Introduction

Detecting sentiment from a piece of text is a key part of Natural Language Processing (NLP). It is a foundational part of recommender systems which track a user's affinities and aversions with the aim of matching the user with a product/ service that's helpful for them.[1, 2] Much work on sentiment analysis has been done on short-form text data such as those derived from micro-blogging social media sites. Because of the succinct nature of these social media posts, it is perhaps easier to glean points of view than from longer pieces of text. [3]

I would therefore like to perform sentiment parsing of long-form text in the form of book reviews. The aim is to see if different models are as capable in situations where the user leaves a more verbose review. Book cataloging websites might benefit from insights gained from this project in order to improve their recommendation system. If longer reviews do result in less reliable recommendations the website might decide to implement a word limit on reviews.

I will use book reviews scraped from various websites including Goodreads stored on Kaggle as CSV files. The goal is to use different machine learning models to parse sentiment (either positive or negative) from each review. For this supervised classification problem, I will compare the performance of a neural network (Long Short Term Memory and Recurrent Neural Network) to a Bernoulli Naive Bayes model.

I decided on the Bernoulli Naive Bayes model because of its popularity in classifying text and its sometimes superior performance despite its less sophisticated assumptions[1]. Neural networks such as Long Short Term Memory (LSTM) and Recurrent Neural Network (RNN) are more complex than Naive Bayes but they make up for this by being exemplary learners on sequential data such as text. The LSTM neural network in particular was chosen as a juxtaposition due to its ability to maintain information in memory for longer periods of time compared to the simple RNN.[2] LSTM are also more capable of working with long range dependencies common in linguistics.[4]

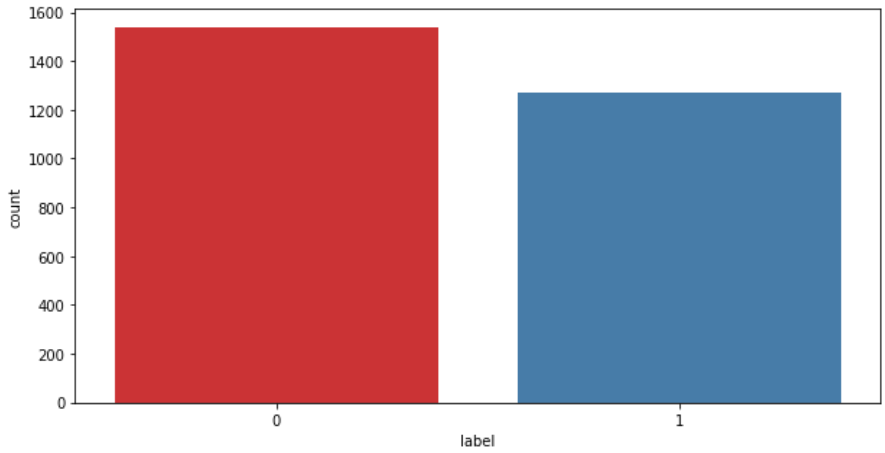
Exploratory Data Analysis:

I obtained the first csv file containing reviews and their labels from the Kaggle website. The file contains two columns, one containing text of the review and the other column containing the rating (__label__1 for negative, and __label__2 for a positive rating). There were around 2,800 ratings. The dataset creator mined the ratings from different public websites but did not specify the particular source. [5]

I exchanged the original __label__1 for zero to signify a negative rating and __label__2 to one to signify a positive rating. I then plotted the labels to get a better

understanding of the proportions of each rating in the whole dataset. It is apparent that the dataset contains more negative ratings (a little over 1,500 instances) compared to positive ratings (around 1,200 instances).

