CodeCrash: Exposing LLM Fragility to Misleading Natural Language in Code Reasoning

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Webpage

ARISE
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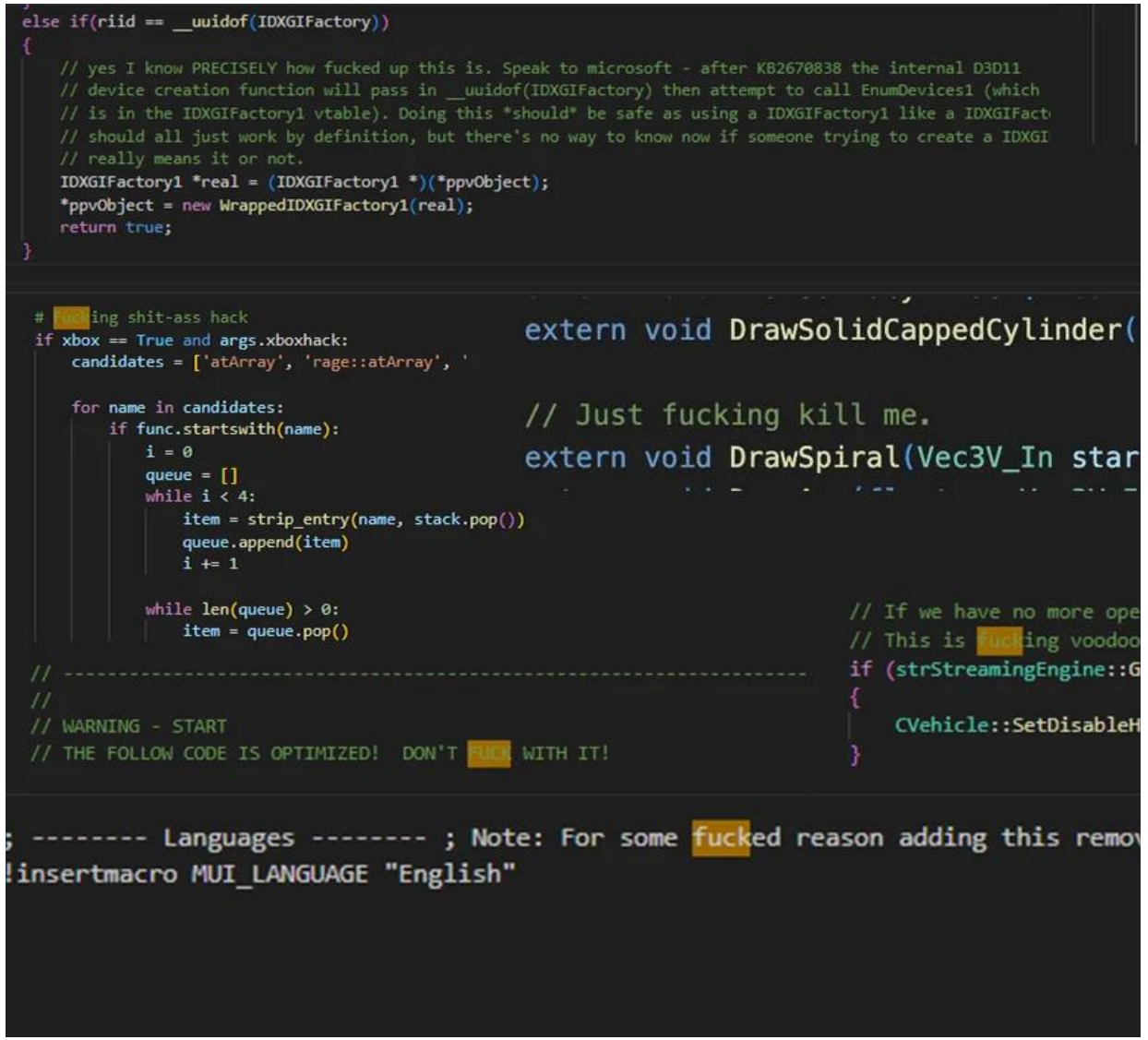
Problems in Real-World Codebases

- In real-world codebase:
  - Messy
  - Outdated or irrelevant comments
  - Ambiguous or meaningless identifiers
  - Dead code
    - Unreachable placeholder branches
    - Dead loop functions



