Unintentional Unalignment: Likelihood Displacement in Direct Preference Optimization

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Deep Learning: Classics and Trends

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Collaborators

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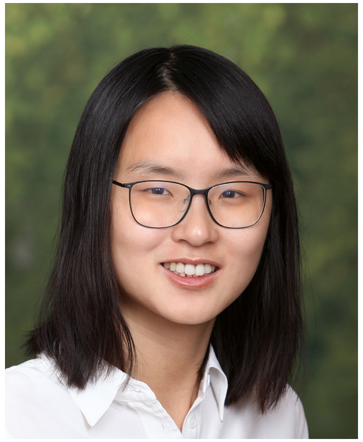


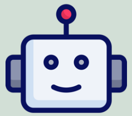
Danqi Chen

Sanjeev Arora

Boris Hanin

Language Models

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



LM π_θ

θ - parameters

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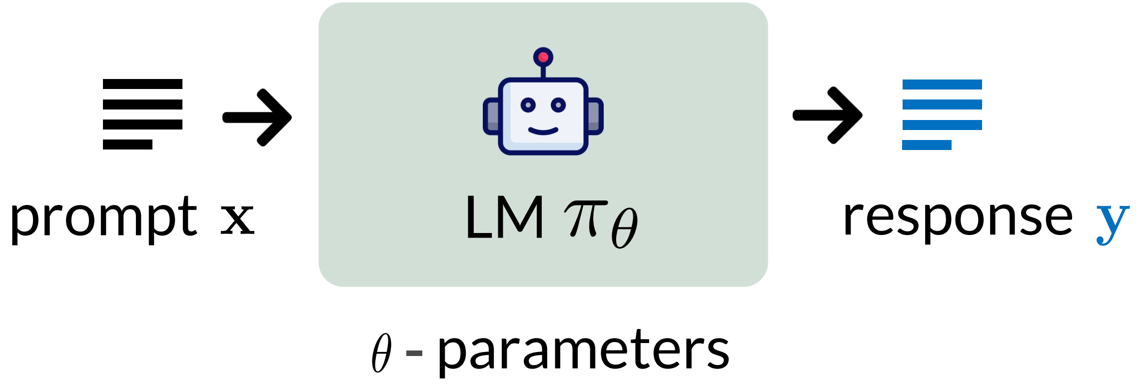

Supervised Finetuning of LMs

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Minimize cross entropy loss over labeled inputs

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

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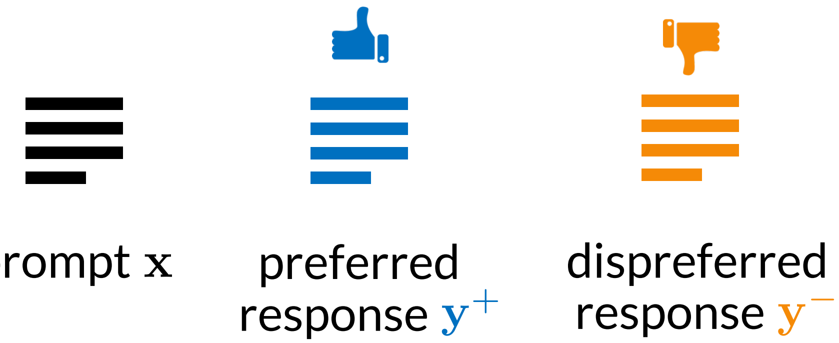

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Data Format:

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

> Obtaining preference data can be easier than high-quality responses

Reinforcement Learning from Human Feedback

Reinforcement Learning from Human Feedback (RLHF; Ouyang et al. 2022**)**

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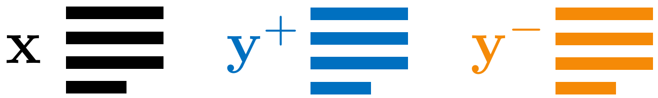
1. Learn a **reward model** $r(\mathbf{x}, \mathbf{y})$ by fitting preference data



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- Expensive in terms of memory and compute

Direct Preference Learning

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

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

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Numerous variants of DPO, differing in choice of 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

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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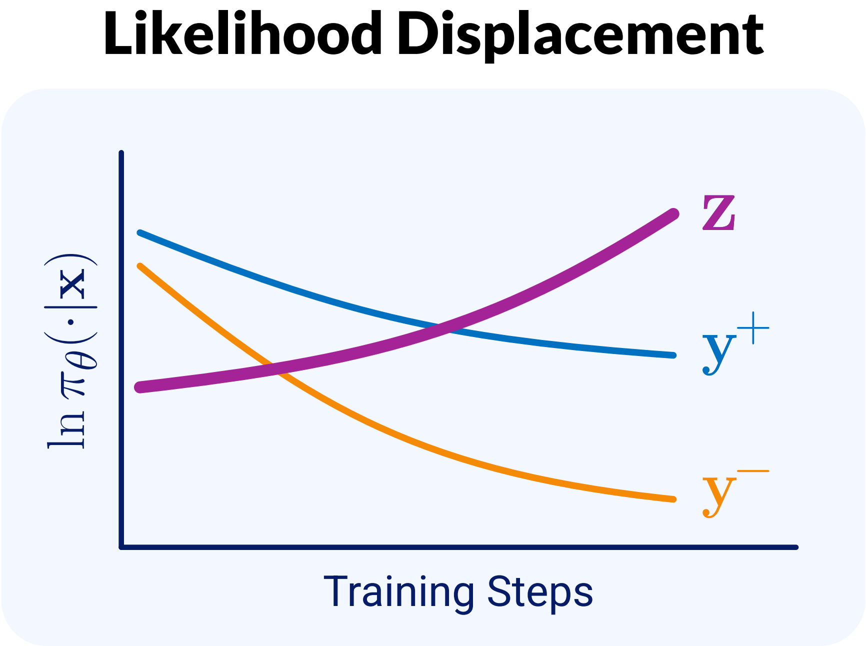

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Likelihood Displacement

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

Catastrophic
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Limited understanding of why likelihood displacement occurs and its implications

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Catastrophic Likelihood Displacement in Simple Settings

Prior Work (e.g. Tajwar et al. 2024, Pal et al. 2024)

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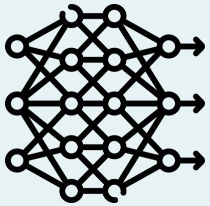
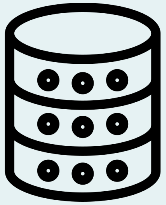


dataset size



token overlap

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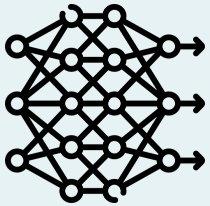

