DeepSeek R1: Reasoning via RL[1]

$6M Is All You Need?

J. Setpal

January 30, 2025

MACHINE LEARNING @ PURDUE

[1] Guo, et. al. [Jan 2025]

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I probably get some things wrong, and definitely can't answer every question. Idea is to work through it together.

Outline

1. RL Review
2. Training Details
3. Performance Evals

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$$\frac{1}{|o|}\sum_{i=1}^{|o|} \min\left(\frac{\pi_{\theta_{old}}(o_i|q, o_{<i})}{\pi_\theta(o_i|q, o_{<i})}A_i, \text{clip}\left(\frac{\pi_{\theta_{old}}(o_i|q, o_{<i})}{\pi_\theta(o_i|q, o_{<i})}, 1 \pm \varepsilon\right) A_i\right) \tag{1}$$

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One issue with this is A_i, which is computed using the **Generalized Advantage Estimator**[2] –

1. Estimates long-range trajectory rewards.
2. However, requires a neural reward model which is expensive to train and can be unstable.

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RLHF Synopsis (1/2)

We'll review the RLHF pipeline per Zeiger et al. It has 3-primary phases:

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   a. Rewards are normalized over x to motivate lower variance.
   b. r_ϕ is π_{SFT} with the final linear layer returning the scalar reward.

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3. **RL Fine-Tuning:** Finally, we use r_ϕ to fine-tune π_{SFT}, with the following objectives:
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Mathematically, RLHF posits the following optimization problem:

$$\max_{\pi_\theta} \mathbb{E}_{x \sim \mathcal{D}, y \sim \pi_\theta(y|x)}(r_\phi(x, y)) - \beta \mathbb{D}_{KL}[\pi_\theta(y|x) \mid\mid \pi_{SFT}(y|x)] \quad (5)$$

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   This is equivalent to the reward function:

$$r(x, y) = r_\phi(x, y) - \beta(\log \pi_\theta(y|x)) - \log(\pi_{SFT}(y|x)) \quad (6)$$

   Which is maximized using **Proximal Policy Optimization**.

GRPO (1/2)

For each question q, GRPO samples outputs $\{o_1, \ldots, o_G\}$ with the training objective being to maximize (1):

$$\mathcal{J}_{GRPO}(\theta) := \mathbb{E}[q \sim P(Q), \{o_i\}_{i=1}^{G} \sim \pi_{\theta_{old}}(O|q)]$$

$$\frac{1}{G}\sum_{i=1}^{G}\left(\min\left(\frac{\pi_{\theta_{old}}(o_i|q)}{\pi_{\theta}(o_i|q)}A_i, \text{clip}\left(\frac{\pi_{\theta_{old}}(o_i|q)}{\pi_{\theta}(o_i|q)}, 1 \pm \varepsilon\right)A_i\right) + \beta D_{KL}(\pi_\theta||\pi_{\text{ref}})\right) \tag{7}$$

$$D_{KL}(\pi_\theta||\pi_{\text{ref}}) = \frac{\pi_{\text{ref}}(o_i|q)}{\pi_\theta(o_i|q)} - \log\frac{\pi_{\text{ref}}(o_i|q)}{\pi_\theta(o_i|q)} - 1 \tag{8}$$

$$A_i = \frac{r_i - \bar{r}}{\sigma_{std}(r)};\ \ r \in \{r_1, \ldots, r_G\} \tag{9}$$

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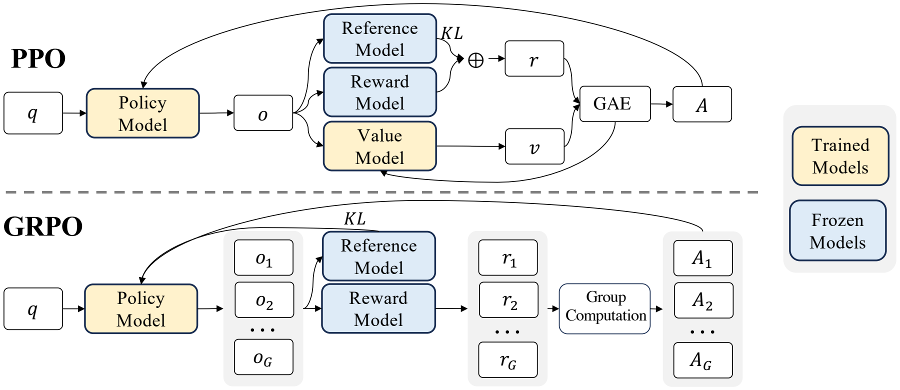

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Approach Overview

The training process can largely can be broken down into three stages:

1. **RL on a base model** – gets us DeepSeek-R1-Zero.
2. **RL+SFT on a checkpoint** – gets us DeepSeek-R1.
3. **Distillation** – gets us DeepSeek-R1-Distill-`<model-name>`.

