

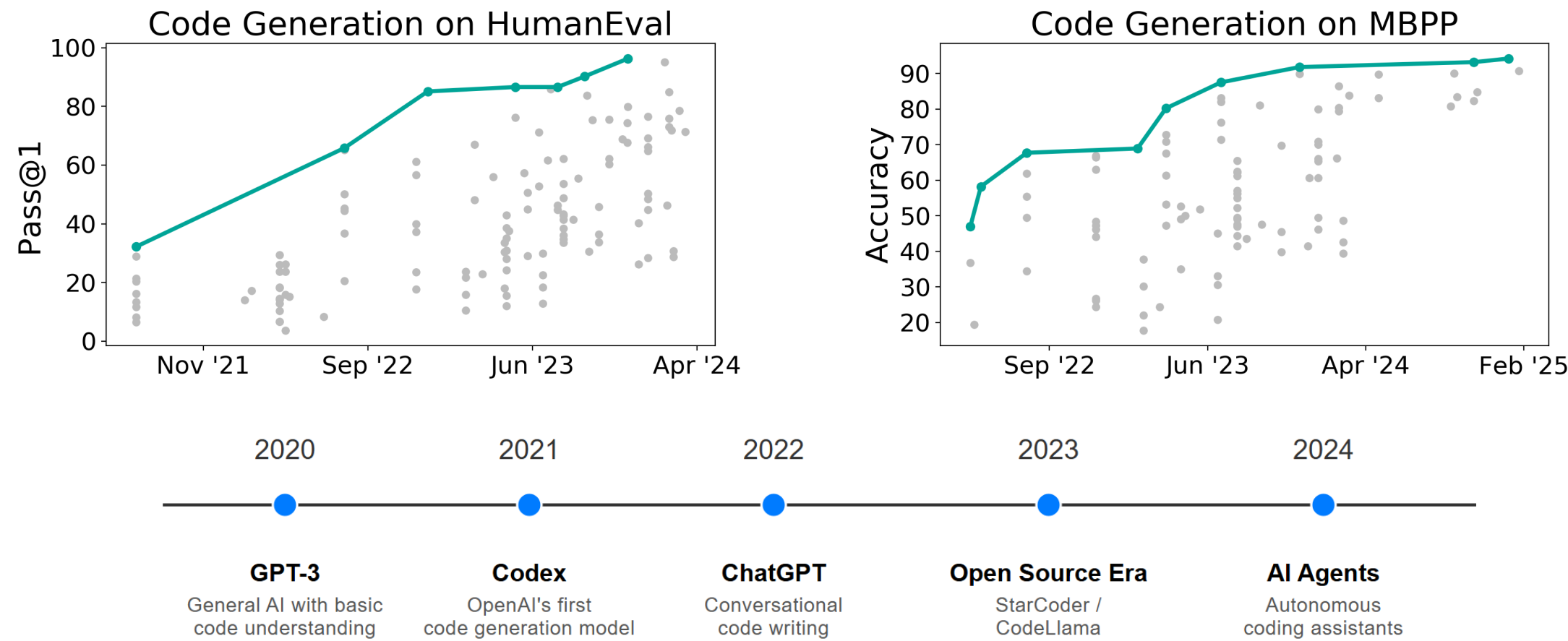
MetaCoder: Generating Code from Multiple Perspectives

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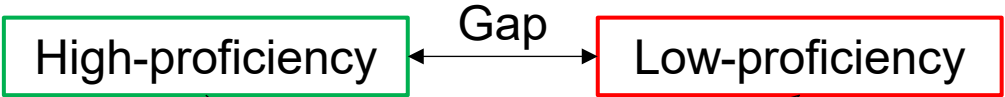
Background

- The code generation capability of LLMs has seen rapid advancements over the past few years



Motivation

- LLMs show the **performance gap** in generating different programming languages



