Prompt Refinement with Image Pivot for Text-to-Image Generation

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Abstract

For text-to-image generation, automatically refining user-provided natural language prompts into the keyword-enriched prompts favored by systems is essential for the user experience. Such a prompt refinement process is analogous to translating the prompt from "user languages" into "system languages". However, the scarcity of such parallel corpora makes it difficult to train a prompt refinement model. Inspired by zero-shot machine translation techniques, we introduce Prompt Refinement with Image Pivot (PRIP). PRIP innovatively uses the latent representation of a user-preferred image as an intermediary "pivot" between the user and system languages. It decomposes the refinement process into two data-rich tasks: inferring representations of user-preferred images from user languages and subsequently translating image representations into system languages. Thus, it can leverage abundant data for training. Extensive experiments show that PRIP substantially outperforms a wide range of baselines and effectively transfers to unseen systems in a zero-shot manner[1].

1 Introduction

Recent breakthroughs in text-to-image generation have markedly expanded the boundaries of digital artistry, enabling the creation of visually compelling images with unprecedented ease (Kingma et al., 2021; Ho et al., 2020; Lu et al., 2023; Zhu et al., 2024; Zhang et al., 2024b). However, the complexity of crafting effective prompts presents a significant challenge to average users. This challenge stems from the significant difference between user-provided natural language prompts and the keyword-enriched prompts required for system's high-quality rendering (Brade et al., 2023; Witteveen and Andrews, 2022; Parsons, 2022; Chen et al., 2023). We term the two kinds of prompts as *user languages* and *system languages*. System languages usually include technical terms and artistic references unfamiliar to non-specialists (Liu and Chilton, 2022; Oppenlaender, 2022). Crafting prompts in system languages is not intuitive, even for the system's developers, and only becomes clear after extensive user experimentation and community-driven insight (Liu and Chilton, 2022; Parsons, 2022; Deckers et al., 2023).

Developing a model that automatically refines user languages into system languages is essential to enhance user experience (OpenAI, 2023; Hao et al., 2022; Brade et al., 2023). Yet, the shortage of high-quality refinement pairs makes it difficult to train such models. On the one hand, refining prompts requires expertise, which makes annotation expensive. On the other hand, humans can hardly refine prompts to the optimum due to the intricate nature of system languages. As demonstrated in Hao et al. (2022) and our experimental results, human-generated refinement data is suboptimal for training prompt refinement models.

As prompt refinement is analogous to a machine translation task that converts the prompts written in user languages into system languages, the lack of high-quality refinement pairs echoes the challenge of machine translation for low-resource languages (Mhaskar and Bhattacharyya; Ranathunga et al., 2023), in which a source language is translated into a target language without sufficient parallel corpora for training. MT researchers tackle this through a "pivoting" approach (Wu and Wang, 2007; Cohn and Lapata, 2007), which utilizes a high-resource language as the intermediate "pivot language". Thus, the source-target translation is achieved by training two separate models: a source-pivot model and a pivot–target model. Text from the source language is first translated to the pivot language and then to the target language.

Inspired by pivot-based MT solutions, we pro-

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[1]We have open-sourced code and data at https://github.com/jingtaozhan/PromptReformulate

Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 941–954
August 11-16, 2024

pose **P**rompt **R**efinement with **I**mage **P**ivot (PRIP). PRIP employs the latent representation of a user-preferred image as the pivot between user and system languages. It decomposes prompt refinement into the following two phases. In the first phase, PRIP takes the prompt in user languages as input and infers what images the user prefers. It outputs a latent representation, which focuses on high-level semantics instead of pixel-level details, for the image that is preferred by the user. In the second phase, PRIP takes the latent representation of an image as input and outputs a prompt in the system language that can guide the text-to-image system in rendering this image. By doing so, PRIP reframes a data-limited prompt refinement problem into two data-rich tasks. For example, user-image preference pairs can be constructed using preference simulation models like HPSv2 (Wu et al., 2023) or user click behaviors, and image-system decoding pairs can be sampled from interaction logs or prompt-sharing websites.

We evaluate PRIP by applying it to various text-to-image models and comparing it with extensive baselines. Results demonstrate that PRIP not only substantially improves the text-to-image system seen during training, but also effectively transfers to various unseen systems in a zero-shot manner. It significantly outperforms a wide range of baselines, including general large language models and prompt refinement models trained with human-generated or synthetic refinement pairs.

2 Related Work

Text-to-Image Prompting. The automatic refinement of user language into system language is a critical enhancement for a user-friendly text-to-image system (Xie et al., 2023). For a typical text refinement model, training relies heavily on large-scale source-target refinement pairs (Stahlberg, 2020). However, acquiring such pairs for image prompt refinement is challenging due to the intricate nature of system language, which often exceeds the annotation capacities of crowdsourced workers. To avoid this, some researchers have shifted towards interactive systems that aid users by suggesting enhancements to their prompts, which mitigates but does not dispense with the need for manual refinement (Feng et al., 2023; Brade et al., 2023; Liu and Chilton, 2022). Others have attempted to train automatic refinement systems using synthetically generated training pairs, mainly through rephrasing well-crafted prompts into simpler user language forms (Hao et al., 2022). Yet its synthetic nature often leads to suboptimal refinement performance. Our PRIP addresses the challenge by leveraging the user-pivot-system pipeline, thus avoiding reliance on direct user-system pair annotations.

