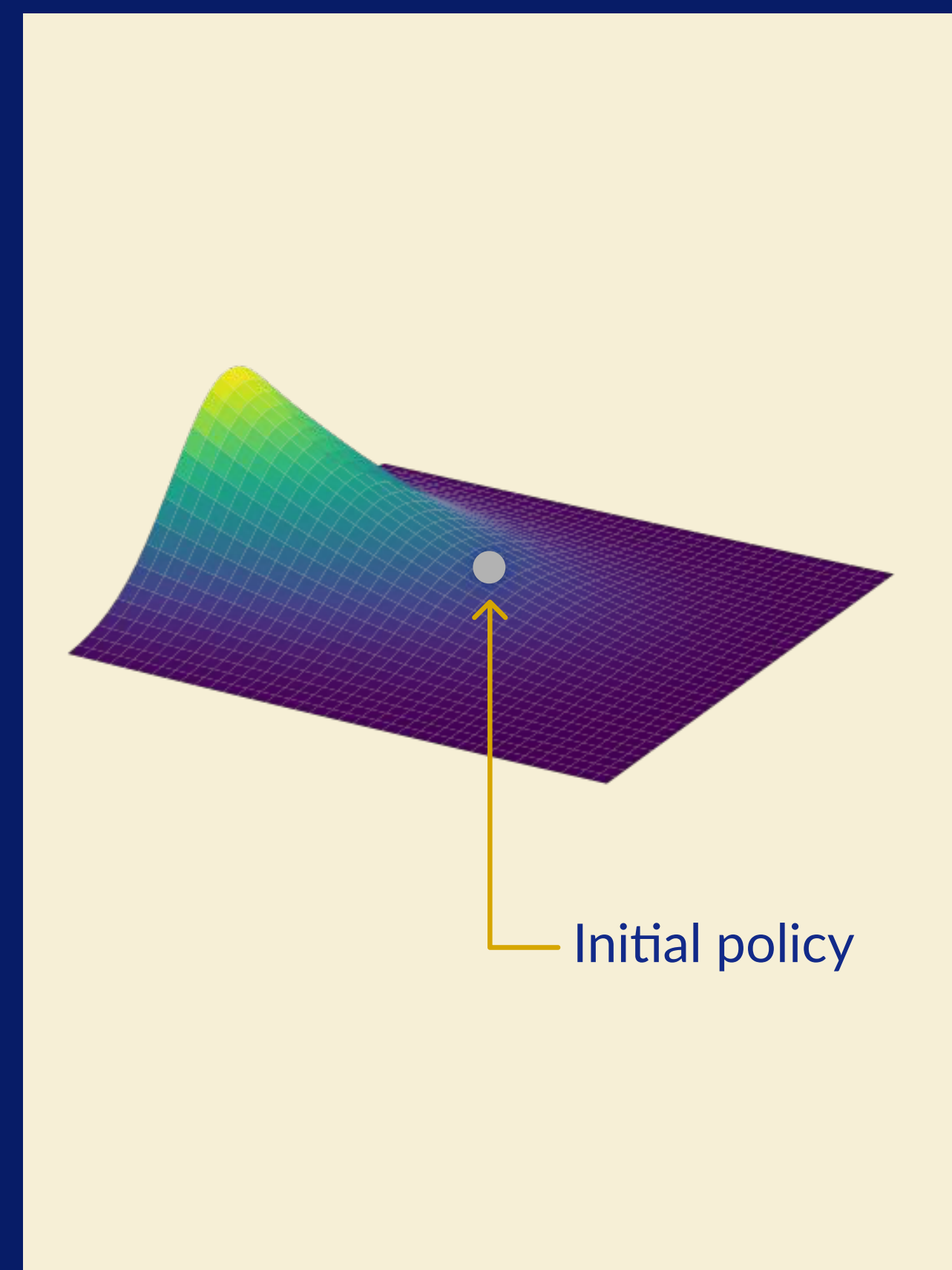


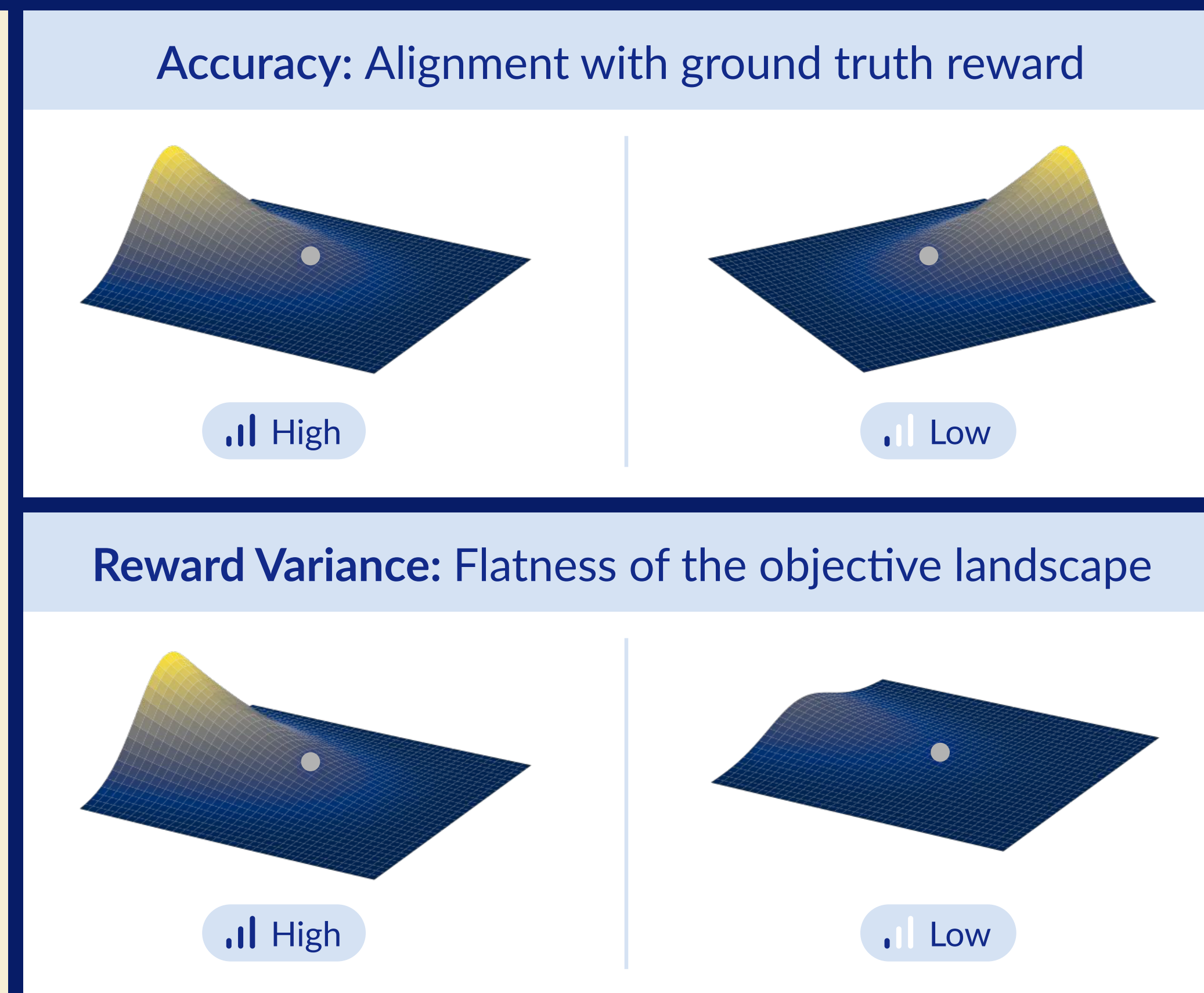


What makes a good reward model for RLHF?

Ground Truth Reward



Reward Model



Aside from being accurate, it needs to induce **sufficient reward variance**!

