Spam Detection Using Natural Language Processing

https://github.com/jonathantanoto/spam_detection_180B
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Abstract

Spam messages in the United States costs approximately $20 billion annually, compared with approximately $200 million in surplus generated by the spam to users. Spamming is a big problem that is not an easy problem to solve manually. With the booming age of technology, spams are generated and sent at an unprecedented rate and this calls for a more innovative way of blocking out spam emails.

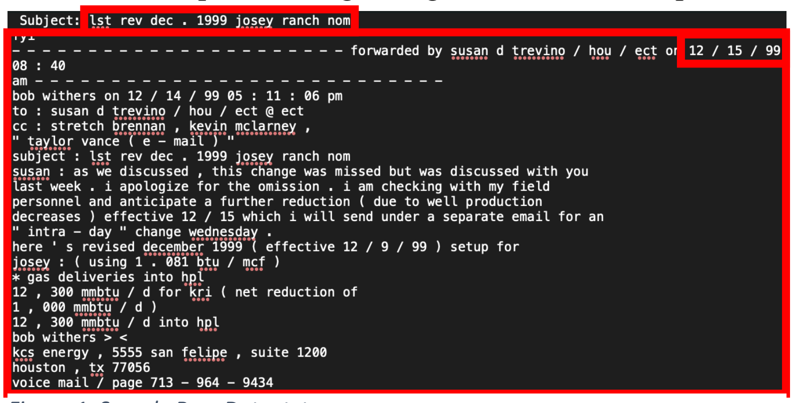
Luckily, we also happen to live in an age where Neural Networks and Natural Language Processing methods can be implemented to build a classification network to distinguish whether a given email is a spam or not.

Data Overview

The data that will be utilized was taken from Enron. The dataset contains ~33k messages, approximately evenly split between spam and not spam. However, the data is not clean and needs a lot of pre-processing before any data manipulation can be done.

Data Cleaning

The raw format of the dataset contains two folders filled with .txt files; one for spam messages and another for non-spam messages. Figure 1 shows a sample .txt file



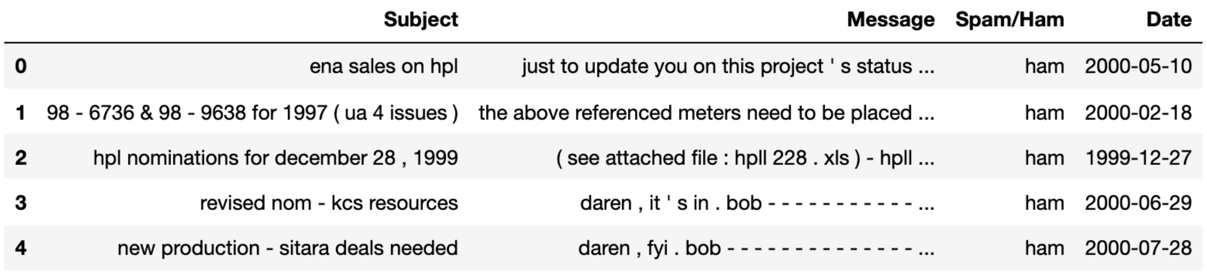
```
 Subject: lst rev dec . 1999 josey ranch nom
fyi
- - - - - - - - - - - - - - - - - - - - - - forwarded by susan d trevino / hou / ect on 12 / 15 / 99
08 : 40
am - - - - - - - - - - - - - - - - - - - - - - - - - - -
bob withers on 12 / 14 / 99 05 : 11 : 06 pm
to : susan d trevino / hou / ect @ ect
cc : stretch brennan , kevin mclarney ,
" taylor vance ( e - mail ) "
subject : lst rev dec . 1999 josey ranch nom
susan : as we discussed , this change was missed but was discussed with you
last week . i apologize for the omission . i am checking with my field
personnel and anticipate a further reduction ( due to well production
decreases ) effective 12 / 15 which i will send under a separate email for an
" intra - day " change wednesday .
here ' s revised december 1999 ( effective 12 / 9 / 99 ) setup for
josey : ( using 1 . 081 btu / mcf )
* gas deliveries into hpl
12 , 300 mmbtu / d for kri ( net reduction of
1 , 000 mmbtu / d )
12 , 300 mmbtu / d into hpl
bob withers > <
kcs energy , 5555 san felipe , suite 1200
houston , tx 77056
voice mail / page 713 - 964 - 9434
```

Figure 1. Sample Raw Data .txt

The steps to clean each .txt files are as follows:

1. Extract first line and record as ‘subject’.
2. Everything else besides the first line will be part of the message.
3. Utilizing *regular expression* (REGEX), extract first date encountered based on format.

