DeepSeek-R1, GRPO, and Agentic Reinforcement Learning

Why this lecture starts with DeepSeek-R1

- Reasoning traces reveal how outcome rewards change model behavior
  - PPO explains clipping, critics, advantages, and policy updates
    - GRPO replaces the critic with same-prompt group comparisons
- Agentic RL adds environment state, temporal credit, and systems constraints
- The lecture ends with evaluation, reliability, and reward-channel integrity

How do reasoning models work?

- Explicitly outputs its reasoning steps as it attempts to answer/solve their query

Isn’t this just **C**hain **o**f **T**hought?

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Key Elements of a **CoT** Prompt:

- **Explicitly** ask for step-by-step reasoning
- Use phrases like "Let’s think step by step" or "Break down the problem"
- Include placeholder steps (e.g., "First... Second...")
- Request verification of the answer to encourage critical thinking

Isn’t this just **C**hain **o**f **T**hought?

Yes / No

…and why?

Isn’t this just Chain of Thought?

CoT

Encourages the model through prompting to generate a sequence of thoughts ***but*** might not be refined, and might produce a bad chain of reasoning.

Reasoning

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Reasoning

Trained to produce multiple paths of reasoning, evaluating them, and selecting the most promised one.

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Why is this different?

Isn’t this just Chain of Thought?

CoT

A clever prompting technique to elicit reasoning steps from instruct capable language models that aren’t trained to reason

Reasoning

Is *explicitly* trained through reinforcement learning to produce **correct** reasoning steps

Isn’t this just Chain of Thought?

CoT

A clever prompting technique to elicit reasoning steps from instruct capable language models that aren’t trained to reason

Prompted to produce things that *sound* logical

Reasoning

Is *explicitly* trained through reinforcement learning to produce **correct** reasoning steps

Trained to produce *logical* steps

DeepSeek-R1-Zero

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- Initial test (hence **Zero**) to see if a reasoning LLM can be taught *purely* through reinforcement learning (**GRPO**)
  - Shows that the typical SFT-then-RL approach wasn't needed
  - Emergent reasoning behaviors:
    - Self-Verification
    - Reflection
    - Longer **C**hain **o**f **T**houghts

DeepSeek-R1-Zero

- **Deep**
- Initial
  throu
  - S
  - E

Question: If $a > 1$, then the sum of the real solutions of $\sqrt{a - \sqrt{a + x}} = x$ is equal to

Response: <think>

To solve the equation $\sqrt{a - \sqrt{a + x}} = x$, let's start by squaring both $\cdots$

$$\left(\sqrt{a - \sqrt{a + x}}\right)^2 = x^2 \implies a - \sqrt{a + x} = x^2.$$

Rearrange to isolate the inner square root term:

$$(a - x^2)^2 = a + x \implies a^2 - 2ax^2 + (x^2)^2 = a + x \implies x^4 - 2ax^2 - x + (a^2 - a) = 0$$

$\ldots$

Wait, wait. Wait. That's an aha moment I can flag here.

Let's reevaluate this step-by-step to identify if the correct sum can be $\cdots$

We started with the equation:

$$\sqrt{a - \sqrt{a + x}} = x$$

First, let's square both sides:

$$a - \sqrt{a + x} = x^2 \implies \sqrt{a + x} = a - x^2$$

Next, I could square both sides again, treating the equation: $\cdots$

$\ldots$

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$\left(\sqrt{a - \sqrt{a+x}}\right)^2$ ^{2} $\overline{x} = x^2$.

Rearrange to is ıare

$(a - x^2)^2 = a + x \implies a^- - 2ax^- + (x^2)^2$ $ax^2 - x + (a^2 - a) = 0$

Interrupts its chain of thought

Self-identifies turning point in its

$\cdots$

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$\cdots$

A reasoning trace becomes a trajectory when actions change state

- **A completion ends in text; an agent episode changes an external environment**
  - The learner needs actions, observations, state evidence, rewards, and termination reasons
  - Only policy-owned tokens should enter the policy loss
  - Environment turns define useful credit boundaries
  - The trace must record what the policy knew before each action
    - Reliable learning begins with a faithful trajectory contract

Let’s talk Reinforcement Learning

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Focus	What it measured
Accuracy	*Correctly providing answers in reasoning tasks*
Format	*Using* **<think>** *and* **<answer>** *tags correctly*

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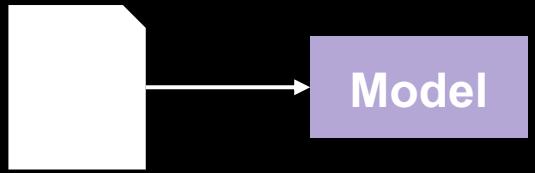

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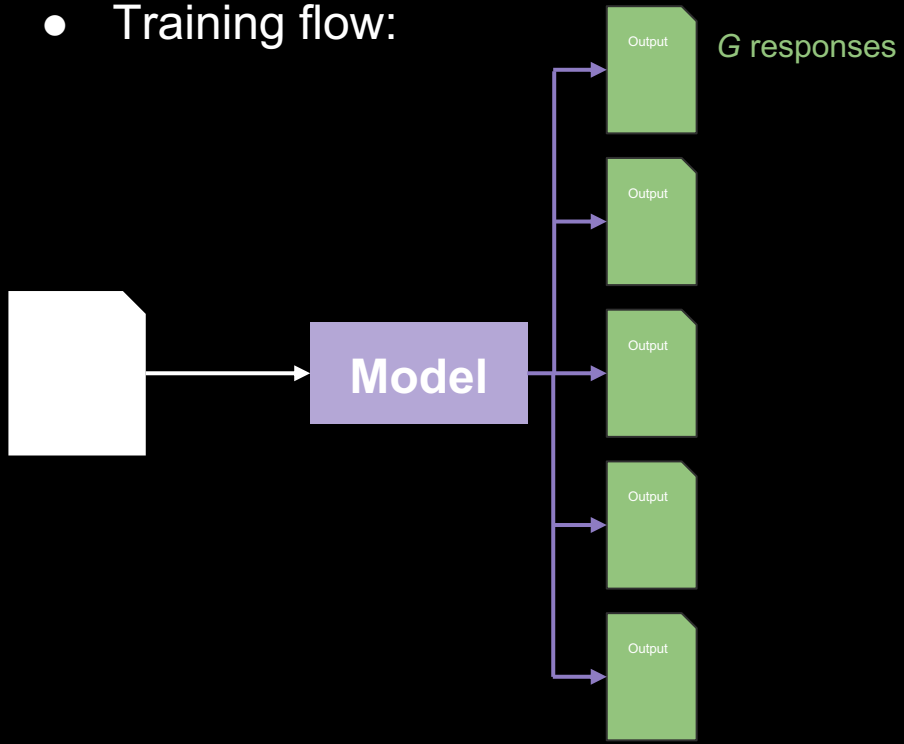

