Automated Emotional Analysis

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Abstract

Social media has allowed for unprecedented access to individuals' thoughts and opinions. In this paper, we studied Twitter data in order to understand the underlying emotion behind a tweet. This expands on the task of learning the binary positive or negative attitude by including more emotions in the classification. Our dataset provided the emotion-labeled uncleaned tweets, enabling us to design several of our own custom text cleaning methods, each with different goals in mind. We then experimented with multiple models, including logistic regression, perceptron, convolutional neural networks (CNNs), and BERT language modeling. As a result from our models, the original uncleaned dataset outperformed each cleaning method based on the F1 Score. This then suggests that deep learning models are sensitive to data cleaning, so aggressive changes to the original raw text can actually reduce model performance. We achieved the best results with BERT on the original uncleaned data, but maintain that some amount of data cleaning is necessary and should be undertaken for tweet classification.

1. Introduction

Social media has provided the public with a platform for personal expression. This new outlet has given businesses the ability to easily assess the opinion of the consumer. By automatically detecting the overall feeling behind social media discourse, businesses can make more accurate decisions. The purpose of this project is to determine the nuanced feeling behind a tweet, which goes even further than just learning the binary positive or negative attitude of the user. More specifically, we want to attempt to detect the actual emotion that is expressed from the text. This is important because it will provide an even better understanding of what the user is trying to communicate. In this paper, we will examine several different data cleaning methods as well as various machine learning models in order to determine what combination of techniques best classifies the emotion of a tweet.

2. Background

Our Twitter data consists of natural language text from 916,575 tweets. The data comes from a dataset that was found on Kaggle (2020) [5]. Each tweet has been labeled with its corresponding emotion: happy, angry, or disappointed. As tweets are often shorter in length and consist of informal language, we will need to employ text preprocessing and deep learning models to determine the feelings behind the text. We chose this data because it includes a cleaned dataset (stripped of retweets, user-tags, and emojis) as well as the original raw, uncleaned tweets. We are interested in applying our own cleaning methods, such as the techniques for handling emojis discussed in Singh (2019) [4].

Next, after the data has been preprocessed, we will build multiple models by implementing several different NLP techniques, with the goal of classifying the tweet's emotion. First, we will create a simple logistic regression classifier as our baseline model. We will also construct a single-layer perceptron classifier, like in Donicke (2019) [1]. Then, we will apply more advanced techniques, such as constructing both shallow and deep convolutional neural networks, similar to Cai (2018) [3], as well utilizing Google's BERT language modeling architecture. To compare all of our results, we will use the F1 Score as our primary accuracy metric. The F1 Score is given by the formula:

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

As we will use multiple techniques for both text preprocessing and the emotional classification, we plan to experiment with different combinations of these methods in order to determine which performs the best.

3. Methods

In order to determine the nuanced emotion of a tweet, we will employ multiple strategies for both data cleaning as well as classification modeling. Each technique will be developed to address Twitter-specific text data, which may have different results compared to text with a more formal language structure.

3.1 Data Cleaning

As our data consists of text from tweets, we are dealing with short, informal language patterns that include more casual phrases as well as emojis, user tags, and reference links. Due to these irregular forms of text, an important part of our analysis will include our approach to cleaning the data before we build our machine learning models. This preprocessing can impact how the model determines the emotional classification of a given tweet.

Initially, our dataset includes the raw tweet text as well as a basic cleaned version of each tweet. We want to expand this dataset with our own custom preprocessing methods. These methods will be designed to try and optimize the classification potential of the text. So, in order to understand how to best accomplish this and create our own methods, we first need to explore the raw tweet data.

	Content
Emotion	
angry	300990
disappointed	313714
happy	301871

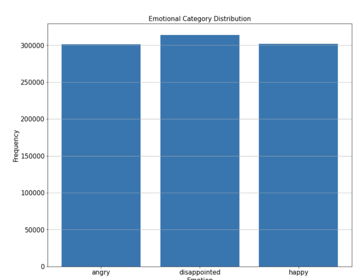

Figure 3.1 Distribution of Text Classification Labels.

From the histogram in Figure 3.1, we can see that each of the classes are relatively balanced, which means that they are each represented equally in the dataset. This is ideal for building our models as there will not be any significant bias towards one group or another.

We also want to know some of the frequent terms that appear in each of the tweets. These terms could be indicative of the sentiment behind the tweet, meaning that certain words could be particularly influential in our model. In order to get a general idea of what some of these key phrases are, we produced a word cloud that displays the top 100 most common words and phrases from the text in the overall tweet data set.

Figure 3.2 General Word Cloud.

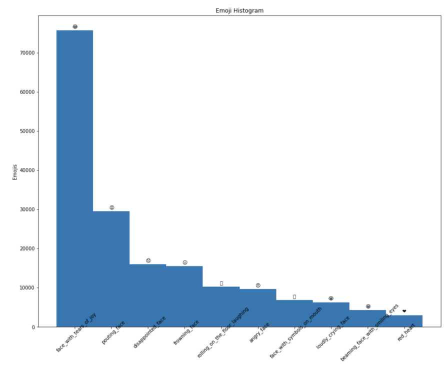

Figure 3.3 Histogram of Emojis.

From the word cloud in Figure 3.2, we know that larger words occur more frequently in the data set. So, it is apparent that verbs and adjectives related to a user's emotion are actually very common in the Twitter text. We can also see that pairs of emojis are a very popular way for users to express themselves in tweets. As emojis are clearly a very expressive part of the text, we want to take a closer look into the emojis that are most commonly used.

From Figure 3.3, we can see that the ‘crying laughing face’ is by far the most common emoji, followed by the ‘pouting’ and ‘disappointed face’ emojis. Although these might be more indicative of a certain emotional class, it is important to keep in mind that users may use certain emojis to express different things, such as sarcastic remarks or general exaggeration.

With the exploration of the data in mind, we designed two different custom text preprocessing techniques that might help to improve the emotional classification of each tweet.

First, we will apply a tweet-specific cleaning technique that makes several changes to the original content. To start, we are going to strip the text of special characters, remove stopwords, and lower the casing of the words. Then, we are going to replace user tags and website instances with the tokens ‘usertaginstance’ and ‘websiteinstance’ respectively, rather than just removing them. This is because there might be an influence in sentiment related to these Twitter interactions that can be useful in our model. These replacements will allow us to generalize these actions similar to how numbers would be replaced in other NLP tasks. Last, we will split up the emoji name descriptions into individual tokens. This is because each emoji name contains phrases that might be more influential as individual tokens compared to as a single token. Therefore, this cleaning approach should have different results than the original data.

Then, we will also construct a more general cleaning method that focuses on just removing special characters from the text. We did this because there are so many special characters in tweet data, such as ‘@’ or ‘:emoij:’. However, we did not remove any other text, like stopwords. This is because we thought that removing words from the data might also remove meaning that the algorithms could capture. Additionally, emoji names were left as a single, unique string (i.e.. “:grinning_similing_face:” was turned into “grinningsmilingface”) as it could be a key contributor for the emotional classification, provided that the algorithms recognize it. This cleaning method leaves most words in the text, allowing the model to rely on smoothing and other techniques in order to gather meaning from the data.

3.2 Classification Modeling

Once the data has been preprocessed, we will need to build different machine learning models that will then be able to classify the emotion that the tweet actually conveys. As our goal is essentially a topic classification problem, there are several different approaches that we can take in order to accomplish this.

3.2.1 Logistic Regression

To start, we will build a logistic regression model to serve as our baseline. Logistic regression is used for binary outcome data, where Y = 0 or Y = 1. Yet, in a one-vs-all approach, a binary classification problem is fit for each of our three emotion-labels. Logistic regression is defined by the following probability mass function:

$$p(y=k|x) = \frac{\exp(\theta_k^\top x)}{\sum_{i=1}^{K} \exp(\theta_i^\top x)}$$

This discriminative regression model allows us to build a simple, yet effective classifier that can determine the multi-class emotion of a tweet based on the vectorized text input.

3.2.2 Single-Layer Perceptron

We also built a single-layer perceptron model. The perceptron algorithm classifies patterns and groups by finding the linear separation between different objects and patterns that are received through its input. Using the GloVE vectorization method, the model structure is very simple. It uses the following formula to back-propagate the weights from the output back to the input, which is represented by:

$$p_j(t) = \sum_i o_i(t) w_{ij}$$

This classifier, similar to our logistic regression model, uses a one-vs-all approach to convert a binary classification problem to a multi-class output for our three class labels. Since the perceptron is a more complex algorithm, we would expect the perceptron to outperform the logistic regression baseline.

3.2.3 Convolutional Neural Networks

Neural networks are computational networks which were vaguely inspired by the neural networks in the human brain. The CNN takes a feature vector, generated from the vectorized text data, as an input and then passes it through hidden layers, concluding with an output layer that then makes the classification. The formula from one layer to the next is represented by:

$$o_j = f\left(\sum_i w_{i,j} a_i + b_i\right)$$

As there can be many different structures for a CNN, we will experiment with both shallow (single-layer) and deep (multi-layer) networks in order to emotionally classify our Twitter text data.

3.2.4 BERT & Sequence Classification

BERT, which stands for Bidirectional Encoder Representations from Transformers, pretrains representations of unlabeled text by learning from both the left and right directions of an input. This allows BERT to produce embeddings that are useful for many different NLP tasks, such as language modeling or text classification. The BERT model captures more complex language understanding, including sentence semantics, which then helps it to make more accurate text classifications. So, the combination of BERT embeddings with sequence classification forms a model that will produce multi-class predictions, which allows us to determine the given emotion of a tweet.

4. Results & Discussion

The purpose of this paper is to determine the best combination of a text preprocessing method as well as a machine learning model that will be able to accurately classify the specific emotion of a given tweet. In order to do this, we will run four different text data sets in each model. These data sets include the original raw tweet text, the original basic cleaned text, our tweet-specific custom cleaning method, as well as our more general custom cleaning method. In order to train and test each model, we did a 70%-30% train-test split.

First, we will train our logistic regression model on the vectorized text data and evaluate how each data set performs based on its resulting F1 Score.

	Cleaning Method	Accuracy	F1 Score
0	Orig. Uncleaned	0.900045	0.900447
1	Orig. Cleaned	0.894895	0.895385
2	Custom Cleaned #1	0.894044	0.894481
3	Custom Cleaned #2	0.852389	0.853353

Figure 4.1 Results from Logistic Regression.

From Figure 4.1, we can see that our baseline logistic regression model performs quite well in classifying the emotion of each tweet with a maximum F1 Score of 0.90. With regards to the various cleaning methods, the original raw tweet text actually performs slightly higher than any of the cleaned text data.

Next, we will train our single-layer perceptron model in the same fashion. The perceptron model takes the tokenized text as an input and consists of a simple flattened embedding and dense ReLU layer.

	Cleaning Method	F1 Score
0	Orig. Uncleaned	0.342268
1	Orig. Cleaned	0.342268
2	Custom Cleaned #1	0.342268
3	Custom Cleaned #2	0.342268

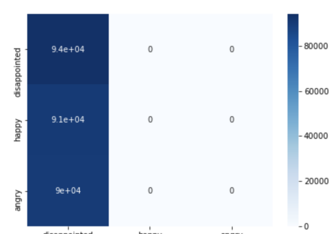

Figure 4.2 Results & Confusion Matrix from Single-Layer Perceptron.

The perceptron model does not perform very well, receiving an average F1 Score of 0.34. This is because the model actually always predicts the same 'disappointed' class label for every single tweet, shown in the confusion matrix in Figure 4.2. The confusion matrices were the same for all four models (see 'Appendix - Figures'). These results make sense because single-layer perceptrons can only separate classes if they are linearly separable. Therefore, the simple structure of the model means it cannot generate enough complexity to fully model this problem.

Then, we will construct both a shallow and deep CNN. The shallow CNN consists of three dense ReLU layers followed by a sigmoid output layer.

	Cleaning Method	Training F1 Score	Training Loss
0	Orig. Uncleaned	0.449804	-2851716.25
1	Orig. Cleaned	0.444784	-2462558.00
2	Custom Cleaned #1	0.443693	-2360606.25
3	Custom Cleaned #2	0.456569	-1676605.75

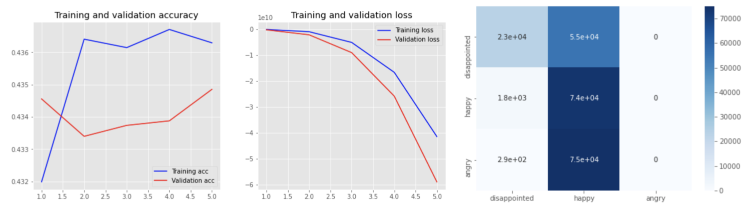

Figure 4.3 Results & Confusion Matrix from Shallow CNN.

We can see that although the shallow CNN performed better than the perceptron model, it still did not do very well with an average F1 Score of 0.45. From the confusion matrix in Figure 4.3, we can see that the model only classified tweets as ‘happy’ or ‘disappointed’, with a general preference for ‘happy’. Although this is an improvement from always selecting a single class, this might be due to the fact that our classes are not equally “distant” and non-separable, making it harder for a neural classifier to distinguish them from one another.

So, we will also train a deep neural network to see how more layers influence the emotional classification. The deep CNN has three convolutional layers, each with dropout, max pooling and flattening. These are then followed by a dense ReLU layer and a sigmoid output layer that produces the predicted classification.

	Cleaning Method	F1 Score	Loss
0	Orig. Uncleaned	0.329369	-7.370033e+04
1	Orig. Cleaned	0.329260	-1.626010e+02
2	Custom Cleaned #1	0.329806	-9.349309e+04
3	Custom Cleaned #2	0.336461	-4.222868e+07

Figure 4.4 Results & Confusion Matrix from Deep CNN.

As a result, the deep CNN receives a lower F1 Score compared to the shallow CNN. Similar to the single-layer perceptron, the deep CNN also always predicts the same ‘disappointed’ class label for every single tweet, which is represented in the confusion matrix in Figure 4.4. Despite adding more layers and increasing the complexity of the model, the data is still not separable. Thus, the deep CNN is unable to appropriately model this problem.

Last, we will apply BERT embeddings and sequence classification modeling. We used the ‘bert-base-uncased’, which limits the embedding length to 512 tokens. The sequence classification model then takes the BERT embeddings as inputs while employing the AdamW adaptive optimizer in order to generate emotion oriented topic classifications.

	Cleaning Method	F1 Score	Training Loss	Validation Loss
0	Orig. Uncleaned	0.924618	0.295197	0.275127
1	Orig. Cleaned	0.920712	0.310757	0.289297
2	Custom Cleaned #1	0.915477	0.316773	0.296010
3	Custom Cleaned #2	0.915809	0.309894	0.289413

Figure 4.5 Results from BERT.

The best F1 Score that the BERT model receives is 0.925, which is on the original uncleaned text data. The different cleaning strategies likely removed a number of important features that BERT could have used to add context, as BERT is able to understand sentence semantics. The inclusion of useless or nonexistent words were of less consequence than the removal of other words. BERT itself also adds a large increase in model performance over the other models on the same cleaning method. As a result, the most accurate emotional tweet classification is a result of the BERT model trained on the raw text data.

5. Conclusion

Overall, we found that additional data cleaning did not actually improve model performance. The original raw tweet text does better despite being "unclean" because our methods were too aggressive and reduced key features by removing stop words or condensing emojis into one "word". However, data cleaning still offers a number of benefits, including handling exceptions and contributing to the smoothing of the input data.

In addition to the issues with text preprocessing, we had problems with handling a non-linearly separable dataset. This meant that all of our neural networks were unable to learn and classify the tweets. One issue was that the three labels were not equally "distant" from each other. The difference between "angry" and "disappointed" is different from the distance between "angry" and "happy". While we chose this dataset so that we could learn this problem, we believe that the 3 labels were not distinct enough for the neural nets to distinguish between them. The transformer model in BERT had much higher performance, demonstrating that architecture's power in deep learning.

This paper isn't suggesting that we not clean data, we believe it's still important depending on your model architecture and computing resources. For example, you may want to clean it to reduce the size of the vocabulary. Also, reducing the vocabulary size could help the model generalize to unseen data better.

Appendix - References

- [1] T. Donicke, F. Lux, and M. Damaschk. 2019; “Multiclass Text Classification on Unbalanced, Sparse and Noisy Data”. University of Stuttgart, Institute for Natural Language Processing. https://www.aclweb.org/anthology/W19-6207.pdf
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- [5] Emotion Dataset from Kaggle, 2020 - https://www.kaggle.com/kosweet/cleaned-emotion-extraction-dataset-from-twitter
- [6] J. Devlin, M. Chang, K. Lee, K. Toutanova. 2019. “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”, https://arxiv.org/pdf/1810.04805.pdf

Appendix - Figures

- In addition to the ‘General Word Cloud’ (Figure 3.2), we were able to generate a word cloud for each individual emotion class label. These provide a more nuanced understanding of the terms that express the specified emotion.

Figure 3.2.1. Angry (left), Disappointed (center), & Happy Word Cloud (right).

In the angry word cloud, upset or angry emojis are very common. There appears to be some profanity and negatively connotated words.

In the disappointed word cloud, the word ‘feel’ is extremely prominent. This means that it is very common in tweets that express disappointment. We can also see that disappointed or frowning emojis are also frequently used.

In the happy word cloud, we can see that most of the terms are smaller in font and are more spread out. This means that there is a wide distribution of terms that make up tweets in the ‘happy’ classification. As a result, "happy" phrases may not be as influential in our model. Yet, we can still see that smiling and laughing emojis are generally more common.

- An important part of our NLP analysis was the comparison of different cleaning methods in each of our models. We utilized four different techniques, which included the original raw tweet text, a basic cleaning method, a tweet-specific cleaning method, as well as a more general cleaning method.

	Emotion	Original Raw Text	Basic Original Cleaned	Tweet-Specific Cleaned	General Custom Cleaned
0	disappointed	b'RT @Davbingodav: @mcrackins Oh fuck.... did ...	oh fuck did i wrote fil grinningfacewithsweat ...	rt usertaginstance usertaginstance oh fuck wro...	b rt davbingodav mcrackins oh fuck wrote fil g...
1	disappointed	i feel nor am i shamed by it	i feel nor am i shamed by it	feel shamed	feel shamed
2	disappointed	i had been feeling a little bit defeated by th...	i had been feeling a little bit defeated by th...	feeling little bit defeated steps faith would ...	feeling little bit defeated steps faith would ...
3	happy	b"@KSIOlajidebt imagine if that reaction guy t...	imagine if that reaction guy that called jj kf...	usertaginstance imagine reaction guy called jj...	b ksiolajidebt imagine reaction guy called jj ...
4	disappointed	i wouldnt feel burdened so that i would live m...	i wouldnt feel burdened so that i would live m...	wouldnt feel burdened would live life testamen...	wouldnt feel burdened would live life testamen...

Figure 3.4. Side-by-side comparison of each text data set.

From Figure 3.4, we can see the actual difference between each of the data sets. The original raw text contains special characters and Twitter-specific interactions. The basic original cleaned text is stripped down to more natural, normal looking text. The tweet-specific data still maintains the Twitter interactions, but in a more generalized way. The general cleaning method looks more like normal text, but still contains some of the tweet characteristics.

- In order to train and test our model, we performed a train-test data split. We decided to use 70% of the data for our model training and the remaining 30% of the data for our validation and testing.

Emotion	label	data_type	Content
angry	2	train	210693
		val	90297
disappointed	0	train	219600
		val	94114
happy	1	train	211309
		val	90562

Figure 4.0. Class distribution for the 70%-30% test-train data split.

From Figure 4.0, we can see that each of the class labels have been evenly distributed into each of our ‘train’ and ‘val’ data sets. This means that each emotion will be equally represented for both training and testing, reducing the potential for bias in the models.

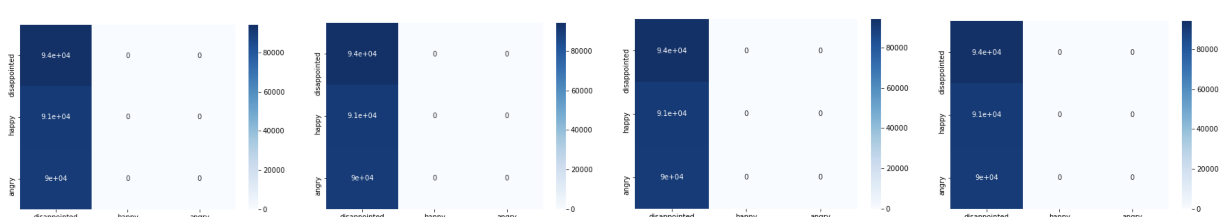
- Our logistic regression baseline model performed quite well, as seen in Figure 4.1. We were also able to generate confusion matrices for each of our datasets in order to further examine any classification issues.

(1) (2) (3) (4)

Figure 4.1.1. Logistic regression confusion matrix for ‘Original Raw Text’ (1), ‘Basic Clean’ (2), ‘Tweet-Specific Clean’ (3), & ‘Custom General Clean’ (4).

As the overall accuracy was quite high, most of the cleaning methods are accurately predicted by the logistic regression. However, a common mistake made by the classifier is the distinction between the ‘angry’ and ‘disappointed’ class labels. This makes sense as those two emotions can be expressed in similar ways.

- Our single-layer perceptron model did not perform well, as seen in Figure 4.2. We were able to generate confusion matrices for each of our datasets.

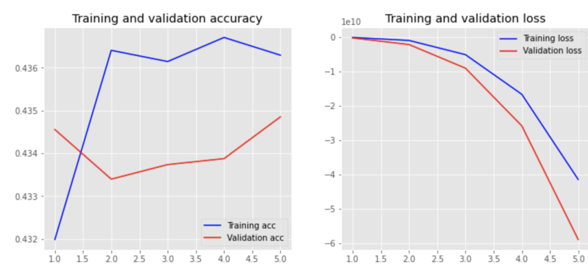


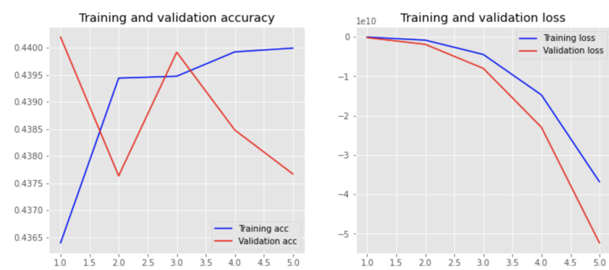
(1) (2) (3) (4)

Figure 4.2.1. Perceptron confusion matrix for ‘Original Raw Text’ (1), ‘Basic Clean’ (2), ‘Tweet-Specific Clean’ (3), & ‘Custom General Clean’ (4).

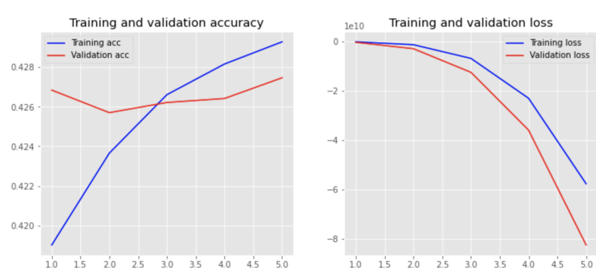
For each of the different datasets, the perceptron model always predicted the same ‘disappointed’ class label for every tweet.

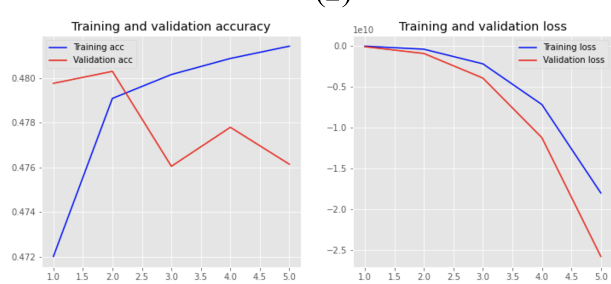
- Our shallow CNN was simple and did not perform very well. Yet, it still did better than the single-layer perceptron model. We were able to generate the accuracy and loss curves across each epoch for each of our datasets.





(1) (2)



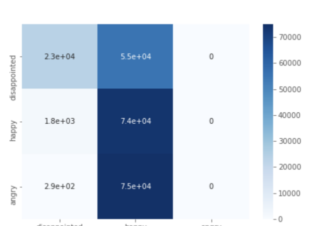


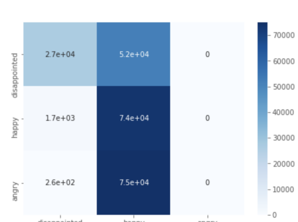
(3) (4)

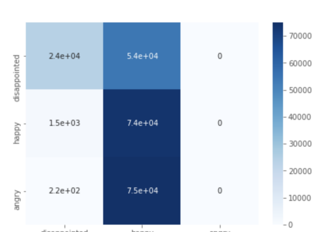
Figure 4.3.1. Shallow CNN accuracy and loss curves for ‘Original Raw Text’ (1), ‘Basic Clean’ (2), ‘Tweet-Specific Clean’ (3), & ‘Custom General Clean’ (4).

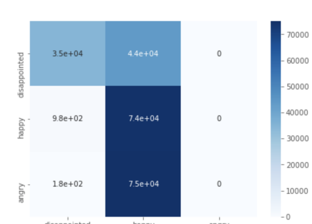
For each of the different datasets, the shallow CNN model varied in terms of accuracy but was quite consistent with its loss. The training accuracy generally increased in five epochs, while the validation accuracy varied for each dataset. Yet, the loss value for both training and validation always decreased exponentially.

- For our shallow CNN, we were also able to generate the confusion matrices for each of our datasets.







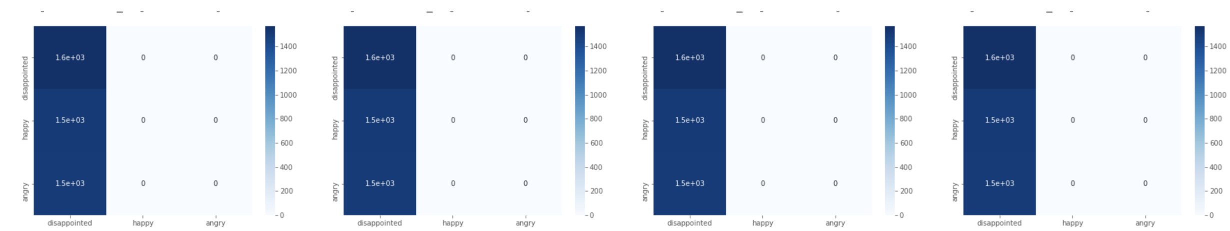


(1) (2) (3) (4)

Figure 4.3.2. Shallow CNN confusion matrix for ‘Original Raw Text’ (1), ‘Basic Clean’ (2), ‘Tweet-Specific Clean’ (3), & ‘Custom General Clean’ (4).

For each of the different datasets, the shallow CNN model always predicted between the ‘happy’ or ‘disappointed’ class labels for every tweet, although there was a general preference to classify the text as ‘happy’.

- Our deep CNN also did not perform well, as seen in Figure 4.4. We were able to generate confusion matrices for each of our datasets.



(1) (2) (3) (4)

Figure 4.4.1. Deep CNN confusion matrix for ‘Original Raw Text’ (1), ‘Basic Clean’ (2), ‘Tweet-Specific Clean’ (3), & ‘Custom General Clean’ (4).

For each of the different datasets, the deep CNN model always predicted the same ‘disappointed’ class label for every tweet.