DCRM: A Heuristic to Measure Response Pair Quality in Preference Optimization

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Abstract

Recent research has attempted to associate preference optimization (PO) performance with the underlying preference datasets. In this work, our observation is that the differences between the preferred response y^+ and dispreferred response y^- influence what LLMs *can learn*, which may not match the desirable differences *to learn*. Therefore, we use distance and reward margin to quantify these differences, and combine them to get Distance Calibrated Reward Margin (DCRM), a metric that measures the quality of a response pair for PO. Intuitively, DCRM encourages minimal noisy differences and maximal desired differences. With this, we study 3 types of commonly used preference datasets, classified along two axes: the source of the responses and the preference labeling function. We establish a general correlation between higher DCRM of the training set and better learning outcome. Inspired by this, we propose a *best-of-*N^2 pairing method that selects response pairs with the highest DCRM. Empirically, in various settings, our method produces training datasets that can further improve models' performance on AlpacaEval, MT-Bench, and Arena-Hard over the existing training sets.[1]

1 Introduction

Preference optimization (PO) methods such as DPO (Rafailov et al., 2024) have shown success in improving LLMs' performance in various tasks (Dubois et al., 2024). These methods usually involve a contrastive learning objective that encourages LLMs to generate a preferred response y^+ with higher probability and a dispreferred response y^- with lower probability, given a query x.

Prior research (Tang et al., 2024; Razin et al., 2024) has shown the importance of selecting suitable response pairs for PO training. In particular, the contrastive training signals sent to LLMs are partly derived from the differences between y^+ and y^-. These differences influence what LLMs *can learn*, which often do not exactly match the set of desirable differences *to learn*. This is because, aside from differences that we want models to learn (useful signals; e.g., y^+ is more helpful than y^- in factoid question answering), there can be noisy differences (noisy signals). For instance, y^+ and y^- can differ in features that are irrelevant for a task (e.g., different writing styles for factoid question answering) or that the differences are in an incorrect direction (e.g., y^+ is less correct than y^-). Intuitively, if there are more noisy differences, then LLMs may not effectively learn the desired differences (e.g., to be more helpful) (See Figure 1).

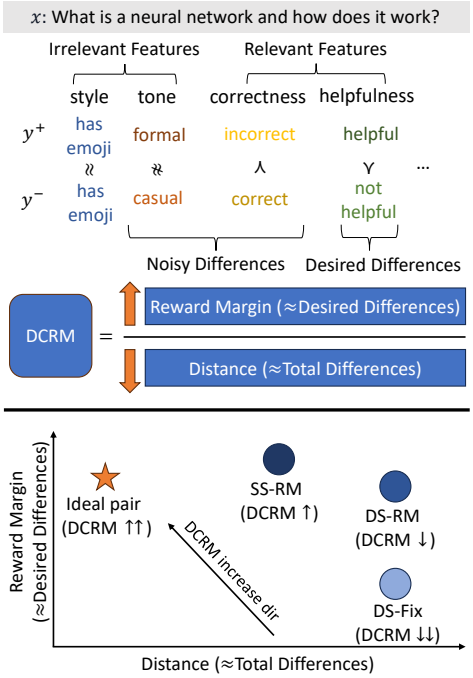

Figure 1: Top: Ideal response pairs should have fewer noisy differences (small distances) and more desired differences (large reward margins). DCRM measures response pair quality with this intuition; Bottom: Common preference datasets (SS-RM, DS-RM, DS-Fix; See § 2.2) have varying locations in the distance-reward margin landscape, but none achieves an ideal combination.

[1] Our code will be released soon.

Although prior research (D'Oosterlinck et al., 2024; Wu et al., 2024) has investigated the correlation between certain proxies of "differences" (e.g., edit distance) and PO learning outcome, it does not distinguish noisy and desired differences, and therefore cannot accurately model the relationship.

Therefore, we develop a metric called Distance Calibrated Reward Margin (DCRM) that aims to measure the density of desired differences among the total differences present. DCRM is the ratio between the reward margin, which is a proxy for the amount of desired differences, and two distance metrics (edit distance, probability difference), which are proxies for the total amount of differences.

To study DCRM, we study three common types of preference datasets, categorized by their (1) response sources and (2) preference labeling scheme. We use Ultrafeedback (Cui et al., 2023) as the seed to construct the datasets, and find that different types of datasets vary in their average DCRM values.

We train three base models (LLaMA-2-7B-Chat, LLaMA-3.2-1B-Instruct, Gemma-2B-IT) on these datasets and use AlpacaEval (Dubois et al., 2024), MT-Bench (Zheng et al., 2023), and Arena-Hard (Li et al., 2024) for evaluation. Across all settings, we notice a correlation between higher DCRM and better training outcomes. We further conduct a feature analysis to inspect the properties of each dataset and understand qualitatively what signals (i.e., noisy or desired differences) models learn after training. Inspired by the aforementioned correlation, we propose a method called Best of N^2 pairing to select response pairs with high DCRM, and show that training LLMs on the new datasets gives higher performance than on the original datasets. Our contribution is summarized as follows.

- We propose a novel metric DCRM that measures the quality of a response pair for PO training.
- We compare three common types of preference datasets and show a positive correlation between the average DCRM value of a training dataset and the training effectiveness.
- We propose *best-of-N^2* pairing, which selects response pairs with high DCRM values for effective PO training.

2 Task Setup

2.1 Problem Definition

Let $\pi(y|x)$ be a language model (LM) that places a probability distribution over response y conditioned on input x. Let $\mathcal{D} = \{x_i, y_i^+, y_i^-\}$ be a preference dataset where responses y^+ are preferred to y^-. Offline preference optimization, like Direct Preference Optimization (DPO)[2] (Rafailov et al., 2024), use $\mathcal{D}$ to train model π_θ starting from the base model π_{ref}, by minimizing the following loss:

$$\mathcal{L}_{DPO} = -E_{(x,y^+,y-)\sim D}\left[\log\sigma\left(\beta\log\frac{\pi_\theta(y^+|x)}{\pi_{\text{ref}}(y^+|x)} - \beta\log\frac{\pi_\theta(y^-|x)}{\pi_{\text{ref}}(y^-|x)}\right)\right]$$

where β is a hyperparameter.

In this work, we aim to understand how qualitative and quantitative differences between y^+ and y^- influence the learning behavior of DPO.

2.2 Preference Datasets

To guide our investigation, we group common techniques for preference dataset curation into 3 categories, according to two axes: source distribution of the response y, and the preference labeling function (see Figure 2).

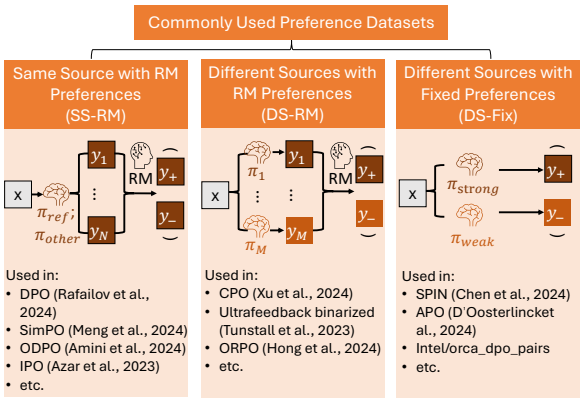

Figure 2: Commonly used preference datasets, categorized into 3 types according to their responses sources and preference labeling functions.

Same Source w/ RM Preference (SS-RM) The original DPO work (Rafailov et al., 2024) proposed to sample y^+ and y^- from the same model, π_{ref} ($\text{SS}_{\pi_{\text{ref}}}$), and derive the preference labels using a reward model. This has been widely adopted in follow-up works (Meng et al., 2024; Amini et al., 2024; Azar et al., 2023; Lai et al., 2024). Note that y^+ and y^- can also be from the same source that

[2]Many variations of DPO have been proposed (Azar et al., 2023; Park et al., 2024; Meng et al., 2024; Hong et al., 2024). Since our focus in this work is investigating the impact of preference dataset choices, we fix DPO as our PO algorithm.

is not π_{ref} ($\text{SS}_{\pi_{\text{other}}}$), meaning that these datasets can be re-used to train a different base LLM too.

`Diff Source w/ RM Preference (DS-RM)` Earlier work in DPO used output pairs sampled from two different humans (Köpf et al., 2023) or models (Ultrafeedback binarized (Cui et al., 2023; Tunstall et al., 2023); Argilla-OpenOrca[3]) to construct the dataset (i.e., y^+ is from a different source than y^-). The preference labels were typically assigned using a reward model or LLM-based judges. This dataset construction is agnostic to the choice of the policy π_{ref}. Once created, these datasets can again be re-used without additional sampling or preference labeling overhead for any new choice of π_{ref} (Wu et al., 2024; Hong et al., 2024; Bai et al., 2022).

`Diff Source w/ Fixed Preference (DS-Fix)` It is possible to have a prior estimate of the relative strengths of two sampling sources (e.g. using rankings on benchmarks like Chatbot-Arena (Chiang et al., 2024)). In such scenarios, instance-level preference between 2 responses from different sources can be assigned based on model-level rankings (i.e., y^+ is always from a "stronger" model than y^-). Methods such as SPIN (Chen et al., 2024) have successfully used such strategies (setting $y^- \sim \pi_{\text{ref}}$) while others (D'Oosterlinck et al., 2024) report suboptimal performance with these datasets.

2.3 Measuring density of desired differences

Our goal is to study how corpus-level differences in preference pairs impact models' learned behavior after DPO. We quantify the difference between y^+ and y^- using a combination of three metrics, which we explain and motivate below:

Token-level edit distance (e_Δ) between y^+ and y^- is the first distance metric that we use. It is the token-level Levenshtein distance between 2 outputs. e_Δ is easily computable and π_{ref} agnostic. It captures differences in length, lexicon, syntax, etc.

π_{ref}'s LogProb Difference (p_Δ) is the second distance metric that we use. It is computed as $|\log \pi_{\text{ref}}(y^+|x) - \log \pi_{\text{ref}}(y^-|x)|$. p_Δ measures the difference in probability mass placed on y^+ and y^- by π_{ref}. It captures a different notion of "distance" from edit-distance; two samples can be very different lexically but be assigned similar probability by π_{ref}, or vice versa. These are tougher for the implicit reward model in DPO to distinguish, and this measure helps us account for such instances.

