In [173…
```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import spacy
import itertools

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, ConfusionMatrixDisplay,
import tensorflow as tf
from tensorflow import keras
```

In [412…
```python
%load_ext watermark
%watermark -v -n -m -p numpy,sklearn,spacy,pandas,seaborn,tensorflow
```

```
The watermark extension is already loaded. To reload it, use:
  %reload_ext watermark
Python implementation: CPython
Python version       : 3.8.8
IPython version      : 7.22.0

numpy     : 1.23.5
sklearn   : 1.2.0
spacy     : 3.4.4
pandas    : 1.4.3
seaborn   : 0.12.2
tensorflow: 2.11.0

Compiler    : MSC v.1916 64 bit (AMD64)
OS          : Windows
Release     : 10
Machine     : AMD64
Processor   : Intel64 Family 6 Model 140 Stepping 1, GenuineIntel
CPU cores   : 8
Architecture: 64bit
```

# Brief Description

This is a binary classification project for NLP. We seek to build a model that predicts whether a given tweet is about real disasters or not. There are a total of 10,000 manually classified tweets of which 7,613 are present in the training dataset and the rest as testing.

We will be using RNNs for the classification, along with a traditional KNN model to compare it against.

In [312…
```python
test = pd.read_csv(r'data\test.csv')
train = pd.read_csv(r'data\train.csv')
```

Data Definitions:

```
id -> Unique Identifier
text -> The text of the tweet
location -> The location the tweet was sent from (can be NA)
keywords -> Relevant keyword from the tweet, maybe blank
target -> Whether tweet is about a disaster
```

In [313…
```python
round(train.isna().sum()/train.shape[0], 3)
```

Out[313…
```
id          0.000
keyword     0.008
location    0.333
text        0.000
target      0.000
dtype: float64
```

We see a lot of blanks for the location, the keyword itself is already a part of the text so we should be fine with removing these columns

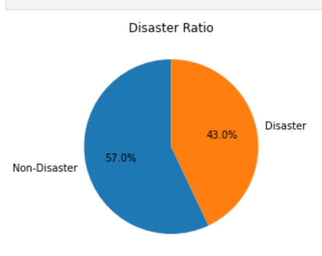
In [314…
```python
# Look at a positive samples for a disaster
train[train['target'] == 1]['text'].sample(5).values
```

Out[314…
```
array(['#news Britons rescued amid Himalaya floods http://t.co/kEPznhXHXd',
       'Such beautiful architecture in #NYC I love those fire escape routes on the bui
ldings. #newyork\x89Û_ https://t.co/fW1PtaElgV',
       'Obama Declares Disaster for Typhoon-Devastated Saipan: Obama signs disaster de
claration for Northern Marians a... http://t.co/Q3DtOqO04c',
       'Powerlines down over tram on GC Highway. Passengers have just been evacuated @
9NewsBrisbane @9NewsGoldCoast http://t.co/KD3Qsakbi5',
       '#Civilian casualties in Afghanistan hit highest number since 2009 U.N. says vi
a @WashingtonPost - http://t.co/xTF5DvgRvh'],
      dtype=object)
```

We already see a lot of URLs present, this will have to cleaned off

# Exploratory Data Analysis (EDA)

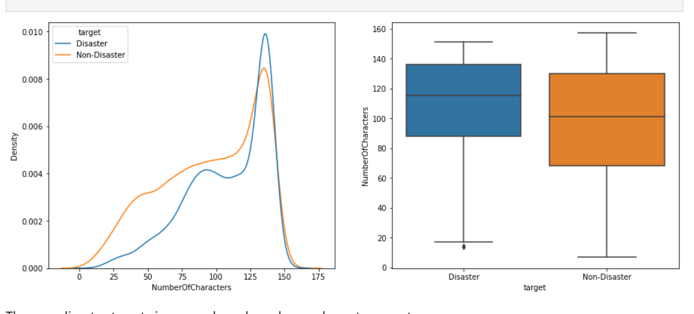
In [315…
```python
# Create a dataframe to show class counts
train_counts = train['target'].value_counts().reset_index()

plt.pie(train_counts['target'].values,
        labels=['Non-Disaster', 'Disaster'],
        autopct='%1.1f%%',
        startangle=90)
plt.title('Disaster Ratio')
plt.show()
```




