This Kaggle competition is about classifying texts. It is an excellent introduction to Natural Language Processing (NLP).

The project has 125 total points. The instructions summarize the criteria you will use to guide your submission and review others' submissions. Note: to receive total points for this section, the learner doesn't need to have a top-performing score on the challenge. This is a mini-project to complete as a weekly assignment, so we don't expect you to iterate over your project until you have a model capable of winning the challenge. The learner needs to show a score that reasonably reflects that they completed the rubric parts of this project, E.g., a model score above 0.00000.

github: https://github.com/zpeople/NLP-Disaster-Tweets

[12/05/2024 Thu 10:56:39] BY Renmin Zhao

Load data

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import torch
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
# pd display setting
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 10)
pd.set_option('display.width', 4000)
pd.set_option('display.unicode.ambiguous_as_wide', True)
pd.set_option('display.unicode.east_asian_width', True)
pd.set_option('display.max_colwidth', None)

#load data
train_path ="./Datasets/train.csv"
test_path="./Datasets/test.csv"
train_data = pd.read_csv(train_path)
test_data =pd.read_csv(test_path)

print('Development  data size:',train_data.shape)
print('Predict data size:',test_data.shape)
```

```
Development  data size: (7613, 5)
Predict data size: (3263, 4)
```

Brief description of the problem and data (5 pts)

Briefly describe the challenge problem and NLP. Describe the size, dimension, structure, etc., of the data.

In [42]:
```
print(train_data.info())
print(train_data)
```

```
<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
None
         id keyword location                                                                                                                                   text  target
0         1     NaN      NaN                                                                  Our Deeds are the Reason of this #earthquake May ALLAH Forgive us all       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 being notified by officers. No other evacuation or shelter in place orders are expected       1
3         6     NaN      NaN                                                                     13,000 people receive #wildfires evacuation orders in California        1
4         7     NaN      NaN                                                      Just got sent this photo from Ruby #Alaska as smoke from #wildfires pours into a school        1
...     ...     ...      ...                                                                                                                                    ...     ...
7608  10869     NaN      NaN                                                                  Two giant cranes holding a bridge collapse into nearby homes http://t.co/STfMbbZFB5       1
7609  10870     NaN      NaN              @aria_ahrary @TheTawniest The out of control wild fires in California even in the Northern part of the state. Very troubling.       1
7610  10871     NaN      NaN                                                                          M1.94 [01:04 UTC]?5km S of Volcano Hawaii. http://t.co/zDtoyd8EbJ       1
7611  10872     NaN      NaN  Police investigating after an e-bike collided with a car in Little Portugal. E-bike rider suffered serious non-life threatening injuries.       1
7612  10873     NaN      NaN                                                   The Latest: More Homes Razed by Northern California Wildfire - ABC News http://t.co/YmY4rSkQ3d       1

[7613 rows x 5 columns]
```

In [3]:
```python
print(test_data.info())
print(test_data.head())
```

```
<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
None
   id keyword location                                                                                text
0   0     NaN      NaN                                                          Just happened a terrible car crash
1   2     NaN      NaN                                            Heard about #earthquake is different cities, stay safe everyone.
2   3     NaN      NaN  there is a forest fire at spot pond, geese are fleeing across the street, I cannot save them all
3   9     NaN      NaN                                                          Apocalypse lighting. #Spokane #wildfires
4  11     NaN      NaN                                                     Typhoon Soudelor kills 28 in China and Taiwan
```

In [4]:
```python
print('location null counts:',train_data['location'].isnull().sum())
print('keyword null counts:',train_data['keyword'].isnull().sum())
```

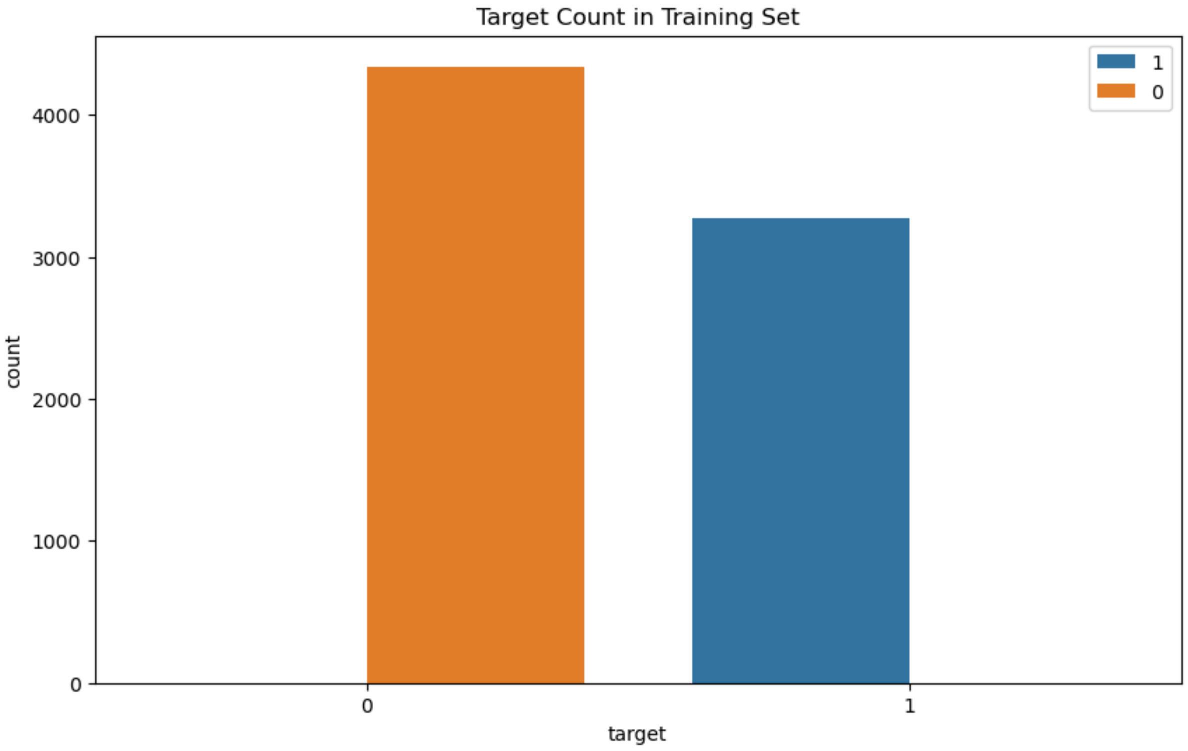
```
location null counts: 2533
keyword null counts: 61
```

The features are keyword, location, text, and only loction has a large amount of missing data

In [5]:
```python
#Null Accuracy
train_data['target'].value_counts(normalize=True)
```

Out[5]:
```
target
0    0.57034
1    0.42966
Name: proportion, dtype: float64
```

In [6]:
```
fig = plt.figure(figsize=(10,6))
plt.tight_layout()

train_data.groupby('target').count()['id']
sns.countplot(x=train_data['target'], hue=train_data['target'].astype(str))
plt.legend(loc=0)
plt.title('Target Count in Training Set')

plt.show()
```



Exploratory Data Analysis (EDA) — Inspect, Visualize and Clean the Data (15 pts)

Show a few visualizations like histograms. Describe any data cleaning procedures. Based on your EDA, what is your plan of analysis?

In [7]:
```
# keyword location text  ---target


loc_tar1=train_data[train_data['target'] == 1]['location']
print(len(loc_tar1.unique())/len(loc_tar1))

loc_tar0=train_data[train_data['target'] == 0]['location']
print(len(loc_tar0.unique())/len(loc_tar0))
```

```
loc_count_tar1 = loc_tar1.value_counts()
loc_count_tar0 = loc_tar0.value_counts()

count= 5

print(loc_count_tar1[loc_count_tar1>count].info(),'\n')
print(loc_count_tar0[loc_count_tar0>count].info(),'\n')

common_locs = set(loc_count_tar1[loc_count_tar1>count].index).intersection(set(loc_count_tar0[loc_count_tar0>count].index))

print("Number of common loc:", len(common_locs))
```

```
0.4628553959033935
0.4935513588208199
<class 'pandas.core.series.Series'>
Index: 30 entries, USA to Ireland
Series name: count
Non-Null Count  Dtype
--------------  -----
30 non-null     int64
dtypes: int64(1)
memory usage: 480.0+ bytes
None

<class 'pandas.core.series.Series'>
Index: 35 entries, New York to Dallas, TX
Series name: count
Non-Null Count  Dtype
--------------  -----
35 non-null     int64
dtypes: int64(1)
memory usage: 560.0+ bytes
None

Number of common loc: 18
```

The proportion of unique data is as high as 0.5, indicating that the data set has considerable diversity, and each instance has its own unique characteristics. By comparing positive and negative data, there are 18 sets of data duplicates in positive and negative data, accounting for about 2/3, and disaster comments are not closely related to location

In [8]:
```
key_tar1=train_data[train_data['target'] == 1]['keyword']
print(len(key_tar1.unique())/len(key_tar1))

key_tar0=train_data[train_data['target'] == 0]['keyword']
print(len(key_tar0.unique())/len(key_tar0))

key_count_tar1 = key_tar1.value_counts()
key_count_tar0 = key_tar0.value_counts()

print(key_count_tar1.head(100) ,'\n')
print(key_count_tar0.head(100),'\n')
# Convert index to set and find intersection


common_keys = set(key_count_tar1[key_count_tar1>20].index).intersection(set(key_count_tar0[key_count_tar0>20].index))
# Output the number of common keys
print("Number of common keys:", len(common_keys))
```

```
0.06756343625802506
0.05043758636573008
keyword
derailment     39
wreckage       39
outbreak       39
debris         37
oil%20spill    37
               ..
disaster       15
casualty       15
hostage        15
bomb           15
collapse       15
Name: count, Length: 100, dtype: int64

keyword
body%20bags          40
harm                 37
armageddon           37
wrecked              36
ruin                 36
                     ..
dead                 23
emergency            23
nuclear%20reactor    22
collapsed            22
damage               22
Name: count, Length: 100, dtype: int64

Number of common keys: 0
```

In [9]:
```
key_train=train_data['keyword'].value_counts()
print(key_train.shape)
key_test =test_data['keyword'].value_counts()
print(key_test.shape)
common_keys = set(key_train[key_train>0].index).intersection(set(key_test[key_test>0].index))

print("The number of keywords common to the training and test data:", len(common_keys))
```

```
(221,)
(221,)
The number of keywords common to the training and test data: 221
```

- keyword has less diversity than location, which may make the correlation between the keyword and the target category easier to detect.
- The number of positive and negative data types of keyword is more balanced, which is usually conducive to detecting the relationship between features and targets
- Keyword for positive and negative data do not have obvious similarities

Clean Text Data

In [ ]:
```
!pip install pyspellchecker
```

In [ ]:
```
from spellchecker import SpellChecker


spell = SpellChecker()
def correct_spellings(text):
    if pd.isna(text) or not isinstance(text, str):
        return text
    corrected_text = []
    misspelled_words = spell.unknown(text.split())
```

```python
    for word in text.split():
        if word in misspelled_words:
            corrected_word = spell.correction(word)
            corrected_text.append(corrected_word if isinstance(corrected_word, str) else word)
        else:
            corrected_text.append(word)
    return " ".join(corrected_text)
```

In [3]:

```python
import re
import string
import nltk
import pandas as pd
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
# retrieve english stop words
stop_words = set(stopwords.words('english'))

# Converts text to lower case
def convert_to_lowercase(text):
    if pd.isna(text):
        return text
    if isinstance(text, str):
        return text.lower()
    return text

# Remove all punctuation from the text
def remove_punctuation(text):
    if pd.isna(text):
        return text
    text = re.sub(f'[{string.punctuation}]', '', text)
    return text

# Removes all numbers from the text
def remove_numbers(text):
    if pd.isna(text):
        return text
    text = re.sub(r'\d+', '', text)
    return text

# Text segmentation, then remove the length of 2 or less and the single word and stop word
def remove_short_words_and_stop_words(text):
    if pd.isna(text):
        return text
    words = word_tokenize(text)
    words = [word for word in words if len(word) > 2 and word not in stop_words]
    cleaned_text = ' '.join(words)
    return cleaned_text

