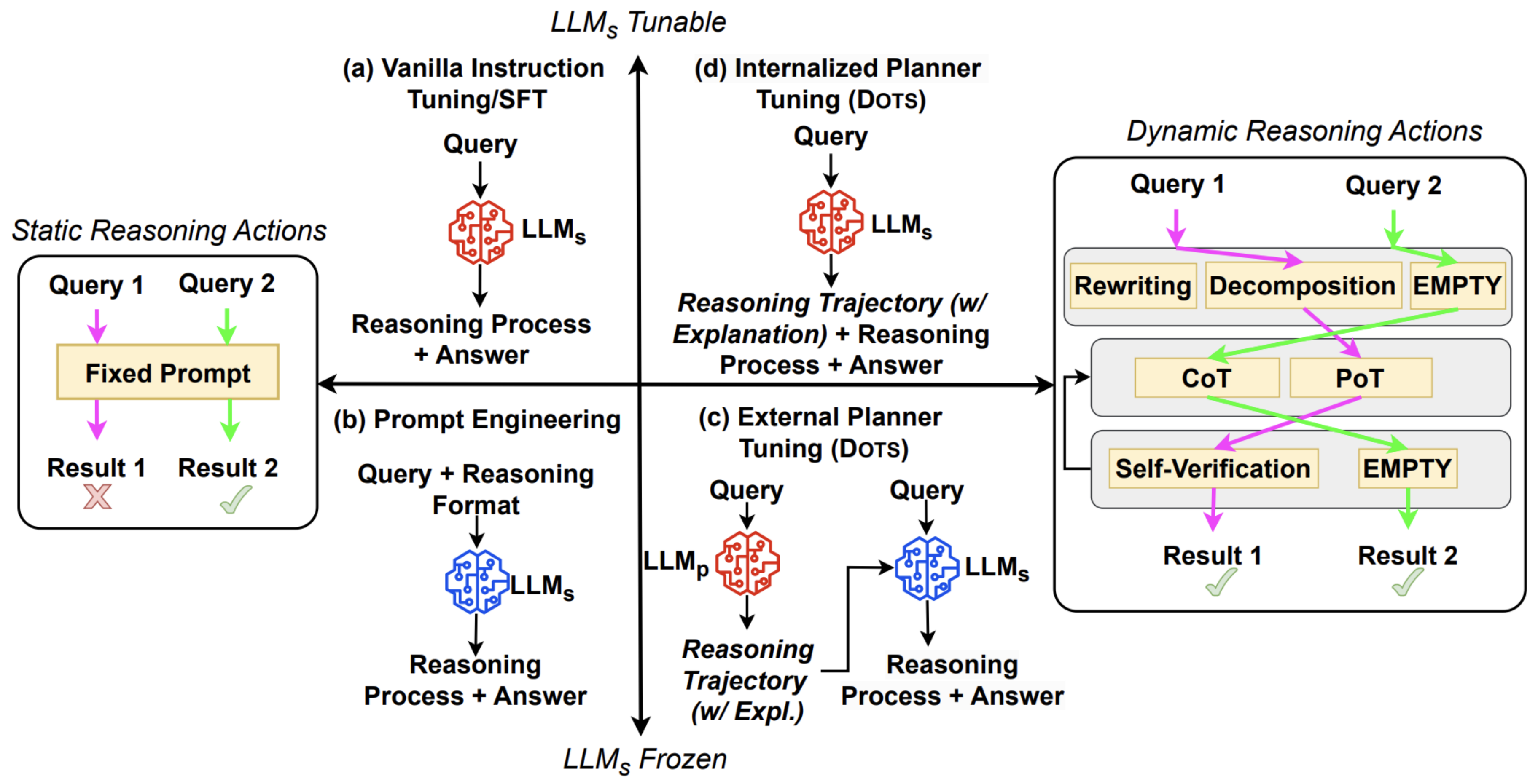
DOTS: Learning to Reason Dynamically in LLMs via Optimal Reasoning Trajectories Search

Murong Yue[1], Wenlin Yao[2], Haitao Mi[2], Dian Yu[2], Ziyu Yao[1], Dong Yu[2]

[1]George Mason University, [2]Tencent AI Lab, Bellevue

Motivation



Static and dynamic paradigms of LLM reasoning

Question II:
How many r in word 'strawberry'?

