

Efficient RL for Large Language Models

with Intrinsic Exploration (PREPO)

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GitHub

Paper

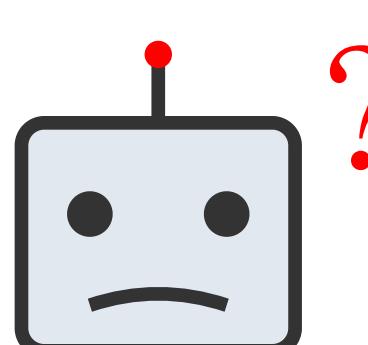
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TL;DR

PREPO reduces Reinforcement Learning (RLVR) training costs by **3x**. It uses "intrinsic" metrics—

Prompt Perplexity & **Rollout Entropy**—to filter data, guiding exploration.

I. The Problem



- Costly:** Standard RLVR generates thousands of rollouts.
- Inefficient:** Many samples are too easy or too hard (zero advantage).
- Goal:** Data-efficient RLVR training using data **intrinsic properties**.

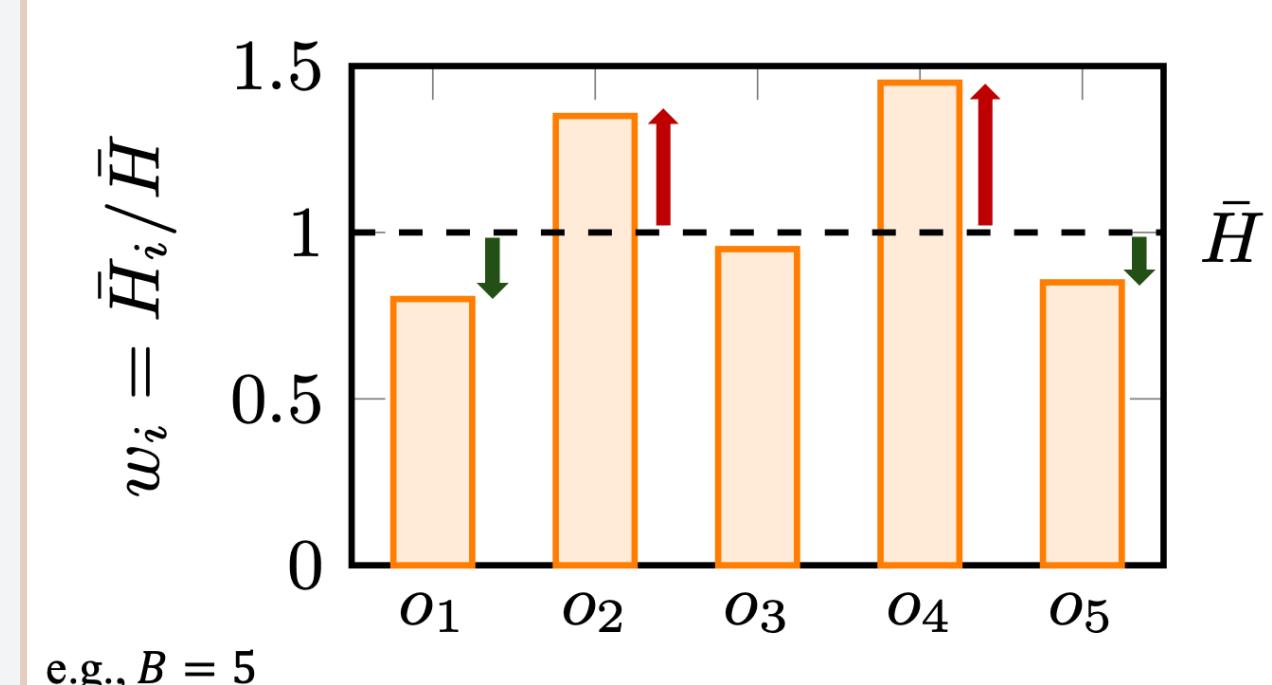
3. Method: Rollout Weighting

Strategy: Relative Entropy

Prioritize diverse reasoning paths. Weight rollouts by their average token-level entropy.