After applying these steps to all .txt files, a DataFrame will be generated by Pandas with the format shown on Figure 2.



	Subject	Message	Spam/Ham	Date
0	ena sales on hpl	just to update you on this project ' s status ...	ham	2000-05-10
1	98 - 6736 & 98 - 9638 for 1997 (ua 4 issues)	the above referenced meters need to be placed ...	ham	2000-02-18
2	hpl nominations for december 28 , 1999	(see attached file : hpll 228 . xls) - hpll ...	ham	1999-12-27
3	revised nom - kcs resources	daren , it ' s in . bob - - - - - - - - - - - ...	ham	2000-06-29
4	new production - sitara deals needed	daren , fyi . bob - - - - - - - - - - - - - - ...	ham	2000-07-28

Figure 2. Cleaned DataFrame

Exploratory Data Analysis

The dataset is relatively balanced with a discrepancy of around 1.8% of the total messages. Figure 3 shows a bar plot of the division between spam and non-spam messages.

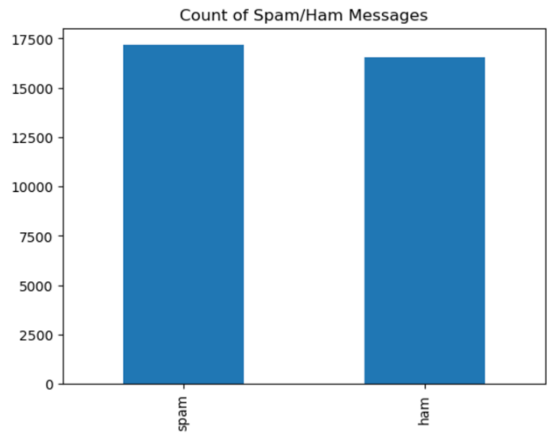


Figure 3. Bar Plot Count

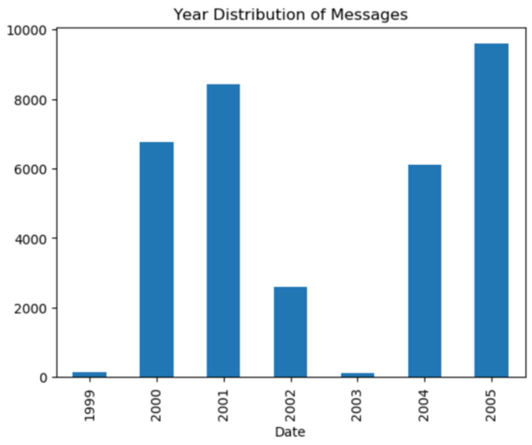


Figure 4. Timeframe of messages

It is shown that the dataset that will be used to train is a well-balanced one. Figure 4 shows the time frame of these messages. Most of the messages being sent are between 2000-2001 and 2004-2005. There seems to be a gap between 2002-2003, but this should not create any significant error.

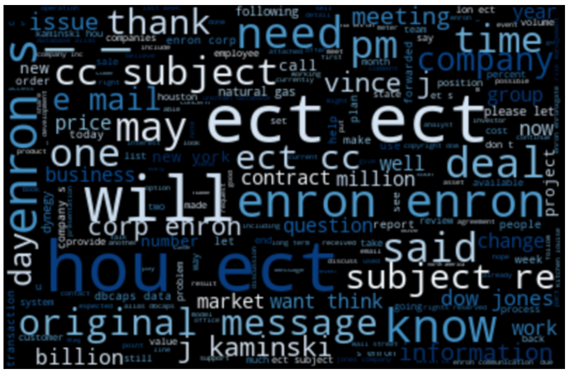


Figure 5. Word Cloud for genuine messages

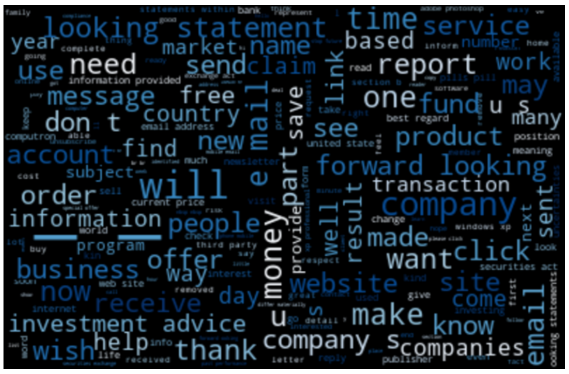


Figure 6. Word Cloud for spam messages

Figure 5 and 6 shows word-clouds for genuine and spam messages, respectively. Notice that official and formal words are likely to be found on the genuine word-cloud, whereas words on the second word-cloud are typically found in spam messages.