Reward Margin (r_Δ) measures the difference in rewards from a reward model RM. It is computed as $r_\Delta = r_{y^+} - r_{y^-}$, where r_y is the reward score RM assigns to an output y. This reward margin quantifies the desired differences in targeted (relevant) features between the two outputs, irrespective of their lexical and probability differences.

We combine these to construct a single metric that measures the density of "desired" differences between two outputs. We call this **distance-calibrated reward margin** (`DCRM`):

$$\text{DCRM}(y^+, y^-) = \frac{\sigma(r_\Delta) - 0.5}{e_\Delta + p_\Delta + \epsilon} \quad (1)$$

We omit (y^+, y^-) as the arguments for $r_\Delta, e_\Delta, p_\Delta$ for brevity and include constant $\epsilon = 1$ for numeric stability. The numerator captures the normalized reward margin[4] between y^+ and y^- (a 0-centered Bradley-Terry model (Bradley and Terry, 1952)), and the denominator measures their distances (i.e., lexical and probabilistic differences).[5]

We hypothesize that when the useful contrast signals (desired differences, measured by r_Δ) are a large fraction of the total differences (measured by $e_\Delta + p_\Delta$) in the response pair (i.e., useful signals are dense), training becomes more effective.

`DCRM` captures this hypothesis. A high `DCRM` implies (1) a high reward margin between y^+ and y^- (i.e. there are many desired differences between the two for π_{ref} to learn from) and (2) low distances between the two (i.e., the total differences are small). In this case, training signals are more meaningful and less noisy for the LLMs to learn effectively.[6]

3 Experiment Setup

3.1 Training Setup

Models We experiment with three options for our base model (π_{ref}). They include LLaMA2 (LLaMA-2-7B-Chat; Touvron et al. (2023b)), LLaMA3.2 (LLaMA-3.2-1B-Instruct; Grattafiori et al. (2024), and an extra model from other series Gemma (Gemma-2B-IT; Mesnard et al. (2024)). We train each of these models using the DPO objective for 2 epochs, and select the best checkpoint

[3] https://huggingface.co/datasets/argilla/distilabel-intel-orca-dpo-pairs

[4] We apply the sigmoid function to normalize r_Δ to be between [0, 1] and subtract 0.5 to preserve the margin sign.

[5] We do not adjust the scales of e_Δ and p_Δ since we find that these are similar across most settings in our experiments.

[6] See Appendix D for the properties of `DCRM`.

Type	Dataset	e_Δ	p_Δ	$r_{\Delta\text{(e-2)}}$	DCRM(e-2)
π_{ref} =LLaMA2 (*LLaMA-2-7B-Chat*)					
SS-RM	π_{ref}	427	**32.48**	**2.82**	**4.54**
	Gma2	**370**	91.78	1.70	2.87
	Mst	526	158.54	2.13	1.59
DS-RM	Gma2-Mst	542	226.47	2.03	1.13
DS-Fix	Gma2-Mst	542	226.47	1.02	0.43
π_{ref} =LLaMA3.2 (*LLaMA-3.2-1B-Instruct*)					
SS-RM	π_{ref}	434	120.07	**4.22**	**7.53**
	Gma2	**370**	**84.78**	1.70	3.15
	Mst	526	176.22	2.13	1.68
DS-RM	Gma2-Mst	542	228.22	2.03	1.17
DS-Fix	Gma2-Mst	542	228.22	1.02	0.44

Table 1: Statistics of the datasets. Each metric value is averaged across examples. Changing π_{ref} changes p_Δ and so we report separate statistics for LLaMA2 and LLaMA3.2. The reported DCRM values are scaled 1k times for visualization, which does not affect correlation analysis. SS-RM datasets have the highest DCRM while DS-Fix ones have the lowest DCRM.

		AP-L	AP-R	MT	AH
	LLaMA2	12.57	10.43	5.41	8.90
SS-RM	+π_{ref}	**22.36**	**16.81**	5.55	**16.67**
	+Gma2	15.89	13.12	**5.50**	11.57
	+Mst	15.49	12.07	5.40	10.42
DS-RM	+Gma2-Mst	14.13	11.51	5.52	10.55
DS-Fix	+Gma2-Mst	13.26	8.99	5.24	6.68
	LLaMA3.2	14.15	15.34	4.66	10.88
SS-RM	+π_{ref}	22.80	25.65	**5.01**	**18.88**
	+Gma2	**24.57**	**27.52**	4.99	15.91
	+Mst	19.43	19.94	4.91	16.03
DS-RM	+Gma2-Mst	20.01	21.61	**5.01**	13.61
DS-Fix	+Gma2-Mst	10.31	8.20	4.54	14.94

Table 2: Main Results; AP-L: Length-Controlled Win Rate on AlpacaEval; AP-R: Raw Win Rate on AlpacaEval; MT: MT-Bench Score; AH: Arena-Hard Win Rate; SS-RM datasets generally lead to the best performance while DS-Fix ones lead to the worst performance.

based on validation performance. Please refer to Appendix B for other training details. Due to length constraints, we report results for LLaMA2 and LLaMA3.2 in the main paper, and put the results for Gemma in Appendix E.

We use the overall scores from the reward model ArmoRM (Wang et al., 2024a) to compute $r\Delta$.

Preference Datasets We use the 60K prompts from Ultrafeedback (Cui et al., 2023). We create our preference datasets using responses sampled from four different models across the three settings (SS-RM, DS-RM, DS-Fix) described in § 2.2.

For **SS-RM**, we sample responses from the base model π_{ref}. We also use Gemma-2-9B-IT (Gma2) and Mistral-7B-Instruct-v0.2 (Mst) as two extra sources of responses. For each source, we follow Meng et al. (2024) and sample $N = 5$ responses and then select the best response pair with the highest r_Δ using the reward model RM.

For **DS-RM**, we fix the source distributions to Gemma-2-9B-IT (Gma2) and Mistral-7B-Instruct-v0.2 (Mst). We sample one response from each, and decide the preference label using RM. We find that roughly 70% of y^+ comes from Gma2 and 70% of y^- comes from Mst.

For **DS-Fix**, we use the same response pairs as DS-RM, but always set y^+ to be from Gemma-2-9B-IT (stronger model) and y^- to be from Mistral-7B-Instruct-v0.2 (weaker model), respectively.

Dataset Statistics Table 1 shows the dataset statistics. As expected, SS-RM datasets, which get the paired responses from the same source, have the lowest e_Δ and p_Δ, leading to the highest overall DCRM. DS-RM has higher distances and consequently lower DCRM. Surprisingly, we find that DS-Fix has the lowest reward margin even though its samples have a higher lexical difference. This makes it have the lowest DCRM across the three settings.

3.2 Quantitative Evaluation

We evaluate the general conversational and instruction-following abilities of our trained models π_θ using three chat benchmarks, AlpacaEval, MT-Bench, and Arena-Hard. AlpacaEval reports the models' win rates against a baseline model, GPT-4-1106-Preview (Achiam et al., 2024). Arena-Hard run similar evaluations, with GPT-4-0314 as the baseline model. MT-Bench is a multi-turn conversational benchmark and uses a judge model to score the model's responses on a scale of 10.[7]

4 Comparing Different Types of Preference Datasets

In this section, we compare models that are trained on different types of preference datasets, and establish a correlation between the dataset-level DCRM value and downstream performances. We report the results in Table 2.

Sampling from the same source distribution (SS-RM) outperforms other methods. Table 2

[7]For all three benchmarks, we use GPT-4o-mini-2024-0718 (Hurst et al., 2024) as the judge to regulate costs.

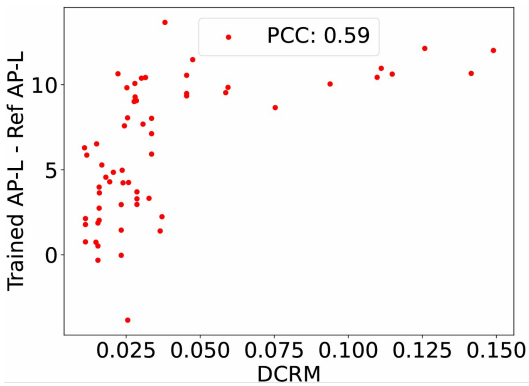

Figure 3: DCRM is positively correlated with models' performance boost on AP-L. PCC: Pearson Correlation Coefficient; Y axis: change in AP-L after training. Each point in the diagram corresponds to a trained model.

shows that sampling response pairs from the same distribution (π_{ref} and others) and deriving preferences using the reward model perform better than DS-RM and DS-Fix. In particular, training with responses from π_{ref} gives the best performance, which mirrors findings from prior work (Tang et al., 2024). Relating back to Table 1, SS-RM datasets also have the highest DCRM value.

To our surprise, SS-RM Gma2 is on par with SS-RM π_{ref} when π_{ref}=LLaMA3.2. Consulting Table 1, we see that SS-RM Gma2 has a lower p_Δ than that of LLaMA3.2, possibly explaining this result.

DS-Fix performs worse than the base model. This technique performs the worst among the three dataset settings. Similar results have also been reported by D'Oosterlinck et al. (2024). In fact, we find that its performance is worse than even the starting model. In Appendix A, we show that there are consistent stylistic differences between the two source distributions (e.g. presence of more emojis in Y^+ than Y^-), which is reflected in the model's output after training. Again, relating back, DS-Fix datasets also have the lowest DCRM value.

DCRM is positively correlated with model performance after training. With the above observations, we formally quantify the correlation between DCRM and downstream performance. To include sufficient data points, we sample multiple outputs from the source distributions and select response pairs that vary the dataset-level p_Δ, e_Δ, and r_Δ.[8] We compute the performance boost, i.e. the AP-L improvement of π_θ against π_{ref}, and show its correlation with DCRM in Figure 3.[9]

[8] See Appendix F for details.

[9] See MT and AH correlations in Appendix G.

We find that DCRM and downstream performance are moderately positively correlated, with a Pearson Correlation of 0.59, which is stronger than the individual metrics – correlation with e_Δ, p_Δ, and r_Δ is -0.51, -0.55, and 0.43 respectively (See Appendix F.1). We observe a saturation effect once DCRM passes 0.075, and suspect this to be caused by the inherent limitations of the reward model.

