Project Proposal for Efficient LLM Supervised Fine-Tuning

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1 Project Title

Efficient LLM Supervised Fine-Tuning: long dialogue conversations

2 Project Summary

Large Language Models (LLMs) have demonstrated remarkable capabilities in knowledge extraction and reasoning, particularly through in-context learning. However, this approach often requires long context windows, leading to substantial memory demands. Our project aims to explore alternatives to in-context learning, focusing on efficient supervised fine-tuning techniques. By investigating methods like context distillation, we seek to enhance LLMs' performance on tasks involving long dialogues, large document comprehension, and extensive code completion, without the need for costly retraining or large-scale fine-tuning. This research could significantly impact the field by making LLMs more adaptable and resource-efficient across various applications.

3 Approach

We will compare the context-distillation method to traditional fine-tuning approaches and also evaluate its performance against the in-context learning (ICL) approach. The key components of our methodology are outlined below.

1. Model Selection: Depending on the compute resources available, different pre-trained large language models (LLMs) model sizes can be selected. Baselines are available from the **OPT model family** with various sizes: opt-125m, opt-350m, opt-1.3b, opt-2.7b, opt-6.7b, opt-13b, and opt-30b. In addition, other model families like **GPT-3**, **T5**, or **LLaMA** variants will be used based on the requirements of the experiments.

All code and benchmarks are open-source and available at https://github.com/uds-lsv/llmft.

2. Dataset: Information about datasets is available in the GitHub repository:

3. Evaluation Approaches: To compare context-distillation, fine-tuning, and in-context learning (ICL) effectively, we will use the following approaches:

Training Procedure: Context Distillation: Implement the context-distillation approach as described by Anthropic, where the model is fine-tuned on prompts to make its output consistent without directly needing the prompt during inference.

Alternative Fine-Tuning:

- Vanilla Fine-Tuning: Fine-tune the entire model with a randomly initialized classification head on top of the pre-trained decoder.
- Pattern-Based Fine-Tuning (PBFT): Use the pre-trained language modeling head for classification tasks.

Parameter-Efficient Techniques:

- BitFit: A parameter-efficient method that fine-tunes only the bias terms, significantly reducing the number of trainable parameters.
- LoRA (Low-Rank Adaptation): Introduce low-rank matrices to adapt the weights of the pre-trained model, fine-tuning only these matrices to lower computational requirements.

4. Metrics:

- Compare in-domain and out-of-domain accuracy, as presented in relevant papers.
- Execution time and memory consumption.

4 Resources / Related Work & Papers

The state-of-the-art for this problem is represented by several key papers and approaches:

- "Few-shot Fine-tuning vs. In-Context Learning" (ACL 2023) compares fine-tuning to in-context learning for task adaptation.
- BitFit (Zaken et al., 2021) and LoRA adapters (Hu et al., 2021) provide parameter-efficient fine-tuning methods that we'll consider in our comparisons.

These works provide a strong foundation for our research, offering various approaches to efficient model adaptation that we can build upon and compare against.

5 Datasets

For this project, we plan to source via https://github.com/uds-lsv/llmft loaded from hugging face GLUE datasets https://huggingface.co/datasets/nyu-mll/glue. This repository includes various datasets that can be used for training and evaluation of large language models (LLMs).

Specifically, for training purposes, we plan to choose one or multiple from the following datasets:

- RTE
- MNLI
- QQP
- CoLA

For model evaluation, we plan to choose from one or multiple from the following as validation data:

- HANS
- PAWS-QQP
- CoLA-OOD

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