



# Reasoning with **Language Model** is Planning with **World Model**



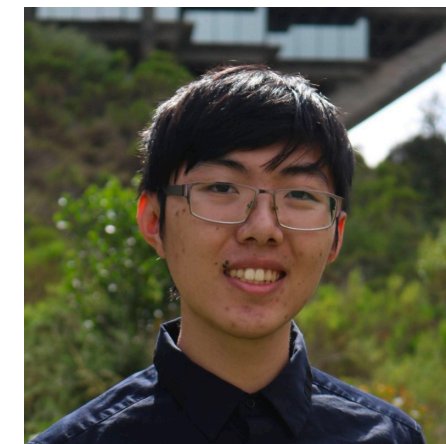
Shibo Hao\*



Yi Gu\*



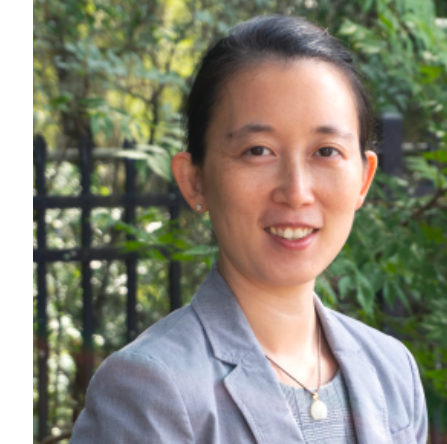
Haodi Ma



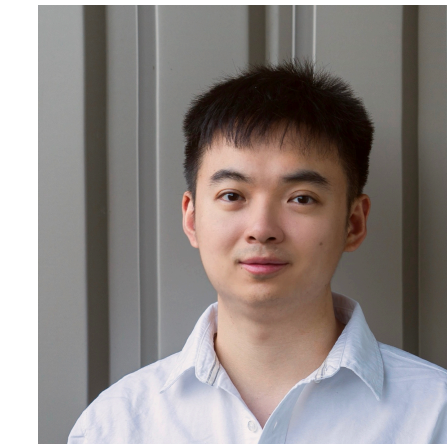
Joshua Hong



Zhen Wang



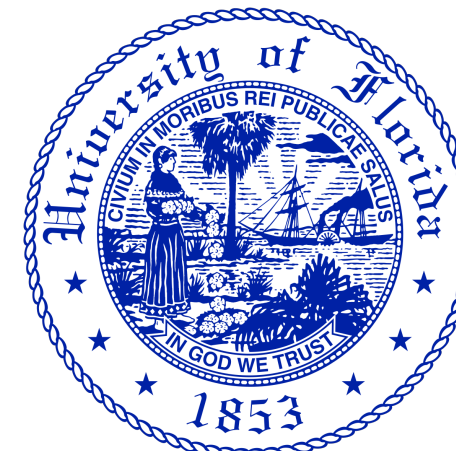
Daisy Wang



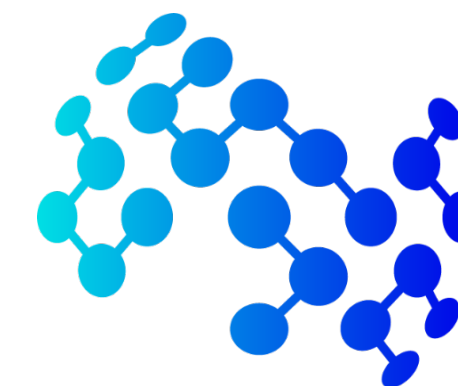
Zhiting Hu



UC San Diego



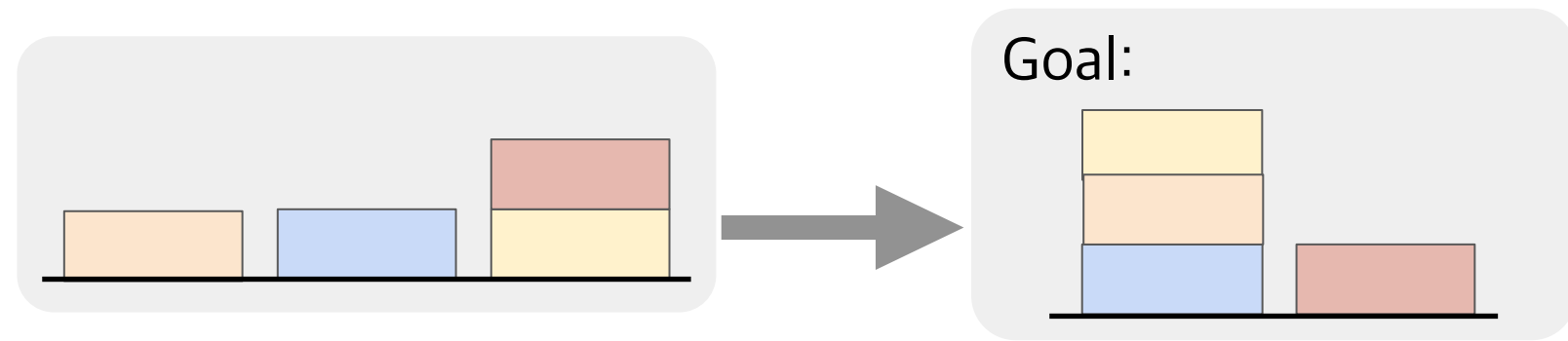
University of Florida



MBZUAI

# Reasoning with LLM vs Human

Blocksworld: How to move the blocks to the goal state?



## A: Chain-of-Thoughts Prompting (CoT) with LLM

- Autoregressive decoding

### System 1

1. Pick up the orange block.
2. Stack it on the blue block.
3. Pick up the yellow block. ❌
4. Stack it on the orange block.
5. Pick up the red block.
6. Put it on the table.