5 Operationalizing DCRM

In § 4, we observe that higher DCRM is correlated with better training outcomes. Can we use this correlation to guide training dataset selection?

Approach An answer is to sample responses from π_{ref}. However, this can be expensive with a large model or dataset. Instead, we want to investigate how to *select* the best response pair from an *existing* pool of responses, Formally, given N responses $\{y_1, \cdots, y_N\}$ (and also $\{y_{N+1}, \cdots, y_{2N}\}$ from a second model in the DS setting), we propose to select the pair (y_i, y_j) with the highest DCRM. We denote this as Best of N^2 pairing (BoN^2), since we select the best pair from $N \times N$ candidates. Our method is different from the conventional method (used in SS-RM), which chooses the pair with the highest reward margin by setting y^+ and y^- to the response with the highest and lowest reward scores.

Setup We apply our method to three baselines. In the Same Source (SS-RM) setting, we reselect the response pair using the existing N responses sampled from (1) π_{ref}, or (2) Mst. In the Different Sources (DS-RM)[10] setting, we use (3) Gma2-Mst as the third baseline, and select a response pair with the highest DCRM while maintaining the condition that y^+ and y^- come from different sources.[11]

Table 3 gives a comparison between the original and reselected datasets. After reselection with DCRM, both e_Δ and p_Δ decrease, while r_Δ stays in a reasonable range without too much drop.

5.1 Main Results

We compare BoN^2 against the baselines in Table 4.

Best of N^2 pairing increases performance across all settings. When training LLaMA3.2, we observe a higher performance across all baselines. When training LLaMA2, performance increases

[10] Applying our method to the DS-Fix setting leads to the same dataset as DS-RM, so we combine them together

[11] Baseline (3) is not strictly a fair comparison. In Appendix E we provide a fair baseline w/ BoN^2 (r_Δ only).

Type	Dataset	e_Δ	p_Δ	$r_{\Delta\text{(e-2)}}$	DCRM(e-2)
	π_{ref} =LLaMA2 (*LLaMA-2-7B-Chat*)				
SS-RM	π_{ref}	427	32.48	**2.82**	4.54
	w/ BoN^2	**370**	**23.87**	2.52	**5.94**
SS-RM	Mst	526	158.54	**2.13**	1.59
	w/ BoN^2	**410**	**79.94**	1.79	**2.07**
DS-RM	Gma2-Mst	542	226.47	2.03	1.13
	w/ BoN^2	**458**	**142.94**	**3.27**	**2.58**
	π_{ref} =LLaMA3.2 (*LLaMA-3.2-1B-Instruct*)				
SS-RM	π_{ref}	434	120.07	**4.22**	7.53
	w/ BoN^2	**356**	**63.55**	3.58	**11.48**
SS-RM	Mst	526	176.22	**2.13**	1.68
	w/ BoN^2	**339**	**78.81**	1.78	**2.44**
DS-RM	Gma2-Mst	542	228.22	2.03	1.17
	w/ BoN^2	**374**	**134.94**	**3.24**	**3.02**

Table 3: Statistics of the original and new datasets; w/ BoN^2 indicates datasets whose response pairs are reselected using best-of-N^2 method. They have a higher DCRM value than their original counterparts.

		AP-L	AP-R	MT	AH
	LLaMA2	12.57	10.43	5.41	8.90
SS-RM	+π_{ref}	22.36	16.81	5.55	**16.67**
	w/ BoN^2	**22.41**	**17.2**	**5.67**	16.07
SS-RM	+Mst	15.49	12.07	5.40	10.42
	w/ BoN^2	**17.42**	**13.29**	**5.48**	**10.99**
DS-RM	+Gma2-Mst	14.13	11.51	**5.52**	10.55
	w/ BoN^2	**16.82**	**13.6**	5.48	**11.75**
	LLaMA3.2	14.15	15.34	4.66	10.88
SS-RM	+π_{ref}	22.80	25.65	5.01	18.88
	w/ BoN^2	**24.77**	**27.64**	**5.10**	**20.25**
SS-RM	+Mst	19.43	19.94	4.91	16.03
	w/ BoN^2	**21.73**	**21.37**	**5.11**	**16.62**
DS-RM	+Gma2-Mst	20.01	21.61	5.01	13.61
	w/ BoN^2	**24.53**	**27.76**	**5.04**	**19.17**

Table 4: Main Results; BoN^2 datasets give a stronger performance than their original counterparts.

notably on top of both Mst (SS-RM) and Gma2-Mst (DS-RM), especially for the latter.

However, performance only increases marginally in the LLaMA2 π_{ref} (SS-RM) setting. We suspect that most responses from LLaMA2 are similar to each other. In this case, maximizing the reward margin will not incur very high distances, so the response pairs from π_{ref} (SS-RM) are already close to the best. There is little room for improvement no matter how we reselect the pairs. This is evident in Table 3, where we observe a smaller reduction in e_Δ and p_Δ compared with every other setting.

5.2 Ablation Study

Since DCRM is composed of three metrics, we do an ablation study of our method in the π_{ref} (SS-RM) setting. We remove one of p_Δ, e_Δ, or r_Δ from DCRM and reselect the response pair. Table 5 shows that **removing p_Δ gives a performance close to that of the complete metric, while removing e_Δ slightly hurts performance**. In Appendix I, we show that removing either of these in the Mst (SS-RM) and DS-RM settings can still give a performance boost over the original datasets, which means in these settings our method can be effective with a cheaper computation.

	AP-L	AP-R	MT	AH
LLaMA2	12.57	10.43	5.41	8.90
+π_{ref}	22.36	16.81	5.55	**16.67**
w/ BoN^2	22.41	17.20	**5.67**	16.07
-p_Δ	22.1	**17.27**	5.59	15.62
-e_Δ	**24.04**	17.14	5.51	14.61
-r_Δ	14.81	12.11	5.54	12.97

Table 5: Ablation Study on DCRM in the SS-RM setting; Removing p_Δ or e_Δ hurts performance slightly, while removing r_Δ significantly reduces performance.

Removing r_Δ makes training much less effective. This is expected, since without r_Δ our method selects response pairs that have the smallest distances and are minimally different. This not only eliminates noisy differences, but also those useful ones.

6 Qualitative Analysis (Feature-Analysis)

§ 4 and § 5 show the correlation between the DCRM value of a training set and *quantitative* performance. We also want to inspect whether these datasets have *qualitative* differences, to validate our starting motivation that connects performance with data quality (i.e., more desired differences and fewer noisy ones between y^+ and y^- make PO more effective), and better ground DCRM with this quality.

We analyze the feature differences between y^+ and y^-. We define *relevant* features (correctness, helpfulness, etc.) as those that the LLMs should learn, and *irrelevant* features (writing style, sarcasm, tone, etc.) as those not targeted by the task.

Features To align with the reward signals, we use the 11 features (de-duplicated) from the ArmoRM reward model as the relevant features. These include helpfulness, truthfulness, etc. We manually define 21 irrelevant features that are roughly orthogonal to these relevant features (See the full lists in Appendix C.1). The useful training signals come from differences between y^+ and y^- that are along *relevant* features and are pointing in the *correct direction* (y^+ is *better* than y^- for a *relevant* feature),

which we call *desired feature differences*.

Metrics We define f_Δ as the number of features along which y^+ and y^- differ. To measure the fraction of desired feature differences, we define f_Δ^{des} as the fraction of features in f_Δ that are (a) relevant and (b) contrasted in the correct direction (i.e. y^+ is "better" than y^- for that feature). Fraction of features that only satisfy condition (a) is denoted by f_Δ^{rel}. Similar to DCRM, f_Δ^{des} indicates the ratio of useful contrast signals among noisy signals.

To compute these, we prompt GPT-4o-mini-0718 to (1) identify the three most prominent features that differ between the two responses (setting f_Δ=3) and (2) indicate a contrast direction for each feature if applicable (i.e., whether y^+ is better). Referring to the list of relevant features, we can then compute f_Δ^{rel} and f_Δ^{des}. Note that we can use this to study the training dataset (i.e. Y^+-Y^-), and the learned differences after training (Y_{trained}-Y_{ref}).

Analysis of training datasets ($Y^+ - Y^-$) To study the feature differences LLMs *see* during training, we compute the average f_Δ^{rel} and f_Δ^{des} across 200 randomly sampled (y^+, y^-) from the training dataset. Higher f_Δ^{des} implies higher dataset quality.

Analysis of learning outcomes ($Y_{\text{trained}} - Y_{\text{ref}}$) To study what LLMs actually *learn* after training, we compute f_Δ^{rel} and f_Δ^{des} for 200 randomly sampled $(y_{\text{trained}} \sim \pi_\theta(x), y_{\text{ref}} \sim \pi_{\text{ref}}(x))$ pairs where x is a test prompt in the AlpacaEval dataset. Higher f_Δ^{des} implies that the model learns more useful signals (e.g., to be more helpful) and fewer noisy ones (e.g., to be more sarcastic).

Following § 4 and § 5, we compare different preference datasets in § 6.1, and then show how BoN^2 can improve response pair quality in § 6.2.

6.1 Comparing Common Preference Datasets

We present the results in Table 6 to understand (1) what the model *sees* during training and (2) what it actually *learns*.

DS-Fix datasets have the lowest proportion of desired feature differences in its training data. Analyzing the training set Y^+-Y^-, we see that response pairs from π_{ref} (SS-RM) have the highest percentage of desired feature differences, indicating the highest quality. On the other hand, DS-Fix has the lowest percentage. These results are consistent with our observations in Table 2. Surprisingly DS-RM has a higher f_Δ^{des} than Gma2 (SS-RM) and Mst (SS-RM). A possible explanation will be their actual marginal differences in dataset quality since at least 1 side of the response sources overlap.

