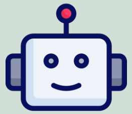
Understanding and Overcoming Pitfalls in Language Model Alignment

Noam Razin

Princeton Language and Intelligence, Princeton University

Language Models

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



LM π_θ

θ - Parameters of the LM

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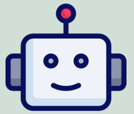

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a.k.a. **policy**

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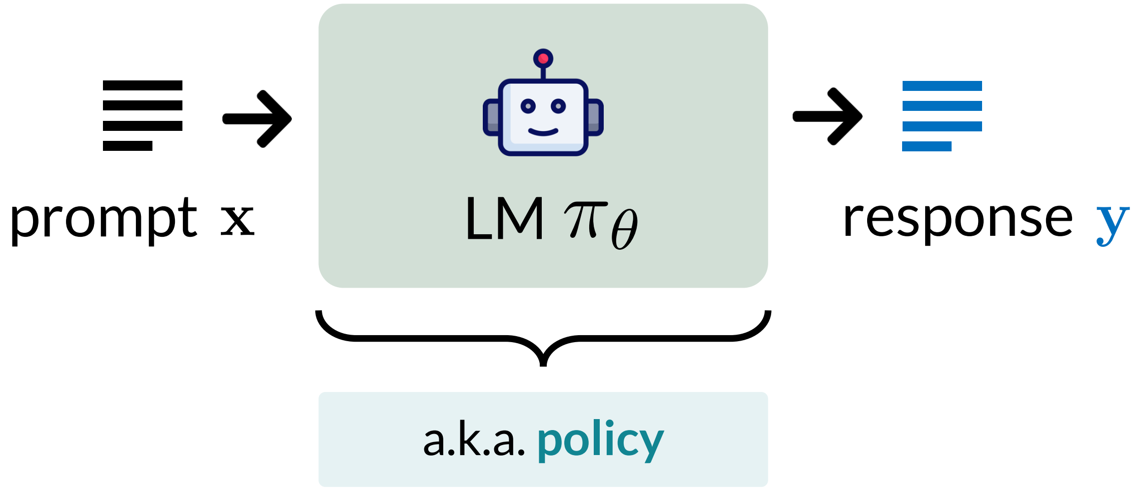

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Supervised Finetuning of LMs

To ensure LMs generate safe and helpful content, they are aligned via **finetuning**

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

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Supervised Finetuning (SFT)

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

prompt $\mathbf{x}$ desired response $\mathbf{y}$

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Limitation of SFT:

Hard to formalize human preferences through labels

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Finetuning LMs via Preference Data

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Preference-Based Finetuning

Limitations of SFT led to wide adoption of approaches using **preference data**

prompt $\mathbf{x}$

preferred response $\mathbf{y}^+$

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prompt $\mathbf{x}$ | preferred response $\mathbf{y}^+$ | dispreferred response $\mathbf{y}^-$

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

$$r_{\mathrm{G}}(\mathbf{x}, \mathbf{y}^+) > r_{\mathrm{G}}(\mathbf{x}, \mathbf{y}^-)$$

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Q: How can we maximize r_{G} if we only have access to it through preference data?

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Reinforcement Learning

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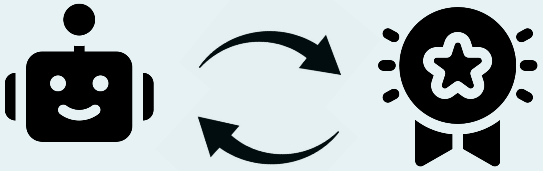

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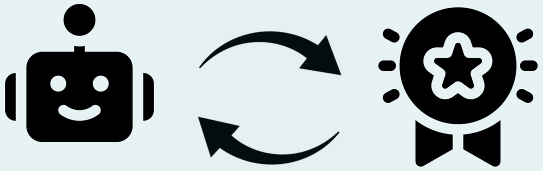

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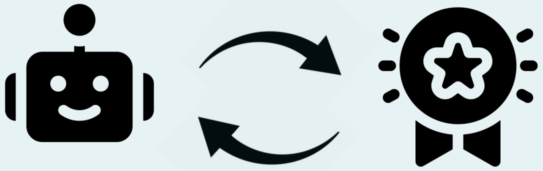

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We Will See: Limited understanding can lead to undesirable outcomes

Part I: Alignment via Reinforcement Learning

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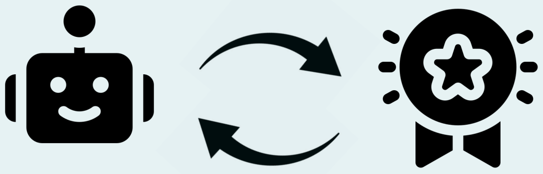

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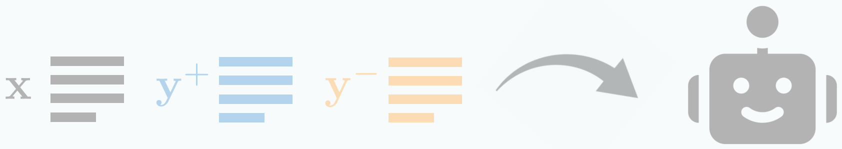

Vanishing Gradients in Reinforcement Finetuning of Language Models

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

Reinforcement Learning from Human Feedback (RLHF)

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

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$$\mathbf{x} \qquad \mathbf{y}^{+} \qquad \mathbf{y}^{-}$$

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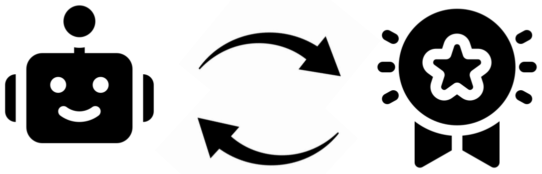
Evaluating RMs

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



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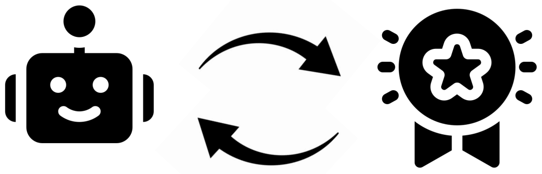

But it is unclear how we should **evaluate this quality**

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Definition: 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?

Q: Are more accurate reward models better teachers for RLHF?

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❌

Not necessarily!

Main Contributions: What Makes a Good RM

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Optimization Perspective: When does an RM enable efficient policy gradient optimization?

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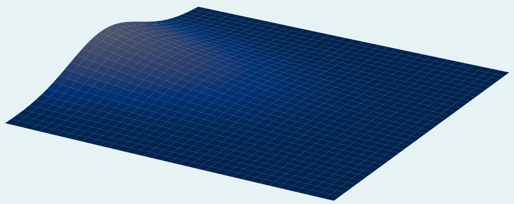

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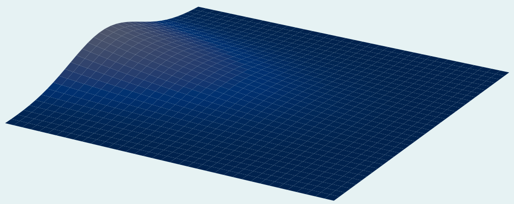

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Implication I:

More accurate RMs are not necessarily better teachers for RLHF

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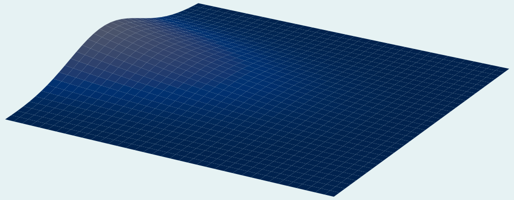

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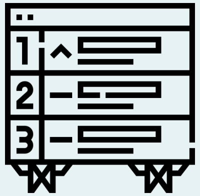
3

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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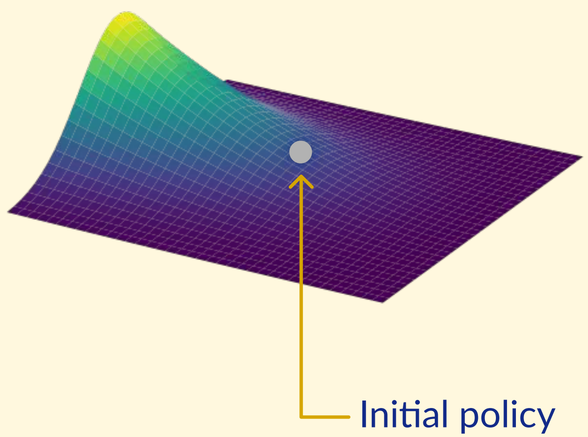
Ground Truth Reward



