SimPO: Simple Preference Optimization with a Reference-Free Reward

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Abstract

Direct Preference Optimization (DPO) is a widely used offline preference optimization algorithm that reparameterizes reward functions in reinforcement learning from human feedback (RLHF) to enhance simplicity and training stability. In this work, we propose SimPO, a simpler yet more effective approach. The effectiveness of SimPO is attributed to a key design: using the *average* log probability of a sequence as the implicit reward. This reward formulation better aligns with model generation and eliminates the need for a reference model, making it more compute and memory efficient. Additionally, we introduce a target reward margin to the Bradley-Terry objective to encourage a larger margin between the winning and losing responses, further enhancing the algorithm's performance. We compare SimPO to DPO and its latest variants across various state-of-the-art training setups, including both base and instruction-tuned models like Mistral and Llama3. We evaluate on extensive instruction-following benchmarks, including AlpacaEval 2, MT-Bench, and the recent challenging Arena-Hard benchmark. Our results demonstrate that SimPO consistently and significantly outperforms existing approaches without substantially increasing response length. Specifically, SimPO outperforms DPO by up to 6.4 points on AlpacaEval 2 and by up to 7.5 points on Arena-Hard. Our top-performing model, built on Llama3-8B-Instruct, achieves a remarkable 53.7 length-controlled win rate on AlpacaEval 2—surpassing Claude 3 Opus on the leaderboard, and a 36.5 win rate on Arena-Hard—making it the strongest 8B open-source model.[1]

Presented by Anton Lavrouk and Loránd Cheng

From Last Time…

Objective: Maximize reward while minimizing the KL divergence from the supervised baseline model

$$R(x, y) = \overbrace{r_\theta(x, y)}^{\text{Normal RL Objective (Reward from Reward Model)}} - \beta \overbrace{\log[\pi_\phi^{\mathrm{RL}}(y|x)/\pi^{\mathrm{SFT}}(y|x)]}^{\text{KL Divergence from Supervised Baseline}}$$

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$$r(x,y) = \beta \log \frac{\pi_\theta(y \mid x)}{\pi_{\mathrm{ref}}(y \mid x)} + \beta \log Z(x),$$

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Plug into Bradley-Terry

$$\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{\text{ref}}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{\text{ref}}(y_l \mid x)} \right) \right]$$

An offline objective function for preference data - DPO

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Using the reference model incurs additional memory and computation costs, and in general feels weird in an offline setting.

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There is a discrepancy between this reward and what is actually used during text generation.

