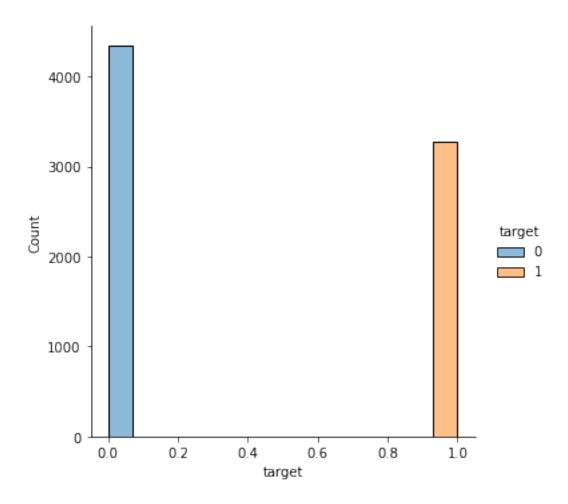
Diaster-Tweets

April 20, 2024

```
import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
    /usr/lib/python3/dist-packages/scipy/__init__.py:146: UserWarning: A NumPy
    version >=1.17.3 and <1.25.0 is required for this version of SciPy (detected
    version 1.26.3
      warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
    0.0.1 EDA
[]: df_train = pd.read_csv("data/train.csv",index_col='id')
     df_test = pd.read_csv("data/test.csv",index_col='id')
[]: df_train.head()
        keyword location
[]:
                                                                          text target
     id
     1
            NaN
                      {\tt NaN}
                           Our Deeds are the Reason of this #earthquake M...
                                                                                    1
     4
            NaN
                      NaN
                                      Forest fire near La Ronge Sask. Canada
                                                                                      1
     5
            NaN
                      {\tt NaN}
                           All residents asked to 'shelter in place' are ...
                                                                                    1
                           13,000 people receive #wildfires evacuation or...
     6
            NaN
                      {\tt NaN}
                                                                                    1
            NaN
                     {\tt NaN}
                           Just got sent this photo from Ruby #Alaska as ...
                                                                                    1
[]: sns.displot(data=df_train, x='target', hue='target')
```

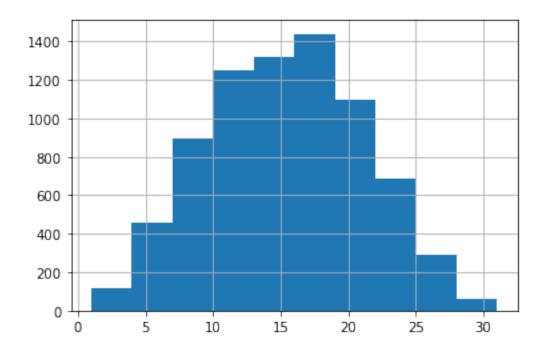
[]: <seaborn.axisgrid.FacetGrid at 0x7f8865821ba0>

[]: import pandas as pd



```
[]: df_train['length'] = df_train['text'].apply(lambda x: len(x.split())).values
df_train['length'].hist()
```

[]: <AxesSubplot:>



0.0.2 Data Cleaning

```
[]: import string, re
import nltk
nltk.download('punkt')
nltk.download('stopwords')
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
```

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

```
[]: def clean_text(t):
    t = "".join([char for char in t if char not in string.punctuation])
    t = re.sub('[0-9]+', '', t)

    t = t.lower() # lowercase

    t = t.replace(r"\#","",True) # replaces hashtags
    t = t.replace(r"http\S+","URL", True ) # remove URL addresses
    t = t.replace(r"0","", True )
    t = t.replace("\s{2,}", " ", True ) # remove multiple contiguous spaces
```

```
return t

[]: df_train['text'] = df_train['text'].apply(lambda t: clean_text(t))
    df_test['text'] = df_test['text'].apply(lambda t: clean_text(t))

#df_train_clean.head()
```

