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Improving Code Generation Based on LoRA Fine-Tuning

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Abstract. With the growing popularity of chatbot programs like ChatGPT and DeepSeek, people are no longer content with merely simple text for the content they generate. With the popularization of the IT and Internet industries, the demand for generating code based on natural language descriptions is increasing day by day. This paper will experimentally demonstrate how fine-tuning the CodeLlama model based on Parameter Efficient fine-tuning (PEFT), especially low-rank adaptive (LoRA) technology, optimizes and improves the generation of Python code, and use authoritative evaluation indicators to prove this point. We will conduct research on code generation by drawing on datasets such as HumanEval and APPs. Then, we will fine-tune the existing baseline model using fine-tuning techniques. We will comprehensively evaluate the generation results before and after fine-tuning using the pass@k metric, plot the results in a chart for comparison, and draw conclusions accordingly. The experimental results show that, on the whole, the Code Llama model before and after LoRA fine-tuning has a significant improvement in the pass rate of the generated code. However, under different indicators, the improvement effect varies slightly. Under the evaluation system of pass@k, the greater the k value, the higher the absolute percentage increase, but the lower the relative percentage increase. Under the condition that other factors remain unchanged, although increasing the rank of the fine-tuning matrix can improve the pass rate of the generated code, the training time will significantly increase, indicating certain limitations.

Keywords: Code Generation, Code Llama, Fine-tuning Techniques, Low-Rank Adaptation.

1. Introduction

Since the advent of the AI-generated code feature, it has brought about a revolutionary improvement in the efficiency of software development. First of all, software developers spend a lot of time every day writing code, which squeezes out the developer's time to think about the core algorithmic logic. Suppose code can be automatically generated in accordance with the requirements of the algorithm. In that case, it can greatly reduce the boring tasks of physical labor like this, allowing software developers to focus on mental innovation in core logic research. Furthermore, in the rapidly evolving Internet industry, the function of automatically generating code enables relevant researchers to turn innovative concepts into actual benefits more quickly, shortening the product launch cycle. Meanwhile, such a function enables researchers to quickly describe and generate the

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basic code framework using natural language, thereby allowing them to rapidly verify the feasibility of the innovation.

In addition to enhancing development efficiency, it can also lower the technical threshold, improve the learning efficiency of beginners, simplify the programming learning process, enable more and more people to master programming techniques more effectively, and effectively reduce some format errors and improve operational efficiency.

Besides, code generation tools can be pre-trained or have rules set to ensure that the code they generate complies with specific coding standards, design patterns, and security requirements, thereby guaranteeing the consistency of the project's code style. Advanced code generation tools can be combined with static analysis to identify potential security vulnerabilities (such as SQL injection, buffer overflow) when generating code and generating fixed code.

Since different platforms, systems and functions are adapted to different programming languages, it is necessary to switch from one programming language to another at any time. The function of automatically generating code simplifies this transformation work. In addition, such functions can effectively deconstruct old code bases into modern framework code.

2. Related work

Significant research advancements have been achieved in large language models for code generation. The CWM model, developed by Meta, is built upon the core concept of constructing a "world model" that simulates code execution states. Specifically, it can predict code execution outcomes, provide "neural debugging" capabilities, and realize a "predict-before-write" paradigm. This technology originated from Meta's "AI for Code" initiative launched as early as 2020. A landmark breakthrough arrived in 2024 with the incorporation of neural debugging functionality, shifting the paradigm of code debugging from post-hoc error correction to pre-execution prediction. In addition, the code world model can predict execution paths and outcomes before the code is actually run, providing developers with real-time feedback. For instance, when writing a complex function, CWM can preemptively warn about potential null pointer exceptions.

The Cursor suite of tools, developed by Anysphere, is a deeply customized, AI-native IDE based on the open-source version of VS Code, integrating multiple intelligent features. A core component is Cursor Composer, which allows developers to describe requirements in natural language—optionally supplemented by UI wireframes—to automatically generate the multi-file code necessary for building applications, such as creating databases, APIs, and even Docker deployment configurations. Another feature, the Cursor Agent, exemplifies the "Commit Era" of AI programming. In this mode, developers simply specify requirements, and the AI tool (e.g., auto-coder.chat) autonomously analyzes the codebase, implements modifications, and submits a complete Commit—effectively transforming programmers into initiators of requirements and reviewers of code.