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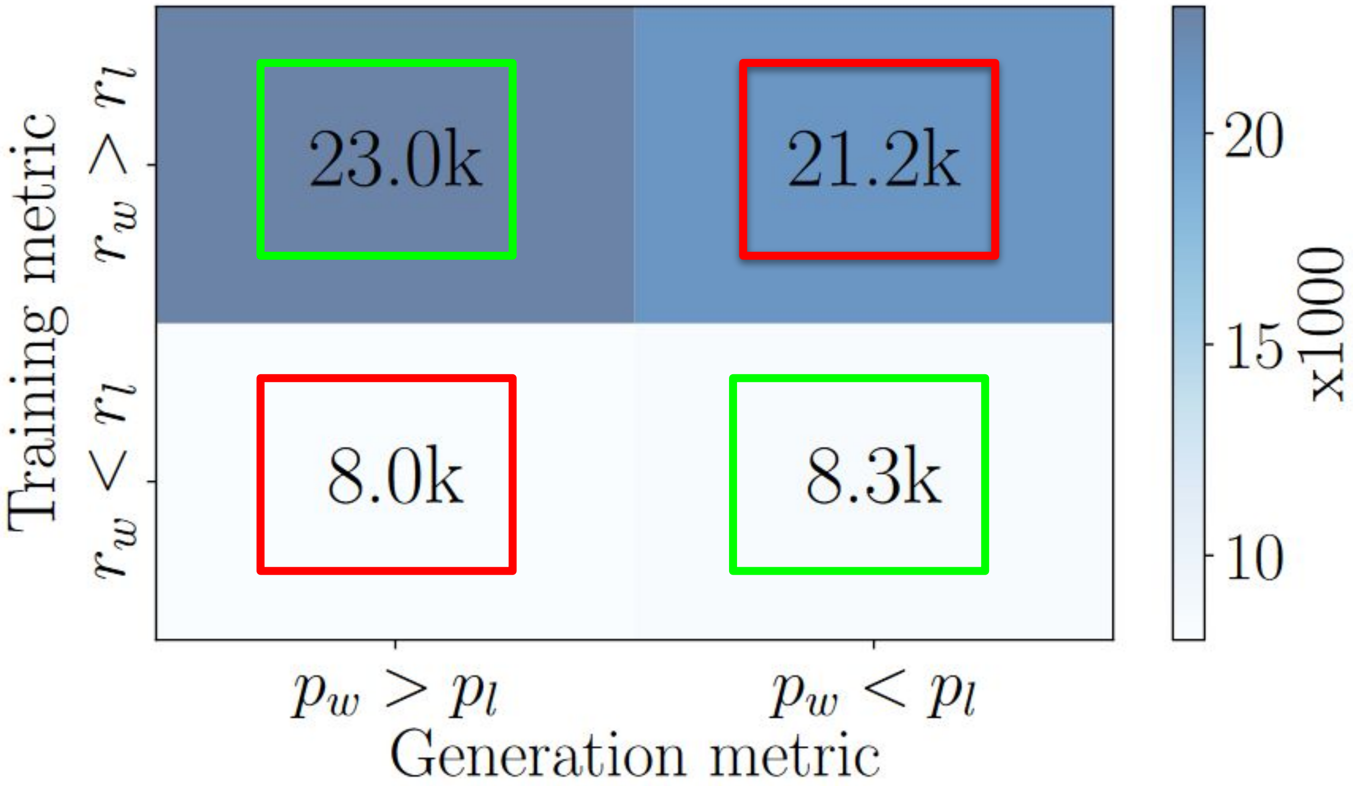
$$p_\theta(y \mid x) = \frac{1}{|y|} \log \pi_\theta(y \mid x) = \frac{1}{|y|} \sum_{i=1}^{|y|} \log \pi_\theta(y_i \mid x, y_{<i}).$$

Computationally intractable during inference: cannot test every single possibility



23.0k
21.2k
8.0k
8.3k
Training metric
$r_w > r_l$
$r_w < r_l$
$p_w > p_l$
$p_w < p_l$
Generation metric
20
15
10
x1000

What if we replace the reward function with the generation metric?

$$p_\theta(y \mid x) = \frac{1}{|y|} \log \pi_\theta(y \mid x) = \frac{1}{|y|} \sum_{i=1}^{|y|} \log \pi_\theta(y_i \mid x, y_{<i}).$$

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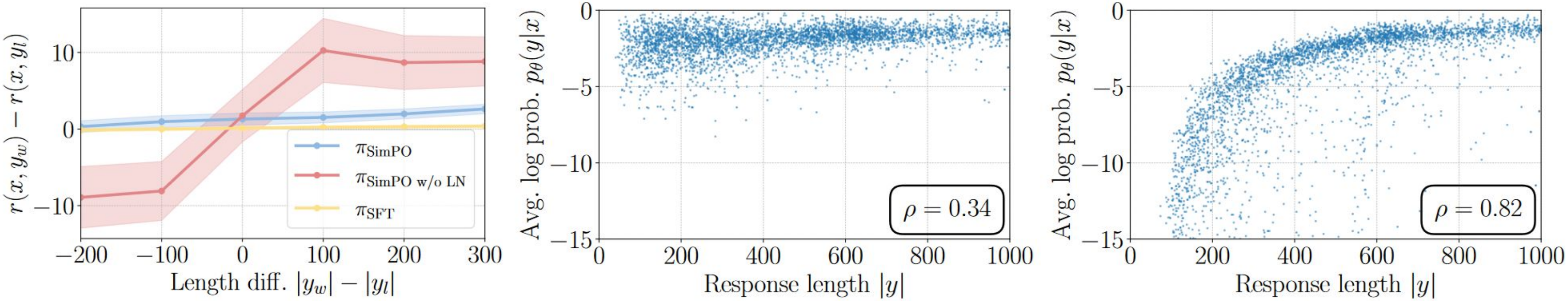
$$r_{\text{SimPO}}(x, y) = \frac{\boxed{\beta}}{|y|} \log \pi_\theta(y \mid x) = \frac{\boxed{\beta}}{|y|} \sum_{i=1}^{|y|} \log \pi_\theta(y_i \mid x, y_{<i}),$$

Aside: length normalization

$$r_{\text{SimPO}}(x, y) = \frac{\beta}{\boxed{|y|}} \log \pi_\theta(y \mid x) = \frac{\beta}{\boxed{|y|}} \sum_{i=1}^{|y|} \log \pi_\theta(y_i \mid x, y_{<i}),$$



(a) Reward optimization. (b) SimPO. (c) SimPO without LN.