Prompting Large Language Models (LLMs). There has been research on how to prompt LLMs, such as chain of thoughts (Wei et al., 2022) and automated template learning (Jiang et al., 2020; Haviv et al., 2021). Interested readers can refer to the survey by Liu et al. (2023). These studies primarily focus on eliciting the knowledge learned by LLMs during pre-training. However, in cross-modal scenarios like text-to-image generation, the monomodal pre-training of LLMs does not truly capture how prompts influence the image generation process. As a result, generic LLMs do not possess the capability to refine text-to-image prompts, which is also demonstrated in our experiments.

Finetuning Generation Models. Several researchers finetune text-to-image models for prompt understanding. Xu et al. (2023) finetune the generation model on user inputs and use ImageReward as reward. Zhong et al. (2023) finetune the text encoder within the generation model to align simple user inputs with complex prompts. deep-floyd (2024) utilize a large language model to process the prompt for better understanding. Our experiments show that PRIP can further improve these models.

3 Method

This section introduces **P**rompt **R**efinement with **I**mage **P**ivot (PRIP). We first analyze the prompt refinement task. Then we describe how to decompose the user-system refinement process into user-pivot and pivot-system sub-tasks, where the pivot is the representation of the image preferred by the user. Finally, we elaborate on the training approaches for the user-pivot-system framework.

3.1 Problem Analysis

For text-to-image generation, there exists a notable divergence between the natural language prompts input by non-specialist users, termed *user language*, and the specialized detail-rich prompts, termed *system language*. User languages are often colloquial and ambiguous. System languages include details and artistic terminology, which can guide the systems to yield visually stunning images.

Prompt refinement systems are optimized to au-

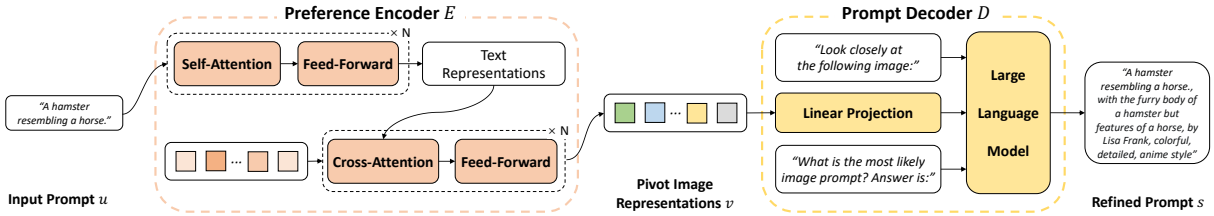


Figure 1: PRIP Model Architecture: a Preference Encoder and a Prompt Decoder. (1) Upon receiving a user prompt, Preference Encoder first applies a transformer to derive a token-level representation. A subsequent transformer leverages cross-attention to deduce the image preference and yields an image representation. (2) Prompt Decoder then employs a linear layer to align the dimensionality. This aligned representation is integrated into a template and input into a large language model, which generates the refined system prompt.

tomatically translate user language into system language. We use $\mathcal{R}$ to denote the refinement system, which refines the user language u into the system language s with probability $\mathcal{R}(s|u)$. The text-to-image generation system is denoted as $\mathcal{G}$, where $\mathcal{G}(i|p)$ represents the likelihood of generating an image i from a prompt p. The function $f(i, p)$ quantifies the user satisfaction probability correlating a prompt p with image i.

Thus, the objective $\mathcal{F}$ of prompt refinement is:

$$\mathcal{F} = \mathop{\mathbb{E}}_{u,s,i}[f(i,u) \cdot \mathcal{G}(i|s) \cdot \mathcal{R}(s|u)], \qquad (1)$$

where the refinement system $\mathcal{R}$ should output system language s that maximizes the user satisfaction within the generation probabilities $\mathcal{G}(i|s)$. Ideally, the training of $\mathcal{R}$ would rely on a rich parallel corpus of user-system pairs $\{u, s\}$. However, the rarity of such paired data makes training $\mathcal{R}$ directly with this objective function a considerable challenge.

Viewing $\mathcal{R}$ as a translation model, with u and s as the respective source and target languages, the above challenge is akin to the zero-shot MT problem (Mhaskar and Bhattacharyya; Ranathunga et al., 2023), where direct source-target translation pairs are absent. Zero-shot MT overcomes this by using a pivot language v, which is a high-resource language and ensures conditional independence between the source and target languages (Wu and Wang, 2007; Cohn and Lapata, 2007; Bertoldi et al., 2008). Thus, the source language u can be first translated into the pivot language v and then to the target language s. $\mathcal{R}(s|u)$ is formally reframed as:

$$\mathcal{R}(s|u) = \textstyle\sum_v [D(s|v) \cdot E(v|u)], \qquad (2)$$

where D and E denote pivot-target and source-pivot translation models, respectively. The pivot language v, being high-resource, addresses the data-scarce problem. During inference, to simplify the translation process, the most probable pivot language v^* is selected $v^* = \arg\max_v E(v|u)$, and the translated output s^* is $s^* = \arg\max_s D(s|v^*)$. In this paper, we adapt this technique to tackle prompt refinement for text-to-image generation.