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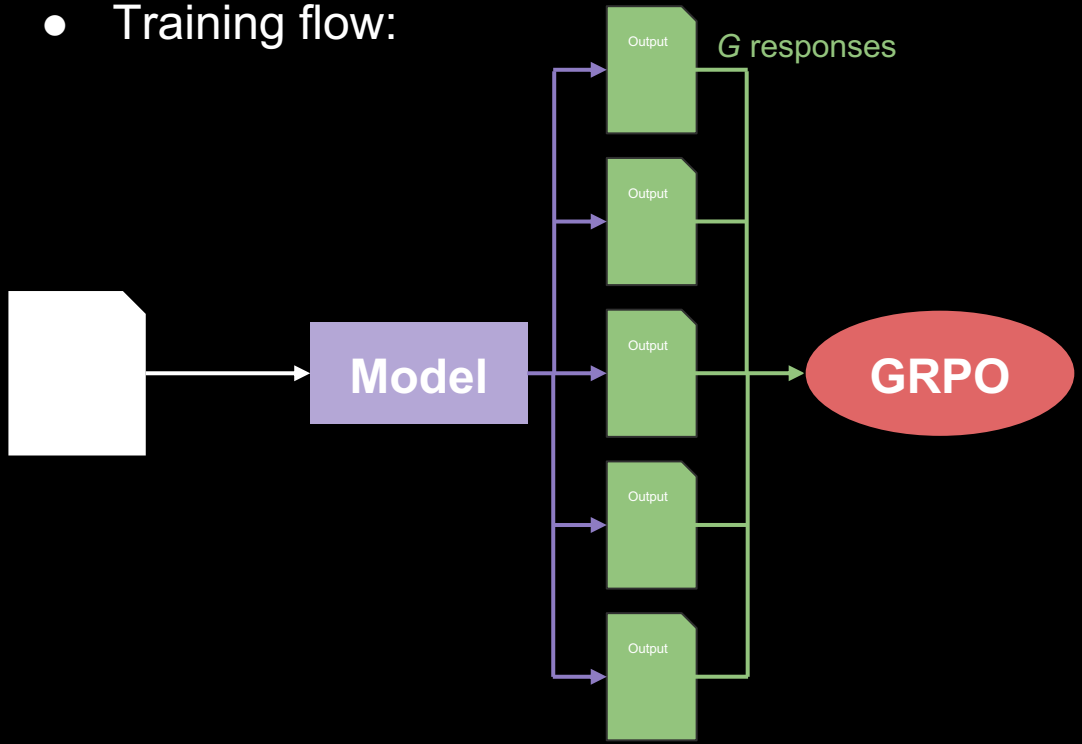

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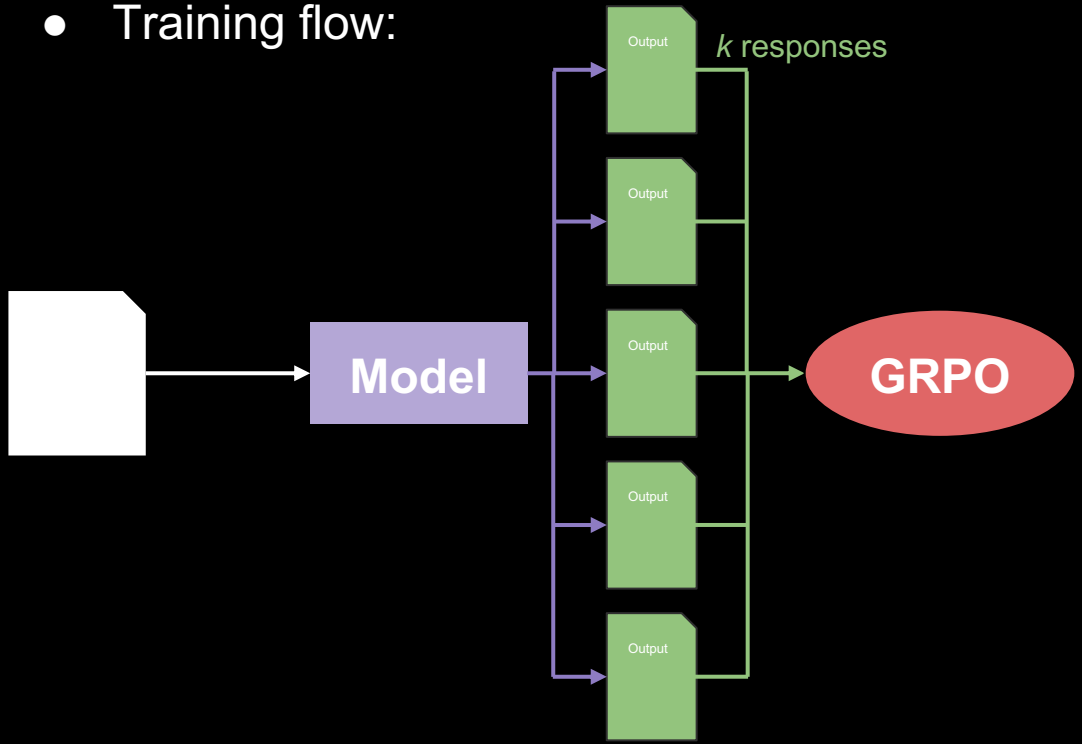

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Proximal Policy Optimization (PPO), briefly

What is PPO?

- Proximal Policy Optimization is a technique published by OpenAI in 2017
  - Probability distribution output (Often Gaussian for continuous, Categorical for discrete, etc)
    - Mean (μ) and standard deviation/variance (σ or σ2, respectively) are the layer's outputs
- It is an **Actor**-**Critic** algorithm - the **Actor** learns our policy π, the **Critic** learns how good chosen actions were (**V**)
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Discounted Rewards

Critic Evaluation

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How good was this action?

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How much better than average did we perform for this action?

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What is PPO?

- Clipped objective function to avoid large policy changes in the actor

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This prevents large changes to the policy for any one action, creating a pessimistic lower bound

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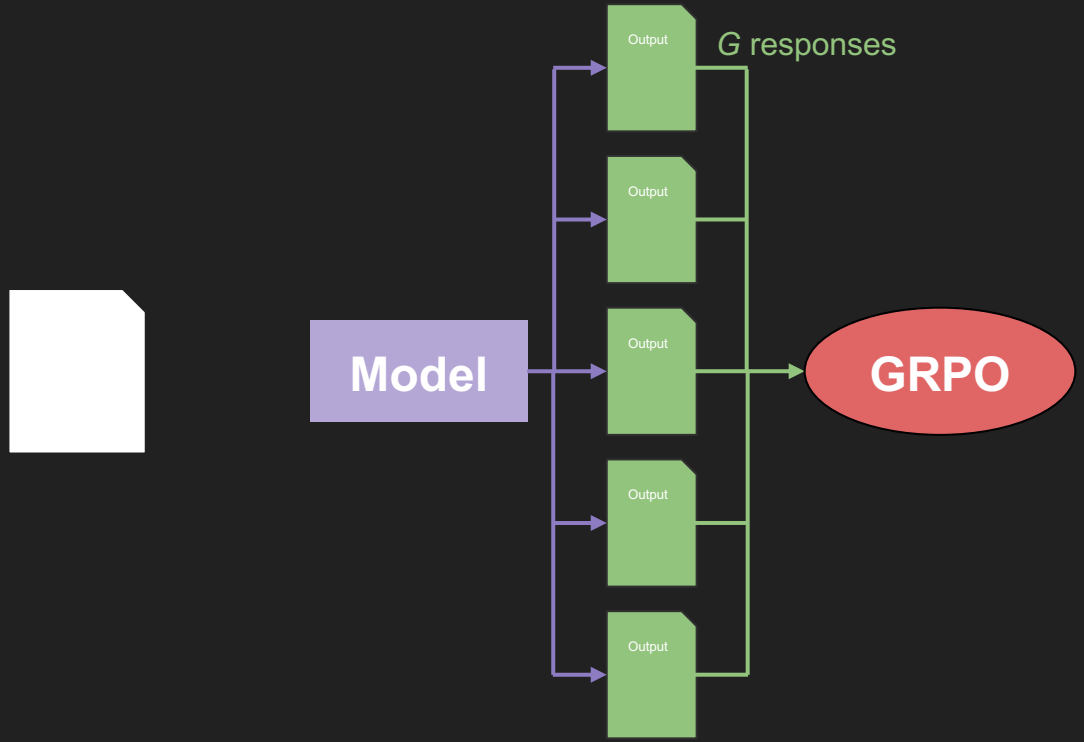

