

# Rethinking the Bradley-Terry Models in Preference-based Reward Modeling: Foundation, Theory, and its Alternatives

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## Abstract

The Bradley-Terry (BT) model is a common and successful practice in reward modeling for Large Language Model (LLM) alignment. However, it remains unclear *why* this model — originally developed for multi-player stochastic game matching — can be adopted to convert pairwise response comparisons to reward values and make predictions. Especially given the fact that only a limited number of prompt-response pairs are sparsely compared with others. In this paper, we first revisit the foundations of using BT models in reward modeling, and establish the convergence rate of BT reward models based on deep neural networks using embeddings, providing a theoretical foundation for their use. Despite theoretically sound, we argue that the BT model is not a necessary choice from the perspective of downstream optimization. This is because a reward model only needs to preserve the correct ranking predictions through a monotonic transformation of the true reward. We highlight the critical concept of *order consistency* in reward modeling and demonstrate that the BT model possesses this property. Consequently, we propose a simple and straightforward upper-bound algorithm, compatible with off-the-shelf binary classifiers, as an alternative order-consistent reward modeling objective. To offer practical insights, we empirically evaluate the performance of these different reward modeling approaches across more than 12,000 experimental setups, using 6 base LLMs, 2 datasets, and diverse annotation designs that vary in quantity, quality, and pairing choices in preference annotations.

**Keywords:** Bradley-Terry Models, Large Language Model Alignment, Preference-based Reward Modeling, Reinforcement Learning from Human Feedback

## 1 Introduction

The alignment of Large Language Models (LLMs) is crucial for their safe and effective deployment across various applications. Current research on reinforcement learning from human feedback (RLHF) (Christiano et al., 2017; Stiennon et al., 2020; Ouyang et al., 2022; Bai et al., 2022a) has largely focused on utilizing preference-based annotations provided by humans or general-purpose LLMs (Bai et al., 2022b; Lee et al., 2023; Guo et al., 2024). In general, there are two primary approaches to RLHF, namely the direct policy optimization (Rafailov et al., 2024; Zhao et al., 2023; Azar et al., 2023) that aligns LLMs with supervised learning objectives, and the alternate method that constructs a reward model to guide the

LLM optimization via either supervised learning or reinforcement learning (Yuan et al., 2023; Dong et al., 2023; Munos et al., 2023; Li et al., 2023).

Among these strategies, the Bradley-Terry (BT) model (Bradley and Terry, 1952) is commonly employed to convert pairwise comparisons into scores and has demonstrated its success in large-scale alignment systems (Ouyang et al., 2022; Touvron et al., 2023). Despite its empirical success, the theoretical justification for using the BT model in this context remains underexplored, particularly when dealing with sparse comparisons on a limited number of prompt-response pairs. Furthermore, it is unclear how necessary it is to use the BT models, and what data format is preferred in annotation. Our work aims to address these key questions by reflecting on reward modeling in LLM alignment. The subsequent sections of this paper are structured to answer those questions:

- **Question 1:** *When the number of players is greater than the number of comparisons (as often the case in LLM alignment settings), is the use of the BT model theoretically sound, and what factors contribute to its success in practice?*

In Section 2 we first review the usage of BT from a statistics perspective. We show that the classical BT model can be seamlessly applied to the LLM arena cases, but falls short in reward modeling due to the extremely sparse comparison and the requirement of making predictions. We explore the regression variants of BT models (e.g., Springall, 1973; Bockenholt, 1988) and their neural network extensions, providing theoretical results on their ability to approximate true reward up to an additive constant in the context of LLM alignment.

- **Question 2:** *What are alternative approaches to reward modeling other than the BT model?*

Since the primary objective of reward modeling is to optimize LLMs outputs by identifying the good response in inferences, learning a reward function up to any monotonic transformation should be sufficient for such an objective. This fact motivates us to propose a simple objective based on *order consistency* in Section 3. We show both the BT model and Classification models fall in this objective class. Corresponding empirical studies are conducted in Section 6.

- **Question 3:** *The conventional applications of the BT model assume randomized pairwise comparisons (e.g., randomized game matches among players). Would cross-prompt comparisons lead to more effective reward modeling?*

Our theoretical analysis emphasizes the necessity of using regression on the embedding space to predict rewards, which hints at the possibility of different types of comparisons. Specifically, we find no inherent advantages in restricting comparisons to responses from the same prompt, as is commonly done in the literature. In Section 4, we theoretically analyze the superiority of cross-prompt annotations in LLM alignment, and we empirically investigate the impact of cross-prompt comparisons and provide insights into their potential benefits in Section 6.

The contributions of this paper can be summarized as follows:

1. Formally, we provide a comprehensive analysis of the application of the BT model in LLM alignment, contrasting its traditional use in multi-player arenas with the unique challenges posed in this context. We analyze the underlying rationale and offer a thorough justification for applying the BT model to LLM reward modeling.

2. Theoretically, we introduce the first asymptotic theory for neural network-based BT regression in preference-based reward modeling. Our work establishes the first risk bound for BT model reward estimation in the context of LLM alignment.
3. Practically, we propose *order consistency* as a core objective of reward modeling, demonstrating how this principle can derive both the BT model and an alternative classification-based approach. This alternative offers greater flexibility compared to the BT model, broadening its applicability.
4. Empirically, we conduct extensive experiments — covering 6 base LLMs, 2 datasets, 3 response sampling methods, 6 annotation noise levels, 3 reward model implementations, 4 annotation availability scenarios, and 5 random seeds — resulting in over 12,000 runs. These experiments demonstrate the statistical efficacy of the classification-based reward models and compare them with the BT model across diverse settings.

## 2 Rethinking the Usage of BT Models in LLM Alignment

### 2.1 Two Different BT Models — Parameter Estimation and Prediction

The original BT model (Bradley and Terry, 1952), aligned with the Luce-Shephard choice rule (Luce, 1959; Shepard, 1957), posits that in a simplified two-option scenario, the **probability** of selecting option  $i$  from a set  $i, j$  is proportional to the utility  $u(\cdot)$  assigned to that option. Formally, this can be expressed as a softmax output of the log utilities  $r(\cdot)$  (Bockenholt, 1988)

$$P(i \succ j) = \frac{u(i)}{u(i) + u(j)} = \frac{\exp(r(i))}{\exp(r(i)) + \exp(r(j))} = \text{softmax}(r(i), r(j)). \quad (1)$$

**LLM Arena with BT Model** One of the classical BT model applications is the LLM chatbot arenas (Chiang et al., 2024), where multiple LLMs compete against one another based on human feedback through paired comparisons. Here, each LLM functions as a player, and the human-annotated preferences represent the outcome of these game matches. The goal is to assign a single performance score to each LLM player. In Chiang et al. (2024) 130 models were compared across more than 1.7 million comparisons, with each model participating in over 26,000 matches on average.

In such a setting, estimating the values of  $r(\cdot)$  is sufficient to achieve the primary goal of evaluating each chatbot’s performance. This aligns closely with the original objective of BT model in ranking sports teams (Bradley and Terry, 1952). Previous work has shown that, with enough pairwise competition, one can estimate these ability scores well (Ford Jr, 1957; Han et al., 2020; Wu et al., 2022) up to a constant additive factor. It is shown that to estimate  $N$  scores via random pairwise comparisons, the theoretical lower bound on the number of comparisons is  $\mathcal{O}(N \log(N))^1$ , while the best-known methods require  $\mathcal{O}(N \log^3(N))$  comparisons (Han et al., 2020).

**Reward Modeling with BT Model: Understanding Implicit Assumptions** In contrast, the application of the BT model to reward modeling is not as straightforward. First, the implications of using the BT model in this context are not well-defined in the

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1. Intuition behind this bound can come from the fact that, given the true underlying scores, a quicksort algorithm requires  $\mathcal{O}(N \log(N))$  comparisons on average.

Table 1: Comparison of the BT model usage in LLM Arena and Reward Modeling.

Usage	LLM Arena	BT Reward Modeling
Objective Prediction	Direct Parameter Estimation Not needed	Model Parameterization Needed
Number of Comparisons	Sufficient (1.7M for $N = 130$ )	Very Sparse ( $N/2$ )
Usage of BT Model Requirement	Classical BT at least $\mathcal{O}(N \log(N))$ Comparisons	BT-Regression Covariates

literature. For instance, if each prompt-response pair is treated as a player, how do we characterize the stochastic nature of human annotations as the game results? What assumptions need to be made? The answers to these questions were not elaborated in the literature (Christiano et al., 2017; Stiennon et al., 2020; Ouyang et al., 2022; Bai et al., 2022a). In the following Section 2.2, we first provide an analysis of the underlying assumptions of applying the BT model to preference-based annotation as a game.

Besides the implicit assumptions, another challenge arises in the application of BT models in reward modeling lies in the comparison sparsity — any given prompt-response is compared to another one **only once**, resulting in far fewer comparisons than in the arena setting (i.e., much less than the  $\mathcal{O}(N \log(N))$  theoretical lower-bound). To understand how a single model would handle these seemingly different tasks, we provide an overview of the BT model and their variants in Section 2.3.

