Two papers to cover:

1. **DeepSeek-Coder-V2: Breaking the Barrier of Closed-Source Models in Code Intelligence**

2. **Language Models for Code Optimization: Survey, Challenges, and Future Directions**

DeepSeek-Coder-V2: Breaking the Barrier of Closed-Source Models in Code Intelligence

Presented by:
Aditya Kakkar (zjq5mr), Aryan Sawhney (ryd2fx), Yagnik Panguluri (yye7pm)

Aditya Kakkar (zjq5mr)

Presentation Outline

- Introduction
- Background & Motivation
- DeepSeek Evolution
- Data Collection & Training Strategy
- Model Architecture & Improvements
- Evaluation & Benchmarks
- Competitive Programming & Code Completion
- Applications & Real-World Impact
- Limitations & Future Improvements
- Conclusion & Q&A

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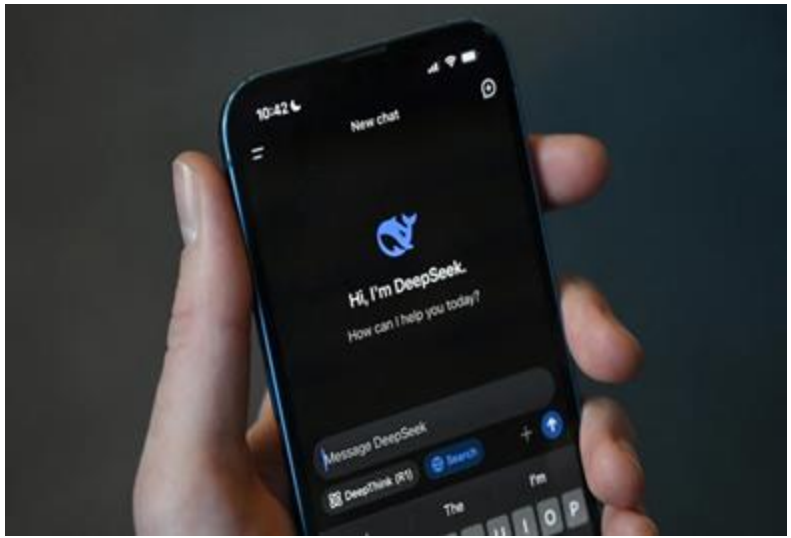
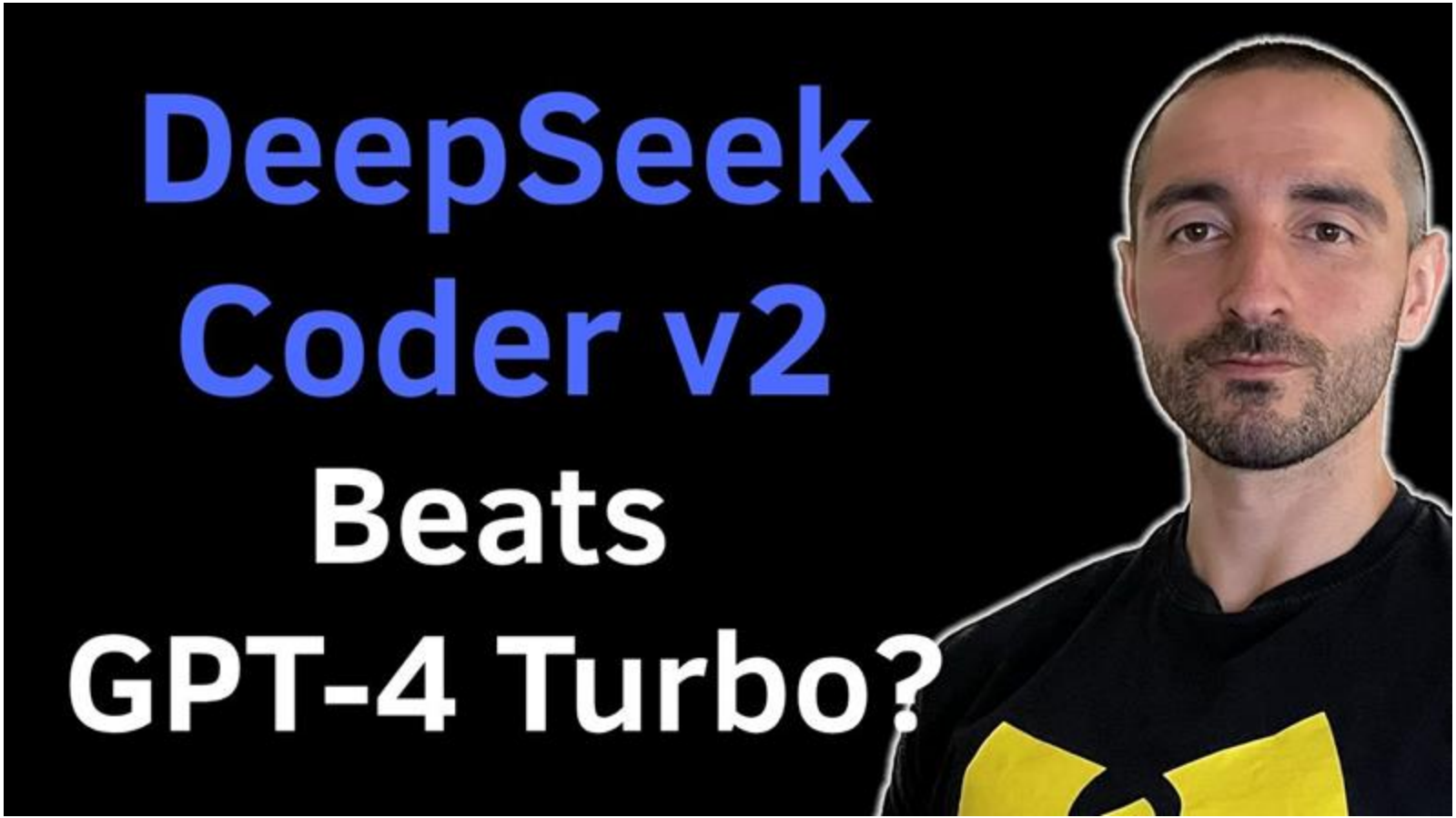
Introduction



DeepSeek-Coder-V2:Breaking the Barrier of Closed-Source Models in Code Intelligence

Background



Motivation


OPEN
SOURCE
software
internet
copyright
choice
free
community


MONEY MOVERS
DEEPSEEK SETS OFF NEW AI RACE
CNBC

What is DeepSeek?

DeepSeek-AI is a leading **Chinese AI research lab**, comparable to OpenAI, specializing in cutting-edge artificial intelligence advancements.

Note

This presentation covers information up to **June 2024** and does not include details on the latest **DeepSeek-R1** model.

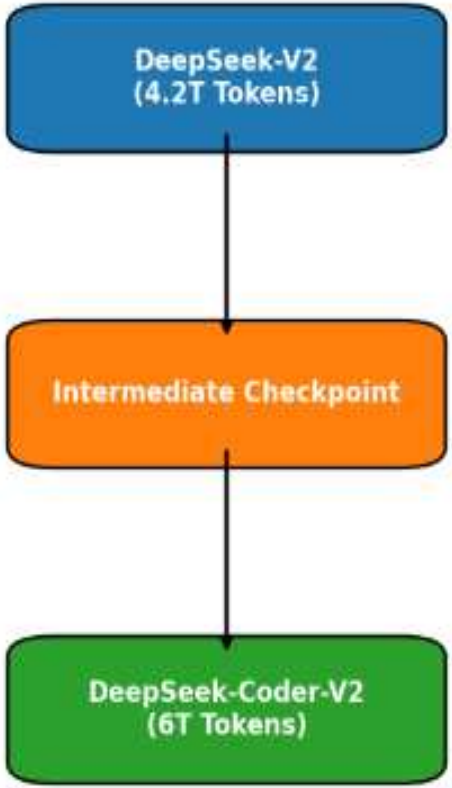
Evolution of DeepSeek Models

- **DeepSeek-V1 (2022):** Focused on NLP with limited coding and math capabilities.
- **DeepSeek-V2 (2023):** Introduced coding and math training with 4.2T tokens.
- **DeepSeek-Coder (2023):** Specialized in programming with 86 languages, 16K token limit.
- **DeepSeek-Coder-V2 (2024):** Expanded to 338 languages, 128K tokens, surpasses GPT-4 Turbo.

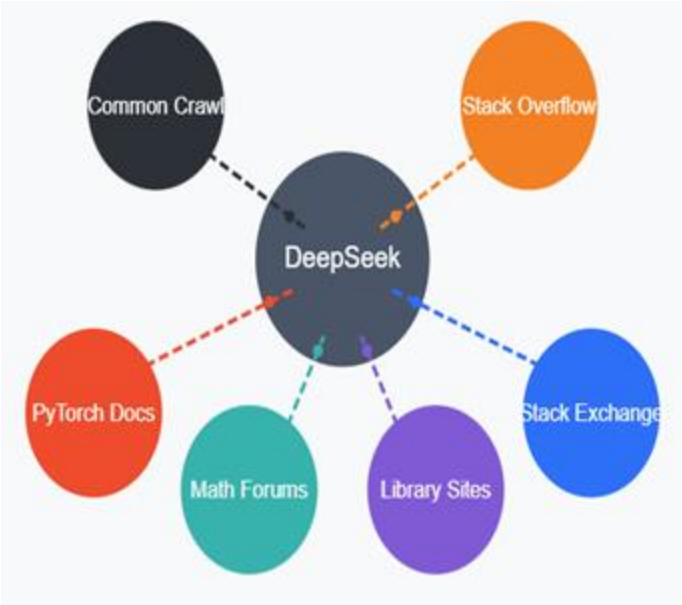
Focus of This Presentation: We will dive into DeepSeek-Coder-V2 and its advancements.

DeepSeek-Coder-V2: Advancing Beyond DeepSeek-V2

	DeepSeek-V2	DeepSeek-Coder-V2
Code	60%	Expanded: 86 → 338 languages
Math	30%	Additional datasets from coding/math forums
Natural Language	10%	Reduced proportion
Total Tokens	4.2T	4.2T+6T = 10.2T



Data Collection



Technique	Purpose	Benefit for DeepSeek-Coder-V2
fastText	Expand the training dataset efficiently	Helps understand rare programming terms and mathematical symbols
BPE Tokenizer	Splits text into frequent subword units	Efficiently tokenizes code across multiple languages, reducing memory usage

Data Filtration

- Removed low-quality and duplicate files.
- Excluded files with excessive line length (>1000 characters) or low alphabetic content (<25%).
- **Filtered out XML files (except XSLT) and ensured readable HTML content.**

Retained only files with character counts between **50 and 5000** to avoid data-heavy content.