Model	Dataset	Python	C++	Java
Llama 3.1 8B Instruct	HumanEval	72.6 \pm 6.8	52.8 \pm 7.7	58.2 \pm 7.7
	MBPP	60.8 \pm 4.3	53.7 \pm 4.9	54.4 \pm 5.0
Llama 3.1 70B Instruct	HumanEval	80.5 \pm 6.1	71.4 \pm 7.0	72.2 \pm 7.0
	MBPP	75.4 \pm 3.8	65.2 \pm 4.7	65.3 \pm 4.8
Llama 3.1 405B Instruct	HumanEval	89.0 \pm 4.8	82.0 \pm 5.9	80.4 \pm 6.2
	MBPP	78.8 \pm 3.6	67.5 \pm 4.6	65.8 \pm 4.7
DS-Coder-V2-Lite-Instruct	HumanEval	81.1	75.8	76.6
DS-Coder-V2-Instruct	HumanEval	90.2	84.8	82.3

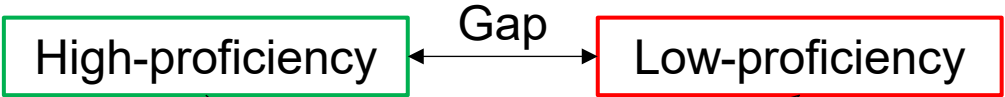
How to bridge the performance gap?

Performance metrics (%) for various LLMs on code generation benchmarks^{[1][2]}

[1] Abhimanyu Dubey, et al. 2024. The llama 3 herd of models. arXiv preprint arXiv:2407.21783 (2024).
[2] Qihao Zhu, et al. 2024. Deepseek-coder-v2: Breaking the barrier of closed-source models in code intelligence. arXiv preprint arXiv:2406.11931 (2024).

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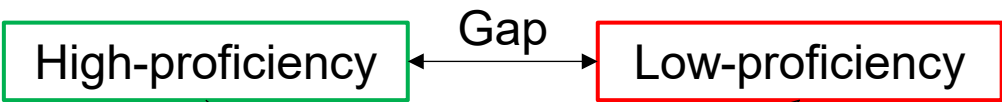
Fine-tuning costs too much!

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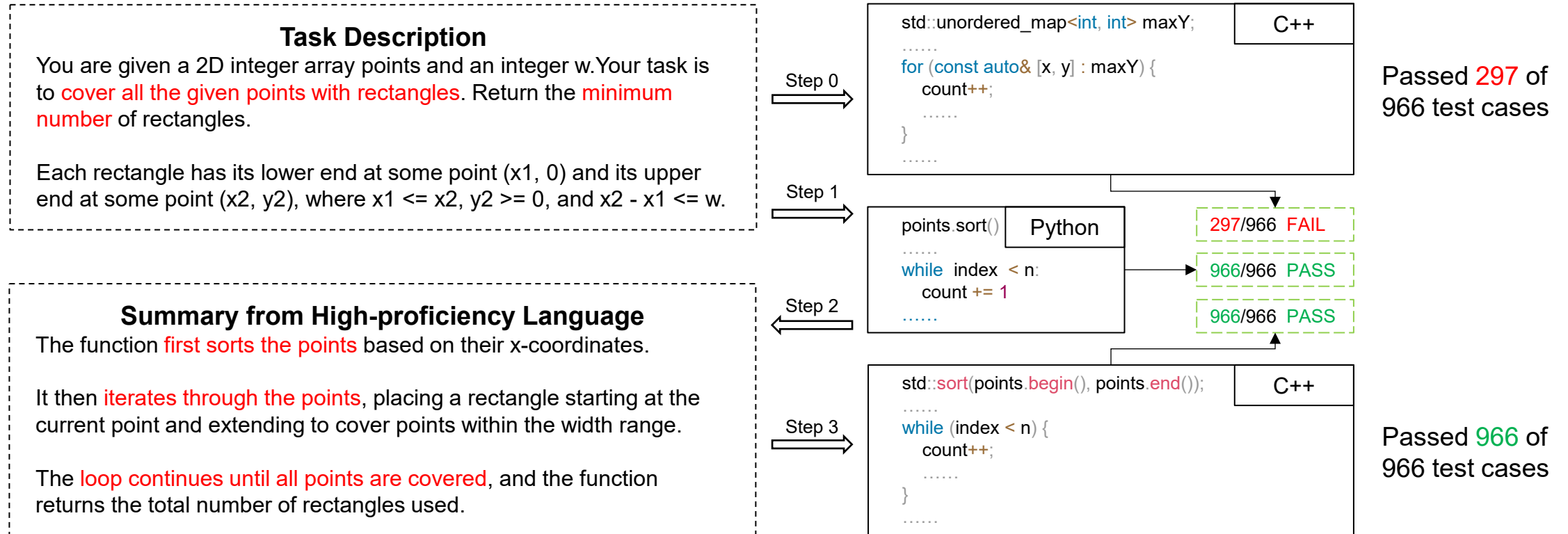
Why not LLM guides itself?
- High-proficiency language guides low-proficiency language