# Replace two or more consecutive Spaces with a single space
def remove_multiple_spaces(text):
    if pd.isna(text):
        return text
    cleaned_text = re.sub(r' {2,}', ' ', text)
    return cleaned_text

# Remove urls
def remove_urls(text):
    if pd.isna(text):
        return text
```

```
    url_pattern = r'(www.|http[s]?://)(?:[a-zA-Z]|[0-9]|[$-_@.&+]|[!*\(\),]|(?:%[0-9a-fA-F][0-9a-fA-F]))+'
    return re.sub(url_pattern, '', text)

# Remove hmtmls
def remove_html(text):
    if pd.isna(text):
        return text
    html_entities = r'<.*?>|&([a-z0-9]+|#[0-9]{1,6}|#x[0-9a-f]{1,6});'
    return re.sub(html_entities, '', text)

# Remove @ and #
def remove_tags(text):
    if pd.isna(text):
        return text
    tag_pattern = r'@([a-z0-9]+)|#'
    return re.sub(tag_pattern, '', text)

def remove_emoji(text):
    if pd.isna(text):
        return text
    emoji_pattern = re.compile("["
                           u"\U0001F600-\U0001F64F"  # emoticons
                           u"\U0001F300-\U0001F5FF"  # symbols & pictographs
                           u"\U0001F680-\U0001F6FF"  # transport & map symbols
                           u"\U0001F1E0-\U0001F1FF"  # flags (iOS)
                           u"\U00002702-\U000027B0"
                           u"\U000024C2-\U0001F251"
                           "]+", flags=re.UNICODE)
    return emoji_pattern.sub(r'', text)

def preprocess_text(text):
    if pd.isna(text):
        return text
    cleaned_text = re.sub(r'[^a-zA-Z\d\s]+', '',text)
    word_list = []
    for each_word in cleaned_text.split(' '):
        word_list.append((each_word).lower())
    word_list = [
        WordNetLemmatizer().lemmatize(each_word.strip()) for each_word in word_list
        if each_word not in stop_words and each_word.strip() != ''
    ]
    return " ".join(word_list)



def clear_text(df, col):
    df[col] = df[col].apply(convert_to_lowercase)
    df[col] = df[col].apply(remove_urls)
    df[col] = df[col].apply(remove_html)
    df[col] = df[col].apply(remove_tags)
    df[col] = df[col].apply(remove_numbers)
    df[col] = df[col].apply(remove_short_words_and_stop_words)
    df[col] = df[col].apply(preprocess_text)
    df[col] = df[col].apply(remove_multiple_spaces)
    # df[col] = df[col].apply(remove_emoji)
    # df[col] = df[col].apply(correct_spellings)
    return df
```

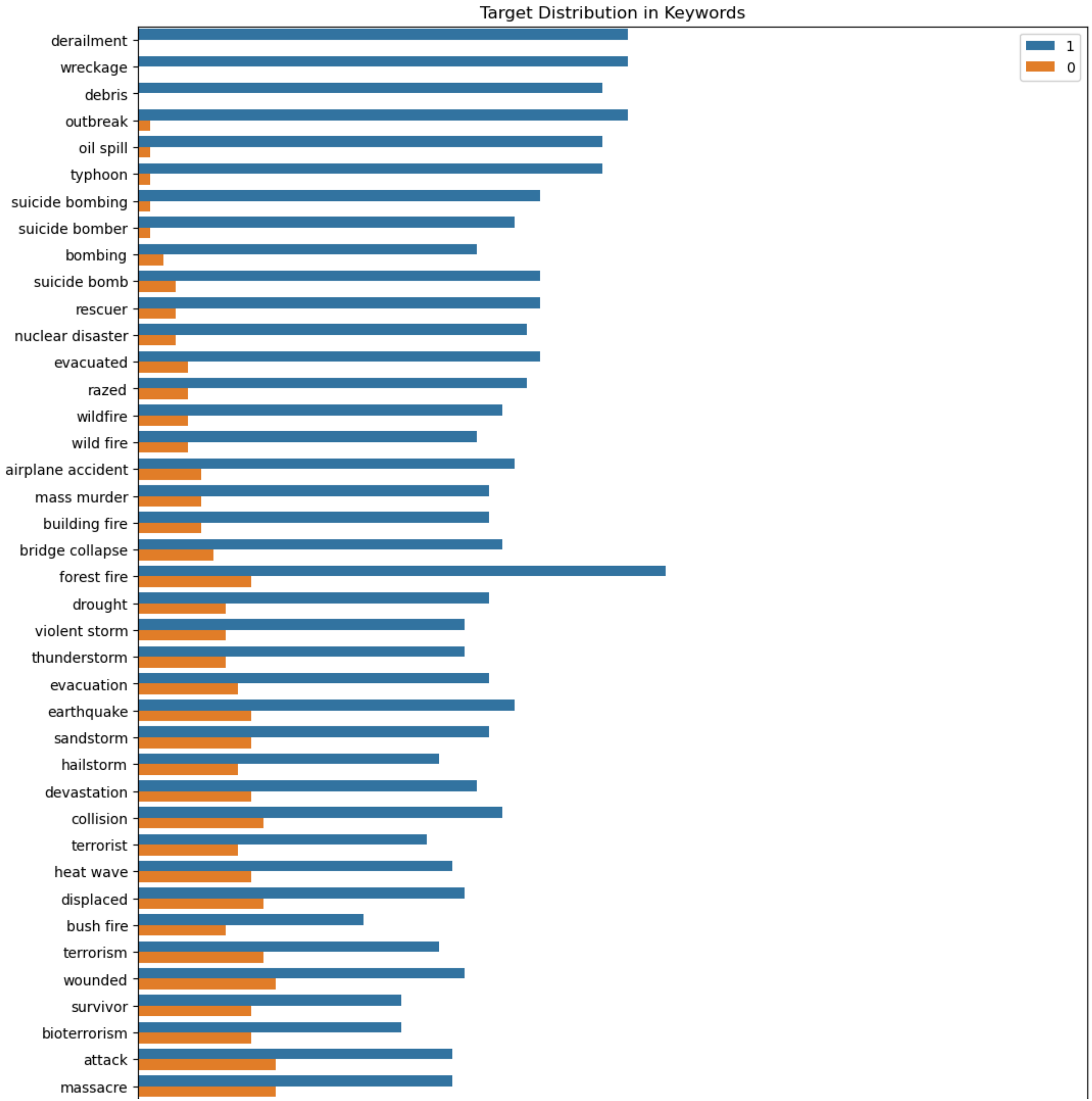
```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\SEELE\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\SEELE\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\SEELE\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