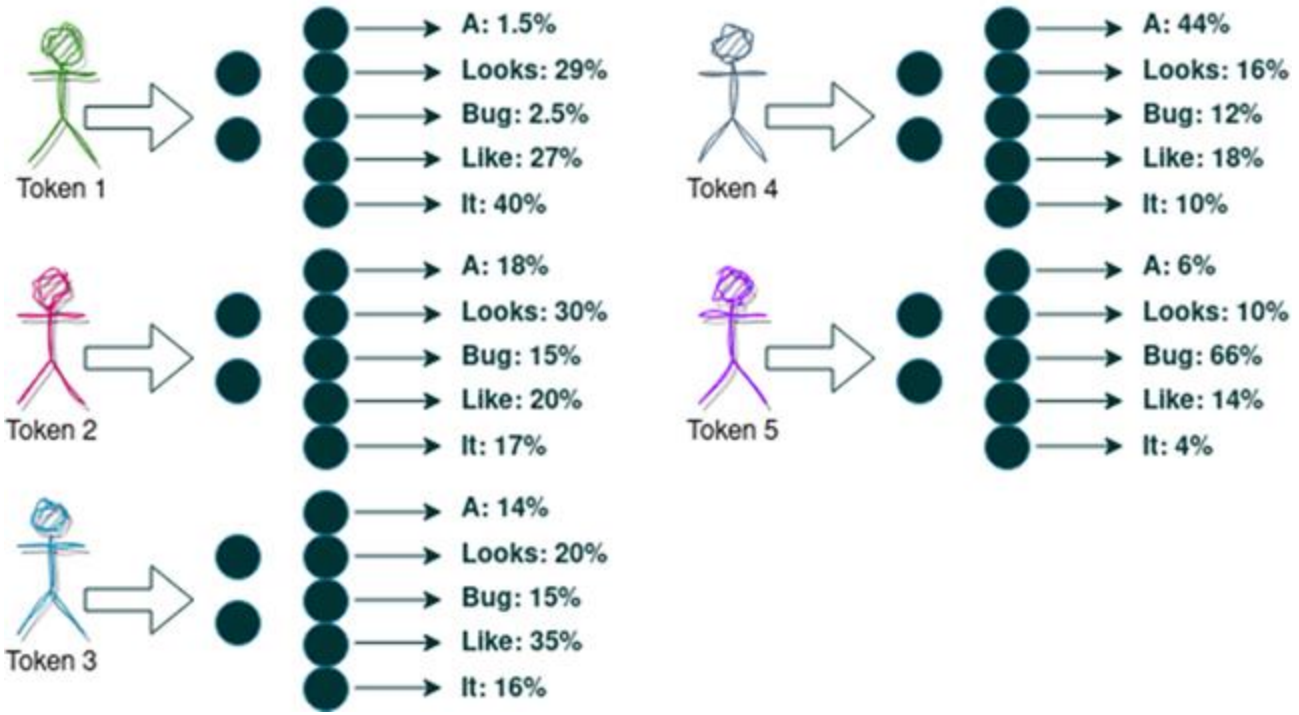
Kept files where visible text is ≥20% of the total code and at least 100 characters.

Training Strategy: Scaling from 4.2T to 6T Tokens

Model	DeepSeek-Coder-V2-Lite	DeepSeek-Coder-V2
# Total Parameters (#TP)	16B	236B
# Active Parameters (#AP)	2.4B	21B
Pre-training Tokens	4.2T+6T	4.2T+6T
LR Scheduler	Cosine	Cosine
FIM	Enable	Disable

- **Context Length Increase: 16K → 128K Tokens** → Enables handling larger codebases and multi-file projects.
- **Advanced Training Methods** → Fill-In-Middle (FIM), Group Relative Policy Optimization (GRPO), and Reinforcement Learning (RL) for better accuracy.

Training Techniques: Probability Distributions



Training Techniques: Next-Token Prediction

```
def factorial(n):
    if n == 0:
        return 1
    else:
        return
```

Model Prediction:

python

```
def factorial(n):
    if n == 0:
        return 1
    else:
        return n * factorial(n - 1)
```

Training Techniques: Fill-In-Middle (DeepSeek-Coder-V2-16B)

The model assigns probabilities to possible completions and selects the most likely one.

```
def factorial(n):
    if n == 0:
        return 1
    <|fim_hole|>
    else:
        return n * factorial(n - 1)
```

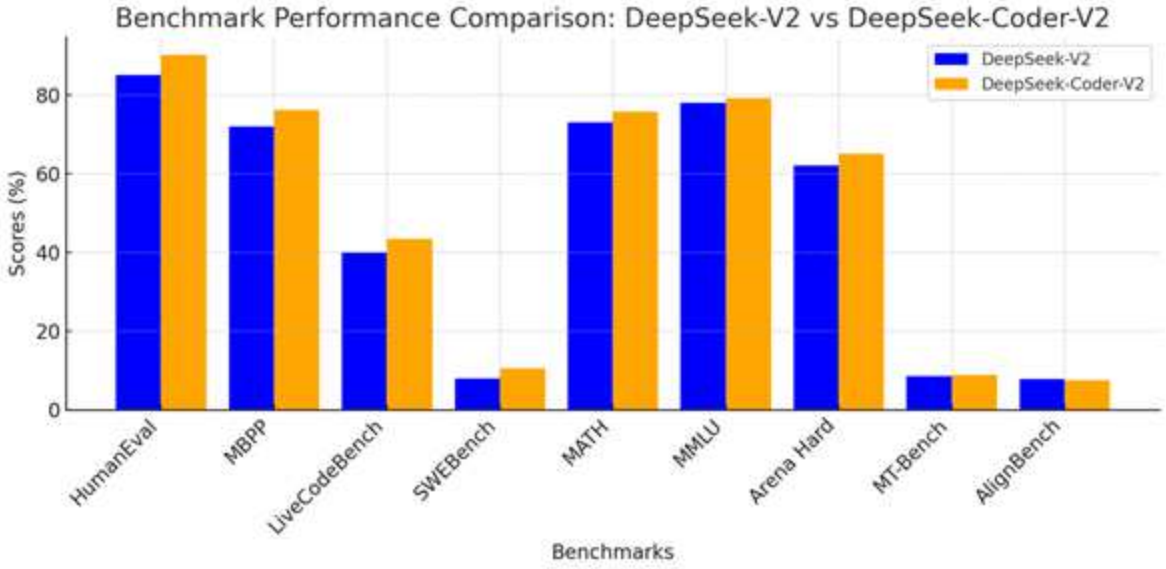
Model Prediction (Middle Completion):

```python
def factorial(n):
    if n == 0:
        return 1
    elif n < 0:
        raise ValueError("Input must be a non-negative integer.")
    else:
        return n * factorial(n - 1)
```

Ablation studies

Model	Tokens	Python	C++	Java	PHP	TS	C#	Bash	JS	Avg	MBPP
DeepSeek-Coder-1B	1T	30.5%	28.0%	31.7%	23.0%	30.8%	31.7%	9.5%	28.6%	26.7%	44.6%
DeepSeek-Coder-V2-1B	1T	36.0%	34.8%	31.7%	27.3%	**37.7%**	34.2%	6.3%	**38.5%**	31.2%	49.0%
DeepSeek-Coder-V2-1B	2T	**37.2%**	**39.1%**	**32.3%**	**31.7%**	34.6%	**36.7%**	**12.0%**	32.9%	**32.0%**	**54.0%**

Table 1 | Performance of 1B base model between DeepSeek-Coder and DeepSeek-Coder-V2.



Ablation studies

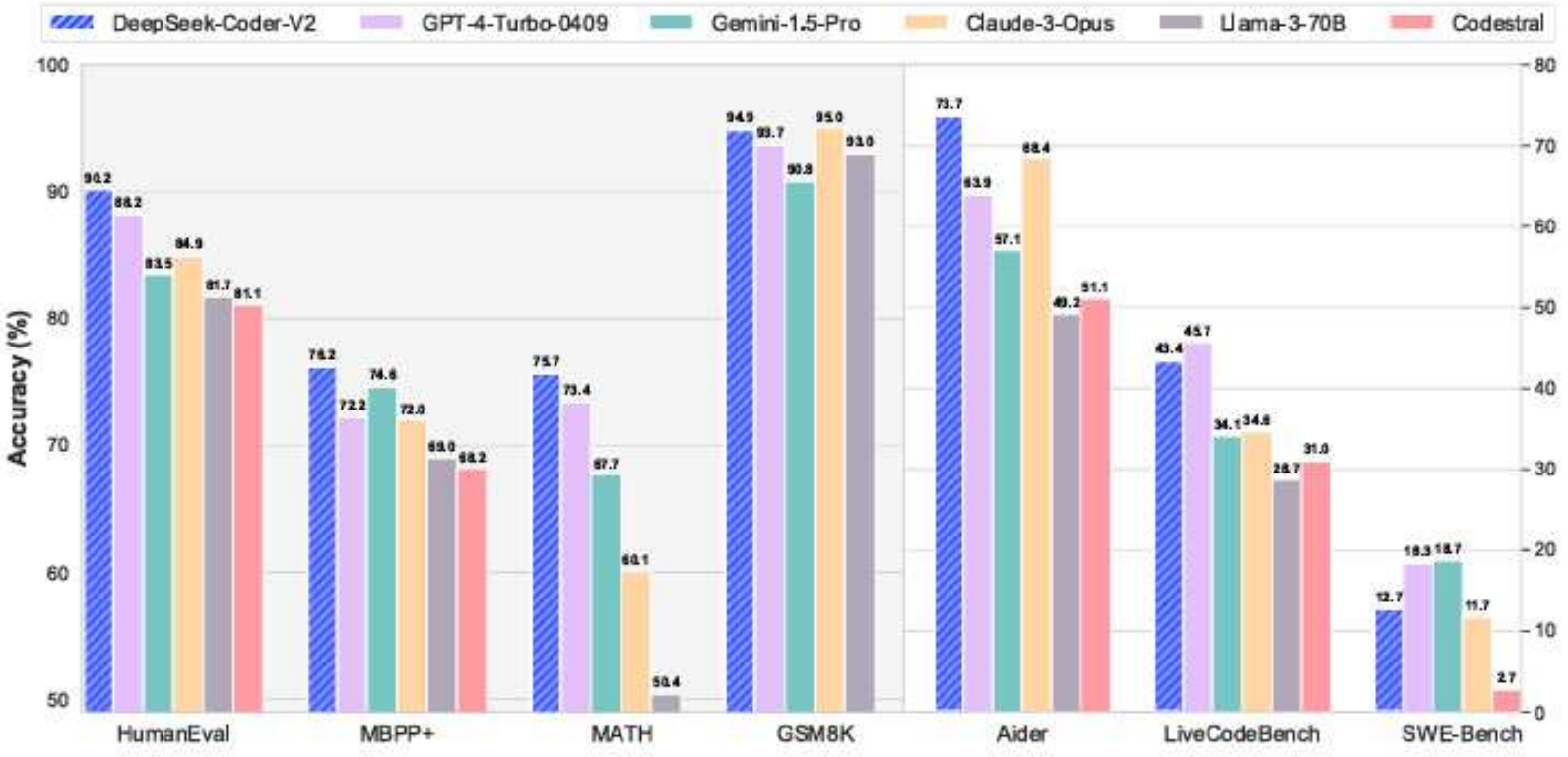


Figure 1 | The Performance of DeepSeek-Coder-V2 on math and code benchmarks.

Yagnik Panguluri (yye7pm)

Training Hyper-Parameters

- **Optimizer:** AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.95$, weight decay = 0.1)
- **Learning rate schedule:** Cosine decay
  a. 2000 warm up steps
  b. Decays to 10% of initial LR
- **Batch size tuning per DeepSeek-V2 methodology**

Model	DeepSeek-Coder-V2-Lite	DeepSeek-Coder-V2
# Total Parameters (#TP)	16B	236B
# Active Parameters (#AP)	2.4B	21B
Pre-training Tokens	4.2T+6T	4.2T+6T
LR Scheduler	Cosine	Cosine
FIM	Enable	Disable

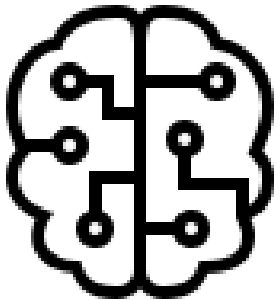
Table 2 | Training Setting of DeepSeek-Coder-V2.

