Context-Aware Sentiment Analysis Using BERT

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Abstract

In this paper, we present a study on Context-Aware Sentiment Analysis using Bidirectional Encoder Representations from Transformers (BERT). The aim of this study is to explore the effectiveness of BERT in detecting sentiment in text while taking into account the conversational context. We experiment with different amounts of context used and compare the performance of BERT with other commonly used classifiers such as Support Vector Machine (SVM) and Naive Bayes. Our results show that BERT outperforms these classifiers in detecting sentiment when contextual information is taken into account. We also analyze the impact of different types of contextual information on the performance of BERT. Overall, our study highlights the importance of considering conversational context in sentiment analysis and demonstrates the effectiveness of BERT in this task.

1 Introduction

Sentiment analysis is a popular research area in natural language processing that aims to automatically identify the sentiment expressed in text. However, most existing sentiment analysis methods treat text as isolated units and do not take into account the conversational context in which the text is used. This can lead to inaccurate results, as the sentiment of a text can be heavily influenced by its surrounding context.

To address this issue, recent studies have explored the use of contextual information in sentiment analysis. One promising approach is to use Bidirectional Encoder Representations from Transformers (BERT), a pre-trained deep learning model that has shown state-of-the-art performance on various natural language processing tasks. BERT has the ability to capture contextual information by considering both left and right contexts of a given word or sentence.

In this paper, we present a study on Context-Aware Sentiment Analysis using BERT. Our goal is to investigate how effectively BERT can detect sentiment in text while taking into account the conversational context. We experiment with different amounts of context used and compare the performance of BERT with other commonly used classifiers such as Support Vector Machine (SVM) and Naive Bayes. We also analyze the impact of different types of contextual information on the performance of BERT.

2 Related work

2.1 BERT

Bidirectional Encoder Representations from Transformers (BERT) is a pre-trained language model that has gained significant attention in the natural language processing (NLP) community due to its ability to capture contextual information in text. Since its introduction by Devlin et al. (2018), BERT has been applied to various NLP tasks such as question answering, named entity recognition, and sentiment analysis.

Several studies have investigated the effectiveness of BERT for these tasks. For example, Liu et al. (2019) showed that fine-tuning a pre-trained BERT model on a large corpus of text can achieve state-of-the-art performance on various NLP tasks including question answering and named entity recognition. Similarly, Sun et al. (2019) demonstrated that using BERT-based models can improve the accuracy of sentiment classification compared to traditional machine learning algorithms.

In addition to improving the accuracy of NLP tasks, there has been growing interest in using BERT for transfer learning across different domains and languages. For example, Peters et al. (2018) proposed a method for training multi-lingual language models using BERT that can be fine-tuned for various downstream tasks in different languages.

Furthermore, there have been several studies investigating ways to optimize and improve the performance of BERT-based models. For example, Wang et al. (2020) proposed a method for compressing large pre-trained language models such as BERT by pruning unimportant neurons and fine-tuning the remaining ones.

2.2 Sentiment Analysis

Automatic sentiment analysis has been an active research area in natural language processing (NLP) for many years. Traditional approaches to sentiment analysis have focused on using machine learning algorithms to classify text as positive, negative, or neutral based on the presence of certain keywords or patterns.

More recently, there has been growing interest in using deep learning models such as BERT for sentiment analysis. BERT is a pre-trained language model that can capture contextual information in text by considering the surrounding words and sentences. This makes it well-suited for tasks such as sentiment analysis where context plays an important role.

Several studies have investigated the effectiveness of BERT for sentiment analysis. For example, Devlin et al. (2018) showed that fine-tuning a pre-trained BERT model on a large corpus of text can achieve state-of-the-art performance on various NLP tasks including sentiment analysis. Similarly, Sun et al. (2019) demonstrated that using BERT-based models can improve the accuracy of sentiment classification compared to traditional machine learning algorithms.

In the context of conversational data such as social media posts and customer feedback, there has been growing interest in using contextual information to improve the accuracy of sentiment analysis. For example, Zhang et al. (2018) proposed a method for Context-Aware Sentiment Analysis using a hierarchical attention network that considers both local and global context in text.

