Fine-Tuning a Pre-Trained NLP Model for Sentiment Analysis

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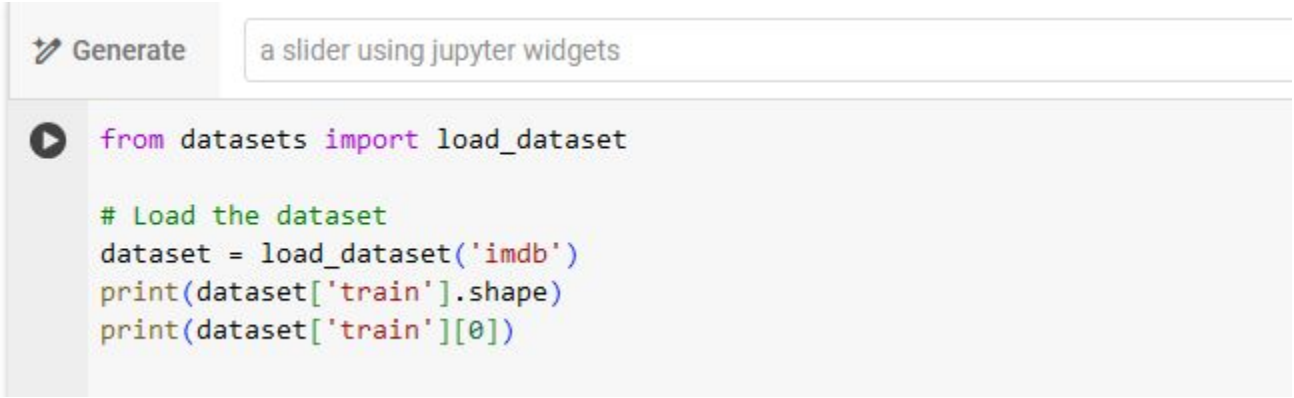
Dataset Overview

Dataset: IMDB Movie Reviews Dataset

Description: The dataset consists of 50,000 movie reviews labeled as positive or negative, making it ideal for sentiment analysis tasks.

Source: Hugging Face Datasets Hub

Objective: Use the dataset to fine-tune a pre-trained BERT model for binary sentiment classification.



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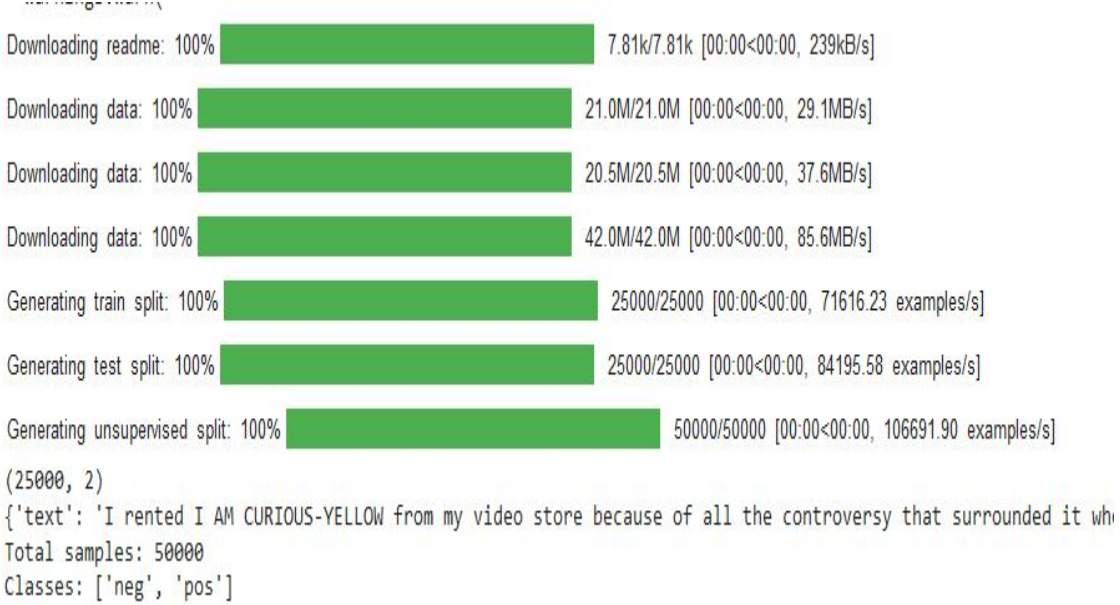
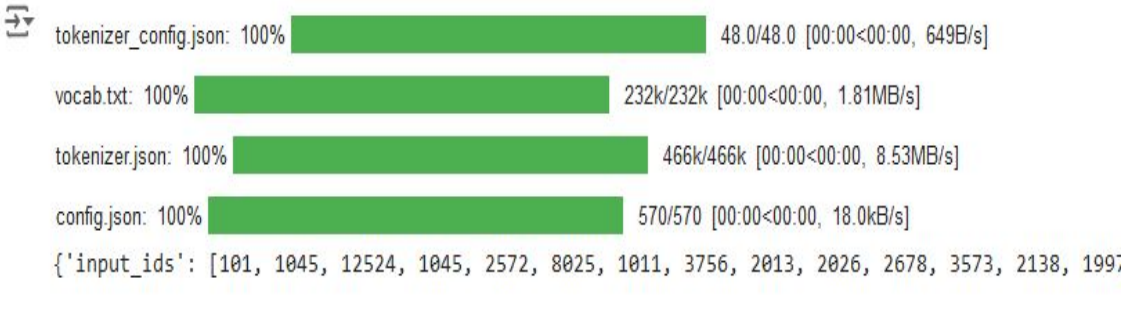