The classes look like they are balanced for the most part. We now look at the distribution of char counts. Twitter used to have a 140 character limit, which has been increase since (depending on when the data was collected)

In [316…
```python
train['NumberOfCharacters'] = train['text'].apply(len)
```

In [320…
```python
figs, axs = plt.subplots(ncols=2,
                         figsize=(15,6))

g1 = sns.kdeplot(data=train,
        x='NumberOfCharacters',
        hue=train['target'].replace({0:'Non-Disaster', 1:'Disaster'}),
        ax=axs[0])

g2 = sns.boxplot(data=train,
           x=train['target'].replace({0:'Non-Disaster', 1:'Disaster'}),
           y='NumberOfCharacters',
          ax=axs[1])
```




The non disaster tweets in general can have lower character counts.

We do see some stop words that need to be removed, which should be a part of our pre-processing step.

Before we build our model, we need to do some additional data cleaning and text feature engineering. We'll use the SpaCy library for this.

# Model

## Lemmatize, clean and create Bag of Words

Some stop words such as 'the', 'if' etc do not provide any classification value, these can be removed along with numbers, URLS and punctuation texts.

In [321…
```python
#Load a medium trained model
nlp = spacy.load("en_core_web_md")
```

In [330…
```python
def cleaner(note):
    """Remove stop words, punctuations, convert words into lemma_"""
    doc = nlp(note)
    note = (" ".join([token.lemma_ for token in doc \
                      if not token.is_stop \
                          and not token.is_punct \
                          and not token.like_num\
                          and not token.like_url\
                          and not token.like_email]))
    note = note.replace('@', '')
    note = note.lower()
    return note
```

In [332…
```python
# Clean both the training and the testing dataset, should take about a min
train['text'] = train['text'].astype(str).apply(cleaner)
test['text'] = test['text'].astype(str).apply(cleaner)
```

In [413…
```python
# Tokenize texts using keras's tokenizer
tokenizer = keras.preprocessing.text.Tokenizer()
tokenizer.fit_on_texts(train['text'])
```

In [344…
```python
# Encode the text
encoded_train = tokenizer.texts_to_sequences(train['text'])
padded_train = keras.preprocessing.sequence.pad_sequences(encoded_train, maxlen=54,
                                                          padding='post')

encoded_test = tokenizer.texts_to_sequences(test['text'])
padded_test = keras.preprocessing.sequence.pad_sequences(encoded_test, maxlen=54,
                                                          padding='post')
```

In [345…
```python
X_train, X_test, y_train, y_test = train_test_split(padded_train, train['target'],
                                                     test_size=0.25,
                                                     random_state=42,
                                                     stratify=train['target'])
```

In [346…
```python
# Create a validation set
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train,
                                                     test_size=0.25,
                                                     random_state=42,
                                                     stratify=y_train)
```

## Fit a RNN Model

In [414…
```python
gnn_model = keras.models.Sequential([
                    keras.layers.Embedding(input_dim=len(tokenizer.word_index)+1,
                                           output_dim=54,
                                           input_length=X_train.shape[1]),
                    keras.layers.Bidirectional(keras.layers.SimpleRNN(64)),
                    keras.layers.Dense(64, activation='relu'),
                    keras.layers.Dense(units=1, activation='sigmoid'),
                ])
```