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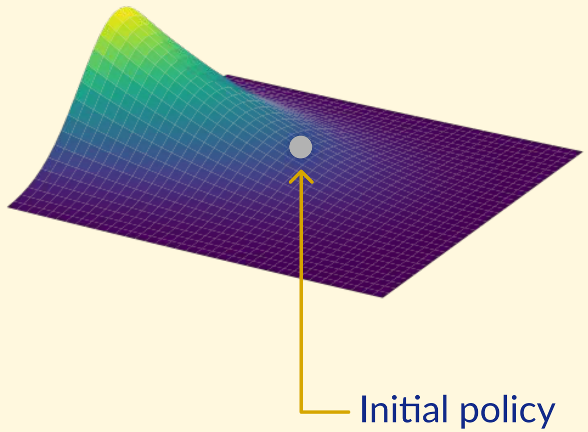

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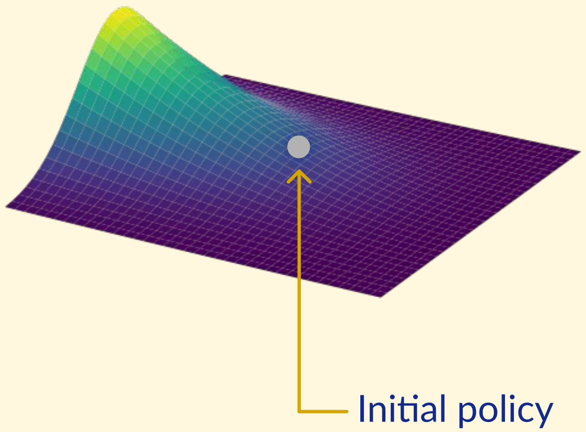

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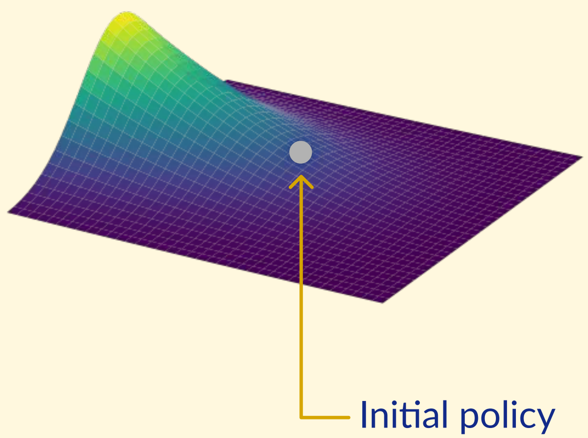

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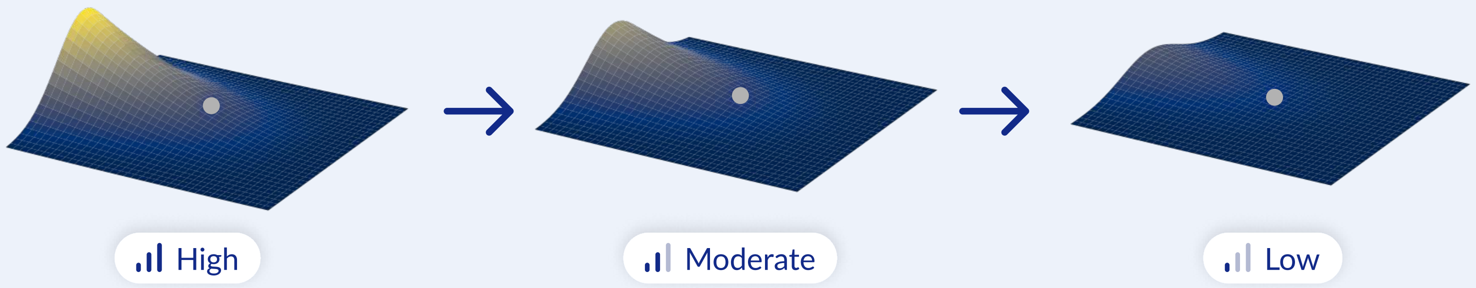
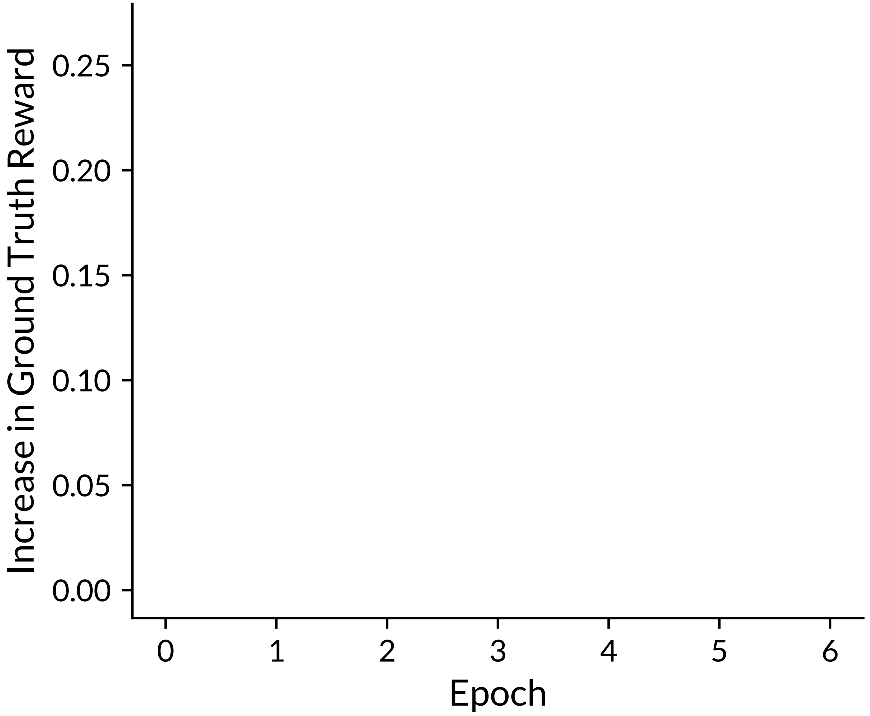


Experiments: More Accurate RMs Are Not Necessarily Better

Setting:

- Ground Truth: ArmoRM
- 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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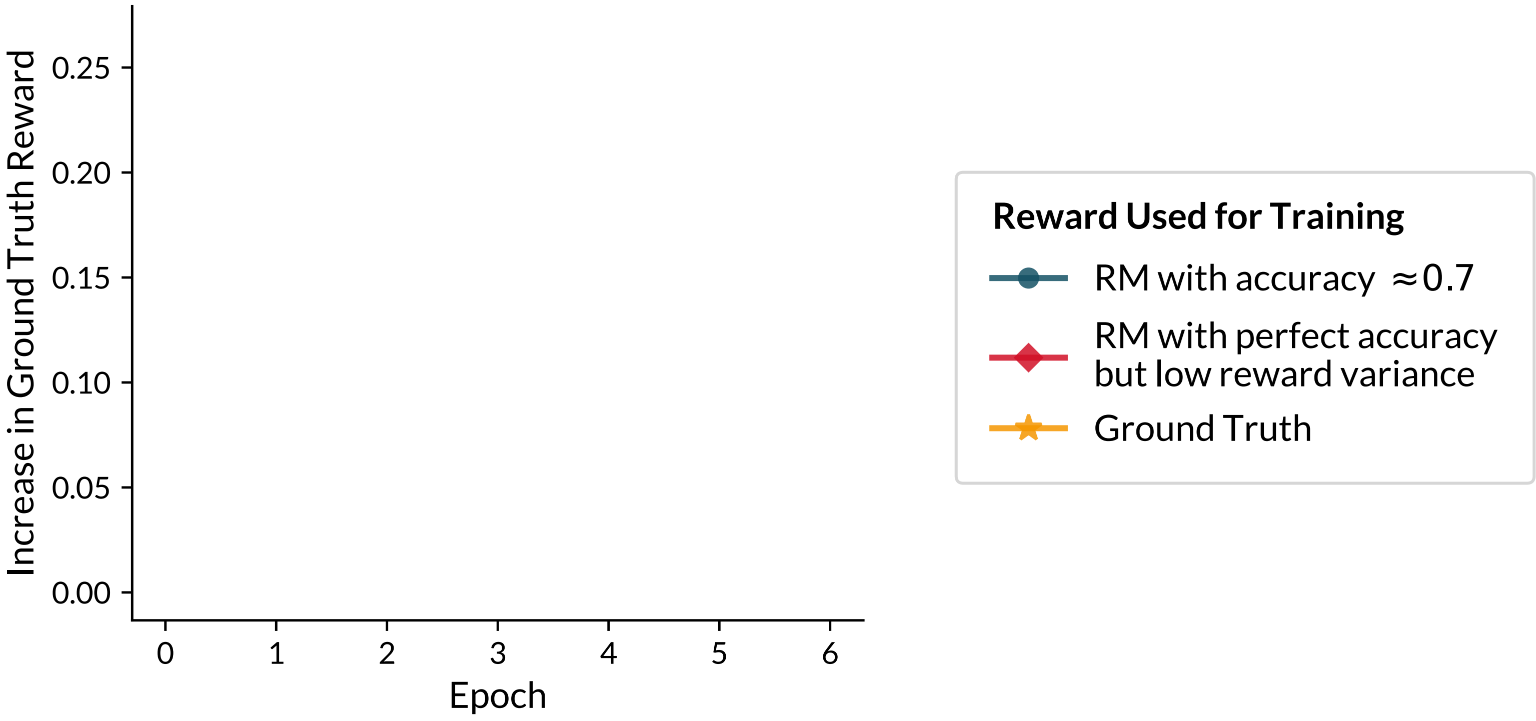

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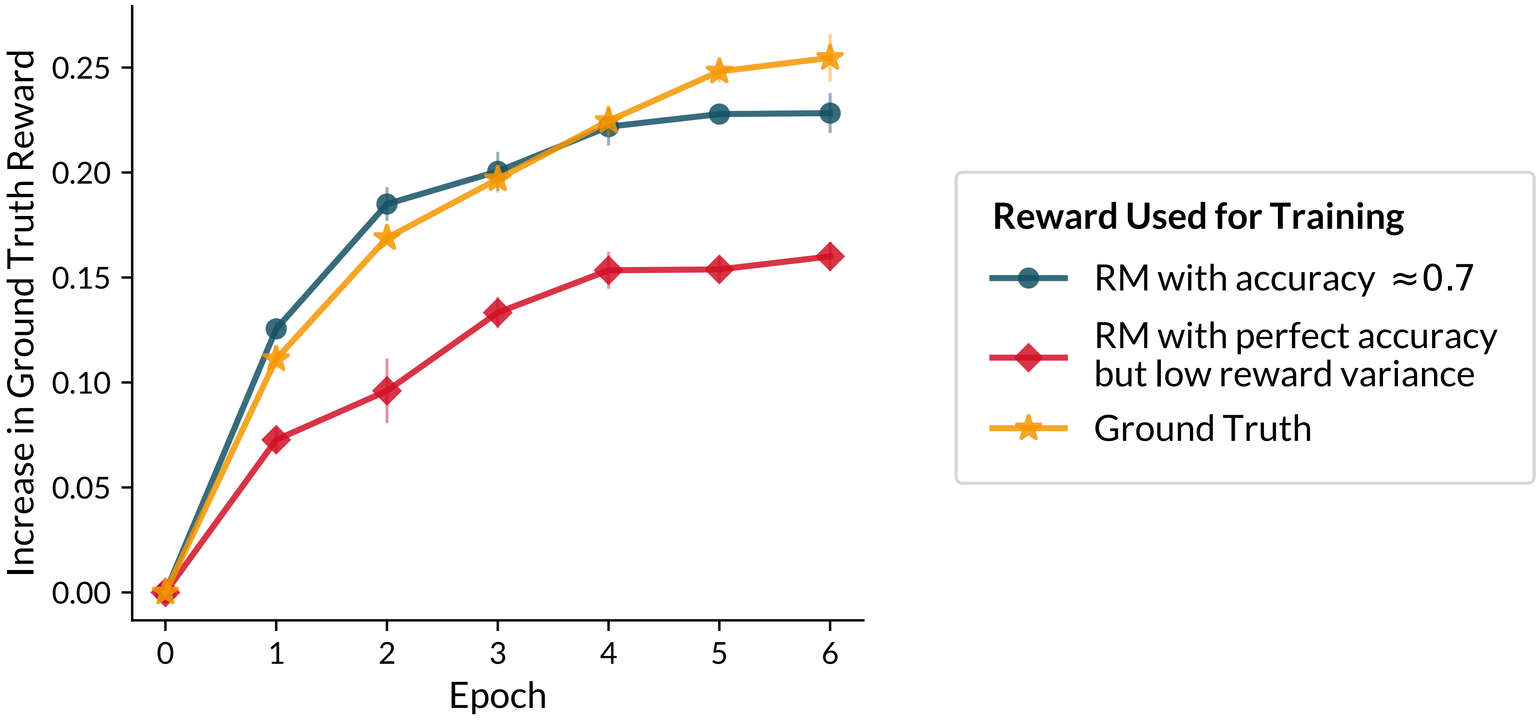

Even perfectly accurate RMs can underperform less accurate ones, due to low reward variance

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What makes a good RM depends on the LM being aligned

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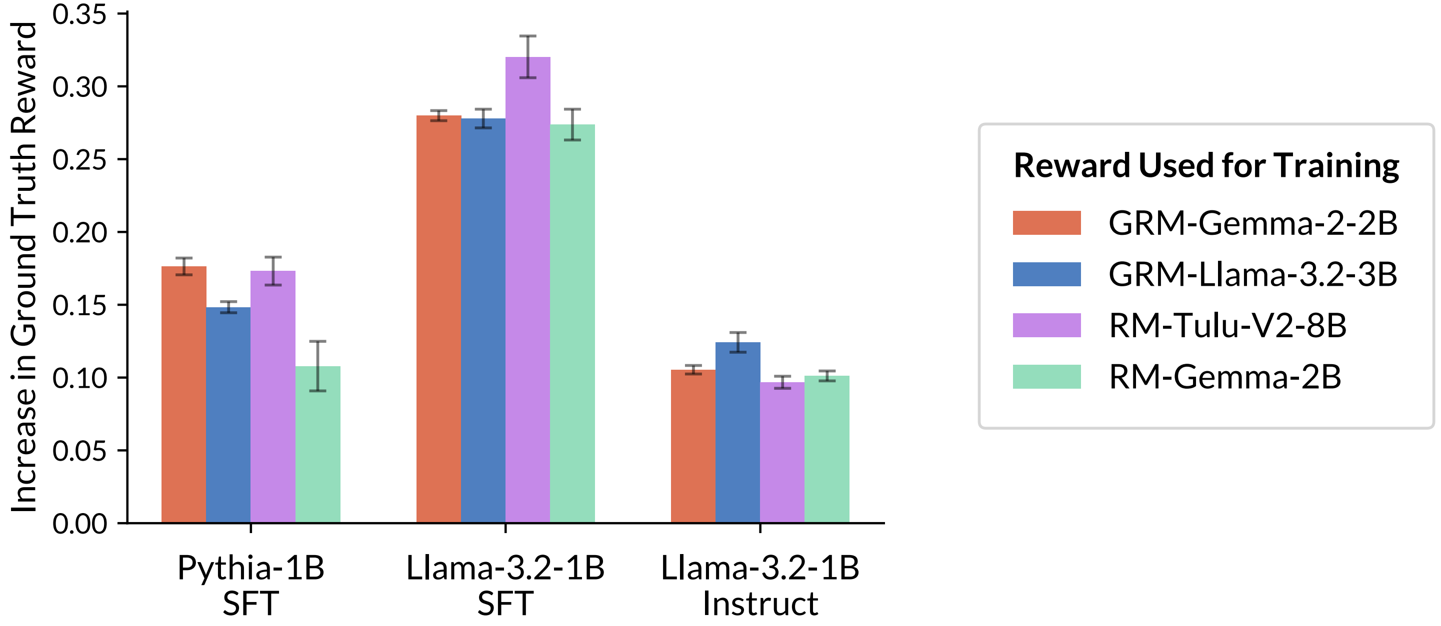

