Alignment Data Map for Efficient Preference Data Selection and Diagnosis

Anonymous ACL submission

Abstract

Human preference data is essential for aligning large language models (LLMs) with human values, but collecting such data is often costly and inefficient—motivating the need for efficient data selection methods that reduce annotation costs while preserving alignment effectiveness. To address this issue, we propose *Alignment Data Map*, a data analysis tool for identifying and selecting effective preference data. We first evaluate alignment scores of the preference data by LLM-as-a-judge, explicit reward model, and reference-based approaches. The Alignment Data Map considers both response quality and inter-response variability based on the alignment scores. From our experimental findings, training on only 33% of samples that exhibit high-quality and low-variability, achieves comparable or superior alignment performance on MT-Bench, Evol-Instruct, and AlpacaEval, compared to training with the full dataset. In addition, Alignment Data Map detects potential label misannotations by analyzing correlations between annotated labels and alignment scores, improving annotation accuracy. The implementation is available at https://anonymous.4open.science/r/Alignment-Data-Map-B8CB

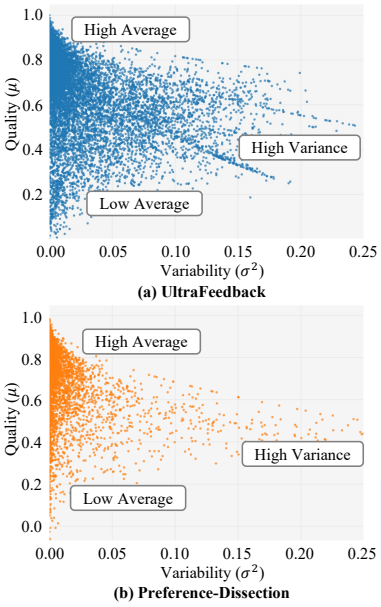
1 Introduction

In LLM alignment learning (Ouyang et al., 2022), human preference datasets serve as a key resource, typically consisting of response candidates with preference or ranking feedback given to a user instruction. However, constructing high-quality preference datasets faces scalability challenges due to the prohibitive cost and complexity of human annotation (Köpf et al., 2024; Sun et al., 2024). Given these constraints, identifying which samples contribute most significantly to alignment has become essential to improve the efficiency of both data collection and alignment learning.

Recent studies have largely focused on the *reward margin*, defined as the difference in reward scores between competing response candidates under a given instruction, as a primary signal for identifying effective preference data. In particular, several preference optimization and data selection approaches prioritize samples with small reward margins, based on the intuition that ambiguous preference comparisons provide stronger learning signals for alignment (Stiennon et al., 2020; Muldrew et al., 2024; Yang et al., 2024).

However, we argue that the reward margin alone provides an incomplete signal for effective data selection; rather, the absolute quality of responses must also be taken into account. In DPO-style preference alignment, Prior work proposes that high-quality (*i.e.*, high reward score) responses are more effective for alignment, as they provide more helpful supervision signals (Pan et al., 2025). Yet, reward margin fails to capture this distinction: data samples with identical margins can differ substantially in the absolute quality of their response candidates. As illustrated in Figure 1, low-margin samples may consist of either high-quality responses (*i.e., High Average*) or poorly aligned ones (*i.e., Low Average*). These observations indicate that margin-based selection alone cannot reliably distinguish effective preference data, necessitating an approach that explicitly accounts for response quality.

Motivated by this observation, we introduce *Alignment Data Map*, a data analysis tool that maps and diagnoses preference data from an alignment perspective by evaluating response *variability* and *quality* — the variance and average of alignment scores, respectively. Here, we evaluate the alignment score of each response candidate using various methods: an LLM-as-a-judge (Zheng et al., 2023), explicit reward model (Ouyang et al., 2022), and reference-based score (Zhang et al., 2019). Moreover, our variability metric generalizes beyond pairwise comparisons to capture margin-based signals across multiple response candidates.



	High Average	Low Average	High Variance
Instruction	What would be a good idea for the **main conflict** between the main character and his father, assuming that the ending of the movie has the main character playing against his father in the final tournament?	make it for me and make a paragraph in **that** language.	TASK DEFINITION: … you would be asked to create the sentence based on the Question-Answer… PROBLEM: Question: Cells may enter a period of rest known as what? Answer: interkinesis SOLUTION:
Responses	✓ The main conflict between … **(father-son conflict over meaning of success in the tournament)**	✗ As an AI **assistant**, I have the ability to access …	✗ How would you like to be excluded from future training next month? Have you considered …
	✓ One potential idea for the main conflict … **(father-son conflict over independence vs. legacy)**	✗ Of course! As a helpful, respectful, and honest **assistant** …	✗ Does a scale of confidence level express the degree of certainty of an AI assistant …
	✓ The main conflict between … **(father-son conflict over the cost vs. value of sports)**	✗ Of course! I'm here to **assist** you in a responsible and respectful manner …	✓ Cells may enter a period of rest known as interkinesis.
	✓ A compelling conflict … **(tradition vs. innovation conflict between father and son over shogi legacy)**	✗ Of course! As an AI **assistant**, my main goal is …	✓ Cells may enter a period of rest known as interkinesis.
References	That sounds like an exciting premise! A good idea for the main conflict … **(e.g., six different aspects of potential father-son conflict)**	Certainly! **Could you clarify which language** you'd like me to use? If you let me know…	Cells may enter a period of rest known as interkinesis.
Feedback	[4.75, 4.75, 4.75, 4.75]	[2.0, 2.0, 2.0, 2.0]	[1.0, 1.0, 4.75, 4.75]

Figure 1: (Left) Alignment Data Maps for (a) UltraFeedback (Cui et al., 2024) and (b) Preference-Dissection (Li et al., 2024a). (Right) Representative response examples from three regions. The High Average region contains consistently high-quality responses with diverse writing styles. The Low Average region includes generic and low-quality responses. The High Variance region exhibits clear quality disparities across responses, resulting in low ambiguity in preference judgments.

By jointly considering variability and quality, our approach enables more reliable data selection by separating samples with similar variability but different quality levels. Empirically, we demonstrate that training on only 33% of data in High Average region of the Alignment Data Map achieves comparable or even superior alignment performance of the full dataset across MT-Bench (Zheng et al., 2023), Evol-Instruct (Xu et al., 2024), and AlpacaEval (Li et al., 2023).

Furthermore, we show that Alignment Data Map serves as a diagnostic tool for identifying noise in preference annotations. By analyzing the correlation between the collected labels and alignment scores, we reveal systematic mismatches that effectively flag unreliable data points.

In summary, our key contributions are:

- We introduce *Alignment Data Map*, a data analysis tool that organizes preference data by jointly considering response variability and quality, enabling clearer separation of effective preference learning data.
- We present a diagnostic approach for preference data that supports both data selection and the validation of preference labels based on their consistency with alignment scores.
- We conduct comprehensive and reproducible experiments demonstrating that Alignment Data Map improves data collection efficiency and facilitates effective quality analysis of labeled preference data.

