Fine-Tuning Diffusion Generative Models via Rich Preference Optimization

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Paper under double-blind review

Abstract

We introduce Rich Preference Optimization (RPO), a novel pipeline that leverages rich feedback signals to improve the curation of preference pairs for fine-tuning text-to-image diffusion models. Traditional methods, like Diffusion-DPO, often rely solely on reward model labeling, which can be opaque, offer limited insights into the rationale behind preferences, and are prone to issues such as reward hacking or overfitting. In contrast, our approach begins with generating detailed critiques of synthesized images, from which we extract reliable and actionable image editing instructions. By implementing these instructions, we create refined images, resulting in synthetic, informative preference pairs that serve as enhanced tuning datasets. We demonstrate the effectiveness of our pipeline and the resulting datasets in fine-tuning state-of-the-art diffusion models.

1 Introduction

Learning from feedback and critiques is essential for enhancing the performance of a generative model by guiding the model to rectify unsatisfactory outputs, e.g. in RLHF (Ouyang et al., 2022). However, improvements can arise not only from distinguishing right from wrong, but also from receiving thoughtful and informative feedback that offers clear direction for enhancement, which we refer as *rich feedback*. For instance, in the natural language tasks, rich feedback has proved to be useful in LLM self-refinement (Saunders et al., 2022), reward model enhancement (Ye et al., 2024; Ankner et al., 2024), code debugging (Chen et al., 2023; McAleese et al., 2024), games (Paglieri et al., 2024; Hudi et al., 2025), and agents (Shinn et al., 2023; Wang et al., 2023; Renze & Guven, 2024). Rich feedback is comparatively less explored in vision tasks, such as human feedback generation model (Liang et al., 2024) and visual commonsense reasoning (Cheng et al., 2024; Chen et al., 2024; Li et al., 2024c).

To effectively leverage rich feedback in model training, it is crucial to ensure that the rich feedback is detailed, informative, and nuanced. Simply relying on numerical scores, as in classical reward models e.g. PairRM (Jiang et al., 2023; Kirstain et al., 2023b), falls short in identifying specific areas for model enhancement. Comprehensive feedback like heat maps of unaligned parts in (Liang et al., 2024) provides insights that extend beyond numerical evaluations, allowing for more targeted and substantial model improvements. In this context, exploring the use of critic models can be highly beneficial, as these models are growing rapidly and could offer deeper insights into the model's intricacies, thus contribute to a more robust understanding of improvement opportunities.

To leverage rich feedback in preference learning, we draw inspiration from the way students learn from their teachers. We introduce Rich Preference Optimization (RPO), a novel approach designed to enhance preference learning for images by leveraging vision-language models (VLMs). These multi-modal models provide detailed critiques for downstream tasks need, offering rich feedback that mirrors the comprehensive guidance students receive in modern educational systems. Rather than merely receiving a final score on assignments or exams, students are given specific feedback that identifies logical errors, misunderstandings, or calculation mistakes. This feedback enables students to iteratively refine their initial responses, fostering deeper learning through a process of continuous improvement. Similarly, in RPO, we extract actionable editing instructions from VLMs and employ instruction-driven image-editing models for refinement. This

Figure 1: **(Top)** Our RPO pipeline for curating informative preference pairs from images generated from the base diffusion models: **(1)** Rich Feedback/Critic generation by a Vision Language Model (for which we choose LLaVA-Critic-7B), **(2)** Actionable editing instruction generation based on the critiques by another VLM (for which we chose Qwen2.5-VL-8B-Instruct), **(3)** Instruction-following image editing from the generated editing instructions (for which we choose ControlNet), and **(4)** Diffusion DPO training using reward model filtered synthetic preference pairs. **(Bottom)** Sample images generated from RPO fine-tuned Stable Diffusion XL, by further aligning the model on our generated synthetic preferences.

scalable method generates informative preference pairs that are crucial for effective preference learning. The process of receiving detailed feedback and making refinements is akin to learning from true preference pairs, reflecting the natural and effective way in which humans learn.

The contribution of our paper is summarized as follows:

(1) We introduce RPO, a novel approach for generating preference datasets for images by leveraging VLMs to provide detailed critiques as rich feedback about misalignment between prompt and generated image. We further extract actionable editing instructions from VLMs, and employ instruction-driven image-editing models for refinement. This scalable data curation approach yields informative preference pairs, which we illustrate in Figure 1.

(2) We show that the intermediate critiques can improve the quality of editing instructions than directly generating them, which is reminiscent to the Chain-of-Thought (Wei et al., 2022) concept in mathematical reasoning for LLMs. We also propose to use ControlNet for image-editing by conditioning on the original image and combine prompts with editing instructions, which ensures fine-grained control over the image to be revised while keeping most of the image unchanged.

(3) We also empirically demonstrate that our curated preferences are scalable and useful offline synthetic preference dataset, by further training Diffusion DPO (trained on the original offline dataset) checkpoints on rich preferences we generate on the preferred images. We observe drastic performance gain, which validates the effectiveness of our pipeline. We include qualitative samples of our obtained checkpoints also in Figure 1.

Related Work. In contemporary RLHF pipelines for LLMs, preference pairs are generated by sampling various responses and subsequently ranking them using either human evaluators or pretrained reward models, which serve as AI-based labels. This approach is widely utilized in both online reinforcement learning (RL)-based techniques (Ouyang et al., 2022; Bai et al., 2022) and offline methods for LLM preference learning, such as DPO (Rafailov et al., 2023), SimPO (Meng et al., 2025), and RainbowPO (Zhao et al., 2025a), which motivates Diffusion-DPO (Wallace et al., 2024) for diffusion models. See Winata et al. (2024) for a comprehensive review.

Concurrent work to ours, (Wang et al., 2025) also investigates on utilizing dedicated feedback and then passing to the editing model in the contents of an inference time scaling method. As a comparison, we focus on alignment and our pipeline has an extra procedure of generating concrete editing instructions before passing to instruction-following editing models, which directly connects two well developed literature of VLMs and Image-editing models. Our pipeline is also easier for plug-in thanks to the recent rapid progress in instruction-following image-editing capability like in GPT-4o (Hurst et al., 2024). Our work is also reminiscent to Aligner (Ji et al., 2024), which directly tries to find a more preferred answer.