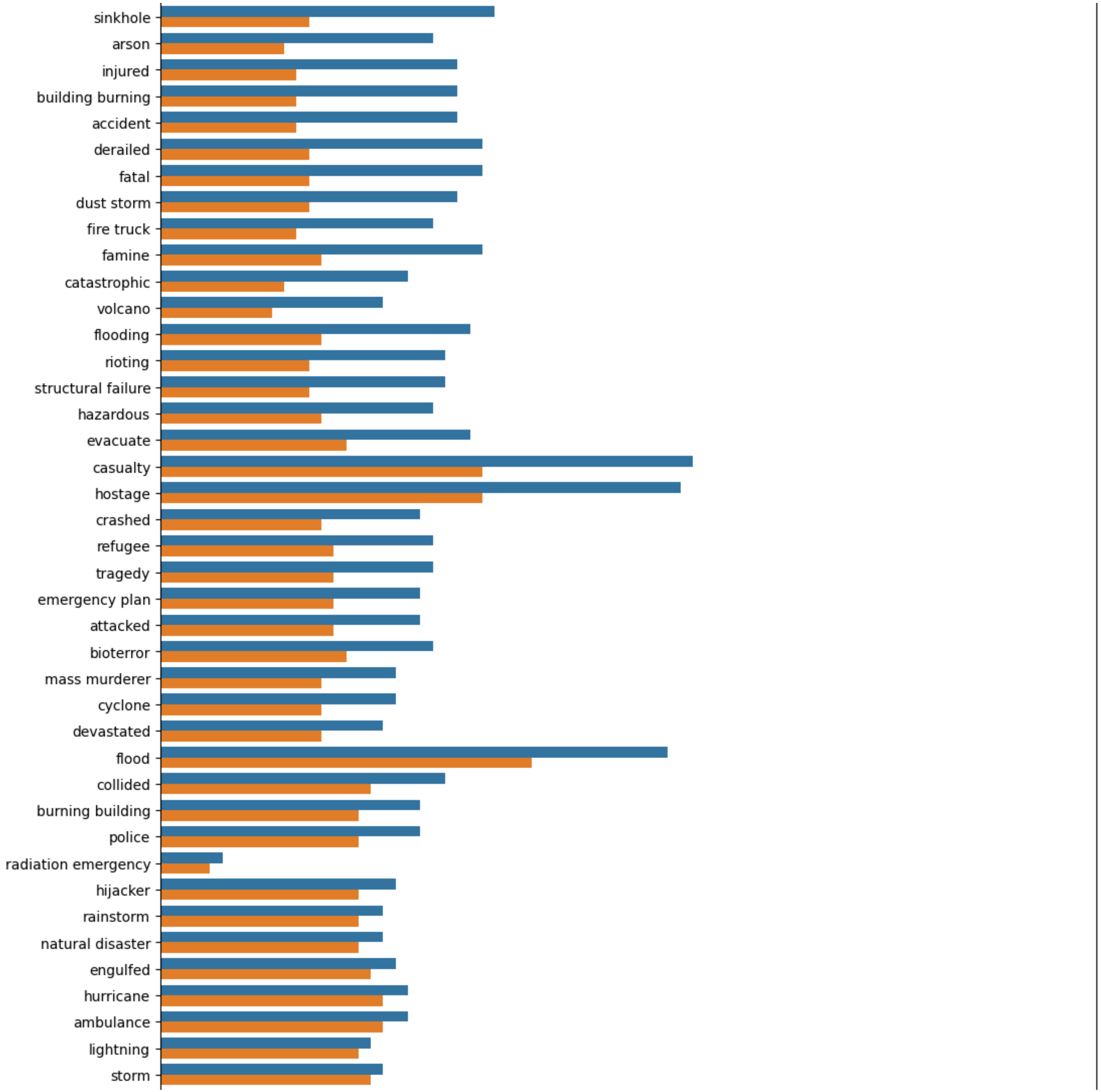
In [11]:
```
train_data['keyword']
```

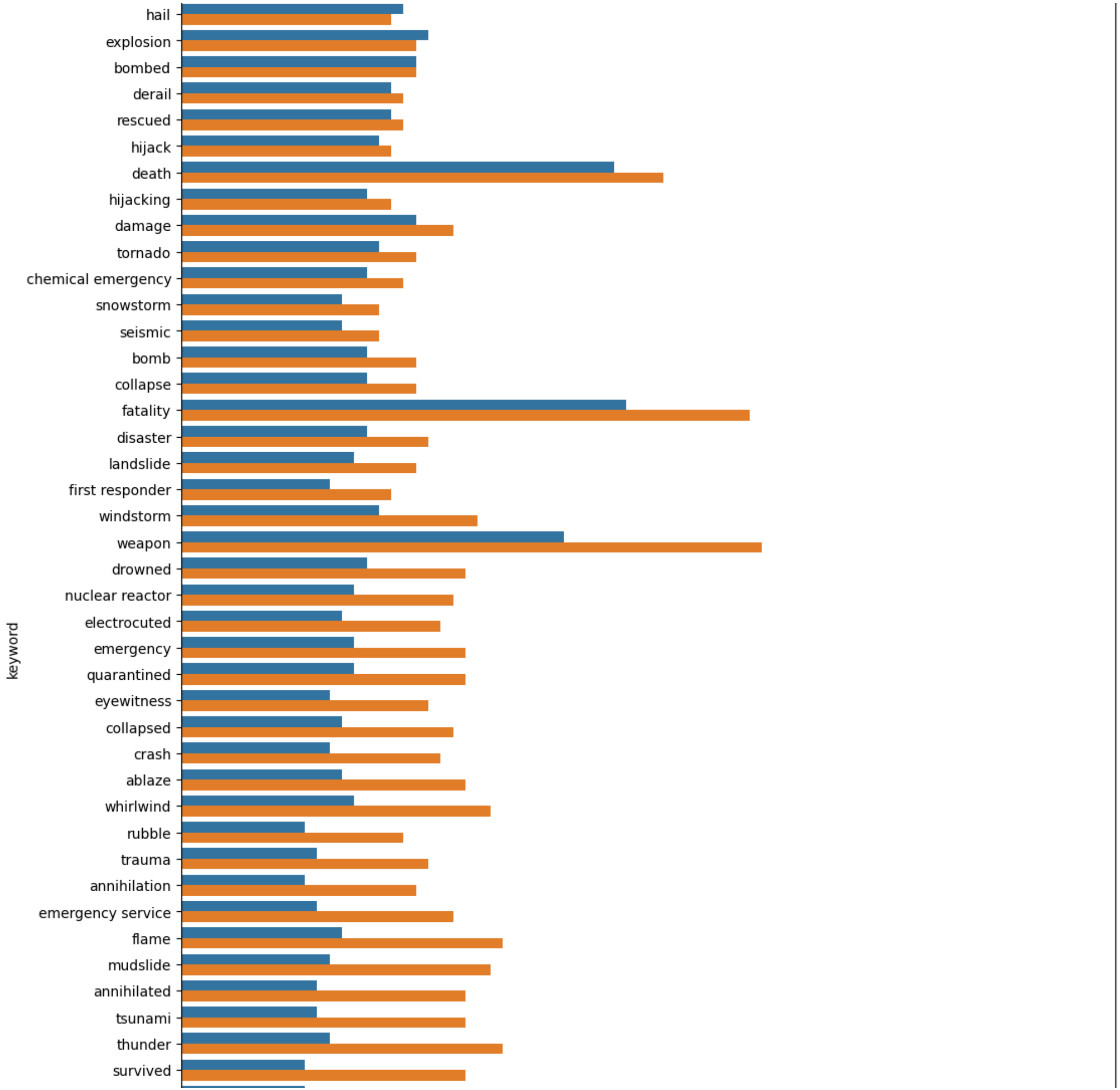
Out[11]:
```
0       NaN
1       NaN
2       NaN
3       NaN
4       NaN
       ...
7608    NaN
7609    NaN
7610    NaN
7611    NaN
7612    NaN
Name: keyword, Length: 7613, dtype: object
```

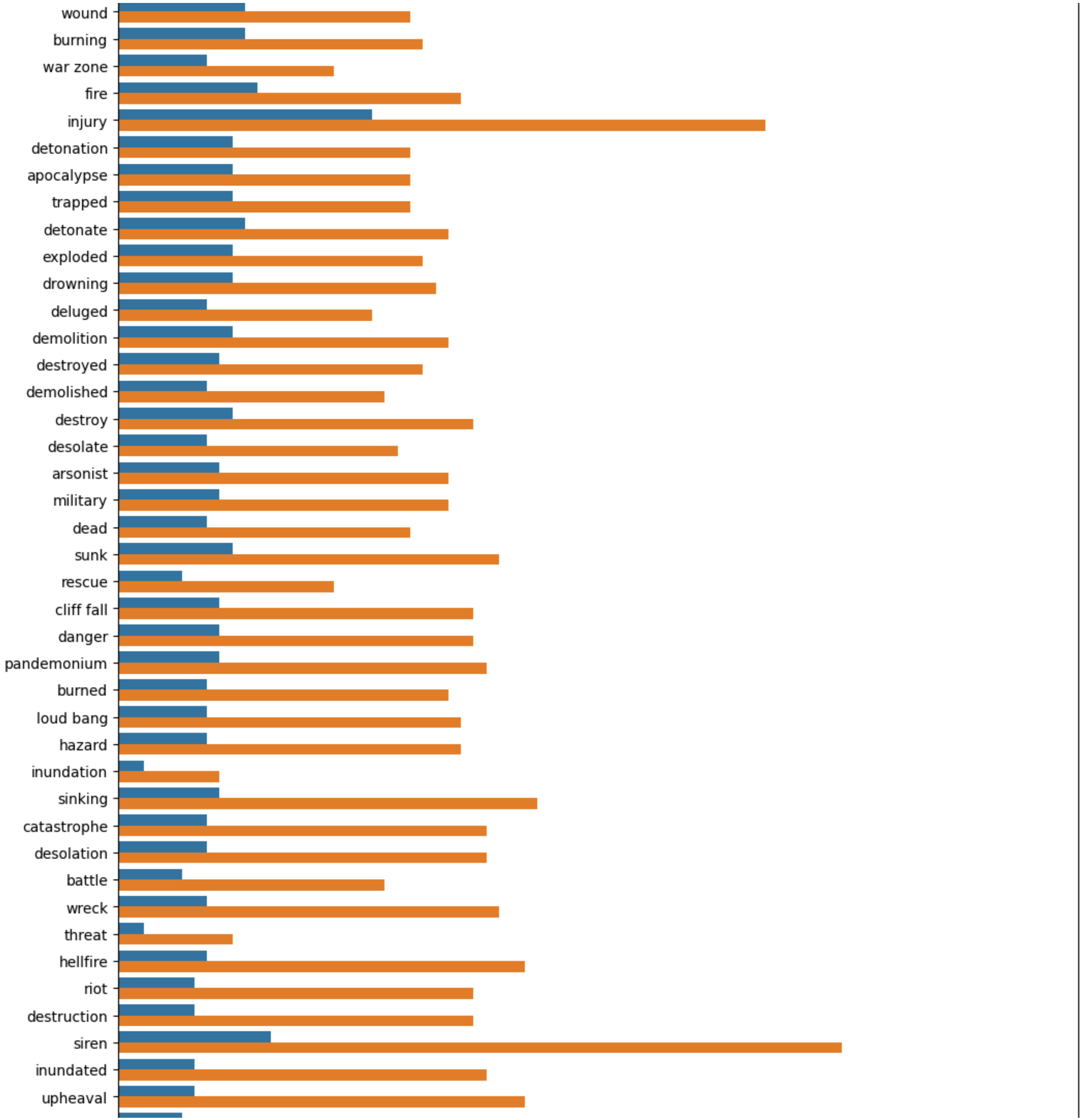
The keyword of the training set and the test set are exactly the same, indicating that the keyword of the training set can be used on the test set.

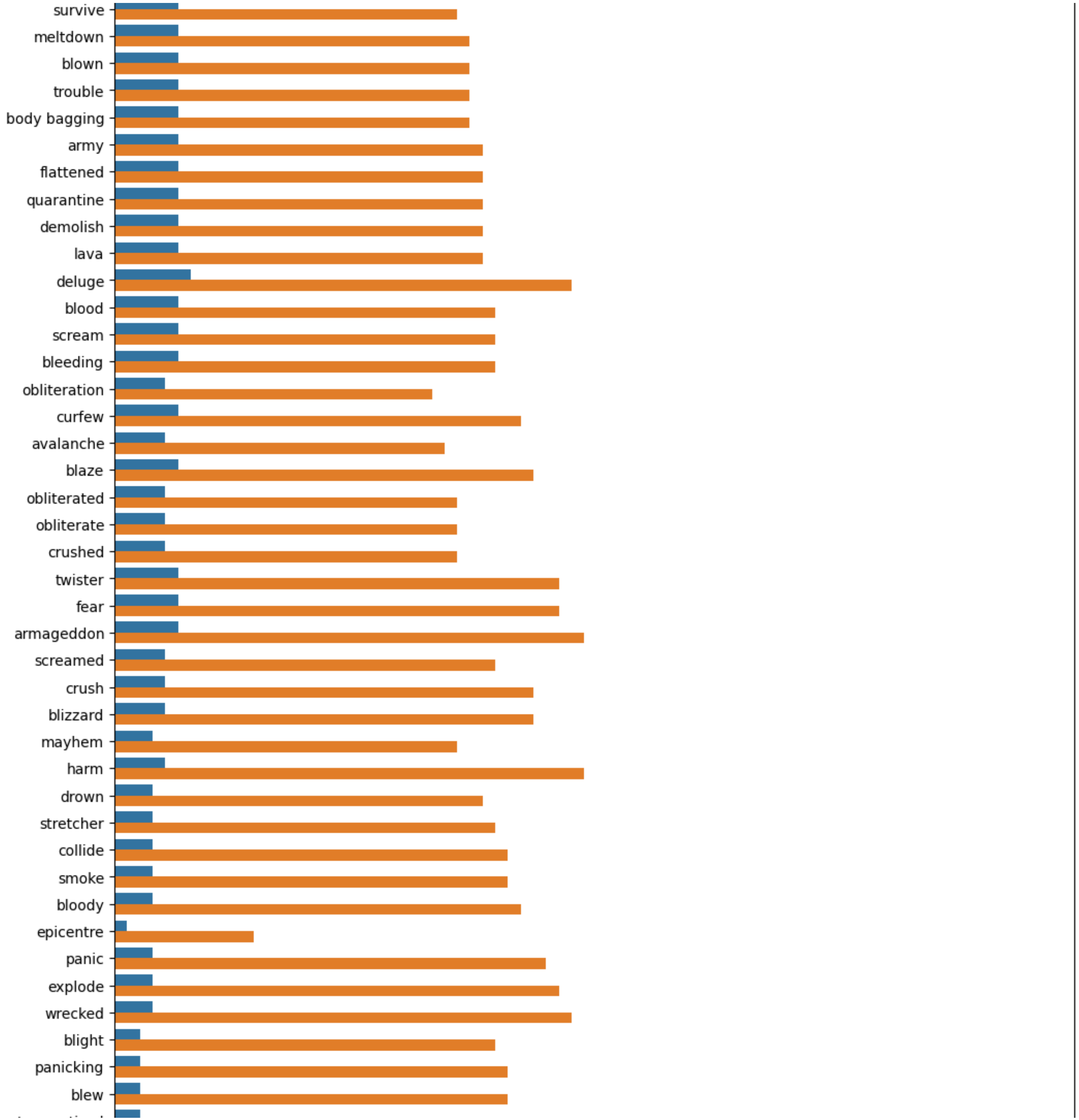
In [4]:
```
# Group by keyword to extract the average value of the target
train_data =clear_text(train_data,'keyword')
train_data['target_mean'] = train_data.groupby('keyword')['target'].transform('mean')

fig = plt.figure(figsize=(12,72))
sorted_data = train_data.sort_values(by='target_mean', ascending=False)
# Graphs are drawn according to keyword and sorted in descending order by target_mean
sns.countplot(y=sorted_data['keyword'], hue=sorted_data['target'].astype(str))

plt.legend(loc=0)
plt.title('Target Distribution in Keywords')

plt.show()

# Drop column
train_data.drop(columns=['target_mean'], inplace=True)
test_data =clear_text(test_data,'keyword')
```

