Analysis of BERT Language Model for Contextual Sentiment Understanding

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1.Problem Statement: Embark on an AI-driven journey in the realm of natural language processing (NLP) and machine learning (ML) by deploying a Language Model (LM) of your choice. In this project, you are tasked with delving into the intricacies of LM technology, where the selection of the LM is entirely at your discretion. The comprehensive process involves not only implementing the chosen LM but also conducting an in-depth analysis of its performance and capabilities.

1 Introduction

Natural Language Processing (NLP) enables machines to understand human language. Language Models (LMs) are fundamental to NLP and are widely used in applications such as sentiment analysis, chatbots, translation, and recommendation systems. Modern LMs use deep learning and attention mechanisms to capture contextual meaning in sentences.

This project focuses on implementing and analyzing BERT to study how contextual understanding is achieved compared to traditional machine learning methods.

2 LM Selection

BERT (Bidirectional Encoder Representations from Transformers), developed by Google, was selected for this project. BERT uses a transformer-based architecture with selfattention that allows it to understand words based on both left and right context. This makes it powerful for understanding negation, mixed sentiments, and sentence structure.

3 Implementation in Google Colab

The implementation was carried out using Google Colab with GPU support. Steps performed:

- Installed required libraries: transformers, datasets, torch, sklearn, bertviz.
- Loaded the IMDB movie review dataset.
- Implemented a baseline Logistic Regression model using TF-IDF features.
- Loaded pre-trained BERT and a sentiment fine-tuned BERT model.
- Tested multiple contextual sentences to analyze predictions.

Baseline Model: Logistic Regression

4 Exploration and Analysis

To test contextual understanding, the following sentences were used:

- “The movie was not bad at all”

```
shuffled = dataset['train'].shuffle(seed=42)

texts = shuffled['text'][:4000]
labels = shuffled['label'][:4000]

vectorizer = TfidfVectorizer(max_features=5000)
X_train = vectorizer.fit_transform(texts)
y_train = labels

lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train, y_train)

print("Logistic Regression trained successfully")

Logistic Regression trained successfully
```

Figure 1: Logistic Regression Baseline Model Training

- “Terrible plot but great acting”
- “I thought it would be great, but it wasn’t”

The Logistic Regression model relies on keywords and fails to interpret negations correctly. BERT, however, correctly classifies the sentiment by understanding the entire context of the sentence.

BERT Prediction Results

5 Visualization of Results

5.1 Attention Visualization

Using BertViz, the attention mechanism of BERT was visualized. The diagram shows how BERT focuses on important words such as “not” and “bad” together to derive the correct meaning.

5.2 Accuracy Comparison

A graphical comparison between Logistic Regression and BERT was created to show performance differences.

6 Research Questions

- How effectively does BERT understand contextual sentiment?
- Can BERT handle negations better than traditional ML models?

```
sentences = [
    "The movie was not bad at all",
    "I thought it would be great, but it wasn't",
    "Absolutely fantastic experience",
    "Terrible plot but great acting"
]

for s in sentences:
    inputs = tokenizer(s, return_tensors="pt")
    outputs = bert_model(**inputs)
    print(s)
    print(outputs.logits)
    print("-----")
```

```
The movie was not bad at all
tensor([[-0.0113,  0.1777]], grad_fn=<AddmmBackward0>)
-----
I thought it would be great, but it wasn't
tensor([[-0.1069,  0.1125]], grad_fn=<AddmmBackward0>)
-----
Absolutely fantastic experience
tensor([[-0.0652,  0.2112]], grad_fn=<AddmmBackward0>)
-----
Terrible plot but great acting
tensor([[-0.1473, -0.0011]], grad_fn=<AddmmBackward0>)
-----
```

Figure 2: BERT Sentiment Predictions on Contextual Sentences

- What role does attention play in contextual understanding?