## 2.2 Comprehending the BT Model Application in Preference Annotations

In the literature, several prior works have challenged the *practical application* of the BT model (Azar et al., 2023; Munos et al., 2023; Tang et al., 2024). While the previous analysis of whether the BT model is a good choice focused on the match-ness between the BT model and data (e.g., transitivity (Gardner, 1970), existence of hard decision boundary (Azar et al., 2023; Tang et al., 2024)). In this section, we revisit the basic assumptions of modeling human preference annotations with the BT model, and focus on answering the following question:

***What are the underlying assumptions when we assume the BT model can be used to model the preference annotations?***

The canonical interpretation of how to apply equation 1 in preference-based learning is that: when randomly sampling a human annotator from the population, the human annotator’s choice of the preferred response is proportional to the response’s utility value. Formally, we use  $x, y_1, y_2$  to denote the prompt and responses, the above interpretation implies the following assumptions:

**Assumption 1 (Existence of Deterministic Oracle Utility Values)** *The (log-)utility value  $r_{x,y}$  of any response  $y$  given  $x$  exists and is deterministic.*

**Definition 2 (Individual Annotations under Deterministic Biases)** *For annotator  $A$ , the annotation result is deterministic and depends on the comparison of their biased evaluation of the utility values of both responses  $y_1$  and  $y_2$ , according to*

$$P_A(y_1 \succ y_2 | x) = \mathbb{1}(r_{x,y_1} - r_{x,y_2} > b(x, y_1, A) - b(x, y_2, A)) \quad (2)$$

Based on the above definitions, we need the following explicit assumption to derive the BT model in this randomized annotation process:

**Assumption 3 (Logistic Difference Assumption)** *The  $b(x, y_1, A) - b(x, y_2, A)$  is sampled i.i.d. from a standard logistic distribution for all  $x, y, A$ :*

$$P(b(x, y_1, A) - b(x, y_2, A) \leq t) = \frac{1}{1 + e^{-t}} \quad (3)$$

**Remark 4** (*Transitive property of difference*) *A reader might be (rightfully) worried if this assumption is consistent with transitive property of difference, e.g., when considering multiple comparisons we have to have  $b(x, y_1, A) - b(x, y_3, A) = b(x, y_1, A) - b(x, y_2, A) + b(x, y_2, A) - b(x, y_3, A)$  while knowing sum of (independent) logistic distributions is not logistic. One should be aware that the two terms being summed are not independent and the assumption can be achieved by assuming all annotator biases are independently Gumbel distributed with the same scale parameter.*

With this assumption, we arrive at the BT-type model

**Proposition 5 (Modeling Annotations under Logistic Difference Assumption)**

$$P(y_1 \succ y_2 | x) = P(r_{x,y_1} - r_{x,y_2} > b(x, y_1, A) - b(x, y_2, A)) = \frac{1}{1 + e^{-(r_{x,y_1} - r_{x,y_2})}} \quad (4)$$

While the above assumption on logistic bias differences lead to the BT-type models, it is also natural to check other assumptions such as the Gaussian difference assumption and its corresponding model:

**Assumption 6 (Gaussian Difference Assumption)** *The  $b(x, y_1, A) - b(x, y_2, A)$  is sampled from a standard Gaussian distribution:*

$$b(x, y_1, A) - b(x, y_2, A) \sim \mathcal{N}(0, 1) \quad (5)$$

**Proposition 7 (Modeling Annotations under Gaussian Difference Assumption)**

$$P(y_1 \succ y_2 | x) = P(r_{x,y_1} - r_{x,y_2} > b(x, y_1, A) - b(x, y_2, A)) = \Phi(r_{x,y_1} - r_{x,y_2}), \quad (6)$$

where  $\Phi$  is the CDF of the Gaussian distribution.

To elaborate implications of those different assumptions and provide an alternative perspective to understand those assumptions, we have the following remark:

**Remark 8 (Assumption on Performance in a Game)** *Assuming the performance of players A and B in a game is a Gaussian distribution centered at their ability scores  $u_A, u_B$ , and the value of performance determines which player wins in the game, we have*

$$P(A \text{ wins}) = P(x_a \geq x_b | x_a \sim \mathcal{N}(u_A, \sigma^2), x_b \sim \mathcal{N}(u_B, \sigma^2)) = \frac{1}{2} + \frac{1}{2} \operatorname{erf}\left(\frac{u_A - u_B}{2\sigma}\right). \quad (7)$$

Alternatively, when assuming the performance of players A and B in a game is a Gumbel distribution located at their ability scores  $u_A, u_B$ , and the value of performance determines which player wins in the game, we have

$$P(A \text{ wins}) = P(x_a \geq x_b | x_a \sim \mathcal{G}(u_A, b), x_b \sim \mathcal{G}(u_B, b)) = \frac{1}{2} + \frac{1}{2} \tanh\left(\frac{u_A - u_B}{2b}\right). \quad (8)$$

While the latter corresponds to the BT model, the former is known to be the Thurstonian model (Thurstone, 1927). In the BT model, the  $\tanh(\cdot)$  rather than the error function  $\text{erf}(\cdot)$  is used, for the sake of a better empirical fit and mathematical convenience (Elo, 1967; Glickman, 1995; Glickman and Jones, 1999). In both models, we use a game-dependent notation of the variance terms  $\sigma^2, b$  to characterize the player-agnostic performance variation. Those constants can be further absorbed in the utility values.

### 2.3 BT Regression: How BT Model Works with Sparse Comparisons

Additionally, estimating a separate  $r(\cdot)$  for each prompt-response pair is impractical. In typical LLM alignment scenarios, we often have only  $N/2$  comparisons for  $N$  pairs, far below the theoretical lower bound for consistent estimation (Han et al., 2020). Furthermore, unlike the arena setting, there is no clear way to predict the score for a new, unseen pair. However, this challenge is not unique to LLM alignment; sports analysts also need to estimate a team’s ability before many competitions or predict the ability of a new team. A common approach in such cases is to use features or covariates, such as team composition or funding status, to predict scores. For LLM, one could have **sentence embeddings** as such covariates.

These extensions of the BT model on regression settings were explored shortly after its original introduction: Springall (1973) assumed that  $r(\cdot)$  could be expressed as a linear combination of covariates. In this scenario, the problem reduces to a classic logistic regression on the difference between two sets of covariates. This allows us to predict the score for a new team or prompt-response pair based on its covariates before any comparisons are made. More complex nonlinear models such as spline models have also been explored (De Soete and Winsberg, 1993). For a more comprehensive review from a statistical perspective, we refer readers to Cattelan (2012).

In practice, reward modeling in LLM alignment often employs neural networks, with multilayer perceptrons (MLPs) being a common choice to map embeddings to scores. However, there is currently no theoretical justification for why this particular choice of model and loss function is effective for learning reward functions. From a theoretical standpoint, this model variant can be viewed as a nonparametric logistic regression problem (Bockenholt, 1988; Schmidt-Hieber, 2020) with additional structural assumptions on the network, and our analysis builds on this framework. In the following section, we establish the asymptotic theory for learning reward models using MLPs and BT loss. Table 1 summarizes the key differences between the two usages.

### 2.4 Asymptotic Theory on MLP-based BT Regression in Reward Modeling

In preference-based LLM alignment, we work with the dataset under the form of  $\mathcal{D}_{\text{pref}} = \{(x_i, y_{1,i}, y_{2,i}, h_i)\}_{i \in [n]}$ , where each tuple consists of the prompt  $x_i$ , the corresponding responses  $y_{1,i}$  and  $y_{2,i}$  sampled from the LLM  $\ell$  to be aligned  $y_{1,i}, y_{2,i} \sim \ell(x_i)$ , and the human-annotated preference  $h_i$ , being 1 if  $y_{1,i}$  is preferred and  $-1$  otherwise.

Assume we have a *known* embedding function  $\Psi(\cdot, \cdot) : \mathcal{X} \times \mathcal{Y} \mapsto [0, 1]^d$ , such that there exists an unknown reward function  $r : \mathbb{R}^d \mapsto \mathbb{R}$ , and can be expressed as  $r(\Psi(x, y))$  for all  $x, y$ . Without loss of generality, we assume the embeddings are scaled within the range  $[0, 1]$  — otherwise, we can scale the embeddings into this range. Under this framework, reward modeling reduces to learning the function  $r$ . Note that under this formalism there is no

need for a comparison to have the same prompt. We will empirically explore the effects of using cross-prompt and same-prompt in our experiment section.

Denote our reward model as  $\hat{r}_\theta$ , parameterized by  $\theta$ , when there is no confusion, we will abbreviate it as  $\hat{r}$ . We denote the vector of two rewards as  $\hat{\mathbf{r}}$  and the class probability is then  $\text{softmax}(\hat{\mathbf{r}})$ . Thus, training this reward model reduces to training a classifier with a cross-entropy loss, where the predicted conditional class probabilities are computed as  $\text{softmax}(\hat{r}(\Psi(x_1, y_1)), \hat{r}(\Psi(x_2, y_2)))$ . Our theoretical analysis follows closely the work of Bos and Schmidt-Hieber (2022) and Schmidt-Hieber (2020). In this setting, we consider a special case of a model that preserves anti-symmetry: if we exchange the roles of  $x_1, y_1$  with  $x_2, y_2$ , the reward difference becomes negative.

We demonstrate that an MLP can approximate the probability that the first pair is preferred over the second, and subsequently show that this approach enables the model to learn the underlying reward function effectively. For notational simplicity, let  $\Psi_1^{(i)}$  and  $\Psi_2^{(i)}$  represent the embeddings of the  $i$ -th pair, where  $i = 1, \dots, n$ . Without loss of generality, we assume  $\Psi^{(i)} \in [0, 1]^d$ . Let the true preference probability for the  $i$ -th pair be  $\mathbf{p}_0^{(i)}$ , and the predicted probability be  $\hat{\mathbf{p}}^{(i)} = (\sigma(\hat{r}^\Delta(\Psi_1^{(i)}, \Psi_2^{(i)})), 1 - \sigma(\hat{r}^\Delta(\Psi_1^{(i)}, \Psi_2^{(i)}))) = \text{softmax}(\hat{\mathbf{r}}(\Psi_1^{(i)}, \Psi_2^{(i)}))$ . The preference label  $\mathbf{h}^{(i)}$  equals  $(1, 0)$  if the first response pair is preferred, and  $(0, 1)$  otherwise. In this way, the BT model can be reduced to a pairwise classification problem, where the likelihood is given by:

$$\tilde{\mathcal{L}}_{\text{CE}}(\mathbf{p}) = -\frac{1}{n} \sum_{i=1}^n (\mathbf{h}^{(i)})^\top \log(\mathbf{p}^{(i)}), \quad \hat{\mathbf{p}} = \arg \min_{\mathbf{p} \in \mathcal{F}_\theta} \tilde{\mathcal{L}}_{\text{CE}}(\mathbf{p}) \quad (9)$$

It is unrealistic to assume we can find an NN that actually attends the global minimum, we denote the difference between the fitted NN and the global minimum as

$$\Delta_n(\mathbf{p}_0, \hat{\mathbf{p}}) = \mathbb{E} \left[ \tilde{\mathcal{L}}_{\text{CE}}(\hat{\mathbf{p}}) - \min_{\mathbf{p} \in \mathcal{F}_\theta} \tilde{\mathcal{L}}_{\text{CE}}(\mathbf{p}) \right] \quad (10)$$

We consider the truncated KL risk following Bos and Schmidt-Hieber (2022) to overcome the divergence problem of KL risk.

