Project Proposal

Team Name: Fine-tuners

Group members
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Project Title: Evaluating The Effectiveness Of Fine-tuning Approaches in LLMs

Project Summary

Language Models like ULMFiT [2], GPT-2 [3], and BERT [4] have demonstrated the remarkable effectiveness of fine-tuning pre-trained models in natural language processing tasks. Before that, using pretrained models was only the norm in computer vision; in the context of NLP, pretraining was limited to word embeddings. Fine-tuning these models is important as it allows for specialization of these general models for specific tasks. However, with the explosion in model sizes, fine-tuning the models is becoming prohibitively expensive. Parameter efficient fine-tuning techniques like LoRA [1] were invented to mitigate this issue.

In this project, we survey the effectiveness of LoRA fine-tuning approaches for several down-stream NLP tasks. We want to produce a practical guide in fine-tuning language models with respect to the fine tuning technique, task, and hyperparameters.

We think that this project is important and interesting because 1) parameter-efficient fine-tuning is the only practical way to harness the power of LLMs when faced with limited compute resources; 2) it gives us the opportunity to gain first-hand experience of working with Transformer-based architectures.

What will we do

This project involves analysis along the following four dimensions:
1) Fine-tuning the full-model vs LoRA fine-tuning.
2) Fine-tuning different parts of the model to compare effectiveness. For example, fine-tuning only the last Transformer block vs the last-two Transformer blocks and so on.
3) Study the effects of hyperparameters when doing LoRA fine-tuning. Specifically, analysis of the LoRA rank, number of layers with LoRA enabled, optimizers, and learning rate schedules.
4) Comparing the effectiveness of different fine-tuning approaches on different down-stream tasks. Specifically, which fine-tuning method is the best for classification, instruction tuning, sentiment-analysis, and natural language entailment.

The tasks in this project will involve:

- Implementing the GPT-2 architecture, and loading the pretrained weights into this. There are resources available in Hugging Face that allow us to do this [6].
    - Implementing the GPT-2 architecture will allow us to 1) learn about implementing an LLM; 2) give us flexibility to adapt the model for different tasks by replacing the output layer; 3) enable us to create a LoRA version of the architecture.
    - We picked GPT-2 since 1) it is part of one of the most popular model families out there, and 2) with O(300M) it can be trained on a single Colab GPU, unlike Llama 3.
- Implement LoRA GPT-2 by replacing Linear layers with LoRA-Linear layers.
- Implement the dataset preparation code and the training loop for fine-tuning.
- Do exhaustive experiments by fine-tuning both full-model and LoRA-model on the four NLP tasks. The experiments will be along the dimensions laid out above.

Stretch goal:
- Implement DPO Preference fine-tuning.
- Carry out experiments on above dimensions on the preference fine tuning task.

Datasets
The work is divided so that each group member works on a single NLP task. This way, there will be less dependencies and blocking.
- Instruction fine tuning: Stanford Alpaca [5]
    - Metric: Perplexity. Stretch goal: External LLM judge.
    - Dataset link: https://github.com/tatsu-lab/stanford_alpaca
    - Owner: Adit Rada
- Classification: UC Irvine: SMS Spam Collection [13]
    - Metric: Accuracy. Goal: Classify: spam SMS.
    - Dataset link: https://doi.org/10.24432/C5CC84
    - Owner: Khanh Nguyen
- Sentiment Analysis: Large Movie Review Dataset [14]:
    - Metric: Accuracy. Goal: Classify text as positive or negative in sentiment.
    - Dataset link: https://ai.stanford.edu/~amaas/data/sentiment/
    - Owner: Feras Alsaiari
- Natural Language Entailment: Medical Judgement Analysis
    - Metric Accuracy: Goal: classify if given a text, determine if a follow-up hypothesis is entailed/neutral/contradicted
    - Dataset link: https://huggingface.co/datasets/presencesw/all_nli_med_v1
    - Owner: Quinn Nguyen

Resources
A substantial amount of work has been done demonstrating the effectiveness of fine-tuning LLMs for various tasks [2, 3, 4]. Work has also been done to show the effectiveness of LoRA in matching the performance of full-model fine-tuning [1]. We have come across experiments investigating LoRA [8, 10], but they lacked comparison of LoRA across different NLP tasks. There was a Google paper [12] comparing LoRA across different NLP tasks, but this was only in

the context of RLHF. In this project, we want to combine the work of Sebastian Raschka [8, 10], and Hakim Sidahmed et al [12] by investigating LoRA (hyperparameter analysis, and full-fine tune comparison), and comparing its performance across several tasks.

[1]: LoRA paper: https://arxiv.org/abs/2106.09685
[2]: ULMFiT paper: https://arxiv.org/abs/1801.06146
[3]: GPT-2 paper: https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf
[4]: BERT paper: https://arxiv.org/abs/1810.04805
[5] Stanford Alpaca: https://github.com/tatsu-lab/stanford_alpaca
[6] Hugging Face GPT-2: https://huggingface.co/docs/transformers/en/model_doc/gpt2
[7]: Sebastian Raschka, Fine Tuning Large Language Models: https://magazine.sebastianraschka.com/p/finetuning-large-language-models
[8]: Sebastian Raschka, Practical Tips for Fine Tuning LLMs Using LoRA: https://magazine.sebastianraschka.com/p/practical-tips-for-finetuning-llms
[9]: Hugging Face, LoRA: https://huggingface.co/docs/peft/main/en/conceptual_guides/lora
[10]: Sebastian Raschka, Fine Tuning LLMs with LoRA and QLoRA: Insights from Hundreds of Experiments: https://lightning.ai/pages/community/lora-insights/
[11]: Jay Alammar, The Illustrated GPT-2: https://jalammar.github.io/illustrated-gpt2/
[12]: Hakim Sidahmed, Parameter Efficient Reinforcement Learning from Human Feedback: https://arxiv.org/abs/2403.10704
[13] Almeida, Tiago and Jos Hidalgo. "SMS Spam Collection." UCI Machine Learning Repository, 2011, https://doi.org/10.24432/C5CC84
[14] Maas, A. L., Daly, R. E., Pham, P. T., Huang, D., Ng, A. Y., & Potts, C. (2011). Learning word vectors for sentiment analysis. Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, 142-150. https://doi.org/10.3115/1626353.1626370