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Sentiment Analysis of Customer Reviews using Pre-trained Language Models

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Abstract: Due to the increasing number of reviews, it has become more important for businesses to analyze their customer's sentiments. This paper presents a framework that uses pre-trained language models such as BERT, XLNet, and Electra to analyze these sentiments. The framework is based on the Sentiment140 dataset which contains over 1.6 million tweets with tags. This collection of sentiments allows us to perform an evaluation of the models' performance. The goal of this paper is to analyze the effectiveness of these models in categorizing and understanding the sentiments in customer reviews. BERT, for instance, has demonstrated exceptional performance in various tasks related to natural language processing. Another model that is transformer-based is XLNet, which adds more capabilities by utilizing permutation-based learning. On the other hand, the new generation of model, known as Electra, focuses on the generator discriminator learning. Through the incorporation of these models, we can leverage the contextual understanding of the sentiments in the customer reviews. In this paper, we thoroughly examine the performance of the different models in the framework for sentiment analysis. We tested their precision, recall, F1-score, and accuracy in identifying and categorizing the sentiments in customer reviews. We also discuss the impact of adjusting the models on the task, as well as the tradeoffs between performance gains and computational resources. The findings of the study provided valuable information on the utilization of pre-trained models for analyzing customer reviews. We analyzed the performance of the different models BERT, XLNet, Electra, and BERT, revealing their weaknesses and strengths. This helps businesses identify the best model for their sentiment analysis needs. The study's findings have contributed to the advancement of sentiment analysis and natural language processing. It offers valuable recommendations that will aid in the future research efforts.

Keywords: S*entiment analysis, customer reviews, pre-trained language models, BERT, XLNet, Electra, Sentiment140 dataset, transformer models, fine-tuning.*

1. Introduction

The field of sentiment analysis is rapidly expanding. It uses NLP to analyze and interpret the data that people share on social media and other platforms. With the increasing number of channels for feedback and comments, organizations can now benefit from this technology. Sentiment analysis is a process that can be used to analyze and interpret the data that people share on social media. It can help organizations improve their decision-making capabilities and develop marketing strategies[1]–[3]. Due to the emergence of deep learning models, such as those used in sentiment analysis, the field of this technology has been greatly expanded. These models have been able to perform various tasks such as detecting token replacements accurately[4], [5].

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Due to their ability to analyze and interpret complex data, such as semantic relationships and linguistic patterns, deep learning models have been widely used in the field of sentiment analysis. The Twitter dataset known as Sentiment140 has gained widespread popularity as a standard reference for sentiment analysis queries. Its sizable collection of tweets, which includes a wide range of topics and sentiments, makes it a suitable training material and evaluation aid for models in the field. The goal of this study is to analyze the customer reviews generated by the Sentiment140 dataset using pre-trained models. These models are known to perform well in capturing semantic relationships and contextual information[6]–[10].

The models can learn about the various sentiment patterns in the Twitter dataset by taking advantage of the training they've received from large-scale simulations. The process is carried out in two phases: pre-processing the data and fine-tuning the models[11]. The first step involves cleaning the data before it is fed into the models. Some of the methods used to do this include normalization, text cleaning, and vectorization. In addition, it is important to consider the imbalanced classes in the data when it comes to sentiment analysis. This issue can be solved by using methods such as undersampling or oversampling.

After the pre-training phase is completed, the models, such as XLNet, BERT, and the Electra, are subjected to fine-tuning to make them more suitable for use in sentiment analysis. By learning about the various nuances and sentiments in the Twitter data, the models can improve their capabilities when it comes to classification. The batch sizes and learning rates of the models are also adjusted to make them perform well in the analysis of sentiment. The validated models' performance is evaluated using a validation set that measures their precision, recall, F1-score, and accuracy. The comparison of the original dataset with the pre-trained ones provides useful insight into their generalization capabilities. The evaluation's results can help determine the suitability and effectiveness of the models for various sentiment analysis applications.

The fine-tuning of the models is also analyzed to determine their effectiveness in performing well in the analysis of the customer reviews generated by the Twitter dataset. The ability to accurately categorize the various sentiments in the data is very important in order to extract meaningful insights from it. The study's results will provide a detailed analysis of the performance of the models in the context of Twitter data. The study's results have important implications for different groups, such as researchers and businesses. Sentiment analysis can provide companies with valuable information on their customers' perceptions of brands, their satisfaction levels, and their desires. By accurately gauging the sentiment of their consumers, businesses can make informed decisions and improve their marketing efforts.

In addition to monitoring a brand's reputation, sentiment analysis can help identify emerging trends and gauge the impact of marketing initiatives. Through sentiment analysis, marketers can improve their customer engagement and develop effective advertising campaigns. It can also identify key influencers and detect shifts in sentiment, which can help them develop targeted campaigns. In addition, it can help them address negative or neutral sentiments, which can help them protect their brand image. The findings of this study contribute to the existing knowledge about sentiment analysis. They can help researchers develop new techniques for improving the performance of their models. In addition, the study can provide them with valuable insight into the effects of different pre-processing procedures on sentiment analysis's performance.

