TeCho Reading Group
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JOHNS HOPKINS
WHITING SCHOOL of ENGINEERING

Absolute Zero:
Reinforced Self-play Reasoning with Zero Data

Spotlight @ NeurIPS ‘25

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Sections

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3. RL from Absolute Zero
4. AZR Training
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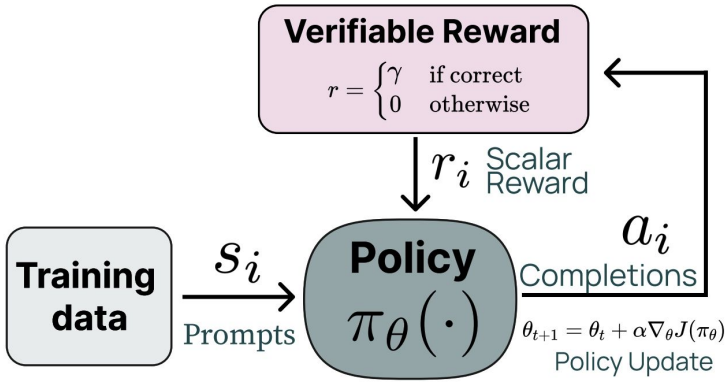
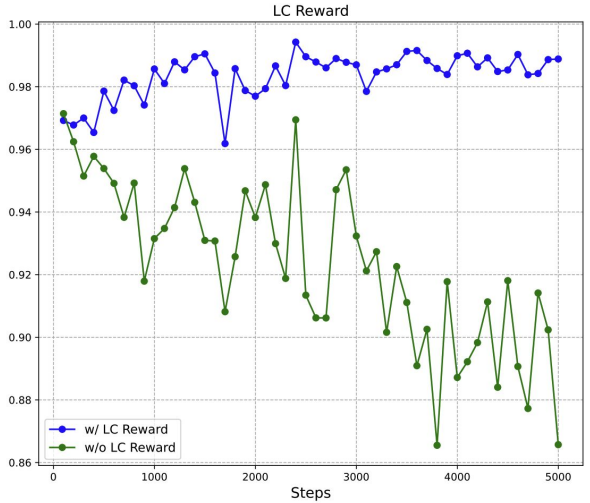
Background

Reinforcement Learning from Verifiable Rewards (RLVR)





Background

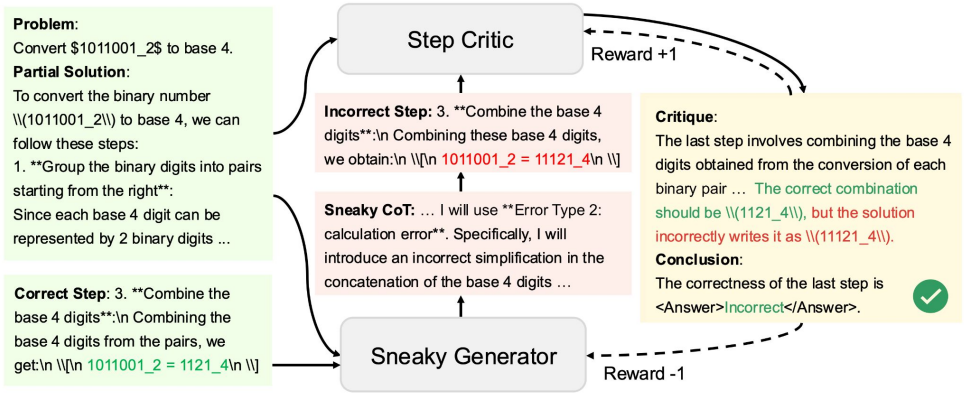
Reinforcement Learning from Verifiable Rewards (RLVR)

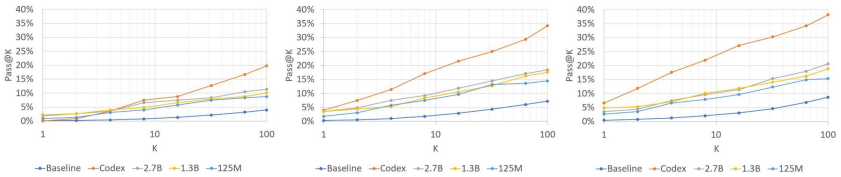
$$J_{\text{RLVR}}(\theta) = \mathbb{E}_{(x,y^\star)\sim\mathcal{D},\ (c,y)\sim\pi_\theta(\cdot\,|x)}\left[r(y,y^\star)\right]$$

$$\mathcal{L}_{\text{SFT}}(\theta) = -\,\mathbb{E}_{(x,c^\star,y^\star)\sim\mathcal{D}}\log\pi_\theta\left(c^\star,y^\star\mid x\right)$$