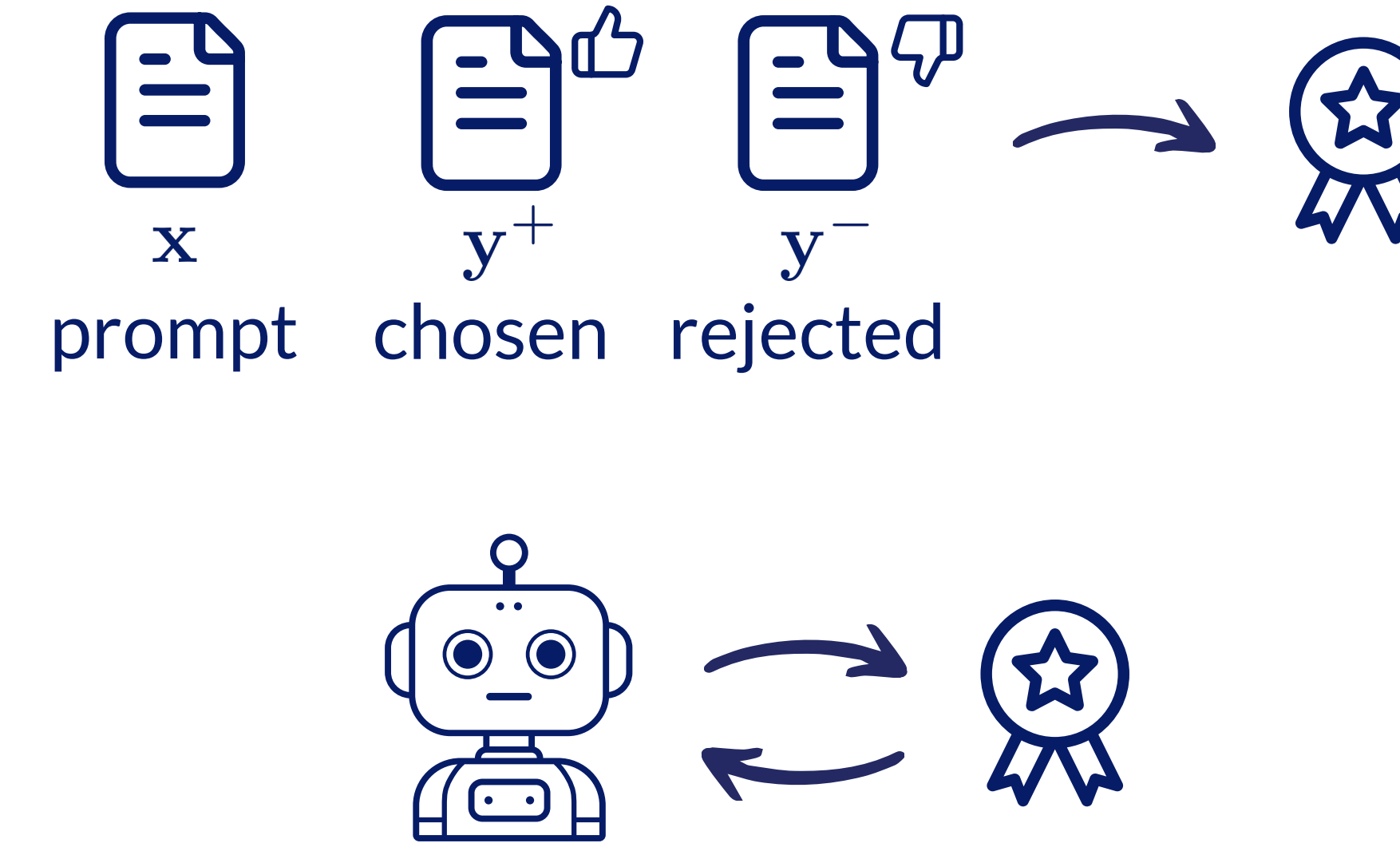
What Makes a Reward Model a Good Teacher? An Optimization Perspective

Noam Razin, Zixuan Wang, Hubert Strauss, Stanley Wei, Jason D. Lee, Sanjeev Arora