a. Proportion of Positive vs. Negative Ratings in First Dataset

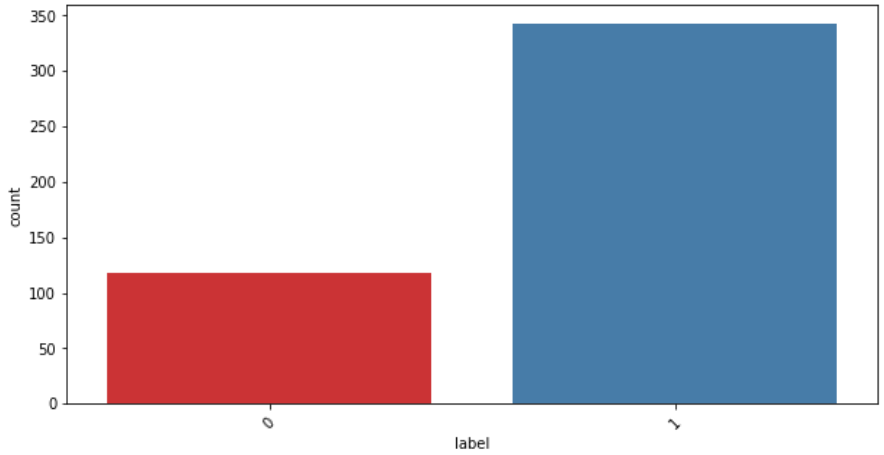


The second dataset was also obtained from Kaggle. It contains around 400 reviews obtained from the book review aggregator website Goodreads. The dataset had 14 columns one of which contained the text of the review and another which contained the rating of the review (from 0 to 5). [6] I sliced the dataset to only focus on the two columns containing the review text (column named 'review_text' and the rating review (column named 'review_rating').

Because the reviews were in a range from 0 (most negative) to 5 (most positive), I arbitrarily chose a cutoff of 3 with ratings less than 4 given a new label of zero for negative. The reviews given a rating of 4 and above were given a new label of 1 for positive in order to be consistent with the first dataset. I also renamed the 'review_text' column to 'text' and the 'review_rating' column to 'label' in order to preserve consistency.

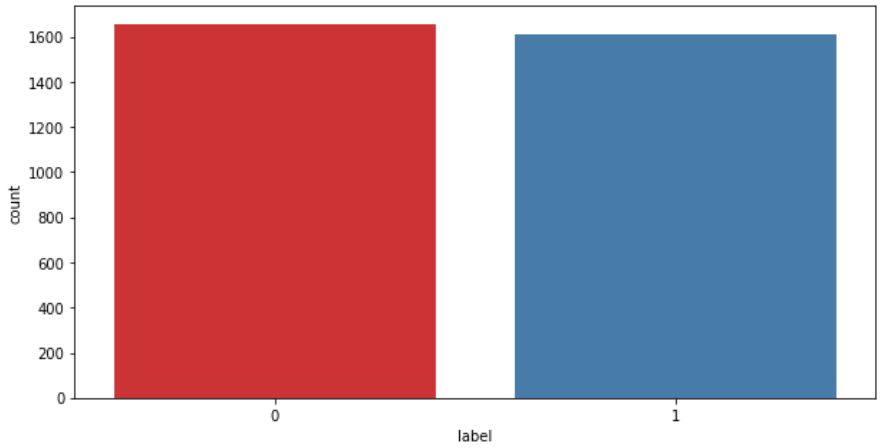
I plotted the 'label' column in order to visualize the proportions of the labels and obtained the following result.

b. Proportion of Positive vs. Negative Ratings in Second Dataset



I then concatenated the two datasets and the resulting data frame had about 3,000 rows and 2 columns. The reviews were in the 'text' column and the ratings were in the numerical column named 'label'. There were no missing values in this new data frame. To visualize the proportions of the two labels in the whole dataset, I plotted the 'label' column to obtain the next plot.