Answer from GPT-4o-2024-08-06 (Incorrect):
The word "strawberry" contains 2 letter "r"s.

Answer from our internal planner tuned Llama-8b-Instruct:
It can efficiently count the occurrences of a specific character (in this case, 'r') in a word. Programming_solver provides a quick and reliable method for counting characters in text, ensuring accuracy in the result.
Required Action: programming

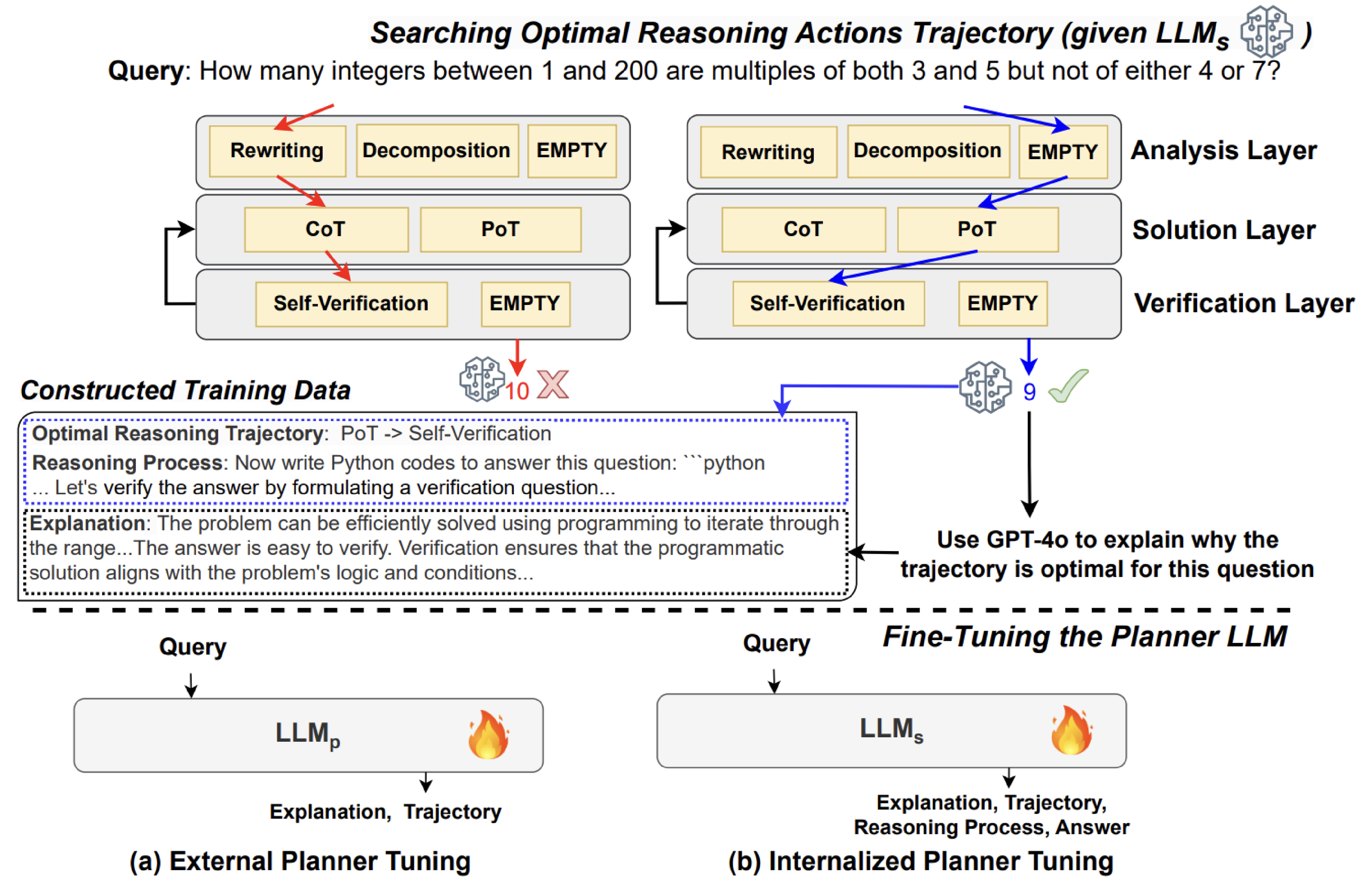
```
word = 'strawberry'
count=word.lower().count('r')
print(count)
```

