

# Mulberry: Empowering MLLM with o1-like Reasoning and Reflection via Collective Monte Carlo Tree Search

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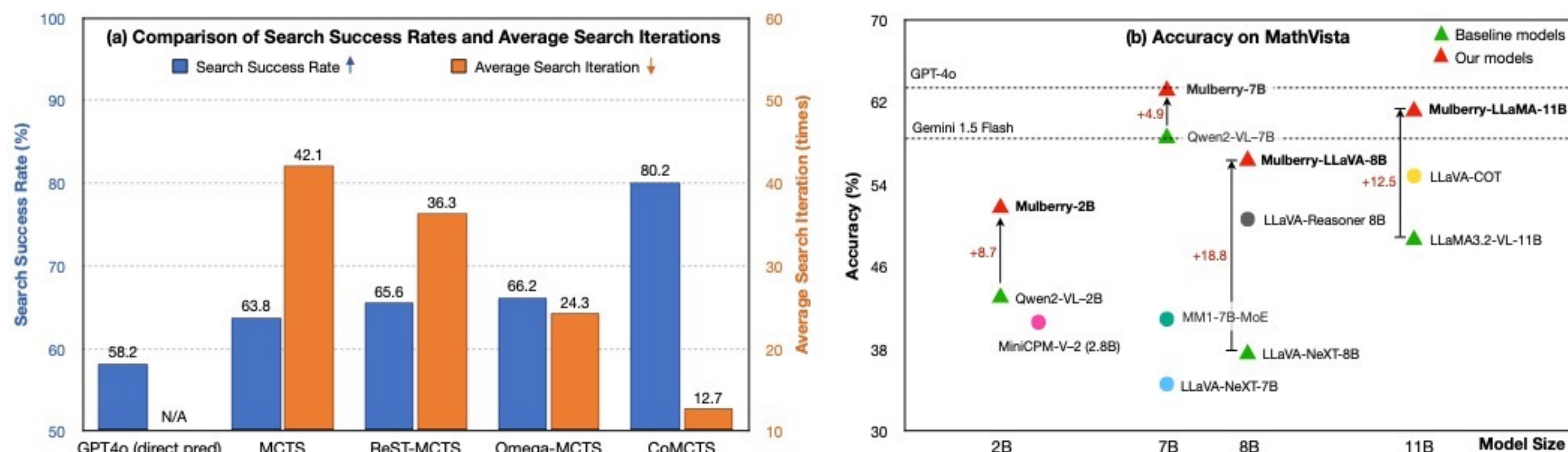
Paper

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## Background (o1-like & MCTS)