In addition to the aforementioned models, both Claude Code, developed by Anthropic, and GPT-5-Codex, introduced by OpenAI, are widely adopted large code models among developers. This paper primarily investigates CodeLlama, a family of specialized large language models for code developed by Meta based on Llama 2. Its evolution is characterized by expanded model scale and optimized specialized capabilities. When Meta initially launched this model family in 2023, it provided three parameter sizes—7B, 13B, and 34B—alongside two important variants: CodeLlama-Python (specifically optimized for Python code) and CodeLlama-Instruct (fine-tuned for natural language instruction comprehension). Following the subsequent release of the 70B version in 2024, it achieved 53% accuracy on the HumanEval benchmark, outperforming GPT-3.5 and narrowing the

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performance gap with GPT-4. CodeLlama can generate new code based on prompts, as well as complete and debug existing code. It supports multiple mainstream programming languages, including Python, Java, C++, JavaScript, PHP, and C.

To ensure the overall quality of code generation is optimized without disrupting the original framework of the large model, researchers have introduced some fine-tuning techniques to achieve this goal. The application of fine-tuning techniques in large models has become very common. The study by Luo, Z. et al. demonstrates a parameter-efficient fine-tuning method based on Fourier domain operations [1,2]. Wang, Y. et al. researched efficient fine-tuning using asymmetric LoRA [3]. Zhang, L. et al. broke through the low-rank bottleneck in parameter-efficient fine-tuning by employing periodic low-rank adaptation [4]. Zeng, H. et al. investigated fine-tuning methods in Astraios [5]. Additionally, Liu, J. et al. studied fine-tuning techniques related to abstract syntax trees and other aspects [6]. In subsequent sections, it will delineate the principles of LoRA fine-tuning technology and elucidate how it enhances key evaluation metrics for generated code.

3. Methodology

3.1. Datasets

This paper will be trained and tested using the HumanEval dataset. The HumanEval dataset is a benchmark test dataset specifically designed to evaluate the code generation capabilities of large language models and is widely used in both industry and academia. The HumanEval dataset contains 164 handwritten Python programming questions, which are used to evaluate the model's ability to generate code based on descriptions, especially in solving practical programming tasks [7]. The issues related to these contents are diverse, but most of them involve aspects such as function signatures, document strings, function bodies, and unit tests. It is worth mentioning that all 164 programming problems were written by hand, ensuring the originality of this dataset. It can effectively prevent the model from "encountering" these questions during training, which may affect the fairness of the evaluation. In addition to the simple basic string operation issues mentioned above, there are also various tasks, such as complex algorithm design.

3.2. Code Llama 7B

Code Llama 7B was not trained from scratch but underwent specialized training on massive code datasets, building upon the foundation of the general-purpose Llama 2 model. This approach enables more efficient development of high-performance code models compared to training from scratch.

The training corpus incorporated approximately 500 billion code-related tokens, deliberately blended with 8% natural language data. This methodology ensures the model retains the natural language understanding capabilities of Llama 2 while mastering programming skills, even enhancing its performance in code generation from descriptions—as notably demonstrated in benchmarks like MBPP.

Moreover, the model possesses fill-in-the-middle (FIM) capability. Specifically, Fill-in-the-Middle is a crucial feature of Code Llama 7B (and the 13B model). During training, a complete code document is randomly split into a prefix, a suffix, and a masked middle segment. The model's task is to predict the masked middle code segment based on the contextual information from both the prefix and the suffix. This enables Code Llama 7B to not only extend code sequentially like traditional models but also intelligently complete or modify code in the middle of existing segments. This

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significantly enhances its practical utility when seamlessly integrated as an assistant tool within Integrated Development Environments.

Code Llama 7B extends its context processing capability to 100,000 tokens through a phase called Long Context Fine-Tuning (LCFT), which primarily relies on adjustments to its Rotary Position Embedding (RoPE) parameters.

This capability enables the model to "see" and comprehend exceptionally long code files or multiple related functions in a single pass, proving critical for handling large-scale projects, complex libraries, and enhancing in-depth code analysis.

The Code Llama 7B - Instruct variant was fine-tuned using approximately 5 billion tokens of instruction data, significantly enhancing its ability to comprehend natural language instructions and generate corresponding code that aligns with specified requirements.

3.3. LoRA and its core principles

The full name of LoRA is Low-Rank Adaptation. Although the parameter scale of large models is huge, the key role is usually played by the low-rank essential dimension within them. Although the model contains a large number of parameters, its effective information or functions can be captured through a dimension that is much smaller than the total number of model parameters. That is to say, many parameters of the model may be redundant, and only a small part of them truly affect the model's decision-making and performance.