Plugging this into the Bradley-Terry model, and then maximizing the log probability of the winning generation over the losing one yields the SimPO objective function (almost)

$$\mathcal{L}_{\text{SimPO}}(\pi_\theta) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}}\left[\log\sigma\left(\frac{\beta}{|y_w|}\log\pi_\theta(y_w|x) - \frac{\beta}{|y_l|}\log\pi_\theta(y_l|x)\right)\right]$$

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No reference model!

Aligned with language modeling objective!

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Ensures that the winning generation beats the losing generation by **at least γ**

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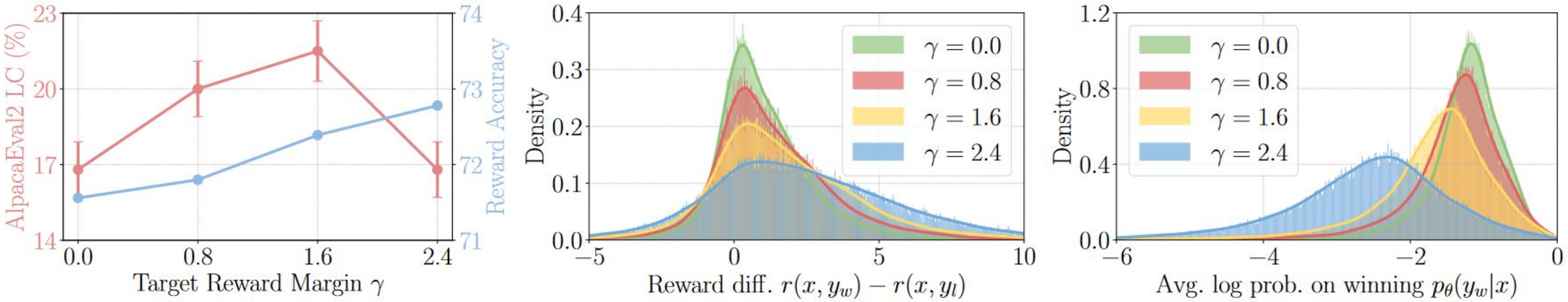


(a) Performance w/ different γ. (b) Reward diff. distribution. (c) Log prob. distribution.

$$\mathcal{L}_{\mathbf{DPO}}(\pi_\theta; \pi_{\text{ref}}) =$$
$$-\mathbb{E}\left[\log \sigma\left(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{\text{ref}}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{\text{ref}}(y_l \mid x)}\right)\right]$$

$$\mathcal{L}_{\mathbf{SimPO}}(\pi_\theta) =$$
$$-\mathbb{E}\left[\log \sigma\left(\frac{\beta}{|y_w|} \log \pi_\theta(y_w \mid x) - \frac{\beta}{|y_l|} \log \pi_\theta(y_l \mid x) - \gamma\right)\right]$$

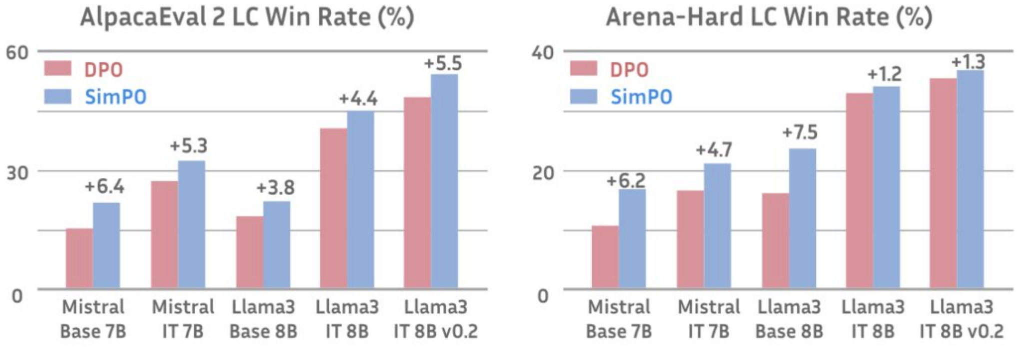


Figure 1: SimPO and DPO mainly differ in their reward formulation, as indicated in the shaded box. SimPO outperforms DPO across a wide range of settings on AlpacaEval 2 and Arena-Hard.

