_csv("./data/npl/sample_submission.csv")
submission_df.head()
```

Out[7]:

	id	target
0	0	0
1	2	0
2	3	0
3	9	0
4	11	0

1.3. Data Inspection

1.3.1. Inspecting for null values

Checking if the train and test dataset contains null values

In [8]:

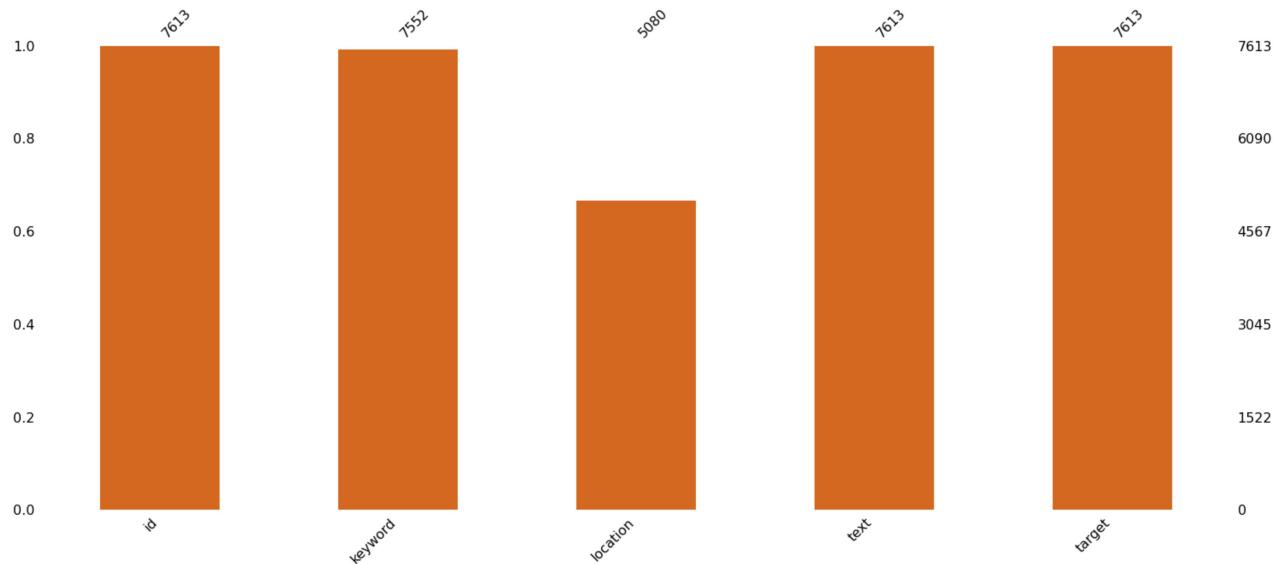
```
# train dataset
train_df.isna().sum()
```

Out[8]:

id	0
keyword	61
location	2533
text	0
target	0
dtype:	int64

```
In [9]: msno.bar(train_df,color = 'chocolate')
plt.title('Missing values in train dataset\n\n',fontsize=30)
plt.show()
```

Missing values in train dataset

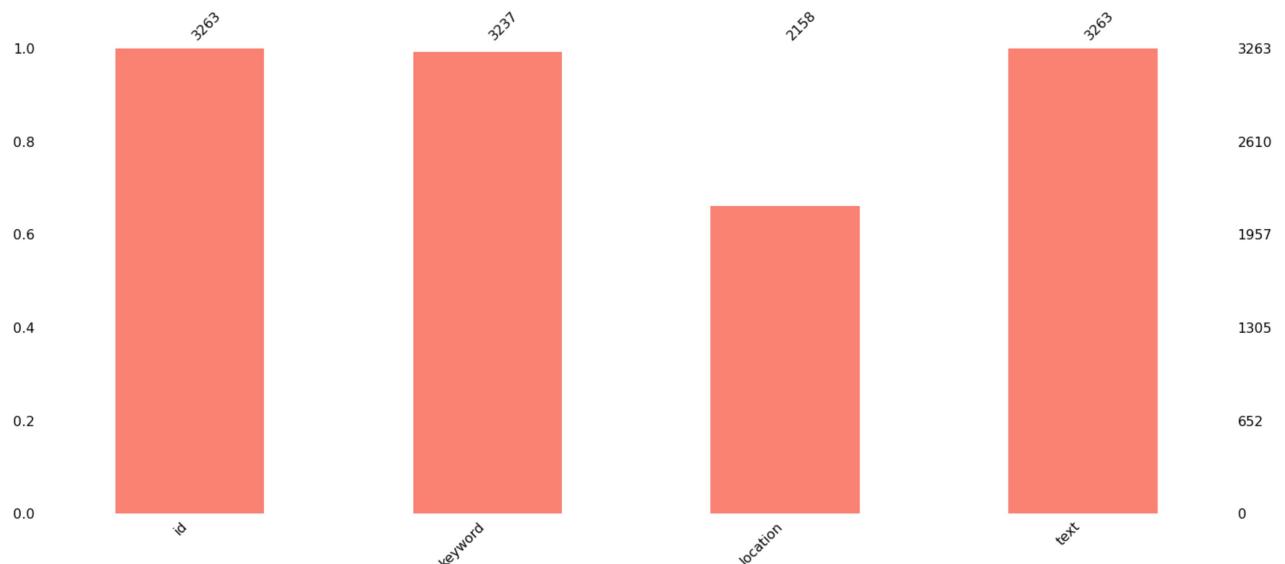


```
In [10]: # test dataset
test_df.isna().sum()
```

```
Out[10]: id      0
keyword    26
location   1105
text       0
dtype: int64
```