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A Motivating Example

- Using high-proficiency language (Python) to **guide** the generation of low-proficiency language (C++)



- Functional perspective** (What does this task want to do?): Task Description
- Implementation perspective** (How to accomplish this task?): Python Code and Summary

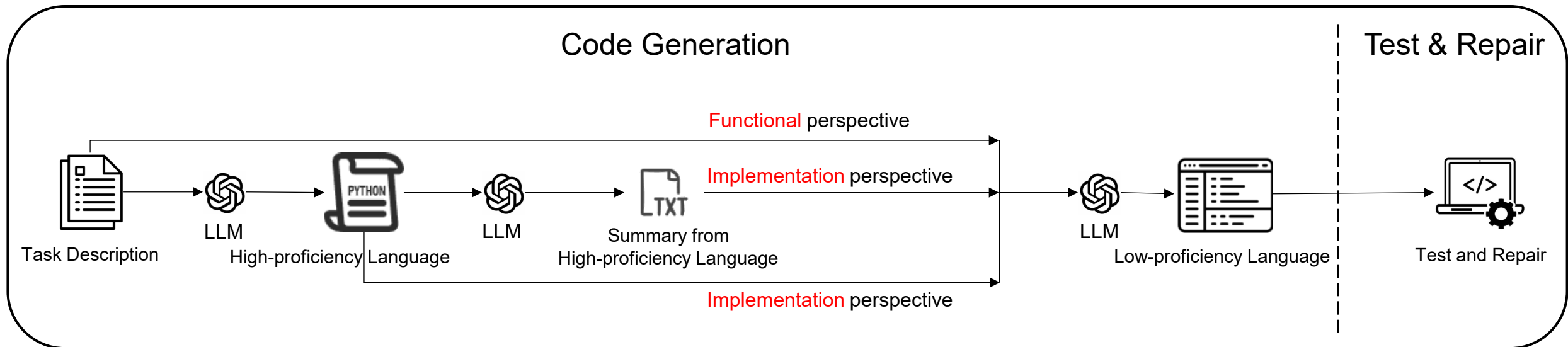
Workflow of MetaCoder

- **Code Generation**

- Use high-proficiency language to guide the generation of low-proficiency language from **multiple perspectives**

