Udacity Machine Learning Engineer Nanodegree

Capstone Project

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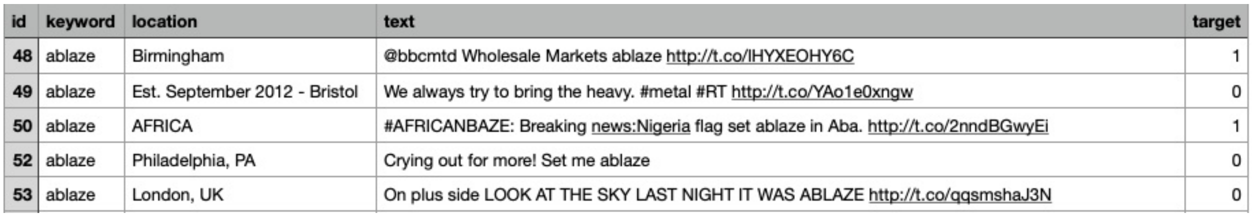
I. Project Overview

This project is about predicting if someone is talking about disaster or not in a tweet. The data was downloaded from a Kaggle challenge called ”Natural Language Processing with Disaster Tweets”, and it has 7613 tweets for training as csv file. There are four columns in the data; keyword, location, text, and target. A few lines of train data are shown below. As can be seen, text is tweet, and target is disaster (1) or non-disaster (0). The goal of this project is to use the left three columns to predict the target.



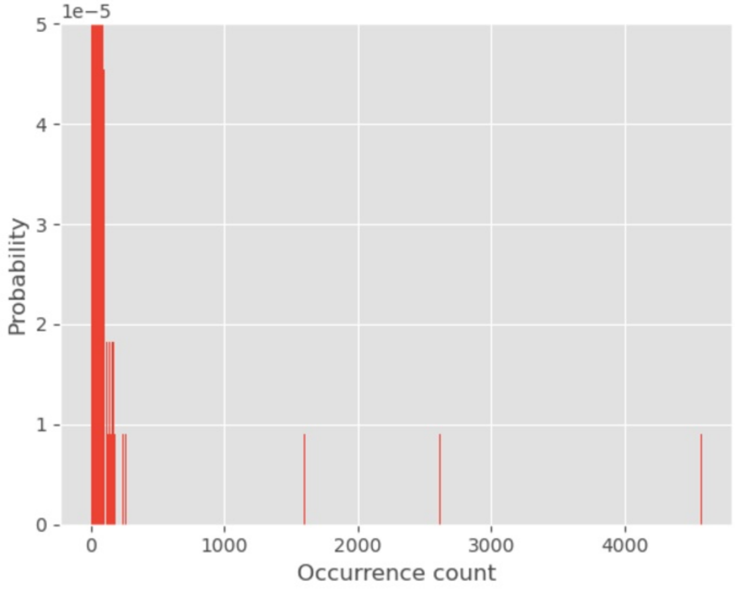
id	keyword	location	text	target
48	ablaze	Birmingham	@bbcmtd Wholesale Markets ablaze http://t.co/lHYXEOHY6C	1
49	ablaze	Est. September 2012 - Bristol	We always try to bring the heavy. #metal #RT http://t.co/YAo1e0xngw	0
50	ablaze	AFRICA	#AFRICANBAZE: Breaking news:Nigeria flag set ablaze in Aba. http://t.co/2nndBGwyEi	1
52	ablaze	Philadelphia, PA	Crying out for more! Set me ablaze	0
53	ablaze	London, UK	On plus side LOOK AT THE SKY LAST NIGHT IT WAS ABLAZE http://t.co/qqsmshaJ3N	0

The data was downloaded from the Kaggle website:
`https://www.kaggle.com/competitions/nlp-getting-started/data`

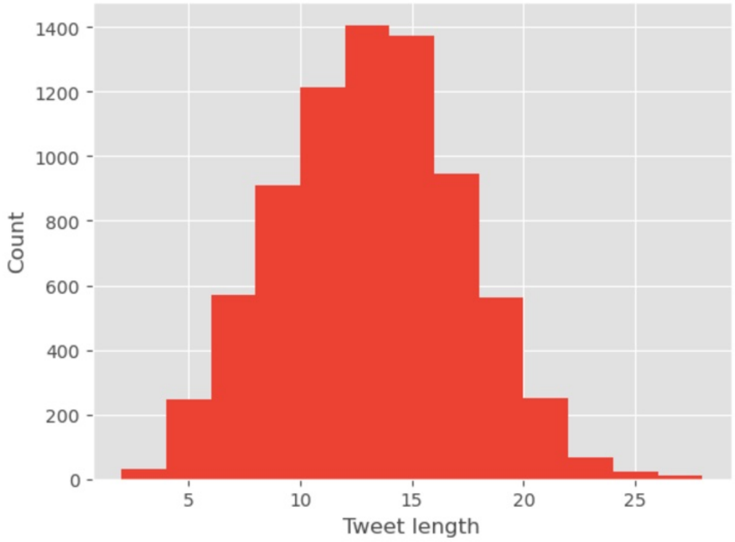
This problem can be tackled from many other algorithms, but in this project Natural Language Processing method (NLP) will be used. First of all, as a benchmark Long short-term memory (LSTM) method will be developed and optimized to show its prediction results. A more powerful Bi-directional Encoder Representations from Transformer (BERT) method will be used to see how much the prediction can be improved. A pre-trained BERT model will be used instead of creating one from scratch.