2 Preliminaries

Diffusion Models. Diffusion models are a class of generative models $p_\theta(x_0)$, whose goal is to turn noisy/non-informative initial distribution $p_{\text{noise}}(x_T)$ to a desired target distribution $p_{\text{tar}}(x_0)$ through a well-designed denoising process (Ho et al., 2020; Song et al., 2021a;b). Here we adopt the discrete-time formulation of diffusion models as in Ho et al. (2020).

Given noise scheduling functions α_t and σ_t (as defined in Rombach et al. (2022)), the forward process is specified by $q(x_t \,|\, x_s) = \mathcal{N}\left(\frac{\alpha_t}{\alpha_s} x_s,\, \left(\sigma_t^2 - \frac{\alpha_t^2}{\alpha_s^2}\sigma_s^2\right) I\right)$ for $s < t$. Its time-reversed process is a Markov chain parameterized by $p_\theta(x_{0:T}) = \prod_{t=1}^{T} p_\theta(x_{t-1} \,|\, x_t)\, p_{\text{noise}}(x_T)$, where

$$p_\theta(x_{t-1} \,|\, x_t) = \mathcal{N}\left(\mu_\theta(t, x_t),\, \Sigma_t I\right), \tag{1}$$

with $\mu_\theta(t,x) := \frac{\alpha_{t-1}}{\alpha_t} x_t - (\frac{\alpha_{t-1}}{\alpha_t} - \frac{\alpha_t \sigma_{t-1}^2}{\alpha_{t-1}\sigma_t^2})\sigma_t \epsilon_\theta(t, x_t)$ and $\Sigma_t = \sigma_{t-1}^2 - \frac{\alpha_t^2 \sigma_{t-1}^4}{\alpha_{t-1}^2 \sigma_t^2}$. The model equation 1 is trained by minimizing the evidence lower bound (ELBO):

$$\min_\theta \mathcal{L}(\theta) := \mathbb{E}_{t,\epsilon,x_0,x_t}\left[\omega\left(\lambda_t\right) ||\epsilon - \epsilon_\theta(t, x_t)||_2^2\right], \tag{2}$$

where $t \sim \mathcal{U}(0,T)$, $\epsilon \sim \mathcal{N}(0, I)$, $x_0 \sim p_{\text{tar}}(x_0)$, $x_t \sim q(x_t \,|\, x_0) = \mathcal{N}(\alpha_t x_0,\, \sigma_t^2 I)$, $\lambda_t := \frac{\alpha_t^2}{\sigma_t^2}$ is the signal-to-noise ratio, and $\omega : \mathbb{R}_+ \to \mathbb{R}_+$ is some weight function. The training process equation 2 is also known as denoising score matching (see Vincent (2011) or (Tang & Zhao, 2024, Section 4.3)). It is expected that for θ_* solving the optimization problem equation 2, the model's output distribution $p_{\theta_*}(x_0) \approx p_{\text{tar}}(x_0)$, see Chen et al. (2022); Li et al. (2024a) for the theory.

Rich Feedback. A good critic allows the recipient to learn and improve from the feedback. In T2I generation, RichHF (Liang et al., 2024) identifies misalignment in a multimodal instruction (i.e., an image-prompt pair), and hence, enriches the feedback. A by-product is the Rich Human Feedback dataset (RichHF-18k), consisting of fine-grained scores, and misalignment image regions and text descriptions on 18K Pick-a-Pic images (Kirstain et al., 2023a). However, the Rich Feedback model and code are both not released.

As an alternative to Rich Feedback, LLaVA-Critic (Xiong et al., 2024) is an open-source VLM that is primarily developed to give evaluation of multimodal tasks. e.g., VLM-as-a-judge and preference learning. It shows a high correlation and comparable performance to proprietary GPT models (GPT-4V/4o). In our approach, we use LLaVA-Critic as an VLM-as-a-judge: the input is a text-image pair, and the output is a critic to image-prompt misalignment. Following the Chain-of-Thought concept (Wei et al., 2022), such obtained critic will be subsequently passed to an open-source LLM to provide an editing instruction. Our experiment shows that the proposed open-source critic + editing pipeline yields more reliable improvements than directly querying a VLM, e.g., GPT4o, for editing instruction generation. See Section 3.2 for examples of critic + editing instruction.

Instruction-following Image Editing Models. The image-editing part in our pipeline is related to the literature of instruction-following image-editing models. We focus on diffusion-based models in this paper due to both their advantage over autoregressive models, and that our base models for fine-tuning are also diffusion-based. The pioneer models include InstructPix2Pix (IP2P) (Brooks et al., 2023), which first enables editing from instructions that inform the model which action to perform. Follow-up works include Magic Brush (Zhang et al., 2023a), Emu Edit (Sheynin et al., 2024), UltraEdit (Zhao et al., 2025b) and HQEdit (Hui et al., 2024) by introducing additional datasets for further fine-tuning based on IP2P and enhancing the performance. Existing work like HIVE (Zhang et al., 2024) has also considered to align IP2P with human feedback to enhance generation capability.

As previously mentioned, we edit images based on ControlNet (Zhang et al., 2023b) to ensure a better coherence to the original image. ControlNet has been widely used for controlling image diffusion models by conditioning the model with an additional input image. Further applications include implementations for the state-of-the-art proprietary models like Stable Diffusion 3, Stable Diffusion XL (Esser et al., 2024) and FLUX (Labs, 2024), multi-image support extensions like ControlNet++ (Li et al., 2024b). We will stick to the original ControlNet implementation in this paper (because the offline dataset is generated by the similar model scaled by Stable Diffusion v1.5), and leave the usage of more advanced ControlNet variants in future work.

Diffusion-DPO. Direct Preference Optimization (DPO) (Rafailov et al., 2023) is an effective approach for learning from human preference for language models. Wallace et al. (2024) proposed Diffusion-DPO, a method to align diffusion models to human preferences by directly optimizing on human comparison data (x_0^w, x_0^l) given the conditional input c (the prompt). Let $\beta > 0$ be the regularization parameter, and $p_{\text{ref}}(x_{0:T}|c)$ be a (pretrained) reference model. The DPO loss objective for diffusion models can be written as:

$$L_{\text{DPO}}(\theta) = -\mathbb{E}_{c,x_0^w,x_0^l} \log \sigma \left(\beta \mathbb{E}_{\substack{x_{1:T}^w \sim p_\theta(x_{1:T}^w|x_0^w,c) \\ x_{1:T}^l \sim p_\theta(x_{1:T}^l|x_0^l,c)}} \left[\log \frac{p_\theta(x_{0:T}^w|c)}{p_{\text{ref}}(x_{0:T}^w|c)} - \log \frac{p_\theta(x_{0:T}^l|c)}{p_{\text{ref}}(x_{0:T}^l|c)} \right] \right). \tag{3}$$

