

### AutoPSV: Automated Process-Supervised Verifier

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### TL;DR

- 1. AutoPSV effectively identifies **variations in model confidence** to annotate the correctness of **intermediate reasoning steps**, enabling **efficient automatic labeling for process supervision.**
- 2. AutoPSV significantly improves the **performance and scalability** of verification models in mathematical and commonsense reasoning tasks.
- 3. AutoPSV's versatility is evident in its applicability to **both labeled and unlabeled dataset settings** after completing the training process.

# Background

**Problem** Response selection from multiple candidates for reasoning tasks

#### **Parameterization**

- $q:$  input question
- $S_i^{(1:t)}$ : *i*-th solution contains from 1 to t-th reasoning steps
- $y_i$ : binary correctness label

### **Outcome-Supervision vs. Process-Supervision**  $y_i$  vs  $y_i^t$

#### **Current Process-Supervision Methods**

- Human annotations: expensive
- Monte Carlo Tree Search (MCTS-based) : computationally inefficient

### Motivation

Finding: Even models exceeding 70 billion parameters demonstrate suboptimal selection performance when relying solely on prompting without fine-tuning.

*response generator*: Mixtral-Instruct (8 x 7b)

Table 1: Performance of Mixtral-Instruct on GSM8K. All results are reported in accuracy (%).



*selectors*: Mistral-Instruct (7b), Mixtral-Instruct, Llama2-chat (70b) and Qwen (72b)

Table 2: Comparison of different selection methods across various model sizes for selecting a response from candidate responses generated by Mixtral-Instruct. All results are reported in accuracy (%).



**Outcome-Supervision**

$$
L\left(S_i^{(1:t)}, y_i; q\right) = \left(f_{\theta}\left(S_i^{(1:t)}; q\right) - y_i\right)^2
$$

We firstly define 
$$
\Delta_{conf}^t = \frac{f_{\theta}\left(s_i^{(1:t+1)}:q\right) - f_{\theta}\left(s_i^{(1:t)}:q\right)}{f_{\theta}\left(s_i^{(1:t)}:q\right)}
$$
 and

**Process-Supervision**

$$
L\left(S_i^{(1:t)}, y_i^t : q\right) = \left(f_\theta\left(S_i^{(1:t)} : q\right) - y_i^t\right)^2
$$

Where

If 
$$
\Delta_{conf}^t > \theta
$$
,  $y_i^t = 1$ , else  $y_i^t = 0$ 

#### Problem:

Anna spent 1/4 of her money, and now she has \$24 left. How much did she have originally?

#### **Solution Sets:**



Given an LLM acting as a response generator, we seek to annotate each reasoning step and perform response selection.



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We then train a process-supervised verifier to annotate steps via confidence variation.

### Preliminary Findings

#### **1. Good Performance of Outcome-Supervised Verifier for Response Selection Task**



Table 3: Performance of OSV models across different configurations.

#### 2. High Efficiency of  $\bm{\varDelta^{t}_{conf}}$  for Detecting Calculation Error During Math Reasoning

Table 5: Process Calculation Error Detection Performance with Varying Threshold  $(\theta)$  Values.



### Experiment: Main Results

#### **Mathematics Reasoning**



#### Table 6: Results on mathematics benchmarks.

#### **Commonsense Reasoning**

#### Table 7: Results on commonsense reasoning benchmarks.



### Experiment: Analysis

#### **Performance in Labeled Settings**

Performance Comparison



Annotation Cost Comparison



#### **Performance in Unlabeled Settings**

Further Performance Improvement



# **Thanks!**