



# AdaptiveStep: Automatically Dividing Reasoning Step through Model Confidence





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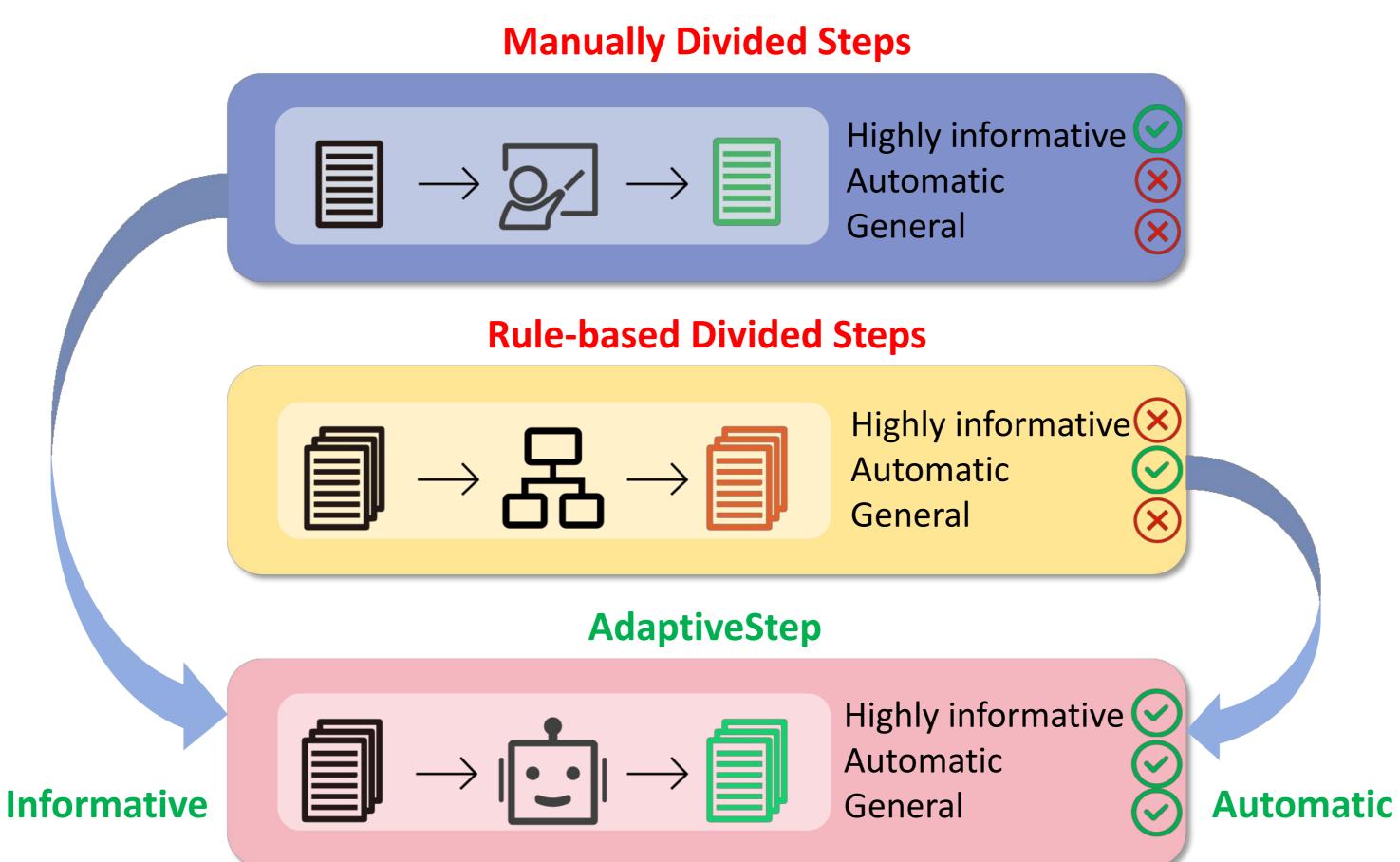
# **Motivation and Advantages**

