Building Coding LLMs for Low, Mid-Resource and Proprietary Languages with Multi-Granular Instruction Tuning and AI-Guided Feedback

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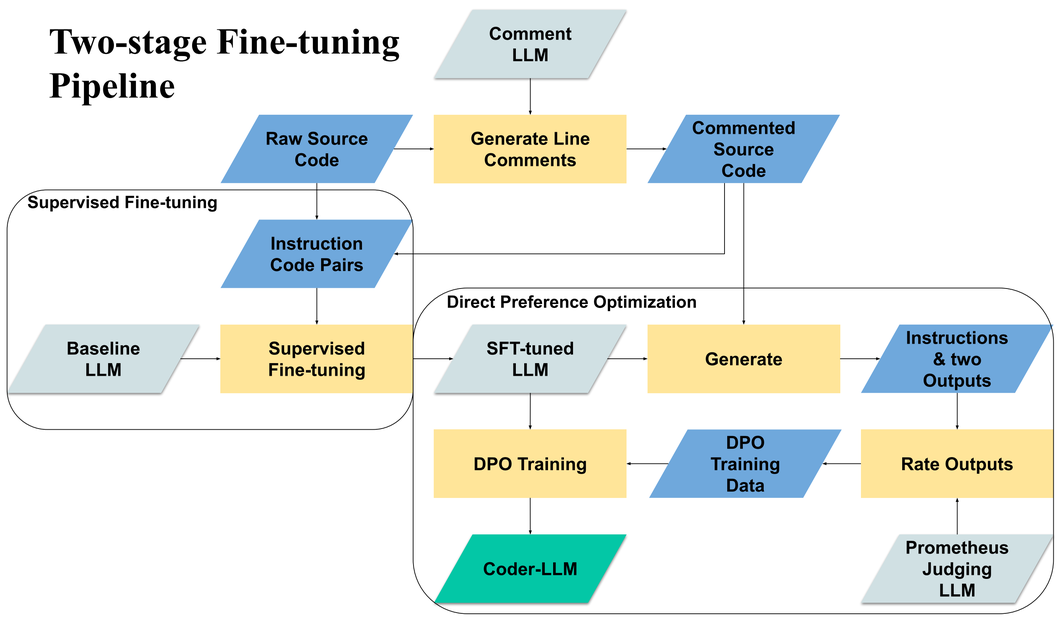
Abstract

Large Language Models (LLMs) have significantly advanced automatic code generation for popular general-purpose programming languages. However, their performance degrades on low-resource and 'proprietary' Domain Specific Languages (DSLs) due to scarce training data. We propose a fully automated pipeline to adapt coding LLMs with parameter-efficient Q-LoRA to 'proprietary', low-resource languages. Our method consists of two stages: (1) we synthesize multi-grained instructions directly from raw code by generating code-comment pairs. These instructions are used for Supervised Fine-Tuning (SFT); (2) we perform Reinforcement Learning with AI Feedback (RLAIF), where a commenting LLM produces entirely new, synthetic instructions, and our SFT model samples two outputs. A judging LLM selects a preference, and we subsequently optimize the model with Direct Preference Optimization (DPO). Results show that our approach improves instruction-following and code quality across languages, demonstrating strong generalization even with limited data and no execution infrastructure at hand.



Methodology

- Chat-based LLM based on Qwen2.5-7B-Coder-Instruct [1]
- Two-stage training process:

1. **Supervised Fine-tuning (SFT)**
   - Generate comments for code blocks
   - Create instructions with comments and original code
   - Apply supervised fine-tuning using Q-LoRA
2. **Direct Preference Optimization (DPO) with Reinforcement Learning with AI Feedback (RLAIF)**
   - Create new instructions with SFT model
   - Output candidate pairs
   - Prometheus v2 [2] judging LLM evaluates outputs based on grading rubrics
   - DPO with Prometheus choices applied to create the final model

How can we best adapt coding LLMs to low-resource, proprietary programming languages with lightweight fine-tuning approaches?

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Grading Rubrics [2]	Description of Rubric
Correct	Is the code that is generated correct, and does it work?
Formatted	Is the code that is generated well-formatted, concise, and readable?
Naming	Are the functions, methods, and variable names understandable and indicative?
Instruction-Following	Does the outputted code follow the original prompt which was defined?
Humble	Does the model's response avoid self-praise and apply self-critique?

Experiments

- **Code Comment Quality**
  - Judging LLMs evaluate the code comments on a 1-7 Likert scale
- **DPO and Grading Rubrics Positional Bias**
  - Positional bias investigation through choices swapping in grading rubrics prompt
- **Proprietary Language Evaluation via Instruction-Based Code Generation**
  - Parsing success
  - Compiler warnings
  - chrF++ [3] similarity metric
- **Proprietary Language Evaluation with LLM-as-a-judge**
  - Judging LLMs evaluate code quality of proprietary language
- **Conventional Code Benchmarks**
  - HumanEval [4]
  - HumanEval+ [5]
  - MultiPl-E [6]

Results

- **Significant increase** in **output quality** in low-resource, mid-resource, and proprietary programming language settings
- Approach **highly effective** in scenarios where few code examples are available for training
- No increase in code quality in high-resource programming languages such as Python

Conclusion

- We present a **lightweight solution applying a two-stage pipeline**: (1) Supervised fine-tuning through Instruction-code pairs, and (2) RLAIF and DPO for the final step
- **Efficient approach** where data or computing power is **limited**

Sources

[1] Hui, B., Yang, J., Cui, Z., Yang, J., Liu, D., Zhang, L., ... & Lin, J. (2024). Qwen2. 5-coder technical report. *arXiv preprint arXiv:2409.12186*.

[2] Kim, S., Suk, J., Longpre, S., Lin, B. Y., Shin, J., Welleck, S., ... & Seo, M. (2024). Prometheus 2: An open source language model specialized in evaluating other language models. *arXiv preprint arXiv:2405.01535*.

[3] Popović, M. (2017, September). chrF++: words helping character n-grams. In Proceedings of the second conference on machine translation (pp. 612-618).

[4] Chen, M., Tworek, J., Jun, H., Yuan, Q., Pinto, H. P. D. O., Kaplan, J., ... & Zaremba, W. (2021). Evaluating large language models trained on code. arXiv preprint arXiv:2107.03374.

[5] Liu, J., Xia, C. S., Wang, Y., & Zhang, L. (2023). Is your code generated by chatgpt really correct? rigorous evaluation of large language models for code generation. Advances in Neural Information Processing Systems, 36, 21558-21572.

[6] Cassano, F., Gouwar, J., Nguyen, D., Nguyen, S., Phipps-Costin, L., Pinckney, D., ... & Jangda, A. (2023). Multipl-e: A scalable and polyglot approach to benchmarking neural code generation. IEEE Transactions on Software Engineering, 49(7), 3675-3691.

https://aisocietylab.github.io/

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