CSE-584 Machine Learning Mid-term Project : Hyperparameter Optimization and Comparative Analysis of LLM-Generated Text Classification Using BERT

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Abstract

The goal of this project is to classify text completions generated by different Large Language Models (LLMs) based on a set of incomplete text inputs. This paper presents a comprehensive study of text classification models designed to identify the LLM responsible for generating each completion. We utilize multiple LLMs to generate completions for a curated set of truncated sentences and develop a BERT-based classifier to predict the originating model. To enhance model performance, we perform hyperparameter tuning using Optuna. The classifier is evaluated on a subset of the dataset, with a focus on metrics such as classification accuracy, F1 score, and confusion matrices. Our findings demonstrate the effectiveness of deep learning approaches in distinguishing between LLM-generated completions, contributing valuable insights into the capabilities and limitations of current language models.

1 Introduction

The advances in large language models (LLMs) such as BERT, GPT-Neo, and T5 have significantly enhanced the ability to generate coherent and contextually appropriate text. However, as these models proliferate, distinguishing between the outputs of different LLMs becomes increasingly challenging. This paper addresses the task of building a classification system capable of identifying which specific model is responsible for generating a given text completion. The primary objective is to develop a high-performance deep learning classifier that leverages pre-trained transformer models to accurately distinguish between completions generated by five major LLMs.

The contributions of this work include the creation of a comprehensive dataset containing completions from these five LLMs, alongside the design of a custom BERT-based classifier specifically tailored for the task of LLM classification. Furthermore, we implement hyperparameter tuning using Optuna to optimize the model's performance. A thorough evaluation of the classifier is conducted on a randomly selected test set, ensuring a robust assessment of its capabilities in identifying the generating model.

2 Dataset

For this study, we utilized the Stanford Natural Language Inference (SNLI) corpus, a prominent resource in the field of Natural Language Processing (NLP). The SNLI corpus (version 1.0) comprises 570,000 human-written English sentence pairs, each meticulously labeled for their inference relation—either entailment, contradiction, or neutral (MacCartney and Manning, 2008). Our focus was to extract relevant information from this rich dataset to create a tailored dataset suitable for our classification task. To prepare the SNLI corpus for our analysis, we followed a series of preprocessing steps to ensure the dataset was clean and relevant. We began by eliminating irrelevant columns from the dataset, retaining only those that provided essential information for our classification task. Next, we focused on extracting only appropriate sentences that aligned with our objectives. To create our input-output pairs, we split sentences near the second noun, generating truncated versions labeled as (xi). We also applied standard preprocessing techniques, including removing special symbols, punctuation, and any empty rows that could interfere with the analysis. After we Additionally, we addressed any missing or incomplete data by removing rows that did not meet the necessary quality criteria, and droping every repeted or duplicate rows thereby ensuring that our dataset was robust and reliable.

2.1 Dataset curation appending xj and intent LLM label

After preprocessing the dataset to obtain properly formatted truncated sentences (xi), we proceeded to

utilize five distinct large language models (LLMs) to generate completions for our 3,500 input samples. The models employed for this task included BERT, DistilGPT-2, Flan-T5, GPT-Neo, and OPT. Each model produced a unique completion (xj) for every(xi), resulting in multiple completions per input. This process allowed us to compile a comprehensive dataset consisting of(xi,xj) (the generated completions), and labels indicating the originating LLM for each completion. After aggregating all the completions, our final dataset encompassed 17,500 samples, thereby enriching the data available for our classification task. The resultant output file included three columns: the original truncated sentences (xi), the respective completions (xj), and the labels identifying the LLM that generated each completion.

3 Releated works

3.1 Baseline model

Recent advancements in natural language processing (NLP) have been driven by transformer-based architectures, with significant contributions from models like BERT, GPT-2, T5, and newer variants such as GPT-Neo and OPT. These models, leveraging attention mechanisms, have become the backbone for various tasks, including text generation, sentence completion, and classification. In this section, we discuss the models employed in our work, alongside relevant research that has used these models for similar tasks.