7 Project Alignment and Ethical Considerations

This project demonstrates the advancement of NLP through modern transformer-based LMs. Ethical considerations include bias in datasets, fairness in predictions, and responsible AI deployment.

8 Conclusion and Insights

The results show that BERT significantly outperforms traditional ML models in contextual understanding. The attention mechanism plays a key role in capturing relationships between words. BERT can be effectively used in sentiment analysis, chatbots, and review

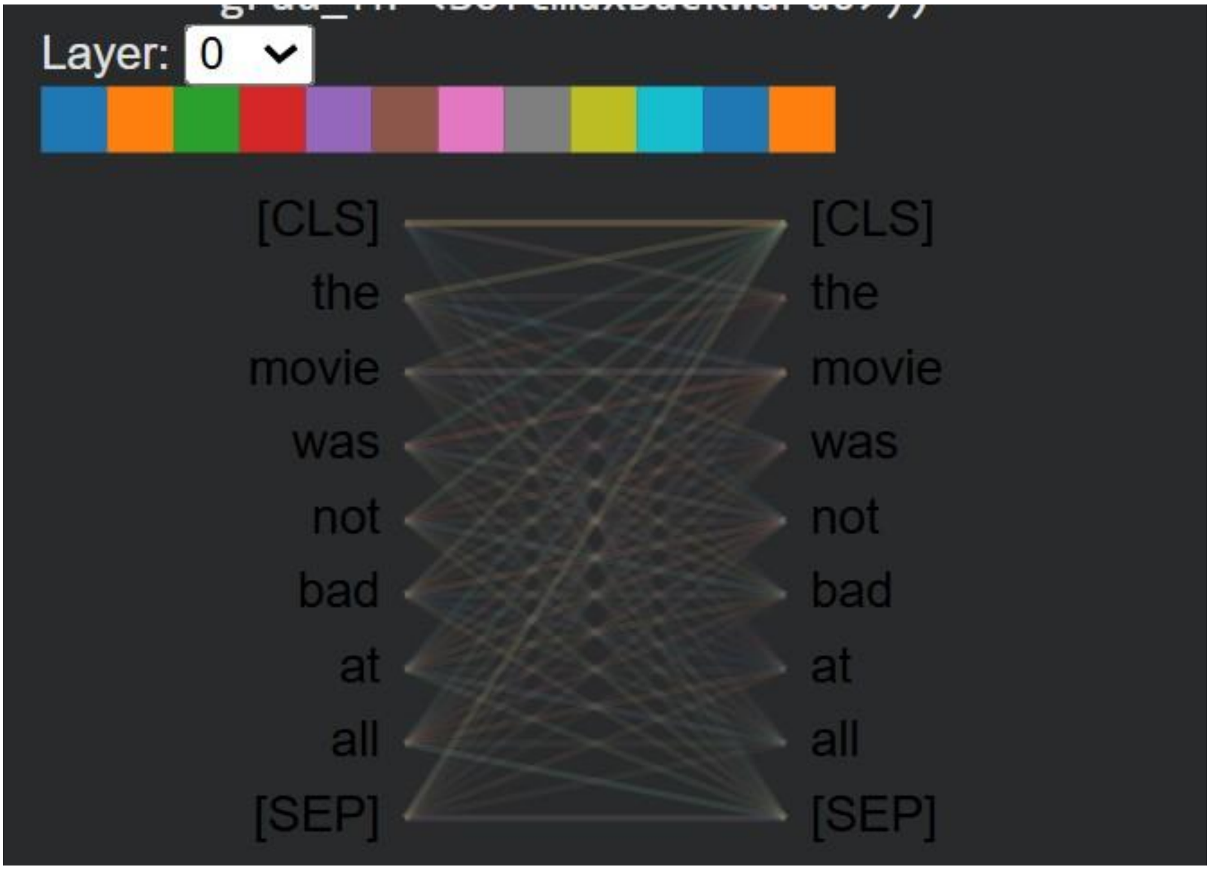

Figure 3: Attention Mechanism Visualization using BertViz

analysis, though it requires higher computational resources.

