Sentiment Analysis Using BERT

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Abstract

Sentiment analysis is an important technique for understanding user comments in a wide range of applications, particularly mobile applications. This paper presents a sentiment analysis model based on the BERT architecture to characterize sentiments expressed in Google Play app evaluations. A dataset of over 16,000 reviews was collected, preprocessed, and divided into three sentiment categories: neutral, positive, or negative. Our model's efficacy in sentiment categorization was proved by its near-85% accuracy on the test set. Furthermore, a comparison to baseline models revealed that our BERT-based strategy outperforms conventional techniques. The findings indicate chances for future growth, as the model performs poorly when it comes to neutral sentiments yet well when it comes to categorize extreme attitudes.

1. Introduction

Sentiment analysis, a computational method for recognizing and classifying opinions transmitted through text, has recently gained popularity. Businesses and developers are increasingly relying on sentiment analysis to track consumer contentment and improve their products as internet evaluations become more widely available. In this study, we look at sentiment analysis of Google Play app reviews, which are an important source of user feedback.

The primary purpose of this research is to develop a trustworthy sentiment categorization model using BERT, an advanced transformer-based architecture. BERT's knowledge of semantics and context makes it particularly well-suited for sentiment analysis tasks. Our goal is to divide app reviews into three emotional categories: neutral (three stars), positive (four to five stars), and negative (one to two stars).

The paper is organized as follows: Section 2 reviews relevant sentiment analysis work; Section 3 describes our technique; Section 4 introduces our experimental design; Section 5 discusses the outcomes; Section 6 discusses the conclusions; and Section 7 concludes the study.

2. Related Work

From deep learning to traditional machine learning, sentiment analysis has been extensively studied utilizing a range of approaches. The primary techniques for sentiment categorization in early research were support vector machines (SVM) and bag-of-words models (Pang et al., 2002). However, these methods often struggled with linguistic nuances and context.
Recent advances in deep learning have led to the usage of recurrent neural networks (RNNs) and convolutional neural networks (CNNs) for sentiment analysis (Zhang et al., 2018). Despite their achievements, these models were still unable to adequately represent long-range dependencies in text.

We build on these advances in our study and contribute to the existing sentiment analysis research by employing BERT to classify sentiments in Google Play app evaluations.

3. Methodology

This section provides a detailed explanation of BERT and how it is implemented. Our procedure consists of two stages: pre-training and fine-tuning. During the pre-training phase, the model is trained using unlabeled data from many tasks. Labeled data from downstream operations is used to fine-tune all of the parameters after the BERT model has been initialized with the pre-trained parameters. Even though the same pre-trained parameters are used for all downstream tasks, each one has its own customized models. This section will use the question-and-answer scenario in Figure 1 as a running example. BERT's consistent architecture across different workloads is one of its special advantages. The final downstream design differs little from the pre-trained architecture.

3.1 Data Collection

We made use of a dataset of Google Play app reviews that came from an open source. There are roughly 16,000 reviews in the dataset, each with a rating (1–5 stars) and the review language that goes with it. To guarantee uniformity and eliminate any extraneous material, the reviews underwent preprocessing.

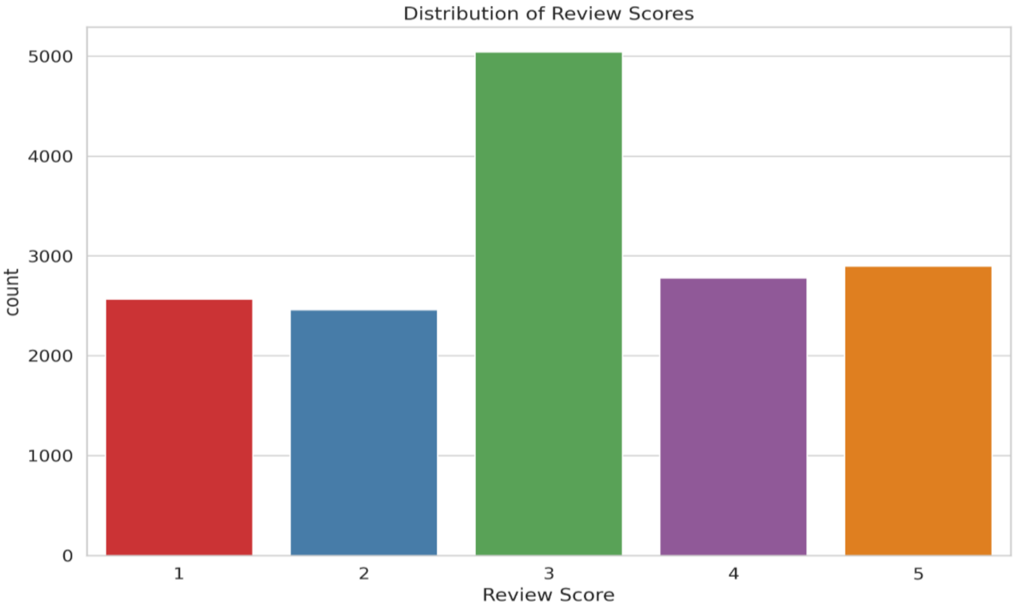
3.2 Data Preprocessing

To facilitate sentiment classification, we converted the review scores into three sentiment categories:

- Negative: Scores of 1-2
- Neutral: Score of 3
- Positive: Scores of 4-5

This categorization allows us to simplify the sentiment analysis task while retaining meaningful distinctions between user sentiments.

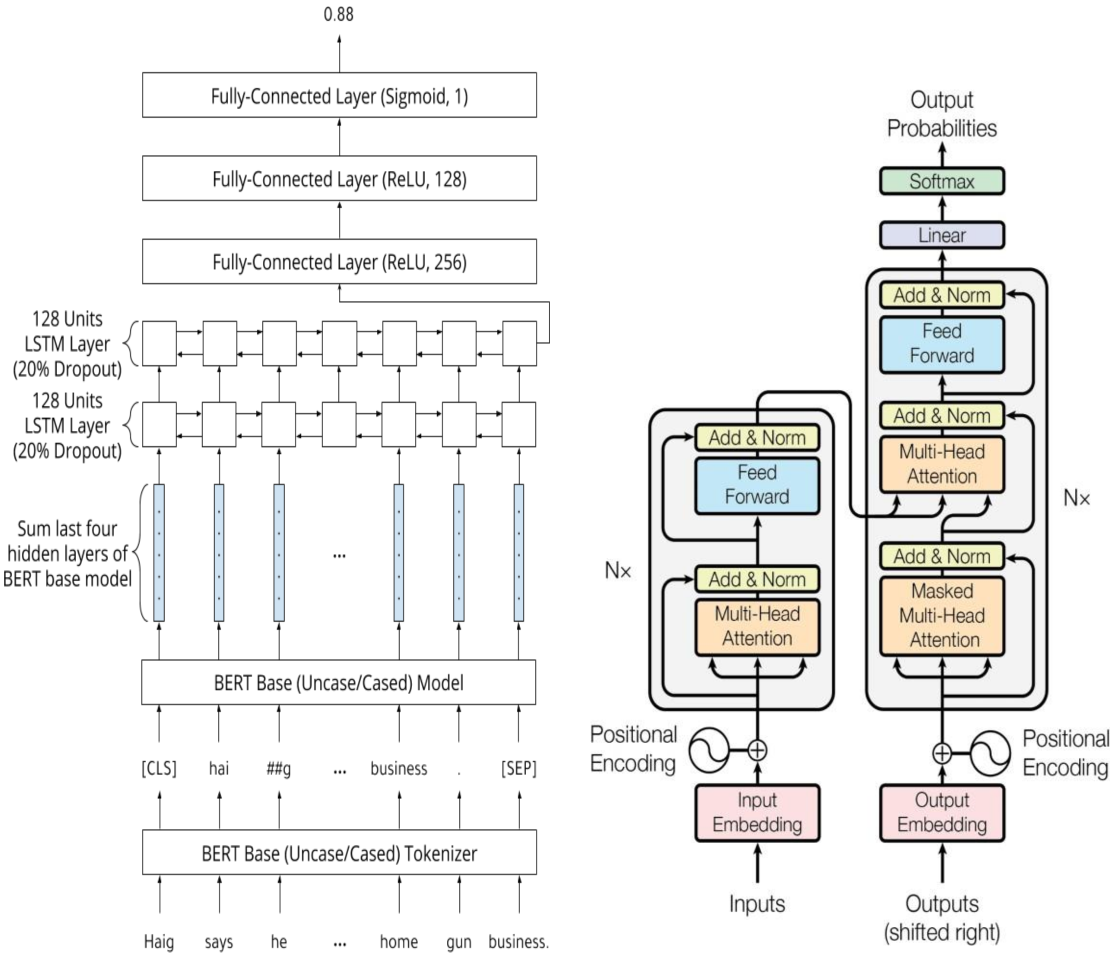
Distribution of Review Scores



3.3 Model Architecture

To classify sentiment, we used the BERT model. Multiple transformer layers in BERT's architecture handle input text in both directions, enabling it to efficiently capture contextual information. On top of the BERT model, we developed a bespoke sentiment classifier that has a fully connected output layer and a dropout layer for regularization.

