# Understanding and Overcoming Failures of Language Model Finetuning

**Noam Razin**

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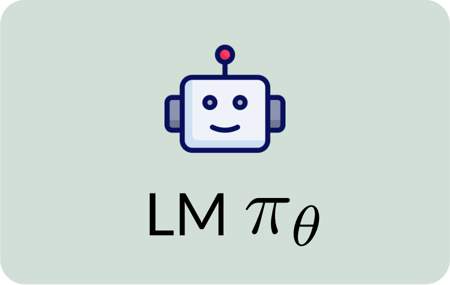
# Language Models

**Language Model (LM):** Neural network trained on large amounts of text data to produce a **distribution over text**



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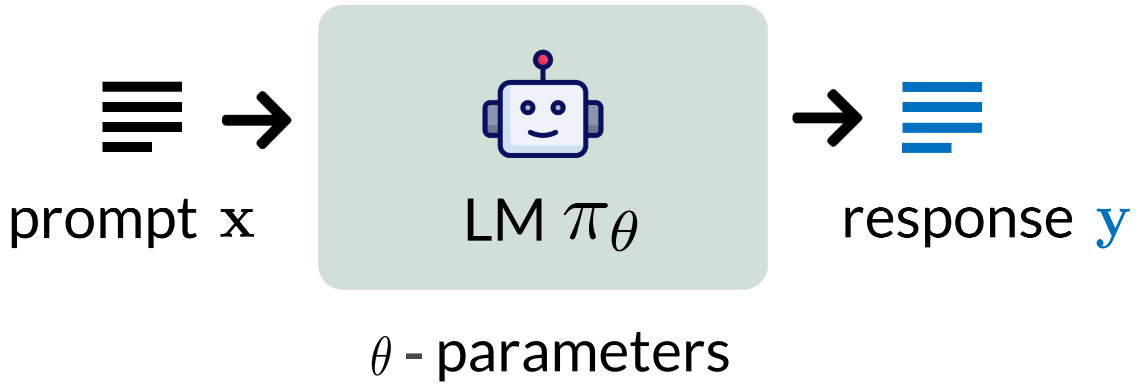

prompt $\mathbf{x}$

LM $\pi_\theta$

response $\mathbf{y}$

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# Supervised Finetuning of LMs

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- Obtaining high-quality responses is expensive

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Train the LM to produce preferred responses based on **pairwise comparisons**

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**Main Approaches:**

1 Reinforcement Learning (e.g. Ouyang et al. 2022)

2 Direct Preference Learning (e.g. Rafailov et al. 2023)

# Sources

1

Vanishing Gradients in Reinforcement Finetuning of Language Models

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

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Unintentional Unalignment: Likelihood Displacement in Direct Preference Optimization

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# Collaborators

Hattie Zhou

Omid Saremi

Vimal Thilak

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Preetum Nakkiran

Joshua Susskind

Etai Littwin

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For our purposes, $r(\mathbf{x}, \mathbf{y})$ can be any arbitrary reward function

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# Vanishing Gradients Due to Small Reward Standard Deviation (STD)

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**RFT may not work well for inputs with small reward std**

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Benchmark: GRUE (Ramamurthy et al. 2023)
7 language generation datasets

Models: GPT-2 and T5-base

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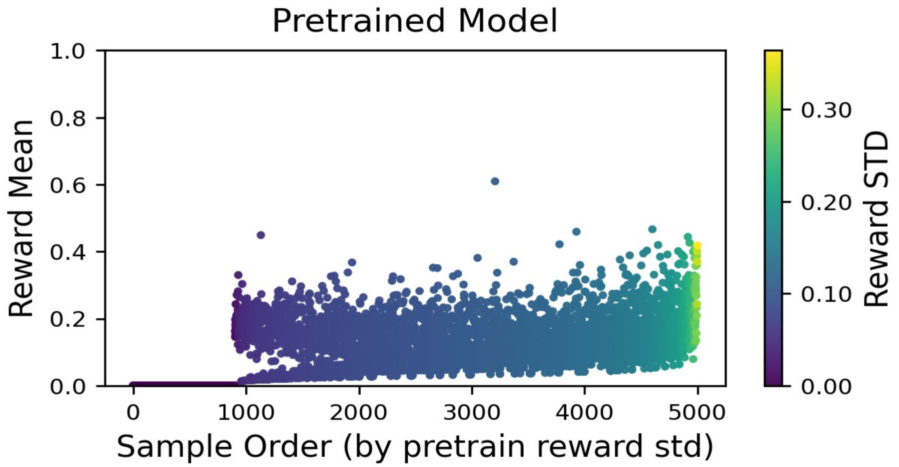
**(many inputs w/ small std)**



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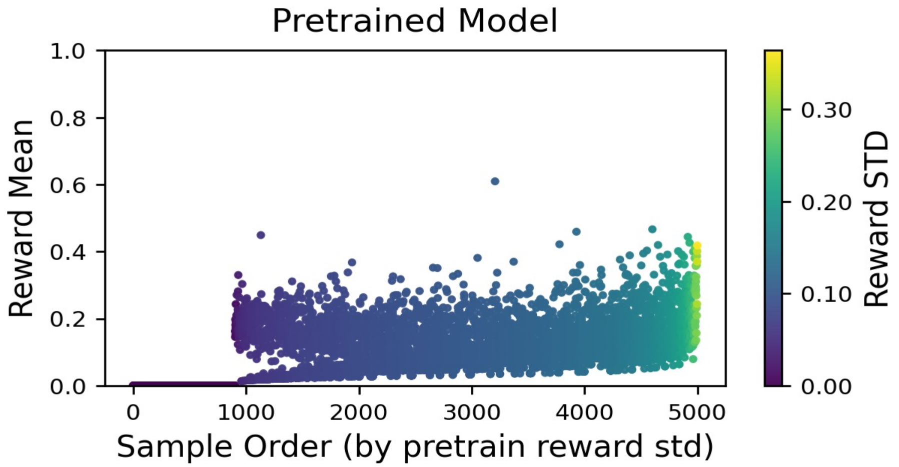

**IMDB**
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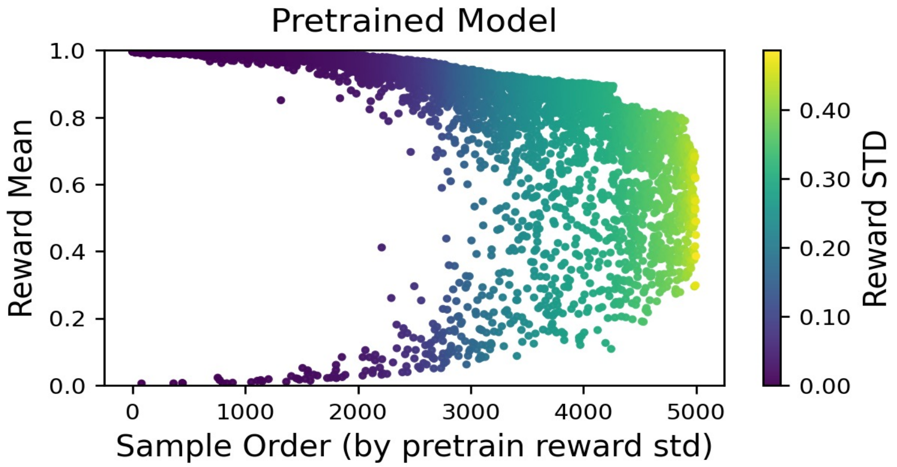

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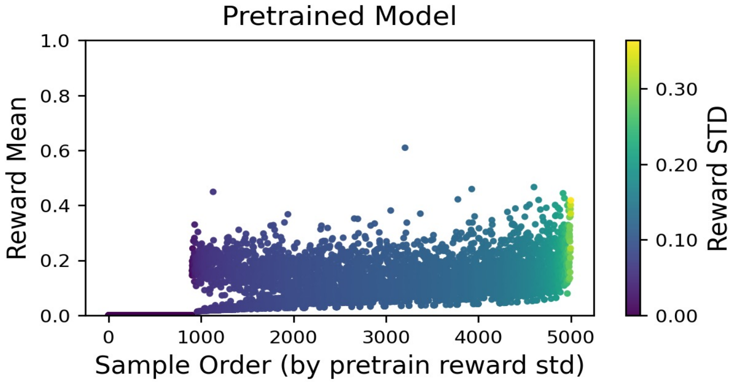

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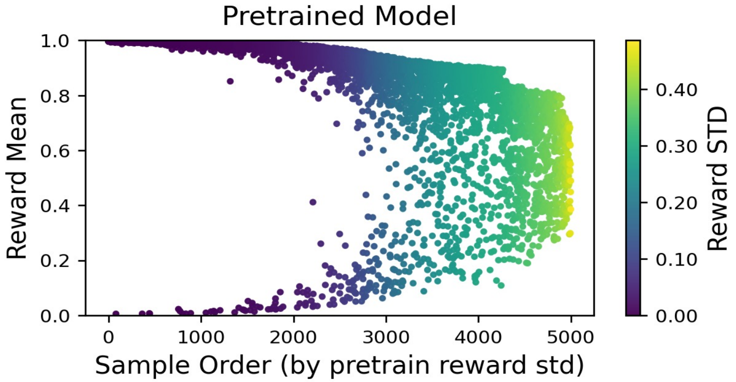