**Definition 9 (Truncated KL risk (Bos and Schmidt-Hieber, 2022))** *The  $B$ -truncated KL risk for a probability estimator  $\hat{\mathbf{p}}$*

$$R_B(\mathbf{p}_0, \hat{\mathbf{p}}) = \mathbb{E} \left[ \mathbf{p}_0^\top \min \left( B, \log \frac{\mathbf{p}_0}{\hat{\mathbf{p}}} \right) \right] \quad (11)$$

Our main theorem establishes that, with regularity assumptions on the true reward function, an MLP reward model can accurately predict preference probabilities, as measured by truncated KL risk.

**Theorem 10 (Truncated KL risk bound, informal)** *Suppose the true utility function induced probability of preference satisfies smoothness and regularity assumptions detailed in Assumption 21 with smoothness characterised by constant  $\beta$  and regularity characterised by constant  $\alpha$  with dimension of embedding being  $d$ . Let  $\hat{\mathbf{p}}$  be an estimator from the family of MLP satisfying regularity assumptions detailed in Assumption 18 with depth  $L$ . Define*

$\phi_n := 2^{\frac{(1+\alpha)\beta+(3+\alpha)d}{(1+\alpha)\beta+d}} n^{-\frac{(1+\alpha)\beta}{(1+\alpha)\beta+d}}$  For sufficiently large  $n$ , there exists constants  $C', C''$  such that when  $\Delta_n(\hat{p}, p_0) \leq C''B\phi_n L \log^2(n)$  then

$$R_B(\mathbf{p}_0, \hat{\mathbf{p}}) \leq C' B \phi_n L \log^2(n) \quad (12)$$

where  $a \lesssim b$  means there exists some constant  $C$  s.t.  $a \leq Cb$  and  $a \asymp b$  means  $a \lesssim b$  and  $b \lesssim a$ .

A detailed formal statement and proof are given as Theorem 27 in the appendix.

**Corollary 11 (Connecting probability to reward)** Given that  $(\sqrt{a} - \sqrt{b})^2 = (a - b)^2 / (\sqrt{a} + \sqrt{b})^2$ , we can apply Theorem 28 to demonstrate that in a large subset of the embedding space,

$$|p_0(\Psi_1, \Psi_2) - \hat{p}(\Psi_1, \Psi_2)| \lesssim |\sqrt{p_0} + \sqrt{\hat{p}}| \sqrt{\phi_n L} \log(n) \quad (13)$$

$$|r(\Psi_1) - r(\Psi_2) - (\hat{r}(\Psi_1) - \hat{r}(\Psi_2))| \lesssim \frac{|\sqrt{p_0} + \sqrt{\hat{p}}|}{\tilde{p}(1 - \tilde{p})} \sqrt{\phi_n L} \log(n) \quad (14)$$

where  $\tilde{p}$  is a probability between  $p_0$  and  $\hat{p}$ , the second line is due to mean value theorem. This indicates that the comparison should be between those pairs that are relatively close in reward to avoid diverging behavior of the logit function.

Formal proofs and detailed theoretical analyses are provided in Appendix A.

### 3 Rethinking Reward Modeling Objectives in LLM Alignment

Practical implementation of the BT model poses several requirements including the paired data, the specially designed anti-symmetric model structure, and the inherent assumptions of the BT model itself. This leads us to question whether we can have alternative approaches to reward modeling. To address this, it is helpful to pause and reflect on the essential requirements of a reward model in LLM alignment. Our data consists of binary preferences, representing the relative ranking between two prompt-response pairs. We can view this as a form of binary classification, with the ultimate goal being to learn a continuous score for optimization. While the Bradley-Terry model serves this purpose through its log-likelihood loss and anti-symmetric structure, we now consider whether these formal elements are indispensable and explore possible simplifications.

#### 3.1 The Unified Target of Order Consistency

In basic binary classification, we prioritize accuracy over modeling output probabilities precisely. For example, neural classifiers, despite being overconfident (Guo et al., 2017), are widely used for their accuracy. Similarly, **we don't require the BT model to predict comparison probabilities accurately, but rather to provide a reliable signal for ranking LLM outputs at inference.**

Since our goal is response optimization using a reward proxy, it is sufficient to learn the reward function up to a monotonic transformation. While this might alter preference probabilities, it won't affect optimization results. To this end, the learned reward function

$\hat{r}$  only needs to satisfy the following condition: for any two distinct prompt-response pairs  $(x_1, y_1)$  and  $(x_2, y_2)$ , we require that  $(\hat{r}(x_1, y_1) - \hat{r}(x_2, y_2))(r(x_1, y_1) - r(x_2, y_2)) > 0$ . In other words, the learned reward function must preserve the ordering as the true reward function.

This condition implies the existence of a strictly monotonic increasing function  $h$  such that  $\hat{r}(\cdot) = h(r(\cdot))$ . Such an equivalence is sufficient for optimizing the reward in settings such as sampling-based optimization, and contextual bandits (Agarwal et al., 2014; Lattimore and Szepesvári, 2020). Ideally, if we have access to the ground truth ordering, we can define  $h = \text{sign}(r(x_1, y_1) - r(x_2, y_2))$ . If we can (1) construct a model  $\hat{H} : \mathcal{X} \times \mathcal{Y} \times \mathcal{X} \times \mathcal{Y} \mapsto \{+1, -1\}$  that predicts the correct ordering with high accuracy (i.e.,  $\hat{H}$  is *order consistent*), and (2) map this ordering into a continuous value, then we can meet the requirements for downstream optimization.

However, this observed ordering is often subject to noise from human annotators. Drawing on insights from the psychological bottleneck literature (Stewart et al., 2005; Guest et al., 2016), it is reasonable to assume that when the true underlying scores of two responses are similar, it becomes more difficult for annotators to distinguish between them. Formally, we have

**Assumption 12 (Imperfect Preference Annotation in Approximating True Scores)**  
*Denote the true utility difference  $\Delta r := |r(x_1, y_1) - r(x_2, y_2)|$ , and the annotator function  $h(x_1, x_2, y_1, y_2)$  provides feedback that probabilistically aligns with the oracle utility  $r(x, y)$ . We will assume it is harder for them to assign correctly when the reward difference between two pairs is  $\Delta r$  according to:*

$$\mathbb{P}\left(h(x_1, x_2, y_1, y_2)(r(x_1, y_1) - r(x_2, y_2)) > 0 \mid \Delta r\right) = \xi(\Delta r), \quad (15)$$

where  $r$  is the unknown oracle utility function, and  $\xi(\cdot)$  any monotonic increasing function to  $[0.5, 1]$ .

With those noisy annotations, the best we can consider is an order consistent with the noisy ordering:

**Definition 13 (Order Consistency)** *We consider the loss over an ordering model  $\hat{H}$*

$$\mathcal{L}_{\text{oc}}(\hat{r}) = \mathbb{E}_{x_1, x_2, y_1, y_2, h} \mathbb{1}[h = \hat{H}] \quad (16)$$

*That is, the probability that a reward model ordering agrees with annotation.*

We show with the following proposition that minimizing this loss would help us achieve order consistency with true reward function:

**Proposition 14 (Lower bound on population level order consistency)** *Suppose a learned model  $\hat{H}$  achieves objective equation 16 up to  $1 - \delta\epsilon$  error for some small  $0 < \delta < 1$  and  $\epsilon < 3/20$ , i.e.,*

$$\mathbb{E}_{x_1, x_2, y_1, y_2, h} \mathbb{1}[h = \hat{H}] \geq 1 - \delta\epsilon \quad (17)$$

Then, with probability at least  $1 - \delta$  over  $\Delta r$ , for any given  $\Delta r$  the order consistency of  $\hat{r}$  with respect to the oracle utility is bounded below by:

$$\mathbb{E}_{x_1, x_2, y_1, y_2} \left[ \mathbb{1} \left( \hat{H} \cdot [r(x_1, y_1) - r(x_2, y_2)] \geq 0 \right) \middle| \Delta r \right] \geq (1 - \epsilon) \cdot \xi^2(\Delta r) + \epsilon \cdot (1 - \xi(\Delta r))^2 \quad (18)$$

Further if we assume that with probability at least  $1 - \kappa$ , that  $\xi(\Delta r) \geq \sqrt{\epsilon^2 + 1 - 3\epsilon} + \epsilon$ , we have

$$\mathbb{E}_{x_1, x_2, y_1, y_2 \sim \ell(x)} \left[ \mathbb{1} \left( \hat{H} \cdot [r(x_1, y_1) - r(x_2, y_2)] > 0 \right) \right] \geq 1 - 4\epsilon - \kappa - \delta \quad (19)$$

In classical classification problems, accuracy is often optimized indirectly using losses like cross-entropy. This hints us to apply techniques for improving prediction accuracy to improve reward modeling. While the BT model uses cross-entropy loss and an antisymmetric structure, in the following, we show an alternative choice that could lead to a simple classification-based algorithm.

