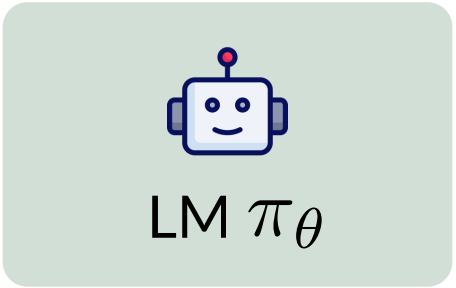
Understanding and Overcoming **Pitfalls in Language Model Alignment**

Noam Razin
Princeton Language and Intelligence, Princeton University

Language Models

Language Model (LM): Neural network trained to produce a **distribution over text**



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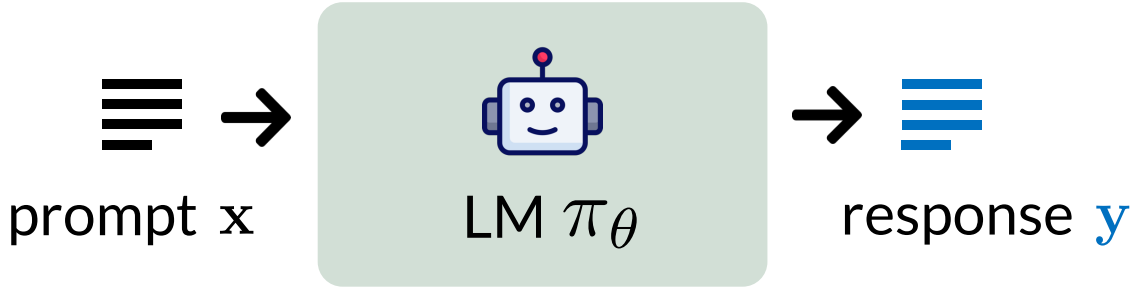

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Supervised Finetuning of LMs

To ensure LMs generate safe and helpful content, they need to be aligned

Wei et al. 2022, Chung et al. 2022, Ouyang et al. 2022, Zhang et al. 2023

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Minimize a standard next-token prediction loss over **desired responses**

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Limitation of SFT:

Hard to formalize human preferences through SFT

Wei et al. 2022, Chung et al. 2022, Ouyang et al. 2022, Zhang et al. 2023

Aligning LMs via Preference Data

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Preference-Based Finetuning

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Underlying Assumption: Preferences are governed by an **unknown ground truth reward**

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Goal of Alignment: Maximize r_{G}

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We Will See: Limited understanding can lead to undesirable outcomes

Part I: Alignment via Reinforcement Learning

Reinforcement Learning

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Direct Preference Learning

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Vanishing Gradients in Reinforcement Finetuning of Language Models

R + Zhou + Saremi + Thilak + Bradley + Nakkiran + Susskind + Littwin | *ICLR 2024*

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

R + Wang + Strauss + Wei + Lee + Arora | *arXiv 2025*

Why is Your Language Model a Poor Implicit Reward Model?

R + Lin + Yao + Arora | *arXiv 2025*

Reinforcement Learning from Human Feedback

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Schulman et al. 2017, Christiano et al. 2017, Ziegler et al. 2019, Stiennon et al. 2020, Ouyang et al. 2022

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a.k.a. **policy**

maximize reward

stay close to initial policy

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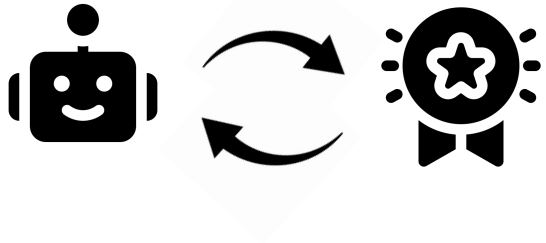
Evaluating RMs

The success of RLHF depends heavily on the **quality of the RM**



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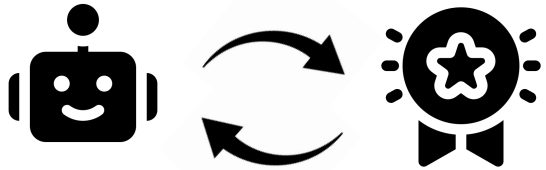

But how should we **evaluate** this quality?

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Currently, RMs are primarily evaluated through **accuracy**

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REWARDBENCH Lambert et al. 2024

	Model	Score
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Intuitively, accuracy quantifies the extent to which maximizing r_{RM} is likely to increase r_{G}

Are More Accurate RMs Always Better?

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Not necessarily!

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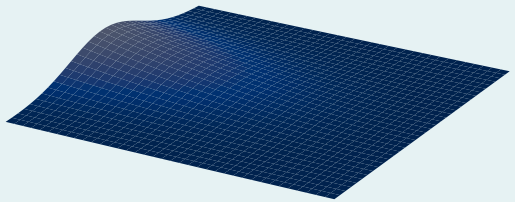

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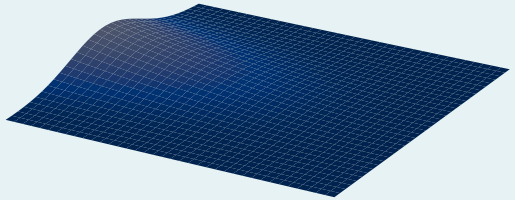

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More accurate RMs are not necessarily better teachers for RLHF

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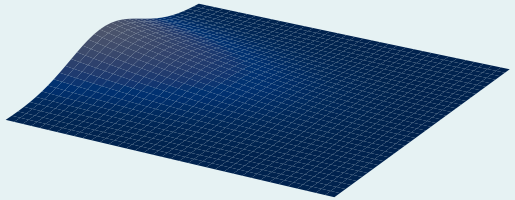

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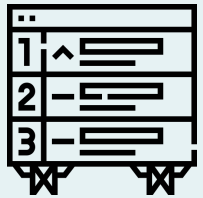
Implication II:
Fundamental limitations of existing RM benchmarks



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In Contrast: Accuracy depends only on how r_{RM} ranks different responses

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RM needs to induce sufficient variance for efficient optimization

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*Same holds with almost any accuracy values for the RMs

Illustration: Effect of Accuracy and Reward Variance

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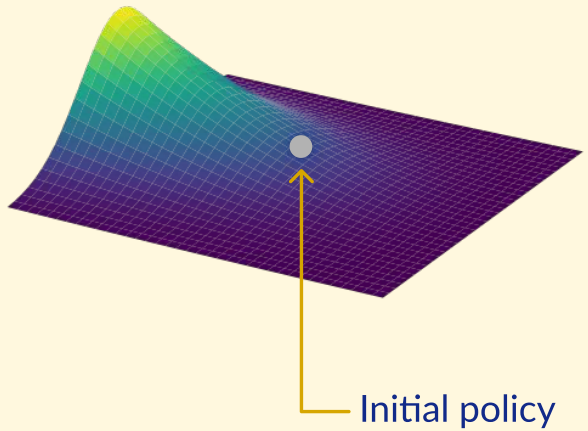
Ground Truth Reward



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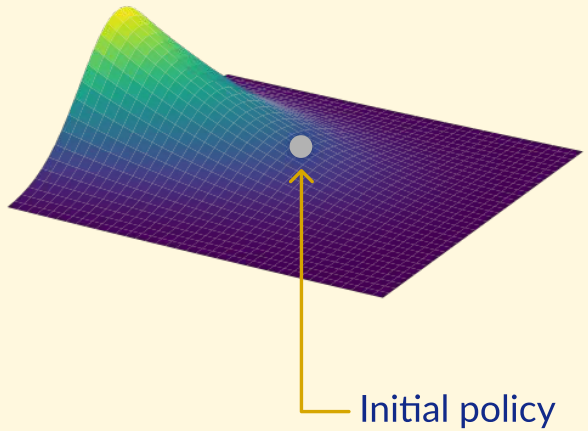

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Accuracy and reward variance capture distinct aspects of an RM