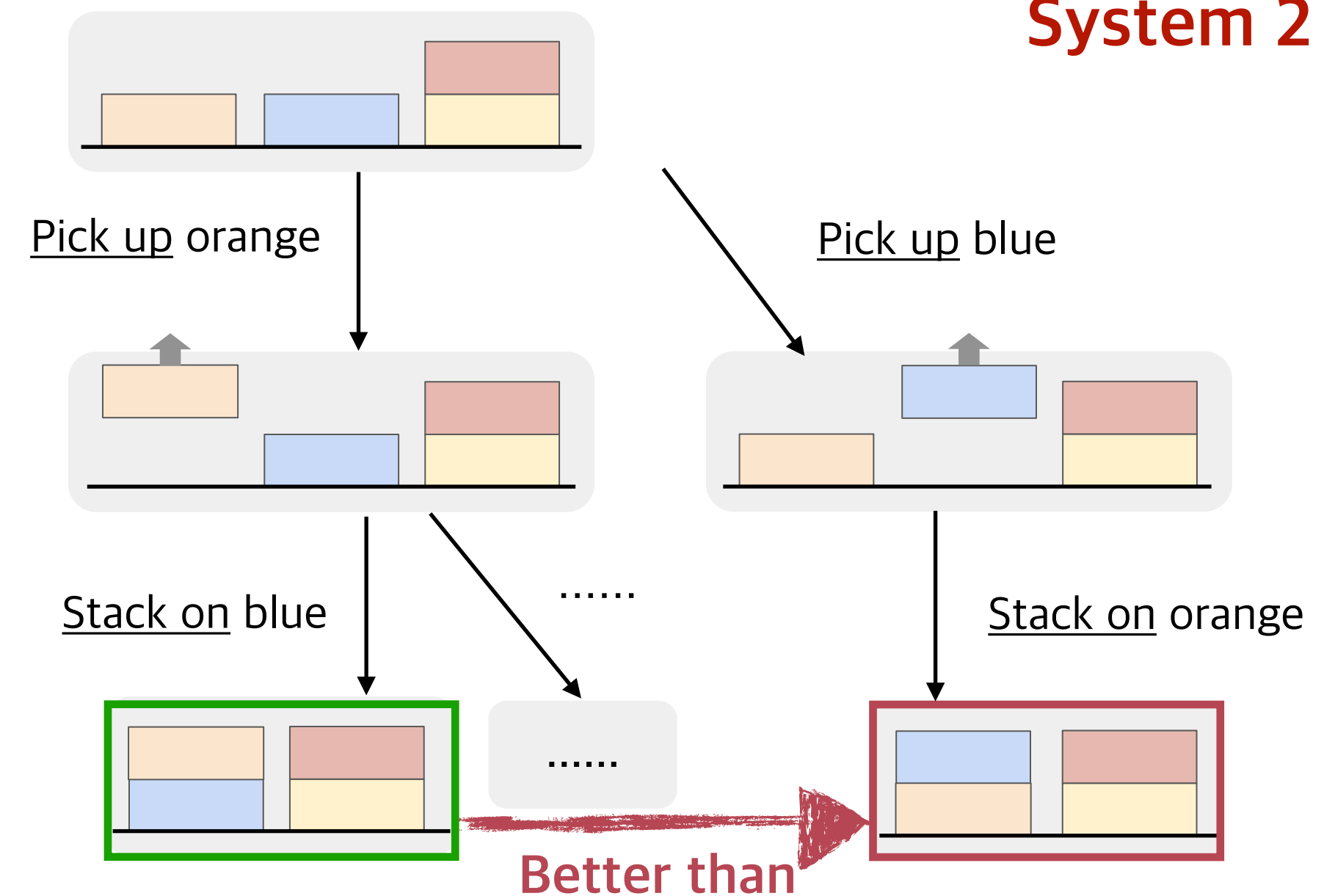
### Invalid Action!

The yellow block is still under the red one.

## B: Human Reasoning

- Internal **world model** to track **states**
- **Explore** alternative reasoning paths
- **Assess outcomes** by looking ahead

### System 2



On the planning abilities of large language models (a critical investigation with a proposed benchmark) [Valmeekam et al, 2023]

Chain-of-thought prompting elicits reasoning in large language models [Wei et al., 2022]

Mental models: Towards a cognitive science of language, inference, and consciousness [Johnson-Laird, 1983]

From System 1 Deep Learning to System 2 Deep Learning [Bengio, 2019]

