Cross-Instruction: Improving Pretrained Language Models using Domain Expert Models

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1 INTRODUCTION

General-purpose Language Models (LMs) have made remarkable advancements in generating coherent and contextually relevant text. However, these models often lack domain-specific knowledge and may not perform optimally in specialized contexts [10, 12]. Gathering domain-specific instructions from human experts can be a costly and time-consuming process, making it challenging to develop LMs with expertise in multiple domains. Recent research by Wang et al. [21] explore an alternative approach to instruction tuning by leveraging LMs to generate the instructions themselves. This method, known as self-instruction, shows promise in aligning LMs by utilizing their own generated instructions. Motivated by the potential of self-instruction as a cost-effective and scalable technique for aligning LMs with domain-specific knowledge, we introduce *Cross-Instruction*, a novel procedure that leverages the expertise of domain-specific models to transfer their knowledge to a general-purpose LM. By incorporating domain-specific knowledge into the model, we can enhance its adaptability and performance in various specialized contexts. Expertise in specialized domains is often limited to a small group of individuals or organizations, making it challenging to access and leverage such knowledge effectively. Traditional instruction tuning methods rely on human experts to manually create instructions, which can be prohibitively costly and time-consuming in domains with limited available expertise. By employing self-instruction techniques, we can leverage existing domain-specific models as instructors, enabling the transfer of rare and expensive domain knowledge to a general-purpose LM. This approach offers a more efficient and cost-effective way to incorporate domain expertise into the model, bypassing the need for extensive manual instruction creation.

To address this challenge, we propose a methodology that leverages multiple instructor models, each specialized in different domains, to provide a broader and more diverse range of instructions for the self-instruction process. By aggregating knowledge from multiple sources, we aim to enhance the domain expertise and overall performance of the resulting LM.

Our primary contributions are as follows:

(1) We create and publish a new synthetic dataset specifically designed for the self-instruction process, focusing on rare and domain-specific knowledge. The dataset is generated in three different sizes, allowing us to investigate the impact of dataset scale on the resulting LM.
(2) We propose a methodology that leverages multiple instructor models, each specialized in a different domain, to provide domain-specific instructions for the self-instruction process.
(3) We evaluate the performance of the resulting LM and compare its performance with commonly used LMs on various benchmarks.

2 RELATED WORK

In this section, we discuss the related work on generative LMs, instruction tuning, and knowledge distillation. Finally, we briefly touch upon the criticism of the self-instruction process and its relevance to our work.

2.1 Generative Language Models

Generative LMs have been at the forefront of natural language processing (NLP) research. The breakthrough in this field came with the introduction of the Transformer architecture [20]. This architecture allows for efficient processing of sequential data, leading to significant advancements in generative language modeling. Prominent among the generative LMs are the GPT series, including GPT-1 to GPT-4. These models, known for their simplicity yet powerful performance at a large scale, have been instrumental in various NLP tasks [2, 13, 15, 16]. Another notable model is LLaMA which comprises a collection of foundation LMs ranging from 7B to 65B parameters [19].

In addition to general-purpose LMs, there has been significant progress in developing domain-specific LMs. For example, BioGPT is a LM specifically designed for the biomedical domain, enabling researchers to generate biomedical texts with improved domain relevance [12]. Similarly, StarCoder focuses on code generation for multiple programming languages, aiding developers in automating code writing tasks [10].

2.2 Instruction Tuning

Instruction tuning techniques have emerged as a means to enhance the performance and adaptability of generative LMs. These techniques involve fine-tuning models based on instructions or demonstrations. InstructGPT utilizes reinforcement learning from human feedback (RLHF) to fine-tune GPT-3. By leveraging RLHF, InstructGPT produces 1.3B parameter models whose outputs are preferred over those generated by the larger 175B GPT-3 model [14]. Another approach to instruction tuning is self-instruction, as demonstrated by Wang et al. [21]. This approach enhances the model by generating instructions using the vanilla model and subsequently training it to adhere to those instructions. ALPACA [18] is a fine-tuned model derived from a 7B LLaMA model [19], using 52K instruction-following data generated by the Self-Instruct techniques. The objective of ALPACA is to develop a robust and cost-effective model, enhancing the capabilities of LLaMA within a budget constraint of less than $600. Other notable works include OpenAssistant [9], an supervised-fine-tuning (SFT) model based on Pythia 12B [1], and Vicuna, an open-source chatbot trained by fine-tuning LLaMA on user-shared conversations [5].

2.3 Knowledge Distillation

Knowledge distillation is a technique where a model is trained to mimic the behavior and outputs of another model, often referred to as the teacher model [6, 8]. In the context of instruction tuning, knowledge distillation can be seen as transferring the knowledge or expertise of a pretrained model to improve the performance of another model. By leveraging the knowledge acquired by the teacher model, the student model can learn from its outputs and generate more accurate and contextually appropriate responses.

2.4 Criticism of the Approach

While instruction tuning has shown promising results in improving the capabilities of LMs, there have been criticisms and limitations associated with this approach.

LIMA (Less Is More for Alignment) [23] highlights the importance of quality over quantity in instruction tuning. It argues that the effectiveness of instruction tuning methods can be significantly improved by focusing on generating high-quality instructions rather than increasing the quantity of training data.

"The False Promise of Imitating Proprietary LLMs" [7] discusses the limitations of imitating proprietary LMs using weaker open-source models. It suggests that there exists a substantial capabilities gap between open and closed LMs, and simply imitating the style of a proprietary model may not guarantee similar factuality or performance. The paper emphasizes the need for developing better base LMs as the most effective strategy for improving open-source models, rather than relying on imitation techniques.

