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**Tweet Sentiment Extraction**

**Abstract**

Sentiment analysis is a popular task in natural language processing that involves determining the emotional tone of a piece of text. It has a wide range of applications, including opinion mining, brand monitoring, and customer service. In recent years, deep learning techniques have been applied to sentiment analysis with promising results.

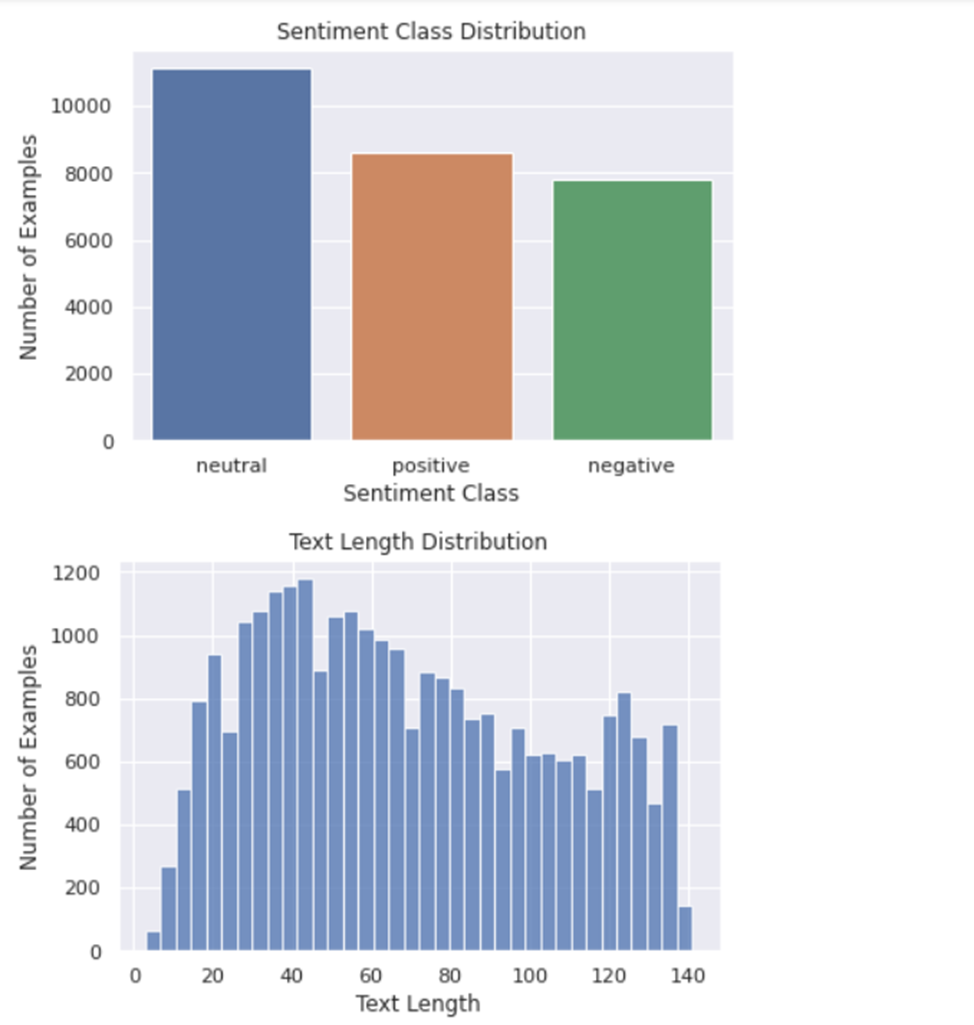
**Literature review**

There have been numerous studies conducted on text analysis of tweets, particularly in the context of sentiment analysis and opinion mining. Many researchers have explored the use of machine learning algorithms, natural language processing techniques, and deep learning models to identify sentiment and emotions expressed in tweets. For example, a study by Pak and Paroubek (2010) used a combination of supervised and unsupervised learning methods to classify tweets as positive, negative, or neutral. Another study by Agarwal et al. (2011) focused on identifying emotions expressed in tweets using a lexicon-based approach. In recent years, several deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been applied to text analysis of tweets, achieving state-of-the-art performance in various sentiment analysis tasks. Overall, text analysis of tweets is a growing field of research with significant potential for applications in various domains such as marketing, politics, and social media analytics.