# Reasoning-via-Planning (RAP 🎵)

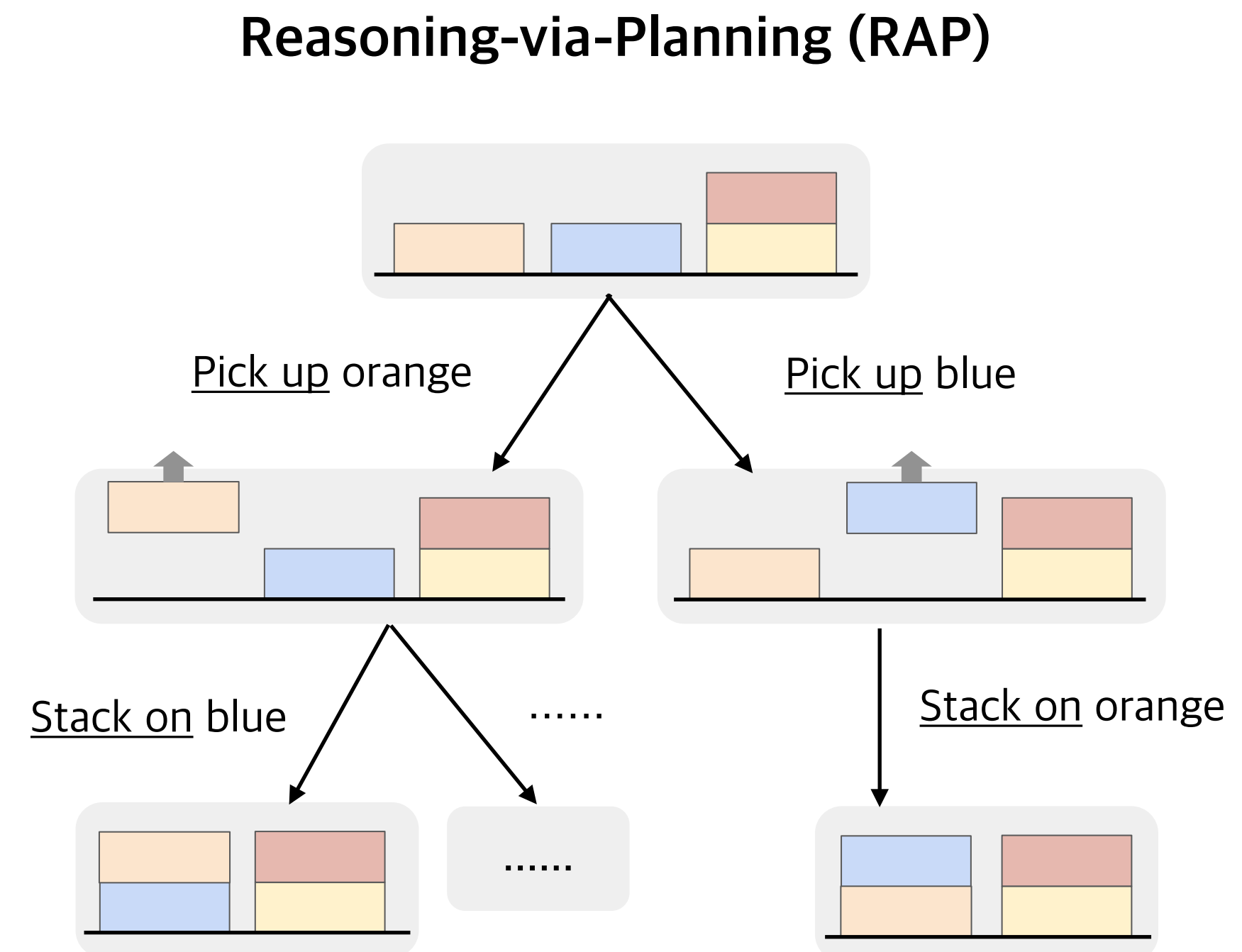
## Human Reasoning

- Internal **world model** to track **states**
- **Explore** alternative reasoning paths
- **Assess outcomes** by looking ahead

How to enable LLMs to reason close to humans?

## Reasoning-via-Planning: RAP 🎵

- Repurpose LLM as **world model**
- Principled **planning** algorithm
- **Rewards** to estimate outcomes