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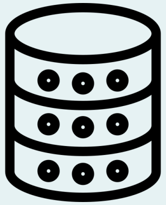

token overlap

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

Catastrophic Likelihood Displacement in Simple Settings

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"

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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

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

Model	$\mathbf{y}^+$	$\mathbf{y}^-$
OLMo-1B	Yes	No
	No	Never
Gemma-2B	Yes	No
	No	Never
Llama-3-8B	Yes	No
	Sure	Yes

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Model	$\mathbf{y}^+$	$\mathbf{y}^-$	$\pi_\theta(\mathbf{y}^+\|\mathbf{x})$ **Decrease**
OLMo-1B	Yes	No	$0.69 \ \ (0.96 \rightarrow 0.27)$
	No	Never	$0.84 \ \ (0.85 \rightarrow 0.01)$
Gemma-2B	Yes	No	$0.22 \ \ (0.99 \rightarrow 0.77)$
	No	Never	$0.21 \ \ (0.65 \rightarrow 0.44)$
Llama-3-8B	Yes	No	$0.96 \ \ (0.99 \rightarrow 0.03)$
	Sure	Yes	$0.59 \ \ (0.98 \rightarrow 0.39)$

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	No	Never	0.84 (0.85 → 0.01)	_No	Yes, _Yes, _yes
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ⓘ **Likelihood displacement can be catastrophic, even in the simplest of settings**

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Setting: Train a (moderately aligned) language model to refuse unsafe prompts via DPO

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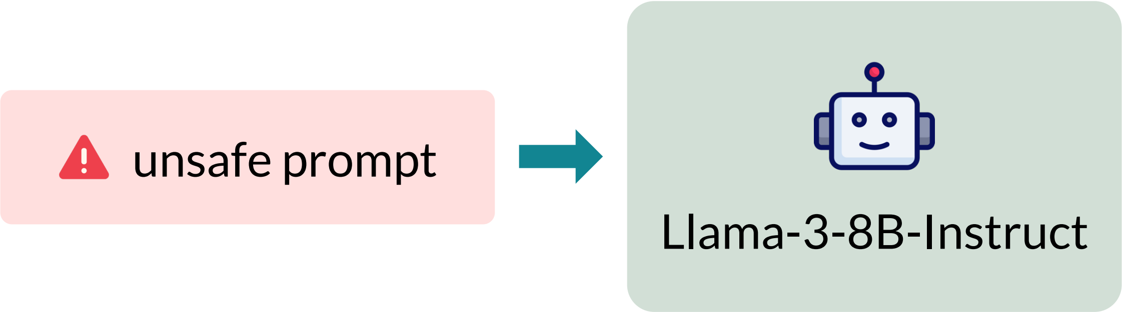

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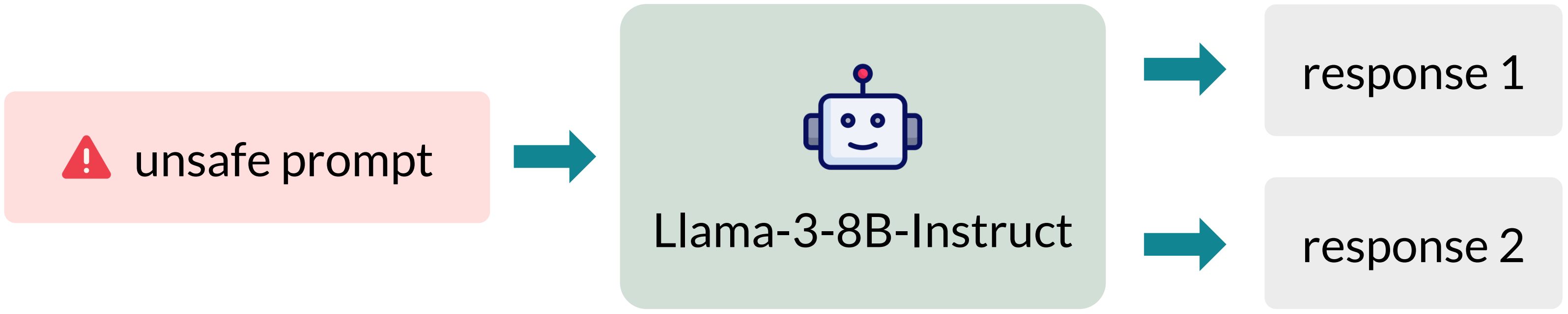

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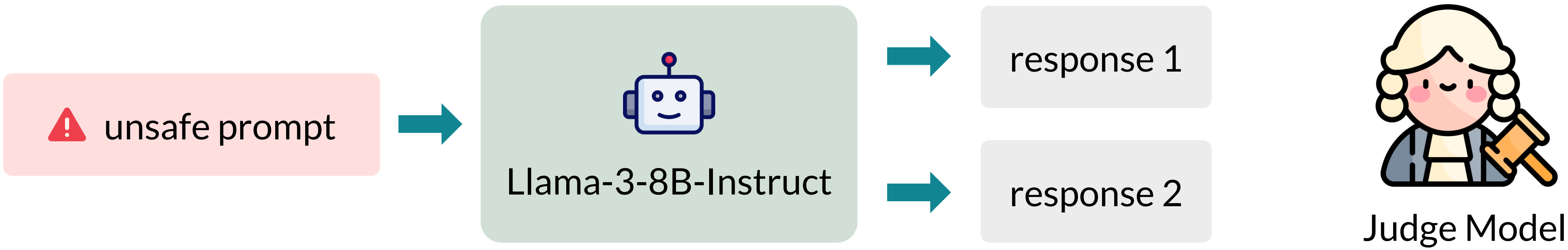

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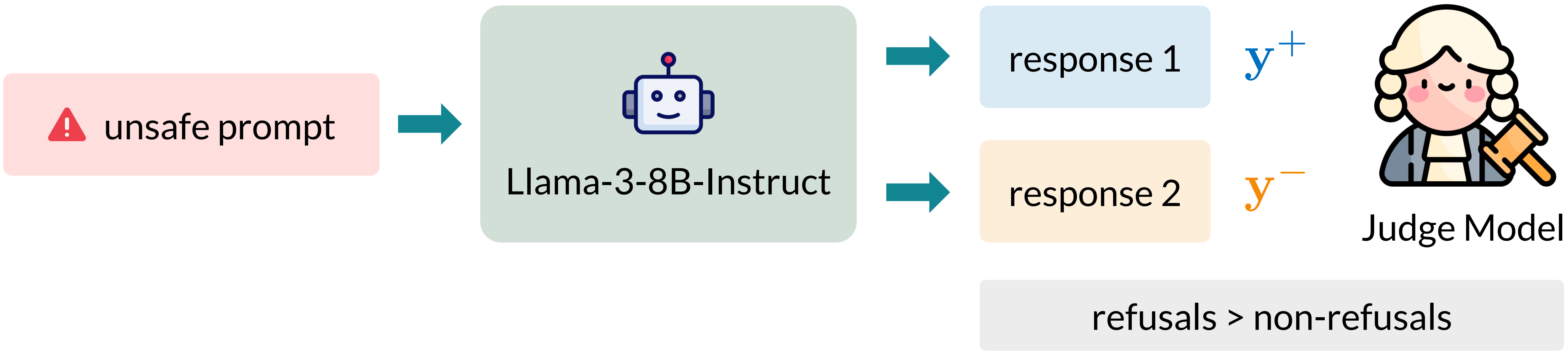