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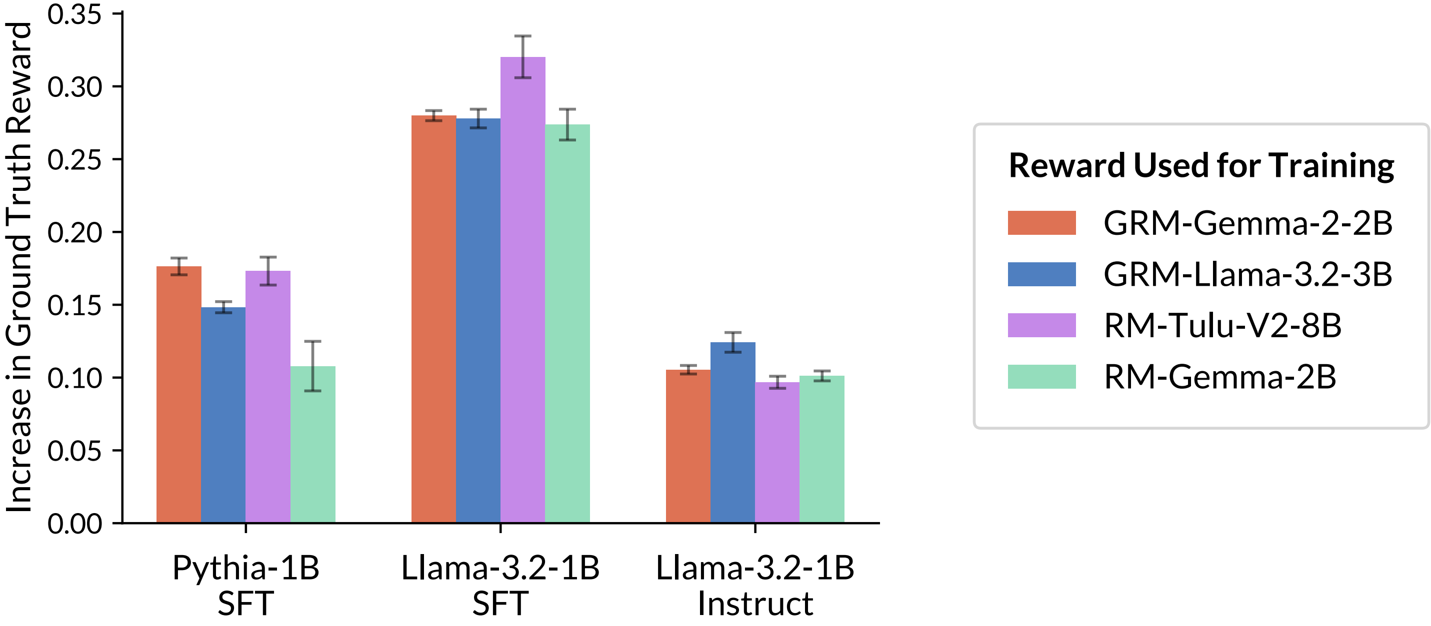

Benchmarks evaluating RMs in isolation from the LM they guide are fundamentally limited

Takeaways: What Makes a Good RM?

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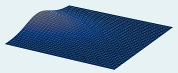

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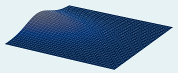

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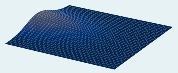

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Our results highlight the need for RM training and evaluation protocols that account for properties beyond accuracy

Importance of SFT in the RLHF Pipeline

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

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

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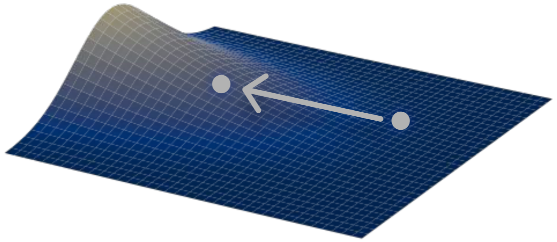
Intuition: SFT finds a less flat initialization



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Limitation of Initial SFT Phase: Requires labeled data

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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

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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

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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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- Can help identify optimization issues
- Useful for developing data selection, policy gradient, and RM training algorithms

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We Discussed: How properties of RM affect RLHF

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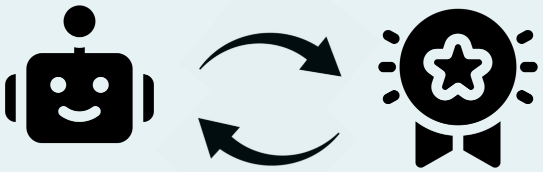
Seemingly minor design choices can substantially affect reward model generalization

Part II: Alignment via Direct Preference Learning

Reinforcement Learning

(e.g. Ouyang et al. 2022)



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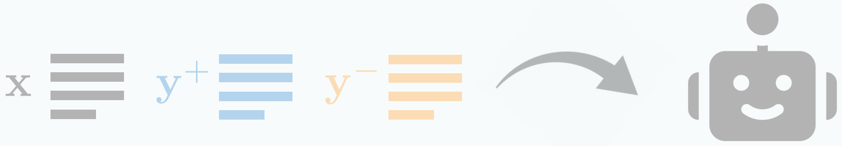

Vanishing Gradients in Reinforcement Finetuning of Language Models

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*

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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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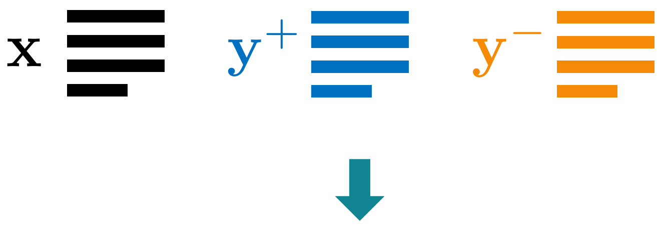

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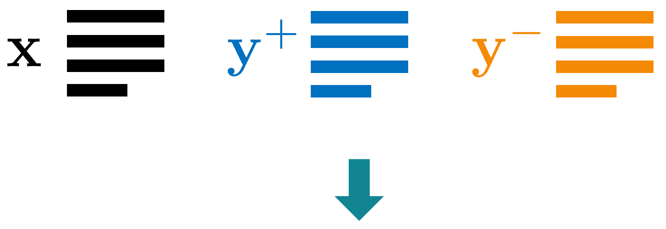

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Numerous variants of DPO, differing in choice of ℓ

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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

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

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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Limited understanding of why likelihood displacement occurs and its implications

Likelihood Displacement Can Cause Unintentional Unalignment

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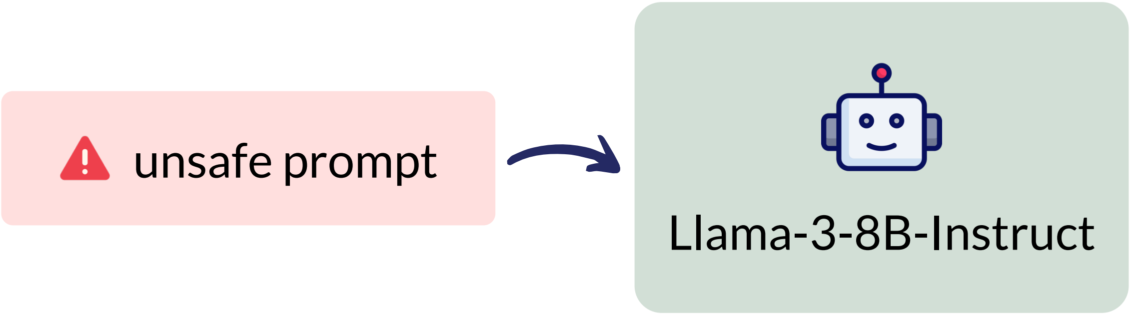