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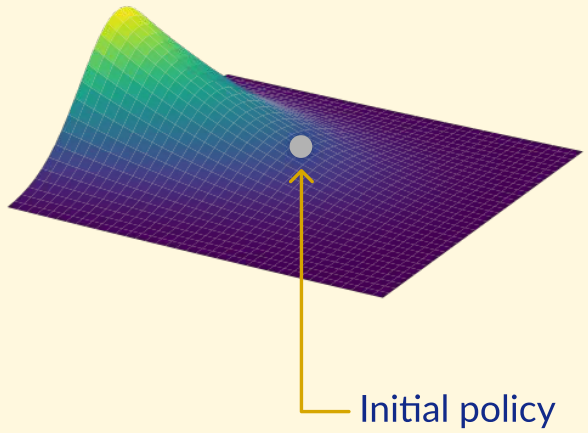

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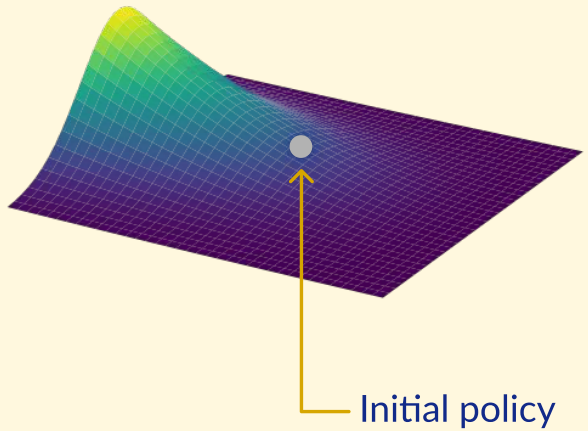

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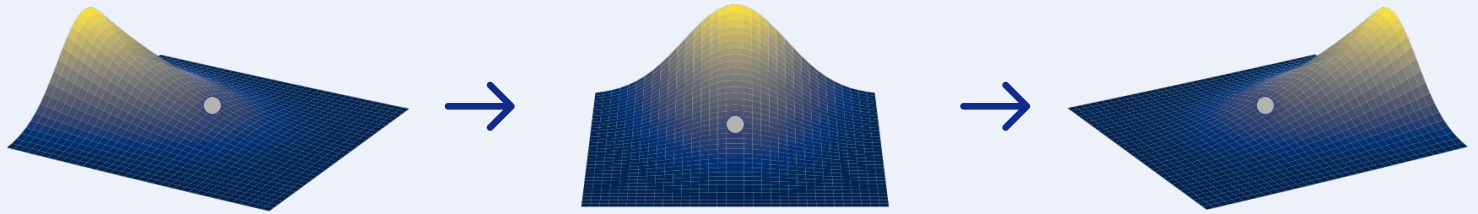

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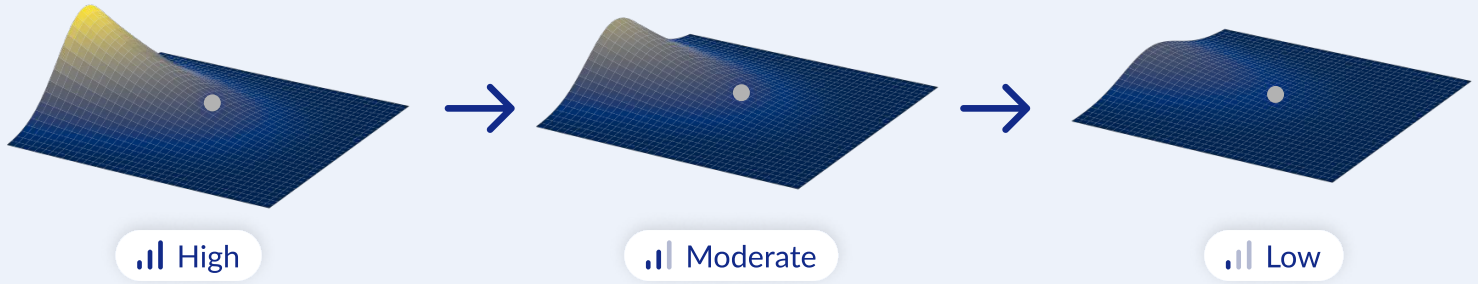
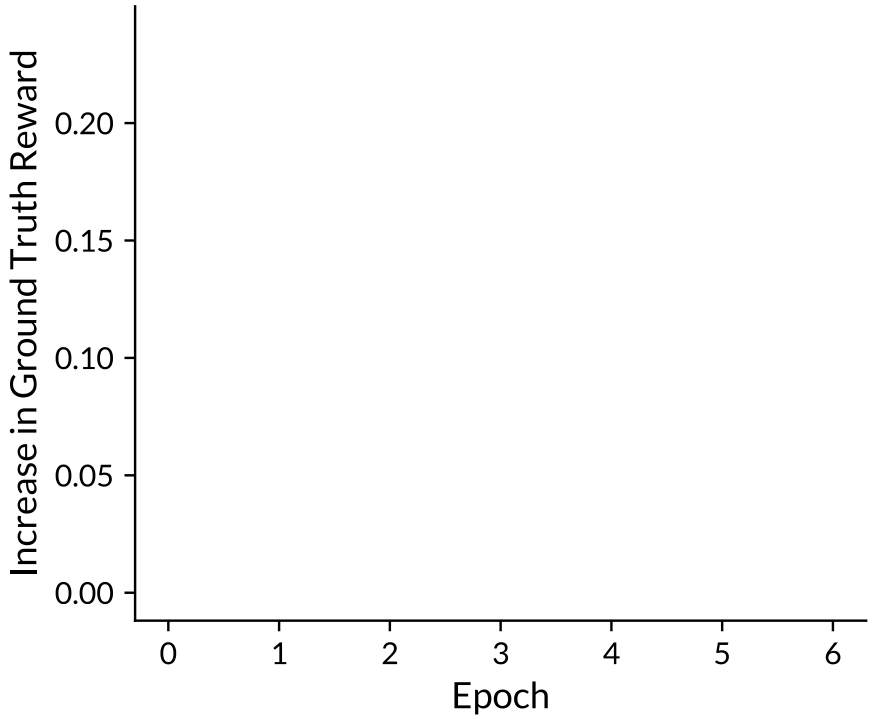


Experiments: More Accurate RMs Are Not Necessarily Better

Setting:

- Dataset: UltraFeedback
- LM: Pythia-2.8B



Chen et al. 2024, Wen et al. 2025: Further experiments showing more accurate RMs are not necessarily better