After execution, we get: 3
Answer: 3

Case Study

Motivation: The current LLM fails to **dynamically** decide the best reasoning strategies, e.g., when to use program.

Method



1. **Module Design**: We manually design atomic reasoning action modules based on prior prompting works, e.g., programming, verification;
2. **Searching Best Trajectory**: We perform multiple trials on all possible modules permutations and select the best one with the highest accuracy;
3. **Training a planner**: We use GPT-4o to generate the reason why the selected trajectory is the best based on the nature of the question, then either finetune a planner LLM as an external planning module (DOTS: External) or directly finetune the solver LLM and internalize the planning ability (DOTS: Internalized).

Experiments

Method	Tuning	Reasoning Format	MATH	BBH	Game of 24	TheoremQA	Average
External Planner: Llama-3-8B-Instruct; Solver: Llama-3-70B-Instruct							
CoT	✗	$\mathcal{L}$	50.4	72.7	27.5	27.4	44.5
LTM	✗	$\mathcal{L}$	50.1	73.8	24.9	28.8	44.4
PA	✓	$\mathcal{L}$	52.5	72.9	26.8	28.8	45.3
PoT	✗	$\mathcal{P}$	54.7	65.8	63.9	31.1	53.9
Self-refine	✗	$\mathcal{L}, \mathcal{P}$	55.9	71.4	**68.3**	30.8	56.6
DOTS: External	✓	$\mathcal{L}, \mathcal{P}$	**57.7**	**77.3**	67.7	**31.2**	**58.5**
External Planner: Llama-3-8B-Instruct; Solver: GPT4o-mini							
CoT	✗	$\mathcal{L}$	70.2	80.3	27.7	38.9	54.2
LTM	✗	$\mathcal{L}$	72.2	79.4	25.5	36.4	53.3
PA	✓	$\mathcal{L}$	73.5	81.1	26.7	38.9	55.1
PoT	✗	$\mathcal{P}$	67.2	73.9	61.4	35.8	59.6
Self-refine	✗	$\mathcal{L}, \mathcal{P}$	73.7	74.8	**68.7**	34.6	63.0
DOTS: External	✓	$\mathcal{L}, \mathcal{P}$	**75.4**	**84.2**	65.2	**41.4**	**66.5**

Method	Tuning	Reasoning format	MATH	BBH	Game of 24	TheoremQA	Average
Solver: Llama-3-8B-Instruct							
CoT	✗	$\mathcal{L}$	29.6	48.9	12.7	14.8	26.5
LTM	✗	$\mathcal{L}$	29.5	50.3	14.4	15.2	27.4
PA	✓	$\mathcal{L}$	31.0	47.2	11.8	15.1	26.3
PoT	✗	$\mathcal{P}$	25.3	44.6	16.8	**16.7**	25.9
Self-refine	✗	$\mathcal{L}, \mathcal{P}$	28.7	46.6	17.0	15.3	30.1
Vanilla SFT	✓	$\mathcal{L}$	33.9	61.0	18.5	14.8	33.6
DOTS: Internalized	✓	$\mathcal{L}, \mathcal{P}$	**34.4**	**69.7**	**21.9**	16.1	**35.5**

- Both the external planner and internal planner are better than the baselines;
- Further analysis show that our method can both adapt to the characteristics of specific questions and the capability of specific task-solving LLMs.