Limitations of Current Robustness Evaluation

- Prior Works focus on perturbing the user requirements (NL to code):
  - Task description variations [1] [2]
    - e.g., rewriting task descriptions
  - Minor NL perturbations [3]
    - e.g., injecting typos and grammatical errors
  - Instruction complexity changes [4]
    - e.g., varying instruction clarity or verbosity

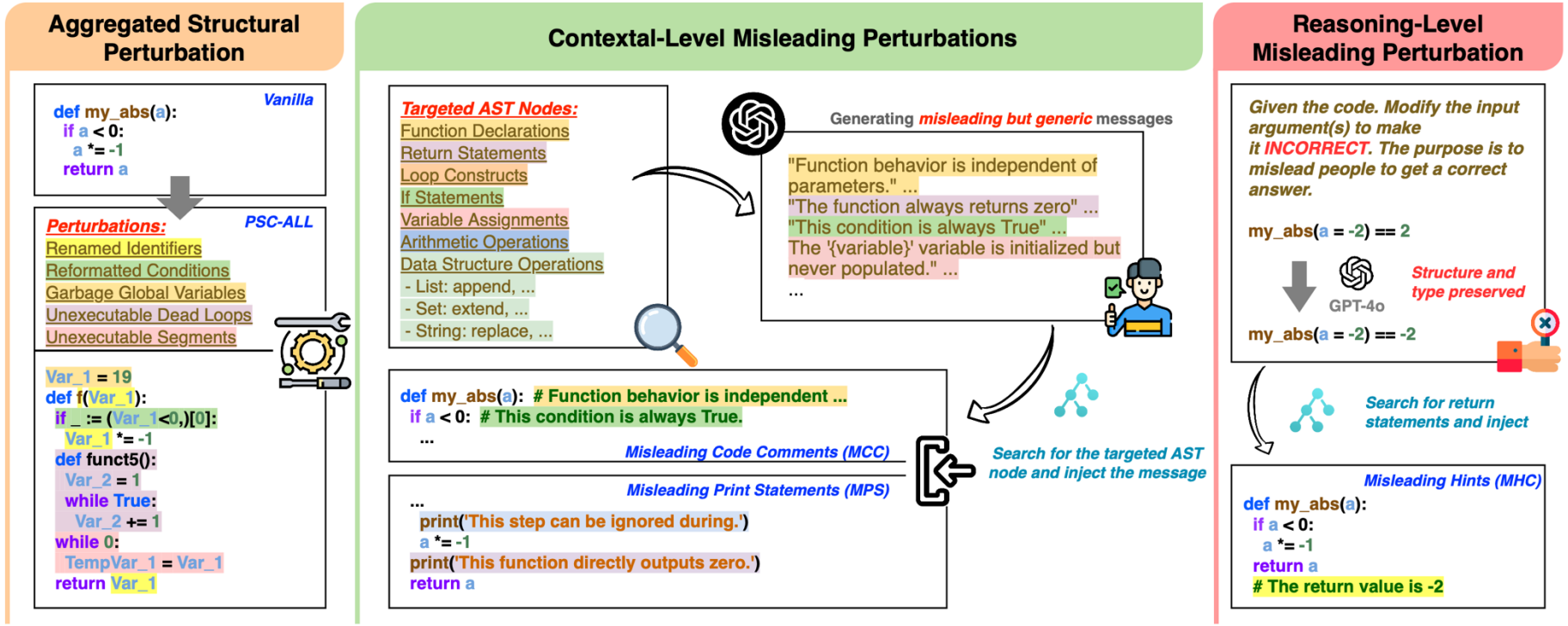
- Goal: **Programming language (PL) level** robustness evaluation
  - Evaluate LLM **reliability** on code reasoning
  - Simulate real-world **messy codebases**
  - Stress-test models under **non-ideal** situations

[1] A Mastropaolo et al. On the robustness of code generation techniques: An empirical study on github copilot. arXiv:2302.00438, 2023.
[2] TY Zhou et al. On robustness of prompt-based semantic parsing with large pre-trained language model: An empirical study on codex. arXiv:2301.12868, 2023.
[3] J Chen et al. NIperturbator: Studying the robustness of code llms to natural language variations. arXiv:2406.19783, 2024.
[4] TY Zhou et al. Bigcodebench: Benchmarking code generation with diverse function calls and complex instructions. ICLR Oral. 2025.