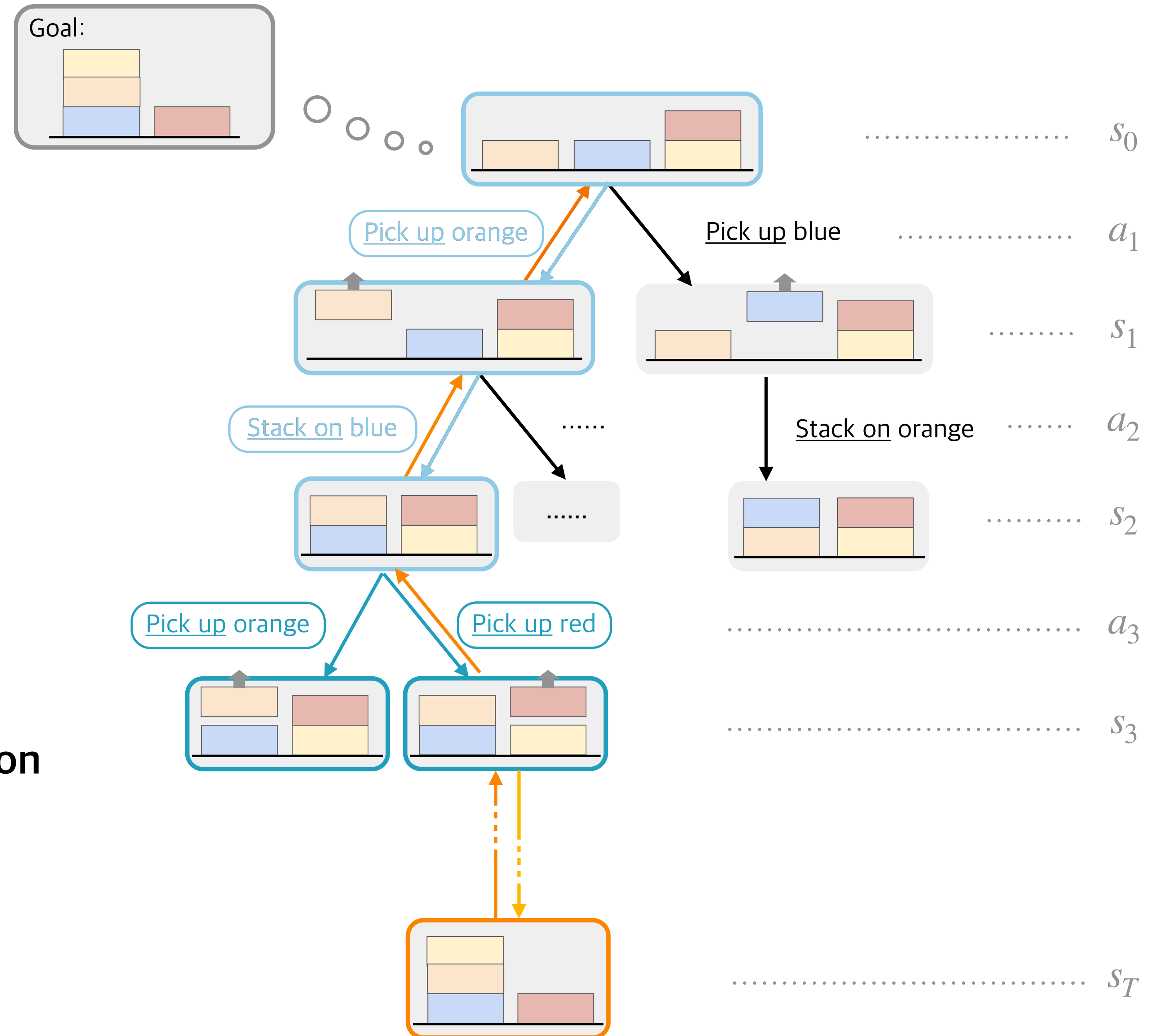


# Planning Algorithm

**Monte Carlo Tree Search (MCTS):**  
Iteratively build reasoning tree

1. Selection
2. Expansion
3. Simulation
4. Back-propagation

Balanced exploration and exploitation





# Rewards in RAP

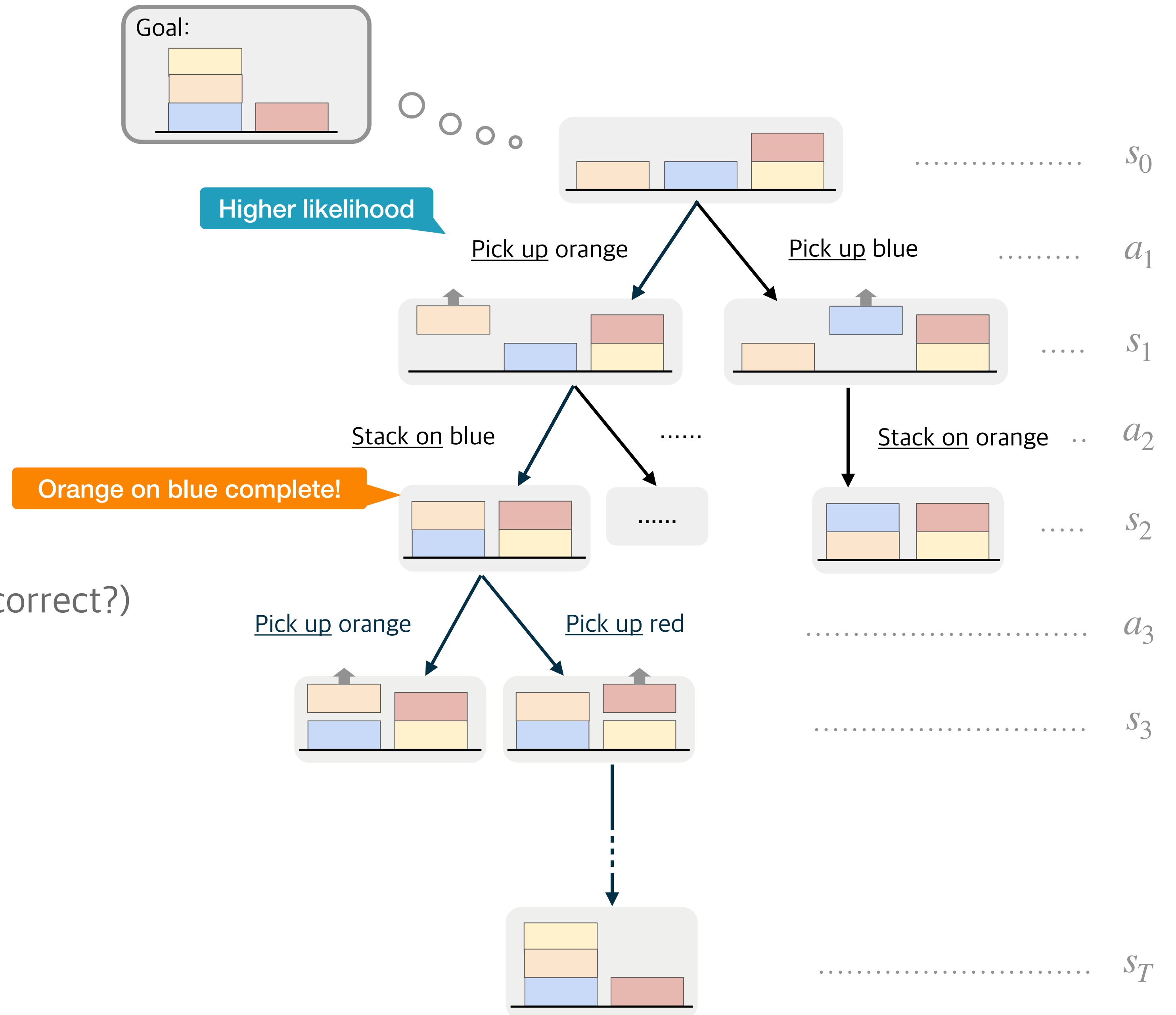
**Reward** design is **flexible**

In Blocksworld:

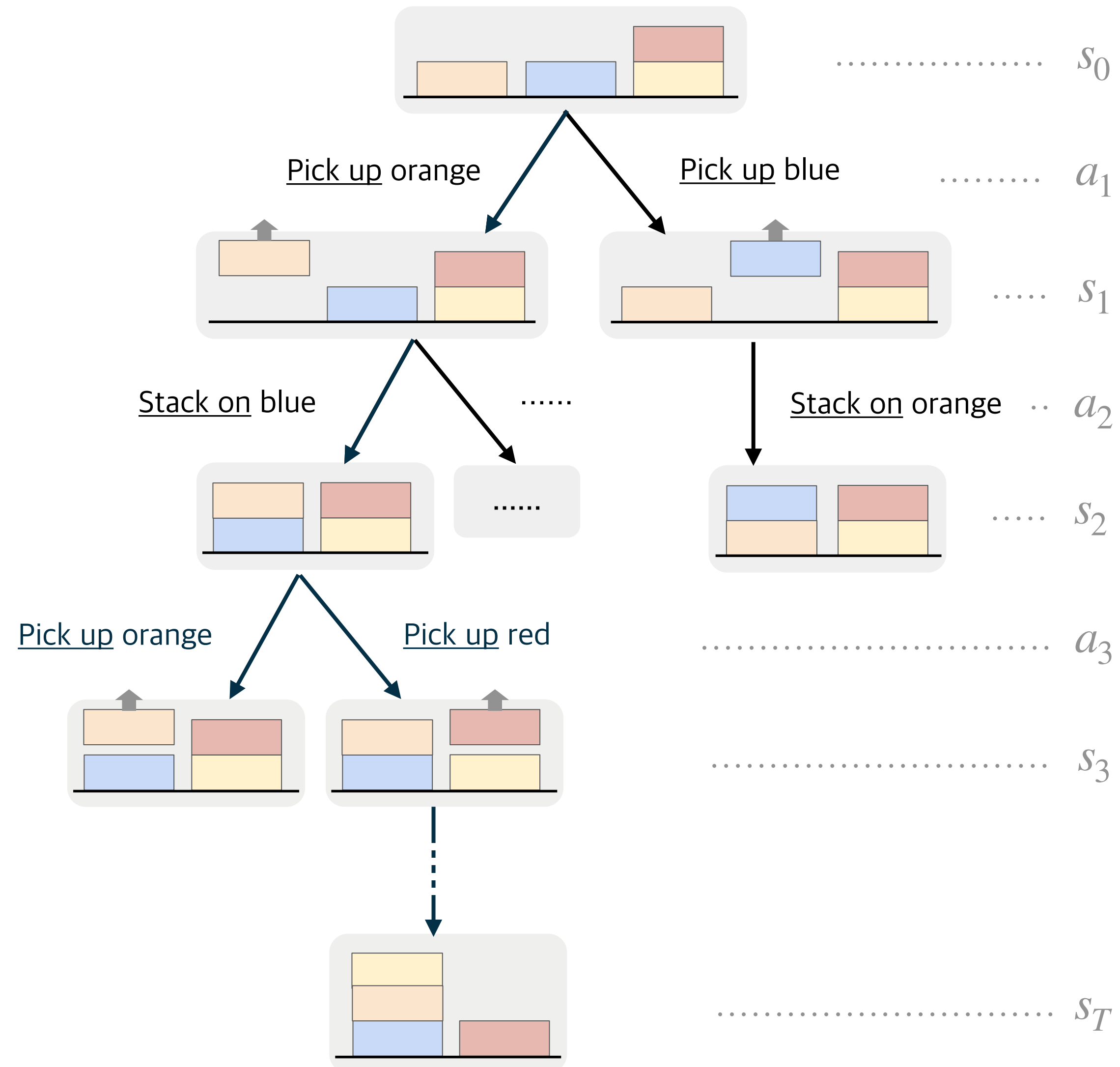
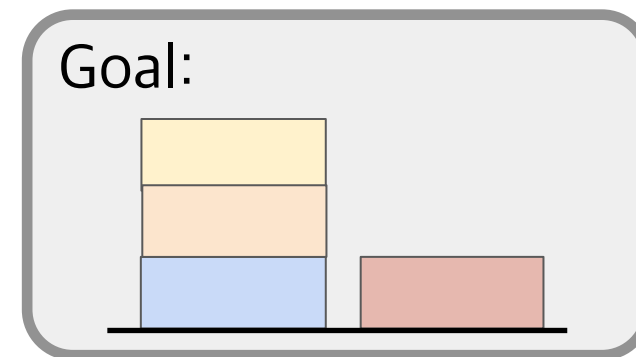
- Likelihood of actions
- Task-heuristic (# of subgoals)

Other possible rewards:

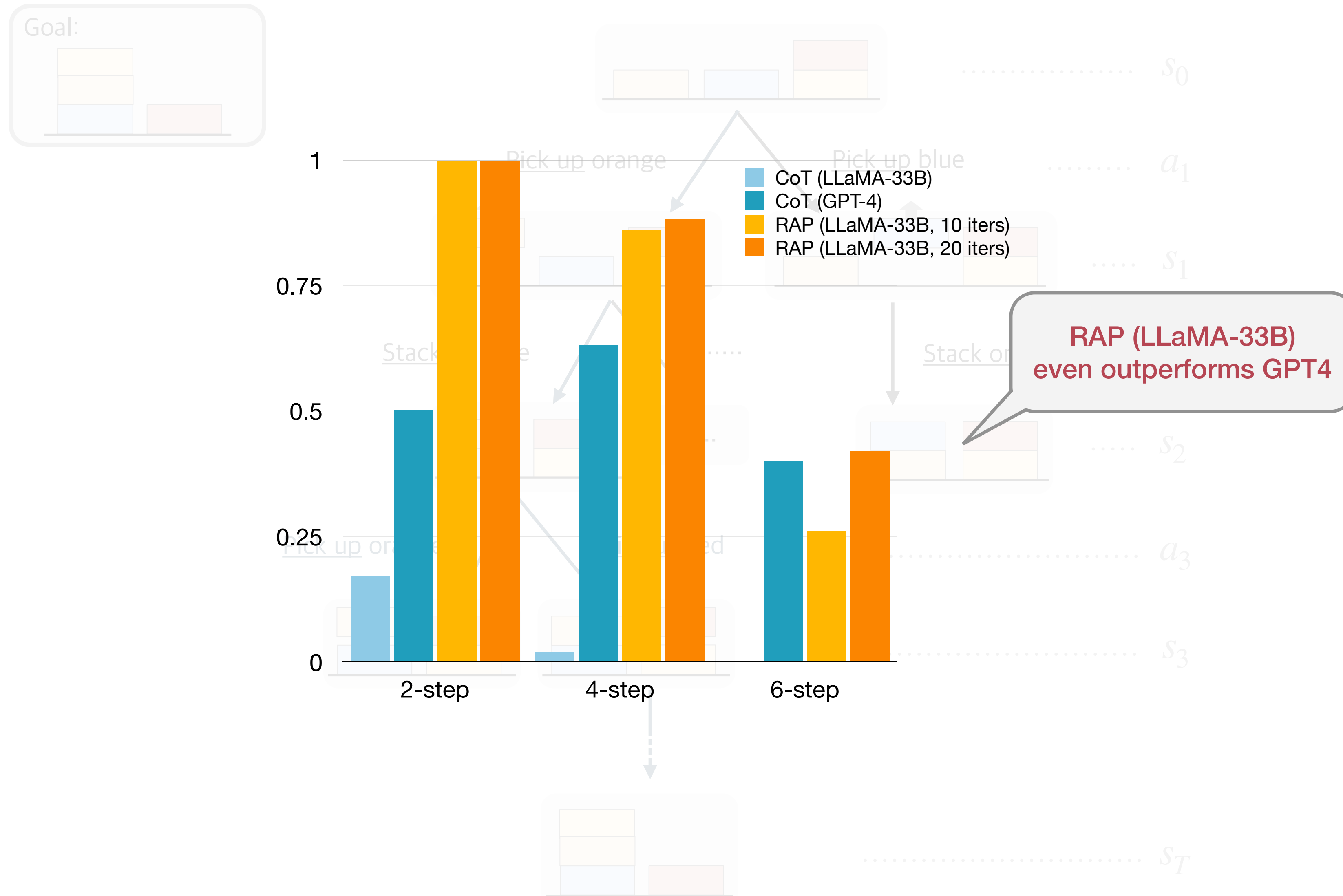
- Self-evaluation by LLM (e.g. useful? correct?)
- Confidence of next state
- .....



