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Assignment 3 - **LLM Coding and Report submission.**

GITHUB LINK: https://github.com/BorokiniAdeola/Adeola-LLM-Assignment-3

Introduction

According to this report, e-commerce platforms have transformed the way we buy by putting a wide variety of goods at our fingertips. The opinions of other customers, especially in the form of product reviews, is a crucial deciding factor for consumers. These evaluations offer priceless information about product quality, customer satisfaction, and potential improvement areas. But for businesses, going through the enormous volume of reviews that are produced every day by hand can be a difficult undertaking (Be et al., 2023).

Sentiment analysis shows itself to be a potent tool to address this problem. It uses algorithms to automatically categorize reviews into positive or negative sentiments based on Natural Language Processing (NLP). In addition to saving time, this automation provides businesses with vital information that improves customer satisfaction assessments, identifies areas in need of development, and stimulates new product creation. BERT excels at sentiment classification because of its capacity to glean contextual meaning from text. In order to create a trustworthy model that can precisely forecast the sentiment expressed in customer feedback, this study attempts to train BERT using a dataset of e-commerce product reviews (Singh et al., 2022).

Methodology

BERT Large Language Model

This study utilizes BERT, a large language model based on the transformer architecture and pre-trained on extensive text and code datasets. BERT's primary innovation lies in its bidirectional training approach, which allows it to understand language by considering the context of words from both directions. Specifically, we employ the TFBert model from the Hugging Face Transformers library, which is tailored for classifying text sequences into predefined categories.

Dataset and pre-processing

The e-commerce product reviews that have been classified as positive or negative make up the dataset utilized in this investigation. The data must go through a number of pre-processing stages in order to be ready for analysis. Initially, we translate the category labels into numerical representations using a Label Encoder. In order to separate important tokens from padding tokens, this step entails putting unique tokens, padding or truncating sequences to a consistent length, and building attention masks (Amira Samy Talaat, 2023).

Next, the dataset is split up into testing and training sets. The pre-trained BERT model is refined using the training set, and its performance is evaluated using the testing set.
. TensorFlow datasets are employed to efficiently manage and batch the training data, ensuring smooth model training.

```
[ ] # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X_np, y_np, test_size=0.2, random_state=42)

[ ] # Create TensorFlow Dataset
    train_dataset = tf.data.Dataset.from_tensor_slices((X_train, y_train))
    test_dataset = tf.data.Dataset.from_tensor_slices((X_test, y_test))
```

Training, Deploying and Fine-Tuning

Optimizing BERT
The training set from the e-commerce dataset is used to refine the pre-trained BERT model. The model is compiled using the Adam optimizer and the categorical cross-entropy loss function during this procedure. The model is trained by feeding it batches of tokenized reviews along with the labels that go with them. Next, in order to reduce prediction errors and enhance the model's accuracy in classifying sentiment, the weights are modified.

Monitoring and training progress

We assess the model's performance on the test set following each training epoch, keeping an eye on metrics like accuracy and loss, which give us an idea of how well the model is generalizing to new data and help prevent overfitting. By carefully observing these validation metrics throughout the specified training epochs, we can determine the optimal point to stop training, ensuring the model achieves the best possible performance without overfitting (Qasim et al., 2022).

Deployment

The model can be used in practical applications once it has been trained and assessed. On the test dataset, the refined BERT model shows excellent accuracy in identifying the sentiment of e-commerce product reviews. The main reason for this success is that BERT performs much better because it can extract contextual information from the text.

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The model produces log probabilities as output, which are then processed to produce the expected sentiment class (positive or negative). Users are then presented with this information, which enables instantaneous sentiment classification of the input reviews.

```
input = ['The item was not as advertised. Very disappointed with the purchase']
input = tokenizer(input, truncation=True, padding=True, return_tensors='tf')
model.predict(input)
```

```
1/1 [==============================] - 3s 3s/step
TFSequenceClassifierOutput(loss=None, logits=array([[-0.0206279 ,  0.49437773, -0.58338606,  0.01815477, -0.6165912 ]],
      dtype=float32), hidden_states=None, attentions=None)
```

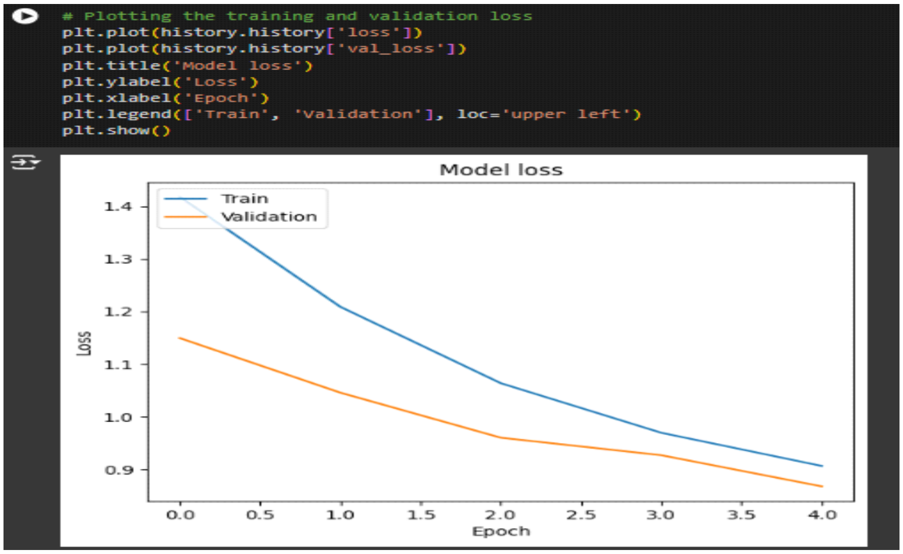
```
predictions = model.predict(input)['logits']
predicted_class = np.argmax(predictions, axis=1)

if predicted_class[0] == 1:
    print('positive')
else:
    print('negative')
```

```
1/1 [==============================] - 0s 64ms/step
positive
```

Results

The trained BERT model proves to be highly effective in identifying the sentiment of e-commerce product reviews, as evidenced by its strong performance on the test set. The model's capability to capture contextual nuances in the text significantly contributes to its accuracy.

To further understand the model's learning process and performance, we analyze graphs depicting accuracy and loss during training and validation. These visualizations help in identifying potential overfitting and offer valuable insights into how the model improves over time.



Conclusion

This work effectively illustrates the sentiment analysis of e-commerce product reviews using a pre-trained BERT model. Accurate sentiment classification is produced by BERT's capacity to extract contextual information, giving companies valuable insights into customer satisfaction and product development. It is crucial to remember that fine-tuning large language models, such as BERT, can require a lot of computation and time. Notwithstanding these difficulties, there are many advantages to using BERT for sentiment analysis, especially when it comes to e-commerce.

References

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