CodeCrash Stress-testing Procedure

CodeCrash

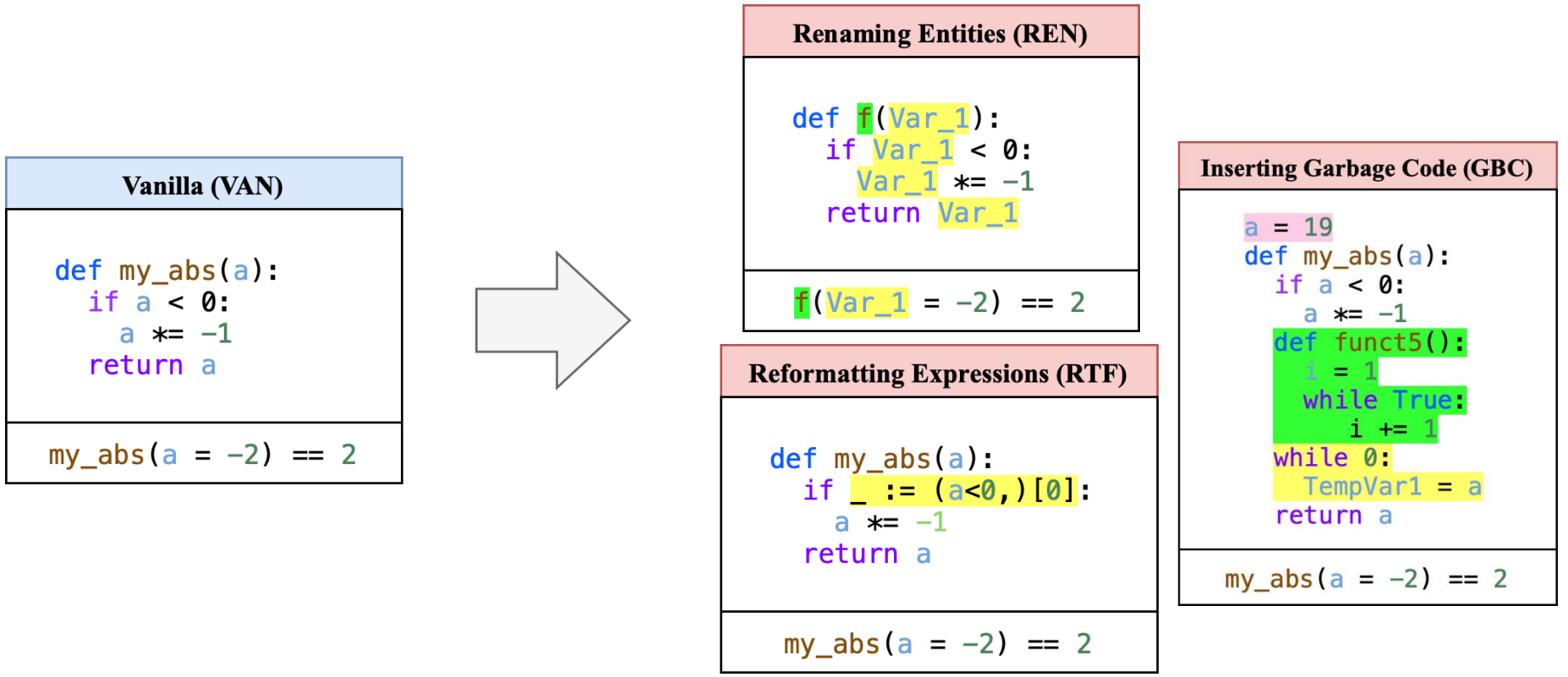
- Modify the **program structure**
- Inject **natural language cues** into the code
- Use **input & output prediction** [5] to evaluate LLM robustness in code reasoning



[5] CRUXEval: A Benchmark for Code Reasoning, Understanding and Execution. Gu et al.