		Y^+-Y^-		Y_{trained}-Y_{ref}	
		f_Δ^{rel}	f_Δ^{des}	f_Δ^{rel}	f_Δ^{des}
π_{ref} =LLaMA2 (*LLaMA-2-7B-Chat*)					
SS-RM	π_{ref}	63.83	**41.83**	53.75	**29.81**
	Gma2	56.42	38.08	53.94	29.53
	Mst	62.83	37.83	54.00	29.19
DS-RM	Gma2-Mst	61.75	39.92	53.31	28.66
DS-Fix	Gma2-Mst	62.5	36.33	52.22	18.83
π_{ref} =LLaMA3.2 (*LLaMA-3.2-1B-Instruct*)					
SS-RM	π_{ref}	64.67	**43.25**	60.08	37.50
	Gma2	56.42	38.08	59.00	**37.58**
	Mst	62.83	37.83	61.00	35.58
DS-RM	Gma2-Mst	61.75	39.92	60.33	34.17
DS-Fix	Gma2-Mst	62.50	36.33	60.17	23.33

Table 6: f_Δ^{des}: Percentage of desired feature differences among the identified feature differences; f_Δ^{rel}: Percentage of relevant feature differences; Y^+-Y^-: differences identified between y^+ and y^- in the training set; Y_{trained}-Y_{ref}: differences identified between model's output on AlpacaEval after training (Y_{trained}) and before training (Y_{ref}). SS-RM datasets typically have the highest f_Δ^{des}, followed by DS-RM and then DS-Fix.

Desired feature differences learned by the model are proportional to their presence in the training set. Our initial observation is that higher f_Δ^{des} in the training dataset (i.e. Y^+-Y^-) generally induces higher f_Δ^{des} in Y_{trained}-Y_{ref}. This indicates a consistency between the training set and learned outcome for desired feature differences. To analyze this trend in a fine-grained manner and for more general feature differences, we do the following case study in the LLaMA2 π_{ref} (SS-RM) setting.

In general, feature differences learned by the model are proportional to their presence in the training set. We inspect the distribution of feature differences per category (i.e., the percentage of each kind of feat. diff. among all the identified feat. diff.). Figure 4 shows that for both relevant and irrelevant features, the distributions for Y^+-Y^- and Y_{trained}-Y_{ref} are similar, with a KL divergence of 0.2109 and 0.1284 respectively, so **more prominent feature differences in the training set are picked up by the model more after training.**[12]

6.2 Effect of Applying Best-of-N^2 Pairing

Best of N^2 pairing produces datasets with a higher proportion of desired feature differences. We conduct the same feature-based analysis as in

[12]See Appendix C.3 for more analysis.

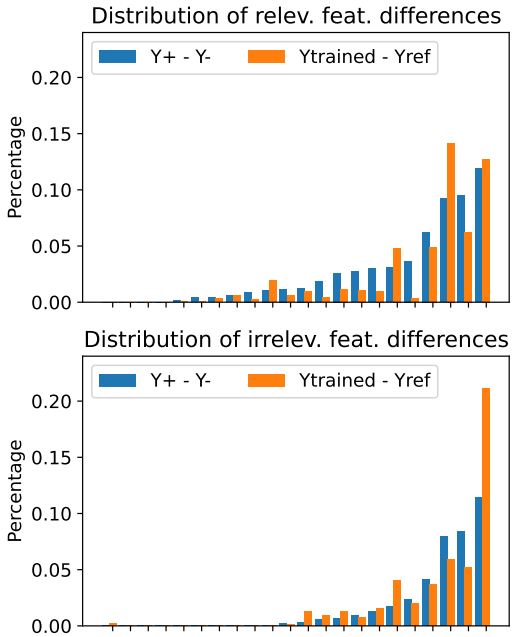

Figure 4: Distributions of relevant (top) and irrelevant (bottom) feature differences. Each pair of adjacent blue and orange bars represents the percentage of a kind of feat. diff. (y^+ more helpful, y^- less truthful, etc.) among the identified feat. diff. Blue: training set differences (Y^+-Y^-); Orange: differences in model outputs on AlpacaEval after or before training (Y_{trained}-Y_{ref}). Y^+-Y^- and Y_{trained}-Y_{ref} have similar distributions.

		Y^+-Y^-		Y_{trained}-Y_{ref}	
		f_Δ^{rel}	f_Δ^{des}	f_Δ^{rel}	f_Δ^{des}
π_{ref} =LLaMA2 (*LLaMA-2-7B-Chat*)					
SS-RM	π_{ref}	63.83	**41.83**	53.75	29.81
	w/ BoN^2	64.17	41.50	54.58	**31.58**
SS-RM	Mst	62.83	37.83	54.00	29.19
	w/ BoN^2	66.25	**39.08**	54.08	**30.25**
DS-RM	Gma2-Mst	61.75	39.92	53.31	28.66
	w/ BoN^2	62.83	**42.75**	55.67	**30.83**
π_{ref} =LLaMA3.2 (*LLaMA-3.2-1B-Instruct*)					
SS-RM	π_{ref}	64.67	43.25	60.08	37.50
	w/ BoN^2	65.00	**44.83**	59.67	**38.42**
SS-RM	Mst	62.83	37.83	61.00	**35.58**
	w/ BoN^2	65.17	**40.25**	59.33	34.25
DS-RM	Gma2-Mst	61.75	39.92	60.33	34.17
	w/ BoN^2	62.83	**41.42**	60.33	**36.75**

Table 7: Results for feature-based analysis. BoN^2 datasets have a higher f_Δ^{des} in most settings.

§ 6.1. Table 7 indicates that in most settings, the datasets produced by our method have a higher percentage of desired feature differences (See f_Δ^{des} in Y^+-Y^-), which guides the models to learn effectively and do better in relevant features after training (See f_Δ^{des} in Y_{trained}-Y_{ref}). In the LLaMA2 π_{ref} (SS-RM) setting, f_Δ^{des} in Y^+-Y^- remains approximately the same after applying our method, which can be caused by what we discuss in § 5.1.

7 Related Work

Preference Optimization Preference Optimization is an alternative to traditional RLHF methods (Ouyang et al., 2022) such as PPO (Schulman et al., 2017). It avoids the need for an explicit reward model. Popular PO algorithms includes DPO (Rafailov et al., 2024), IPO (Azar et al., 2023), KTO (Ethayarajh et al., 2024), R-DPO (Park et al., 2024), SimPO (Meng et al., 2024), CPO (Xu et al., 2024), ORPO (Hong et al., 2024), and so on. Many papers report performance increases on AlpacaEval when training LLMs using PO methods on chat datasets (Ding et al., 2023; Cui et al., 2023).

Response Pairs The choice of response pairs in PO affects training outcomes. Tajwar et al. (2024) and Tang et al. (2024) investigate response sources and illustrate the benefits of sampling responses on policy. Another line of work focuses on the differences between y^+ and y^-. Prior work (Fisch et al., 2024; Amini et al., 2024; Furuta et al., 2024) suggests that LLMs should learn a different reward margin for each example, since different response pairs can vary in their contrastiveness (i.e., y^+ is *much* or *only a little* better than y^-).

In reality, however, y^+ and y^- often differ in features irrelevant for the task, and a larger gap between them is not always desirable. Certain work focuses on eliminating specific irrelevant differences such as length (Singhal et al., 2023). Others take a more general perspective. Wu et al. (2024) use reward margins to measure differences and dynamically scales the training signals for each example. D'Oosterlinck et al. (2024) and Guo et al. (2024) construct minimally different pairs by revising y^- with a stronger LLM to get y^+. However, these methods either do not accurately model the relationship between response pair differences and quality, or require a stronger LLM to be present.

8 Conclusion

We propose a metric called DCRM that measures the density of useful training signals in response pairs and show its correlation with the PO training outcome. Inspired by this correlation, we design a Best of N^2 pairing method, which can curate high-quality datasets to train LLMs with PO effectively. In addition, we provide a feature analysis to inspect the characteristics of various common datasets with varying DCRM values.

Limitations

Due to time constraints, we only focus on general chat datasets and benchmarks for training and evaluation. While we do provide evaluation results for more task-specific benchmarks such as GSM8K, more efforts can be made to instead train LLMs in these task-specific settings to validate our claims.

In addition, our BoN^2 method works with an existing pool of responses. Instead of having to sample multiple responses per prompt, an alternative to our method will be to use constrained decoding to guide the response generation process toward a high DCRM value.

Ethics Statement

After manual inspection, we are confident that our work adheres to ethical guidelines. We use Ultrafeedback prompts to curate our datasets, which are open-sourced and publicly available, without the presence of sensitive or private content.

References

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, and Shyamal Anadkat et al. 2024. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

Afra Amini, Tim Vieira, and Ryan Cotterell. 2024. Direct preference optimization with an offset. *arXiv preprint arXiv:2402.10571*.

Mohammad Gheshlaghi Azar, Mark Rowland, Bilal Piot, Daniel Guo, Daniele Calandriello, Michal Valko, and Rémi Munos. 2023. A general theoretical paradigm to understand learning from human preferences. *arXiv preprint arXiv:2310.12036*.

Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, and et al. 2022. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv preprint arXiv:2204.05862*.

Ralph Allan Bradley and Milton E. Terry. 1952. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika*, 39:324–345.

Zixiang Chen, Yihe Deng, Huizhuo Yuan, Kaixuan Ji, and Quanquan Gu. 2024. Self-play fine-tuning converts weak language models to strong language models. *arXiv preprint arXiv:2401.01335*.

Wei-Lin Chiang, Lianmin Zheng, Ying Sheng, Anastasios Nikolas Angelopoulos, Tianle Li, Dacheng Li, Hao Zhang, Banghua Zhu, Michael Jordan, Joseph E. Gonzalez, and Ion Stoica. 2024. Chatbot arena: An open platform for evaluating llms by human preference. In *International Conference on Machine Learning*.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. 2021. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*.

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. 2023. Ultrafeedback: Boosting language models with scaled ai feedback. *arXiv preprint arXiv:2310.01377*.

Ning Ding, Yulin Chen, Bokai Xu, Yujia Qin, Zhi Zheng, Shengding Hu, Zhiyuan Liu, Maosong Sun, and Bowen Zhou. 2023. Enhancing chat language models by scaling high-quality instructional conversations. *arXiv preprint arXiv:2305.14233*.

Karel D'Oosterlinck, Winnie Xu, Chris Develder, Thomas Demeester, Amanpreet Singh, Christopher Potts, Douwe Kiela, and Shikib Mehri. 2024. Anchored preference optimization and contrastive revisions: Addressing underspecification in alignment. *arXiv preprint arXiv:2408.06266*.