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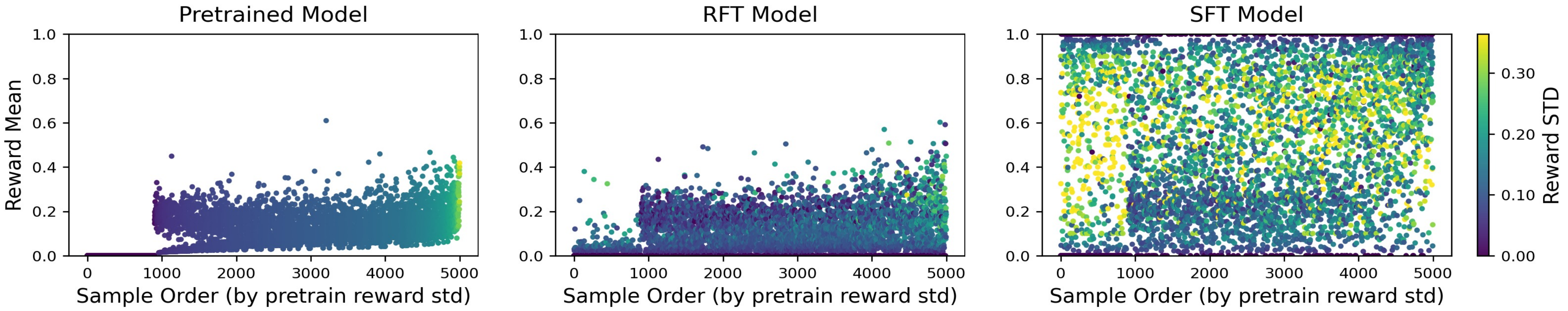

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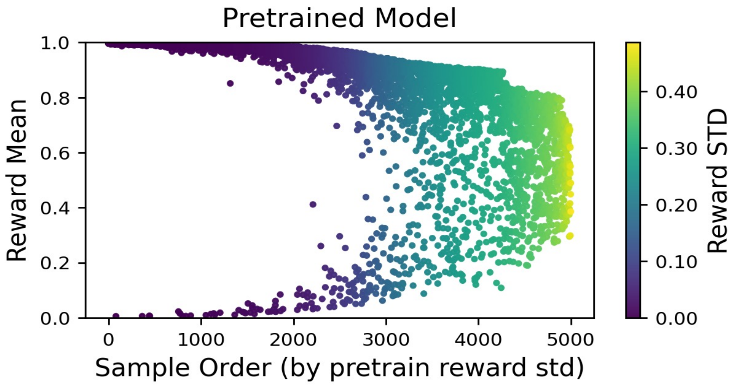

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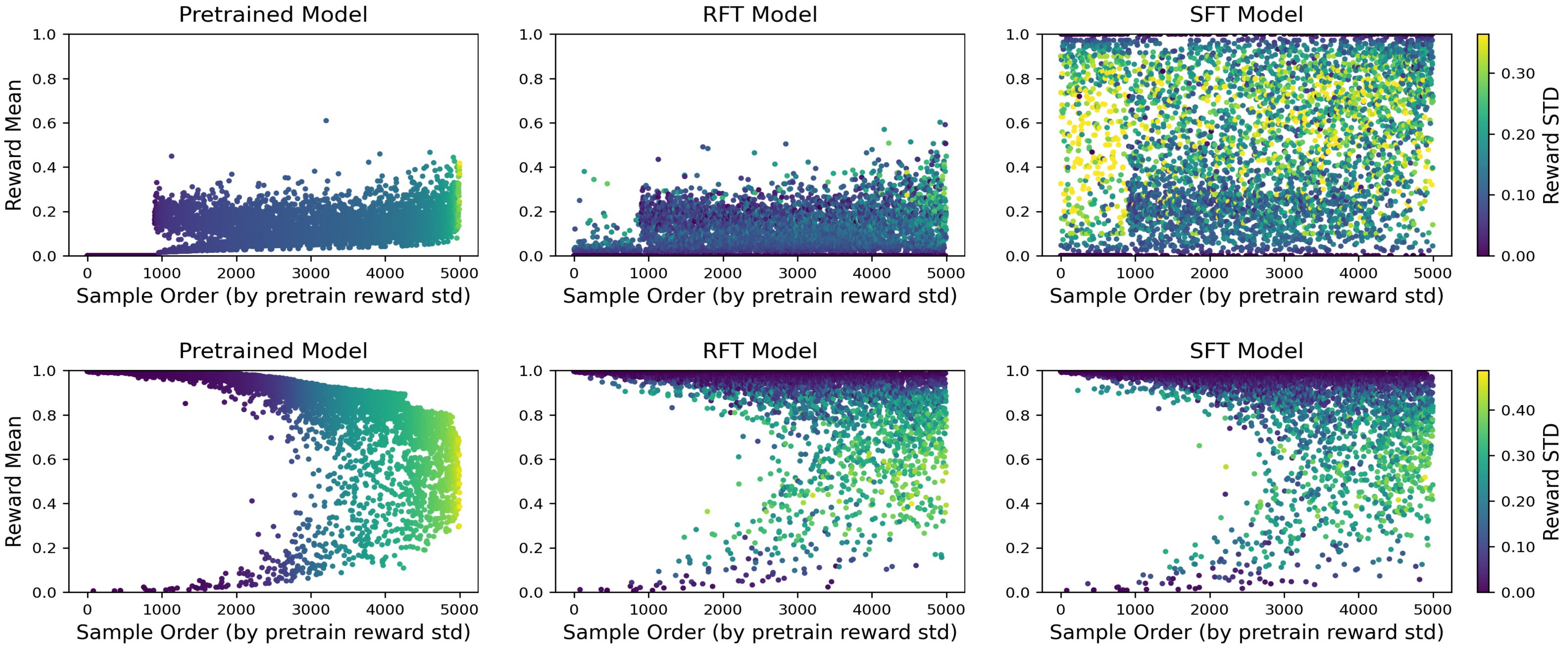

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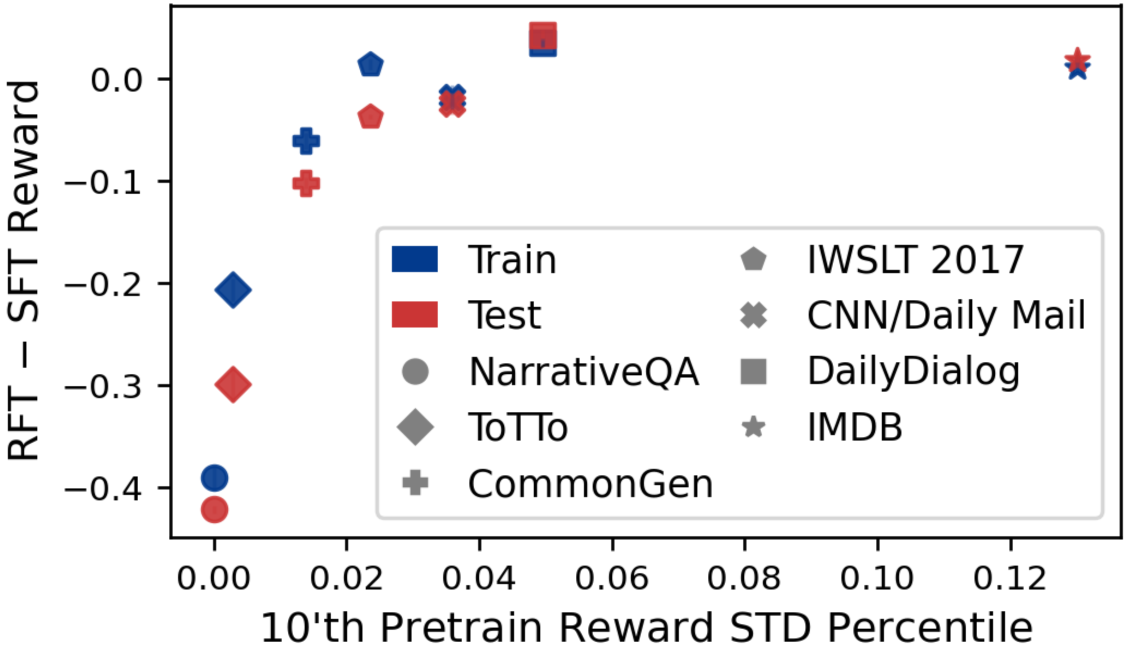

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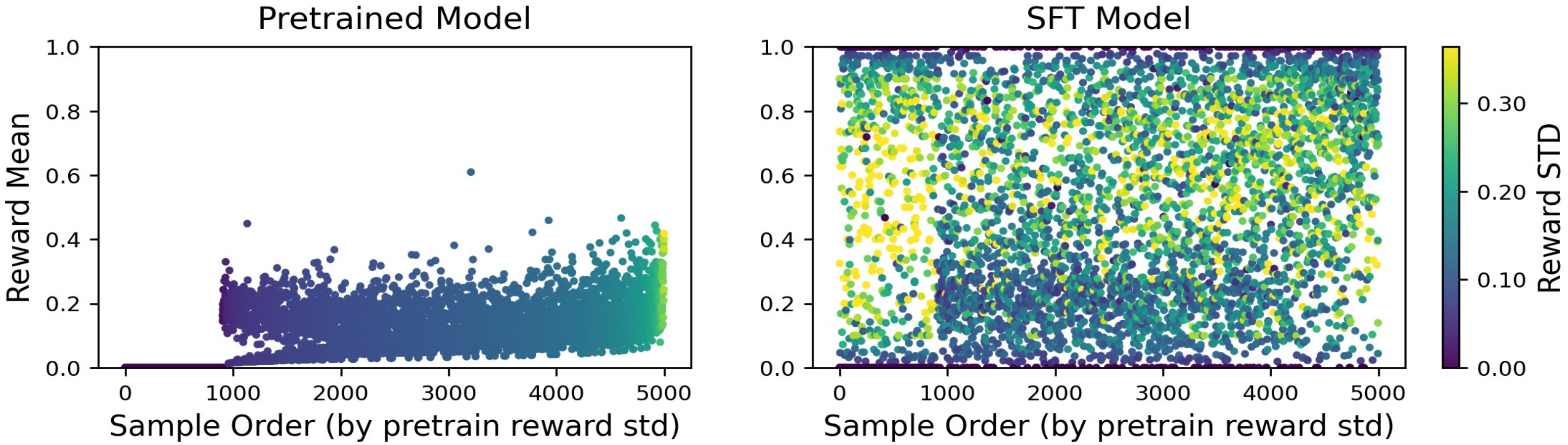