II. Exploratory Data Analysis

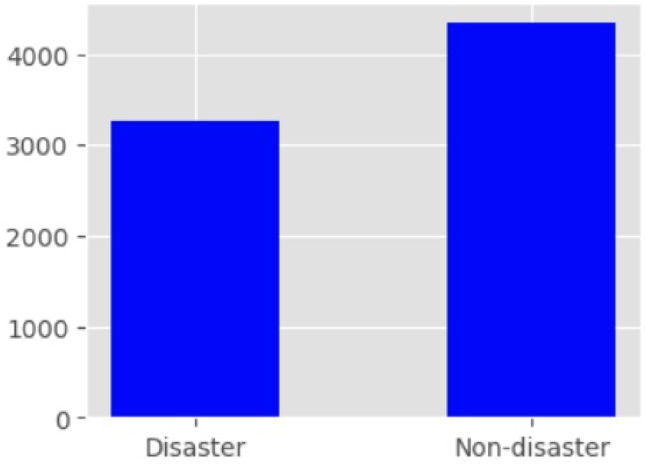
To select the size of vocabulary, the number of occurrences of words in the corpus were counted and shown in a plot below. Out of 12025 unique words in the corpus, 4776 words appeared more than once. Therefore, the vocabulary size is set at 5000.



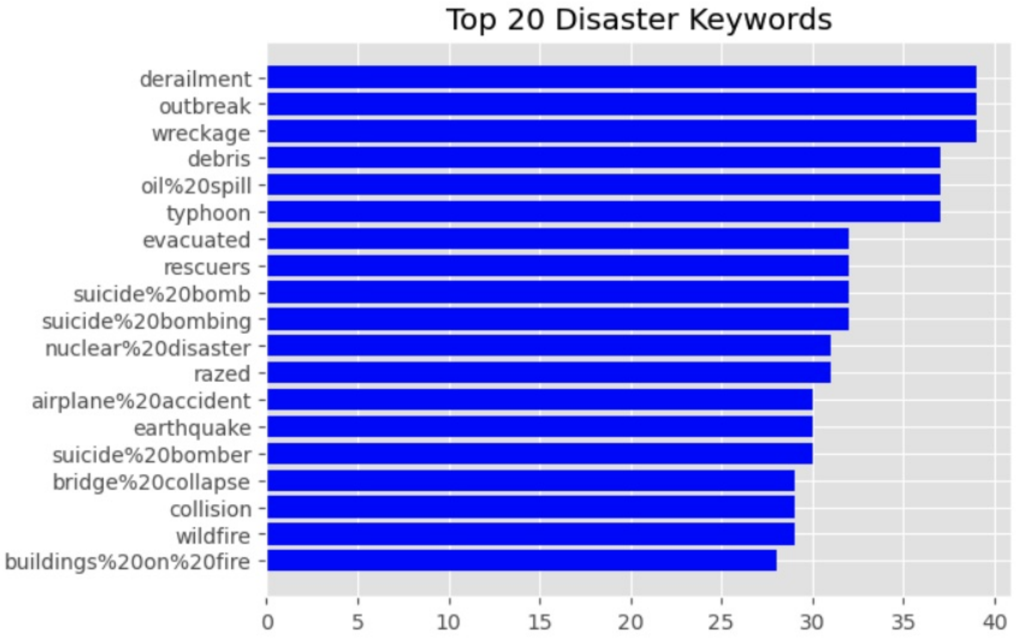
To get an idea of how many words are used in tweets, tweet lengths were counted in the training data set. Distribution of number of words in each tweet is plotted, showing that most of the tweets are 6 to 20 words long.