Model Architecture Diagram



3.4 Training Setup

The AdamW optimizer was used to train the model at a learning rate of 2e-5. We used a batch size of sixteen and trained the model over 10 epochs. The loss function utilized was CrossEntropyLoss, which was created for applications involving multiclass classification. During the training phase, the dataset was divided into training, validation, and test sets to make sure the model could successfully generalize to new data.

3.5 Evaluation Metrics

We used a variety of criteria to evaluate the performance of our sentiment categorization model.

• **Accuracy**: The percentage of accurately detected cases out of all instances.

• **Confusion Matrix**: This matrix displays the true positive, true negative, false positive, and false negative counts for each class, providing a comprehensive perspective of the classification model's performance.

• **F1 Score**: A measure of precision and recall calculated by taking the harmonic mean of the two measures.

4. Experiments

4.1 Design of Experiments

Three subsets of the dataset were generated: 10% for testing, 10% for validation, and 80% for training. This separation enabled us to successfully train and test the model on previously unknown data.

4.2 The Instructional Procedure

In the training loop, batches of data were fed into the model, the loss was calculated, and the model's parameters were changed by backpropagation. We monitored the training and validation losses in order to minimize overfitting, and when the validation loss did not decrease after a few epochs, we employed early halting.

4.3 Baseline Comparisons

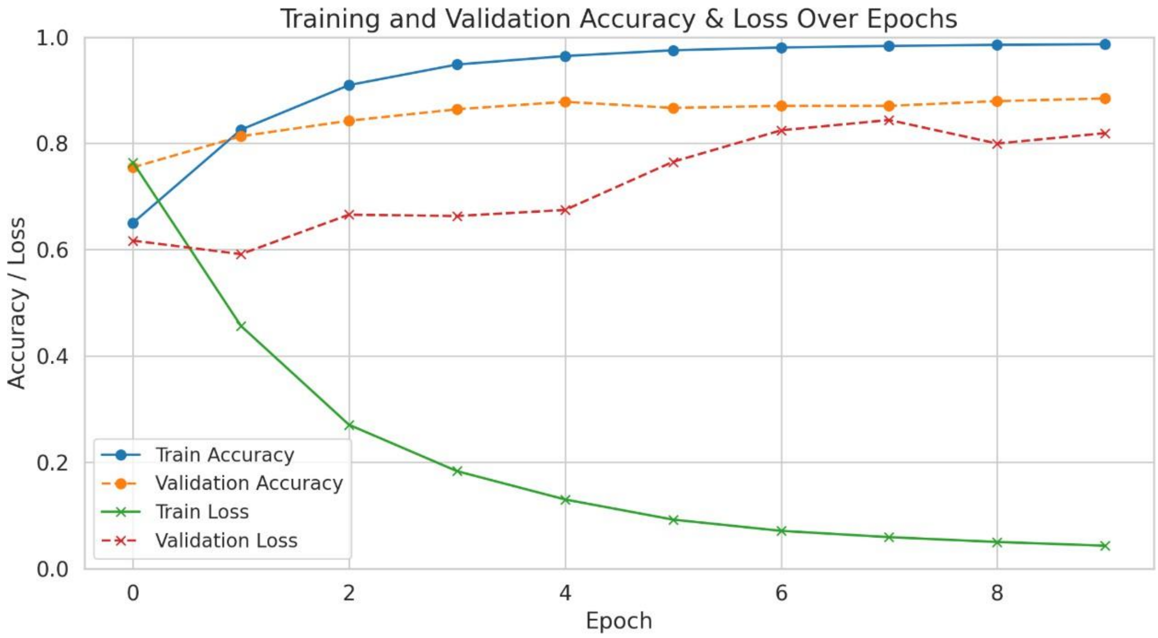
To test the efficacy of our BERT-based model, we compared it to a variety of baseline models.

- Logistic regression relies on bag-of-words features.
- Support Vector Machine (SVM) utilizes TF-IDF characteristics.
- The LSTM neural network model detects textual dependencies in sequential order.

