

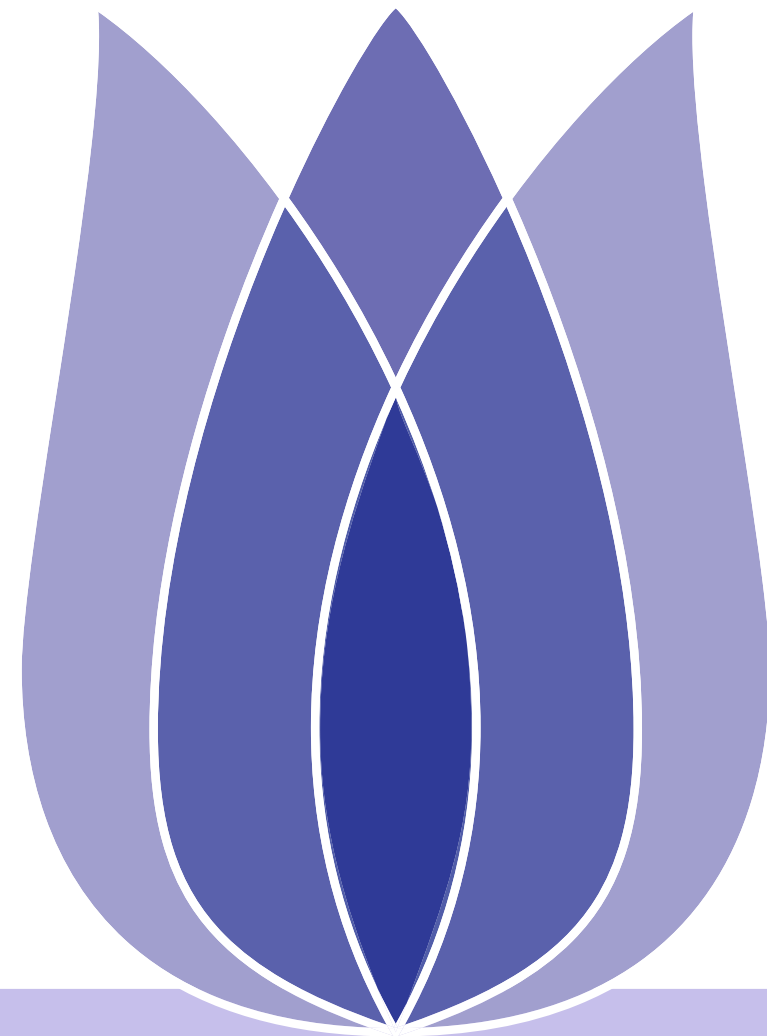


# FLIP01 Final Assessment

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# Overview

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## Problem Definition

Problem Description

## Data Visualization

Data Visualization

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Model:roBERTa

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Problem Definition

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# Problem Definition



# Problem Description

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Defn

With all of the tweets circulating every second it is hard to tell whether the sentiment behind a specific tweet will impact a company, or a person’s, brand for being viral (positive), or devastate profit because it strikes a negative tone.

- What’s the **Sentiment** of this tweet.
- What’s the part of the tweet (**word or phrase**) that reflects the sentiment.

ID	text	selected_text	sentiment
<i>cb774db0d1</i>	Uh oh, I am sunburned	I am sunburned	negative
<i>549e992a42</i>	We saw that the baddie’s the best	best	positive
<i>f84b89a828</i>	Sounds like me	Sounds like me	neutral



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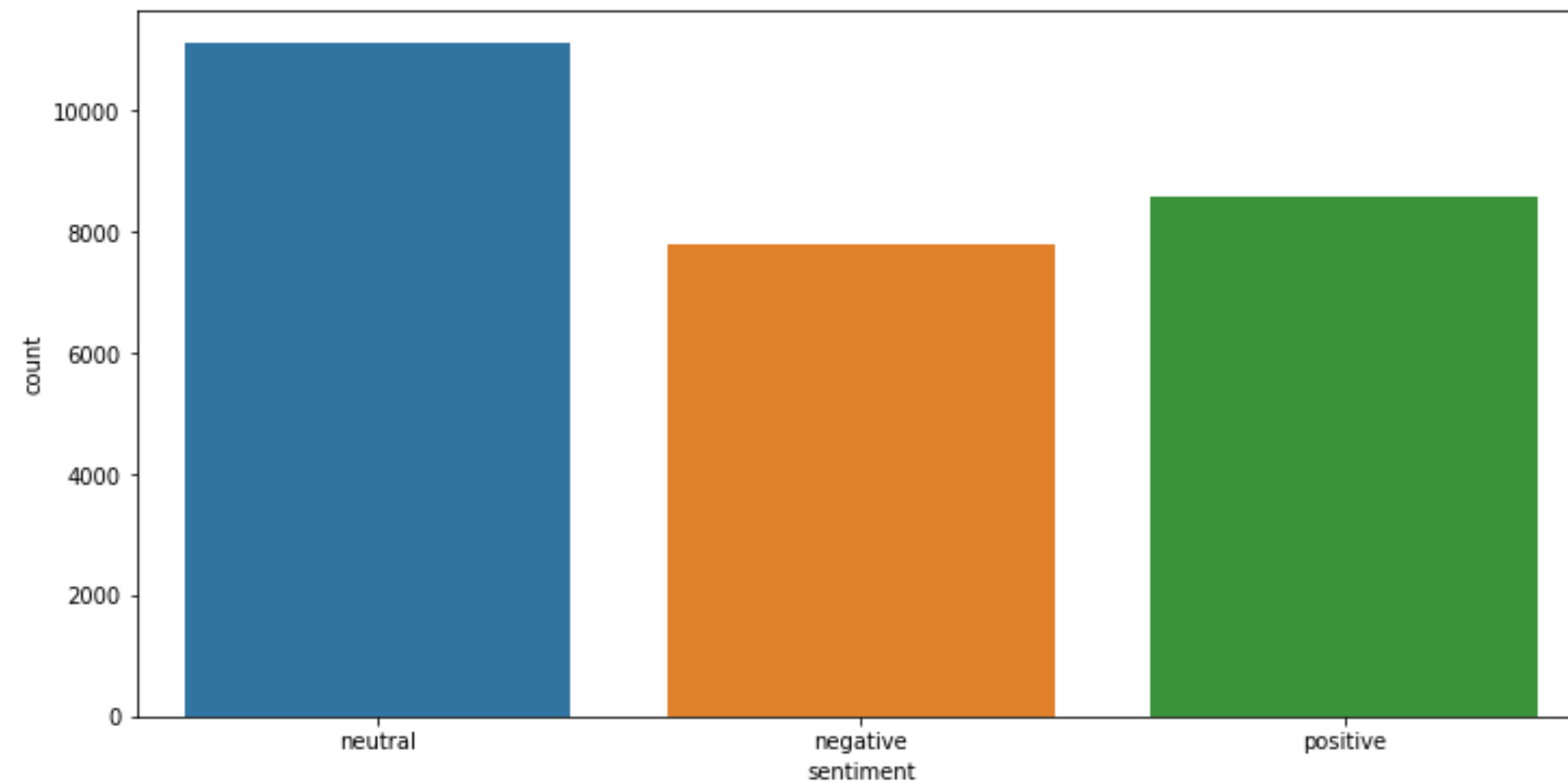
# Data Visualization



