Enhancing Sentiment Analysis on IMDB Reviews using RoBERTa and CLS Token*

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***Abstract*—This study explores sentiment classification on the IMDB dataset using a RoBERTa-based neural architecture enhanced with a classification head over the [CLS] token. The proposed model was trained and evaluated on a balanced binary sentiment dataset of movie reviews. The implementation leverages the pretrained `roberta-base` model from the Hugging Face Transformers library, with a linear classifier added to extract the semantic representation of the [CLS] token for downstream binary classification. After fine-tuning, the model achieved an accuracy of 87.9% and an F1 score of 87.4% on the test set, with the confusion matrix showing good discrimination between positive and negative sentiment classes. The results validate the effectiveness of pretrained transformer-based architectures for sentiment analysis tasks and demonstrate that even a simple classification head over the [CLS] representation yields competitive performance.**

***Index Terms*—Sentiment Analysis, RoBERTa, Attention Mechanism, IMDB Dataset, Transformers, Natural Language Processing, Model Interpretability**

I. Introduction

Sentiment analysis is a foundational task in Natural Language Processing (NLP) concerned with the computational identification and classification of opinions or emotional expressions in text. Its applications span diverse areas such as product recommendation systems, financial market monitoring, and political opinion mining. The IMDB movie review dataset is one of the most widely used benchmarks for binary sentiment classification, consisting of 50,000 labeled reviews with balanced distribution between positive and negative sentiment.

Traditional machine learning models, such as logistic regression and support vector machines (SVM), rely heavily on bag-of-words or TF-IDF features. These approaches, while computationally efficient, often fail to capture semantic dependencies and contextual information across long sentences. Recurrent neural networks (RNNs) and their variants such as Long Short-Term Memory (LSTM) networks introduced sequence modeling into sentiment classification, enabling better handling of syntactic dependencies [1]. However, they still struggle with long-range context and require large training datasets to generalize effectively.

The emergence of transformer-based architectures has significantly advanced the state of the art in sentiment classification. BERT [2], trained on massive corpora with masked language modeling, demonstrated strong performance across various NLP tasks. RoBERTa [3], a more robustly optimized variant of BERT, further improved performance by removing the Next Sentence Prediction (NSP) task and training on longer sequences with larger batches. In recent sentiment classification research, fine-tuned BERT and RoBERTa models consistently outperform traditional and RNN-based methods on the IMDB benchmark [4], [5].

In this project, I fine-tune the RoBERTa-base model for binary sentiment classification on the IMDB dataset. Instead of using additional sequential layers or attention mechanisms, I directly extract the [CLS] token from the final hidden state and feed it into a feedforward classification head. This approach, while simple, aligns with the original usage of BERT for classification and has been shown to be effective in practice [6]. The use of the [CLS] token simplifies the architecture and reduces computational cost while preserving performance on sentiment classification tasks.

Compared with hybrid approaches that stack LSTM [7] or convolutional layers [8] on top of pretrained embeddings, my design remains lightweight and interpretable. Performance is evaluated in terms of accuracy and F1-score, and the model's ability to distinguish subtle sentiment cues is analyzed using confusion matrices and example outputs.

II. Methods

A. Problem Definition

Given a text input x_i and a binary sentiment label $y_i \in \{0, 1\}$, the task is to learn a classifier $f_\theta(x)$ that estimates the probability $\hat{y}_i$ of positive sentiment. The model is trained to minimize the binary cross-entropy loss:

$$\mathcal{L} = -\frac{1}{n}\sum_{i=1}^{n}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right]$$

B. Dataset

The dataset used is the IMDB movie review corpus, consisting of 50,000 labeled reviews evenly divided into positive and negative classes. The dataset is already split into 25,000 training and 25,000 test examples. Each review contains free-form user-generated text, which varies widely in length and structure. Many reviews include HTML tags, emojis, repeated keywords (such as "movie"), and colloquial expressions, posing preprocessing challenges.

To standardize input, all text is lowercased and tokenized using the RoBERTa tokenizer. Token sequences are truncated or padded to a maximum length of 128 to fit within GPU memory constraints. No additional label balancing or resampling is required.