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The math behind GRPO

Objective Function
(what we are optimizing)

$$J_{\text{GRPO}}(\theta) = E\left[q \sim P(Q), \{o_i\}_{i=1}^{G} \sim \pi_{\theta_{\text{old}}}(q)\right]$$

Objective functions represents a quantity to be optimized in a problem

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Objective Function
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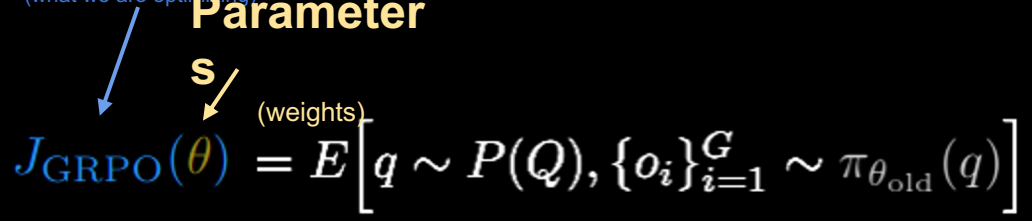
Parameter
s
(weights)



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Expectation
(aka average value over many iterations)

An ***expectation*** is the average over many samples or repetitions.

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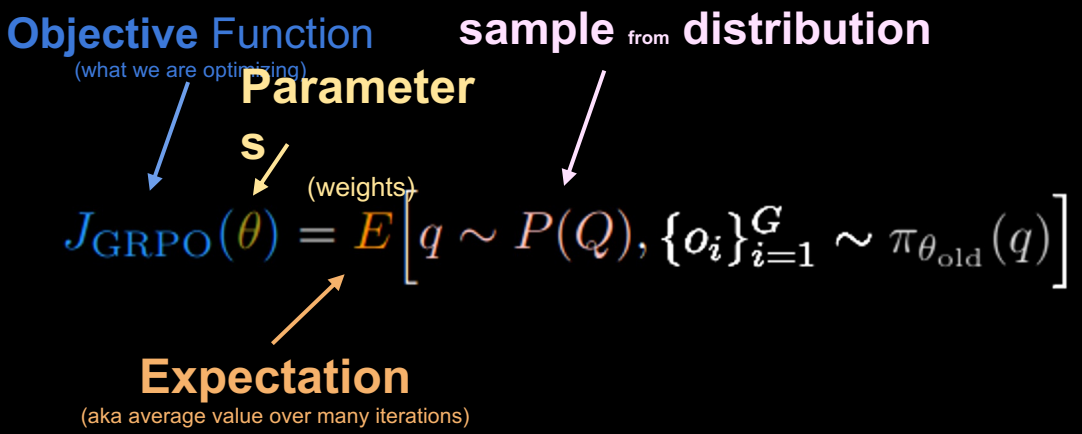

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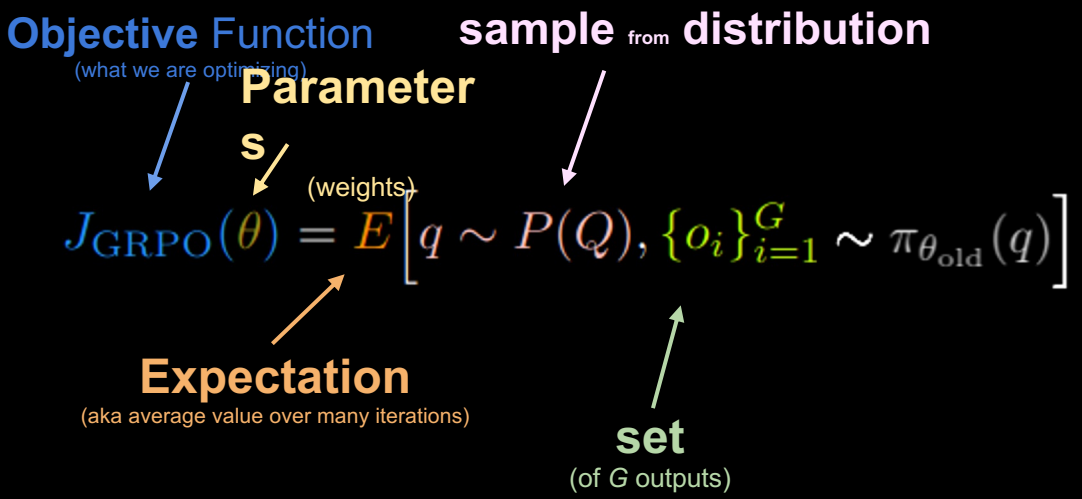

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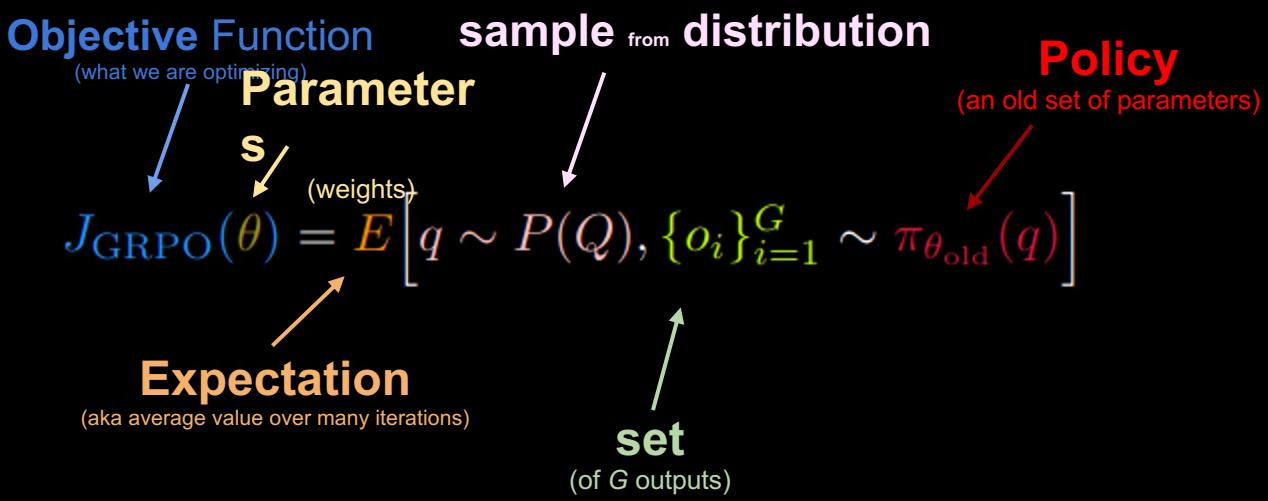