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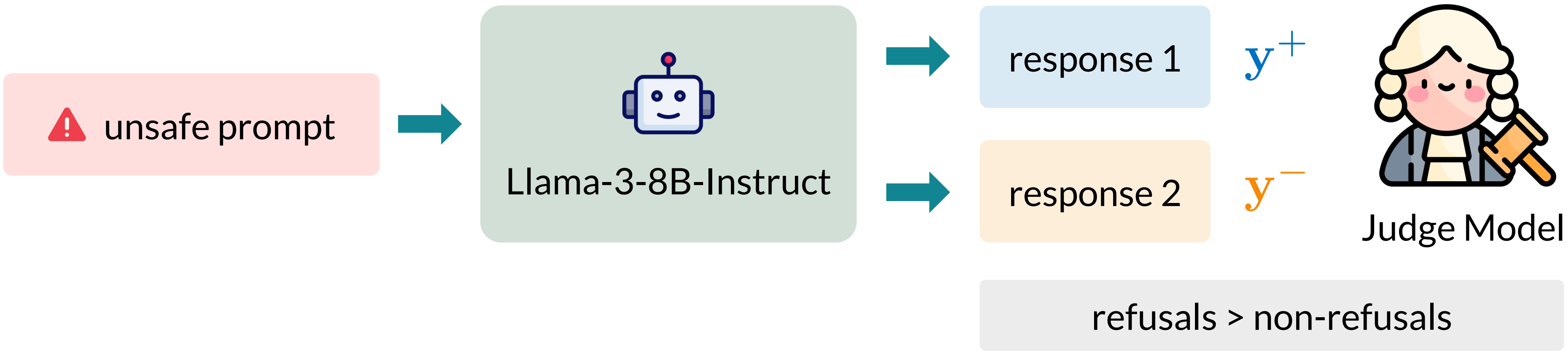
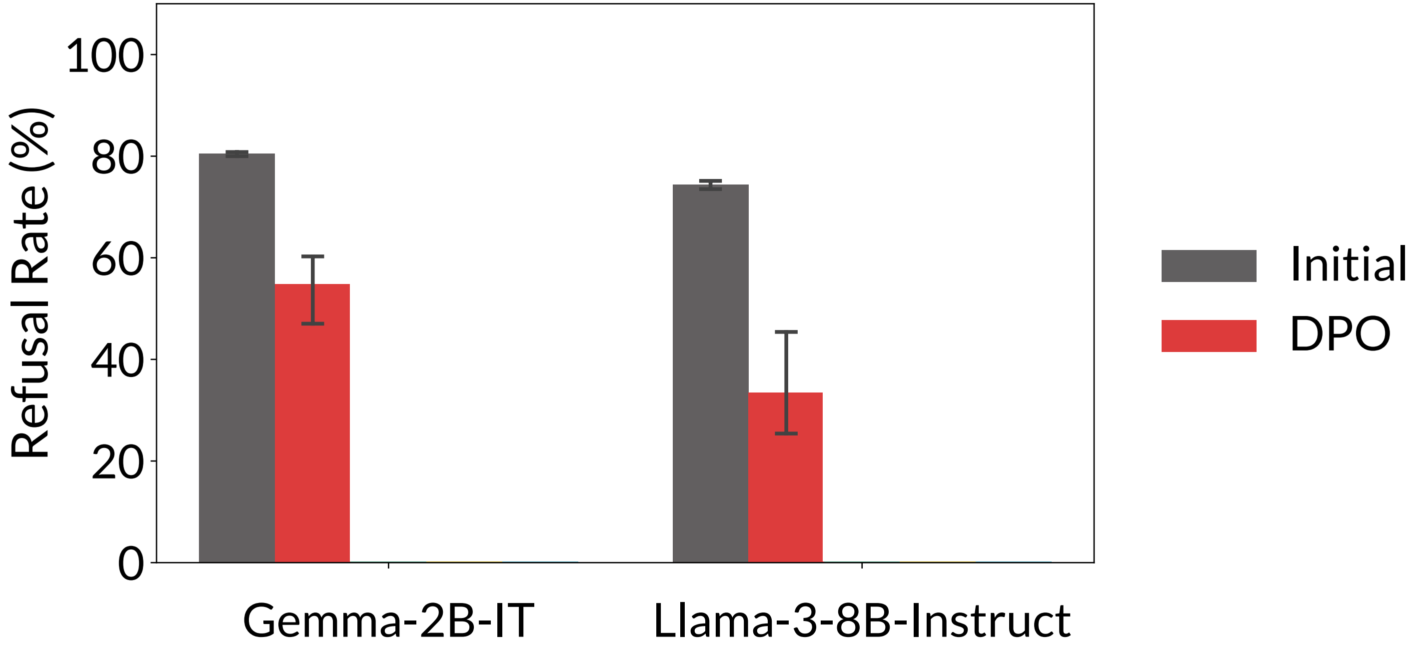


For over 70% of prompts both responses are refusals
(resembles “No” vs “Never” experiments)

Likelihood Displacement Can Cause Unintentional Unalignment



Likelihood displacement leads to unintentional unalignment!

