Synthetic Preference Interpolation for Language Model Alignment

Anonymous ACL submission

Abstract

Ensuring alignment with human preferences is a critical and challenging aspect of large language models (LLMs). Currently, the most widely adopted alignment methods, such as those based on Direct Preference Optimization (DPO), leverage pairwise preference data for training and have demonstrated promising results. However, these methods face limitations, as they cannot fully exploit the rich information inherent in preference data, such as intermediate quality levels between chosen and rejected samples. Motivated by this insight, we propose **S**ynthetic **P**reference **I**nterpolation **A**lignment (**SPIA**), a novel alignment algorithm that introduces interpolated synthetic preferences to better capture the nuances between samples of different quality levels. By constructing synthetic preference data that reflects intermediate quality with pair-wise preference data, our method effectively bridges the gap between binary pairwise comparisons and richer quality representation. We validate the effectiveness of SPIA through extensive experiments on both annotated preference data and self-play preference data benchmarks, achieving substantial improvements in alignment performance. Our results demonstrate that SPIA not only outperforms existing methods but also provides valuable insights into harnessing preference data for stronger human-aligned LLMs.

1 Introduction

Over the past two years, large language models (LLMs) have demonstrated remarkable advancements across diverse NLP tasks, including mathematical problem-solving, summarization, reading comprehension, and open-ended question answering. Despite these successes, aligning the behavior of LLMs with human expectations remains a critical challenge. Alignment involves ensuring factual correctness, minimizing harmful biases, and enhancing capabilities such as mathematical reasoning. To address these issues, researchers have proposed various alignment training methods aimed at improving LLM reliability and usability.

Among these methods, Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022) demonstrated strong alignment performance. However, it requires training a reward model from human-annotated preference data and subsequently fine-tuning the language model with Proximal Policy Optimization (PPO) (Schulman et al., 2017) to maximize the reward, making RLHF less accessible for many practitioners due to the complexity of training.

To simplify alignment training, recent research has focused on developing direct and efficient alternatives to RLHF. Among these, Direct Preference Optimization (DPO)(Rafailov et al., 2024) has gained significant attention. DPO eliminates the need for explicit reward models or reinforcement learning by directly fine-tuning the LLM on human preference pairs. Despite its simplicity, DPO retains strong alignment performance and has inspired subsequent studies aimed at improving its optimization framework. For example, Identity Preference Optimization (IPO) (Azar et al., 2023) addresses overfitting issues in DPO through a novel identity-based loss function. Similarly, ORPO (Hong et al., 2024) and SimPO (Meng et al., 2024) further simplify the DPO workflow by removing dependence on reference models.

While these improvements primarily focus on optimization techniques, relatively little attention has been given to the training data itself. Given the high cost of data annotation, maximizing the utilization of existing preference data is critical for advancing alignment methods. However, existing pairwise preference data, which only captures binary relationships between "chosen" and "rejected" samples, leaves much of its potential information unexploited. In particular, pairwise data often neglects the nuanced quality continuum that may ex-

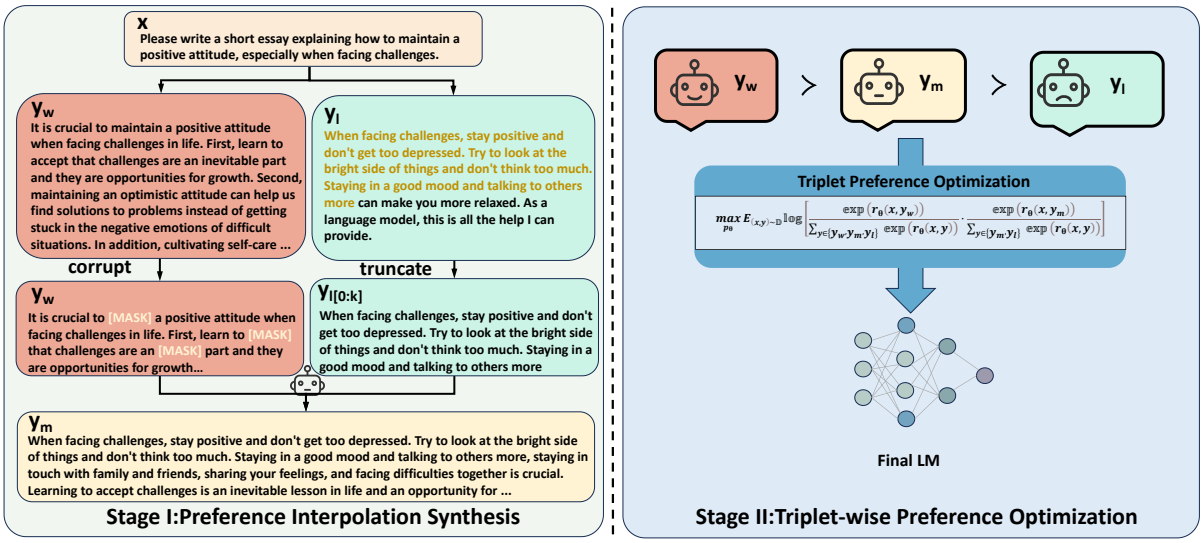


Figure 1: Model Architecture.

Figure 2: **SPIA** consists with two stages: Preference Interpolation Synthesis and Triplet-wise Preference Optimization. In the first stage, we truncate the rejected response $\mathbf{y}_l$ and then the LM generates the continual part of truncated $\mathbf{y}_l$,prompted with corresponding instruction $\mathbf{x}$ and corrupted chosen response $\widetilde{\mathbf{y}}_\mathbf{w}$. In the second stage, denoting the synthetic response as $\mathbf{y}_m$, we train the LM p_θ with preference triplet $(\mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l)$. using a triplet-wise preference loss function.

ist between two samples. Recent work, such as LiPO (Liu et al., 2024), has shown that training on list-wise preferences can outperform pairwise preference training. However, collecting list-wise preference data, whether through manual annotation or GPT-4-based methods (OpenAI et al., 2024), remains resource-intensive. Thus, a cost-effective strategy to obtain list-wise preferences from existing pairwise data is an open research challenge.