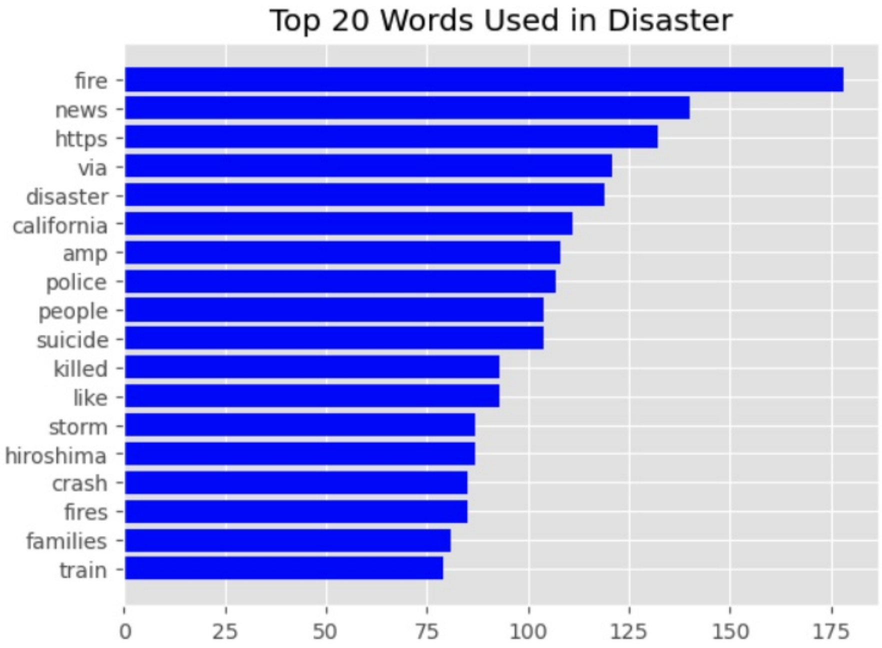
The numbers between disaster and non-disaster tweets are compared and shown below. There is a data imbalance, and this will be addressed during the data preprocessing step.



Keywords are explored to see what kind of words are used in disaster tweets. Top 20 disaster keywords are shown below.



The top 20 words used most in disaster tweets are shown below.



III. LSTM Analysis: Benchmark

1. Data Preprocessing

1. The text column is combined with location and keyword columns to make one combined text column to feed to NLP model.
2. Since there is a data imbalance as seen in the EDA section (negative tweets: 4342, positive tweets: 3271), the positive tweets were oversampled by randomly selecting duplicate 1071 tweets from itself.
3. Empty cells in location and keyword columns were replaced with a string ”NA”. This is a unique word, so that it can be distinguished from all the other words.
4. The dataset was split into three groups; train 60%, validation 20%, and test 20%. Here the test dataset is a hold-out set for final testing of optimized models. Scikit-learn was used to split the dataset.
5. Using nltk module, the train and validation datasets are tokenized, and their stop words were removed.
6. The total number of vocabulary is 12025. But as seen in the EDA section, majority of the words appear only once. The vocabulary size is set at 5000.
7. The maximum length of tokenized tweets is 28 in the entire train/valid/test dataset. Any tweets longer than 28 were truncated, and any ones shorter than 28 were padded with 0’s.

8. The tokenized and padded words for train and validation dataset were saved as csv files for reuse in the later analysis steps.

9. Using PyTorch's TensorDatset and DataLoader classes, train dataset were converted to dataloaders with a given batch size.

2. LSTM Model Development

1) LSTM algorithm

Long short-term memory (LSTM) algorithm is a type of recurrent neural network (RNN) that can retains long term dependencies of previous inputs. From this retention it can influence the decision that is made much later from a particular input. Just like in a long sentence, a certain word in front influences a form of words (tense or meaning) near the end of the sentence. RNN suffered the vanishing gradient problem, but LSTM mitigated it.

The LSTM architectures involves the memory cell which is controlled by three gates: the input gate, the forget gate, and the update gate. These gates decide what information to add to, remove from, and output from the memory cell. In the image below, the three σ operations are the gates, and they determine if the C value running horizontally above them should be forgotten or retained.

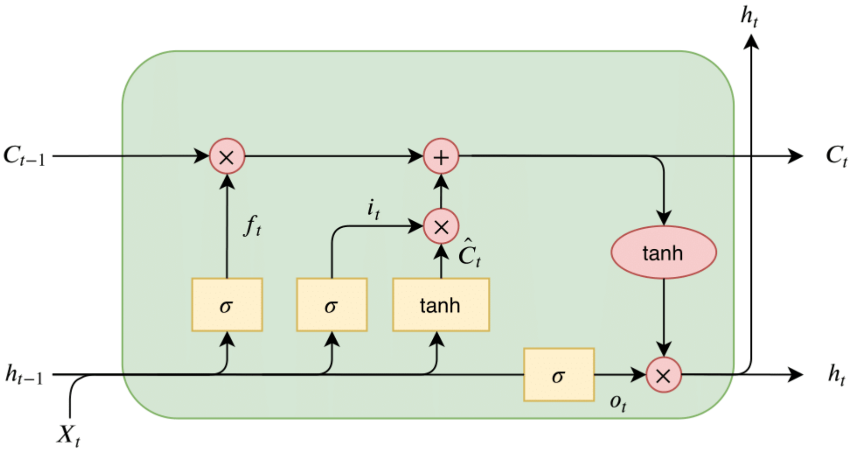
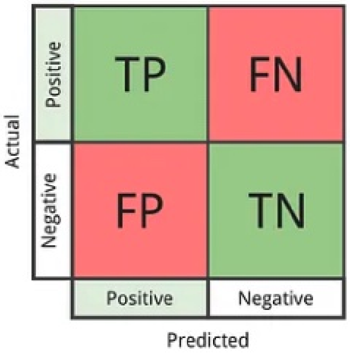


Image from www.projectpro.io/article/lstm-model/832

2) Metrics

The confusion matrix is used to calculate the metrics used in the analysis; accuracy, precision, recall, and F1 score.