Main Contributions

- Likelihood displacement can be catastrophic and lead to surprising failures in alignment
- Theory: Likelihood displacement is driven by the model’s embedding geometry
- Mitigating likelihood displacement via data filtering

Theoretical Analysis of Likelihood Displacement: Approach

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Goal: Characterize how $\ln \pi_\theta(\mathbf{z}|\mathbf{x})$ changes during training

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2 token unembeddings matrix $\mathbf{W}$

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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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2. $\langle \mathbf{W}_{\mathbf{z}}, \mathbf{W}_{\mathbf{y}^+} - \mathbf{W}_{\mathbf{y}^-} \rangle$ for tokens $\mathbf{z} \neq \mathbf{y}^+, \mathbf{y}^-$

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$$\underbrace{\qquad\qquad\qquad\qquad\qquad\qquad}$$

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

Multiple Token Responses: Role of Hidden Embedding Geometry

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$$\sum_{k=1}^{|\mathbf{y}^+|}\sum_{k'=1}^{|\mathbf{y}^-|} \alpha^-_{k,k'} \cdot \underbrace{\left\langle \mathbf{h}_{\mathbf{x},\mathbf{y}^+_{<k}}, \mathbf{h}_{\mathbf{x},\mathbf{y}^-_{<k'}} \right\rangle}_{\text{preferred-dispreferred alignment}} - \sum_{k=1}^{|\mathbf{y}^+|}\sum_{k'=1}^{|\mathbf{y}^+|} \alpha^+_{k,k'} \cdot \underbrace{\left\langle \mathbf{h}_{\mathbf{x},\mathbf{y}^+_{<k}}, \mathbf{h}_{\mathbf{x},\mathbf{y}^+_{<k'}} \right\rangle}_{\text{preferred-preferred alignment}}$$

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Theorem: When does likelihood displacement occur?

At any training step, in addition to the dependence on token unembeddings, $\ln \pi_\theta\left(\mathbf{y}^+|\mathbf{x}\right)$ decreases more the larger the following term is:

$$\sum_{k=1}^{|\mathbf{y}^+|} \sum_{k'=1}^{|\mathbf{y}^-|} \alpha^-_{k,k'} \cdot \underbrace{\left\langle \mathbf{h}_{\mathbf{x},\mathbf{y}^+_{<k}}, \mathbf{h}_{\mathbf{x},\mathbf{y}^-_{<k'}} \right\rangle}_{\text{preferred-dispreferred alignment}} - \sum_{k=1}^{|\mathbf{y}^+|} \sum_{k'=1}^{|\mathbf{y}^+|} \alpha^+_{k,k'} \cdot \underbrace{\left\langle \mathbf{h}_{\mathbf{x},\mathbf{y}^+_{<k}}, \mathbf{h}_{\mathbf{x},\mathbf{y}^+_{<k'}} \right\rangle}_{\text{preferred-preferred alignment}}$$

$\alpha^-_{k,k'}, \alpha^+_{k,k'} \in [-2, 2]$ are determined by the model's next-token distributions

Centered Hidden Embedding Similarity (CHES) Score

Empirical Observation: $\alpha^{-}_{k,k'}, \alpha^{+}_{k,k'}$ coefficients are mostly positive

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Definition: Centered Hidden Embedding Similarity (CHES) Score

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

*The CHES score is model-dependent

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*The CHES score is model-dependent

Our theory indicates that a higher CHES score leads to more likelihood displacement

Main Contributions

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

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

Mitigating likelihood displacement via data filtering

Identifying Sources of Likelihood Displacement

Q: How indicative is the CHES score of likelihood displacement?

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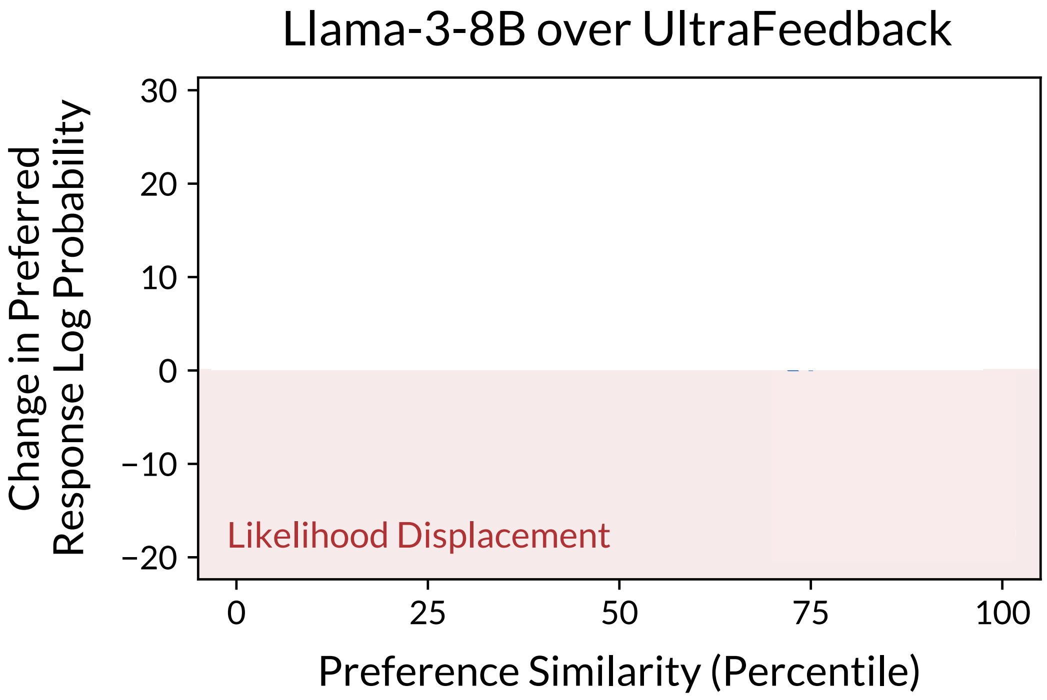