### 3.2 The BT Model as a Choice

The BT model is designed to enforce order consistency in the following way: it models the probability that  $h = 1$  using  $\sigma(\hat{r}_{\text{BT}}(x_1, y_1) - \hat{r}_{\text{BT}}(x_2, y_2))$ , where  $\sigma$  is the sigmoid function. This allows training with a binary cross-entropy loss:

$$\mathcal{L}_{\text{BT}} = \mathbb{E} [\mathbb{1}_{h=1} \sigma(\hat{r}_{\text{BT}}(x_1, y_1) - \hat{r}_{\text{BT}}(x_2, y_2)) + \mathbb{1}_{h=-1} (1 - \sigma(\hat{r}_{\text{BT}}(x_1, y_1) - \hat{r}_{\text{BT}}(x_2, y_2)))] \quad (20)$$

This structure guarantees that flipping the comparison order will also flip the prediction.

### 3.3 Relaxing the Anti-Symmetry Constraint: a Classification-based Method

BT's difference-in-reward structure inherently enforces antisymmetry. To better understand this, consider an order model  $\hat{H}$  that outputs a preference vector for both prompt-response pairs, i.e.,  $\hat{H} := (\hat{H}_1, \hat{H}_2)$ , where  $\hat{H}_1, \hat{H}_2 : \mathcal{X} \times \mathcal{Y} \mapsto \{1, -1\}$  and ideally align with  $(h, -h)$ . The BT model imposes a hard constraint such that  $\hat{H}_1 = -\hat{H}_2$ . With sufficient data, instead of explicitly enforcing this constraint, the structure could be learned implicitly by ensuring order consistency, i.e.,  $\hat{H}_1 \approx h$  and  $\hat{H}_2 \approx -h$ . Consider a single model e.g., a neural network or tree  $\hat{H}_{\text{clf}}$ . Under this construction, the order consistency could be written as  $\mathcal{L}_{\text{oc}} := \mathbb{E}(h = \hat{H}_{\text{clf}}(x_1, y_1) \wedge -h = \hat{H}_{\text{clf}}(x_2, y_2))$ , we could train a model targeting on predicting these two parts separately, and if the model predicts well, it should satisfy the antisymmetry constraint. A union bound of order consistency is

$$\mathcal{L}_{\text{oc}} \leq \mathcal{L}_{\text{clf}} := \mathbb{E}(h = \hat{H}_{\text{clf}}(x_1, y_1)) + \mathbb{E}(-h = \hat{H}_{\text{clf}}(x_2, y_2)) \quad (21)$$

instead of directly enforcing order consistency, we can use the classification accuracy of each prompt-response pair as a surrogate. In practice, this means training a classifier by treating the annotations and prompt-response pairs independently. Then the logit can be used as a proxy for the reward model. For an alternative perspective: instead of learning the joint probability  $\mathbb{P}(i \succ j)$  that depends on both players  $i$  and  $j$ , we focus on learning the marginal probability  $\mathbb{P}(i \text{ wins})$ . These two are related via Jensen's inequality, with further details provided in Proposition 31.

## 4 Rethinking the Preference Annotation Process for Reward Modeling

In both BT and classification-based reward modeling, there is no theoretical requirement to limit comparisons to the same prompts. For classification models, this is straightforward, as they do not rely on paired data at all. Similarly, in traditional BT applications, random pairwise comparisons among players are common. This further motivates our investigation into how randomized comparisons across different prompts affect reward modeling performance.

To further motivate the usage of cross-prompt comparison, we introduce the following notation on annotation quality and analysis as a case study under a Gaussian assumption on score distributions. In equation 15, we consider a special case of  $\xi(\cdot) = \sigma(\beta(\cdot))$ , that the annotators' ability is characterized by  $\beta$ . When  $\beta = 0$ , we have **random annotations**:

$$\mathbb{P}\left(h(x_1, x_2, y_1, y_2)(r(x_1, y_1) - r(x_2, y_2)) > 0 \mid \Delta r\right) = \sigma(\beta \Delta r) \xrightarrow{\beta \rightarrow 0} 0.5, \quad (22)$$

and when  $\beta \rightarrow \infty$ , we have **perfect annotations**:

$$\mathbb{P}\left(h(x_1, x_2, y_1, y_2)(r(x_1, y_1) - r(x_2, y_2)) > 0 \mid \Delta r\right) = \sigma(\beta \Delta r) \xrightarrow{\beta \rightarrow \infty} 1. \quad (23)$$

In a nutshell, the annotators abilities and the differences among prompt-response pairs together determine how much preference are correctly labeled in annotation. In the following, we show a special case when two responses of a prompt  $x$  are randomly sampled from a single LLM  $\ell$ .

**Example 1 (Annotation Quality under Gaussian Score)** *When data for pairwise annotation is generated through random sampling of two responses  $y_1, y_2 \sim \ell(x)$ , we further assume the utility of those two responses are sampled from a Gaussian distribution with variance  $\sigma_x^2$ , i.e.,  $y \sim \ell(x), r(x, y) \sim \mathcal{N}(\mu_x, \sigma_x^2)$ . Then the annotation quality  $\mathcal{Q}_{\text{pair}}^\beta$  can be defined as the averaged annotation order consistency:*

$$\mathcal{Q}_{\text{pair}} = \mathbb{E}_{y_1, y_2|x}[\tau_x] = \mathbb{E}_{y_1, y_2|x}[\sigma(\beta|r(x, y_1) - r(x, y_2)|)] \quad (24)$$

where  $\tau_x = \sigma(\beta|r(x, y_1) - r(x, y_2)|)$  is a random variable (over  $y_1, y_2$ ) and the probability density function of  $\tau_x$  is

$$f_{\tau_x}(t) = \frac{1}{\sqrt{\pi \beta^2 \sigma_x^2}} \exp\left(-\frac{\left(\log\left(\frac{t}{1-t}\right)\right)^2}{4\beta^2 \sigma_x^2}\right) \cdot \frac{1}{t(1-t)} \quad (25)$$

The derivation is provided in Appendix C.1. In this special case, it is easy to get some numerical results: when  $\beta^2 \sigma_x^2 = 1$ , we have  $\mathcal{Q}_{\text{pair}} \approx 0.6749$ , e.g., roughly 67.5% of data are correctly labeled by annotators. Similarly, when  $\beta^2 \sigma_x^2 = 2$ ,  $\mathcal{Q}_{\text{pair}} \approx 0.7251$ ; when  $\beta^2 \sigma_x^2 = 4$ ,  $\mathcal{Q}_{\text{pair}} \approx 0.7781$ ; when  $\beta^2 \sigma_x^2 = 10$ ,  $\mathcal{Q}_{\text{pair}} \approx 0.8428$ ; This suggests that the effect of better annotators and the effect of response utility diversity are always coupled: in order to improve data quality, we may either improve the ability of annotators or further **diversify the generation utilities** — as both of those parameters control the annotation quality. Next, we show that cross-prompt comparison in this example can be an effective practice to increase response utility diversity. And show that cross-prompt annotation can improve annotation quality.

**Cross-Prompt Annotation Improves Quality under Gaussian Score** When considering multiple prompts  $x_i, i = 1, 2, \dots, N$ , we denote the corresponding responses as  $y_i$ , and scores  $r(x_i, y_i) \sim \mathcal{N}(\mu_i, \sigma_i^2)$ . In the following, we show that cross-prompt annotation can improve annotation quality.

**Proposition 15 (Cross-Prompt Comparisons Increase Utility Diversity)** *When data for pairwise annotation is generated through random sampling of two responses  $y_1, y_2 \sim \ell(x)$ , and the utility of those two responses are sampled from a Gaussian distribution with variance  $\sigma_x^2$ , i.e.,  $y \sim \ell(x), r_{x,y} \sim \mathcal{N}(\mu_x, \sigma_x^2)$ , when there are multiple prompts  $x$ , we have*

$$\mathbb{E}_x \mathbb{E}_{y_1, y_2|x} [|r_{x, y_1} - r_{x, y_2}|] \leq \mathbb{E}_{x_1, x_2} \mathbb{E}_{y_1|x_1, y_2|x_2} [|r_{x_1, y_1} - r_{x_2, y_2}|] \quad (26)$$

The proof is provided in Appendix C.2. This gives us an intuitive result that, in expectation, the reward differences between cross-prompt comparisons are larger than the reward differences between prompt-response pairs sharing the same prompt.

More generally, cross-prompt comparisons improve data quality when the utility distribution of different randomly sampled responses given a single prompt is unimodal and symmetric (e.g., Gaussian).

**Theorem 16 (Cross-Prompt Annotation Improves Annotation Quality)** *When data for pairwise annotation is generated through random sampling of two responses  $y_1, y_2 \sim \ell(x)$ , and the utility of those two responses are sampled from a location-scale family with probability density function  $g_x(x) = f((x - \mu_x)/\sigma_x)$  for  $f$  being unimodal and symmetric to 0. For any  $\xi : \mathbb{R}_+ \rightarrow [1/2, 1]$ , first order differentiable, monotone increasing and concave, we have*

$$\mathbb{E}_x \mathbb{E}_{y_1, y_2|x} [\xi(|r_{x, y_1} - r_{x, y_2}|)] \leq \mathbb{E}_{x_1, x_2} \mathbb{E}_{y_1|x_1, y_2|x_2} [\xi(|r_{x_1, y_1} - r_{x_2, y_2}|)]. \quad (27)$$

Theorem 16 highlights that cross-prompt comparisons improve annotation quality for a broad class of utility distributions and  $\xi$ . The proof is provided in Appendix C.3.