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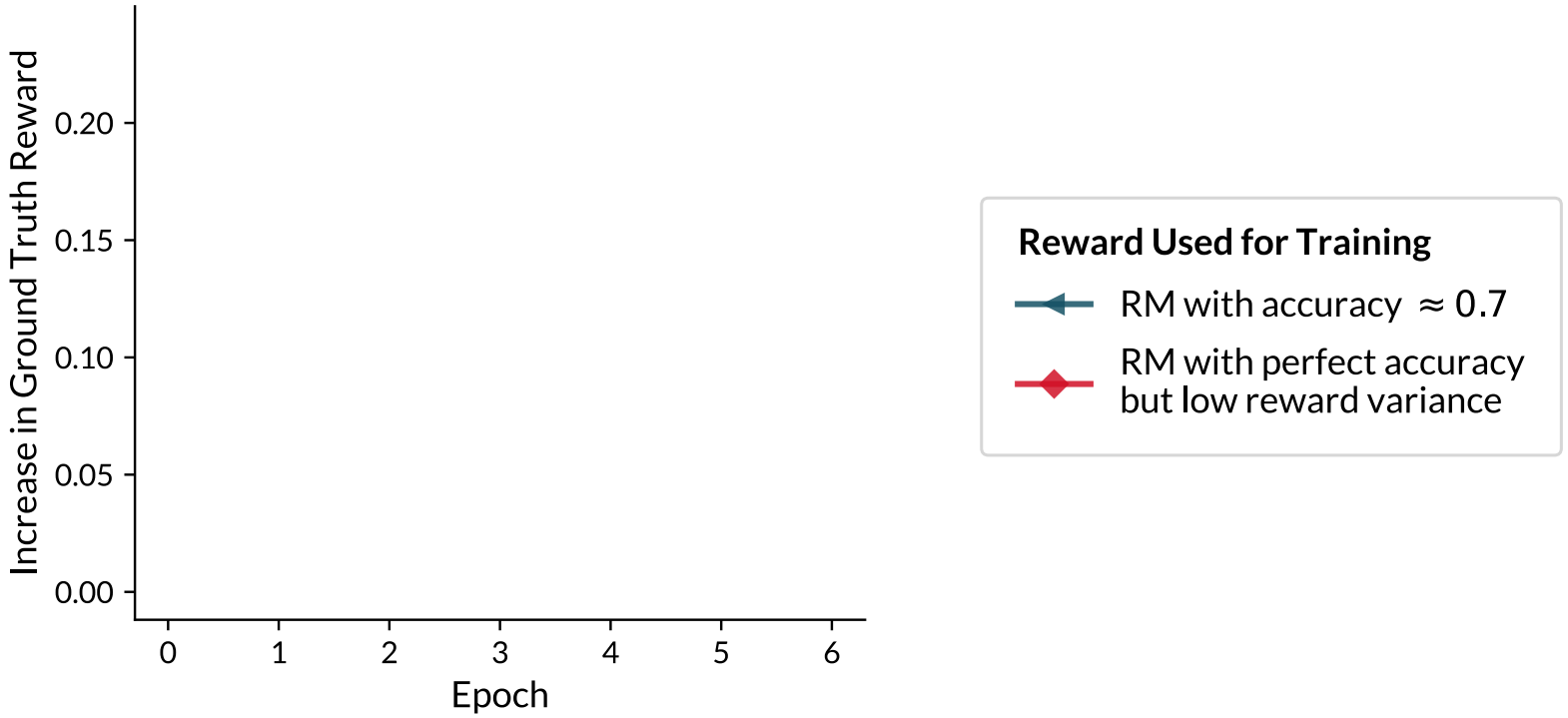

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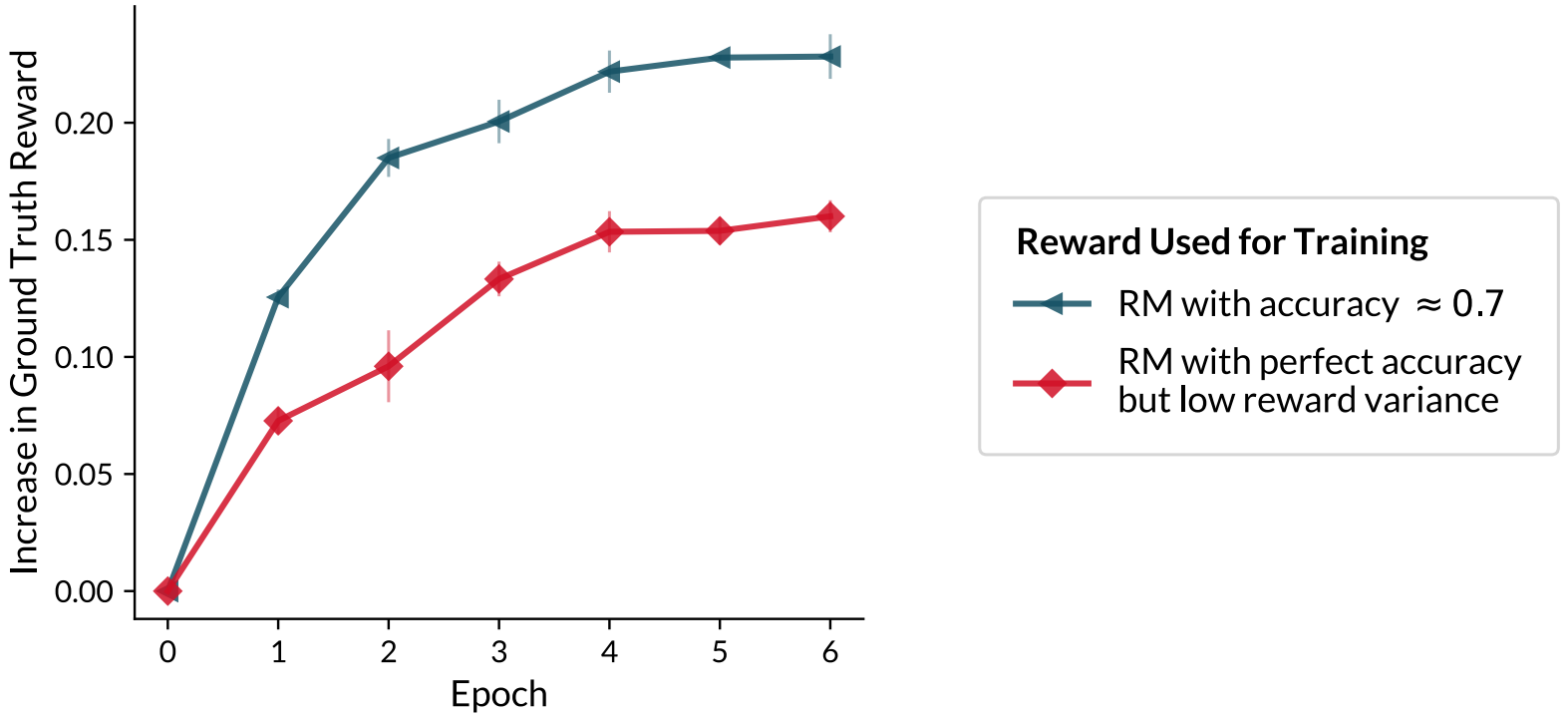

Even perfectly accurate RMs can underperform less accurate ones, due to low reward variance

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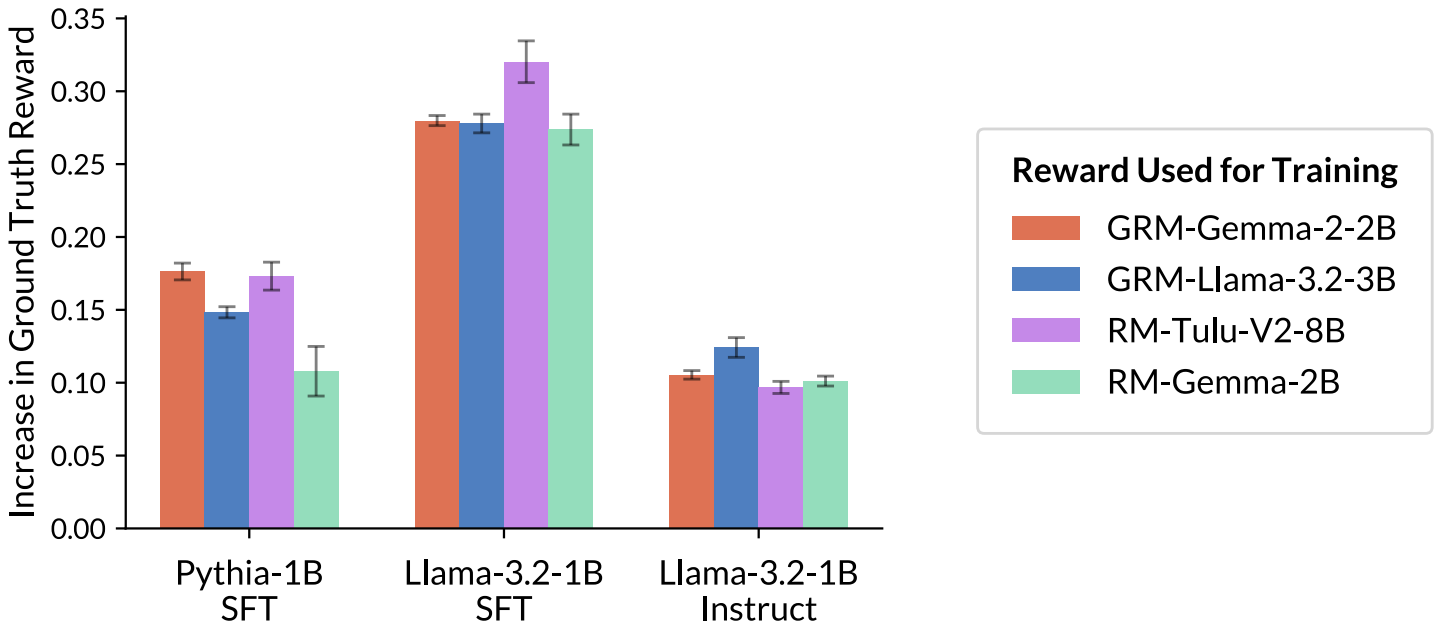