3.2 Model Architecture

Building upon the principles of zero-shot MT, we introduce **P**rompt **R**efinement with **I**mage **P**ivot (PRIP). PRIP utilizes the representation of the user-desired image as the pivot v during the prompt refinement process. The refinement workflow, depicted in Figure 1, unfolds in two distinct stages: (1) initially, PRIP uses a Preference Encoder E to infer the user's preferred image from the user language prompt. The Preference Encoder adopts a T5-like architecture (Raffel et al., 2020). It first encodes the user language prompt into token-level latent representations and then employs a cross-attention mechanism to produce the pivot image representations. (2) subsequently, PRIP uses a Prompt Decoder D to decode the corresponding system language prompt. The Prompt Decoder is based on a large language model. It accepts the pivot image representations as input, which are then projected to the required dimensionality by a linear layer. The generation process is guided by a prompt template. The Prompt Decoder's output is the refined, system language prompt.

Both user-pivot and pivot-system stages can leverage extensive training data. The user-pivot stage requires user-image preference data. The data can be easily sourced from click logs or synthesized with user preference simulation models like HPSv2 (Wu et al., 2023). This data may also be annotated, which requires less specialized expertise compared with annotating refinement pairs. The pivot-system stage uses image-prompt pairs. Such data is readily-available from the system's genera-

tion logs or from online websites where users share prompts (sta; pro). It does not require annotation and simply relies on the input and output correspondences of the system.

PRIP reframes the refinement objective $\mathcal{F}$ as:

$$\mathcal{F} = \mathop{\mathbb{E}}_{u,s,i}[f(i,u)\ \mathcal{G}(i|s)\ \textstyle\sum_v D(s|v)E(v|u)] \quad (3)$$

To effectively optimize this objective, the training process of PRIP is in two stages. The initial stage involves deriving an approximate objective and employing rich parallel data $\{u, v\}$ and $\{v, s\}$ to warm up PRIP. The subsequent stage leverages reinforcement learning to directly optimize the above objective. They are detailed in the following.

3.3 Disentangled Supervised Training

We adopt two objectives approximate to Eq. (3) to warm up PRIP. They enable the use of rich, readily-available data for training. They are derived as:

$$\mathcal{F} \geq \mathop{\mathbb{E}}_{u,s,i}[f(i,u) \cdot \mathcal{G}(i|s) \cdot D(s|i) \cdot E(i|u)]$$

$$= \mathop{\mathbb{E}}_{u,i}[f(i,u)\ E(i|u)] \cdot \mathop{\mathbb{E}}_{s,i}[\mathcal{G}(i|s)\ D(s|i)] + \mathrm{Cov}$$

The inequality approaches equality when the evaluated expression is zero for $v \neq i$. This is possible when $\mathcal{G}$ and D form perfect one-to-one correspondences, zeroing $\mathcal{G}(i|s) \cdot D(s|v)$ for all $v \neq i$. For text-to-image systems with strong prompt-following abilities, this simplification of a one-to-one mapping is close and the approximation is reasonable. The term Cov is the covariance between $f(i,u) \cdot E(i|u)$ and $\mathcal{G}(i|s) \cdot D(s|i)$. When they are uncorrelated, the covariance term reduces to zero. We temporarily disregard the covariance and adopt the product of expectations as an approximate surrogate for the original objective. The resulting training objectives are individually focused:

$$\max_E \mathop{\mathbb{E}}_{u,i}[f(i,u) \cdot E(i|u)] \quad (4)$$

$$\max_D \mathop{\mathbb{E}}_{s,i}[\mathcal{G}(i|s) \cdot D(s|i)] \quad (5)$$

These refocused optimization targets permit disentangled training of each module. The subsequent sections detail the specific training processes.

3.3.1 Training User-Pivot Preference

User-pivot transition is guided by Eq. (4), The Preference Encoder is trained to predict the image that can maximize user satisfaction.

As shown in Figure 2, the training process is in two steps. (1) Firstly, we sample the image i^* that can maximize user satisfaction $f(i,u)$, namely $i^* = \arg\max_i f(i,u)$. Sampling such data is easier than annotating user-system refinement pairs: annotating preference does not require special expertise for annotators and preference can also be extracted from click behaviors in interaction logs. (2) Secondly, The Preference Encoder E is trained to predict i^* given u. The user language u is processed by the Preference Encoder, outputting the predicted representation $\hat{u}$. The image i^* is input into an image encoder and results in its semantic representation $\hat{i}^*$. The discrepancy between these representations is minimized with MSE loss:

$$\mathcal{L}_{MSE} = ||\hat{i}^* - \hat{u}||_2^2 \quad (6)$$

With this training process, the Preference Encoder aligns with user preferences by learning to imagine the user-preferred images.

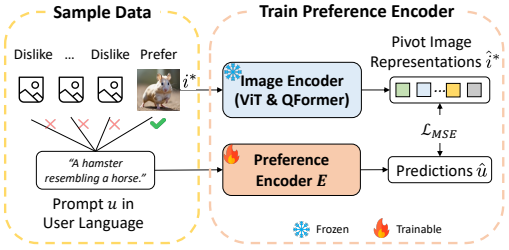


Figure 2: Training Preference Encoder: Prompts and preferred images are paired to create the training set. The objective is to minimize the Mean Squared Error between the ground-truth image representations and the predictions from the Preference Encoder.

