

GENERATIVE REWARD MODELS

Dakota Mahan*¹ **Duy Van Phung***¹ **Rafael Rafailov***^{1,2}
Chase Blagden¹ **Nathan Lile**¹ **Louis Castricato**¹
Jan-Philipp Fränken² **Chelsea Finn**² **Alon Albalak***¹

¹SynthLabs, ²Stanford University

ABSTRACT

Reinforcement Learning from Human Feedback (RLHF) has greatly improved the performance of modern Large Language Models (LLMs). The RLHF process is resource-intensive and technically challenging, generally requiring a large collection of human preference labels over model-generated outputs. Reinforcement Learning from AI Feedback (RLAIF) addresses this data collection challenge by leveraging synthetic preferences generated by an LLM. However, recent work has shown that synthetic preference labels may not align well with human preference judgments (Zeng et al., 2023). To address this, we propose a hybrid approach that unifies RLHF and RLAIF methodologies. We introduce **GenRM**, an iterative algorithm that trains an LLM on self-generated reasoning traces, leading to synthetic preference labels matching human preference judgments. Empirically, we show that zero-shot LLM-based judgments under-perform compared to Bradley-Terry reward models on in-distribution tasks (between 9-36%). In contrast, GenRM achieves in-distribution accuracy comparable to Bradley-Terry models, while significantly outperforming them on out-of-distribution tasks (between 10-45%). Moreover, GenRM surpasses the performance of using LLMs as judges on both in-distribution (by 9-31%) and out-of-distribution tasks (by 2-6%). Our results show that combining the strengths of RLHF and RLAIF offers a promising approach for improving the quality of synthetic preference labels.

1 INTRODUCTION

Reinforcement Learning from Human Feedback (RLHF) has significantly improved the performance of modern Large Language Models (LLMs) (see e.g., Reid et al., 2024; OpenAI, 2023). Despite its effectiveness, the RLHF process presents several challenges. First, it requires a large amount of human preference data to train reward models that reflect human preferences (Stiennon et al., 2022; Bai et al., 2022a). Second, it necessitates additional architecture and infrastructure to handle reward model training (Wang et al., 2024a; von Werra et al., 2020; Havrilla et al., 2023). Third, it requires a sophisticated online optimization loop using algorithms, such as Proximal Policy Optimization [PPO; Schulman et al. (2017)], to fine-tune an LLM-based policy to align with the reward model (Zheng et al., 2023c).

To address the challenge of collecting large-scale human preference data, synthetic preference data has emerged as a promising alternative. For example, Bai et al. (2022b) introduced Reinforcement Learning from AI Feedback (RLAIF). Instead of relying on human users for feedback, their method utilizes an LLM guided by a predefined set of principles—referred to as a “constitution”—to generate and select model outputs that are helpful and harmless (Askell et al., 2021). Employing AI-generated preference labels has demonstrated meaningful Pareto improvements in balancing helpfulness and harmlessness in assistant responses (Bai et al., 2022b; Kundu et al., 2023).

Direct alignment algorithms, such as Direct Preference Optimization (DPO) (Rafailov et al., 2023) and Implicit Preference Optimization (IPO) (Azar et al., 2023), were developed to address the challenges of reward model training and online optimization. These works demonstrated that the reward model and the optimal policy can be mathematically interchanged, allowing the policy to be trained

* Equal contribution. Correspondence to team@synthlabs.ai

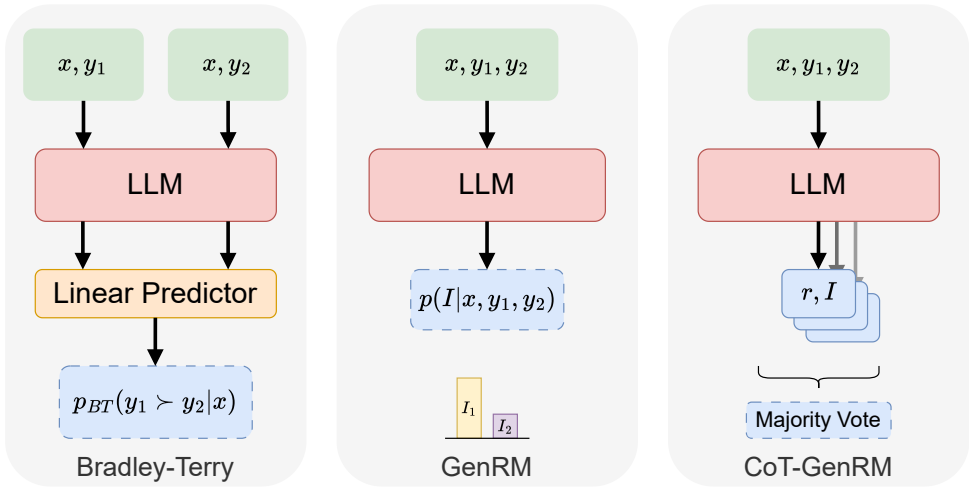


Figure 1: **Methods overview.** *Bradley-Terry* methods directly output the probability of y_1 being preferred over y_2 , while *GenRM* compares the LLMs next-token probabilities of answer indicator tokens (I_1, I_2). *CoT-GenRM* samples reasoning traces (r) followed by the answer indicator token.

directly from preference data in an entirely offline manner, significantly simplifying the RLHF pipeline. Benchmark evaluations (Lambert et al., 2024) have shown that DPO-based approaches are competitive with traditional reward models based on the Bradley-Terry algorithm. However, recent empirical evidence suggests that purely offline methods may underperform compared to online approaches in both reward model-based reinforcement learning (Xu et al., 2024b;a) and in the RLAIIF setting (Guo et al., 2024). As a result, state-of-the-art models such as the LLaMA-3 family (Dubey et al., 2024) have adopted hybrid strategies that combine online DPO optimization with separate reward models.

In this work, we identify two key **limitations** in current alignment approaches: (1) Explicitly parameterized reward models, while effective and accurate for in-distribution tasks, struggle with robustness and generalization to out-of-distribution (OOD) data. (2) RLAIIF approaches, such as utilizing an LLM-as-a-judge, offer a more robust alternative but may not always align well with actual user preferences when acting as the sole evaluator. To **address these limitations**, we propose a unified framework for RLHF and RLAIIF. Our approach begins with a strong pre-trained LLM, which we employ as an evaluator. Using a dataset of user preferences, we adopt a STaR-like methodology (Zelikman et al., 2022) to align the LLM with user choices, effectively training it to function as a reward model. We **demonstrate empirically** that this fine-tuned judge model matches Bradley-Terry reward models for in-distribution prompts while significantly improving generalization on OOD prompts. Additionally, it outperforms the base LLM on both in-distribution and OOD scenarios.

2 PRELIMINARIES

In this section, we first outline the core components of the standard RLHF post-training pipeline (Ziegler et al., 2020; Stiennon et al., 2022; Bai et al., 2022a; Ouyang et al., 2022), then summarize the Self-Taught Reasoner (STaR) approach (Zelikman et al., 2022), and finally review LLM-as-a-judge (Zheng et al., 2023a).

2.1 REINFORCEMENT LEARNING FROM HUMAN FEEDBACK

The RLHF pipeline consists of three stages designed to align an LLM with human preferences: (1) Supervised finetuning (SFT); (2) Reward Modeling; and (3) Reinforcement Learning (RL).

2.1.1 SUPERVISED FINE-TUNING (SFT)

In the first stage, an LLM is trained to follow instructions using a dataset of prompts x and responses y using maximum likelihood estimation (MLE) over the next-token predictions. The resulting model is referred to as $\pi_{\text{SFT}}(y | x)$, where both the prompt and response strings are treated as single variables. This model is used as a base for the next stages.

2.1.2 BRADLEY-TERRY REWARD MODELING

Next, the SFT model $\pi_{\text{SFT}}(y | x)$ is leveraged to construct a reward model that captures human preferences. Specifically, the SFT model is sampled, generating pairs of responses $(y_1, y_2) \sim \pi_{\text{SFT}}(y | x)$ for each prompt x in the dataset. Human annotators then rank the responses, producing pairs of preferences $y_w \succ y_l | x$, where y_w and y_l represent the preferred and non-preferred responses, respectively. This ranking process is typically modeled using the Bradley-Terry (BT) preference model (Bradley & Terry, 1952), which assumes the preference distribution:

$$p_{\text{BT}}(y_1 \succ y_2 | x) = \frac{\exp(r(x, y_1))}{\exp(r(x, y_1)) + \exp(r(x, y_2))} = \sigma(r(x, y_1) - r(x, y_2)), \quad (1)$$

where the preference distribution p is driven by a latent reward function $r(x, y)$, and σ is the logistic function (although other objectives can be used). Using this framework and a dataset of rankings $\mathcal{D} = \{x^{(i)}, y_w^{(i)}, y_l^{(i)}\}_{i=1}^N$, a parameterized reward model $r_\phi(x, y)$ is trained via maximum likelihood estimation to predict the unobserved reward:

$$\mathcal{L}_{\text{rew}}(r_\phi) = -\mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} [\log \sigma(r_\phi(x, y_w) - r_\phi(x, y_l))]. \quad (2)$$

This reward model is based on $\pi_{\text{SFT}}(y | x)$ with an additional linear predictor on top of the final embedding layer of the model which produces the scalar reward estimate.

2.1.3 REINFORCEMENT LEARNING (RL)

In the final stage, the learned reward model $r_\phi(x, y)$ is used to further optimize the LLM π_ϕ via an on-policy RL algorithm, such as Proximal Policy Optimization (PPO; Schulman et al., 2017). The goal is to refine the LLM’s behavior so that it produces responses preferred by human evaluators. The common optimization objective is:

$$\max_{\theta} \mathbb{E}_{x \sim \mathcal{D}, y \sim \pi_\phi(\cdot | x)} [r_\phi(x, y) - \beta \mathbb{D}_{\text{KL}}[\pi_\theta(y | x) \| \pi_{\text{ref}}(y | x)]], \quad (3)$$

where \mathbb{D}_{KL} represents the Kullback-Leibler (KL) divergence, and $\pi_{\text{ref}}(y | x)$ is typically the supervised fine-tuned model $\pi_{\text{SFT}}(y | x)$. The KL divergence penalty prevents the LLM π_ϕ from deviating too far from its initial behavior, with the hyperparameter β controlling the trade-off between exploiting the reward model and maintaining consistency with the reference model.