*Similar results for OLMo-1B, Gemma-2B models and AlpacaFarm dataset

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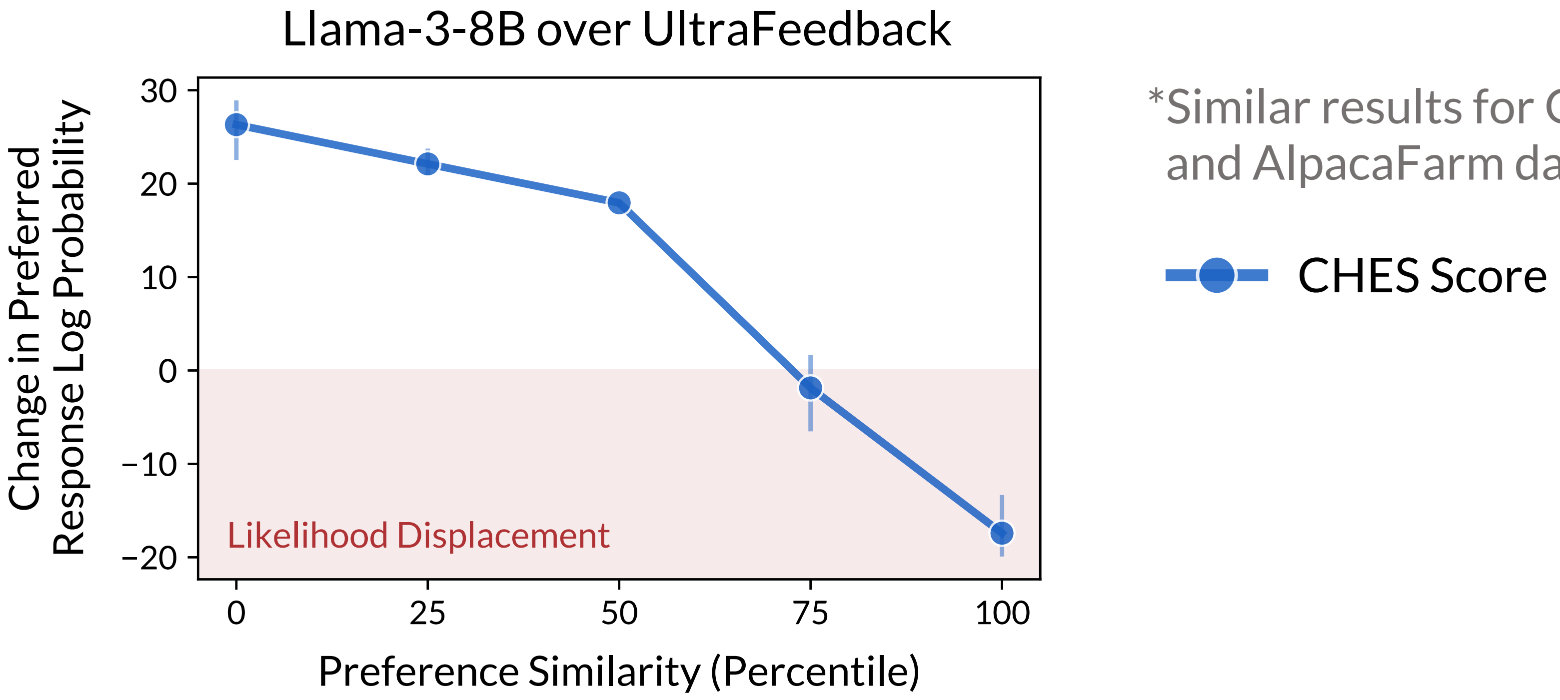

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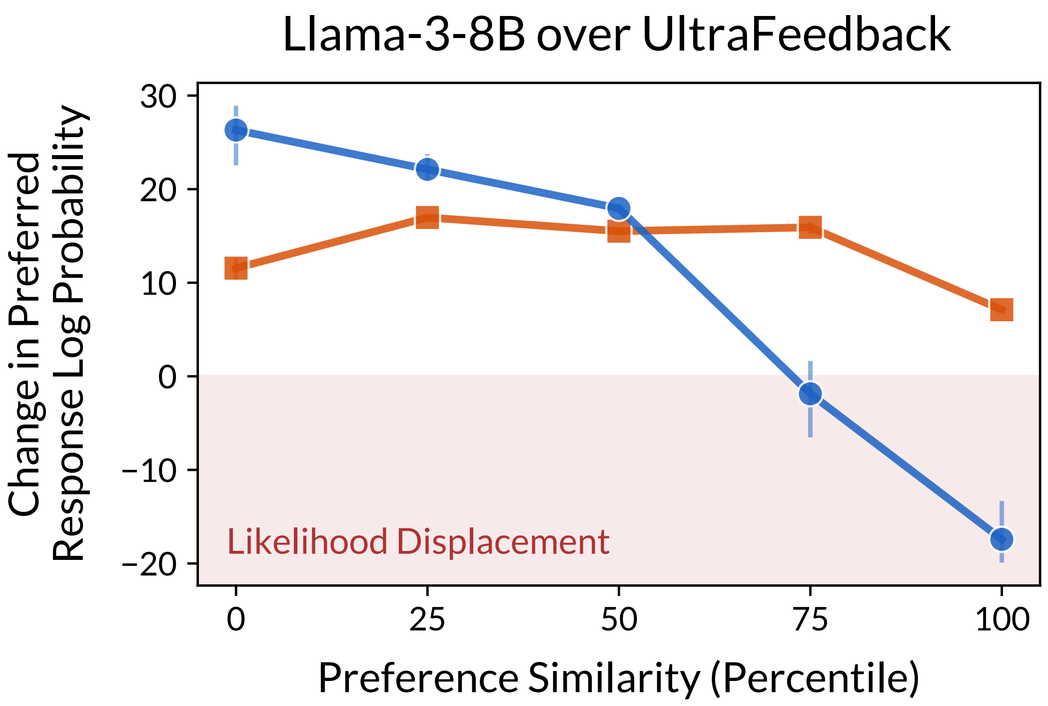

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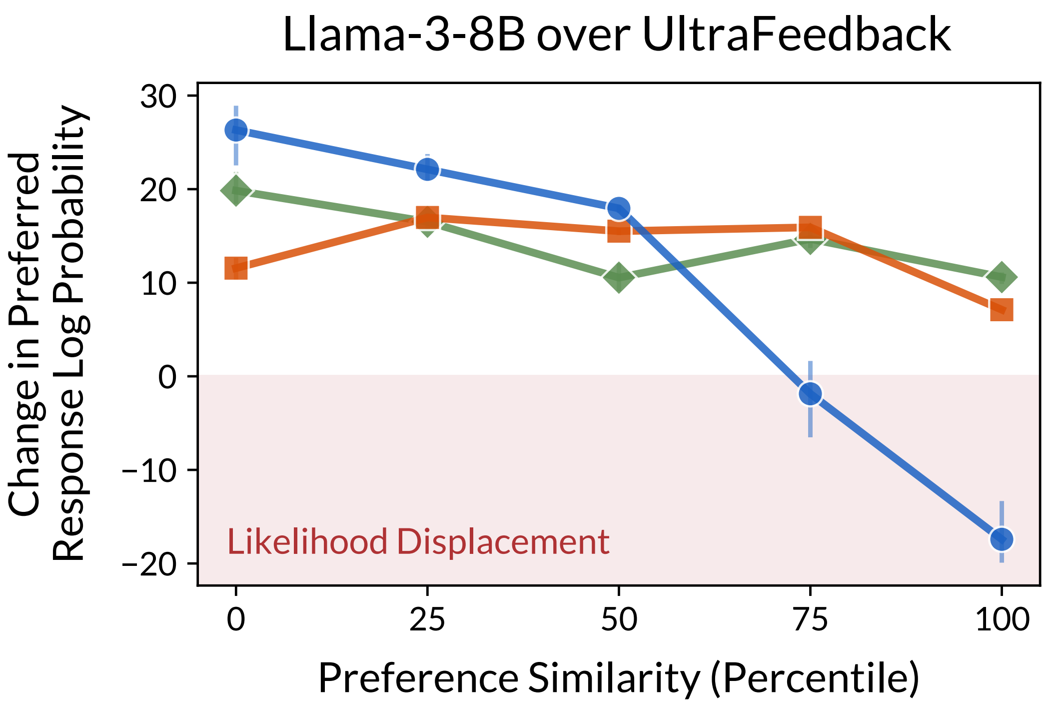