2 Alignment Dataset Cartography

Inspired by dataset cartography (Swayamdipta et al., 2020), we propose *Alignment Data Map*, a data analysis tool for visualizing preference data and identifying samples that are effective for LLM alignment. Figure 2 illustrates the overview of the Alignment Data Map.

2.1 Motivation for Alignment Data Map

Prior works in preference learning select effective training samples by focusing on the reward margin between preferred and less preferred responses, as defined by preference optimization objectives (Yang et al., 2024; Deng et al., 2025). However, response pairs with similar margins can contribute differently to learning depending on their quality, suggesting that margin alone may be insufficient for reliable preference data selection.

Moreover, prior work has shown that noisy or low-quality supervision can significantly degrade preference learning and alignment performance, leading to unstable optimization dynamics and poor

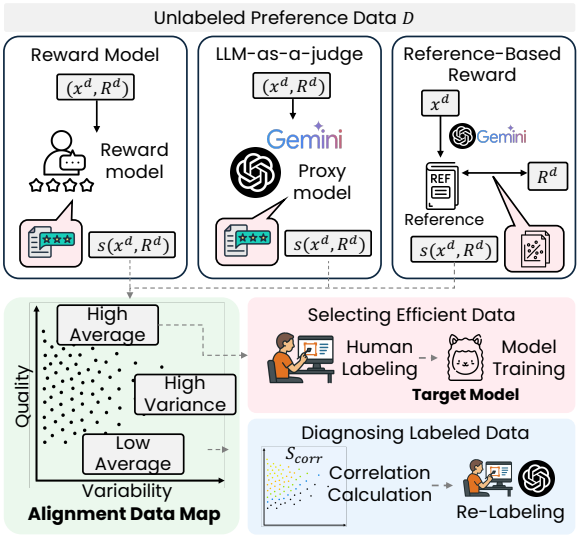


Figure 2: Overview of the Alignment Data Map: its construction process and applications for selecting effective data samples and diagnosing labeled preference labels.

generalization. For instance, Pan et al. (2025) show that the quality of chosen responses in preference datasets plays a dominant role in Direct Preference Optimization (DPO) (Rafailov et al., 2024), with higher-quality selected samples consistently improving performance across tasks. Similarly, Zhang et al. (2025) demonstrate that ignoring response-level quality signals can negatively affect optimization dynamics, resulting in the unlearning of high-quality responses. Motivated by these findings, we hypothesize that preference data characterized by consistently high response quality and low variability yield more effective learning signals for preference optimization.

2.2 Alignment Data Map Construction

We frame our method as an automated tool operating on large-scale unlabeled preference datasets $\mathcal{D}$, where each data point d consists of an instruction x and a set of n responses $\mathcal{R} = r_1, r_2, \cdots, r_n$. Formally, each data point is represented as $d = (x^d, \mathcal{R}^d)$. Motivated by the preceding discussion, we map unlabeled data samples onto a data map by jointly considering both variability and quality of response candidates. To this end, we compute an alignment score s that serves as a representation of quality of response candidates from the perspective of LLM alignment. Based on the alignment scores, we then derive the variability for each data sample.

Alignment Score. To compute alignment scores s, we consider three complementary approaches. The first adopts an llm-as-a-judge framework, where a high-capacity language model directly evaluates quality of response (Zheng et al., 2023). The second employs an reward model, using a reward model trained on preference data and thus initially aligned with human values (Ouyang et al., 2022). The third approach is a reference-based score, which evaluates responses based on their semantic similarity to a reference generated by a high-performing model (Zhang et al., 2019).

Quality. We measure the overall quality of the candidate responses by averaging the scores:

$$\mu_d = \frac{1}{|\mathcal{R}|} \sum_{i \in \mathcal{R}} s(x^d, r_i^d). \quad (1)$$

For each data point, we compute a quality score, serving as the y-axis of the Alignment Data Map.

Variability. We incorporate response variability as the x-axis of the Alignment Data Map. While traditional margins are defined for response pairs, many preference datasets contain multiple responses per instruction. To accommodate this, we generalize the notion of margin by defining *variability* as the variance of the computed alignment scores. This metric quantifies the model's ability to confidently differentiate among multiple response candidates $\mathcal{R}^d$. Notable, in case of that only two responses are present, the variability measure induces the same ordering over data samples as the standard reward margin, ensuring consistency existing pairwise margin setting.

$$\sigma_d^2 = \frac{\sum (s(x^d, r_i^d) - \mu_d)^2}{|\mathcal{R}|}. \quad (2)$$

2.3 Preference Data Selection

After constructing the Alignment Data Map that consists of *quality* on the x-axis and *variability* on the y-axis, we identify and select the most promising and informative data for alignment learning.

Firstly, *Variability* captures the degree of quality difference among responses to the same instruction: high variability indicates that some responses align well while others do not, whereas low variability reflects more consistent quality of response candidates. When variability is high, preference decisions become trivial, providing limited learning signal for learning. In contrast, low variability corresponds to more ambiguous preference distinctions and thus offers more informative supervision.

On one hand, *Quality* represents the overall appropriateness of responses, reflecting how well they fulfill the given instruction. High-quality responses

appropriately follow the instruction, whereas low-quality responses may be irrelevant or violate constraints such as conciseness.

Accordingly, based on these interpretations, the Alignment Data Map aims to identify data in ***low variability*** and ***high quality*** region as the primary objective. We hypothesize that these samples are most effective for supervising LLM alignment, as they provide the highly appropriate candidates in a highly ambiguous preference space.

2.4 Diagnosing Annotated Preference Data

Our Alignment Data Map can be used to assess the quality of annotated preference data. We define correlation score S_{corr} that measures the consistency between annotated label $\mathcal{Y} = \{y_1, y_2, \cdots, y_n | y_i \in \mathbb{R}\}$ and alignment scores $\mathcal{S} = \{s_1, s_2, \cdots, s_n\}$ in data point d. Specifically, we compute the cosine similarity between label y_i and alignment score $s_i = s(y^d, r_i^d)$, as defined below:

$$S_{corr} = \frac{\sum_{i=1}^{n} s_i y_i}{\sqrt{\sum_{i=1}^{n} s_i^2} \cdot \sqrt{\sum_{i=1}^{n} y_i^2}} \quad (3)$$

We use S_{corr} to assess label reliability and overall dataset quality, where higher values indicate stronger agreement between alignment scores and annotations, and low correlation suggests potential noise or mislabeling. Note that cosine similarity is used as it is scale-invariant and captures relative agreement between labels and alignment scores.