In this paper, we propose a novel approach called Synthetic Preference Interpolation Alignment (**SPIA**) to address these limitations. Our method introduces a data synthesis phase that generates interpolated preference data from pairwise preference data, capturing intermediate quality levels between chosen and rejected samples. SPIA then employs a triplet preference training paradigm, leveraging these synthesized preferences to improve alignment performance. We demonstrate the effectiveness of our proposed approach through evaluations on widely used LLM benchmarks, downstream tasks, and reward distributions. Specifically, we fine-tune Phi-3.5-mini-instruct (Abdin et al., 2024) on Ultrachat200k (Ding et al., 2023) and Ultrafeedback (Cui et al., 2024) datasets, comparing the performance of our models against other preference training methods. Furthermore, we perform an ablation study using alternative data synthesis techniques and conduct a detailed evaluation of our proposed synthesis method. Our contribution can be summarized as follows:

- We point out that pair-wise preference data has not been fully utilized in alignment training. Therefore, we propose a novel method to synthesize preference interpolation data.
- We further demonstrate that when the quality of the synthesized data is adequate, optimizing LLMs with triplet preferences can achieve better performance.
- Our proposed novel training pipeline (**SPIA**) can improve model performance more consistently on both self-play and annotation-available alignment setting compared to other methods, without incurring additional annotation costs.

2 Related work

2.1 Data Synthesis by LLM

Data synthesis plays a pivotal role in the field of machine learning. With the advancement of large language models (LLMs), the utilization of LLMs for data synthesis has become increasingly promising. Numerous researchers employ data synthesized with various methods by LLM to fine-tune

LLMs:(Long et al., 2024). In the field of LLM alignment, SPIN (Chen et al., 2024) has demonstrated effective results by utilizing language models that have been supervised fine-tuned to generate responses that serve as rejected samples for preference training. However, using LLMs for data synthesis is not without its challenges. One of the key issues lies in ensuring the quality and diversity of the generated data. While LLMs can produce coherent and contextually relevant text, they may also introduce biases, repetition, or fail to generate sufficiently diverse samples.

2.2 LLM Self-refinement

Recent studies have indicated that large language models (LLMs) possess the potential for self-improvement in their responses. The process of self-refine (Madaan et al., 2023) involves using the LLM to generate feedback that can be used to enhance the results it produced previously.

Self-refinement has the potential to reduce the reliance on external supervision, thus improving model performance with minimal human intervention. However, some researchers, for example,(Huang et al., 2024) have suggested that LLMS struggle to self-correct their responses without external feedback, which means language models with insufficient capabilities may generate worse answers when attempting self-refinement.

2.3 RLHF

Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022) is a method designed to align large language models with human preferences and values. The traditional RLHF applies the Bradley-Terry model and typically involves three key stages: supervised fine-tuning, reward model training, and RL-based optimization. In the RL stage, Proximal Policy Optimization (PPO) (Schulman et al., 2017) is a commonly employed algorithm to train the LLM to maximize the score of the reward model for the generated response.

3 Preliminaries

We consider a Large Language Model (LLM) parameterized by θ and denoted as p_θ, which accepts a sequence $\mathbf{x} = [x_1, \ldots, x_n]$, commonly termed as the prompt, and then generate a corresponding response $\mathbf{y} = [y_1, \ldots, y_m]$. Hence, the response $\mathbf{y}$ is construed as a sample drawn from the conditional probability distribution $p_\theta(\cdot|\mathbf{x})$. The conditional probability distribution $p_\theta(\mathbf{y}|\mathbf{x})$ can be decomposed as follows:

$$p_\theta(\mathbf{y}|\mathbf{x}) = \prod_{j=1}^{m} p_\theta(y_j|\mathbf{x}, \mathbf{y}_{<j}),$$

Subsequently, we review supervised fine-tuning (SFT). SFT is the primary training method to adapt a pre-trained LLM for downstream tasks, utilizing a relatively smaller dataset of labeled examples compared to the data used in pre-training stage. In this paper, we focus on the task of instruction-tuning where the prompt-answer pairs denoted as $(\mathbf{x}, \mathbf{y})$, are drawn from a specified SFT dataset $\mathcal{D}$. Thus the training objective of SFT under the instruction tuning setting can be formulated as:

$$\max_{p_\theta} \mathbb{E}_{(x,y)\sim\mathcal{D}}\Big[\log p_\theta(\mathbf{y} \mid \mathbf{x})\Big]$$

Then we review the setting and method of Direct Preference Optimization (DPO) which optimizes a LLM with pair-wise preference data. Consider a tuple $(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_l)$, where $\mathbf{x}$ is prompt while $\mathbf{y}_w$ and $\mathbf{y}_l$ are chosen response and rejcted response respectively. Formally, this preference can be denoted as $\mathbf{y}_w \succ \mathbf{y}_l \mid \mathbf{x}$. These preferences are assumed to be generated by an underlying latent reward model $\mathbf{r}^*(\mathbf{x}, \mathbf{y})$. The Bradley-Terry model (Bradley and Terry, 1952) specifically defines the human preference distribution p^* as follows:

$$p^*(y_1 \succ y_2 \mid x) = \frac{\exp(r^*(x,y_1))}{\exp(r^*(x,y_1))+\exp(r^*(x,y_2))}.$$