By Jensen's inequality and approximate $p_\theta(x_{1:T}|x_0, c)$ by the forward process $q(x_{1:T}|x_0)$, Wallace et al. (2024) yields the following loss function for efficient training:

$$\begin{aligned} L_{\text{Diffusion-DPO}}(\theta) = -\mathbb{E}_{x_0^w,x_0^l,t,x_t^w \sim q(x_t^w|x_0^w),x_t^l \sim q(x_t^l|x_0^l)} \log \sigma \Big(\beta T \omega(\lambda_t) \\ \Big(-\|\epsilon^w - \epsilon_\theta(x_t^w, t)\|_2^2 + \|\epsilon^w - \epsilon_{\text{ref}}(x_t^w, t)\|_2^2 + (\|\epsilon^l - \epsilon_\theta(x_t^l, t)\|_2^2 - \|\epsilon^l - \epsilon_{\text{ref}}(x_t^l, t)\|_2^2) \Big) \Big), \end{aligned} \tag{4}$$

where $x_t^{w,l} \sim q(x_t^{w,l} \mid x_0^{w,l}) = \mathcal{N}(\alpha_t x_0^{w,l} \sigma_t^2 I)$, and $\epsilon^{w,l} \in \mathcal{N}(0, I)$.

3 Curating Preference Pairs with Rich Feedback Signals

In this section, we present the concrete components in our pipeline for creating preference pairs. We utilize 1.6k rows of prompts and images from the test set of RichHF dataset provided by Liang et al. (2024) as the validation set for ablation study. We first discuss instruction-following editing (despite it being the last part before preference tuning in our pipeline), and then use the best instruction-following image-editing model we find for further ablation study on the first two components: utilizing multimodal models/VLMs for generating feedback information, and providing concise and actionable editing instructions.

3.1 Instruction-Following Image Editing

Despite the numerous proposed image-editing methods, either based on diffusion models or not in the literature, we find that they struggle to perform fine-grained control to follow specific editing instructions, which is crucial to generating images that are direct improvements over the existing ones. Existing methods usually change the image to another one which may yield higher score but looks fundamentally different.

To tackle the above issue, we propose a ControlNet (Zhang et al., 2023b) based image-editing approach. Concretely, we exploit the image2image (pipeline) of the ControlNet by setting the conditional image to be

the same as the original one, which guarantees that the changes adhere to the original image. In addition, we concatenate the prompt that generates the image with our generated editing instructions, which we find will greatly enhance the quality of the edited image generation as illustrated in Figure 2.

Figure 2: **(L)** We utilize ControlNet by using the same input image as the conditional image, and concatenating the prompt with the editing instruction as the textual control.
(R) We compare ControlNet with InstructPix2Pix and also ablate the necessity of concatenating the prompt with the editing instructions, which are generated by ChatGPT-4o. ***(Top)***: The prompt is *"Italian coastline, buildings, ocean, architecture, surrealism by Michiel Schrijver."* The editing instruction is *"Incorporate iconic Italian elements like olive trees or Vespa scooters. Enhance the coastline with more distinct Mediterranean features. Add intricate architectural details typical of Italian structures. Intensify the ocean's depth with gradient blues, and ensure the surrealism reflects Michiel Schrijver's style by blending dreamlike elements."* In this case, InstructPix2Pix struggles to make any fine-grained modifications. ***(Bottom)***: The prompt is *"Mickey Mouse in a Superman outfit bodybuilding."* The editing instruction is *"Adjust the character to have Mickey Mouse's face, including distinct ears, in a Superman outfit. Include bodybuilding elements such as visible muscles or weights. Ensure the outfit is accurate with the Superman logo prominently displayed."* In this case, InstructPix2Pix distorts the image. In both cases, adding the image prompt to the editing instruction for the final instruction yields better results in terms of following the instructions while keeping most of the original image unchanged.

Additionally, we quantitatively assess the instruction-following capabilities of various diffusion-based image-editing models. We also examine the impact of incorporating prompts before editing instructions, using GPT-4o for pairwise comparisons on both a standard instruction-following dataset and a test set. Our findings indicate that ControlNet-based editing is particularly effective. However, we highlight that the choice of image-editing model is flexible and can be updated to include more advanced options, such as ControlNet SDXL and other variants. We plan to explore these options in future work.

3.2 Generating Rich Feedback Signals

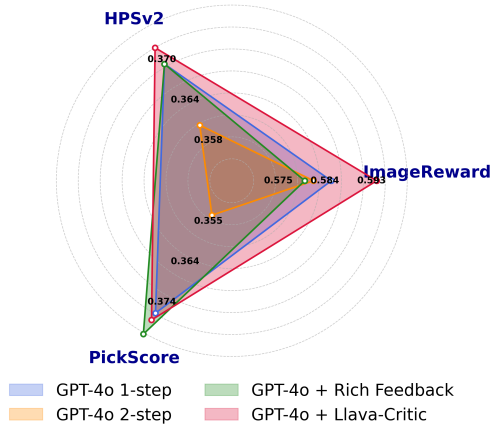
Unlike RichFB (Liang et al., 2024) which requires to train a model to detect the heatmaps and misaligned words thus providing more accurate rewards, we leverage the textual feedback on the quality of generation, like a movie critic, as in Figure 3.

To compare and ablate about what type of feedback will be more useful for yielding better editing instructions for improving the images, we prompt GPT-4o to generate them based on the given feedback, and then compute the rewards of new images (evaluated by different reward models) after using ControlNet to edit the image with the instructions as in Figure 4a. Concretely, we let GPT-4o generate editing instructions based on various types of feedback, including those from RichFB, LLaVA-Critic, and even ChatGPT-4o itself.

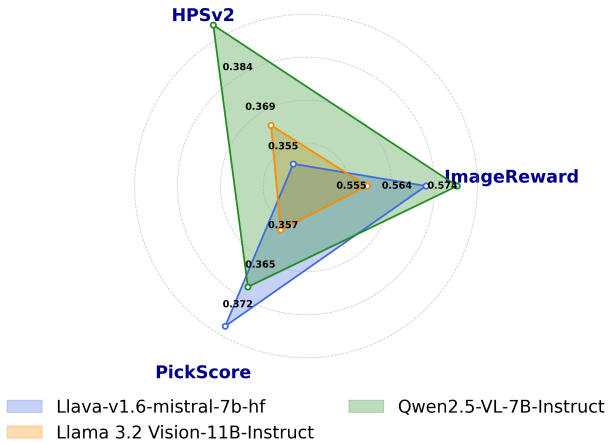
Figure 3: Comparison of RichFB generated informative feedback and our adopted textual criticism generate by carefully prompting a capable VLM.