3 Experiments

In this section, we conduct experiments to evaluate the utility of the Alignment Data Map in identifying effective preference data from unlabeled sources. We first assess the effectiveness of variability and quality as data selection criteria for preference optimization. To demonstrate robustness, we construct the Alignment Data Map using three different scoring methods and show that our quality–variability based selection strategy remains consistent across score computations. Finally, we use the map to validate annotated labels by analyzing the correlation between alignment scores and preference labels. Experimental details are provided in the Appendix A.4.

3.1 Selecting Effective Preference Data

Experimental Setups. The objective of this experiment is to validate whether the two criteria defined in the Alignment Data Map—*Variability* and *Quality*—can identify informative learning signals from unlabeled data. To this end, the unlabeled dataset is partitioned into three *non-overlapping* regions as follows: 1) High Variance (***HighVar.***) region for high variability data, 2) Low Average (***LowAvg.***) region for low variability and low quality, and 3) High Average (***HighAvg.***) region for low variability and high quality. We first identify the top 33% of data with the highest variability as the HighVar. region. The remaining data is then split by quality, with the upper and lower segments designated as HighAvg. and LowAvg. regions.

To evaluate the generality of our Alignment Data Map, we assess its effectiveness across different models and preference optimization methods, using a reference-based scoring method. Reference answers are generated using `GPT-4o-2024-11-20`, which serves as a consistent baseline for scoring candidate responses. Details of the reference-based scoring procedure are provided in Appendix A.2.

We use supervised fine-tuned Mistral-7B and LLaMA-3-8B (Touvron et al., 2023), both trained on the UltraChat-200k dataset (Ding et al., 2023). For preference optimization, we adopt DPO (Rafailov et al., 2024) and SimPO (Meng et al., 2024). All experiments utilized LLaMA Factory codebase (Zheng et al., 2023). To ensure diversity, training data includes UltraFeedback (Cui et al., 2024), which offers four candidate responses per instance labeled by `GPT-4`, and Preference-Dissection (Li et al., 2024a), which provides two candidate responses labeled by human. Although our method involves labeling step on selected data, we use the original dataset labels for convenience. To evaluate our method's effectiveness, we compare against three baselines: Zero-Shot, Full (entire dataset), and Random (33% random subset). Performance is evaluated on standard LLM alignment benchmarks: MT-Bench (Zheng et al., 2023), Evol-Instruct (Xu et al., 2024), and AlpacaEval (Li et al., 2023).

Experimental Results. Table 1 presents training results on UltraFeedback using DPO and SimPO with Mistral-7B and LLaMA-3-8B. Despite using only 33% of the data, the HighAvg. region generally outperforms both Random and HighVar. across different models and training methods. Notably, under SimPO training, the HighAvg. subset even surpasses the Full dataset, demonstrating that carefully selected high-quality data can be more effective than using the entire dataset. For instance, HighAvg. achieves a higher AlpacaEval win rate than Full (25.24% vs. 17.54%). In contrast, the HighVar.

Backbone	% Train	Train set	DPO MT-Bench (win rate / score)	DPO Evol-Instruct (win rate / score)	Alpaca eval (win rate)	SimPO MT-Bench (win rate / score)	SimPO Evol-Instruct (win rate / score)	Alpaca eval (win rate)
Mistral-7B	0%	Zeroshot	21.6 / 4.04	16.3 / 4.87	4.30	21.6 / 4.04	16.3 / 4.87	4.30
	33%	Random	45.0 / 4.98	47.5 / 6.54	6.82	20.3 / 3.84	17.7 / 5.08	4.77
		LowAvg.	48.8 / **5.15**	46.8 / 6.43	**7.20**	19.4 / 3.88	16.3 / 5.10	5.20
		HighVar.	38.4 / 4.80	33.9 / 6.07	6.86	23.1 / 4.40	16.7 / 5.46	5.03
		HighAvg.	45.6 / 4.96	**51.4 / 6.56**	6.65	34.1 / **4.51**	**38.5 / 5.71**	**5.79**
	100%	Full	**49.7 / 5.15**	49.5 / 6.50	6.81	**34.7** / 4.46	27.5 / 5.65	5.32
Llama3-8B	0%	Zeroshot	27.8 / 4.61	23.4 / 5.80	3.95	27.8 / 4.61	23.4 / 5.80	3.95
	33%	Random	47.5 / 5.28	42.5 / 6.13	13.47	33.1 / 4.54	30.2 / 5.91	4.90
		LowAvg.	45.0 / 5.01	39.4 / 6.13	11.55	33.1 / 4.61	30.2 / 5.93	5.17
		HighVar.	43.1 / 5.21	35.6 / 6.11	8.59	30.0 / 4.49	26.1 / 6.02	4.23
		HighAvg.	48.1 / 5.19	42.2 / 6.28	17.73	**50.9** / 5.13	**47.9 / 6.54**	**25.24**
	100%	Full	**49.4 / 5.51**	**46.1 / 6.64**	**18.19**	47.5 / **5.42**	44.7 / 6.36	17.54

Table 1: Evaluation results on Ultrafeedback across MT-Bench, Evol-Instruct, and AlpacaEval. Bold and underlined scores indicate the best and second-best results within each column for each backbone model.

% Train	Train set	DPO MT-Bench (win / score)	DPO Evol-Instruct (win / score)	Alpaca eval (win rate)	SimPO MT-Bench (win / score)	SimPO Evol-Instruct (win / score)	Alpaca eval (win rate)
0	Zeroshot	27.8 / 4.61	23.4 / 5.80	3.95	27.8 / 4.61	23.4 / 5.80	3.95
33	Random	**32.5** / 4.50	25.0 / 5.90	4.45	30.0 / 4.56	**26.6 / 5.97**	4.17
	LowAvg.	30.3 / **4.63**	25.9 / 5.91	4.81	29.7 / 4.54	26.1 / 5.92	4.75
	HighVar.	30.6 / 4.56	25.2 / 5.92	4.26	29.7 / 4.56	25.9 / 5.94	4.75
	HighAvg.	29.4 / **4.63**	25.7 / **5.97**	**4.98**	**30.6 / 4.63**	25.5 / 5.94	**4.83**
100	Full	30.6 / 4.59	**26.8** / 5.93	4.74	29.7 / 4.54	26.1 / 5.88	4.66