Yann Dubois, Balázs Galambosi, Percy Liang, and Tatsunori B. Hashimoto. 2024. Length-controlled alpacaeval: A simple way to debias automatic evaluators. *arXiv preprint arXiv:2404.04475*.

Kawin Ethayarajh, Winnie Xu, Niklas Muennighoff, Dan Jurafsky, and Douwe Kiela. 2024. Kto: Model alignment as prospect theoretic optimization. *arXiv preprint arXiv:2402.01306*.

Adam Fisch, Jacob Eisenstein, Vicky Zayats, Alekh Agarwal, Ahmad Beirami, Chirag Nagpal, Pete Shaw, and Jonathan Berant. 2024. Robust preference optimization through reward model distillation. *arXiv preprint arXiv:2405.19316*.

Hiroki Furuta, Kuang-Huei Lee, Shixiang Shane Gu, Yutaka Matsuo, Aleksandra Faust, Heiga Zen, and Izzeddin Gur. 2024. Geometric-averaged preference optimization for soft preference labels. In *Advances in Neural Information Processing Systems*.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, and Alex Vaughan et al. 2024. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*.

Geyang Guo, Ranchi Zhao, Tianyi Tang, Wayne Xin Zhao, and Ji-Rong Wen. 2024. Beyond imitation: Leveraging fine-grained quality signals for alignment. In *International Conference on Learning Representations*.

Jiwoo Hong, Noah Lee, and James Thorne. 2024. Orpo: Monolithic preference optimization without reference model. *arXiv preprint arXiv:2403.07691*.

Aaron Hurst, Adam Lerer, Adam P. Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, and Alec Radford et al. 2024. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*.

Jiaming Ji, Mickel Liu, Juntao Dai, Xuehai Pan, Chi Zhang, Ce Bian, Chi Zhang, Ruiyang Sun, Yizhou Wang, and Yaodong Yang. 2023. Beavertails: Towards improved safety alignment of llm via a human-preference dataset. In *Advances in Neural Information Processing Systems*.

Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, and Lucile Saulnier et al. 2023. Mistral 7b. *arXiv preprint arXiv:2310.06825*.

Andreas Köpf, Yannic Kilcher, Dimitri von Rütte, Sotiris Anagnostidis, Zhi-Rui Tam, Keith Stevens, Abdullah Barhoum, Nguyen Minh Duc, Oliver Stanley, and Richárd Nagyfi et al. 2023. Openassistant conversations – democratizing large language model alignment. In *Advances in Neural Information Processing Systems*.

Xin Lai, Zhuotao Tian, Yukang Chen, Senqiao Yang, Xiangru Peng, and Jiaya Jia. 2024. Step-dpo: Step-wise preference optimization for long-chain reasoning of llms. *arXiv preprint arXiv:2406.18629*.

Tianle Li, Wei-Lin Chiang, Evan Frick, Lisa Dunlap, Tianhao Wu, Banghua Zhu, Joseph E. Gonzalez, and Ion Stoica. 2024. From crowdsourced data to high-quality benchmarks: Arena-hard and benchbuilder pipeline. *arXiv preprint arXiv:2406.11939*.

Yu Meng, Mengzhou Xia, and Danqi Chen. 2024. Simpo: Simple preference optimization with a reference-free reward. *arXiv preprint arXiv:2405.14734*.

Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, and Pouya Tafti et al. 2024. Gemma: Open models based on gemini research and technology. *arXiv preprint arXiv:2403.08295*.

Jinjie Ni, Fuzhao Xue, Xiang Yue, Yuntian Deng, Mahir Shah, Kabir Jain, Graham Neubig, and Yang You. 2024. Mixeval: Deriving wisdom of the crowd from llm benchmark mixtures. In *Advances in Neural Information Processing Systems*.

Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, and et al. 2022. Training language models to follow instructions with human feedback. *arXiv preprint arXiv:2203.02155*.

Ryan Park, Rafael Rafailov, Stefano Ermon, and Chelsea Finn. 2024. Disentangling length from quality in direct preference optimization. *arXiv preprint arXiv:2403.19159*.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D. Manning, Stefano Ermon, and Chelsea Finn. 2024. Direct preference optimization: Your language model is secretly a reward model. In *Advances in Neural Information Processing Systems*.

Noam Razin, Sadhika Malladi, Adithya Bhaskar, Danqi Chen, Sanjeev Arora, and Boris Hanin. 2024. Unintentional unalignment: Likelihood displacement in direct preference optimization. *arXiv preprint arXiv:2410.08847*.

Morgane Riviere, Shreya Pathak, Pier Giuseppe Sessa, Cassidy Hardin, Surya Bhupatiraju, Léonard Hussenot, Thomas Mesnard, Bobak Shahriari, Alexandre Ramé, and Johan Ferret et al. 2024. Gemma 2: Improving open language models at a practical size. *arXiv preprint arXiv:2408.00118*.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, , and Oleg Klimov. 2017. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*.

Prasann Singhal, Tanya Goyal, Jiacheng Xu, and Greg Durrett. 2023. A long way to go: Investigating length correlations in rlhf. In *Conference on Language Modeling*.

Fahim Tajwar, Anikait Singh, Archit Sharma, Rafael Rafailov, Jeff Schneider, Tengyang Xie, Stefano Ermon, Chelsea Finn, and Aviral Kumar. 2024. Preference fine-tuning of llms should leverage suboptimal, on-policy data. In *International Conference on Machine Learning*.

Yunhao Tang, Daniel Guo, Zeyu Zheng, Daniele Calandriello, Yuan Cao, Eugene Tarassov, Rémi Munos1, Bernardo Ávila Pires, Michal Valko, Yong Cheng, and Will Dabney. 2024. Understanding the performance gap between online and offline alignment algorithms. *arXiv preprint arXiv:2405.08448*.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, and Shruti Bhosale et al. 2023b. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.

Lewis Tunstall, Edward Beeching, Nathan Lambert, Nazneen Rajani, Kashif Rasul, Younes Belkada, Shengyi Huang, Leandro von Werra, Clementine Fourrier, Nathan Habib, and et al. 2023. Zephyr: Direct distillation of lm alignment. *arXiv preprint arXiv:2310.16944*.

Haoxiang Wang, Wei Xiong, Tengyang Xie, Han Zhao, and Tong Zhang. 2024a. Interpretable preferences via multi-objective reward modeling and mixture-of-experts. *arXiv preprint arXiv:2406.12845*.

Zhilin Wang, Yi Dong, Jiaqi Zeng, Virginia Adams, Makesh Narsimhan Sreedhar, Daniel Egert, Olivier Delalleau, Jane Polak Scowcroft, Neel Kant, Aidan Swope, and Oleksii Kuchaiev. 2024b. Helpsteer: Multi-attribute helpfulness dataset for steerlm. In *Nations of the Americas Chapter of the Association for Computational Linguistics*.

Junkang Wu, Yuexiang Xie, Zhengyi Yang, Jiancan Wu, Jinyang Gao, Bolin Ding, Xiang Wang, and Xiangnan He. 2024. beta-dpo: Direct preference optimization with dynamic beta. *arXiv preprint arXiv:2407.08639*.

Haoran Xu, Amr Sharaf, Yunmo Chen, Weiting Tan, Lingfeng Shen, Benjamin Van Durme, Kenton Murray, and Young Jin Kim. 2024. Contrastive preference optimization: Pushing the boundaries of llm performance in machine translation. *arXiv preprint arXiv:2401.08417*.

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. 2023. Judging llm-as-a-judge with mt-bench and chatbot arena. In *Advances in Neural Information Processing Systems*.

A Preliminary Study in the DS-Fix setting

Although prior work (D'Oosterlinck et al., 2024) has shown that sampling responses from different sources gives different performances on chat benchmarks like AlpacaEval (Dubois et al., 2024), a missing piece is a qualitative understanding of how the choice of these sources shapes the learned behaviors of LLMs.

In an early pilot study in the DS-Fix setting, we observe a trend for LLMs to over-exploit benign features when y^+ and y^- have consistent stylistic differences, which in turn leads to worse performance after training. The following are 2 examples that demonstrate this.

Case Study I: Chat Benchmark We use the 60K prompts from Ultrafeedback (Cui et al., 2023) and sample y^+ from a strong model Gemma-2-9B-IT (Riviere et al., 2024) and y^- from a weak model Mistral-7B-Instruct-v0.2 (Jiang et al., 2023). We set π_{ref} to LLaMA-2-7B-Chat (Touvron et al., 2023b) and train it with DPO for 2 epochs. We evaluate its performance on AlpacaEval.

Surprisingly, the model's raw win rate decreases after training (See Table 8). We then closely inspect the model's output. Compared with π_{ref}, the trained model tends to generate more emojis and other stylistic symbols (See example on the top left of Figure 5).

	AlpacaEval		
	LC	WR	Length
LLaMA-2-7B-Chat	12.57	10.43	1502
+Gma2-Mst	13.26	8.99	1166

Table 8: Result on AlpacaEval. LC: length controlled win rate; WR: raw win rate. The model's raw win rate decreases after training.

Quantitatively, we conduct a token-level analysis, where we calculate the average frequency for each token to appear in models' responses to AlpacaEval questions before training (Y_{ref}) or after training ($Y_{trained}$) (See details in Appendix A.1). We then check the tokens whose frequency increases the most when going from Y_{ref} to $Y_{trained}$ (See Figure 5 top right). As expected, 5 out of the top 10 tokens are emoji tokens (those surrounded by <>). The rest are mostly also stylistic tokens (** and * are used to bold text and create bullet points).

These stylistic features are indeed learned from the training set. We calculate the same frequency differences for each token when changing from dispreferred responses Y^- to preferred responses Y^+, and found the same emoji token (<0x0A>) and other stylistic tokens (**, *, etc.) to appear much more frequently in Y^+ than in Y^-.

Case Study II: Math Benchmark We also conduct experiments on a Math Benchmark, GSM8K (Cobbe et al., 2021). We adopt the setting from SPIN (Chen et al., 2024) and set y^+ to be the responses from human annotators and y^- to be the responses from π_{ref} (LLaMA-2-7B-Chat). We then use DPO to train π_{ref} for 5 epochs, on 6,725 examples from GSM8K's original training split. We use the remaining 748 examples for validation and select the best checkpoint. Similar to the previous case study, we again observe a surprising performance drop on GSM8K's test split.