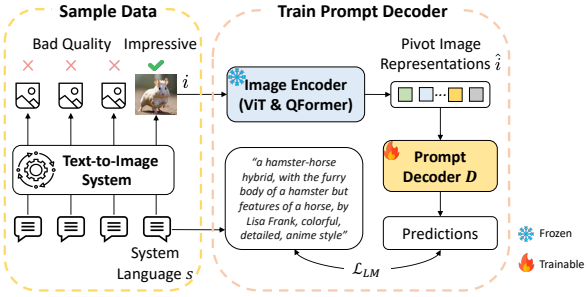


Figure 3: Training Prompt Decoder: Prompts that can generate impressive images are sampled as the system language. The objective is to predict the system language based on the associated image representation.

3.3.2 Training Pivot-System Decoding

Pivot-system transition is guided by Eq. (5). The Prompt Decoder is trained to reconstruct the system language from the pivot image representation.

As illustrated in Figure 3, the training process is in two steps. (1) Firstly, we collect system lan-

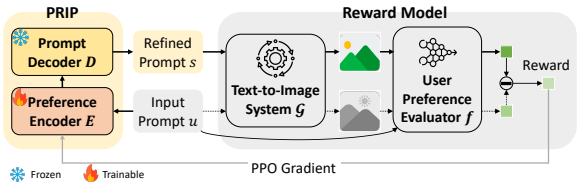


Figure 4: End-to-End RL Training: Given a user prompt, PRIP generates a refined prompt, and Reward Model evaluates user preference scores for generated images. The differential in scores serves as the reward, and PRIP is updated with PPO Gradient.

guage prompts s and their corresponding generated images i. The system languages are high-quality prompts suitable for the generation system. They can be sampled from the user-submitted prompts in the generation log or from websites where users share well-performing prompts. (2) The Prompt Decoder is trained to generate system language s from the image i. A frozen image encoder processes the image i, creating its representation $\hat{i}$. This representation serves as the training context for the Prompt Decoder to predict the system language. Autoregressive language modeling objective is used and is formulated as follows:

$$\mathcal{L}_{LM} = -\sum_n \log D(s_n | s_{1:n-1}, \hat{i}), \qquad (7)$$

where s_n is the n-th token of s. In this way, the Prompt Decoder aligns with the generation systems by learning to reverse the generation process.

3.4 End-to-End User-Pivot-System Training

While the previously described training stages effectively optimize the user-pivot and pivot-system transitions on supervised data, they serve primarily as approximations of the ultimate objective presented in Eq. (3). To bridge this gap, we leverage the previous training as a warm-up stage and subsequently employ Eq. (3) for end-to-end training.

We adopt reinforcement learning (RL) and define the reward as the differential in preference scores. This is equivalent to Eq. (3):

$$\arg\max_{D,E} \mathcal{F} = \arg\max_{D,E} \mathbb{E}\left[\text{reward}\ D(s|v)E(v|u)\right],$$
$$\text{reward} = \sum_i f(i,u)\mathcal{G}(i|s) - \sum_{i'} f(i',u)\mathcal{G}(i'|u)$$

The training workflow is depicted in Figure 4. For any given prompt, we generate two image sets: one set from the initial prompt and another from the refined system prompt. The reward is computed as the differential in preference scores between these two sets. To enhance training efficiency, Prompt Decoder remains frozen due to the significant computational costs of training a large language model. Only Preference Encoder is updated with proximal policy optimization (PPO) (Schulman et al., 2017), a well-regarded RL algorithm.

3.5 Inference Process

During inference, the Preference Encoder and the Prompt Decoder are concatenated as a user-pivot-system pipeline. Given a prompt, the Preference Encoder predicts the representation of the user-preferred image. Then, the Prompt Decoder decodes the representation and outputs the refined prompt. The refined prompt is input to the generation system for image rendering.

Furthermore, since the Prompt Decoder cannot directly access the initial prompt, it might result in a hallucination problem (Ji et al., 2023) when the refined prompt is generated. A solution is to provide the initial prompt as additional context to the Prompt Decoder during inference. This paper uses a straightforward approach: prepending the initial prompt as a prefix and using the Prompt Decoder for expansion. The refined prompt starts with the initial prompt and consists of many details added by the Prompt Decoder. Future studies may investigate other methods. For example, constrained beam search can also use the initial prompts as additional context by constraining the refined prompts to be semantically close to the initial prompts. We leave this exploration to future work.

4 Experimental Setup

4.1 Evaluation Setup

Generation Systems. We evaluate the prompt refinement performance for a wide range of generation systems. When PRIP and other refinement baselines are trained, they are optimized for **Stable Diffusion 1.4 (SD1.4)** (Rombach et al., 2022). Thus, the refinement performance on SD1.4 corresponds to the in-distribution performance. We also employ various advanced generation systems to evaluate the out-of-distribution performance. They are: (1) **Stable Diffusion XL base 1.0 (SDXL)** (Podell et al., 2023), a state-of-the-art generation model that is much stronger than SD1.4. (2) **Deepfloyd-IF (IF)** (deep-floyd, 2024), an advanced model for high degree of prompt understanding. It employs a T5-XXL model for prompt processing. (3) **SUR** (Zhong et al., 2023), which is specifically proposed to understand simple user

inputs for high-quality rendering. (4) **ReFL** (Xu et al., 2023), which is initialized from SD1.4 and further trained with the same reward model as PRIP. The difference is that ReFL trains the generation model while PRIP modifies the input. We also attempted to evaluate on DALL-E 3 (OpenAI, 2023). However, due to restrictions on its inputs, such as not allowing artists' names, our test prompts and refined prompts often do not meet these restrictions and make evaluation impossible.

Dataset. We conduct evaluations using the HPS prompt dataset (Wu et al., 2023), which includes a wide variety of prompts mined from user interactions and image captions. It is a standard benchmark to evaluate text-to-image generation performance (Clark et al., 2023; Wallace et al., 2023). The prompts are categorized into Anime, ConceptArt, Painting, and Photo. Each category contains 800 prompts. For each prompt, we generate four images to ensure a robust assessment.

Metrics. We employ both automated and human judgment. Automated assessments utilize ImageReward (Xu et al., 2023) and HPSv2 (Wu et al., 2023), which are trained to mimic human preferences and have been demonstrated to accurately align with actual human judgments. Humans annotate relevance and win ratios. Relevance is the prompt-image alignment on a scale of 0 (irrelevant) to 2 (highly relevant). Win ratio (and tie) shows pairwise prompt-image preference between two generation systems. We randomly sample 30 prompts per category and report the annotation results averaged on all 120 prompts. Each pair is annotated by three people who are familiar with text-to-image generation and of different backgrounds.

4.2 Baselines

We compare PRIP against a comprehensive set of prompt refinement baselines: (1) **GPT3.5 & 4**: They are generic language models and are not tailored for prompt refinement. To guide them, we use a popular prompt template from bluelovers (2023) and slightly modify it for this task. The template contains guidance and examples. (2) **PromptistSFT** & **PromptistRL** (Hao et al., 2022): PromptistSFT is trained on synthesized parallel data: system languages are collected from prompt-sharing websites, while user languages are rephrased from the system languages to simple form by ChatGPT. Initialized from PromptistSFT, PromptistRL undergoes an RL process with CLIP (Radford et al., 2021) and Aesthetic scores (Schuhmann, 2022) as reward. (3) **Rew-Syn** & **Rew-Syn+RL**: We enhance PromptistSFT and PromptistRL by aligning them with user preference. Rew-Syn uses ImageReward and HPSv2 to filter out the PromptistSFT training pairs whose refinement does not improve satisfaction scores. Rew-Syn+RL utilizes ImageReward and HPSv2 as reward, which is identical to PRIP's. (4) **Rew-Log** & **Rew-Log+RL**: Rew-Log extracts human rewriting pairs from a large-scale interaction log (Wang et al., 2023) by pairing the first and the last prompts in the same session. It filters out the pairs that do not improve ImageReward or HPSv2 scores. Rew-Log+RL is initialized from Rew-Log and undergoes the same RL training process as PRIP's.

4.3 Implementation Details

Architecture. The model architecture is as follows. Preference Encoder and Prompt Decoder are initialized with FLAN-T5-Large (Chung et al., 2022) and Llama2-7B (Touvron et al., 2023), respectively. We use the vision component of BLIP-2 (Li et al., 2023) as the frozen Image Encoder.

Data. Training data for PRIP can be easily acquired, as discussed in Section 3.2. In this paper, we collect data from DiffusionDB (Wang et al., 2023), a real interaction log between 10k users and SD1.4. Since this dataset logs the multiple generated images for each prompt, we can sample the most-preferred image for training the user-pivot model (the Preference Encoder). We use ImageReward to simulate user preference and select the highest-scored image as the pivot. We also observe that there exist high-quality prompts in the log that can serve as the system languages. Therefore, we sample these prompts and the associated images for training the Prompt Decoder model. The sampling criterion is empirically set: the CLIP and Aesthetic scores are above 0.28 and 5.2, respectively. Future studies can explore other data resources.

Please refer to Appendix A.4 for more details.

5 Experimental Results

This section presents the experimental results. We first evaluate models on various generation systems, including the one used during training (in-distribution scenario) and several unseen, advanced systems (out-of-distribution scenario). Then, we show how PRIP refines the prompt by presenting several cases. Finally, a comprehensive ablation study demonstrates the effectiveness of pivoting.

Evaluation Metric	ImageReward				HPSv2				Relevance	Win	Win+Tie
Dataset	Anime	ConceptArt	Painting	Photo	Anime	ConceptArt	Painting	Photo	All	All	All
SD1.4	0.038*	0.185*	0.190*	0.130*	27.42*	26.86*	26.86*	27.57*	1.38	1%*	**100%**
+ GPT3.5	-0.037*	0.030*	0.126*	-0.005*	27.36*	26.77*	26.87*	27.41*	–	–	–
+ GPT4	-0.143*	-0.024*	0.030*	-0.196*	27.29*	26.71*	26.76*	27.28*	–	–	–
+ PromptistSFT	-0.140*	-0.083*	0.010*	-0.287*	27.19*	26.60*	26.77*	26.88*	–	–	–
+ Rew-Syn	-0.015*	0.056*	0.223*	-0.221*	27.35*	26.79*	26.99*	26.96*	–	–	–
+ Rew-Log	0.066*	0.151*	0.173*	0.063*	27.44*	26.87*	26.86*	27.51*	–	–	–
+ PromptistRL	-0.009*	0.092*	0.211*	-0.060*	27.29*	26.73*	26.89*	26.97*	1.20*	38%*	84%
+ Rew-Syn+RL	0.079*	0.135*	0.246*	0.138*	27.46*	26.85*	26.99*	27.70*	1.31*	40%*	89%
+ Rew-Log+RL	0.028*	0.177*	0.187*	0.105*	27.42*	26.85*	26.86*	27.55*	1.33*	6%*	96%
+ **PRIP**	**0.346**	**0.443**	**0.576**	**0.252**	**27.97**	**27.45**	**27.65**	**28.03**	**1.45**	**73%**	94%

Table 1: In-distribution refinement performance on the seen system (SD1.4). Win/Tie ratio shows preference against SD1.4, and SD1.4's "Win+Tie" is always 100%. Human annotation is only conducted on RL-based methods to save costs. * indicates PRIP significantly outperforms the baseline with p-value < 0.01 measured by T-Test. PRIP substantially outperforms baselines.

Evaluation Metric	ImageReward				HPSv2				Relevance	Win	Win+Tie
Generation Model	SDXL	IF	SUR	ReFL	SDXL	IF	SUR	ReFL	SDXL	SDXL	SDXL
w\ o refine	0.866*	0.624*	0.596*	0.421*	27.76*	27.63*	27.82*	27.64*	1.67	1%*	**100%**
+ GPT3.5	0.753*	0.569*	0.431*	0.316*	27.67*	27.57*	27.72*	27.57*	–	–	–
+ GPT4	0.702*	0.455*	0.360*	0.214*	27.67*	27.41*	27.67*	27.49*	–	–	–
+ PromptistSFT	0.679*	0.298*	0.374*	0.229*	27.54*	26.93*	27.53*	27.44*	–	–	–
+ Rew-Syn	0.817*	0.464*	0.513*	0.347*	27.72*	27.17*	27.67*	27.60*	–	–	–
+ Rew-Log	0.850*	0.591*	0.561*	0.401*	27.75*	27.57*	27.79*	27.62*	–	–	–
+ PromptistRL	0.833*	0.509*	0.547*	0.404*	27.67*	27.21*	27.65*	27.56*	1.52*	40%*	88%
+ Rew-Syn+RL	0.874*	0.579*	0.596*	0.459*	27.81*	27.46*	27.83*	27.77*	1.62	51%*	89%
+ Rew-Log+RL	0.861*	0.619*	0.573*	0.406*	27.77*	27.60*	27.79*	27.63*	1.67	4%*	98%
+ **PRIP**	**0.983**	**0.741**	**0.789**	**0.640**	**28.15**	**27.90**	**28.22**	**28.14**	**1.68**	**82%**	96%

Table 2: Out-of-distribution refinement performance on unseen systems. Results are averaged on four categories. Human annotation is only conducted on RL-based methods for SDXL to save costs. Win/Tie ratio shows preference against generation without refinement. Note that the first row is generation without refinement and its "Win+Tie" is 100%. * indicates PRIP significantly outperforms the baseline with p-value < 0.01 measured by T-Test. PRIP effectively transfers to unseen systems.

5.1 In-Distribution Performance

Table 1 presents the in-distribution refinement performance. We have the following observations: (1) Results indicate that generic language models like GPT3.5 and GPT4 do not excel at refining image prompts. We find that GPT3.5 merely rephrases prompts without adding details and sometimes hallucinates, which results in its output being mostly ineffective. As for GPT4, it can effectively add rich details compared with GPT3.5. Yet its added details often misalign with the initial prompts, leading to even worse performance. (2) Synthetically generated refinement pairs also demonstrate limited efficacy, with neither PromptistSFT nor Rew-Syn surpassing the SD1.4 baseline. The user languages are synthesized by rephrasing high-quality prompts. Yet such synthesized user inputs are different from real inputs and compromise the model performance. (3) In contrast, PRIP does not rely on any synthesized or human-generated refinement pairs that are usually low-quality and noisy. Results demonstrate that PRIP significantly outperforms all baselines.

5.2 Out-of-Distribution Performance

Table 2 shows the performance on four state-of-the-art generation systems that are unseen during training. As introduced in Section 4.1, these systems employ special techniques to improve prompt-understanding abilities. For example, IF uses a large language model to process prompts, and ReFL is finetuned on user inputs with preference feedback. Even on these systems, PRIP still presents significant improvements. Furthermore, according to the human annotation results in Table 1 and 2, PRIP's performance improvement is more pronounced on SDXL than SD1.4. We closely examine the output and find that SD1.4 sometimes struggles to process the rich details added by PRIP while SDXL can. The results indicate that PRIP is even more suitable for advanced generation systems. It also implies that existing generation systems all prefer prompts with rich details and professional terms. In Appendix A.1, we provide an additional analysis showing how PRIP leads to robust improvement.