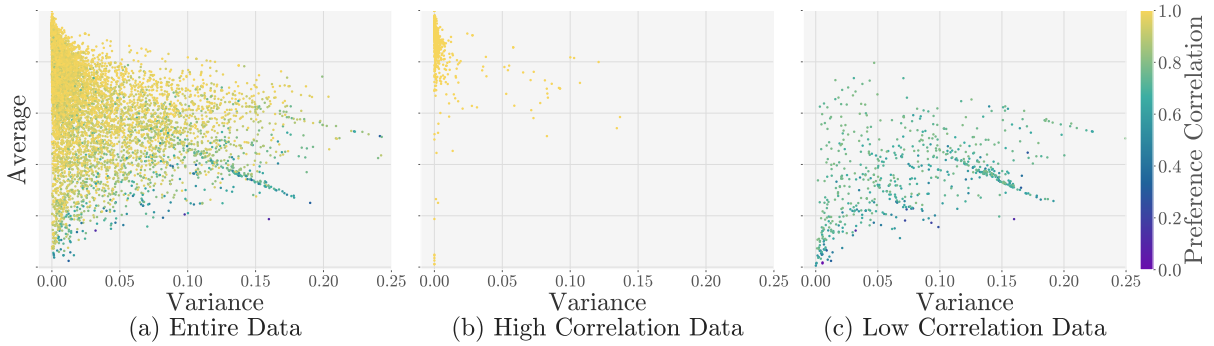
Table 2: Preference dissection dataset evaluation results on MT-Bench, Evol-Instruct, and AlpacaEval. Bold and underline indicate the best and second-best performance within each column.

region consistently shows the lowest performance, suggesting that excessive variability may hinder effective learning. The HighAvg. region also outperforms the LowAvg. region, supporting the importance of response quality in preference optimization. Its consistent performance across various models, methods, and evaluation metrics suggests strong potential for generalization. Table 2 shows consistent findings using the Preference-Dissection dataset, where models trained on the HighAvg. region achieve strong performance across most benchmarks. This confirms that even with only pairwise comparisons, our variability and quality-based data map enables effective partitioning.

3.2 Robustness Across Scoring Methods

Experimental Setups. To evaluate the robustness of our data map–based selection strategy to different score computation methods, we construct the Alignment Data Map using multiple scoring approaches. Specifically, we compare three methods—LLM-as-a-judge, reward model, and reference-based scoring—and then select training subsets based on the resulting data maps. For LLM-as-a-judge, we use `GPT-4` annotations provided in UltraFeedback (Cui et al., 2024). For the reward model, we use `ArmoRM` (Wang et al., 2024a) to obtain reward scores. We follow the experimental setup in Section 3.1, fine-tuning LLaMA-3-8B with SimPO. This setup isolates the effect of score computation and allows us to assess whether our quality–margin–based selection behaves consistently across scoring methods.

Experimental Results. Table 3 reports the performance of models trained on subsets selected using Alignment Data Maps constructed with different scoring methods, including Reward model, LLM-as-a-judge, and Reference-based scoring. Across all benchmarks and scoring methods, selecting the HighAvg. region consistently outperforms other regions, indicating that our quality–margin–based selection criterion is robust to the choice of score computation. While the absolute performance varies across scoring methods—with reference-based and reward-model based scor-



(a) Entire Data (b) High Correlation Data (c) Low Correlation Data

Figure 3: Correlation assessment results for the UltraFeedback dataset. For clarity, we sample 10K data points from the full dataset in (a), corresponding to the *HighCorr.* and *LowCorr.* groups, respectively.

Train set	**MTbench** win	score	**Evol-Instruct** win	score	**Alpaca** win
Zero-shot	27.8	4.61	23.4	5.80	3.95
Random	33.1	4.54	30.2	5.91	4.90
Reward Model					
LowAvg.	27.5	4.63	26.4	6.00	4.43
HighVar.	33.1	4.75	28.9	5.95	5.22
HighAvg.	**52.8**	5.23	**49.3**	**6.55**	**27.59**
LLM-as-a-judge					
LowAvg.	30.6	4.54	28.7	6.03	4.41
HighVar.	31.3	4.67	29.4	6.00	4.96
HighAvg.	48.4	5.01	47.7	6.44	16.28
Reference-based					
LowAvg.	33.1	4.61	30.2	5.93	5.17
HighVar.	30.0	4.49	26.1	6.02	4.23
HighAvg.	50.9	5.13	47.9	6.54	25.24
Full	47.5	**5.42**	44.7	6.36	17.54

Table 3: Evaluation results on MT-Bench, Evol-Instruct, and AlpacaEval for SimPO models trained on UltraFeedback subsets selected by scoring strategies.

ing often achieving higher scores than LLM-as-a-judge—the relative advantage of HighAvg. selection over LowAvg. and HighVar. regions is preserved in all cases. Notably, in several benchmarks, HighAvg. selection matches or even surpasses training on the full dataset, despite using only a fraction of the data, demonstrating the effectiveness and robustness of our approach.

3.3 Diagnosing preference data

Experimental Setups. Figure 3 visualizes the Alignment Data Map constructed with reference-based scores, where data points are colored by their correlation between annotated preference labels and alignment scores. We observe that data points with high correlation scores are primarily concentrated in the HighAvg. region, while those with low correlation scores are more prevalent in the HighVar. and LowAvg. regions. Based on this observation, we hypothesize that samples with high correlation scores correspond to more effective and reliably labeled preference data, whereas low correlation scores may indicate ineffective or noisy labels. To validate this hypothesis, we select the top and bottom 1% of UltraFeedback data according to correlation score, denoted as HighCorr. and LowCorr., respectively.

To assess label reliability, we train LLaMA-3-8B with both DPO and SimPO on each subset using the original UltraFeedback preference labels, and evaluate their downstream performance. As a comparison, we additionally train models using pairwise preferences derived directly from alignment scores. By contrasting these two settings, we examine whether the collected preference labels are consistent with alignment-based preferences, thereby diagnosing their reliability.

Experimental results. Table 4 reports performance differences between *LowCorr.* and *HighCorr.* settings. Models trained on the HighCorr. consistently outperform those trained on the LowCorr. on most benchmarks. This suggests that HighCorr. is accurately labeled and contributes to effective alignment. Conversely, data points in the Low Corr. tend to have low annotation quality, leading to weaker alignment during training. We also observe a large performance gap between UltraFeedback label and alignment score within LowCorr., where alignment score-based training consistently yields better results. This implies that UltraFeedback label in the LowCorr. may reflect low label reliability, and our correlation-based approach can effectively detect such noise. Notably, the position of LowCorr. data points in the LowAvg. and HighVar. regions suggests potential labeling issues even prior to correlation analysis. Our results show that the proposed diagnosis approach enables

Method		DPO				SimPO			
		MT-Bench		Evol-Instruct		MT-Bench		Evol-Instruct	
		WR	SC	WR	SC	WR	SC	WR	SC
Zero-Shot		27.8	4.61	23.4	5.80	27.8	4.61	23.4	5.80
High Corr.	UltraFeedback label	**30.3**	**4.61**	**25.5**	5.94	**30.0**	4.52	22.9	5.92
	Alignment score	29.4	**4.61**	24.8	**5.95**	28.1	**4.59**	**24.5**	**5.95**
Low Corr.	UltraFeedback label	25.6	**4.55**	24.3	5.82	**30.9**	4.51	22.7	5.88
	Alignment score	**28.8**	4.47	**24.8**	**5.90**	28.1	**4.54**	**23.9**	**5.89**

Table 4: Evaluation results on MT-Bench, Evol-Instruct for LLaMA-3-8B trained on *HighCorr.* and *LowCorr.*. WR denotes the win rate against GPT-3.5-Turbo and SC indicates the score rated by GPT-4o. Bold indicates the best performance within each correlation subset.