In [415…
```python
gnn_model.summary()
```

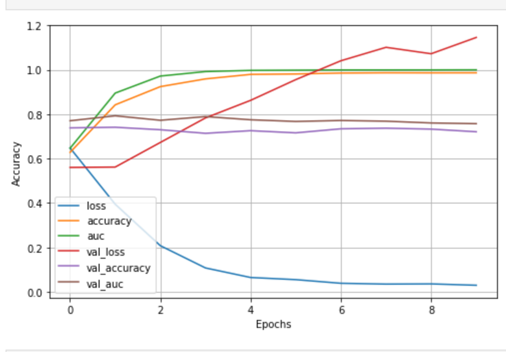
```
Model: "sequential_28"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_9 (Embedding)     (None, 54, 10)            149920

 bidirectional_20 (Bidirecti  (None, 128)              9600
 onal)

 dense_42 (Dense)            (None, 64)                8256

 dense_43 (Dense)            (None, 1)                 65

=================================================================
Total params: 167,841
Trainable params: 167,841
Non-trainable params: 0
_________________________________________________________________
```

In [416…
```python
gnn_model.compile(loss="binary_crossentropy", # Loss function
                  optimizer="adam", # Gradient Descent
                  metrics=["accuracy", "AUC"])
```

In [417…
```python
gnn_model_history = gnn_model.fit(X_train, y_train,
                                  epochs=10,
                                  validation_data =(X_valid, y_valid))
```

```
Epoch 1/10
134/134 [==============================] - 3s 16ms/step - loss: 0.6709 - accuracy: 0.5
833 - auc: 0.5864 - val_loss: 0.6451 - val_accuracy: 0.6071 - val_auc: 0.6857
Epoch 2/10
134/134 [==============================] - 2s 14ms/step - loss: 0.5225 - accuracy: 0.7
655 - auc: 0.8093 - val_loss: 0.5610 - val_accuracy: 0.7283 - val_auc: 0.7877
Epoch 3/10
134/134 [==============================] - 2s 14ms/step - loss: 0.3592 - accuracy: 0.8
624 - auc: 0.9138 - val_loss: 0.6111 - val_accuracy: 0.7346 - val_auc: 0.7814
Epoch 4/10
134/134 [==============================] - 2s 14ms/step - loss: 0.2250 - accuracy: 0.9
267 - auc: 0.9584 - val_loss: 0.7771 - val_accuracy: 0.7094 - val_auc: 0.7141
Epoch 5/10
134/134 [==============================] - 2s 14ms/step - loss: 0.1593 - accuracy: 0.9
530 - auc: 0.9756 - val_loss: 0.7215 - val_accuracy: 0.7353 - val_auc: 0.7817
Epoch 6/10
134/134 [==============================] - 2s 15ms/step - loss: 0.1143 - accuracy: 0.9
657 - auc: 0.9882 - val_loss: 0.9142 - val_accuracy: 0.7080 - val_auc: 0.7615
Epoch 7/10
134/134 [==============================] - 2s 15ms/step - loss: 0.0952 - accuracy: 0.9
682 - auc: 0.9918 - val_loss: 0.9098 - val_accuracy: 0.7416 - val_auc: 0.7651
Epoch 8/10
134/134 [==============================] - 2s 15ms/step - loss: 0.0843 - accuracy: 0.9
715 - auc: 0.9940 - val_loss: 0.9962 - val_accuracy: 0.7367 - val_auc: 0.7584
Epoch 9/10
134/134 [==============================] - 2s 15ms/step - loss: 0.0538 - accuracy: 0.9
813 - auc: 0.9977 - val_loss: 1.1130 - val_accuracy: 0.7269 - val_auc: 0.7601
Epoch 10/10
134/134 [==============================] - 2s 15ms/step - loss: 0.0430 - accuracy: 0.9
853 - auc: 0.9981 - val_loss: 1.2516 - val_accuracy: 0.7080 - val_auc: 0.7548
```

In [353…
```python
pd.DataFrame(gnn_model_history.history).plot(figsize=(8, 5))
plt.grid(True)
#plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.show()
```




In [355…
```python
gnn_model.evaluate(X_test, y_test)
```

```
60/60 [==============================] - 1s 9ms/step - loss: 1.0925 - accuracy: 0.7122
- auc: 0.7633
```

Out[355…
```
[1.0924943685531616, 0.7121848464012146, 0.7632977366447449]
```

As our training score improves, our validation score remains constant and the loss overshoots. This is an indicator that our model is overfitting the training data. This is also evident by the low accuracy and AUC score for the testing set we created.