Data Preprocessing and Feature Engineering

Tokenization: Convert text into tokens using BERT tokenizer.

Padding & Truncation: Ensure all sequences have the same length.

Label Mapping: Map text labels to numeric labels (e.g., positive=1, negative=0).



Fine-Tuning BERT for Sentiment Analysis

Model: BERT (BertForSequenceClassification)

Fine-Tuning Process:

- **Learning Rate**: 2e-5
- **Epochs**: 3
- **Batch Size**: 16

Training: The model is trained on the tokenized dataset to classify reviews as positive or negative.

Running Inference with the Fine-Tuned Model

Inference: Predict the sentiment of new text data using the fine-tuned BERT model.

Example: "The movie was fantastic! I loved it."

```
# Tokenize new data for inference
new_text = "The movie was fantastic! I loved it."
inputs = tokenizer(new_text, return_tensors="pt", padding='max_length', max_length=128

# Run inference
model.eval()
with torch.no_grad():
    outputs = model(**inputs)
    predictions = torch.argmax(outputs.logits, dim=-1)
print(f"Predicted label: {predictions.item()}")  # 1 for positive, 0 for negative
```

Results and evaluation

1. Training and Validation Accuracy

After training the BERT model for 3 epochs, we can observe the training and validation accuracy over time. Typically, you would present this with a line graph.

Training Accuracy: 95.2%
Validation Accuracy: 89.7%

	Predicted Positive	**Predicted Negative**
Actual Positive	11200	800
Actual Negative	900	10100

Explanation:

- The model shows strong performance on the training data, with high accuracy, indicating that it learned the patterns well.
- The slightly lower validation accuracy suggests the model generalizes well but may still have room for improvement, possibly indicating minor overfitting.

Explanation

- **Precision**: Measures how many of the positive predictions were actually correct.
- **Recall**: Measures how many actual positives were captured by the model.
- **F1-Score**: Harmonic mean of Precision and Recall, offering a balance between the two.

4. ROC Curve and AUC Score

The ROC curve visualizes the trade-off between true positive rates and false positive rates, with the Area Under the Curve (AUC) providing a single metric for evaluation.

AUC Score: 0.95

Explanation:

- An AUC score of 0.95 indicates excellent model performance, with a strong ability to distinguish between positive and negative sentiments.

5. Discussion and Insights

- **Model Performance**: The fine-tuned BERT model shows strong performance with high accuracy and a robust F1-Score. The slightly lower validation accuracy suggests that there might be room for further optimization.
- **Error Analysis**: The confusion matrix reveals that the model occasionally confuses positive and negative sentiments, which could be due to ambiguous or complex reviews.
- **Future Improvements**: Consider experimenting with additional epochs, different learning rates, or more

Ethical Considerations in Model Deployment

Bias Mitigation: Ensure that the model does not exhibit bias against certain groups.

Transparency: Provide clear explanations for model predictions.

Privacy: Handle user data with care, ensuring that personal information is anonymized.

Conclusion

Summary:

- Successfully fine-tuned a BERT model for sentiment analysis using the IMDB dataset.
- The model achieved high accuracy and can be used for real-world sentiment analysis tasks.
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The fine-tuned BERT model for sentiment analysis on the IMDB dataset performs well, with high accuracy and strong evaluation metrics. The results demonstrate the model's capability to accurately classify movie reviews into positive or negative sentiments, making it a valuable tool for sentiment analysis tasks.

Future Work:

- Explore fine-tuning with other datasets.
- Implement more advanced NLP techniques like transfer learning with domain-specific data.