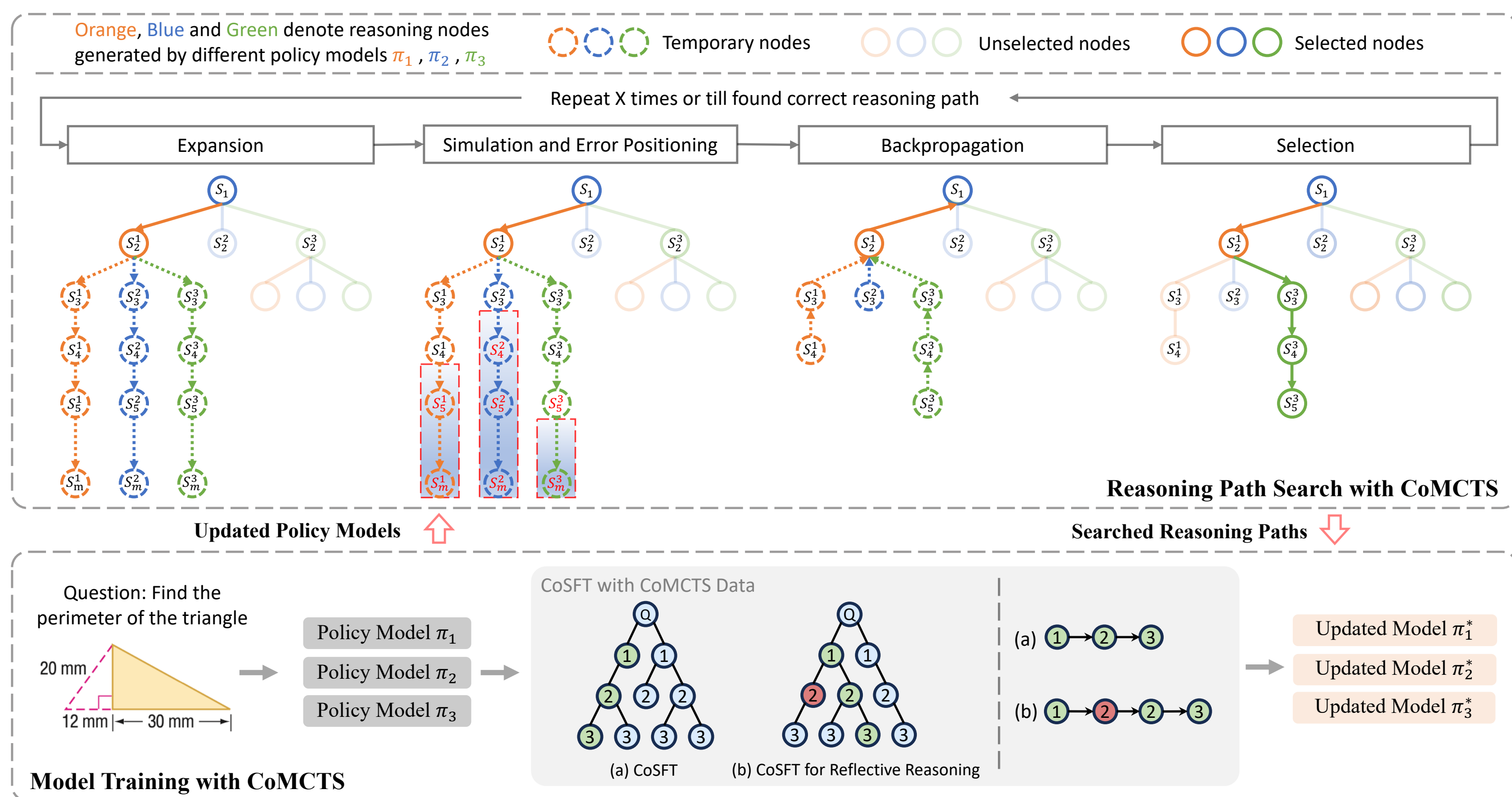
Step-by-step reasoning enables LLMs to tackle complex tasks, with MCTS being a key technique. However, applying MCTS to MLLMs poses challenges in both search **effectiveness** and search **efficiency**.



## Method (CoMCTS)

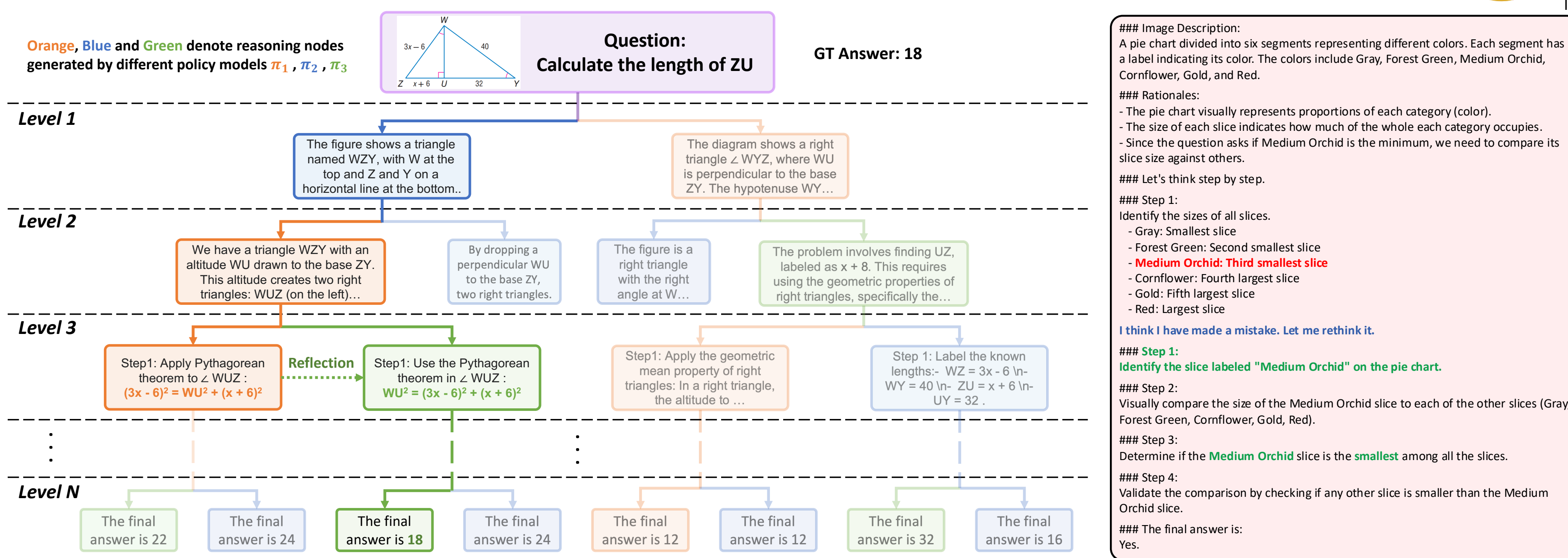
Introduce Collective Learning into MCTS for effective and efficient reasoning-path searching.