## LTSM model

In [378…
```python
ltsm_model = keras.models.Sequential([
                    keras.layers.Embedding(len(tokenizer.word_index)+1,
                                           50,
                                           mask_zero=True),
                    keras.layers.Bidirectional(tf.keras.layers.LSTM(64,  return_se
                    keras.layers.Bidirectional(tf.keras.layers.LSTM(32)),
                    keras.layers.Dense(64, activation='sigmoid'),
                    tf.keras.layers.Dropout(0.5),
                    keras.layers.Dense(units=1, activation='sigmoid'),
                ])
```

In [379…
```python
ltsm_model.compile(loss="binary_crossentropy", # Loss function
                   optimizer=keras.optimizers.Adam(1e-2), # Gradient Descent
                   metrics=["accuracy", "AUC"])
```

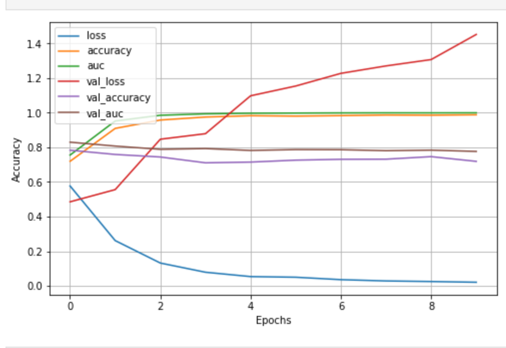
In [380…
```python
ltsm_model.summary()
```

```
Model: "sequential_27"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_8 (Embedding)     (None, None, 50)          749600

 bidirectional_18 (Bidirecti  (None, None, 128)        58880
 onal)

 bidirectional_19 (Bidirecti  (None, 64)               41216
 onal)

 dense_40 (Dense)            (None, 64)                4160

 dropout_5 (Dropout)         (None, 64)                0

 dense_41 (Dense)            (None, 1)                 65

=================================================================
Total params: 853,921
Trainable params: 853,921
Non-trainable params: 0
_________________________________________________________________
```

In [381…
```python
ltsm_model_history = ltsm_model.fit(X_train, y_train,
                                    epochs=10,
                                    validation_data =(X_valid, y_valid))
```

```
Epoch 1/10
134/134 [==============================] - 22s 102ms/step - loss: 0.5773 - accuracy:
0.7195 - auc: 0.7555 - val_loss: 0.4854 - val_accuracy: 0.7836 - val_auc: 0.8300
Epoch 2/10
134/134 [==============================] - 12s 93ms/step - loss: 0.2615 - accuracy: 0.
9096 - auc: 0.9523 - val_loss: 0.5560 - val_accuracy: 0.7591 - val_auc: 0.8076
Epoch 3/10
134/134 [==============================] - 14s 103ms/step - loss: 0.1318 - accuracy:
0.9580 - auc: 0.9855 - val_loss: 0.8470 - val_accuracy: 0.7444 - val_auc: 0.7888
Epoch 4/10
134/134 [==============================] - 11s 79ms/step - loss: 0.0787 - accuracy: 0.
9752 - auc: 0.9937 - val_loss: 0.8791 - val_accuracy: 0.7108 - val_auc: 0.7930
Epoch 5/10
134/134 [==============================] - 9s 70ms/step - loss: 0.0535 - accuracy: 0.9
829 - auc: 0.9974 - val_loss: 1.0980 - val_accuracy: 0.7150 - val_auc: 0.7823
Epoch 6/10
134/134 [==============================] - 9s 66ms/step - loss: 0.0498 - accuracy: 0.9
806 - auc: 0.9981 - val_loss: 1.1544 - val_accuracy: 0.7262 - val_auc: 0.7872
Epoch 7/10
134/134 [==============================] - 9s 67ms/step - loss: 0.0358 - accuracy: 0.9
834 - auc: 0.9992 - val_loss: 1.2276 - val_accuracy: 0.7311 - val_auc: 0.7866
Epoch 8/10
134/134 [==============================] - 9s 68ms/step - loss: 0.0284 - accuracy: 0.9
869 - auc: 0.9995 - val_loss: 1.2706 - val_accuracy: 0.7318 - val_auc: 0.7809
Epoch 9/10
134/134 [==============================] - 9s 68ms/step - loss: 0.0250 - accuracy: 0.9
860 - auc: 0.9994 - val_loss: 1.3072 - val_accuracy: 0.7465 - val_auc: 0.7840
Epoch 10/10
134/134 [==============================] - 10s 72ms/step - loss: 0.0208 - accuracy: 0.
9883 - auc: 0.9997 - val_loss: 1.4524 - val_accuracy: 0.7192 - val_auc: 0.7767
```