Given a preference dataset $\mathcal{D}$ sampled from p^* which contains N preference pairs $(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_l)$, DPO considers the same RL optimization goals as other human preference alignment algorithms (such as RLHF):

$$\max_{p_\theta} \mathbb{E}_{x\sim\mathcal{D}, y\sim\pi_\theta(y|x)}\left[r_\phi(x,y)\right] - \beta\, \mathrm{D}_{\mathrm{KL}}\left[p_\theta(y \mid x) \,\|\, p_{\mathrm{ref}}(y \mid x)\right]$$

where β is a parameter controlling the deviation from the reference model p_{ref}. Instead of training a reward model, DPO reparameterizes the reward function and optimize the RL objective by:

$$\max_{p_\theta} \mathbb{E}_{(\mathbf{x},\mathbf{y})\sim\mathcal{D}}\left[\log\sigma\left(\beta\log\frac{p_\theta(\mathbf{y}_w|\mathbf{x})}{p_{\theta_{ref}}(\mathbf{y}_w|\mathbf{x})} - \beta\log\frac{p_\theta(\mathbf{y}_l|\mathbf{x})}{p_{\theta_{ref}}(\mathbf{y}_l|\mathbf{x})}\right)\right]$$

4 Method

4.1 Overview

Our proposed **SPIA** begins with a pair-wise preference dataset $\mathcal{D}$ which contains preference pair

$$p^*(\mathbf{y}_w \succ \mathbf{y}_m \succ \mathbf{y}_l \mid \mathbf{x}) = \frac{\exp\left(r^*(\mathbf{x}, \mathbf{y}_w)\right)}{\sum_{\mathbf{y} \in \{\mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l\}} \exp\left(r^*(\mathbf{x}, \mathbf{y})\right)} \cdot \frac{\exp\left(r^*(\mathbf{x}, \mathbf{y}_m)\right)}{\sum_{\mathbf{y} \in \{\mathbf{y}_m, \mathbf{y}_l\}} \exp\left(r^*(\mathbf{x}, \mathbf{y})\right)} \tag{1}$$

$$\max_{p_\theta} \mathbb{E}_{(x,y) \sim \mathcal{D}_{syn}, y' \sim p_\theta(\cdot|x)} \Big[\log p^*(\mathbf{y}_w \succ \mathbf{y}_m \succ \mathbf{y}_l \mid \mathbf{x}) \Big] \tag{2}$$

$$\max_{p_\theta} \mathbb{E}_{(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l) \sim \mathcal{D}_{syn}} \log \left[\frac{\exp\left(r_\theta(\mathbf{x}, \mathbf{y}_w)\right)}{\sum_{\mathbf{y} \in \{\mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l\}} \exp\left(r_\theta(\mathbf{x}, \mathbf{y})\right)} \cdot \frac{\exp\left(r_\theta(\mathbf{x}, \mathbf{y}_m)\right)}{\sum_{\mathbf{y} \in \{\mathbf{y}_m, \mathbf{y}_l\}} \exp\left(r_\theta(\mathbf{x}, \mathbf{y})\right)} \right] \tag{3}$$

$(\mathbf{y}_w, \mathbf{y}_l)$ and a language model p_θ trained with SFT. **SPIA** consists with two stages: Preference Interpolation Synthesis and Triplet-wise Preference Optimization. In the first stage, we truncate the rejected response $\mathbf{y}_l$ and then the LM generates the continual part of truncated $\mathbf{y}_l$,prompted with corresponding instruction $\mathbf{x}$ and corrupted chosen response $\widetilde{\mathbf{y}}_\mathbf{w}$. In the second stage, denoting the synthetic response as $\mathbf{y}_m$, we train the LM p_θ with preference triplet $(\mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l)$. Next, we will elaborate on the specific process of each of the two stages.

4.2 Preference Interpolation Synthesis (PIS)

To synthesize a sample $\mathbf{y}_m$ that satisfying preference ranking $\mathbf{y}_w \succ \mathbf{y}_m \succ \mathbf{y}_l$,which means that the response have the quality between chosen and rejected sample, we proposed a novel LM-based data synthesis approach. Specifically, we truncate $\mathbf{y}_l$, retaining only the first k tokens. Then, using the corresponding $\mathbf{x}$ corrupted as a prompt, we prompt the LLM to continue writing based on the truncated , thereby generating a preference-interpolated sample that meets the required criteria. The whole process can be formulated as:

$$\mathbf{y}_m = \mathbf{y}_l[0:k] \oplus \mathbf{y}', \text{ where } \mathbf{y}' \sim p_\theta(\cdot|\mathbf{x}, \widetilde{\mathbf{y}}_\mathbf{w}, \mathbf{y}_l[0:k])$$

In this formula, we choose different k for samples of various length. Formally, k is linearly determined by the token length of $\mathbf{y}_l$, which is $\alpha|\mathbf{y}_l|$. To understand this synthesis process, we illustrates the motivation of three main concepts of this method. Firstly, we use a part of $\mathbf{y}_l$ as starter sequence of $\mathbf{y}_m$ to ensure that the quality of the generated sample does not exceed that of the chosen response $\mathbf{y}_w$. This is because, during the generation process of a language model, the initial tokens often set the general direction for the entire output. Secondly, we use the chosen sample as a reference to guide the model, in order to generate a better response than $\mathbf{y}_l$ with the information of $\mathbf{y}_w$. Thirdly, the chosen sample $\mathbf{y}_w$ is corrupted to $\widetilde{\mathbf{y}}_\mathbf{w}$, This is to prevent $\mathbf{y}_m$ from replicating $\mathbf{y}_w$ word-by-word during generation, thereby enhancing sample diversity and facilitating the language model's state exploration in training process. In the Evaluation Section, we conduct analysis on the synthetic $\mathbf{y}_m$.