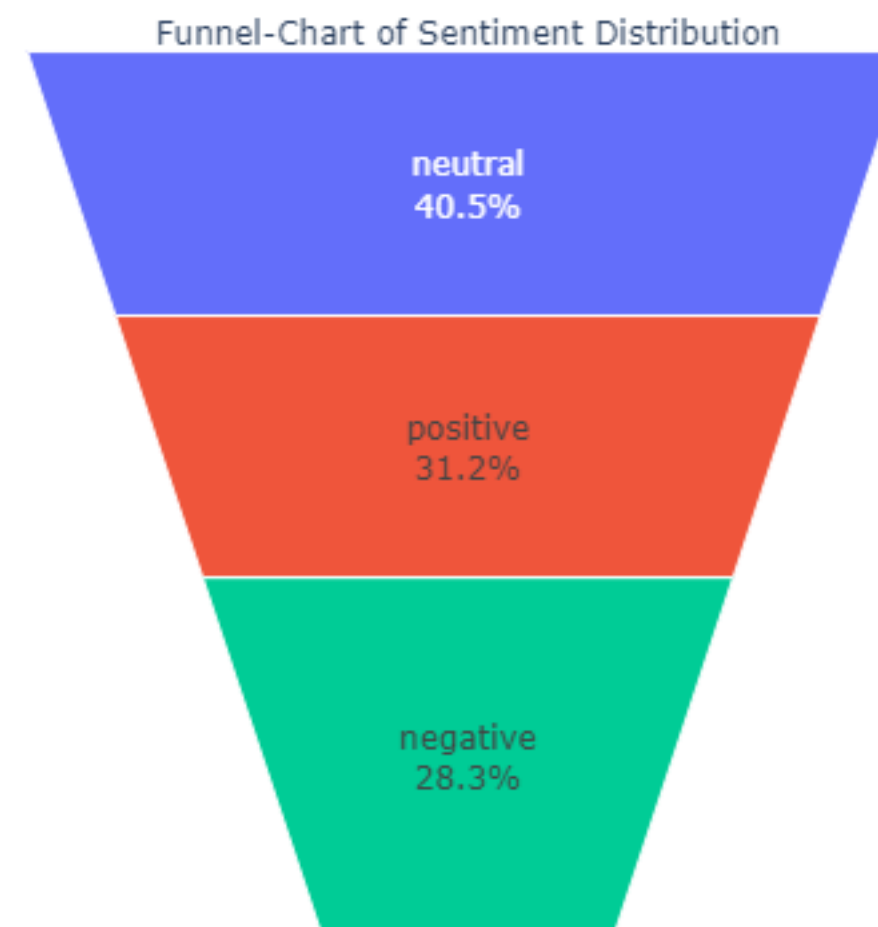
# Data Visualization

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- First, check the data. The training set contains 27482 data.
  - ◆ Take a look at the proportion of different types of text in the training set
  - ◆ It can be seen that the number of three kinds of data is relatively average. In addition, there are more neutral texts.



- Let's take a look at the proportion of each category of text in another visualization method.
- ◆ Most of them are neutral emotions, has 40.5 percent. Positive are 31.2 percent. Negative are 28.3 percent.