Experiments and Results

Base Models

Four models were used as the base LM for preference optimization:

Base versions:

- Mistral-7B-v0.1
- Llama-3-8B

Instruction-tuned versions:

- Mistral-7B-Instruct-v0.2
- Llama-3-8B-Instruct

Training Data

Base versions:

- First trained on UltraChat-200k to obtain SFT model
- Then trained on UltraFeedback preference data

Instruction-tuned versions:

- Take instruction-tuned model as SFT model
- Only trained on preference data
    - Re-generate UltraFeedback preference dataset responses using SFT model
    - Use a reward model (PairRM, ArmoRM) to obtain synthetic preferences

Benchmarks

Use 3 main benchmarks for evaluation:

1. **AlpacaEval 2:** 805 Qs from 5 datasets
2. **Arena-Hard:** 500 technical problem solving Qs
3. **MT-Bench:** 80 Qs from 8 categories

All use GPT-4 (+variants) for automatic evaluation

	# Exs.	Baseline Model	Judge Model	Scoring Type	Metric
AlpacaEval 2	805	GPT-4 Turbo	GPT-4 Turbo	Pairwise comparison	LC & raw win rate
Arena-Hard	500	GPT-4-0314	GPT-4 Turbo	Pairwise comparison	Win rate
MT-Bench	80	-	GPT-4/GPT-4 Turbo	Single-answer grading	Rating of 1-10

Baselines

Method	Objective
RRHF [87]	$\max\left(0, -\frac{1}{\lvert y_w \rvert}\log \pi_\theta(y_w \lvert x) + \frac{1}{\lvert y_l \rvert}\log \pi_\theta(y_l \lvert x)\right) - \lambda \log \pi_\theta(y_w \lvert x)$
SLiC-HF [92]	$\max\left(0, \delta - \log \pi_\theta(y_w \lvert x) + \log \pi_\theta(y_l \lvert x)\right) - \lambda \log \pi_\theta(y_w \lvert x)$
DPO [64]	$-\log \sigma\left(\beta \log \frac{\pi_\theta(y_w \lvert x)}{\pi_{\text{ref}}(y_w \lvert x)} - \beta \log \frac{\pi_\theta(y_l \lvert x)}{\pi_{\text{ref}}(y_l \lvert x)}\right)$
IPO [6]	$\left(\log \frac{\pi_\theta(y_w \lvert x)}{\pi_{\text{ref}}(y_w \lvert x)} - \log \frac{\pi_\theta(y_l \lvert x)}{\pi_{\text{ref}}(y_l \lvert x)} - \frac{1}{2\tau}\right)^2$
CPO [84]	$-\log \sigma\left(\beta \log \pi_\theta(y_w \lvert x) - \beta \log \pi_\theta(y_l \lvert x)\right) - \lambda \log \pi_\theta(y_w \lvert x)$
KTO [27]	$-\lambda_w \sigma\left(\beta \log \frac{\pi_\theta(y_w \lvert x)}{\pi_{\text{ref}}(y_w \lvert x)} - z_{\text{ref}}\right) + \lambda_l \sigma\left(z_{\text{ref}} - \beta \log \frac{\pi_\theta(y_l \lvert x)}{\pi_{\text{ref}}(y_l \lvert x)}\right)$, where $z_{\text{ref}} = \mathbb{E}_{(x,y)\sim\mathcal{D}}\left[\beta \text{KL}\left(\pi_\theta(y \lvert x) \Vert \pi_{\text{ref}}(y \lvert x)\right)\right]$
ORPO [40]	$-\log p_\theta(y_w \lvert x) - \lambda \log \sigma\left(\log \frac{p_\theta(y_w \lvert x)}{1-p_\theta(y_w \lvert x)} - \log \frac{p_\theta(y_l \lvert x)}{1-p_\theta(y_l \lvert x)}\right)$, where $p_\theta(y \lvert x) = \exp\left(\frac{1}{\lvert y \rvert}\log \pi_\theta(y \lvert x)\right)$
R-DPO [62]	$-\log \sigma\left(\beta \log \frac{\pi_\theta(y_w \lvert x)}{\pi_{\text{ref}}(y_w \lvert x)} - \beta \log \frac{\pi_\theta(y_l \lvert x)}{\pi_{\text{ref}}(y_l \lvert x)} - (\alpha \lvert y_w \rvert - \alpha \lvert y_l \rvert)\right)$
SimPO	$-\log \sigma\left(\frac{\beta}{\lvert y_w \rvert}\log \pi_\theta(y_w \lvert x) - \frac{\beta}{\lvert y_l \rvert}\log \pi_\theta(y_l \lvert x) - \gamma\right)$

