Efficient RL for Large Language Models with Intrinsic Exploration (PREPO)

GitHub

Paper

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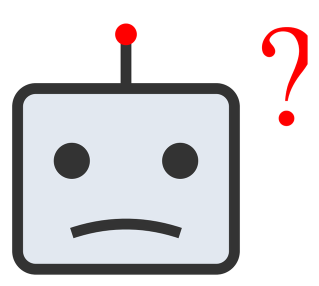
TL;DR

PREPO reduces Reinforcement Learning (RLVR) training costs with "intrinsic" metrics—Prompt Perplexity & Rollout Entropy—to filter data, guiding exploration.

1. The Problem



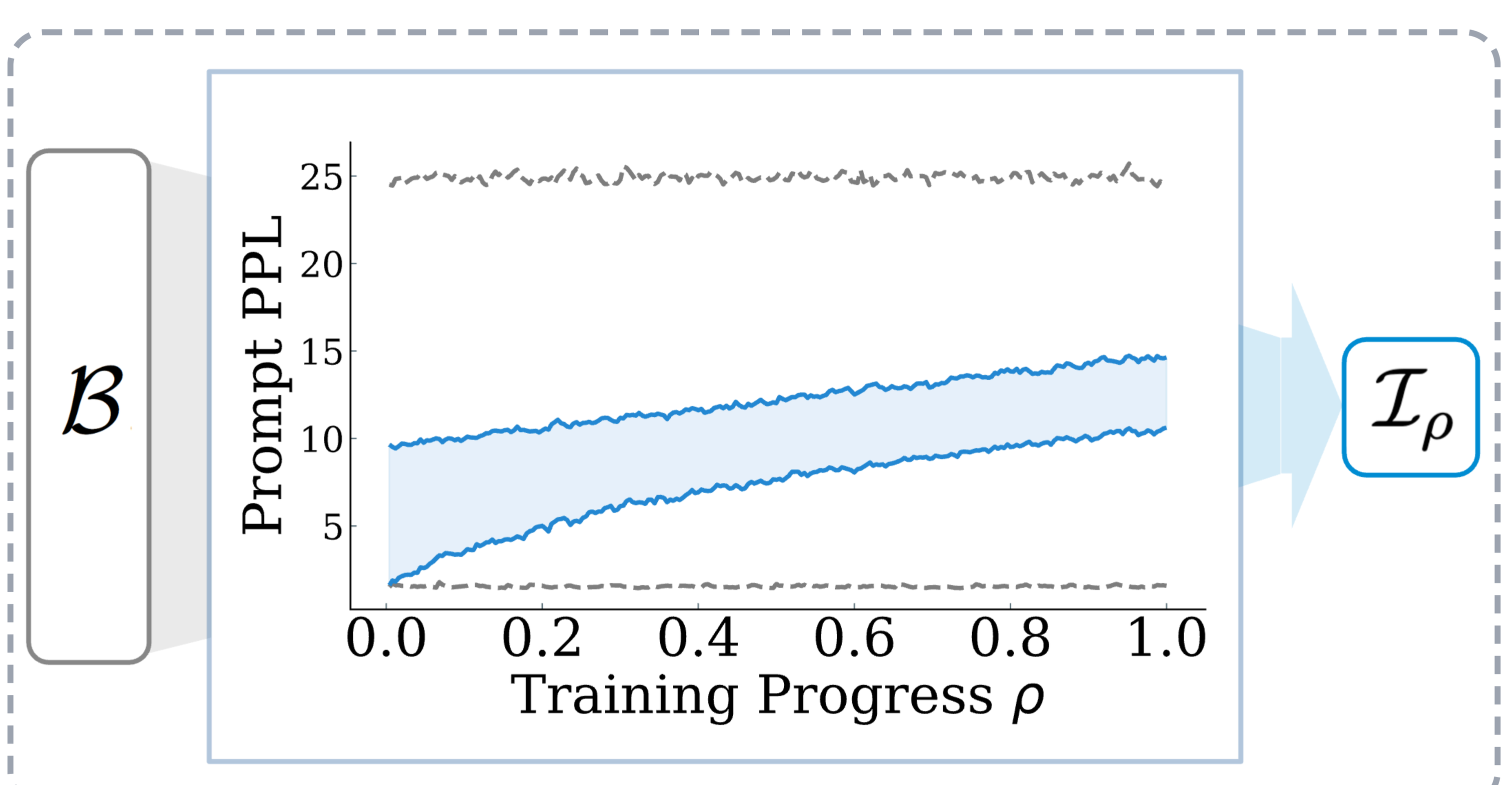
- **Costly:** Standard RLVR generates thousands of rollouts.
- **Inefficient:** Many samples are too easy or too hard (zero advantage).
- **Goal:** Data-efficient RLVR training using data intrinsic properties.