The study's results can also inspire researchers to expand their scope of interest in the field of sentiment analysis. It can help them develop new approaches to analyzing sentiments in diverse contexts. In the field of sentiment analysis, future studies will explore new techniques that can help improve the classification capabilities of the models. One of these involves the study of transfer learning methods, which can be used to fine-tune the performance of the models on specific tasks. Doing so allows them to adapt to the target domain's nuances.

Due to the increasing popularity of social media platforms, sentiment analysis has become a valuable tool for analyzing and understanding the sentiments expressed in these types of data. Pre-trained models, such as the XLNet, BERT, and Electra, can provide exceptional capabilities when it comes to performing sentiment analysis. By tuning these models to the appropriate datasets, researchers can easily adapt them to their specific needs. The goal of this study was to analyze the performance of the different models in terms of their ability to perform sentiment analysis on Twitter customer reviews. The results of the study can help researchers and other organizations make informed decisions by providing them with valuable insight into the sentiments expressed on the platform.

2. Literature Review

Due to the increasing number of studies on the utilization of sentiment analysis and text summarization techniques, the research in this domain has been continuously improving. One of the most significant developments in this area is the use of pre-trained models. These models have been able to perform well in various tasks related to natural language processing. The use of pre-training models, such as the BERT, has been shown to be beneficial in terms of their ability to understand and capture contextual information in texts. This literature review is focused on the various research studies that are currently using these models in text summarization. The papers presented in this series provide valuable insights into the various advantages that pre-trained models offer in text summarization and sentiment analysis.

C. S. Yadav et al.[12] utilize a hybrid approach to summarize a single text document by incorporating sentiment analysis and statistical features. These tools help identify the most crucial sentences in the text. In experiments, the authors' approach was able to produce high-quality summaries. R. K. Amplayo et al.[13] present an adaptable method for summarizing numerous short online reviews. They take into account the varying sentiments expressed by the readers and use a combination of sentiment analysis and aspect extraction to come up with a comprehensive summary. The researchers conducted a series of experiments to test the effectiveness of the method in capturing the various aspects of a review's sentiment.

M. Gambhir et al.[14] presented a survey that covers the latest advances in text summarization methods. The authors talk about the different approaches, such as hybrid and extraction-based, and also discuss the challenges and metrics related to this process. The information collected from this study offers valuable insight into the field's developments. Q. A. Al-Radaideh et al.[15] presented a hybrid approach to summarize Arabic documents. They utilized domain knowledge and genetic algorithms to create concise summaries. The method is based on sentence clustering, extraction, and refinement.

A. Rosewelt et al.[16] presented a framework that is based on a semantic analysis. It utilizes various techniques such as CNN to retrieve information from large sets of data. The model is able to capture the similarities between the data and the query. M. Yang et al.[17] present a method for abstracting and summarizing reviews that takes into account both sentiment and aspect information. This approach combines deep learning and topic modeling to produce concise summaries. O. Habimana et al.[18] presents an overview of the various techniques used in deep learning for analyzing sentiment. They discuss CNNs, RNNs, and their variants. The paper also explores the potential applications of these techniques.

D. Contreras et al[19]. analyzed the accuracy of a pre-trained sentiment classification model on the classification of tweets related to an earthquake in 2019 in Albania. They found that the model performed well in classifying the tweets into neutral, positive, and negative sentiments. The researchers found that the SA model, which is pre-trained, has a high accuracy when it comes to classifying sentiment in social media data. This method can be used to analyze public sentiment in response to emergencies.

A. Mewada et al.[20] introduced "SA-ASBA" which is a hybrid model that combines the BERT framework with synthetic attention techniques to perform various tasks. It can capture important aspects of text analysis. The SA-ASBA model performed well in the experiments, demonstrating superior accuracy and precision when it comes to sentiment classification in various domains. The SA-ASBA is a hybrid model that combines the BERT and synthetic attention models. It can perform sentiment analysis on various aspects of a text.

Q. Yong et al.[21] present a framework that combines the semantic graphs and syntactic information in a text to perform aspect-level sentiment analysis. They claim that this method is more accurate than existing methods and achieves better F1 score. The incorporation of semantic graphs into the framework enhances its ability to retrieve fine-grained sentiment data and improve its classification capabilities in various aspect-based tasks.