2.2 SELF-TAUGHT REASONER

The Self-Taught Reasoner (STaR) method introduces an iterative bootstrapping approach designed to improve the reasoning capabilities of LLMs (Zelikman et al., 2022). STaR focuses on training models to generate and refine rationales, particularly for tasks requiring complex reasoning in a reinforcement learning-based manner. We outline the main points of the approach below.

2.2.1 RATIONALE GENERATION BOOTSTRAPPING

In our formulation we assume we have access to a dataset $\mathcal{D} = \{x^{(i)}, y^{(i)}\}_{i=1}^N$ of questions x that require strong reasoning and the corresponding answers y . Notice that we do not require access to strong or ground-truth rationales for these problems. We begin by prompting a model $\hat{y}^{(i)}, \hat{r}^{(i)} \sim \pi(y, r | x^{(i)})$ to provide CoT rationale $\hat{r}^{(i)}$ and final answer $\hat{y}^{(i)}$. We then filter the generated data, keeping only rationales leading to a correct final answer (i.e. $\hat{y}^{(i)} = y^{(i)}$) to generate a dataset of questions, (bootstrapped) rationales and answers $\mathcal{D}_{\text{STaR}} = \{x^{(i)}, \hat{r}^{(i)}, y^{(i)}\}_{i=1}^N$. $\mathcal{D}_{\text{STaR}}$ is then used to train a model with the standard supervised fine-tuning objective:

$$\mathcal{L}_{\text{STaR}}(\pi_\phi) = -\mathbb{E}_{(x, \hat{r}, y) \sim \mathcal{D}_{\text{STaR}}} [-\log \pi_\phi(y, \hat{r} | x)]. \quad (4)$$

The above procedure is repeated over several iterations and has since been adopted in various related works (e.g., Hosseini et al., 2024; Andukuri et al., 2024; Fränken et al., 2024; Zelikman et al., 2024).

2.2.2 POST-RATIONALIZATION

One limitation of bootstrapping rationale generation is that the model cannot improve on examples it initially fails to solve. To address this issue, STaR introduces *rationalization*, a backward reasoning process. For prompts where the model generates an incorrect rationale and answer, the correct answer is provided to the model as a hint. The model then generates a new rationale based on the correct answer, reasoning backward to generate a “post-rationale”. In technical terms there is a rationalization model q which generates rationales $\hat{r}^{(i)} \sim q(r|x^{(i)}, y^{(i)})$ to justify the final answer. This synthetic data is in turn used in the STaR objective in Eq. 4. We will also use this approach to evaluate the effect of the quality of the bootstrapped reasoning chains, using samples from rationalization models q with different capabilities.

2.3 RLAIF AND LLM-AS-A-JUDGE

Reinforcement Learning from AI Feedback (RLAIF) presents an alternative approach to the standard RLHF pipeline. Bai et al. (2022b) demonstrate the efficacy of RLAIF in training helpful and harmless models without relying on human feedback labels for harmfulness assessment. Their work shows that as language model capabilities improve, AI identification of harms increases significantly, particularly when leveraging chain-of-thought reasoning. Notably, they demonstrate that utilizing self-supervised preference labels for reinforcement learning can yield improvements in model behavior that are competitive with or surpass those achieved using human feedback for harmfulness evaluation. Zheng et al. (2023a) introduce the LLM-as-a-Judge method, further extending the RLAIF paradigm. They demonstrate that strong language models, even without explicit training for evaluation tasks, can provide judgments that exhibit agreement with human preferences. Their study finds that LLMs can achieve over 80% agreement with human preferences, a level comparable to inter-expert agreement. This finding establishes a foundation for developing LLM-based evaluation frameworks.

3 CONNECTIONS BETWEEN RLHF AND PREFERENCE MODELLING

We begin by pointing out a theoretical connection between the RLHF post-training approach outlined in the previous section and general preference modeling. One of the key observations of the DPO approach (Rafailov et al., 2023) is that the reward modeling objective in Eq. 1 is under-constrained, which can create significant optimization challenges for the RL problem in Eq. 3 (Wu et al., 2023; Ahmadian et al., 2024) (in fact, theoretically, it can have arbitrarily low signal-to-noise ratio). To alleviate this issue, prior works (Stiennon et al., 2022; Ouyang et al., 2022) use a baseline reward from on a fixed reference distribution:

$$\max_{\pi_{\theta}} \mathbb{E}_{x \sim \mathcal{D}, y \sim \pi_{\phi}(\cdot|x)} \left[r_{\phi}(x, y) - r_{\phi}(x, y_{\text{ref}}) \right] - \beta \mathbb{D}_{\text{KL}} [\pi_{\theta}(y | x) \| \pi_{\text{ref}}(y | x)]. \quad (5)$$

Here the reference y_{ref} is a human completion from an SFT dataset or a sample from the base SFT model. However, notice that by inverting Eq. 1 we have:

$$r_{\phi}(x, y) - r_{\phi}(x, y_{\text{ref}}) = \log \left(\frac{p_{\text{BT}}(y \succ y_{\text{ref}}|x)}{1 - p_{\text{BT}}(y \succ y_{\text{ref}}|x)} \right). \quad (6)$$

That is, under the Bradley-Terry formulation the standard RLHF optimization procedure is actually optimizing a preference likelihood objective.

The **core contribution** of our work is that we replace the Bradley-Terry reward modelling approach with a strictly more general preference modelling objective $p(y_w \succ y_l|x)$ that does not assume a point-wise reward estimate, a special model architecture, or a specific preference distribution parameterization as in Eq. 1. That is, we assume a standard preference dataset and model the preference distribution $p_{\phi}(y_w \succ y_l|x)$ using an LLM, without any additional assumptions. Notice that this formulation is fully general as we can extract preference probabilities either from the likelihoods of the LLM output or from majority voting counts. This can be used in the standard pipeline with

PPO (Stiennon et al., 2022; Ouyang et al., 2022) in Eq. 5 using the reward formulation in Eq. 6. Alternatively, if we sample preferences from the above model, we can also utilize an iterative or online *PO optimization manner following Munos et al. (2024) or Calandriello et al. (2024).

4 GENERATIVE REWARD MODELS: A UNIFIED RLHF-RLAIF APPROACH

In our proposed framework we begin with an LLM π_ϕ acting as a zero-shot judge in an RLAIF setting, as outlined in Section 2.3. That is, given a task x and two responses y_1 and y_2 , we directly prompt the model π_ϕ to provide an answer indicator token I indicating a preference over the answers. We consider two variants of our approach:

1. The Generative Reward Model (GenRM) approach prompts the model to act as a classifier directly providing the answer token probabilities for each response $\hat{I} \sim \pi_\phi(I, |x, y_1, y_2)$.
2. The CoT-GenRM approach additionally prompts the model to provide intermediate Chain-of-Thought reasoning $\hat{I}, \hat{r} \sim \pi_\phi(I, r|x, y_1, y_2)$ before providing the final answer indicator token.

Our prompts are based on the standard MT-Bench prompt (Zheng et al., 2023b), and can be found in Appendix A. We use the LLM judge as a prior and further train it to align with the ground-truth dataset judgements. We begin with the preference dataset $\mathcal{D} = \left\{x^{(i)}, y_1^{(i)}, y_2^{(i)}, I^{(i)}\right\}_{i=1}^N$ as outlined in Section 2.1.2, however we consider unranked answers $y_1^{(i)}, y_2^{(i)}$ and the corresponding winning choice $I^{(i)}$. We design several training techniques for the generative reward model π_ϕ .

GenRM (no CoT): To train the GenRM model, we use the standard supervised fine tuning objective

$$\mathcal{L}_{\text{GenRM}}(\pi_\phi) = \mathbb{E}_{(x, y_1, y_2, I) \sim \mathcal{D}}[-\log \pi_\phi(I|x, y_1, y_2)] \quad (7)$$

essentially using the LLM as a classifier trained with next-token prediction.

CoT-GenRM with Rationalization: To train the CoT-GenRM we will also consider two settings—bootstrapping intermediate reasoning from ground-truth or, potentially, a stronger rationalization model $r \sim q_\phi(r|x^{(i)}, y_1^{(i)}, y_2^{(i)})$. We can then train the model with maximum likelihood over both the reasoning chain and ranking:

$$\mathcal{L}_{\text{GenRM-Rationalization}}(\pi_\phi) = \mathbb{E}_{(x, y_1, y_2, r, I) \sim \mathcal{D}}[-\log \pi_\phi(I|x, y_1, y_2, r) - \log \pi_\phi(r|x, y_1, y_2)] \quad (8)$$

we refer to this as a post-rationalization approach, similar to the approach described in Section 2.2.2.

CoT-GenRM-STaR: Finally we consider an approach where the model self-bootstraps intermediate reasoning using a STaR approach as outlined in Section 2.2.1. We will also consider two loss objectives here—following the filtering strategy described in the above section, we use the standard SFT loss similar to Eq. 8 on reasoning chains that yield the correct judgement. We denote models trained with this objective as STaR-SFT.