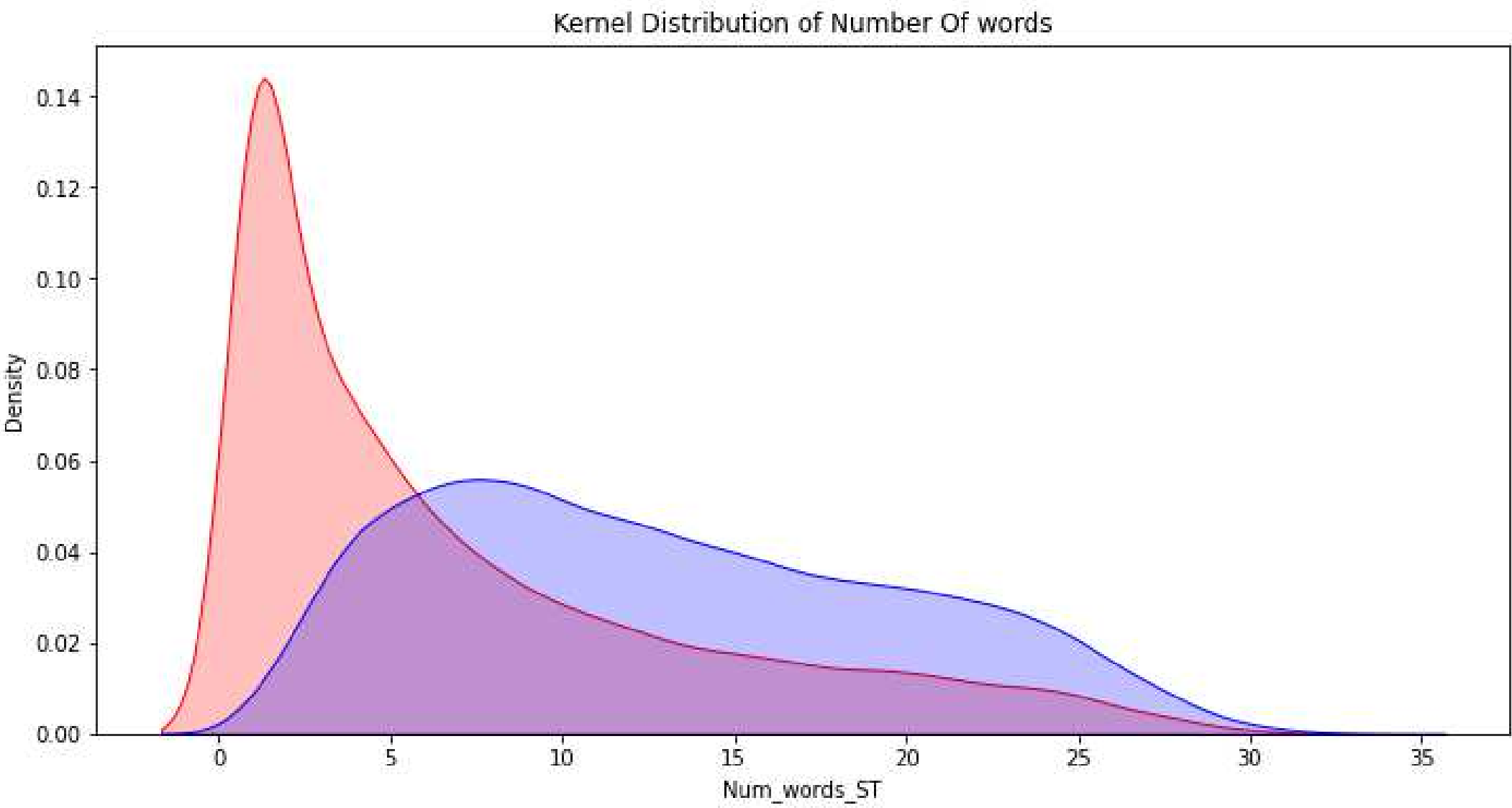






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- Count the distribution interval of the length of the given text and the selected text.

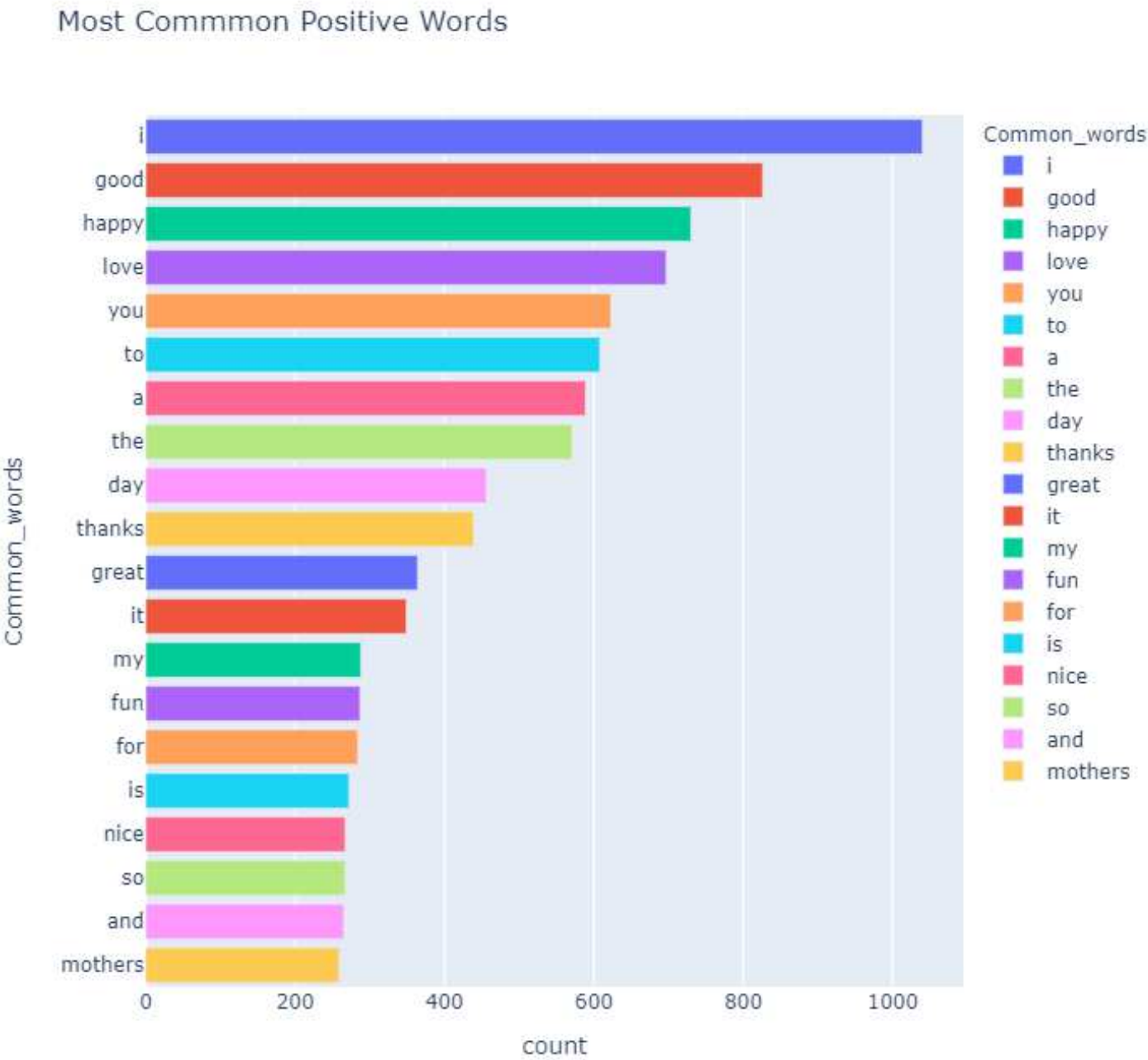




# Data Visualization

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- Statistics of positive emotions were selected in the text of the highest frequency of the first few words.

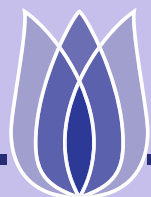




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- The statistical results will be generated word cloud to more intuitive look at the frequency of words.