```
In [11]: msno.bar(test_df,color = 'salmon')
plt.title('Missing values in test dataset\n\n',fontsize=30)
plt.show()
```

Missing values in test dataset



The plots show that keyword and location have missing value but location has more missing values than keyword on both datasets.

1.3.2. Inspecting the target distribution

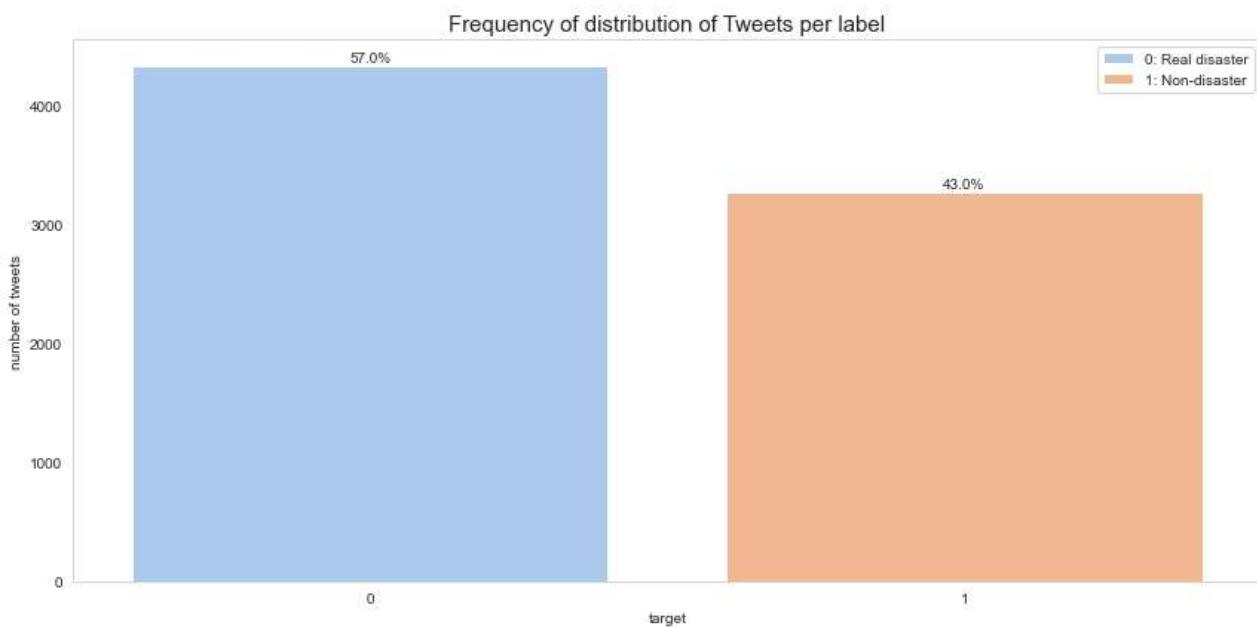
Checking the distribution of the target feature on the train dataset.

In [12]:

```
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(12,6))

ax = sns.countplot(x='target',data=train_df, palette="pastel",hue="target",dodge=False)
ax.grid(False) #remove grid
# Labels
plt.title('Frequency of distribution of Tweets per label',fontsize=15)
plt.ylabel("number of tweets")

# Percentage
total = len(train_df)
for p in ax.patches:
    percentage = f'{100 * p.get_height() / total:.1f}\n'
    x = p.get_x() + p.get_width() / 2
    y = p.get_height()
    ax.annotate(percentage, (x, y), ha='center', va='center')
plt.tight_layout()
# legend
plt.legend(loc='upper right',labels = [ '0: Real disaster', '1: Non-disaster'])
plt.show()
```



The plot shows that there are more tweets with real disasters than non-real ones.

1.3.3. Counting the keywords

Counting on train and test datasets the number of words on keyword feature.

In [13]:

```
# train dataset
kwd_cnt_train = train_df['keyword'].value_counts()
kwd_cnt_train
```

```
Out[13]:
```

fatalities	45
deluge	42
armageddon	42
sinking	41
damage	41
	..
forest%20fire	19
epicentre	12
threat	11
inundation	10
radiation%20emergency	9

Name: keyword, Length: 221, dtype: int64

```
In [14]:
```

```
# test dataset
kwd_cnt_test = test_df['keyword'].value_counts()
kwd_cnt_test
```

```
Out[14]:
```

deluged	23
demolished	22
rubble	22
first%20responders	21
seismic	21
	..
threat	5
fatalities	5
forest%20fire	5
inundation	4
epicentre	1

Name: keyword, Length: 221, dtype: int64

1.3.4. Top 20 keywords in tweets

Plotting the top 20 keywords in tweets on train and test datasets.

```
In [15]:
```

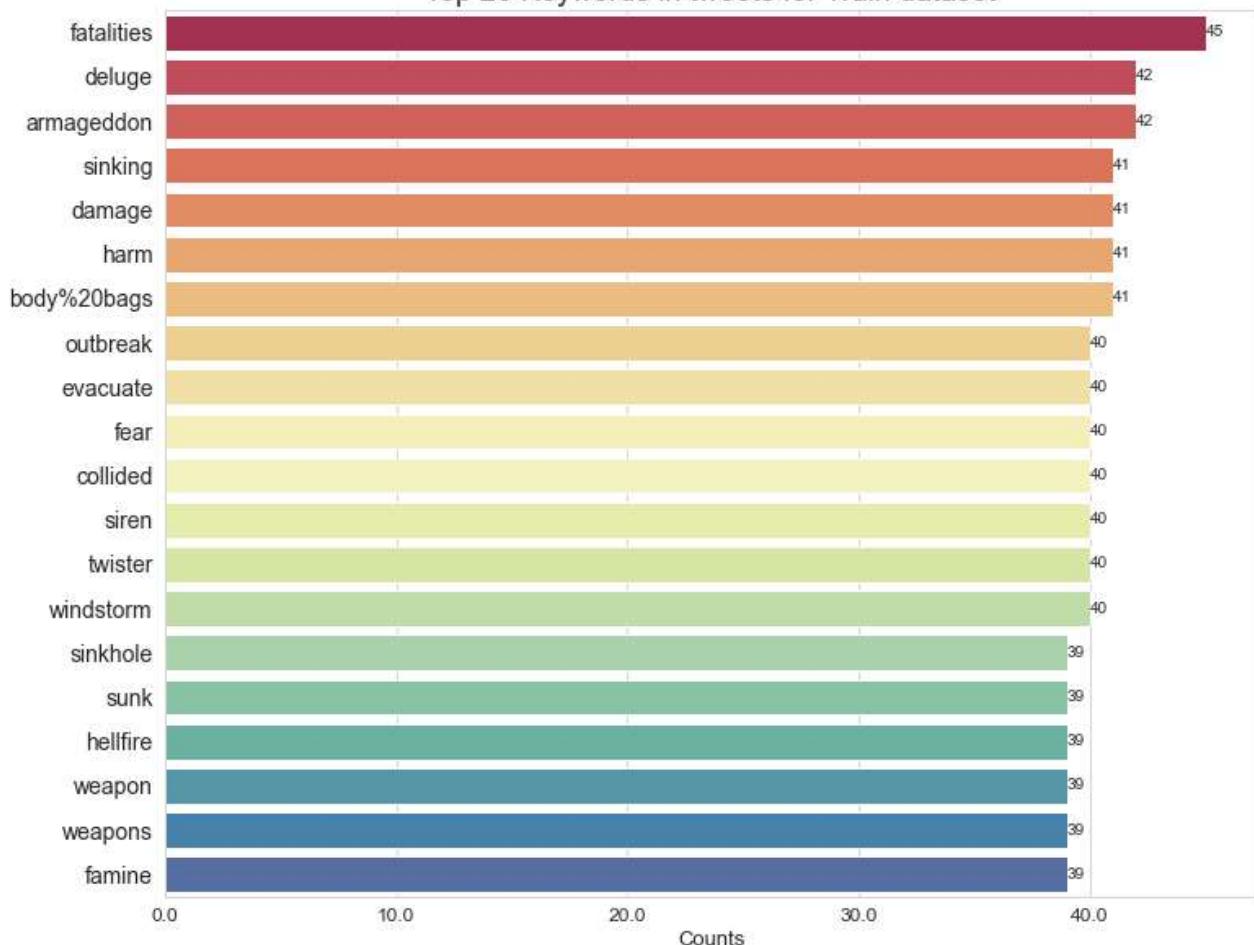
```
def top_tweet_keyword(df, dtype, color, ntop=20):
    sns.set_style('whitegrid')
    fig,axes = plt.subplots(figsize=(12,10))