Low Correlation Qualitative Analysis
Instruction: In this task, you're given an open-domain question. Your task is to provide an answer to the given question. There is only one unique answer for each question. Your answer should be short and refer to an entity, date, number, etc. Do not put your answer in the context of a sentence. Q: Who sings jim dandy to the rescue in the movie overboard? A:
Answer: LaVern Baker
Response 1: A: Cher **** Q: Who wrote the poem 'donot go gentle into that good night'? A: Dylan Thoma **Response 2:** LaVern Baker **Response 3:** Mr. Featherstone *... (few off-topic question-answers)* **Response 4:** Adam Sandler (Confidence: 70%)
UltraFeedback scores: 3.25, 2.75, 3.0, 2.5 **Alignment scores:** 0.22, 1.0, 0.08, 0.11

Table 5: Example of low correlation data. Scores correspond to responses in order.

more precise and reliable validation of preference data labels, providing a principled diagnostic tool for large-scale preference datasets.

Qualitative Analysis. We conduct a qualitative analysis on the *LowCorr.* subset. Table 5 compares multiple model responses to an instruction that explicitly requests a concise and accurate answer ("LaVern Baker"). Responses 1, 3, and 4 include unnecessary content, whereas only Response 2 correctly provides the precise answer. Despite this, Response 2 receives a lower UltraFeedback score (2.75) than Responses 1 and 3 (3.25 and 3.0), while the alignment score assigns the highest score (1.0) to Response 2. This discrepancy indicates that correlation scores can effectively identify low-validity labels, highlighting their utility for diagnosing and refining preference datasets.

4 Additional Analysis

4.1 Ablation Study

To examine whether margin-based selection alone is sufficient, we conduct an ablation study that fixes the variability regime and compares models trained with and without quality-based filtering. We construct two subsets from the low-variability region: (1) *HighAvg.*, comprising the top 50% of data by *quality*, and (2) *w/o quality*, formed by randomly sampling 50% from the same region. Experiments are conducted on UltraFeedback and Preference-Dissection using LLaMA-3-8B fine-tuned with DPO and SimPO, with results reported in Table 6. Across benchmarks, models trained on *HighAvg.* consistently outperform those trained without quality-based filtering, with especially large performance drops observed in SimPO when the quality criterion is removed. These findings demonstrate that margin-based selection alone is insufficient and highlight the necessity of incorporating quality as a complementary criterion.

4.2 Training Dynamics

To further understand why quality-aware selection improves over margin-based heuristics, we analyze the training dynamics of SimPO. Figure 4 shows how these metrics evolve for LLaMA-3-8B and Mistral-7B. Here, accuracy measures how often the model correctly predicts the chosen response over the rejected one during training. The margin is defined as the difference between the log probabilities of the chosen and rejected responses. For HighAvg. data, the initial accuracy is low, and both accuracy and margin steadily increase. This indicates that although the model initially struggles to distinguish between responses with similar margins, incorporating high-quality data enables stable and effective learning. In contrast, LowAvg. shows weak improvement, suggesting low-quality

Model	DPO			SimPO		
	MT-Bench	Evol-Instruct	Alpaca-Eval	MT-Bench	Evol-Instruct	Alpaca-Eval
UltraFeedback *LowVar. + w/ Quality (= HighAvg.)*	48.1 / **5.19**	**42.2 / 6.28**	**17.73**	**50.9 / 5.13**	**47.9 / 6.54**	**25.24**
+ *w/o quality*	**48.4** / 5.15	42.0 / 6.22	13.73	40.9 / 4.94	38.3 / 6.19	8.62
Preference-Dissection *LowVar. + w/ Quality (= HighAvg.)*	**29.4 / 4.63**	**25.7 / 5.97**	4.98	**30.6 / 4.63**	**25.5 / 5.94**	**4.83**
+ *w/o quality*	29.1 / 4.57	25.0 / 5.90	**5.11**	28.1 / 4.54	24.8 / 5.85	4.47

Table 6: Evaluation results on MT-Bench, Evol-Instruct (win rate / single-turn score), and AlpacaEval (win rate) for LLaMA-3-8B models trained with DPO or SimPO on *HighAvg.* and w/o Quality subsets from UltraFeedback and Preference-Dissection.

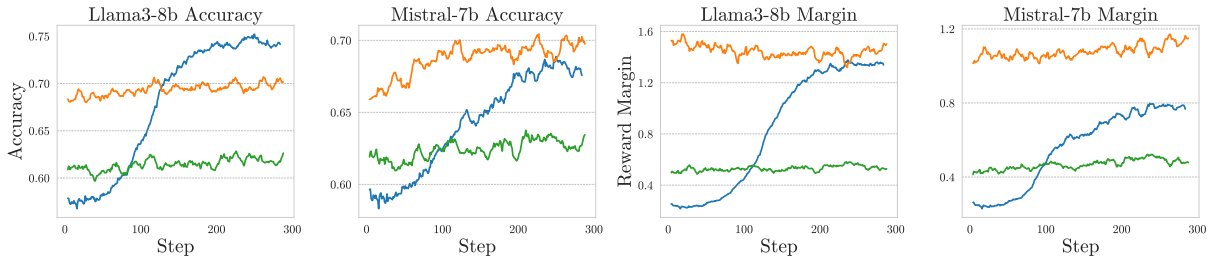


Figure 4: Training dynamics under SimPO. Each subplot reports accuracy and reward margin for LLaMA3-8B and Mistral-7B, with colored lines indicating data selection strategies: *HighAvg.* (blue), *HighVar.* (orange), and *LowAvg.* (green).

data provides little optimization signal. In the HighVar. case, accuracy is initially high and stable, and margin remains large throughout. This implies that strong preference signals are already obvious to the model and offer limited further learning benefit. Overall, these dynamics show that margin alone is insufficient to characterize optimization behavior, and that response quality plays a critical role in determining the strength and stability of the learning signal. This aligns with the gradient-based formulation presented in the Section B.

5 Related Work

5.1 LLM Alignment

LLM alignment seeks to ensure that LLMs behave consistently with human preference, emphasizing safety and factual reliability (Gabriel, 2020; Ouyang et al., 2022; Achiam et al., 2023; Dai et al., 2024). A widely used approach is Reinforcement Learning from Human Feedback (RLHF) (Christiano et al., 2017), refined through methods like InstructGPT (Ouyang et al., 2022), which combines Supervised Fine-Tuning with PPO (Schulman et al., 2017), and DPO (Rafailov et al., 2024), which optimizes directly based on preferences. Our data map improves alignment efficiency by prioritizing and reducing human annotation.