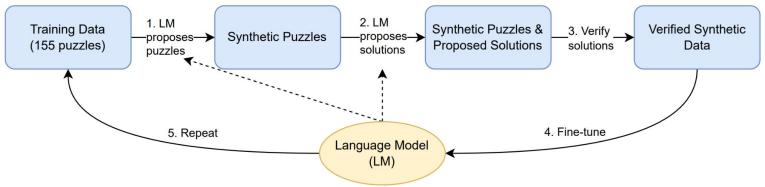
Background

Self-play for self-improvement

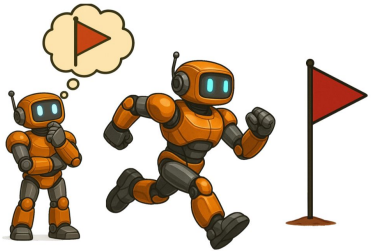




(a) GPT-Neo 125M Model (b) GPT-Neo 1.3B Model (c) GPT-Neo 2.7B Model



Introduction



Intuition: *LMs can autonomously learn to define & solve challenging tasks.*

Task: ***Code reasoning*** –

Fill-in any element of the triplet:

{*program, inputs, outputs*}

Predominant approaches:

- **Supervised Fine-Tuning (SFT):** requires strongly supervised task-rationale-answer demonstrations.
- **RLVR:** Generally uses expert-curated task-answer datasets, limiting scalability.

Limitation: **Existing approaches are expensive & limited in scalability.**

- Remove expert data-curation constraint – much cheaper.
- Remove data availability bottleneck – can theoretically learn infinitely.

This paper:
Can we self-learn problem creation & solving using a grounded environment?

Absolute Zero

Overview

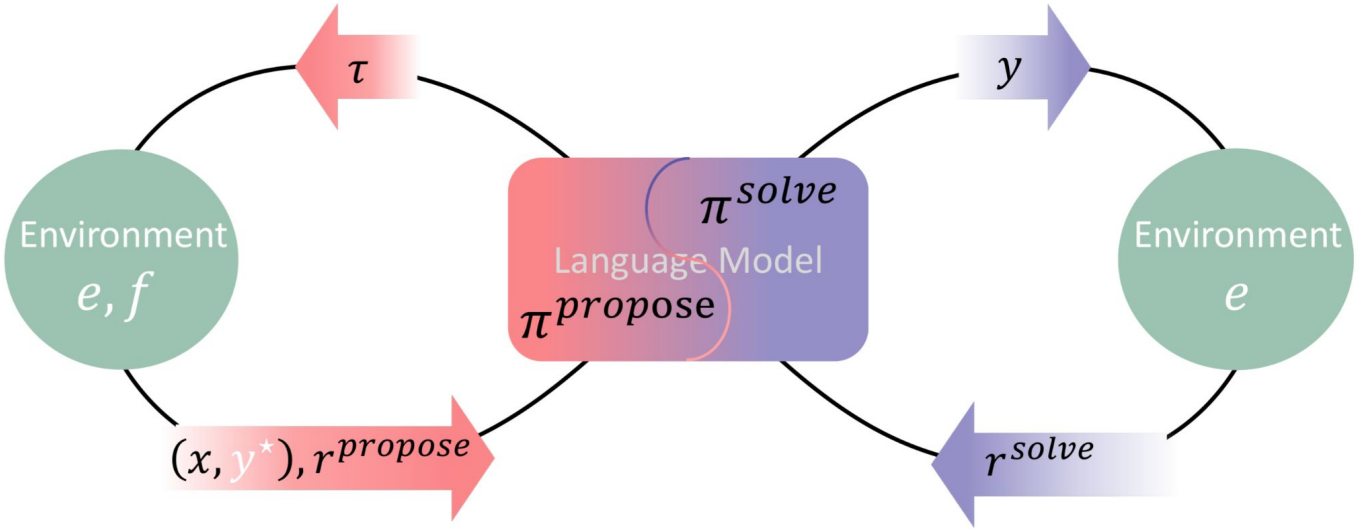


Figure 3

Absolute Zero

Two roles

The model simultaneously:

- Proposes tasks:
  - $\tau \sim \pi_\theta^{\text{propose}}(\cdot|z)$
  - $(x, y^\star) \sim f_e(\cdot|\tau)$
- Solves them:
  - $y \sim \pi_\theta^{\text{solve}}(\cdot \mid x)$

And learns from both stages:

- Learnability reward:
  - $r_e^{\text{propose}}(\tau, \pi_\theta)$
  - How much can π_θ improve by solving $\mathcal{T}$?
- Solution reward:
  - $r_e^{\text{solve}}(y, y^\star)$
  - How correct is y?

Absolute Zero

Two roles

$$r_{\text{propose}} = \begin{cases} 0, & \text{if } \bar{r}_{\text{solve}} = 0 \\ 1 - \bar{r}_{\text{solve}}, & \text{otherwise.} \end{cases}$$

$$r_{\text{solve}} = \mathbb{I}_{(y=y^\star)}$$

$$\mathcal{J}(\theta) := \max_{\theta} \; \mathbb{E}_{z\sim p(z)} \left[\mathbb{E}_{(x,y^\star)\sim f_e(\cdot|\tau),\tau\sim\pi_\theta^{\text{propose}}(\cdot|z)} \left[\lambda r_e^{\text{propose}}(\tau,\pi_\theta) + \mathbb{E}_{y\sim\pi_\theta^{\text{solve}}(\cdot|x)} \left[r_e^{\text{solve}}(y,y^\star) \right] \right] \right]$$

Equations 4, 5 & 3.

Absolute Zero

Three tasks

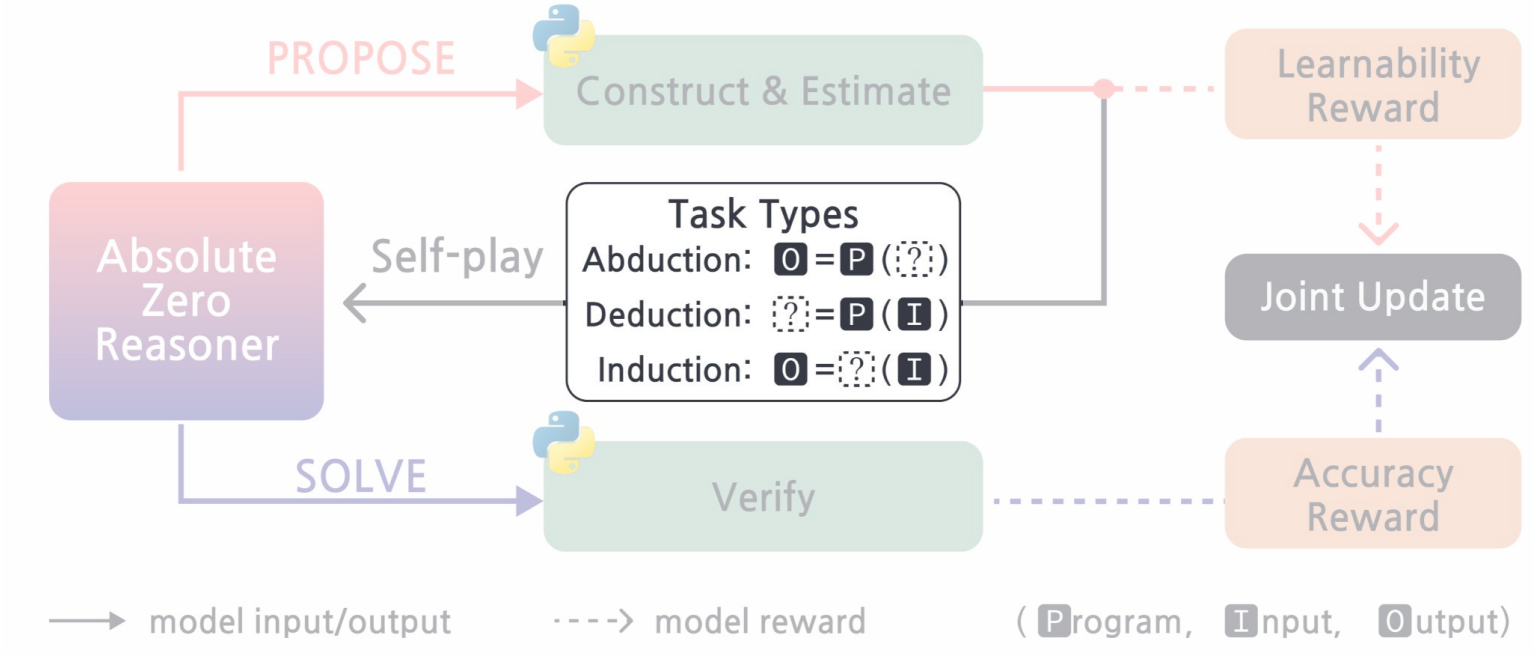


Figure 4

Absolute Zero

Three tasks

Abduction:

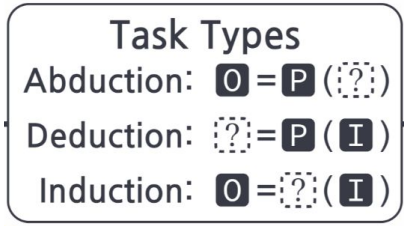
Predict input given program & output.

$$x = (p, o)$$

Deduction:

Predict output given program & input.

$$x = (p, i)$$



Induction:

Predict program given *n* input-output pairs, and a natural-language description *m*.

$$x = (\{i^n, o^n\}_{n=1}^{N//2}, m)$$

Absolute Zero

Algorithm

Task buffers:

- Problem caches for each task. (all the same size, 4 x Batch Size)
- Generated by the LLM:
  - Deduction & Abduction buffers generated as *(p,i)* pairs.
  - These are passed to *e* to get *(p, i, o)* triplets.
  - Sample from this & generate *m* to create Induction buffer.

Task Validation:

- Program Integrity
- Program Safety
- Program Determinism

TRR++

$$A^{\text{norm}}_{\text{task,role}} = \frac{r - \mu_{\text{task,role}}}{\sigma_{\text{task,role}}}, \quad \text{task} \in \{\text{ind,ded,abd}\}, \text{role} \in \{\text{propose,solve}\}$$