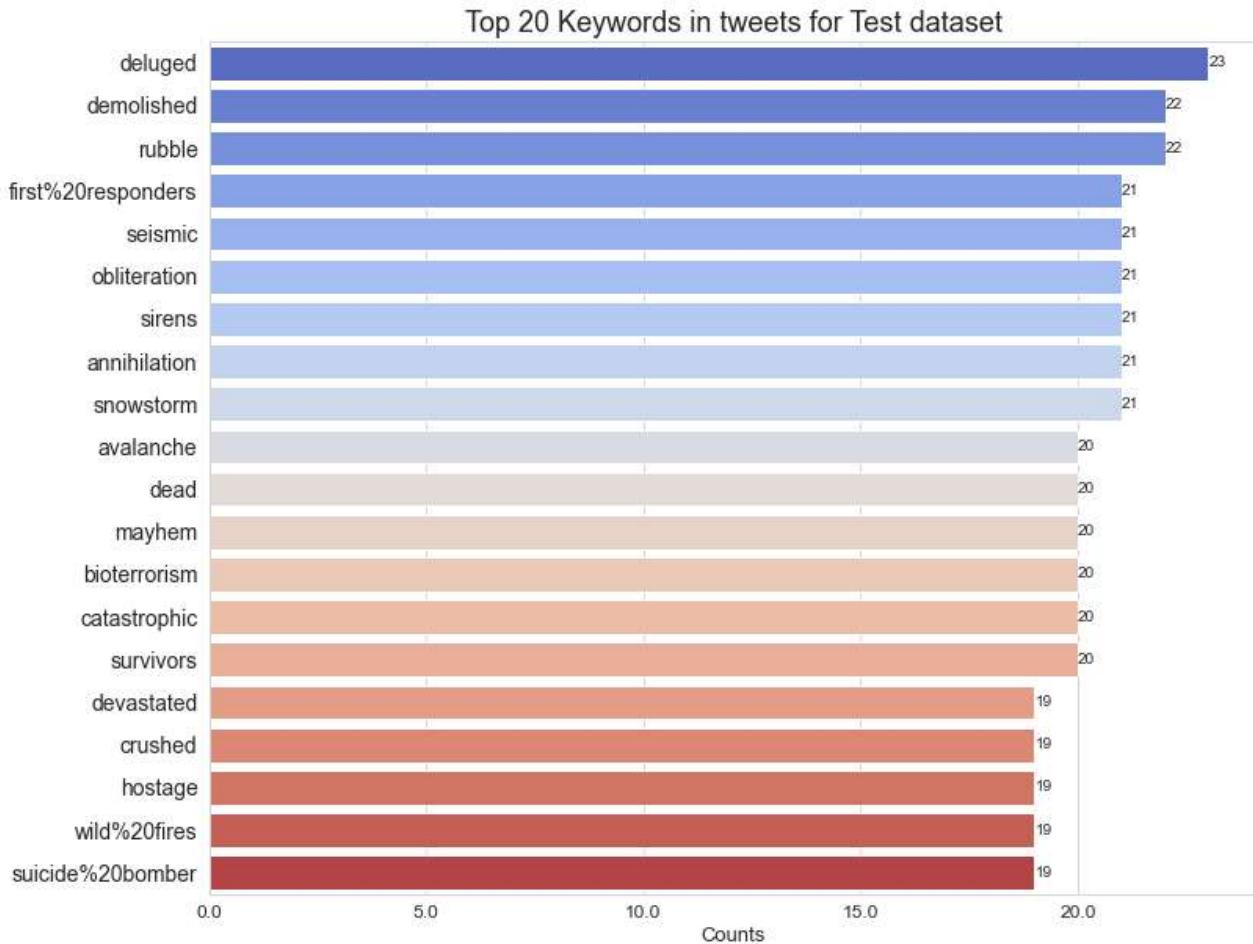
    top_keywords=df['keyword'].value_counts()[:ntop]
    ax = sns.barplot(y=top_keywords.index,x=top_keywords,palette=color,data=df)
    for container in ax.containers:
        ax.bar_label(container)

    ax.set_xticklabels([str(i) for i in ax.get_xticks()], fontsize = 12)
    ax.set_yticklabels([t.get_text() for t in ax.get_yticklabels()], fontsize = 14)
    plt.title('Top %d Keywords in tweets for %s dataset' %(ntop, dtype), fontsize=18)
    plt.xlabel('Counts', fontsize=13)
    plt.show()