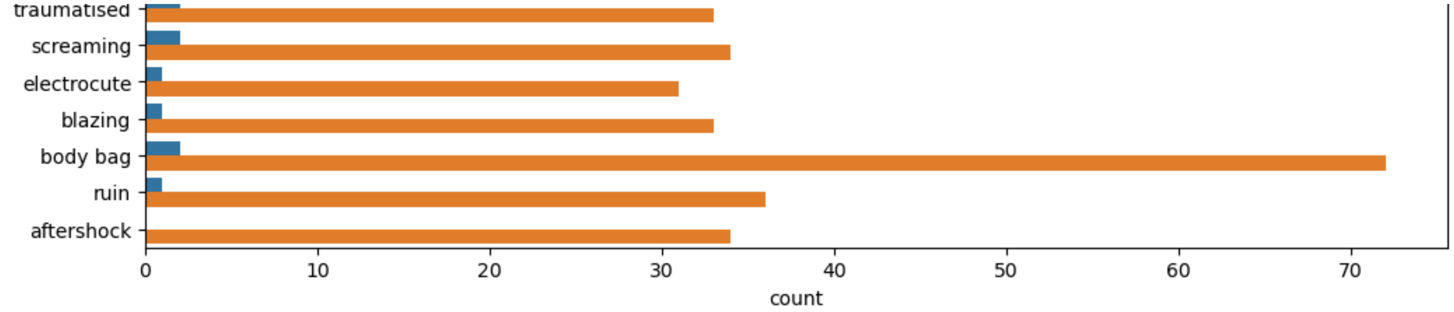

Target Distribution in Keywords
1
0
derailment
wreckage
debris
outbreak
oil spill
typhoon
suicide bombing
suicide bomber
bombing
suicide bomb
rescuer
nuclear disaster
evacuated
razed
wildfire
wild fire
airplane accident
mass murder
building fire
bridge collapse
forest fire
drought
violent storm
thunderstorm
evacuation
earthquake
sandstorm
hailstorm
devastation
collision
terrorist
heat wave
displaced
bush fire
terrorism
wounded
survivor
bioterrorism
attack
massacre


sinkhole
arson
injured
building burning
accident
derailed
fatal
dust storm
fire truck
famine
catastrophic
volcano
flooding
rioting
structural failure
hazardous
evacuate
casualty
hostage
crashed
refugee
tragedy
emergency plan
attacked
bioterror
mass murderer
cyclone
devastated
flood
collided
burning building
police
radiation emergency
hijacker
rainstorm
natural disaster
engulfed
hurricane
ambulance
lightning
storm


keyword
hail
explosion
bombed
derail
rescued
hijack
death
hijacking
damage
tornado
chemical emergency
snowstorm
seismic
bomb
collapse
fatality
disaster
landslide
first responder
windstorm
weapon
drowned
nuclear reactor
electrocuted
emergency
quarantined
eyewitness
collapsed
crash
ablaze
whirlwind
rubble
trauma
annihilation
emergency service
flame
mudslide
annihilated
tsunami
thunder
survived


wound
burning
war zone
fire
injury
detonation
apocalypse
trapped
detonate
exploded
drowning
deluged
demolition
destroyed
demolished
destroy
desolate
arsonist
military
dead
sunk
rescue
cliff fall
danger
pandemonium
burned
loud bang
hazard
inundation
sinking
catastrophe
desolation
battle
wreck
threat
hellfire
riot
destruction
siren
inundated
upheaval


survive
meltdown
blown
trouble
body bagging
army
flattened
quarantine
demolish
lava
deluge
blood
scream
bleeding
obliteration
curfew
avalanche
blaze
obliterated
obliterate
crushed
twister
fear
armageddon
screamed
crush
blizzard
mayhem
harm
drown
stretcher
collide
smoke
bloody
epicentre
panic
explode
wrecked
blight
panicking
blew



Some words appear only in disaster tweets, while others appear only in non-disaster tweets. Description keyword is an available field

Merge data and clear data in a unified manner ==> Fulldata

In [5]:
```
# concat train and test data
full_data = pd.concat([train_data,test_data],ignore_index=True)
full_data['keyword'] = full_data['keyword'].fillna('UNK')
full_data = full_data.drop(['id','location'],axis=1)


print(full_data['text'].head(-10))

#clear text
full_data = clear_text(full_data,'text')
```

```
0                                                                        Our Deeds are the Reason of this #earthquake May ALLAH Forgive us all
1                                                                                                       Forest fire near La Ronge Sask. Canada
2            All residents asked to 'shelter in place' are being notified by officers. No other evacuation or shelter in place orders are expected
3                                                                            13,000 people receive #wildfires evacuation orders in California 
4                                                     Just got sent this photo from Ruby #Alaska as smoke from #wildfires pours into a school 
                                                                                ...                                                        
10861                                                            Smackdown tyme this should put me in a good mood again since it got wrecked smh
10862                            @thrillhho jsyk I haven't stopped thinking abt remus slumped against the bathroom door all day I was wrecked ??????????
10863                               @stighefootball Begovic has been garbage. He got wrecked by a Red Bull reserve team and everyone else this preseason
10864                                                                                                           Wrecked today got my hattrick ????
10865    #Ebola #EbolaOutbreak Ebola Virus: Birmingham Ala. Firefighters Quarantined After Possible Exposure Officials Say http://t.co/tjpYlU9fOX
Name: text, Length: 10866, dtype: object
```

In [6]:
```
print('-------------cleardata:\n',full_data['text'].head(-10)) #Check if clear succeeds
print(full_data.shape)  # full_data.shape[1]==3
print(full_data[full_data['target'].notnull()].shape)
```

```
-------------cleardata:
 0                                                   deed reason earthquake may allah forgive
1                                                        forest fire near ronge sask canada
2                      resident asked shelter place notified officer evacuation shelter place order expected
3                                                   people receive wildfire evacuation order california
4                                                 got sent photo ruby alaska smoke wildfire pours school
                                                    ...                                 
10861                                                    smackdown tyme put good mood since got wrecked smh
10862                                  jsyk nt stopped thinking abt remus slumped bathroom door day wrecked
10863                             begovic garbage got wrecked red bull reserve team everyone else preseason
10864                                                                        wrecked today got hattrick
10865    ebola ebolaoutbreak ebola virus birmingham ala firefighter quarantined possible exposure official say
Name: text, Length: 10866, dtype: object
(10876, 3)
(7613, 3)
```

View the number of keyword features after cleaning

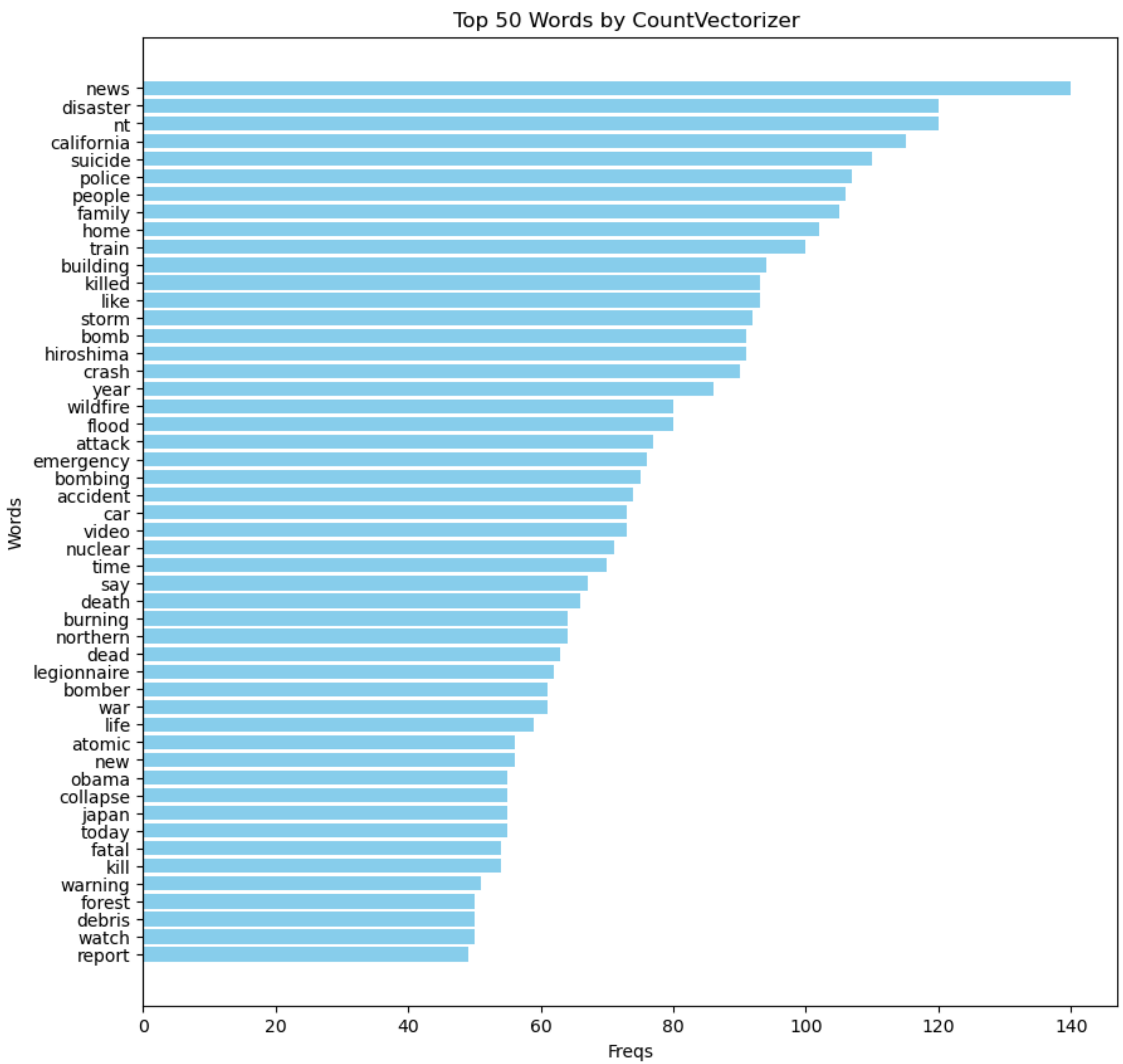
In [15]:
```
from sklearn.feature_extraction.text import CountVectorizer


vec = CountVectorizer(lowercase=True,stop_words='english')
kw_X_train =vec.fit_transform( full_data[full_data['target'].notnull()]['keyword'].values).todense()
kw_X_test = vec.transform( full_data[full_data['target'].isnull()]['keyword'].values).todense()
kw_X_train.shape  #==(7613, 212)
```

Out[15]:
```
(7613, 216)
```

View the number of features in the cleaned text

In [16]:
```
from sklearn.feature_extraction.text import CountVectorizer



vec = CountVectorizer(lowercase=True,stop_words='english')
# texts_with_target_1 = full_data[full_data['target'] == 1]['text']
texts_with_target_1=  full_data[full_data['target'] == 1]['text']
text_X_cv = vec.fit_transform(texts_with_target_1)
print(text_X_cv.shape)
vocab = vec.get_feature_names_out()

freqs = text_X_cv.sum(axis=0).tolist()[0]
feature_names = vec.get_feature_names_out()
print(feature_names.shape)
freqs_data = pd.DataFrame({
    'word': feature_names,
    'freqs': freqs
})
top_n = 50
top_n_freqs = freqs_data.sort_values(by='freqs', ascending=False).head(top_n)


plt.figure(figsize=(10, 10))
plt.barh(top_n_freqs['word'], top_n_freqs['freqs'], color='skyblue')
plt.xlabel('Freqs')
plt.ylabel('Words')
plt.title(f'Top {top_n} Words by CountVectorizer ')
plt.gca().invert_yaxis()
plt.show()
```

```
(3271, 7019)
(7019,)
```