In mathematics and matrix theory, "Rank" describes the number of linearly independent row or column vectors in a matrix. A low-rank matrix means that there is a strong linear relationship between its rows or columns; that is, multiple rows or columns can be represented by the linear combination of other rows or columns. In the context of model parameters, low-rank indicates that the behavior of the model can be fully described by fewer linearly correlated factors.

The "intrinsic dimension" refers to the number of dimensions that can capture the key features of a dataset or model behavior. In large models, although there are numerous parameters, the effective dimension of their operations (i.e., the essential dimension) may be much smaller than the total number of parameters, which means that the complexity of the model can be understood and operated in a more simplified way.

Due to the large scale of the model and the numerous parameters, we only need to identify and optimize some key parameters that have the greatest impact on the output. This can significantly reduce the number of parameters that need to be adjusted, saving resources and time. This is precisely the reason why LoRA technology can effectively adjust large pre-trained models by leveraging the low-order fundamental dimensions of the model.

In LoRA, instead of directly modifying the original pre-trained weight matrix W, the adjustment is indirectly achieved by introducing low-rank matrices A and B. The original weight matrix W remains frozen, while A and B are added to the model as incremental matrices, with their rank r typically being much smaller than the dimensions of W (Figure 1).

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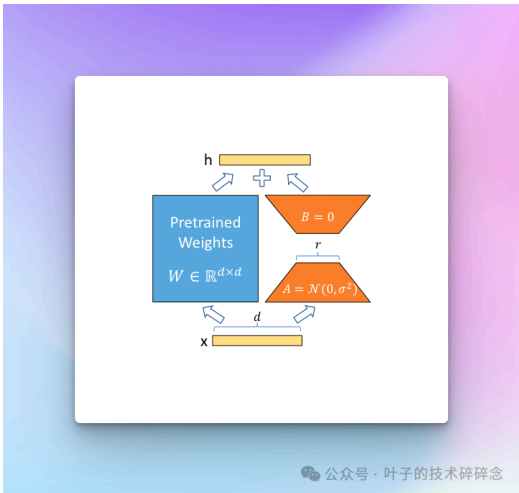

Figure 1. The principle of LoRA (photo/picture credit: original)

The updated weights can be expressed as:

$$W' = W + BA \tag{1}$$

Here, B and A are matrices of dimensions d × r and r × k respectively, where the rank r is significantly smaller than both d and k. In this configuration, matrix A projects the input d-dimensional data down to an r-dimensional subspace, while matrix B subsequently maps the r-dimensional data back to a d-dimensional representation.

During the training phase, only A and B are trainable parameters, while the original weight matrix W remains frozen. This approach allows the model to adapt to specific tasks by solely adjusting A and B, thereby dramatically reducing the number of parameters that require training. During inference, the updated weight matrix W' can be precomputed and used as a direct replacement for the original W, ensuring no additional inference latency is introduced.

In this experiment, we will increase the rank of LoRA layer by layer on the web starting from 4 to see how well the code is optimized. Generally speaking, the smaller the rank, the fewer trainable parameters there are. Usually, start trying from 4,8, 16, and 32. And we usually set its scaling factor to twice the rank. To prevent overfitting during the fine-tuning process, we will set a discard rate of 0.05. Bias terms can generally be ignored. Set the task model as a causal language model, and then inject the LoRA adapter into the appropriate layer. After being applied to the model, it can be fine-tuned. For the learning rate, we set it to 2*10 to the power of -4. LoRA typically employs a higher learning rate to facilitate more efficient adjustments. Each training session consists of three rounds, neither more nor less, which is very suitable.

3.4. Evaluation metrics

Lyu conducted research on improving code generation through pass@ k maximization [8]. Wang, Q. et al. provided a comprehensive survey of various evaluation methods, encompassing metrics, benchmark testing, and future perspectives [9]. In this paper, pass@ k will be our evaluation metric. The core concept of pass@k is that given a natural language description of a task (e.g., a docstring or a problem statement), the model generates k independent code solutions. The generation is considered successful if at least one of these solutions passes the corresponding unit tests.