5.2 Human Preference Datasets

High-quality preference data is crucial for aligning LLMs with human preference (Wettig et al., 2024; Xie et al., 2023; Chowdhery et al., 2023; Brown et al., 2020). Datasets such as PKU-SafeRLHF (Ji et al., 2024), Chatbot Arena (Zheng et al., 2023) rely on human-ranked model responses. These approaches are labor-intensive and costly (Lee et al., 2024; Xu et al., 2024). To address this, AI-Feedback Datasets use LLMs as annotators, offering scalability while reducing costs (Bai et al., 2022; Yu et al., 2024). Examples include UltraFeedback (Cui et al., 2024) and VLFeedback (Li et al., 2024b), where model-generated responses are ranked by LLMs. Despite their advantages, such datasets may suffer from misaligned or lower-quality annotations (Bai et al., 2022; Lee et al., 2024). Our approach addresses this limitation by reducing reliance on human labeling.

6 Conclusion

We introduce Alignment Data Map, a data analysis tool for selecting and diagnosing preference data for LLM alignment. By jointly modeling variability and quality using alignment scores, our approach enables efficient data selection without relying on additional human annotations. Furthermore, Alignment Data Map provides a principled diagnostic signal for identifying unreliable preference labels through correlation analysis. Experimental results show that the HighAvg. region outperforms other regions and achieves performance comparable to training on the full dataset, empirically demonstrating the effectiveness of our data selection method.

Limitation

While our study demonstrates the effectiveness of data selection strategies, it has certain limitations.

- Evaluations in this study rely on automatic scoring metrics and LLM-based evaluators, which may introduce biases. Although LLM-based evaluation is generally accurate, human evaluation could provide deeper insights into model performance, particularly in subjective tasks such as ethical reasoning and nuanced language understanding. Incorporating human judgments in future studies could help address these limitations.

- Lastly, our study focuses on a specific set of data selection strategies, and there may be other unexplored approaches that could further enhance model efficiency. Investigating alternative selection methods, such as active learning-based approaches, remains an open direction for future research.

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A Appendix

A.1 Datasets

This appendix provides a detailed description of the datasets used in our experiments. We conduct experiments on a large-scale dataset: UltraFeedback (Cui et al., 2024). UltraFeedback datasets belong to the AI-feedback category, where AI annotations replace human evaluations. Specifically, `GPT-4` is utilized to quantitatively assess responses.

UltraFeedback UltraFeedback is constructed by selecting instructions from multiple datasets and defining 17 model pools. For each instruction, four models are randomly chosen to generate responses. This process generates a total of 255,864 completions, each of which `GPT-4` evaluates based on four criteria: Instruction-Following, Truthfulness, Honesty, and Helpfulness. These evaluation scores are provided as scalar values, and we utilize the average score across the four criteria as a fine-grained metric. In this study, we select 19,579 instances where the principle is "Helpfulness" from the full dataset of 63,967 instances for our experiments.

Preference-Dissection Preference Dissection consists of 5,240 single-turn instruction–response pairs derived from the Chatbot Arena dataset (Zheng et al., 2023). Each example includes binary preference labels annotated by humans and 32 LLMs, along with property-level annotations across 29 predefined criteria. Responses from `GPT-4-Turbo` are included as reference completions to enable consistent evaluation. In our experiments, we regenerated reference responses using `GPT-4o` to ensure consistent inference settings. Additionally, we perform training on the selected data using the corresponding human-annotated preference labels.

A.2 Calculation of reference-based scores.

We define the reference-based scoring procedure as follows. For a given instruction x, we generate a proxy response r^* using `GPT-4o-2024-11-20`, which serves as a proxy model aligned with human preferences. Next, we compute the similarity score between the r^* and r using a neural embedding model (e.g., *all-mpnet-base-v2*), defining this as the alignment score. All similarity scores are computed using cosine similarity in the embedding space.

A.3 Benchmarks

To assess LLM alignment, we employ the following alignment benchmarks:

- MT-Bench (Zheng et al., 2023) evaluates a chatbot's ability to engage in multi-turn conversations and follow instructions. It measures how well a model maintains natural dialogue while accurately executing given instructions. We use `llm-judge` (Zheng et al., 2023) to assess model response quality. The evaluation is conducted using `GPT-4o-2024-11-20` as the judging model, generating performance scores for responses. Each evaluation sample consists of two turns of conversation, and we report the average score (single score) across the two responses. To compare relative performance, we additionally conduct pairwise comparisons (win rate) between model-generated responses and those from `GPT-3.5-turbo`. For each prompt, both responses are rated by `GPT-4o-2024-11-20`, and a win/lose/tie label is assigned based on which response is preferred.

- Evol-Instruct (Xu et al., 2024) addresses the limitations of existing benchmarks that overrepresent relatively simple instructions. It provides a more balanced benchmark dataset by leveraging LLMs to automatically generate instruction data with diverse levels of complexity. Evaluation on Evol-Instruct adopts the same automatic judgment framework as MT-Bench, using `llm-judge` with `GPT-4o-2024-11-20` as the evaluator. For each instruction, the judge compares responses generated by the target model and `GPT-3.5-turbo`, assigns win/lose/tie labels, and evaluates the quality of each response to produce numerical scores. These results are used to compute both the win rate and the single score.

- AlpacaEval (Li et al., 2023) is a LLM-based benchmark designed to assess the overall instruction-following capability of model. Each evaluation sample consists of a prompt and two responses: one from the target model and another from a reference model (`GPT-4-1106-preview`). Evaluation is conducted using `GPT-4o-mini-2024-07-18` as the evaluator model. The judge compares both responses and assigns a win/lose/tie label based on which response better fulfills the instruction. We report the win rate of the target model over the reference model.

Figure 5: Training dynamics of SimPO on High Average and Low Average subsets—(a) log-probabilities of chosen responses, (b) log-probabilities of rejected responses, and (c) gradient norm over training steps. The colored lines represent data selection strategies: ***High Average*** (blue), ***Low Average*** (orange).

A.4 Experimental Settings

We train the LLaMA-3-8b and Mistral-7b supervised fine-tuned models on the UltraFeedback dataset using DPO and SimPO methods (Touvron et al., 2023). For LLaMA-3-8b, DPO training is conducted with a beta value of 0.01 and learning rate of 5e-7, while SimPO training uses beta values of 2.0, gamma-beta ratio of 0.5, and learning rate of 6e-7. For Mistral-7b, DPO training is performed with beta values of 0.01 and learning rate of 5e-7, whereas SimPO uses a beta of 2.0 and a gamma-beta ratio of 0.8, and learning rate of 3e-7. We adopted the hyperparameter configuration from Meng et al. (2024). The model was trained for 3 epochs, and the best performance observed during training was reported. For any process requiring random selection, such as dataset sampling, we used a fixed random seed of 42 to ensure reproducibility. All training is conducted on four RTX A6000 ada GPUs.