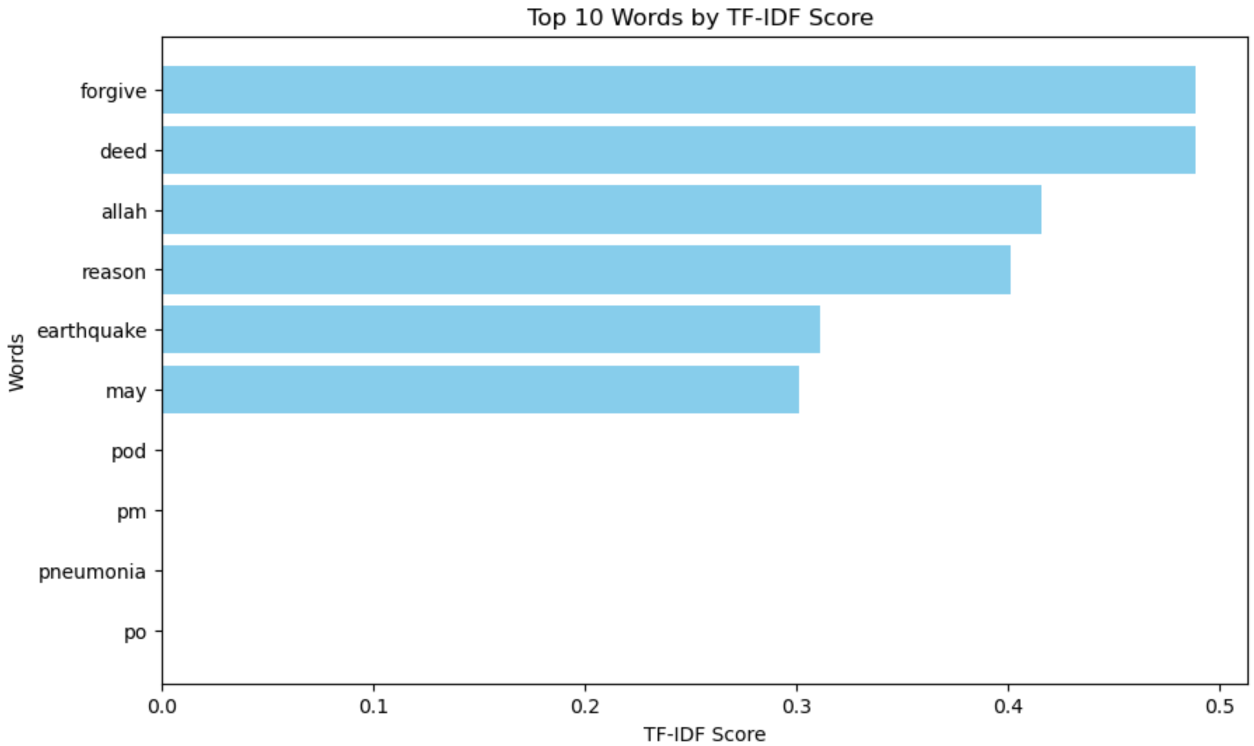


It can be found that using CountVectorizer with too many features will not only lead to excessive memory consumption, but also significantly reduce the speed of model training and prediction

In [17]:
```
from sklearn.feature_extraction.text import TfidfVectorizer


tfidf_vec  = TfidfVectorizer() #A measure of how important a word is in a document or corpus

#The text data in full_data was fitted and transformed using tfidf_vec to generate the TF-IDF feature matrix full_tfidf
texts_with_target_1 = full_data[full_data['target'] == 1]['text']
text_X_tfidf  = tfidf_vec.fit_transform(texts_with_target_1)
```

```python
print('feature sizs:',text_X_tfidf.shape[1]) #Shows how many features the text has been converted into




feature_names = tfidf_vec.get_feature_names_out()
print(feature_names.shape)
tfidf_scores = text_X_tfidf[0].toarray().flatten()
print(tfidf_scores.shape)
tfidf_data = pd.DataFrame({
    'word': feature_names,
    'tfidf': tfidf_scores
})


# The top N terms with the highest TF-IDF value are selected
top_n = 10
top_n_tfidf = tfidf_data.sort_values(by='tfidf', ascending=False).head(top_n)



plt.figure(figsize=(10, 6))
plt.barh(top_n_tfidf['word'], top_n_tfidf['tfidf'], color='skyblue')
plt.xlabel('TF-IDF Score')
plt.ylabel('Words')
plt.title(f'Top {top_n} Words by TF-IDF Score ')
plt.gca().invert_yaxis()
plt.show()
type(top_n_tfidf)
```

```
feature sizs: 7166
(7166,)
(7166,)
```



Out[17]:
```
pandas.core.frame.DataFrame
```

Due to the small amount of text, TfidfVectorizer is not as effective as CountVectorizer

Model Architecture (25 pts)

Describe your model architecture and reasoning for why you believe that specific architecture would be suitable for this problem.

Since we did not learn NLP-specific techniques such as word embeddings in the lectures, we recommend looking at Kaggle tutorials, discussion boards, and code examples posted for this challenge. You can use any resources needed, but make sure you "demonstrate" you understood by including explanations in your own words. Also importantly, please have a reference list at the end of the report.

There are many methods to process texts to matrix form (word embedding), including TF-IDF, GloVe, Word2Vec, etc. Pick a strategy and process the raw texts to word embedding. Briefly explain the method(s) and how they work in your own words.

Build and train your sequential neural network model (You may use any RNN family neural network, including advanced architectures LSTM, GRU, bidirectional RNN, etc.).

In [7]:
```
from torch import nn
from torch.utils.data import TensorDataset, DataLoader
import matplotlib.pyplot as plt
device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
device
```

Out[7]:
```
device(type='cuda', index=0)
```

In [19]:
```
def text2vec(type,train_data,test_data):
    vec=None
    if type=='CountVectorizer':
```

```
        # vec = CountVectorizer(lowercase=True,stop_words='english',min_df=.0005)
        vec = CountVectorizer(lowercase=True,stop_words='english',max_features=1000)
        pass
    elif type=='TfidfVectorizer':
        vec  = TfidfVectorizer(lowercase=True,stop_words='english')
        pass
    else :
        pass
    if vec is not None:
        text_X_train = vec.fit_transform(train_data)
        text_X_test =vec.transform(test_data)
        print('text_X_train',text_X_train.shape,'text_X_test',text_X_test.shape)
        return text_X_train.todense() ,text_X_test.todense()

    return None
```

In [20]:
```
text_X_train,text_X_test =text2vec('CountVectorizer',
                                   full_data[full_data['target'].notnull()]['text'],
                                   full_data[full_data['target'].isnull()]['text'])

X_train =np.concatenate([kw_X_train,text_X_train],axis=1)
X_test =np.concatenate([kw_X_test,text_X_test],axis=1)

X_train =np.asarray(X_train)
X_test =np.asarray(X_test)
y_train =np.asarray(full_data[full_data['target'].notnull()]['target'])


X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size = .2, stratify = y_train)
print(X_train.shape)
print(X_valid.shape)
print(type(X_train))
```

```
text_X_train (7613, 1000) text_X_test (3263, 1000)
(6090, 1216)
(1523, 1216)
<class 'numpy.ndarray'>
```

Define the LSTM model

In [21]:
```
class LSTM(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, output_dim, num_layers, dropout=0.5):
        super(LSTM, self).__init__()
        self.num_layers = num_layers
        self.hidden_dim = hidden_dim
        self.embedding = nn.Embedding(vocab_size, embedding_dim)
        self.lstm = nn.LSTM(embedding_dim, hidden_dim, num_layers=num_layers, batch_first=True)
        self.fc = nn.Linear(hidden_dim, output_dim)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x, hidden):
        x = self.embedding(x)
        x, hidden = self.lstm(x, hidden)
        x = x[:, -1, :]
        x = self.dropout(x)
        x = self.fc(x)
        return x, hidden

    def init_hidden(self, batch_size):
         # Initialize hidden states
         h0 = torch.zeros((self.num_layers, batch_size, self.hidden_dim)).to(device)
         c0 = torch.zeros((self.num_layers, batch_size, self.hidden_dim)).to(device)
         hidden = (h0, c0)
```

```
        return hidden
```

In [22]:
```
torch.manual_seed(42)
# Hyper Parameters
BATCH_SIZE = 16

train_dataset = TensorDataset(torch.from_numpy(X_train), torch.from_numpy(y_train))
train_dataloader = DataLoader(train_dataset, batch_size = BATCH_SIZE, shuffle = True, drop_last = True)

valid_dataset = TensorDataset(torch.from_numpy(X_valid),torch.from_numpy(y_valid))
valid_dataloader = DataLoader(valid_dataset, batch_size = BATCH_SIZE, shuffle = True, drop_last = True)
```