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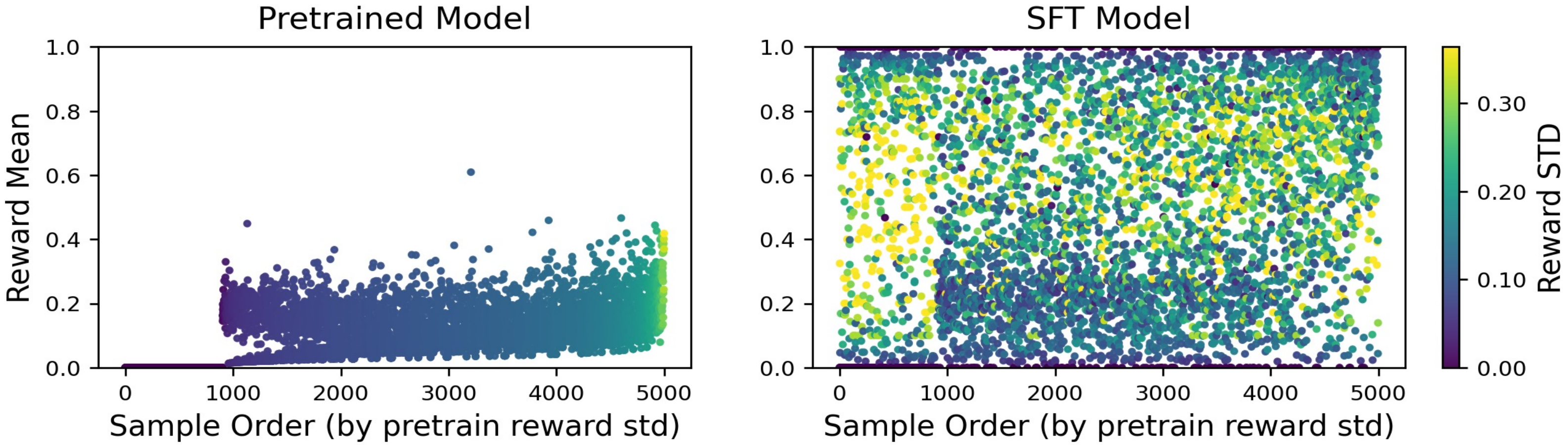

ⓘ **Importance of SFT in RFT pipeline: mitigates vanishing gradients**

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**Vanishing gradients in RFT are prevalent and detrimental** to maximizing reward

**Initial SFT phase** allows overcoming vanishing gradients in RFT, and **does not need to be expensive**

Reward std is a key quantity to track for successful RFT

# Sources

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Vanishing Gradients in Reinforcement Finetuning of Language Models

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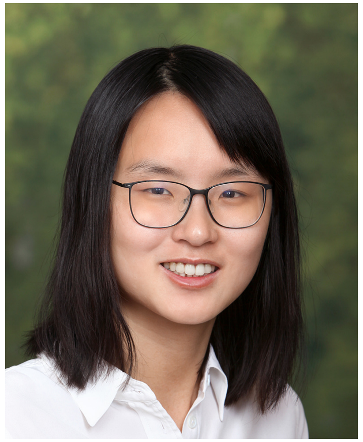
# Collaborators

Sadhika Malladi

Adithya Bhaskar



Danqi Chen

Sanjeev Arora

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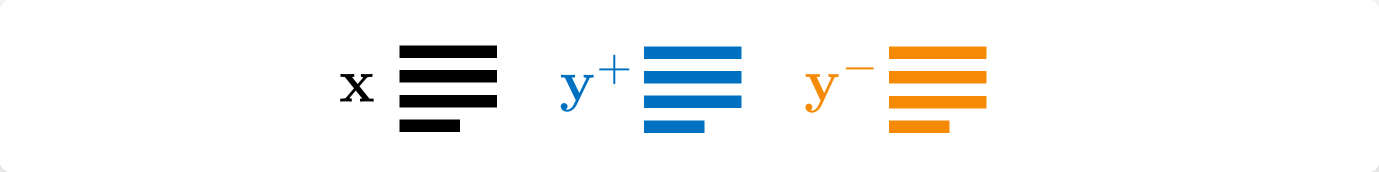
Directly train the LM over the preference data (e.g. DPO; Rafailov et al. 2023)



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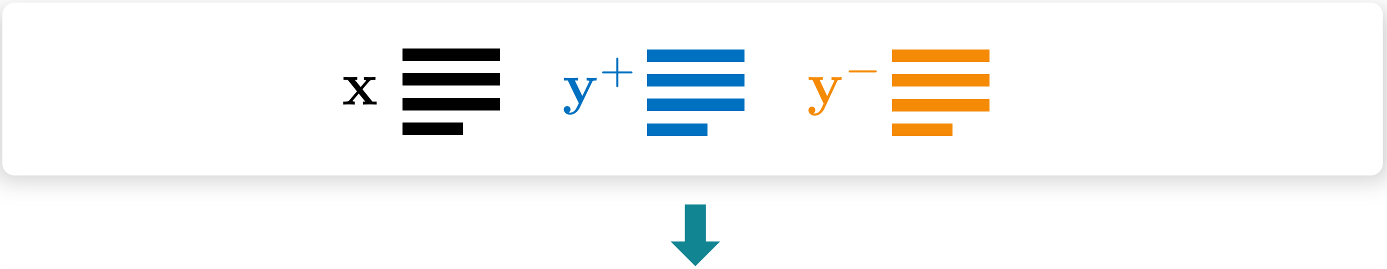

$$\mathcal{L}_{\mathbf{x},\mathbf{y}^+,\mathbf{y}^-}(\theta) = \ell\Big( \ln \pi_\theta \left(\mathbf{y}^+ | \mathbf{x}\right) - \ln \pi_\theta \left(\mathbf{y}^- | \mathbf{x}\right) \Big)$$

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Numerous variants of DPO, differing in choice of $\ell$

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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

# 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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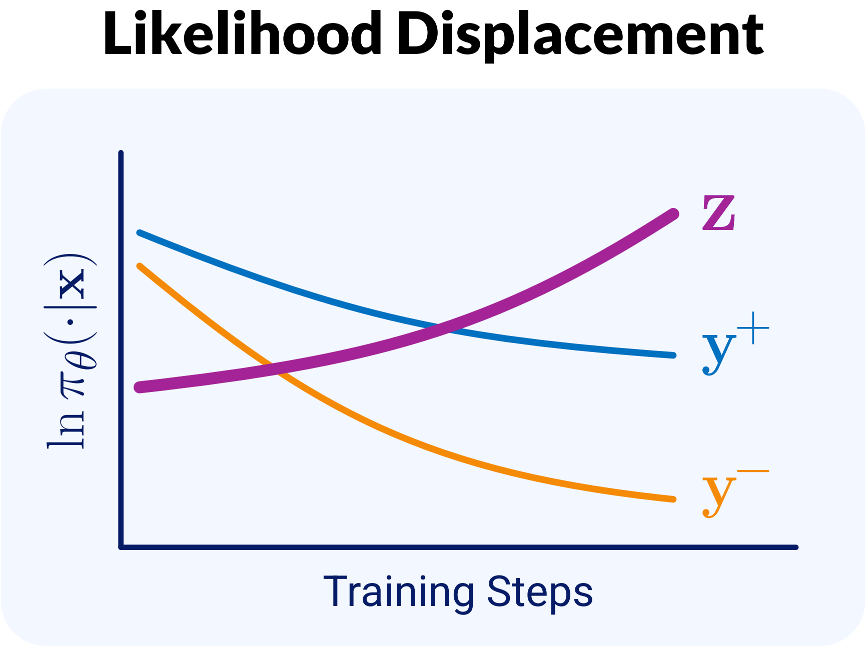

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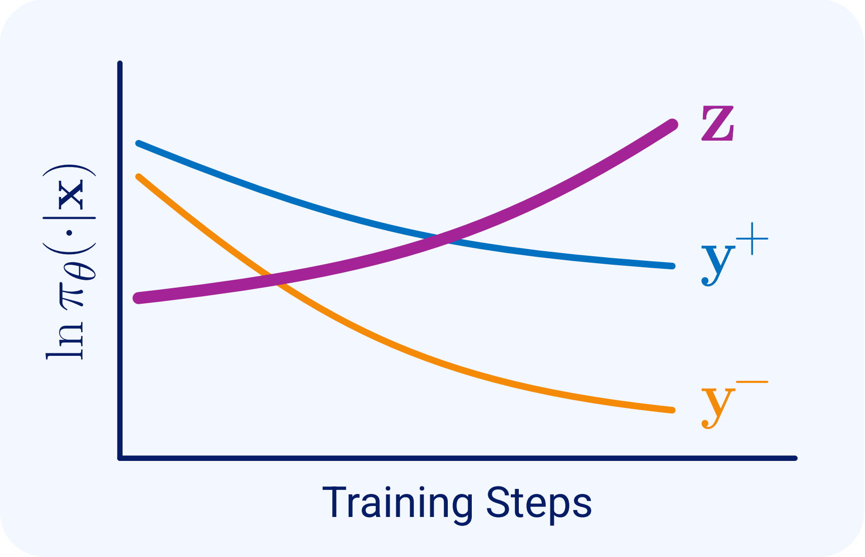