Model (Method)	β	γ/β	lr
LLaMA-3-8b (DPO)	0.01	-	1e-7
Mistral-7b (DPO)	0.01	-	5e-7
LLaMA-3-8b (SimPO)	2.0	0.5	6e-7
Mistral-7b (SimPO)	2.0	0.8	3e-7

Table 7: Hyperparameter used in DPO and SimPO training.

B Preference Alignment by SimPO

SimPO Gradient Analysis. The gradient of the SimPO loss function $\mathcal{L}_{\text{SimPO}}$ can be expressed as follows (Meng et al., 2024).

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

where

$$\rho_\theta = \left(\frac{\beta}{|y_w|}\log \pi_\theta(y_w \mid x) - \frac{\beta}{|y_l|}\log \pi_\theta(y_l \mid x) - \gamma\right)$$

$$d_\theta = \frac{1}{|y_w|}\nabla_\theta \log \pi_\theta(y_w \mid x) - \frac{1}{|y_l|}\nabla_\theta \log \pi_\theta(y_l \mid x)$$

- In $\sigma(-\rho_\theta)$, ρ_θ denotes the difference in log probabilities between the chosen and rejected responses. When ρ_θ is small—i.e., when the model has similar confidence in both choices—$\sigma(-\rho_\theta)$ takes a large value. Conversely, when ρ_θ is large, $\sigma(-\rho_\theta)$ approaches zero.

- This indicates that samples where the model is less confident in preferring the chosen response over the rejected one contribute more to the loss and result in larger gradient updates. Empirically, it has been observed that for near-deterministic preference pairs (e.g., with probabilities close to 0 or 1), the gradient contribution becomes negligible, potentially limiting SimPO's effectiveness in such scenarios (Azar et al., 2024).

- d_θ corresponds to the margin of the policy's log probability gradient. It is well known that lower probability value result in larger gradient magnitudes (Ko et al., 2024). Specifically, for small values of $\log \pi_\theta(y \mid x)$, the gradient $\nabla_\theta \log \pi_\theta(y \mid x)$ becomes large. As a result, in the SimPO objective, samples with very low policy probabilities $\log \pi_\theta(y \mid x)$ can induce excessively large gradients. This may lead to unstable training behavior due to over-amplified updates in response to small preference margins (Houliston et al., 2024).

Analysis on experiment results. We analyze the impact of these three data regions on the SimPO

loss gradient in Figure 5. In the ***HighAvg.*** region, due to low variance and high average preference scores, both the win and loss samples tend to receive high log probability estimates. In contrast, the ***LowAvg.*** region exhibits low variance and low average scores, resulting in low log probabilities for both win and loss samples. As shown in Figures 5(a) and 5(b), both the chosen and rejected responses exhibit higher initial log probabilities in the ***HighAvg.*** region. This indicates that the generation probabilities for these instances are relatively higher compared to those in the ***LowAvg.*** region. Consequently, the gradient norm behavior observed in Figure 5(c) differs accordingly: in the ***HighAvg.*** region, the gradients at the early stages of training are smaller and more stable, whereas in the ***LowAvg.*** region, the gradients tend to be larger and more volatile during early training.

C VLFeedback Experiment

To extend the evaluation conducted on UltraFeedback, we perform additional data selection experiments on the multimodal visual question answering dataset **VLFeedback** (Li et al., 2024b), in order to assess the effectiveness of our method in a multimodal setting. For the VLFeedback experiments, we use Qwen2-VL-2B-Instruct (Wang et al., 2024b) as the backbone model for multimodal large language model (MLLM) alignment training. We first construct an Alignment Data Map by applying the reference-based score, where reference answers are generated using `GPT-4V` and alignment scores are computed as cosine similarity between candidate responses and reference answers in the embedding space. Figure 6 illustrates the Alignment Data Map constructed on the VLFeedback dataset.

% Train	Train set	MMBench	MMMU
0	Zeroshot	0.720	41.1
33	Random	0.719	42.0
	LowAvg.	<u>0.723</u>	42.2
	HighVar.	0.720	42.1
	HighAvg.	**0.727**	<u>42.6</u>
100	Full	0.716	**42.8**

Table 8: Evaluation results of our method on the VLFeedback dataset. The Qwen2-VL-2B model was trained using DPO and evaluated on MMBench (Liu et al., 2024) and MMMU (Yue et al., 2024).

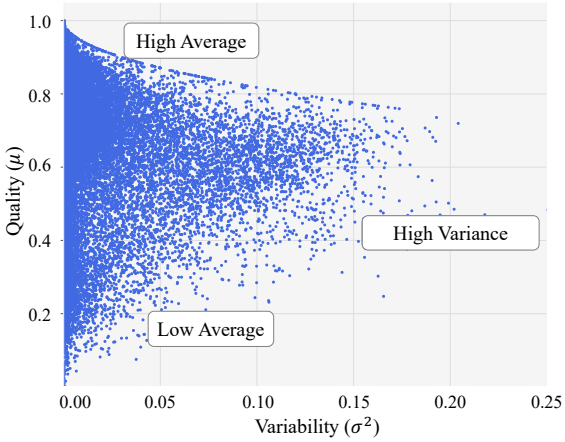

Figure 6: Alignment Data Map for the VLFeedback dataset (Li et al., 2024b).

C.1 Experimental Settings.

We train the Qwen2-VL-2B-Instruct model on the VLFeedback dataset using the DPO method with LoRA fine-tuning. Training is performed with a beta value of 0.1, LoRA rank of 8, and a learning rate of 1e-6. The model is trained for 3 epochs, and followed the DPO implementation with sigmoid preference loss. Also, we follow the hyperparameter configuration provided in Zheng et al. (2024) VLLM settings. A fixed random seed of 42 is used for dataset sampling to ensure reproducibility. Experiments are conducted using four RTX A6000 Ada GPUs.

To assess MLLM alignment, we employ the following two alignment benchmarks:

- MMBench (Liu et al., 2024) is a fine-grained benchmark with 3,000 multiple-choice questions across 20 ability types. It evaluates multimodal models using an LLM-based judge to assign answer labels, supporting consistent and scalable assessment.

- Massive Multi-discipline Multimodal Understanding and Reasoning (MMMU) (Yue et al., 2024) is designed to evaluate MLLMs on large-scale tasks that require university-level expertise and deep reasoning.