Long Context Extension

DeepSeek-Coder-V2

YARN (Yet Another Retrieval Network)

DeepSeek-Coder-V2-128K



16K Tokens

Limitation for handling longer codebases, documents, and complex tasks

128K Tokens

Helps in long-form reasoning, retrieval tasks, and handling entire software repositories in a single pass

NIAH Performance

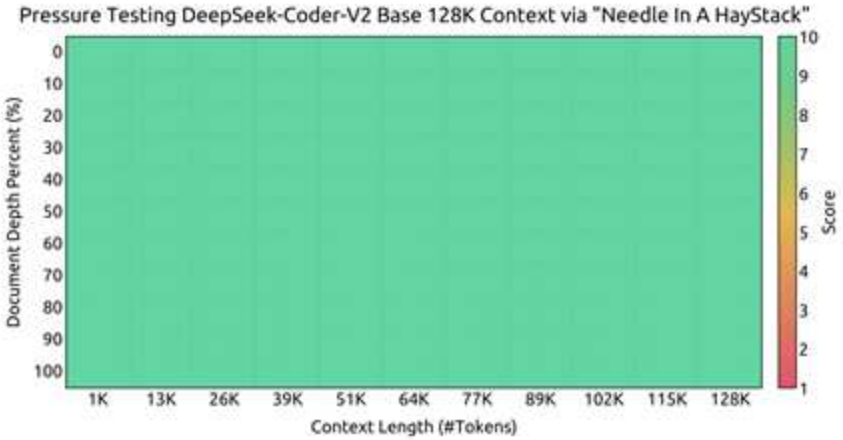


Figure 2 | Evaluation results on the "Needle In A Haystack" (NIAH) tests. DeepSeek-Coder-V2 performs well across all context window lengths up to 128K.

- DeepSeek-Coder-V2 maintains strong retrieval performance across all testing context lengths
- Model demonstrates consistent accuracy up to 128K tokens, outperforming many prior open source models
- Upsampling of long-context data during training enhances model robustness for long-context tasks.

Alignment

Alignment ensures the model generates accurate, human-preferred responses

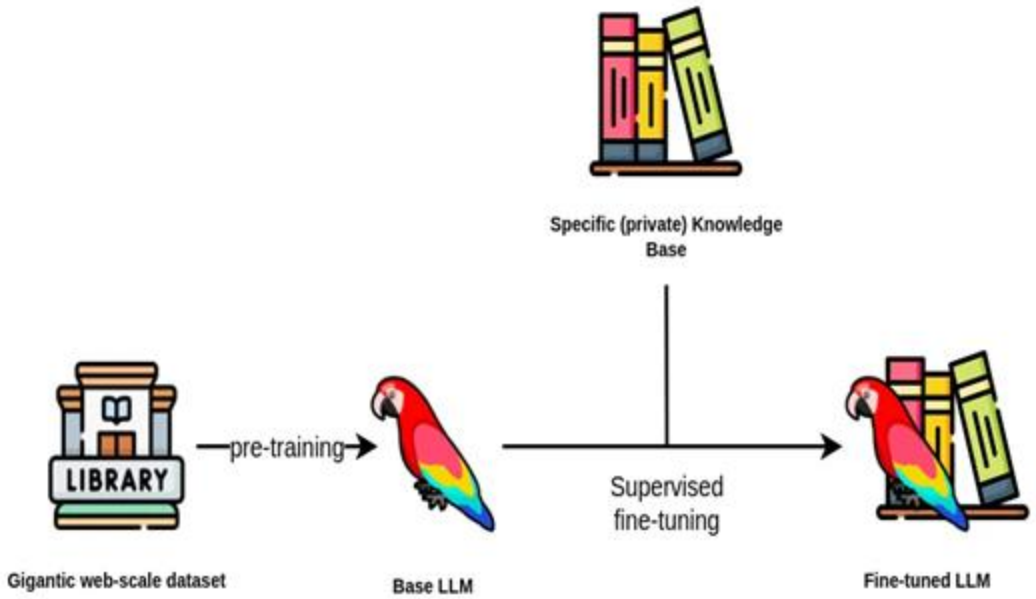
Optimizes the model behavior for code generation, math reasoning, and instruction-following

Supervised Fine Tuning

Reinforcement Learning

Supervised Fine Tuning

- A method to refine the model's capabilities by training it on curated instruction-following datasets
- Ensures the model understands instructions and generates accurate code/math responses
- Prepares the model for RL alignment



Source

SFT - Setup

Configurations

- **Learning rate:** 5e-6
- **Learning rate schedule:** Cosine decay with 100 warm-up steps
- **Batch size**: 1M tokens per batch
- **Total training tokens:** 1B tokens

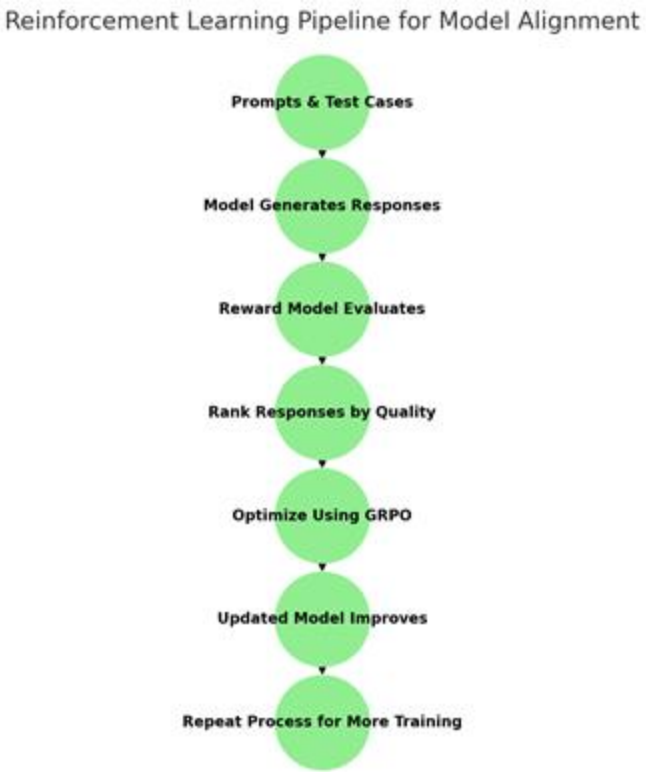
Optimizations

- Cosine decay learning rate
- High quality instruction dataset
- Large batch size

Outcomes

- Better instruction-following performance
- Stronger generalization across coding and mathematical tasks
- Reduces errors in multi-step reasoning

Reinforcement Learning



- SFT helps, but it's limited by static datasets
- RL further optimizes the model's response by learning from dynamic feedback
- Improves performance on code/math tasks by training with real-world prompts
- Reduces errors and hallucinations

Prompts

Prompts serve as inputs to the model, helping refine its code generation and problem solving abilities

Each code prompt is paired with test cases to validate correctness

Collected and filtered 40K+ prompts

Prompt Type	Description
Code Prompts	Algorithmic tasks, debugging challenges
Math Prompts	Complex problem-solving, theorem proving
General Instructions	Instruction-based reasoning tasks

Reward Modeling

A model which assigns a quality score to generated responses

Helps train the model to prefer better responses based on correctness, efficiency, and alignment with human preferences

Replaces raw compiler signal, which only provides binary (pass/fail) feedback

Collects human preferences or ground truth labels

Trains a model to predict response quality

Uses the predicted reward to fine-tune the main model via

Reward Modeling Results

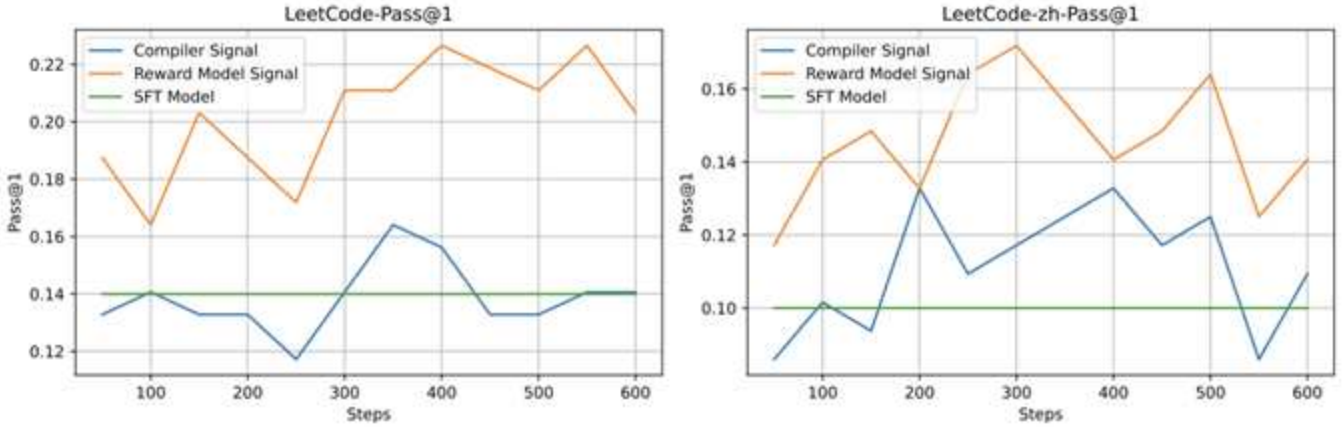


Figure 3 | Performances of Different Methods

Reinforcement Learning - GRPO

GRPO - Group Relative Policy Optimization

An efficient RL algorithm used to improve the DeepSeek-Coder-V2

Similar to PPO but more efficient and cost effective

Model generates multiple responses for a given prompt

Reward model ranks the responses based on quality

GRPO optimizes the model to favor higher-ranked responses

Process repeats

Aryan Sawhney (ryd2fx)

Results - Comparison Models

Evaluate DeepSeek-Coder-V2 on three types of tasks:

- Coding
- Mathematics
- General natural language

Compared DeepSeek-Coder-V2 with the previous state-of-the-art large language models:

Open Source

- StarCoder
- StarCoder2
- CodeLlama
- DeepSeek-Coder (previous version)
- Codestral
- Llama3

Closed Source

- GPT-4
- GPT-4 Turbo
- GPT-4o
- Claude 3 Opus
- Gemini 1.5 Pro

Results - HumanEval & MBPP

	#TP	#AP	Python	Java	C++	C#	TS	JS	PHP	Bash
Closed-Source Models										
Gemini-1.5-Pro	-	-	83.5%	81.0%	78.3%	75.3%	77.4%	80.8%	74.5%	39.9%
Claude-3-Opus	-	-	84.2%	78.5%	81.4%	74.7%	76.1%	75.8%	78.3%	48.7%
GPT-4-1106	-	-	87.8%	**82.3%**	78.9%	80.4%	81.8%	80.1%	77.6%	**55.7%**
GPT-4-Turbo-0409	-	-	88.2%	81.7%	78.3%	79.1%	79.3%	80.8%	78.9%	**55.1%**
GPT-4o-0513	-	-	**91.0%**	80.4%	**87.0%**	**82.9%**	**86.2%**	**87.6%**	**79.5%**	53.8%
Open-Source Models										
Codestral	22B	22B	78.1%	71.5%	71.4%	77.2%	72.3%	73.9%	69.6%	47.5%
DS-Coder-instruct	33B	33B	79.3%	73.4%	68.9%	74.1%	67.9%	73.9%	72.7%	43.0%
Llama3-Instruct	70B	70B	81.1%	67.7%	64.0%	69.6%	69.8%	70.2%	65.8%	36.1%
DS-Coder-V2-Lite-Instruct	16B	2.4B	81.1%	76.6%	75.8%	76.6%	80.5%	77.6%	74.5%	43.0%
DS-Coder-V2-Instruct	236B	21B	**90.2%**	**82.3%**	**84.8%**	**82.3%**	**83.0%**	**84.5%**	**79.5%**	**52.5%**

	#TP	#AP	Swift	R	Julia	D	Rust	Racket	MBPP+	Average
Closed-Source Models										
Gemini-1.5-Pro	-	-	66.5%	53.4%	71.7%	55.8%	73.1%	48.4%	**74.6%**	68.9%
Claude-3-Opus	-	-	63.9%	55.9%	76.1%	60.3%	71.2%	**64.6%**	72.0%	70.8%
GPT-4-1106	-	-	62.7%	57.8%	69.2%	60.9%	**78.8%**	64.0%	69.3%	72.5%
GPT-4-Turbo-0409	-	-	63.9%	56.5%	69.8%	**61.5%**	**78.8%**	63.4%	72.2%	72.3%
GPT-4o-0513	-	-	**75.9%**	**65.2%**	**78.0%**	60.9%	**80.1%**	**64.6%**	73.5%	**76.4%**
Open-Source Models										
Codestral	22B	22B	63.3%	49.7%	67.9%	32.1%	67.3%	37.3%	68.2%	63.2%
DS-Coder-instruct	33B	33B	61.4%	44.7%	53.5%	31.4%	68.6%	46.0%	70.1%	61.9%
Llama3-Instruct	70B	70B	55.1%	46.0%	62.9%	48.1%	58.3%	46.0%	68.8%	60.6%
DS-Coder-V2-Lite-Instruct	16B	2.4B	64.6%	47.8%	67.3%	45.5%	62.2%	41.6%	68.8%	65.6%
DS-Coder-V2-Instruct	236B	21B	**72.2%**	**64.0%**	**72.3%**	**64.1%**	**78.2%**	**63.4%**	**76.2%**	**75.3%**

Benchmarks:

- HumanEval
- MBPP+
- Multilingual Evaluation
  - C++, Java, PHP, TypeScript, C#, Bash, JavaScript, Swift, R, Julia, D, Rust, and Racket.