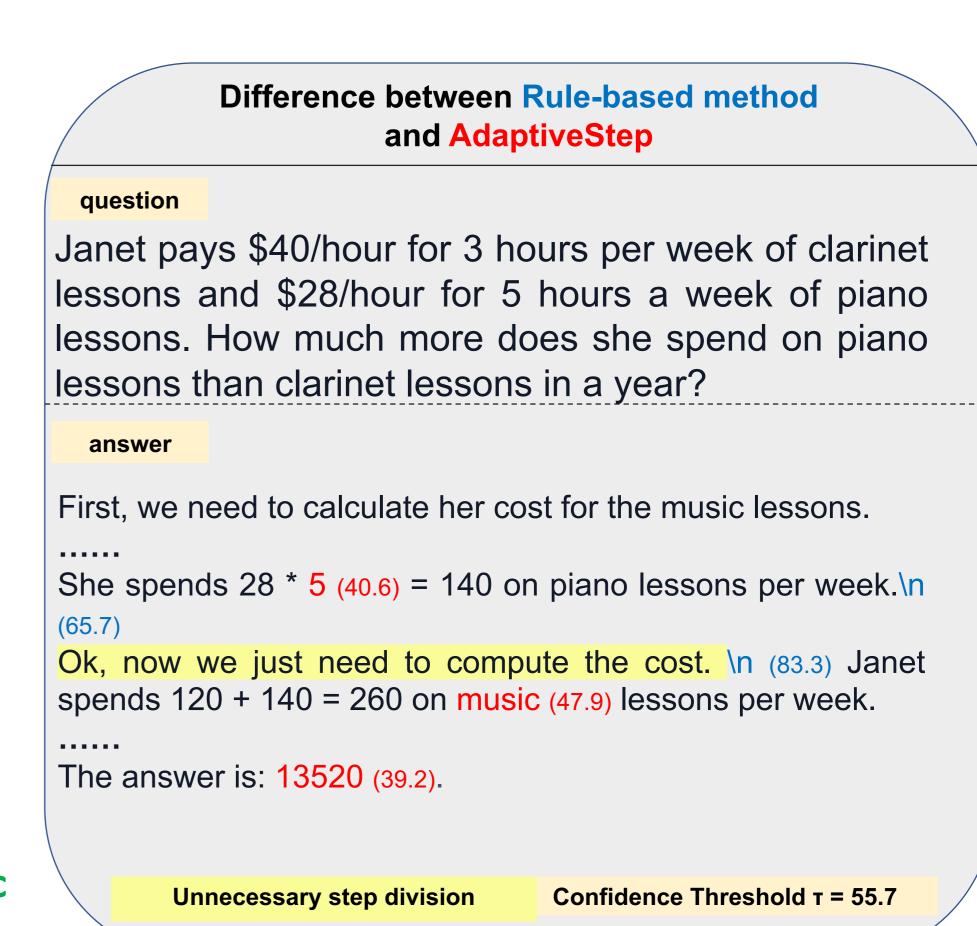
Recognize the signs that you are in a cognitive minefield, slow down, and ask for reinforcement from System 2.

——Daniel Kahneman

《Thinking, Fast and Slow》

To this end, we use inference confidence (e.g. predict probability), to recognize "cognitive minefield" in LLM reasoning process. We believe that these positions should receive more attention.





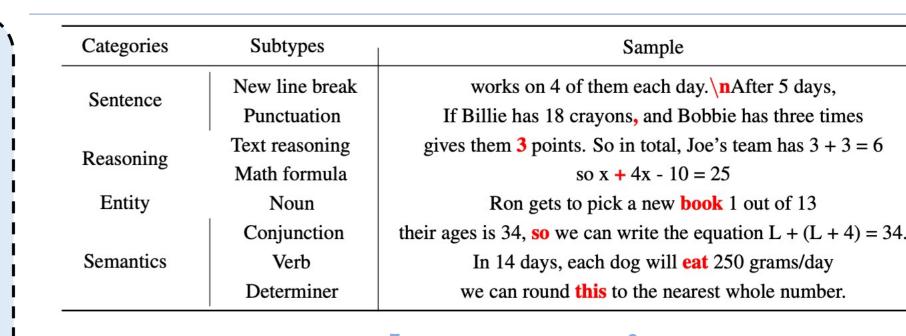
# An Implementation on Process Reward Model