Data Preprocessing

Each row (message) from the DataFrame goes through a flow of data pre-processing before it is used to train models. The flow is depicted in Figure 7.

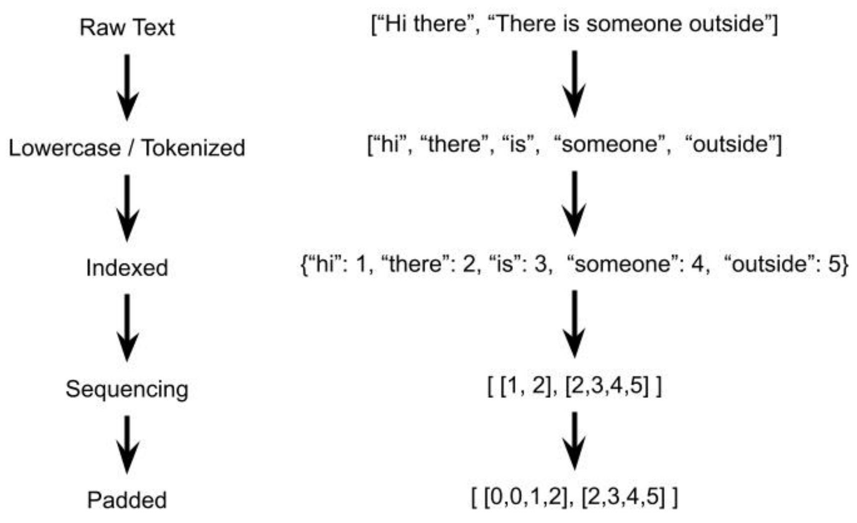

Raw Text
["Hi there", "There is someone outside"]
Lowercase / Tokenized
["hi", "there", "is", "someone", "outside"]
Indexed
{"hi": 1, "there": 2, "is": 3, "someone": 4, "outside": 5}
Sequencing
[[1, 2], [2,3,4,5]]
Padded
[[0,0,1,2], [2,3,4,5]]

Figure 7. Pre-processing data flowchart.

The raw data consists of the Message column of the DataFrame. The next step is to convert to lowercase and tokenize word-per-word. Unique words will then be put inside an index, denoted by an integer. Each message is then converted to an array of integers based on the word index. Lastly, the sequences are padded in the front so that all messages have the same length. Now, since the text is converted to a numerical representation, it can be quantified and used to train the models later on.

The word index is used to filter out rare words. In order to detect spam messages, the words that the model will look for in messages would be common words that appear in spam messages; hence the need to record rare words are insignificant. Other than converting to lowercase, punctuations are also removed.

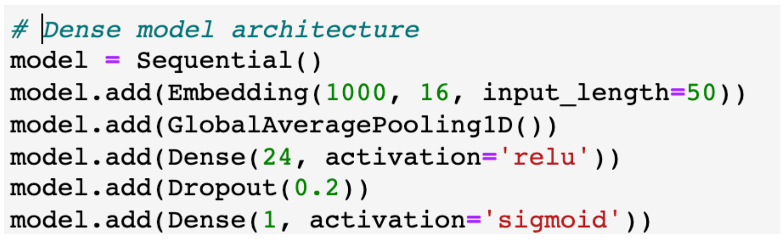
```
tokenizer = Tokenizer(num_words = 1000, char_level=False, oov_token = "<OOV>")
tokenizer.fit_on_texts(train_msg)
```

Figure 8. Tokenizer Parameters.

In Figure 8, we utilize Keras's Tokenizer to create the word index. The size that was chosen for the index is 1000 words, meaning 1000 unique words will be loaded into the index. *char_level* is set to False since we are evaluating word-per-word not letter-per-letter. The *oov_token* parameter is to specify that we want to take into account words that do not get added into the word index corpus. After the tokenizing above, the messages are sequenced and padded accordingly. The feature length of each message will be limited to the first 50 words.