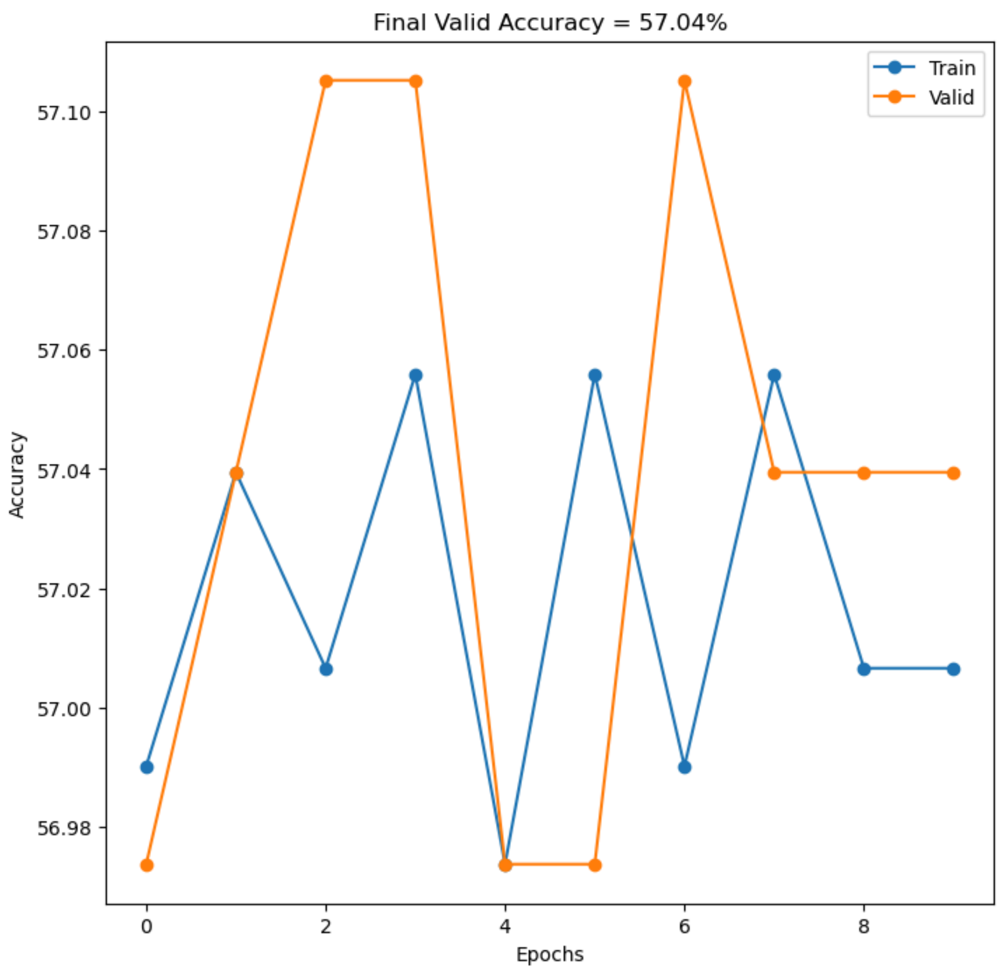
Training by CountVectorizer data

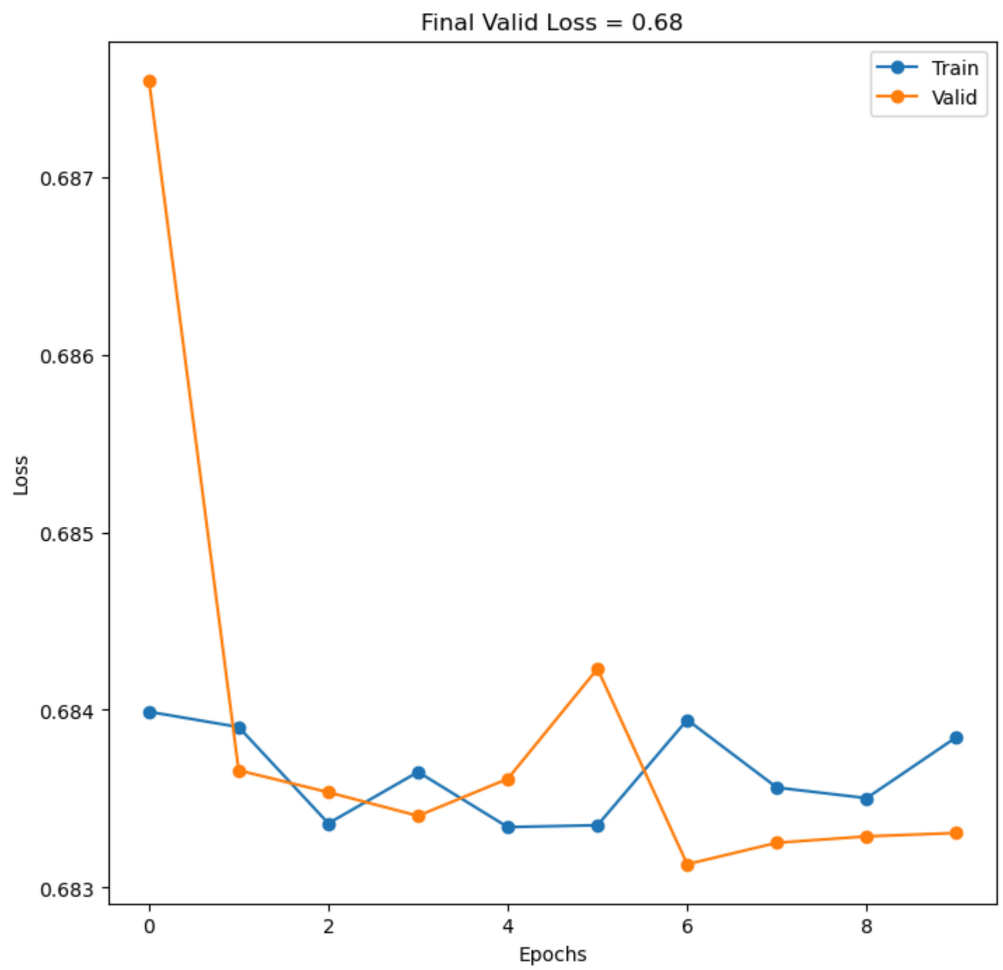
In [23]:
```
max_norm = 5
EPOCH = 10
LR = 0.001    # Learning rate




# Create the model with modified layer dimensions
lstm = LSTM(
    num_layers=3,
    hidden_dim=256,
    output_dim=1,
    embedding_dim=128,
    vocab_size=100000,
).to(device)
# Loss function and optimizer with L2 regularization
lossfun = nn.BCEWithLogitsLoss()  # Binary classification
optimizer = torch.optim.Adam(lstm.parameters(), lr=LR, weight_decay=0.001)  # L2 regularization



lstm.to(device)
trainAcc = []
trainLoss = []
devAcc = []
devLoss = []

yTrue, yPred = [], []

for epochi in range(EPOCH):
    batchAcc = []
    batchLoss = []

    h = lstm.init_hidden(BATCH_SIZE)

    lstm.train()

    for X, y in train_dataloader:
        X, y = X.to(device, dtype=torch.int), y.to(device)
        h = tuple([each.detach()for each in h])
        yHat, h = lstm.forward(X,h)
        yHat = yHat.squeeze()
        loss = lossfun(yHat, y)

        # print("Raw outputs (yHat):", yHat)
        optimizer.zero_grad()
        loss.backward()
```

```python
        nn.utils.clip_grad_norm_(lstm.parameters(), max_norm)
        optimizer.step()

        preds = (torch.sigmoid(yHat) > .5).cpu().numpy()
        acc = accuracy_score(y.cpu().numpy(), preds)
        batchAcc.append(acc * 100)
        batchLoss.append(loss.item())

    trainAcc.append(np.mean(batchAcc))
    trainLoss.append(np.mean(batchLoss))

    lstm.eval()
    yTrue, yPred = [], []
    with torch.no_grad():

        h = lstm.init_hidden(BATCH_SIZE)

        batchAcc = []
        batchLoss = []
        for X, y in valid_dataloader:
            X, y = X.to(device, dtype=torch.int), y.to(device)
            h = tuple([each.detach()for each in h])
            yHat, h = lstm.forward(X,h)
            yHat = yHat.squeeze()
            loss = lossfun(yHat, y)

            preds = (torch.sigmoid(yHat) > .5).cpu().numpy()
            yPred.extend(preds)
            yTrue.extend(y.cpu().numpy())

            # print(preds)
            batchAcc.append(accuracy_score(y.cpu().numpy(), preds) * 100)
            batchLoss.append(loss.item())
        devAcc.append(np.mean(batchAcc))
        devLoss.append(np.mean(batchLoss))
```

In [24]:

```python
fig, ax = plt.subplots(1, 2, figsize = (18, 8))

ax[0].plot(trainAcc, 'o-', label = 'Train')
ax[0].plot(devAcc, 'o-', label = 'Valid')
ax[0].set_title(f'Final Valid Accuracy = {devAcc[-1]:.2f}%')
ax[0].set_xlabel('Epochs')
ax[0].set_ylabel('Accuracy')
ax[0].legend()

ax[1].plot(trainLoss, 'o-', label = 'Train')
ax[1].plot(devLoss, 'o-', label = 'Valid')
ax[1].set_title(f'Final Valid Loss = {devLoss[-1]:.2f}')
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('Loss')
ax[1].legend()

plt.show()
```





Word Embedding by Tokenizer

In [8]:
```
from tensorflow import keras
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

MAX_FEATURES = 5000


feature ='final_text'
full_data['final_text'] = full_data['keyword'] + ' ' + full_data['text']


word_tokenizer = Tokenizer(num_words=MAX_FEATURES)
feature_text =full_data[full_data['target'].notnull()][feature].values
print(feature_text.shape)
word_tokenizer.fit_on_texts(feature_text)

vocab_length = len(word_tokenizer.word_index) + 1
print(word_tokenizer)
```

```python
print('vocab_length:',vocab_length)
token_X = word_tokenizer.texts_to_sequences(feature_text)
print('token_X',len(token_X))
# print(token_X)

max_seq_len = 20  # Sets the maximum sequence length
X_padded = pad_sequences(token_X, maxlen=max_seq_len,padding='post', truncating='post')
print(X_padded.shape)

token_df = pd.DataFrame(X_padded)


X_train =full_data[full_data['target'].notnull()]
if len(X_train) != len(token_df):
    raise ValueError("The number of rows in full_data and token_df must match.")
X_train = pd.concat([X_train, token_df], axis=1)
```

```
(7613,)
<keras.preprocessing.text.Tokenizer object at 0x00000265CB589990>
vocab_length: 13106
token_X 7613
(7613, 20)
```

In [26]:
```python
token_df
```

Out[26]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	268	3766	470	80	85	1328	3767	0	0	0	0	0	0	0	0	0	0	0	0	0
1	268	53	1	301	1021	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	268	1456	1329	1784	471	409	90	1784	471	427	917	0	0	0	0	0	0	0	0	0
3	268	15	3768	54	90	427	49	0	0	0	0	0	0	0	0	0	0	0	0	0
4	268	47	1022	220	1604	102	54	196	0	0	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
7608	268	71	659	1003	904	137	31	549	36	0	0	0	0	0	0	0	0	0	0	0
7609	268	596	125	1	49	159	244	397	251	0	0	0	0	0	0	0	0	0	0	0
7610	268	608	281	1319	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7611	268	20	953	2694	107	59	340	4382	2694	1611	3299	1034	4383	2202	27	0	0	0	0	0
7612	268	276	36	212	244	49	54	583	16	0	0	0	0	0	0	0	0	0	0	0

7613 rows × 20 columns

In [27]:
```python
X_train.head(-50)
```

Out[27]:

	keyword	text	target	final_text	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	UNK	deed reason earthquake may allah forgive	1.0	UNK deed reason earthquake may allah forgive	268	3766	470	80	85	1328	3767	0	0	0	0	0	0	0	0	0	0	0	0	0
1	UNK	forest fire near ronge sask canada	1.0	UNK forest fire near ronge sask canada	268	53	1	301	1021	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	UNK	resident asked shelter place notified officer evacuation shelter place order expected	1.0	UNK resident asked shelter place notified officer evacuation shelter place order expected	268	1456	1329	1784	471	409	90	1784	471	427	917	0	0	0	0	0	0	0	0	0
3	UNK	people receive wildfire evacuation order california	1.0	UNK people receive wildfire evacuation order california	268	15	3768	54	90	427	49	0	0	0	0	0	0	0	0	0	0	0	0	0
4	UNK	got sent photo ruby alaska smoke wildfire pours school	1.0	UNK got sent photo ruby alaska smoke wildfire pours school	268	47	1022	220	1604	102	54	196	0	0	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
7558	wrecked	coleslaw wrecked	0.0	wrecked coleslaw wrecked	133	133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7559	wrecked	exotic car wrecked train accident	1.0	wrecked exotic car wrecked train accident	133	59	133	55	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7560	wrecked	twin pitcher ego wrecked	0.0	wrecked twin pitcher ego wrecked	133	1354	3461	3505	133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7561	wrecked	wgg lol got wrecked	0.0	wrecked wgg lol got wrecked	133	185	47	133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7562	wrecked	wrecked whole world	0.0	wrecked wrecked whole world	133	133	383	56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

7563 rows × 24 columns

In [9]:

```
y_train =X_train['target']
print(y_train.shape)
exclude_labels = [ 'target','keyword','text','final_text']
columns_to_keep = [col for col in X_train.columns if col not in exclude_labels]
X_train =X_train.loc[:, columns_to_keep]
print(X_train.shape)
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size = .2, stratify = y_train)
print(X_train.shape)
print(X_valid.shape)
```

```
(7613,)
(7613, 20)
(6090, 20)
(1523, 20)
```

In [29]:

```
y_train.head(-10)
```

Out[29]:

```
3375    1.0
5751    1.0
2224    0.0
297     0.0
3841    0.0
       ...
5497    1.0
2109    0.0
3098    0.0
4602    0.0
4519    1.0
Name: target, Length: 6080, dtype: float64
```

In [30]:

```
X_train.head(-10)
```

Out[30]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
3375	90	3556	366	919	891	962	548	2347	90	0	0	0	0	0	0	0	0	0	0	0
5751	138	2693	138	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2224	123	1718	403	867	621	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0
297	223	2993	509	1358	740	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3841	73	3085	65	2635	73	2999	4994	0	0	0	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
5497	194	257	194	564	307	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2109	18	1927	1234	3376	254	3377	1051	1714	4533	18	492	0	0	0	0	0	0	0	0	0
3098	216	4803	1223	47	216	185	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4602	27	4587	1762	701	7	560	4100	65	70	27	65	463	0	0	0	0	0	0	0	0
4519	113	113	2030	274	3675	2337	3676	3677	0	0	0	0	0	0	0	0	0	0	0	0

6080 rows × 20 columns

In [10]:

```
torch.manual_seed(42)
# Hyper Parameters
BATCH_SIZE = 64


train_dataset = TensorDataset(torch.tensor(X_train.values), torch.tensor(y_train.values))
train_dataloader = DataLoader(train_dataset, batch_size = BATCH_SIZE, shuffle = True, drop_last = False)

valid_dataset = TensorDataset(torch.tensor(X_valid.values),torch.tensor(y_valid.values))
valid_dataloader = DataLoader(valid_dataset, batch_size = BATCH_SIZE, shuffle = True, drop_last = False)
```