Alternatively, we would like to utilize all the sampled data, including reasoning chains that yield wrong judgments. Similar to the reasoning approach in Pang et al. (2024) we create a dataset of preference pairs $\mathcal{D} = \{x^{(i)}, y_1^{(i)}, y_2^{(i)}, r_w^{(i)}, I_w^{(i)}, r_l^{(i)}, I_l^{(i)}\}$, where r_w are rationales that lead to correct rankings I_w and r_l are rationales that lead to incorrect rankings I_l . We then use a DPO optimization objective of the form:

$$\mathcal{L}_{\text{GenRM-DPO}}(\pi_\phi) = \mathbb{E}_{\mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\pi_\phi(I_w, r_w|x, y_1, y_2)}{\pi_{\text{ref}}(I_w, r_w|x, y_1, y_2)} - \beta \log \frac{\pi_\phi(I_l, r_l|x, y_1, y_2)}{\pi_{\text{ref}}(I_l, r_l|x, y_1, y_2)} \right) \right]. \quad (9)$$

We denote models trained with this objective as STaR-DPO.

5 EXPERIMENTS

In this section we evaluate the performance of our proposed Generative Reward Modelling approaches as compared to classical Bradley-Terry reward models (Bradley & Terry, 1952), a more

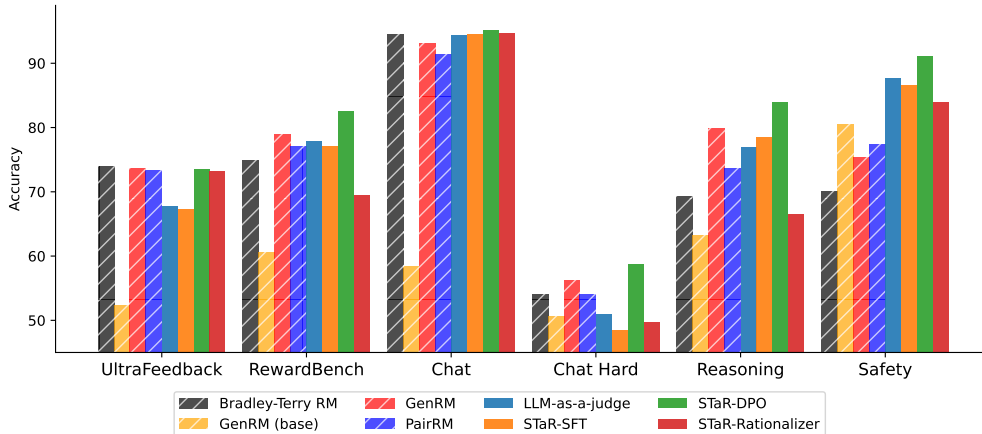


Figure 2: **Comparing generative reward models with prior reward modeling methods** on in-domain (UltraFeedback) data and out-of-domain data (RewardBench). All generative model scores are the result of a majority vote over 32 samples.

recent reward variant called PairRM (Jiang et al., 2023), as well as zero-shot RLAIIF evaluation. All models are based on the LLaMa-3.1-8B-Instruct model (Dubey et al., 2024).

We consider two separate training datasets: UltraFeedback (Cui et al., 2023), a large-scale feedback dataset of 61k pairs focusing on general instruction following, and UltraInteract (Yuan et al., 2024b), a dataset consisting of multi-turn reasoning trees focusing on math, code and logic, including advanced capabilities such as tool use and environment interaction. We evaluate models on each training dataset as well as on RewardBench (Lambert et al., 2024), a general reward modeling benchmark which consists of four subsets—Chat, Chat (Hard), Reasoning, and Safety. Full training details can be found in Appendix A.

In our experiments we evaluate the following questions:

1. Do generative reward models match the performance of classical reward models?
2. How robust are reward models and how well do they generalize to OOD data?
3. Does reasoning improve reward modelling and can we use inference time compute to improve results?
4. Do we need strong reasoning data to train generative RMs or can we bootstrap the reasoning from the model itself?

5.1 PERFORMANCE OF GENERATIVE RMs ON GENERAL ASSISTANT TASKS

We show our first main set of results in Fig. 2. All models are trained on the UltraFeedback dataset and evaluated on a held-out split of in-domain data as well as on RewardBench.

We first evaluate the zero-shot performance of the LLaMa 3.1 8B Instruct model as an evaluator using both CoT prompting with self-consistency (LLM-as-a-judge in Figure 2) and acting as a classifier directly outputting the response ranking (GenRM (base) in 2). We see that using that prompting the model to reason over the answers significantly boosts performance from 52.25% to 67.75% on the UltraFeedback evaluation dataset and from 60.60% to 75.18% accuracy on RewardBench.

However, when we compare the zero-shot methods with trained models, we find that both approaches substantially under-perform the Bradley-Terry RM, PairRM and trained GenRM models which all have comparable accuracies, around 73-74%. We see that the STaR-DPO model also matches these accuracies in-distribution at 73.9%. On the other hand, the STaR-SFT model achieves in-distribution accuracy of only 67.4%, which essentially shows no change of performance compared to the base LLM.

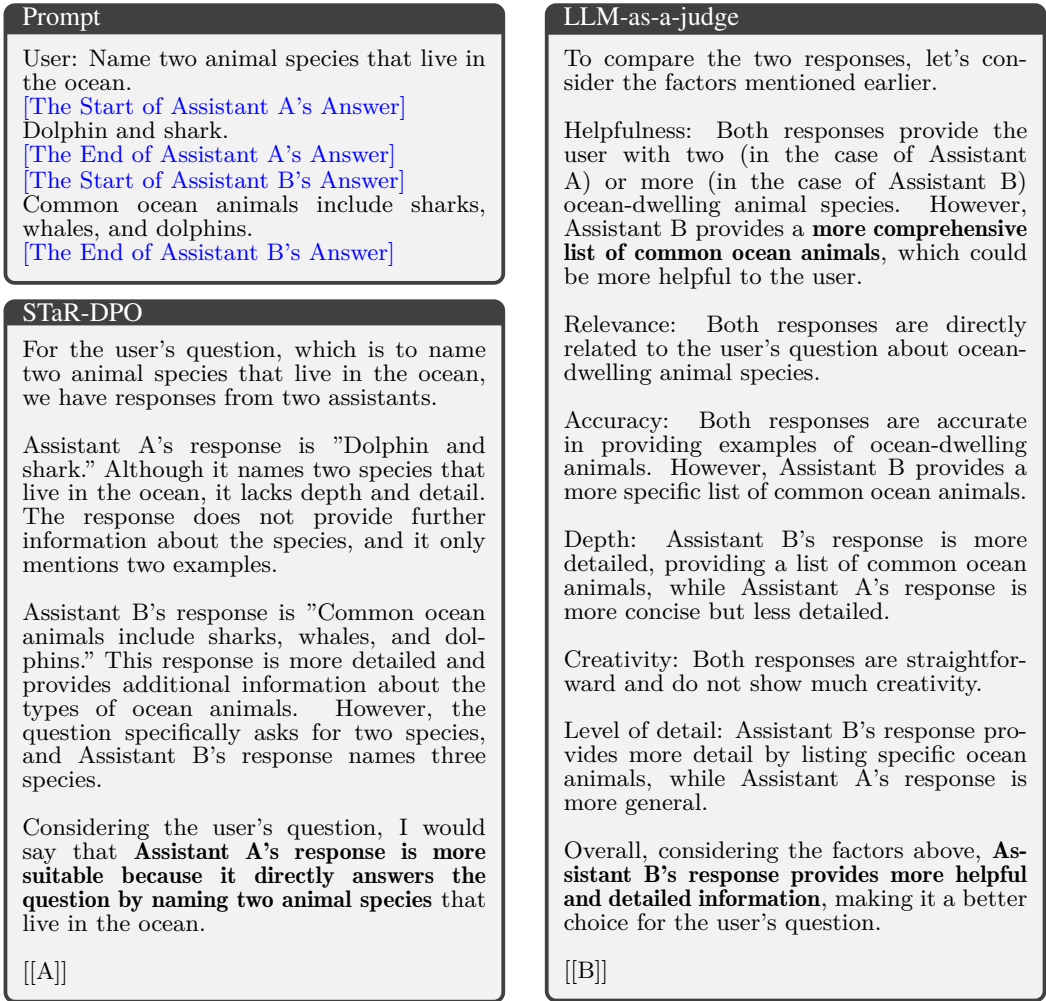


Figure 3: An example where LLM-as-a-judge fails to provide an accurate judgement, but STaR-DPO succeeds. Sentences where critical reasoning takes place are bolded for emphasis.

When we evaluate these models on out-of-distribution tasks (RewardBench) we see that STaR-DPO achieves the strongest result, over both the base model prior (81.9% versus 77.8%) and trained RM with the GenRM having the stronger performance at 78.9%. The STaR-DPO model outperforms or matches baselines across all RewardBench categories. On the other hand, the STaR-SFT model still does not substantially differ from the base model. The GenRM model outperforms the Bradley-Terry RM and PairRM with performance comparable to STaR-DPO across Chat, Chat (Hard) and Reasoning. However, one notable observation is that reasoning-based approaches show significantly stronger performance on the Safety category with the STaR-DPO model achieving 91.0% accuracy versus the best performing PairRM model, which achieves accuracy of 81.8%. Figure 3 demonstrates an interesting case where LLM-as-a-judge fails to accurately judge a general assistant task but the STaR-DPO model succeeds. The STaR-DPO model response recognizes that Assistant A's response "lacks depth and detail", but correctly recognizes that Assistant B's response does not follow the instruction and prefers Assistant A's response. To the contrary, the LLM-as-a-judge response repeatedly emphasizes how Assistant B's response is more helpful and detailed, even though the user requests a short list of 2 animals, incorrectly preferring Assistant B's response.

Overall, we see that the STaR-DPO reasoning model matches the best performance on the in-distribution dataset and has the strongest out-of-domain generalization across evaluation categories on RewardBench.

