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Research method

[GitHub]

[Google Colab]

Sentiment Analysis on YELP POLARITY with BERT.

Bidirectional Encoder Representations from Transformers (**BERT**) was introduced by Google in 2018, represents a groundbreaking development in sentiment analysis and NLP. BERT's architecture and training methodology have set new benchmarks for understanding and processing text. The BERT models were influential and inspired many variants as RoBERTa, DistilBERT, TinyBERT, ALBERT, ELECTRA, DeBERTa. (Devlin, et al., 2018)

In this report, we utilize DistilBERT, a variant of BERT designed to be a more compact general-purpose language model. DistilBERT can be fine-tuned to deliver robust performance across various tasks, like its larger counterparts. While earlier research predominantly applied distillation to develop task-specific models, our method incorporates knowledge distillation during the pre-training phase. This approach enables us to reduce the size of a BERT model by 40%, while retaining 97% of its language understanding capabilities and achieving a 60% improvement in processing speed. (Sanh, et al., 2020)

▪Introduction;

The exponential growth of user-generated content on platforms like Yelp has made sentiment analysis with the use of *Hugging face Dataset*, an invaluable tool for understanding consumer opinions. Sentiment analysis aims to determine the underlying sentiment expressed in text data, typically classifying it into categories such as positive or negative. The Yelp Polarity Dataset, a prominent dataset for sentiment analysis, consists of reviews labelled with sentiment indicators, making it ideal for training and evaluating sentiment classification models. (Zhang, 2015)

In this report, we utilize the DistilBERT model, a distilled version of the BERT model, for sentiment classification on the Yelp Polarity Dataset. DistilBERT offers a more compact and efficient alternative to BERT, maintaining strong performance while being less resource-intensive. The focus of this report is to demonstrate how DistilBERT can be applied to sentiment analysis, including the process of data preparation, model training, and fine-tuning.

▪Methodology;

The Yelp Polarity Dataset was accessed and loaded using the datasets library, which provides easy access to various NLP datasets. Our dataset consists of two primary subsets: training data and testing data. The preparation of the dataset showcases as below;
A loaded dataset ("yelp polarity") command is used to access Test and train datasets. The dataset consists nearly 630,000 examples of reviews. In which we have split the data between 2 parts, Training dataset as 560,000 examples and testing datasets 38,000 examples.

Furthermore, the dataset was converted into Pandas Data Frames for easier manipulation and exploration. Sample entries from both the training and testing sets were displayed to verify the data format and content. Then we moved to prepare the DistillBERT model for the text data, so it is necessary to tokenize the text. This Tokenization involves the raw text into a format that the our choosen model process the data.

The DistilBertTokenizer from the transformer library was adjusted with the distilbert-base-uncased pre-trained model. A custom function was defined to tokenize the dataset. This function applied padding and truncation to ensure uniform input lengths. The tokenization function was applied to the entire dataset using the dataset.map() method. The resulting datasets were then converted into PyTorch tensors.

To enable training and evaluation, the dataset was randomly sampled and split into two subsets with:

- **Training Subset:** A subset of 20,000 samples was selected from the training dataset.
- **Testing Subset:** A subset of 5,000 samples was selected from the testing dataset.

Once we split the data between Training and Testing data into smaller volumes of example, we moved to Model Initialization, in which the ‘DistilBertForSequenceClassification’ model was loaded with the distilbert-base-uncased weights, configured for binary classification (positive and negative sentiments).

▪Training and Fine-Tuning;

The initial step of training and fine-tuning is begun from the define Training arguments. To set the parameters for training, learning rate, batch size as well as thr number of epochs, and logging strategies we have used ‘TrainingArguments’ class. Secondly, we have defined the custom metrics to evaluate the model performance, F1-score, accuracy, precision, and recall. To train the model and to get the high accuracy we have used 3 epochs over training datasets. Below we can see the results after each epoch,

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	0.278600	0.141305	0.952200	0.951863	0.945957	0.957844
2	0.142300	0.169236	0.953600	0.953748	0.938407	0.969599
3	0.002000	0.194722	0.959000	0.958409	0.959383	0.957438

Above results strongly advocates that the accuracy of model in 1st Epoch reached at 95.22% with 0.9519 F1 Score. In the 2nd Epoch accuracy improved to 95.36% with a F1 score of 0.9537. Epoch 3 is the final Epoch which is showing accuracy 95.90% and F1 score of 0.9584.