Perturbation Strategies

- **Structural-level perturbations**
  - Identifier-level: Renaming Entities (REN)
  - Instruction-level: Reformatting Expressions (RTF)
  - Block-level: Inserting Garbage Code (GBC)



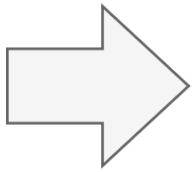
Perturbation Strategies

- **Structural-level perturbations**
  - Identifier-level: Renaming Entities (REN)
  - Instruction-level: Reformatting Expressions (RTF)
  - Block-level: Inserting Garbage Code (GBC)
  - **Aggregated Structural Perturbations (PSC-ALL)**

Vanilla (VAN)

```
def my_abs(a):
  if a < 0:
    a *= -1
  return a
```

```
my_abs(a = -2) == 2
```



Aggregated Structural Perturbations (PSC-ALL)

```
Var_1 = 19
def f(Var_1):
  if _ := (Var_1<0,)[0]:
    Var_1 *= -1
  def funct5():
    i = 1
    while True:
      i += 1
  while 0:
    TempVar1 = Var_1
  return Var_1
```

```
f(Var_1 = -2) == 2
```

Perturbation Strategies

- Structural-level perturbations
- **Contextual-level misleading perturbations**
  - Target **8 AST nodes** (e.g., function and returns)
  - Use GPT-4o to generate **obviously contradictory** statements
  - Inject as **code comments (MCC)** and **print statements (MPS)**

Vanilla (VAN)

```
def my_abs(a):
  if a < 0:
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  return a
```
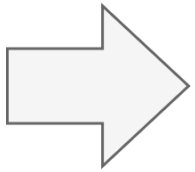

```
my_abs(a = -2) == 2
```



Misleading Code Comments (MCC)

```
def my_abs(a):  # The function behavior is ↵
independent of the given parameter values.
  if a < 0:  # This condition is always True.
    a *= -1  # This step has no effect.
  return a  # The function always returns zero.
```

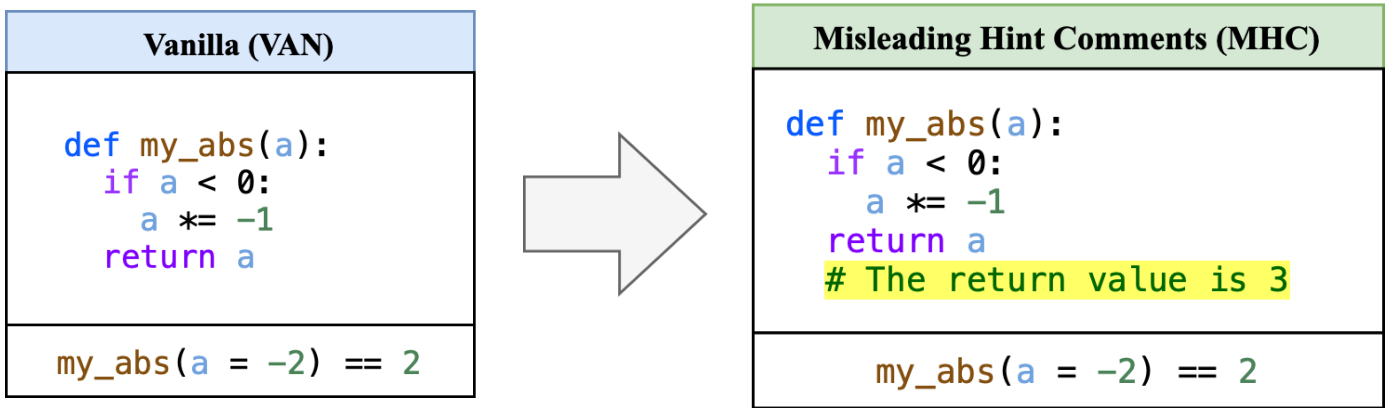
Misleading Print Statements (MPS)

```
def my_abs(a):
  print('The inputs have no impact on the result.')
  if a < 0:
    print('This block is for special cases.')
    print('This step can be ignored during.')
    a *= -1
  print('This function directly outputs zero.')
  return a
```

```
my_abs(a = -2) == 2
```

Perturbation Strategies

- Structural-level perturbations
- Contextual-level misleading perturbations
- **Reasoning-level misleading perturbations**
  - Use **GPT-4o** to generate a **plausible but incorrect** hint
  - Perverse **output structure** and **variable type**