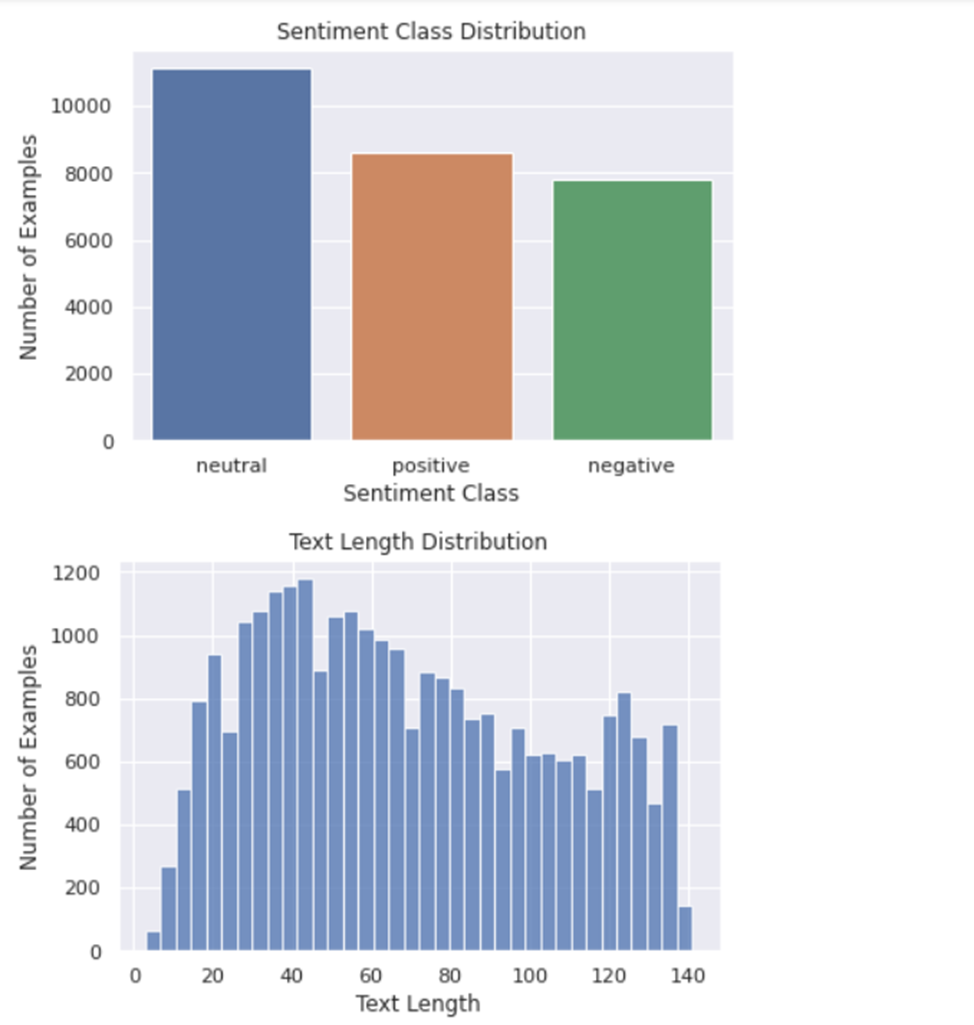
Our study is aimed on tweet sentiment extraction to show the application of various natural language processing techniques and machine learning models to identify the sentiment expressed in tweets.