c. Proportion of Positive vs. Negative Ratings in Final Dataset



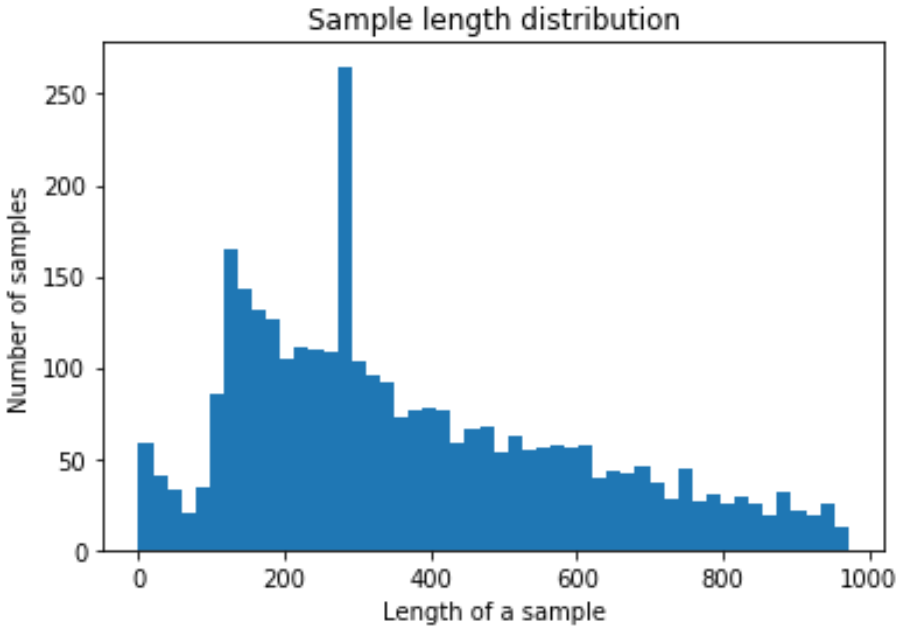
The proportions of negative (rated zero) vs positive (rated one) became more even with the addition of the second dataset of reviews. Obtaining value counts of the 'label' column revealed zero rated (negative) ratings to be 1, 656 while the one rated (positive) ratings were numbered at 1, 612.

Pre-processing Text

I ran the text through different functions to clean and lemmatize the test in preparation for the first model which was the Bernoulli Naive Bayes. The first function was to remove accented characters after noticing some of the reviews written in Spanish and Arabic. I used the default english language statistical model from the spaCy library to create nlp objects from each review, then I obtained the lemmas for each word that was not identified as a pronoun. The decision to lemmatize the text instead of stemming was taken in order to keep some of the context surrounding the word. [7]

I then ran the text through another function sweeping for any left over special characters. I decided to keep digits in the reviews in order to have the model learn from entries where a reviewer might leave a numerical rating instead of a text rating. I then removed extra white space from the text before plotting the following sample distribution of the text length.

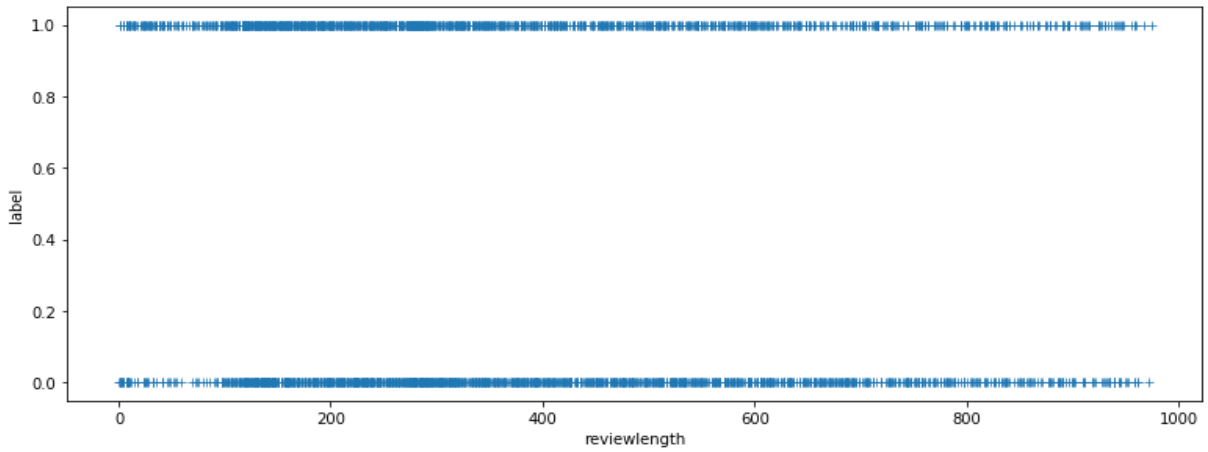
d. Distribution of Cleaned Text Length in final dataset