## WordCloud of Postive Tweets

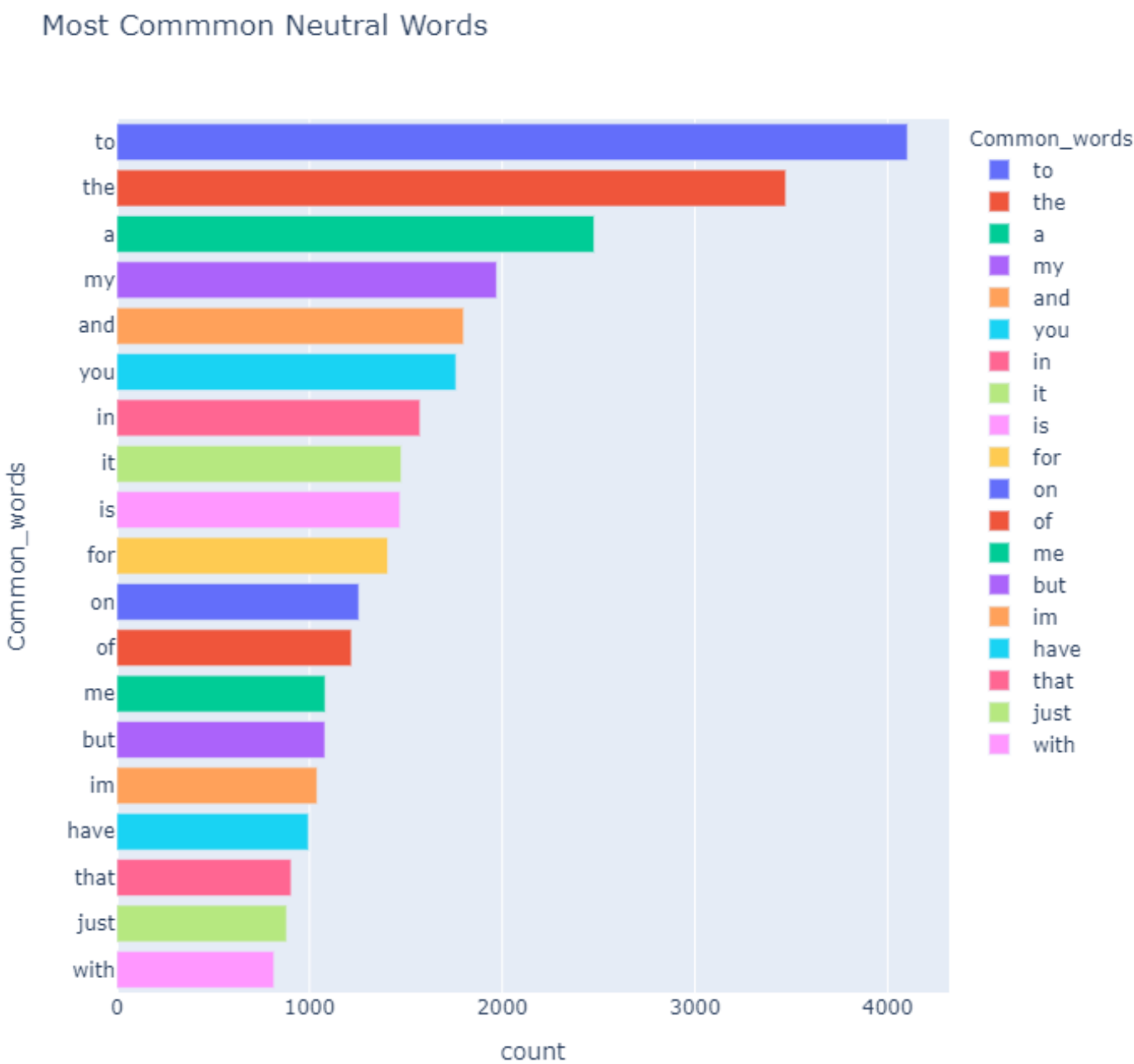




# Data Visualization

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- Statistics of neutral emotions were selected in the text of the highest frequency of the first few words.

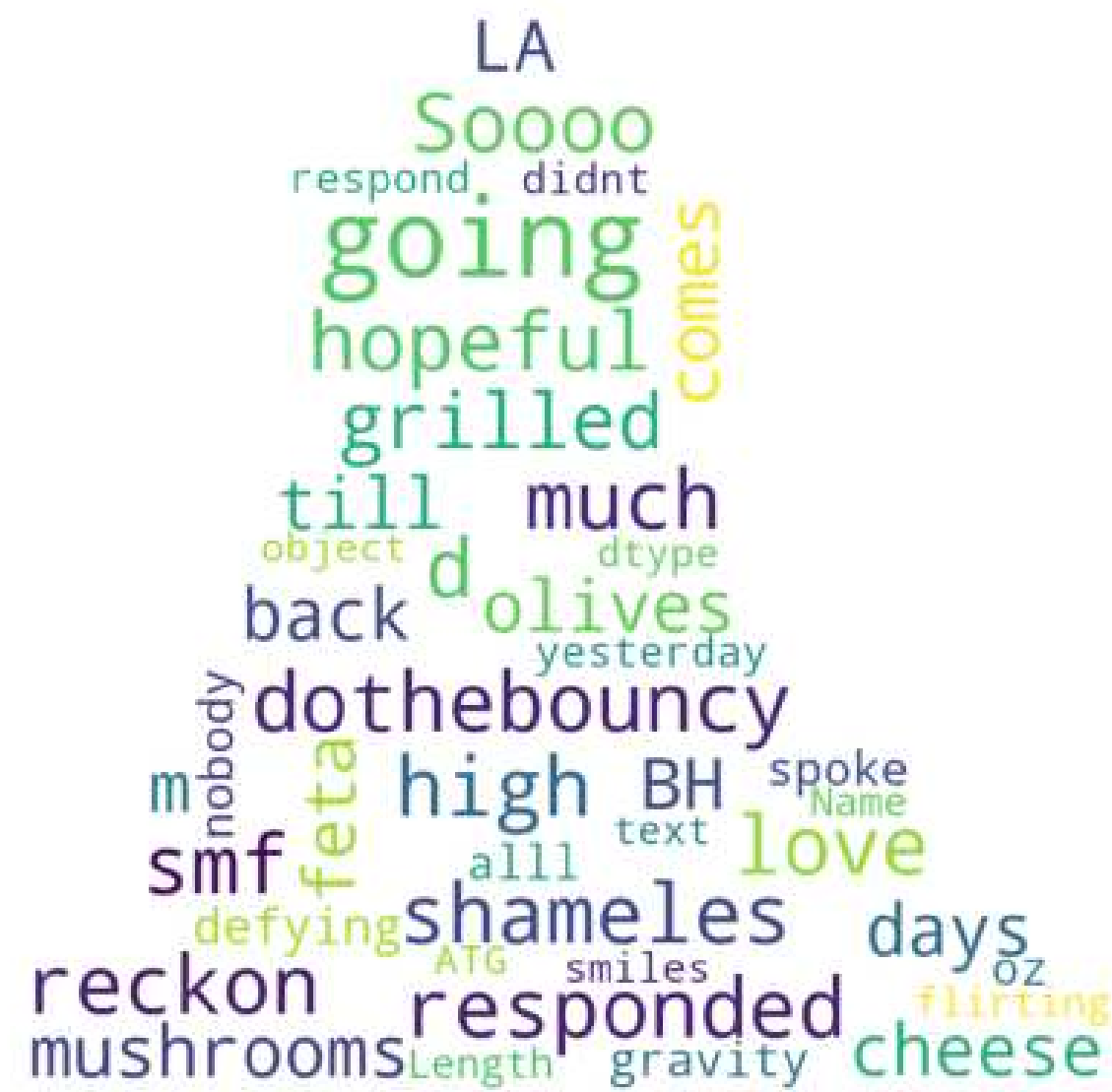




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- The statistical results will be generated word cloud to more intuitive look at the frequency of words.