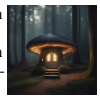
Input Prompt	User	PRIP
User : A monkey is pictured acting as a DJ. **PRIP**: A monkey is pictured acting as a DJ., he is wearing headphones and has a large smile on his face, he is holding a record, he is at a rave, he is on the cover of a tourism pamphlet for Florida, he is a resident DJ at ...		
User : A Walter White funko pop figurine. **PRIP**: A Walter White funko pop figurine., intricate, highly detailed, photorealistic, 4k, HDR, smooth, sharp focus, high resolution, award-winning photo, taken at the 2022 EPCOT International Flower and Food Festival		
User : A mushroom house in a dark forest, with warm light emitting from its windows. **PRIP**: A mushroom house in a dark forest, with warm light emitting from its windows., by Thomas Kinkade, colorful, vibrant, intricate, highly detailed, deviantart, ...		
User : Frog emerging from yogurt. **PRIP**: Frog emerging from yogurt., detailed, intricate, 4k, by Pauline Baynes, whimsical, award-winning, highly detailed, fantasy, magical, sparkle		
User : A little cat is running in the woods **PRIP**: A little cat is running in the woods, smiling, friendly, colorful, happy, laughing, cute, adorable		
User : A billboard posed by the side of a street in a rural town. **PRIP**: A billboard posed by the side of a street in a rural town., Christchurch, New Zealand, Hawaiian, small town, tropical, warm, fountain, happy, fun, touristy, cute, quaint		
User : A crowd of pink elephants playing steampunk instruments during a grindcore show. **PRIP**: A crowd of pink elephants playing steampunk instruments during a grindcore show., cute, adorable, pastel colors, Thomas Kinkade, Colorful, Lisa Frank, family		
User : an empty bench sitting on the side of a sidewalk **PRIP**: an empty bench sitting on the side of a sidewalk, in christchurch new zealand, small town, lots of flowers, small city, small town atmosphere, neighborhood, neighborhood atmosphere		

Table 3: Refinement cases. Column one details user inputs and PRIP outputs. The next two columns show SDXL-generated images for different prompts. PRIP substantially enhances the image quality.

5.3 Case Studies

Table 3 presents several refinement examples. We can see that PRIP expands user inputs with details and stylistic elements. The details are rich, professional, and tailored for each user input. For example, in the first case, PRIP adds the monkey's wearing, action, and environment. It also specifies that the image is a tourism pamphlet cover. These make the rendered image both closely relevant to the user input and aesthetically-pleasing. Moreover, some added terms are professional artist names and beyond the capability of average users, such as "Thomas Kinkade" in the third case, "Pauline Baynes" in the fourth case, and "Lisa Frank" in the seventh case. With PRIP automatically adding these professional terms, the text-to-image systems can become more user-friendly.

5.4 Ablation Study

To evaluate the contributions of PRIP's components, we perform a detailed ablation study, examining the exclusion of the following elements: (1) \User-Pivot Preference: For user-pivot training as in Eq. (6), the ground truth is a random image generated from this prompt instead of the image with the highest preference score. This investigates whether the pivot should be a user-preferred image. (2) \Pivot-System Decoding: In pivot-system training as in Eq. (7), Prompt Decoder is not provided with image as input and is trained using a basic language modeling loss. The trained model is familiar with prompts but not capable of decoding image pivots. (3) Without RL (PRIP\RL): We evaluate the PRIP model that does not undergo an end-to-end RL process, as presented in Section 3.4.

Evaluation Metric	ImageReward		HPSv2	
Generation Model	SD1.4	SDXL	SD1.4	SDXL
without Reinforcement Learning				
PRIP\RL	**0.122**	**0.888**	**27.24**	**27.87**
\User-Pivot Preference	0.072	0.862	27.17	27.80
\Pivot-System Decoding	0.058	0.810	27.04	27.69
with Reinforcement Learning				
PRIP	**0.404**	**0.983**	**27.77**	**28.15**
\User-Pivot Preference	0.198	0.917	27.33	27.92
\Pivot-System Decoding	0.047	0.821	27.04	27.71

Table 4: Ablation Study Results. The table presents the performance when various components of PRIP are removed. Results demonstrate their importance.

Table 4 presents the ablation results. It demonstrates that all three components are vital to PRIP. According to the performance of \Pivot-System Decoding, pivot-system training is critical. Without it, the performance substantially degenerates. This indicates that PRIP relies on this process to learn to decode the image pivot. "\User-Pivot Preference" replaces the user-preferred image with a random image, which also results in a performance drop. This demonstrates the importance of aligning user preference by using the best image as the pivot during training. RL can substantially improve the effectiveness of PRIP. Yet, it still relies on the user-pivot and pivot-system to provide a good warmup process. This is in line with the observations by Zheng et al. (2023) that the exploration space of the language model is too large and convergence of RL is formidable without a good start point.

5.5 Scaling Analysis

We investigate how the model size affects PRIP performance. We use two smaller models, TinyLlama with 1.1B parameters (Zhang et al., 2024a) and GPT2-Large with 0.78B parameters (Radford et al., 2019). Although TinyLlama has fewer parameters than Llama2-7B (Touvron et al., 2023), it

Evaluation Metric	ImageReward		HPSv2	
Dataset	Anime	Painting	Anime	Painting
SD1.4	0.038	0.190	27.42	26.89
+ PRIP\RL prompt refinement				
GPT2-Large 0.78B	0.047	0.197	27.49*	27.00*
TinyLlama 1.1B	0.059	0.253*	27.51*	26.99*
Llama2 7B	**0.065**	**0.269***	**27.53***	**27.03***

Table 5: PRIP performance when prompt decoder is initialized from different language models, including GPT2-large, TinyLlama, and Llama2. Results show that a larger model leads to better performance. * indicates the refinement model significantly outperforms the SD1.4 baseline (without refinement) with p-value < 0.01 measured by T-Test.

was trained on 2.5T tokens, compared to 2T tokens for the latter. Thus, TinyLlama is a strong "small" model, while GPT2-Large is a relatively weaker "small" model.