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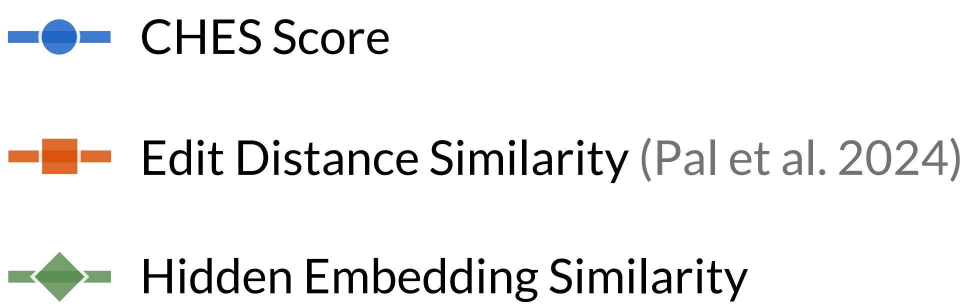

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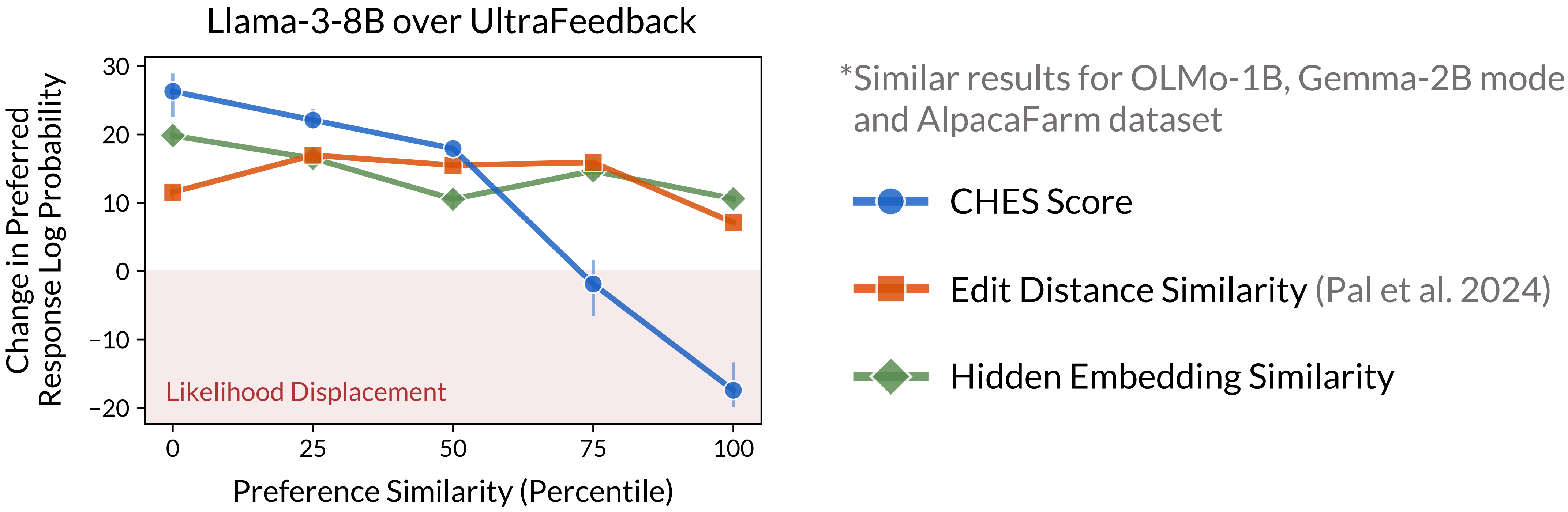

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CHES score identifies training samples causing likelihood displacement, whereas alternative measures do not

Data Filtering via CHES Score Mitigates Unintentional Unalignment

Recall: Unintentional unalignment due to likelihood displacement experiments

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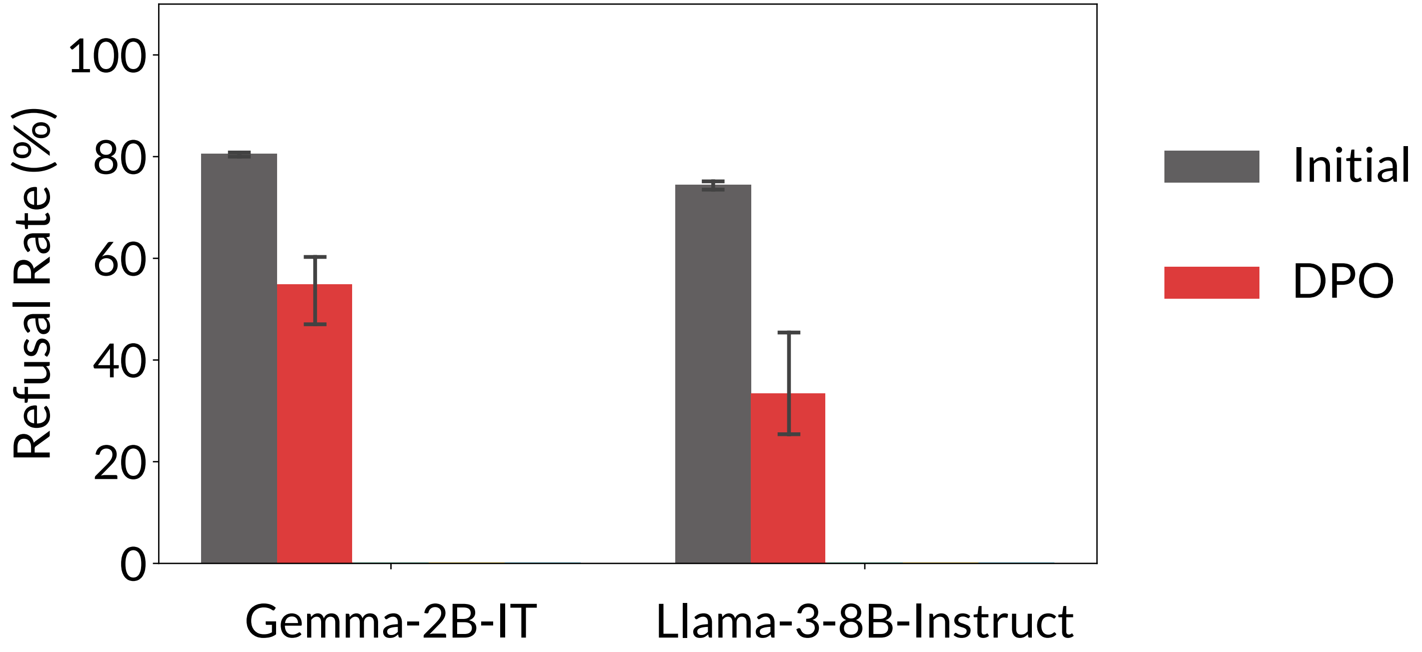