3.2 BERT: Bidirectional Encoder Representations from Transformers

BERT (Bidirectional Encoder Representations from Transformers), introduced by Devlin et al. (2019), revolutionized NLP by introducing bidirectional training, where the model looks at both the left and right context in all layers. BERT has excelled in various downstream tasks such as question answering, sentiment analysis, and sentence completion due to its ability to deeply understand contextual embeddings. The fine-tuning of BERT on sentence completion tasks, as employed in our work, has demonstrated robust performance in capturing complex contextual information from input sequences. Several works have leveraged BERT for sentence-level prediction tasks. Joshi et al. (2021) explored sentence completion using BERT for its robust encoding of bidirectional context, achieving strong results on multiple completion benchmarks. Their findings highlight BERT's effectiveness in understanding sentence structure and grammar, which aligns with the sentence completion task undertaken in this project.

3.3 DistilGPT-2: Lightweight GPT for Efficient Text Generation

DistilGPT-2, a distilled version of GPT-2, was developed by Sanh et al. (2019) to reduce the size of the original model while maintaining most of its generative capabilities. The distillation process reduces computational cost, which is critical for resource-limited settings while retaining the original model's performance on generative tasks. DistilGPT-2 is widely used for text generation, sentence completion, and dialogue systems, where inference time is critical. In our experiments, DistilGPT-2 performed well on the text completion task, showing notable efficiency in comparison to larger models like GPT-Neo and OPT. Previous works such as Radford et al. (2019) have demonstrated the versatility of GPT models, especially in tasks like sentence generation, making DistilGPT-2 a suitable candidate for smaller scale, high-efficiency tasks.

3.4 Flan-T5: Fine-tuned Language Models for Multi-Task Learning

Flan-T5 is a fine-tuned variant of the T5 (Text-to-Text Transfer Transformer) model, introduced by Raffel et al. (2020). T5 reframes all NLP tasks as text-to-text problems, making it highly versatile for a range of tasks, including summarization, translation, and sentence completion. The Flan (fine-tuned language model) version benefits from instruction tuning across multiple tasks, allowing it to generalize well in multi-task settings. Wei et al. (2022) demonstrated the power of fine-tuned models like Flan-T5 in zero-shot and few-shot learning scenarios, further emphasizing its capabilities in multi-task NLP problems. In our experiments, Flan-T5 provided strong completions and generalizations, outperforming other models on certain aspects of language fluency and accuracy.

3.5 GPT-Neo: Open-Source Alternative to GPT-3

GPT-Neo, developed by EleutherAI, is an open-source language model similar in architecture to OpenAI's GPT-3. Black et al. (2021) highlighted the importance of GPT-Neo as an open-source alternative, trained on a large corpus, and demonstrated

its efficacy across a wide range of NLP tasks, including text generation, sentence completion, and few-shot learning. In our experiments, GPT-Neo performed competitively on text completion tasks, providing diverse outputs across contexts. Gale and Feizi (2022) have explored GPT models for classification tasks, highlighting their strengths in generative settings, further validating GPT-Neo's suitability for tasks that require both completion and generation.

3.6 OPT: Open Pretrained Transformers from Meta AI

OPT, developed by Meta AI, is a large-scale pretrained language model designed to provide an open-source alternative to GPT-3, with an emphasis on transparency and reproducibility. Zhang et al. (2022) introduced OPT as a competitive model capable of handling large-scale NLP tasks such as text generation and summarization.

In our work, OPT demonstrated robust performance across sentence completion tasks, producing contextually coherent and grammatically sound completions. Lin et al. (2020) explored the use of large-scale transformers like OPT in probing tasks, which aligns with the text generation tasks in our study. Across these models, transformer architectures have demonstrated the ability to handle a wide array of NLP tasks, including sentence completion, text classification, and generation. Each model presents unique strengths: BERT's bidirectional encoding, GPT-Neo's open-access generative power, Flan-T5's instruction tuning, and DistilGPT-2's lightweight efficiency, all contribute to different aspects of performance in NLP tasks. Our study builds on this work, applying these models to a unified task of sentence completion and classification, with comparative results analyzed through confusion matrices and performance metrics.

3.7 Optuna

Optuna is an open-source hyperparameter optimization framework, designed to automate the process of finding the best hyperparameters for machine learning models. It's particularly well-suited for deep learning models where the selection of optimal hyperparameters can significantly impact model performance.The user defines an objective function that takes a set of hyperparameters and returns a numerical score indicating the performance of a model trained with those hyperparameters. This score is usually a validation metric like accuracy, F1-score, etc. Within the objective function, Optuna's API is used to suggest values for hyperparameters. Optuna supports various types of hyperparameters such as categorical, numerical (both discrete and continuous), and even conditional hyperparameters.