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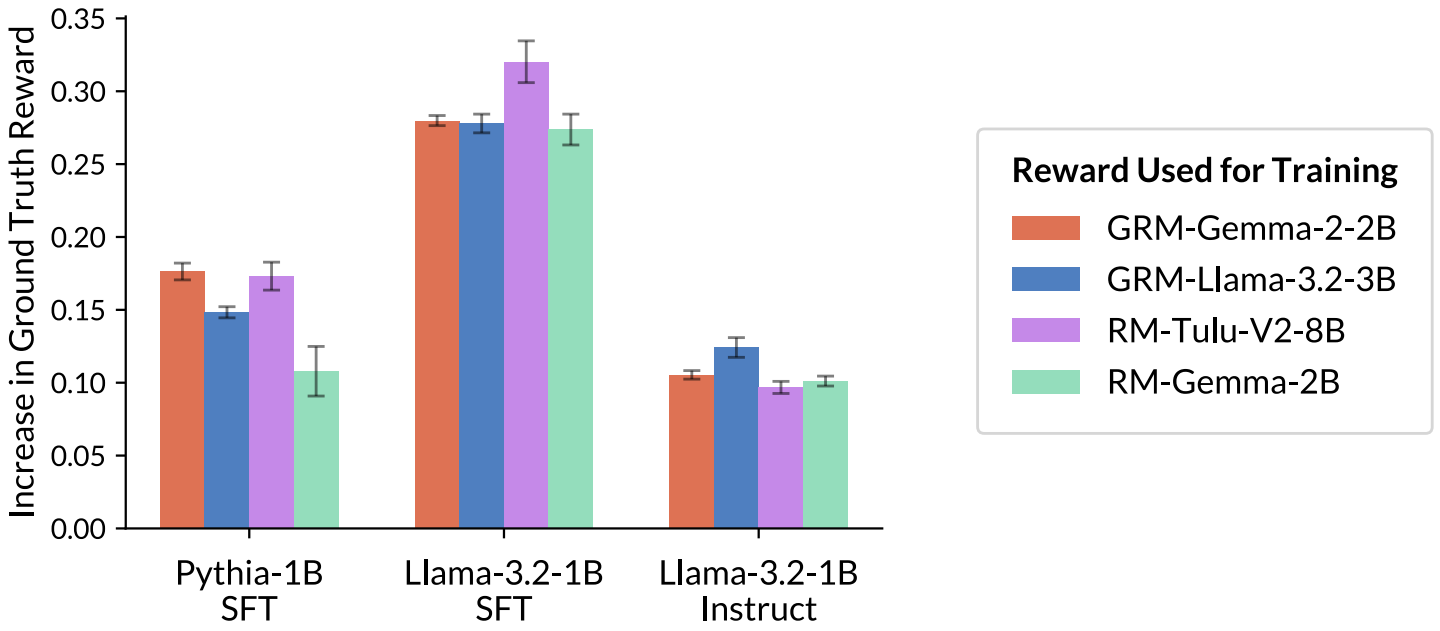

Benchmarks evaluating RMs in isolation from the LM they guide are fundamentally limited

Takeaways: What Makes a Good RM?

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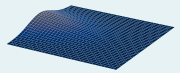

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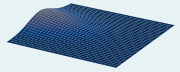

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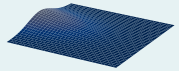

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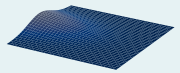

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Our results highlight the need for RM training and evaluation protocols that account for properties beyond accuracy

Importance of SFT in the RLHF Pipeline

Aside from the RM, reward variance depends on the **prompt and LM**

$$\mathrm{Var}_{\mathbf{y}\sim\pi_\theta(\cdot|\mathbf{x})}[r_{\mathrm{RM}}(\mathbf{x},\mathbf{y})]$$

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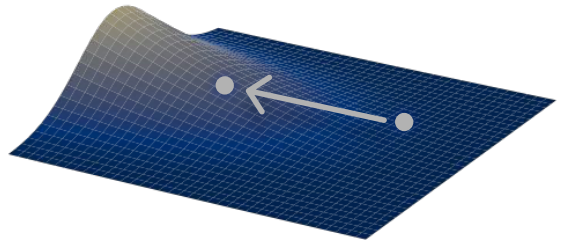
Intuition: SFT finds a less flat initialization



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Llama 4

Kept only 5% of their SFT data for maximizing RLHF performance

Released April 5th, 2025

Practical Application II: Data Selection via Reward Variance

Data Selection Algorithms: Choose prompts for RL via reward variance

Not All Rollouts are Useful: Down-Sampling Rollouts in LLM Reinforcement Learning

Xu et al. 2025

Reinforcement Learning for Reasoning in Large Language Models with One Training Example

Wang et al. 2025

Learning to Reason at the Frontier of Learnability

Foster et al. 2025

Improving Generalization in Intent Detection: GRPO with Reward-Based Curriculum Sampling

Feng et al. 2025

Practical Application III: Policy Gradient Methods

∇ **Policy Gradient Methods:** Develop new update rules and reward transformations

Accelerating RLHF Training with Reward Variance Increase

Yang et al. 2025

DGRO: Enhancing LLM Reasoning via Exploration-Exploitation Control and Reward Variance Management

Su et al. 2025

RePO: Replay-Enhanced Policy Optimization

Li et al. 2025

ReDit: Reward Dithering for Improved LLM Policy Optimization

Wei et al. 2025

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Useful for developing data selection, policy gradient, and RM training algorithms

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Part II: Alignment via Direct Preference Learning

Reinforcement Learning

(e.g. Ouyang et al. 2022)

Direct Preference Learning

(e.g. Rafailov et al. 2023)

Vanishing Gradients in Reinforcement Finetuning of Language Models

R + Zhou + Saremi + Thilak + Bradley + Nakkiran + Susskind + Littwin | *ICLR 2024*

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

R + Wang + Strauss + Wei + Lee + Arora | *arXiv 2025*

Why is Your Language Model a Poor Implicit Reward Model?

R + Lin + Yao + Arora | *arXiv 2025*

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Unintentional Unalignment: Likelihood Displacement in Direct Preference Optimization

R + Malladi + Bhaskar + Chen + Arora + Hanin | *ICLR 2025*

Finetuning LMs via Direct Preference Learning

RLHF can be computationally expensive and unstable

Rafailov et al. 2023, Azar et al. 2024, Tang et al. 2024, Xu et al. 2024, Meng et al. 2024

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Intuitively, $\pi_\theta\left(\mathbf{y}^+|\mathbf{x}\right)$ should increase and $\pi_\theta\left(\mathbf{y}^-|\mathbf{x}\right)$ should decrease

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Likelihood Displacement

However, the probability of preferred responses **often decreases!**

(Pal et al. 2024; Yuan et al. 2024, Rafailov et al. 2024, Tajwar et al. 2024, Pang et al. 2024, Liu et al. 2024)