## WordCloud of Neutral Tweets

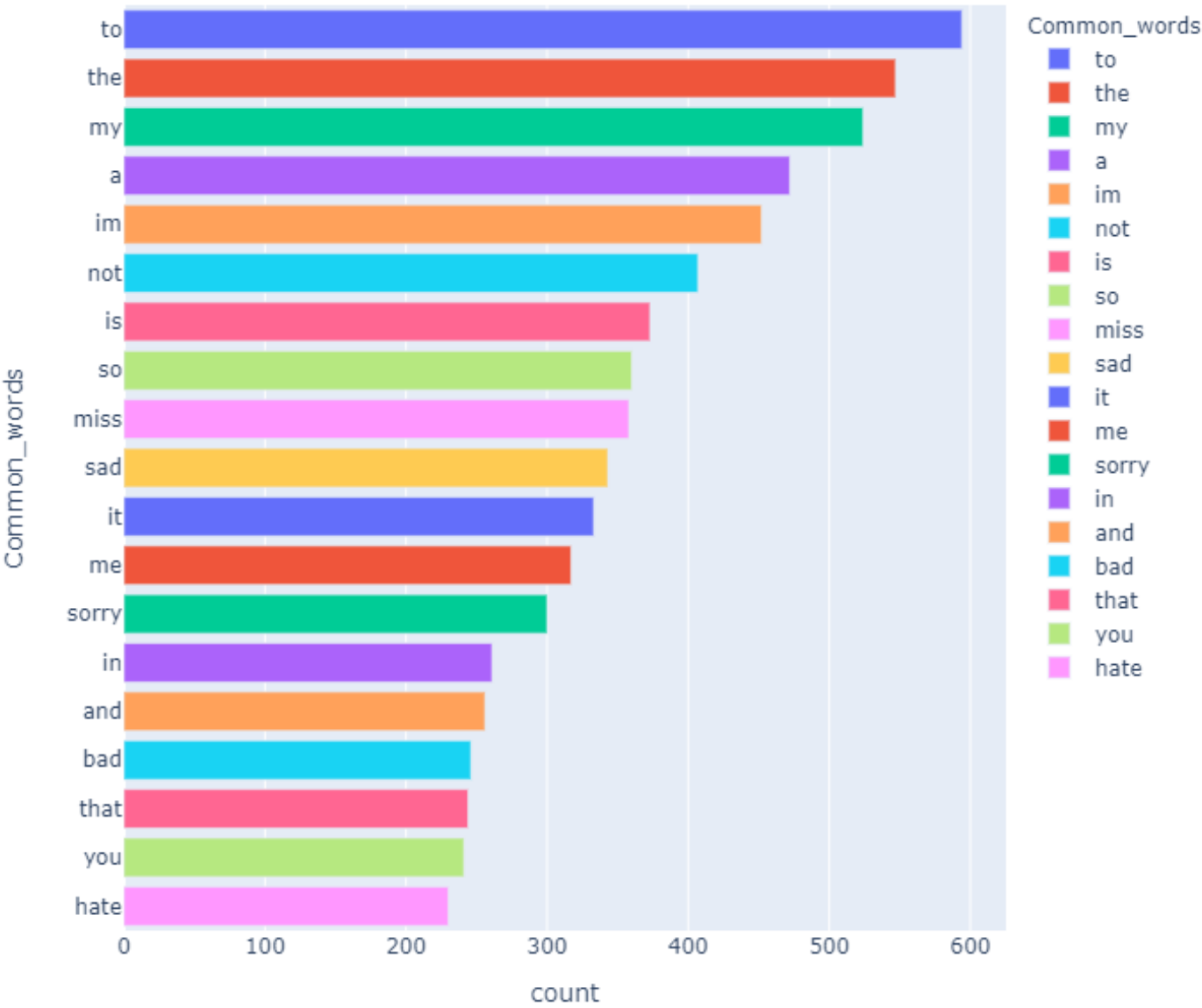




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- Statistics of negative emotions were selected in the text of the highest frequency of the first few words.

Most Common negative Words







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- The statistical results will be generated word cloud to more intuitive look at the frequency of words.

WordCloud of negative Tweets





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- It can be seen that our previous statistical text contains some words without emotional tendency.
- After we delete these words, we count the frequency of each word.



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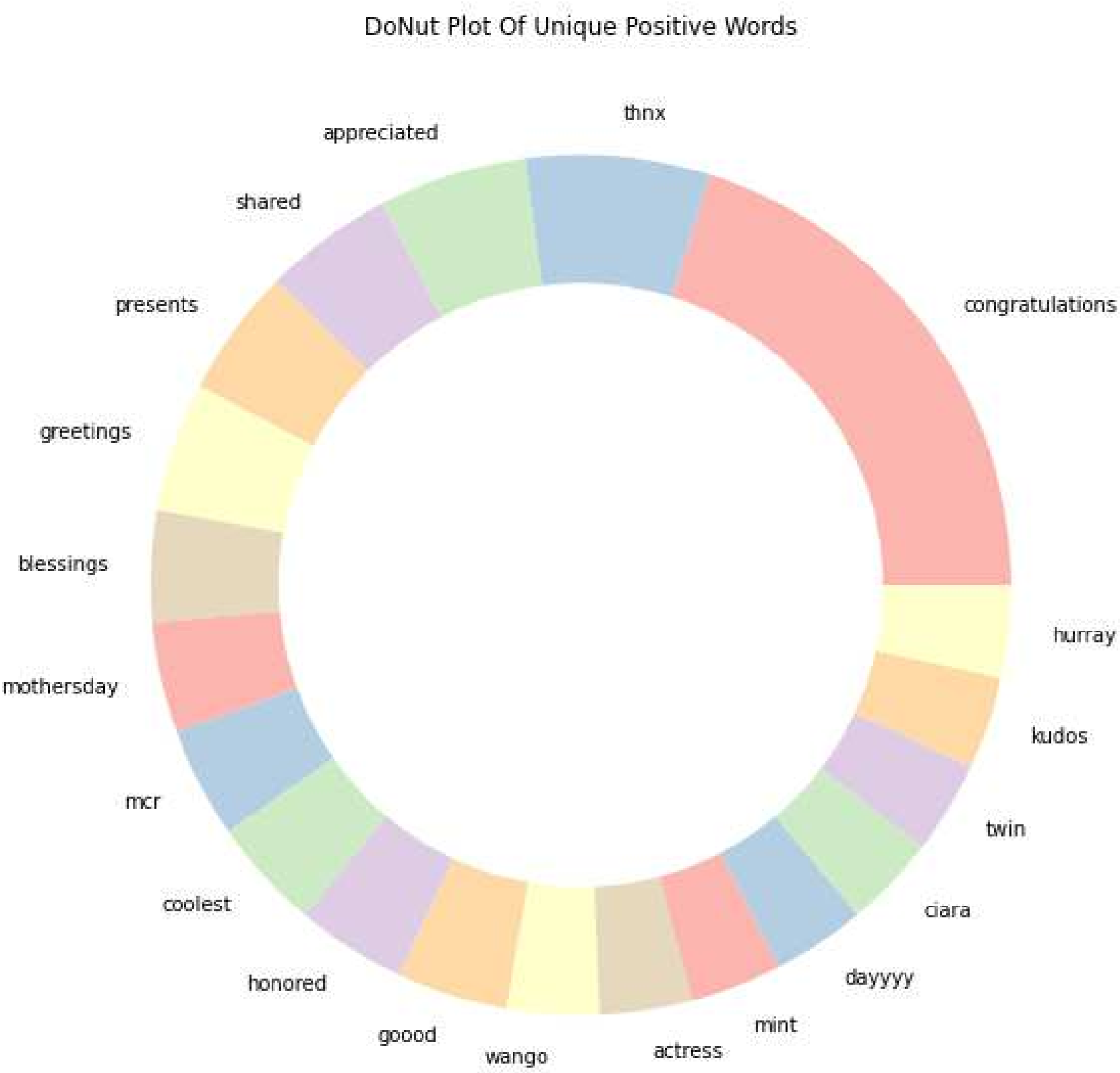
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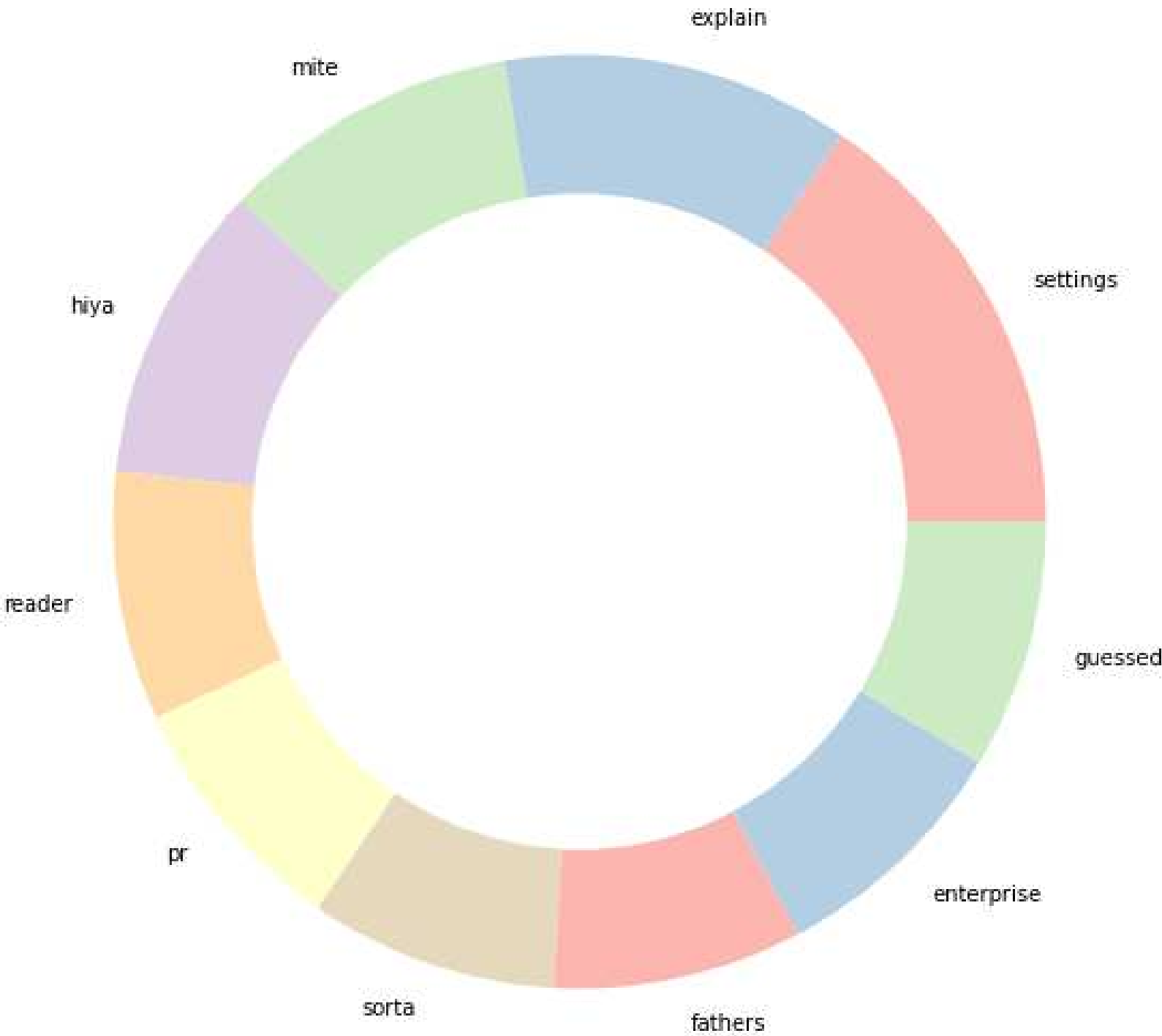




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DoNut Plot Of Unique Neutral Words

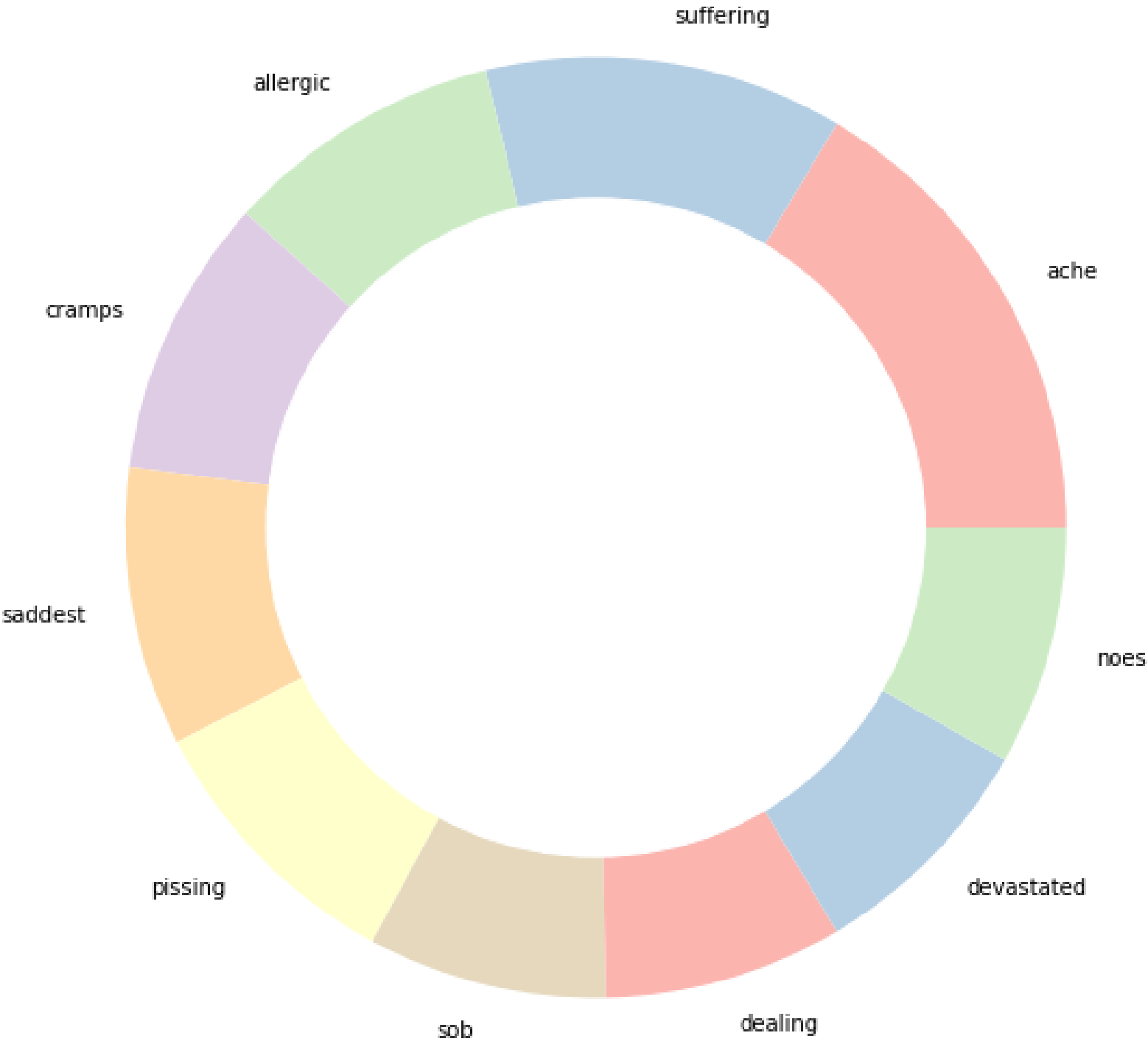




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DoNut Plot Of Unique Negative Words





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**[Build The Model](#)**

Model:MLP

Model:roBERTa

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# Build The Model

# Model:MLP

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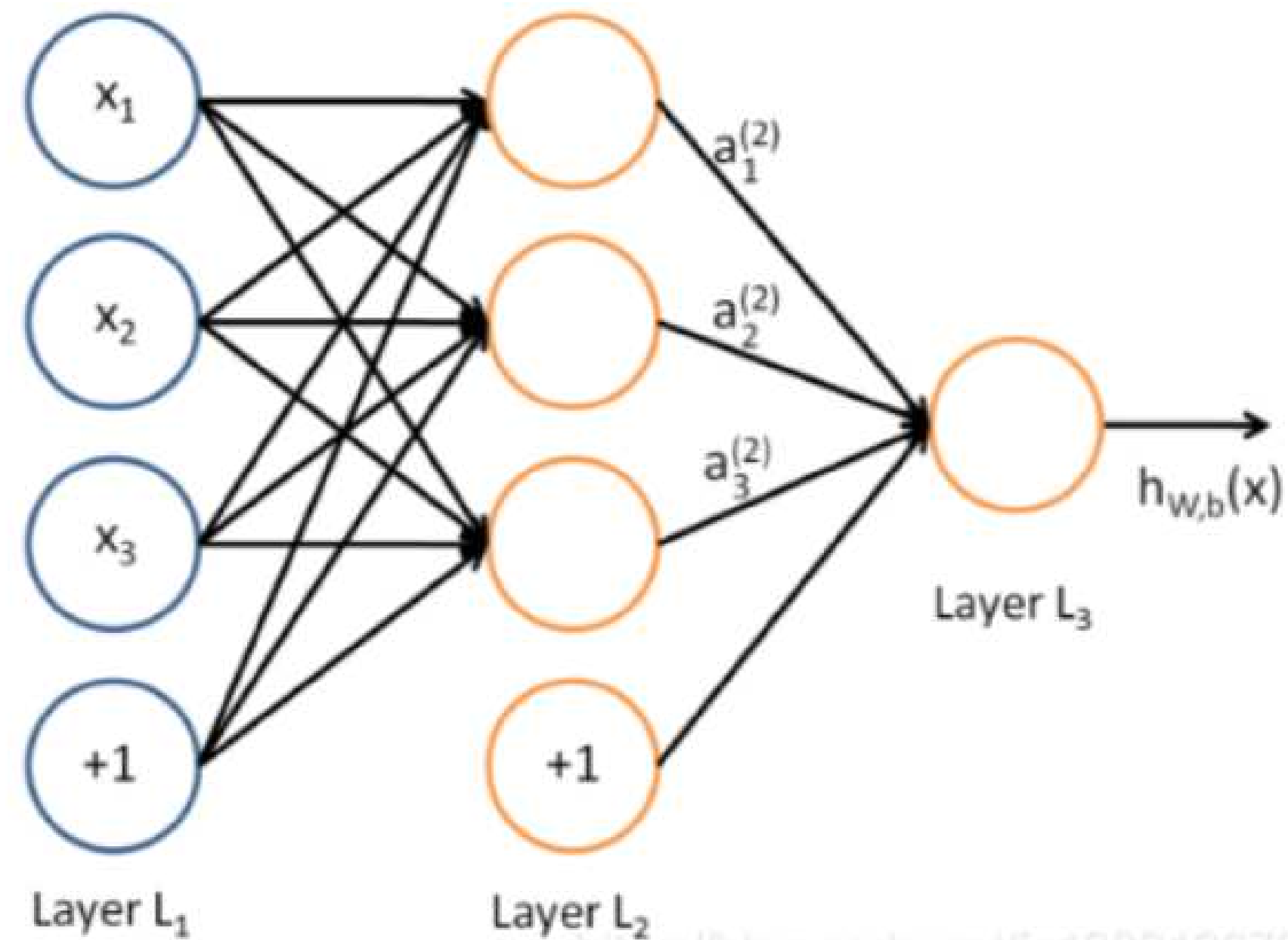
Build The Model