The distribution does not follow any obviously identifiable pattern, but it is evident that the majority of reviews had a length of over 300 words (average of 374 words). The longest review had 974 words while the shortest review had no words. The text in this dataset seems to be longer than most social media texts used for sentiment analysis. For comparison, posts on the social media website Twitter which imposes a character limit contain an average of 33 characters.[8]

I then created a scatter plot to see whether longer reviews were more likely to be rated positive/ negative compared to the shorter reviews. The plot shows no relationship between the length of a review and its likelihood to be rated positive or negative.

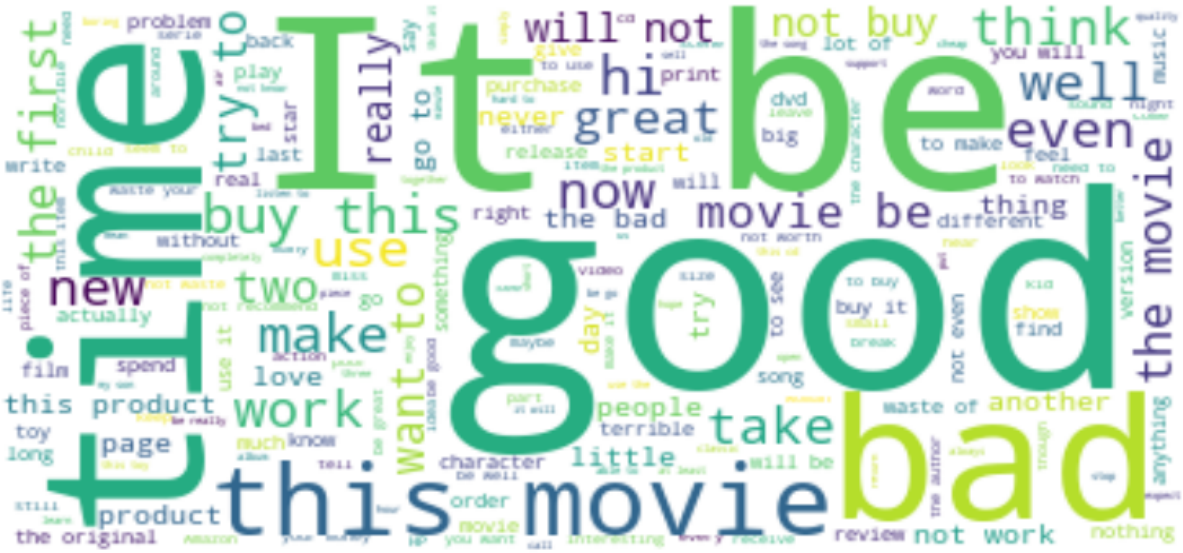
e. Investigating the Correlation Between Review Length and Label



I then split the dataset into two with the first one containing only the positive reviews while the second one contained only the negative reviews. I created a wordcloud of the text in the respective dataframes. After removing common stop words including “book”, “this”, “it”, and “be” I obtained the following results. The most prominent words in the positive reviews are largely positive as is expected with the words “great” and “good” crowding out the rest of the words in the visualization. The word cloud for the negative reviews was less clear cut with the most prominent words being “time”, “good” and “bad”.

f. Visualising the Most Common Words in the Positive Reviews

g. Visualising the Most Common Words in the Negative Reviews



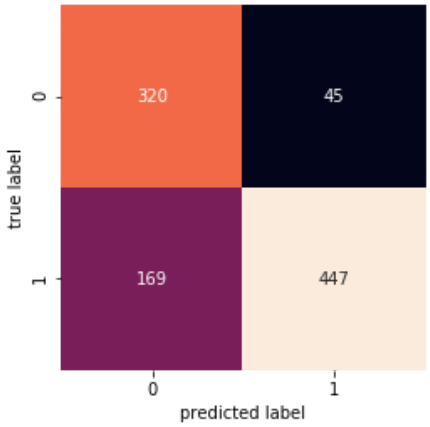
Bernoulli Naive Bayes

After vectorizing the preprocessed text and removing stop words, I divided the text into training and test sets along a 70% - 30% split. I then fit the classifier on the training data and thereafter used the test data to get a new set of predicted labels. Comparing the true labels to the set of predicted labels yielded 78% correct predictions and an area under the curve (AUC) of 78%.

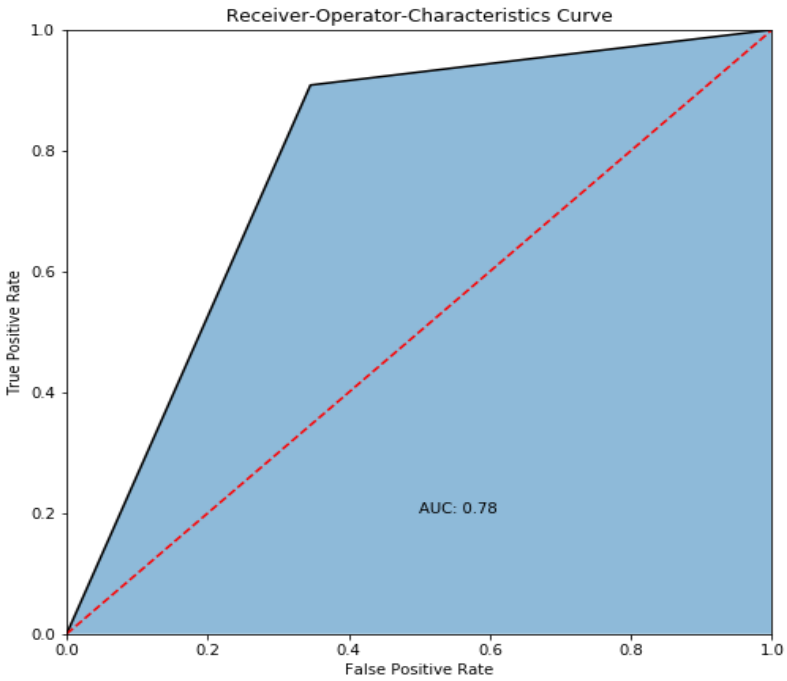
To get a better sense of the performance of the model, I created a confusion matrix shown next. The classifier had more false negatives (Type II Error) compared to false positives (Type I Error). This might be less acceptable if a book review aggregator website is using prior reviews left by a user to recommend the next book. This inability to correctly label positive reviews would hamper the effectiveness of the recommendation system. This is surprising given the wordcloud's visualization of the positively rated reviews which contained more positive words.

Since our dataset is small, this signals more work needs to be done to train the model on positively labeled reviews in order for the classifier to better learn on this class.

h. Confusion Matrix for Bernoulli Naive Bayes Classifier



i. ROC-AUC Curve for Bernoulli Naive Bayes Classifier



Long Short Term Memory Neural Network

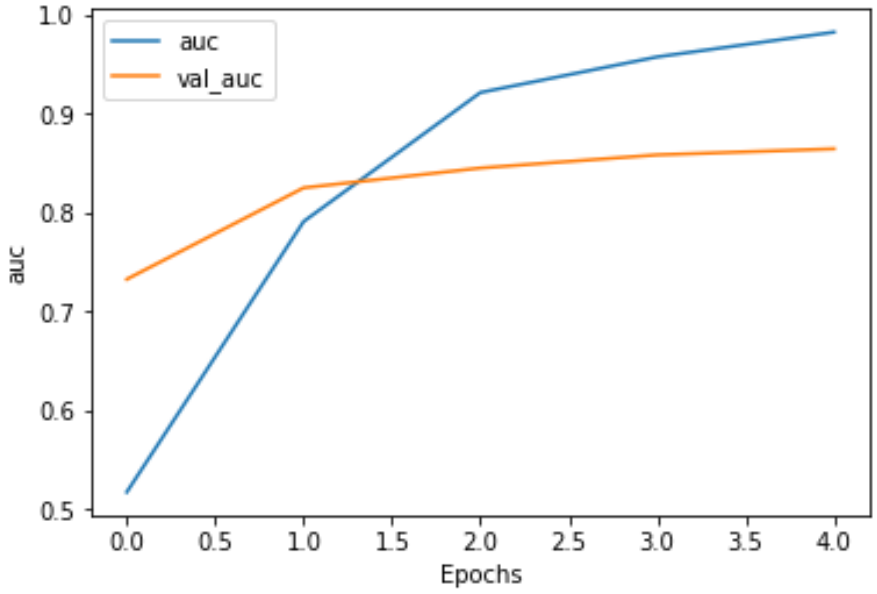
I decided to use a new set of steps to preprocess the data in preparation for the LSTM neural network in order to familiarize myself with TensorFlow's suite of implementations. Instead of using Sci-kit learn's Countvectorizer, I used Tokenizer from the TensorFlow library in combination with spaCy for lemmatization to preprocess the text. This transformed the text into vectors and removed special characters and digits. I

also transformed the column containing the labels into an array. After optimizing the model, I found the ideal train-test split to be an even 50%.

I then built the layers of the neural network setting the shape of the embedding layer equal to the size of the vectorized text. I then added two bidirectional LSTM networks followed by a dense layer with regularization. The next layer was a dropout layer dropping 20% of the output units chosen randomly from the applied layer. The final layer was a dense layer containing a sigmoid activation function to ensure the predictions were between 0 and 1. I then fit the model to the training set over 5 epochs to minimize the training time.

Comparing the true labels to the set of predicted labels yielded 79% correct predictions only slightly outperforming the Naive Bayes classifier. The AUC was 86%, also similarly outperforming the Naive Bayes Classifier.

j. AUC Curve for Long Short Term Memory Network

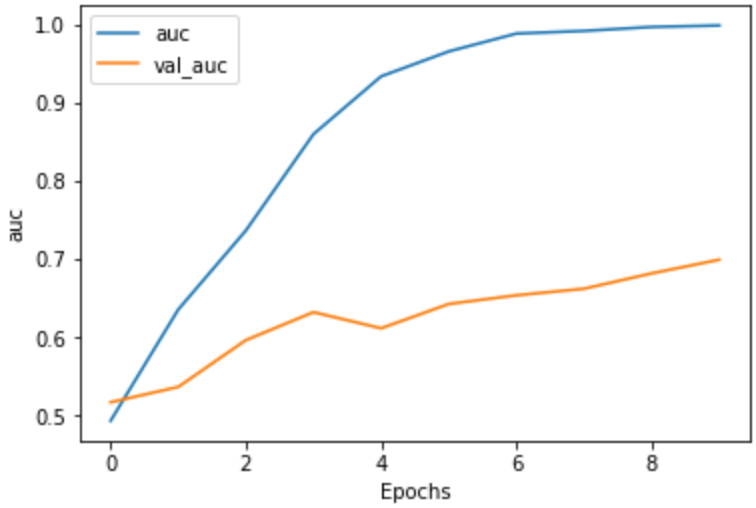


Simple Recurrent Neural Network

The preprocessing steps for the Simple RNN were similar to those performed in preparation for running the LSTM model. The model was composed of an embedding layer similar to the LSTM with one bidirectional RNN layer and a dropout layer randomly removing 10% of the output units. The last layer was a dense layer containing a sigmoid activation function similar to the LSTM neural network.