	GSM8K ACC (0-shot)
LLaMA-2-7B-Chat	23.88
+Human-π_{ref}	18.20

Table 9: Result on GSM8K; ACC: Accuracy; The model's accuracy decreases after training.

Manual inspection suggests that the model tends to generate repetitive sentences that include nonsensical math calculations (Figure 5 bottom left). The token-level analysis reveals that the model learns to

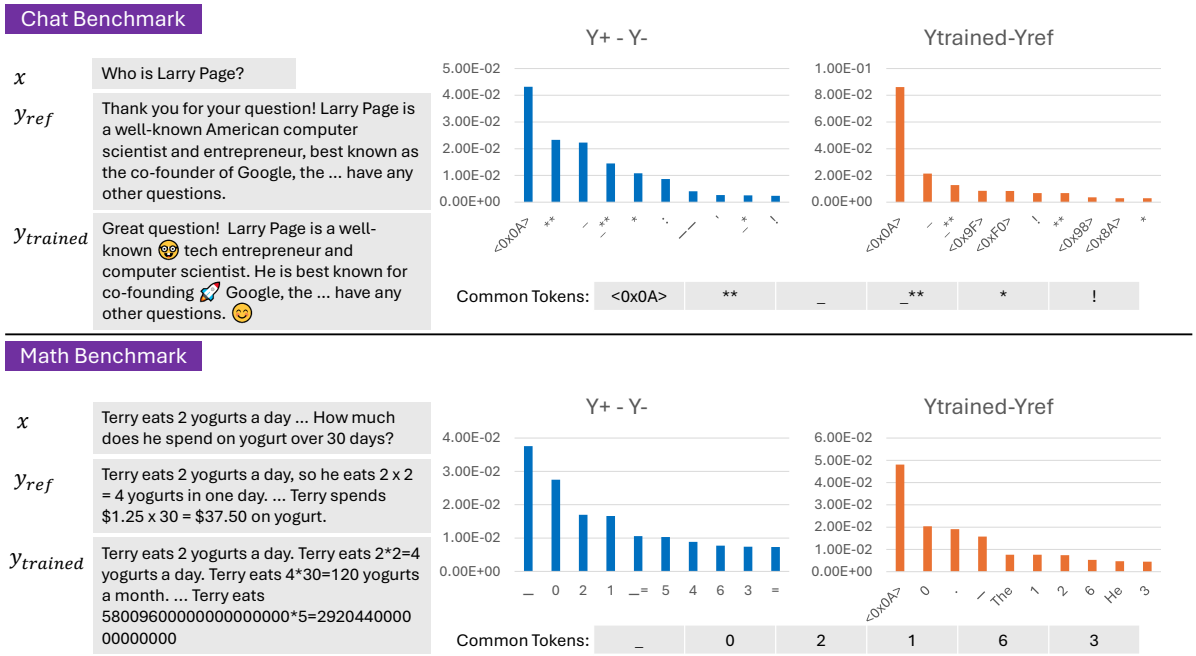

Figure 5: Top: Case Study with Chat Benchmark; Bottom: Case Study with Math benchmark; Left: Example of LLM's output before training (y_{ref}) and after training ($y_{trained}$); Middle: Top 10 tokens whose frequency increases the most when changing from Y^- to Y^+ in the training set; Right: Top 10 tokens whose frequency increases the most when changing from the model's output before training (Y_{ref}) to after training (Y_{ref}) on the test set.

generate more digits, which is also attributable to the difference between Y^+ and Y^- in the training set (Figure 5 bottom right and middle).

The above suggests that differences between y^+ and y^- in irrelevant spurious features in the training set cause LLMs to pick up these features instead of those targeted ones (correctness, etc.). This leads us to hypothesize that when the *proportion* (or *density*) of truly useful contrast signals decreases among all the contrast signals in the response pair, training becomes less effective.

A.1 Token-level Analysis

We define a length normalized bag of words representation of a sequence y as follows: we count for each token t in the vocabulary V its number of occurrences in y, which we denote as $n(t, y)$. We then divide it by the length of y, $|y|$, to get $bow_n(t, y) = \frac{n(t,y)}{|y|}$. This tells how much of y is made up of t. We then compute the average of this value across the model's responses to AlpacaEval queries after training ($Y_{trained}$) to get $bow_n(t, Y_{trained}) = \frac{\sum_{y \in Y_{trained}} bow_n(t,y)}{|Y_{trained}|}$, and similarly $bow_n(t, Y_{ref})$ for model's responses before training (Y_{ref}).

The difference between $bow_n(t, Y_{trained})$ and $bow_n(t, Y_{ref})$ tells how much more frequently t appears in the model's responses after training. Similarly, we can take the preferred responses Y^+ and dispreferred responses Y^- in the training set, and search for tokens that occur more frequently in Y^+.

B Training Details

We set $\beta = 0.1$, and train the model for 2 epochs. We use Adam Optimizer with a learning rate of 5e-7, warmup ratio of 0.1, and a cosine learning schedule.

C Feature Difference Analysis

C.1 Relevant and Irrelevant Features

We define the relevant features to be the 11 features synthesized from the 19 reward features modeled by ArmoRM. As for the irrelevant features, we manually select 21 features that are not directly related to the relevant features and include an additional "other" feature that refers to all other features not specified in the list. See details in Table 10.

C.2 Prompt

The prompt is shown in Table 11. We instruct the judge to identify the top 3 features in which the 2 given responses differ, and the corresponding

Relevant Features
"helpfulness", "correctness", "factuality", "coherence", "verbosity", "instruction following", "truthfulness", "honesty", "harmlessness", "code complexity", "code readability"
Irrelevant Features
"writing style", "tone", "politeness", "friendliness", "caring or not", "intimacy", "empathy", "language type", "casual or formal", "authoritative or not", "creativity", "certainty", "humor", "passive or active", "pessimistic or optimistic", "explicit or implicit", "sarcastic or not", "passion", "repetitiveness", "word usage diversity", "structure of presentation", "other"

Table 10: Complete List of Relevant and Irrelevant Features

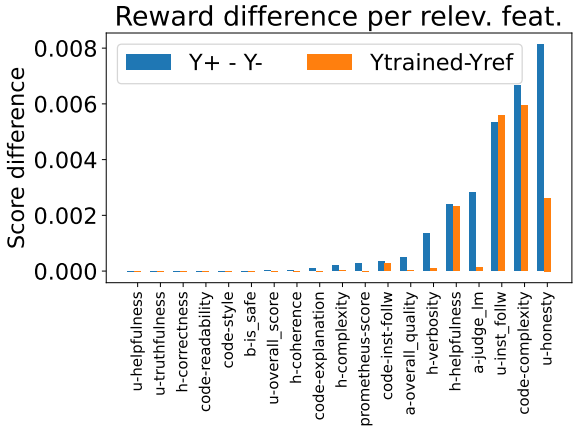

Figure 6: The fine-grained, per feature reward score differences in both settings overlap significantly. X-axis: relevant feature. u: Ultrafeedback, h: Helpsteer (Wang et al., 2024b), a: Argilla, b: BeaverTails (Ji et al., 2023); Y-axis: reward score difference per feature when going from Y^- (Y_{ref}) to Y^+ (Y_{trained}).

contrast directions if applicable. To avoid potential biases, we do not reveal the source of each response (y^+ or y^-; $y_{trained}$ or y_{ref}). Additionally, we ask the judge to give 2 separate predictions where in the first prediction $y_1 = y^+(y_{trained}), y_2 = y^-(y_{ref})$ and in the second prediction $y_1 = y^-(y_{ref}), y_2 = y^+(y_{trained})$, respectively.

C.3 Reward differences for relevant features

Reward differences of relevant features follow similar distributions between Y^+-Y^- and Y_{trained}-Y_{ref}. Since we have the fine-grained reward score for each of the relevant features from ArmoRM[13], we compute the change in reward score per feature. Consistent with what we notice in § 6.1, Figure 6 shows that the reward score changes in Y^+-Y^- and Y_{trained}-Y_{ref} are similar. In particular, the top 3 features with the highest changes, which explain over 50 percent of the total reward score changes, are the same for both settings (i.e., the top 3 are honesty, code complexity, and instruction following in both settings).

D DCRM Properties

Our DCRM metric has the following properties.

1. Encourage high reward margin, low distance. Denote the distance $e_\Delta + p_\Delta$ as d. For any response pairs p_{ij} and $p_{i'j'}$, if $r_\Delta(p_{ij}) > r_\Delta(p_{i'j'})$ and $d(p_{ij}) = d(p_{i'j'})$, then $DCRM(p_{ij}) > DCRM(p_{i'j'})$. Similarly, if $r_\Delta(p_{ij}) = r_\Delta(p_{i'j'})$ and $d(p_{ij}) < d(p_{i'j'})$, then $DCRM(p_{ij}) > DCRM(p_{i'j'})$.

2. Preserve reward margin sign. DCRM always has the same sign as the reward margin. For any pairs p_{ij}, $p_{i'j'}$, $p_{i''j''}$ where $r_\Delta(p_{ij}) < 0$, $r_\Delta(p_{i'j'}) = 0$, and $r_\Delta(p_{i''j''}) > 0$, we should have $DCRM(p_{i''j''}) > DCRM(p_{i'j'}) > DCRM(p_{ij})$. This means any pair with a positive overall training signal has a higher DCRM value than those with an overall neutral signal, followed by those with an overall negative signal. Additionally, for any pairs p_{ij} and $p_{i'j'}$ where $r_\Delta(p_{ij}) = r_\Delta(p_{i'j'}) = 0$, we have $DCRM(p_{ij}) = DCRM(p_{i'j'})$. This means any pairs with an overall neutral training signal have the same DCRM value.

E Complete Results

Table 12, 13, 14 show the complete results and dataset statistics for each π_{ref} that we have trained.

Similar to the main results in § 5.1, we observe that SS-RM generally performs the best and DS-Fix generally performs the worst, and that there is a positive correlation between the average DCRM value of the training dataset and the model's performance boost after training.