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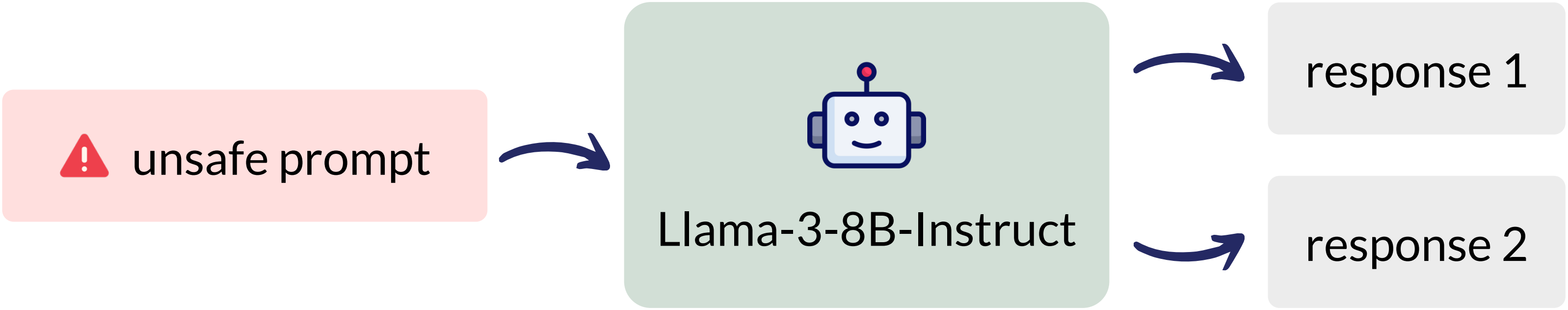

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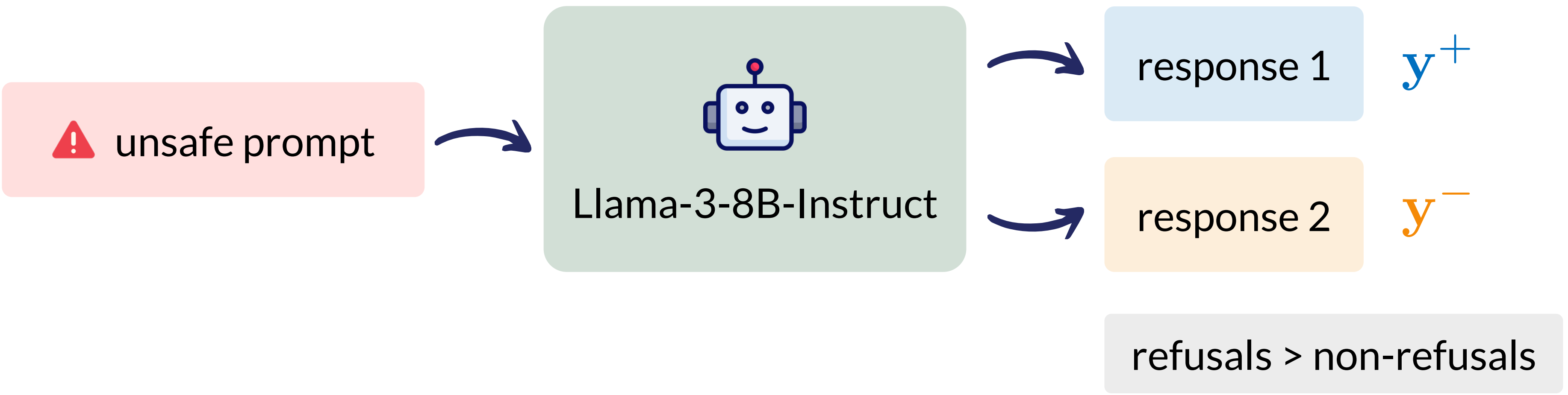

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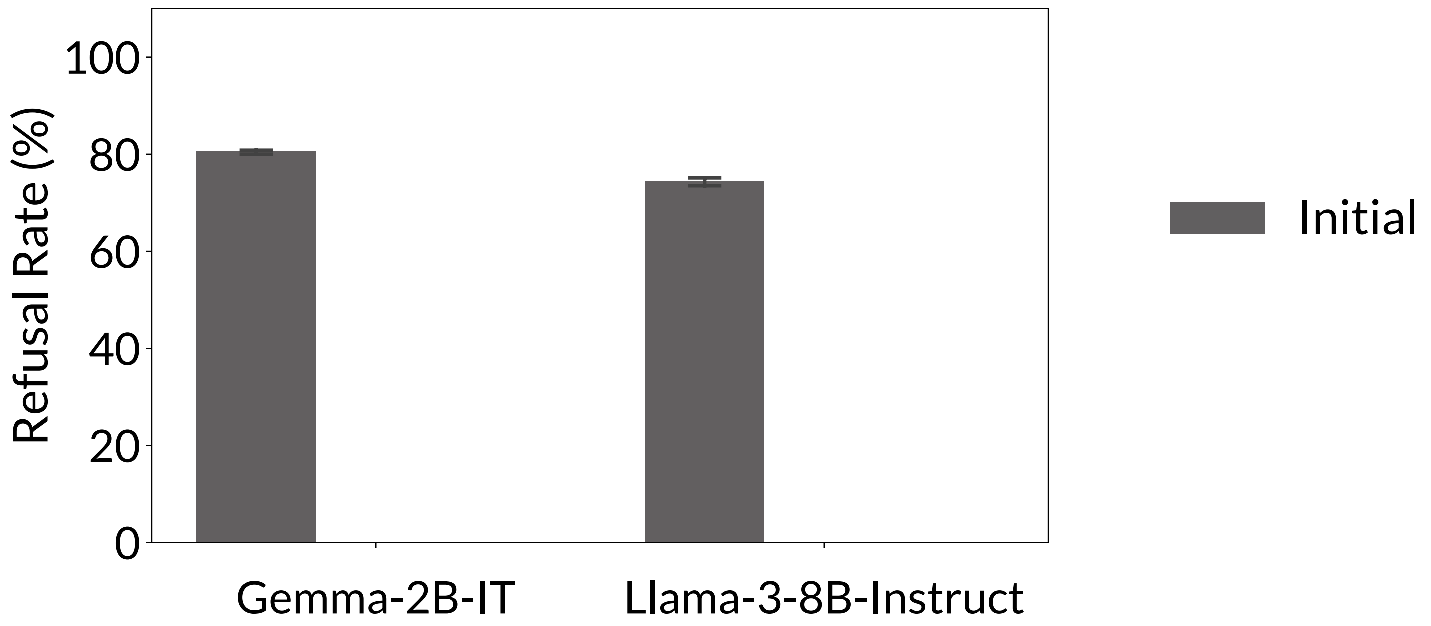

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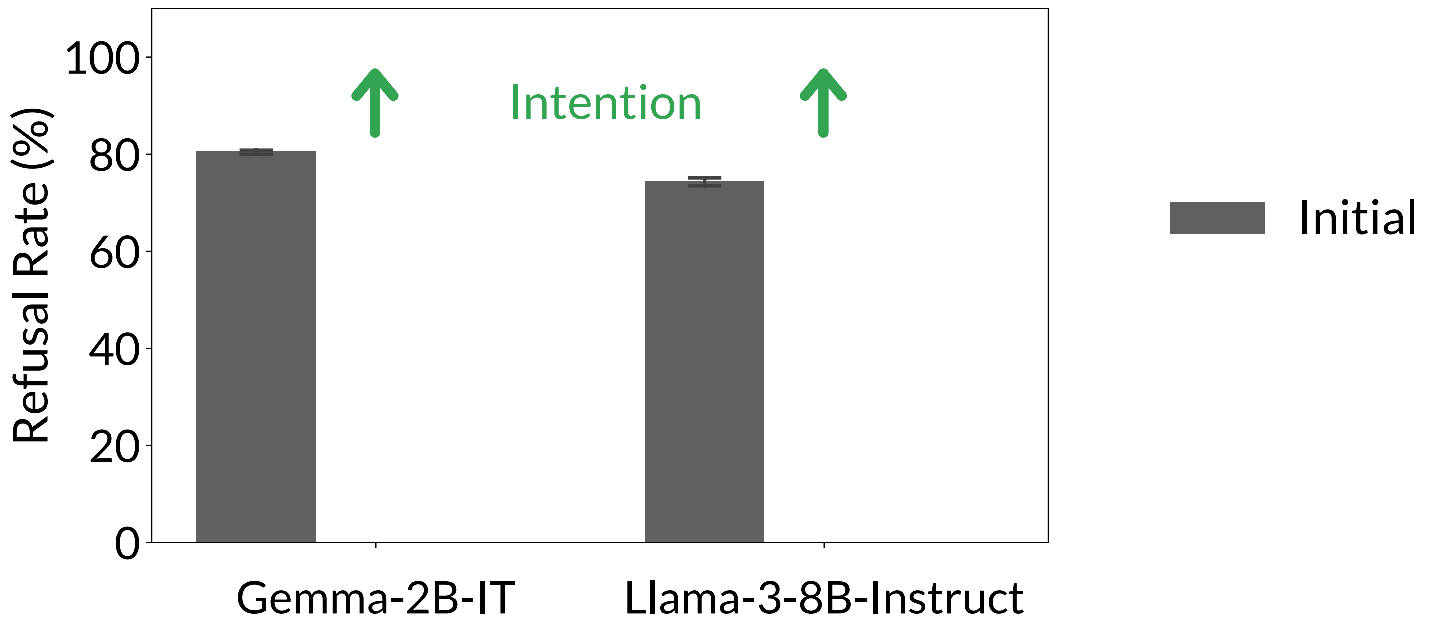