top_tweet_keyword(train_df, 'Train', 'Spectral')
top_tweet_keyword(test_df, 'Test', 'coolwarm')
```

Top 20 Keywords in tweets for Train dataset





1.3.5. Top 20 locations tweets sent from

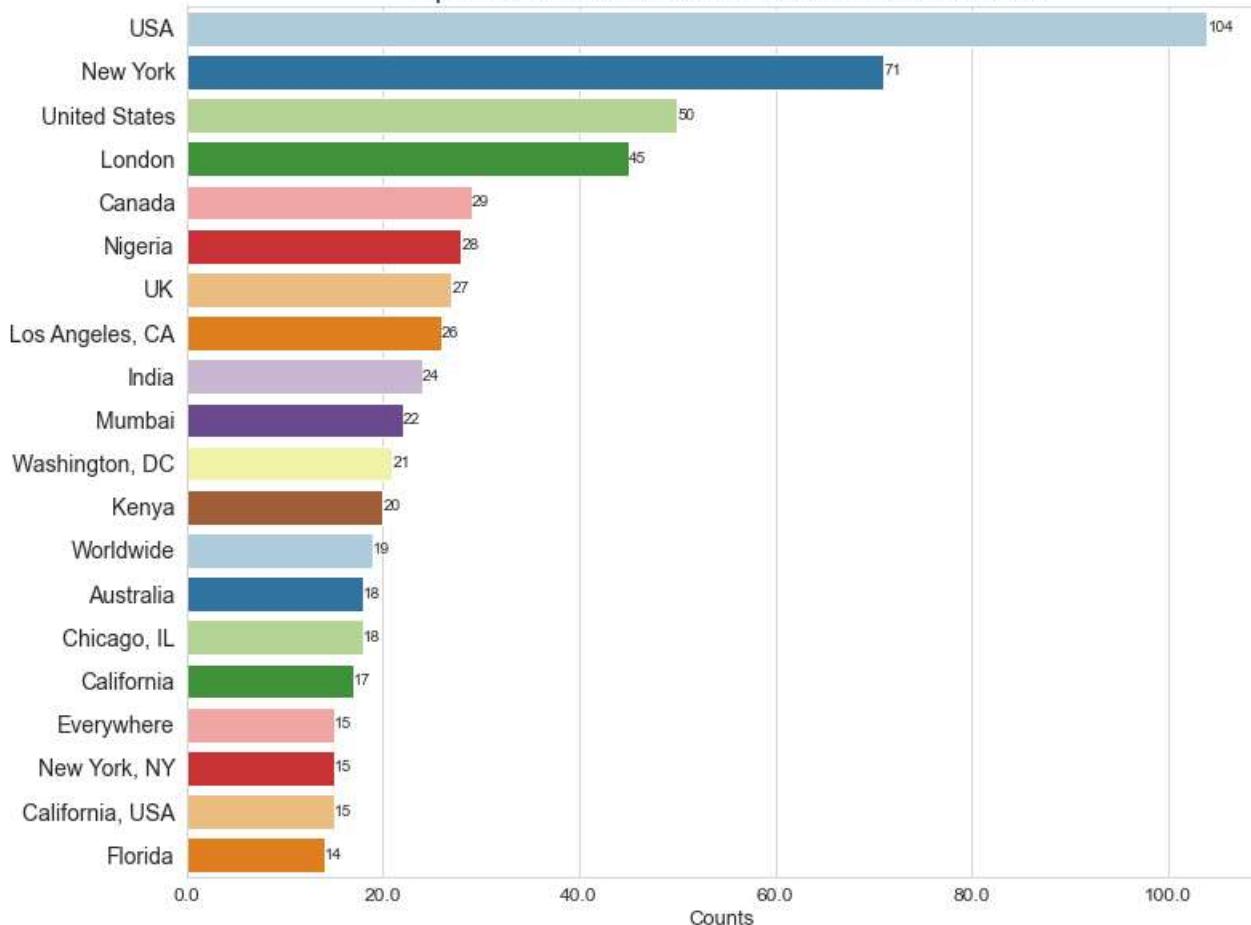
Plotting the top 20 locations tweets sent from on train and test datasets.

```
In [16]: def top_tweet_location(df, dtype, color, ntop=20):
    sns.set_style('whitegrid')
    fig,axes = plt.subplots(figsize=(12,10))

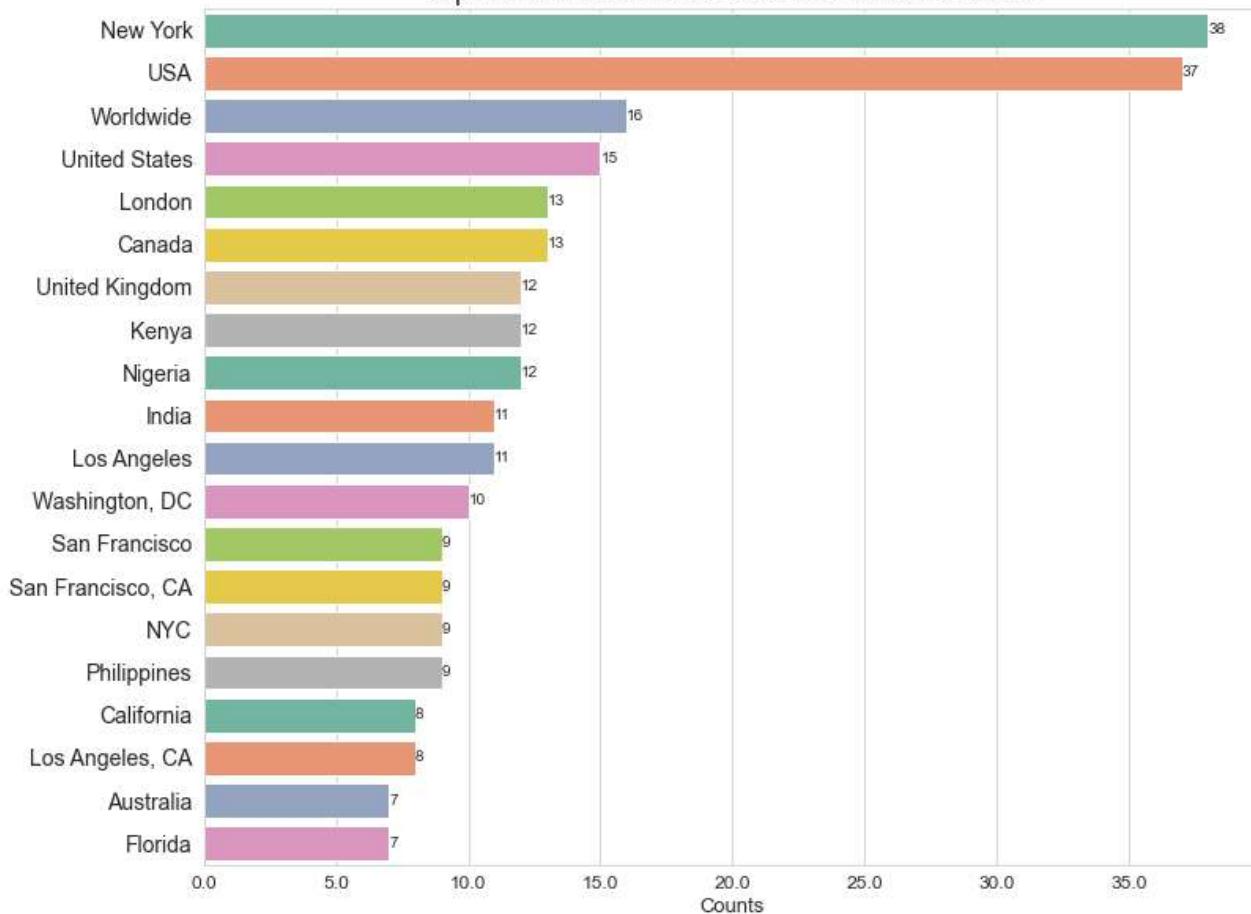
    locations = df["location"].value_counts()
    ax = sns.barplot(y=locations[0:20].index,x=locations[0:20],palette=color,data=df)
    for container in ax.containers:
        ax.bar_label(container)
    ax.set_xticklabels([str(i) for i in ax.get_xticks()], fontsize = 12)
    ax.set_yticklabels([t.get_text() for t in ax.get_yticklabels()], fontsize = 14)
    plt.title('Top %d locations tweets sent from in %s dataset' %(ntop, dtype),fontsize=16)
    plt.xlabel('Counts', fontsize=14)
    plt.show()