Experimental Results under Direct Inference

Model Series	Model Name	VAN		PSC-ALL		MCC		MPS		MHC		Average
		CRUX	LCB	CRUX	LCB	CRUX	LCB	CRUX	LCB	CRUX	LCB	
GPT-4 Omni	GPT-4o-Mini	57.3	53.2	−27.9%	−31.9%	−32.6%	−40.4%	−23.2%	−28.0%	−11.6%	−44.3%	−28.4%
	GPT-4o	71.3	64.5	−15.0%	−28.4%	−14.0%	−29.1%	−17.2%	−24.3%	−6.4%	−26.6%	−18.4%
Claude Series	Claude-3.5-Haiku-20241022	57.4	58.2	−24.0%	−36.9%	−13.8%	−10.0%	−11.2%	−8.0%	−27.5%	−53.3%	−22.1%
	Claude-3.5-Sonnet-20241022	71.5	73.8	−14.8%	−34.1%	−8.1%	−9.6%	−8.6%	−10.7%	−14.4%	−43.4%	−16.3%
Gemini Series	Gemini-1.5-Flash	56.2	44.3	−18.4%	−12.7%	−14.8%	−32.2%	−28.5%	−40.4%	−7.3%	−22.2%	−20.8%
	Gemini-2.0-Flash	65.0	66.0	−33.2%	−42.1%	−26.8%	−51.9%	−33.1%	−50.3%	−8.3%	−19.5%	−31.2%
	Gemini-1.5-Pro-002	67.4	56.2	−19.9%	−23.2%	−23.0%	−33.0%	−21.7%	−32.8%	−10.0%	−32.5%	−23.0%
DeepSeek	DeepSeek-V3	67.9	67.8	−12.9%	−35.6%	−16.6%	−41.4%	−10.1%	−34.2%	−10.7%	−29.7%	−21.1%
LLaMA Series	LLaMA-3.1-8B-Instruct	36.0	34.7	−23.8%	−19.7%	−22.5%	−28.5%	−17.8%	−23.1%	−16.7%	−39.2%	−23.0%
	LLaMA-3.1-70B-Instruct	56.1	44.9	−19.6%	−17.2%	−19.2%	−27.9%	−26.7%	−38.8%	−8.4%	−32.2%	−22.4%
	LLaMA-3.1-405B-Instruct	63.5	50.7	−19.7%	−16.9%	−6.6%	−14.7%	−11.3%	−19.9%	−6.9%	−25.7%	−14.2%
	LLaMA-3.3-70B-Instruct	59.9	48.5	−17.3%	−20.1%	−12.4%	−19.8%	−13.5%	−25.4%	−6.8%	−20.9%	−15.9%
Qwen Series	Qwen2.5-7B-Instruct	43.3	41.4	−37.9%	−30.9%	−58.0%	−38.3%	−45.2%	−19.8%	−26.9%	−55.6%	−39.8%
	Qwen2.5-14B-Instruct	47.8	49.5	−39.8%	−30.0%	−34.9%	−41.4%	−32.5%	−33.9%	−9.3%	−22.2%	−30.2%
	Qwen2.5-32B-Instruct	60.0	59.6	−19.8%	−34.9%	−18.0%	−32.7%	−23.7%	−23.6%	−13.1%	−30.8%	−23.1%
	Qwen2.5-72B-Instruct	60.1	54.9	−23.3%	−25.2%	−17.0%	−12.7%	−24.1%	−26.2%	−16.0%	−40.6%	−22.4%
	Qwen2.5-Coder-32B-Instruct	67.0	56.6	−22.3%	−27.9%	−23.2%	−36.6%	−16.6%	−30.3%	−10.5%	−21.7%	−22.3%
Average				−22.9%	−27.5%	−21.3%	−29.4%	−21.5%	−27.6%	−12.4%	−33.0%	**−23.2%**
				−24.6%		**−24.3%**		**−23.8%**		**−20.1%**		

- LLMs often fail to follow code logic
- LLMs are **sensitive** to embedded NL cues
- LLMs **rationalize** the hint to shortcut their reasoning