Princeton Language and Intelligence, Princeton University

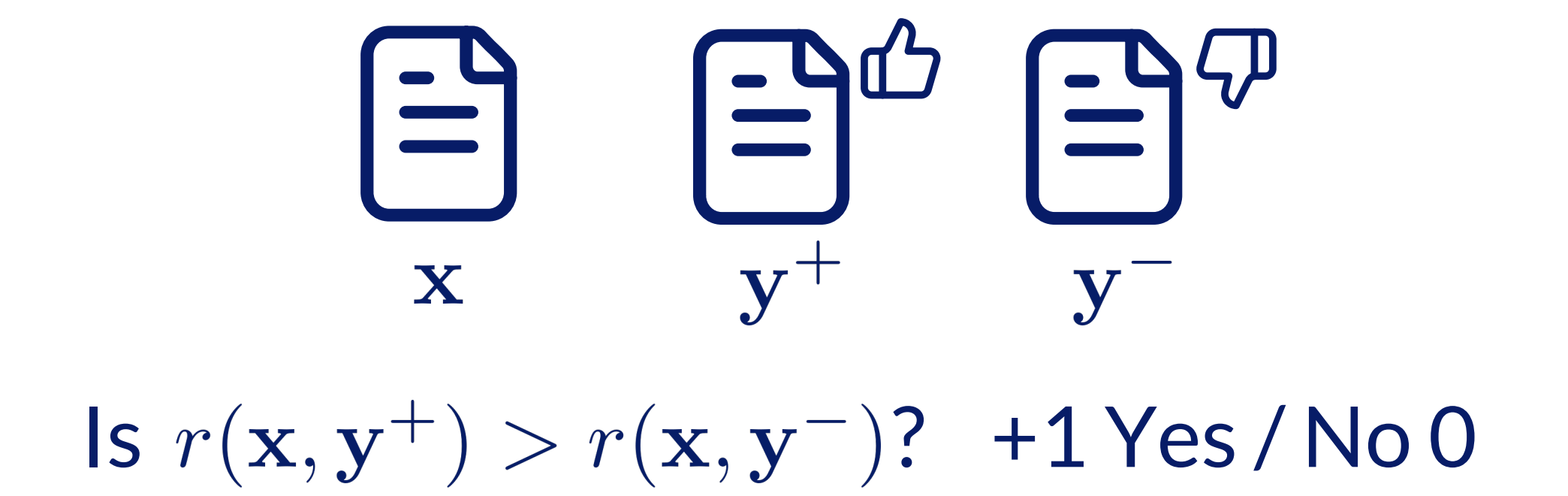
Reinforcement Learning from Human Feedback (RLHF)

- Train reward model (RM) to approximate ground truth reward
- Align language model (LM) by maximizing learned reward via policy gradient



Evaluation: Accuracy

RMs are typically evaluated via **accuracy** (e.g., RewardBench; Lambert et al. 2024)



Q: Are more accurate reward models (RMs) necessarily better teachers?

1

Main Result

Low reward variance leads to slow optimization, even if the RM is highly accurate

$$\text{Var}_{\mathbf{y} \sim \pi_{\theta}(\cdot | \mathbf{x})} [r(\mathbf{x}, \mathbf{y})]$$



2

Implication I

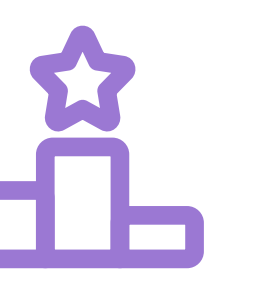
More accurate RMs are not necessarily better teachers for RLHF



3

Implication II

Existing RM benchmarks suffer from fundamental limitations



Notation

r - RM π_{θ} - LM \mathcal{S} - training prompts

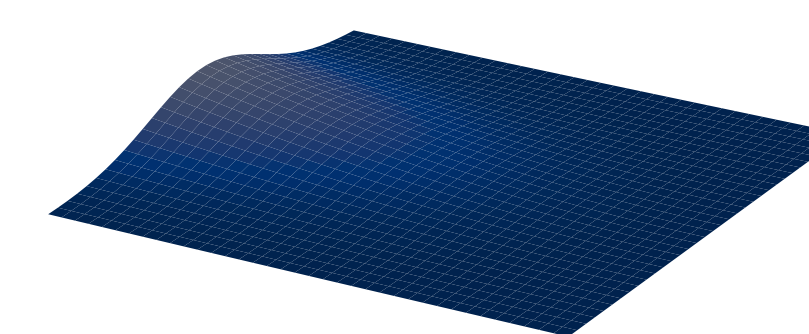
Theorem (low reward variance \rightarrow slow optimization)