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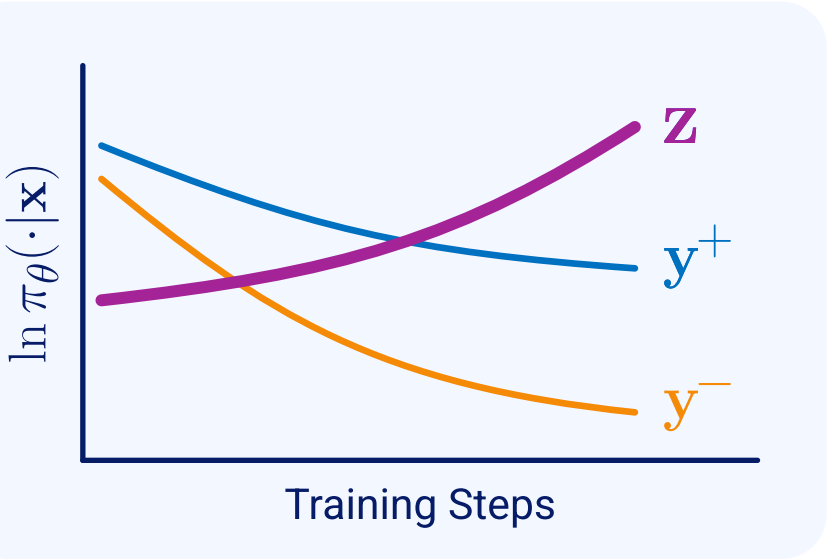

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Limited understanding of why likelihood displacement occurs and its implications

Likelihood Displacement Can Cause Unintentional Unalignment

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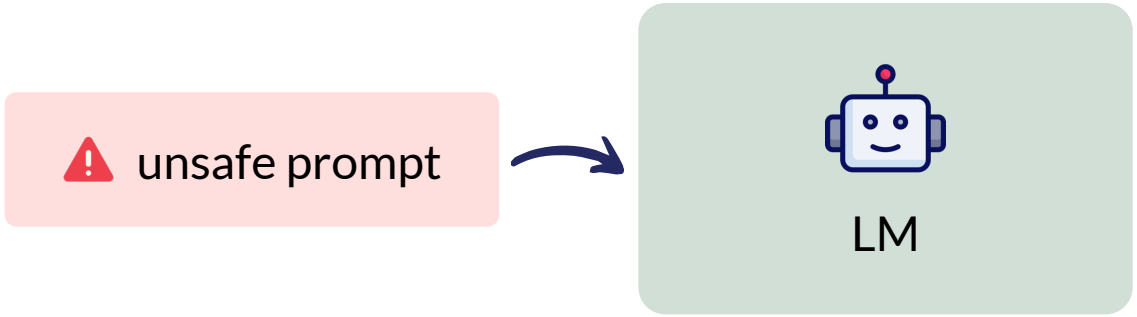

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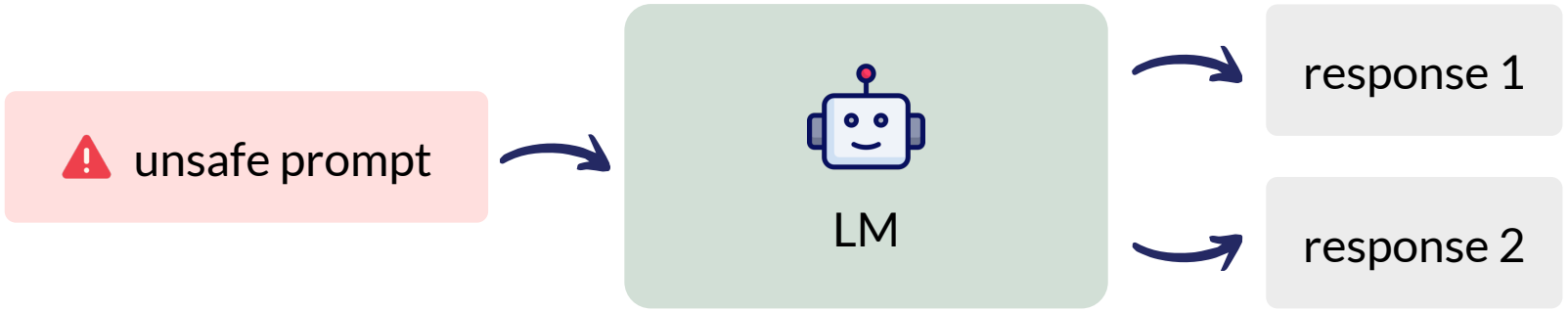

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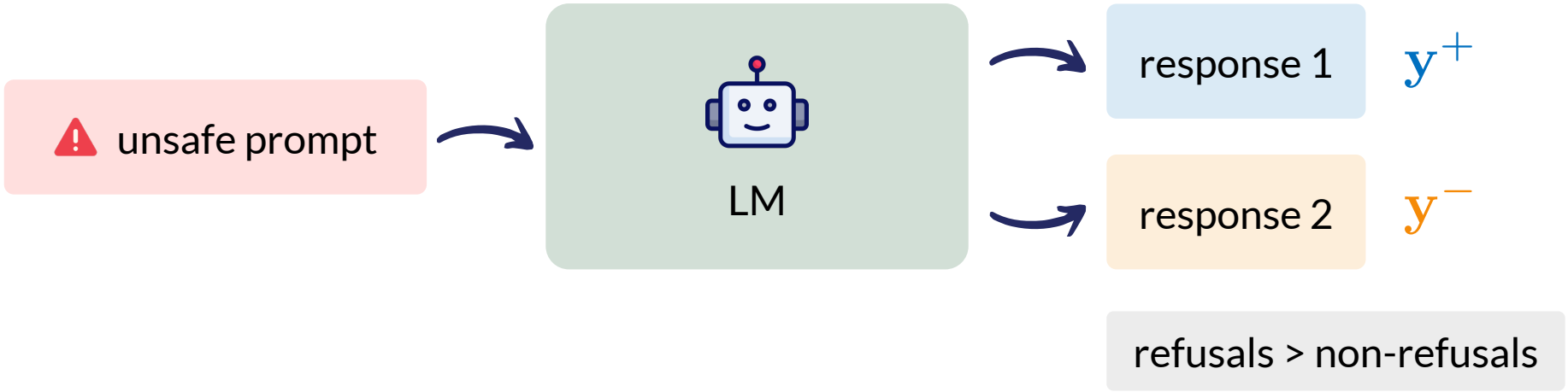

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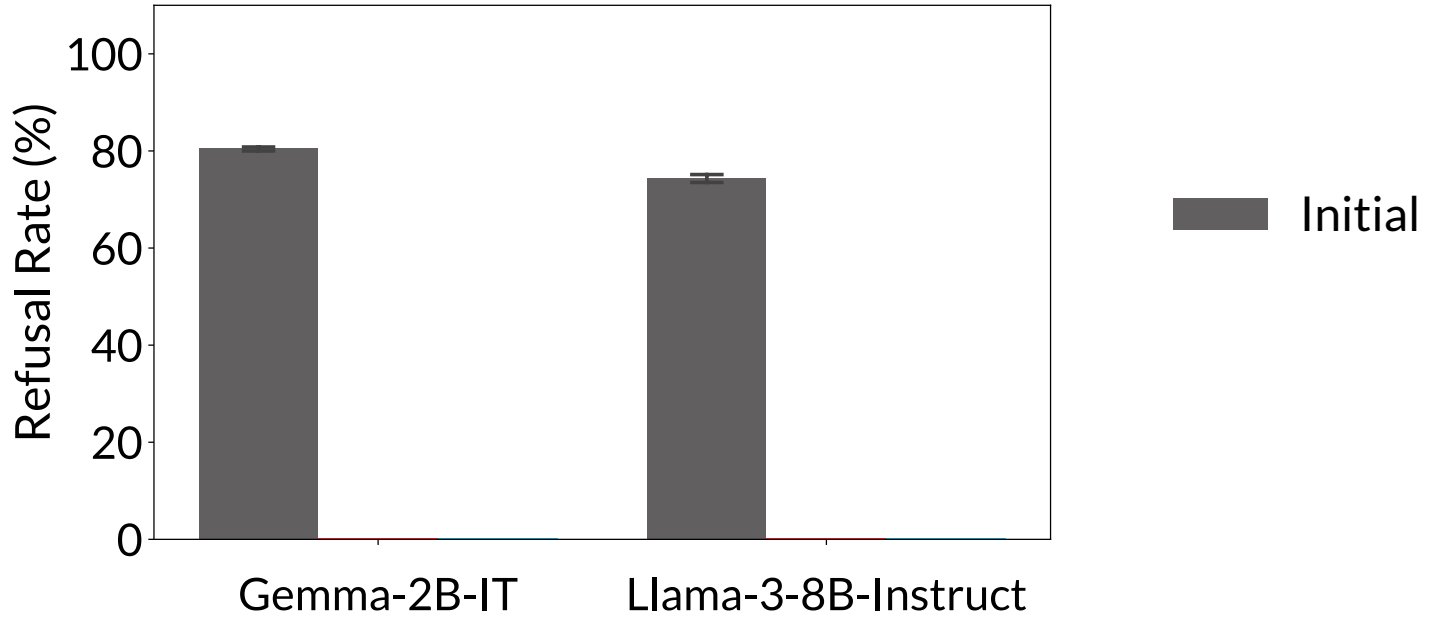