- (a) **Expansion**: Generate diverse, complementary subsequent reasoning nodes till the end.
- (b) **Simulation and Error Positioning**: Simulate reasoning outcomes, position error candidate nodes and prune them along with their child nodes.
- (c) **Backpropagation**: Update score and visit count of each node in a bottom-up manner.
- (d) **Selection**: Select the leaf reasoning node with the highest UCB value as next start node.



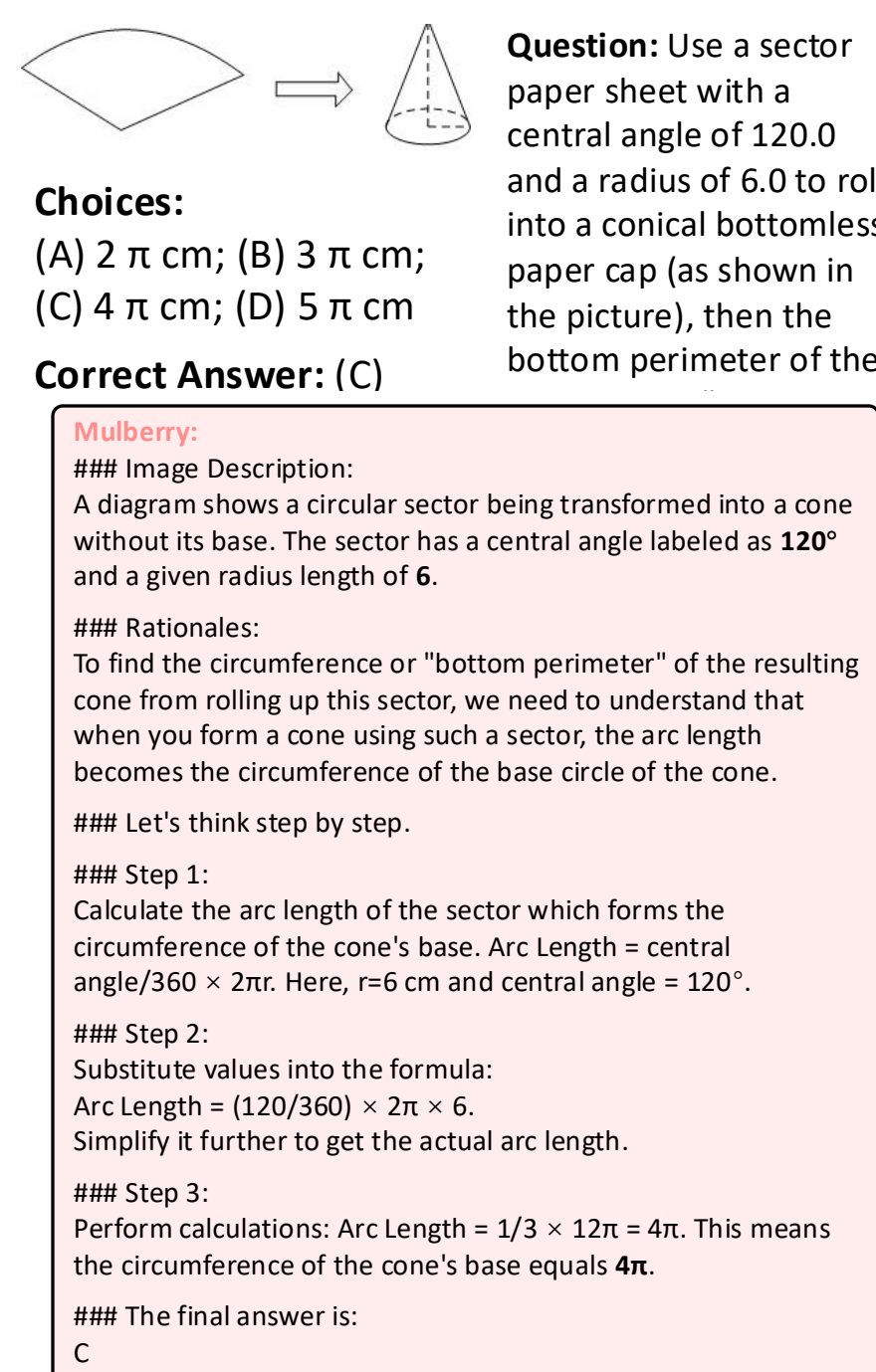
## Visualization of CoMCTS Data Construction