		Predicted	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

Image from mlee-articles.medium.com

Accuracy, precision, recall, and F1 values will be used to evaluate the models.

$$\text{accuracy} = \frac{TP + TN}{\text{All Samples}}$$

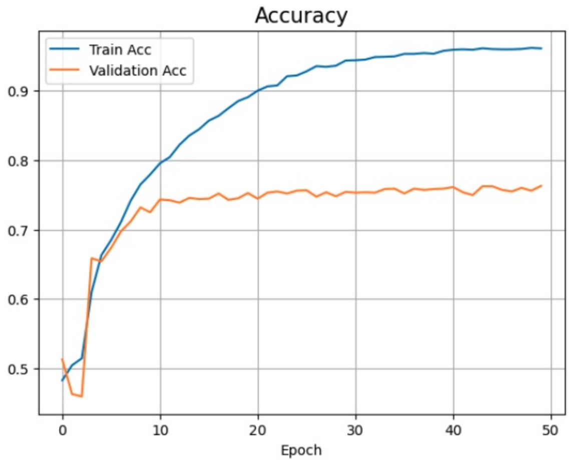
$$\text{precision} = \frac{TP}{TP + FP}$$

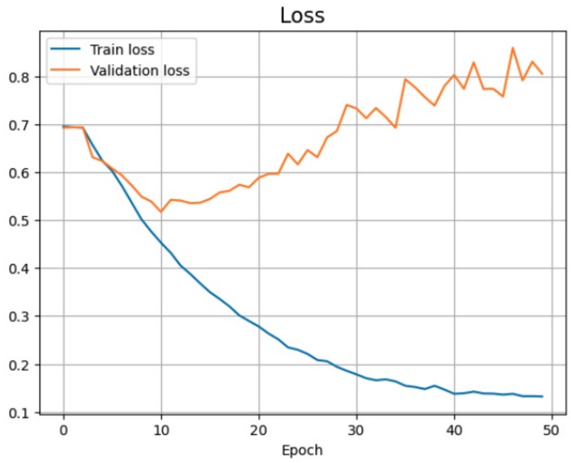
$$\text{recall} = \frac{TP}{TP + FN}$$

$$F_1 = 2 * \frac{\text{precision * recall}}{\text{precision + recall}}$$

3) Hyperparameter tuning

Epoch number was tuned from validation accuracy and loss. The plot below shows that the validation accuracy increased quite steeply initially and then plateaued after the epoch number of 12. The loss plot tells us that after the epoch number of 12, there appeared overfitting. From these observations, the epoch number will be set at 12.