## 5 Related Work

### 5.1 The Bradley-Terry Model in RLHF

Hark back to the seminal paper on RLHF (Christiano et al., 2017), the motivation for using the Bradley-Terry-type model is to understand it as a specialization of the Luce-Shephard choice rule (Luce, 1959; Shepard, 1957). In a simplified version of the two-option setting, the Luce-Shephard choice rule says the probability of choosing a particular option from a set of alternatives is proportional to the utility assigned to that option. The application of such a rule is well aligned with the Bradley-Terry model Bradley and Terry (1952) where pairwise comparisons between players can be used to estimate their ability (utility) scores, where a game is inherently stochastic while the ability of a player is fixed. In later work of alignment from human feedback Stiennon et al. (2020); Ouyang et al. (2022); Rafailov et al. (2023), such a model is directly applied and has achieved great success in improving the quality of LLMs in various tasks when direct evaluation is impossible.

The usage of the Bradley-Terry model in RLHF has been challenged in the literature from different perspectives: Munos et al. (2023) points that the Bradley-Terry model can

not capture non-transitive preferences, and maximizing the corresponding Elo score can be a different objective as compared to the objective of optimizing preferences. Azar et al. (2023) points out that using the Bradley-Terry modelization in the direct preference optimization methods (Rafailov et al., 2023) could lead to problematic overfitting when sampled preferences are deterministic.

## 5.2 Bradley-Terry Model for Parameter Estimation and Prediction

The most classic Bradley-Terry model suitable for arena setting has been extensively studied theoretically started by Bradley and Terry (1952) themselves. Ford Jr (1957) established identifiability and asymptotic theory. More recently Wu et al. (2022) compared asymptotic theory under different identifiability assumptions. Simons and Yao (1999) studied Bradley-Terry when number of players diverge under the assumption number of competitions each players played also diverge. In contrast Han et al. (2020) studied the setting when comparisons are sparse and proposed a consistent procedure needs only  $O(N \log^3(N))$  comparisons. On prediction side, using features to predict ability was explored soon after Bradley and Terry (1952), Springall (1973) assumed ability was a linear combination of features while De Soete and Winsberg (1993) used spline functions. Bockenholt (1988) cast Bradley-Terry as a special logistic regression problem and opened investigation from this lens. Chen and Pouzo (2012) developed theory for a general class of nonparametric models including logistic regression. On deep learning side Schmidt-Hieber (2020) studied asymptotic theory on deep neural network for nonparametric regression and a follow up paper Bos and Schmidt-Hieber (2022) studied nonparametric logistic regression using deep neural net. However these theory cannot be directly applied Bradley-Terry model because we need a unique reward model for all prompt-response pairs and the probability is not arbitrary but soft max from passing two pairs to a *single* network. Studies like Bos and Schmidt-Hieber (2022) could be seen as two pairs passing two arbitrary neural networks rather than one.

## 5.3 Non-Pairwise Data and Cross-Prompt Comparisons in RLHF

Non-pairwise data (Ethayarajh et al., 2024) and cross-prompt comparisons (Yin et al., 2024) were explored in the literature. The KTO (Ethayarajh et al., 2024) is rooted in prospect theory (Tversky and Kahneman, 1992) that risk-averse human prospective theories assign different values to losses and gains. And RPO (Yin et al., 2024) proposed to reflect the complex nature of human learning in alignment through involving response comparisons among both identical and similar questions. On one hand, RPO supports our insight into making cross-prompt comparisons in practice by drawing inspiration from human learning. On the other hand, the motivations and implementations between our work and RPO are both different: in our work, the cross-prompt annotation practice is motivated by a “*why not*” observation — given the fact that there is no specialty of considering single-prompt comparisons in our order-consistency theory and the BT model for predictions. Besides different motivations, there are several significant differences between RPO and our cross-prompt comparison: RPO does not study the annotation efficiency, or what is the optimal way of doing annotation under a budget, yet our focus is on studying the cross-prompt annotation as an alternative way of doing annotations. Moreover, RPO considers a strategic re-weighting method based on embedding space similarity among responses, leading to a

direct alignment method. All of those works are direct alignment methods (Zheng et al., 2024; Liu et al., 2024; Zhao et al., 2023; Azar et al., 2023; Ethayarajh et al., 2024), which do not explicitly build reward models as their intermediate steps. One potential drawback of those methods without explicit reward models is that it will be challenging or impossible to conduct inference-time optimization (Liu et al., 2023) — especially when compared with our embedding based light-weighted reward models. And recent work has demonstrated the superiority of two stage methods over direct alignment methods (Ivison et al., 2024).

#### 5.4 Representation Learning in Reward Modeling

In our work, we separate the reward model learning from the representation learning task and focus only on the reward modeling part to better isolate the source of gains. Recent advance in generative reward models highlight it is possible to use generation tasks to regularize the learned embeddings and improve reward modeling performance (Yang et al., 2024a). Also in Zhang et al. (2024), the generative verifiers construct reward predictions through next-token prediction to maximally leverage the ability of LLM as token generators to improve their evaluation ability. While our research on the reward models is orthogonal to this line of research, future exploration on combining either embedding learning or generative ability of LLMs with different order consistency objectives could be highly promising directions to enjoy the improvements from both sides.

### 6 Experiments

**Objectives of Experiments** In this section, we present empirical results to validate our key insights and methodological contributions. We begin by elaborating on our high-level design motivations for experiments. We aim to address the following questions:

1. How effective are different learning objectives given by the order consistency framework? Specifically, how does the performance of a classification-based model compare to the widely used BT model in reward modeling? (Section 6.1)
2. How do various reward modeling methods perform as annotation quality and availability changes? (Section 6.2)
3. How good is the cross-prompt comparison in annotations? What is essential in determining whether this annotation design is beneficial or not in practice when it is available? (Section 6.3)

**Key Design Principles: Reproducibility, Controllability, and Computational Efficiency** Our experiments are designed with three key desiderata in mind: high reproducibility, controllability to enable diverse ablation studies and computational efficiency. We prioritized these principles in all aspects of our experimental setup:

- **Base Models.** We conducted experiments using three open-source LLMs at different scales: Gemma2b, Gemma7b, and LLaMA3-8b (Team et al., 2024; Meta, 2024), alongside their SFT-ed versions (Gemma2b-SFT, Gemma7b-SFT, LLaMA3-8b-SFT), following the setup in Stiennon et al. (2020). Details are provided in Appendix D.
- **Annotations.** To ensure controllability in generation and annotation, and closely simulate human annotation processes, we followed approaches from Gao et al. (2023); Liu et al. (2023); Tran and Chris Glaze (2024); Dong et al. (2024) to utilize open-source golden reward models as annotators to maintain affordability for the community.

- **Datasets.** We used the `Anthropic-Harmless` and `Anthropic-Helpful` datasets (Bai et al., 2022a), as these are extensively studied in the context of reward modeling, and open-source golden reward models are available (Yang et al., 2024b; Dong et al., 2023, 2024).
- **Evaluation of Learned Reward Models.** We evaluated the effectiveness of different reward models using Best-of-N (BoN) sampling following Gao et al. (2023). This choice was driven by three key considerations:
  - (1) Performance: Empirical studies show BoN achieves better performance than PPO (Dong et al., 2023; Yuan et al., 2023; Gao et al., 2023; Coste et al., 2023).
  - (2) Stability and Reduced Engineering Overhead: BoN requires no hyperparameter tuning and is more stable than PPO, leading to more consistent and interpretable results (Ivison et al., 2024; Xu et al., 2024).
  - (3) Computational Efficiency and Reproducibility: BoN’s reusability across N generations during test time makes it more computationally efficient compared to policy-gradient optimizations (Li et al., 2023; Stiennon et al., 2020). In contrast, using PPO (Schulman et al., 2017) for our 12,000 experimental setups would be computationally prohibitive since each setup requires distinct LLM fine-tuning.

For more details on experiment setup, please refer to Appendix D.

## 6.1 Comparing The Bradley-Terry and Classification Objectives

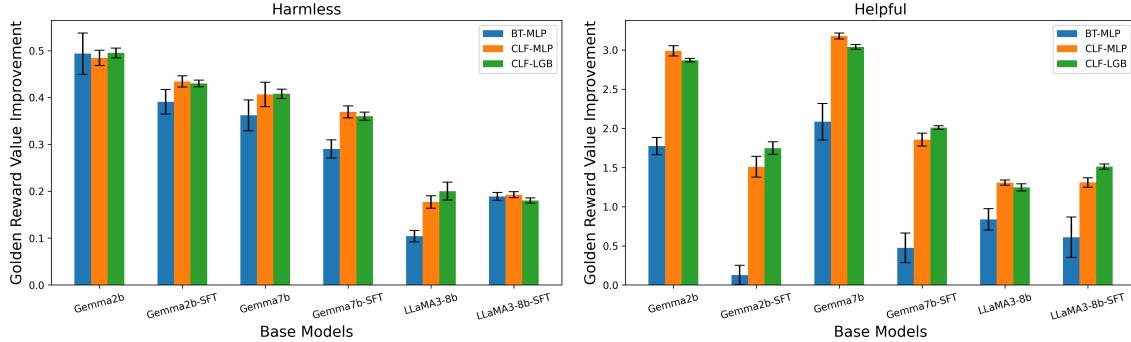


Figure 1: *Comparison between BT and Classification reward models.* In general, the classification reward models achieve better performance than the BT reward models, with the added flexibility of using off-the-shelf classifiers beyond MLPs. Error bars are given by 5 runs with different seeds.

**Experiment Setups.** In this section, we compare reward models trained with different learning objectives — the BT model and the Classification model — as well as their different implementations. For the BT model, the Siamese structure (Bromley et al., 1993) is required, making MLP the only viable backbone implementation (denoted in the plots as **BT-MLP**). For a fair and clear comparison to BT and to isolate the source of gains from implementation, we implement the classification model with both MLP (denoted in the plots as **CLF-MLP**) and the LightGBM (Ke et al., 2017) (denoted in the plots as **CLF-LGB**) given its wide success in machine learning applications (Bentéjac et al., 2021) and especially its successful application in embedding-based reward modeling (Sun et al.,

2023). We evaluate those reward models using BoN with  $N=500$ , reporting improvements over base models to provide a clear comparison of their performance.