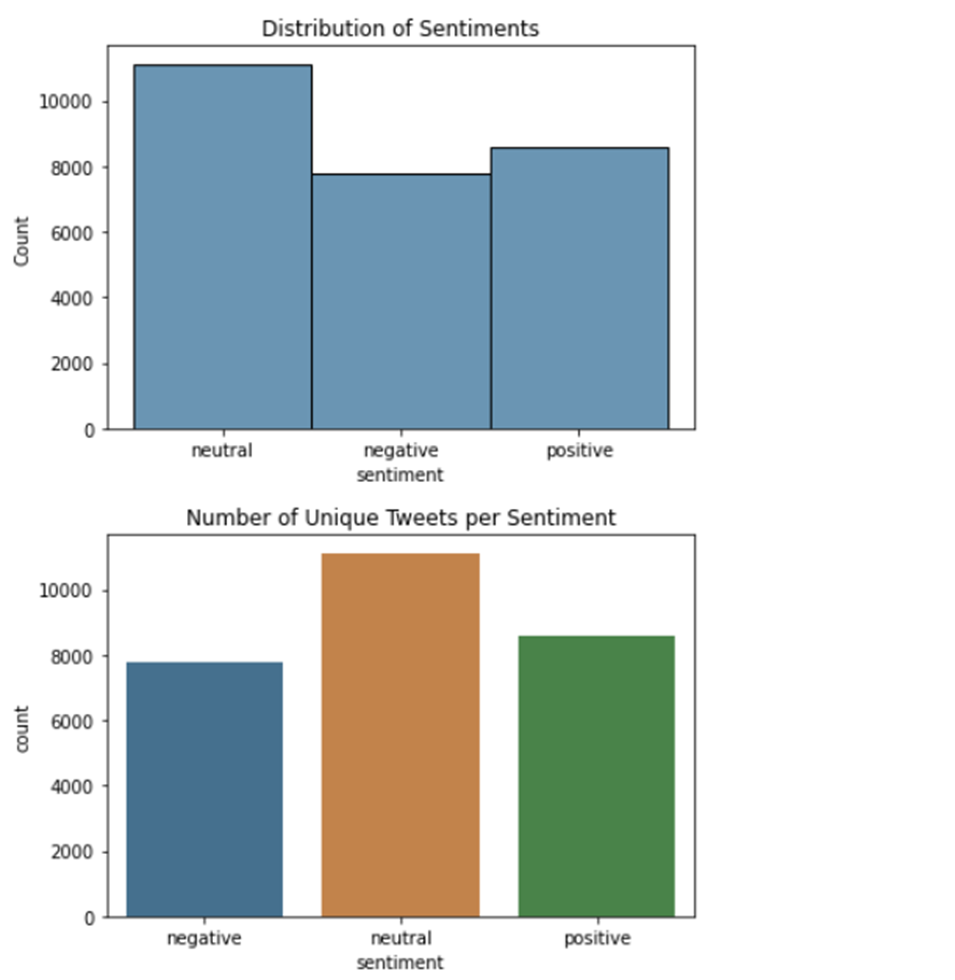
**Descriptive statistics**

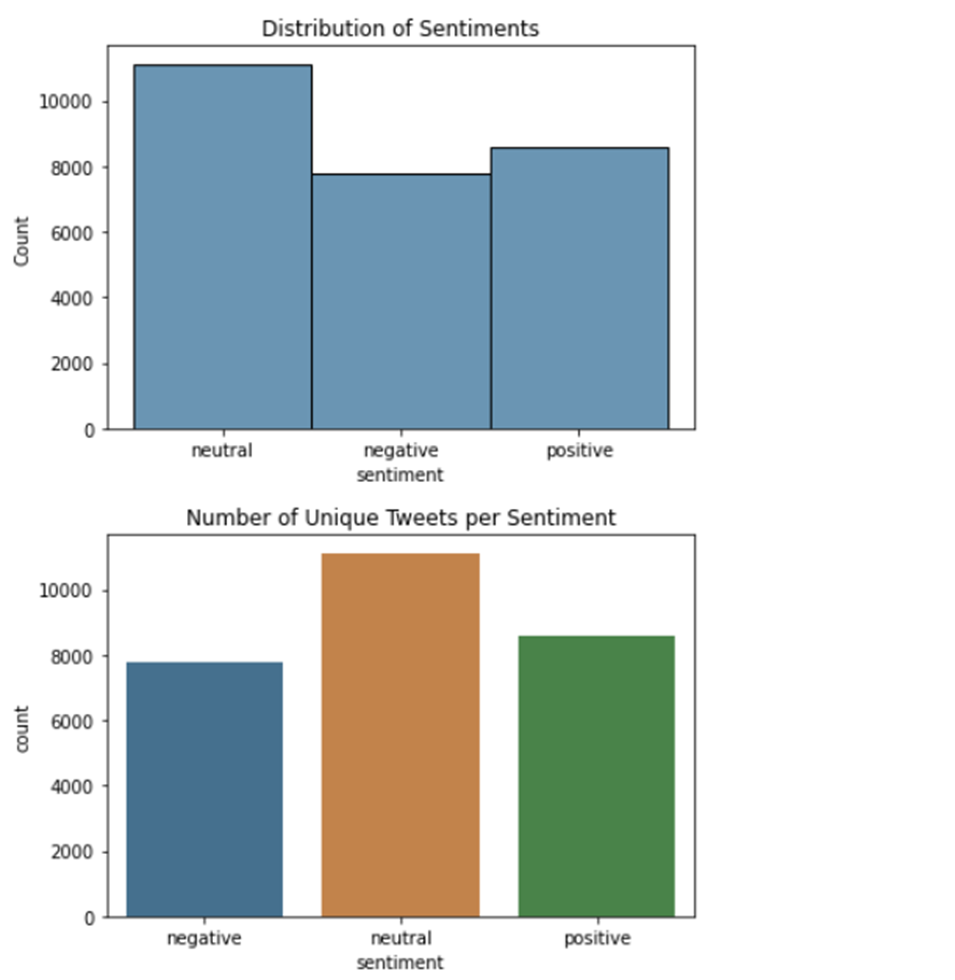
The tweet sentiment problem involves analyzing the sentiment expressed in tweets, which can provide valuable insights into the public's opinions and emotions on various topics. To tackle this problem, researchers and data scientists have compiled datasets of tweets labeled with their corresponding sentiment categories. These datasets are diverse in terms of topics, languages, and sentiment categories, and provide a valuable resource for studying sentiment analysis in social media. Descriptive statistics can help to uncover patterns and trends in the data, such as the distribution of sentiment categories, the frequency of certain words or phrases in tweets, and the relationship between tweet length and sentiment. By