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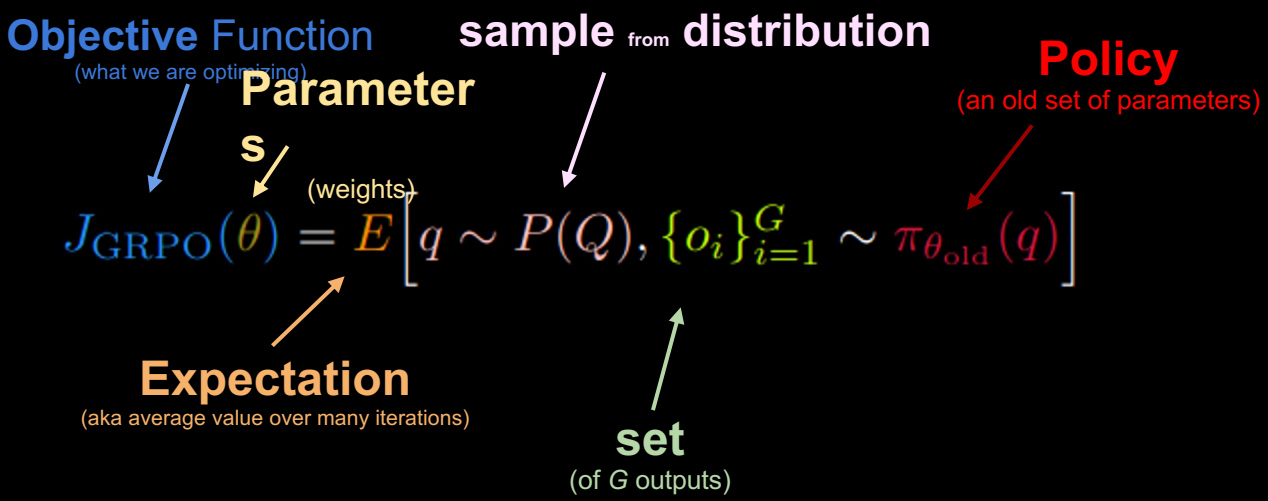

This says:
Sample a query from a collection of prompts, creating a set of *G* outputs using the old policy, then take the average of its scores over many iterations to iteratively improve our weights.

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Take the **average**

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Probability **ratio**

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Take the **average**

Advantage

Probability **ratio**

Here, **advantage** is looking at *relative* improvement by comparing each response to the group's average, driving model updates towards better relative responses

Also, by not having to train a critic model, we are more stable *and* more efficient!

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Probability **ratio**

How aggressive are our updates? Forms a ***trust region***

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Take the **average**

Advantage

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

Probability **ratio**

How aggressive are our updates? Forms a ***trust region***

The math behind **GRPO**

$$A_i = \frac{r_i - \text{mean}(\{r_1, r_2, \ldots, r_G\})}{\text{std}(\{r_1, r_2, \ldots, r_G\})}$$

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

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KL Divergence

KL Divergence (**K**ullback–**L**eibler), also known as relative entropy, measures how different two probability distributions are.

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Prior policy

New policy

The math behind **GRPO**

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Take the **average**

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How aggressive are our updates? Forms a ***trust region***

KL Divergence

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

New policy

KL divergence is seeing how different the new policy is from the old policy - we are *penalizing* large changes!

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KL Divergence

This says:

Update its **strategy** based on how much better an action performed compared to the average (**advantage**). However, it only makes small, careful adjustments (**trust region**) by clipping the size of the update and discouraging big changes (**KL** divergence), then averages these adjustments over multiple experiences to find the best overall improvement.

The math behind **GRPO**

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

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

$$\mathbb{D}_{KL}\left(\pi_\theta||\pi_{ref}\right) = \frac{\pi_{ref}(o_i|q)}{\pi_\theta(o_i|q)} - \log\frac{\pi_{ref}(o_i|q)}{\pi_\theta(o_i|q)} - 1,$$

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From single-turn GRPO to agent trajectories

Multi-turn GRPO must mask policy-owned tokens

- **Tool outputs, user messages, and observations are context for the policy**
  - Apply the objective only where the ownership mask m_i,t equals one
  - Store behavior-policy log probabilities with every generated token
  - Store the owner mask and environment turn with the same trace
  - A missing boundary trains on data the policy did not produce
    - Ownership is part of the objective, not a logging convenience

Equal-reward groups carry no relative learning signal

- **GRPO compares samples generated for the same prompt**
  - If every sample succeeds, normalized advantages approach zero
  - If every sample fails, the same collapse occurs
  - Mixed-outcome groups provide the relative evidence GRPO needs
  - Sampling and curriculum should track the moving frontier
    - Group composition controls whether the update contains signal

Agent rewards should verify goals and invariants

- **Success requires the intended goal predicates**
  - Safety and integrity constraints must remain true
  - Permission and consent checks belong in the reward gate
  - Evaluator integrity belongs in the same protected boundary
  - Terminal-state checks remain defensible when dense credit is uncertain
    - Reward design specifies both achievement and admissible behavior

DeepSeek-R1-**Zero** Performance problems

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- **Readability** was poor, especially in its thinking
  - Lack of markdown formatting or structure in thinking tokens
  - Few steps noted
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  - Redundant and **unconventional** text
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    - Not human friendly/aligned
- **Mixed language** responses/thinking
  - No RL penalty, so it mixed languages as long as accuracy improved
- **Reward hacking**
  - RL resulted in focusing on the reward, not a useful model

DeepSeek-R1-Zero Performance

Model	AIME 2024		MATH-500	GPQA Diamond	LiveCode Bench	CodeForces
	pass@1	cons@64	pass@1	pass@1	pass@1	rating
OpenAI-o1-mini	63.6	80.0	90.0	60.0	53.8	1820
OpenAI-o1-0912	74.4	83.3	94.8	77.3	63.4	1843
DeepSeek-R1-Zero	71.0	86.7	95.9	73.3	50.0	1444

Benchmark scores support only the claims their harness measures

- **Report the environment version, tools, policy, budget, and evaluator**
  - Measure repeated-run success and constraint violations
  - Measure recovery, efficiency, and failure severity
  - A frozen benchmark score does not establish deployment reliability
  - Match observable state and failure modes to the research claim
    - Evaluation quality is bounded by the harness contract

DeepSeek-R1

- DeepSeek-Zero gave us a good blueprint, but can we fix its limitations?