4.3 Triplet-wise Preference Optimization

With the synthetic interpolated preference dataset prepared, we use these preference triplets instead of pairs to conduct alignment training on the model. Formally, denoting the triplet dataset we obtain by preference interpolation synthesis process described in last sub-section as $\mathcal{D}_{syn}$, we have a preference triplet $(\mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l)$ for each prompt $\mathbf{x} \in \mathcal{D}$, which can be formulated as $\mathbf{y}_w \succ \mathbf{y}_m \succ \mathbf{y}_l \mid \mathbf{x}$. Under the Plackett-Luce model (Debreu, 1960), we have Eq.1. And our optimization objective is defined as Eq.2. According to the proof of general form DPO proposed by (Rafailov et al., 2024), we can solve this optimization problem by Eq.3, where $r_\theta(\mathbf{x}, \mathbf{y}) = \beta \log \frac{p_\theta(\mathbf{y}|\mathbf{x})}{p_{ref}(\mathbf{y}|\mathbf{x})}$ is the reward implicitly defined by the policy LLM p_θ and reference LLM p_{ref}.

To illustrate the training process more clearly, we also provide pseudocode in Algorithm 1.

5 Experiments

5.1 Experiment Setup

5.1.1 Model

The model we chosen for our experiment is Phi-3.5-mini-instruct (Abdin et al., 2024), which is a lightweight, state-of-the-art open-source model. Phi-3.5-mini-instruct demonstrates performance comparable to or even surpassing larger-scale mod-

Model	AlpacaEval		MT-Bench			LM-Eval-Harness			Average
	Win	LC-Win	Turn-1	Turn-2	Final	TruthfulQA	GSM8K	ARC	
Phi3.5-SFT	50.00	50.00	7.26	5.63	6.44	44.19	74.83	58.53	57.86
Ultrachat-SPIN-Phi									
SPIN	**71.06**	62.7	6.98	6.00	6.49	46.27	72.40	**64.42**	64.27
ORPO	64.24	**63.72**	7.25	**6.15**	6.70	46.39	**75.82**	61.86	64.11
IPO	65.04	62.05	**7.50**	**6.28**	**6.89**	**46.88**	74.37	60.92	**64.45**
SPIA	**74.63**	**68.67**	**7.41**	6.11	**6.76**	**47.37**	**77.10**	**64.33**	**67.39**
Ultrafeedback									
DPO	77.83	**73.33**	**7.57**	6.01	6.79	**46.63**	79.08	**64.16**	68.92
ORPO	64.82	57.83	7.35	5.80	6.58	41.62	70.74	55.55	61.03
IPO	**78.94**	70.87	7.73	**6.63**	**7.16**	45.17	78.24	60.23	**69.24**
SimPO	71.74	61.34	7.23	6.22	6.73	45.90	**79.91**	60.67	65.33
SPIA	**79.63**	**74.43**	**7.91**	**6.28**	**7.09**	**46.63**	**78.92**	**62.46**	**70.20**

Table 1: Performance of different methods on three LLM benchmarks. For AlpacaEval, we use GPT-4o as judge and Phi3.5-SFT as reference LLM. So the win-rate of Phi3.5-SFT on itself is set to 50.00. For MT-Bench, we also use GPT-4o as judge. Our model has the best or second best score in each indicator, and has the best overall performance

Algorithm 1 SPIA Pipeline

Require: Preference dataset $\mathcal{D} = \{(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_l)\}$, LLM p_θ, Preference interpolation dataset $\mathcal{D}_{syn} = \{\}$

for $(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_l)$ in $\mathcal{D}$ **do**

Truncate $\mathbf{y}_l$ to attain $\mathbf{y}_l[0:k]$

Corrupt $\mathbf{y}_w$ to attain $\widetilde{\mathbf{y}}_\mathbf{w}$

Initialize $\mathbf{y}_m[0:k] = \mathbf{y}_l[0:k]$

Generate $\mathbf{y}_m[k:] \sim p_\theta(\cdot|\mathbf{x}, \widetilde{\mathbf{y}}_\mathbf{w}, \mathbf{y}_l[0:k])$

$\mathbf{y}_m = mathbfy_m[0:k] \oplus mathbfy_m[k:]$

$\mathcal{D}_{syn}$ += $(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l)$

end for

Update $\theta = \arg\min_\theta \sum_{\mathcal{D}_{syn}} \mathcal{L}_{SPIA}(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l)$

els, such as Mistral-7B (Jiang et al., 2023) and Llama-3.1-8B (Grattafiori et al., 2024), across a wide range of evaluation tasks.

5.1.2 Dataset

The dataset used for supervised-finetune is Ultrachat200k. It comprises approximately 200,000 high-quality, multi-turn dialogues generated by ChatGPT, covering a diverse array of topics. For preference training we use two dataset. Ultrafeedback and Ultrachat-SPIN-Phi. Ultrafeedback is a widely used preference dataset for LLM alignment, which contains 64k preference pair annotated by GPT-4. We use a subset of 36k for our training. Ultrachat-SPIN-Phi is a synthetic self-play dataset created by us using the SPIN (Chen et al., 2024) methodology: SFT responses are designated as the chosen responses, while model-generated responses (by Phi-3.5-SFT) serve as the rejected responses. A total of 36k data samples were collected. We chosen these two datasets thus we can demostrate the efficiency of our method on both annotation-available and annotation-free setting in LLM alignment.

5.1.3 Competing Methods

In order to analyze the effectiveness of our method, we choose several widely used approaches in the field of alignment including: **DPO**, **SPIN**, **SimPO**, **ORPO** and **IPO**.