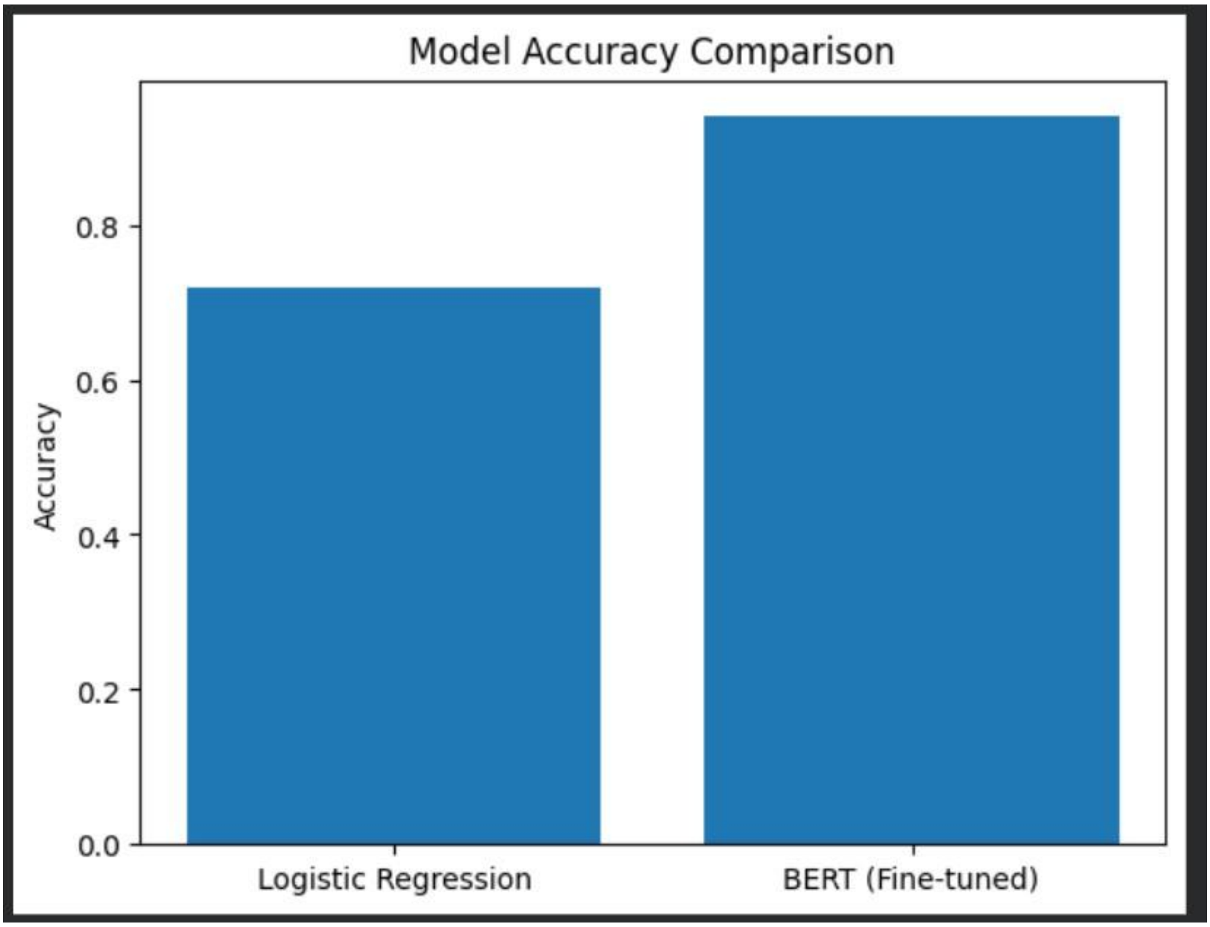

Figure 4: Accuracy Comparison between Logistic Regression and BERT