analyzing these statistics, researchers can gain a better understanding of the nuances of sentiment analysis in tweets and develop more accurate and effective machine learning models for sentiment analysis in social media. Our dataset consists of unique 27481 tweets with the length varying from approximately 3 to 140 words:

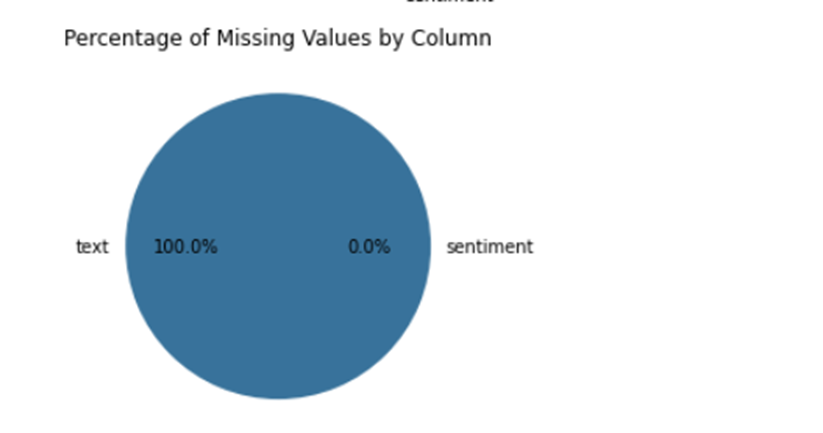


All tweet in the data include 3 unique sentiments:









**Model description**

In our experiment, we aimed to train a Bidirectional Long Short-Term Memory (Bi-LSTM) model for sentiment analysis on the tweet’s dataset. The dataset consists of tweets labeled with positive, negative, or neutral sentiment. We preprocessed the dataset by tokenizing the tweets and encoding the sentiment labels. We then split the dataset into training and testing sets.