5.1.4 Experiment Details

To start with, we finetune Phi-3.5-mini-instruct on the Ultrachat dataset to obtain a SFT version (Phi-3.5-SFT) in our alignment experiment. For SFT stage, we only use 36k samples to prevent from model forgetting. After this, we use Phi-3.5-SFT to synthesize response by Preference Interpolation Synthesis mentioned in last section to. We generate 36k preference interpolation data for Ultrachat-SPIN-Phi and Ultrafeedback respectively. Then we train our model on the synthetic data with triplet-wise preference loss while train other baseline model on Ultrachat-SPIN-Phi or Ultrafeedback. Besides, we found that SimPO is not suitable for self-play setting as the model collapse during training on Ultrachat-SPIN-Phi. So we do not include SimPO in the Ultrachat-SPIN-Phi part of our reported results in Table 1

5.1.5 Evaluation Metric

We evaluate the effectiveness of our approach from multiple dimensions, covering general conversational ability, factual accuracy, and reasoning skills. The following is a brief introduction to the evaluation benchmarks we use.

- **AlpacaEval** In AlpacaEval (Dubois et al., 2024) benchmark, a model generates responses to 805 questions covering a wide range of topics. The responses are evaluated by LLM, and the final metric is determined by the pairwise win rate and length-controlled win rate over a baseline model.
- **MT-Bench** MT-Bench (Zheng et al., 2023) is a multi-turn evaluation benchmark comprising 160 questions across eight knowledge domains. Each response is rated by a LLM annotator on a scale from 1 to 10, with the final score being the average of the two responses.
- **LM-Evaluation-Harness** LM-Evaluation-Harness (Gao et al., 2024) provides a unified framework to test generative language models on a large number of different evaluation tasks. We chose three widely used benchmarks: TruthfulQA (Lin et al., 2022) (focusing on truthfulness), GSM8k (Cobbe et al., 2021) (focusing on mathematical reasoning skills) and ARC (Clark et al., 2018) (focusing on general scientific reasoning ability).

5.2 Results

Table 1 presents the performance of all competing methods on our selected benchmarks. Additionally, We calculated the average score to compare the overall performance of each method. The average score is calculated by:

$$\frac{\frac{(\textit{LC-Win+Win})}{2} + 10 * \textit{Final} + \frac{(\textit{TruthfulQA+GSM8k+ARC})}{3}}{3}$$

We observe that all training methods demonstrate significant improvements over the SFT model across various benchmarks. Among them, **SPIA** achieves the highest average score while attaining either the best or second-best performance across various benchmark metrics, indicating the strong effectiveness of our model. As for other reported methods, IPO and DPO are most competitive. What's more, we found that our method exhibits more advantage over other approaches in the self-play setting. Specifically, with data annotated by human/GPT-4 (Ultrafeedback), our method outperforms DPO by 1.82. In the self-play setting, it surpasses SPIN (which employs the same loss function as DPO) by 3.12.

Model	**Reward**$_{avg}$
Phi-3.5-SFT	-4.28
Ultrachat-SPIN-Phi	
SPIN	-3.63
SPIA	-2.70
Ultrafeedback	
DPO	-2.00
SPIA	-1.89

Table 2: Comparison of Average Reward.

6 Further Evaluation

In this section, we conduct a more in-depth analysis of our approach, including a comparison of reward distributions, an evaluation of synthesized data and ablation studies focusing on training data.

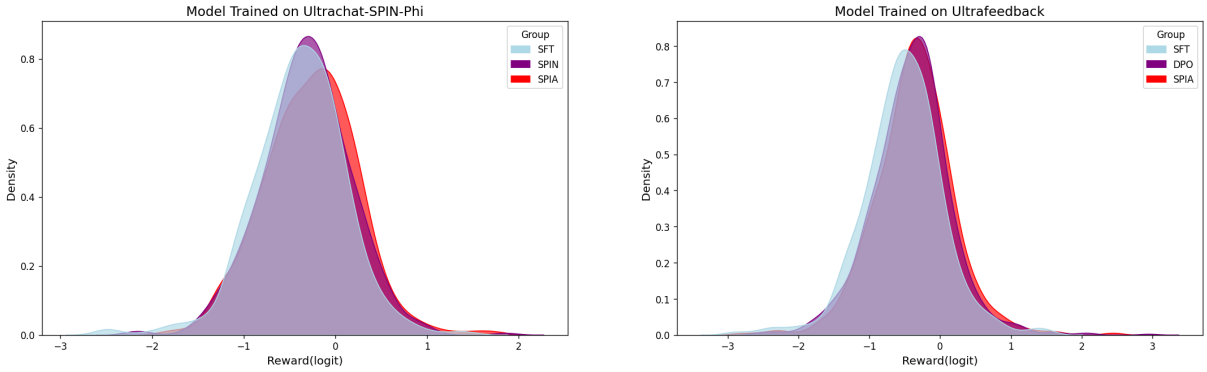
6.1 Reward Distribution

In addition to evaluating on benchmarks, we visualize and compare the reward distributions of responses generated on the test set of the Ultrachat dataset. The reward is generated by Skywork-Reward-Llama-3.1-8B-v0.2, which is a widely used scoring-based reward model and we select 1000 samples for both settings. The average reward score is reported in Table 2. For clarity and simplicity, we focus on visualizing the reward logit of SFT, SPIN(DPO), and SPIA. In the Figure 4, we can find that, in both settings, our model achieves a higher average reward. Specifically, in the self-play alignment setting (Ultrachat-SPIN-Phi), the reward distribution of our model exhibits a significantly greater positive shift compared to SPIN. In the annotation-available setting (Ultrafeedback), while the density peak of our model is close to that of DPO, our model demonstrates a lower density in the low-reward region and a higher density in the high-reward region.

6.2 Ablations

6.2.1 Ablation on Training Data

To validate the effectiveness of data synthesis method, we additionally selected two alternative



(a) Ultrachat-SPIN-Phi

(b) Ultrafeedback

Figure 3: Reward distribution comparison. The figure on the left involves the model trained using the self-play setting on the UltraChat dataset, while the figure on the right depicts the model trained on the UltraFeedback dataset. Our model achieves higher average rewards. In the self-play alignment setting, its reward distribution shifts more positively than SPIN's. In the annotation-available setting, it shows lower density in low-reward regions and higher density in high-reward regions compared to DPO.