From the RichFB dataset, we use the image, prompt, misalignment information within the prompt, and the misalignment heatmap of the image as inputs. From LLaVA-Critic, we incorporate its textual feedback. For ChatGPT-4o, we first prompt it to also generate textual feedback based on the image-prompt pair, which is then used to derive editing instructions. For studing the necessity of rich feedback, we also let GPT 4o generate editing instructions directly from the input image and prompt, bypassing the intermediate step of critique.

Somewhat surprisingly, as in Figure 4a, we found that GPT-4o produced better editing instructions when generating them directly, rather than conditioning on its own critiques about the misalignment between the prompt and the image. However, GPT-4o generates much better editing instructions (measured by average reward) conditioning on the critiques provided by LLaVA-Critic. Based on this result, we adopt LLaVA-Critic as the feedback generator in our RPO pipeline.



(a) Comparison of RichFB generated informative feedback and our adopted textual criticism generated by carefully prompting a capable VLM.



(b) Comparison of open-source VLMs combined with LLaVA-Critic in image editing quality, showing that Qwen2.5-VL-7B-Instruct is the most capable VLM model.

Figure 4: Comparisons of feedback approaches and VLM performance for enhanced image editing, evaluated by ImageReward, HPSv2 and PickScore.

Notably, here we implicitly make a hypothesis that refined images of higher reward yield better preference pairs, which also makes the corresponding VLM more preferrable. We verify this hypothesis in the experiment section 4.4 by directly comparing the trained models upon these different preference pairs, which showcases that this intuition is indeed correct.

3.3 Generating Editing Instructions

We also compare the performance of Llama 3.2 Vision 11B Instruct (Grattafiori et al., 2024), Llava-v1.6 Mistral 7B (Liu et al., 2024), and Qwen2.5 VL 7B Instruct (Wang et al., 2024) generated editing instructions, in combined with LLaVA-Critic and ControlNet based editing as we argued earlier. As shown in Figure 4b, Qwen2.5-VL-7B-Instruct yield the best results in leading to highest rewards in both HPSv2 and ImageReward after adopting the image-editing instructions. We thus choose Qwen2.5-VL-7B-Instruct as the VLM for editing instruction generation in our RPO pipeline.

3.4 Reward Model Relabeling

After obtaining the pair of original and edited images, we rearrange them into preferences by further querying a reward model or an LLM-as-a-judge. On the test set of size 16K, we find that roughly 60% of our images yield a higher score than the original image under the ImageReward (Xu et al., 2023) metric. As a remark, it is possible to use RL fine-tuning methods to encourage the VLM to generate better editing instructions, which may get a higher score of edited images; we leave this for future work. Nevertheless, the edited images that fail to have higher scores than the original ones can still serve as the non-preferred images, and hence, yield the flipped preference pair.

To conclude, our RPO pipeline provides a generic and training-model-free way to generate preference pairs, as we do not need extra generations from the base model. We further use our curated dataset for fine-tuning large-scale SOTA diffusion models which validates the effectiveness of our pipeline.

4 Experiments

In this section, we evaluate our RPO pipeline by first fine-tuning different baseline models on our synthetic preferences data using the Diffusion-DPO algorithm, and then utilizing a couple of reward models to score the images generated by the fine-tuned models.

4.1 Settings

Baseline Models. We use SD1.5 (Rombach et al., 2022) and SDXL-1.0 (Podell et al., 2024) as our starting point. We create the following checkpoint models by Diffusion-DPO fine-tuning the two base models on the Pick-a-Pic v2 dataset: (a) DPO-SD1.5-100k, which is fine-tuned from SD1.5 using the first 100k rows; (b) DPO-SD1.5-200k, fine-tuned from SD1.5 using the first 200k rows; (c) DPO-SD1.5-100k (ImageReward-Aligned), fine-tuned from SD1.5 using the first 100k rows, with the preference modified by the relative order of ImageReward scores; (d) DPO-SDXL-100k, fine-tuned from SDXL-1.0 using the first 100k rows.

Produced Models. To evaluate our curated dataset, we produce the following models by Diffusion-DPO fine-tuning the baseline models using our 100k synthetic preferences data: (a) DPO-SD1.5-100k+RPO100k, which is fine-tuned from model DPO-SD1.5-100k; (b) DPO-SD1.5-100k (ImageReward-Aligned)+RPO100k, fine-tuned from model DPO-SD1.5-100k (ImageReward-Aligned); (c) DPO-SDXL-100k + RPO100k, fine-tuned from model DPO-SD1.5-100k (ImageReward-Aligned).

Diffusion-DPO Training. For Diffusion-DPO training, we follow the same setting and use the same hyperparameters in Wallace et al. (2024) when fine-tuning SD1.5-based models. More specifically, we use AdamW (Loshchilov & Hutter, 2019) as the optimizer; the effective batch size is set to 2048; we train at fixed square resolutions, and use a learning rate of $\frac{2000}{\beta} 2.048 \cdot 10^{-8}$ with 25% linear warmup; for the divergence penalty parameter, we keep $\beta = 5000$. When fine-tuning SDXL-based models, we use the LoRA implementation provided by the Github project (Suzukimain & Liu, 2024) to improve training efficiency.

Model	PickScore	ImageReward	Aesthetic	HPSv2
SD1.5	20.33	0.1733	5.949	0.2622
DPO-SD1.5-100k	20.66	0.2784	6.044	0.2650
DPO-SD1.5-200k	20.74	0.3638	6.088	0.2657
DPO-SD1.5-100k + RPO100k	**20.75**	**0.4395**	**6.113**	**0.2663**
DPO-SD1.5-100k (ImageReward-Aligned)	20.45	0.3913	6.097	0.2645
DPO-SD1.5-100k (ImageReward-Aligned) + RPO100k	**20.54**	**0.5252**	**6.105**	**0.2660**
SDXL1.0	21.74	0.8473	6.551	0.2692
DPO-SDXL-100k	**21.92**	0.9183	6.566	0.2706
DPO-SDXL-100k + RPO100k	21.89	**0.9353**	**6.585**	**0.2707**

Table 1: Model performance on the Pick-a-Pic Test Set by four different metrics.