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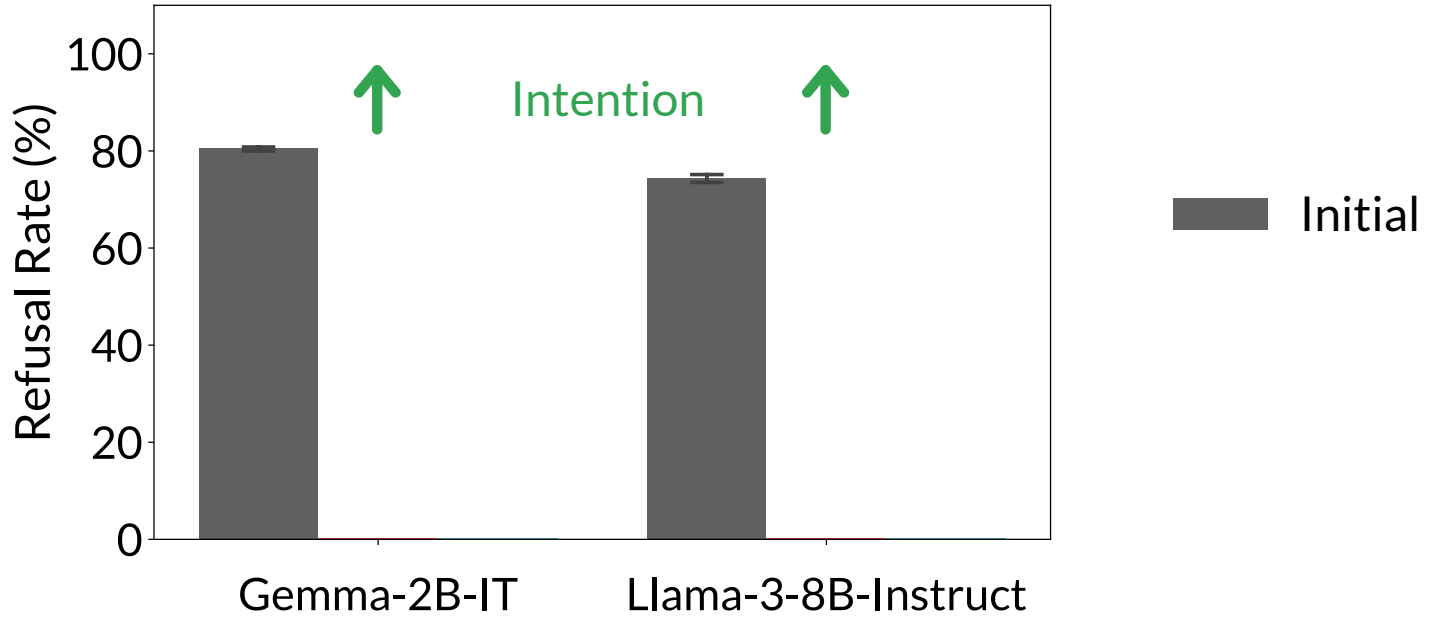

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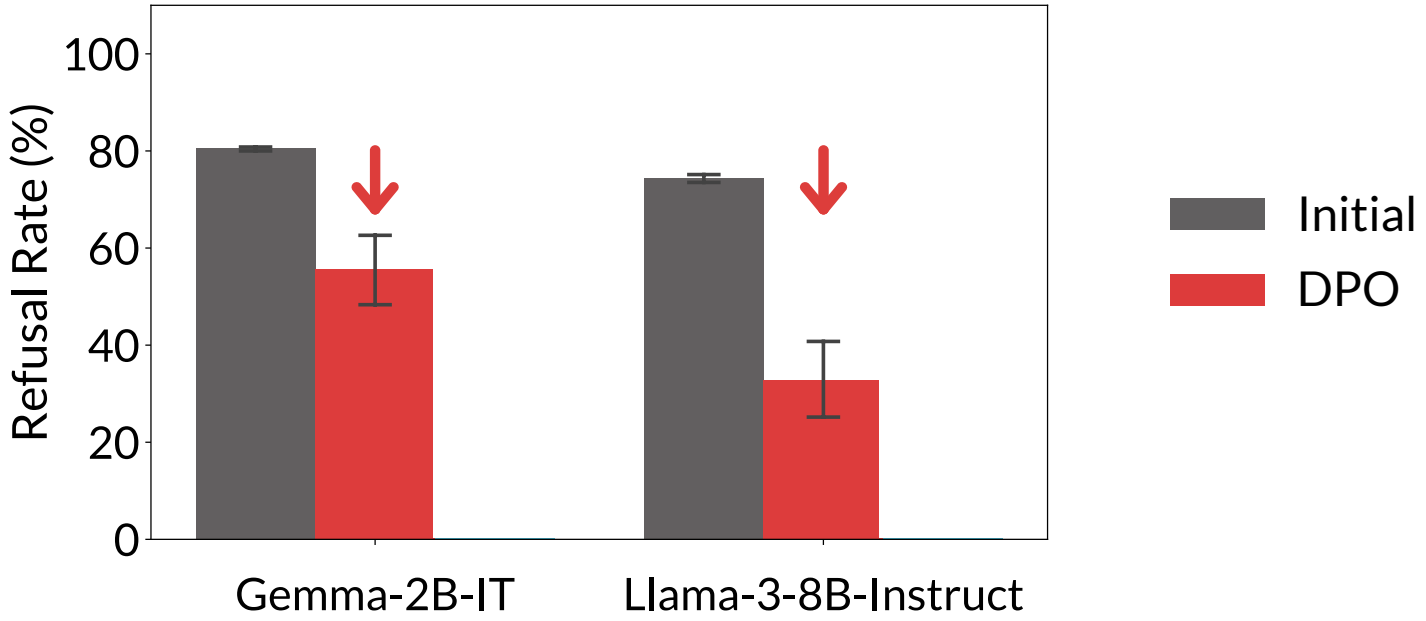