predict confidence

# **Dividing Cases**

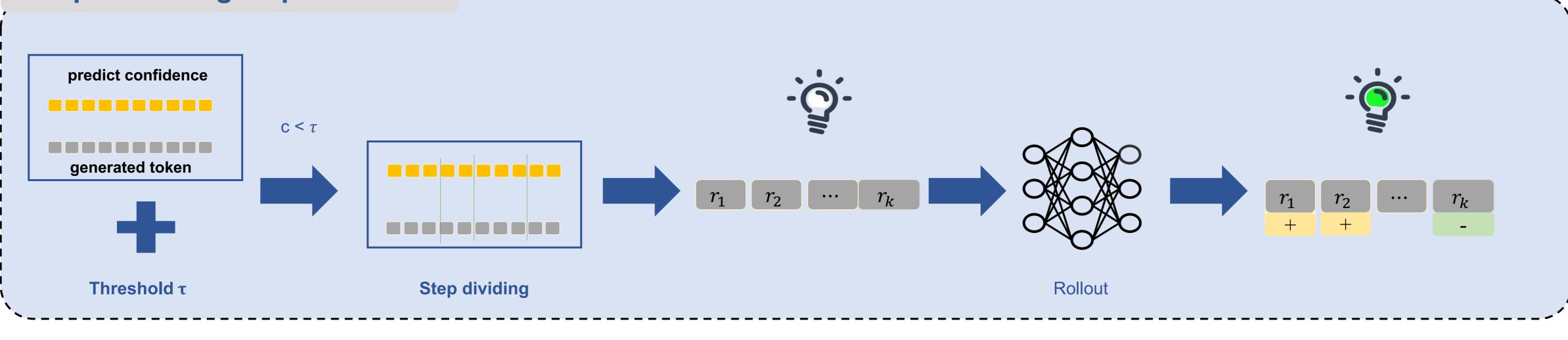
### **Math Domain**

**Code Domain** 

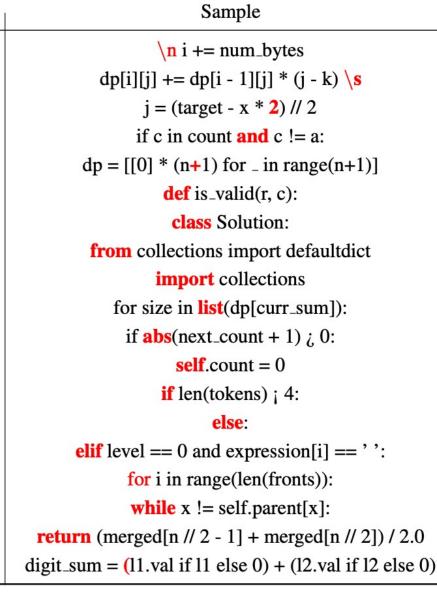


# Step2: Dividing step & Rollout

Step1: Sample & Calculate threshold



#### Subtypes Categories New line break Syntax Symbol Space Character Numbers Number **Boolean Operators Logical Operators Arithmetic Operators** Def Definition Class Import Statement **Import** Type Defination **Build-in Function** Function **Instance Method Control Statements** Else Elif For Loop Statements While Return Others **Punctuation Mark**