top_tweet_location(train_df, 'Train', 'Paired')
top_tweet_location(test_df, 'Test', 'Set2')
```

Top 20 locations tweets sent from in Train dataset



Top 20 locations tweets sent from in Test dataset



The locations registered in the data can be countries, states, cities or worldwide. Most tweets are sent from the USA in train dataset. But most tweets are sent from New York in test dataset.

1.3.6. Distribution of tweets

Plotting how the tweets are distributed before cleaning the data.

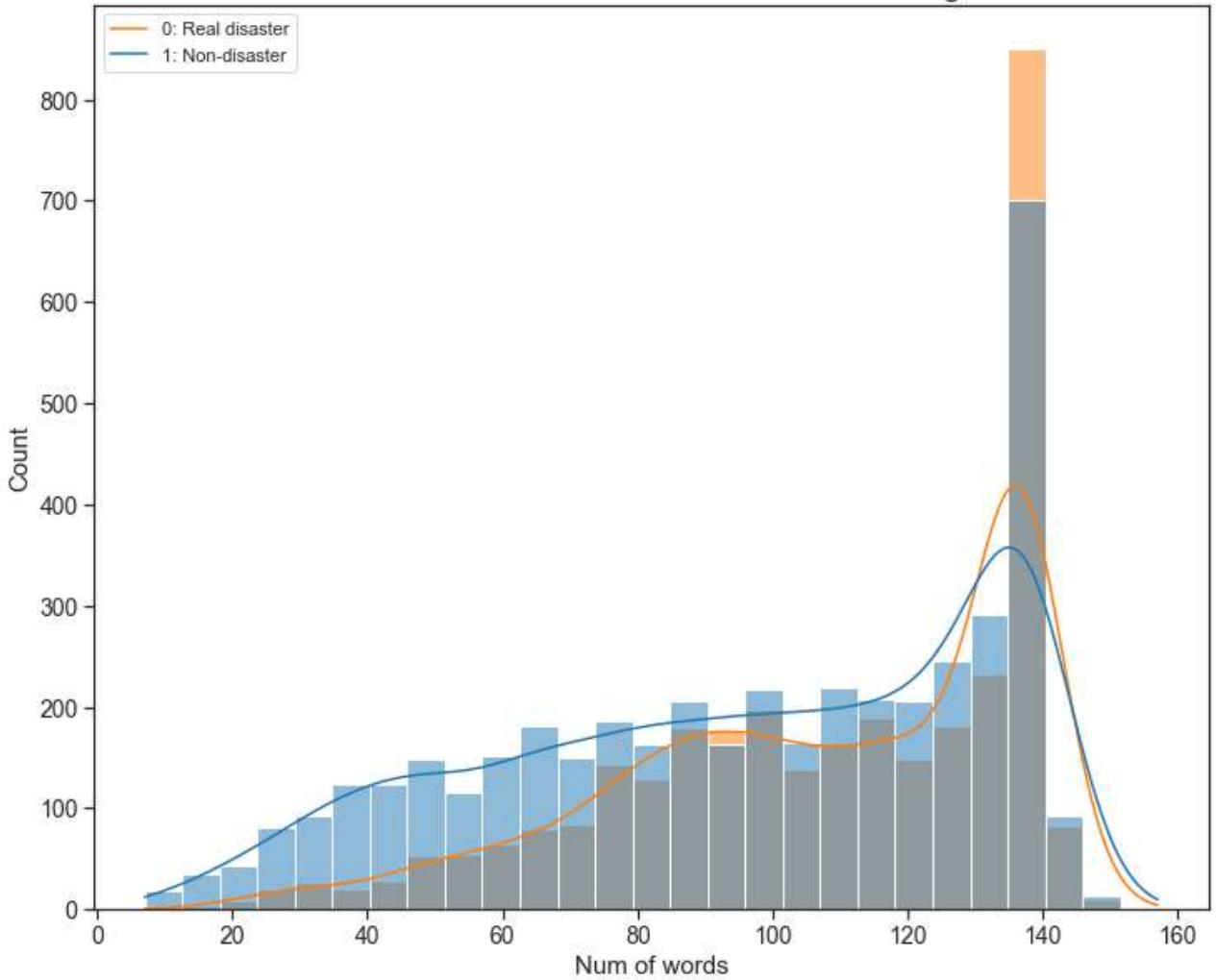
In [17]:

```
# Add tweets Length column
train_df['numwords'] = train_df["text"].apply(len)
test_df['numwords'] = test_df["text"].apply(len)

# Plot histogram of tweets Length
def dist_tweet(df, title, col, color):
    sns.set(rc={"figure.figsize":(12, 10)})
    sns.set_style("ticks")
    plot = sns.histplot(
        data = df,
        x = col,
        kde = True,
        hue = 'target',
        palette = color
    )
    plot.set_xlabel('Num of words', fontsize = 15)
    plot.set_ylabel('Count', fontsize = 15)
    plot.set_title(title, fontsize = 20)
    plt.tick_params(labelsize = 14)
    plt.legend(loc='upper left',labels = ['0: Real disaster', '1: Non-disaster'])
    plt.show()

dist_tweet(train_df, "Distribution of tweets before data cleaning", 'numwords', 'tab10'
```

Distribution of tweets before data cleaning



From the above distribution, it can be seen that the most length of tweets lies between the range of 130 - 140 characters.

1.3.7. Top 3 tweets according to the length of tweets train dataset

Displaying the top 3 tweets on the train dataset.

```
In [18]: for tweet in train_df.sort_values(by="numwords", ascending=False)[ "text"][:3]:
    print(f"Tweet: \n{tweet}\n")
```

Tweet:

when you're taking a shower and someone flushes the toilet and you have .1 second to GTF 0 or you get burned???

Tweet:

It's was about 2:30 in the morning& I went downstairs to watch some telly& I accidentally made a loud bang& my dad(who has a broken leg)walked-

Tweet:

@CAGov If 90BLKs&8WHTs colluded 2 take WHT F @USAgov AUTH Hostage&2 make her look BLK w/Bioterrorism&use her lg1/org IDis ID still hers?@VP

1.4. Data Pre-processing

From the previous step, we can conclude from the data that there is no standard format on the tweets, there are many symbols on the tweets, there are several special characters on the tweets, and some tweets have URLs.

To deal with these problems, I am performing the following data cleaning:

- Removing punctuations.
- Removing numbers.
- Converting to lowercase.
- Removing stopwords.
- Removing html tags
- Removing URLs
- Removing special characters
- Lemmatization
- Removing single characters

In [19]:

```
def data_cleaning(tweet):
    # remove punctuations
    tweet = re.sub(r'[^w\s]', '', tweet)

    # remove numbers
    tweet = re.sub(r'[0-9]', '', tweet)

    # converting to lowercase
    tweet = tweet.lower()

    # Stop word removal
    lemma = WordNetLemmatizer()
    tweet = " ".join(word for word in word_tokenize(tweet) if word not in stopwords.words('english'))