Model Training
Three different neural models will be trained with the pre-processed dataset. Each model is built with Keras's sequential model. Layers will be added sequentially according to what each model specifies for.

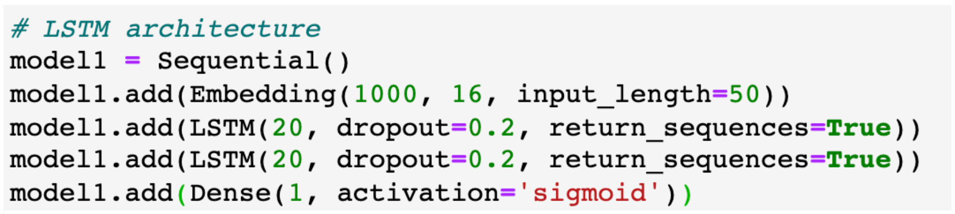
1. Dense Model
- The first layer of the dense model will be the embedding layer which is useful for algorithms involving NLP to convert the padded sequence of length 50, into an array of 16 numbers. This involves one-hot encoding as well as dimensionality reduction. Also, the *input_length* will be 50 as it is the length of our padded sequence.
- The second layer involves a global average pooling layer to reduce the parameters used in the model to avoid overfitting.
- The third layer is a dense layer with Rectified Linear Unit as its activation function, along with 24 neurons
- The fourth layer is a dropout layer to further prevent overfitting. The parameter is 0.2 which randomly assigns input as 0 every (1/0.2=) 5 steps.
- The final layer uses Sigmoid as its activation function, outputs probability between 0 and 1, and only has 1 neuron since it is a binary label (Spam/Not Spam).



```
# Dense model architecture
model = Sequential()
model.add(Embedding(1000, 16, input_length=50))
model.add(GlobalAveragePooling1D())
model.add(Dense(24, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))
```

Figure 9. Dense Architecture.

2. Long Short-Term Memory (LSTM) Model
- The first layer of the LSTM model will be the embedding layer, same as the previous model.
- The second and third layers are LSTM layers stuck horizontally. The point of stacking two LSTM layers as to create a hierarchical feature representation. LSTM is a Recurrent Neural Network, which is useful in sequenced data types, such as words in a sentence in this case. Having multiple layers of LSTM will uncover features derived from the position of words in a sentence relative to other words. It has an integrated Dropout to prevent overfitting which is crucial due to the high complexity nature of LSTM layers.
- The final layer uses Sigmoid as its activation function, outputs probability between 0 and 1, and only has 1 neuron since it is a binary label (Spam/Not Spam).



```
# LSTM architecture
model1 = Sequential()
model1.add(Embedding(1000, 16, input_length=50))
model1.add(LSTM(20, dropout=0.2, return_sequences=True))
model1.add(LSTM(20, dropout=0.2, return_sequences=True))
model1.add(Dense(1, activation='sigmoid'))
```

Figure 10. LSTM Architecture.

3. Bidirectional Long Short-Term Memory (Bi-LSTM) Model

- The first layer will be the embedding layer, same as the previous models.
- The second layer is an LSTM layer wrapped with Bidirectional. The point of using the Bidirectional wrapper is to allow the LSTM nature to propagate both forwards and backwards. It is natural to extract features that relate to the position of word in a sentence, and also incorporating whether a word is before or after another word. It has an integrated Dropout to prevent overfitting which is crucial due to the high complexity nature of Bi-LSTM.
- The final layer uses Sigmoid as its activation function, outputs probability between 0 and 1, and only has 1 neuron since it is a binary label (Spam/Not Spam).

```python
# Bi-directional LSTM Spam detection architecture
model2 = Sequential()
model2.add(Embedding(1000, 16, input_length=50))
model2.add(Bidirectional(LSTM(20, dropout=0.2, return_sequences=True)))
model2.add(Dense(1, activation='sigmoid'))
```

Figure 11. Bi-LSTM Architecture

Evaluation / Model Selection

While training the three neural models, accuracy was above 96% and all models perform similarly with each other. Figure 12 shows the test set accuracy for each of the three models. Figures 13.a-c depicts the train and test set accuracy through epochs of training for all models.