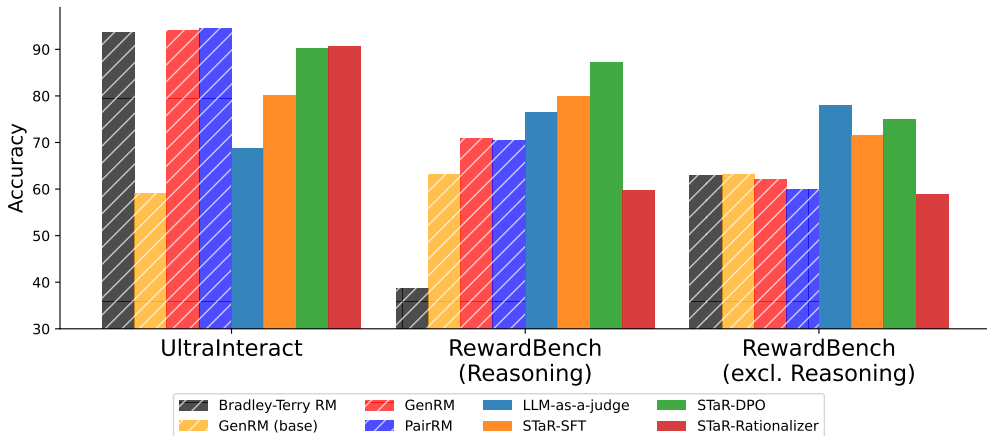


Figure 4: **Comparing generative reward models with prior reward modeling methods** on in-domain (UltraInteract) data and out-of-domain data (RewardBench) split into reasoning and non-reasoning subsets. All generative model scores are the result of a majority vote over 32 samples.

5.2 PERFORMANCE ON REASONING TASKS

We also evaluate performance specifically on reasoning tasks by training models on the UltraInteract dataset, which specifically focuses on challenging evaluations of reasoning chains. The experiments in this section focus on *meta*-reasoning, i.e. the capability to reason about reasoning steps. Figure 4 shows that the STaR-DPO model outperforms STaR-SFT on the UltraInteract evaluation dataset and achieves a significant improvement of 90.2% versus 68.8% for the base model. This is slightly lower than the explicit RM models, which all achieve comparable performance around 94%.

However, we see an interesting divergence on the RewardBench evaluation. For this experiment we show performance on the Reasoning category in RewardBench versus all other categories. We see that the Bradley-Terry RM, PairRM, and GenRM struggle to generalize to the RewardBench data, with the Bradley-Terry model scoring worse than random and the best performing GenRM model achieving 70.8% accuracy, which is worse than the LLM-as-a-judge performance at 76.6%. On the other hand the STaR-DPO significantly outperforms both baselines with 87.2%. This shows that the model successfully generalizes the meta-reasoning capabilities from the training dataset to a different distribution of reasoning prompts and answers. Additionally, on the non-reasoning evaluations in RewardBench, unsurprisingly the LLM-as-a-judge achieves the strongest result with 78.0% accuracy, while all explicit reward models struggle to generalize to these tasks and distributions. At the same time STaR-DPO only suffers a small loss of accuracy on these domains at 75.0%.

Based on the prior experiments we observe that the STaR-DPO model significantly outperforms the base LLM-as-a-judge, but also the GenRM model which does not use reasoning on held out tasks in RewardBench. One major variable is how to generate the reasoning chains used for training. In the experiments described so far rationales were sampled following a STaR-based approach using the same base model. We also evaluate an approach sampling rationales from a post-rationalization model $r \sim q_\phi(r|x, y_1, y_2, I)$, which are then used for SFT training using Eq. 8, we refer to this as STaR-Rationalizer. Results from this approach on UltraFeedback are shown in Fig. 2 and for UltraInteract in Fig. 4. Interestingly we observe that the STaR-Rationalizer model matches the performance of the STaR-DPO model on both datasets, significantly out-performing the STaR-SFT approach, which uses the same training objective. However, we see that this model struggles to generalize to the RewardBench tasks, under-performing not only the STaR-DPO model, but the base LLM as well on both datasets. This is an interesting empirical phenomenon that warrants further study, but we hypothesize that the core issue is that the training rationales from the post-rationalization model are off-policy for the base model, creating a distribution mismatch during training. While the model is able to learn those rationales on the training distribution it fails on more novel tasks where it generates rationales different from those seen during training.

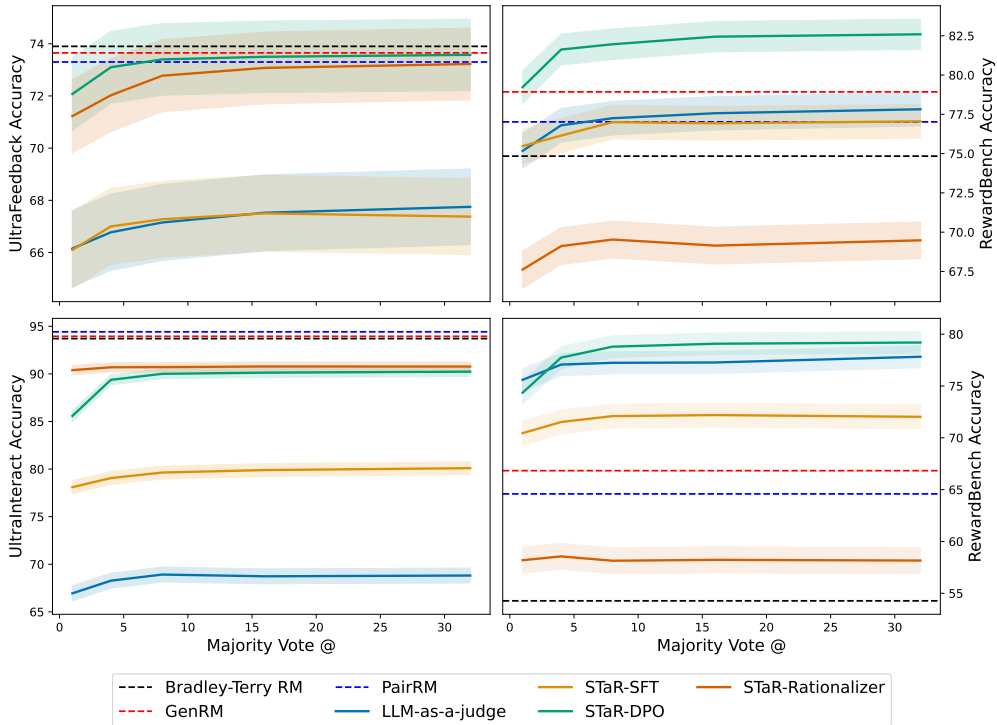


Figure 5: **Comparing generative reward models with prior reward modeling methods** with majority vote evaluation. Top row models are trained on UltraFeedback (Cui et al., 2024), and bottom row models are trained on UltraInteract (Yuan et al., 2024a). Left column models are evaluated on either UltraFeedback or UltraInteract, and right column models are evaluated on RewardBench (Lambert et al., 2024). Solid line methods are sampled to produce final answers and shading reflects a 95% confidence interval.

5.3 BOOTSTRAPPING RATIONALES

We show additional evaluations in Table 1 using different models to bootstrap reasoning on the UltraFeedback domain. We see similar results to the above when using rationales generated by a strong GPT-4 model, which significantly under-performs the standard STaR methods, however this is alleviated with additional on-policy training. Finally we see that bootstrapping reasoning with samples from the stronger LLaMa 3.1 70B Instruct model from the same family slightly improves performance on UltraFeedback, but leads to somewhat worse generalization to RewardBench. Our results indicate that on-policy training of the critic models can meaningfully impact performance.

5.4 USING INFERENCE-TIME COMPUTE

In addition to the previously discussed benefits, using LLMs as reward models also allows us to utilize additional inference time compute to improve performance. Indeed our results from the previous sections show that using COT prompt-

Bootstrap Source	UltraFeedback	RewardBench
Llama3.1 8B	68.63	77.34
	67.68	77.61
	67.38	77.05
Llama3.1 70B	70.50	77.09
	70.13	68.78
	69.58	63.43
GPT-4	62.85	69.58
	68.55	75.63
	71.73	78.29
GPT-4 (full)	62.60	70.52

Table 1: **Bootstrapping STaR-SFT with models of different capabilities.** All methods train a Llama3.1 8B model using rejection sampling from the bootstrap source. Only the first iteration of data comes from the bootstrap source. GPT-4 (full) is trained entirely on the reasoning from GPT-4. Scores are majority vote over 32 samples.

ing to induce reasoning in the evaluator model can significantly improve performance on new prompts and tasks over the base GenRM approach (which does not use CoT). In this section we show further results on accuracy using self-consistency and majority voting. Our results are shown in Fig. 5. We see that majority voting at 32 improves performance consistently and adds 1.6% accuracy on the UltraFeedback Dataset and 3.8% on RewardBench in that case. On UltraInteract majority voting improves performance by 4.6% and 4.9% on RewardBench. This indicates that "System 2" types of reasoning approaches can significantly improve the accuracy of the critic model. We believe using models with strong reasoning to provide feedback and evaluation to other models is a promising direction.

6 RELATED WORK

The concept of using language models for providing feedback, also known as constitutional AI or RLAIIF Bai et al. (2022b) has gained significant traction in recent years. Zheng et al. (2023b) further popularized the paradigm of LLM evaluation ("LLM-as-a-judge"), demonstrating that strong language models can effectively perform judgments with chain-of-thought (CoT) reasoning that approximate human evaluation. Building on this, Kim et al. (2024) proposed Prometheus, employing supervised fine-tuning from a powerful model to provide CoT reasoning and scoring, demonstrating strong evaluation performance from a smaller open model. In the current work we show that zero-shot LLM evaluations may not fully align with human feedback and significant improvements in accuracy can be gained from additional fine-tuning. Moreover, in our proposed approach of combining RLAIIF with STaR-based tuning we do not require ground-truth reasoning or supervision from a stronger model. Concurrently with this work, Zhang et al. (2024) presented Generative Verifiers, training CoT-GenRM with an SFT objective to act as a verifier for mathematical reasoning. They find similar observations to our experiments in Sections 5.2 and 5.4. However, one notable exception is that unlike our approach they rely on access to full reference solutions at training time. Another concurrent work in this direction is Ankner et al. (2024), which combines CoT reasoning generation with Bradley-Terry reward modelling. They present empirical findings on the benefits of reasoning, similar to the ones we show in Section 5.1, although crucially, they rely on a separate strong model to provide rationales and require the Bradley-Terry reward model hybrid architecture, while we use fully self-bootstrapped rationales in a full language modelling setup without the need for any additional architecture overhang.