**Results and Takeaways.** Figure 1 presents the results on both datasets. The x-axis shows different base models, and the y-axis shows the **improvement on golden reward values** on test prompts using BoN (i.e., the relative performance gains achieved through the reward models). The results indicate that classification-based reward models not only perform better than the BT reward models but also offer greater flexibility by allowing the use of diverse off-the-shelf machine learning algorithms. This makes them a competent alternative to BT models in reward modeling.

## 6.2 How Annotation Qualities and Quantities Affect Performance

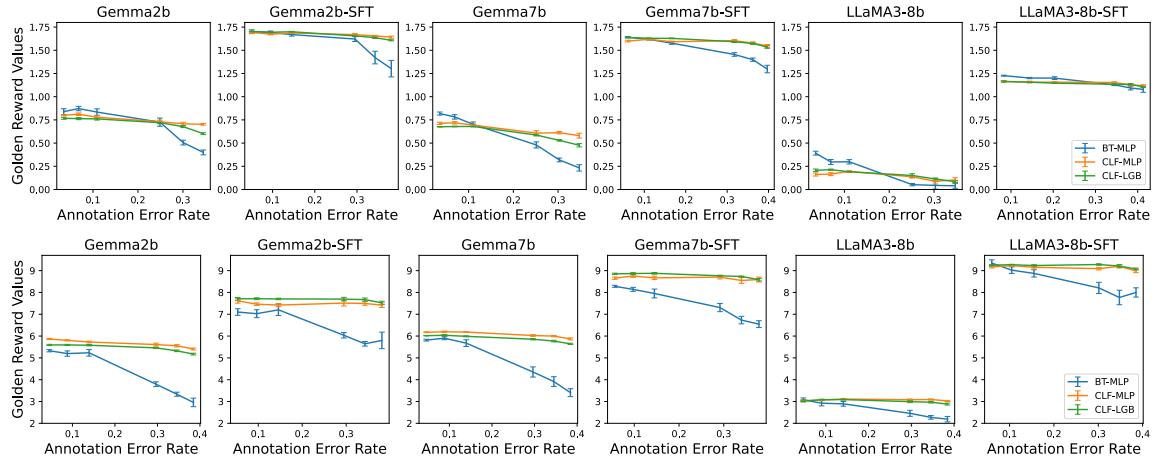


Figure 2: Results on changing the annotation quality. Error bars are given by 5 seeds.

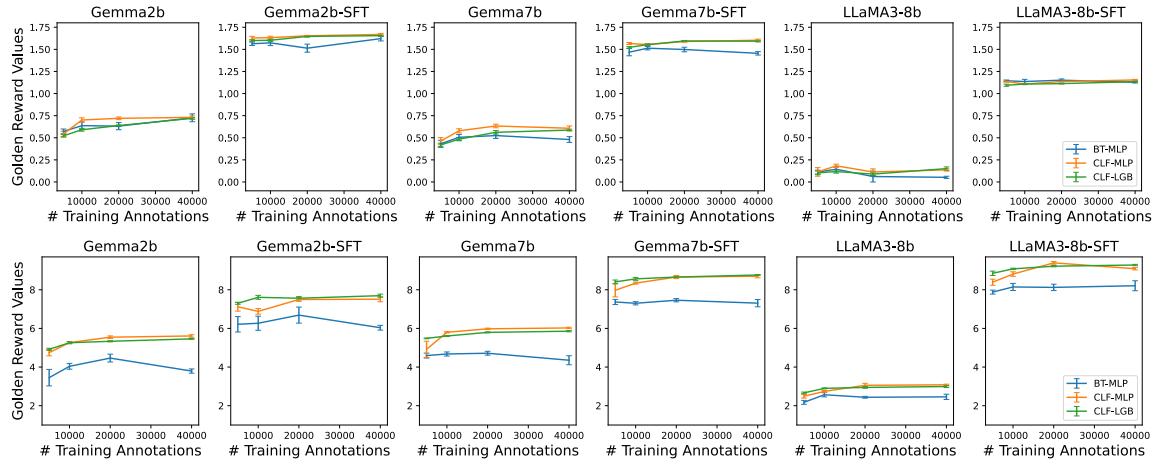


Figure 3: Results on changing the annotation availability. Error bars are given by 5 seeds.

**Experiment Setups.** In this section, we systematically vary both the quality and quantity of annotations to empirically assess the performance of different reward models under diverse conditions. For annotation quality, we use the sigmoid instantiation of equa-

tion 15, i.e.,  $\xi(\Delta r) = \sigma(\beta\Delta r)$ , and vary the annotation quality parameter  $\beta$  over the range  $[0.5, 0.7, 1.0, 3.0, 5.0, 10.0]$ , using a fixed set of 40000 annotations for training. These  $\beta$  values correspond to annotation error rates ranging from 5% to 38%, which aligns with realistic human annotations (Zheng et al., 2023; Coste et al., 2023; Dubois et al., 2024). To explore the impact of annotation quantity, we experiment with datasets containing  $[5000, 10000, 20000, 40000]$  annotations, while holding  $\beta = 1$  constant. Additional results cross-sweeping those two set-ups can be found in Appendix E.

**Results and Takeaways.** Figure 2 presents the results of varying annotation quality. From the plots, it is evident that as annotation error rates increase, the classification models exhibit greater robustness compared to the BT models, experiencing smaller performance drops. On the other hand, the BT models outperform classification models when annotation quality is high (i.e., less than 10% wrong labels). Figure 3 shows the results of varying annotation quantities. We can conclude from the results that the classification models consistently outperform BT models, not only delivering superior performance with the same number of annotations but also demonstrating more consistent improvements as the number of annotations increases.

### 6.3 LLM Alignment with Preference Annotations Between Different Prompts

**Experiment Setups.** In this section, we examine how cross-prompt comparisons, as opposed to annotations on the same prompt, affect the performance of different reward models. Specifically, for each training prompt, two responses are randomly generated by the LLMs and then presented to annotators (the golden reward model) for preference labeling. In the standard reward modeling setup, the annotators label response pairs generated from the same prompt. In the cross-prompt annotation setup (denoted by the postfix **X-Prompt** in the legends), we randomly select two prompt-response pairs from the dataset for comparison and annotation. We present the results with  $\beta = 1$  in the preference annotation processes and 40000 pairs of annotations in our main text as the most common setting. We provide full results over other experimental configurations in Appendix E.

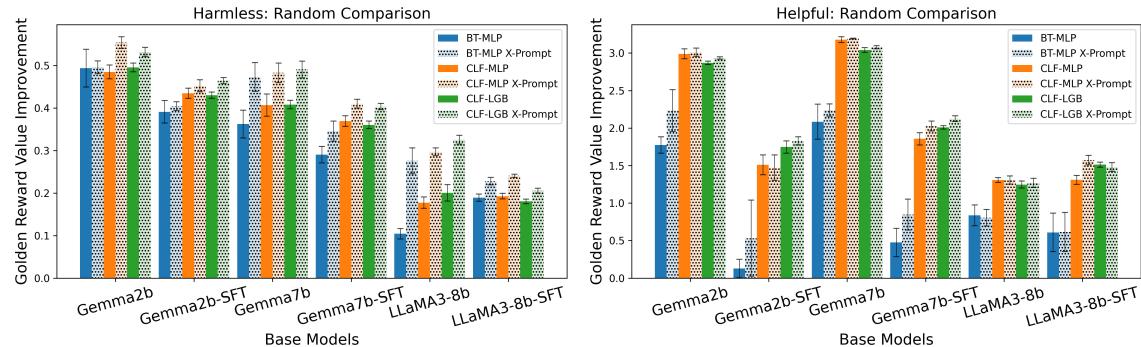


Figure 4: *Results comparing cross-prompt comparison based annotations.* Preference annotations on cross-prompt comparisons outperform same-prompt comparisons. Error bars are from 5 runs with different seeds.

**Results and Takeaways.** Figure 4 shows the results across 2 datasets, 6 base models, and 3 different reward modeling methods. Shaded plots represent results from cross-prompt comparisons. The y-axis measures golden reward value improvements achieved

through BoN sampling using the respective reward models. From these results, it is clear that cross-prompt comparisons outperform same-prompt comparisons, offering substantial improvements in reward model performance.

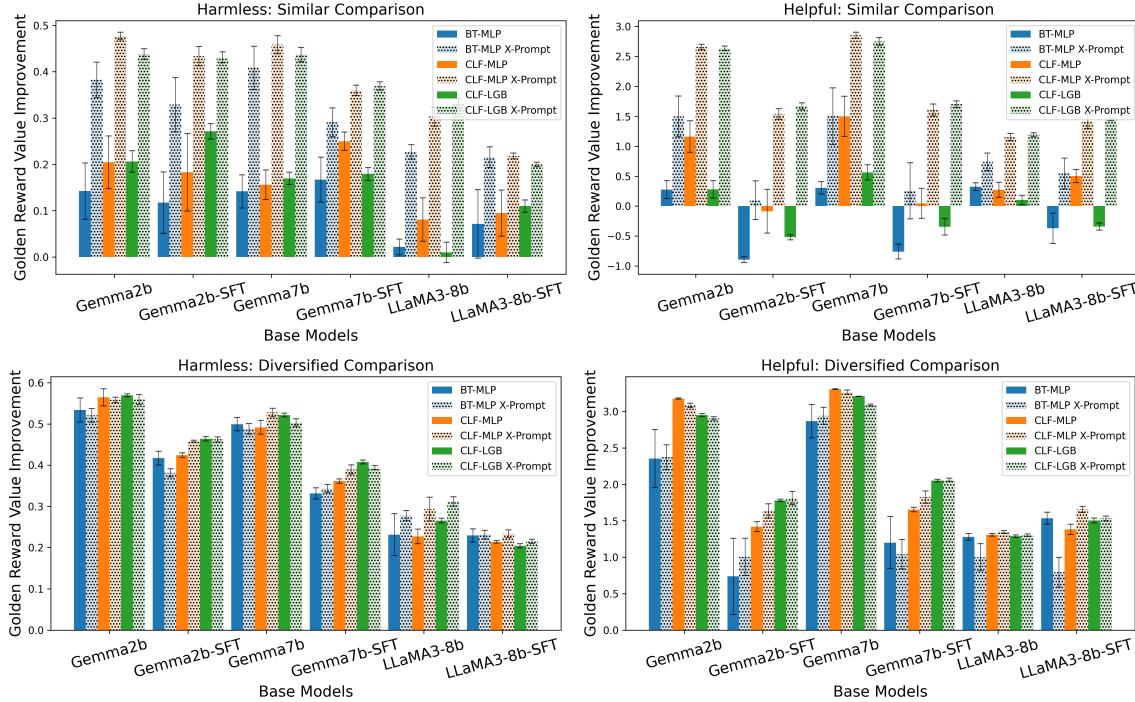


Figure 5: Results comparing cross-prompt comparison-based annotations on synthetically generated similar or diversified comparison pairs. Cross-prompt comparison significantly improves the performance of reward modeling with same-prompt response pairs lacking diversity. Error bars are from 5 runs with different seeds.