Overall, it is crystal clear that DistilBERT effectively classifies sentiment with high accuracy and holds significant performance while being computationally more proficient.

▪ Model Evaluation Report;

After fine-tuning the DistilBERT model on the Yelp Polarity Dataset, the model was evaluated on the test dataset to assess its performance.

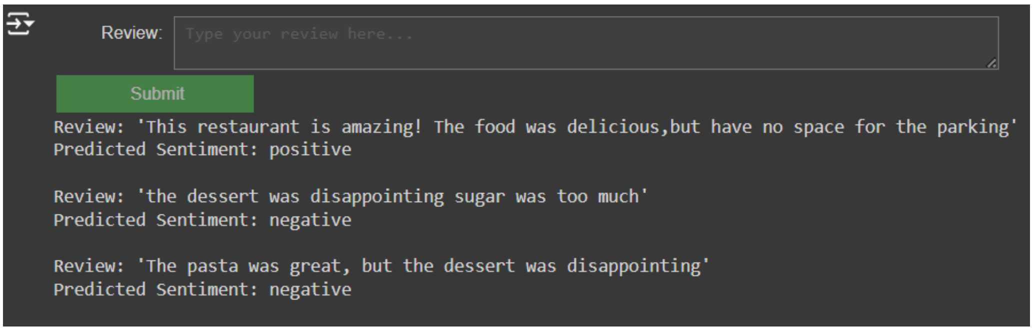
{'eval_loss': 0.19472192227840424, 'eval_accuracy': 0.959, 'eval_f1': 0.9584094136741732, 'eval_precision': 0.9593826157595451, 'eval_recall': 0.9574381840291852, 'eval_runtime': 86.486, 'eval_samples_per_second': 57.813, 'eval_steps_per_second': 3.619, 'epoch': 3.0}

The model's loss on the test dataset is 0.1947 which showcases that the model's estimates are close to the actual labels, suggesting effective learning and generalization from the training data.
The Evaluation accuracy on the test dataset is 95.5%, indicates that the reviews were correctly classified as positive or negative, demonstrating the model's strong performance in sentiment classification.

▪PREDICTING REVIEWS;

After training and fine-tuning the DistilBERT model, we can now use it to forecast the sentiment real world example. The review text is tokenized using the pre-trained DistilBertTokenizer. The tokenized inputs are converted into PyTorch tensors and adjusted for padding and truncation, ensuring the text fits the model's input size constraints (with a max_length of 512). In which the predict_sentiment function is designed to categorize the sentiment of a given review as either "positive" or "negative". The model is set to evaluation mode using model.eval() to ensure that dropout layers, then the model processes the inputs without tracking gradients (torch.no_grad()), which is plays a major role for the reduction of memory usage and speeding up the prediction. Then we moved to Sentiment Classification, if the If the predicted class is 1, the review is classified as "positive." Or else If the predicted class is 0, the review is classified as "negative."

▪Results



According to Review 1, The model correctly identified the positive sentiment, recognizing the praise for the food and ambiance. Review 2 showcased that the model accurately classified the negative sentiment, as the review criticizes both the service and food. Whereas Review 3 Despite the positive comment about the pasta, the overall negative sentiment due to the disappointing dessert led the model to classify it as negative.

To conclude, the sentiment analysis conducted using DistilBERT on Yelp reviews demonstrates the model's exceptional ability to accurately classify diverse sentiments, capturing both overt and nuanced expressions of customer satisfaction and dissatisfaction. By leveraging advanced NLP techniques, this model proves to be a powerful tool for understanding consumer feedback, offering businesses invaluable insights for enhancing customer experiences. The model's precision and reliability in real-world applications like optimizations in retail, Restaurant review or review marketing as well we can use this to the development in the tech products and improve user feedback.

References

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