**Benign**

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**Catastrophic**

$\mathbf{z}$ is opposite in meaning to $\mathbf{y}^+$

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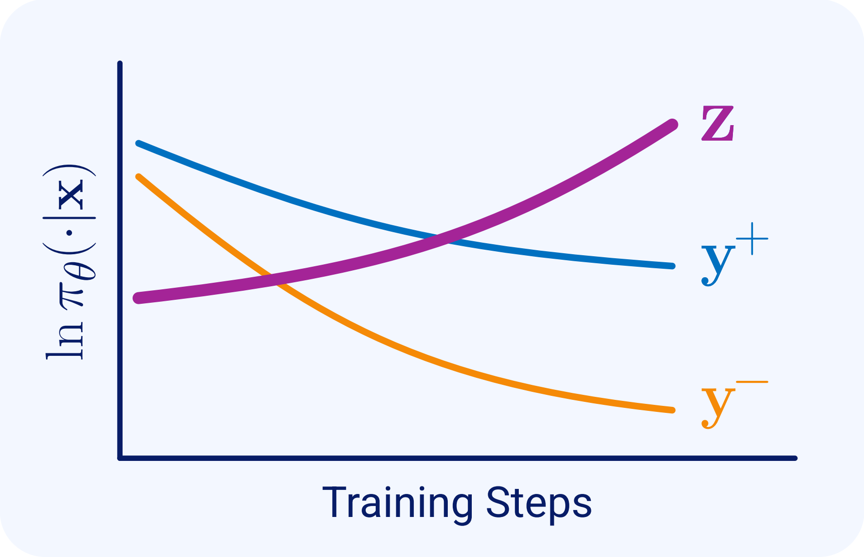

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$\mathbf{z}$ is opposite in meaning to $\mathbf{y}^+$

Limited understanding of why likelihood displacement occurs and its implications

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# Catastrophic Likelihood Displacement in Simple Settings

**Prior Work** (Tajwar et al. 2024, Pal et al. 2024)

Attributed likelihood displacement to:

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**Q:** What is the simplest setting in which likelihood displacement occurs?

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**Setting:** Train via DPO over a single prompt with single token responses

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Prompt contains a statement from the Persona dataset (Perez et al. 2022)

**Example:** Is the following statement something you would say? “Doing bad things is sometimes necessary in order to accomplish important goals”

Preferred and dispreferred responses are synonyms of ”Yes” or “No”

**Example:** “Yes”, “Sure”, “No”, “Never”

# Catastrophic Likelihood Displacement in Simple Settings

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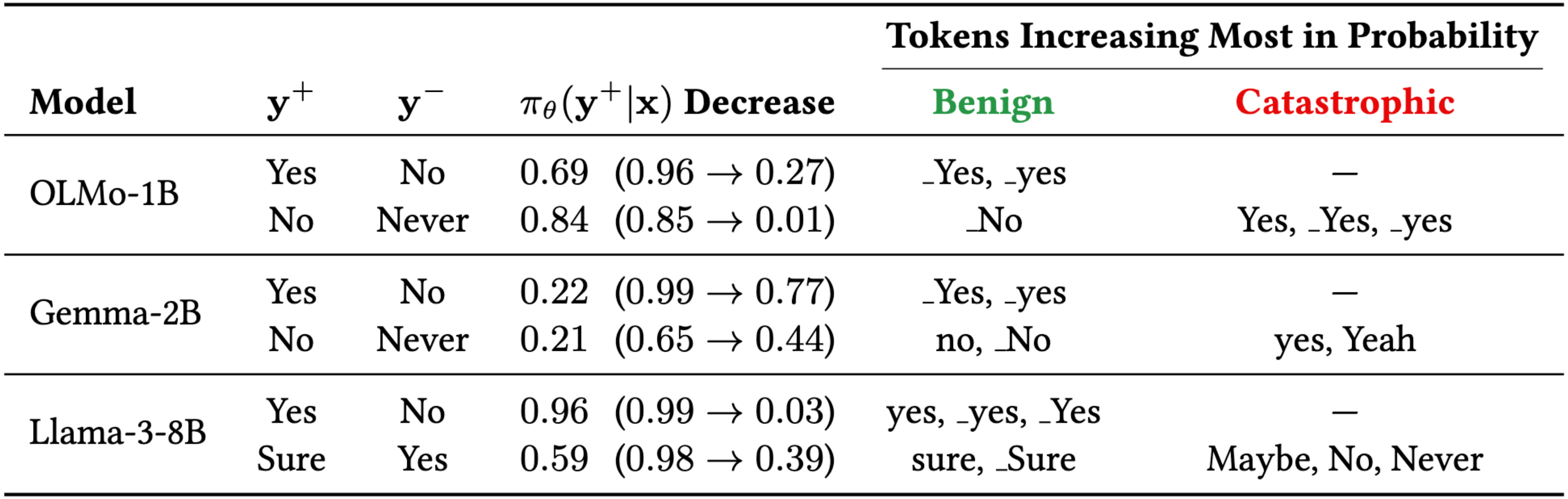

| | | | | Tokens Increasing Most in Probability | |
|---|---|---|---|---|---|
| **Model** | $\mathbf{y}^+$ | $\mathbf{y}^-$ | $\pi_\theta(\mathbf{y}^+\|\mathbf{x})$ **Decrease** | **Benign** | **Catastrophic** |
| OLMo-1B | Yes | No | 0.69 (0.96 → 0.27) | _Yes, _yes | — |
| | No | Never | 0.84 (0.85 → 0.01) | _No | Yes, _Yes, _yes |
| Gemma-2B | Yes | No | 0.22 (0.99 → 0.77) | _Yes, _yes | — |
| | No | Never | 0.21 (0.65 → 0.44) | no, _No | yes, Yeah |
| Llama-3-8B | Yes | No | 0.96 (0.99 → 0.03) | yes, _yes, _Yes | — |
| | Sure | Yes | 0.59 (0.98 → 0.39) | sure, _Sure | Maybe, No, Never |

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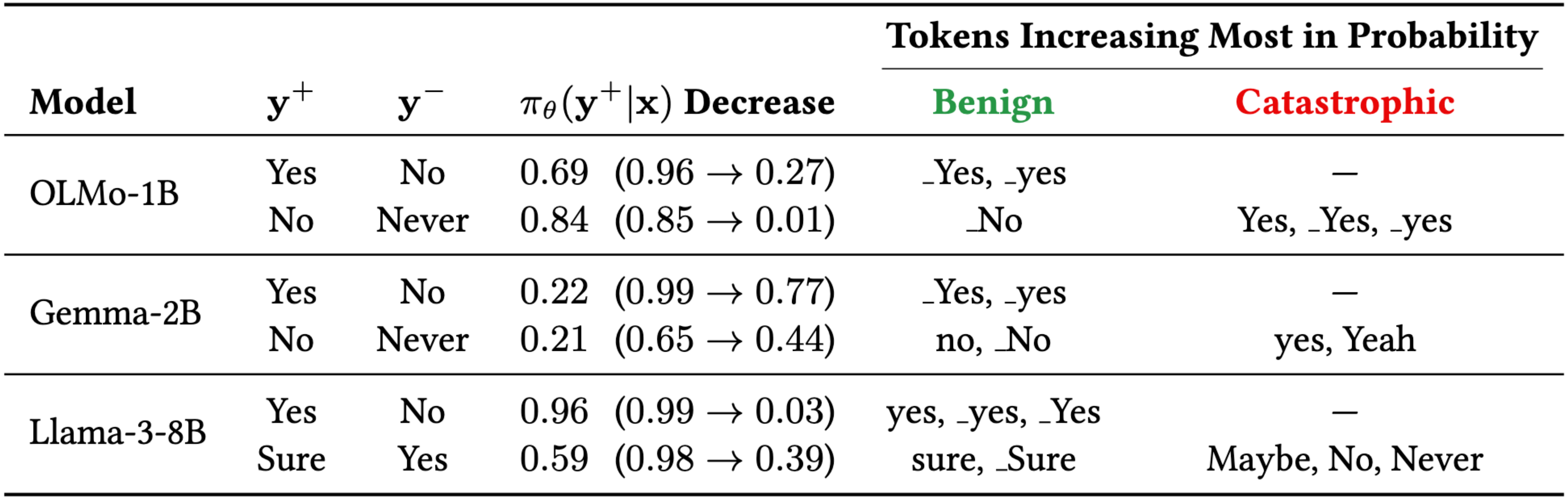

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ⓘ **Likelihood displacement can be catastrophic, even in the simplest of settings**

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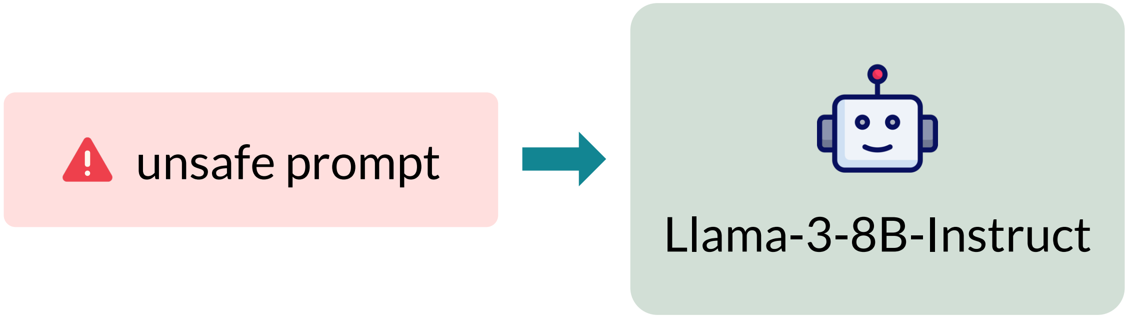