PIPELINE:

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    - Fine tune *DeepSeek-V3-Base* high quality human-readable **CoT** examples
        - Improve Readability - demonstrate format
        - Get rid of language mixing

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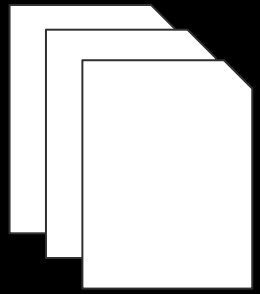
DeepSeek-R1 Stage 3 - Refined Reasoning Rejection Sampling SFT



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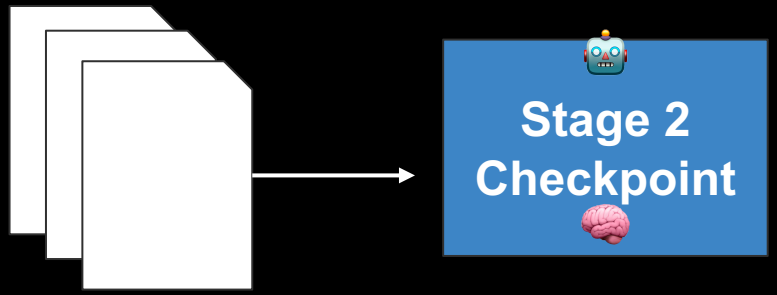

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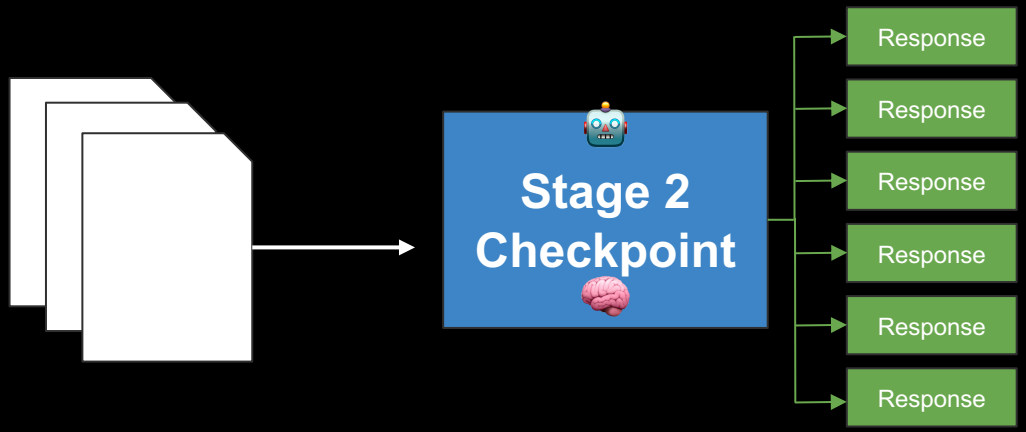

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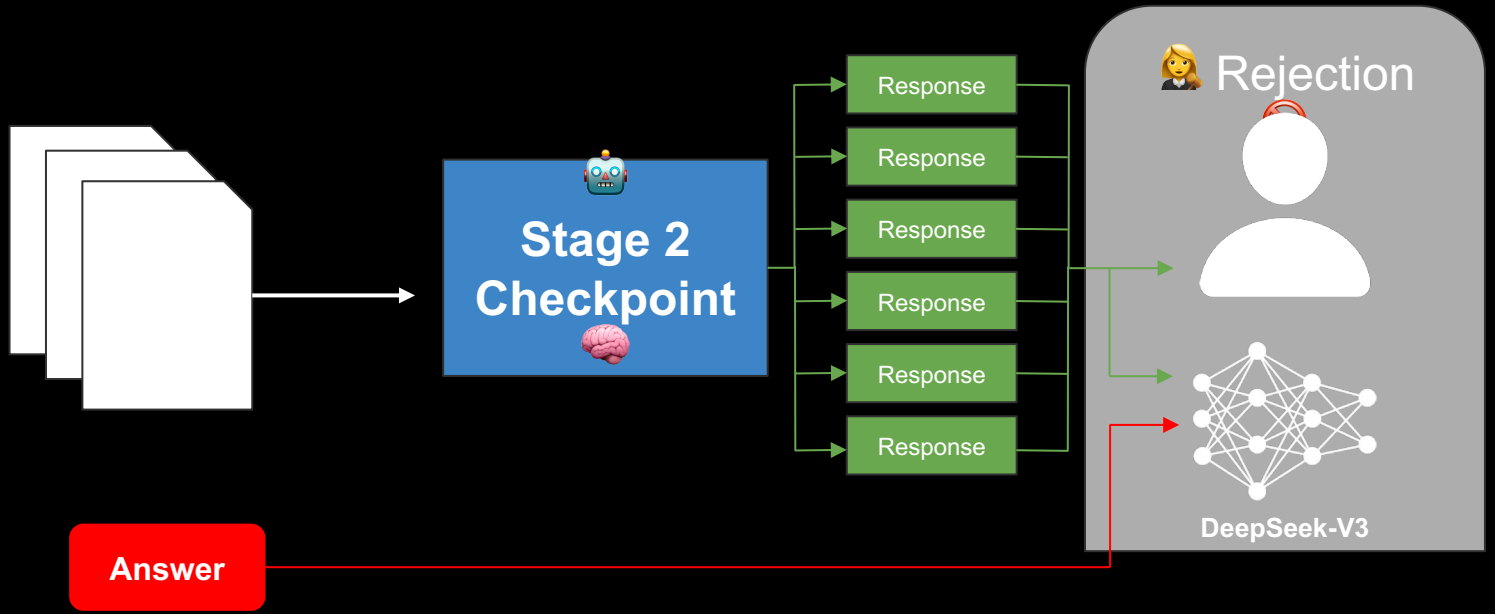

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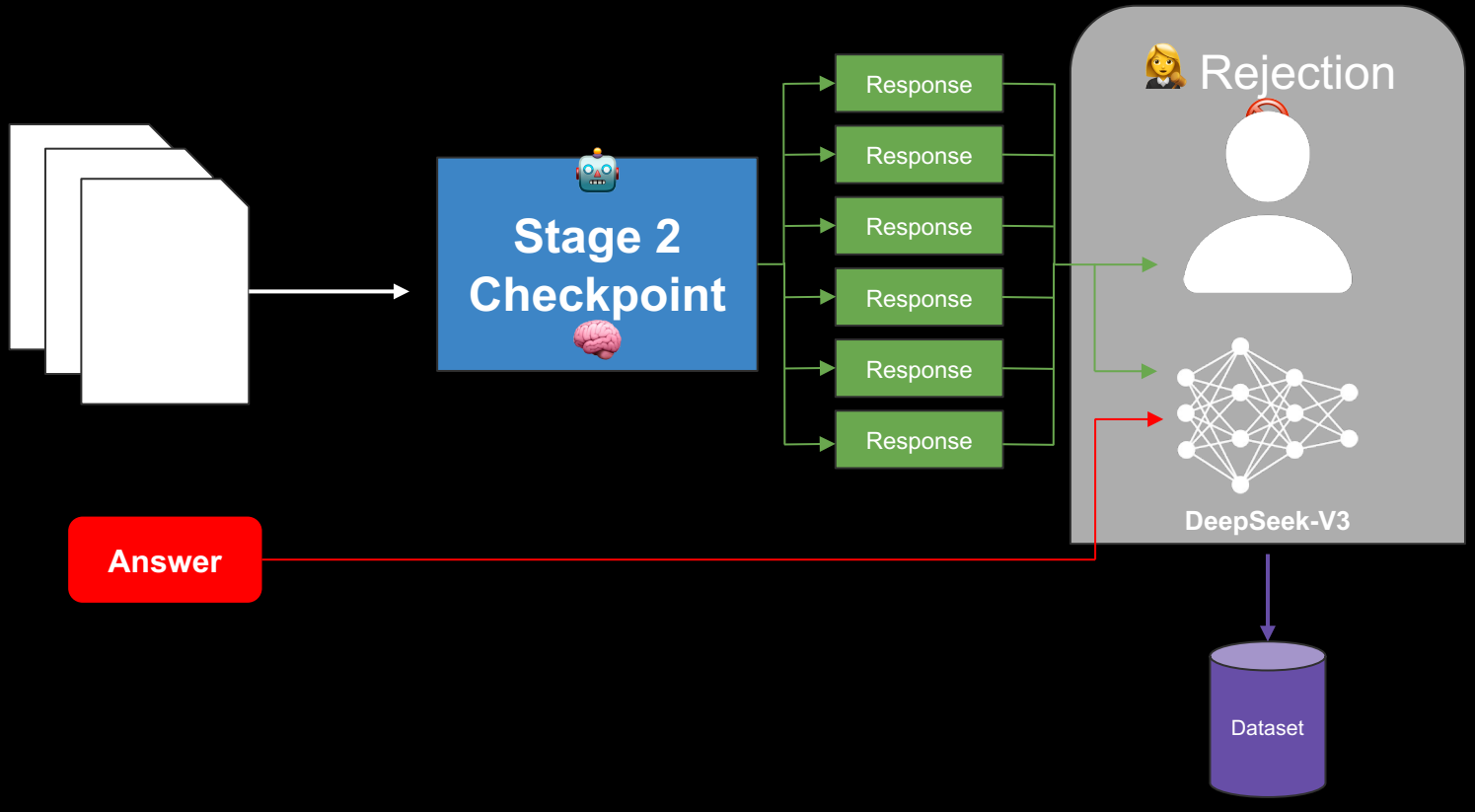