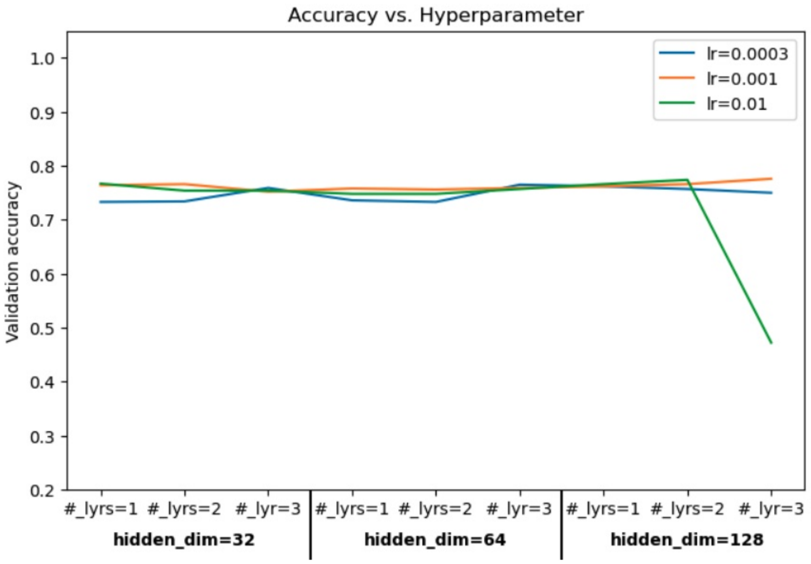




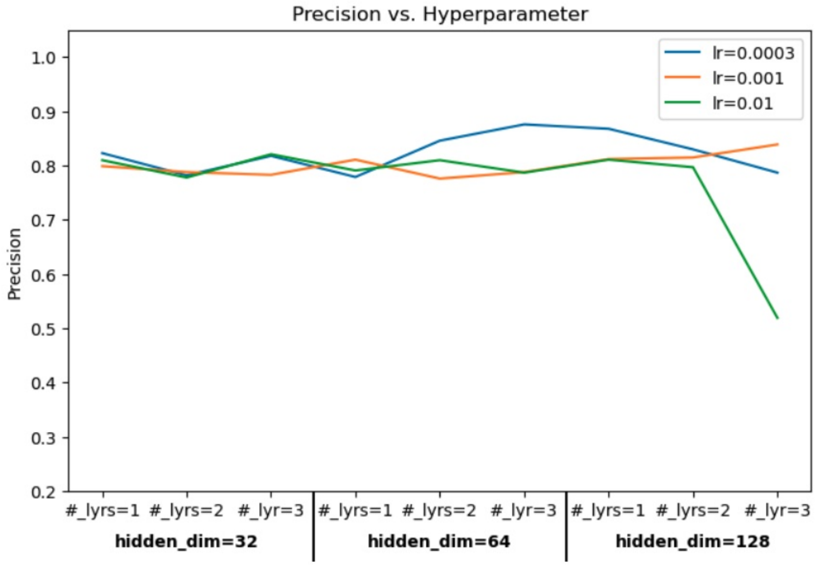
With epoch number tuned in, the following hyperparameters were tuned with a grid search.

- hidden dimension = [32, 64, 128]
- number of LSTM layers = [1, 2, 3]
- learning rate = [0.0003, 0.001, 0.01]

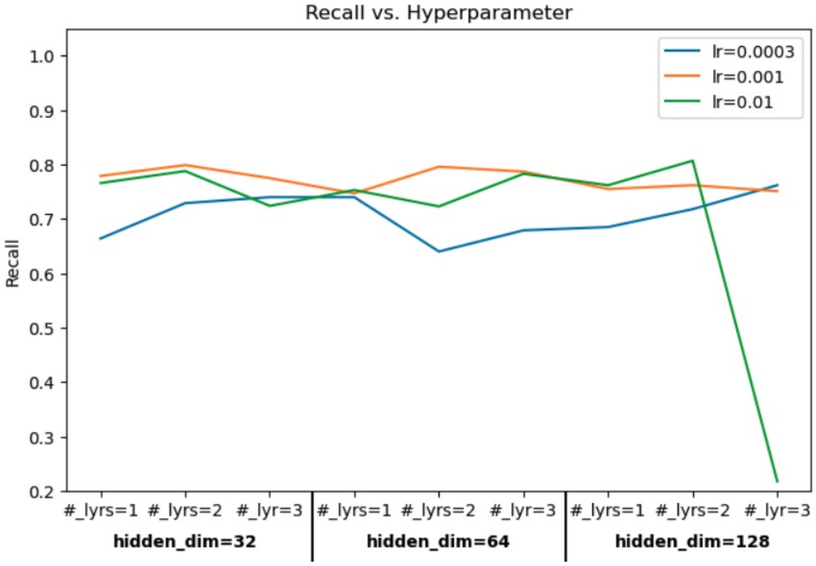
Accuracy:
Learning rate 0.001 performs the best throughout. Hidden dim and number of layers do not matter much.



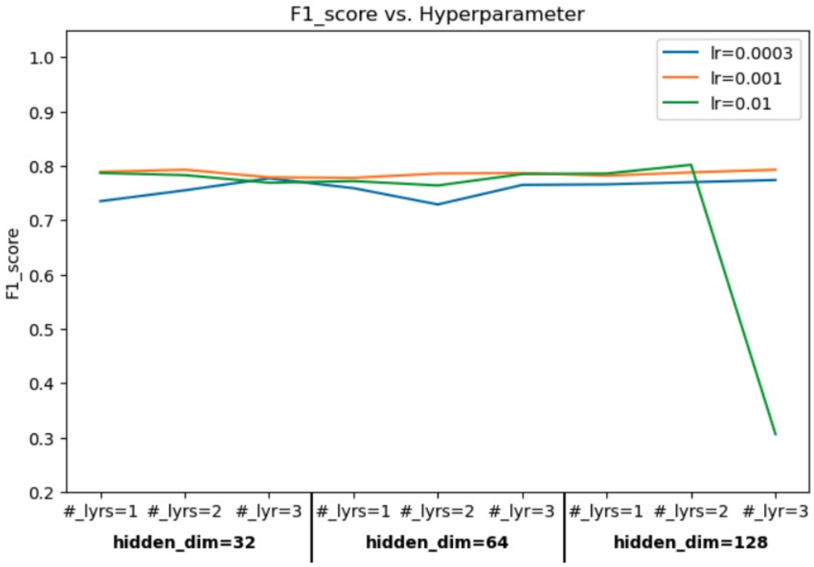
Precision:
Learning rate 0.0003 performs the best when hidden dim=64 and number of layers = 3. Learning rate 0.001 performs decent throughout.



Recall:
Learning rate 0.001 performs the best with number of layers of 2. Hidden dim of 32 and 64 perform better than 128.