# RAP on Plan Generation (Blocksworld)

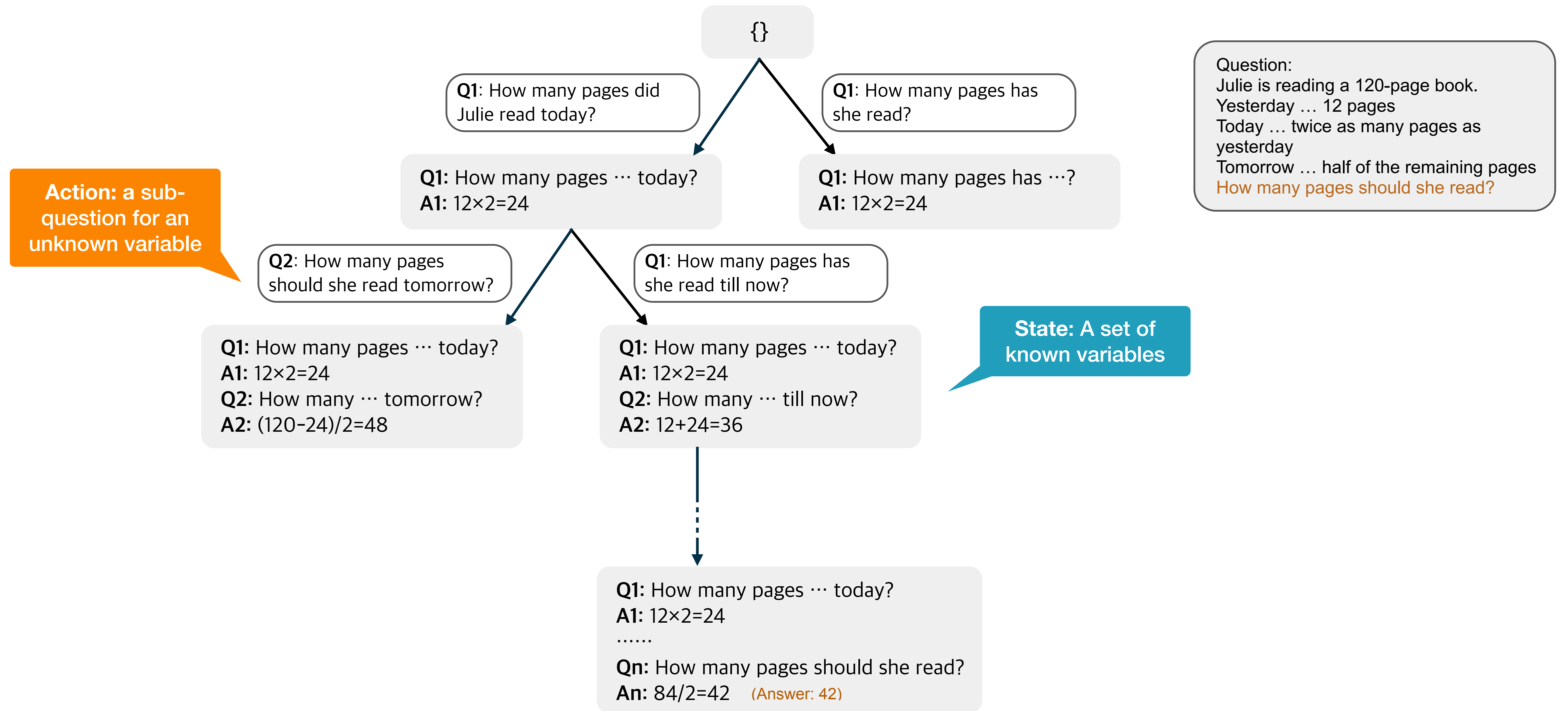


# RAP on Plan Generation (Blocksworld)

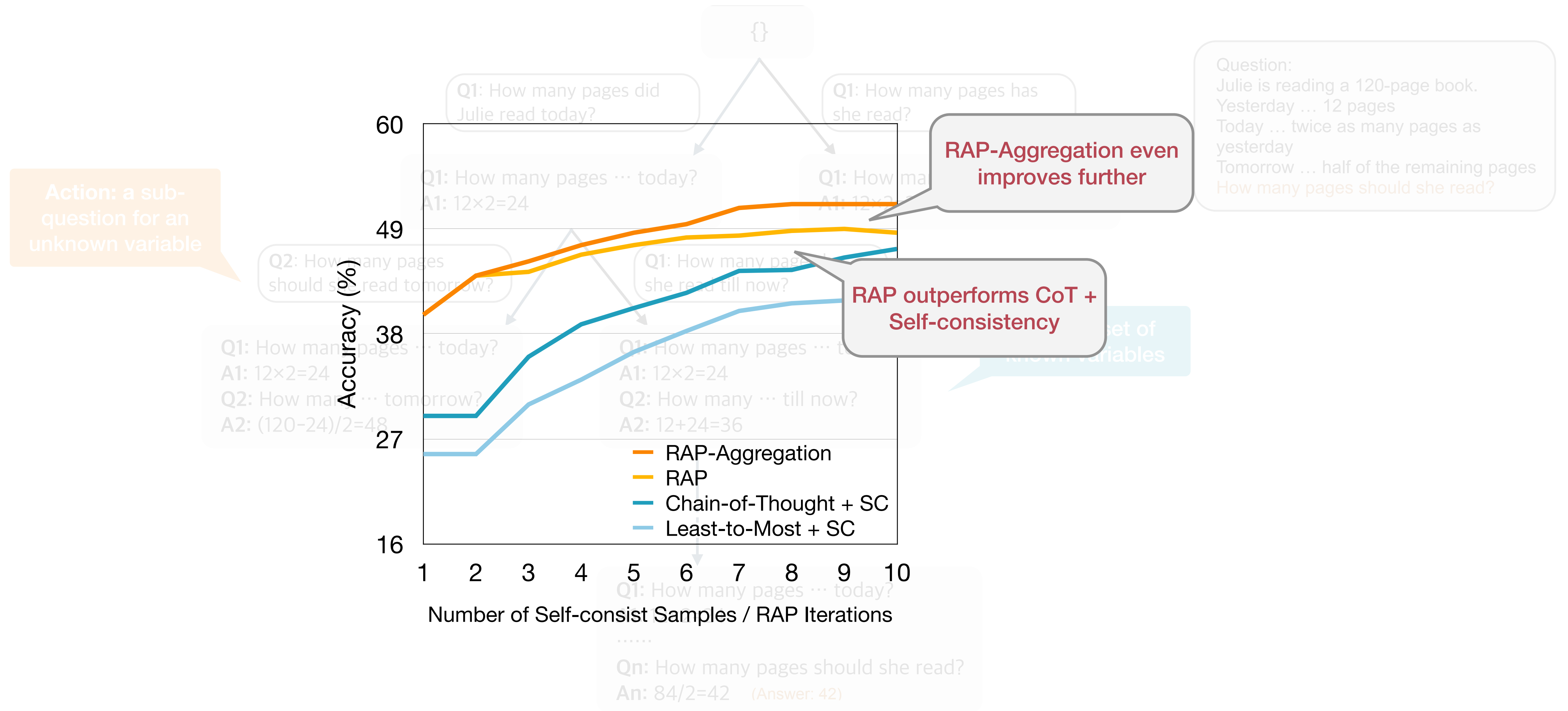




# RAP on Mathematical Reasoning (GSM8k)

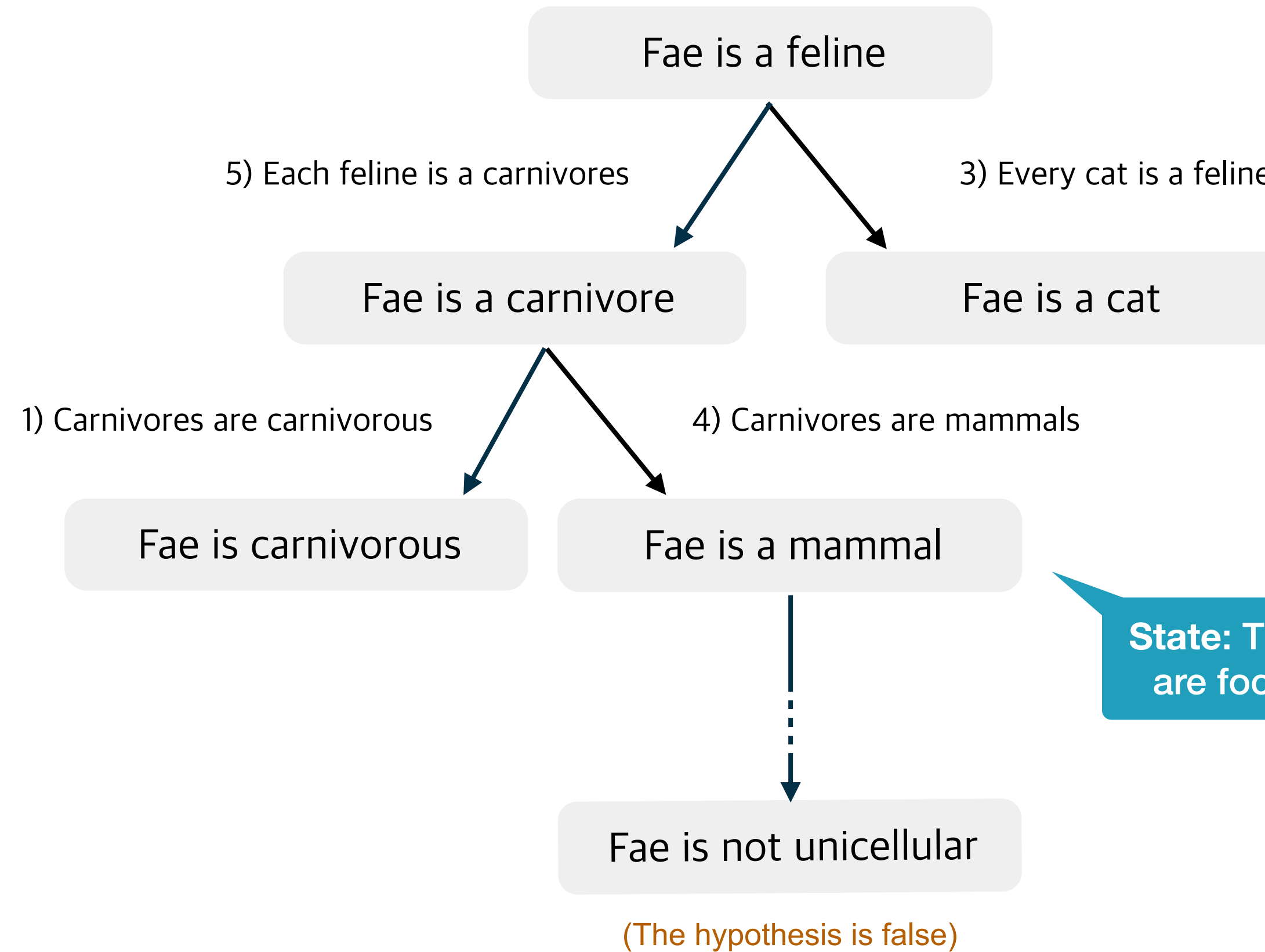


# RAP on Mathematical Reasoning (GSM8k)



# RAP on Logical Reasoning (PrOntoQA)

Action: selecting a rule from the rule set



State: The fact we are focusing on

## Rules:

- (1) Carnivores are carnivorous
- (2) Animals are not unicellular
- (3) Every cat is a feline
- (4) ...