    # removing html tags
    tweet = re.sub(r"|<.*?>", " ", tweet)

    # url removal
    tweet = re.sub(r"https?:\/\/\S+|www\.\S+", " ", tweet)

    # non word removals (special chars)
    tweet = re.sub(r"[^a-zA-Z]", " ", tweet)

    # Lemmatization
    tweet = " ".join(lemma.lemmatize(word) for word in word_tokenize(tweet))

    # Single char removal
    tweet = re.sub(r"\b\w\b", "", tweet).strip()

return tweet
```

In [20]:

```
# apply data cleaning to the train and test datasets
train_df["cleaned_text"] = train_df["text"].apply(data_cleaning)
test_df["cleaned_text"] = test_df["text"].apply(data_cleaning)
```

In [21]:

```
# find the number of words after cleaning the data
```

```
train_df["cleaned_words"] = train_df["cleaned_text"].apply(lambda x: len(re.sub(r"\W_
```

In [22]: train_df

		id	keyword	location	text	target	numwords	cleaned_text	cleaned_words	
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M...	1	69	deed reason earthquake may allah forgive		6	
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1	38	forest fire near la ronge sask canada		7	
2	5	NaN	NaN	All residents asked to 'shelter in place' are ...	1	133	resident asked shelter place notified officer ...		11	
3	6	NaN	NaN	13,000 people receive #wildfires evacuation or...	1	65	people receive wildfire evacuation order calif...		6	
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as ...	1	88	got sent photo ruby alaska smoke wildfire pour...		9	
...	
7608	10869	NaN	NaN	Two giant cranes holding a bridge collapse int...	1	83	two giant crane holding bridge collapse nearby...		9	
7609	10870	NaN	NaN	@aria_ahraray @TheTawniest The out of control w...	1	125	aria ahraray thetawniest control wild fire cali...		12	
7610	10871	NaN	NaN	M1.94 [01:04 UTC]?5km S of Volcano Hawaii. htt...	1	65	utckm volcano hawaii httpcozdttoydebj		4	
7611	10872	NaN	NaN	Police investigating after an e-bike collided ...	1	137	police investigating ebike collided car little...		14	
7612	10873	NaN	NaN	The Latest: More Homes Razed by Northern Calif...	1	94	latest home razed northern california wildfire...		9	

7613 rows × 8 columns

1.4.1. Handling null values

Removing irrelevant feature and filling missing values

In [23]:

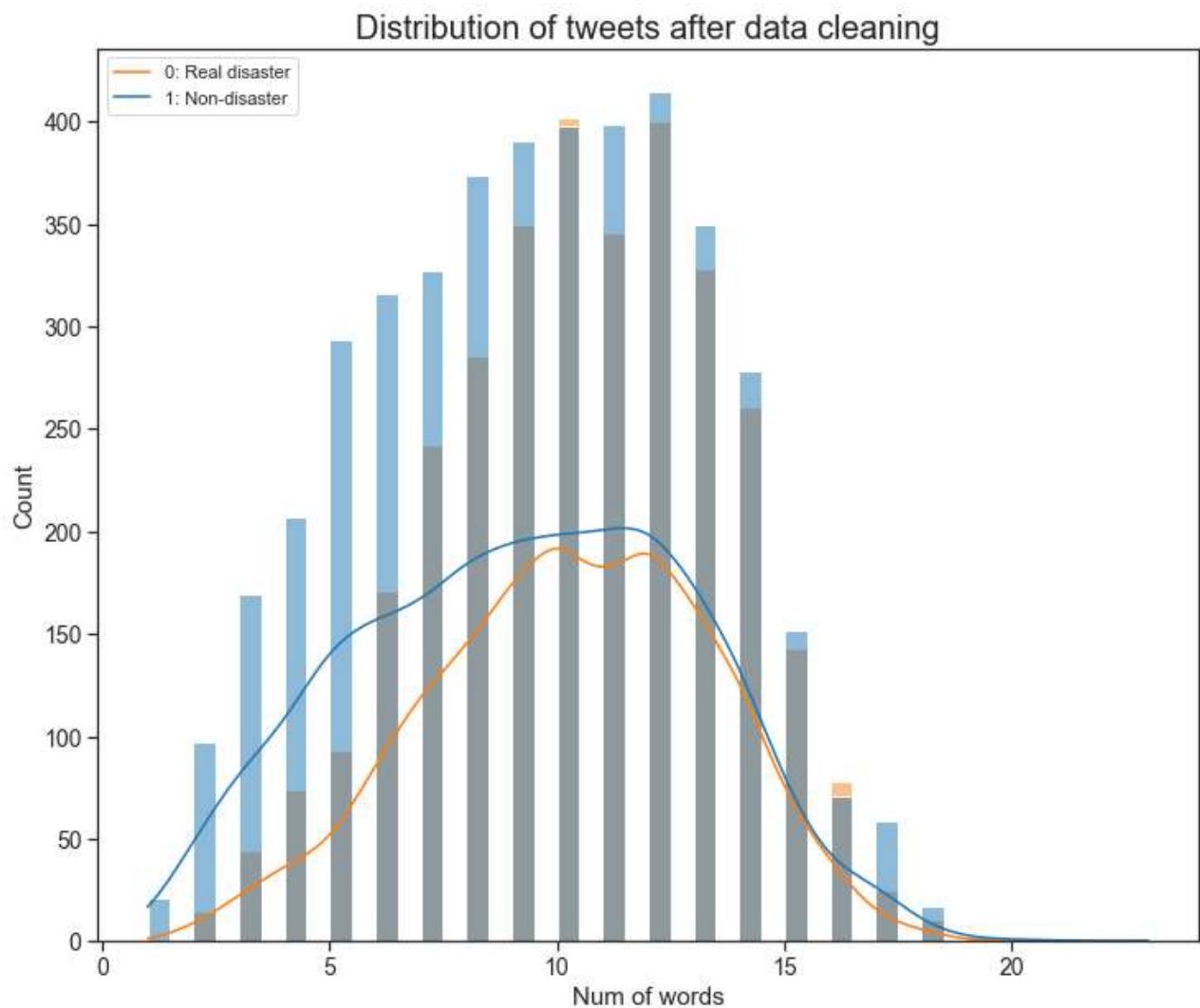
```
# Removing irrelevant feature  
train_df.drop(["location", "id"], axis=1)  
  
# filling keyword missing value  
train_df['keyword'].replace({ "Na": 'notkey' }, inplace=True)
```

1.4.2. Distribution of tweets after data cleaning

Plotting how the tweets are distributed after cleaning the data.

In [24]:

```
dist_tweet(train_df, "Distribution of tweets after data cleaning", 'cleaned_words', 'ta
```



1.4.3. Wordcloud generation

Highlighting essential textual data points on the cleaned text feature.

In [25]:

```
text1=[ ]
```

```

for i in train_df.loc[train_df['target']==1,'cleaned_text'].dropna():
    for j in i.lower().strip().split():
        text1.append(j)