Optimization Algorithm: Optuna uses a Bayesian optimization approach, specifically the Tree-structured Parzen Estimator (TPE) algorithm, to decide which hyperparameters to evaluate next. TPE models the probability of a hyperparameter set given the observed performances and selects new hyperparameters to minimize (or maximize) the objective function. Each iteration where the model is trained and evaluated with a particular set of hyperparameters is called a trial. A collection of trials is referred to as a study. Optuna supports both single-objective and multi-objective optimization studies. Optuna provides a feature called pruning, which stops a trial if it's unlikely to lead to a better result than the best trial so far. This saves computation time and resources.

3.8 BERT and ROBERTa Classifier

Recent advancements in natural language processing (NLP) have been significantly shaped by transformer-based architectures, particularly BERT and its derivatives like RoBERTa. BERT (Bidirectional Encoder Representations from Transformers), introduced by Devlin et al. (2018), set a new benchmark in various NLP tasks due to its unique approach of bidirectional training. This methodology allows the model to capture nuanced contextual relationships in text, proving effective in tasks such as question answering and text classification. Building on this foundation, RoBERTa, proposed by Liu et al. (2019), enhanced BERT's pretraining process by optimizing the training data and techniques, resulting in superior performance across standard benchmarks like GLUE and SQuAD. These models have inspired subsequent research exploring their capabilities in distinguishing between outputs generated by different LLMs. For instance, studies have demonstrated BERT's effectiveness in fine-tuning scenarios, particularly in sentence completion tasks, where its contextual understanding is critical (Joshi et al., 2021). Additionally, the application of hyperparameter tuning has been shown to further improve performance, illustrating the importance of optimization in deploying these models effectively.

Furthermore, the emergence of various LLMs necessitates robust classification methods to differentiate between their outputs. In this context, classifiers based on BERT have shown promise in not only generating coherent text but also in accurately identifying the source model responsible for a given text completion. Prior research has employed similar classification approaches to evaluate outputs from models like GPT-2 and T5, highlighting their strengths and weaknesses in generating contextually appropriate text (Sanh et al., 2019; Raffel et al., 2020). Moreover, the use of frameworks like Optuna for hyperparameter optimization has gained traction, allowing researchers to systematically enhance model performance in classification tasks (Akiba et al., 2019). The effectiveness of these deep learning approaches, combined with a thorough evaluation of performance metrics such as classification accuracy and F1 scores, contributes significantly to our understanding of LLM capabilities and limitations. Our study builds on this body of work, employing a BERT-based classifier to distinguish between completions generated by multiple LLMs, thus providing valuable insights into the evolving landscape of natural language generation.

4 Training

The training of the classifier model focused on leveraging the power of pre-trained transformers like BERT to classify sentence completions generated by five distinct LLMs. The goal was to fine-tune the classifier by optimizing key hyperparameters and ensuring generalization through early stopping and validation performance tracking.

4.1 Model Architecture

The architecture of the model is based on two BERT models, each independently processing the original sentence (xi) and the generated completion (xj), followed by concatenation of their respective outputs. This dual-input structure allows the model to capture the relationship between the input sentence and the generated completion, which is crucial for differentiating between completions from different models. The key components of the model include: Two BERT Encoder Layers: Separate BERT encoders were used for (xi)and (xj), initialized with pre-trained BERT weights from the Hugging Face library. Concatenation Layer: The pooler outputs from the BERT encoders were concatenated to form a combined representation of (xi) and (xj). Fully Connected Layer: The concatenated embeddings were passed through a fully connected layer, which maps the combined representation to the output classes (BERT, GPT-Neo, etc.). A dropout layer was included after concatenation to prevent overfitting. The dropout rate was optimized through hyperparameter tuning.

4.2 Training Setup

The model was trained on an NVIDIA A40 GPU using PyTorch. The Adam optimizer was employed to minimize the cross-entropy loss, a standard loss function for multi-class classification tasks. The learning rate, dropout rate, and batch size were carefully tuned to achieve the best possible performance. Early stopping was used during training to prevent overfitting. The model's validation loss was monitored, and training was halted if the validation loss did not improve for two consecutive epochs. Mixed precision training was utilized to improve memory efficiency and accelerate computations. The training process consisted of the following key steps: Forward Pass: Inputs (xi) and (xj) were independently encoded using BERT models. The pooler outputs were concatenated and passed through the classifier head. Loss Calculation: The cross-entropy loss between the predicted outputs and the true labels was computed. Backpropagation: The gradients of the loss function were computed and used to update the model parameters using the Adam optimizer. Validation: After each epoch, the model was evaluated on the validation set to assess its performance and check for improvements in validation loss and accuracy.