Comparing the true labels to the set of predicted labels yielded 57% correct predictions, the worst performance out of the three models. The AUC was 62%, also the poorest performance of the three. The layers of this model differ from the LSTM model in the absence of a regularization layer which might diminish the model's ability to learn on sparse data.

k. AUC Curve for Simple Recurrent Neural Network



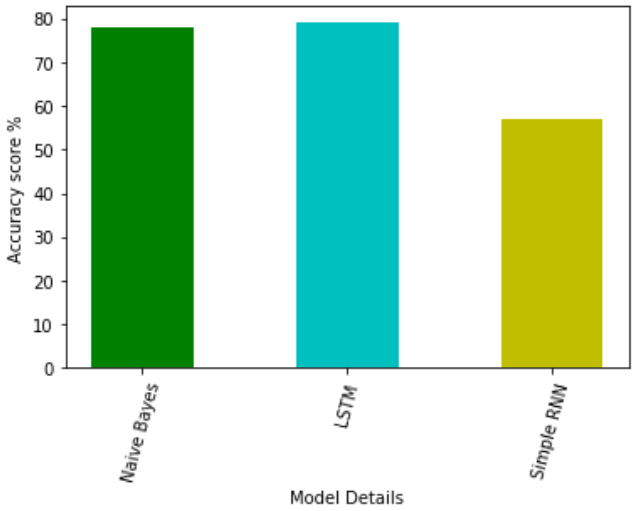
Conclusion

The objective for this project was to compare the effectiveness of different classifiers' ability to parse sentiment from long form text data in the form of book reviews. The idea for this came from work done by Bermingham et al which hypothesized that it might be easier to identify sentiment from short text instead of long text. They used long form movie reviews from USENET with 1000 documents per class compared with short form text from Twitter. The results from the study seemed to disprove this hypothesis with the Naive Bayes classifier having a 74% accuracy on the short form text compared to 85% on the longer movie review text.[3]

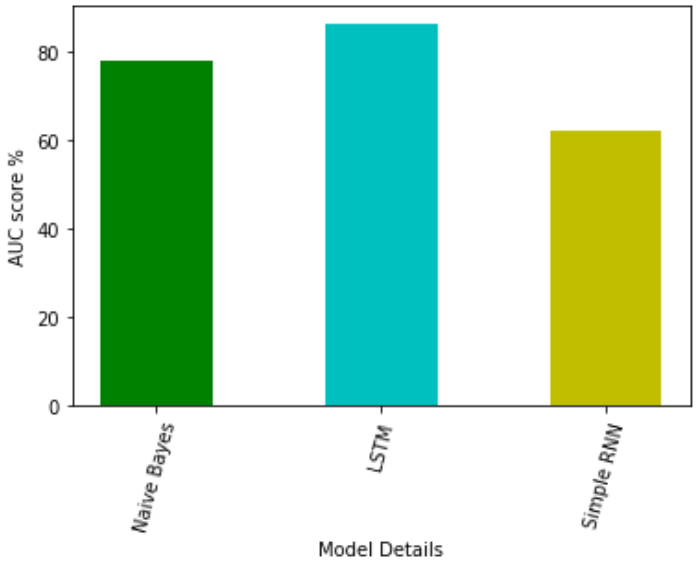
This project builds on this work, this time focusing on long form text, comparing the performance of a Naive Bayes classifier against neural networks (LSTM and simple RNN). The LSTM neural network outperformed all three models (accuracy 79%, AUC 86%) perhaps due to it's more complex layers designed to optimize learning on sparse matrices. This was followed closely by the Bernoulli Naive Bayes classifier coming in at 78% accuracy and an AUC of 78%. The poorest performer was the simple RNN with an accuracy of 57% and AUC of 62%.

All the classifiers had a poorer performance in contrast to the performance on long form text cited in Bermingham et al perhaps due to data quality. During preprocessing, I discovered that my dataset had reviews in different languages including Spanish and Arabic and removing these resulted in a smaller corpus to train on.

l. Comparing the Performance (Accuracy) of the Three Models



m. Comparing the Performance (AUC) of the Three Models



Future Scope

1. Adding more text in the English Language to train the models

References:

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