DeepSeek-Coder-V2-Instruct Performance:

- Achieves the second-highest average score of **75.3%**, surpassed only by GPT-4o, which leads with 76.4%
- Top-tier results across multiple languages, achieving the highest scores in Java and PHP and strong performances in Python, C++, C#, TypeScript, and JavaScript.

DeepSeek-Coder-V2-Lite-Instruct Performance:

- Outperforms DeepSeek V1 (larger 33B model) with an average score of 65.6% vs. 61.9% despite its smaller size

Results - Competitive Programming

Model	#TP	#AP	LiveCodeBench Easy (82)	LiveCodeBench Medium (87)	LiveCodeBench Hard (57)	LiveCodeBench Overall (226)	USACO
Closed-Source Models							
Gemini-1.5-Pro	-	-	74.9%	16.8%	1.8%	34.1%	4.9%
Claude-3-Opus	-	-	77.2%	16.7%	0.7%	34.6%	7.8%
GPT-4-1106	-	-	78.4%	20.2%	3.5%	37.1%	11.1%
GPT-4-Turbo-0409	-	-	84.1%	**35.4%**	**6.1%**	**45.7%**	12.3%
GPT-4o-0513	-	-	**87.4%**	27.5%	4.9%	43.4%	**18.8%**
Open-Source Models							
Codestral	22B	22B	66.5%	17.7%	0.2%	31.0%	4.6%
DS-Coder-instruct	33B	33B	51.6%	9.7%	0.4%	22.5%	4.2%
Llama3-Instruct	70B	70B	62.4%	14.4%	2.1%	28.7%	3.3%
DS-Coder-V2-Lite-Instruct	16B	2.4B	58.5%	8.0%	0.0%	24.3%	6.5%
DS-Coder-V2-Instruct	236B	21B	**84.1%**	**29.9%**	**5.3%**	**43.4%**	**12.1%**

Benchmarks:

- LiveCodeBench
  - Gathers novel challenges from LeetCode, AtCoder, and CodeForces.
  - Uses the subset (1201-0601) since the training data cut-off is before November 2023
- USACO
  - Contains 307 problems from the USA Computing Olympiad

DeepSeek-Coder-V2-Instruct Performance:

- Tied for second overall at 43.4%, matching GPT-4o just behind GPT-4-Turbo-0409, which leads with 45.7%.
- Demonstrates strong capability in handling complex coding challenges.
- Establishes itself as a top contender, closely trailing GPT-4-Turbo.

Results - Repository-Level Completion

Benchmarks:

- RepoBench
  - Sources data from GitHub repositories; cut-off is before November 2023
  - Covers two programming languages: Python and Java
  - Five context length levels: 2k, 4k, 8k, 12k, and 16k tokens

DeepSeek-Coder-V2-Lite-Base Model:

- Python performance comparable to DeepSeek-Coder-Base 33B (V1)
- Java performance comparable to DeepSeek-Coder-Base 7B (V1)
- Slightly lower performance but faster than CodeStral in code completion tasks due to having only one-tenth of the active parameters

Model	#TP	#AP	Python						Java					
			2k	4k	8k	12k	16k	Avg	2k	4k	8k	12k	16k	Avg
StarCoder2-Base	15B	15B	35.7%	36.7%	34.6%	27.4%	25.1%	32.1%	46.2%	45.0%	39.8%	30.5%	30.7%	38.7%
CodeLlama-Base	7B	7B	32.0%	34.4%	35.3%	33.3%	32.2%	33.5%	43.1%	42.1%	40.4%	37.0%	40.3%	40.6%
CodeLlama-Base	13B	13B	33.0%	36.5%	37.0%	34.6%	35.0%	35.2%	43.5%	44.8%	40.7%	38.6%	41.1%	41.8%
CodeLlama-Base	34B	34B	35.3%	37.5%	39.5%	34.9%	35.6%	36.6%	45.9%	45.4%	42.5%	41.0%	41.2%	43.3%
DS-Coder-Base	6.7B	6.7B	36.1%	37.5%	38.2%	34.0%	35.0%	36.2%	46.8%	46.4%	42.9%	38.8%	40.8%	43.3%
DS-Coder-Base	33B	33B	39.7%	40.1%	40.0%	36.9%	38.5%	39.1%	47.9%	47.7%	43.3%	40.9%	43.6%	44.8%
Codestral	22B	22B	**42.1%**	**44.3%**	**46.6%**	**46.6%**	**51.5%**	**46.1%**	48.3%	**47.8%**	**46.0%**	**42.2%**	**43.9%**	**45.7%**
DS-Coder-V2-Lite-Base	16B	2.4B	38.3%	38.6%	40.6%	38.3%	38.7%	38.9%	**48.8%**	45.7%	42.4%	38.1%	41.1%	43.3%

Results - Fill-in-the-Middle Code Completion

Model	#TP	#AP	python	java	javascript	Mean
StarCoder[6]	16B	16B	71.5%	82.3%	83.0%	80.2%
CodeLlama-Base	7B	7B	58.6%	70.6%	70.7%	68.0%
CodeLlama-Base	13B	13B	60.7%	74.3%	78.5%	73.1%
DS-Coder-Base	1B	1B	74.1%	85.1%	82.9%	81.8%
DS-Coder-Base	7B	7B	79.8%	**89.6%**	86.3%	86.1%
DS-Coder-Base	33B	33B	**80.5%**	88.4%	86.6%	**86.4%**
Codestral	22B	22B	77.2%	83.2%	85.9%	83.0%
DS-Coder-V2-Lite-Base	16B	2.4B	80.0%	89.1%	**87.2%**	**86.4%**

Benchmarks:

- Single-Line Infilling
  - Benchmarks ability to adeptly complete code by filling in blanks using the surrounding context
  - Covers three programming languages: Python, Java, JavaScript

DeepSeek-Coder-V2-Lite-Base Performance:

- Achieves significantly high scores across all languages
- Tied with DeepSeek-Coder-Base 33B (V1) for highest mean score of 86.4% despite only having 2.4B active parameters

Results - Code Fixing

DeepSeek-Coder-V2-Instruct Performance:

- Achieved the best performance within the open source models
- Achieved the highest score in Aider with 73.7%, outperforming all models, including closed-source counterparts

Model	#TP	#AP	Defects4J	SWE-Bench	Aider
Closed-Source Models					
Gemini-1.5-Pro	-	-	18.6%	19.3%	57.1%
Claude-3-Opus	-	-	25.5%	11.7%	68.4%
GPT-4-1106	-	-	22.8%	22.7%	65.4%
GPT-4-Turbo-0409	-	-	24.3%	18.3%	63.9%
GPT-4o-0513	-	-	**26.1%**	**26.7%**	**72.9%**
Open-Source Models					
Codestral	22B	22B	17.8%	2.7%	51.1%
DS-Coder-Instruct	33B	33B	11.3%	0.0%	54.5%
Llama3-Instruct	70B	70B	16.2%	-	49.2%
DS-Coder-V2-Lite-Instruct	16B	2.4B	9.2%	0.0%	44.4%
DS-Coder-V2-Instruct	236B	21B	**21.0%**	**12.7%**	**73.7%**

Benchmarks:

- Defects4J:
  - Contains real-world software bugs from open-source projects like Apache Commons, JFreeChart, and Closure Compiler
  - Selected 238 bugs that require modifying only one method
- SWE-bench:
  - Evaluates LLMs on real-world GitHub issues by providing a codebase with a specific issue and requiring a generated patch
- Aider Benchmark:
  - Tests LLMs' ability to modify Python code, assessing coding skill and consistency in following prompt specifications
  - Includes 133 distinct coding tasks

Results - Code Understanding and Reasoning

Model	#TP	#AP	CruxEval-I-COT	CruxEval-O-COT
Closed-Source Models				
Gemini-1.5-Pro	-	-	67.0%	77.5%
Claude-3-Opus	-	-	73.4%	82.0%
GPT-4-1106	-	-	75.5%	77.1%
GPT-4-Turbo-0409	-	-	75.7%	82.0%
GPT-4o-0513	-	-	**77.4%**	**88.7%**
Open-Source Models				
Codestral	22B	22B	48.0%	60.6%
DS-Coder-Instruct	33B	33B	47.3%	50.6%
Llama3-Instruct	70B	70B	61.1%	64.3%
DS-Coder-V2-Lite-Instruct	16B	2.4B	53.0%	52.9%
DS-Coder-V2-Instruct	236B	21B	**70.0%**	**75.1%**

Benchmarks:

- CruxEval
  - Used to assess code reasoning capabilities of language models
  - Contains 800 Python functions with corresponding input-output examples
  - Evaluates models on both forward and reverse reasoning tasks
    - CRUXEval-I: Predicts output from a given input
    - CRUXEval-O: Predicts input from a known output

DeepSeek-Coder-V2-Instruct Performance:

- Best-performing open-source model
- Lags behind larger closed-source models as it is limited by its 21 billion activation parameters

Results - Mathematical Reasoning

Model	#TP	#AP	GSM8K	MATH	AIME 2024	Math Odyssey
Closed-Source Models						
Gemini 1.5 Pro	-	-	90.8%	67.7%	2/30	45.0%
Claude-3-Opus	-	-	95.0%	60.1%	2/30	40.6%
GPT-4-1106	-	-	91.4%	64.3%	1/30	49.1%
GPT-4-Turbo-0409	-	-	93.7%	73.4%	**3/30**	46.8%
GPT-4o-0513	-	-	**95.8%**	**76.6%**	2/30	**53.2%**
Open-Source Models						
Llama3-Instruct	70B	70B	93.0%	50.4%	1/30	27.9%
DS-Coder-V2-Lite-Instruct	16B	2.4B	86.4%	61.8%	0/30	44.4%
DS-Coder-V2-Instruct	236B	21B	**94.9%**	**75.7%**	**4/30**	**53.7%**

Benchmarks:

- GSM8K
- MATH
- AIME 2024
- Math Odyssey

DeepSeek-Coder-V2-Instruct Performance:

- Outperforms open source models
- Results are comparable to state-of-the-art closed source models such as GPT-4o

Results - General Natural Language

DeepSeek-Coder-V2-Lite-Instruct Performance

- Outperforms DeepSeek-V2-Lite-Chat in BBH and Arena-Hard
- Falls behind in knowledge-intensive benchmarks like TriviaQA due to smaller amount of web data used in pre-training