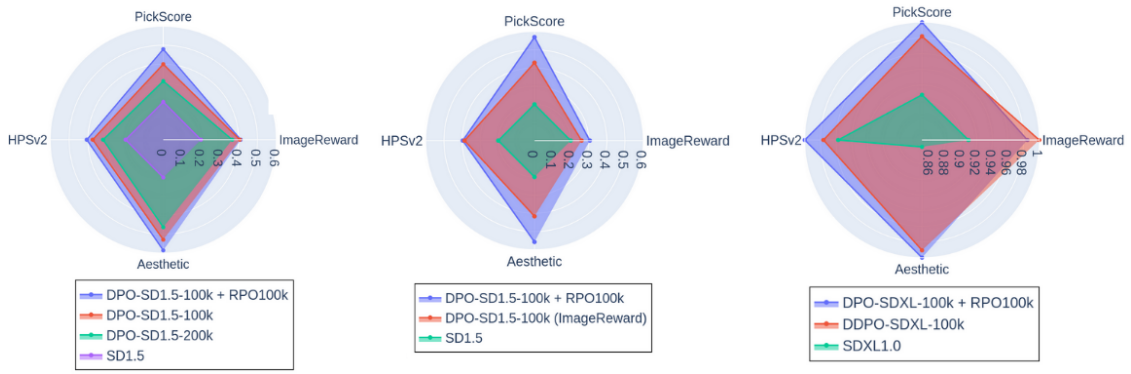


Figure 5: Model performance evaluated by PickScore, ImageReward, Aesthetic, and HPSv2.

Evaluation. We generate images using the prompts from Pick-a-Pic test set (Kirstain et al., 2023b) (which contains 500 unique prompts) and evaluate the generation with reward models including PickScore (Kirstain et al., 2023b), ImageReward (Xu et al., 2023), HPSv2 (Wu et al., 2023) and LAION-Aesthetic Predictor (a ViT-L/14 CLIP model trained with SAC dataset (Pressman et al., 2022)). The PickScore, ImageReward, HPSv2 reward models are used to evaluate human-preference alignment, and Aesthetic Score is expected to evaluate visual aesthetic appeal. For each model, we report average scores over all prompts.

4.2 Improving Diffusion-DPO via RPO

We present the performance of all models evaluated by different reward models in Table 1. Above all, models obtained by fine-tuning on our 100k synthetic preferences data achieve comparable levels of the baseline models by all metrics and outperform the corresponding baseline models in most cases. This confirms our hypothesis that the pipeline we designed for synthesizing preference pairs yields improved results when combined with preference-based training algorithms such as Diffusion-DPO.

Comparing the fine-tuned model DPO-SD1.5-100k+RPO100k with the baseline model DPO-SD1.5-200k, we note that our pipeline leads to a higher data efficiency for Diffusion-DPO training, in the sense that the former model utilizes a mixture of 100k human-labeled data and 100k synthetic data, while the latter uses 200k human-labeled data, which is naturally considered to be of higher quality. We have thus verified the effectiveness and potential of the synthetic preferences data generated by rich feedback to augment the given (high-quality) dataset, which enhances the performance of fine-tuning. This is of crucial importance when human annotationed data is limited (which is usually always the case) .

We also present a qualitative comparison of the three SDXL-based models in Figure 6. In addition to generating images with better visual qualities, we remark that the RPO fine-tuned model is better at connecting different elements in the prompts in a deep and profound way (see the first and the third columns).

Figure 6: A comparison of generations made by SDXL1.0, DPO-SDXL-100k, and DPO-SDXL-100k+RPO100k. Prompts (from left to right): “tiger wearing casual outfit", “an adventurer walking along a riverbank in a forest during the golden hour in autumn", “samurai pizza cat", “anime portrait of a beautiful vamire witch, sci fi suit, intricate, elegant, highly detailed, digital painting, artstation, concept art, smooth, sharp focus, illustration, art by grep rutkowski and" (truncated due to the limit of number of tokens).

Understanding how rich feedback and guided revision help fine-tuning diffusion models will be left for future work.

4.3 Data Scaling Analysis and Generalization to Diverse Prompt Distributions

To further evaluate the robustness and scalability of our method, we conduct additional experiments on data scaling. Specifically, we subsample the vanilla preference dataset used in Diffusion-DPO training at sizes of 5K, 10K, 20K, 50K, and 100K, and compare performance between Diffusion-DPO and our Diffusion-DPO+RPO pipeline. The metrics of full Diffusion-DPO (denoted as star in Figure 7 and 8) are reported based on the evaluation of checkpoints released by Wallace et al. (2024), which is trained on near 1M offline preference pairs.

Scalability. As shown in Figure 7, DPO + RPO consistently improves upon DPO across all preference set sizes, with gains becoming increasingly pronounced as the number of training data increases. This trend holds across multiple evaluation metrics, including PickScore, ImageReward, LAION-Aesthetic and HPSv2, and on different prompt sets such as Pick-a-Pic, PartiPrompts.

Data efficiency. Notably, our DPO-SD1.5 model fine-tuned with only 100K vanilla preferences and enriched with 100K rich-feedback pairs (DPO-SD1.5-100k + RPO100k) outperforms the Diffusion-DPO model trained on approximately 900K Pick-a-Pic preferences on all major metrics except LAION-Aesthetic. In contrast, we observe the full DPO model exhibits inconsistent performance across reward metrics (e.g., similar ImageReward scores on Pick-a-pic and PartiPrompts and lower LAION-Aesthetic score on PartiPrompts), suggesting overfitting to narrow preference signals. These findings highlight the strong data efficiency and