# **Experiments Results and Findings**

2% steps

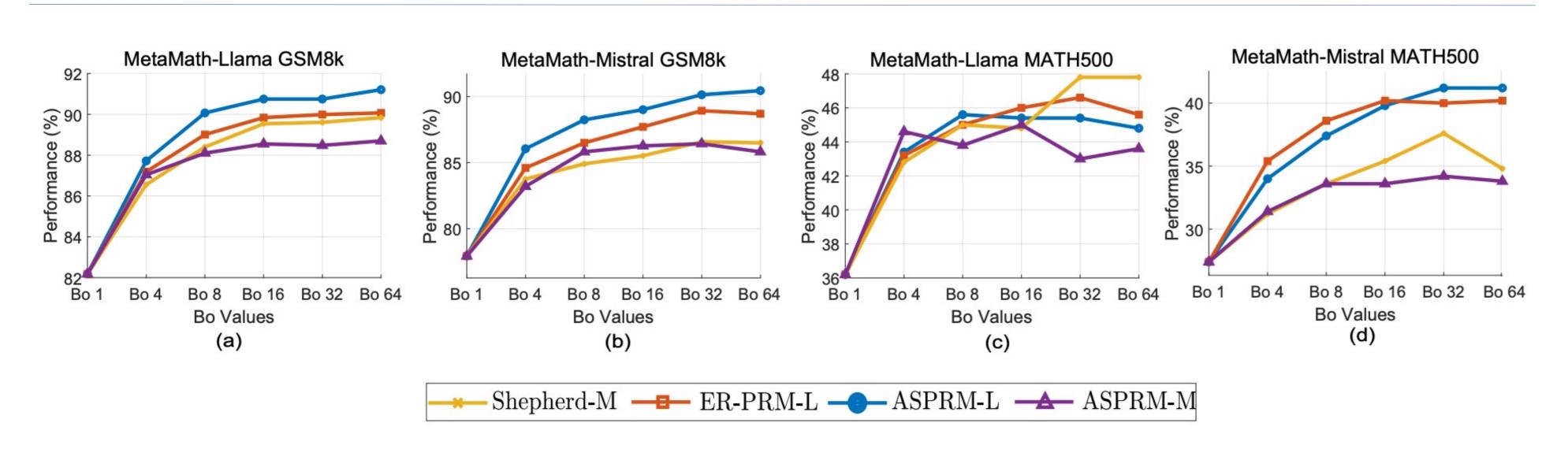
**Tokens** 

Calculate threshold a

**Tokens** 

Confidence distribution

### Math Reasoning Results (PRM as Verifier)

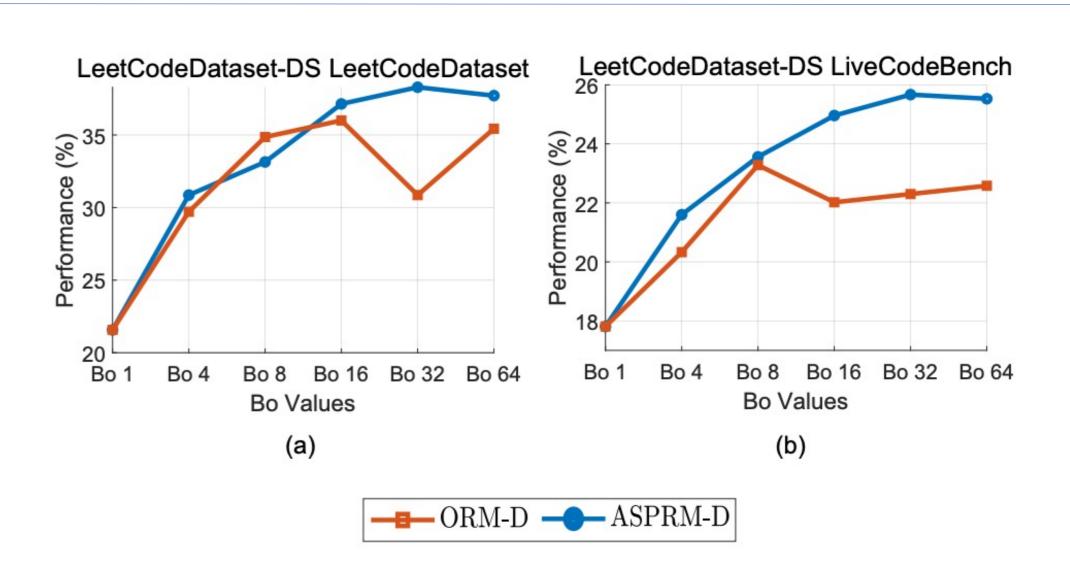


### Token Level Value-guided Decoding Results

Table 1: Token-level Value-guided Decoding results. A/P@1 refers to the inference model's greedy search performance, we use Accuracy@1 for math tasks and Pass@1 for code tasks as the metrics.  $\uparrow$  and  $\downarrow$  represent the performance improvement or decline compared to A/P@1.

Dataset	Inference Model	A/P@1	Math-Shepherd	ER-PRM	ASPRM-L / -M	ASPRM-D
GSM8k	MetaMath-M	77.10	75.66↓	75.13↓	<b>79.53</b> <sup>†</sup> / 77.33 <sup>†</sup>	1
	MetaMath-L	81.80	81.73↓	81.58↓	<b>83.47</b> ↑ / 82.56↑	/
MATH500	MetaMath-M	25.00	27.60	27.80	<b>28.60</b> <sup>†</sup> / 26.80 <sup>†</sup>	/
	MetaMath-L	38.80	41.00	38.60↓	<b>42.00</b> ↑ / 41.20↑	/
LeetCodeDataset	LCD-DS	26.28	1	/	/	28.00↑
LiveCodeBench	LCD-DS	19.21	1	/	/	19.92

### **Code Generation Results**



### **Features and Findings**

- · In terms of construction costs, about 70% of the overhead in the mathematics domain used other methods, in the code domain, the construction overhead was one-third based on line-wise division.
- · Generalization and transferability are both superior to rigid partitioning methods, and the capabilities of the selected domains can mutually reinforce each other.
- · In the mathematics domain, 21% of the division points are located within mathematical expressions, even though these tokens only account for 3.85% of the total.
- Only 2.7% of the division points are newline characters.
- · Although tokens in the comment section account for 19% in the code domain, division points located within comments make up 80% of the total and are mostly found in comments preceding the corresponding code. This indicates that, for the model, planning is more challenging than code generation.