5 Experimentation

We performed hyperparameter optimization using Optuna, a state-of-the-art hyperparameter tuning library. The following hyperparameters were tuned: Learning Rate: We explored a range of learning rates between 1e-5 and 5e-5. The final learning rate was set to 2.73e-5, which offered the best trade-off between speed of convergence and model generalization. Dropout Rate: The dropout rate was varied between 0.1 and 0.4 to reduce overfitting. The best-performing dropout rate was 0.31, which was selected based on validation accuracy. Batch Size: We experimented with batch sizes of 16, 32, and 64. A batch size of 32 was selected as it provided a good balance between computational efficiency

and model performance. Optuna used a Bayesian optimization strategy to search the hyperparameter space. Each trial in the optimization process involved training the model with a specific combination of hyperparameters, after which the performance was evaluated using the validation set. The hyperparameters yielding the lowest validation loss and highest accuracy were chosen for the final model.

6 Results

The results of the training process demonstrated the effectiveness of the BERT-based classifier in distinguishing between sentence completions from different LLMs. Below are the key results:

Training Accuracy: The model achieved a training accuracy of 96.7% after the fourth epoch, indicating that it successfully learned to classify the completions during training. Validation Accuracy: The best validation accuracy recorded was 89.5%, with a corresponding validation loss of 0.3176. The training was halted after four epochs due to early stopping, as validation loss plateaued. Confusion Matrix: The confusion matrix generated on the validation set revealed that the model had high precision and recall for completions generated by BERT, Flan-T5, and OPT. However, the model encountered some difficulty in distinguishing between completions from DistilGPT-2 and GPT-Neo.

6.1 Model Saving and Testing

The best-performing model (with the lowest validation loss) was saved after each epoch, allowing us to retain the most accurate model. After the final epoch, the model was evaluated on a random subset of 700 samples from the unseen dataset. The evaluation process yielded an overall test accuracy of 87%, with a weighted F1-score of 0.87, as detailed in the test set evaluation section of this paper.

The confusion matrix for the test set is shown in Figure 1, and it demonstrates strong performance across all classes, with the highest accuracy in predicting BERT and Flan-T5 completions.

7 Discussion

The results of our experiments demonstrate that transformer-based models can effectively classify completions generated by different large language models (LLMs). The combination of two independent BERT encoders for the original sentence and the generated completion allowed the model to capture the contextual differences between the completions produced by BERT, DistilGPT-2, Flan-T5, GPT-Neo, and OPT.

BERT and Flan-T5 consistently produced completions that were easily distinguishable from the other models. This is likely due to their advanced contextual understanding and pre-training on a wide variety of tasks. The model had the highest accuracy in identifying completions from these two LLMs, as evidenced by their high precision and recall scores in the classification report. On the other hand, completions generated by DistilGPT-2 and GPT-Neo were occasionally misclassified, particularly with respect to each other. This suggests that these models produce somewhat similar outputs, potentially due to their shared generative architecture and smaller sizes compared to full-scale LLMs like GPT-3. As a result, the classifier faced challenges distinguishing their completions with absolute certainty.

Hyperparameter tuning using Optuna was essential in refining the model's performance. The optimized dropout rate of 0.31 and learning rate of 2.73e-5 were crucial in preventing overfitting and ensuring generalization to the validation set. Early stopping was effective in ensuring that the model did not overtrain, with validation loss consistently monitored after every epoch. The use of mixed precision training also helped to significantly reduce memory overhead during training, allowing the model to be trained efficiently on a GPU.

Overall, the combination of these techniques led to a robust model capable of achieving 87% accuracy on the test set, with high F1-scores across all five classes.

8 Conclusion

In this work, we successfully developed a BERT-based classification model that can accurately predict which LLM generated a given text completion. By using separate BERT encoders for the original sentence and the completion, we enabled the model to capture intricate contextual relationships between input and output pairs. The model performed strongly across all five LLMs, particularly excelling in distinguishing completions generated by BERT and Flan-T5.