F Correlation Analysis on AlpacaEval

In addition to the 3 SS-RM, 1 DS-RM, and 1 DS-Fix settings discussed in § 3, we also include the 8

[13]These are the 19 original, unsynthesized features, containing duplications.

Given 2 responses y1 and y2 to a query x, identify the top 3 most prominent features in which y1 and y2 differ. Provide a justification for each feature that you identified. The features that you identified should only come from the following set of potential features:

{explicit or implicit, instruction following, code readability, caring or not, pessimistic or optimistic, writing style, certainty, truthfulness, casual or formal, tone, intimacy, code complexity, passion, friendliness, passive or active, authoritative or not, word usage diversity, correctness, politeness, language type, factuality, empathy, creativity, coherence, repetitiveness, verbosity, sarcastic or not, structure of presentation, harmlessness, humor, helpfulness, honesty}

Note that the features "code complexity" and "code readability" are only applicable for programming or coding tasks. Do not indicate these for non programming or coding tasks.

If you think none of the feature listed above can explain the differences between y1 and y2, propose new features that can explain the differences. Again, provide a justification for each proposed new feature.

Additionally, for any feature where it makes sense to say y1 is "better" or "worse" than y2 in terms of that feature (e.g., helpfulness, where more helpful is better; verbosity, where less verbose is better), identify which response is better. You should put "y1" or "y2". For other features where differences do not imply "better" or "worse" (writing style, tone, formal or casual, language type, etc.), put "Not applicable".

Give your response in the following JSON format:

```
{
        feature 1: {
                "justification": justification 1,
                "better response": "y1" or "y2" or "Not applicable"
        },
        ...
        feature 3: {
                "justification": justification 3,
                "better response": "y1" or "y2" or "Not applicable"
        }
}
```

Query x: {x}

Response y1: {y1}

Response y2: {y2}

Answer:

Table 11: Prompt for Sequence-level Analysis.

		Performance				Dataset Statistics			
		AP-L	AP-R	MT	AH	e_Δ	p_Δ	r_Δ(e-2)	DCRM(e-2)
	LLaMA-2-7B-Chat	12.57	10.43	5.41	8.90	-	-	-	-
SS-RM	+π_{ref}	22.36	16.81	5.55	16.67	427	32.48	2.82	4.54
	w/ BoN^2	22.41	17.2	5.67	16.07	370	23.87	2.52	5.94
	+Mst	15.49	12.07	5.40	10.42	526	158.54	2.13	1.59
	w/ BoN^2	17.42	13.29	5.48	10.99	410	79.94	1.79	2.07
	+Lma3	19.59	15.49	5.38	12.62	427	74.07	2.01	1.82
	+Gma2	15.89	13.12	5.50	11.57	370	91.78	1.70	2.87
DS-RM	+Gma2-Mst	14.13	11.51	5.52	10.55	542	226.47	2.03	1.13
	w/ BoN^2 (r_Δ only)	16.20	13.17	5.48	11.98	495	257.84	3.78	2.21
	w/ BoN^2	16.82	13.6	5.48	11.75	458	142.94	3.27	2.58
DS-Fix	+Gma2-Lma3	14.02	9.53	5.63	10.62	490	212.21	2.21	2.08
	+Gma2-Mst	13.26	8.99	5.24	6.68	542	226.47	1.02	0.43

Table 12: Results on LLaMA-2-7B-Chat. Lma3: LLaMA-3-8B-Instruct

		Performance				Dataset Statistics			
		AP-L	AP-R	MT	AH	e_Δ	p_Δ	r_Δ(e-2)	DCRM(e-2)
	Gemma-2B-IT	16.07	10.31	4.80	5.40	-	-	-	-
SS-RM	+π_{ref}	27.03	18.01	4.97	9.58	229	56.48	4.15	11.11
	w/ BoN^2	28.08	17.64	4.93	10.50	197	35.93	3.74	14.90
	+Mst	22.96	14.66	5.02	8.39	526	244.81	2.13	1.50
	w/ BoN^2	26.71	16.89	5.03	9.58	342	99.29	1.74	2.22
	+Lma3	25.49	17.04	5.15	8.63	427	110.00	2.01	3.07
	+Gma2	25.13	17.76	5.19	10.22	370	103.15	1.70	2.85
DS-RM	+Lma3-Mst	22.36	15.03	4.96	7.70	466	295.38	1.77	1.10
	w/ BoN^2 (r_Δ only)	24.41	15.16	4.98	7.09	515	355.66	3.59	2.03
	w/ BoN^2	26.14	17.76	5.09	9.21	393	170.61	3.03	2.80
DS-Fix	+Lma3-Mst	16.81	16.15	4.53	6.23	466	295.38	0.71	0.32

Table 13: Results on Gemma-2B-IT. Note that for symmetrical purposes, we include an additional Lma3-Mst (DS-RM/DS-Fix) setting in place of the Gma2-Mst (DS-RM/DS-Fix) setting since Gemma and Gma2 are from the same series.

		Performance				Dataset Statistics			
		AP-L	AP-R	MT	AH	e_Δ	p_Δ	r_Δ(e-2)	DCRM(e-2)
	LLaMA-3.2-1B-Instruct	14.15	15.34	4.66	10.88	-	-	-	-
SS-RM	+π_{ref}	22.80	25.65	5.01	18.88	434	120.07	4.22	7.53
	w/ BoN^2	24.77	27.64	5.10	20.25	356	63.55	3.58	11.48
	+Mst	19.43	19.94	4.91	16.03	526	176.22	2.13	1.68
	w/ BoN^2	21.73	21.37	5.11	16.62	339	78.81	1.78	2.44
	+Lma3	27.81	32.73	5.16	19.35	427	61.33	2.01	3.81
	+Gma2	24.57	27.52	4.99	15.91	370	84.78	1.70	3.15
DS-RM	+Gma2-Mst	20.01	21.61	5.01	13.61	542	228.22	2.03	1.17
	w/ BoN^2 (r_Δ only)	21.72	24.66	4.99	17.84	495	269.60	3.78	3.02
	w/ BoN^2	24.53	27.76	5.04	19.17	374	134.94	3.24	3.02
DS-Fix	+Gma2-Lma3	10.31	8.20	4.84	13.23	490	211.42	2.21	2.27
	+Gma2-Mst	17.79	13.79	4.54	14.94	542	228.22	1.02	0.44

Table 14: Results on LLaMA-3.2-1B-Instruct

additional settings for more accurate computation of the correlation. These include the 3 settings in § 5 where we apply our Best of N^2 method with DCRM and 5 settings from the ablation study (e_Δ only, p_Δ only, e_Δ+p_Δ, e_Δ+r_Δ, p_Δ+r_Δ).

F.1 Correlation with individual metrics

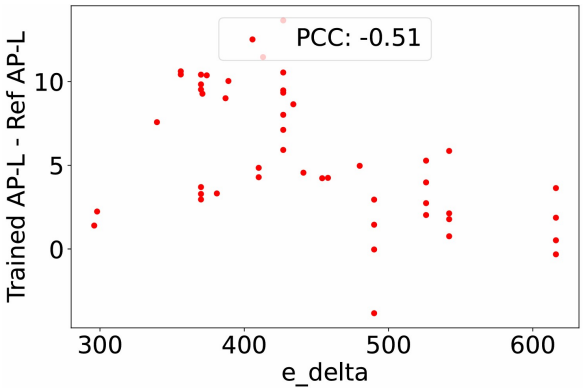

Figure 7: Correlation with e_Δ

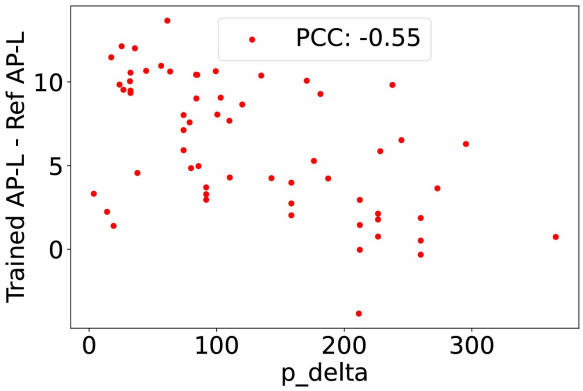

Figure 8: Correlation with p_Δ

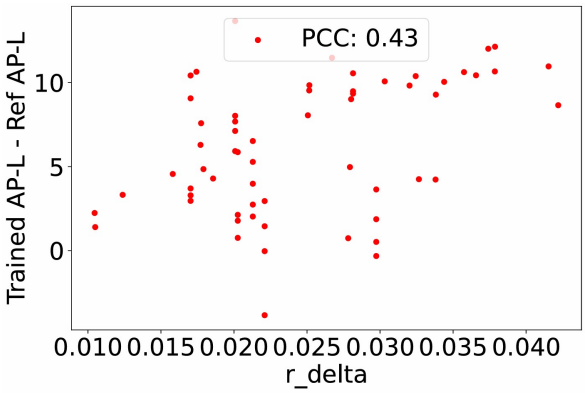

Figure 9: Correlation with r_Δ

In Figure 7, 8, and 9, for each individual component of DCRM (e_Δ, p_Δ, and r_Δ), we show the correlation between the training set's metric value and the change in the model's length controlled win rate on AlpacaEval post-training. DCRM has a stronger correlation than these individual metrics.