3 MODELS

In this section, we describe the models used in our approach, including the LM for training and the domain-specific models for instruction generation.

Base Model: To train our LM, we utilize the LLaMA-65B model [19]. LLaMA-65B is a large-scale LM with 65 billion parameters that is openly available for research purposes. We choose this model as our base LM due to its extensive capacity and proven performance in various natural language processing tasks.

General Instruction Model: For generating general instructions during the self-instruction process, we employ the GPT-4 API[1] as our general instruction model. GPT-4 is a powerful LM that can generate coherent and contextually relevant text.

Domain Expert Models: In order to incorporate domain-specific knowledge into our LM, we employ two domain expert models: Starcoder and BioGPT.

Starcoder [10]: The Starcoder model is a domain-specific LM designed specifically for code generation across multiple programming languages. It leverages its expertise in code-related tasks.

BioGPT [12]: BioGPT is a domain-specific LM that focuses on the biomedical domain. It has been trained on a large corpus of biomedical literature and exhibits strong performance in understanding and generating text specific to biomedical concepts and terminology.

4 EXPERIMENTAL APPARATUS

4.1 Datasets

For evaluation purposes, we utilize several benchmark datasets that cover both general instructions and domain-specific tasks. These datasets include:

- **Super-NaturalInstructions [22]:** This benchmark dataset contains 1,616 diverse NLP tasks accompanied by expert-written instructions. It serves as a general instruction benchmark.
- **HumanEval [4]:** This dataset consists of 164 samples of Python code, each accompanied by hand-written instructions.
- **MultiPL-E [3]:** Building upon the HumanEval dataset, MultiPL-E extends the evaluation to 18 programming languages.
- **MedNLI [17]:** This dataset contains 14,049 unique sentence pairs, annotated by medical professionals. It serves as a domain-specific benchmark in the biomedical domain.

By utilizing these benchmark datasets, we can evaluate the LM's performance on both general and domain-specific tasks.

4.2 Assumptions

(1) **Strong Overall Capability of Large Language Models (LLMs):** We assume that large language models, such as GPT-4 and LLaMA, possess a strong overall capability that enables them to generate high-quality instructions, identify the appropriate domain model in a few-shot setup, and effectively learn new content that was not extensively present during the pretraining phase. This assumption forms the basis for leveraging the self-instruction process and integrating domain expertise into the LM.

(2) **Domain Models' Domain-specific Superiority:** We assume that domain models are stronger within their respective domains compared to general models. This is because domain models are specifically trained and fine-tuned on domain-specific data, enabling them to possess a deeper understanding and expertise in their designated domains.

4.3 Procedure

To develop and evaluate our approach, we follow the following procedure:

(1) **Dataset Creation:** We start by creating datasets that encompass a wide range of domain-specific tasks. We incorporate three different domains: general, biomedical, and code generation. For each domain, we collect a seed set of tasks and their corresponding domain labels.

(2) **Training LLaMA:** LLaMA-65B is trained on the generated datasets, and we iterate the process of dataset creation and LLaMA training across three different dataset sizes. This iterative approach allows us to investigate the influence of dataset scale on the model's performance.

(3) **Evaluation:** We evaluate every LM performance on both general and domain-specific benchmark tasks: Super-NaturalInstructions [22], HumanEval [4], MultiPL-E [3] and MedNLI [17].

To generate the necessary data for training, we set up the following data creation pipeline:

(1) We start with a seed of tasks and their corresponding domains (e.g., general, bio, code) to form the task pool.

(2) Using the task pool, we employ a general instruction model, which in our case is the GPT-4 API, to generate a set of instructions.

(3) Based on the task pool, the general instruction model identifies the appropriate domain model to generate the response or instance in a few-shot setup with 10 examples.

(4) The selected domain model then generates the response or instance based on the provided instruction and task.

[1] https://platform.openai.com/docs/models/gpt-4

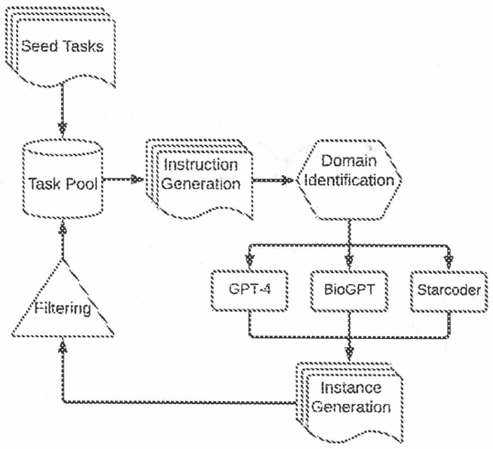

Figure 1: An illustration of the dataset creation procedure. The steps marked in red are performed by the general instruction model, while the steps marked in green are carried out by domain expert models

(5) After generating the instructions, we apply the quality filtering procedure proposed by Wang et al. [21] to ensure the inclusion of high-quality instruction-answer pairs.

The steps (2) to (5) are repeated iteratively until the desired number of instruction-answer pairs is generated, which in our case is 5,000, 52,000, and 100,000 instruction-answer pairs. An illustration of this can be seen in Figure 1.

4.4 Metrics

To evaluate the performance of our LMs, we employ the Recall-Oriented Understudy for Gisting Evaluation (ROUGE) metric, specifically ROUGE-L [11]. ROUGE is a widely used metric in the field of natural language processing for assessing the quality of generated text. ROUGE-L measures the longest common subsequence of words between the generated text and the reference text. It focuses on capturing the recall aspect of the generated text by evaluating the overlapping content with the reference text.

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