We'll discuss each of these in detail next.

Less is More Philosophy

A core finding from Less is More for Aligment (LIMA)[3] – a small set of *synethetic* examples encourages better generalization.

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This, combined with **carefully selected data** are key to the incredible benchmark performance.

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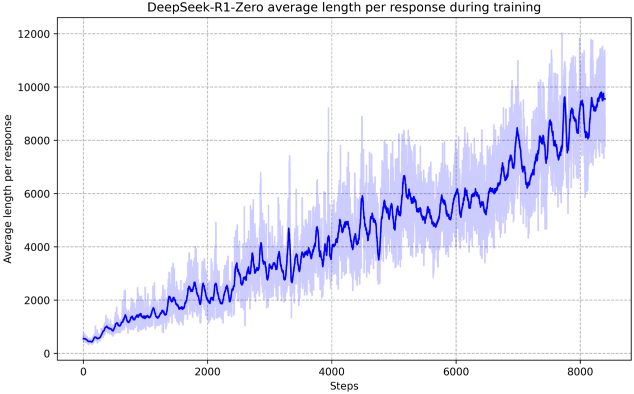

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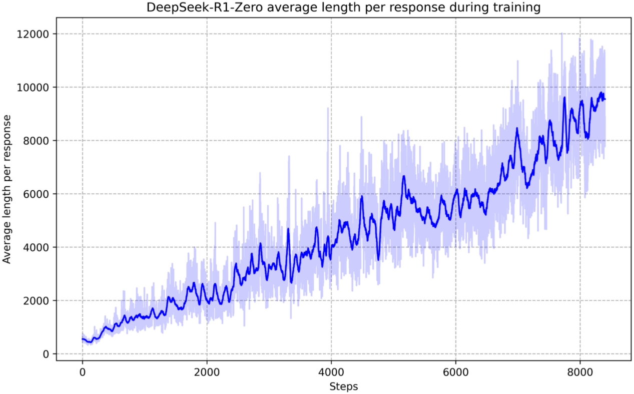

Thinking more, and thinking anthropomorhically as emergent properties.

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Solution? **Cold Start**. Use SFT *briefly*, to encourage approaching problems consistently.

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3. Manually refining DeepSeek-R1-Zero outputs to remove language mixing, fixing readibility and general response refinment.

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Secondary RL Stage

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Quiet Part Out Loud

Probably was used to filter out Tiananmen Square Massacre information, whatever additional censorship they desire.

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Opinion

I disagree, they could've used RL to fine-tune DeepSeek-V3-Base with RL-checkpointed data but chose SFT.

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Aside

Approaches do exist that combine these two and exhibit strong performance in specific specialized domains.[a][b]

[a] https://arxiv.org/abs/2406.03816
[b] https://arxiv.org/abs/2501.07301

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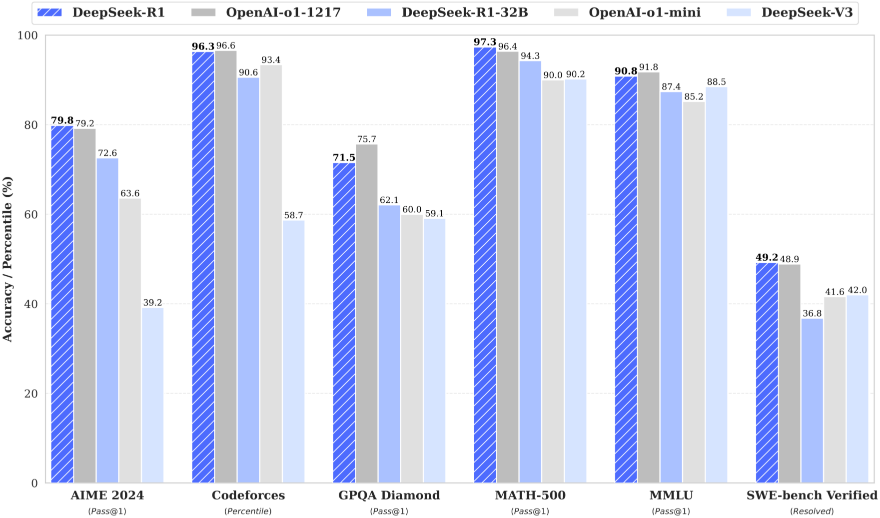

DeepSeek-R1
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Accuracy / Percentile (%)
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20
0
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79.2
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96.3
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93.4
58.7
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60.0
59.1
97.3
96.4
94.3
90.0
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AIME 2024
(Pass@1)
Codeforces
(Percentile)
GPQA Diamond
(Pass@1)
MATH-500
(Pass@1)
MMLU
(Pass@1)
SWE-bench Verified
(Resolved)

Other Stuff

[Refer to paper directly]

Thank you!

Have an awesome rest of your day!

Slides: `https://jinen.setpal.net/slides/dsr1.pdf`