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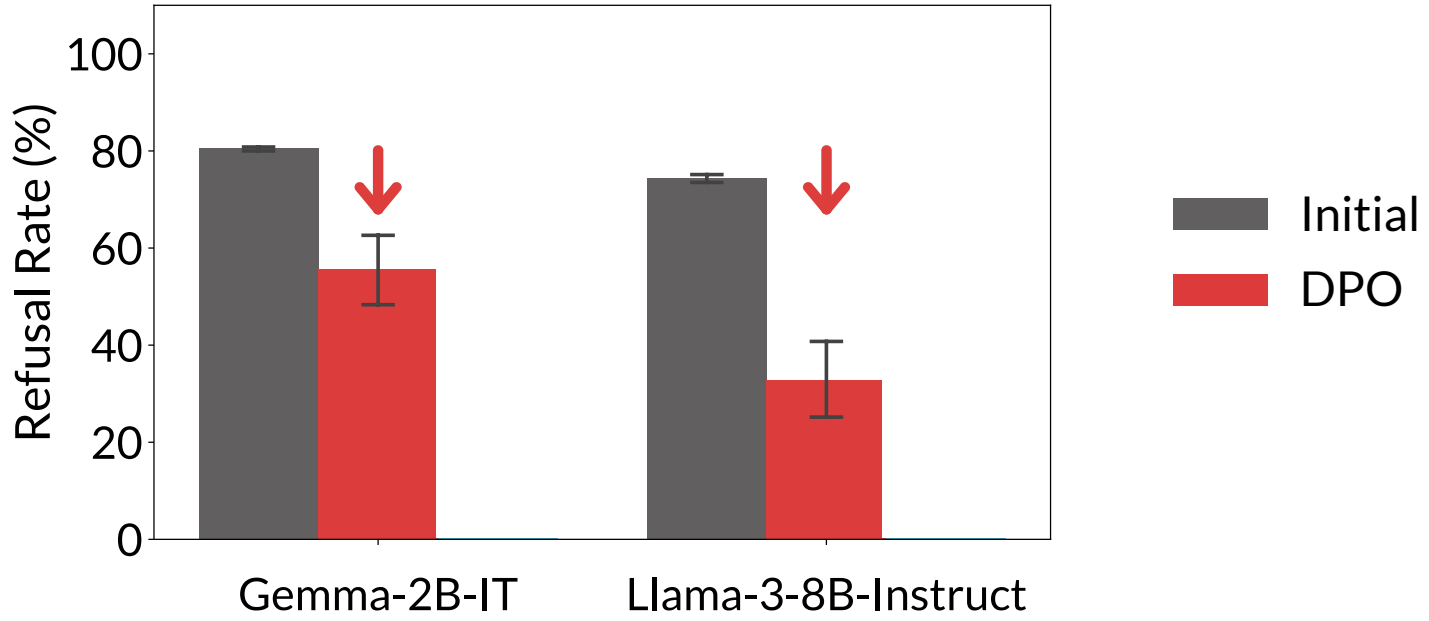

Likelihood displacement leads to unintentional unalignment!

Theoretical Analysis of Likelihood Displacement

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Approach: Characterize how $\pi_\theta(\mathbf{y}^+|\mathbf{x})$ changes during training

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Mitigating Unintentional Unalignment via Data Filtering

Recall: Unintentional unalignment due to likelihood displacement experiments

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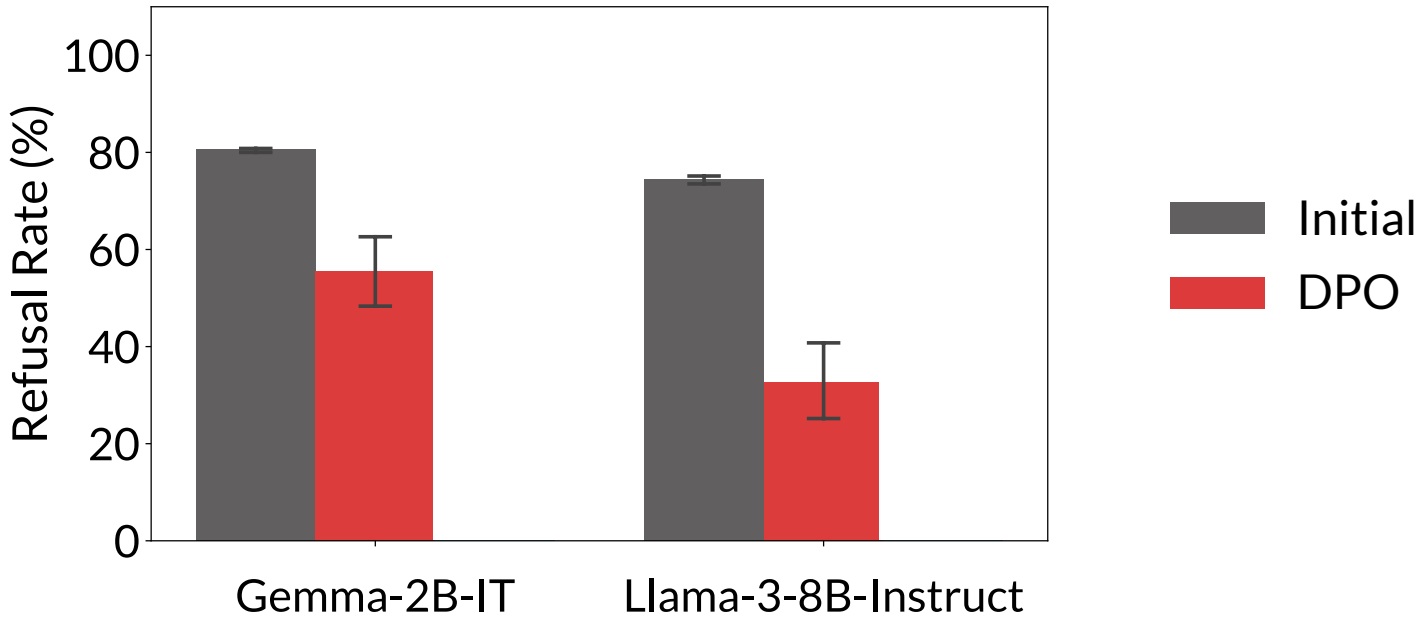

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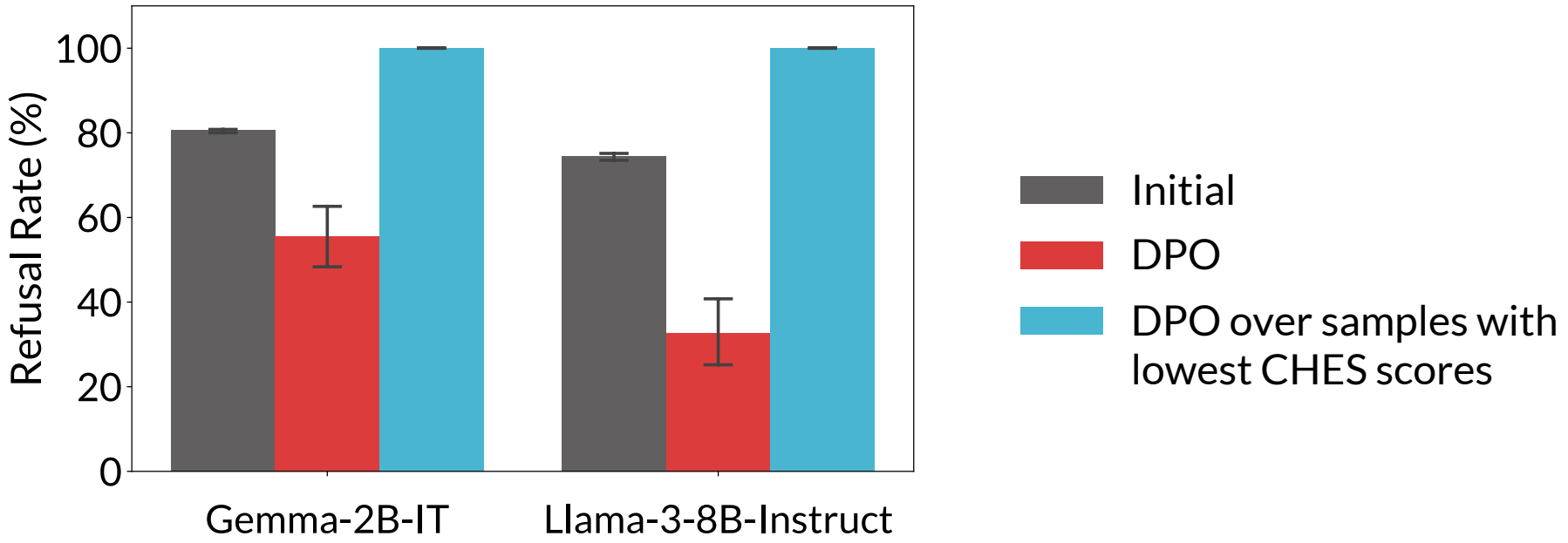
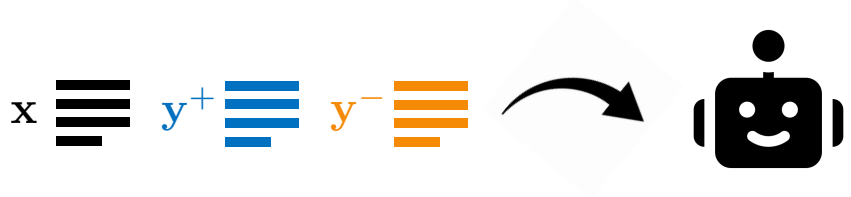