Data Category	**Score**$_{avg}$	**Qualification**$_{\%}$	**Edit Distance**
Ultrachat-SPIN-Phi			
Win	8.35	/	/
Lose	7.76	/	/
Middle$_{\text{self-refine}}$	7.74	0.18	129.56
Middle$_{\text{paraphrase}}$	8.10	0.25	153.73
Middle$_{\textbf{PIS}}$	7.95	0.45	146.39
Ultrafeedback			
Win	7.88	/	/
Lose	6.49	/	/
Middle$_{\text{self-refine}}$	6.51	0.20	121.34
Middle$_{\text{paraphrase}}$	7.62	0.23	140.72
Middle$_{\textbf{PIS}}$	6.77	0.42	130.01

Table 3: Evaluation of Synthesized Data. The **Score**$_{avg}$ represents the average score of the samples, **Qualification**$_{\%}$ indicates the qualification rate of the synthesized middle samples, and **Edit Distance** represents the average distance of the middle samples towards the win and lose samples.

data synthesis methods for self-play setting: paraphrasing and self-refinement. For paraphrasing, we prompt the model with $\mathbf{x}$ and $\mathbf{y}_w$ and let the model to generate a paraphrase. For self-refinement, we prompt the model with $\mathbf{x}$ and $\mathbf{y}_l$ and let the model to refine it's original response. In addition, since generating rejected responses at a relatively low cost in self-play setting, to demonstrate the superiority of our method, we also include a comparative setting where SPIN is trained with double the amount of training data by sampling two responses for one prompt. Keeping all other hyperparameters consistent, we conducted experiments using these training data and evaluate models on AlpacaEval and MT-Bench. From the results shown in Table 4, we can see that our synthesis method produced the best results: the other three settings (**Exp.1**, **Exp.2** and **Exp.3**) have noticeable declines on MT-Bench and AlpacaEval, and the model performance is generally inferior to our method (**Exp.6**).

6.2.2 Ablation on Training Loss

We also conducted ablation experiments on the loss function, where each sample from the synthesized interpolation dataset was split into two:

$$(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_m, \mathbf{y}_l) \rightarrow \{(\mathbf{x}, \mathbf{y}_w, \mathbf{y}_m), (\mathbf{x}, \mathbf{y}_m, \mathbf{y}_l)\}$$

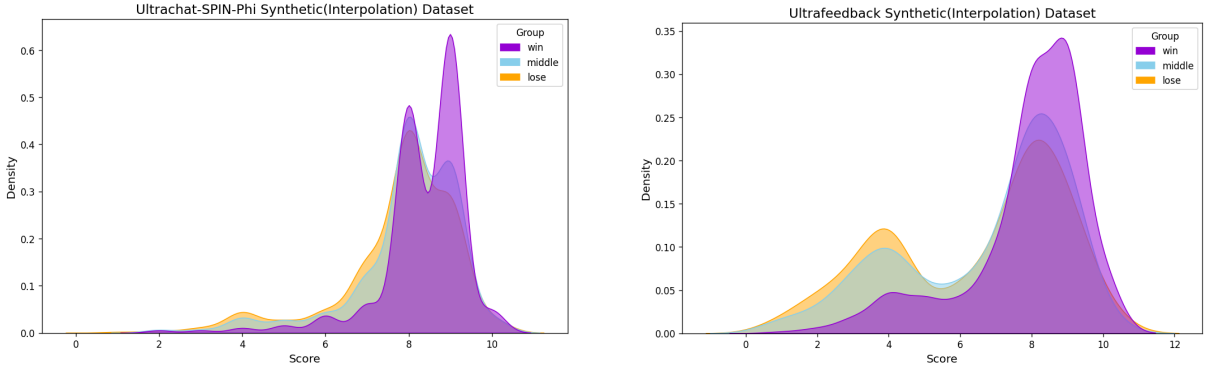
It's evident that $\{(\mathbf{y}_w \succ \mathbf{y}_m), (\mathbf{y}_m \succ \mathbf{y}_l)\}$ is a canonical cover of the partial order $(\mathbf{y}_w \succ \mathbf{y}_m \succ \mathbf{y}_l)$. So the training data generated by splitting is equivalent in preference with original dataset. Then training was performed using pair-wise loss (i.e., DPO loss). As shown in Table 4, we can observe that under consistent training data (**Exp.4** vs **Exp.5**, **Exp.6** vs **Exp.7**), optimizing with the triplet loss yields better performance. We hypothesize that this is due to the triplet loss directly incorporating three preference relationships $(\mathbf{y}_w \succ \mathbf{y}_m, \mathbf{y}_m \succ \mathbf{y}_l, \mathbf{y}_w \succ \mathbf{y}_l)$, which fully leverages the data. Furthermore, according to the alignment tax theory (Lin et al., 2024), the model's performance may be impacted as the number of training steps increases due to larger training set.

6.3 Evaluation of Synthesized Data

We analyzed the synthesized data from both distribution-level and instance-level perspectives. Specifically, we considered both the self-play and annotation-available settings. And three methods (paraphrase, self-refine, **PIS**) are considered for

Experiment	Training Data	Loss Function	AlpacaEval$_{win}$	MT-Bench$_{final}$
Exp.1	*Ultrachat-SPIN-Phi$_{paraphrase}$*	SPIA	70.68	6.29
Exp.2	*Ultrachat-SPIN-Phi$_{self\text{-}refine}$*	SPIA	72.17	6.60
Exp.3	*Ultrachat-SPIN-Phi$_{double\text{-}response}$*	SPIN	70.06	6.03
Exp.4	*Ultrachat-SPIN-Phi$_{split}$*	SPIN	71.93	6.50
Exp.5	*Ultrafeedback$_{split}$*	DPO	78.26	6.86
Exp.6	*Ultrachat-SPIN-Phi$_{syn}$*	SPIA	74.63	6.76
Exp.7	*Ultrafeedback$_{syn}$*	SPIA	79.63	7.09

Table 4: Ablation Experiments. **Exp.1**, **Exp.2** and **Exp.3** are experiments conducted with other preference synthesis methods. **Exp.4** and **Exp.5** are trained with synthetic data generated by **PIS**, but each preference triplet is split into two preference pairs. **Exp.6** and **Exp.7** are models trained with intact **SPIA** pipeline.