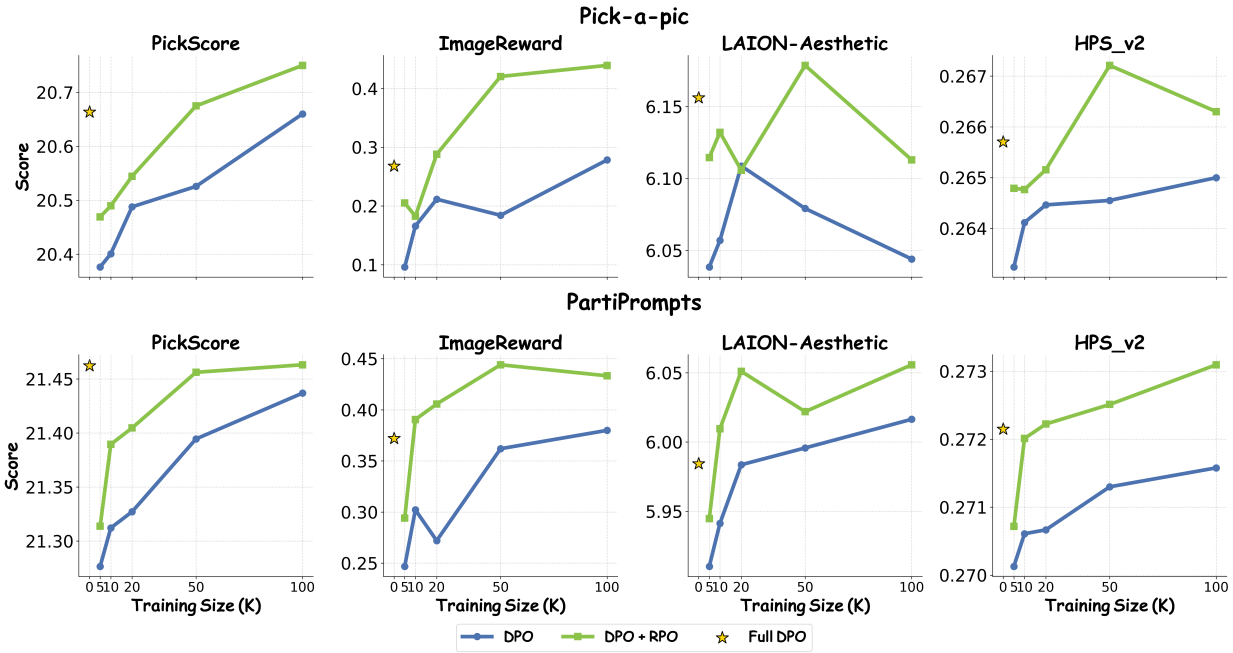


Figure 7: RPO Improves DPO performance across data scales and prompt sets (Pick-a-Pic and PartiPrompts).

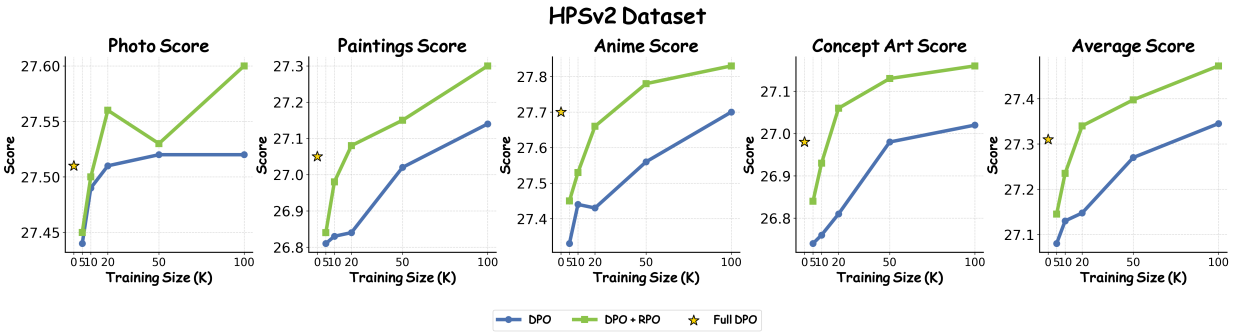


Figure 8: RPO Improves DPO performance across data scales and evaluation metrics on HPSv2 prompt set.

generalization capabilities of RPO: it achieves superior or comparable performance using an order of magnitude less training data, without requiring additional inference or human labeling to generate new data.

Generalization. We further examine generalization behavior of RPO using the out of domain HPSv2 benchmark, which includes subcategories such as Photo, Paintings, Anime, and Concept Art. As shown in Figure 8, RPO-enhanced models consistently outperform the DPO baseline across all style types and dataset sizes. The improvements are especially notable in the Paintings and Concept Art categories, where DPO+RPO exhibits steeper and more consistent gains as the number of preference pairs increases. The average HPSv2 score reflects this trend, with DPO+RPO achieving a significant margin over DPO at every scale. These results highlight RPO's robustness in handling stylistic diversity and confirm that the gains from rich feedback generalize across varied visual domains within the HPSv2 dataset.

4.4 Direct Abalations on VLM Critics

To assess the impact of different VLM critics within our RPO pipeline, we conducted a controlled ablation study in which we varied only the critic component while keeping the rest of the training pipeline fixed. Specifically, we used 1.4k prompts to generate preference pairs based on different VLM critics, including

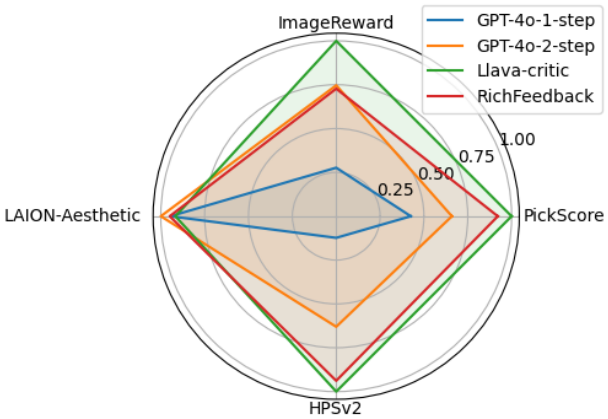


Figure 9: Radar plot comparing RPO fine-tuning performance using preference data generated by different VLM critics (GPT-4o-1-step, GPT-4o-2-step, RichFeedback, Llava-critic).

GPT-4o (1-step and 2-step), RichFeedback, and Llava-critic. We then fine-tuned models using these preference datasets and evaluated their performance across four metrics: PickScore, ImageReward, Aesthetic, and HPSv2. As summarized in Table 2, Llava-critic consistently achieved the best overall performance, with the highest scores in PickScore, ImageReward, and HPSv2. This trend is further confirmed by the radar plot in Figure 9, where Llava-critic demonstrates the most balanced and elevated performance profile. These results validate our design choice of using Llava-critic as the default VLM for generating rich feedback, given its ability to produce high-quality preference data that leads to more effective RPO fine-tuning.

Model	PickScore	ImageReward	Aesthetic	HPSv2
GPT-4o-1-step	20.37	0.0684	6.072	0.2629
GPT-4o-2-step	20.41	0.1675	**6.133**	0.2635
RichFeedback	20.46	0.1634	6.076	0.2639
Llava-critic	**20.47**	**0.2209**	6.039	**0.2640**

Table 2: RPO VLM critic ablation via training on 1.4k pairs of preference data generated by different VLM critics.