Our study builds upon these previous works by investigating how effectively BERT can detect sentiment while taking into account conversational context. We experiment with different amounts of context used and compare the performance of BERT with traditional classifiers such as SVM and Naive Bayes. By taking into account conversational context, our approach provides more accurate and nuanced insights into the sentiment expressed in text, which has important implications for various applications such as social media monitoring and customer feedback analysis.

3 Approaches

Our main approach for Context-Aware Sentiment Analysis using BERT involves the following steps:

3.1 Preprocessing

We preprocess the dataset by removing stop words, punctuation, and special characters. We also perform stemming and lemmatization to reduce the dimensionality of the data.

3.2 Feature Extraction

We use BERT to extract contextualized word embeddings for each sentence in the dataset. We experiment with different amounts of context used, ranging from a single sentence to multiple sentences before and after the target sentence.

3.3 Classification

We experiment with different algorithms such as Support Vector Machine (SVM) and Naive Bayes, which are commonly used classifiers in sentiment analysis.

For SVM, we use the scikit-learn library to train a linear SVM classifier on the extracted features. We tune the hyperparameters of the SVM classifier using grid search to find the best combination of parameters that maximizes the performance of the classifier.

For Naive Bayes, we use the Multinomial Naive Bayes algorithm, which is suitable for text classification tasks. We also tune the hyperparameters of this algorithm using grid search.

In addition to these traditional classifiers, we also train a BERT-based classifier using a fine-tuning approach. We fine-tune a pre-trained BERT model on our dataset by adding an additional output layer and training it on our labeled data. This allows us to leverage the power of BERT in capturing contextual information while still being able to classify sentiment.

We evaluate the performance of each classifier using standard evaluation metrics such as accuracy, precision, recall, and F1-score. By comparing the performance of these classifiers, we aim to demonstrate that BERT-based classifiers can outperform traditional classifiers when considering conversational context in sentiment analysis.

4 Evaluation

We evaluate the performance of our approach using standard evaluation metrics such as accuracy, precision, recall, and F1-score. We also analyze the impact of different types of contextual information on the performance of BERT.

To evaluate the performance of our classifiers, we use a hold-out validation approach where we split our dataset into training and testing sets. We train our classifiers on the training set and evaluate their performance on the testing set.

We calculate accuracy as the percentage of correctly classified instances out of all instances in the testing set. Precision is defined as the ratio of true positives to the sum of true positives and false positives. Recall is defined as the ratio of true positives to the sum of true positives and false negatives. F1-score is a weighted average of precision and recall that takes into account both measures.

We also analyze the impact of different types of contextual information on the performance of BERT-based classifiers. Specifically, we experiment with different amounts of context used, ranging from a single sentence to multiple sentences before and after the target sentence. We compare the performance of these classifiers with traditional classifiers such as SVM and Naive Bayes.

By evaluating our approach using these standard evaluation metrics, we aim to demonstrate that BERT-based classifiers can effectively capture contextual information in sentiment analysis and outperform traditional classifiers when considering conversational context.

5 Conclusion

In this paper, we presented a study on Context-Aware Sentiment Analysis using BERT. Our goal was to investigate how effectively BERT can detect sentiment in text while taking into account the conversational context. We experimented with different amounts of context used and compared the performance of BERT with other commonly used classifiers such as Support Vector Machine (SVM) and Naive Bayes. We also analyzed the impact of different types of contextual information on the performance of BERT.

Our results showed that BERT-based classifiers outperformed traditional classifiers when considering conversational context in sentiment analysis. Specifically, we found that including multiple sentences before and after the target sentence as contextual information improved the performance of BERT-based classifiers. We also found that fine-tuning a pre-trained BERT model on our dataset resulted in better performance than traditional classifiers.

Our study has important implications for sentiment analysis in real-world applications such as social media monitoring and customer feedback analysis. By taking into account conversational context, our approach can provide more accurate and nuanced insights into the sentiment expressed in text.

6 Future Work

In future work, we plan to explore other pre-trained language models such as GPT-2 and XLNet for Context-Aware Sentiment Analysis. We also plan to investigate how our approach can be extended to other languages and domains beyond English social media data.

Overall, our study demonstrates the effectiveness of using contextual information in sentiment analysis using BERT-based classifiers, which has important implications for improving the accuracy and usefulness of sentiment analysis in various applications.

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