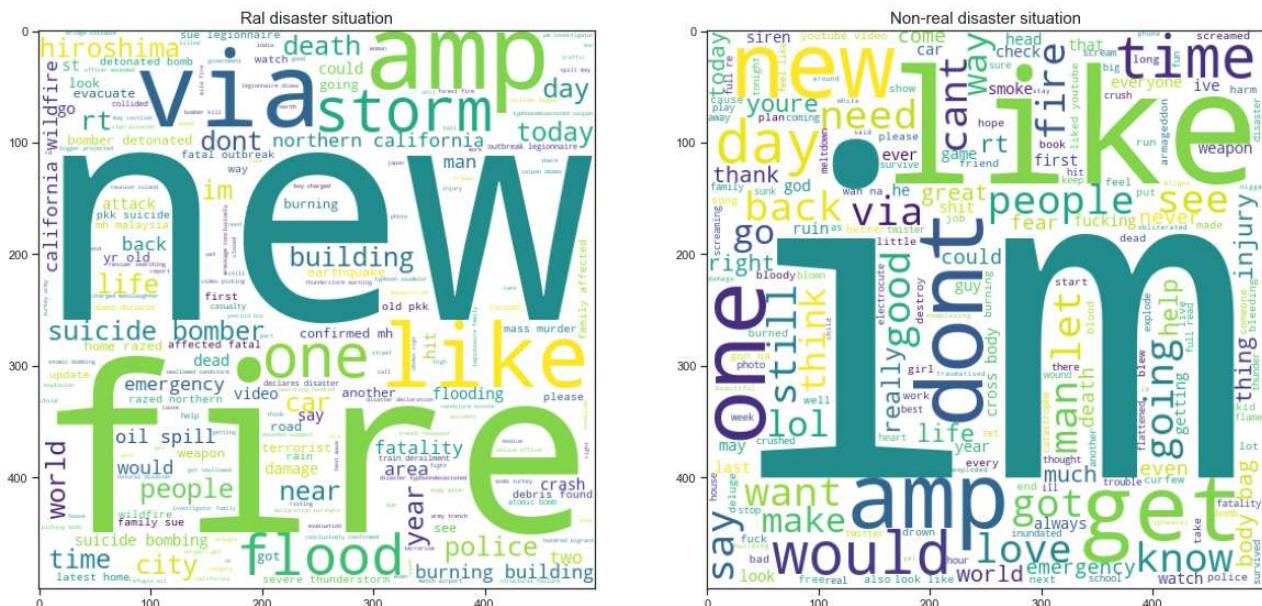
text0=[]
for i in train_df.loc[train_df['target']==0,'cleaned_text'].dropna():
    for j in i.lower().strip().split():
        text0.append(j)

# Word cloud of clean word has real disaster situation
plt.figure(figsize=(20,20))
plt.subplot(1,2,1)
cloud1=WordCloud(background_color="white",max_font_size=400,width=500,height=500,stopwords)
cloud1.generate(' '.join(text1))
plt.title("Real disaster situation",size=15)
plt.imshow(cloud1)

# Word cloud of keyword has non-disaster Situation
plt.subplot(1,2,2)
cloud1=WordCloud(background_color="white",max_font_size=400,width=500,height=500,stopwords)
cloud1.generate(' '.join(text0))
plt.title("Non-real disaster situation",size=15)
plt.imshow(cloud1)

```

Out[25]: <matplotlib.image.AxesImage at 0x275d0ea4910>



2. Training, modeling and prediction

Feeding with clean train data into the LSTM model for modeling and prediction.

2.1. Token and vocabulary creation

Processing the raw text for the NLP.

```
In [27]: max_features=3000  
tokenizer=Tokenizer(num_words=max_features,split=' ')
```

```

tokenizer.fit_on_texts(train_df['cleaned_text'].values)
X = tokenizer.texts_to_sequences(train_df['cleaned_text'].values)
X = pad_sequences(X)
y = train_df['target']

```

2.2. Train and test split

Splitting the data set into two pieces: a training set and a testing set. The test_size is given as 0.2 , it means 20% of our data goes into our test size. 1-test_size is our train size.

```
In [28]: X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.2, random_state
```

2.3. Model creation

Creating the LSTM model.

```
In [29]: model = Sequential()
model.add(Embedding(max_features, 32, input_length = X.shape[1]))
model.add(Dropout(0.2))
model.add(LSTM(32, dropout=0.2, recurrent_dropout=0.4))
model.add(Dense(1, activation='sigmoid'))
adam = optimizers.Adam(learning_rate=0.002)
model.compile(loss = 'binary_crossentropy', optimizer=adam, metrics = ['accuracy'])
print(model.summary())
```

Model: "sequential"

Layer (type)	Output Shape	Param #
<hr/>		
embedding (Embedding)	(None, 19, 32)	96000
dropout (Dropout)	(None, 19, 32)	0
lstm (LSTM)	(None, 32)	8320
dense (Dense)	(None, 1)	33
<hr/>		
Total params: 104,353		
Trainable params: 104,353		
Non-trainable params: 0		
<hr/>		
None		

2.4. Fitting the model

Measuring how well the LSTM model performs with the train dataset.

```
In [30]: callbacks = [ ReduceLROnPlateau(monitor='val_loss', patience=5, cooldown=0),
                  EarlyStopping(monitor='val_accuracy', min_delta=1e-4, patience=5)]

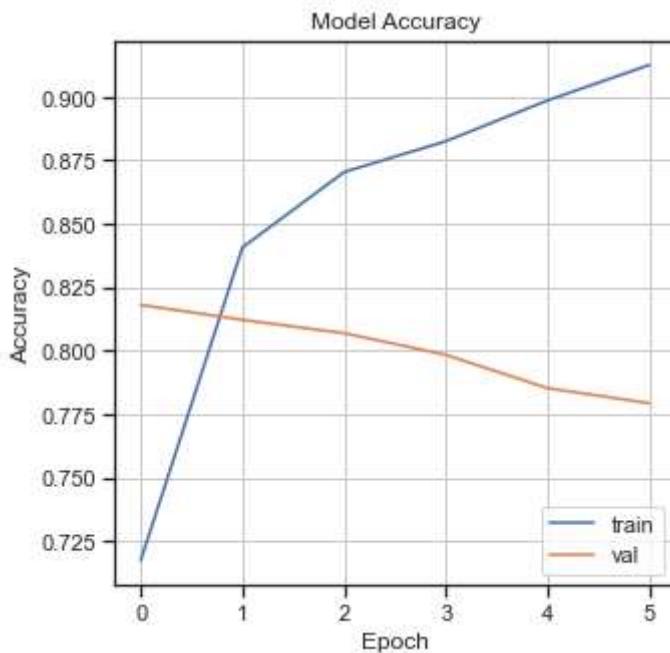
history = model.fit(X_train, y_train, epochs = 10, batch_size=32, validation_data=(X_te
```

Epoch 1/10