**Further Investigation.** Intuitively, the cross-prompt comparison can improve the quality of annotation since it increases the diversity in generation. To further explore this, we introduce two *synthetic setups*<sup>2</sup> designed to analyze the source of gains. In the **Similar Comparison** setup, response pairs generated for a single prompt exhibit similar quality and lack diversity. In the **Diversified Comparison** setup, response pairs for a single prompt are of different qualities. Specifically, we use a golden reward model to score 10 generated responses per prompt and select the two middle-ranked responses to simulate the **Similar Comparison** setup. Whereas in the **Diversified Comparison** setting, we use the highest and lowest-scored responses to construct the response pair for each prompt.

**Results and Takeaways.** Figure 5 shows the results of those two synthetic setups. We can conclude that cross-prompt comparisons are essential when responses for a single prompt lack diversity. In the **Similar Comparison** setting, the conventional same-prompt comparisons often fail to produce informative reward models that can improve golden reward values. In contrast, cross-prompt annotations substantially enhance performance in such

2. It is worth noting that none of those two synthetic setups is realizable in practice without a reward model. And the randomly sampled pairs are the only realistic setups for annotations.

cases. In the **Diversified Comparison** setting, the need for cross-prompt comparisons diminishes as response diversity increases, though they do not have an evident negative impact on reward modeling performance. Comparing results across both settings, as well as results in Figure 4, we find the superiority of cross-prompt comparison is reflected in its general capability regardless of response diversities — the performance achieved by cross-prompt annotations is more stable and has lower dependence of the response diversities.

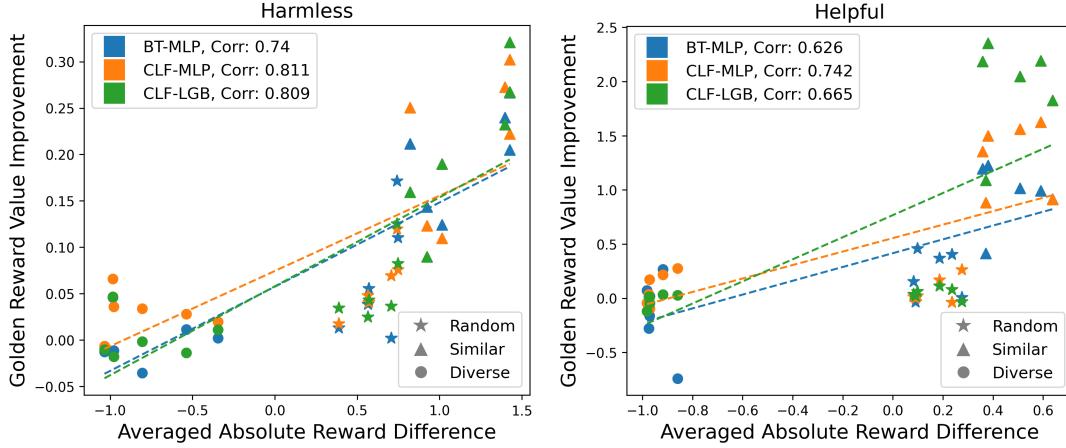


Figure 6: Comparing the averaged absolute difference in scores in pairwise annotations (x-axis) and improvements achieved by using cross-prompt annotations (y-axis). The two variables are highly correlated.

Finally, we examine the relationship between the *average absolute score differences in pairwise annotations* (x-axis) across three setups (i.e., **Random** for randomly select two responses for each pair, **Similar** and **Diverse** for the two synthetic settings) and the corresponding *performance improvements from cross-prompt annotations* (y-axis). Scatter plots with linear fits are shown in Figure 6. The strong correlation indicates that cross-prompt annotations are most beneficial when same-prompt responses lack diversity. Importantly, we find the averaged reward differences between pairwise data in the synthetic setting of **Similar** cases and the **Random** settings are similar, this implies that in practice, when randomly selecting two responses for a single prompt to be annotated, those pairs are likely facing the challenge of high response similarity. And this is the case when cross-prompt annotation can be applied to improve performance.

**Conclusive Remark on Experiments** Our experimental results highlight the advantages of classification-based reward models over traditional BT models, particularly in terms of flexibility and robustness to annotation quality and quantity. While BT models perform better under high-quality annotations, classification models demonstrate superior overall performance and resilience to increasing annotation error rates. Additionally, our empirical studies on cross-prompt comparisons show it significantly improves reward modeling, especially when responses to the same prompt lack diversity. Through synthetic experiments, we further demonstrate that the challenge of limited diversity is likely to occur in practice, providing additional justification for exploring this annotation method in future research.

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## References

- A. Agarwal, D. Hsu, S. Kale, J. Langford, L. Li, and R. Schapire. Taming the monster: A fast and simple algorithm for contextual bandits. In *International conference on machine learning*, pages 1638–1646. PMLR, 2014.
- M. G. Azar, M. Rowland, B. Piot, D. Guo, D. Calandriello, M. Valko, and R. Munos. A general theoretical paradigm to understand learning from human preferences. *arXiv preprint arXiv:2310.12036*, 2023.
- Y. Bai, A. Jones, K. Ndousse, A. Askell, A. Chen, N. DasSarma, D. Drain, S. Fort, D. Ganguli, T. Henighan, et al. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv preprint arXiv:2204.05862*, 2022a.
- Y. Bai, S. Kadavath, S. Kundu, A. Askell, J. Kernion, A. Jones, A. Chen, A. Goldie, A. Mirhoseini, C. McKinnon, et al. Constitutional ai: Harmlessness from ai feedback. *arXiv preprint arXiv:2212.08073*, 2022b.
- C. Bentéjac, A. Csörgő, and G. Martínez-Muñoz. A comparative analysis of gradient boosting algorithms. *Artificial Intelligence Review*, 54:1937–1967, 2021.
- U. Bockenholt. A logistic representation of multivariate paired-comparison models. *Journal of mathematical psychology*, 32(1):44–63, 1988.
- T. Bos and J. Schmidt-Hieber. Convergence rates of deep relu networks for multiclass classification. *Electronic Journal of Statistics*, 16(1):2724–2773, 2022.
- R. A. Bradley and M. E. Terry. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika*, 39(3/4):324–345, 1952.
- J. Bromley, I. Guyon, Y. LeCun, E. Säckinger, and R. Shah. Signature verification using a “siamese” time delay neural network. *Advances in neural information processing systems*, 6, 1993.
- M. Cattelan. Models for paired comparison data: A review with emphasis on dependent data. *Statistical Science*, 2012.
- X. Chen and D. Pouzo. Estimation of nonparametric conditional moment models with possibly nonsmooth generalized residuals. *Econometrica*, 80(1):277–321, 2012.
- W.-L. Chiang, L. Zheng, Y. Sheng, A. N. Angelopoulos, T. Li, D. Li, H. Zhang, B. Zhu, M. Jordan, J. E. Gonzalez, et al. Chatbot arena: An open platform for evaluating llms by human preference. *arXiv preprint arXiv:2403.04132*, 2024.
- P. F. Christiano, J. Leike, T. Brown, M. Martic, S. Legg, and D. Amodei. Deep reinforcement learning from human preferences. *Advances in neural information processing systems*, 30, 2017.
- T. Coste, U. Anwar, R. Kirk, and D. Krueger. Reward model ensembles help mitigate overoptimization. *arXiv preprint arXiv:2310.02743*, 2023.