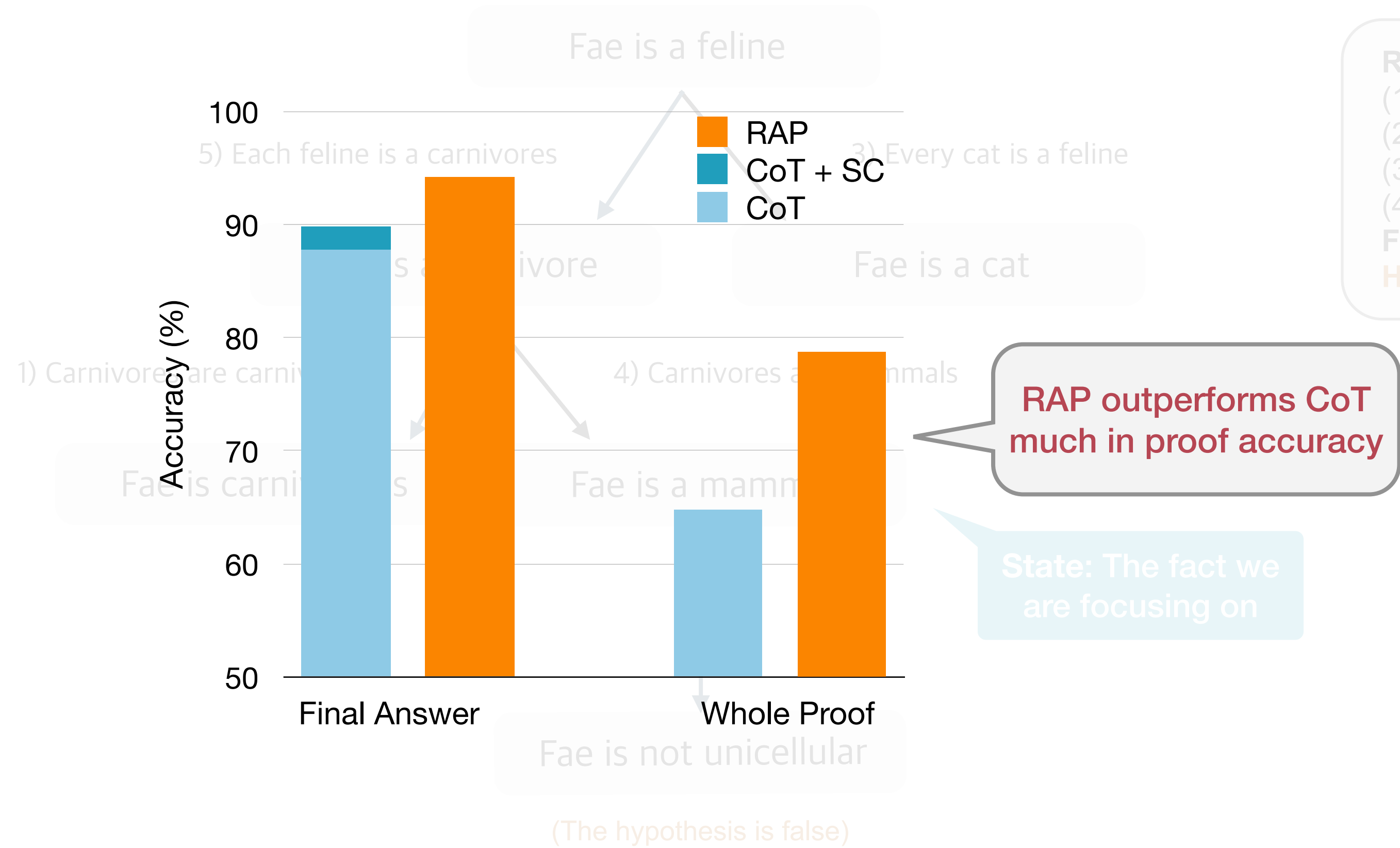
Fact: Fae is a feline

Hypothesis: Fae is unicellular?




# RAP on Logical Reasoning (PrOntoQA)

Action: selecting a rule from the rule set



**Rules:**  
 (1) Carnivores are carnivorous  
 (2) Animals are not unicellular  
 (3) Every cat is a feline  
 (4) ...  
**Fact:** Fae is a feline  
**Hypothesis:** Fae is unicellular?

# Discussion and Future Works

- We are developing  **LLM Reasoners** - a library to conduct complex reasoning with advanced algorithms
  - Covering multiple algorithms (**BeamSearch**, **ToT**, **RAP** 🎵, etc.)
  - Flexible LLM interfaces and intuitive visualization of reasoning trees
- **Possible future works**
  - **Fine-tuning LLMs** to better reason and **serve as a world model**
  - Building **multi-modal world model**
  - Combining LLM with **external tools** as a more **powerful** world model



LLM Reasoners

[llm-reasoners.net](https://llm-reasoners.net)

# Takeaways

## RAP 🎵: LLM reasoning as human-like strategic planning

- Repurpose LLM as **world model** to explicitly simulate future states
- Principled **planning** algorithm to balance exploration and exploitation
- Flexible **rewards** to estimate outcomes
- **Superior results in diverse domains**