A number of concurrent works have also proposed approaches for self-bootstrapping generative critics. In Wang et al. (2024c), the authors present an approach similar to our STaR-SFT method using data augmentation to create synthetic preference pairs. On the other hand Wu et al. (2024) instead uses DPO for optimizing the evaluator, but the feedback is based on additional meta-judge evaluator. Similarly, Wang et al. (2024b) also generates data using a number of augmentation techniques and deploys DPO training. We note that these data generation techniques are complementary to our approach which focuses on using STaR-based methods to align LLM generative reward models and replace explicit reward models.

7 CONCLUSION AND FUTURE DIRECTIONS

To conclude, this work introduces Generative Reward Models (GenRM) as a novel framework that combines the strengths of Reinforcement Learning from Human Feedback (RLHF) and Reinforcement Learning from AI Feedback (RLAIIF) to improve preference modeling for large language models (LLMs). By leveraging self-generated reasoning traces and iterative training loops, GenRM can fine-tune LLMs to better align with human preferences, addressing some of the key limitations associated with both human and AI feedback mechanisms.

The GenRM approach demonstrates that integrating chain-of-thought reasoning within preference modeling can significantly improve both in-distribution and out-of-distribution performance. In particular, the model surpasses traditional Bradley-Terry reward models on out-of-distribution tasks, showcasing a promising avenue for scaling reinforcement learning systems beyond their training data. We proposed a Chain-of-Thought (CoT) GenRM variant, which augments preference judgment tasks with intermediate reasoning traces. This addition boosted model performance by encouraging more logical, step-wise decision-making, leading to better generalization on complex

tasks such as reasoning and safety-related scenarios. Empirical results show that GenRM and its variants maintain competitive in-distribution accuracy while outperforming traditional methods on out-of-distribution tasks. Notably, STaR-DPO models, which rely on reasoning-based preference optimization, demonstrated superior robustness and performance across different benchmarks. Implications of the Proposed Approach The implications of the GenRM framework are multifaceted and offer significant contributions to both theoretical and practical advancements in AI alignment, reward modeling, and scalable preference optimization:

Scalability and Efficiency: By utilizing AI-generated feedback in the form of synthetic preferences, GenRM reduces the need for resource-intensive human annotation, making it a more scalable solution for improving LLM behavior in real-world applications.

Generalization to Out-of-Distribution Tasks: One of the persistent challenges in reinforcement learning and reward modeling is ensuring robust performance across a wide range of tasks, especially those not represented in training data. The proposed model shows improved generalization to out-of-distribution tasks, which is essential for deploying LLMs in diverse, dynamic environments.

Alignment with Human Values: While the method still incorporates human feedback in initial stages, the reliance on AI feedback allows for more rapid iterations and refinement. This hybrid approach ensures that the model remains aligned with human values while benefiting from the flexibility and speed of AI-driven optimization. The nature of the generative reward model also holds promise for the problem of pluralistic alignment Sorensen et al. (2024); Castricato et al. (2024) - i.e. aligning a model with diverse and potentially conflicting views, since they can model the underlying rational driving those preferences. This is something which classical Bradley-Terry reward model formulation, which uses a single point estimate, is not able to accommodate.

While this study has shown the promise of Generative Reward Models, several areas remain open for further exploration.

Refining Post-Rationalization Techniques: One limitation observed in the current CoT-GenRM approach is the potential misalignment when incorrect rationales are generated. Developing more sophisticated post-rationalization techniques, such as leveraging stronger models for intermediate reasoning or implementing novel correction mechanisms, could further enhance performance.

Exploring Iterative Online Optimization: Although GenRM benefits from the offline fine-tuning approach, the integration of iterative online optimization techniques could enhance its ability to adapt to new environments and feedback in real-time. Online preference optimization could reduce the lag between model deployment and alignment improvements, making it more responsive in dynamic settings.

Adapting to Multimodal Feedback: Future research could explore the extension of GenRM beyond textual preferences to multi-modal tasks. Integrating visual, auditory, and even environmental feedback could broaden the application of this approach to more complex real-world problems and VLMs have already proven to provide reasonable feedback in a zero-shot setting Chen et al. (2024).

Addressing Robustness in Adversarial Settings: An interesting direction for further work is the robustness of the model in adversarial settings. A particular pertinent direction is evaluation the "reward hacking" Gao et al. (2023); Rafailov et al. (2024) issues with Generative RMs Our results on out-of-distribution generalization of GenRMs make this a promising direction.

Improving Data Selection for Iterative Methods: Data selection has proven to be critical for model performance in pretraining and task-specific fine-tuning (Xie et al., 2023; Albalak et al., 2024; Li et al., 2024; Albalak et al., 2023). However, selecting optimal prompts and optimal completions for both SFT and pairwise versions of iterative training methods in RLAIIF remains an understudied issue, with large potential for progress (Wang et al., 2023; Zhu et al., 2024).

In summary, Generative Reward Models (GenRM) present a significant advancement in combining human and AI feedback to enhance preference modeling and alignment in LLMs. The hybrid approach improves scalability, out-of-distribution generalization, and model performance, making it a compelling framework for developing more reliable, aligned, and efficient AI systems. Moving forward, further exploration into online optimization, robust reasoning, and adaptation to multimodal tasks will be key to realizing the full potential of this framework in practical deployments.

REFERENCES

- Arash Ahmadian, Chris Cremer, Matthias Gallé, Marzieh Fadaee, Julia Kreutzer, Olivier Pietquin, Ahmet Üstün, and Sara Hooker. Back to basics: Revisiting reinforce style optimization for learning from human feedback in llms, 2024. URL <https://arxiv.org/abs/2402.14740>.
- Alon Albalak, Colin A Raffel, and William Yang Wang. Improving few-shot generalization by exploring and exploiting auxiliary data. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, and S. Levine (eds.), *Advances in Neural Information Processing Systems*, volume 36, pp. 24754–24780. Curran Associates, Inc., 2023. URL https://proceedings.neurips.cc/paper_files/paper/2023/file/4e3c5399729e06d2f0c22d04416904ab-Paper-Conference.pdf.
- Alon Albalak, Yanai Elazar, Sang Michael Xie, Shayne Longpre, Nathan Lambert, Xinyi Wang, Niklas Muennighoff, Bairu Hou, Liangming Pan, Haewon Jeong, Colin Raffel, Shiyu Chang, Tatsunori Hashimoto, and William Yang Wang. A survey on data selection for language models, 2024. URL <https://arxiv.org/abs/2402.16827>.
- Alex Andonian, Quentin Anthony, Stella Biderman, Sid Black, Preetham Gali, Leo Gao, Eric Hallahan, Josh Levy-Kramer, Connor Leahy, Lucas Nestler, Kip Parker, Michael Pieler, Jason Phang, Shivanshu Purohit, Hailey Schoelkopf, Dashiell Stander, Tri Songz, Curt Tigges, Benjamin Thérien, Phil Wang, and Samuel Weinbach. GPT-NeoX: Large Scale Autoregressive Language Modeling in PyTorch, 9 2023. URL <https://www.github.com/eleutherai/gpt-neox>.
- Chinmaya Andukuri, Jan-Philipp Fränken, Tobias Gerstenberg, and Noah D. Goodman. Star-gate: Teaching language models to ask clarifying questions, 2024.
- Zachary Ankner, Mansheej Paul, Brandon Cui, Jonathan D. Chang, and Prithviraj Ammanabrolu. Critique-out-loud reward models, 2024. URL <https://arxiv.org/abs/2408.11791>.
- Amanda Askell, Yuntao Bai, Anna Chen, Dawn Drain, Deep Ganguli, Tom Henighan, Andy Jones, Nicholas Joseph, Ben Mann, Nova DasSarma, et al. A general language assistant as a laboratory for alignment. *arXiv preprint arXiv:2112.00861*, 2021.
- Mohammad Gheshlaghi Azar, Mark Rowland, Bilal Piot, Daniel Guo, Daniele Calandriello, Michal Valko, and Rémi Munos. A general theoretical paradigm to understand learning from human preferences, 2023.
- Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, Nicholas Joseph, Saurav Kadavath, Jackson Kernion, Tom Conerly, Sheer El-Showk, Nelson Elhage, Zac Hatfield-Dodds, Danny Hernandez, Tristan Hume, Scott Johnston, Shauna Kravec, Liane Lovitt, Neel Nanda, Catherine Olsson, Dario Amodei, Tom Brown, Jack Clark, Sam McCandlish, Chris Olah, Ben Mann, and Jared Kaplan. Training a helpful and harmless assistant with reinforcement learning from human feedback, 2022a.
- Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, Carol Chen, Catherine Olsson, Christopher Olah, Danny Hernandez, Dawn Drain, Deep Ganguli, Dustin Li, Eli Tran-Johnson, Ethan Perez, Jamie Kerr, Jared Mueller, Jeffrey Ladish, Joshua Landau, Kamal Ndousse, Kamile Lukosuite, Liane Lovitt, Michael Sellitto, Nelson Elhage, Nicholas Schiefer, Noemi Mercado, Nova DasSarma, Robert Lasenby, Robin Larson, Sam Ringer, Scott Johnston, Shauna Kravec, Sheer El Showk, Stanislav Fort, Tamera Lanham, Timothy Telleen-Lawton, Tom Conerly, Tom Henighan, Tristan Hume, Samuel R. Bowman, Zac Hatfield-Dodds, Ben Mann, Dario Amodei, Nicholas Joseph, Sam McCandlish, Tom Brown, and Jared Kaplan. Constitutional ai: Harmlessness from ai feedback, 2022b.
- Ralph Allan Bradley and Milton E. Terry. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika*, 39(3/4):324–345, 1952. doi: <https://doi.org/10.2307/2334029>.