F1 score:
Learning rate 0.001 performs the best with number of layers of 2. Hidden dim does not matter much.



Hyperparameter selection:
From the considerations of accuracy, precision, recall, and f1 score shown above, the hyperparameters were selected as follows.

Learning rate: 0.001
Hidden dim: 32
Number of LSTM layers: 2
Epoch number: 12

3. Inference test on hold-out test data set

Data preprocessing was done without using dataloader method. To be able to run all of the test data, one tweet was tested at a time.

Number of test data set: 1737
Accuracy: 77.0%
Precision: 75.6%
Recall: 79.9%
F1 score: 77.7%

IV. BERT Analysis

1. Data Preprocessing

1. The text column is combined with location and keyword columns to make a combined text column to feed to NLP model.

2. Since there is a data imbalance as seen in the EDA section (negative tweets: 4342, positive tweets: 3271), the positive tweets were oversampled by randomly selecting duplicate 1071 tweets from itself.

3. Empty cells in location and keyword columns were replaced with a string "NA". This is a unique word, so that it can be distinguished from all the other words.

4. To use BERT, special tokens were added at the beginning (["[CLS] ") and end (" [SEP]") of each sentence for BERT to work properly.

5. To use in BERT model, attention masks were created by converting each token to 1 and leaving 0's untouched.

6. The dataset was split into three groups; train 60%, validation 20%, and test 20%. Here the test dataset is a hold-out set for final testing of optimized models. Scikit-learn was used to split the dataset.

7. Using BertTokenizer module from Hugging Face transformers library, the train and validation datasets were tokenized, and their stop words were removed.

8. The maximum length of tokenized tweets is 28 in the entire train/valid/test data set. Any tweets longer than 28 were truncated, and any ones shorter than 28 were padded with 0's.

9. Using PyTorch's TensorDatset and DataLoader classes, train dataset were converted to dataloaders with a given batch size.

2. BERT Model Development

1) BERT algorithm

Bi-directional Encoder Representations from Transformer (BERT) algorithm is a deep learning model that adopts the mechanism of self-attention to capture dependencies and relationships within input sequences. Self-attention allows the model to identify and weigh the importance of different parts of the input sequence.

As can be seen in the image below, multiple self-attentions are embedded in Multi-Head Attention, and BERT architecture uses encoding and decoding blocks, where decoding block receives input from encoding block's result. Essentially encoding figures out the meaning of the input text, and decoding would typically generate an output using the input from the encoder.

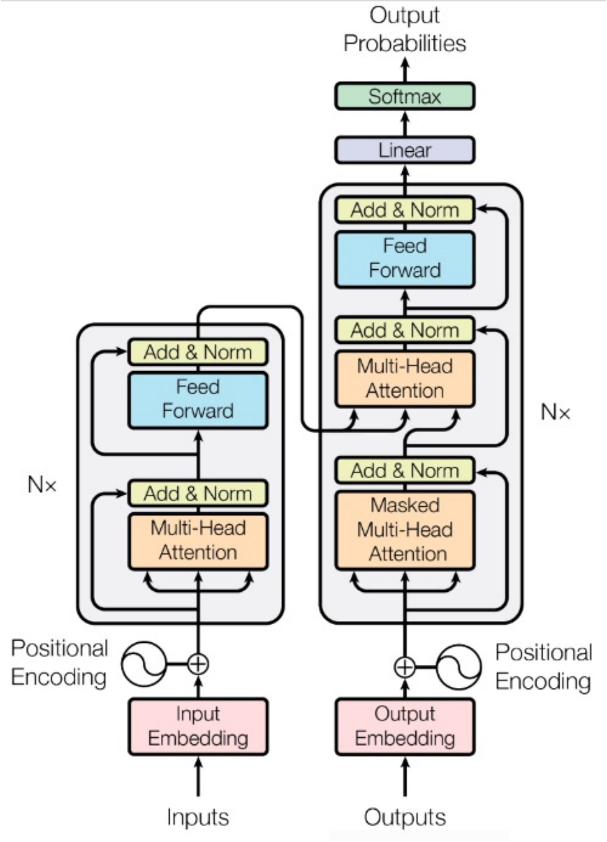


Image from heidloff.net/article/foundation-models-transformers-bert-and-gpt

In this present project, a pre-trained BERT model from Hugging Face will be used. It is available as a module called transformers that can be installed.

2) Hyperparameter tuning

Since a pre-trained BERT is used, the hyperparameter tuning process is considerably different from LSTM's. First of all, most of the hyperparameters are already optimized. So there will not be much optimization to be done as for hyperparameters, unless there are any warning signs that force us to touch upon particular hyperparameters.