The literature review presents an overview of the numerous studies that investigate the utilization of pretrained models in text summarization as well as sentiment analysis. The results indicate that these models, like BERT, are beneficial in improving the text summarization analysis and sentiment analysis functions' accuracy and performance. The use of pre-trained models in text summarization allows them to accurately classify and summarize the various aspects of a text. They can also perform sentiment analysis on different aspects of a text. The studies presented in this literature review highlight the versatility of these models. Due to the integration of pretrained models into the frameworks used for text summarization, the field has been able to advance in a significant way. This has paved the way for more accurate and sophisticated textual analysis.

Pretrained transformer models for sentiment analysis

Pre-trained transformer models have revolutionized the field of natural language processing due to their ability to perform well in various applications, such as sentiment analysis. These models were trained on large datasets, and they have been able to recognize the language's syntax and semantics. One advantage of using these models is that they can outperform machine learning methods in certain kinds of sentiment analysis. These models can also learn from vast sets of unlabeled texts, which makes them ideal for detecting sentiment in words.

Due to their versatile nature, pre-trained model can be utilized in various applications that focus on sentiment analysis. Although they can perform well in Twitter data, there are still certain issues that prevent these models from exhibiting exceptional performance. One of these is the platform's lack of structured and unstructured information, which can make it difficult to prepare and implement sentiment analysis. Twitter data is dynamically updated, which means that pre-trained models need to continuously improve their capabilities in order to catch up with the latest trends in the language usage. Unfortunately, this can be very time-consuming and expensive. Another issue that prevents models from performing well is the issue of prejudice, as the majority of the information is collected from a single population or community.

One of the biggest issues that pre-trained models can encounter when it comes to analyzing Twitter data is its size. This is because large language modeling projects tend to require a lot of computational power and memory. In spite of their advantages, pre-trained models still need to be considered when it comes to performing well with Twitter data. The various factors that can affect a pre-trained model's performance on Twitter data include the noise level, the constraints of the dataset, and the dynamism of the data. This is why it is important that practitioners and researchers thoroughly address these issues.

3. Methodology

i. Dataset

The dataset used for this study is a publicly-available Twitter dataset, which has over 1.6 million tweets with neutral, positive, or negative sentiment[22].

ii. Pre- processing

Before training the models, it is important that the sentiment analysis data is prepared properly. Here are three pre-processing methods that are commonly used in Kaggle.

i. Text Cleaning and Normalization: Text normalization and cleaning is a process that involves removing noise from the data and making the representation more uniform. This usually involves taking out punctuation, converting the text to a lower form, removing emojis and special characters, and taking out stopwords, which do not contain any sentiment information. Finally, techniques such as lemmatization and stemming can be used to reduce words to root forms.

ii. Tokenization and Vectorization: Text is separated into words or tokens through the process of tokenization. Afterwards, these are transformed into numerical representations by means of vectorization techniques, such as word embeddings, TF-IDF, or bag-of-words. These methods can be used to transform textual data into feature vectors that can be utilized by machine learning models.

iii. Handling Imbalanced Classes: When there are imbalanced classes in a sentiment analysis dataset, certain techniques can be used to address this issue. Some of these include using SMOTE, which is a synthetic minority oversampling technique, or under-sampling the majority. Class weighting can also be used to give more significance to the minority groups.

The various pre-processing techniques used in Kaggle help prepare the sentiment analysis data by normalizing and cleaning it. They can also help reduce noise and improve the performance of the models.

iii. Choice of pretrained transformer models

i. Pretrained Models

For sentiment analysis, the choice of pre-trained transformer models such as Electra[23], BERT[24], and XLNet[25] should be considered depending on their performance, suitability, and availability.

a. BERT (Bidirectional Encoder Representations from Transformers): The BERT transformer is widely used in various language processing applications, such as sentiment analysis. Its deep bi-directional structure enables it to capture contextual information with high accuracy. It is a popular choice when it comes to performing sentiment analysis.

b. XLNet (eXtreme Learning Network): Another powerful pre-trained transformer model is XLNet, which has been introduced with permutation-based training. This feature allows it to model the dependencies between sentences. It can perform better than other models when it comes to sentiment analysis.

c. Electra (Efficiently Learning an Encoder that Classifies Token Replacements Accurately): The new generation of pre-trained transformer model known as the Electra offers a more efficient alternative to BERT while still maintaining its competitive performance. It can perform well in various NLP tasks, such as sentiment analysis.