- Daniele Calandriello, Daniel Guo, Remi Munos, Mark Rowland, Yunhao Tang, Bernardo Avila Pires, Pierre Harvey Richemond, Charline Le Lan, Michal Valko, Tianqi Liu, Rishabh Joshi, Zeyu Zheng, and Bilal Piot. Human alignment of large language models through online preference optimisation, 2024. URL <https://arxiv.org/abs/2403.08635>.
- Louis Castricato, Nathan Lile, Rafael Rafailov, Jan-Philipp Fränken, and Chelsea Finn. Persona: A reproducible testbed for pluralistic alignment, 2024. URL <https://arxiv.org/abs/2407.17387>.
- Zhaorun Chen, Yichao Du, Zichen Wen, Yiyang Zhou, Chenhang Cui, Zhenzhen Weng, Haoqin Tu, Chaoqi Wang, Zhengwei Tong, Qinglan Huang, Canyu Chen, Qinghao Ye, Zhihong Zhu, Yuqing Zhang, Jiawei Zhou, Zhuokai Zhao, Rafael Rafailov, Chelsea Finn, and Huaxiu Yao. Mj-bench: Is your multimodal reward model really a good judge for text-to-image generation?, 2024. URL <https://arxiv.org/abs/2407.04842>.
- Ganqu Cui, Lifan Yuan, Ning Ding, Guanming Yao, Wei Zhu, Yuan Ni, Guotong Xie, Zhiyuan Liu, and Maosong Sun. Ultrafeedback: Boosting language models with high-quality feedback, 2023.
- Ganqu Cui, Lifan Yuan, Ning Ding, Guanming Yao, Bingxiang He, Wei Zhu, Yuan Ni, Guotong Xie, Ruobing Xie, Yankai Lin, Zhiyuan Liu, and Maosong Sun. Ultrafeedback: Boosting language models with scaled ai feedback, 2024. URL <https://arxiv.org/abs/2310.01377>.
- Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurelien Rodriguez, Austen Gregerson, Ava Spataru, Baptiste Roziere, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux, Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret, Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Allonsius, Daniel Song, Danielle Pintz, Danny Livshits, David Esiobu, Dhruv Choudhary, Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Graeme Nail, Gregoire Mialon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel Kloumann, Ishan Misra, Ivan Evtimov, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason Park, Jay Mahadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia, Kalyan Vasuden Alwala, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Lauren Rantala-Yearly, Laurens van der Maaten, Lawrence Chen, Liang Tan, Liz Jenkins, Louis Martin, Lovish Madaan, Lubo Malo, Lukas Blecher, Lukas Landzaat, Luke de Oliveira, Madeline Muzzi, Mahesh Pasupuleti, Manan Singh, Manohar Paluri, Marcin Kardas, Mathew Oldham, Mathieu Rita, Maya Pavlova, Melanie Kambadur, Mike Lewis, Min Si, Mitesh Kumar Singh, Mona Hassan, Naman Goyal, Narjes Torabi, Nikolay Bashlykov, Nikolay Bogoychev, Niladri Chatterji, Olivier Duchenne, Onur Çelebi, Patrick Alrassy, Pengchuan Zhang, Pengwei Li, Petar Vasic, Peter Weng, Prajjwal Bhargava, Pratik Dubal, Praveen Krishnan, Punit Singh Koura, Puxin Xu, Qing He, Qingxiao Dong, Ragavan Srinivasan, Raj Ganapathy, Ramon Calderer, Ricardo Silveira Cabral, Robert Stojnic, Roberta Raileanu, Rohit Girdhar, Rohit Patel, Romain Sauvestre, Ronnie Polidoro, Roshan Sumbaly, Ross Taylor, Ruan Silva, Rui Hou, Rui Wang, Saghar Hosseini, Sahana Chennabasappa, Sanjay Singh, Sean Bell, Seohyun Sonia Kim, Sergey Edunov, Shaoliang Nie, Sharan Narang, Sharath Rapparthi, Sheng Shen, Shengye Wan, Shruti Bhosale, Shun Zhang, Simon Vandenhende, Soumya Batra, Spencer Whitman, Sten Sootla, Stephane Collot, Suchin Gururangan, Sydney Borodinsky, Tamar Herman, Tara Fowler, Tarek Sheasha, Thomas Georgiou, Thomas Scialom, Tobias Speckbacher, Todor Mihaylov, Tong Xiao, Ujjwal Karn, Vedanuj Goswami, Vibhor Gupta, Vignesh Ramanathan, Viktor Kerkez, Vincent Gonguet, Virginie Do, Vish Vogeti, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyin Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaoqing Ellen Tan, Xinfeng Xie, Xuchao Jia, Xuwei Wang, Yaelle Goldschlag, Yashesh Gaur, Yasmine Babaei, Yi Wen, Yiwen Song, Yuchen Zhang, Yue Li, Yuning Mao, Zacharie Delpierre Coudert, Zheng Yan, Zhengxing Chen, Zoe Papakipos, Aaditya Singh, Aaron Grattafiori, Abha

Jain, Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay Menon, Ajay Sharma, Alex Boesenberg, Alex Vaughan, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit Sangani, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu, Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Franco, Aparajita Saraf, Arkabandhu Chowdhury, Ashley Gabriel, Ashwin Bharambe, Assaf Eisenman, Azadeh Yazdan, Beau James, Ben Maurer, Benjamin Leonhardi, Bernie Huang, Beth Loyd, Beto De Paola, Bhargavi Paranjape, Bing Liu, Bo Wu, Boyu Ni, Braden Hancock, Bram Wasti, Brandon Spence, Brani Stojkovic, Brian Gamido, Britt Montalvo, Carl Parker, Carly Burton, Catalina Mejia, Changhan Wang, Changkyu Kim, Chao Zhou, Chester Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Damon Civin, Dana Beaty, Daniel Kreymer, Daniel Li, Danny Wyatt, David Adkins, David Xu, Davide Testuggine, Delia David, Devi Parikh, Diana Liskovich, Didem Foss, Dingkang Wang, Duc Le, Dustin Holland, Edward Dowling, Eissa Jamil, Elaine Montgomery, Eleonora Presani, Emily Hahn, Emily Wood, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers, Fei Sun, Felix Kreuk, Feng Tian, Firat Ozgenel, Francesco Caggioni, Francisco Guzmán, Frank Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee, Gil Halpern, Govind Thattai, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hamid Shojanazeri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Ibrahim Damla, Igor Molybog, Igor Tufanov, Irina-Elena Veliche, Itai Gat, Jake Weissman, James Geboski, James Kohli, Japhet Asher, Jean-Baptiste Gaya, Jeff Marcus, Jeff Tang, Jennifer Chan, Jenny Zhen, Jeremy Reizenstein, Jeremy Teboul, Jessica Zhong, Jian Jin, Jingyi Yang, Joe Cummings, Jon Carvill, Jon Shepard, Jonathan McPhie, Jonathan Torres, Josh Ginsburg, Junjie Wang, Kai Wu, Kam Hou U, Karan Saxena, Karthik Prasad, Kartikay Khandelwal, Katayoun Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kun Huang, Kunal Chawla, Kushal Lakhota, Kyle Huang, Lailin Chen, Lakshya Garg, Lavender A, Leandro Silva, Lee Bell, Lei Zhang, Liangpeng Guo, Licheng Yu, Liron Moshkovich, Luca Wehrstedt, Madian Khabsa, Manav Avalani, Manish Bhatt, Maria Tsimpoukelli, Martynas Mankus, Matan Hasson, Matthew Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keaneally, Michael L. Seltzer, Michal Valko, Michelle Restrepo, Mihir Patel, Mik Vyatskov, Mikayel Samvelyan, Mike Clark, Mike Macey, Mike Wang, Miquel Jubert Hermoso, Mo Metanat, Mohammad Rastegari, Munish Bansal, Nandhini Santhanam, Natascha Parks, Natasha White, Navyata Bawa, Nayan Singhal, Nick Egebo, Nicolas Usunier, Nikolay Pavlovich Laptev, Ning Dong, Ning Zhang, Norman Cheng, Oleg Chernoguz, Olivia Hart, Omkar Salpekar, Ozlem Kalinli, Parkin Kent, Parth Parekh, Paul Saab, Pavan Balaji, Pedro Rittner, Philip Bontrager, Pierre Roux, Piotr Dollar, Polina Zvyagina, Prashant Ratanchandani, Pritish Yuvraj, Qian Liang, Rachad Alao, Rachel Rodriguez, Rafi Ayub, Raghotham Murthy, Raghu Nayani, Rahul Mitra, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Rohan Maheswari, Russ Howes, Ruty Rinott, Sai Jayesh Bondu, Samyak Datta, Sara Chugh, Sara Hunt, Sargun Dhillon, Sasha Sidorov, Satadru Pan, Saurabh Verma, Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Shaun Lindsay, Sheng Feng, Shenghao Lin, Shengxin Cindy Zha, Shiva Shankar, Shuqiang Zhang, Shuqiang Zhang, Sinong Wang, Sneha Agarwal, Soji Sajuyigbe, Soumith Chintala, Stephanie Max, Stephen Chen, Steve Kehoe, Steve Satterfield, Sudarshan Govindaprasad, Sumit Gupta, Sungmin Cho, Sunny Virk, Suraj Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez, Tamar Glaser, Tamara Best, Thilo Kohler, Thomas Robinson, Tianhe Li, Tianjun Zhang, Tim Matthews, Timothy Chou, Tzook Shaked, Varun Vontimitta, Victoria Ajayi, Victoria Montanez, Vijai Mohan, Vinay Satish Kumar, Vishal Mangla, Vitor Albiero, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu Mihalescu, Vladimir Ivanov, Wei Li, Wenchen Wang, Wenwen Jiang, Wes Bouaziz, Will Constable, Xiaocheng Tang, Xiaofang Wang, Xiaoqian Wu, Xiaolan Wang, Xide Xia, Xilun Wu, Xinbo Gao, Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin Nam, Yu, Wang, Yuchen Hao, Yundi Qian, Yuzi He, Zach Rait, Zachary DeVito, Zef Rosnbrick, Zhaoduo Wen, Zhenyu Yang, and Zhiwei Zhao. The llama 3 herd of models, 2024. URL <https://arxiv.org/abs/2407.21783>.