4.5 Effectiveness of Critic-Instruction-Editing Data Curation and RPO Fine-Tuning

To evaluate the effectiveness of our curated preference data and the resulting RPO fine-tuned model, we compared images generated by the model against the ControlNet-edited images used during training, using multiple reward metrics (Table 3). The ControlNet-edited images consistently achieve higher scores, demonstrating the high quality of our training targets. Despite this, the RPO fine-tuned model yields competitive performance across all metrics, confirming the value of preference-based fine-tuning via Diffusion-DPO. More importantly, the RPO model eliminates the need for a separate critic and editing module at inference time, resulting in substantial savings in computational and memory resources. These results underscore both the quality of our critic-instruction-editing pipeline and the practical efficiency of our end-to-end generation framework.

Model	PickScore	ImageReward	Aesthetic	HPSv2
ControlNet	21.61	0.4689	6.161	0.2813
RPO	21.02	0.4395	6.113	0.2663

Table 3: Comparison of RPO fine-tuned data and RPO fine-tuned model generation.

5 Discussions

Learning from AI-labeled preferences is the dominant methods in current alignment methods nowadays, but they often lack transparency since reward scores are typically black-box, and they are also not very informative, as they provide minimal insight into why a particular choice (an answer or a generated image) is preferred. Consequently, while the current preference curation pipeline is scalable, it is less efficient for aligning the model or agent based on these preferences. This inefficiency can even lead to issues like reward hacking, as noted in existing literature (Amodei et al., 2016; Denison et al., 2024).

Our RPO pipeline makes a step towards addressing the challenge of creating high-quality synthetic preferences for generative models post-training. Our procedures are straighforward compliment to existing offline RLHF methods like DPO. In addition, although not explored in this paper, our pipeline can also be catered to online algorithms, such as iterative DPO or RL based methods. We consider this as a promising avenue for future research. Our pipeline also combines the existing progress and improvements in two rapidly growing research directions: VLM and image-editing models, which makes our pipeline pretty robust for future improvement by adopting more capable models as plug-ins.

6 Conclusion

In this work, we present **Rich Preference Optimization (RPO)**, a method that utilizes rich feedback about the prompt image alignment to improve the curation of synthetic preference pairs for fine-tuning text-to-image diffusion models. After extracting actionable editing instructions from VLMs, we employ ControlNet to modify the images, thereby producing a diverse range of refined samples. The edited images are then combined with the original versions and undergo a relabeling process using a reward model to create a curated set of preference data. By further fine-tuning checkpoint models on this synthetic dataset, we significantly enhance the performance of Diffusion-DPO training and achieve greater data efficiency. Moreover, we believe that our pipeline represents a promising direction and avenue for the data curation of synthetic vision language preference data, one that lies between two fast growing literature-VLMs and Image-editing, showcasing significant potential for future research advancements.

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A Input Prompts

In this section, we present the prompts used for generating critiques and editing instructions.

A.1 Input Prompts to ChatGPT-4o for Instruction Generation

- **LLaVA-Critic feedback to editing instructions**:

Prompt

You are an AI assistant that provides 2-3 concise suggestions (separated by a semicolon) with each suggestion being no more than 8 words. Please make sure that each suggestion suggests concrete change, not just a high-level idea. Your goal is to improve images so they better align with the prompt: `prompt`.

I want you to give short, concise editing instructions based on the following inputs regarding misalignment information. Some instructions are (1) Keep it concise: "Change the red dog to yellow" is better than "Please make the dog that is red in the image a bright yellow color". (2) Be specific: Avoid ambiguous instructions like Make it more colorful. Instead, use Change the red dog to yellow and make the background green. (3) Avoid redundancy: Don't repeat the same intent multiple times. The image is the generated image based on the prompt: `prompt`.

Here, we have the feedback given by the llava critic model: fb. Please give short editing instructions for the image to solve the misalignment as a text string, where instructions are separated by a semicolon.

- **Rich feedback to editing instructions:**

Prompt

You are an AI assistant that provides 2-3 concise suggestions (separated by a semicolon) with each suggestion being no more than 8 words. Please make sure that each suggestion suggests concrete change, not just a high-level idea. Your goal is to improve images so they better align with the prompt: `prompt`. The first image is the generated image that we want to improve. The second image is a heatmap highlighting areas that misalign with the prompt.

I want you to give short, concise editing instructions based on the following inputs regarding misalignment information. Some instructions are (1) Keep it concise: "Change the red dog to yellow" is better than "Please make the dog that is red in the image a bright yellow color". (2) Be specific: Avoid ambiguous instructions like Make it more colorful. Instead, use Change the red dog to yellow and make the background green. (3) Avoid redundancy: Don't repeat the same intent multiple times. The image is the generated image based on the prompt: `prompt`.

Here, we have the list of pairs where the first element is a word in the prompt, and the second element is 1 if there's misalignment for this word, and 0 otherwise.The list of pairs are: {misalignment-pairs}. If the pairs are None, this means that this info is unavailable, please use the image and the prompt to give advice. We also have a heatmap, which is the second image attached, highlighting the misalignment area in the original (first) generated image.
Now please give short editing instructions for the image to solve the misalignment as a text string, where instructions are separated by a semicolon.

- **ChatGPT image-prompt to editing instructions**

Prompt

You are an AI assistant that provides 2-3 concise suggestions (separated by a semicolon) with each suggestion being no more than 8 words. Please make sure that each suggestion suggests concrete change, not just a high-level idea. Your goal is to improve images so they better align with the prompt: `prompt`.

I want you to give short, concise editing instructions based on the following inputs regarding misalignment information. Some instructions are (1) Keep it concise: "Change the red dog to yellow" is better than "Please make the dog that is red in the image a bright yellow color". (2) Be specific: Avoid ambiguous instructions like Make it more colorful. Instead, use Change the red dog to yellow and make the background green. (3) Avoid redundancy: Don't repeat the same intent multiple times. The image is the generated image based on the prompt: `prompt`.

Now please give short editing instructions for the image to solve the misalignment as a text string, where instructions are separated by a semicolon.