Main Results

- SimPO outperforms in most evals

- MT-Bench obtains poor separability

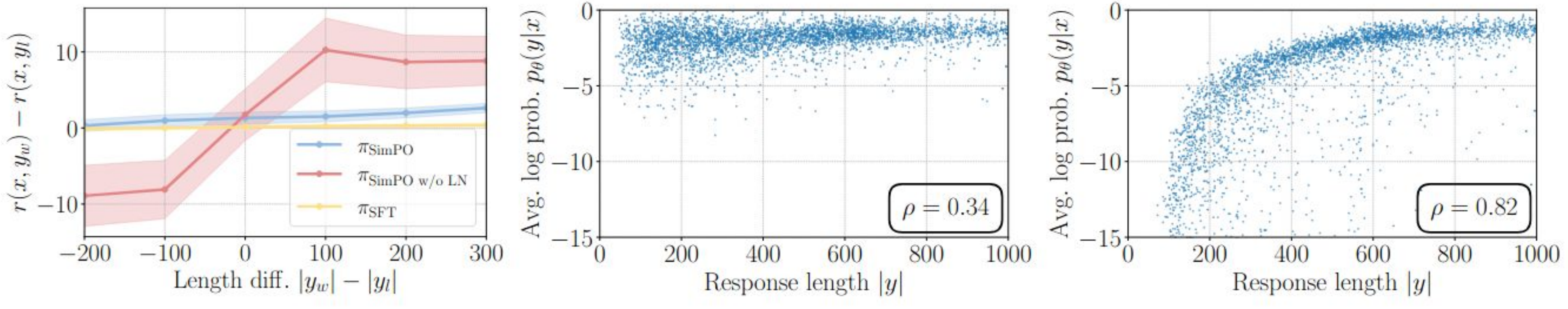
- Instruct versions perform better

- When controlling for length, SimPO does better

Method	Mistral-Base (7B)					Mistral-Instruct (7B)				
	AlpacaEval 2		Arena-Hard	MT-Bench		AlpacaEval 2		Arena-Hard	MT-Bench	
	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4
SFT	8.4	6.2	1.3	4.8	6.3	17.1	14.7	12.6	6.2	7.5
RRHF [87]	11.6	10.2	5.8	5.4	6.7	25.3	24.8	18.1	6.5	7.6
SLiC-HF [92]	10.9	8.9	7.3	5.8	**7.4**	24.1	24.6	18.9	6.5	**7.8**
DPO [64]	15.1	12.5	10.4	5.9	7.3	26.8	24.9	16.3	6.3	7.6
IPO [6]	11.8	9.4	7.5	5.5	7.2	20.3	20.3	16.2	6.4	**7.8**
CPO [84]	9.8	8.9	6.9	5.4	6.8	23.8	28.8	**22.6**	6.3	7.5
KTO [27]	13.1	9.1	5.6	5.4	7.0	24.5	23.6	17.9	6.4	7.7
ORPO [40]	14.7	12.2	7.0	5.8	7.3	24.5	24.9	20.8	6.4	7.7
R-DPO [62]	17.4	12.8	8.0	5.9	**7.4**	27.3	24.5	16.1	6.2	7.5
SimPO	**21.5**	**20.8**	**16.6**	**6.0**	7.3	**32.1**	**34.8**	21.0	**6.6**	7.6