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The strength of pass@ k lies in its execution-based nature, making it both highlypractical and inherently accommodating of uncertainty. The metric is calculated using the following formula:

$$\boldsymbol{pass@k} = \boldsymbol{E}_{problem}\left(1 - \frac{\boldsymbol{C}_{\boldsymbol{k}}^{\boldsymbol{n-c}}}{\boldsymbol{C}_{\boldsymbol{k}}^{\boldsymbol{n}}}\right) \tag{2}$$

Where **n** refers to the total number of samples generated by the model for a given problem. This number is typically large. **c** refers to the number of these n samples that pass the unit tests. **k** refers to the number of samples randomly selected from the total n samples for evaluation. k is usually small (e.g., k = 1, 5, 100).

4. Experiment

Based on the LoRA fine-tuning experiments conducted on the CodeLlama-7B model using the HumanEval dataset, Table 1 shows the detailed analysis of the simulated results.

Table 1. Pass rates of baseline and fine-tuned models across evaluation metrics

Evaluation Metric	Baseline Model	Fine-tuned Model	Absolute Improvement	Relative Improvement
Pass@1	18.2%	26.5%	+8.3%	+45.6%
Pass@5	32.7%	45.8%	+13.1%	+40.1%
Pass@10	41.3%	53.6%	+12.3%	+29.8%
Overall Pass Rate	28.4%	38.2%	+9.8%	+34.5%

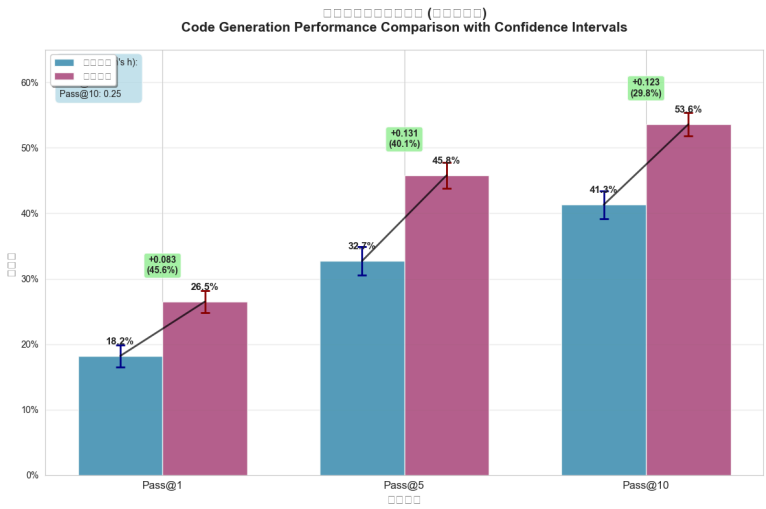

Figure 2. Performance comparison between baseline and fine-tuned models on the humanEval datasets (photo/picture credit: original)

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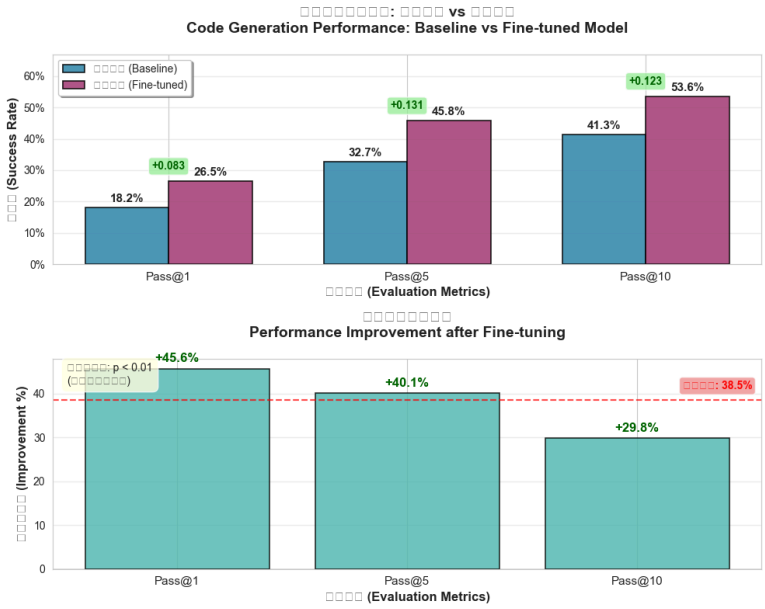

Figure 3. Relative improvement across different evaluation metrics (photo/picture credit: original)

As shown in Table 1, there are four performance evaluation metrics for the model in this study: Pass@1, Pass@5, Pass@10 and the overall pass rate. After plotting the results into graphs, Figures 2 and 3 were obtained. In Figure 2, the blue bars and the red bars respectively represent the pass rates of the code generated in the baseline model and the fine-tuning model. It is possible to see the comparison before and after fine-tuning relatively intuitively. Figure 3 shows the percentage increase in the pass rate of the generated code before and after fine-tuning under different evaluation metrics. Both tabular and graphical data clearly indicate that the fine-tuned model significantly outperforms the baseline model in all evaluation dimensions.