- **ChatGPT image-prompt to feedback and then editing instructions**

Prompt

You are an AI assistant that helps improve a text-to-image model. Your task is to first analyze and critique whether the image aligns with the given prompt (i.e., give some feedback) and then provide 2-3 concise suggestions (separated by a semicolon) with each suggestion being no more than 8 words. Please separate the feedback and the editing instructions with an asterisk. Please make sure that each suggestion suggests concrete change, not just a high-level idea. Your goal is to improve images so they better align with the prompt: `prompt`.

I want you to first generate feedback based on the given input image (and the prompt) and then give short, concise editing instructions based on the given image and the given prompt. For the feedback, it should be a couple of sentences. Some instructions for the editing instructions are ((1) Keep it concise: "Change the red dog to yellow" is better than "Please make the dog that is red in the image a bright yellow color". (2) Be specific: Avoid ambiguous instructions like Make it more colorful. Instead, use Change the red dog to yellow and make the background green. (3) Avoid redundancy: Don't repeat the same intent multiple times. The image is the generated image based on the prompt: `prompt`.

Now please give feedback and short editing instructions for the image to solve the misalignment as a text string, where feedback and instructions are separated by an asterisk and the instructions are separated by a semicolon.

A.2 Input Prompt to LLaVA-Critic for Critique Generation

Prompt

You are a visual-language critic. An image was generated by a diffusion model using this prompt: [`prompt`]
Analyze the image relative to the prompt. Please:
1. Identify any deviations from the prompt and explain how they differ.
2. Note which keywords or phrases are poorly represented or misinterpreted.
3. Highlight any additional issues (e.g., artifacts, distortions, low detail) and their impact on quality.

Provide a clear, structured critique.

A.3 Input Prompts to VLMs for Instruction Generation

- **Generating editing instruction from Rich Feedback**

Prompt

You are an AI assistant providing exactly 2 to 3 concise, specific image editing suggestions (separated by semicolons), each no more than 8 words. Suggestions must describe only how to modify the *image itself* to better align with the prompt. Do not instruct changes to the text prompt.
Formatting rules:

1. Output a single-line string with edits, separated by semicolons.
2. No explanations, bullet points, or extra details."
3. Do not repeat exact misaligned words; describe the needed visual change.
4. Avoid vague edits. Instead of 'Make it colorful,' say 'Turn the red dog bright yellow.'
5. Always generate a response unless no relevant objects exist.

The image is generated from this prompt: `prompt`.

Below is a list of (concept, flag) pairs. A flag of 0 means the image is misaligned; a flag of 1 means it is correct. For each concept flagged 0, provide one specific visual correction. List of pairs: `mis_pairs`. Output only the editing instructions in a single line. image: `base64_combined_image`.

- **Generating editing instruction from LLaVA-Critic**

Prompt

You are an AI assistant providing exactly 2 to 3 concise, specific image editing suggestions (separated by semicolons), each no more than 8 words. Suggestions must describe only how to modify the *image itself* to better align with the prompt. Do not instruct changes to the text prompt.
Formatting rules:

1. Output a single-line string with edits, separated by semicolons.
2. No explanations, bullet points, or extra details."
3. Do not repeat exact misaligned words; describe the needed visual change.
4. Avoid vague edits. Instead of 'Make it colorful,' say 'Turn the red dog bright yellow.'
5. Always generate a response unless no relevant objects exist.

The image is generated from this prompt: `prompt`.

Below is an image critique highlighting deviations from the prompt. Identify the specific visual misalignments and suggest precise edits to correct them.

Critique: `critique`.

Output only the editing instructions in a single line. image: `base64_combined_image`.

B Qualitative Examples

B.1 Qualitative Examples from Feedback Mechanism–VLM Combinations

We present qualitative results from different combinations of feedback methods and VLMs, using a fixed image and prompt.

Table 10: Prompt: *An old, and broken refrigerator, open door and empty.*

GPT-4o with Various Feedback Mechanisms. Table 11 shows that GPT-4o is able to generate accurate instructions to improve alignment with the prompt. However, in the 1-step generation, it enhances only two aspects in the prompt, which are *old* and *empty*. In contrast, 2-step generation, GPT-4o with Rich Feedback and GPT-4o with LLaVA-Critic successfully reinforce three elements of the prompt. In particular, GPT-4o with LLaVA-Critic's feedback produces more detailed and informative instructions.

Rich Feedback and LLaVA-Critic with open-source VLMs. Tables 12 and 13 show the editing instructions generated by LLaVA, Llama and Qwen using Rich Feedback and LLaVA-Critic. We observe that LLaVA-1.6, when paired with Rich Feedback and LLaVA-Critic, can occasionally generate unhelpful instructions like "Fill empty refrigerator" and "repair the broken parts". Llama-3.2 with both feedback types, as well as Qwen-2.5 with Rich Feedback, produce reasonably good instructions but still sometimes include unnecessary parts like "lighten door" and "Add a small, empty shelf" etc. In contrast, Qwen-2.5 with LLaVA-Critic produces concise and helpful instructions that enhance three key aspects of the prompt.

Prompt	An old, and broken refrigerator, open door and empty.	
GPT-4o	1-step	Make exterior rusty and dented; Add dust on surfaces; Remove all items inside.
	2-step	Add dust and dirt to surfaces; Remove all items inside; Add visible damage to fridge exterior.
	Rich Feedback	Add more dirt and grime; Ensure the door is open wider; Remove all items inside the fridge.
	LLaVA-Critic	Add rust and scratches to the exterior; cover surfaces with visible dust; make shelves appear broken and empty.

Table 11: Qualitative examples of critiques generated by GPT-4o with different feedback generating mechanisms.

Prompt	An old, and broken refrigerator, open door and empty.	
Rich Feedback	Llava-v1.6-mistral-7b-hf	Clean dusty refrigerator; Fix broken door; Fill empty refrigerator.
	Llama-3.2-Vison-11B-Instruct	Adjust refrigerator brightness; darken dusty areas; lighten door.
	Qwen2.5-VL-7B-Instruct	Add a small, empty shelf inside the refrigerator; make the refrigerator appear older and worn.

Table 12: Qualitative examples of critiques generated by Rich Feedback with different VLMs.

Prompt	An old, and broken refrigerator, open door and empty.	
LLaVA-Critic	Llava-v1.6-mistral-7b-hf	Clean the dust; repair the broken parts; remove any trash
	Llama-3.2-Vison-11B-Instruct	Turn the fridge light bright white; turn the floor brown; darken the edges.
	Qwen2.5-VL-7B-Instruct	Add dust and scratches; replace contents with old food items.

Table 13: Qualitative examples of critiques generated by LLaVA-Critic with different VLMs.