Improving General Purpose Language Models using Self-Instruction with Domain Knowledge Models

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CCS CONCEPTS

• **Information systems → Language models**; • **Computing methodologies → Natural language generation**.

KEYWORDS

LLM, NLP, instruction-tuning, self-instruction

1 INTRODUCTION

Although general purpose language models have demonstrated impressive language generation capabilities, they have limitations in some contexts. Manually creating instructions for tuning takes time and money. However, recent research by Wang et al. [2] revealed that language models could be used to generate these instructions. In this paper, it is proposed that large language models could be utilized to transform domain-specific skills into general purpose language models via self-instruction. We desire to develop a versatile and affordable language model that performs well across a few domains without requiring extensive human-created instructions by transferring domain model expertise.

1.1 Motivation/Scenario

1.2 Problem Statement/Problem Formalization

1.3 Contribution and Organization of the Work

1.4 Organization

Below, we summarize the related works. Section 3 provides a problem statement and introduces our models/methods. The experimental apparatus is described in Section 4. An overview of the achieved results is reported in Section **??**. Section **??** discusses the results, before we conclude.

2 RELATED WORK

just a rough outline

2.0.1 *Self-Instruct [2].* :

Refining model performance through instruction tuning, utilizing instructions generated by the vanilla model itself.

2.0.2 *ALPACA.* [1]:

Developing a robust and cost-effective model, incorporating self-instruction techniques and utilizing GPT-4 API calls, to enhance LLaMA (7B) capabilities within a budget of under $600.

2.0.3 *InstructGPT [1].* : InstructGPT uses reinforcement learning from human feedback (RLHF) to fine-tune GPT-3. The resulting 1.3B parameter model outputs are preferred to outputs from the 175B GPT-3.

[1]https://crfm.stanford.edu/2023/03/13/alpaca.html

3 METHODS

3.1 [Problem Statement/Problem Formalization]

3.2 Assumptions

We assume that the reality lies somewhere between Hypothesis 1 and Hypothesis 2. As our setup provides advantageous for the language model in exactly this scenario.

Hypothesis 1. *Instruction-tuning holds significance in the context of language models because it enables them to acquire knowledge about topics or aspects that were not fully covered during the pre-training phase.*

Hypothesis 2. *Language models are already well-acquainted with instructions due to their pre-training. As such, instruction-tuning serves as a straightforward technique to bring their pre-training distribution/objective in alignment with the specific task at hand.*

3.3 Summary

4 EXPERIMENTAL APPARATUS

4.1 Datasets

4.1.1 *Super-NaturalInstructions [3].* : Super-NaturalInstructions is a benchmark of 1,616 diverse NLP tasks and their expert-written instructions

add domain specific benchmarks like CodeSearchNet for code or MedNLI

4.2 Preprocessing

4.3 Procedure

create datasets
test different number of models that generate data
test different dataset sizes??
evaluate on benchmarks

4.4 Hyperparameter Optimization

4.5 Metrics

Recall-Oriented Understudy for Gisting Evaluation (ROUGE), a common metric used in related research, will be used in the form of ROUGE-L.

Alternatively, BLEU or ImaginE would also fit, but is not used in the corresponding literature.
ImaginE: https://arxiv.org/abs/2106.05970?s=33

REFERENCES

[1] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. In *NeurIPS*. http://papers.nips.cc/paper_files/paper/2022/hash/b1efde53be364a73914f58805a001731-Abstract-Conference.html