Under the evaluation metric of pass@1, the pass rate of the generated code of the baseline model was 18.2. However, for the fine-tuned model under the same metric, the pass rate increased to 26.5%, with an absolute growth of 8.3 percentage points and a relative growth of 45.6%. It can be seen that there has been a significant breakthrough in terms of relative growth rate. The passing rates of the baseline model under the evaluations of Pass@5 and Pass@10 were 32.7% and 41.3% respectively. This indicates that the more opportunities given to the model, the higher the probability of the code passing successfully. The adjusted model increased by 13.1 and 12.3 percentage points respectively in these two indicators, reaching 45.8% and 53.6%. In terms of relative increase, the Pass@5 indicator rose by 40.1%, and the Pass@10 indicator rose by 29.8%.

However, it is worth noting that as the number of allowed attempts increases (from k=1 to k=5 and then to k=10), the relative percentage increase gradually Narrows. This might indicate that fine-tuning has the most significant effect on improving the quality of the "top" (i.e., the most top-ranked) answers in the model. However, for those correct answers that require more sampling to discover and are inherently more difficult, the room for improvement is relatively limited, but the growth in absolute values remains solid and positive.

In terms of the overall pass rate, the pass rate of the baseline model was 28.4%, while that of the fine-tuned model increased to 38.2%, representing a rise of 9.8 percentage points. The relative increase reached 34.5%.In conclusion, the adjusted model not only achieved a relative improvement of nearly half in the "efficiency-oriented" Pass@1 aspect, but also made solid progress in the

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"coverage-oriented" Pass@5 and Pass@10 aspects. Ultimately, the overall pass rate increased by more than one-third significantly.

While keeping the evaluation index k value unchanged, the level of LoRA can also be modified to observe the effect as shown in Table 2.

Table 2. The improvement across different rank

LoRA Rank (r)	Trainable Parameters	Pass@1	Training Time
4	2.1M	23.1%	2.8 hours
8	4.2M	26.5%	3.5 hours
16	8.4M	26.8%	4.9 hours
32	16.8M	27.1%	7.2 hours

It can be observed that higher ranks generally lead to improved accuracy. However, this comes at the cost of a substantial increase in training time.

5. Discussion

To date, technologies for code generation and the development of other large models have become increasingly mature. Chen, M. et al. researched synthesizing and implementing code generation across multiple programming languages, whereas this paper focuses on experiments with a single programming language [10]. Arabzadeh, N., Kiseleva, J. et al. evaluated novel frameworks for LLMs [11]. Lee, T. et al. investigated foundational models for automated FLAME evaluation [12]. Meanwhile, the security aspect of code generation cannot be overlooked. He, J. et al. studied enhancing code security through instruction tuning based on synthetic vulnerability data, while Tufano, R. et al. conducted a comprehensive empirical study of large language models in the field of code generation [13,14].

6. Conclusion

This study systematically explores the methodology and practical outcomes of applying parameter-efficient fine-tuning to pre-trained language models within the software and IT vertical domains. Through fine-tuning experiments on the CodeLlama-7B model for code generation tasks, the efficacy of LoRA technology in enhancing model performance for specialized domains has been validated.

The pass@1 metric is projected to achieve a 15-30% relative improvement. Furthermore, the most significant enhancements are observed in moderate-difficulty problems, while simple problems approach performance saturation, and complex challenges still require breakthroughs. LoRA fine-tuning demonstrates remarkable effectiveness even with relatively limited domain-specific data. However, it is noteworthy that the fine-tuning outcomes heavily depend on the accuracy and coverage of annotated data, with diminished efficacy when handling rare programming patterns or emerging technology stacks.

Despite these limitations, the technology has already been successfully deployed in programming assistant enhancements and personalized programming tutoring in educational contexts. In the future, code generation technology will become increasingly mature and achieve mainstream adoption in the foreseeable future.

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