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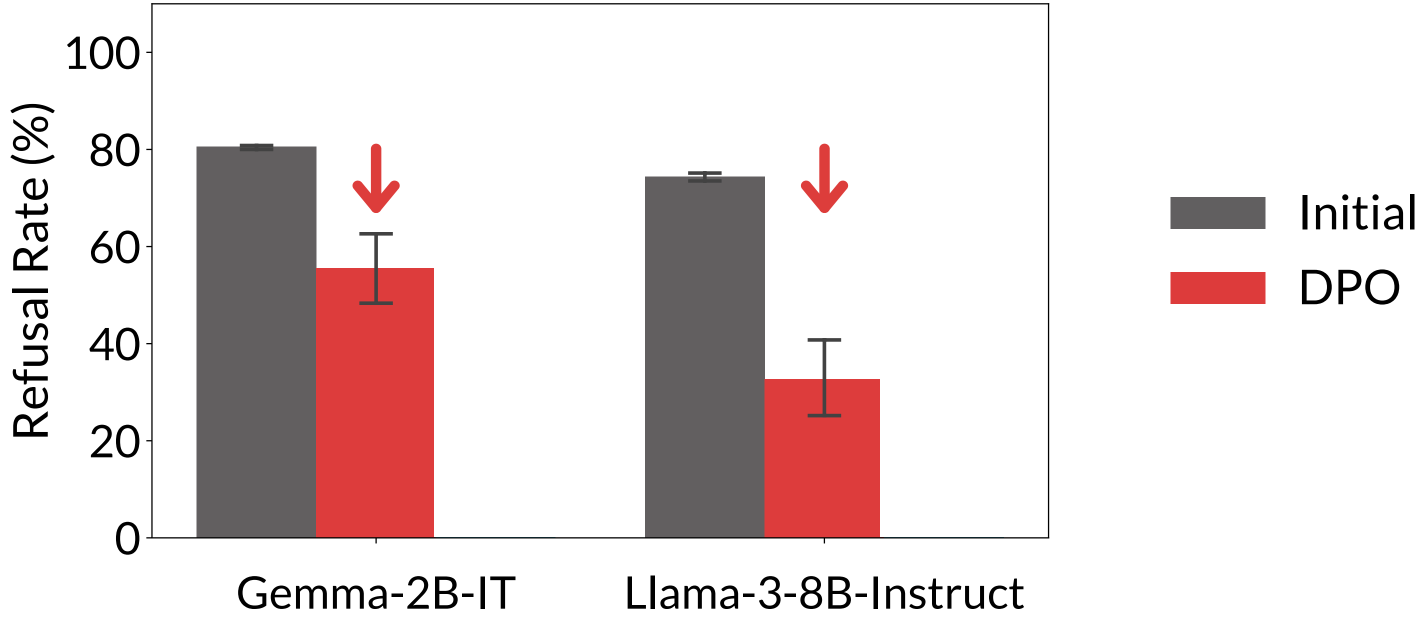

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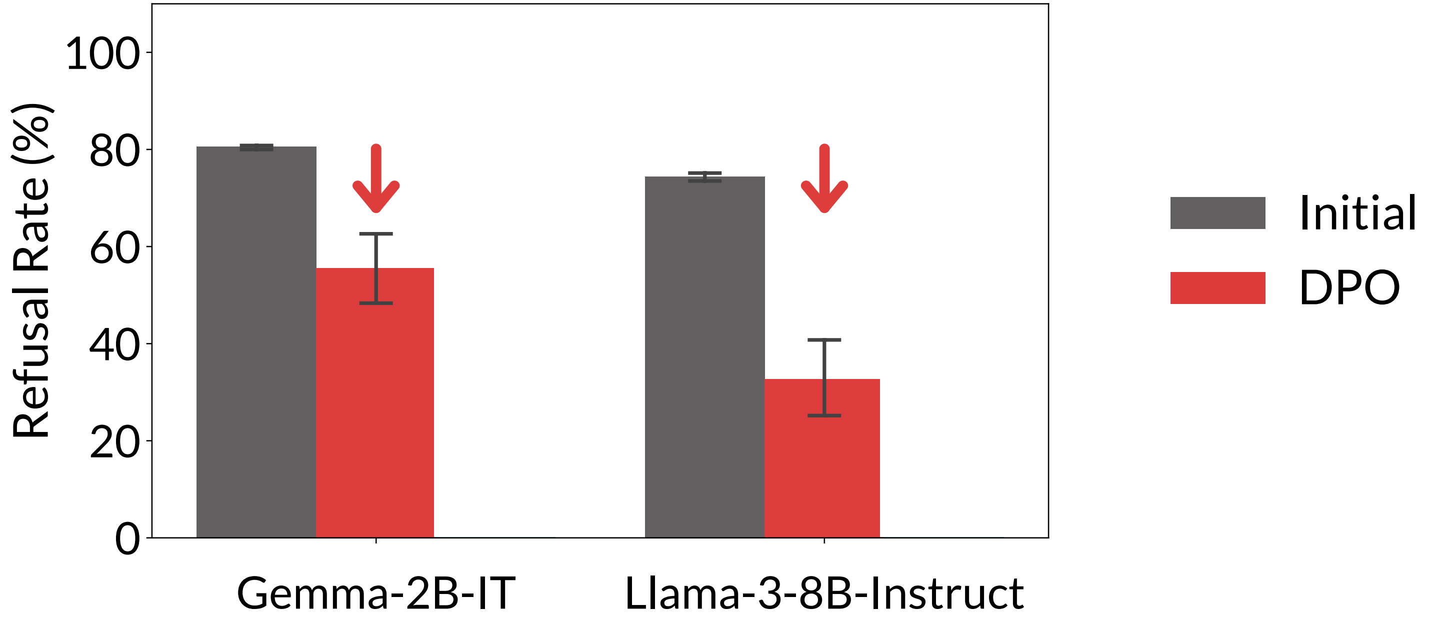

Likelihood displacement leads to unintentional unalignment!