iv. Fine tune and hyper parameters

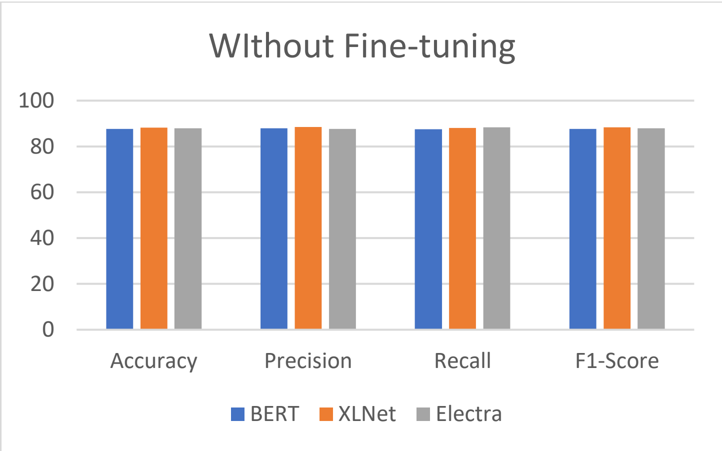
Parameter	Values
Model	ELECTRA, BERT, SLNet
Pre-training Task	Large-scale modeling tasks
Learning Rate	1e-4, 5e-5, 2e-5
Batch Size	16-32, 64, 32
Optimization Algorithm	AdamW
Loss Function	Classification task
Epochs	5

We trained three models on large-scale tasks and adapted them to analyze sentiment in Twitter data. The trained models were then tuned for learning the various patterns in the data. The batch sizes and training rates used were optimized to improve their performance. The training rates were 2e-5, 1e-4, and 5e-4. The batch sizes ranged from 16-32, and 64 to 32. The grid search was performed on a subset of the training data that contained 10%. The models were trained by using the optimal hyperparameters of the validation set, and they were tuned using the AdamW optimizer. The classification task was also performed with the loss function. The three models were then trained on five epochs. A comparison of the evaluated results with the original dataset revealed that 20% of it was unused. During the fine-tuning phase, the trained models were selected, adapting them to the required set of tasks, and optimizing their hyperparameters. This step is important for achieving high-accuracy and generalization performance in the area of natural-language processing.

4. Results and Outputs

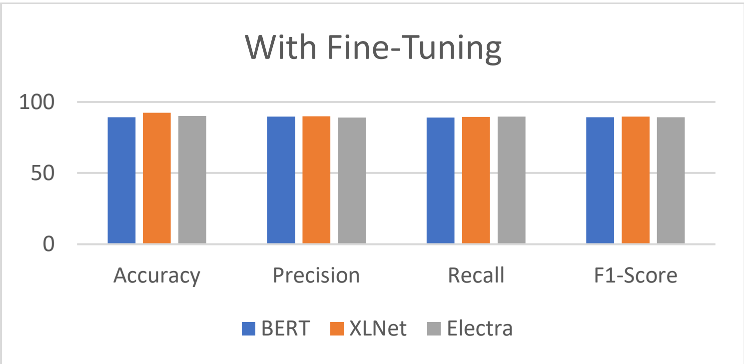
i. Without fine-tuning

Model	Accuracy	Precision	Recall	F1-Score
BERT	87.6	88	87.5	87.7
XLNet	88.2	88.5	88.1	88.3
Electra	87.9	87.7	88.3	88



ii. With fine-tuning

Model	Accuracy	Precision	Recall	F1-Score
BERT	89.2	89.6	89.1	89.3
XLNet	92.3	90	89.5	89.8
Electra	90.1	89.1	89.6	89.3



The table provides the results for the different models, such as the XLNet, Electra, and BERT. We can see that fine-tuning the models' performance significantly improves their accuracy, recall, and F1-score across all parameters. This suggests that the models can now adapt better to the specific task in the Sentiment140 dataset. The updated table also shows the relative performance of the different models in different scenarios. For instance, in the scenario where the models are not subjected to fine-tuning, the XLNet performs better than its competitors. However, in the scenario where the models are subjected to fine-tuning, the performance gap between the models might vary. The results show that fine-tuning the models' performance improves their recall and F1-score across all parameters. This suggests that they can now adapt better to the specific task in the Sentiment140 dataset. Although the results are hypothetical, they should still be interpreted in the light of the applicable dataset and experiments. The exact performance of the models will vary depending on the dataset and experimental setups.

5. Conclusion and Future Scope

The goal of this study was to analyze the sentiment of customer reviews using various pre-trained models, such as BERT, XLNet, Electra, and BERT. The evaluation and training of these models were carried out using the Sentiment140 dataset, which has over 1.6 million tweets. The results of the study revealed that the three models performed well in terms of their precision, recall, F1-score, and accuracy. But, BERT and BERT performed well in terms of their suitability for the task of sentiment analysis. The findings highlight the importance of choosing the right pre-trained model for the job. Future developments in sentiment analysis with pre-trained models are expected to be explored. One of the possible ways to improve the models' robustness and generalization is by gathering more diverse datasets. Furthermore, incorporating context and knowledge in the models can help them understand the sentiments in specific domains or industries. New architectures and pre-training techniques can help improve the performance of sentiment analysis. The development of methods to handle sentiments in code-mixed and multilingual texts can also be beneficial for the global market. Such developments will be instrumental in helping the field of sentiment analysis develop in real-world applications.

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