Jan-Philipp Fränken, Eric Zelikman, Rafael Rafailov, Kanishk Gandhi, Tobias Gerstenberg, and Noah D Goodman. Self-supervised alignment with mutual information: Learning to follow principles without preference labels. *arXiv preprint arXiv:2404.14313*, 2024.

Leo Gao, John Schulman, and Jacob Hilton. Scaling laws for reward model overoptimization. *International Conference on machine Learning*, 2023.

- Shangmin Guo, Biao Zhang, Tianlin Liu, Tianqi Liu, Misha Khalman, Felipe Llinares, Alexandre Rame, Thomas Mesnard, Yao Zhao, Bilal Piot, Johan Ferret, and Mathieu Blondel. Direct language model alignment from online ai feedback, 2024. URL <https://arxiv.org/abs/2402.04792>.
- Alexander Havrilla, Maksym Zhuravynskyi, Duy Phung, Aman Tiwari, Jonathan Tow, Stella Biderman, Quentin Anthony, and Louis Castricato. triX: A framework for large scale reinforcement learning from human feedback. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 8578–8595, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.530. URL <https://aclanthology.org/2023.emnlp-main.530>.
- Arian Hosseini, Xingdi Yuan, Nikolay Malkin, Aaron Courville, Alessandro Sordoni, and Rishabh Agarwal. V-star: Training verifiers for self-taught reasoners, 2024.
- Dongfu Jiang, Xiang Ren, and Bill Yuchen Lin. Llm-blender: Ensembling large language models with pairwise ranking and generative fusion, 2023. URL <https://arxiv.org/abs/2306.02561>.
- Seungone Kim, Jamin Shin, Yejin Cho, Joel Jang, Shayne Longpre, Hwaran Lee, Sangdoon Yun, Seongjin Shin, Sungdong Kim, James Thorne, and Minjoon Seo. Prometheus: Inducing fine-grained evaluation capability in language models, 2024. URL <https://arxiv.org/abs/2310.08491>.
- Sandipan Kundu, Yuntao Bai, Saurav Kadavath, Amanda Askell, Andrew Callahan, Anna Chen, Anna Goldie, Avital Balwit, Azalia Mirhoseini, Brayden McLean, et al. Specific versus general principles for constitutional ai. *arXiv preprint arXiv:2310.13798*, 2023.
- Nathan Lambert, Valentina Pyatkin, Jacob Morrison, LJ Miranda, Bill Yuchen Lin, Khyathi Chandu, Nouha Dziri, Sachin Kumar, Tom Zick, Yejin Choi, Noah A. Smith, and Hannaneh Hajishirzi. Rewardbench: Evaluating reward models for language modeling, 2024.
- Jeffrey Li, Alex Fang, Georgios Smyrnis, Maor Ivgi, Matt Jordan, Samir Gadre, Hritik Bansal, Etash Guha, Sedrick Keh, Kushal Arora, Saurabh Garg, Rui Xin, Niklas Muennighoff, Reinhard Heckel, Jean Mercat, Mayee Chen, Suchin Gururangan, Mitchell Wortsman, Alon Albalak, Yonatan Bitton, Marianna Nezhurina, Amro Abbas, Cheng-Yu Hsieh, Dhruva Ghosh, Josh Gardner, Maciej Kilian, Hanlin Zhang, Rulin Shao, Sarah Pratt, Sunny Sanyal, Gabriel Ilharco, Giannis Daras, Kalyani Marathe, Aaron Gokaslan, Jieyu Zhang, Khyathi Chandu, Thao Nguyen, Igor Vasiljevic, Sham Kakade, Shuran Song, Sujay Sanghavi, Fartash Faghri, Sewoong Oh, Luke Zettlemoyer, Kyle Lo, Alaaeldin El-Nouby, Hadi Pouransari, Alexander Toshev, Stephanie Wang, Dirk Groeneveld, Luca Soldaini, Pang Wei Koh, Jenia Jitsev, Thomas Koliar, Alexandros G. Dimakis, Yair Carmon, Achal Dave, Ludwig Schmidt, and Vaishaal Shankar. Datacomp-lm: In search of the next generation of training sets for language models, 2024. URL <https://arxiv.org/abs/2406.11794>.
- Rémi Munos, Michal Valko, Daniele Calandriello, Mohammad Gheshlaghi Azar, Mark Rowland, Zhaohan Daniel Guo, Yunhao Tang, Matthieu Geist, Thomas Mesnard, Andrea Michi, Marco Selvi, Sertan Girgin, Nikola Momchev, Olivier Bachem, Daniel J. Mankowitz, Doina Precup, and Bilal Piot. Nash learning from human feedback, 2024.
- OpenAI. Gpt-4 technical report. *arXiv preprint*, 2023. <https://arxiv.org/abs/2303.08774>.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 27730–27744. Curran Associates, Inc., 2022. URL https://proceedings.neurips.cc/paper_files/paper/2022/file/b1efde53be364a73914f58805a001731-Paper-Conference.pdf.

- Richard Yuanzhe Pang, Weizhe Yuan, Kyunghyun Cho, He He, Sainbayar Sukhbaatar, and Jason Weston. Iterative reasoning preference optimization, 2024. URL <https://arxiv.org/abs/2404.19733>.
- Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023. URL <https://arxiv.org/abs/2305.18290>.
- Rafael Rafailov, Yaswanth Chittooru, Ryan Park, Harshit Sikchi, Joey Hejna, Bradley Knox, Chelsea Finn, and Scott Niekum. Scaling laws for reward model overoptimization in direct alignment algorithms, 2024. URL <https://arxiv.org/abs/2406.02900>.
- Machel Reid, Nikolay Savinov, Denis Teplyashin, Dmitry Lepikhin, Timothy Lillicrap, Jean-baptiste Alayrac, Radu Soricut, Angeliki Lazaridou, Orhan Firat, Julian Schrittwieser, et al. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. *arXiv preprint arXiv:2403.05530*, 2024.
- John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms, 2017.
- Taylor Sorensen, Jared Moore, Jillian Fisher, Mitchell Gordon, Niloofar Miresghallah, Christopher Michael Rytting, Andre Ye, Liwei Jiang, Ximing Lu, Nouha Dziri, Tim Althoff, and Yejin Choi. A roadmap to pluralistic alignment, 2024. URL <https://arxiv.org/abs/2402.05070>.
- Nisan Stiennon, Long Ouyang, Jeff Wu, Daniel M. Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul Christiano. Learning to summarize from human feedback, 2022.
- Leandro von Werra, Younes Belkada, Lewis Tunstall, Edward Beeching, Tristan Thrush, Nathan Lambert, Shengyi Huang, Kashif Rasul, and Quentin Gallouédec. Trl: Transformer reinforcement learning. <https://github.com/huggingface/trl>, 2020.
- Binghai Wang, Rui Zheng, Lu Chen, Yan Liu, Shihan Dou, Caishuang Huang, Wei Shen, Senjie Jin, Enyu Zhou, Chenyu Shi, Songyang Gao, Nuo Xu, Yuhao Zhou, Xiaoran Fan, Zhiheng Xi, Jun Zhao, Xiao Wang, Tao Ji, Hang Yan, Lixing Shen, Zhan Chen, Tao Gui, Qi Zhang, Xipeng Qiu, Xuanjing Huang, Zuxuan Wu, and Yu-Gang Jiang. Secrets of rlhf in large language models part ii: Reward modeling, 2024a. URL <https://arxiv.org/abs/2401.06080>.
- Peifeng Wang, Austin Xu, Yilun Zhou, Caiming Xiong, and Shafiq Joty. Direct judgement preference optimization, 2024b. URL <https://arxiv.org/abs/2409.14664>.
- Tianlu Wang, Ping Yu, Xiaoqing Ellen Tan, Sean O’Brien, Ramakanth Pasunuru, Jane Dwivedi-Yu, Olga Golovneva, Luke Zettlemoyer, Maryam Fazel-Zarandi, and Asli Celikyilmaz. Shepherd: A critic for language model generation, 2023. URL <https://arxiv.org/abs/2308.04592>.
- Tianlu Wang, Ilia Kulikov, Olga Golovneva, Ping Yu, Weizhe Yuan, Jane Dwivedi-Yu, Richard Yuanzhe Pang, Maryam Fazel-Zarandi, Jason Weston, and Xian Li. Self-taught evaluators, 2024c. URL <https://arxiv.org/abs/2408.02666>.
- Tianhao Wu, Banghua Zhu, Ruoyu Zhang, Zhaojin Wen, Kannan Ramchandran, and Jiantao Jiao. Pairwise proximal policy optimization: Harnessing relative feedback for llm alignment, 2023. URL <https://arxiv.org/abs/2310.00212>.
- Tianhao Wu, Weizhe Yuan, Olga Golovneva, Jing Xu, Yuandong Tian, Jiantao Jiao, Jason Weston, and Sainbayar Sukhbaatar. Meta-rewarding language models: Self-improving alignment with llm-as-a-meta-judge, 2024. URL <https://arxiv.org/abs/2407.19594>.
- Sang Michael Xie, Shibani Santurkar, Tengyu Ma, and Percy Liang. Data selection for language models via importance resampling, 2023. URL <https://arxiv.org/abs/2302.03169>.