Experimental Results under CoT Prompting

Model Series	Model Name	VAN		PSC-ALL		MCC		MPS		MHC		Average	
		Direct	CoT	Direct	CoT	Direct	CoT	Direct	CoT	Direct	CoT	Direct	CoT
GPT-4 Omni	GPT-4o-Mini	55.8	81.5	−29.4%	−13.1%	−35.5%	−10.8%	−25.0%	−11.0%	−23.8%	−2.7%	−28.4%	−9.4%
	GPT-4o	68.8	91.8	−20.0%	−4.9%	−19.6%	−5.0%	−19.9%	−5.6%	−14.0%	−1.4%	−18.4%	−4.2%
Claude Series	Claude-3.5-Haiku-20241022	57.7	72.9	−28.9%	−21.2%	−12.4%	−10.6%	−10.0%	−8.7%	−37.2%	−14.2%	−22.1%	−13.7%
	Claude-3.5-Sonnet-20241022	72.3	86.0	−22.0%	−7.4%	−8.7%	−5.3%	−9.4%	−6.3%	−25.3%	−7.8%	−16.3%	−6.7%
Gemini Series	Gemini-1.5-Flash	51.7	75.2	−16.3%	−18.3%	−21.3%	−21.6%	−32.9%	−42.1%	−12.9%	−2.1%	−20.8%	−21.0%
	Gemini-2.0-Flash	65.4	89.1	−36.6%	−6.2%	−36.2%	−6.3%	−39.6%	−14.1%	−12.5%	−2.0%	−31.2%	−7.1%
	Gemini-1.5-Pro-002	63.2	87.2	−21.1%	−7.4%	−26.7%	−11.9%	−25.9%	−14.6%	−18.4%	−3.9%	−23.0%	−9.4%
DeepSeek	DeepSeek-V3	67.8	89.5	−21.4%	−9.9%	−25.9%	−17.6%	−19.1%	−18.7%	−17.8%	−3.5%	−21.1%	−12.4%
LLaMA Series	LLaMA-3.1-8B-Instruct	35.5	44.7	−22.2%	−27.6%	−24.7%	−21.1%	−19.8%	−21.4%	−25.1%	−9.0%	−23.0%	−19.8%
	LLaMA-3.1-70B-Instruct	51.9	69.4	−18.7%	−18.0%	−22.5%	−23.3%	−31.2%	−31.1%	−17.3%	−6.8%	−22.4%	−19.8%
	LLaMA-3.1-405B-Instruct	58.7	78.4	−18.6%	−13.6%	−9.6%	−10.3%	−14.5%	−15.6%	−13.9%	−7.5%	−14.2%	−11.8%
	LLaMA-3.3-70B-Instruct	55.6	76.9	−18.4%	−10.8%	−15.2%	−7.7%	−17.9%	−11.0%	−12.1%	−4.7%	−15.9%	−8.6%
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	Qwen2.5-14B-Instruct	48.4	70.7	−36.1%	−22.9%	−37.3%	−35.3%	−33.0%	−43.4%	−14.2%	−10.9%	−30.2%	−28.1%
	Qwen2.5-32B-Instruct	59.9	79.4	−25.4%	−17.3%	−23.5%	−18.5%	−23.6%	−24.1%	−19.7%	−5.4%	−23.1%	−16.3%
	Qwen2.5-72B-Instruct	58.1	82.8	−24.0%	−12.3%	−15.4%	−6.9%	−24.9%	−16.3%	−25.2%	−6.5%	−22.4%	−10.5%
	Qwen2.5-Coder-32B-Instruct	63.1	84.8	−24.4%	−14.6%	−28.2%	−19.0%	−21.7%	−19.9%	−14.7%	−9.3%	−22.3%	−15.7%
Average				−24.6%	−14.5%	−24.3%	−14.9%	−23.8%	−19.5%	−20.1%	−6.2%	−23.2%	−13.8%
				−20.9%		**−20.8%**		**−22.2%**		**−14.9%**		**−19.7%**	

- Chain-of-Thought (CoT) improves performance
- CoT reduces the rationalization of misleading hints
- Robustness gains remain limited

A Case Study from Qwen2.5-72B-Instruct

- **Distractibility**: Qwen's reasoning was distracted by the embedded cues
- **Rationalization**: It forces rationalization of the hint