```
191/191 [=====] - 4s 11ms/step - loss: 0.5483 - accuracy: 0.717
4 - val_loss: 0.4221 - val_accuracy: 0.8181 - lr: 0.0020
Epoch 2/10
191/191 [=====] - 2s 10ms/step - loss: 0.3724 - accuracy: 0.840
7 - val_loss: 0.4315 - val_accuracy: 0.8122 - lr: 0.0020
Epoch 3/10
191/191 [=====] - 2s 10ms/step - loss: 0.3161 - accuracy: 0.870
4 - val_loss: 0.4603 - val_accuracy: 0.8070 - lr: 0.0020
Epoch 4/10
191/191 [=====] - 2s 9ms/step - loss: 0.2764 - accuracy: 0.8826
- val_loss: 0.5372 - val_accuracy: 0.7984 - lr: 0.0020
Epoch 5/10
191/191 [=====] - 2s 10ms/step - loss: 0.2407 - accuracy: 0.898
7 - val_loss: 0.6437 - val_accuracy: 0.7853 - lr: 0.0020
Epoch 6/10
191/191 [=====] - 2s 10ms/step - loss: 0.2117 - accuracy: 0.912
6 - val_loss: 0.7676 - val_accuracy: 0.7794 - lr: 0.0020
```

In [38]:

```
plt.figure(figsize=(5, 5))
plt.grid()
plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label = 'val')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.show()
```



2.5. Prediction

Predicting the model on the test dataset to get the results.

In [39]:

```
# Tokenization on full train dataset
max_features=5000
tokenizer=Tokenizer(num_words=max_features,split=' ')
tokenizer.fit_on_texts(train_df['cleaned_text'].values)
```

```
X = tokenizer.texts_to_sequences(train_df['cleaned_text'].values)
X = pad_sequences(X, maxlen = 50)
```

In [40]:

```
# Tokenixation on full test dataset
tokenizer.fit_on_texts(test_df['cleaned_text'].values)
test_token = tokenizer.texts_to_sequences(test_df['cleaned_text'].values)
test_token = pad_sequences(test_token, maxlen = 50)
```

In [41]:

```
# Model call with little bit of optimisation based on previous results
lstm_out = 100
model = Sequential()
model.add(Embedding(max_features, 100, input_length = X.shape[1]))
model.add(Dropout(0.2))
model.add(LSTM(lstm_out, dropout=0.2, return_sequences=True, recurrent_dropout=0.4))
model.add(Dropout(0.2))
model.add(LSTM(lstm_out, dropout=0.2, recurrent_dropout=0.2))
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))
adam = optimizers.Adam(learning_rate=2e-3)
model.compile(loss = 'binary_crossentropy', optimizer=adam ,metrics = ['accuracy'])
print(model.summary())
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
<hr/>		
embedding_1 (Embedding)	(None, 50, 100)	500000
dropout_1 (Dropout)	(None, 50, 100)	0
lstm_1 (LSTM)	(None, 50, 100)	80400
dropout_2 (Dropout)	(None, 50, 100)	0
lstm_2 (LSTM)	(None, 100)	80400
dropout_3 (Dropout)	(None, 100)	0
dense_1 (Dense)	(None, 1)	101
<hr/>		
Total params: 660,901		
Trainable params: 660,901		
Non-trainable params: 0		

None

In [48]:

```
modelsub = model.fit(X,y, epochs = 10, validation_split = 0.2 ,callbacks=[callbacks], ba
```

```
Epoch 1/10
191/191 [=====] - 13s 68ms/step - loss: 0.1041 - accuracy: 0.95
60 - val_loss: 1.1184 - val_accuracy: 0.7295 - lr: 2.0000e-04
Epoch 2/10
191/191 [=====] - 13s 68ms/step - loss: 0.0885 - accuracy: 0.96
12 - val_loss: 1.2813 - val_accuracy: 0.7249 - lr: 2.0000e-04
Epoch 3/10
```

```

191/191 [=====] - 13s 68ms/step - loss: 0.0804 - accuracy: 0.96
34 - val_loss: 1.3644 - val_accuracy: 0.7308 - lr: 2.0000e-04
Epoch 4/10
191/191 [=====] - 13s 69ms/step - loss: 0.0748 - accuracy: 0.96
63 - val_loss: 1.4930 - val_accuracy: 0.7282 - lr: 2.0000e-04
Epoch 5/10
191/191 [=====] - 13s 67ms/step - loss: 0.0744 - accuracy: 0.96
75 - val_loss: 1.4991 - val_accuracy: 0.7275 - lr: 2.0000e-04
Epoch 6/10
191/191 [=====] - 13s 67ms/step - loss: 0.0680 - accuracy: 0.96
83 - val_loss: 1.6549 - val_accuracy: 0.7223 - lr: 2.0000e-04
Epoch 7/10
191/191 [=====] - 13s 68ms/step - loss: 0.0662 - accuracy: 0.97
01 - val_loss: 1.6631 - val_accuracy: 0.7216 - lr: 2.0000e-05
Epoch 8/10
191/191 [=====] - 13s 70ms/step - loss: 0.0623 - accuracy: 0.96
96 - val_loss: 1.6728 - val_accuracy: 0.7236 - lr: 2.0000e-05

```

In [47]:

```

y_hat = model.predict(test_token).round()
submission_df['target'] = np.round(y_hat).astype('int')
submission_df.to_csv('submission.csv', index=False)
submission_df.describe()

```

102/102 [=====] - 1s 10ms/step

Out[47]:

	id	target
count	3263.000000	3263.000000
mean	5427.152927	0.414343
std	3146.427221	0.492684
min	0.000000	0.000000
25%	2683.000000	0.000000
50%	5500.000000	0.000000
75%	8176.000000	1.000000
max	10875.000000	1.000000

3. Discussion

3.1. Conclusion

From the data inspection, I found that location and keyword features contain null values on train and test datasets. By inspecting the target feature, the distribution shows that there are more tweets with real disasters than non-real ones. I also concluded from the data inspection the following: there is no standard format on the tweets, there are many symbols on the tweets, there are several special characters on the tweets, and some tweets have URLs. Thus, I created a function to deal with all these problems.

Once the data was cleaned, I created the token and vocabulary for the NLP method. For model creation, I added embedding layer to enable the conversion of each word into a fixed length vector

of defined sized followed by dropout layer for prevention against overfitting. For the LSTM layer, I added 50 units that represent the dimensionality of outer space. For adding dropot lauers, I specified the percentage of layers that should be dropped. The next step was to add the dense layer, and to compile the model with the adam optmizer. The perfect accuracy for train and validation is reached by getting close to 1 epoch.

3.2. Further improvement

Tune better the parameters on the model to get 90% on the leaderboard for NLP with disaster tweek in Kaggle.

In []: