# Effective Text-to-Image Alignment with Quality Aware Pair Ranking

**Kunal Singh*** **Mukund Khanna** **Pradeep Moturi**
Fractal AI Research
Mumbai

## Abstract

Fine-tuning techniques such as Reinforcement Learning with Human Feedback (RLHF) and Direct Preference Optimization (DPO) allow us to steer Large Language Models (LLMs) to align better with human preferences. Alignment is equally important in text-to-image generation. Recent adoption of DPO, specifically Diffusion-DPO, for Text-to-Image (T2I) diffusion models has proven to work effectively in improving visual appeal and prompt-image alignment. The mentioned works fine-tune on Pick-a-Pic dataset, consisting of approximately one million image preference pairs, collected via crowdsourcing at scale. However, do all preference pairs contribute equally to alignment fine-tuning? Preferences can be subjective at times and may not always translate into effectively aligning the model. In this work, we investigate the above-mentioned question. We develop a quality metric to rank image preference pairs and achieve effective Diffusion-DPO-based alignment fine-tuning.We show that the SD-1.5 and SDXL models fine-tuned using the top 5.33% of the data perform better both quantitatively and qualitatively than the models fine-tuned on the full dataset. The code is available at this link.

## 1 Introduction

Currently, diffusion-based Text-to-Image (T2I) [3, 4, 11, 14] models are state-of-the-art (SOTA) in image generation. These models are trained in a single stage on a large-scale dataset of images scraped from the internet, enabling them to have huge knowledge. However, their outputs often fail to align with human preferences, as they are not explicitly optimized for this purpose. In contrast, Large Language Models (LLMs) undergo training in two distinct stages: the first stage involves pre-training on large web-scale datasets, while the second stage uses Supervised Fine-tuning (SFT) and Reinforcement Learning based on Human Feedback (RLHF) to align outputs with human preferences. While significant progress has been made in alignment fine-tuning for LLMs, aligning T2I outputs with human preferences remains a difficult challenge.

Recent works have begun exploring how to better align T2I models with human preferences. These approaches can be broadly classified into two broad categories – they either use a reward model trained on human preference data to guide the T2I model, or they directly fine-tune the T2I model on pairwise preference data. Reinforcement Learning (RL) based approaches like DRAFT[5], Alignprop[12], ImageReward[19], ReFl[19], do not scale well to large datasets and are highly prone to problems like overfitting and mode collapse. Additionally, training good reward models and using them to fine-tune diffusion models introduces significant operational challenges, as it adds a lot of computational overhead. DPOK[6] and DDPO[2] maximize the scores from the reward model over a set of limited prompts which limits the performance of these methods as the number of prompts increases. DOODL[17] attempts to generate more aesthetically pleasing images by doing iterative

*Corresponding author: Kunal Singh (kunal.singh@fractal.ai)

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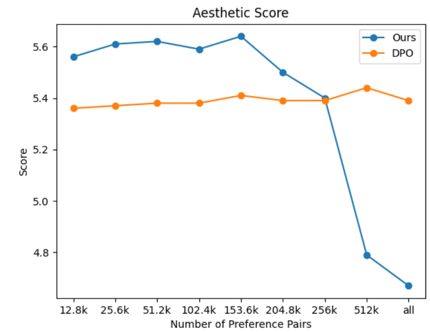
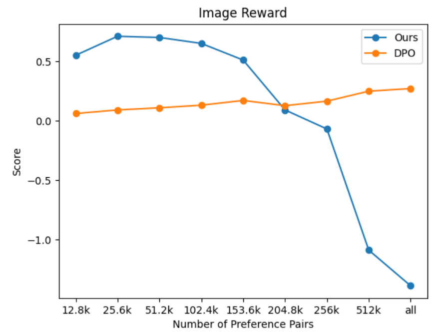
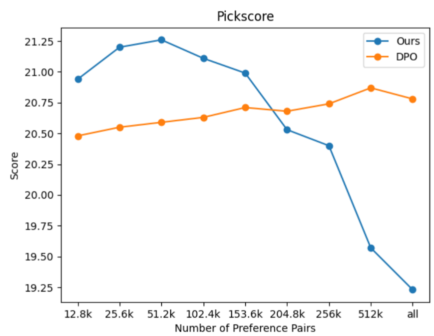


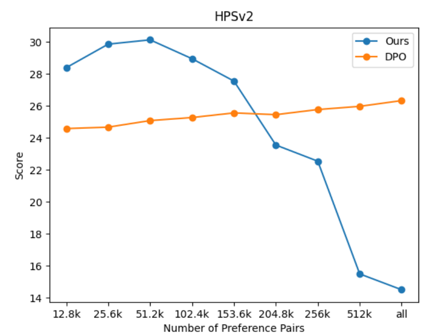

(a) Aesthetic Score vs Number of Preference pairs used for fine-tuning




(b) Image Reward vs Number of Preference pairs used for fine-tuning




(c) Pick Score vs Number of Preference pairs used for fine-tuning




(d) HPS-v2 vs Number of Preference pairs used for fine-tuning

Figure 1: Trend of aesthetic score, Image Reward, PickScore and HPS-v2 while Diffusion-DPO fine-tuning of SD 1.5 on our quality-sorted dataset vs full dataset.

improvements to the generation at run-time. Parrot [9] does multi reward RL finetuning in parallel with a prompt-expansion network.

Taking inspiration from direct preference optimisation (DPO) [13] for aligning LLMs and to overcome challenges with reward modelling based methods, approaches like Diffusion-DPO[16] have emerged, reformulating the loss function to completely remove the reward model and directly fine-tune on pairwise image preference data, which solves the problems of traditional RL-based approaches. In recent works, more preference alignment approaches like Diffusion-KTO[10] and IPO[1] have emerged, building on Diffusion-DPO to further improve diffusion model alignment. Additionally, D3PO[20] suggest creating its own image pairs from a set of prompts and then using a reward model to identify preferred images. Despite all these advances, these approaches still suffer from noisy pairwise preference datasets and over-optimization.

To address these shortcomings, we propose our novel approach — **Effective Text-to-Image Alignment with Quality Aware Pair Ranking**. We introduce a quality metric to assess the quality of a pair of images and the corresponding prompt as a fine-tuning sample. We use this metric to rank all samples from the alignment fine-tuning dataset. We use ranking to prioritise stronger samples over weaker samples during training by fine-tuning on the dataset sorted using this ranking, which we call the Quality-Sorted Dataset (QSD). We observe over 10x improvement in fine-tuning efficiency and demonstrate that over 90% of the samples in Pick-a-Pic v2 [8] dataset send conflicting signals which do more harm than good during RLHF fine-tuning. Finally, we demonstrate through human and AI evaluations that our ranking method improves the performance of SOTA fine-tuning techniques and is preferred by human raters. For brevity, we refer to our approach as DPO-QSD or QSD. Figure 3 (in appendix section) shows the generated image outputs from SDXL base, SDXL-DPO checkpoint fine-tuned on full Pick-a-Pic v2 dataset [8] of approximately 1 million image preference pairs, and SDXL-DPO-QSD fine-tuned on top 50k image preference pairs selected via our method.

## 2 Method: Quality metric for ranking preference pairs

We capture human preferences from online forums, but these judgments are influenced by factors such as malicious intent, varying expertise, and subjectivity. To address this, we focus on pairs that align with overall preferences. Diffusion-KTO selects pairs where the winning image always wins, and the losing image always loses. However, in the Pick-a-Pic dataset [8], less than 5% of images were compared more than five times, and only 25% were compared more than once, making this metric unreliable due to limited comparisons by random users.

We propose a quality metric for pair selection, where a higher score indicates a greater likelihood of the pair being influential. Through experiments, we demonstrate that fine-tuning with higher-quality pairs leads to improved model performance. However, as lower-quality pairs are introduced, performance begins to decline, supporting the importance of ranking image preference pairs.

Consider any paired preference dataset $D = \{(c^1, x_w^1, x_l^1), (c^2, x_w^2, x_l^2), ...., (c^n, x_w^n, x_l^n)\}$, where each sample consists of a caption ($c$), a winning image ($x_w$), and a losing image($x_l$). We use an AI reward model trained to model human preferences to get the probability of the winning image to be winning and the losing image to be losing. We use the HPSv2[18] model that is trained on a expert-reviewed dataset for human preference to output preference for image given the prompt. This preference value will ranges from 0-1, allowing us to interpret them as the probability of the image being preferred. We refer to this model as $\psi$. Now quality $Q$ of each sample pair can be written as

$$Q(c, x_w, x_l) = \psi(x_w/c) * (1 - \psi(x_l/c)) \tag{1}$$

This can be viewed as probability of pair being correct i.e. probability of the winning image being the winning image and the losing image being the losing image. In appendix section A.1, we show the plot of quality scores of all the preference pairs from Pick-a-pic v2 dataset and discuss the segregation of pairs using the plot.

## 3 Experiments

### 3.1 Dataset and Hyper-parameters

We demonstrate the efficacy of our model on the Pick-a-Pic v2 dataset. The dataset contains 1 million rows split into 959.5k rows, 20.5k rows, 20.5k rows of train, validation and test sets respectively. The training set contains approximately 58k distinct captions. We run experiments on SD1.5 and SDXL models. For pairwise preference fine-tuning we use the fine-tuning approach as highlighted in Diffusion-DPO. For both set of experiments we use the ADAMW optimizer. For all SD1.5 and SDXL experiments we use a batch size of 128. All experiments are run on a cluster of 8 NVIDIA 80 GB A100 GPUs. We train at fixed square resolution of 512x512 for SD1.5 and 1024x1024 for SDXL. We train for 1 epoch with a learning rate of $1e^{-4}$ for SD1.5 and $1e^{-5}$ for SDXL. In line with the Diffusion-DPO paper, we use a Beta value of 2000 for SD1.5 and 5000 for SDXL. We do not use any dataset augmentations and keep learning rate constant with no warm-up. For all our experiments we fine-tune using the LoRA approach and use a rank of 64 for both SD1.5 and SDXL.

### 3.2 Evaluation

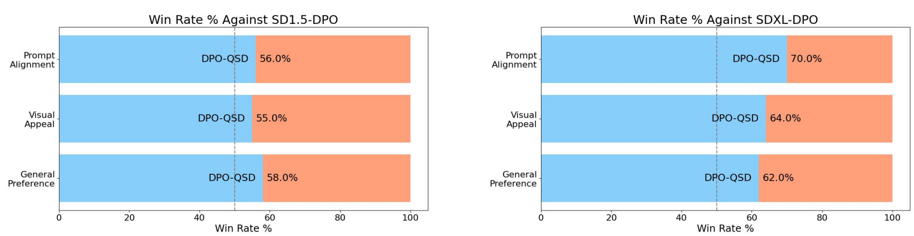
To verify the effectiveness of our approach, we compare against SOTA human preference learning approache, Diffusion-DPO, fine-tuned on the entire training dataset. As we use the LoRA technique, we also fine-tune LoRAs for the SOTA approaches and compare against them. We evaluate all checkpoints on the Pick-a-Pic v2 validation set, which consists of 500 unique prompts. We choose four AI reward models: ImageReward, Pickscore, HPS-v2, and Laion aesthetics classifier. Additionally, we perform a user study to compare our approach to the SOTA Diffusion-DPO. Similar to Diffusion-DPO, we employ reviewers to select the preferred generation under three different criteria: Q1 General Preference (Which image do you prefer given the prompt?), Q2 Visual Appeal (prompt not considered) (Which image is more visually appealing?) Q3 Prompt Alignment (Which image better fits the text description?). 5 responses are collected for each comparison with majority vote (3+) being considered the collective decision. For the user study, we randomly sample 25 prompts from each of the 4 sub-sections of the HPS-v2 test set: photos, anime, paintings and concept-art.

## 4 Results

In Figure 1 for SD1.5 (also, in appendix section, Figure 7 for SDXL), we show that the models fine-tuned using Diffusion-DPO on our QSD significantly outperform the baseline models fine-tuned using Diffusion-DPO on randomly ordered data across 4 key metrics. These results are also presented in Table 1. We also observe a significant improvements in fine-tuning efficiency with our SD1.5 DPO-QSD model and the SDXL DPO-QSD model outperforming the baseline models with just 5.33% of the data. As our fine-tuning data increases, we see a peak in the performance of both models after which the metrics start decreasing or start plateauing. This proves our initial hypothesis that not all fine-tuning pairs are equal and that some fine-tuning data does more harm than good by sending adverse signals. By using only 5.33% of the Pick-a-Pic dataset we achieve our best models, which vastly outperform the baseline models fine-tuned on the full training dataset. This also proves that over 90% of the preference pairs in Pick-a-Pic v2 dataset negatively impact training and can be discarded. Similarly, the user study in Figure 2 shows that our models are preferred by human raters over baseline Diffusion-DPO models. Our SDXL DPO-QSD model is preferred by human annotators 70% of the time in prompt alignment, 64% of the time in visual appeal and 62% of the time in general preference. Similarly, our SD1.5 DPO-QSD model is preferred by human annotators 54% of the time in prompt alignment, 55% of the time in visual appeal and 58% of the time in general preference. In appendix section, we highlight few examples of the high-quality pairs in Figure 5 & low-quality pairs in Figure 6, ranked using our approach.

Table 1: Comparison of our DPO-QSD approach with baseline DPO for SD1.5 and SDXL.

| Method | Aesthetic Score | Image Reward | PickScore | HPSv2 | Samples used |
|---|---|---|---|---|---|
| SD1.5 DPO | 5.39 | 0.27 | 20.78 | 26.34 | 100% |
| **SD1.5 DPO-QSD** | **5.62** | **0.70** | **21.26** | **30.14** | **5.33%** |
| SDXL DPO | 5.97 | 0.85 | 22.20 | 29.40 | 100% |
| **SDXL DPO-QSD** | **6.21** | **1.09** | **22.42** | **31.62** | **5.33%** |




(a) SD1.5-DPO vs SD1.5-DPO

(b) SDXL-DPO-QDS vs SDXL-DPO

Figure 2: SD1.5 & SDXL QSD-DPO outperforms the baseline DPO models in human evaluation.

### 4.1 Effect of Different scoring models

We test the importance of various scoring models by using different reward models to score each pair of images . We run this ablation using LoRA approach for SD1.5 with rank 64, learning rate 1e-4, and a batch size of 128. We keep the quality function constant as $\psi_z(c, x_w) * (1 - \psi_z(c, x_l))$. For this experiment, we try out four different scoring models $\psi_z(c, x_w)$ - HPSv2, Laion aesthetic score predictor, PickScore model, and ImageReward model. To view theses scoring models as probabilities, we standardized the PickScore and Image reward score. We clip the values to +/- 3 and shift scale to 0-1. Aesthetic score is simply divided by 10. As we can observe from Table 2, the model fine-tuned on pairs ranked best using HPS-v2 as the scoring model all other scoring models. ImageReward fails to serve as a good ranking metric for pairs. While the Laion aesthetic predictor shows great improvement in aesthetic score as expected, it fails to show similar improvement across other metrics. HPS-v2 outperforms PickScore and achieves the best results using only 5.33% of the dataset. This ablation reinforces our use of HPS-v2 as a scoring metric.

Table 2: Effect of different scoring models.

| Scoring Method | Aesthetic Score | Image Reward | PickScore | HPSv2 | Samples used |
|---|---|---|---|---|---|
| Baseline Diffusion-DPO | 5.39 | 0.27 | 20.78 | 26.34 | 100% |
| Image Reward | 5.40 | 0.32 | 20.88 | 26.91 | 100% |
| Laion Aesthetics | **5.80** | 0.49 | 21.09 | 27.30 | 16% |
| PickScore | 5.44 | 0.38 | 21.05 | 27.52 | **5.33%** |
| HPS-v2 | 5.62 | **0.70** | **21.26** | **30.14** | **5.33%** |

### 4.2 Effect of LoRA rank

To test the effect of capacity of the LoRA layers and their effect on the model's capability to learn the new information from the dataset, we run experiments with different dimensions of the LoRA layers. Specifically, we want to see how the performance of the model and the fine-tuning efficiency varies with our QSD dataset as we vary the LoRA rank. We run this experiment using SD1.5 as the base model with a learning rate of 1e-4 and a batch size of 128. To this end, we fine-tune with three different LoRA ranks - 32, 64 and 256. For comparison with the baseline, we fine-tune dpo models with the same hyper-parameters and ranks. We present the results in Table 3. As we can observe, we achieve the best results with rank 256 LoRA; however, the improvements over rank 64 are minimal. Therefore, we decide to use rank 64 for our main results. The key observation is that despite the capacity of the LoRA model we get the best fine-tuning efficiency with just 5.33% of the data.

Table 3: Effect of LoRA rank on training efficiency and model performance.

| Model | Rank | Aesthetic Score | Image Reward | PickScore | HPSv2 | Samples used |
|---|---|---|---|---|---|---|
| Diffusion-DPO | 32 | 5.43 | 0.25 | 20.93 | 26.39 | 100% |
| DPO-QSD | 32 | **5.58** | **0.68** | **21.24** | **29.82** | **5.33%** |
| Diffusion-DPO | 64 | 5.39 | 0.27 | 20.78 | 26.34 | 100% |
| DPO-QSD | 64 | **5.62** | **0.70** | **21.26** | **30.14** | **5.33%** |
| Diffusion-DPO | 256 | 5.42 | 0.35 | 20.91 | 26.65 | 100% |
| DPO-QSD | 256 | **5.66** | **0.70** | **21.24** | **30.06** | **5.33%** |

We also make an attempt to study the efficacy of our approach on couple of more fine-tuning methods apart from DPO, using their implementations present in Diffusers [15] in appendix section A.2.

## 5 Conclusion

In this paper, we address the problem of optimal fine-tuning of diffusion models to better align them with human preferences. Unlike previous approaches, we solve this problem by introducing a quality metric that prioritizes high-quality preference pairs and fine-tune in a sorted fashion on this dataset. We demonstrate that our data ranking strategy significantly enhances diffusion model alignment, achieving superior results across multiple AI-based metrics and human evaluators. Our experiments show that models fine-tuned with less than top 10% of the Pick-a-Pick v2 dataset outperform baseline models in both quantitative metrics and human preference evaluations. We run multiple ablations to showcase the effectiveness of our data ranking approach across multiple methods. We validate our initial hypothesis that not all preference pairs contribute equally, and fine-tuning on the entire dataset can be detrimental. By applying our fine-tuning strategy alongside early stopping, one can significantly enhance training efficiency, leading to a more robust & powerful model. **Limitations & Ethics**: We verified our method on pick-a-pic crowd sourced dataset collected from anonymous users whose decisions might be effected by various factors. Any T2I generation poses ethical risks, including the potential for harmful, biased, or explicit content due to web-collected data & humans biases. Efforts to mitigate these risks include diverse labeling & safety filtering during development.

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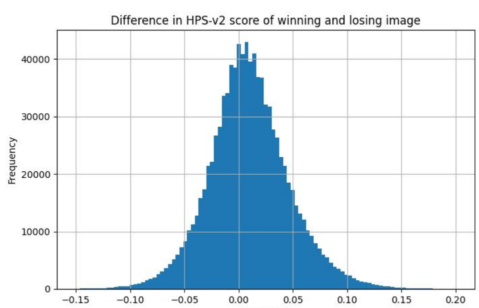
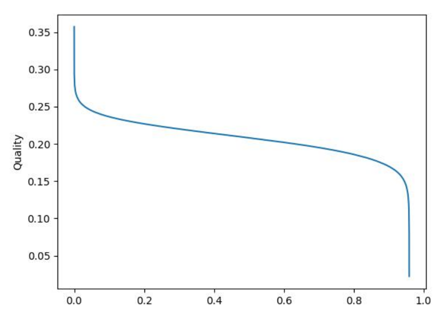
# A Appendix / supplemental material

Figure 3: Top to Bottom: *SDXL-DPO-QSD, SDXL-DPO, SDXL* Prompts: *(1) A smiling beautiful sorceress wearing a high necked blue suit surrounded by swirling rainbow aurora, hyper-realistic, cinematic, post-production (2) Concept art of a mythical sky alligator with wings, nature documentary (3) A galaxy-colored figurine is floating over the sea at sunset, photorealistic (4) close up headshot, steampunk middle-aged man, slick hair big grin in front of gigantic clocktower, pencil sketch (5) A swirling, multicolored portal emerges from the depths of an ocean of coffee, with waves of the rich liquid gently rippling outward. The portal engulfs a coffee cup, which serves as a gateway to a fantastical dimension. The surrounding digital art landscape reflects the colors of the portal, creating an alluring scene of endless possibilities.*




(a) Difference in HPSv2 scores (which can be viewed as probability of being preferred) of the winning image and the losing image.




(b) Quality metric plotted in a sorted order for preference pairs in the Pick-a-Pic dataset.

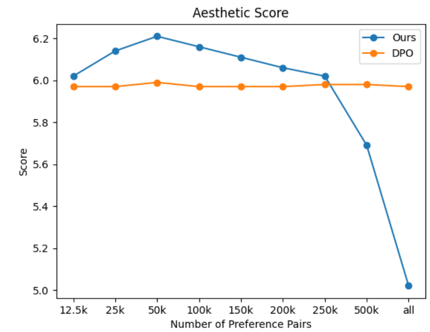
Figure 4: Left - plot of difference in HPSv2 sores for Pick-a-Pic train dataset, Right - plot of quality metric on Y-axis with the sorted dataset index on X-axis.


Figure 5: Examples of good pairs ranked best using our method. *Top row: Winning Image, Bottom row: losing image*. The winning images of good samples have better prompt adherence, aesthetic score and are more preferable to humans. Caption from left to right: *(1) A closeup portrait of a playful maid, undercut hair, apron, amazing body, pronounced feminine features, kitchen, freckles, flirting with camera, (2) A nun holding a sign that says repent, (3) Roman emperor, photo, palace background, (4) A rabbit in a 3 piece suit, sitting in a cafe. Hyper Realistic, ultra realistic, 8k, (5)a painting of a woman with an owl on her shoulder, james gurney and andreas rocha, owl princess with crown, also known as artemis or selene, wlop and sakimichan, detaild, portrait character design, falcon, portrait of modern darna, crowned, golden goddess, white witch, by Johannes Helgeson, goddess of travel*

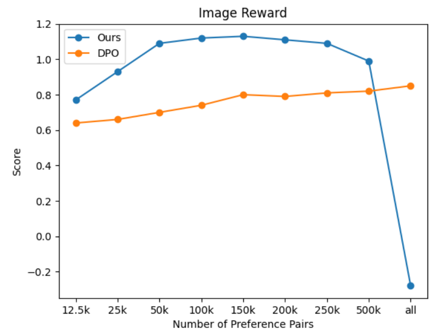
Figure 6: Examples of bad pairs identified by our method. *Top row: Winning Image, Bottom row: losing image*. As can be observed, in these pairs the losing image is better in some quality like aesthetics or prompt adherence over the winning image. Caption from left to right: *(1)a little faery floating in the style of dan hipp, (2) cat wearing a hat, (3) "Hello world" text, space, planets style, (4) face close up woman Jean-Baptiste Monge, watercolour and ink, intricate details, a masterpiece, dynamic backlight, (5) Design a logo for a modern, high-end medical clinic that specializes in personalized, holistic healthcare. The clinic is called "C" and focuses on improving patients' overall well-being through nutrition, exercise, and mental health support. The logo should be simple, sleek, and convey a sense of warmth and approachability while still exuding professionalism and expertise*