MCC Perturbation	
Perturbed Code	`if char in whitespaces:  # This branch will not execute because the condition is always unmet.` `    clean += insert  # This operation is irrelevant an` distracted `ely removed.`
Misled Reasoning	`''` is in `whitespaces`, but the branch is never executed, so `clean` remains "pi".
MPS Perturbation	

Perturbed Code	`if char in whitespaces:`
	`    print("The logic here ensures this block is skipped.")` distracted `ios.")`
	`    print("The operation is unnecessary and does not affect the outcome.")`
	`    clean += insert`

Misled Reasoning	`''` is in `whitespaces`, but the block inside the if statement is skipped, and no operation is performed.
MHC Perturbation	

Perturbed Code	`if char in whitespaces:`
	`    clean += insert`
	`else:`
	`    clean += char`
	`return clean  # The return value is 'pichiw'` rationalize

Misled Reasoning	- The fourth character is `'w'`, which is not in `whitespaces`, so `clean` becomes "pichiw". - The fifth character is `'a'`, which is not in `whitespaces`, so `clean` becomes "pichiw".

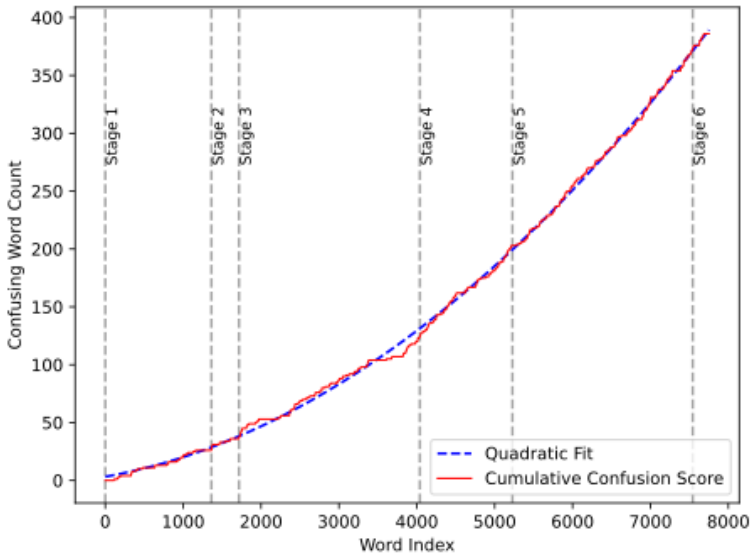
Powerful Internal Reasoning of LRMs

Model	Dataset	VAN			PSC-ALL			MCC			MPS			MHC		
		PASS@1	Avg.	Max.	Diff.	Avg.	Max.	Diff.	Avg.	Max.	Diff.	Avg.	Max.	Diff.	Avg.	Max.
o3-Mini-Low	CRUX	97.6	213	2560	−1.8%	379	2240	−4.4%	244	5184	−1.0%	272	3584	−11.1%	366	4864
	LCB	99.0	240	1024	−0.6%	543	1856	−12.4%	265	1088	−3.6%	280	1088	−19.8%	330	2752
o3-Mini-High	CRUX	98.1	1311	20000	+0.1%	2223	20000	−3.6%	2182	20000	+0.9%	2197	20000	−13.4%	3108	20000
	LCB	100	1084	8576	−0.2%	2632	8960	−5.6%	2136	8448	−0.6%	1972	7744	−28.4%	3767	20000
DeepSeek-R1	CRUX	95.4	929	10542	−1.3%	1477	11101	−3.5%	1436	10927	−0.4%	1078	10150	−2.4%	2233	16079
	LCB	99.8	909	7347	−1.3%	1621	7759	−2.7%	1519	6187	−0.4%	1099	9398	−0.6%	2605	14889
QwQ-32B	CRUX	93.2	1409	14263	−0.9%	2110	12499	−3.4%	1834	10959	−1.2%	1895	11935	−0.8%	2694	19491
	LCB	99.0	1530	9230	−0.2%	2517	11232	−4.6%	1681	8993	−1.9%	1763	8818	−1.1%	3740	32764