Neural Network Model	Loss	Accuracy
Dense	0.0893	0.9680
LSTM	0.1092	0.9632
Bidirectional LSTM	0.0905	0.9663

Figure 12. Model Results

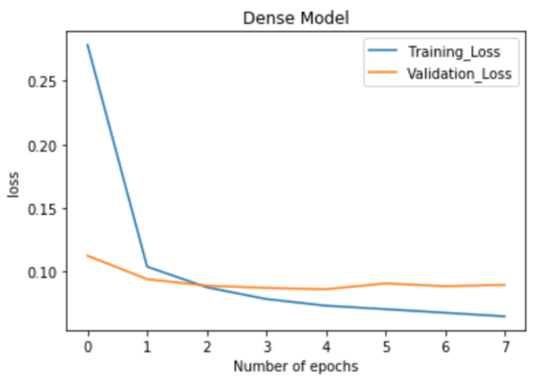


Figure 13a. Dense Model Loss

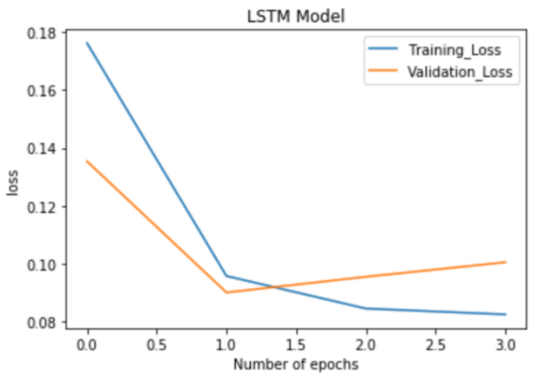


Figure 13b. LSTM Model Loss

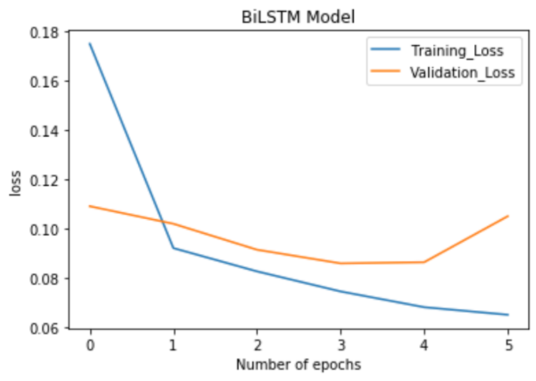
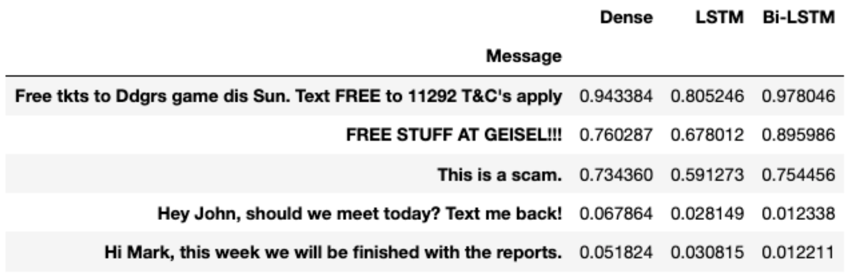


Figure 13c. Bi-LSTM Model Loss

The results from each of three models are strikingly similar and highly accurate. The models that are built from the message dataset seems to be possessing features that are extractable and recognized by all three neural network models above. As a matter of fact, it seems that both the LSTM and Bi-LSTM models are high in complexity due to the validation error being more steeply increasing than the Dense model. This is crucial to note as the data that was fed into the models comes from one source, specifically a single company. It is likely that the models will be overfitting to features like formal language and company jargons.

In Figure 14, sample messages are passed on to each model to predict. The results are shown on the table. The values shown denote the probability that the message is a spam, classified by each model.



Message	Dense	LSTM	Bi-LSTM
Free tkts to Ddgrs game dis Sun. Text FREE to 11292 T&C's apply	0.943384	0.805246	0.978046
FREE STUFF AT GEISEL!!!	0.760287	0.678012	0.895986
This is a scam.	0.734360	0.591273	0.754456
Hey John, should we meet today? Text me back!	0.067864	0.028149	0.012338
Hi Mark, this week we will be finished with the reports.	0.051824	0.030815	0.012211

Figure 14. Sample Predictions

Precision as Metric

The neural networks trained above utilizes accuracy as its metric. This means that through every run of the training step, it will reconfigure weights of the neurons with the objective of increasing accuracy. Sometimes accuracy is not the perfect metric to use when training. An unbalanced dataset might introduce a bias in the algorithm to predict a label as the more dominant one. Having multiple-class labels may result in only a few of the labels being considered in the labeling process.