In [388…
```python
pd.DataFrame(ltsm_model_history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.show()
```




In [383…
```python
gnn_model.evaluate(X_test, y_test)
```

```
60/60 [==============================] - 0s 4ms/step - loss: 1.0925 - accuracy: 0.7122
- auc: 0.7633
```

Out[383…
```
[1.0924943685531616, 0.7121848464012146, 0.7632977366447449]
```

In [389…
```python
predictions = ltsm_model.predict(X_test)
```

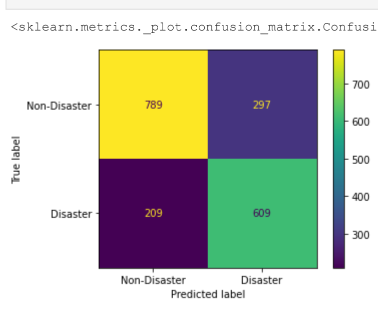
```
60/60 [==============================] - 4s 14ms/step
```

In [411…
```python
print(classification_report(y_test, pd.Series(predictions[:,0]).apply(lambda x: 1 if
```

```
              precision    recall  f1-score   support

           0       0.79      0.73      0.76      1086
           1       0.67      0.74      0.71       818

    accuracy                           0.73      1904
   macro avg       0.73      0.74      0.73      1904
weighted avg       0.74      0.73      0.74      1904
```

In [401…
```python
cf_m = ConfusionMatrixDisplay(confusion_matrix(y_test,
                                               pd.Series(predictions[:,0]).apply(lamb
                                               labels=[0, 1]),
                                               display_labels=['Non-Disaster', 'Disas
cf_m.plot()
```

Out[401…
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x177afe45e80>
```




## Test Submission Predictions

In [402…
```python
main_test_prediction = ltsm_model.predict(padded_test)
```

```
102/102 [==============================] - 1s 14ms/step
```

In [408…
```python
ltsm_predictions = test.copy()
ltsm_predictions['target'] = pd.Series(main_test_prediction[:,0]).apply(lambda x: 1 i
```

In [410…
```python
ltsm_predictions[['id', 'target']].to_csv(r'predictions\unsupervised_predictions.csv',
```

**Submission Details**

unsupervised_predictions.csv
Complete · now

Score: 0.73827

UPLOADED FILES

unsupervised_predictions.csv (25 KiB)

The unsupervised test public score was **0.738**

## Fit a KNN model

We will now predict the categories using a trained KNN model

To generate our text document, we first get word counts and then calculate their tf-dif (term frequency-inverse document frequency) that will be passed onto our model. This is an important step because tf-dif helps capture relevant words that do not appear frequently throughout the document.

In [209…
```python
# Bag contains a sparse matix of all document, word combinations as a 1-gram model (b
counter = CountVectorizer()
bag = counter.fit_transform(train['text'].values)