0.0.3 Model Architecture

LTSM and Gated Recurrent Unit In this lesson we will use LTSM and Gradient Recurrent Units to train models. Both LTSM and GRU are types of RRN's. We will start by downloading and using some pre made embeddings then train models on top of the embeddings. These embeddings have had a hight amount of training behind them already, training on a scale that I couldn't acheive on my own. So this gives us a headstart for training our models.

```
2024-03-08 17:27:21.827539: I external/local tsl/tsl/cuda/cudart stub.cc:31]
Could not find cuda drivers on your machine, GPU will not be used.
2024-03-08 17:27:22.307256: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
2024-03-08 17:27:22.307408: E
external/local_xla/xtream_executor/cuda/cuda_fft.cc:607] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
2024-03-08 17:27:22.372958: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable to
register cuBLAS factory: Attempting to register factory for plugin cuBLAS when
one has already been registered
2024-03-08 17:27:22.541057: I external/local_tsl/tsl/cuda/cudart_stub.cc:31]
Could not find cuda drivers on your machine, GPU will not be used.
2024-03-08 17:27:22.549496: I tensorflow/core/platform/cpu_feature_guard.cc:182]
```

```
This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
```

To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

2024-03-08 17:27:24.826278: W

tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find TensorRT

```
[]: xtrain_pad = sequence.pad_sequences(xtrain_seq, maxlen=max_text_len)
    xtest_pad = sequence.pad_sequences(xtest_seq, maxlen=max_text_len)
    word_index = tokenizer.word_index

print('text example:', xtrain[0])
    print('sequence of indices(before padding):', xtrain_seq[0])
    print('sequence of indices(after padding):', xtrain_pad[0])
```

```
[]: #Run on first time only

#https://nlp.stanford.edu/projects/glove/
#!wget https://nlp.stanford.edu/data/glove.6B.zip
#!unzip g*zip
```

```
embedding_vectors = {}
     with open('glove.6B.300d.txt','r',encoding='utf-8') as file: #qlove.42B.300d.txt
         for row in file:
            values = row.split(' ')
             word = values[0]
             weights = np.asarray([float(val) for val in values[1:]])
             embedding_vectors[word] = weights
     print(f"Size of vocabulary in GloVe: {len(embedding_vectors)}")
    Size of vocabulary in GloVe: 400000
    CPU times: user 19.9 s, sys: 6.31 s, total: 26.2 s
    Wall time: 26.2 s
[]: emb_dim = 300
     vocab_len = max_words if max_words is not None else len(word_index)+1
     embedding_matrix = np.zeros((vocab_len, emb_dim))
     oov_count = 0
     oov_words = []
     for word, idx in word_index.items():
         if idx < vocab_len:</pre>
             embedding_vector = embedding_vectors.get(word)
             if embedding_vector is not None:
                 embedding_matrix[idx] = embedding_vector
             else:
                 oov_count += 1
                 oov_words.append(word)
     #print some of the out of vocabulary words
     print(f'Some out of valubulary words: {oov_words[0:5]}')
     print(f'{oov_count} out of {vocab_len} words were OOV.')
    Some out of valubulary words: ['\x89û', '\x89ûo', 're\x89û', 'yearold',
    'typhoondevastated']
    8059 out of 50000 words were 00V.
[]: earlystopper = EarlyStopping(monitor='val_loss', patience=2, verbose=1,__
     →restore_best_weights=True)
     reducel = ReduceLROnPlateau(monitor='val_loss', patience=1, verbose=1, factor=0.
      ⇒1)
     callbacks_list = [reducel, earlystopper]
[ ]: def plot_model_acc(model_history):
         acc = model_history.history['accuracy']
         val_acc = model_history.history['val_accuracy']
         loss = model_history.history['loss']
```

```
val_loss = model_history.history['val_loss']

epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, 'bo', label='Training Accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()
plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and Validation loss')
plt.legend()
plt.figure()
```

After seting up some general model stuructre above I create and train an LSTM model.