Traning by Tokenizer Data

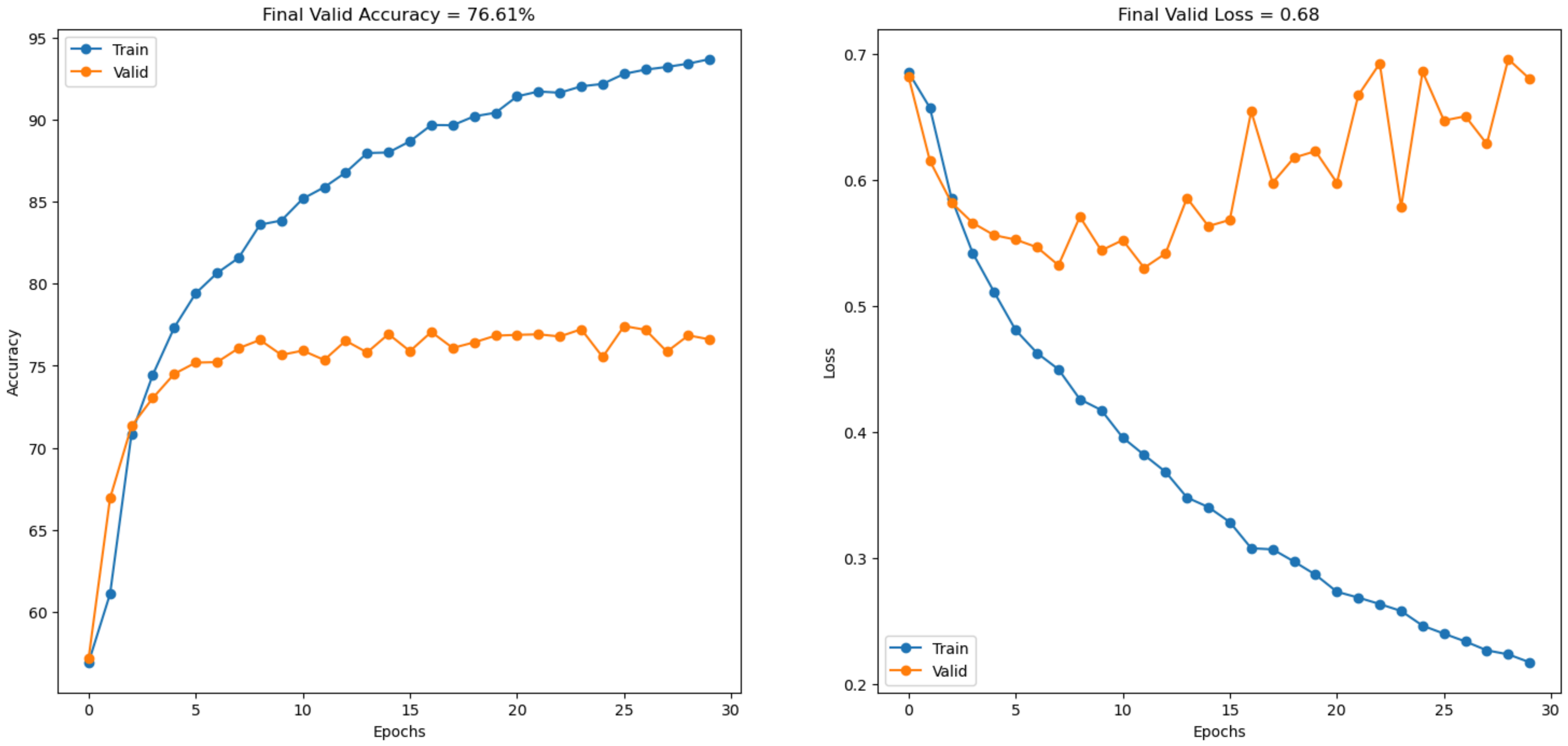
In [32]:

```
# Hyper Parameters
max_norm = 5
EPOCH = 30
LR = 0.001


# Create the model with modified layer dimensions
lstm = LSTM(
    num_layers=3,
    hidden_dim=256,
    output_dim=1,
    embedding_dim=128,
    vocab_size=vocab_length,
).to(device)

# Loss function and optimizer with L2 regularization
lossfun = nn.BCEWithLogitsLoss()  # Binary classification
optimizer = torch.optim.Adam(lstm.parameters(), lr=LR, weight_decay=0.001)  # L2 regularization


lstm.to(device)
trainAcc = []
trainLoss = []
devAcc = []
```

```
devLoss = []

yTrue, yPred = [], []

for epochi in range(EPOCH):
    batchAcc = []
    batchLoss = []



    lstm.train()

    for X, y in train_dataloader:
        X, y = X.to(device, dtype=torch.int), y.to(device)
        current_batch_size = X.size(0)
        h = lstm.init_hidden(current_batch_size)

        yHat, h = lstm.forward(X,h)
        yHat = yHat.squeeze()
        loss = lossfun(yHat, y)

        # print("Raw outputs (yHat):", yHat)
        optimizer.zero_grad()
        loss.backward()

        nn.utils.clip_grad_norm_(lstm.parameters(), max_norm)
        optimizer.step()

        preds = (torch.sigmoid(yHat) > .5).cpu().numpy()
        acc = accuracy_score(y.cpu().numpy(), preds)
        batchAcc.append(acc * 100)
        batchLoss.append(loss.item())

    trainAcc.append(np.mean(batchAcc))
    trainLoss.append(np.mean(batchLoss))

    lstm.eval()
    yTrue, yPred = [], []


    with torch.no_grad():
        batchAcc = []
        batchLoss = []
        for X, y in valid_dataloader:
            X, y = X.to(device, dtype=torch.int), y.to(device)
            current_batch_size = X.size(0)
            h = lstm.init_hidden(current_batch_size)

            yHat, h = lstm.forward(X,h)
            yHat = yHat.squeeze()
            loss = lossfun(yHat, y)

            preds = (torch.sigmoid(yHat) > .5).cpu().numpy()
            yPred.extend(preds)
            yTrue.extend(y.cpu().numpy())

            # print(preds)
            batchAcc.append(accuracy_score(y.cpu().numpy(), preds) * 100)
            batchLoss.append(loss.item())
        devAcc.append(np.mean(batchAcc))
        devLoss.append(np.mean(batchLoss))
```

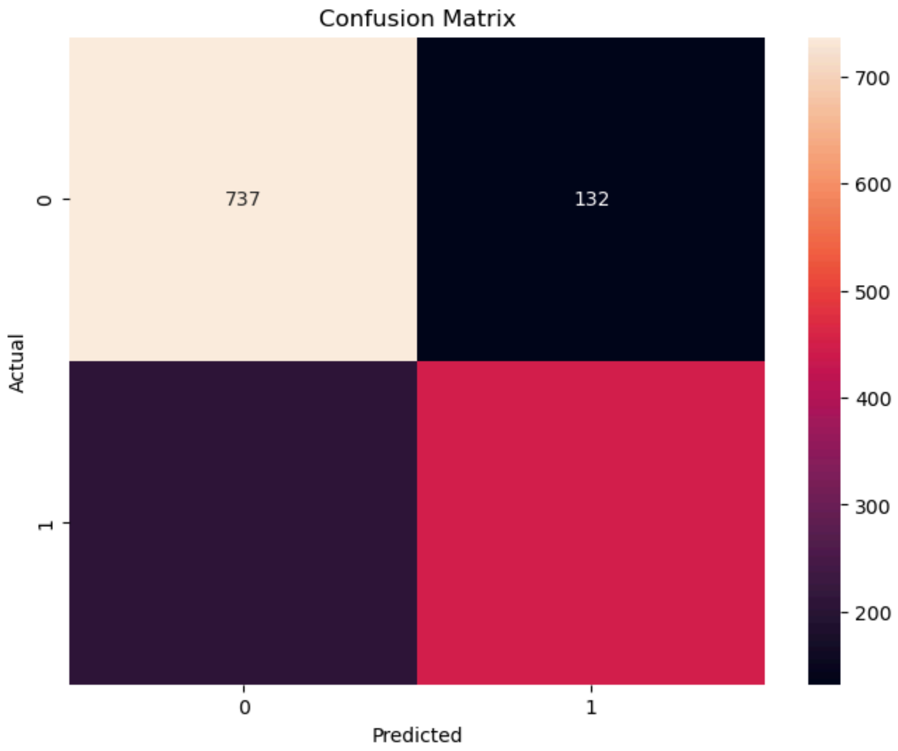
In [ ]:

```
fig, ax = plt.subplots(1, 2, figsize = (18, 8))

ax[0].plot(trainAcc, 'o-', label = 'Train')
ax[0].plot(devAcc, 'o-', label = 'Valid')
ax[0].set_title(f'Final Valid Accuracy = {devAcc[-1]:.2f}%')
ax[0].set_xlabel('Epochs')
ax[0].set_ylabel('Accuracy')
ax[0].legend()

ax[1].plot(trainLoss, 'o-', label = 'Train')
ax[1].plot(devLoss, 'o-', label = 'Valid')
ax[1].set_title(f'Final Valid Loss = {devLoss[-1]:.2f}')
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('Loss')
ax[1].legend()

plt.show()
```



```
The Kernel crashed while executing code in the current cell or a previous cell.

Please review the code in the cell(s) to identify a possible cause of the failure.

Click <a href='https://aka.ms/vscodeJupyterKernelCrash'>here</a> for more info.

View Jupyter <a href='command:jupyter.viewOutput'>log</a> for further details.
```

In [33]:
```python
from sklearn.metrics import confusion_matrix, f1_score, precision_score, recall_score

cm = confusion_matrix(yTrue, yPred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='g')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



lstm_result.csv Complete · 2d ago		0.75237
lstm_result.csv Complete · 2d ago		0.72142

Word Embedding by Word2Vec

In [ ]:
```
! pip install  gensim
```

In [30]:
```
from gensim.models import Word2Vec
EMBEDDING_DIM = 256
feature_text =full_data[full_data['target'].notnull()][feature].values
feature_text = [text.split() for text in feature_text] #[[a,b,c],[d,e,f]]
print(len(feature_text),feature_text[0])
w2v_model = Word2Vec(sentences=feature_text, vector_size=EMBEDDING_DIM, window=5, min_count=0,sg=1)
w2v_model.train(feature_text, total_examples=len(feature_text), epochs=10)
```

```
7613 ['UNK', 'deed', 'reason', 'earthquake', 'may', 'allah', 'forgive']
```

Out[30]:
```
(716548, 726560)
```

In [31]:
```
print("Vocabulary count:",len(w2v_model.wv.key_to_index))
# for word in w2v_model.wv.key_to_index:
#     print(word)

if "unk" not in w2v_model.wv:
    # Add a randomly initialized vector to <UNK>
    w2v_model.wv.add_vector("unk", np.random.uniform(-0.25, 0.25, EMBEDDING_DIM))

if 'unk' in w2v_model.wv:
    print("Word 'unk' is in the vocabulary.")
else:
    print("Word 'unk' is NOT in the vocabulary.")
```

```
Vocabulary count: 13105
Word 'unk' is in the vocabulary.
```

```
c:\Users\SEELE\.conda\envs\python_env\lib\site-packages\gensim\models\keyedvectors.py:551: UserWarning: Adding single vectors to a KeyedVectors which grows by one each time can be costly. Consider adding in b
atches or preallocating to the required size.
  warnings.warn(
```

In [13]:
```
w2v_model.wv.most_similar('dead', topn=10)
```

Out[13]:
```
[('exchanging', 0.7616621851921082),
 ('emmerdale', 0.7535473108291626),
 ('aim', 0.7430902719497681),
 ('kaduna', 0.7351449728012085),
 ('shot', 0.7258478403091431),
 ('ross', 0.7247518301010132),
 ('ushed', 0.7209054231643677),
 ('dozen', 0.7141162753105164),
 ('val', 0.7137678861618042),
 ('askcharley', 0.7106947898864746)]
```

In [14]:
```
def get_weight_matrix_w2v(model, vocab):
    # total vocabulary size plus 0 for unknown words
    vocab_size = len(vocab) + 1
    # define weight matrix dimensions with all 0
    weight_matrix = np.zeros((vocab_size, EMBEDDING_DIM))
    # step vocab, store vectors using the Tokenizer's integer mapping
    for word, i in vocab.items():
        weight_matrix[i] = model.wv[word]
    return weight_matrix

def get_weight_matrix_glove(model, vocab):
    # total vocabulary size plus 0 for unknown words
    vocab_size = len(vocab) + 1
    # define weight matrix dimensions with all 0
```

```python
    weight_matrix = np.zeros((vocab_size, EMBEDDING_DIM))
    # step vocab, store vectors using the Tokenizer's integer mapping
    for word, i in vocab.items():
        weight_matrix[i] = model.word_vectors[model.dictionary[word]]
    return weight_matrix

word_index = word_tokenizer.word_index
embedding_vectors_w2v = get_weight_matrix_w2v(w2v_model, word_index)
```

In [15]:

```python
class LSTM_w2v(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, output_dim, num_layers, dropout=0.8,pretrained_weights=None):
        super(LSTM_w2v, self).__init__()
        self.num_layers = num_layers
        self.hidden_dim = hidden_dim
        self.embedding = nn.Embedding(vocab_size, embedding_dim)
        if pretrained_weights is not None:
            self.embedding.weight.data.copy_(torch.from_numpy(pretrained_weights))
        self.lstm = nn.LSTM(embedding_dim, hidden_dim, num_layers=num_layers, batch_first=True)
        self.fc = nn.Linear(hidden_dim, output_dim)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x, hidden):
        x = self.embedding(x)
        x, hidden = self.lstm(x, hidden)
        x = x[:, -1, :]
        x = self.dropout(x)
        x = self.fc(x)
        return x, hidden

    def init_hidden(self, batch_size):
         # Initialize hidden states
         h0 = torch.zeros((self.num_layers, batch_size, self.hidden_dim)).to(device)
         c0 = torch.zeros((self.num_layers, batch_size, self.hidden_dim)).to(device)
         hidden = (h0, c0)
         return hidden
```

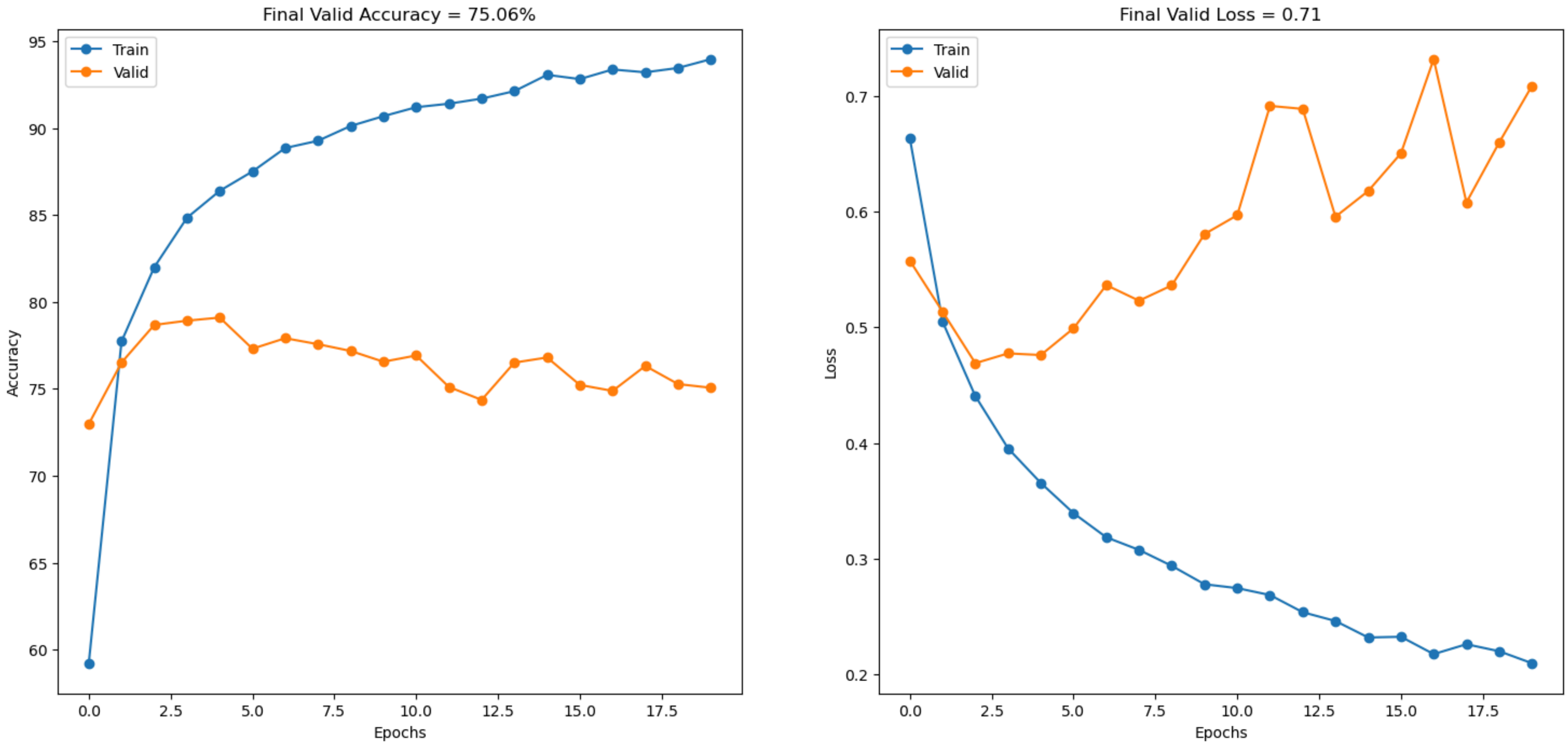
In [26]:

```python
# Hyper Parameters
max_norm = 5
EPOCH = 20
LR = 0.001


# Create the model with modified layer dimensions
lstm = LSTM_w2v(
    num_layers=3,
    hidden_dim=256,
    output_dim=1,
    embedding_dim=EMBEDDING_DIM,
    vocab_size=len(w2v_model.wv.key_to_index),
    pretrained_weights=embedding_vectors_w2v
).to(device)

# Loss function and optimizer with L2 regularization
lossfun = nn.BCEWithLogitsLoss()  # Binary classification
optimizer = torch.optim.Adam(lstm.parameters(), lr=LR, weight_decay=0.001)  # L2 regularization


lstm.to(device)
trainAcc = []
trainLoss = []
```

```python
devAcc = []
devLoss = []

yTrue, yPred = [], []

for epochi in range(EPOCH):
    batchAcc = []
    batchLoss = []

    lstm.train()

    for X, y in train_dataloader:
        X, y = X.to(device, dtype=torch.int), y.to(device)
        current_batch_size = X.size(0)
        h = lstm.init_hidden(current_batch_size)

        yHat, h = lstm.forward(X,h)
        yHat = yHat.squeeze()
        loss = lossfun(yHat, y)

        # print("Raw outputs (yHat):", yHat)
        optimizer.zero_grad()
        loss.backward()

        nn.utils.clip_grad_norm_(lstm.parameters(), max_norm)
        optimizer.step()

        preds = (torch.sigmoid(yHat) > .5).cpu().numpy()
        acc = accuracy_score(y.cpu().numpy(), preds)
        batchAcc.append(acc * 100)
        batchLoss.append(loss.item())

    trainAcc.append(np.mean(batchAcc))
    trainLoss.append(np.mean(batchLoss))

    lstm.eval()
    yTrue, yPred = [], []


    with torch.no_grad():
        batchAcc = []
        batchLoss = []
        for X, y in valid_dataloader:
            X, y = X.to(device, dtype=torch.int), y.to(device)
            current_batch_size = X.size(0)
            h = lstm.init_hidden(current_batch_size)

            yHat, h = lstm.forward(X,h)
            yHat = yHat.squeeze()
            loss = lossfun(yHat, y)

            preds = (torch.sigmoid(yHat) > .5).cpu().numpy()
            yPred.extend(preds)
            yTrue.extend(y.cpu().numpy())

            # print(preds)
            batchAcc.append(accuracy_score(y.cpu().numpy(), preds) * 100)
            batchLoss.append(loss.item())
        devAcc.append(np.mean(batchAcc))
        devLoss.append(np.mean(batchLoss))
```

In [27]:

```
fig, ax = plt.subplots(1, 2, figsize = (18, 8))

ax[0].plot(trainAcc, 'o-', label = 'Train')
ax[0].plot(devAcc, 'o-', label = 'Valid')
ax[0].set_title(f'Final Valid Accuracy = {devAcc[-1]:.2f}%')
ax[0].set_xlabel('Epochs')
ax[0].set_ylabel('Accuracy')
ax[0].legend()

ax[1].plot(trainLoss, 'o-', label = 'Train')
ax[1].plot(devLoss, 'o-', label = 'Valid')
ax[1].set_title(f'Final Valid Loss = {devLoss[-1]:.2f}')
ax[1].set_xlabel('Epochs')
ax[1].set_ylabel('Loss')
ax[1].legend()

plt.show()
```



lstm_wv_result.csv

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In [35]:
```
# # Save the state at some point during training
# torch.save({
#     'model_state_dict': model.state_dict(),
#     'optimizer_state_dict': optimizer.state_dict(),
#     'epoch': epoch,
#     'loss': loss,
# }, 'checkpoint.tar')

# # After that, you can restore the model and optimizer
# checkpoint = torch.load('checkpoint.tar')
# model.load_state_dict(checkpoint['model_state_dict'])
# optimizer.load_state_dict(checkpoint['optimizer_state_dict'])
# epoch = checkpoint['epoch']
# loss = checkpoint['loss']
```

Results and Analysis (35 pts)

Run hyperparameter tuning, try different architectures for comparison, apply techniques to improve training or performance, and discuss what helped.

Includes results with tables and figures. There is an analysis of why or why not something worked well, troubleshooting, and a hyperparameter optimization procedure summary.

In [39]:
```
test_token_X = word_tokenizer.texts_to_sequences(full_data[full_data['target'].isnull()][feature].values)
test_token_X = pad_sequences(test_token_X, maxlen=max_seq_len, padding='post', truncating='post')
test_token_df = pd.DataFrame(test_token_X)

X_test = full_data[full_data['target'].isnull()]
X_test = X_test.reset_index(drop=True)
print(X_test.shape,test_token_df.shape)
if len(X_test) != len(test_token_df):
    raise ValueError("The number of rows in X_test and test_token_df must match.")
X_test = pd.concat([X_test, test_token_df], axis=1)

X_test =X_test.loc[:, columns_to_keep]
print(X_test.shape)
```

```
(3263, 4) (3263, 20)
(3263, 20)
```

In [ ]:
```
test_token_df
```

In [40]:
```
y_test =np.empty((X_test.shape[0], 1))
print(y_test.shape)
test_dataset = TensorDataset(torch.tensor(X_test.values), torch.tensor(y_test))
test_dataloader = DataLoader(test_dataset, batch_size = BATCH_SIZE)
```

```
(3263, 1)
```

In [41]:
```
yPreds = []

lstm.eval()

with torch.no_grad():
    for X, y in test_dataloader:
```

```
        current_batch_size = X.size(0)
        h = lstm.init_hidden(current_batch_size)
        X, _ = X.to(device, dtype=torch.int), y.to(device)
        yHat, h = lstm.forward(X, h)
        yHat = yHat.squeeze()
        preds = (torch.sigmoid(yHat) > .5).cpu().numpy()
        yPreds.extend(preds)

yPreds = np.array(yPreds, dtype=bool)
print(yPreds)
```

```
[ True False  True ...  True  True  True]
```

In [42]:
```
def save_data(y_pred,filename):
    submission=pd.DataFrame ( {
    "id" : test_data [ "id" ],
    "target" : y_pred.astype (int)
    })
    submission.to_csv ( filename+'_result.csv',index=False)
```

In [43]:
```
yPreds
save_data(yPreds,'lstm_wv')
```

Conclusion (15 pts)

Discuss and interpret results as well as learnings and takeaways. What did and did not help improve the performance of your models? What improvements could you try in the future?

First, we imported the data and gained a thorough understanding of what the training data looks like before cleaning it. We also visualized most of the data, cleaned the location field which had missing data, and through graphical analysis, we discovered the effectiveness of the keyword field. Then, as part of our exploratory data analysis (EDA), we preprocessed the training data by calculating punctuation, the appearance of numbers, and modifying the Text field to make it easier for computers to understand.

After preparing the training data, we split it into two subsets—training and validation—to better train our model.

Upon testing, we found that using Bag-of-Words (BOW) and Term Frequency-Inverse Document Frequency (TF-IDF) for processing text data led to an excessive number of dimensions, which heavily consumed resources during training and was not conducive for deep learning models. Additionally, the training accuracy (ACC) values were relatively low. Therefore, we reduced the dimensionality by directly applying tokenizer and word2vec methods on strings and retrained with LSTM. Under the same environment, the training time was reduced from 60 minutes to 2 minutes, and the test ACC reached 0.75. However, the training accuracy was significantly higher than the validation accuracy, indicating an overfitting issue. The model performed well on the training data but poorly on the validation data. The volatility in validation accuracy and loss was greater compared to the training metrics, suggesting that the model's performance on unseen data is unstable and inconsistent, showing poor generalization capability on validation or test data.

We speculate that due to hyperparameter reasons, the training results of the model are unstable, with abnormal fluctuations at certain moments.