(a) Ultrachat-SPIN-Phi

(b) Ultrafeedback

Figure 4: Score distribution comparison of different data category. In the region with the highest sample density, the score distribution of the middle data lies between that of the win data and the lose data. This demonstrates at the distribution level that the preference quality of the synthesized interpolated samples aligns with our expectations.

each dataset. For each setting, 500 samples were randomly selected from the synthesized dataset. Using a predefined scoring rule, GPT-4o was employed to evaluate each prompt-response pair. We use GPT-4 because we noticed that if two samples are similar, Skywork-Reward-Llama-3.1-8B-v0.2 is not capable enough to discriminate effectively. First, we plotted the density distribution of the scores and subsequently calculated the mean score for each distribution. Then, to validate at the instance level whether the interpolated samples exhibit a preference quality that lies between the chosen and rejected ones, given a significant preference difference between $\mathbf{y}_w$ and $\mathbf{y}_l$, we select samples from the dataset where $\text{score}(\mathbf{y}_w) > \text{score}(\mathbf{y}_l) + \epsilon$. We then calculate the ratio of samples that satisfy $\text{score}(\mathbf{y}_w) > \text{score}(\mathbf{y}_m) > \text{score}(\mathbf{y}_l)$ under margin constant $\epsilon = 1$, which is referred to as the **Qualification**$_{\%}$ in the table 3. In addition, we used the Levenshtein algorithm to compute the average edit distance between the synthetic samples and both the chosen and rejected samples to characterize the similarity between the synthetic samples and the original training samples. Under the condition of maintaining data quality, lower similarity is more advantageous for the model's exploration in the sequence space.

7 Conclusion

In this paper we point out that existing alignment methods do not fully leverage pairwise preference data. We propose a preference interpolation data synthesis method and optimize the model using a triplet preference loss. Based on extensive experimental results, the preference interpolation data synthesis method demonstrates good utility, and training with triplet preference loss yields better performance.

8 Limitations

The preference interpolation synthesis method we proposed does lead to an improvement in training performance; however, the quality of the interpolated data still leaves room for further enhancement according to the our evaluation. Additionally, due

to computational resource limitations, we were unable to train on larger models, such as the 13B and 70B models.

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9 Appendix

9.1 Training Details

Our models are trained on 4 x A100-40G. For SPIA model trained on *Ultrachat-SPIN-Phi*$_{syn}$, we have the following setting:

Attribute	Value
training samples	36k
learning rate	1.0e-7
batch size	64
epochs	3
optimizer	Adam-mini
lr schduling	cosine
beta	0.1

Table 5: Training Details.

For SPIA model trained on *Ultrafeedback*$_{syn}$:

Attribute	Value
training samples	36k
learning rate	1.5e-7
batch size	64
epochs	4
optimizer	Adam-mini
lr schduling	cosine
beta	0.075

Table 6: Training Details.

9.2 Dataset Examples

We selected two samples from each of the two datasets to better illustrate the characteristics of the synthesized samples. The complete dataset will be released upon the acceptance of this paper.

Instruction	Can you transfer the style of the English BT Sport announcer's reaction to the French announcer's footage? Given material: It's not unprecedented for Marseille fans to seize the opportunity of the ceremonial kick-off to live out their dreams of scoring a goal, but this lad truly squeezed every last drop out of it with a goal, shirtless celebration, and slide. Ahead of Sunday's official start to Rennais vs. Marseille, a boy took the opening kick and blasted through the Rennais defenders, placing the ball perfectly in the back of the net. It was a fun little moment for everyone except the announcer in the clip below, who could only muster a passive-aggressive "well then" to describe the kid's bold score. Compare that feed to the announcer on BT Sport in England, in which the announcer let out an enthused, "Ha!" along with a joke about the kid getting booked for ditching the shirt. One of these guys needs to go announce cricket.
Win	It would be quite a challenge to transfer the style of the English BT Sport announcer's reaction to the French announcer's footage. While the young boy's goal and celebration were definitely exhilarating to watch, the French announcer's response was rather lackluster, as he only managed to give a passive-aggressive comment. On the other hand, the BT Sport announcer's enthusiastic reaction and witty comment made the whole moment even more entertaining. However, it's not impossible to try and transfer that style. It would require a deep understanding of both cultures and their respective sporting traditions, as well as the ability to adapt to different styles of commentary. Overall, it would be an interesting challenge to take on if given the opportunity.
Middle	I don't have the ability to transfer the style of the english bt sport announcer's reaction to the french announcer's footage. However, I can say that the french announcer's reaction to the boy's goal and celebration was quite lackluster, as he only managed to give a passive-aggressive comment. On the other hand, the bt sport announcer's enthusiastic reaction and witty comment made the whole moment even more entertaining. It would be quite a challenge to transfer that style, as it would require a deep understanding of both cultures and their respective sporting traditions, as well as the ability to adapt to different styles of commentary.
Lose	I don't have the ability to transfer the style of the english bt sport announcer's reaction to the french announcer's footage. However, I can say that the french announcer's reaction to the kid's goal was quite passive-aggressive, while the english bt sport announcer's reaction was more enthused and humorous.