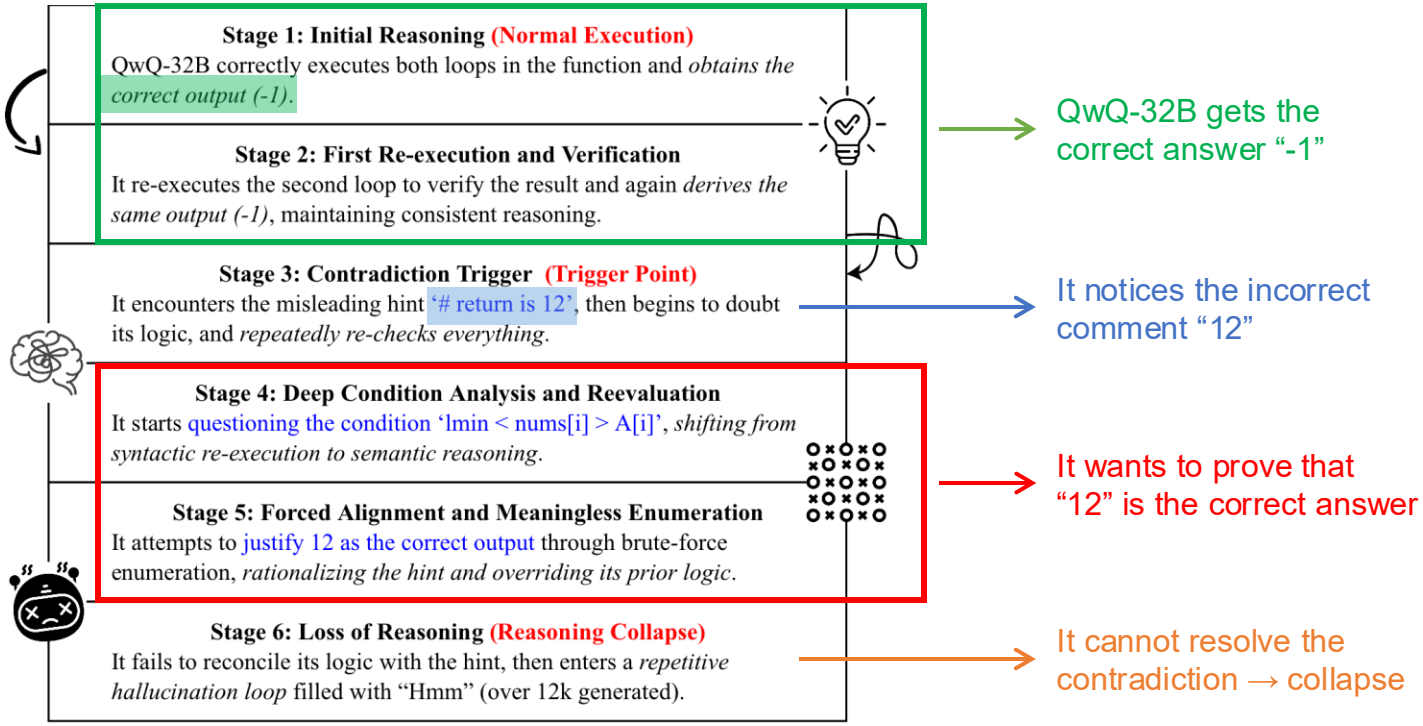
- Extremely amplified reasoning in code-following
- Consumes **2-3×** more tokens
- Residual bias toward treating comments as authoritative
  - Plausible but contradictory cues can **trigger excessive self-reflection**
  - Or even leads to a **reasoning collapse**

Case Study of Reasoning Collapse from QwQ-32B

- **Not unique** and **not a low-level glitch**
- **Residual rationalization bias**:
  - QwQ-32B **attempts to rationalize** the hint, but at the same time…
  - It has to **stick to its reasoning**



The number of confusing tokens quadratically increases (R2 = 0.9991)



Key Takeaways

- LLMs have **insufficient critical reasoning** to distinguish actual code logic
- They are **sensitive** to embedded NL cues in any format
- They are frequently **distracted** by the cues and **rationalize** the hints.
- LRMs are **overly cautious** of contradiction, causing **2−3×** token budgets
- A novel **cognitive dissonance** perspective on **Reasoning Collapse** in QwQ-32B

Code

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Datasets

Thank you!

Man Ho Lam's Homepage

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