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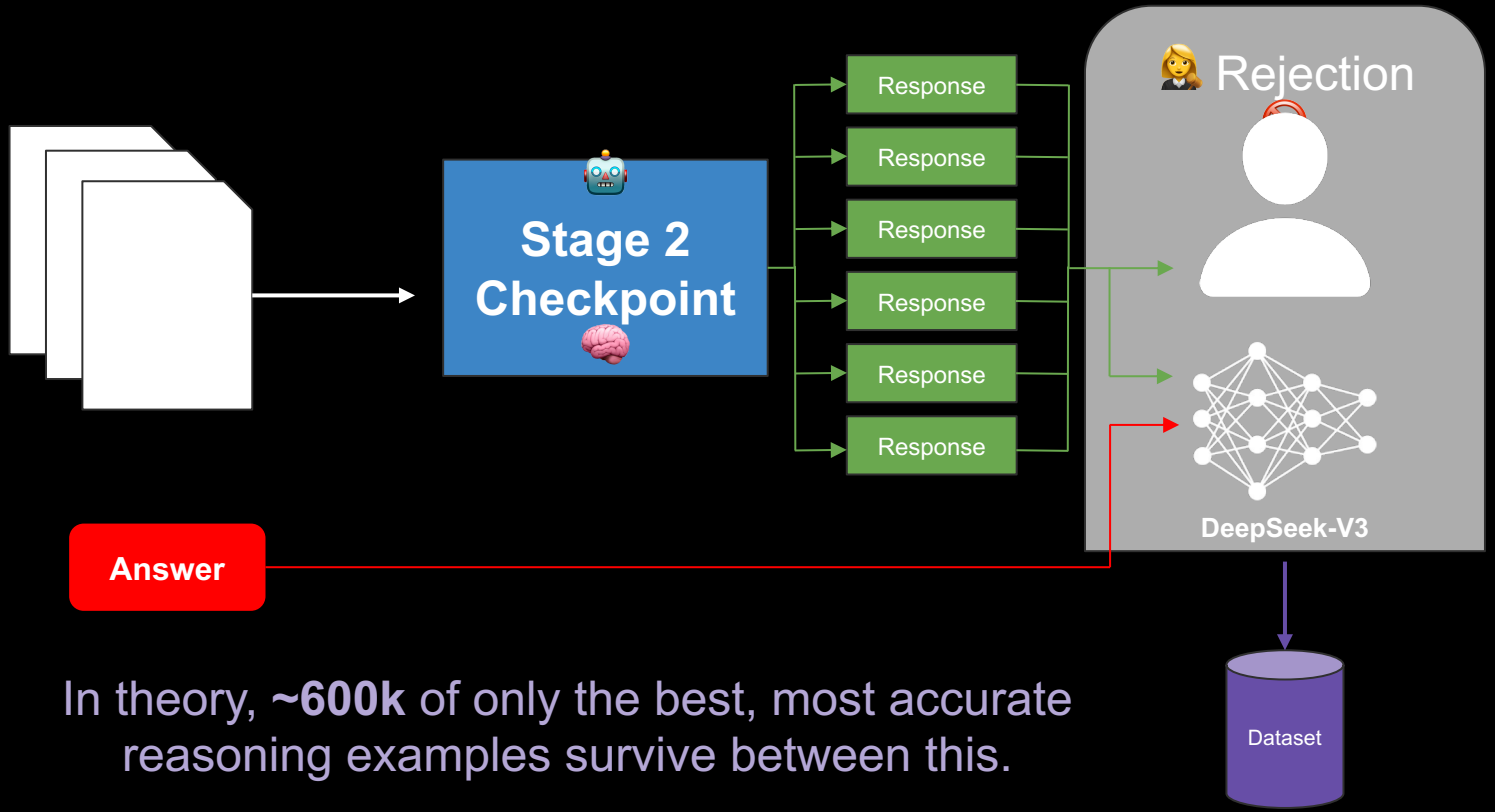
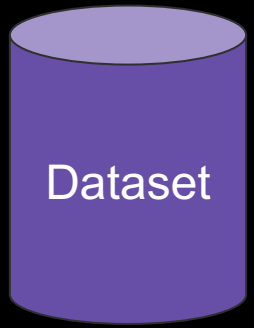


In theory, **~600k** of only the best, most accurate reasoning examples survive between this.

DeepSeek-R1 Stage 3 - Refined Reasoning Rejection Sampling SFT



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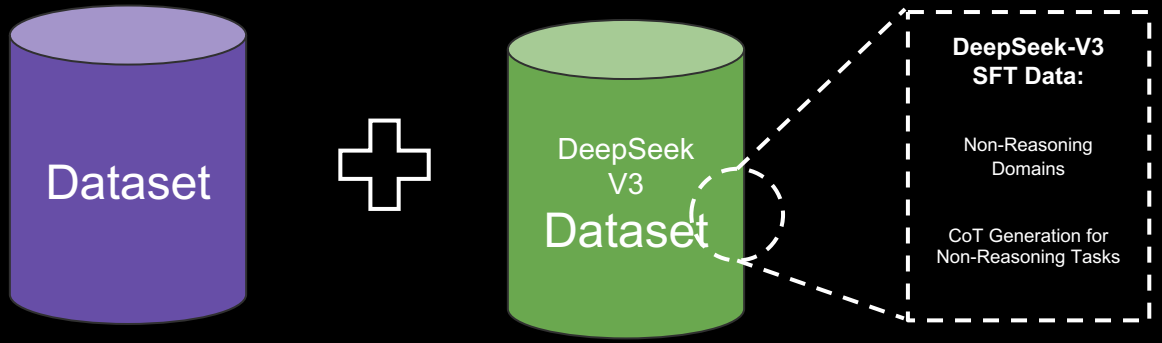

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Speculation: Probably to avoid **overfitting** the rejection SFT dataset and to better incorporate **broader language** capabilities

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This is essentially **knowledge distillation**.