$$w_i = \frac{\bar{H}_i}{\bar{H}}, \quad \bar{H}_i = -\frac{1}{|o_i|} \sum_{t=1}^{|o_i|} \sum_{v \in V} p(v|x_t) \log p(v|x_t)$$

mini-batch
(B rollouts)



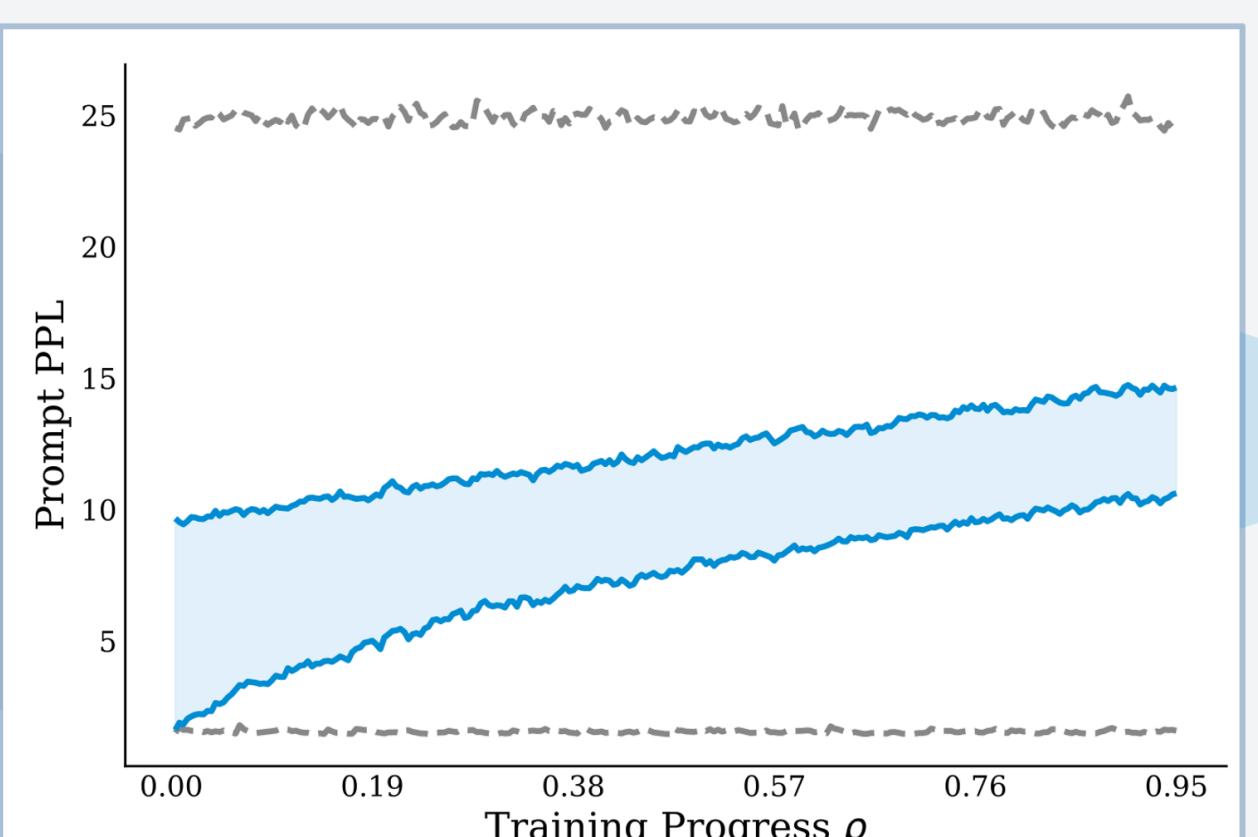
2. Method: Online Prompt Selection

Strategy: Prompt Perplexity

Use perplexity as a proxy for adaptability. Train on Low PPL to High PPL prompts.

$$P(\rho) = \exp \left(-\frac{1}{N} \sum_{t=1}^N \log p(x_t | x_{prev}) \right)$$

\mathcal{B}



4. Results

Tested on Qwen & Llama (MATH500, AIME, Olympiad).