The time it takes for the expected RM and ground truth rewards to increase by any additive constant is:

$$\Omega \left(\mathbb{E}_{\mathbf{x} \sim \mathcal{S}} \left[\text{Var}_{\mathbf{y} \sim \pi_{\theta_{\text{init}}}(\cdot | \mathbf{x})} [r(\mathbf{x}, \mathbf{y})] \right]^{-\frac{1}{3}} \right)$$

*Result applies to any RL setting with softmax policies

Proof Idea: Low reward variance causes a flat objective landscape for softmax policies (includes LMs as a special case)

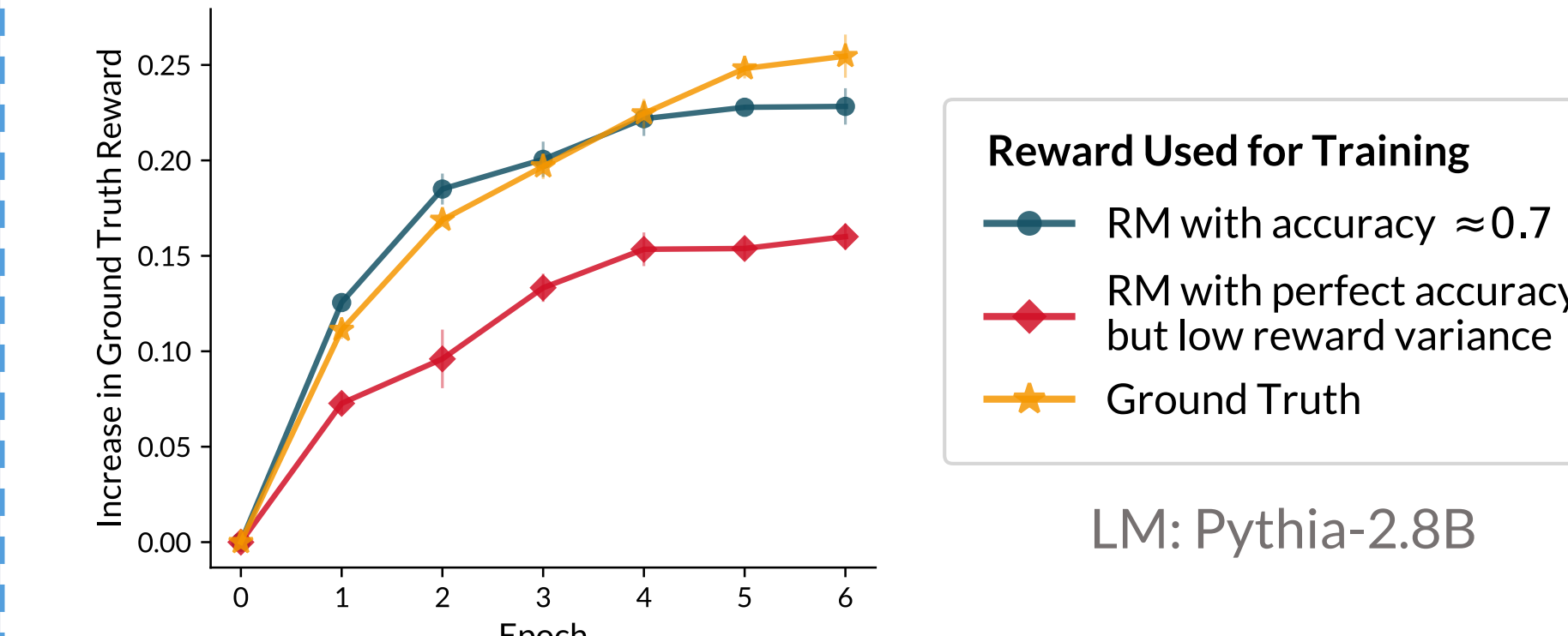


Theorem (more accurate RMs are not always better)