Method	Llama3-Base (8B)					Llama3-Instruct (8B)				
	AlpacaEval 2		Arena-Hard	MT-Bench		AlpacaEval 2		Arena-Hard	MT-Bench	
	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4
SFT	6.2	4.6	3.3	5.2	6.6	26.0	25.3	22.3	6.9	8.1
RRHF [87]	12.1	10.1	6.3	5.8	7.0	31.3	28.4	26.5	6.7	7.9
SLiC-HF [92]	12.3	13.7	6.0	6.3	7.6	26.9	27.5	26.2	6.8	8.1
DPO [64]	18.2	15.5	15.9	6.5	7.7	40.3	37.9	32.6	**7.0**	8.0
IPO [6]	14.4	14.2	17.8	6.5	7.4	35.6	35.6	30.5	**7.0**	**8.3**
CPO [84]	10.8	8.1	5.8	6.0	7.4	28.9	32.2	28.8	**7.0**	8.0
KTO [27]	14.2	12.4	12.5	6.3	**7.8**	33.1	31.8	26.4	6.9	8.2
ORPO [40]	12.2	10.6	10.8	6.1	7.6	28.5	27.4	25.8	6.8	8.0
R-DPO [62]	17.6	14.4	17.2	**6.6**	7.5	41.1	37.8	33.1	**7.0**	8.0
SimPO	**22.0**	**20.3**	**23.4**	**6.6**	7.7	**44.7**	**40.5**	**33.8**	**7.0**	8.0

Length Normalization



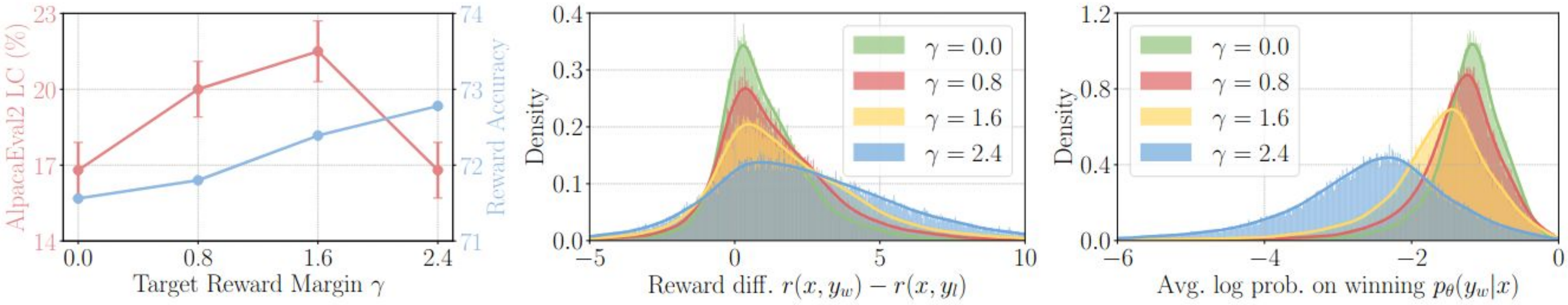
(a) Reward optimization.

(b) SimPO.

(c) SimPO without LN.

- LN leads to positive reward margin for all response pairs regardless of length
- Removing LN leads to signs of length exploitation

Target Reward Margin



(a) Performance w/ different γ. (b) Reward diff. distribution. (c) Log prob. distribution.

- Reward accuracy increases with target margin, but generation quality doesn't only depend on reward accuracy
- γ flattens the distributions of reward differences and log probabilities
- Added parameter that requires tuning

Ablation of Length Normalization and Reward Margin

Both elements are crucial to the success of SimPO

Method	Mistral-Base (7B) Setting					Mistral-Instruct (7B) Setting				
	AlpacaEval 2		Arena-Hard	MT-Bench		AlpacaEval 2		Arena-Hard	MT-Bench	
	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4
DPO	15.1	12.5	10.4	5.9	7.3	26.8	24.9	16.3	6.3	7.6
SimPO	21.5	20.8	16.6	6.0	7.3	32.1	34.8	21.0	6.6	7.6
w/o LN	11.9	13.2	9.4	5.5	7.3	19.1	19.7	16.3	6.4	7.6
$\gamma = 0$	16.8	14.3	11.7	5.6	6.9	30.9	34.2	20.5	6.6	7.7

Ablation of Length Normalization and Reward Margin

Method	Mistral-Base (7B) Setting					Mistral-Instruct (7B) Setting				
	AlpacaEval 2		Arena-Hard	MT-Bench		AlpacaEval 2		Arena-Hard	MT-Bench	
	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4
DPO	15.1	12.5	10.4	5.9	7.3	26.8	24.9	16.3	6.3	7.6
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The same changes do not necessarily improve DPO