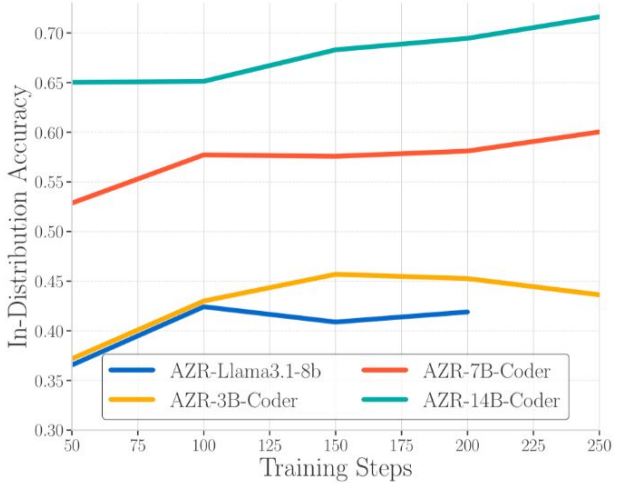
Absolute Zero

Results

Model	Base	#data	HEval+	MBPP+	LCB v1-5	AME24	AME25	AMC	M500	Minva	Olypiad	CAvg	MAvg	AVG
Base Models														
Qwen2.5-7B[87]	-	-	73.2	65.3	17.5	6.7	3.3	37.5	64.8	25.0	27.7	52.0	27.5	39.8
Qwen2.5-7B-Ins[87]	-	-	75.0	68.5	25.5	13.3	6.7	52.5	76.4	35.7	37.6	56.3	37.0	46.7
Qwen2.5-7B-Coder[32]	-	-	80.5	69.3	19.9	6.7	3.3	40.0	54.0	17.3	21.9	56.6	23.9	40.2
Qwen2.5-7B-Math[88]	-	-	61.0	57.9	16.2	10.0	16.7	42.5	64.2	15.4	28.0	45.0	29.5	37.3
Zero-Style Reasoners Trained on Curated Coding Data														
AceCoder-RM[98]	Ins	22k	79.9	71.4	23.6	20.0	6.7	50.0	76.4	34.6	36.7	58.3	37.4	47.9
AceCoder-Rule[98]	Ins	22k	77.4	69.0	19.9	13.3	6.7	50.0	76.0	37.5	37.8	55.4	36.9	46.2
AceCoder-RM[98]	Coder	22k	78.0	66.4	27.5	13.3	3.3	27.5	62.6	29.4	29.0	57.3	27.5	42.4
AceCoder-Rule[98]	Coder	22k	80.5	70.4	29.0	6.7	6.7	40.0	62.8	27.6	27.4	60.0	28.5	44.3
CodeR1-LC2k[44]	Ins	2k	81.7	71.7	28.1	13.3	10.0	45.0	75.0	33.5	36.7	60.5	35.6	48.0
CodeR1-12k[44]	Ins	12k	81.1	73.5	29.3	13.3	3.3	37.5	74.0	35.7	36.9	61.3	33.5	47.4
Zero-Style Reasoners Trained on Curated Math Data														
PRIME-Zero[13]	Coder	484k	49.4	51.1	11.0	23.3	23.3	67.5	81.2	37.9	41.8	37.2	**45.8**	41.5
SimpleRL-Zoo[99]	Base	8.5k	73.2	63.2	25.6	16.7	3.3	57.5	77.0	35.7	41.0	54.0	38.5	46.3
Oat-Zero[47]	Math	8.5k	62.2	59.0	15.2	30.0	16.7	62.5	80.0	34.9	41.6	45.5	44.3	44.9
ORZ[29]	Base	57k	80.5	64.3	22.0	13.3	16.7	60.0	81.8	32.7	45.0	55.6	41.6	48.6
Absolute Zero Training w/ No Curated Data (Ours)														
AZR (Ours)	Base	**0**	71.3$^{-1.9}$	69.1$^{+3.8}$	25.3$^{+7.8}$	13.3$^{+6.6}$	13.3$^{+10.0}$	52.5$^{+15.0}$	74.4$^{+9.6}$	38.2$^{+13.2}$	38.5$^{+10.8}$	55.2$^{+3.2}$	38.4$^{+10.9}$	46.8$^{+7.0}$
AZR (Ours)	Coder	**0**	83.5$^{+3.0}$	69.6$^{+0.3}$	31.7$^{+11.8}$	20.0$^{+13.3}$	10.0$^{+6.7}$	57.5$^{+17.5}$	72.6$^{+22.6}$	36.4$^{+19.1}$	38.2$^{+16.3}$	**61.6**$^{+5.0}$	39.1$^{+15.2}$	**50.4**$^{+10.2}$

Absolute Zero

Results



(a)

Model Family	Variant	Code Avg	Math Avg	Total Avg
Llama3.1-8b		28.5	3.4	16.0
Llama3.1-8b	+ SimpleRL[99]	33.7$^{+5.2}$	7.2$^{+3.8}$	20.5$^{+4.5}$
Llama3.1-8b	+ AZR (Ours)	31.6$^{+3.1}$	6.8$^{+3.4}$	19.2$^{+3.2}$
Qwen2.5-3B Coder		51.2	18.8	35.0
Qwen2.5-3B Coder	+ AZR (Ours)	54.9$^{+3.7}$	26.5$^{+7.7}$	40.7$^{+5.7}$
Qwen2.5-7B Coder		56.6	23.9	40.2
Qwen2.5-7B Coder	+ AZR (Ours)	61.6$^{+5.0}$	39.1$^{+15.2}$	50.4$^{+10.2}$
Qwen2.5-14B Coder		60.0	20.2	40.1
Qwen2.5-14B Coder	+ AZR (Ours)	63.6$^{+3.6}$	43.0$^{+22.8}$	53.3$^{+13.2}$

(b)

Absolute Zero

Research Questions

1. Performance comparison: AZR-ed vs. RL-ed models (ie. with expert data)?
    - *AZR is SoTA; maintains performance cross-domain unlike other RL-ed models.*
2. Initializing AZR from base vs. coder?
    - *AZR Coder is SoTA & surprisingly surpasses (non-AZR) Coder on math.*
3. Does model size affect generalization?
    - *AZR helps more when the base model is larger.*

- Interesting behaviors/patterns:
    - Intermediate planning during code response
    - Cognitive behavior in Llama
    - Token length increase depends on task type.