DeepSeek-R1

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4. 🦺👷 Alignment RL - Helpfulness, Harmlessness, & Reasoning in All Scenarios

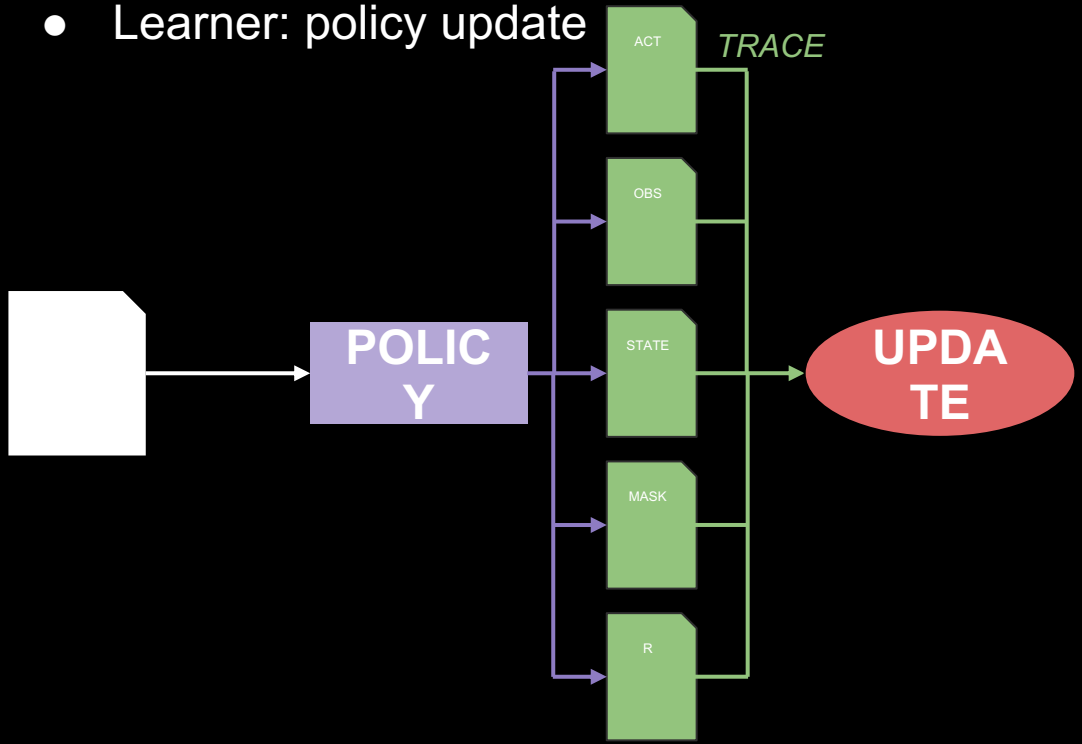
Agentic RL requires a training system

Rollout design is part of the algorithm

- **Task sampler: difficulty, failure modes, and domains**
  - Initial state: snapshot, seed, and perturbation
  - Policy: checkpoint, temperature, and tool set
  - Interaction: turn granularity, timeout, and budget
  - Selection: keep, retry, filter, and replay—with reasons
    - These choices define the data distribution seen by the learner

Trace contracts connect RL

- Harness: interaction
- Learner: policy update



Owner	Contract
Harness	*Tools, context, control flow*
Learner	*Masks, advantages, updates*

Asynchrony buys throughput and creates policy lag

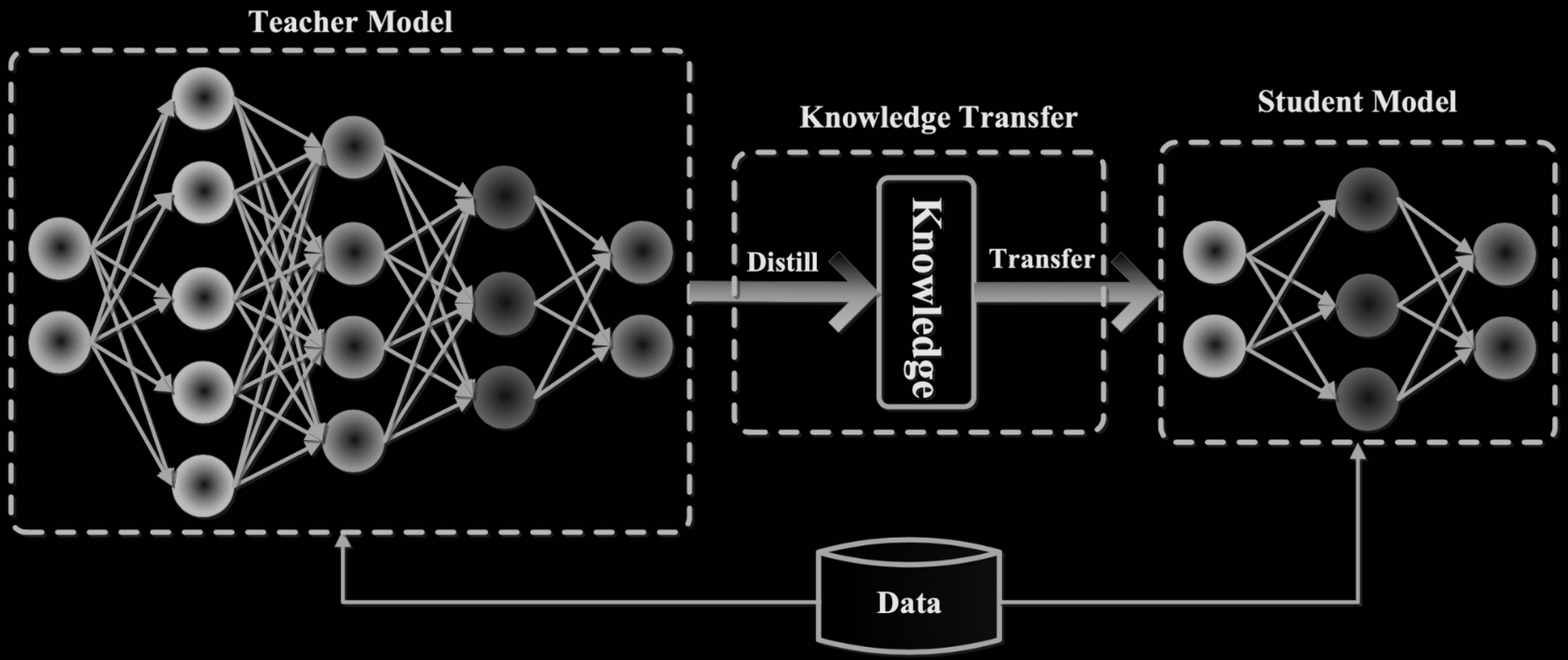
- **Actors generate with behavior policy μ while the learner updates πθ**
  - Queue age and importance-ratio tails reveal stale traces
  - Clipping controls variance but cannot make old data on-policy
  - Choose a staleness rule before training begins
  - Accept, reweight, clip, or drop traces by explicit criteria
    - Throughput gains are valid only with measured off-policy drift