Method	Mistral-Base (7B) Setting					Mistral-Instruct (7B) Setting				
	AlpacaEval 2		Arena-Hard	MT-Bench		AlpacaEval 2		Arena-Hard	MT-Bench	
	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4	LC (%)	WR (%)	WR (%)	GPT-4 Turbo	GPT-4
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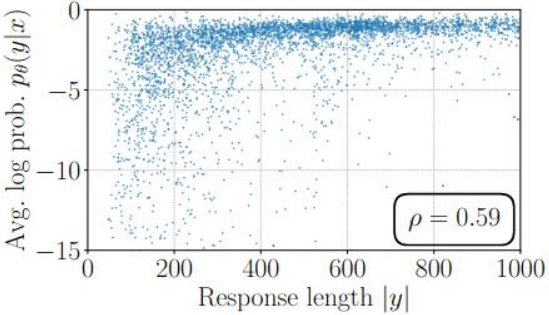
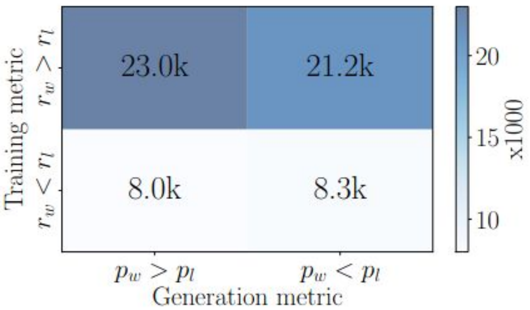
DPO	15.1	12.5	10.4	5.9	7.3	26.8	24.9	16.3	6.3	7.6
w/ LN	21.0	17.7	15.2	5.9	7.2	21.7	20.9	15.6	6.4	7.7
w/ γ	15.2	12.1	10.3	5.7	7.3	23.0	24.6	14.7	6.3	7.6

Comparisons with DPO

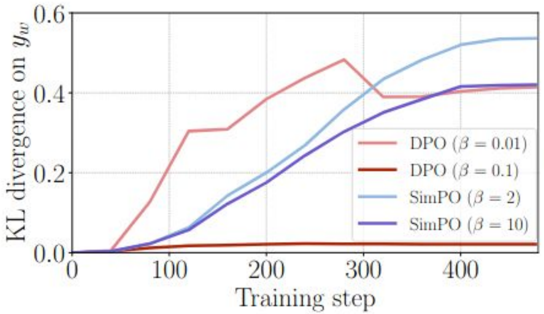


(a) Length correlation (DPO).

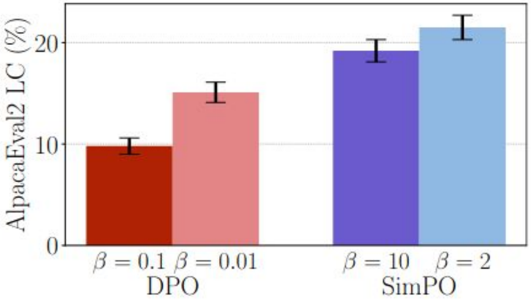


(b) Contingency table (DPO).

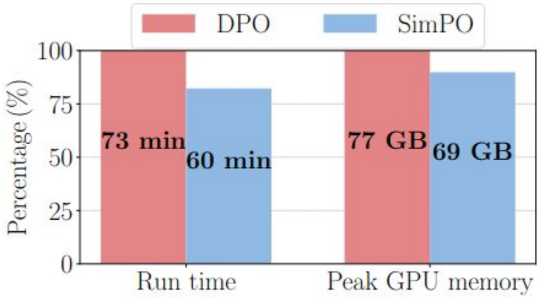
(c) Reward Accuracy.



(a) KL divergence w/ different β.



(b) Performance w/ different β.



(c) Efficiency of DPO vs. SimPO.

Other interesting points

- Empirically did not find much difference in other offline preference learning methods
- MMLU and general knowledge is largely retained across all methods
- Reading comprehension/common sense improves
- Truthfulness improves
- Math performance degrades
- Enhanced reward model (ArmoRM vs. PairRM) yields significant perf increase
- Strong SFT baselines and high-quality preference data make algorithm differences pretty minor
- SFT regularization added to SimPO leads to performance drop

Limitations

- No theoretical grounding or understanding of why this method works
- Evaluations only focus on helpfulness, not on other factors like safety or honesty which may be very important in real scenarios
- Performance drops on some downstream tasks, notably math