Absolute Zero

Results

```
<think>
Design an absolutely ludicrous and convoluted Python function that is extremely difficult to
↪  deduce the output from the input, designed to keep machine learning models such as Snippi
↪  guessing and your peers puzzling.

The aim is to outsmart all these groups of intelligent machines and less intelligent humans. This
↪  is for the brains behind the future.
</think>
- Absolute Zero Reasoner-Llama3.1-8b @ step 132
```

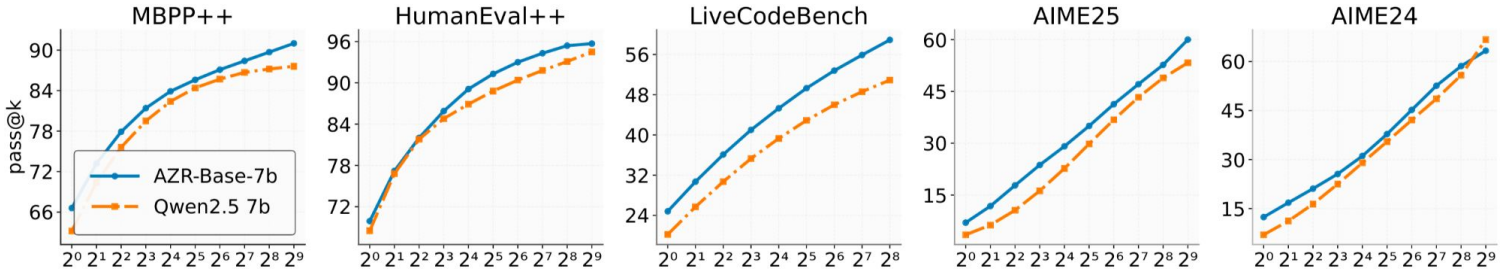


Figure 34 & 8

Absolute Zero

Algorithm

Algorithm 1 Self-Play Training of Absolute Zero Reasoner (AZR)

Require: Pretrained base LLM π_θ; batch size B; #references K; iterations T

$\mathcal{D}_{\text{ded}}, \mathcal{D}_{\text{abd}}, \mathcal{D}_{\text{ind}} \leftarrow \textsc{InitSeeding}(\pi_\theta)$ ▷ see §3.3.1

for $t \leftarrow 1$ to T **do**

  for $b \leftarrow 1$ to B **do** ▷ **PROPOSE PHASE**

    $p \sim \mathcal{D}_{\text{abd}} \cup \mathcal{D}_{\text{ded}}$ ▷ sample a program for induction task proposal

    $\left(\{i_\pi^n\}_{n=1}^N,\ m_\pi\right) \leftarrow \pi_\theta^{\text{propose}}(\text{ind}, p)$ ▷ generate N inputs and a description

    if $\{(i_\pi^n, o_\pi^n)\}_{n=1}^N \leftarrow \textsc{ValidateAndConstruct}(p, \{i_\pi^n\}, \textsc{syntax})$ **then** ▷ validate I/Os, see §3.3.3

      $\mathcal{D}_{\text{ind}} \leftarrow \mathcal{D}_{\text{ind}} \cup \{(p, \{(i_\pi^n, o_\pi^n)\}, m_\pi)\}$ ▷ update *induction* buffer

    for $\alpha \in \{\text{ded}, \text{abd}\}$ **do**

      $(p_k, i_k, o_k)_{k=1}^K \sim \mathcal{D}_\alpha$ ▷ sample K reference examples

      $(p_\pi, i_\pi) \leftarrow \pi_\theta^{\text{propose}}(\alpha, \{(p_k, i_k, o_k)\})$ ▷ propose new task

      if $o_\pi \leftarrow \textsc{ValidateAndConstruct}(p_\pi, i_\pi, \textsc{syntax,safety,determinism})$ **then** ▷ see §3.3.3

        $\mathcal{D}_\alpha \leftarrow \mathcal{D}_\alpha \cup \{(p_\pi, i_\pi, o_\pi)\}$ ▷ update *deduction* or *abduction* buffers

  for all $\alpha \in \{\text{ded}, \text{abd}, \text{ind}\}$ **do** ▷ **SOLVE PHASE**

    $(x, y^\star) \leftarrow \textsc{SamplePrepareTasks}(\mathcal{D}_\alpha, B, t)$ ▷ $x, y^\star$ prepared based on α and t, see §3.3.3

    $y_\pi \sim \pi_\theta^{\text{solve}}(x)$

  Reward: Use proposed task triplets and solved answers to get $r_{propose}$ & r_{solve} ▷ see §3.1

  RL update: use Task Relative REINFORCE++ to update π_θ ▷ see §3.3.5