# Apply tf-idf technique to weight down frequent words appearing in all docs
tfidf_vec = TfidfTransformer(use_idf=True,
                             norm='l2', # Apply l2 normalization
                             smooth_idf=True) # Assigns zero weights to terms occurin

tfidf_run = tfidf_vec.fit_transform(bag)
```

In [111…
```python
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
```

Out[111…
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [112…
```python
category_predictions = knn.predict(X_test)
```

In [113…
```python
accuracy_score(y_test, category_predictions)
```

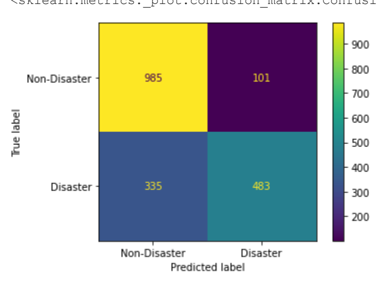
Out[113…
```
0.7710084033613446
```

In [385…
```python
print(classification_report(y_test, category_predictions))
```

```
              precision    recall  f1-score   support

           0       0.75      0.91      0.82      1086
           1       0.83      0.59      0.69       818

    accuracy                           0.77      1904
   macro avg       0.79      0.75      0.75      1904
weighted avg       0.78      0.77      0.76      1904
```

In [116…
```python
cf_m_sup = ConfusionMatrixDisplay(confusion_matrix(y_test,
                                                   category_predictions,
                                                   labels=[0, 1]),
                                                   display_labels=['Non-Disaster', 'D
cf_m_sup.plot()
```

Out[116…
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x176a6993490>
```




## KNN - Test Submission Predictions

In [100…
```python
test_category_predictions = knn.predict(tfidf_test_run.toarray())
```

In [101…
```python
test_results_supervised = test.copy().assign(target=test_category_predictions)
test_results_supervised.sample(5)
```

Out[101…

| | id | keyword | location | text | target |
|---|---|---|---|---|---|
| 257 | 831 | bioterror | NaN | fedex long transport bioterror germ wake anthr... | 1 |
| 1317 | 4340 | dust storm | The Universe | kid disappear Dust storm Atmospheric Aussie Th... | 1 |
| 1256 | 4130 | drought | NaN | water conservation urge North Thompson B.C. go... | 1 |
| 3159 | 10480 | wild fires | NaN | wild fire California drought state sad | 1 |
| 1694 | 5728 | forest fire | NaN | crew respond small brush fire burn Tahoe Fores... | 0 |

In [102…
```python
test_results_supervised[['id', 'target']].to_csv(r'predictions\supervised_predictions
```

supervised_predictions.csv
Complete · now

Score: 0.75635

UPLOADED FILES

supervised_predictions.csv (25 KiB)

The unsupervised test public score was **0.756**

# Result, Analysis and Conclusion

Results: The LTSM model had a score of 0.73. The plot for training vs validation accuracy and loss plots suggest that the model was over fitting the training data.

- The model was modified by adding a Dropout layer, this helped the validation loss ever so slightly.
- The learning rate was modified from 0.0001 to 0.01, the accuracy remained unchanged after 10 epochs but the over fitting behaviour did not however improve.

The bidirectional RNN model achieved a score of 0.71, suggesting that the LTSM model did improve on this.

The RNN model did not do better than the KNN one. For future exploration we could segment the hastagged keyword differently than other keywords, this might give us additional data to work with. The number of characters could also be an additional feature. In terms of the issue with generalization, additional knowledge of the word vectorization portion of the code can be helpful. This would be a good project to come back to and reanalyze after learning about Transformers.

# References


Competition https://www.coursera.org/learn/introduction-to-deep-learning-boulder/peer/HYQbb/week-4-nlp-disaster-tweets-kaggle-mini-project

Spacy https://spacy.io/usage/spacy-101

ML Book https://github.com/rasbt/machine-learning-book