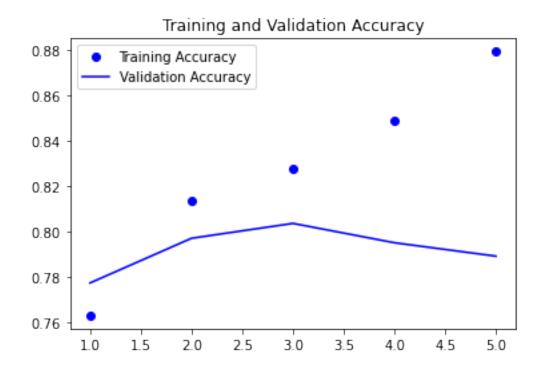
```
[]: model lstm = Sequential(name='model lstm')
     model_lstm.add(Embedding(vocab_len, emb_dim, trainable = False,__
      ⇔weights=[embedding matrix]))
     #model_lstm.add(Embedding(vocab_len, emb_dim, trainable = True))
     model_lstm.add(LSTM(64, activation='tanh', return_sequences=False))
     model_lstm.add(Dense(128, activation='relu'))
     model_lstm.add(tf.keras.layers.BatchNormalization())
     model_lstm.add(Dropout(0.2)) # Adding Dropout layer with rate of 0.2
     model lstm.add(Dense(256, activation='relu'))
     model lstm.add(Dense(128, activation='relu'))
     model_lstm.add(Dense(64, activation='relu'))
     model_lstm.add(Dense(1, activation='sigmoid'))
     model_lstm.compile(loss='binary_crossentropy', optimizer='adam',_
      metrics=['accuracy',tf.keras.metrics.Recall(), tf.keras.metrics.AUC()])
     model_lstm.summary()
    2024-03-08 17:28:53.217237: W
    external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
    60000000 exceeds 10% of free system memory.
    2024-03-08 17:28:53.263367: W
    external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
    60000000 exceeds 10% of free system memory.
    2024-03-08 17:28:53.314626: W
    external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
    60000000 exceeds 10% of free system memory.
    2024-03-08 17:28:53.659213: W
    external/local_tsl/tsl/framework/cpu_allocator_impl.cc:83] Allocation of
    60000000 exceeds 10% of free system memory.
    Model: "model_lstm"
```

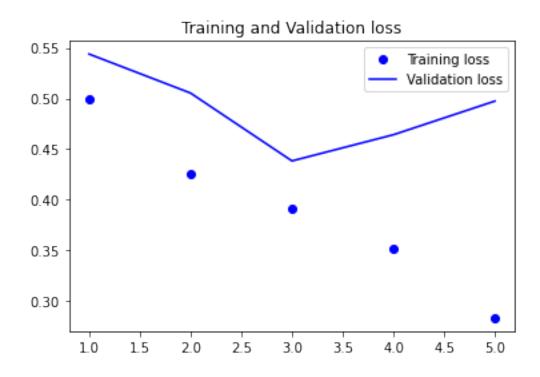
Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, None, 300)	15000000
lstm (LSTM)	(None, 64)	93440
dense (Dense)	(None, 128)	8320
batch_normalization (Batch Normalization)	(None, 128)	512
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 256)	33024
dense_2 (Dense)	(None, 128)	32896
dense_3 (Dense)	(None, 64)	8256
dense_4 (Dense)	(None, 1)	65

Total params: 15176513 (57.89 MB)
Trainable params: 176257 (688.50 KB)
Non-trainable params: 15000256 (57.22 MB)

```
Epoch 2/20
accuracy: 0.8138 - recall: 0.7018 - auc: 0.8739 - val_loss: 0.5053 -
val_accuracy: 0.7971 - val_recall: 0.5764 - val_auc: 0.8629 - lr: 0.0010
Epoch 3/20
accuracy: 0.8281 - recall: 0.7238 - auc: 0.8955 - val loss: 0.4382 -
val_accuracy: 0.8037 - val_recall: 0.6252 - val_auc: 0.8700 - lr: 0.0010
Epoch 4/20
0.8491 - recall: 0.7568 - auc: 0.9143
Epoch 4: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
accuracy: 0.8491 - recall: 0.7568 - auc: 0.9143 - val_loss: 0.4641 -
val_accuracy: 0.7951 - val_recall: 0.7118 - val_auc: 0.8495 - 1r: 0.0010
Epoch 5/20
0.8795 - recall: 0.7951 - auc: 0.9474
Epoch 5: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
Restoring model weights from the end of the best epoch: 3.
accuracy: 0.8795 - recall: 0.7951 - auc: 0.9475 - val_loss: 0.4974 -
val_accuracy: 0.7892 - val_recall: 0.7339 - val_auc: 0.8490 - lr: 1.0000e-04
Epoch 5: early stopping
CPU times: user 1min 22s, sys: 32 s, total: 1min 54s
Wall time: 29.9 s
```

[]: plot_model_acc(history_lstm)





<Figure size 432x288 with 0 Axes>

Here we see that the preformance of the LTSM is not great. I played arround with many differnet

setting and optimisers but this was the best performance I was able to acheive with the LSTM.