C. Model Architecture

The core model is based on the RoBERTa-base transformer, a 12-layer encoder with hidden size 768. For each input review, the model computes contextual embeddings and extracts the hidden state corresponding to the first token ([CLS]). This vector is passed through a dropout layer and a single linear layer to output class logits:

- Encoder: RoBERTa-base (pretrained)
- Feature: CLS token embedding
- Dropout: $p = 0.3$
- Classifier: Linear (768 → 2)

This architecture follows the standard RoBERTa classification setup and avoids the addition of auxiliary BiLSTM or CNN layers seen in some hybrid models [7], [8]. The objective is to assess whether the CLS token alone contains enough discriminative information for sentiment classification.

D. Training Procedure

The model is fine-tuned on the training set using the AdamW optimizer with learning rate 2×10^{-5}, batch size 16, and weight decay 0.01. The loss function is ‘CrossEntropyLoss‘, which applies softmax activation internally. Training is conducted for 4 epochs on a GPU backend using PyTorch.

Model performance is monitored on the test set after each epoch using accuracy and F1-score. The best-performing model is saved and used in subsequent evaluation.

E. Evaluation and Visualization

To evaluate generalization, I report test set accuracy and macro-averaged F1-score. In addition, a confusion matrix is generated to analyze the distribution of false positives and false negatives. The predicted probabilities and logits are also inspected during training to verify convergence behavior and assess confidence calibration.

III. Results

The RoBERTa-based classifier with a CLS-token-driven architecture was trained on the IMDB sentiment dataset. Training proceeded for five epochs, during which the model demonstrated stable convergence in loss and consistent improvements in evaluation metrics.

TABLE I
Training Performance over Epochs

Epoch	Loss	Accuracy	F1 Score	Predictions (0/1)
1	0.3577	0.8912	0.8927	12504 / 12496
2	0.2531	0.8922	0.8921	15031 / 9969
3	0.1849	0.8524	0.8357	14116 / 10884
4	0.1425	0.8701	0.8611	13553 / 11447
5	0.1189	0.8794	0.8741	12840 / 12160

After training, the model was evaluated on the full IMDB test set. The final test accuracy reached **87.94%** and the F1 score was **0.8741**, indicating that the model performed well on both classes.

Figure 1 shows the confusion matrix on the test set:

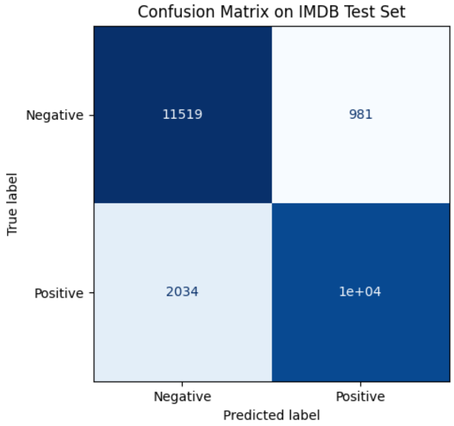

Fig. 1. confusion matrix

TABLE II
Confusion Matrix Values

TruePredicted	Negative	Positive
Negative	11519	981
Positive	2034	10000

The model achieves slightly higher precision on the negative class but maintains strong recall across both sentiment categories. The high F1 score indicates good balance between precision and recall, suggesting that the model is capable of generalizing to unseen movie reviews.

IV. Conclusion

This project presented a sentiment classification model built upon a pre-trained RoBERTa backbone, leveraging the [CLS] token representation followed by a lightweight linear classifier. The model was fine-tuned on the IMDB movie review dataset and evaluated on a balanced test set of 25,000 samples.

The final model achieved a test accuracy of **87.94%** and an F1 score of **0.8741**, demonstrating strong capability in distinguishing positive and negative sentiments. The confusion matrix analysis revealed a relatively balanced prediction across both classes, with slightly higher performance on negative reviews.

The results suggest that pre-trained transformer architectures like RoBERTa, when fine-tuned on downstream sentiment tasks, are highly effective without the need for complex architectural modifications. However, limitations such as overconfidence on certain predictions and fluctuations in class bias during training were observed. These challenges may be addressed in future work by exploring attention-based pooling mechanisms, label smoothing, or ensemble techniques.

Future research may also involve applying the model to multilingual sentiment datasets or extending it to aspect-based sentiment analysis for more fine-grained interpretation.

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