- G. De Soete and S. Winsberg. A thurstonian pairwise choice model with univariate and multivariate spline transformations. *Psychometrika*, 58(2):233–256, 1993.
- H. Dong, W. Xiong, D. Goyal, R. Pan, S. Diao, J. Zhang, K. Shum, and T. Zhang. Raft: Reward ranked finetuning for generative foundation model alignment. *arXiv preprint arXiv:2304.06767*, 2023.
- H. Dong, W. Xiong, B. Pang, H. Wang, H. Zhao, Y. Zhou, N. Jiang, D. Sahoo, C. Xiong, and T. Zhang. Rlhf workflow: From reward modeling to online rlhf. *arXiv preprint arXiv:2405.07863*, 2024.
- Y. Dubois, C. X. Li, R. Taori, T. Zhang, I. Gulrajani, J. Ba, C. Guestrin, P. S. Liang, and T. B. Hashimoto. Alpacafarm: A simulation framework for methods that learn from human feedback. *Advances in Neural Information Processing Systems*, 36, 2024.
- A. E. Elo. The proposed uscf rating system, its development, theory, and applications. *Chess life*, 22(8):242–247, 1967.
- K. Ethayarajh, W. Xu, N. Muennighoff, D. Jurafsky, and D. Kiela. Kto: Model alignment as prospect theoretic optimization. *arXiv preprint arXiv:2402.01306*, 2024.
- L. R. Ford Jr. Solution of a ranking problem from binary comparisons. *The American Mathematical Monthly*, 64(8P2):28–33, 1957.
- L. Gao, J. Schulman, and J. Hilton. Scaling laws for reward model overoptimization. In *International Conference on Machine Learning*, pages 10835–10866. PMLR, 2023.
- M. Gardner. Paradox of nontransitive dice and elusive principle of indifference. *Scientific American*, 223(6):110, 1970.
- M. E. Glickman. A comprehensive guide to chess ratings. *American Chess Journal*, 3(1): 59–102, 1995.
- M. E. Glickman and A. C. Jones. Rating the chess rating system. *CHANCE-BERLIN THEN NEW YORK-*, 12:21–28, 1999.
- D. Guest, J. S. Adelman, and C. Kent. Relative judgement is relatively difficult: Evidence against the role of relative judgement in absolute identification. *Psychonomic Bulletin & Review*, 23:922–931, 2016.
- C. Guo, G. Pleiss, Y. Sun, and K. Q. Weinberger. On calibration of modern neural networks. In *International conference on machine learning*, pages 1321–1330. PMLR, 2017.
- S. Guo, B. Zhang, T. Liu, T. Liu, M. Khalman, F. Llinares, A. Rame, T. Mesnard, Y. Zhao, B. Piot, et al. Direct language model alignment from online ai feedback. *arXiv preprint arXiv:2402.04792*, 2024.
- R. Han, R. Ye, C. Tan, and K. Chen. Asymptotic theory of sparse bradley–terry model. *The Annals of Applied Probability*, 30(5):2491–2515, 2020.

- H. Ivison, Y. Wang, J. Liu, Z. Wu, V. Pyatkin, N. Lambert, N. A. Smith, Y. Choi, and H. Hajishirzi. Unpacking dpo and ppo: Disentangling best practices for learning from preference feedback. *arXiv preprint arXiv:2406.09279*, 2024.
- G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, 30, 2017.
- W. Kwon, Z. Li, S. Zhuang, Y. Sheng, L. Zheng, C. H. Yu, J. E. Gonzalez, H. Zhang, and I. Stoica. Efficient memory management for large language model serving with page-dattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023.
- T. Lattimore and C. Szepesvári. *Bandit algorithms*. Cambridge University Press, 2020.
- H. Lee, S. Phatale, H. Mansoor, K. Lu, T. Mesnard, C. Bishop, V. Carbune, and A. Rastogi. Rlaif: Scaling reinforcement learning from human feedback with ai feedback. *arXiv preprint arXiv:2309.00267*, 2023.
- Z. Li, T. Xu, Y. Zhang, Y. Yu, R. Sun, and Z.-Q. Luo. Remax: A simple, effective, and efficient method for aligning large language models. *arXiv preprint arXiv:2310.10505*, 2023.
- T. Liu, Y. Zhao, R. Joshi, M. Khalman, M. Saleh, P. J. Liu, and J. Liu. Statistical rejection sampling improves preference optimization. *arXiv preprint arXiv:2309.06657*, 2023.
- Z. Liu, M. Lu, S. Zhang, B. Liu, H. Guo, Y. Yang, J. Blanchet, and Z. Wang. Provably mitigating overoptimization in rlfh: Your sft loss is implicitly an adversarial regularizer. *arXiv preprint arXiv:2405.16436*, 2024.
- R. D. Luce. *Individual choice behavior*, volume 4. Wiley New York, 1959.
- A. Meta. Introducing meta llama 3: The most capable openly available llm to date. *Meta AI*, 2024.
- R. Munos, M. Valko, D. Calandriello, M. G. Azar, M. Rowland, Z. D. Guo, Y. Tang, M. Geist, T. Mesnard, A. Michi, et al. Nash learning from human feedback. *arXiv preprint arXiv:2312.00886*, 2023.
- L. Ouyang, J. Wu, X. Jiang, D. Almeida, C. Wainwright, P. Mishkin, C. Zhang, S. Agarwal, K. Slama, A. Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744, 2022.
- R. Rafailov, A. Sharma, E. Mitchell, S. Ermon, C. D. Manning, and C. Finn. Direct preference optimization: Your language model is secretly a reward model. *arXiv preprint arXiv:2305.18290*, 2023.
- R. Rafailov, A. Sharma, E. Mitchell, C. D. Manning, S. Ermon, and C. Finn. Direct preference optimization: Your language model is secretly a reward model. *Advances in Neural Information Processing Systems*, 36, 2024.

- J. Schmidt-Hieber. Nonparametric regression using deep neural networks with relu activation function. *Annals of Statistics*, 2020.
- J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.
- R. N. Shepard. Stimulus and response generalization: A stochastic model relating generalization to distance in psychological space. *Psychometrika*, 22(4):325–345, 1957.
- G. Simons and Y.-C. Yao. Asymptotics when the number of parameters tends to infinity in the bradley-terry model for paired comparisons. *The Annals of Statistics*, 27(3):1041–1060, 1999.
- A. Springall. Response surface fitting using a generalization of the bradley-terry paired comparison model. *Journal of the Royal Statistical Society Series C: Applied Statistics*, 22(1):59–68, 1973.
- N. Stewart, G. D. Brown, and N. Chater. Absolute identification by relative judgment. *Psychological review*, 112(4):881, 2005.
- N. Stiennon, L. Ouyang, J. Wu, D. Ziegler, R. Lowe, C. Voss, A. Radford, D. Amodei, and P. F. Christiano. Learning to summarize with human feedback. *Advances in Neural Information Processing Systems*, 33:3008–3021, 2020.
- H. Sun, A. Hüyük, and M. van der Schaar. Query-dependent prompt evaluation and optimization with offline inverse rl. In *The Twelfth International Conference on Learning Representations*, 2023.
- Y. Tang, Z. D. Guo, Z. Zheng, D. Calandriello, R. Munos, M. Rowland, P. H. Richemond, M. Valko, B. Á. Pires, and B. Piot. Generalized preference optimization: A unified approach to offline alignment. *arXiv preprint arXiv:2402.05749*, 2024.
- G. Team, T. Mesnard, C. Hardin, R. Dadashi, S. Bhupatiraju, S. Pathak, L. Sifre, M. Rivière, M. S. Kale, J. Love, et al. Gemma: Open models based on gemini research and technology. *arXiv preprint arXiv:2403.08295*, 2024.
- L. Thurstone. A law of comparative judgment. *Psychological Review*, 34(4), 1927.
- H. Touvron, L. Martin, K. Stone, P. Albert, A. Almahairi, Y. Babaei, N. Bashlykov, S. Batra, P. Bhargava, S. Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.
- H. Tran and B. Chris Glaze. Snorkel-mistral-pairrm-dpo, 2024.
- A. Tversky and D. Kahneman. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5:297–323, 1992.
- L. von Werra, Y. Belkada, L. Tunstall, E. Beeching, T. Thrush, N. Lambert, and S. Huang. Trl: Transformer reinforcement learning. <https://github.com/huggingface/trl>, 2020.

- W. Wu, B. W. Junker, and N. Niezink. Asymptotic comparison of identifying constraints for bradley-terry models. *arXiv preprint arXiv:2205.04341*, 2022.
- S. Xu, W. Fu, J. Gao, W. Ye, W. Liu, Z. Mei, G. Wang, C. Yu, and Y. Wu. Is dpo superior to ppo for llm alignment? a comprehensive study. *arXiv preprint arXiv:2404.10719*, 2024.
- R. Yang, R. Ding, Y. Lin, H. Zhang, and T. Zhang. Regularizing hidden states enables learning generalizable reward model for llms. *arXiv preprint arXiv:2406.10216*, 2024a.
- R. Yang, X. Pan, F. Luo, S. Qiu, H. Zhong, D. Yu, and J. Chen. Rewards-in-context: Multi-objective alignment of foundation models with dynamic preference adjustment. *arXiv preprint arXiv:2402.10207*, 2024b.
- A. Yara and Y. Terada. Nonparametric logistic regression with deep learning. *arXiv preprint arXiv:2401.12482*, 2024.
- Y. Yin, Z. Wang, Y. Gu, H. Huang, W. Chen, and M. Zhou. Relative preference optimization: Enhancing llm alignment through contrasting responses across identical and diverse prompts. *arXiv preprint arXiv:2402.10958*, 2024.
- Z. Yuan, H. Yuan, C. Tan, W. Wang, S. Huang, and F. Huang. Rrhf: Rank responses to align language models with human feedback without tears. *arXiv preprint arXiv:2304.05302*, 2023.
- L. Zhang, A. Hosseini, H. Bansal, M. Kazemi, A. Kumar, and R. Agarwal. Generative verifiers: Reward modeling as next-token prediction. *arXiv preprint arXiv:2408.15240*, 2024.
- Y. Zhao, R. Joshi, T. Liu, M. Khalman, M. Saleh, and P. J. Liu. Slic-hf: Sequence likelihood calibration with human feedback. *arXiv preprint arXiv:2305.10425*, 2023.
- R. Zheng, S. Dou, S. Gao, Y. Hua, W. Shen, B. Wang, Y. Liu, S. Jin, Q. Liu, Y. Zhou, et al. Secrets of rlhf in large language models part i: Ppo. *arXiv preprint arXiv:2307.04964*, 2023.
- R. Zheng, H. Guo, Z. Liu, X. Zhang, Y. Yao, X. Xu, Z. Wang, Z. Xi, T. Gui, Q. Zhang, et al. Toward optimal llm alignments using two-player games. *arXiv preprint arXiv:2406.10977*, 2024.
- D. M. Ziegler, N. Stiennon, J. Wu, T. B. Brown, A. Radford, D. Amodei, P. Christiano, and G. Irving. Fine-tuning language models from human preferences. *arXiv preprint arXiv:1909.08593*, 2019.