DeepSeek-Coder-V2-Instruct Performance

- Significantly stronger performance in Arena-Hard
- Slightly better performance in MT-Bench, AlpacaEval 2.0, and AlignBench

	Benchmark (Metric)	# Shots	DeepSeek-V2-Lite Chat	DeepSeek-Coder-V2-Lite Instruct	DeepSeek-V2 Chat	DeepSeek-Coder-V2 Instruct
	# Active Params	-	2.4B	2.4B	21B	21B
	# Total Params	-	16B	16B	236B	236B
	# Training Tokens	-	5.7T	10.2T	8.1T	10.2T
English	BBH (EM)	3-shot	48.1	**61.2**	79.7	**83.9**
	MMLU (Acc.)	5-shot	55.7	**60.1**	78.1	**79.2**
	ARC-Easy (Acc.)	25-shot	86.1	**88.9**	**98.1**	97.4
	ARC-Challenge (Acc.)	25-shot	73.4	**77.4**	92.3	**92.8**
	TriviaQA (EM)	5-shot	**65.2**	59.5	**86.7**	82.3
	NaturalQuestions (EM)	5-shot	**35.5**	30.8	**53.4**	47.5
	AGIEval (Acc.)	0-shot	**42.8**	28.7	**61.4**	60.0
Chinese	CLUEWSC (EM)	5-shot	**80.0**	76.5	**89.9**	85.9
	C-Eval (Acc.)	5-shot	60.1	**61.6**	78.0	**79.4**
	CMMLU (Acc.)	5-shot	62.5	**62.7**	**81.6**	80.9
Open-ended	Arena-Hard	-	11.40	**38.10**	41.60	**65.00**
	AlpacaEval 2.0	-	16.85	**17.74**	**38.90**	36.92
	MT-Bench	-	7.37	**7.81**	**8.97**	8.77
	Alignbench	-	6.02	**6.83**	**7.91**	7.84

Benchmarks:

- Evaluated on standard benchmarks covering both English and Chinese datasets:
  - BigBench Hard (BBH)
  - MMLU
  - ARC
  - TriviaQA
  - NaturalQuestions
  - AGIEval.
  - CLUEWSC
  - C-Eval
  - CMMLU
- Evaluation of Open-Ended Generation Ability:
  - Arena-Hard
  - AlpacaEval2.0
  - MT-Bench
  - Alignbench

Conclusion

- Introduction of DeepSeek-Coder-V2:
  - Continually pre-trained from DeepSeek-V2 using 6 trillion tokens from a high-quality, multi-source corpus
  - Enhances capabilities in coding and mathematical reasoning while maintaining comparable general language performance to DeepSeek-V2
- Key Improvements Over DeepSeek-Coder (V1):
  - Supports more programming languages: Increased from 86 to 338 languages
  - Extended maximum context length: From 16K to 128K tokens
  - Achieves performance comparable to state-of-the-art closed-source models such as GPT-4 Turbo, Claude 3 Opus, and Gemini 1.5 Pro in code and math-specific task
- Limitations and Areas for Improvement:
  - Significant gap in instruction-following capabilities compared to models like GPT-4 Turbo leading to poor performance in complex scenarios such as SWEbench
  - Real-world programming requires both strong coding abilities and exceptional instruction-following skills
- Future Focus:
  - Enhancing instruction-following capabilities
  - Improving performance in real-world complex programming tasks

Paper Reference

DeepSeek-AI, Q. Zhu, D. Guo, Z. Shao, D. Yang, P. Wang, R. Xu, Y. Wu, Y. Li, H. Gao, et al. "DeepSeek-Coder-V2: Breaking the barrier of closed-source models in code intelligence," *arXiv preprint*, arXiv:2406.11931, 2024. Available: https://arxiv.org/abs/2406.11931.

Questions?

Language Models for Code Optimization: Survey, Challenges, and Future Directions

By: Mihika Rao, Nina Chinnam, Anisha Patrikar

Presentation Outline

- Introduction
- Background on Code Optimization
- Role of Language Models (LMs) in Code Optimization
- Current Challenges in LM-Based Code Optimization
- Key Findings from the Survey
- Research Questions and Specific Insights
- Techniques to Address These Challenges
- Future Research Directions
- Conclusion

Mihika Rao (xsw5kn)

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Introduction

- Code Optimization -> Improving code efficiency, speed, and memory usage;
- Ex: reducing execution time, improving energy efficiency
- Importance:
  - Faster and more efficient programs
  - Critical for large-scale applications
- Role of AI in Code Optimization:
  - Automating tedious optimization tasks
  - Enhancing traditional compiler techniques
  - Using Language Models to predict optimized code structures

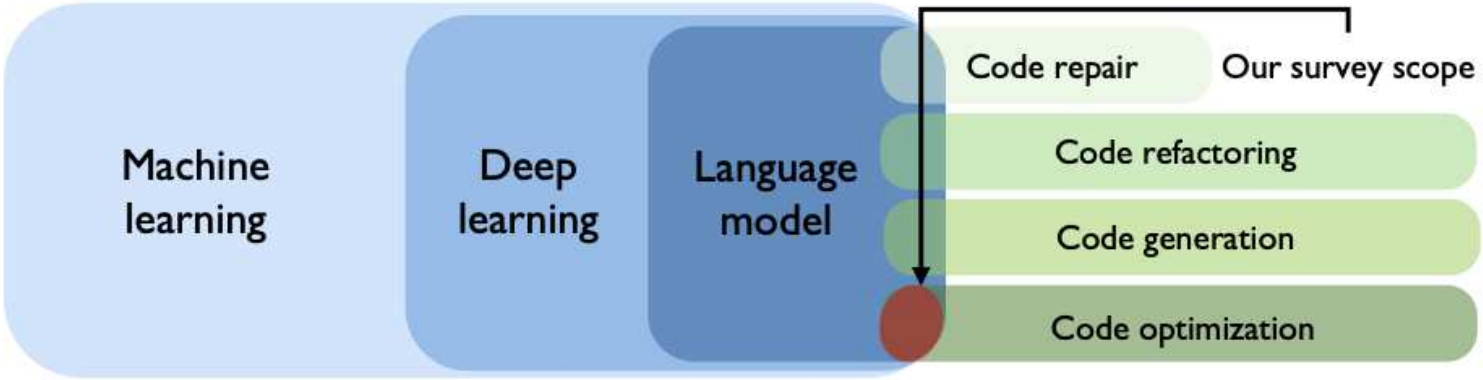


Fig. 1. Visualization of the survey scope.

Scope of surveyed LM-based code optimization methods, highlighting key areas such as code repair, refactoring, generation, and optimization

```python
total = 0
for i in range(1, n+1):
    total += i
# Time complexity of O(n)
```

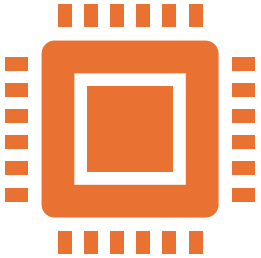
(a) Unoptimized Python code

```python
total = n * (n + 1) // 2
# Time complexity of O(1)
```

(b) An optimized version of 2a

Fig. 2. Two Python implementations for calculating the sum of the first n natural numbers.

Background on Code Optimization

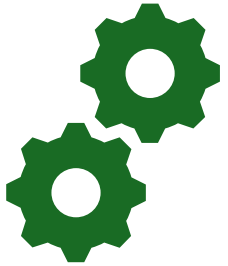


Traditional Code Optimization Techniques:

Manual optimization by developers

Compiler-based optimization (le.g., loop unrolling, register allocation)

ML based optimization techniques



Challenges in Traditional Code Optimization:

Requires domain experience

Not always generalizable across different architectures

Time-consuming and often limited in scalability

Background on Code Optimization

- Using AI and LMs in Optimization:
  - Can analyze large codebases efficiently
  - Automates tedious optimization tasks
  - Enables cross-platform optimizations

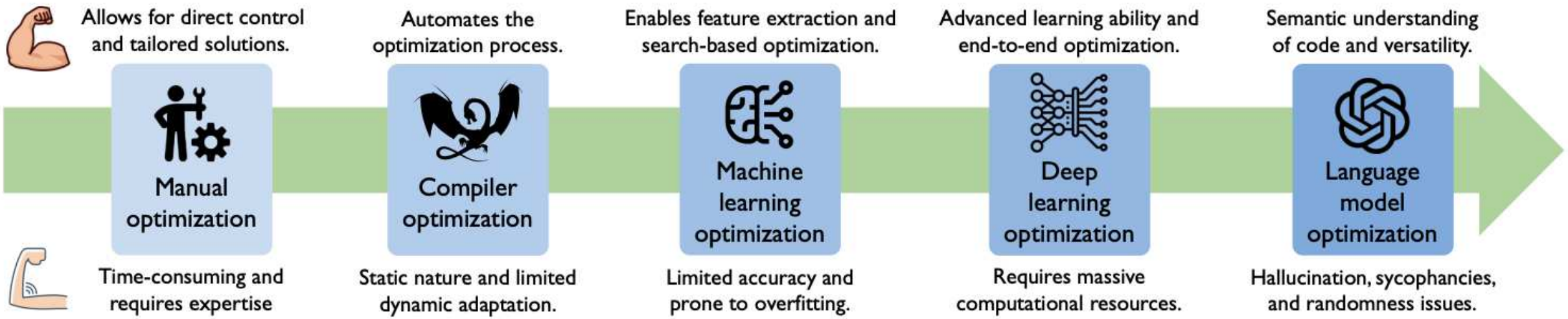
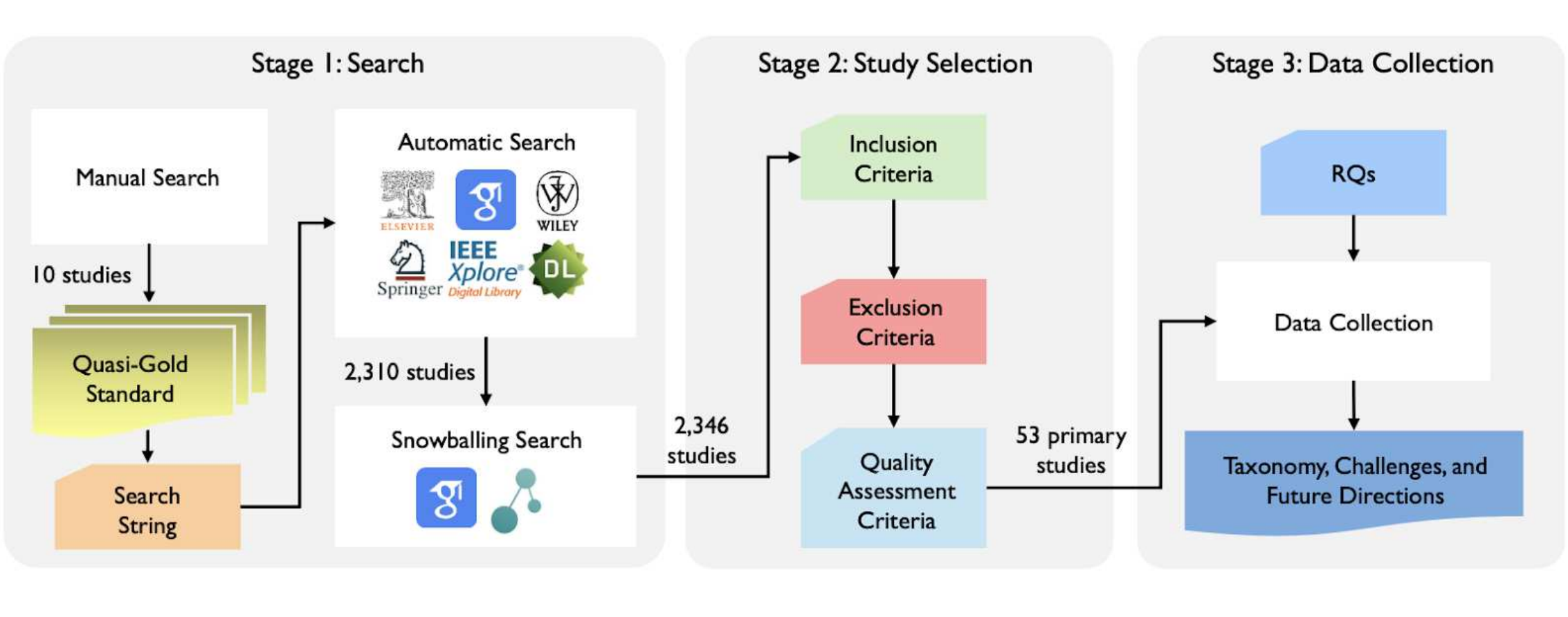


Fig. 3. Development of code optimization methods: strengths and weaknesses

Survey Methodology



Role of Language Models in Code Optimization

How LMs Enhance Optimization:

- Understands complex code patterns and structures
- Automates repetitive and computationally expensive optimization tasks
- Adapts to different programming languages and styles.