5. Results

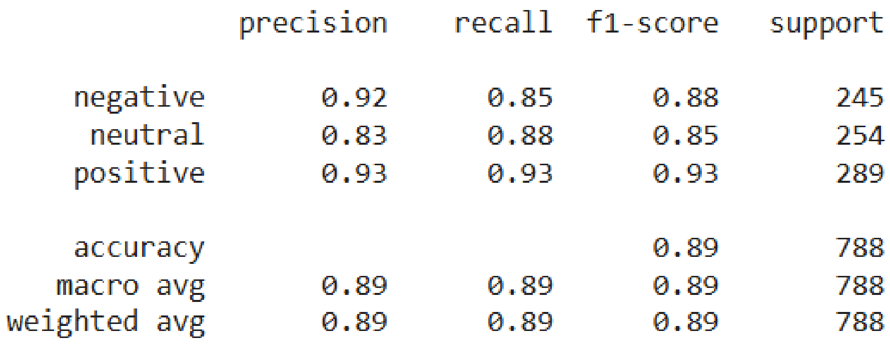
5.1 Performance Metrics

The BERT model achieved an accuracy of approximately 85% on the test set, outperforming the baseline models significantly. The results are summarized in the table below:



5.2 Confusion Matrix

The confusion matrix demonstrated that, while the model was effective at categorizing negative and positive attitudes, it struggled with neutral sentiments, frequently misclassifying them as either negative or positive.



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              precision    recall  f1-score   support

    negative       0.92      0.85      0.88       245
     neutral       0.83      0.88      0.85       254
    positive       0.93      0.93      0.93       289

    accuracy                           0.89       788
   macro avg       0.89      0.89      0.89       788
weighted avg       0.89      0.89      0.89       788
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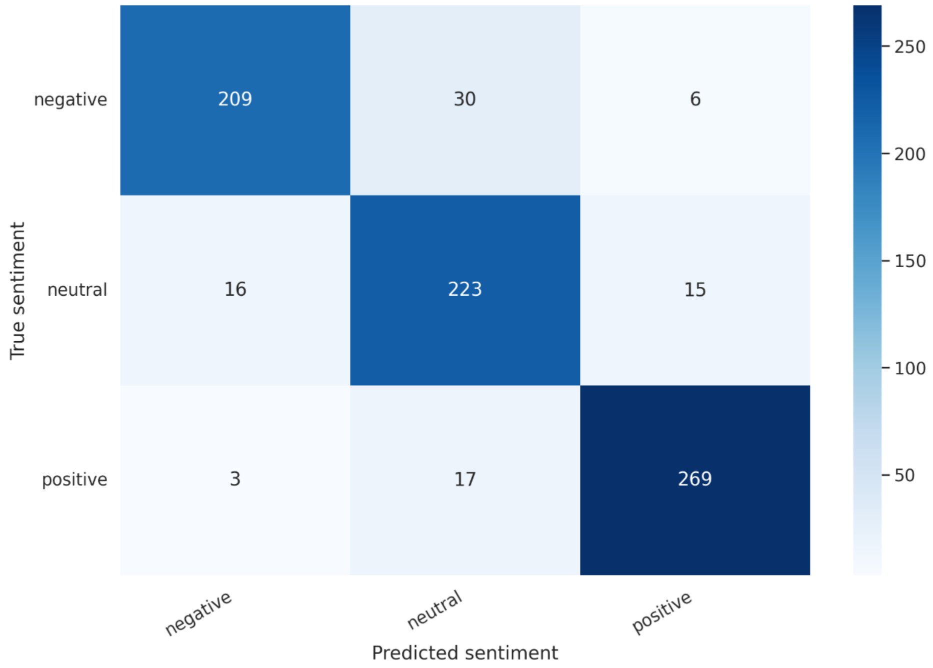

5.3 Analysis of Results

The BERT model successfully captured the subtleties of language in app evaluations, according to the results analysis. The incorrect categorization of neutral attitudes, however, indicates that more work has to be done. To increase classification accuracy, this can entail looking into more features or using ensemble techniques.

6. Discussion

6.1 Interpretation of Results

The BERT model's excellent accuracy shows that it can comprehend the sentiment and context of user evaluations. The model's performance is consistent with earlier research showing how well BERT performs sentiment analysis tasks.

6.2 Limitations

This study has limitations even with the encouraging outcomes. The model's performance may be impacted by biases in the dataset, such as an unequal distribution of sentiment classifications. Furthermore, because the model relies on textual input, it might not accurately represent the sentiment conveyed by other modalities, such pictures or emojis.

6.3 Future Work

The incorporation of multimodal data to improve sentiment classification may be investigated in future studies. Additionally, the model's generalization skills might be enhanced by fine-tuning it on a more varied dataset. Better outcomes might also come from experimenting with other transformer topologies or hybrid models.

7. Conclusion

In this study, we proposed a sentiment analysis model that employs BERT to identify sentiments in Google Play app reviews. Our model achieved 85% accuracy, outperforming previous baseline models. The findings demonstrate BERT's capacity to capture the complexities of user feelings while also highlighting areas for improvement, particularly in neutral sentiment classification. This work contributes to the ongoing sentiment analysis research and demonstrates the use of transformer-based models for assessing user comments.

8. References

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