The results demonstrate that transformer-based architectures are well-suited for this type of classification task, where the challenge lies in identifying subtle stylistic and contextual differences in gener-

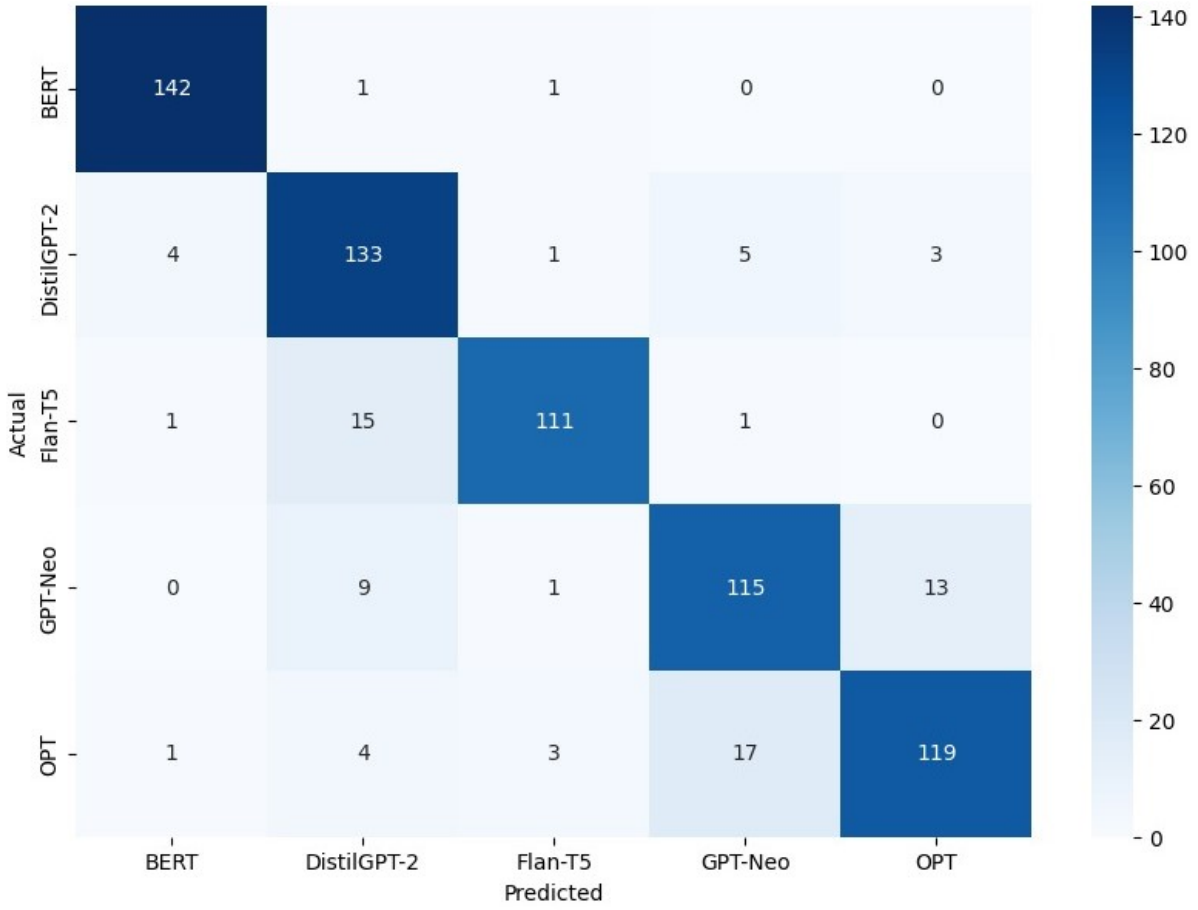

Figure 1: accuracy result for all tested model

ated completions. The validation and test accuracies indicate that the model is highly effective at generalizing to unseen data, making it a promising approach for tasks involving model attribution or text completion evaluation.

9 Future Work

While our model achieved high accuracy and performed well on the classification task, there are several areas for future research. One potential improvement would be to explore additional LLMs beyond the five used in this study, including models like RoBERTa, T5, or even GPT-3. Incorporating these models could provide more diversity in the generated completions and further challenge the classifier.

Additionally, fine-tuning the pre-trained BERT models used for xi and xj on specific tasks related to text completion could enhance the model's ability to differentiate between the completions of similar LLMs. For instance, task-specific fine-tuning or domain adaptation could be explored to make the classifier more robust to subtle variations in completions.

Another interesting direction for future work could involve multi-modal inputs, where the classifier takes into account additional metadata, such as the length of the completions or the nature of the task that generated the completion (e.g., summarization, translation). These additional features could provide a richer input space, potentially improving classification accuracy.

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