Precision is an alternative to Accuracy. Precision is defined as the ratio between True Positives and All Predicted Positives. In other words, it measures how many percent of the messages that are tagged as spam, are actually spam. If precision is used as the metric in training the models, then the classifier will maximize the percentage of actual spam messages of all the predicted spams. This minimizes the amount of genuine messages labeled as spam.

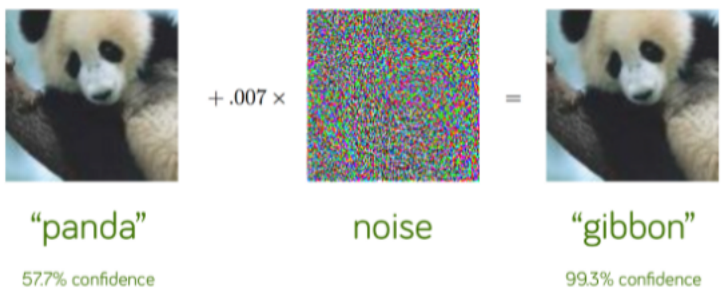
Another alternative is Recall. Recall is defined as the ratio between True Positives and All Positive Observations. In other words, it measures the percentage of spam message observations that are labeled by the model as spam. If recall is used as the metric in training the models, then the classifier will maximize the percentage of correctly predicted spam messages of all spam message observations. This minimizes the amount of spam messages that are labeled as genuine.

Notice how Precision and Recall are somehow two sides of the same coin. An example where Precision is used would be identifying a good stock to purchase. In this case, the algorithm would rather make a mistake identifying a good stock to buy as bad, rather than misleading users by labeling a bad stock to buy as good. The algorithm **cannot** afford to make the mistake of labeling a stock as a good one (predicting True, when False) and would play it safe in identifying good stocks when it is certain. An example where Recall is used would be identifying criminals at security checkpoints. In this case, officers would rather make a mistake of identifying a normal person as a criminal than identifying a criminal as a normal person. They **can** afford to make the mistake of being too careful (predicting True, when False) rather than letting a criminal go through.

In the case of spam detection, precision should be used. Would a person rather receive a spam promotional email in his/her primary inbox or have a very important document sent into the spam inbox? The former should be the more desirable outcome. The algorithm cannot afford to predict a message as spam when it is genuine and should rather predict a message as genuine when it is spam.

Adversarial Attacks

Neural network models can be considered the epitome of machine learning. Although it is a new discipline that has outperformed most machine learning models, it has some serious flaws. In 2014, NYU and Google conducted a research into fooling Convolution Neural Networks. The neural network that they tinkered around with was an image detection network that can properly identify the subject of the image.



Source: Explaining and Harnessing Adversarial Examples, Goodfellow et al, ICLR 2015.

Figure 15. Adversarial Attack

In Figure 15, the attack starts with a clear picture of a panda. The neural network classifies it as "panda" with 57.7% confidence. However, when the image is altered with noise, the model classifies it as a "gibbon" with 99.3 confidence. The odd fact here is that the image after tampered with the noise seems to not have changed since initially, to the human eye; one can clearly see that it is still a picture of a panda. On top of that, it misclassifies the image as "gibbon" with a confidence level of being close to 100%.

In the case of adversarial attacks to spam filters, a carefully constructed sequence of words might be able to have the same effect as the noise did on the neural network above. Adversarial attacks are much simpler to execute with text since there are more loopholes to watch. For instance, one way to get around the filtering of a spam message would be to convert spam "trigger" words by putting spaces between letters of the word. With this technique, the tokenizer of the pre-processing stage will miss the fact that these letters are part of the same word and will lead to a spam message being classified as genuine.

The brute-force technique of preventing adversarial attacks is to be the attacker and generate “noise” examples that might mess up the model. The model will then be “told” to not be fooled by manual override and learn not to misclassify with that specific adversarial attack. However, this becomes taxing as it turns into a race between the pseudo-attacker and the attacker.

The intuition behind why neural networks are vulnerable relies on some of its activation functions. It depends on a certain threshold that can easily be manipulated through small tweaks in the datum’s features. It also lies on the fact that most neural network models train on a very small subset of data that it might encounter. Considering that there are usually tens of thousands of parameters in a neural network, a small discrepancy might lead to a large change in its output and overall robustness.