For any LM, there exist a **perfectly accurate** r_{per} and **relatively inaccurate** \bar{r} s.t. ground truth reward increases **arbitrarily slower** when using r_{per}

*Same result holds with almost any accuracy values

Experiments: RLHF on UltraFeedback using different RMs

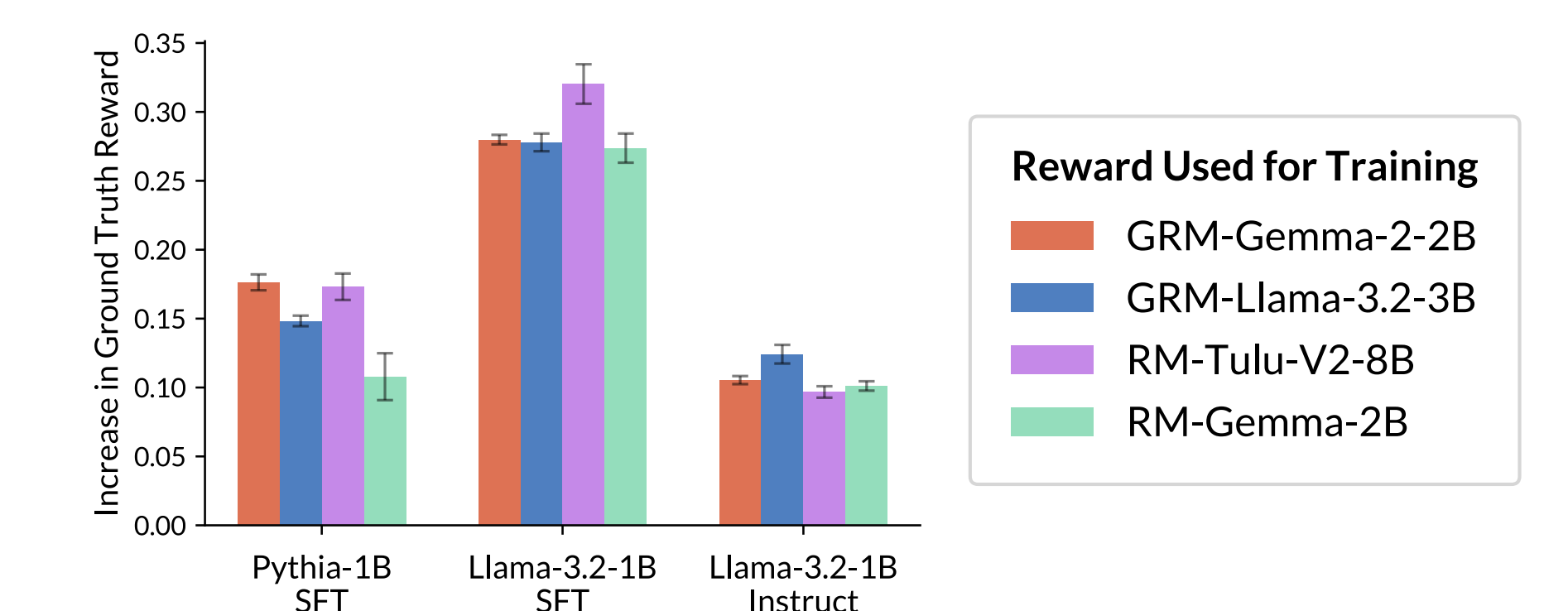


Result: Even perfectly acc RMs can underperform less acc RMs due to low reward variance!

Theorem (for different LMs different RMs are better)

The same RM can induce high reward variance and work well for one LM, but induce low reward variance and work poorly for another LM

Experiments: RLHF on UltraFeedback using different LMs and RMs



Result: For different LMs different RMs are better

Benchmarks evaluating RMs in isolation of the LM being aligned are fundamentally limited