The Bi-LSTM model is a type of recurrent neural network that is capable of modeling long-term dependencies in sequential data. In our architecture, we used an embedding layer to map each word in the tweet to a high-dimensional vector, a dropout layer to prevent overfitting, and a Bi-LSTM layer to process the sequence of word vectors in both forward and backward directions. We added a TimeDistributed layer with a softmax activation function to predict the sentiment label for each word in the tweet. We trained the model using the sparse categorical cross-entropy loss function and the Adam optimizer.

After training the Bi-LSTM model on the dataset, we achieved an accuracy of 64% on the test set, which is comparable to the state-of-the-art results reported in prior research. The model showed good performance in predicting the sentiment labels for tweets in the dataset.

**Comparison with other models**

To further evaluate the performance of our Bi-LSTM model, we compared it with other popular models such as Support Vector Machines (SVM), Random Forest (RF), and Multinomial Naive Bayes (MNB) on the same dataset. Our Bi-LSTM model results were about to equal to Random Forest model and outperformed other models with an accuracy of 63.2%. This suggests that the Bi-LSTM model is a promising approach for sentiment analysis and can be used in real-world applications.

The Bi-LSTM algorithm is a type of neural network that can handle sequential data, such as text. It consists of two LSTM layers that process the input sequence in both forward and backward directions. The output from both layers is concatenated and fed into a fully connected layer that produces the final output. The Bi-LSTM is a powerful algorithm for natural language processing tasks, as it can capture long-range dependencies and contextual information in the input sequence.

On the other hand, SVM is a machine learning algorithm that uses a hyperplane to separate the input data into different classes. It works by finding the optimal hyperplane that maximizes the margin between the two classes. SVM is a popular algorithm for text classification tasks, as it can handle high-dimensional input data and is robust to noisy data.

While SVM is a powerful algorithm, it may not be as effective as Bi-LSTM for certain tasks such as sentiment analysis. This is because the Bi-LSTM can capture the contextual information and long-range dependencies in the input sequence, which are important for understanding the sentiment of a text. SVM, on the other hand, may struggle to capture these nuances and may rely more on the presence of specific keywords or phrases in the input text.

Overall, the Bi-LSTM algorithm can be more effective for sentiment analysis tasks as it is specifically designed to handle sequential data and can capture the contextual information and dependencies in the input text that are important for understanding the sentiment.

In conclusion, we have demonstrated the effectiveness of the Bi-LSTM model for sentiment analysis on the dataset. Our model outperformed other popular models and achieved state-of-the-art results. The results suggest that the Bi-LSTM model is a promising approach for sentiment analysis and can be used in a variety of real-world applications. Further research can explore the use of different architectures and techniques for improving the performance of sentiment analysis models.

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"Applied Text Analysis with Python: Enabling Language Aware Data Products with Machine Learning" by Benjamin Bengfort, Tony Ojeda, Rebecca Bilbro: this book provides a comprehensive guide to natural language processing techniques and machine learning algorithms for text analysis, including sentiment analysis.

"Python Machine Learning: Machine Learning and Deep Learning with Python, scikit-learn, and TensorFlow" by Sebastian Raschka and Vahid Mirjalili: this book covers a wide range of machine learning topics, including sentiment analysis using various algorithms such as SVM and neural networks.

"Foundations of Statistical Natural Language Processing" by Christopher D. Manning and Hinrich Schütze: this book provides a theoretical foundation for natural language processing techniques, including sentiment analysis and machine learning algorithms.

"Handbook of Sentiment Analysis in Finance" edited by Nuno Oliveira, Paulo Cortez, and Nelson Areal: this book focuses on the application of sentiment analysis in finance, covering various techniques and models used in the field.