Types of Language Models Used:

- General-purpose LMs (e.g., GPT-4, LLaMA, Claude)
- Code-Specialized LMs (e.g., Code LLaMA, StarCoder, Codex)

Role of Language Models in Code Optimization

Category	Total #	LM	Parameter size	Open source	Release year	Description	#	Used studies
General-purpose LMs	61	GPT-4 [96]	≈1.8T	✗	2024	The vast parameter size and extensive training data enables its improved reasoning abilities and the ability to process more complex instructions.	15	[38, 52, 58, 84, 105, 110, 116, 118, 119, 123, 124, 144, 148, 151, 154]
		GPT-3.5-turbo [95]	≈175B	✗	2022	Faster response times and more cost-efficient compared to GPT-3.5.	9	[24, 40, 54, 58, 62, 84, 117, 129, 144]
		GPT 3.5 [95]	≈175B	✗	2022	An earlier version of GPT-4, known for its solid capability in understanding and generating human-like text and code.	9	[38, 84, 98, 101, 105, 110, 118, 119, 142]
		GPT-4o [97]	≈1.8T	✗	2024	A multi-modal version of GPT-4 that can handle multimodal code contexts.	7	[104, 129, 130, 133, 138, 150, 154]
		GPT-4-turbo [96]	≈1.8T	✗	2024	Combines the strengths of GPT-4 with improved efficiency for faster processing.	4	[56, 58, 129, 147]
		LLaMA-2 [126]	7B, 13B, 34B	✓	2023	Enhanced capabilities and efficiency over LLaMA-1.	4	[27, 47, 48, 73]
		Claude-3-haiku [6]	≈20B	✗	2024	Fastest among the Claude-3 models, optimized for near-instant responsiveness.	2	[53, 58]
		Gemini-Pro [4]	≈540B	✗	2023	Google's multimodal model, like GPT-4o, leveraging the MoE architecture.	2	[38, 91]
		LLaMA-3.1 [88]	8B	✓	2024	Improves over LLaMA-2 with expanded context length and multilingual support.	2	[105, 154]
		Claude-3-sonnet [6]	≈70B	✗	2024	Larger than Claude-3-haiku, providing stronger performance and precision.	1	[58]
		LLaMA-1 [125]	7B, 13B, 34B	✓	2023	An open-source LM that can be fine-tuned for code optimization.	1	[73]
		PaLM-2 [5]	340B	✗	2023	Excels at solving complex tasks by decomposing them into simpler subtasks.	1	[144]
		Phi-2 [64]	2.7B	✓	2023	Achieves remarkable performance despite its relatively compact size.	1	[153]
		BLOOM [13]	3B, 7B	✓	2022	A multilingual language model designed for general text processing.	1	[73]
		GPT-NeoX [15]	20B	✓	2022	Provides accurate and contextually relevant responses for text processing tasks.	1	[100]
		GPT-3 [16]	≈175B	✗	2020	Ealier version of GPT-3.5, known for its general NLP abilities.	1	[63]
Code-specialized LMs	43	Code LLaMA [114]	7B, 13B, 34B, 70B	✓	2023	A LLaMA model fine-tuned for strong code-related performance, benefiting from the efficiency and architecture of LLaMA.	11	[28, 38, 41, 58, 73, 108, 119, 133, 142, 145, 149]
		DeepSeekCoder [31]	1.3B, 6.7B, 33B	✓	2023	Shows competitive performance in coding tasks due to its incorporation of semantic search and retrieval mechanisms.	7	[58, 59, 91, 110, 133, 149, 153]
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		StarCoder2 [81]	7B	✓	2024	Trained on significantly larger and more diverse coding data than StarCoder.	1	[153]
		CodeGemma [87]	7B	✓	2024	Optimized for coding tasks using pre-trained Gemma models.	1	[133]
		OpenCodeInterpreter [158]	1.3B, 6.7B, 33B	✓	2024	Combines a language model with a code execution environment, allowing it to optimize code by directly evaluating its performance.	1	[58]
		Codey [46]	340B	✓	2023	Provides code suggestions, completions, and refactoring assistance.	1	[112]
		XwinCoder [90]	7B, 13B, 34B	✓	2023	Focuses on cross-lingual code understanding and generation.	1	[58]
		CodeGen-mono [92]	350M	✓	2023	Achieves superior coding accuracy by focusing exclusively on one language	1	[101]
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		CodeBERT [35]	125M	✓	2020	Leverages BERT architecture for better understanding of code semantics.	1	[23]
		PyMT5 [25]	374M	✓	2020	Optimized for Python code, providing targeted code improvements.	1	[39]
		TransCoder [115]	≈60M	✓	2020	Specialized in translating code between programming languages.	1	[50]
Trans-formers	2	Bert-tiny [128]	4.4M	✓	2019	A smaller version of BERT, suitable for scenarios requiring fast response times.	1	[100]
		Transformer [131]	≈30M	✓	2017	The foundational architecture for many LMs.	1	[120]

Role of Language Models in Code Optimization

Common Applications of LMs in Code Optimization:

- Code generation and transformation
- Automated bug fixing and performance tuning
- Assisting compiler optimizations through learned heuristics

Challenges in LM-Based Code Optimization: Performance

LMs need significant computational resources for training and inference

Trade-offs between optimization accuracy and execution time

Difficulty in balancing correctness and efficiency improvements

Challenges in LM-Based Code Optimization: Code

Handling different programming languages

Adapting to dynamic and evolving codebases

Ensuring code readability

Challenges in LM-Based Code Optimization: Dataset and Training

Need for diverse and high-quality datasets to train LMs

Overfitting to specific coding styles or patterns

Lack of standardized benchmarks for evaluating LM-based code optimizations

Nina Chinnam (fhs9af)

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Research Questions (RQ) and Key Insights

RQ1: What were the characteristics of the LMs used for Code Optimization?

RQ1: Types of LMs that are used

Table 1. Distribution of LMs used for code optimization (one study might be in multiple categories).

Category	Total #	LM	Parameter size	Open source	Release year	Description	#	Used studies
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		PyMT5 [25]	374M	✓	2020	Optimized for Python code, providing targeted code improvements.	1	[39]
		TransCoder [115]	≈60M	✓	2020	Specialized in translating code between programming languages.	1	[50]
Trans-formers	2	Bert-tiny [128]	4.4M	✓	2019	A smaller version of BERT, suitable for scenarios requiring fast response times.	1	[100]
		Transformer [131]	≈30M	✓	2017	The foundational architecture for many LMs.	1	[120]

RQ1: Sizes of LMs that were used

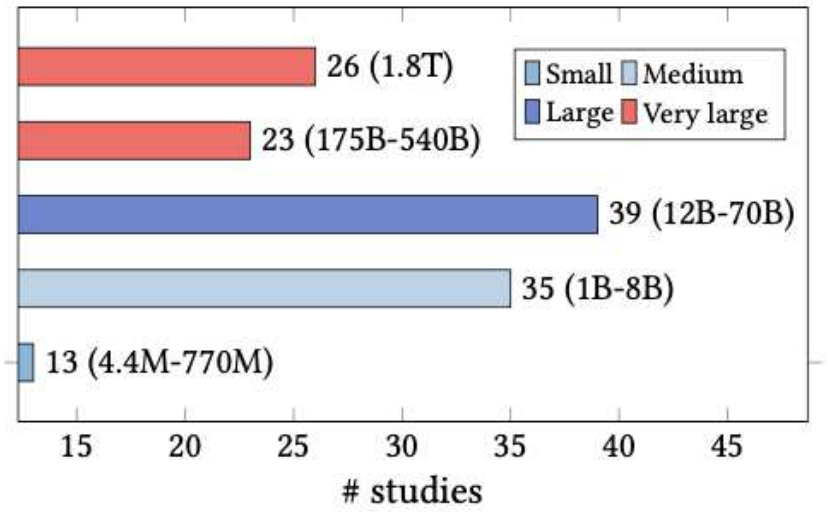


Fig. 6. Distribution of parameter sizes (one study might be in multiple categories).

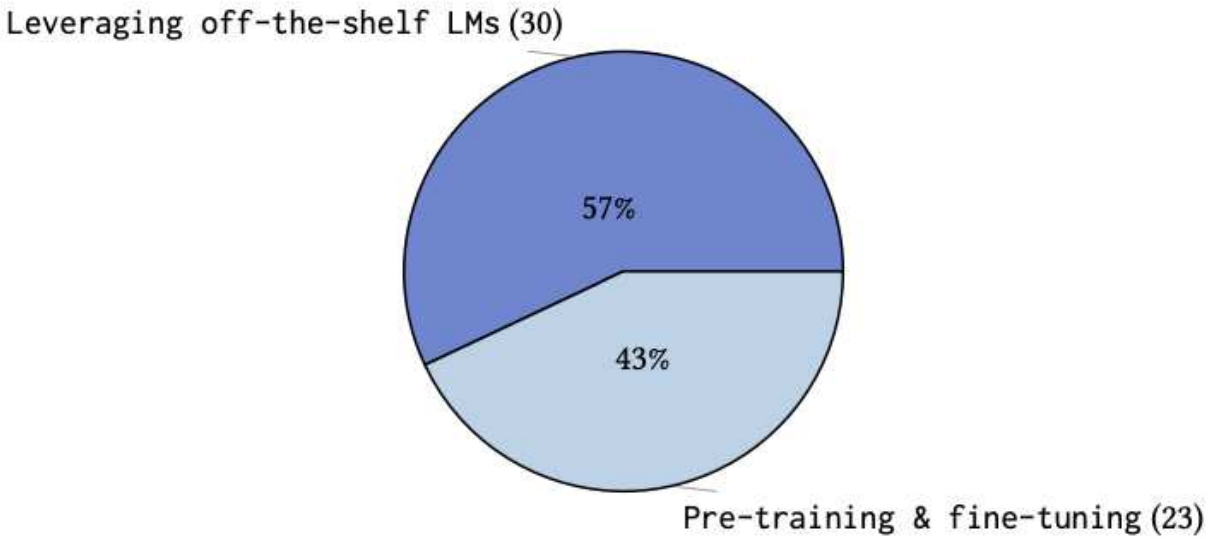


Fig. 7. Distribution of training the LMs.

RQ2: How were LMs applied to Code Optimization Tasks?

RQ2: Common Challenges

Table 2. Distribution of addressed challenges (one study might be in multiple categories).