I am now going to use the slightly different archtechure of GRU's to hopefully have better preformance.

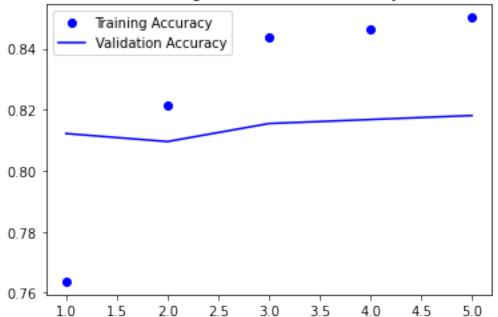
Model: "model_gru"

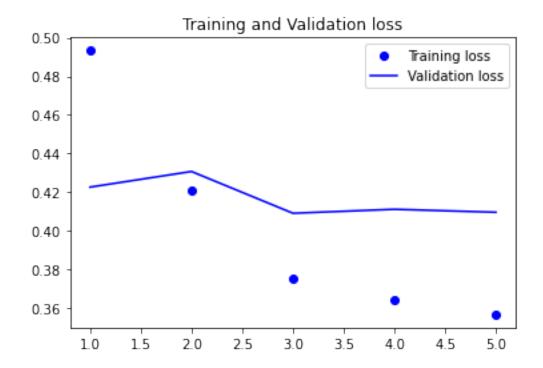
Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, None, 300)	15000000
gru (GRU)	(None, 128)	165120
dropout_1 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 1)	129

Total params: 15165249 (57.85 MB)
Trainable params: 165249 (645.50 KB)
Non-trainable params: 15000000 (57.22 MB)

```
0.8215
Epoch 2: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
accuracy: 0.8215 - val_loss: 0.4307 - val_accuracy: 0.8096 - lr: 0.0010
Epoch 3/20
accuracy: 0.8438 - val_loss: 0.4090 - val_accuracy: 0.8155 - lr: 1.0000e-04
Epoch 4/20
                ========] - ETA: Os - loss: 0.3639 - accuracy:
191/191 [===:
0.8463
Epoch 4: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
accuracy: 0.8463 - val_loss: 0.4111 - val_accuracy: 0.8168 - lr: 1.0000e-04
0.8502
Epoch 5: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
Restoring model weights from the end of the best epoch: 3.
accuracy: 0.8502 - val_loss: 0.4095 - val_accuracy: 0.8181 - lr: 1.0000e-05
Epoch 5: early stopping
```







<Figure size 432x288 with 0 Axes>

0.1 Results and Analysis

After some tinkering with the setting and number of layers I finally ended with this model. While this isnt superb performance it is much better than LTSM so this is what I will use for my submission. 81% accuracy on the validation set is a solid preformance. especially since I am training my a laptop without dedicated graphics. If I had more computational power I would probably look to do more instensive layers and modeling.

0.2 Conclusion

GRU models are better for this dataset than LTSM models. While this should be expected as GRU models have been replacing LTSM models for many NLP problems it is good to see that the results are consistent and work well. In the future I would hope to have a cluster of GPU's that would allow for more layers and epochs to be ran at the same time. This increase in computational power would certainly improve my results.

Generating submission

```
[]: X_test= df_test['text'].values
    X_test_seq = tokenizer.texts_to_sequences(X_test)
    X_test_pad = sequence.pad_sequences(X_test_seq, maxlen=max_text_len)
    predictions_prob = model_gru.predict(X_test_pad)
    predictions = tf.round(predictions_prob)
#print(predictions)
```

```
print(df_test.columns)
df_out = pd.DataFrame()
df_out.index = df_test.index
df_out['target'] = predictions
df_out = df_out.astype({"target": int})
df_out.to_csv('submission.csv')
```

```
102/102 [======] - 1s 11ms/step Index(['keyword', 'location', 'text'], dtype='object')
```