Monitor policy lag with data

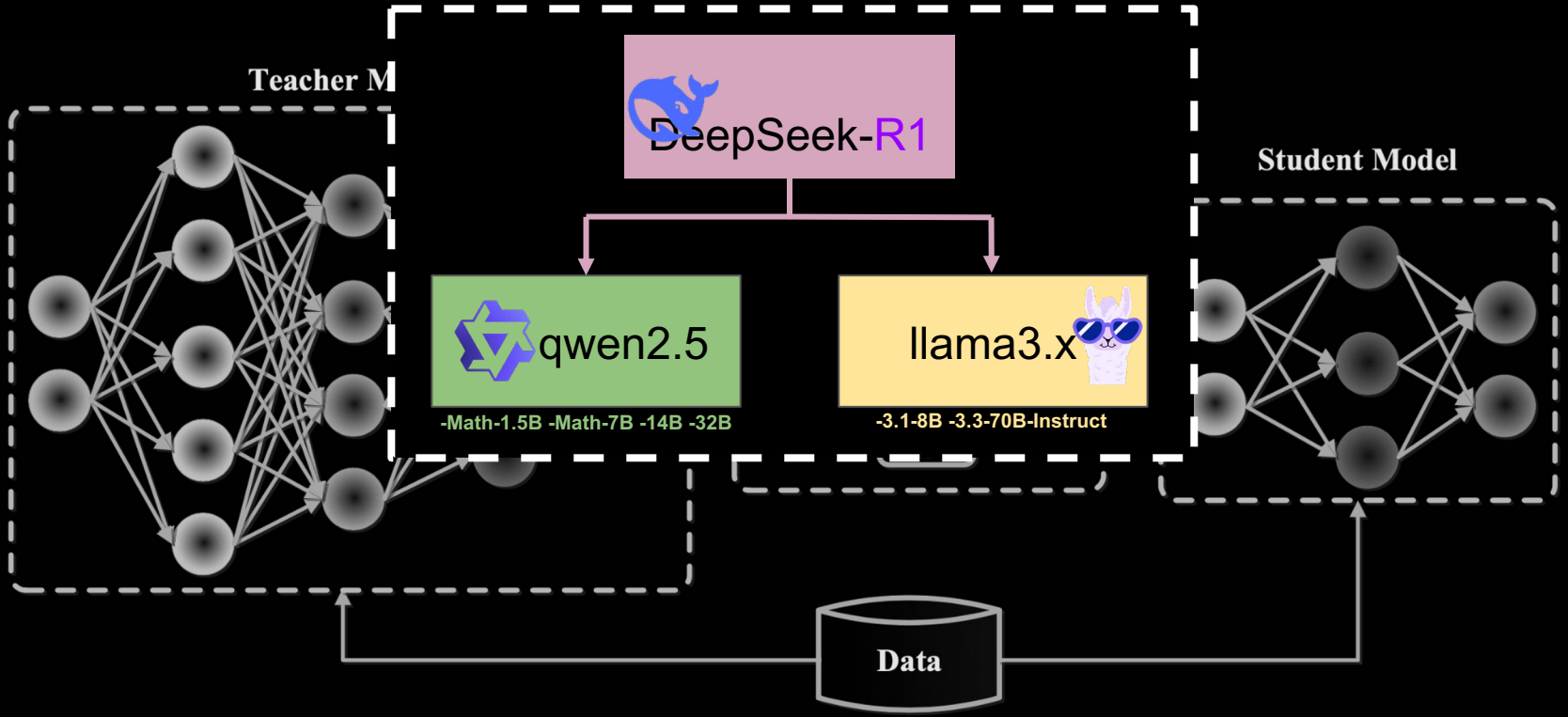
- **Policy age: updates between rollout and learner**
  - Ratio tails: p95, p99, and maximum importance weights
  - Effective sample size and behavior-to-learner KL
  - Reward, violation, and drop rate by trace age
  - Gradient norm, loss spikes, and clipping fraction
    - A queue metric alone cannot diagnose off-policy learning

Knowledge Distillation

Knowledge Distillation



Knowledge Distillation



Knowledge Distillation

3.2. Distilled Model Evaluation

Model	AIME 2024		MATH-500	GPQA Diamond	LiveCode Bench	CodeForces
	pass@1	cons@64	pass@1	pass@1	pass@1	rating
GPT-4o-0513	9.3	13.4	74.6	49.9	32.9	759
Claude-3.5-Sonnet-1022	16.0	26.7	78.3	65.0	38.9	717
OpenAI-o1-mini	63.6	80.0	90.0	60.0	53.8	**1820**
QwQ-32B-Preview	50.0	60.0	90.6	54.5	41.9	1316
DeepSeek-R1-Distill-Qwen-1.5B	28.9	52.7	83.9	33.8	16.9	954
DeepSeek-R1-Distill-Qwen-7B	55.5	83.3	92.8	49.1	37.6	1189
DeepSeek-R1-Distill-Qwen-14B	69.7	80.0	93.9	59.1	53.1	1481
DeepSeek-R1-Distill-Qwen-32B	**72.6**	83.3	94.3	62.1	57.2	1691
DeepSeek-R1-Distill-Llama-8B	50.4	80.0	89.1	49.0	39.6	1205
DeepSeek-R1-Distill-Llama-70B	70.0	**86.7**	**94.5**	**65.2**	**57.5**	1633

Table 5 | Comparison of DeepSeek-R1 distilled models and other comparable models on reasoning-related benchmarks.

Failed Experiments

- **PRM** - **P**erplexity **R**eward **M**odel

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  - Determining if an intermediate step is correct is *hard*

Failed Experiments

- **PRM** - **P**erplexity **R**eward **M**odel - a reward function that is designed to evaluate and reward step-by-step reasoning processes
  - A normal reward might be 0 or 1 for correct or not, but **PRM** would reward individual steps being correct. For example - solving an algebra problem would give *partial credit* to correct steps towards solving it, even if wrong.
  - Tries to encourage good behavior throughout the <*think*> tags rather than just the <*answer*> tags.
- Abandoned because:
  - Challenging to define a fine-grain step in reasoning
  - Determining if an intermediate step is correct is *hard*
  - Reward hacking

Failed Experiments

- **MCTS** (**M**onte **C**arlo **T**ree **S**earch)

Failed Experiments

- **MCTS** (**M**onte **C**arlo **T**ree **S**earch) - a tree search algorithm to guide decision making

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- Utilized at test-time to enhance the model exploring solution space
- Abandoned because:
  - Language models have a huge search space as it's an unstructured space - setting search depth limits risked getting stuck in local optima
  - Couldn't effectively create a value model to guide token-level search in complex reasoning tasks

Reliability needs repeated evidence

- **Report mean success with confidence intervals**
  - Measure pass^k across repeated runs
  - Track constraint violations and safe recovery
  - Track efficiency and failure severity
  - Audit a frozen policy on held-out environment versions
    - A single successful trajectory is a demonstration, not reliability evidence

The reward channel belongs outside the agent’s control

- **The policy may write working state and request tool actions**
  - Tests, graders, permissions, and evaluator prompts stay protected
  - Reward services stay outside the writable workspace
  - The agent must not edit evidence that determines its reward
  - Audit logs and state receipts should be append-only
    - Trust boundaries are part of the learning objective’s validity

Train over trajectories; deploy only on repeated evidence