Using CoMCTS, we searched 260K reasoning and reflection step-by-step training data, named Mulberry-260K.



## Results (Qualitative & Quantitative)

We conduct extensive experiments with four powerful baseline models, and comprehensively benchmark our Mulberry with various state-of-the-arts, including general and reasoning-based MLLMs.



Qualitative Results

Method	MathVista	MMStar	MMMU	ChartQA	DynaMath	HallBench	MM-Math	MME <sub>sum</sub>	AVG
<strong>Closed-Source Model</strong>									
GPT-4o [37]	63.8	63.9	69.1	85.7	63.7	55.0	31.8	2329	64.5
Claude-3.5 Sonnet [38]	67.7	62.2	68.3	90.8	64.8	55.0	-	1920	-
<strong>Open-Source Model</strong>									
MM-1.5-7B [39]	47.6	-	41.8	78.6	-	-	-	1861	-
Idefics3-LLaMA3-8B [40]	58.4	55.9	46.6	74.8	-	-	-	1937	-
InternVL2-8B [41]	58.3	<b>61.5</b>	51.8	83.3	39.7	-	-	2210	-
MiniCPM-V-2.6-8B [42]	60.6	57.5	49.8	-	-	48.1	-	2348	-
DeepSeek-VL2-MOE-4.5B [43]	62.8	61.3	51.1	86.0	-	-	-	2253	-
<strong>Reasoning Model</strong>									
LLaVA-CoT-11B [4]	54.8	57.6	-	-	-	47.8	-	-	-
LLaVA-Reasoner-8B [3]	50.6	54.0	40.0	83.0	-	-	-	-	-
Insight-V-8B [44]	49.8	57.4	42.0	77.4	-	-	-	2069	-
LLaVA-NeXT-8B [45]	37.5	42.1	41.7	69.5	22.7	33.4	0.6	1957	39.7
Mulberry-LLaVA-8B	56.3	54.5	43.0	79.5	34.1	47.5	18.9	2021	50.7 <sup>11↑</sup>
Llama-3.2-11B-V-Ins. [46]	48.6	49.8	41.7	83.4	34.3	40.3	4.1	1787	45.8
Mulberry-Llama-11B	61.1	58.5	45.6	83.5	37.2	48.9	18.7	2035	53.3 <sup>7.5↑</sup>
Qwen2-VL-2B [2]	43.0	48.0	41.1	73.5	24.9	41.7	1.0	1872	42.5
Mulberry-2B	51.7	51.3	42.0	77.7	30.0	44.9	13.9	2013	47.9 <sup>5.4↑</sup>
Qwen2-VL-7B [2]	58.2	60.7	54.1	83.0	42.1	50.6	5.9	2327	54.7
Mulberry-7B	<b>63.1</b>	61.3	<b>55.0</b>	<b>83.9</b>	<b>45.1</b>	<b>54.1</b>	<b>23.7</b>	<b>2396</b>	<b>58.9<sup>4.2↑</sup></b>

Quantitative Results