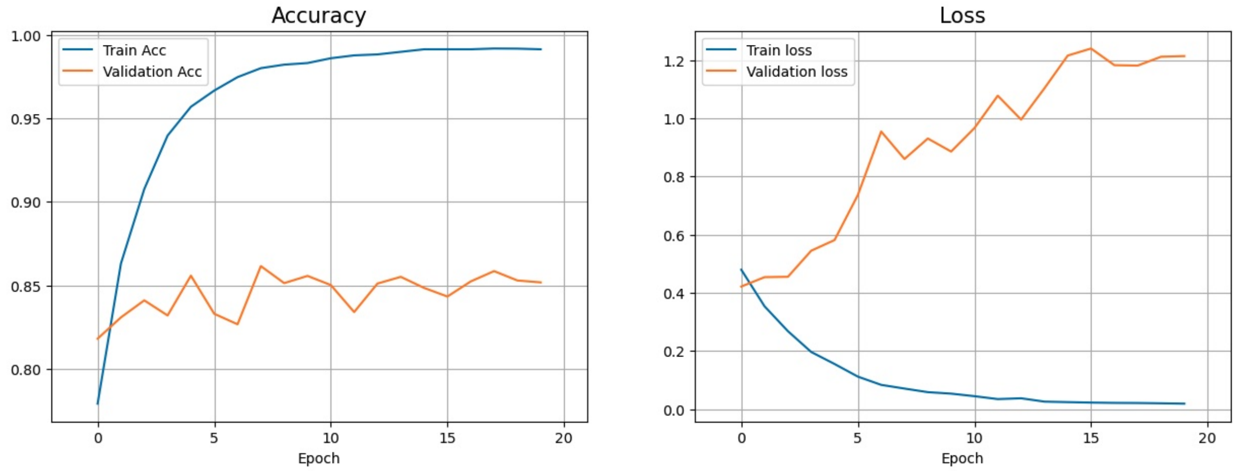
Learning rate:

There is no need to optimize the learning rate, since BERT model can utilize an automatic learning rate optimizer; optimizer and scheduler. Also training warmup steps are used to start with a very low learning rate at the beginning and then increase its value after a few steps later.

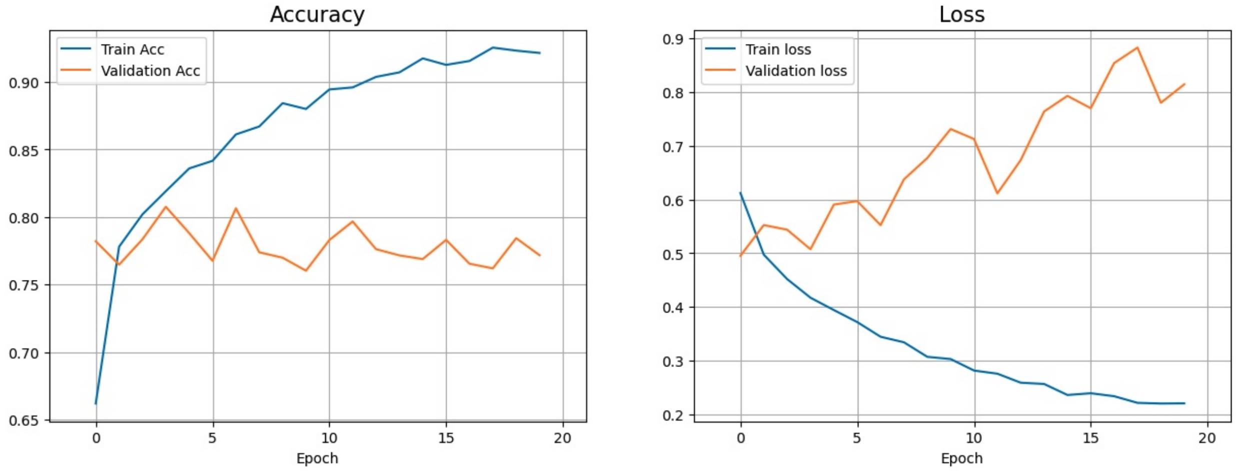
Epoch number tuning:

When the BERT model was run on the train dataset with multiple epochs, an overfitting was observed as seen in the plot below. To remedy this, drop out probability hyperparameter was changed in the pre-trained BERT model's configuration. Drop out probability is a hyperparameter that controls how many percentage of neurons are to be turned off randomly to reduce overfitting. The plot below uses the default drop out probability of 0.1.