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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$$\mathrm{CHES}_{\mathbf{x}}(\mathbf{y}^+, \mathbf{y}^-) :=$$

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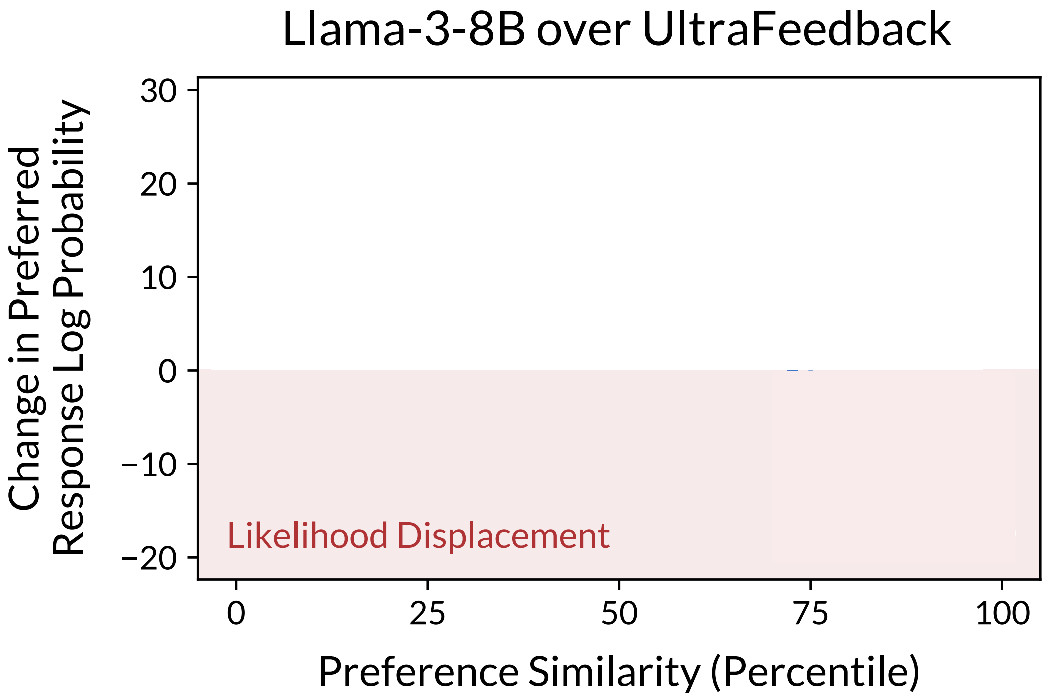

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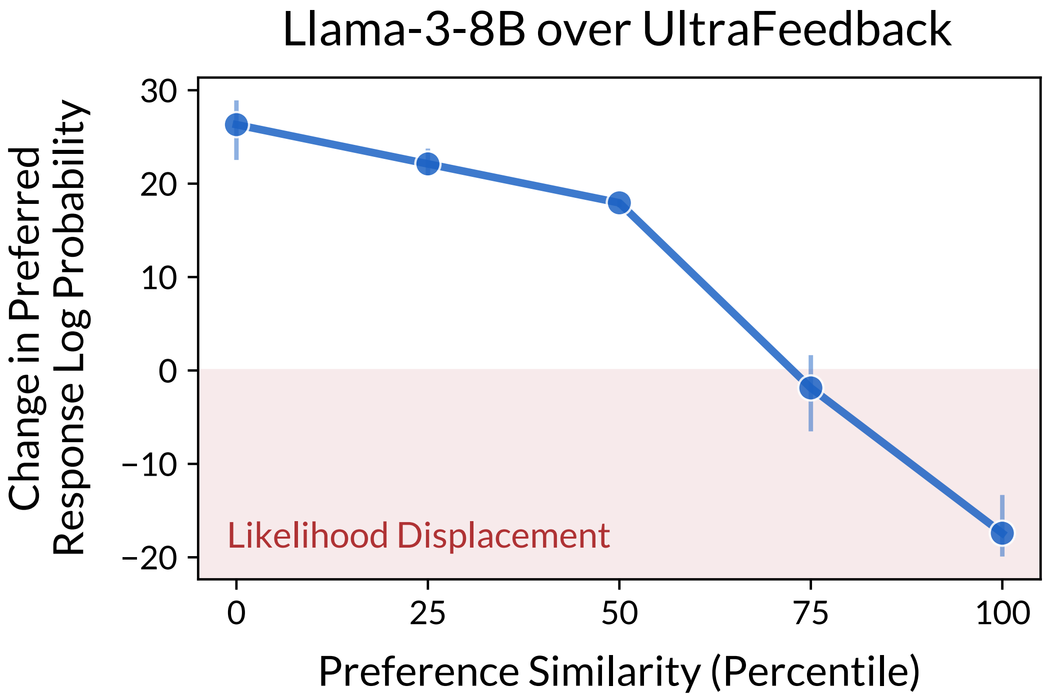

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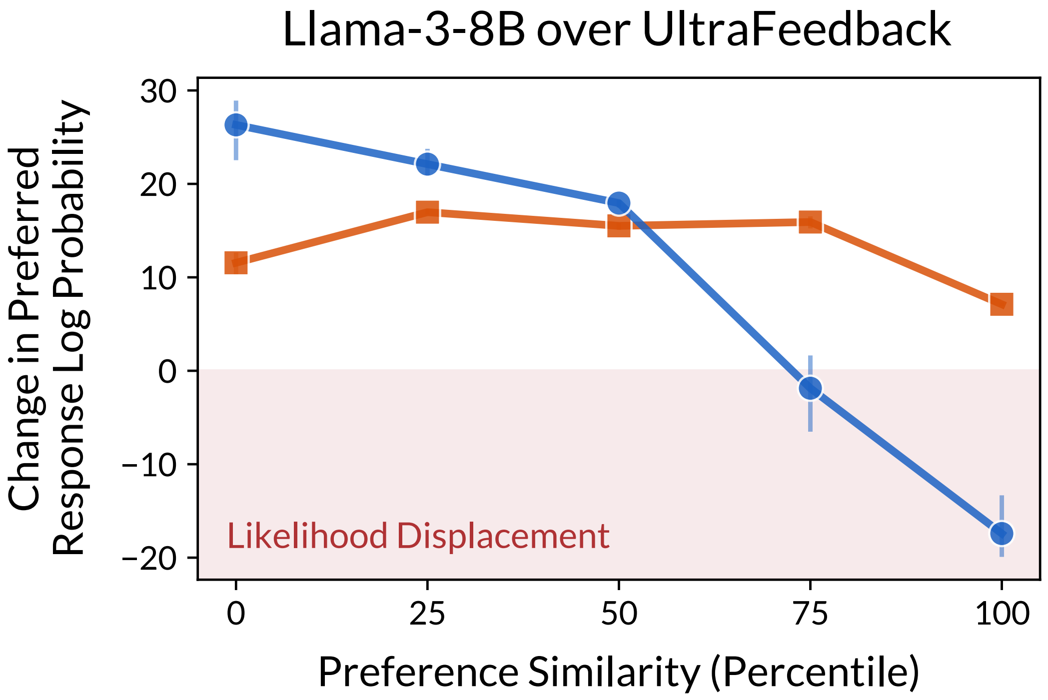

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Edit Distance Similarity (Pal et al. 2024)

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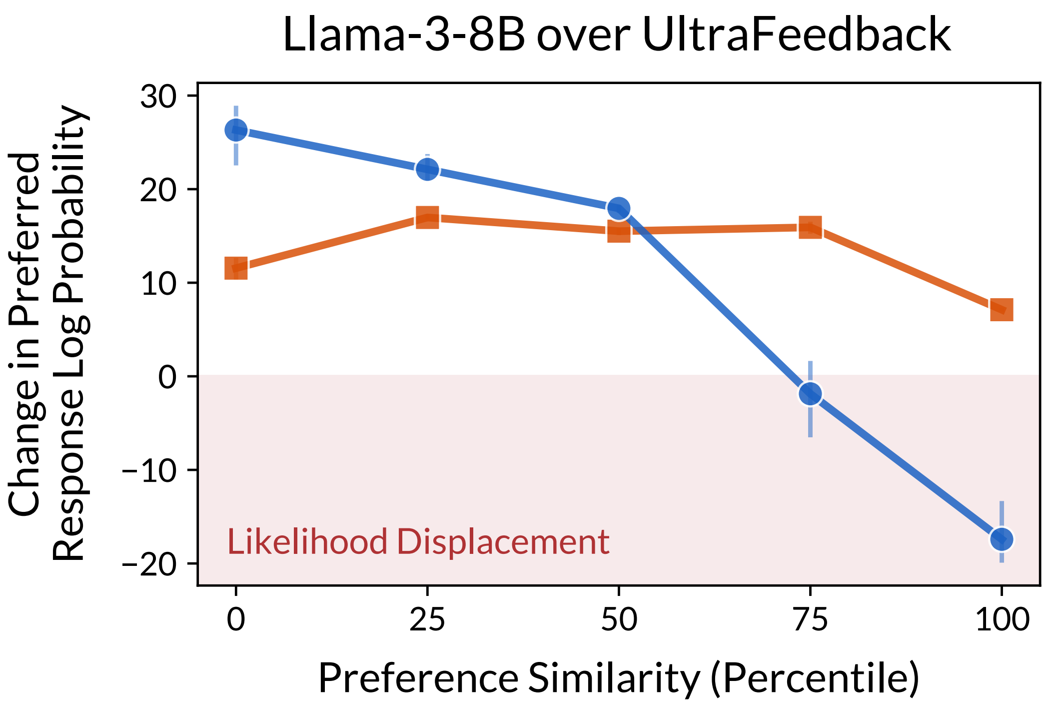