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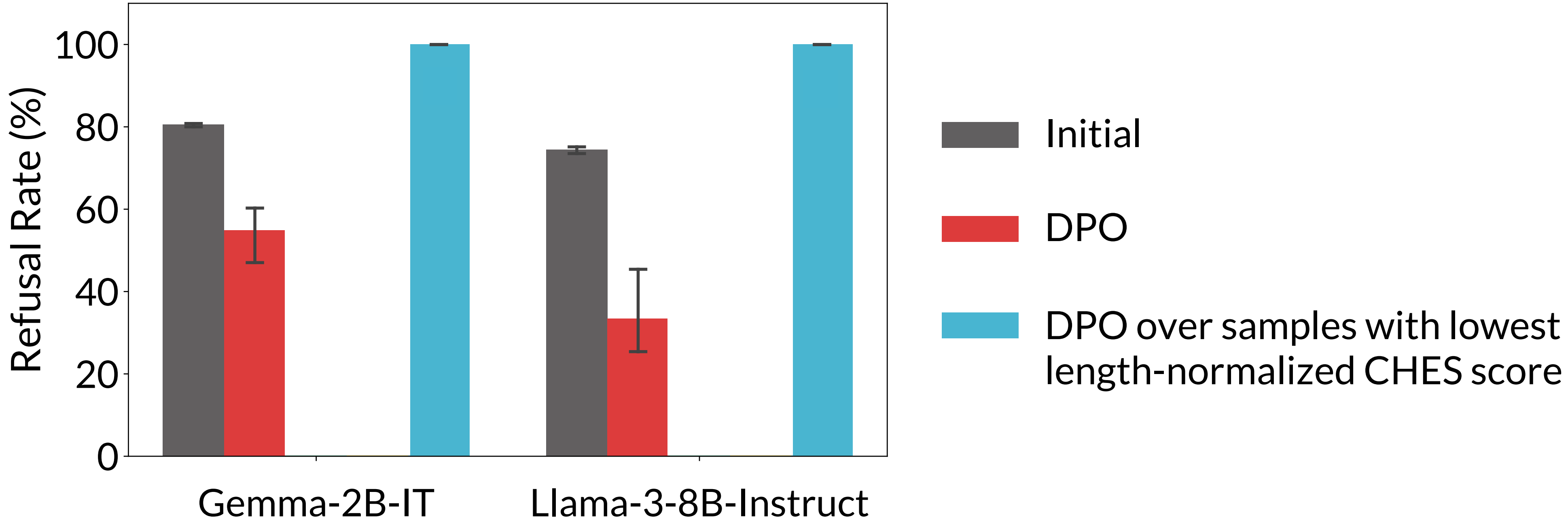

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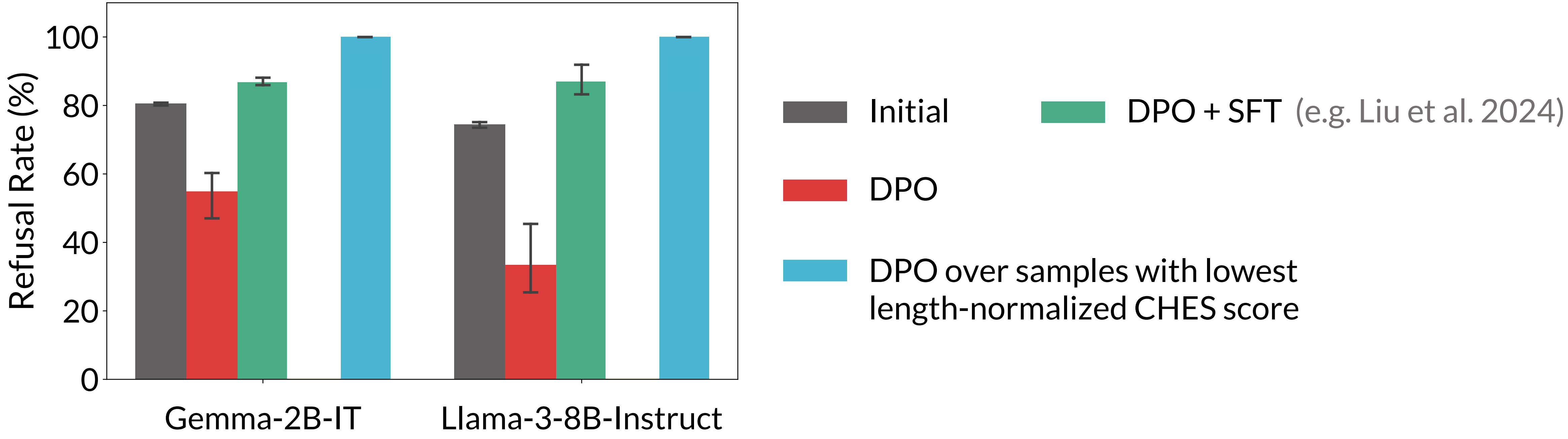