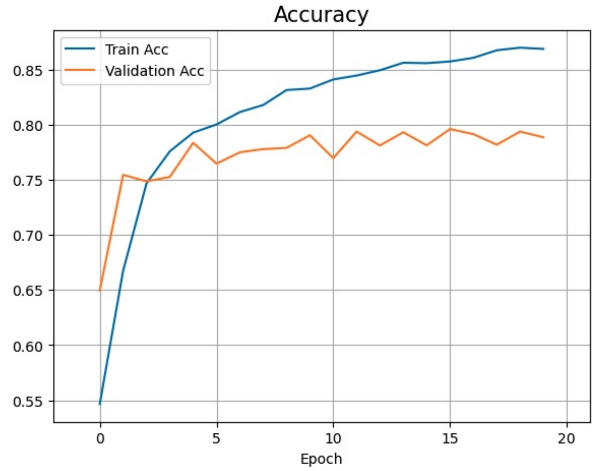
hidden_dropout_prob = 0.1
attention_probs_dropout_prob = 0.1

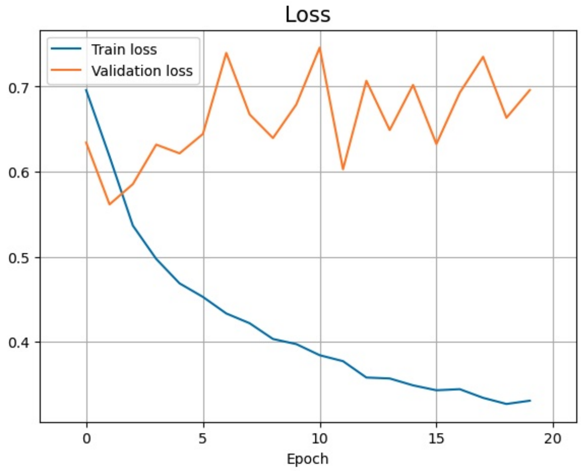


When the default drop out probability of 0.4 was used, there is still an overfitting over epoch number.



Drop out probabilities were increased to 0.5. The overfitting was somewhat alleviated. However, after the epoch number of 3, there appears an overfitting again shown in the loss plot.





The drop out probability changes were made hoping that we were allowed to increase the epoch number to get a better accuracy and a lower loss. However, as seen in the above three plots, even though higher drop out probability alleviated the overfitting with higher epoch number, its accuracy was worse than lower drop out probability's. So we will have to select an epoch number that gives higher accuracy regardless of drop out probability.

Comparison between drop out probabilities:
The following table shows that the drop out probability of 0.1 performs the best with a smaller epoch number. It performs better with higher epochs, but loss gets much worse.

	Drop out probability (Epoch number)		
	0.1 (4)	0.4 (7)	0.5 (15)
Validation accuracy	0.84	0.81	0.79
Validation loss	0.58	0.56	0.64

Hyperparameter selection:
From the analysis done above, there is an overfitting over epoch number in this pre-trained BERT model. It can be alleviated with higher drop out probability. However, the best validation accuracy score (84%) comes from the drop out probability of 0.1 with epoch number of 4 before validation loss shoots up much above the train loss. Therefore, the following hyperparameters are selected.

Epoch number: 4
Drop out probability: 0.1

3. Inference test on hold-out test data set

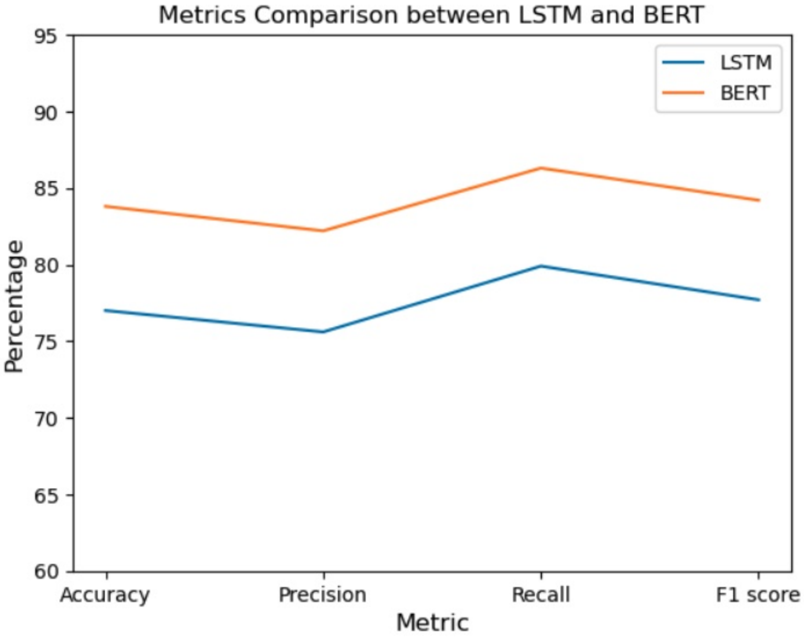
Data preprocessing was done using dataloader method with batch size of 1.

Number of test data set: 1737
Accuracy: 83.8%
Precision: 82.2%
Recall: 86.3%
F1 score: 84.2%

V. Results

Robustness of BERT model:
The validation accuracy run on the train dataset was 84% as seen in the table in the previous section. When the model was run on the hold-out dataset, the accuracy was 83.8%. This serves as robustness of the model.

Comparison between LSTM and BERT:
Compared to LSTM, BERT performed about 6 $\sim$ 7% better for all four metrics. This justifies that the final model adequately solved the problem.



Both models were run on the same hold-out dataset.