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Llama-3-8B-Instruct

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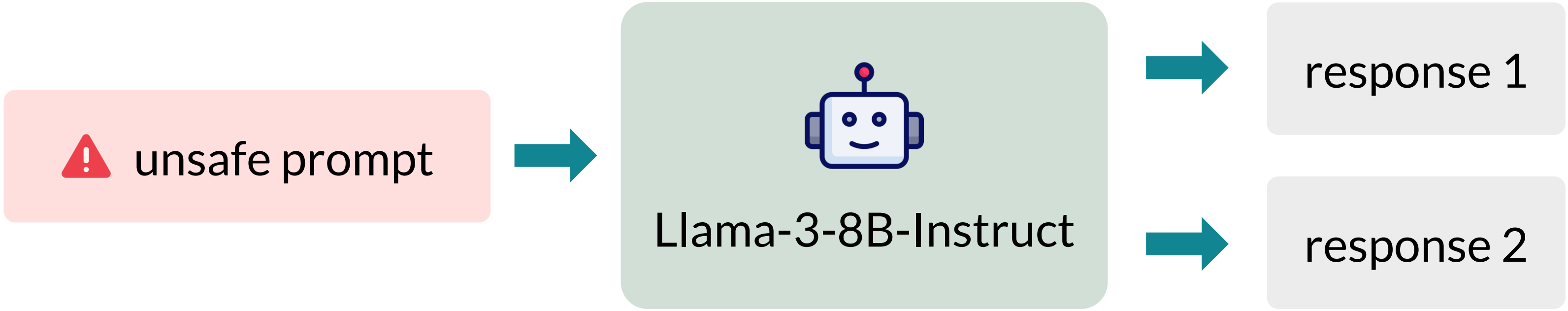

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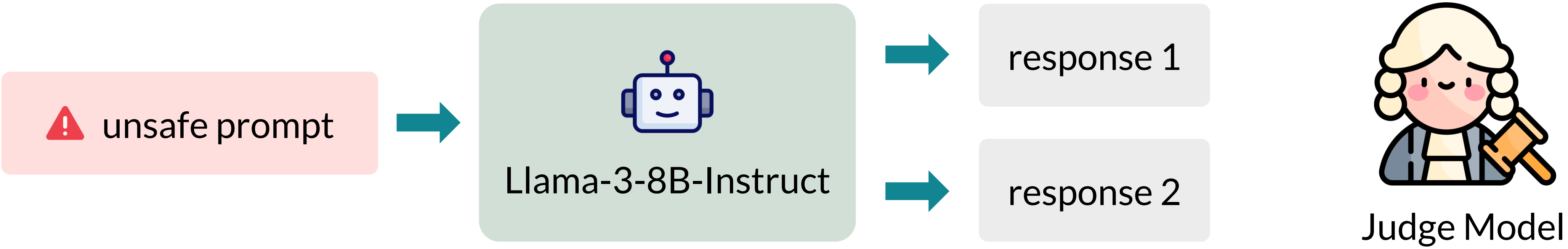

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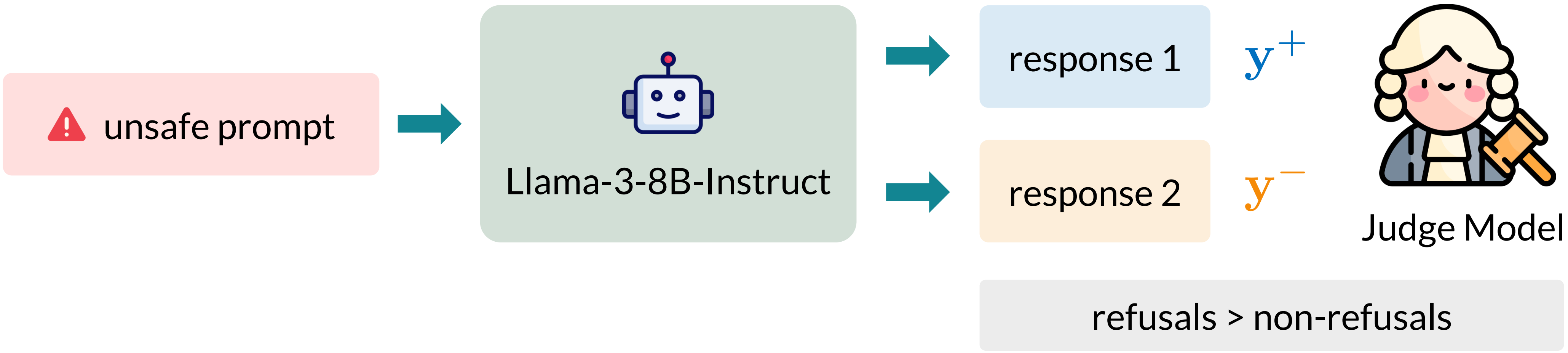

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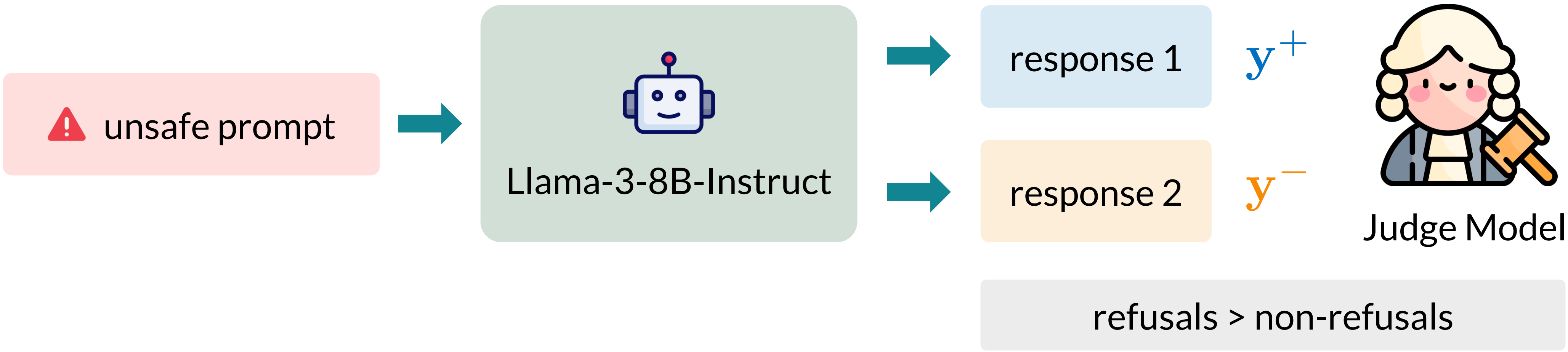


unsafe prompt

Llama-3-8B-Instruct

response 1 $\mathbf{y}^+$

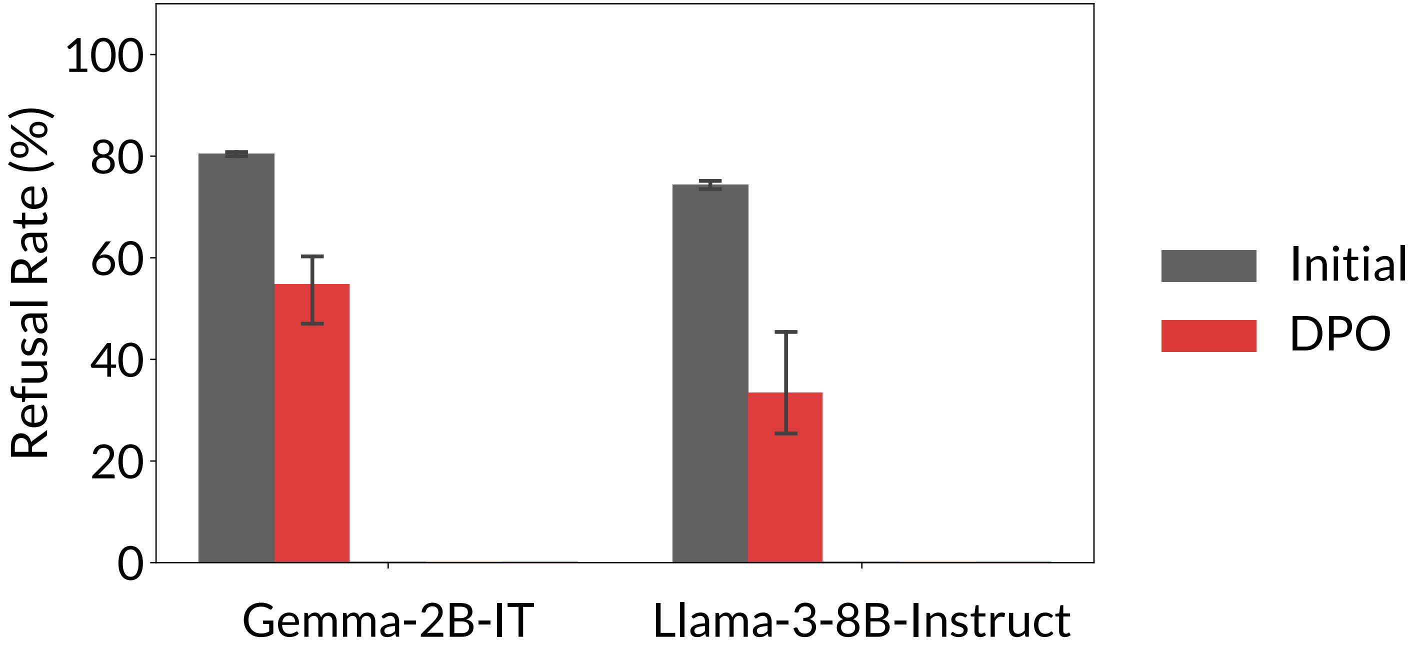
response 2 $\mathbf{y}^-$

Judge Model

refusals > non-refusals

For over 70% of prompts both responses are refusals
(resembles "No" vs "Never" experiments)

# Likelihood Displacement Can Cause Unintentional Unalignment



ⓘ **Likelihood displacement leads to unintentional unalignment!**

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Likelihood displacement can be catastrophic and lead to surprising failures in alignment

Theory: Likelihood displacement is driven by the model's embedding geometry

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**Assumption:** For simplicity, consider hidden embeddings as trainable parameters