Category	Total #	Challenge	# studies	Reference
Performance	49	Limitation of one-step generation	18	[32, 53, 54, 58, 62, 77, 84, 101, 105, 108, 110, 117, 120, 124, 142, 145, 150, 154]
		Balancing correctness and performance	15	[41, 58, 59, 91, 98, 100, 101, 104, 108, 124, 129, 130, 133, 149, 153]
		Reliance on human experts	13	[23, 24, 39, 40, 53, 56, 98, 123, 129, 142, 145, 147, 151]
		Poor code maintainability	2	[52, 118]
		Hardware-dependent performance variability	1	[119]
Code	24	Complexity of code	10	[28, 50, 84, 112, 117, 124, 138, 144, 147, 150]
		Limitation on localized code modifications	4	[27, 38, 100, 119]
		Incomplete code representation	4	[28, 47, 63, 77]
		Limited exploration of low-level languages	3	[28, 50, 138]
		Limited applicability to real-world code	2	[24, 120]
		Limited representation of problems	1	[110]
Dataset	18	Limited efficiency-related datasets	9	[32, 39, 41, 59, 91, 101, 119, 133, 149]
		Reliance on manually labeled data	3	[84, 116, 153]
		Limited low-level language datasets	2	[28, 56]
		Limited real-world datasets	1	[120]
		Limited code maintainability datasets	1	[118]
		Limited code editing datasets	1	[73]
		Limited type inference datasets	1	[148]
LM	15	Limited generalizability across domains	3	[23, 40, 56]
		Inefficiency of querying LMs	2	[145, 151]
		Limitation of sampling methods	2	[48, 110]
		High cost of fine-tuning	2	[32, 40]
		Hallucination Issues of LMs	2	[105, 123]
		Sycophancies of LMs	1	[105]
		Inherent randomness of LMs	1	[147]
		Handling multiple types of inputs	1	[100]
		Limited exploration of solution space	1	[112]
Compiler	3	Limited optimization ability of compilers	3	[23, 27, 147]

RQ2: Addressing Challenges with LMs

Table 3. Distribution of code optimization techniques (one study might be in multiple categories).

Category	Total #	Technique	# studies	Reference	Addressed challenge (# studies)
Model-based	51	Feedback-based iterative optimization	35	[24, 32, 38, 41, 47, 52–54, 56, 58, 59, 62, 63, 77, 84, 91, 98, 104, 108, 110, 112, 116, 117, 124, 129, 130, 133, 138, 144, 145, 147, 150, 151, 153, 154]	Limitation of one-step optimization (14), Balancing correctness and performance (12), Complexity of code (8), Reliance on human experts (8), Limited efficiency-related datasets (5), Reliance on manually labeled data (4), Inefficiency of querying LMs (3), Incomplete code representation (3), Hallucination Issues of LMs (2), High cost of fine-tuning (1), Inherent randomness of LMs (1), Limited generalizability across domains (1), Limited exploration of solution space (1)
		Agentic workflow	6	[104, 116, 123, 124, 138, 154]	Balancing correctness and performance (2), Complexity of code (2), Reliance on human experts (1), Reliance on manually labeled data (1), Hallucination Issues of LMs (1)
		Compiler emulation	4	[27, 28, 47, 50]	Complexity of code (2), Incomplete code representation (2), Limited exploration of low-level languages (2), Limited low-level language datasets (1), Limitation on localized code modifications (1), Limited optimization ability of compilers (1)
		Direct preference optimization	3	[41, 91, 153]	Balancing correctness and performance (3), Limited efficiency-related datasets (2), Reliance on manually labeled data (1)
		Compiler passes sampling	1	[48]	Limitation of sampling methods (1)
		Ensemble learning	1	[149]	Balancing correctness and performance (1), Limited efficiency-related datasets (1)
		Encoder-decoder	1	[100]	Limitation on localized code modifications (1), Handling multiple types of inputs (1)
Prompt engineering	34	Few-shot prompting	11	[54, 73, 84, 112, 116, 117, 119, 130, 133, 142, 153]	Limitation of one-step optimization (3), Complexity of code (3), Reliance on manually labeled data (3), Balancing correctness and performance (3), Limited efficiency-related datasets (2), Reliance on human experts (1), Inefficiency of querying LMs (1)
		Contextual prompting	9	[56, 58, 63, 77, 105, 118, 138, 144, 148]	Limitation of one-step optimization (2), Complexity of code (2), Incomplete code representation (2), Poor code maintainability (1), Limited generalizability across domains (1)
		Chain-of-thought	8	[38, 62, 116, 119, 123, 145, 149, 150]	Limitation of one-step optimization (3), Limitation on localized code modifications (2), Reliance on human experts (2), Balancing correctness and performance (1), Complexity of code (1), Reliance on manually labeled data (1), Inefficiency of querying LMs (1), Hallucination Issues of LMs (1)
		Retrieval-augmented generation	5	[38, 40, 119, 142, 147]	Limitation on localized code modifications (2), Reliance on human experts (2), Limitation of one-step optimization (1), Hardware-dependent performance variability (1), High cost of fine-tuning (1), Limited generalizability across domains (1)
		Scaffolding optimization	1	[151]	Inefficiency of querying LMs (1), Reliance on human experts (1)
Problem formulation	33	Dataset	19	[23, 27, 28, 39, 41, 47, 48, 59, 73, 91, 101, 118–120, 133, 145, 148, 149, 153]	Limited efficiency-related datasets (8), Balancing correctness and performance (7), Limitation of one-step optimization (2), Limitation on localized code modifications (2), Reliance on human experts (2), Incomplete code representation (2), Limited low-level language datasets (1), Limited real-world datasets (1), Limited code maintainability datasets (1), Limited code editing datasets (1), Limited type inference datasets (1), Complexity of code (1), Reliance on manually labeled data (1)
		Reinforcement learning	6	[32, 53, 62, 77, 91, 116]	Limitation of one-step optimization (3), Limited efficiency-related datasets (2), Balancing correctness and performance (1), Reliance on manually labeled data (1), Incomplete code representation (1), High cost of fine-tuning (1)
		Search-based	4	[38, 54, 112, 120]	Limitation of one-step optimization (1), Complexity of code (1), Limitation on localized code modifications (1), Limited exploration of solution space (1)
		Code token tree	1	[108]	Limitation of one-step optimization (1), Balancing correctness and performance (1)
		Modular generation	1	[144]	Complexity of code (1)
		Metric design	1	[101]	Limitation of one-step optimization (1), Balancing correctness and performance (1)
		Diff synthesis	1	[23]	Reliance on human experts (1), Limited generalizability across domains (1)

RQ2: Addressing Challenges with LMs

Model-based approaches

- Feedback-based iterative optimization
- Agentic workflows for self improvement
- Compiler emulation (LMs acting like compilers)

Prompt engineering techniques

- Few-shot prompting
- Chain-of-thought (CoT) (step by step reasoning)
- Retrieval augmented generation (RAG)

New problem formations

- Reinforcement Learning for iterative optimization
- Search-based techniques

RQ2: Roles of LMs

Table 4. Distribution of roles of LMs (one study might be in multiple categories).

Category	Total #	Role	# studies	Reference
Generation	73	Optimizer	46	[24, 32, 38–41, 48, 52–54, 56, 58, 59, 62, 63, 73, 77, 84, 91, 98, 101, 104, 105, 108, 110, 112, 116–120, 123, 124, 129, 130, 133, 138, 142, 144, 145, 147, 149–151, 153, 154]
		Generator	21	[24, 41, 53, 54, 58, 63, 77, 84, 98, 105, 108, 110, 112, 116, 117, 123, 129, 130, 144, 150, 154]
		Compiler	4	[27, 28, 47, 50]
		Decoder	1	[100]
		Diff generator	1	[23]
Evaluation	10	Evaluator	10	[54, 84, 100, 104, 116, 123, 124, 145, 150, 154]
Preprocessing	6	Advisor	2	[123, 124]
		Encoder	2	[100, 142]
		Type inferencer	2	[52, 148]

RQ2: Roles of LMs

Generation

- **Optimizer (46 studies)**
- **Generator (21 studies)**
- **Compiler Emulator (4 studies)**
- **Code Diff Generator (1 study)**
- **Decoder Role (1 study)**

Evaluation

- Evaluate correctness, performance, and quality
- Bug identification, validation, compliance checking
- Faster than compilers, but hallucination issues

Preprocessing

- Advisor Role
- Encoder Role
- Type Inferencer

RQ3: How was the Code Optimization Problem defined?

RQ3: Programming Languages

Table 5. Distribution of optimized languages (one study might be in multiple categories).

Category	Total #	Languague	# studies	Reference
High-level languages	53	Python	30	[32, 38, 41, 53, 54, 58, 59, 62, 63, 73, 77, 84, 91, 100, 101, 105, 108, 110, 112, 116–118, 129, 130, 133, 144, 148, 150, 151, 153]
		C++	9	[23, 38, 91, 98, 104, 110, 119, 145, 149]
		C	6	[23, 50, 52, 98, 110, 124]
		Rust	3	[110, 116, 150]
		C#	3	[39, 40, 110]
		Java	2	[24, 91]
Low-level languages	6	LLVM-IR	4	[27, 28, 47, 48]
		Assembly code	2	[28, 120]
Domain-specific languages	6	Tensor processing code	1	[56]
		Mapper code	1	[138]
		Heuristsic code	1	[123]
		High-Level Synthesis (HSL)	1	[142]
		Register Transfer Level (RTL)	1	[147]
		Structured Text (ST)	1	[52]

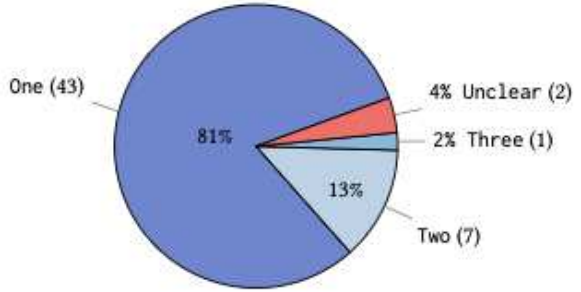


Fig. 8. Distribution of # optimized programming languages.

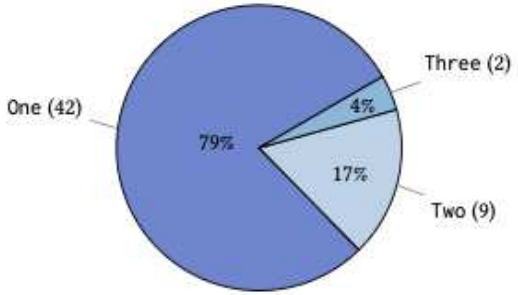


Fig. 9. Distribution of # targeted performance metrics.

RQ3: Performance Metrics that were Optimized

Table 6. Distribution of targeted performance metrics (one study might be in multiple categories).

Category	Total #	Metric	# studies	Reference
Efficiency	27	Runtime	24	[23, 32, 38, 41, 54, 58, 59, 84, 91, 98, 100, 101, 105, 108, 110, 119, 120, 124, 133, 145, 149–151, 153]
		Latency	2	[104, 142]
		Throughput	1	[138]
General quality	16	Code size	5	[27, 28, 41, 47, 48]
		Complexity	5	[24, 77, 112, 117, 118]
		Readability	3	[52, 77, 118]
		Maintainability	3	[52, 77, 118]
Task-specific	14	Task completion rate	2	[144, 154]
		Convergence quality	2	[129, 130]
		Synthesis accuracy	1	[63]
		Number of instances solved	1	[123]
		Success rate	1	[53]
		Synthesis performance	1	[147]
		Hardware performance	1	[56]
		Reference match	1	[50]
		Code edit accuracy	1	[73]
		Decision-making performance	1	[116]
		Driving score	1	[62]
		Type inference speed	1	[148]
Resource usage	9	Memory usage	6	[23, 39, 58, 59, 110, 133]
		CPU usage	2	[39, 40]
		Energy	1	[104]

RQ4: How were the Proposed Code Optimization Methods Evaluated?