Removing samples with high CHES scores mitigates unintentional unalignment

Practical Impact

Our work inspired **new direct preference learning algorithms** for mitigating likelihood displacement



ComPO: Preference Alignment via Comparison Oracles

Chen et al. 2025

AlphaPO: Reward Shape Matters for LLM Alignment

Gupta et al. 2025

DPO-Shift: Shifting the Distribution of Direct Preference Optimization

Yang et al. 2025

Decoupling Contrastive Decoding: Robust Hallucination Mitigation in Multimodal Large Language Models

Chen et al. 2025

Conclusion

Recap

Reinforcement Learning (RLHF)

Direct Preference Learning

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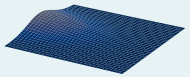

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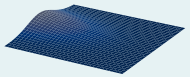

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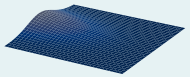

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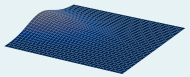

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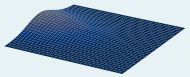

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Recap

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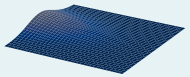

Beyond accuracy, RM needs to induce sufficient **reward variance**

Implications: More accurate RMs are not better teachers for RLHF + existing RM benchmarks are fundamentally limited

Practical Applications: Data selection and policy gradient methods

Direct Preference Learning

Likelihood displacement can cause **unintentional unalignment**

Theory & Experiments: Samples with **high CHES scores lead to likelihood displacement**

Practical Applications: Data curation and direct preference learning algorithms

Fundamentals of Language Model Alignment

There are countless alignment methods

RLHF	DPO	IPO	SimPO	KTO	...
Ouyang et al. 2022	Rafailov et al. 2023	Azar et al. 2023	Meng et al. 2024	Ethayarajh et al. 2024	

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As We Saw: Limited understanding can lead to undesirable outcomes

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- Safety concerns

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As We Saw: Limited understanding can lead to undesirable outcomes

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Theory (mathematical or empirical) may be necessary for efficient and reliable deployment of modern AI systems

Future Direction I: Policy Gradient Optimization

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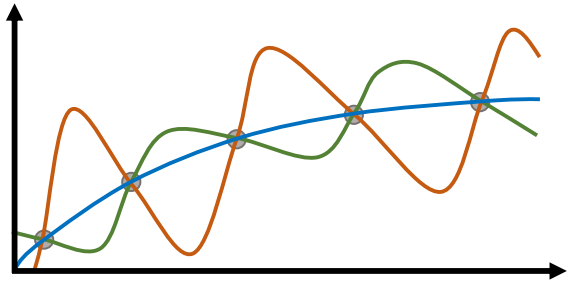
Supervised Learning



Setting: Minimize loss over labeled data via gradient-based methods

Future Direction I: Policy Gradient Optimization

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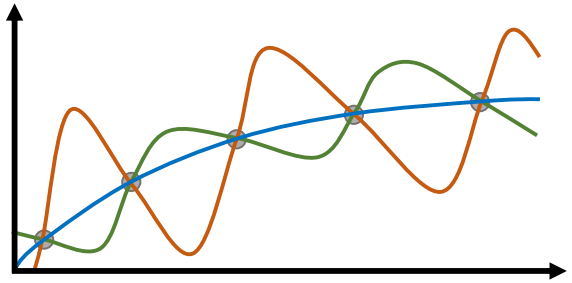

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Optimization Dynamics and Implicit Bias

Extensively Studied

(e.g., Neyshabur et al. 2014, Gunasekar et al. 2017, Soudry et al. 2018, Arora et al. 2019, Ji & Telgarsky 2019, **R** et al. 2020/21/22, Pesme et al. 2021, Lyu et al. 2021, Boursier et al. 2022, Andriushchenko et al. 2023, Frei et al. 2023, Jin & Montúfar 2023, Abbe et al. 2023, Chou et al. 2023/24, Fojtik et al. 2025)

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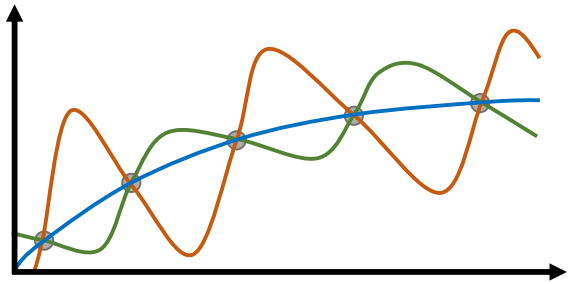

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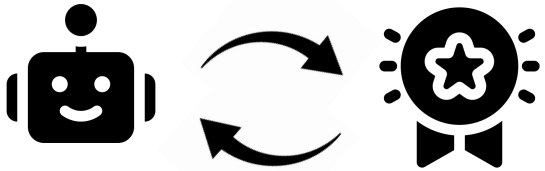
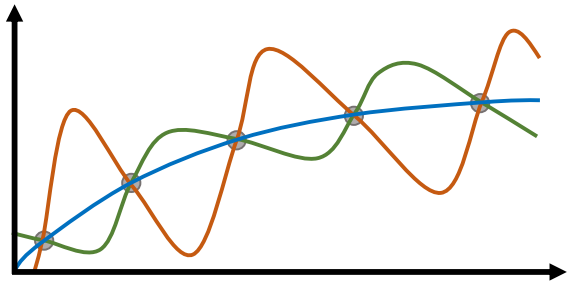
Reinforcement Learning



Setting: Maximize reward via **policy gradient**

Future Direction I: Policy Gradient Optimization

Supervised Learning



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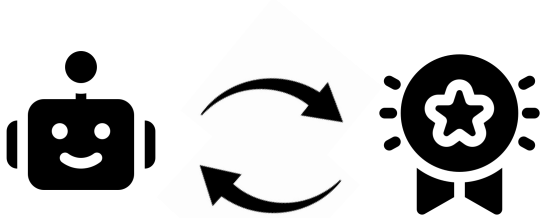

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Limited Understanding

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Future Direction II: Beyond Reward-Based Alignment

This talk focused on **reward-based alignment** (RLHF & DPO)

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Limitation 1

Can only account for transitive preferences

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How/when should we relax this restriction?

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$\mathbf{y}_B$	0.3	0.5	0.8
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E.g., game-theoretic approaches (Swamy et al. 2024, Munos et al. 2024)

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Limitation 2

Single scalar/bit feedback

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How to leverage richer forms of human feedback?












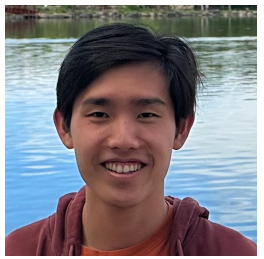

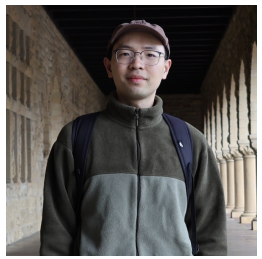
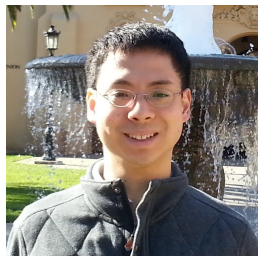


Thank You!

Work supported in part by the
Zuckerman STEM Leadership Program

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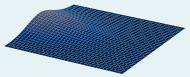

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