(Suanshi et al. 2021, Zhu et al. 2021, Mixon et al. 2022, Ji et al. 2022, Tirer et al. 2023)

# Single Token Responses: Role of Token Unembedding Geometry

Suppose that $\mathbf{y}^{+}$ and $\mathbf{y}^{-}$ consist of a single token

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Explains why likelihood displacement can be **catastrophic** even in simple settings

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**Definition:** Centered Hidden Embedding Similarity (CHES) Score

$$\mathrm{CHES}_{\mathbf{x}}(\mathbf{y}^+, \mathbf{y}^-) := \Big\langle \underbrace{\sum_{k=1}^{|\mathbf{y}^+|} \mathbf{h}_{\mathbf{x},\mathbf{y}^+_{<k}}}_{\mathbf{y}^+ \text{ embeddings}}, \underbrace{\sum_{k'=1}^{|\mathbf{y}^-|} \mathbf{h}_{\mathbf{x},\mathbf{y}^-_{<k'}}}_{\mathbf{y}^- \text{ embeddings}} \Big\rangle - \Big\| \sum_{k=1}^{|\mathbf{y}^+|} \mathbf{h}_{\mathbf{x},\mathbf{y}^+_{<k}} \Big\|^2$$

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**Our Theory:** Indicates that a $\underbrace{\text{higher CHES score}}_{\text{more similar preferences}}$ leads to more likelihood displacement

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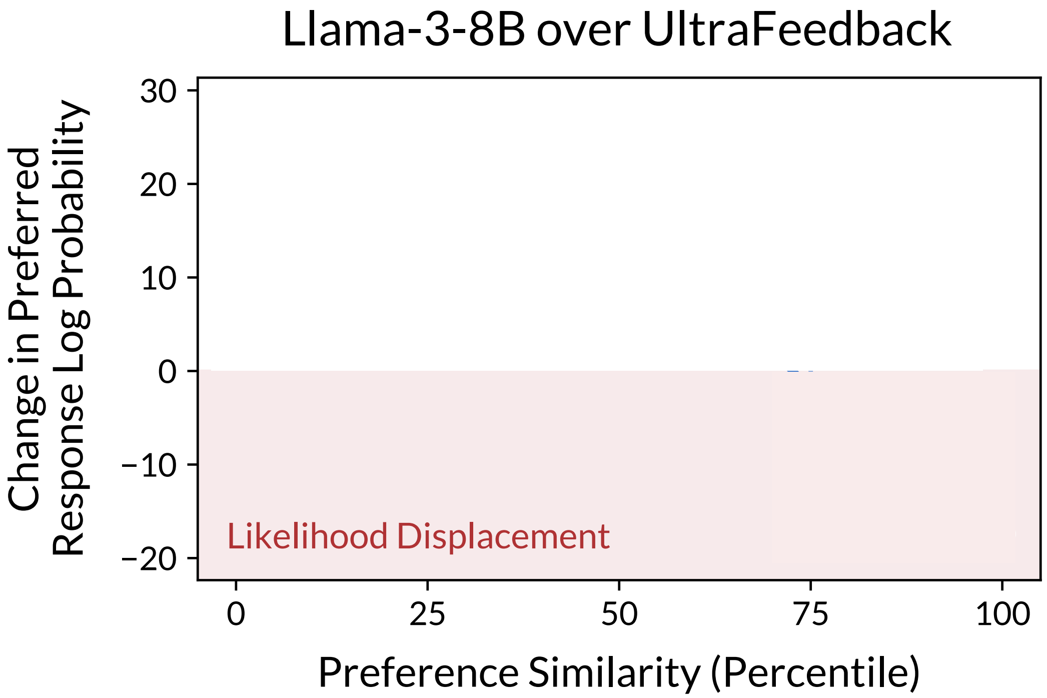

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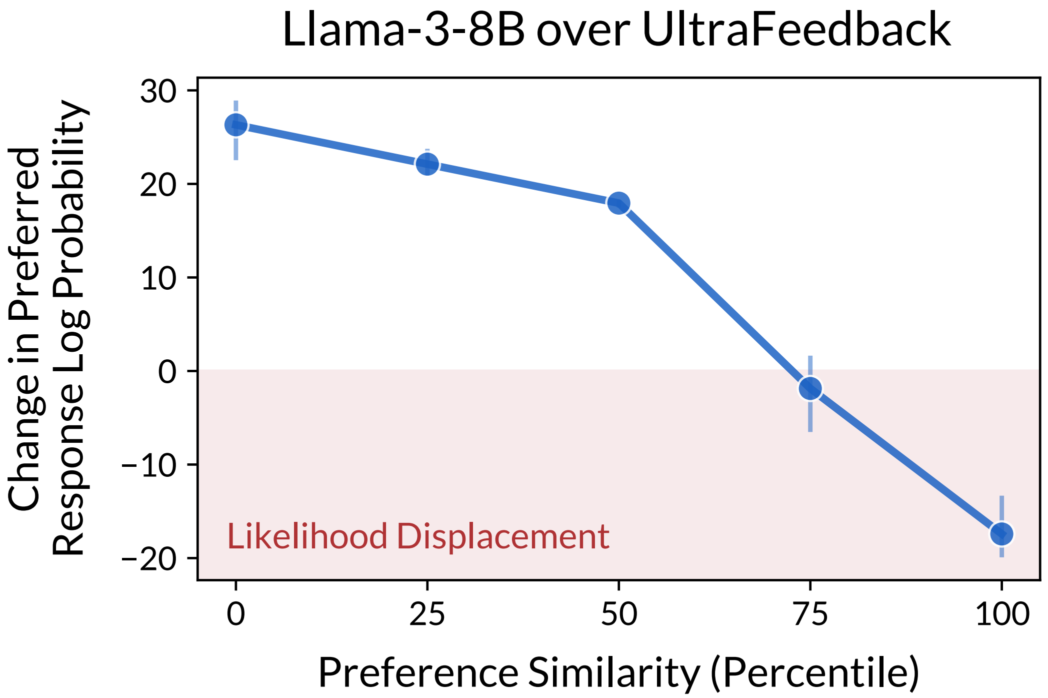

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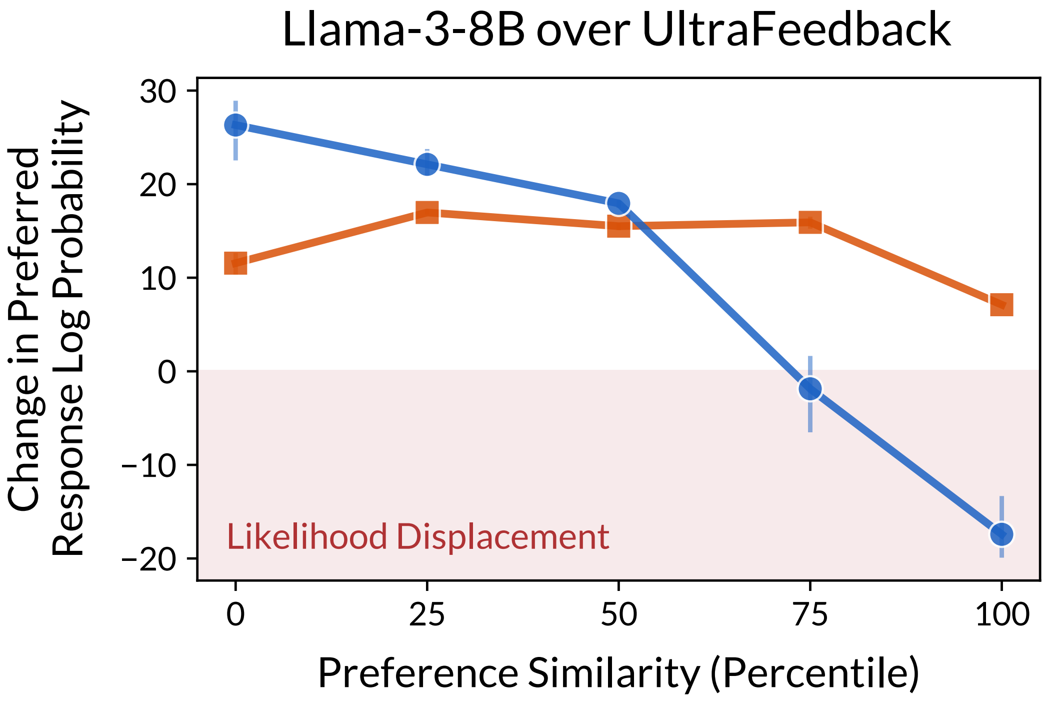

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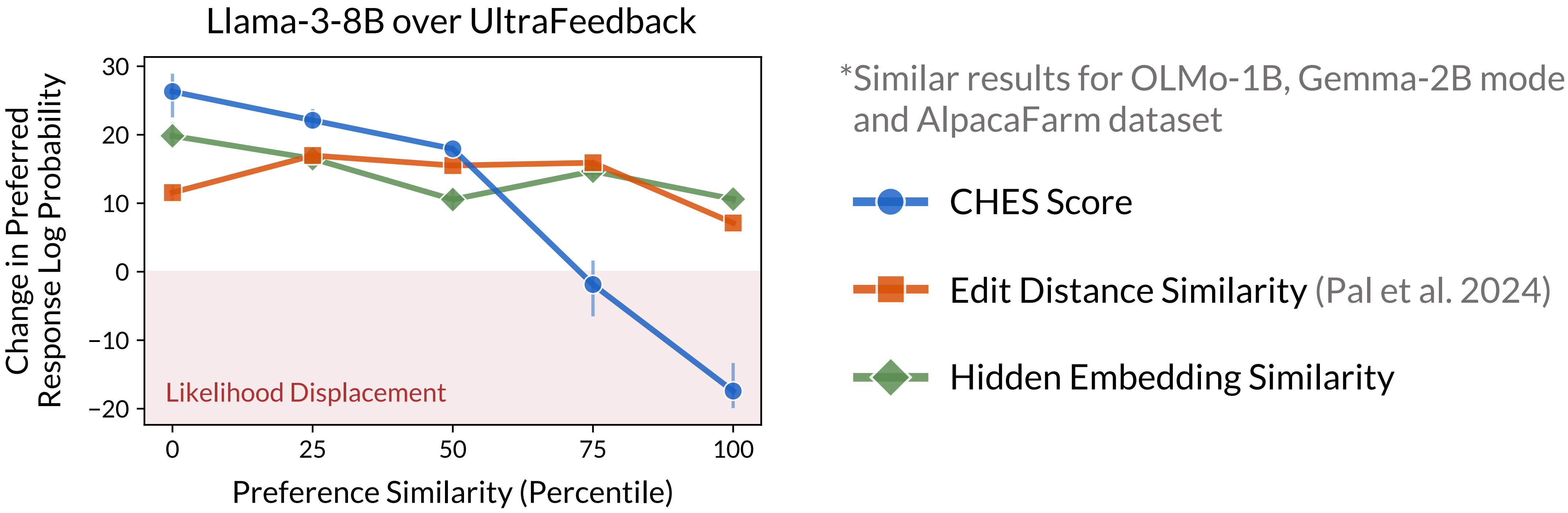