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CHES Score

Edit Distance Similarity (Pal et al. 2024)

CHES score identifies training samples causing likelihood displacement, whereas alternative measures do not

Mitigating Unintentional Unalignment via Data Filtering

Recall: Unintentional unalignment due to likelihood displacement experiments

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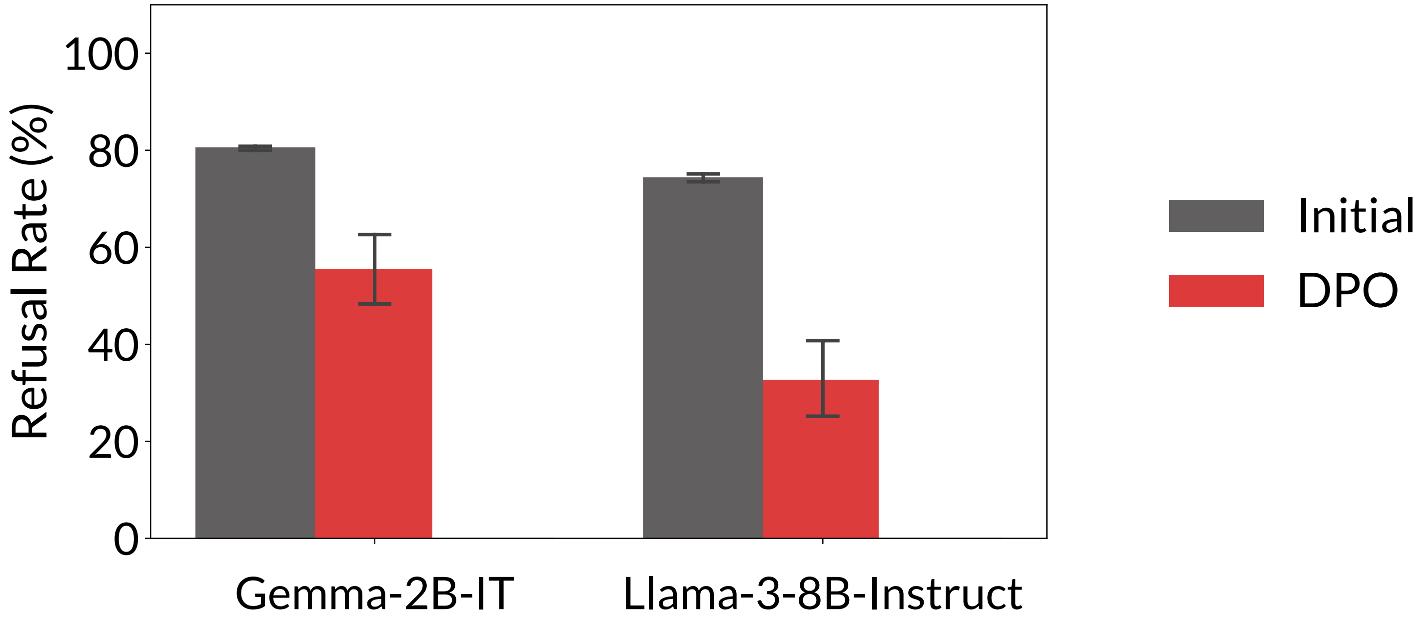

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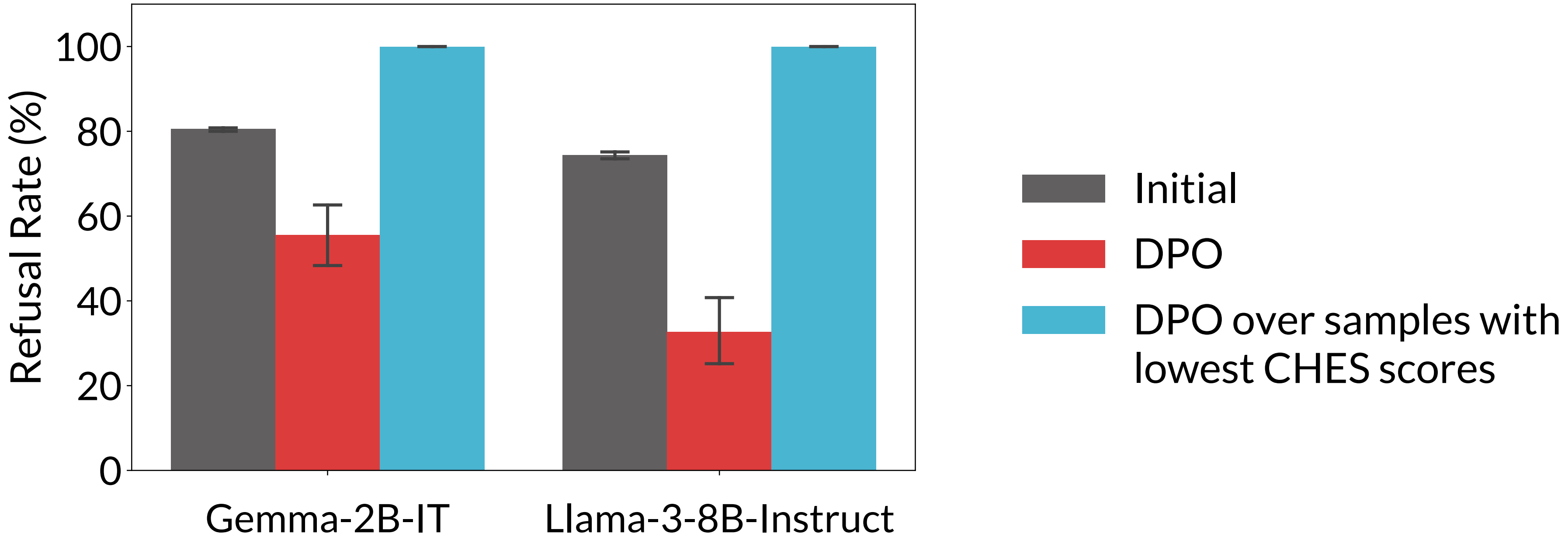
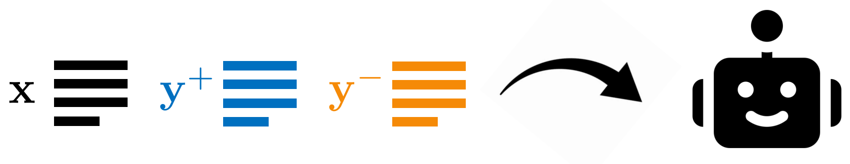
Recall: Unintentional unalignment due to likelihood displacement experiments



Removing samples with high CHES scores mitigates unintentional unalignment

Practical Impact

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



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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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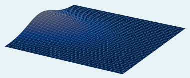

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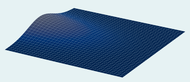

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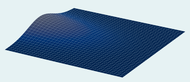

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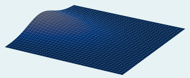

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Theory & Experiments: Samples with **high CHES scores lead to likelihood displacement**

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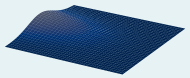

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Practical Applications: Data curation and direct preference learning algorithms

Fundamentals of Language Model Alignment

There are countless methods for aligning language models

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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As We Saw: Limited understanding can lead to undesirable outcomes

- Inefficient training
- Safety concerns

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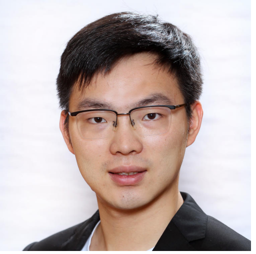
Theory (mathematical or empirical) may be necessary for efficient and reliable deployment of modern AI systems

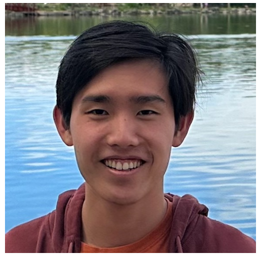














Thank You!

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