2. Preliminary Analysis

3. Method: Online Prompt Selection

Strategy: Prompt Perplexity

Use perplexity as a proxy to select from a candidate batch $\mathcal{B}$ to the actual batch $\mathcal{I}_\rho$ at every training step. Train on **Low PPL** to **High PPL** prompts.

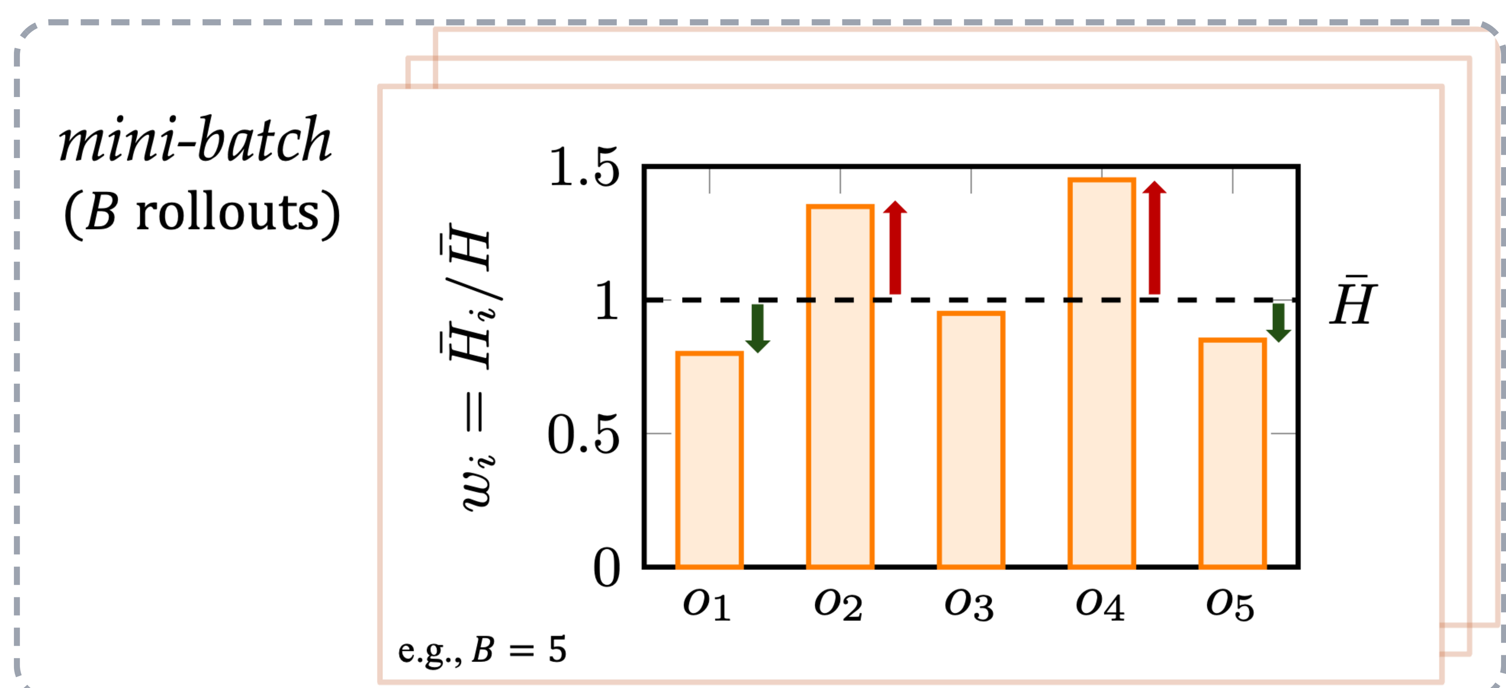


4. Method: Rollout Weighting

Strategy: Relative Entropy

Prioritize diverse reasoning paths. Weight rollouts by their average token-level entropy. (V: vocabulary size)

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



5. Results

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

Model	Method	Avg Acc.	Rollouts
Qwen2.5-Math-7B	Random	39.45%	905K
	PREPO	39.59%	540K (1.7x)
Qwen3-4B	Random	71.33%	553K
	PREPO	75.99%	348K (1.6x)