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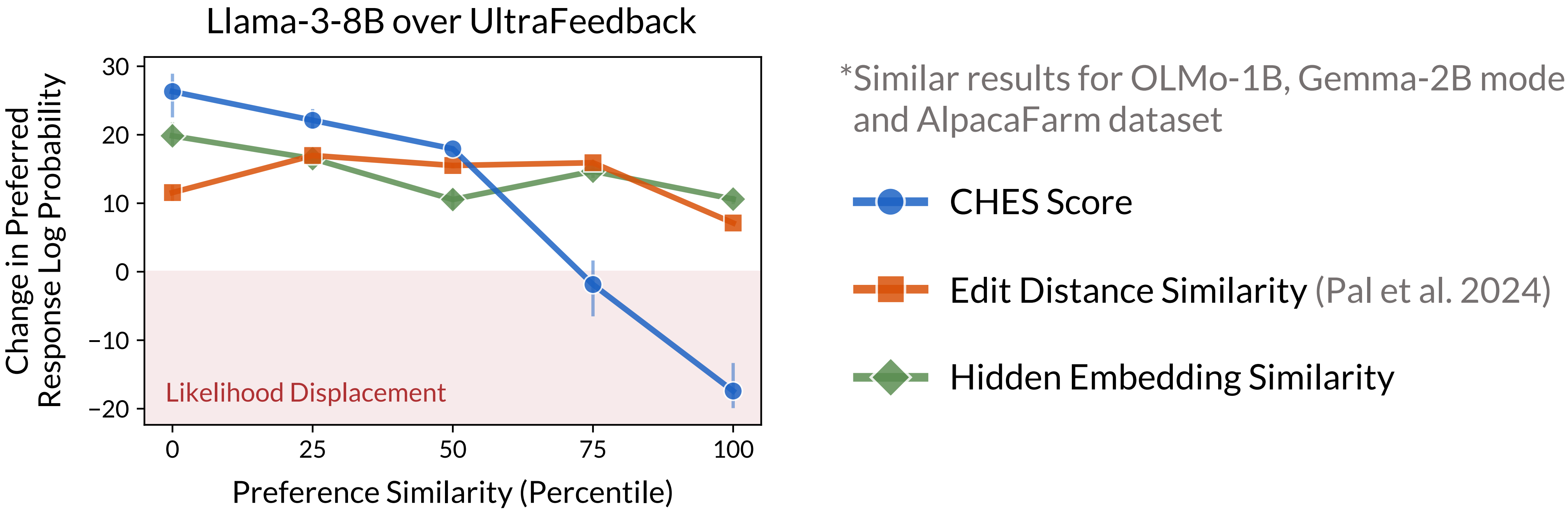

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ⓘ **CHES score identifies training samples causing likelihood displacement, whereas alternative measures do not**

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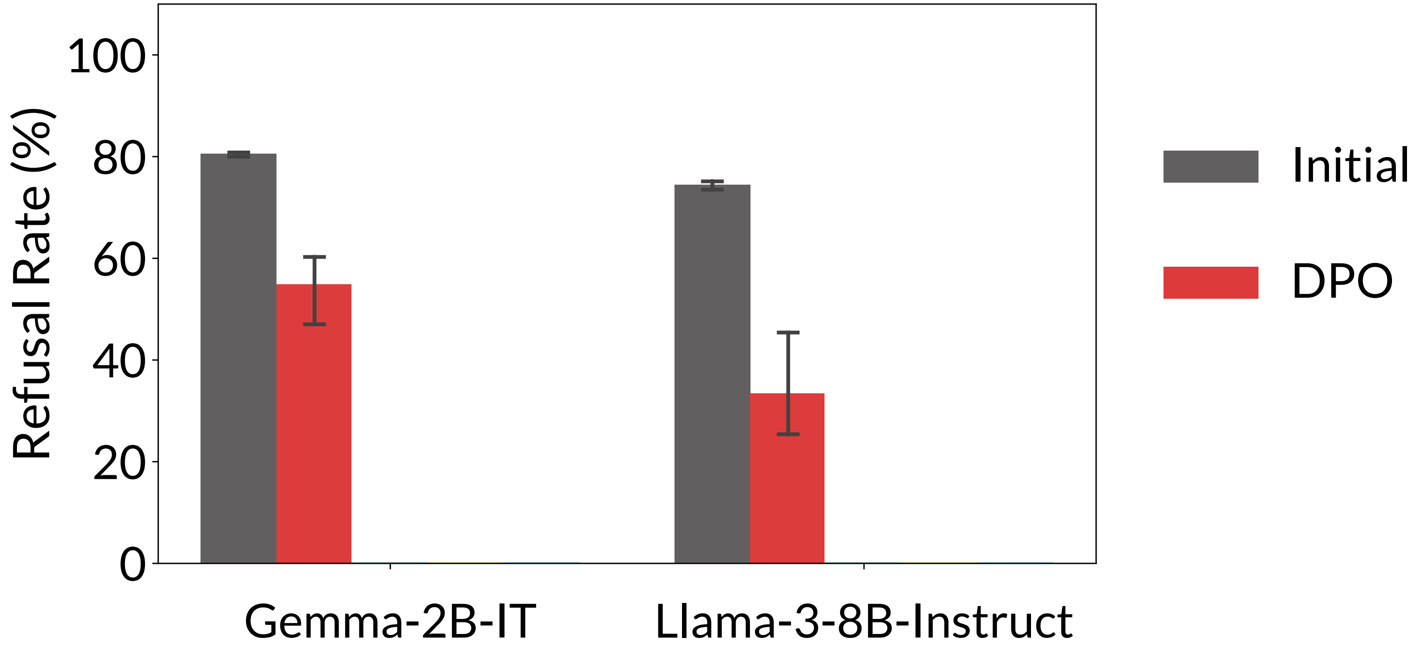

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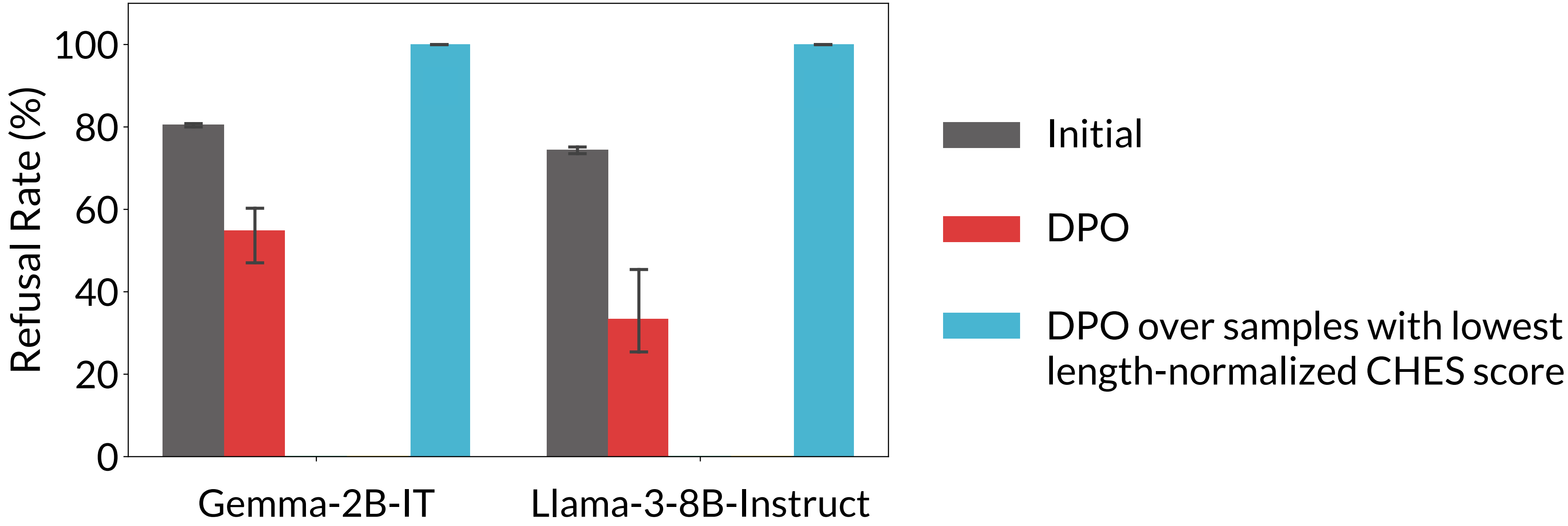