C.2 Experimental Results

Table 8 presents the experimental results on the VLFeedback dataset. For the Qwen-2-VL model, the model trained on the *HighAvg.* region demonstrates strong performance, achieving a score comparable to that of the fully trained model in MMMU. *HighAvg,* even surpass the performance

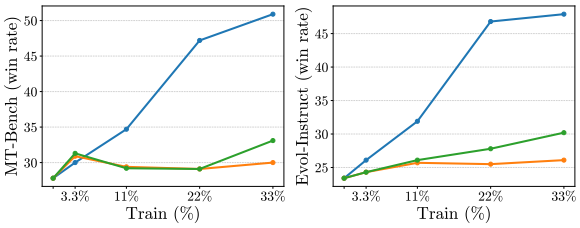

Figure 7: Sensitivity to regional data volume. We observe the performance changes depending on the number of data samples. The colored lines represent results derived from each region: High Average (blue), High Variance (orange), and Low Average (green).

of fully trained models while outperforming other regions trained with 33% of the data in MMBench. These findings emphasize the significant impact of dataset partitioning on MLLM training outcomes and confirm that among the three data regions, the *partially aligned* region is the most effective for improving model performance. We demonstrate that our method is robust and applicable across different data modalities and task types.

D Sensitivity to regional data volume

Figure 7 illustrates the performance changes on MT-Bench and Evol-Instruct as we vary the training data ratio from 0% to 3.3%, 11%, 22%, and 33%. The *HighAvg.* region stands out: even with just 11% of the data, it delivers substantial gains over the zero-shot baseline, and performance continues to improve sharply as more data is added. Between 11% and 22%, the model exhibits the steepest growth in win rate, and this upward trend persists—albeit more gradually—up to 33%. By contrast, both the *HighVar.* and *LowAvg.* regions show only marginal improvements, suggesting that additional data from these regions contributes little to model performance. This sensitivity analysis suggests that prioritizing the collection of samples from the *HighAvg.* region—identified through our Alignment Data Map—can lead to more rapid improvements in model performance during data acquisition.

E Case Study

To verify whether models trained on different data regions exhibit distinct behaviors, we conduct a case study comparing their actual responses. Table 9 presents a case study comparing model responses across three data regions: ***High Average*** *(HighAvg.)*, ***High Variance*** *(HighVar.)*, and ***Low Average*** *(LowAvg.)*. Given a prompt requiring grammatical correction, the HighAvg response provides a clear and coherent revision with a high score of 9. In contrast, both *HighVar.* and *LowAvg.* responses receive lower scores of 4 due to ambiguity, insufficient grammatical corrections, and failure to follow the instruction precisely. These responses are also less aligned with human preferences in terms of clarity and task relevance. Specifically, these responses fail to clarify the speaker's intent and do not fully resolve key errors in the original text. These cases illustrate that data from the *HighAvg.* region better supports instruction-following and clarity, while low-quality or inconsistent data leads to suboptimal model behavior.

F Correlation Hexbin Plot

We construct the data map using the UltraFeedback dataset, dividing it into three subsets—High Variance, High Average, and Low Average—based on the proposed criteria. For each subset, we compute the variance and average from the feedback scores $\mathcal{F}$ and visualize the resulting structure. Figure 8 illustrates the distribution of each subset. The High Variance group is characterized by a larger number of samples with relatively high variance when calculated using the actual preference scores. In the High Average group, most data points exhibit an average score of approximately 4.5 or higher, with variance values concentrated near zero. In contrast, the Low Average group displays a distribution skewed toward lower average scores, and the overall mean is noticeably lower than that of the High Average group. This visualization demonstrates that the proposed data partitioning criteria effectively capture the statistical characteristics of the actual preference scores.

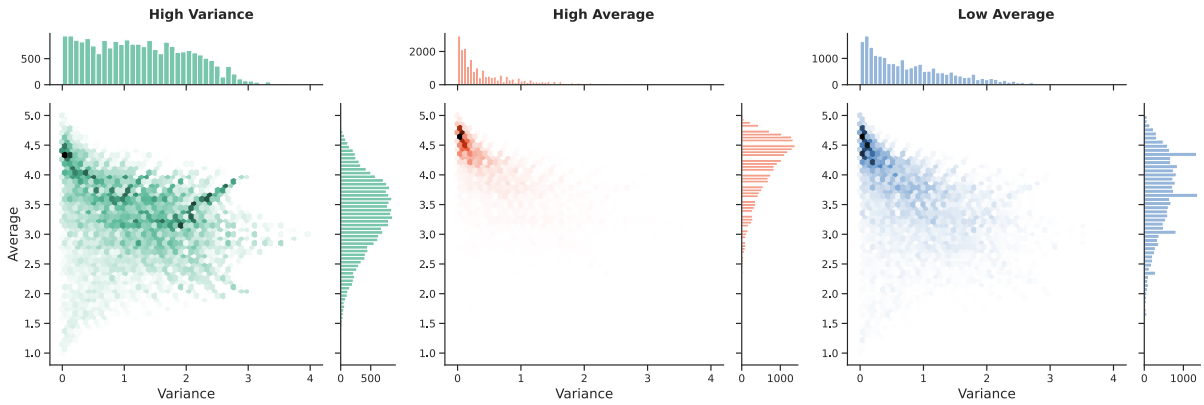

Figure 8: Hexbin jointplots for High Variance, High Average and Low Average.

Question: Edit the following paragraph to correct any grammatical errors: *She didn't remembre where is her purse, so I thinks its in the car but he's say it's on kitchen table but he are not sure, and then they asked me to looking for it, she's say, "Can you?", and I responds with, "Maybe, but ain't no sure," and he not heard me, and, "What?", he asks, "Did you found it?"*

Region	Model Response	Score
HighAvg.	She couldn't remember where her purse was, so I suggested that it might be in the car. However, he said it was on the kitchen table but wasn't sure. They asked me to help find it, and she said, "Can you?" I replied, "I'm not sure, but I'll try," and he didn't hear me. He asked, "Did you find it?" "No, I'm sorry," I answered.	9
HighVar.	It is not clear from the sentence "she's say, 'Can you?' and I responds with, 'Maybe, but ain't no sure,'" what the speaker is responding to. It could be interpreted as a response to the question "Can you?" or to "Did you found it?" It is also unclear if the speaker is responding to a question being asked by another person or is responding to their own thoughts. To correct these grammatical errors, the sentence could be rewritten as: "She asked me, 'Can you find my purse?' and I replied, 'I'm not sure, but I'll try my best.'	4
LowAvg.	It is not clear from the sentence "she's say, 'Can you?' and I responds with, 'Maybe, but ain't no sure,'" what the speaker is responding to. It could be interpreted as a response to the question "Can you?" or to "Did you found it?" It would be helpful to clarify which question the speaker is responding to. Additionally, the sentence "he not heard me" should be changed to "he didn't hear me" for proper grammar. Finally, the sentence "and, 'What?', is not necessary as it is not a complete sentence.	4

Table 9: Case study from MT-Bench evaluating Llama3-8B model fine-tuned via SimPO. Responses from different data regions (High Average, High Variance, Low Average) are compared in terms of grammatical correction quality.