### A.1 Quality

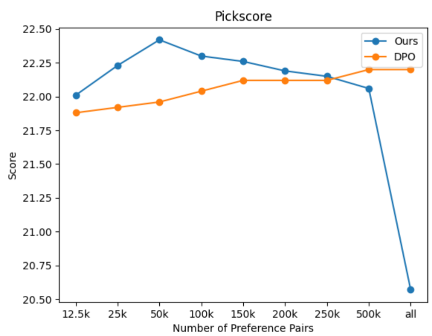
In Figure 4b, we see a sharp decrease in quality score for the initial 100k pairs, followed by a gradual decline for the majority of the dataset, and finally, another sharp drop towards the end, where the samples are of the poorest quality. This plot illustrates that the dataset has good samples where the winning image is clearly better, average samples where the preference is more subjective and bad samples where the reward model does not agree with human labels.



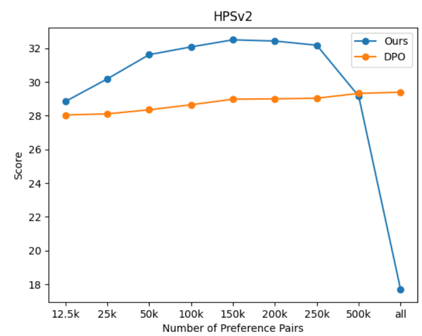

(a) Aesthetic Score vs Number of preference pairs used for fine-tuning




(b) Image Reward vs Number of preference pairs used for fine-tuning




(c) Pick Score vs Number of preference pairs used for fine-tuning




(d) HPS-v2 vs Number of preference pairs used for fine-tuning

Figure 7: Trend of aesthetic score, Image Reward, PickScore and HPS-v2 while Diffusion-DPO fine-tuning of SDXL on our quality-sorted dataset vs full dataset.

### A.2 Efficacy with different fine-tuning methods

We fine-tune the base model using different fine-tuning methods to show that our QSD is effective in improving performance across different fine-tuning approaches. For all experiments, we fine-tune the baseline on the train dataset with random ordering, while our approach uses the quality sorted dataset. We experiment with the loss function of Diffusion ORPO and loss function defined in SLIC-HF[21], we use their implementations from diffusers[15]. We run this ablation using LoRA approach for SD1.5 with rank 64, a batch size of 128, and a learning rate of 1e-4. For Diffusion-ORPO inspired from ORPO[7], we use a learning rate of 1e-3 for baseline model and our model as well. We use the quality metric as described in the methodology section. For these experiments, we select the best-performing model and present the results in table 4. As we can observe, our approach performs considerably better than the baseline across both the methods. Moreover, our approach achieves these results while using only the top 5.33% of the data in case of SLIC-HF and top 10.6% of the data for ORPO, demonstrating over a 10x gain in fine-tuning efficiency. This ablation proves that our pair ranking method improves performance across different fine-tuning paradigms and is not limited to the Diffusion-DPO loss formulation. We believe that the loss in efficiency for Diffusion-ORPO stems from the inclusion of the mean squared error loss of the winning image in the overall loss function, which dominates the other loss terms

Table 4: Efficacy of our ranking method on different fine-tuning paradigms using Pick-a-Pic dataset.

| Method | Aesthetic Score | Image Reward | PickScore | HPSv2 | Samples used |
|---|---|---|---|---|---|
| SLIC-HF baseline | 5.45 | 0.33 | 20.93 | 26.71 | 100% |
| **SLIC-HF-QSD** | **5.69** | **0.72** | **21.24** | **29.65** | **5.33%** |
| ORPO baseline | 5.51 | 0.30 | 20.57 | 26.97 | 100% |
| **ORPO-QSD** | **5.60** | **0.60** | **20.80** | **28.25** | **10.6%** |

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