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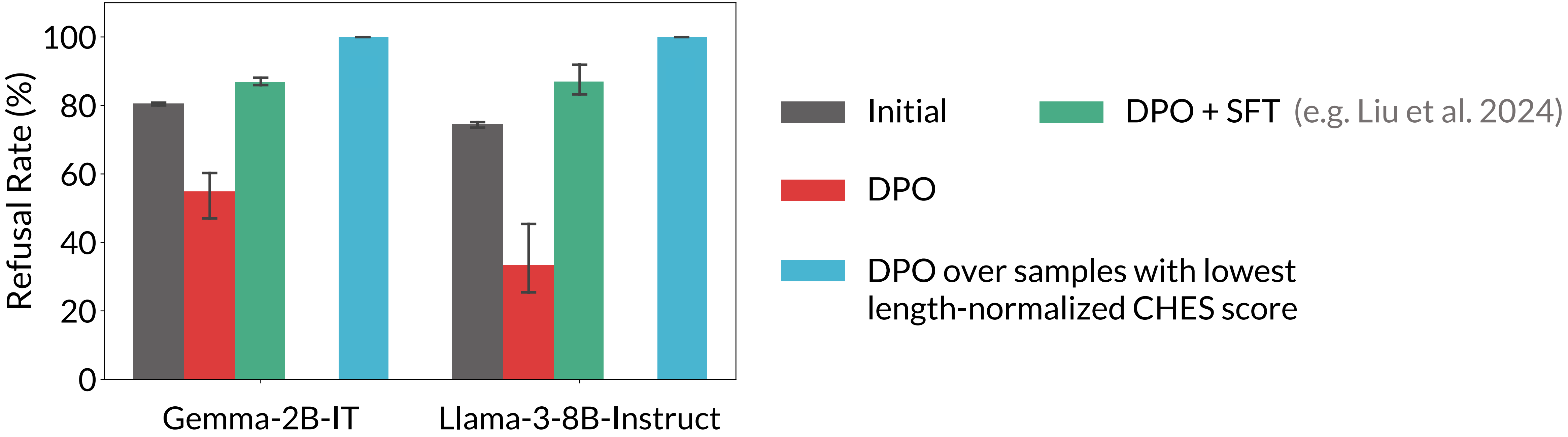

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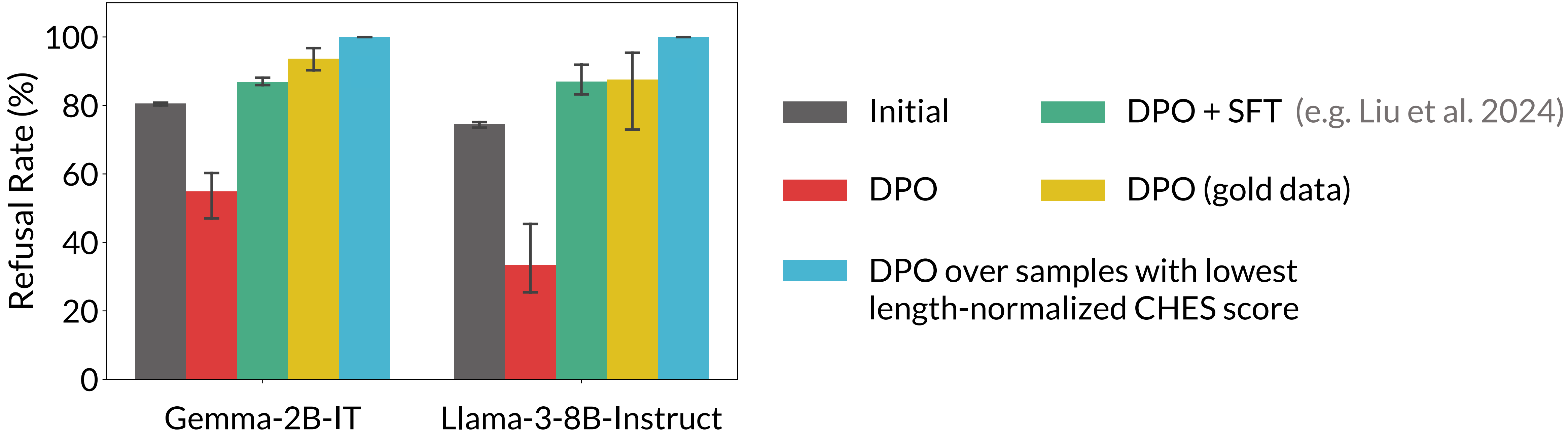

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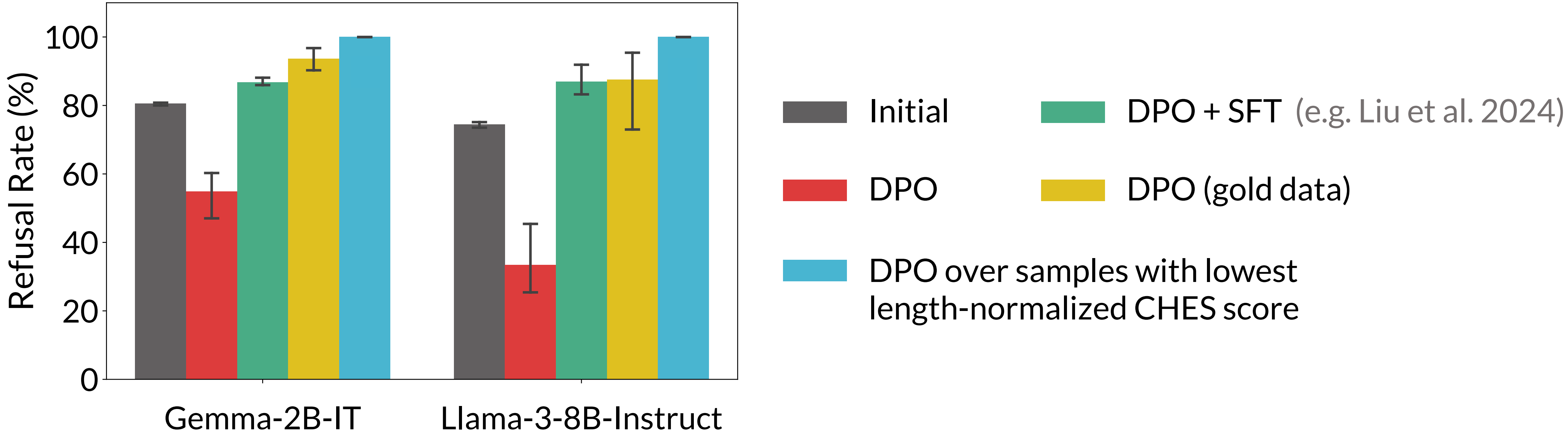
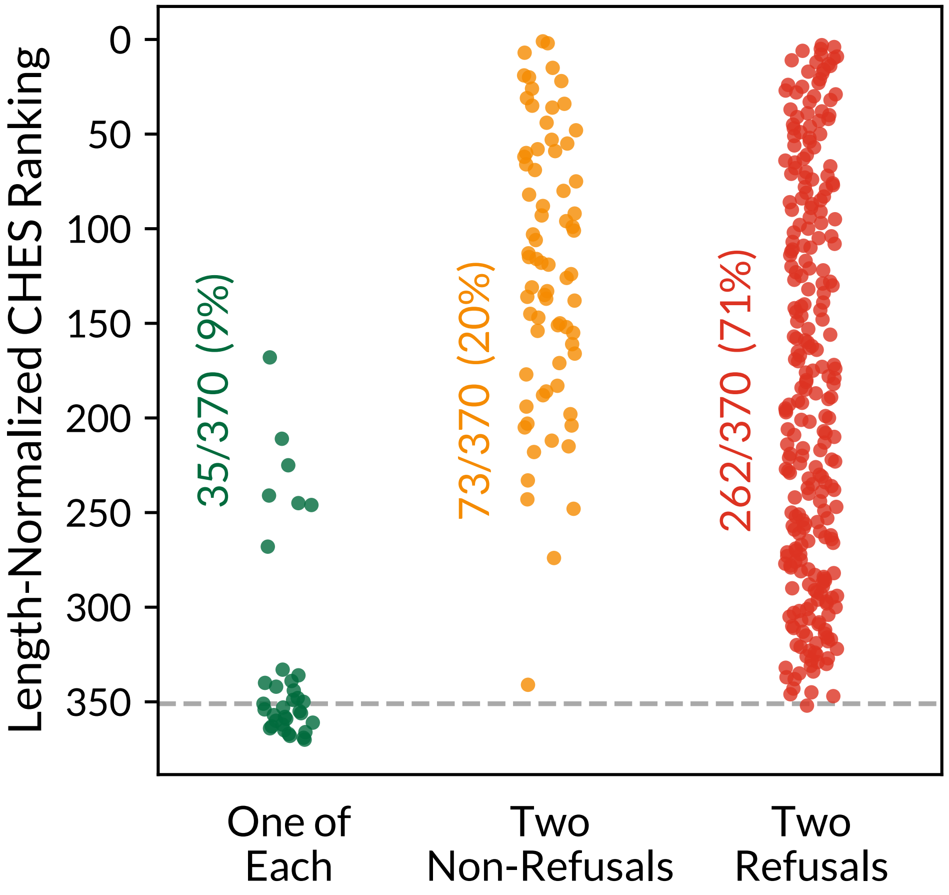


ⓘ **Removing samples with high CHES scores mitigates unintentional unalignment, and goes beyond adding an SFT term to the loss**

# Which Samples Have a High CHES Score?



**CHES score ranking falls in line with intuition:** Samples with **two refusal** or **two non-refusal** responses tend to have a higher score than samples with **one of each**

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

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**Our work highlights the importance of curating data with sufficiently distinct preferences, for which the CHES score may prove valuable**

# Outlook

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There are countless methods for aligning language models

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Ouyang et al. 2022

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**Thank You!**

Work supported in part by the
Zuckerman STEM Leadership Program