Tech Review Assignment

Tags

Intro

In this article I will be giving an overview of how cutting edge chat based language models such as GPT-4, LLaMA 2 have been trained, what the different modes of training add to the model, and research that has come out that will enable organizations without Microsoft, Meta level resourcing to also be able to train these models. I will first go into what made models like GPT-4 so disproportionately capable, then look at LIMA, which was a model trained by a group of researchers which allowed us to understand what skills each phase of training was helping the model attain.

How do we get to a Large Language Model

The are three phases that are in most language models training end to end. Once the architecture of the model is finished. The below steps are run in order before these models are vended for use. The difficulty of the model training stems from a wide variety of factors, ranging from model size to the underlying framework that is being used, but the three phases are usually the same.

What is LIMA

The researchers investigate the comparative significance of pre-training and alignment by conducting a study on LIMA, which is a modified version of LLaMA-65B . LIMA undergoes SFT (without RLHF) across a curated alignment dataset. Notably, the fine-tuning set employed in LIMA consists of a concise collection of 1,000 meticulously chosen prompt-and-response examples, characterized by a consistent output style and diverse inputs.

Unsupervised Training

The first phase is unsupervised fine tuning based on a huge corpus of data. The language models are trained to predict the next word in a sentence without any specific guidance. This is called the language model training objective. This helps the model learn grammar, syntax, and context from the vast amount of text it is exposed to. The LIMA paper has discovered that this step is where the model learns all of the knowledge. It does not yet know how to **express that knowledge** in a way that aligns with humans, but the knowledge is encoded nevertheless.

Supervised Training

SFT, or Simple Fine-Tuning, is a straightforward alignment method wherein we procure instances of the desired behavior and directly fine-tune the Large Language Model (LLM) using a language modeling objective on this data. To illustrate, if the goal is to instruct a base LLM to follow directions, a multitude of instances with precise responses to instruction-based prompts can be collected to train the base model. This technique, emphasized in this overview, is both uncomplicated and potent. Nevertheless, achieving optimal results with SFT hinges on the meticulous curation of a high-quality dataset.

RLHF

RLHF empowers us to fine-tune the parameters of a Large Language Model (LLM) based on feedback from humans. Here's how it works: starting with a set of prompts, we let the LLM generate multiple potential outputs for each. After that, we involve human annotators who rank the quality of these responses, essentially choosing the "best" one. These rankings are then used to train a reward model—a smaller LLM that predicts human preferences based on a model's response. This reward model's output serves as a scalar reward, and we optimize the LLM to maximize this reward using the Proximal Policy Optimization (PPO) algorithm. This process allows RLHF to capture a variety of human preferences and guide the model toward improved performance.

Alignment vs Knowledge Gain

The findings from the LIMA paper reveal that alignment occurs in both the Supervised Training and RLHF loops, while knowledge acquisition takes place during the Unsupervised Training phase. Notably, LIMA diverges by not employing an RLHF loop, which relies on a relatively intricate Reinforcement Learning technique called PPO. This method is data-intensive, acting as a potential entry barrier for model creation.

Despite forgoing RLHF, LIMA achieves GPT-4-level performance solely through the use of SFT, a practice widely adopted by AI practitioners for years. The key insight lies in the realization that the data fed into the SFT pipeline must be meticulously curated and diverse to attain satisfactory levels of performance.

Custom Model Building and Trainings

Numerous organizations possess custom and proprietary knowledge bases that they aspire to leverage for training Large Language Models (LLMs). However, the substantial costs and extensive resources associated with such endeavors often act as prohibitive factors, deterring many organizations from pursuing this path. LIMA presents a promising solution to this challenge by demonstrating that it is feasible to take a base model like LLaMA, which has undergone computationally intensive unsupervised training on an internet-level corpus, and repurpose it for domain-specific knowledge. By training the model on a proprietary knowledge base and subsequently running a relatively cost-effective Simple Fine-Tuning (SFT) loop, organizations can attain highly performant Generative AI solutions that exhibit a profound understanding of their proprietary knowledge, all without incurring the extensive resource investments typically associated with such endeavors. This approach offers a practical and efficient means for organizations to harness the power of large language models tailored to their specific domains.

Tools for Custom Fine Tuning

Hugging Face

Hugging Face, a leading platform in the field of natural language processing, provides a versatile environment for training custom language models from scratch. Leveraging Hugging Face's powerful Transformers library and user-friendly interfaces, developers can seamlessly integrate and fine-tune models like LLama for specific tasks and domains. Through Hugging Face's extensive collection of pre-trained models and convenient tools, the process of training a custom model becomes more accessible. Users can take advantage of LLama (just like the LIMA creators did) as a starting point, benefiting from its pre-trained weights and then fine-tuning the model on a domain-specific dataset using Hugging Face's training pipelines. This approach allows for the efficient creation of tailored language models with reduced complexity and resource requirements, making advanced natural language processing capabilities accessible to a broader range of developers and organizations.

Mosaic ML

The platform streamlines the process of fine-tuning these models on specific tasks or domains, enabling users to harness the capabilities of LLama while tailoring it to their unique requirements. Mosaic ML is also a fully managed platform that lets you target any cloud, and automatically applies the latest research in LLM training to speed up your training process.

Conclusion

In conclusion, the LIMA paper stands as a pivotal contribution in unraveling the intricacies of training Large Language Models (LLMs) like LLaMA and GPT-4, shedding light on the reasons behind their remarkable performance. The insights gained from this study have ushered in newfound efficiencies in the training pipeline, significantly broadening the accessibility of LLM training. This breakthrough empowers organizations and individuals to embark on the creation of models tailored to understand custom knowledge bases. The democratization of LLM training not only fosters innovation but also opens up exciting possibilities, allowing individuals to craft their own personalized virtual assistants. The implications of this research extend far beyond the academic realm, promising a future where advanced language models are not just the domain of large institutions but are accessible tools for diverse applications and individual creativity.

References

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