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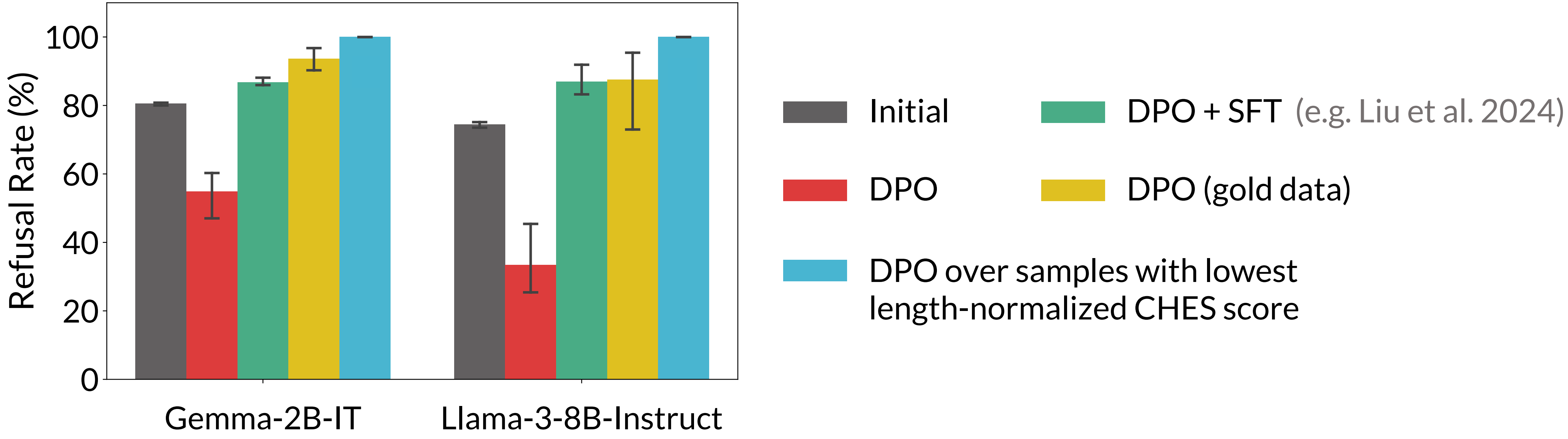

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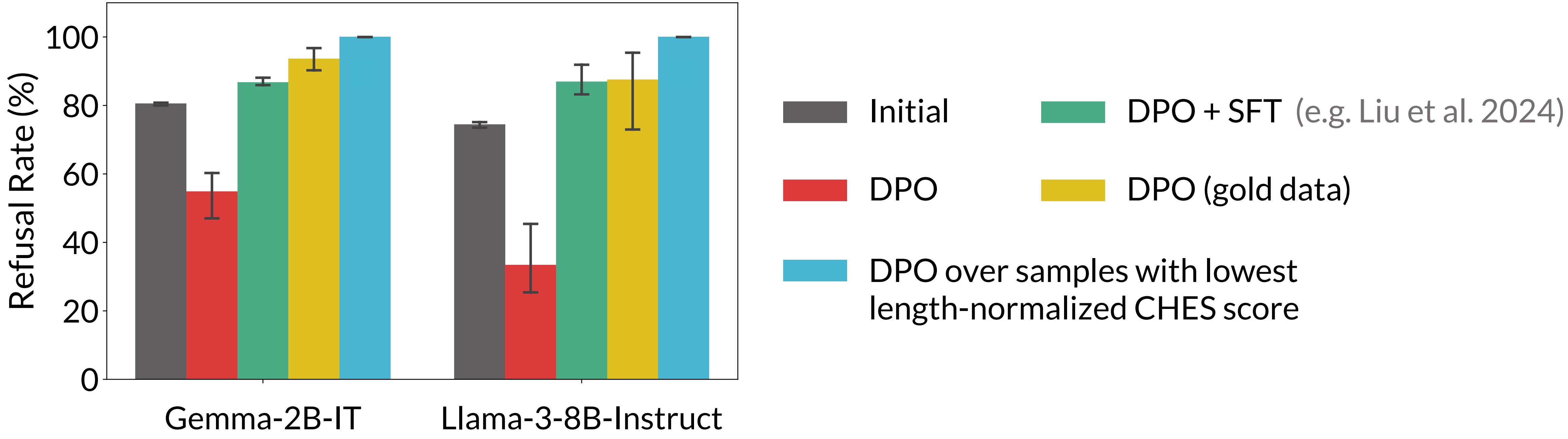
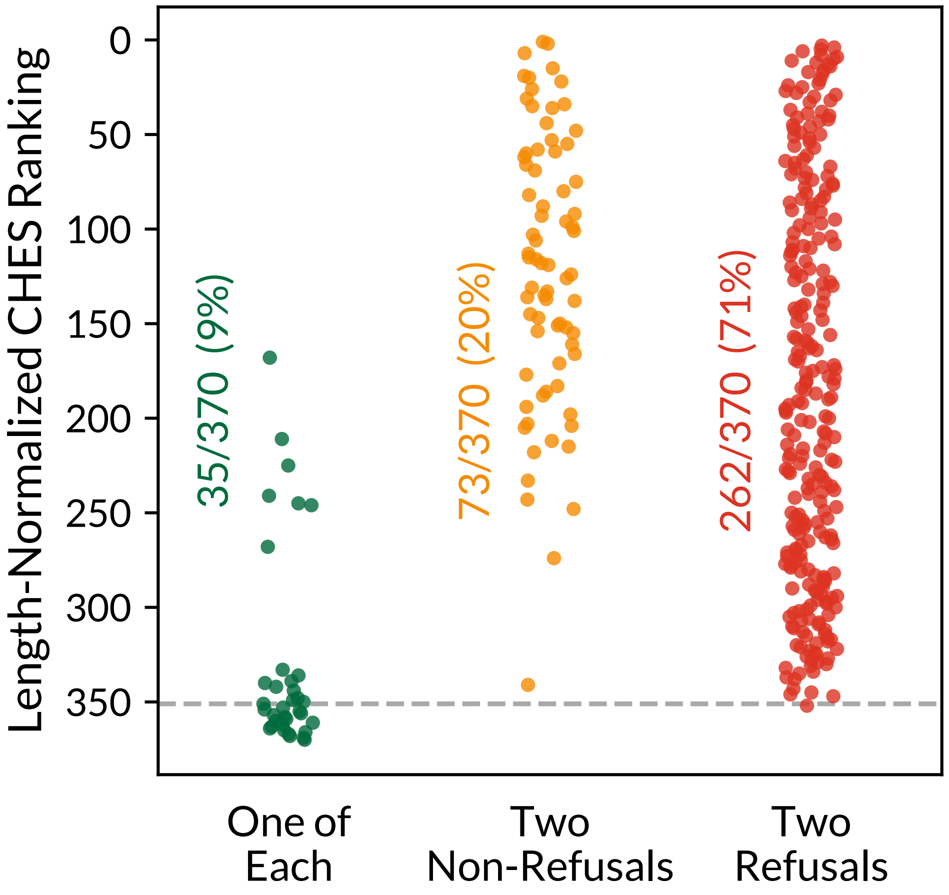


Removing samples with high CHES scores mitigates unintentional unalignment, and goes beyond adding an SFT term to the loss

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**

Filtering out samples with high CHES score can mitigate unintentional unalignment

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

Outlook

Fundamentals of Language Model Alignment

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There are countless methods for aligning language models

RLHF Ouyang et al. 2022	RAFT Dong et al. 2023	IPO Azar et al. 2023	REBEL Gao et al. 2024	KTO Ethayarajh et al. 2024
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Thank You!

Work supported in part by the Zuckerman STEM Leadership Program