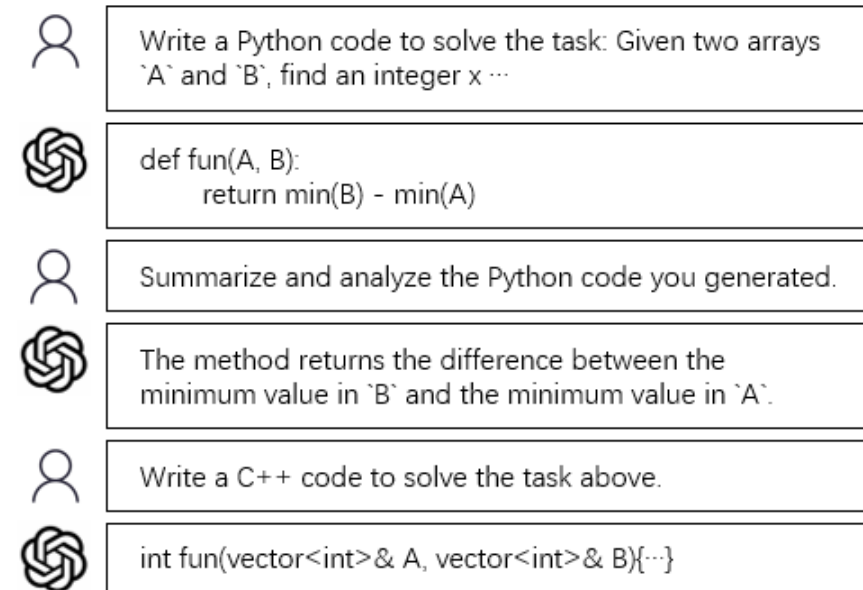
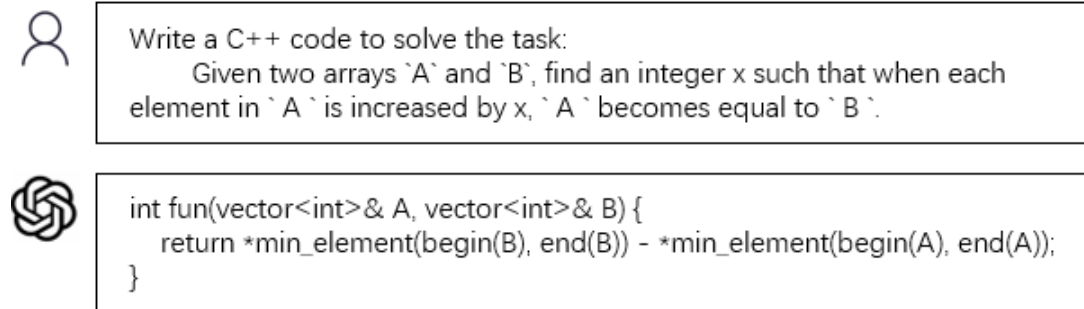
- **Test & Repair**

- Find out errors and repair



Code Generation

- **Provide information to LLMs in the form of dialogue**
 - Prompts are simple and add little workload to users
 - The process is easy and intuitive



- **Why add summary to guide?**

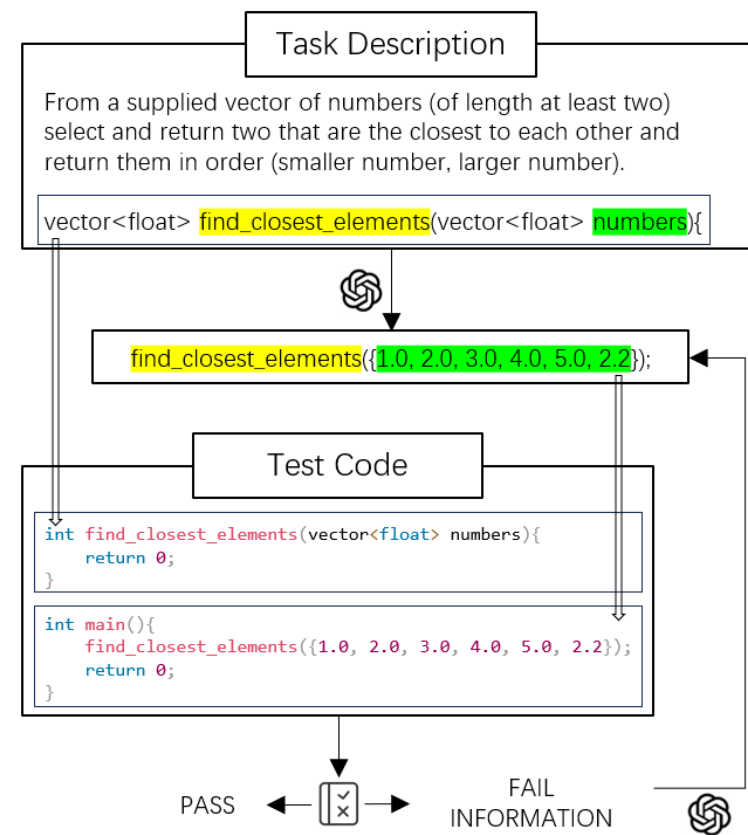
Syntactic gap between two different languages may lead to syntax errors