Model:MLP

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Conclusion

- First, the MLP model with simple structure is used.



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# Model:MLP

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- Based on our previous data visualization.We set the `MAX_LEN = 48`.
  - The learning rate is 0.8.
  - Activation function is “Relu”.
  - The output is one dimension and the convolution kernel size is  $1 * 1$ .
  - The optimizer is “SGD”.
  - The loss function is “categorical\_crossentropy”.
  - Epochs = 10.
- 
- ◆ Finally, the loss rate of the trained model is 0.5393.



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# Model:roBERTa

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In order to obtain higher accuracy, I choose the widely used model named roBERTa.

- Roberta: a robust method to optimize the pre training of Bert.
- Roberta is an improved algorithm of bert.
  - ◆ With bigger batch and more data, let the model train longer.
  - ◆ Removed the NSP (next sense prediction) task.
  - ◆ Train on a longer sequence.
  - ◆ Mask mechanism for dynamically modifying training data.



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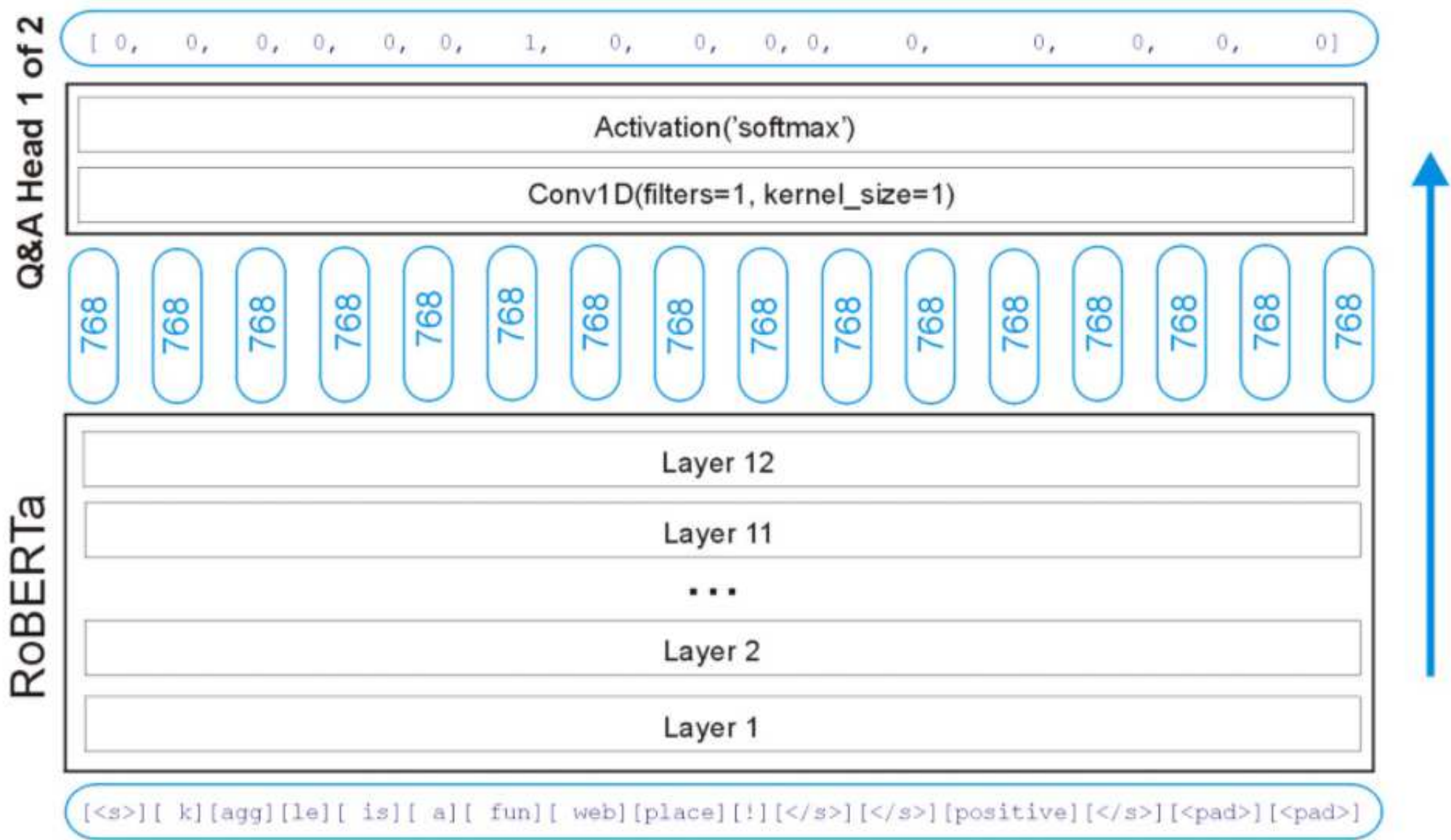




# Model:roBERTa

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- Activation function is “softmax”.
- The output is one dimension and the convolution kernel size is 1 \* 1.







# Model:roBERTa

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- Based on our previous data visualization. We set the `MAX_LEN = 48`.
- The learning rate is 0.9.
- The optimizer is “Adam”.
- The loss function is “categorical\_crossentropy”.
- Using k-fold cross validation, it is divided into five parts. Train five times.
- Finally, the loss rate of the trained model is 0.7.



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# Conclusion



# Conclusion

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- Formalize the problem of *Group Outlying Aspects Mining* by extending outlying aspects mining;
- Propose a novel method **GOAM algorithm** to solve the *Group Outlying Aspects Mining* problem;
- Utilize the pruning strategies to reduce time complexity.



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# Contact Information

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