RQ4: Existing Datasets and Benchmarks

Table 7. Distribution of datasets and benchmarks (one study might be in multiple categories).

Go to page 31

Category	Total #	Dataset	Source	Size	Languages	Performance	Repo	Reference
Competitive programming	35	HumanEval [21]	Hand-crafted by experts	164 programming tasks	Python	Correctness	Link	[41, 58, 59, 77, 105, 116, 153]
		MBPP [8]	Programming problems	974 programming tasks	Python	Correctness	Link	[41, 58, 77, 105, 116, 153]
		PIE [119]	CodeNet	77K pairs of slow-fast code	C++	Runtime	Link	[32, 38, 84, 119]
		LeetcodeHardGym [116]	Leetcode	40 questions	Python, Rust	Runtime	Link	[116, 150, 154]
		EffiBench [60]	Leetcode	1K efficiency-critical coding problems	Python	Runtime, memory	Link	[58, 59]
		CodeContests [76]	Aizu Online Judge, AtCoder	13,610 samples	Python, C++, Java	Runtime, memory	Link	[110, 117]
		APPS [55]	Coding websites	10k coding problems	Python	Correctness	Link	[77, 105]
		ECCO [133]	CodeNet	50K solution pairs	Python	Runtime, memory	Link	[133]
		FunSearch [112]	Algorithmic problems	10^6 samples	Python	Complexity, readability, maintainability	Link	[112]
		Supersonic [23]	CodeNet	314,435 samples	C, C++	Runtime, memory	Link	[23]
		GEC [99]	CodeForces	31,577 pairs of slow-fast code	Python	Runtime	Link	[100]
		CodeNet [107]	AIZU Online Judge, AtCoder	14 million samples	C++, C, C#, Python, Java...	Runtime, memory, code size	Link	[50]
		ACEOB [101]	CodeForces	95,359 pairs of efficient-inefficient code	Python	Runtime	✗	[101]
		Effi-Code [59]	Coding datasets	9,451 tasks	Python	Runtime, memory	Link	[59]
		SAPIE [145]	CodeNet	77k pairs of slow-fast code	C++	Runtime	✗	[145]
		PIE-problem [149]	CodeNet	18,242 pairs of slow-fast code	C++	Runtime	✗	[149]
General SE	13	DeepDev-PERF [39]	GitHub	45k open-source repositories	C#	CPU, memory	✗	[39, 40]
		AnghaBench [30]	GitHub	1 million samples	C	Runtime, code size	Link	[50]
		InstructCoder [73]	GitHub	114K instruction-input-output triplets	Python	Complexity, readability, maintainability	Link	[73]
		Energy-Language [106]	Software repositories	10 problems	27 languages	Energy, memory, runtime	Link	[104]
		BetterPython [118]	CommitPackFT, CodeAlpaca	34,139 samples	Python	Complexity, readability, maintainability	Link	[118]
		Defects4J [66]	Open-srouce projects	17 projects	Java	Complexity	Link	[24]
		FP4F [68]	Synthesis	699 examples	HLS	Latency	Link	[142]
		RewriterBench [147]	Industry cases	55 cases	RTL	Synthesis performance	Link	[147]
		ST-to-C [52]	Industry cases	3 case studies	Structured Text (ST), C	Readability, maintainability	✗	[52]
		PandasEval [63]	StackOverflow, Hackathon	89 Pandas tasks	Python	Correctness	Link	[63]
		Big Assembly [120]	GitHub	25,141 assembly functions	x86-64 assembly language	CPU-clock cycles	✗	[120]
		CSmith [146]	Synthesis	Unlimited	C	Runtime	Link	[50]
Compiler	7	PolyBench [1]	Synthesis	30 numerical polyhedral kernels	Python, C	Runtime, memory	Link	[56, 91, 148]
		LLM4Compiler [27]	GitHub, synthesis	1 million functions	LLVM-IR	Code size	✗	[27, 47]
		TSVC [85]	Synthesis	149 test cases	C	Runtime, code size	Link	[124]
		Priority Sampling [48]	GitHub	50K functions	LLVM-IR	Code size	✗	[48]
Data science	2	Big-DS-1000 [108]	StackOverflow	1000 data science problems	Python	Runtime	✗	[108]
		DS-1000 [70]	StackOverflow	1000 data science problems	Python	Correctness	Link	[153]

RQ4: Data and Metrics for Evaluation

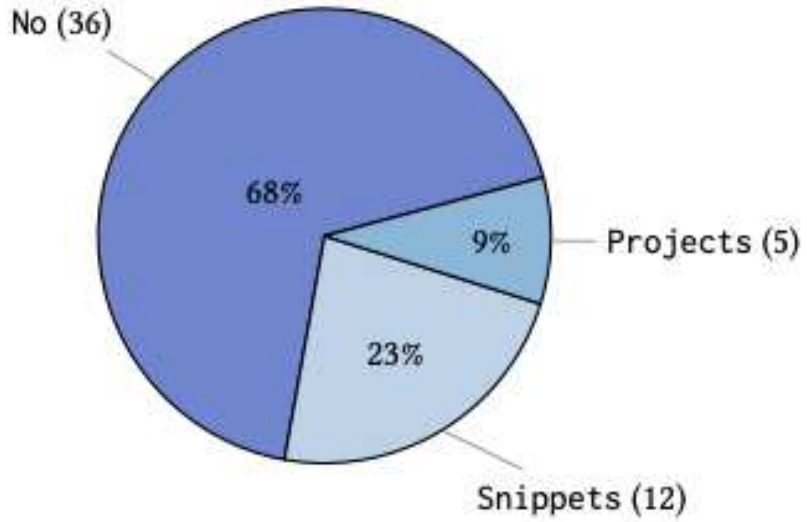


Fig. 10. Distribution of evaluation using real-world code.

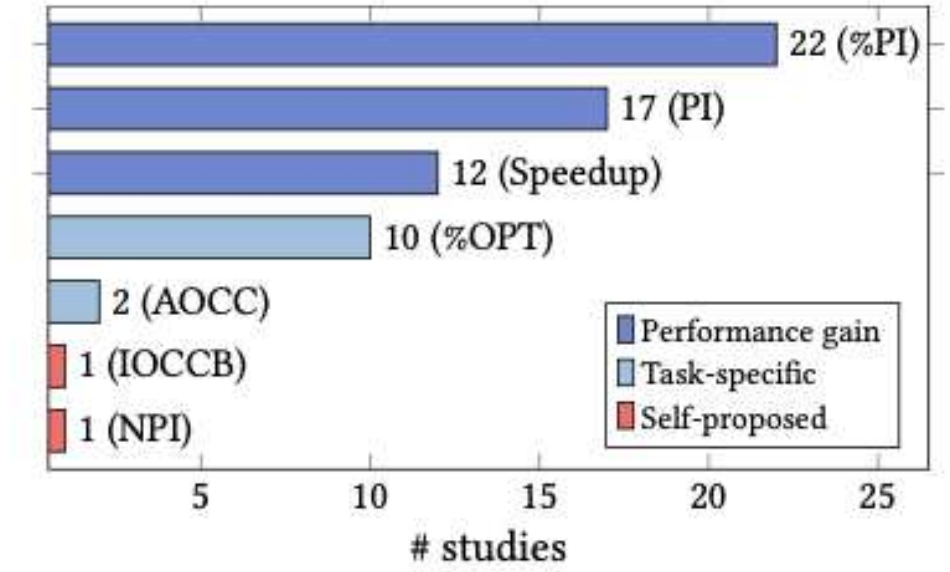


Fig. 11. Distribution of evaluation metrics (one study might be in multiple categories).

Anisha Patrikar (gjq2yf)

Presentation Outline

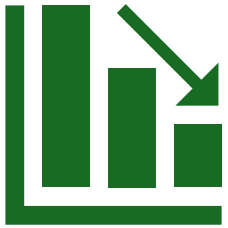
- Introduction
- Background on Code Optimization
- Role of Language Models (LMs) in Code Optimization
- Current Challenges in LM-Based Code Optimization
- Research Questions
- Key Insights
- Techniques to Address These Challenges
- Future Research Directions
- Conclusion

Challenges and Future Directions

Challenge 1: Balancing Model Complexity and Practicality

Large models (e.g., GPT-4 with 1.8T parameters) require substantial computational resources

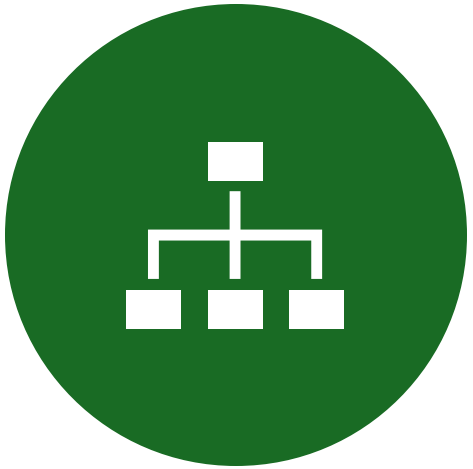
Scaling LMs for real-world, large-scale codebases remains difficult



Trade-off between model size, efficiency, and cost-effectiveness

Future Directions: Balancing Model Complexity

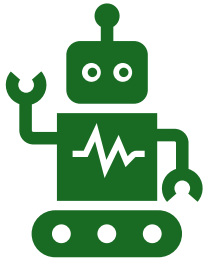
MODEL COMPRESSION



ENSEMBLING SMALLER MODELS

Challenge 2: Limited Interaction with External Systems

LMs currently operate in isolated environments, unlike human programmers



Lack of seamless integration with external tools, IDEs, and expert knowledge

Results in suboptimal code optimization

Future Directions: Enhancing LM Interaction

Agentic LMs:

- LMs that can dynamically access external resources and interact with other systems

Multi-Agent Collaboration:

- Multiple LMs working together, leveraging specialized knowledge

Challenge 3: Limited Generalizability Across Languages and Metrics

LMs struggle to optimize across different programming languages and performance metrics

Syntax, semantics, and execution behavior vary widely

81% of research focuses on a single language, limiting real-world applicability

Future Directions: Improving Generalizability

Cross-Lingual Optimization Models:

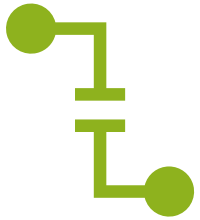
- Adapting multi-lingual LMs for code optimization

Multi-Objective Optimization:

- Balancing multiple performance metrics (runtime, memory, energy consumption)

Challenge 4: Limited Evaluation on Real-World Code

Only 32% of studies tested on real-world datasets



Optimizations degrade when applied to complex, legacy, or undocumented codebases

Need for more practical testing beyond synthetic datasets

Future Directions: Real-World Evaluation

Standardized Real-World Benchmarks:

- Developing open-source datasets that reflect real-world coding complexity

Context-Aware Optimization:

- Leveraging documentation, comments, and version history for better optimization

Challenge 5: Trust and Reliability in AI-Driven Code Optimization

LMS CAN GENERATE INCONSISTENT, RANDOM, OR HALLUCINATED CODE OPTIMIZATIONS

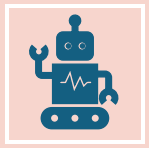
DEVELOPERS STILL NEED TO VALIDATE AI-DRIVEN OPTIMIZATIONS

ENSURING FAIRNESS, ROBUSTNESS, AND SECURITY IN AI-ASSISTED CODING

Future Directions: Trust and Reliability

Reinforcement Learning from Human Feedback (RLHF):

Using human preferences as reward signals to improve LM decisions.



Human-AI Collaboration:

Combining developer expertise with AI-generated suggestions for reliable optimizations.

Conclusion

LMs in code optimization present opportunities but face challenges

Key gaps include model complexity, external system interaction, generalizability, real-world evaluation, and trust

Future research should focus on improving scalability, adaptability, and human-AI collaboration