- Jing Xu, Andrew Lee, Sainbayar Sukhbaatar, and Jason Weston. Some things are more cringe than others: Iterative preference optimization with the pairwise cringe loss, 2024a. URL <https://arxiv.org/abs/2312.16682>.
- Shusheng Xu, Wei Fu, Jiakuan Gao, Wenjie Ye, Weilin Liu, Zhiyu Mei, Guangju Wang, Chao Yu, and Yi Wu. Is dpo superior to ppo for llm alignment? a comprehensive study, 2024b. URL <https://arxiv.org/abs/2404.10719>.
- Lifan Yuan, Ganqu Cui, Hanbin Wang, Ning Ding, Xingyao Wang, Jia Deng, Boji Shan, Huimin Chen, Ruobing Xie, Yankai Lin, Zhenghao Liu, Bowen Zhou, Hao Peng, Zhiyuan Liu, and Maosong Sun. Advancing llm reasoning generalists with preference trees, 2024a. URL <https://arxiv.org/abs/2404.02078>.
- Lifan Yuan, Ganqu Cui, Hanbin Wang, Ning Ding, Xingyao Wang, Jia Deng, Boji Shan, Huimin Chen, Ruobing Xie, Yankai Lin, et al. Advancing llm reasoning generalists with preference trees. *arXiv preprint arXiv:2404.02078*, 2024b.
- Eric Zelikman, Yuhuai Wu, Jesse Mu, and Noah Goodman. Star: Bootstrapping reasoning with reasoning. *Advances in Neural Information Processing Systems*, 35:15476–15488, 2022.
- Eric Zelikman, Georges Harik, Yijia Shao, Varuna Jayasiri, Nick Haber, and Noah D Goodman. Quiet-star: Language models can teach themselves to think before speaking. *arXiv preprint arXiv:2403.09629*, 2024.
- Zhiyuan Zeng, Jiatong Yu, Tianyu Gao, Yu Meng, Tanya Goyal, and Danqi Chen. Evaluating large language models at evaluating instruction following. *arXiv preprint arXiv:2310.07641*, 2023.
- Lunjun Zhang, Arian Hosseini, Hritik Bansal, Mehran Kazemi, Aviral Kumar, and Rishabh Agarwal. Generative verifiers: Reward modeling as next-token prediction, 2024. URL <https://arxiv.org/abs/2408.15240>.
- Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena. *Conference on Neural Information Processing Systems Track on Datasets and Benchmarks.*, 2023a.
- Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena, 2023b. URL <https://arxiv.org/abs/2306.05685>.
- Lianmin Zheng, Liangsheng Yin, Zhiqiang Xie, Chuyue Sun, Jeff Huang, Cody Hao Yu, Shiyi Cao, Christos Kozyrakis, Ion Stoica, Joseph E. Gonzalez, Clark Barrett, and Ying Sheng. Sglang: Efficient execution of structured language model programs, 2024. URL <https://arxiv.org/abs/2312.07104>.
- Rui Zheng, Shihan Dou, Songyang Gao, Yuan Hua, Wei Shen, Binghai Wang, Yan Liu, Senjie Jin, Qin Liu, Yuhao Zhou, Limao Xiong, Lu Chen, Zhiheng Xi, Nuo Xu, Wenbin Lai, Minghao Zhu, Cheng Chang, Zhangyue Yin, Rongxiang Weng, Wensen Cheng, Haoran Huang, Tianxiang Sun, Hang Yan, Tao Gui, Qi Zhang, Xipeng Qiu, and Xuanjing Huang. Secrets of rlhf in large language models part i: Ppo, 2023c. URL <https://arxiv.org/abs/2307.04964>.
- Banghua Zhu, Evan Frick, Tianhao Wu, Hanlin Zhu, Karthik Ganesan, Wei-Lin Chiang, Jian Zhang, and Jiantao Jiao. Starling-7b: Improving helpfulness and harmlessness with RLAIIF. In *First Conference on Language Modeling*, 2024. URL <https://openreview.net/forum?id=GqDntYTTbk>.
- Daniel M. Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B. Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. Fine-tuning language models from human preferences, 2020.

A ADDITIONAL EXPERIMENT DETAILS

A.1 PROMPTS

Our prompts follow Zheng et al. (2023a) with the following differences. For our LLM-as-a-judge and STaR (Figure 6), we remove the tie. For GenRM (Figure 8), we remove the brackets, and remove the explanation request in the system prompt. For Rationalizer (Figure 7), we remove the output instructions from the system prompt, and add a prompt to explain why A or B is better.

All prompts are using llama 3.1 instruct chat templates to format the prompts

<p>System: Please act as an impartial judge and evaluate the quality of the responses provided by two AI assistants to the user question displayed below. You should choose the assistant that follows the user’s instructions and answers the user’s question better. Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses. Begin your evaluation by comparing the two responses and provide a short explanation. Avoid any position biases and ensure that the order in which the responses were presented does not influence your decision. Do not allow the length of the responses to influence your evaluation. Do not favor certain names of the assistants. Be as objective as possible. After providing your explanation, output your final verdict by strictly following this format: "[[A]]" if assistant A is better, "[[B]]" if assistant B is better</p> <p>User: [Chat Context] {chat}</p> <p>[The Start of Assistant A’s Answer] {answer_a} [The End of Assistant A’s Answer]</p> <p>[The Start of Assistant B’s Answer] {answer_b} [The End of Assistant B’s Answer]</p>
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Figure 6: Prompt structure for LLM-as-a-Judge and STaR-SFT/DPO methods

<p>System: Please act as an impartial judge and evaluate the quality of the responses provided by two AI assistants to the user question displayed below. You should choose the assistant that follows the user’s instructions and answers the user’s question better. Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses. Begin your evaluation by comparing the two responses and provide a short explanation. Avoid any position biases and ensure that the order in which the responses were presented does not influence your decision. Do not allow the length of the responses to influence your evaluation. Do not favor certain names of the assistants. Be as objective as possible.</p> <p>User: [Chat Context] {chat}</p> <p>[The Start of Assistant A’s Answer] {answer_a} [The End of Assistant A’s Answer]</p> <p>[The Start of Assistant B’s Answer] {answer_b} [The End of Assistant B’s Answer]</p> <p>Explain why response (A/B) is better than response (B/A).</p>

Figure 7: Prompt structure for generating rationals for rationalizer methods

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System: Please act as an impartial judge and evaluate the quality of the responses provided by two AI
assistants to the user question displayed below. You should choose the assistant that follows the user’s
instructions and answers the user’s question better. Your evaluation should consider factors such as the
helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses. Avoid any position
biases and ensure that the order in which the responses were presented does not influence your decision.
Do not allow the length of the responses to influence your evaluation. Do not favor certain names of the
assistants. Be as objective as possible. Output your verdict by strictly following this format: "A" if assistant
A is better, "B" if assistant B is better

User:
[Chat Context]
{chat}

[The Start of Assistant A’s Answer]
{answer_a}
[The End of Assistant A’s Answer]

[The Start of Assistant B’s Answer]
{answer_b}
[The End of Assistant B’s Answer]
    
```

Figure 8: Prompt structure for GenRM methods

A.2 HYPERPARAMETERS

A.2.1 TRAINING HYPERPARAMETERS

For all training, we use the GPT-NeoX framework (Andonian et al., 2023). Models use the same hyperparameters across each dataset. Table 2 contains our hyperparameter choices for each training method.

Model	AdamW LR	AdamW (β_1, β_2)	Optimizer Weight Decay	Optimizer Schedule	LR warmup	β
STaR-SFT	1.0e-6					n/a
STaR-DPO	1.0e-6					1.0
STaR-SFT Rationalizer	2.0e-5					n/a
STaR-IPO Rationalizer	1.0e-6	(0.9, 0.95)	0.1	cosine	0.1	0.4
Bradley-Terry RM	1.0e-6					n/a
GenRM	1.0e-6					n/a
PairRM	1.0e-6					n/a

Table 2: Hyperparameters for different models.

A.2.2 GENERATION HYPERPARAMETERS

All models use the following settings for generation:

- SGLang version: 0.3.0 (Zheng et al., 2024)
- Temperature: 1.0
- Top-p: 0.95

A.3 STAR ITERATIONS

For each training run, we only sample from each pairwise data point one time. We split each dataset into three equal portions, and then apply the model to one of these splits without reusing any splits. We do not share any data between iterations, each iteration is fully sampled from the split, and does not include any of the previously generated data into the training. To generate the new data points, we sample from the latest model on the current split. From there, we train the latest model on that

split in an online manner. In order to accomplish roughly the same number of training steps for each dataset, ultrafeedback uses 3 epochs from this generated data, while ultrainteract uses 1 epoch on this data.

B RESULTS ACROSS ITERATIONS

Training Dataset	UltraFeedback				UltraInteract			
Evaluation Dataset	UltraFeedback		RewardBench		UltraInteract		RewardBench	
Method (iteration)	Maj@1	Maj@32	Maj@1	Maj@32	Maj@1	Maj@32	Maj@1	Maj@32
STaR-SFT (1)	67.42	68.62	76.10	77.34	72.33	75.03	72.33	74.20
STaR-SFT (2)	67.05	67.67	75.71	77.60	76.26	79.18	72.95	74.52
STaR-SFT (3)	66.10	67.38	75.48	77.05	78.10	80.10	70.45	72.03
STaR-DPO (1)	69.30	71.28	78.29	81.27	82.23	86.46	73.13	78.04
STaR-DPO (2)	71.70	72.98	78.46	81.94	84.70	88.40	76.31	79.92
STaR-DPO (3)	72.08	73.58	79.23	82.60	85.58	90.23	74.36	79.20
Rationalizer (1)	70.90	73.05	71.73	75.83	84.31	85.11	67.04	68.61
Rationalizer (2)	71.05	73.62	68.54	71.91	88.19	88.55	60.28	61.37
Rationalizer (3)	71.23	73.22	67.62	69.48	90.39	90.77	58.19	58.16

Table 3: STaR method evaluation results throughout training iterations.