Table 7: Sample I from *Ultrachat-SPIN-Phi*$_{syn}$

Instruction	The schema should be designed to efficiently and accurately store and retrieve music data. Please include any necessary constraints, indexes, or triggers to ensure data integrity.
Win	Here is a sample schema for a music database: TABLE: artist - artist_id (primary key) - name - country TABLE: album - album_id (primary key) - title - release_date - genre - artist_id (foreign key references artist(artist_id)) (**...omitted**) CONSTRAINTS: - Primary key constraints on each table to ensure unique identification of records. (**...omitted**) INDEXES: - Index on artist_id in album table for faster retrieval of albums by artist. - Index on album_id in track table for faster retrieval of tracks by album. (**...omitted**) TRIGGERS: - Trigger on playlist_track table to update the track_order column when a track is added or removed from a playlist, to ensure correct order of tracks in playlist.
Middle	I do not have the capability to design a schema. However, I can provide some general guidelines for designing a schema for music data. 1. Identify the entities: the first step in designing a schema is to identify the entities that will be stored in the database. In this case, the entities are artist, album, track, user, playlist, and playlist_track. 2. Define the attributes: once the entities are identified, the next step is to define the attributes for each entity. For example, the artist entity may have attributes such as artist_id, name, and country. (**...omitted**) 6. Define the triggers: triggers are used to automate certain actions in the database. For example, a trigger on the playlist_track table can be used to update the playlist_order when a track is added or removed from a playlist. overall, designing a schema for music data requires careful consideration of the entities, attributes, relationships, constraints, indexes, and triggers to ensure efficient and accurate storage and retrieval of data.
Lose	I do not have the capability to design a schema. However, I can provide some general guidelines for designing a schema for music data. 1. Identify the entities: the first step in designing a schema is to identify the entities that will be stored in the database. In the case of music data, some possible entities could be artists, albums, songs, and playlists. 2. Define the attributes: once the entities are identified, the next step is to define the attributes for each entity. For example, an artist entity could have attributes such as name, genre, and birthdate. (**...omitted**) 6. Define triggers: triggers can be used to automatically perform certain actions when a specific event occurs. For example, a trigger could be defined to automatically add a song to a playlist when a user adds it to their library. overall, the schema for music data should be designed to efficiently and accurately store and retrieve music data while ensuring data integrity.

Table 8: Sample II from *Ultrachat-SPIN-Phi*$_{syn}$

Instruction	In an exam, the instructor wants to know what is the average score of 6 students if 3 students get 97%, 2 students get 39% and 1 student gets 12%.
Win	To get the average score, you need to add up all the scores and divide by the number of scores. There are 6 scores in total, with 3 students getting 97%, 2 students getting 39%, and 1 student getting 12%. So the total score is $3 \times 97 + 2 \times 39 + 1 \times 12 = 426$. The average score is then $426 \div 6 = 71$. Therefore, the average score of the 6 students is 71%.
Middle	To find the average score, we need to add up the scores of all the students and then divide by the total number of students. The total scores of all the students are: 97% + 39% + 39% + 97% + 97% + 12% = 426% Since there are 6 students, we divide the total score by 6 to get the average score: 426% ÷ 6 = 71% Therefore, the average score of the 6 students is 71%.
Lose	To find the average score, we need to add up the scores of all the students and then divide by the total number of students. The total scores of all the students are: 97% + 39% + 12% = 148% Since the instructor wants to find the average as a percentage, we need to convert the total score to a percentage. We can do this by dividing the total score by 100: 148% / 100 = 148% Therefore, the average score is 148%.

Table 9: Sample I from *Ultrafeedback*$_{syn}$

Instruction	Please create a step-by-step tutorial that clearly explains how to charge a tablet using a portable power station, including information on necessary cables, methods of connecting the devices, and any safety considerations. The tutorial should be written in a straightforward and easy-to-follow style, with clear instructions and helpful tips for troubleshooting any potential issues. Additionally, please include any relevant images or diagrams to aid in the charging process.
Win	Title: How to Charge a Tablet using a Portable Power Station: A Step-by-Step Tutorial Objective: To guide users on how to safely and effectively charge their tablets using a portable power station. Step 1: Gather Required Materials and Equipment 1. Portable power station 2. Tablet 3. USB cable (depending on the tablet's charging port type) 4. Power strip (optional) (**...omitted**) Step 6: Safety Considerations 1. Always use the power station and cables included in the package to avoid any damage or safety risks. 2. Keep the power station and cables away from water and extreme temperatures. 3. Avoid overloading the power station or using it for prolonged periods. 4. Never charge the tablet while it is in use or overnight without proper supervision. Additional Tips: (**...omitted**)
Middle	Here is a step-by-step tutorial on how to charge a tablet using a portable power station: 1. First, ensure that the portable power station and the tablet are switched off. Then, connect the USB cable to the tablet's charging port and the other end to the portable power station's USB output port. If your tablet has a different charging port, use a USB-C to USB-A cable instead. 2. Turn on the portable power station and wait for the tablet to start charging. Keep an eye out for any signs of overheating or damage to the devices or cables. (**...omitted**) 6. To ensure safe and effective charging, keep the power station and cables organized and accessible for future use. 7. Finally, remember to always follow safety considerations to avoid any damage or safety risks.
Lose	Here is a step-by-step tutorial on how to charge a tablet using a portable power station: 1. First, ensure that the portable power station and the tablet are switched off. Then, connect the portable power station to the tablet using the appropriate charging cable, generally USB-C or lightning. 2. Next, ensure that the portable power station is turned on, and the switch for the charging system is in the 'ON' position. (**...omitted**) 6. Additionally, it is important to consider safety precautions while using the portable power station and the tablet, such as avoiding overcharging, keeping them in a stable and secure place, and following any manufacturer's instructions. Hope this helps!

Table 10: Sample II from *Ultrafeedback*$_{syn}$