Test and Repair

LLMs make mistakes in function declarations:

Wrong function name, wrong parameter order and data type

- **Generate one test case without answer**
 - According to the function declaration
- **Test**
 - Compile to check errors
 - Collect fail information
- **Repair**
 - Add fail information to the dialogue
 - Generate and retest for several rounds



Experimental Design

- **Model selection**
 - GPT-3.5、GPT-4o、Llama 3.1、Qwen 2.5、DeepSeek V2.5、DeepSeek R1
- **Comparison Baselines**
 - Zero-Shot、Few-Shot、CoT、INTERVENOR、Self-Collaboration
- **Benchmarks**
 - HumanEval-x
- **Evaluation Metrics**
 - Pass@1 (5 samples for each task)
- **Research Questions**
 - RQ1: What is the effectiveness of our method?
 - RQ2: What is the effectiveness of each component of our method?
 - RQ3: What is the cost of our method?

Results

- **RQ1: What is the effectiveness of our method?**
 - Effectively improve the ability to generate low-proficiency languages

	GPT 3.5		GPT 4o		DeepSeek V2.5		Llama3.1 70B		Qwen2.5 72B	
	C++	Java	C++	Java	C++	Java	C++	Java	C++	Java
Zero-Shot	66.22	64.27	84.63	87.2	82.56	81.95	73.78	72.2	85.98	86.59
Few-Shot	60	67.68	80.98	85	85.37	83.54	<u>78.05</u>	78.65	86.58	85.37
CoT	64.51	66.34	84.39	85.73	86.59	87.2	76.22	81.1	85.98	86.58
INTERVENOR	66.95	<u>71.95</u>	84.02	<u>88.41</u>	83.41	80.73	71.95	74.27	<u>88.41</u>	85.98
Self-Collaboration	<u>72.56</u>	69.51	<u>85.98</u>	90.85	83.54	85.24	75.61	76.22	90.24	89.02
MetaCoder	74.89	74.76	87.2	85.49	86.59	<u>86.34</u>	80	<u>78.65</u>	86.58	<u>87.8</u>
Relative Improvement	13.09%↑	16.32%↑	3.04%↑	-1.96%↓	4.88%↑	5.36%↑	8.43%↑	8.93%↑	0.7%↑	1.4%↑

	Qwen2.5 32B		Qwen2.5 14B		Qwen2.5 7B		DeepSeek R1(C++)			
	C++	Java	C++	Java	C++	Java	7B	8B	14B	32B
Zero-Shot	78.9	74.02	72.2	77.44	68.29	69.39	47.93	50.61	54.88	53.05
MetaCoder	84.76	86.59	73.54	79.63	71.95	71.59	63.41	62.8	80.49	81.1
Relative Improvement	7.43%↑	16.98%↑	1.86%↑	2.83%↑	5.36%↑	3.17%↑	32.3%↑	24.09%↑	46.67%↑	52.87%↑

Results

- **RQ2: What is the effectiveness of each component of our method?**
 - Each component contributes to the improvement of ability
 - Summary and Python code complement each other and achieve better results
 - For more powerful LLMs, Test and Repair may provide less return