G Correlation with MT-Bench and Arena-Hard

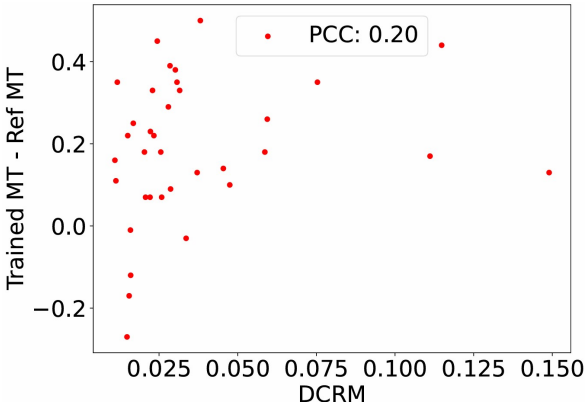

Figure 10: Correlation with MT-Bench Performance

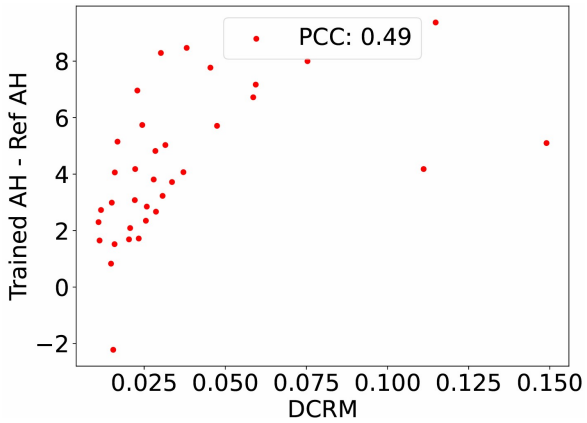

Figure 11: Correlation with Arena-Hard Performance

In Figure 10 and 11 we show the correlations between DCRM and the model's performance changes on MT-Bench and Arena-Hard. We observe a weak positive correlation with MT-Bench scores with a Pearson Correlation Coefficient of 0.20, possibly due to the fact that MT-Bench evaluates the model's multi-turn conversation abilities, while our dataset and training are for single-turn conversation. Arena-Hard shows a moderate positive correlation, with a Pearson Correlation Coefficient of 0.49, similar to the case with AlpacaEval discussed in § 4.

H Task-specific and OOD Downstream Performance

We also investigate more task-specific and out-of-distribution downstream performance for each set-

		GSM8K	ME-Hard
	LLaMA-2-7B-Chat	23.28	24.55
SS-RM	+π_{ref}	21.51	24.3
	w/ BoN^2	23.35	25.75
	+Mst	21.76	**26.5**
	w/ BoN^2	22.14	25.4
	+Lma3	**23.91**	26.1
	+Gma2	23.76	26.1
DS-RM	+Gma2-Mst	22.16	25.65
	w/ BoN^2	22.90	**26.5**
DS-Fix	+Gma2-Lma3	19.82	21.1
	+Gma2-Mst	18.62	20.55

Table 15: Task-specific and out-of-distribution downstream performance of each setting. GSM8K: 5-shot accuracy on GSM8K; ME-Hard: MixEval-Hard overall score; Training on DS-Fix datasets hurts models' performance while training on other datasets generally preserves or even increases the performance.

	AP-L	AP-R	Length
LLaMA-2-7B-Chat	12.57	10.43	1502
+(SS-RM) π_{ref}	22.36	16.81	1530
w/ BoN^2	22.41	17.20	1561
-p_Δ	22.1	**17.27**	1526
-e_Δ	**24.04**	17.14	1513
-r_Δ	14.81	12.11	1529

Table 16: Ablation Study on DCRM

ting, using GSM8K (Cobbe et al., 2021)[14] and MixEval-Hard (Ni et al., 2024). As shown in Table 15, the model's performance trained in the DS-Fix settings decreases compared with the base model π_{ref}, while in other settings the performance is maintained close to π_{ref} or even increases. This suggests that noisy signals learned from the DS-Fix datasets not only hurt LLMs' general conversational abilities but also their task-specific downstream effectiveness.

I Ablation Study for best-of-N^2 pairing

We also do an ablation study in the LLaMA-2-7B-Chat π_{ref} (SS-RM) setting. In particular, we remove 1 of e_Δ, p_Δ, and r_Δ from DCRM. Removing e_Δ or p_Δ means setting DCRM's denominator to $p_\Delta + \epsilon$ or $e_\Delta + \epsilon$. Removing r_Δ means setting DCRM to just $\frac{1}{e_\Delta + p_\Delta + \epsilon}$, in which case the new Best of N^2 method effectively selects the pair with the smallest distance.

[14]We use the lm-evaluation-harness library version 0.4.5 at https://github.com/EleutherAI/lm-evaluation-harness/tree/v0.4.5 to compute GSM8K results.

Table 16 shows that **the performance after removing either e_Δ or p_Δ is close to that of the complete metric**. In Table 17, 18, and 19 we have similar observations in other settings too. A merit entailed by this insight is that, in certain settings such as Mst (SS-RM) and DS-RM, our method can work well with just e_Δ and r_Δ, without the need for a forward pass on the model to compute p_Δ. r_Δ are usually collected during the preference annotation process and given in the preference dataset. In this case, we only need to compute e_Δ to apply our selection strategy, which is cheap and simple.

	AP-L	AP-R	Length
LLaMA-2-7B-Chat	12.57	10.43	1502
+(SS-RM) π_{ref}	22.36	16.81	1530
w/ BoN^2	22.41	17.20	1561
-p_Δ	22.1	**17.27**	1526
-e_Δ	**24.04**	17.14	1513
+(SS-RM) Mst	15.49	12.07	1463
w/ BoN^2	**17.42**	**13.29**	1456
-p_Δ	16.86	12.80	1446
-e_Δ	17.13	13.04	1446
+(DS-RM) Gma2-Mst	14.13	11.51	1511
w/ BoN^2	16.82	13.6	1522
-p_Δ	16.8	13.54	1528
-e_Δ	**17.54**	**13.98**	1518

Table 17: On LLaMA-2-7B-Chat, keeping r_Δ and 1 distance metric also works reasonably well and gives performance close to the complete metric.

	AP-L	AP-R	Length
Gemma-2B-IT	16.07	10.31	1224
+(SS-RM) π_{ref}	27.03	**18.01**	1357
w/ BoN^2	**28.08**	17.64	1343
-p_Δ	26.73	16.02	1311
-e_Δ	28.2	17.76	1331
+(SS-RM) Mst	22.96	14.66	1349
w/ BoN^2	**26.71**	**16.89**	1328
-p_Δ	25.37	16.67	1355
-e_Δ	25.89	15.65	1278
+(DS-RM) Lma3-Mst	22.36	15.03	1379
w/ BoN^2	**26.14**	17.76	1432
-p_Δ	25.89	**18.63**	1458
-e_Δ	24.12	15.78	1364

Table 18: On Gemma-2-9B-IT, keeping r_Δ and 1 distance metric also works reasonably well and gives performance close to the complete metric.

Removing r_Δ makes training less effective. In general, we observe in Table 20 that purely optimizing against distances with either e_Δ, p_Δ, or both is much less effective than when r_Δ is included.

	AP-L	AP-R	Length
LLaMA-3.2-1B-Instruct	14.15	15.34	1980
+(SS-RM) π_{ref}	22.8	25.65	2725
w/ BoN^2	**24.77**	27.64	2825
-p_Δ	24.58	**27.89**	2582
-e_Δ	24.19	27.33	2716
+(SS-RM) Mst	19.43	19.94	1980
w/ BoN^2	**21.73**	**21.37**	1915
-p_Δ	21.08	20.56	1892
-e_Δ	21.00	20.68	1882
+(DS-RM) Gma2-Mst	20.01	21.61	2062
w/ BoN^2	**24.53**	**27.76**	2145
-p_Δ	23.43	26.52	2181
-e_Δ	23.16	26.21	2127

Table 19: On LLaMA-3.2-1B-Instruct, keeping r_Δ and 1 distance metric also works reasonably well and gives performance close to the complete metric.

	AP-L	AP-R	Length
LLaMA-2-7B-Chat	12.57	10.43	1502
+ (SS-RM) π_{ref}	22.36	16.81	1530
w/ BoN^2	**22.41**	**17.20**	1561
e_Δ only	13.97	11.68	1538
p_Δ only	15.89	13.11	1537
e_Δ +p_Δ(DCRM-r_Δ)	14.81	12.11	1529

Table 20: Ablation Study on DCRM without reward margins. Selecting response pairs with the smallest distances leads to suboptimal performance.

This is expected, since selecting the pair with the smallest distance reduces the reward margin significantly, indicating that not only the noisy differences but also the desired differences are eliminated in the selected pair.

J Discussion on Computational cost

The term N^2 in BoN^2 comes from pairing the N responses. We analyze the cost BoN^2 incurs and compare that with the cost of the conventional response pairing methods (e.g., selecting the response pair with the largest r_Δ).

Firstly, in the sampling stage, similar to conventional methods, we sample N responses (not N^2 responses) from the model, which means we do not incur extra sampling cost.

Secondly, in the reward scoring stage, we again follow conventional methods and use the reward model to give each response a reward score.

Thirdly, during pairing, we compute r_Δ, e_Δ, and p_Δ for each response pair. Computing r_Δ just needs simple arithmetic. For p_Δ, again only simple arithmetic is needed, and the log probability of each response is a readily available byproduct when sampling the responses. e_Δ can be efficiently computed using existing libraries such as the edit distance library from Python. After this, we compute the DCRM value of each response pair and select the pair with the highest DCRM value.

Although the third stage incurs quadratic costs in terms of the number of responses N, we argue that these costs are still minimal, since (1) a relatively small N is usually sufficient and large N gives diminishing returns (See Appendix K), (2) the cost for each pair is minimal either due to arithmetic simplicity (r_Δ and p_Δ) or implementation efficiency (e_Δ).

Therefore, the bulk of computation is still spent on response sampling and reward scoring, which are the same in our and conventional methods, and applied to each output separately (i.e., O(N) compute). Consequently, the total extra cost our method incurs is comparable to the conventional methods.

K Increasing Number of Responses

The hyperparameter N controls the number of responses in the response pool. Increasing N should help create a more diverse set of responses, boost the quality of the response pairs identified by our BoN^2 method, and raise the trained model's performance on benchmarks. To inspect the effect of increasing N, we change N from the original value of 5 to 8 and curate a new dataset to train LLaMA-2-7B-Chat. Table 21 shows the results.

	AP-L	AP-R	Length
LLaMA-2-7B-Chat	12.57	10.43	1502
+ (SS-RM) π_{ref}	22.36	16.81	1530
w/ $BoN^2, N = 5$	22.41	17.20	1561
w/ $BoN^2, N = 8$	**23.35**	**17.89**	1548

Table 21: Results with different values of N. Increasing N beyond 5 gives diminishing returns.

As N increases, we observe diminishing returns. We suspect the reason to be that we are only sampling from one single source model, which puts an upper bound on the response diversity. However, this is not a deficiency specific to our method. In fact, all methods that sample multiple responses from the same model will eventually suffer from diminishing returns as N increases.