	GPT 3.5		GPT 4o		DeepSeek V2.5		Llama3.1 70B		Qwen2.5 72B	
	C++	Java	C++	Java	C++	Java	C++	Java	C++	Java
Zero-Shot	66.22	64.27	84.63	87.2	82.56	81.95	73.78	72.2	85.98	86.59
- Python Solution	73.66	74.02	85.98	85.61	84.76	85.98	77.93	78.17	85	86.84
- Python Summary	71.34	73.78	86.71	84.51	85.98	84.39	76.22	77.44	83.41	84.27
- Test and Repair	72.56	71.95	86.59	85.12	85	85.37	76.71	76.45	86.21	86.34
MetaCoder	74.89	74.76	87.2	85.49	86.59	86.34	80	78.65	86.58	87.8

Results

- **RQ3: What is the cost of our method?**
 - The cost of generating code has not increased significantly
 - There is a big difference in cost between various LLMs

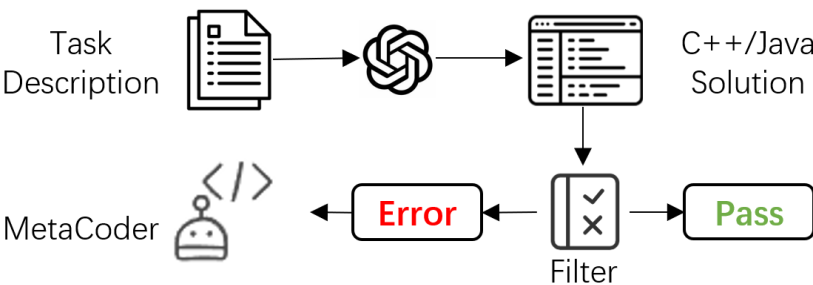
The output token consumption of different LLMs under different methods

	GPT 3.5		GPT 4o		DeepSeek V2.5		Llama3.1 70B		Qwen2.5 72B	
	C++	Java	C++	Java	C++	Java	C++	Java	C++	Java
Zero-Shot	90.8	177.26	274.74	572.6	673.27	737.4	465.9	542.93	582.32	614.86
Few-Shot	109.35	113.54	171.44	130.39	195.15	167.01	144.62	118.43	253.71	136.36
CoT	302.41	327.21	499.53	545.56	507.34	540.45	364.76	370.88	568.46	407.27
INTERVENOR	99.23	190.32	292.62	611.46	681.23	815.26	510.07	545.45	614.49	627.62
Self-Collaboration	730.81	750.21	1231.91	1833.1	1606.19	1556.74	919.16	908.2	1697.06	1608.95
MetaCoder	396.61	421.35	690.47	824.3	738.02	848.67	438.99	459.13	637.67	609.41

Results

- **More detailed research: Real world performance**

- After adding the filter, the effect is significantly improved
- Enhance the diversity of LLM-generated code
- Practical in the real world



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	C++	Java	C++	Java	C++	Java	C++	Java	C++	Java
MetaCoder	74.89	74.76	87.2	85.49	86.59	86.34	80	78.65	86.58	87.8
MetaCoder + Filter	81.59	81.22	90.73	91.22	90.85	90	86.58	86.58	91.46	92.07

	Qwen2.5 32B		Qwen2.5 14B		Qwen2.5 7B		DeepSeek R1(C++)			
	C++	Java	C++	Java	C++	Java	7B	8B	14B	32B
MetaCoder	84.76	86.59	73.54	79.63	71.95	71.59	63.41	62.8	80.49	81.1
MetaCoder + Filter	90.12	91.46	85.12	88.41	80.73	85.85	71.34	74.39	84.76	85.37

Thanks!

Github: <https://github.com/cx-hub/MetaCoder>

Contact: chenxin19@nudt.edu.cn