The setup is as follows. We use both models to initialize the Prompt Decoder. We do not use the RL training process as described in Section 3.4 to save cost. We only train the models with pivot-system pairs as shown in Section 3.3.2. We pair the Preference Encoder with these two new Prompt Decoders to form two new PRIP models. We test the prompt refinement performance on the Anime and Painting datasets using the SD1.4 model for image generation.

Based on the results in the table, we can observe: (1) As the capability of the base model increases, the model's prompt refinement ability also improves gradually. A more capable base model helps PRIP better infer the system prompt language from the pivot image representation, thus achieving better image generation results. (2) TinyLlama demonstrates a substantial improvement over GPT2-Large in our task, suggesting that the extensive pre-training contributes to the superior performance in this downstream task. (3) We also observed that the performance of TinyLlama is approaching that of Llama2-7B, even though their parameter scales differ by a factor of 7. This suggests that with the help of PRIP's extensive training data, the demand for the size of the base model has become smaller. A well-optimized small model can achieve performance close to that of a large model.

6 Conclusion

In this paper, we present PRIP, a pioneering pivot-based approach tailored for text-to-image prompt refinement. By formulating the refinement process as user-pivot preference encoding and pivot-system prompt decoding, PRIP sidesteps the scarcity of user-system refinement pairs and leverages large-scale data for effective model training. Extensive experiments demonstrate PRIP's effectiveness in prompt refinement. The improvement is pronounced for both text-to-image systems seen and unseen during training, highlighting its remarkable effectiveness and robust generalizability.

7 Limitation and Future Work

There are several limitations for future studies:

(1) Dependence on Supervised Data: PRIP's Preference Encoder relies on image preference data to align with user preferences. This data requires manual annotation or user click logs. Future work should explore how to effectively train the Preference Encoder with minimal preference data.

(2) Dependence on System Language Corpus: PRIP's Prompt Decoder requires a corpus of system language prompts for training. Obtaining this data can rely on scraping prompts from websites or using interaction logs, which should be done with user consent and possibly compensation. Future work should investigate acquiring this data while protecting users' intellectual property and privacy.

(3) Usage of a Frozen Image Encoder: During PRIP's training, we use a frozen image encoder to encode images. Due to resource limitations, we did not explore the impact of different image encoders. Future work can explore how to select and train image encoders for PRIP.

(4) Transferability to New Systems: While PRIP shows promise in transferring to unseen systems, its long-term adaptability to rapidly evolving generation systems remains to be fully tested. Future work should investigate how to further improve PRIP's transferability, possibly by adapting the pivot-system module for different systems.

(5) Hallucination Problem: Since the Prompt Decoder cannot directly access user inputs when generating system language, hallucinations may occur. We address this issue by using the user input as a prefix during inference. Yet this restricts PRIP's capabilities, as using redundant or unclear user inputs as prefixes can affect the refinement effectiveness. Future work should further investigate this problem.

8 Ethical Considerations

The development and deployment of PRIP raise several ethical considerations that should be addressed in future applications:

(1) Intellectual Property Protection: PRIP relies on system languages provided by users for training. It is crucial to implement appropriate incentives and revenue-sharing mechanisms to protect the intellectual property of these users.

(2) Privacy Protection: When using prompt logs for training, user privacy must be fully respected. It is necessary to obtain users' consent in advance and implement appropriate anonymization measures.

(3) Bias and Fairness: Like all AI systems, PRIP's outputs are influenced by the data it is trained on. If image preference data contains biases, these biases can be reflected in the refined prompts, potentially showing societal stereotypes and biases in generated images.

(4) Misuse Potential: The enhanced capability in text-to-image generation can be misused for creating misleading or harmful content. Ensuring that PRIP and similar technologies are used responsibly requires robust guidelines and possibly technological safeguards against such misuse.

(5) Accessibility and Inclusion: By facilitating more intuitive interaction with text-to-image systems, PRIP contributes to making these technologies more accessible. However, it is crucial to ensure that these advancements are equally accessible to users across different languages, cultures, and socio-economic backgrounds.

9 Broad Impact

PRIP's development has broad implications for both society and the field of AI:

(1) Enhancing Creative Expression: By simplifying the process of prompt refinement, PRIP enables users, especially those without technical expertise, to more effectively leverage the power of text-to-image generation systems for creative expression, educational purposes, and more.

(2) Research in AI and Human-Computer Interaction: PRIP's novel approach to prompt refinement contributes to the understanding of how humans interact with AI systems. It opens new avenues for research in natural language processing, computer vision, and human-computer interaction, particularly in the context of improving the intuitiveness and effectiveness of AI interfaces.

(3) Potential Negative Consequences: While PRIP enhances user experience, the technology's ability to generate realistic images from refined prompts raises concerns about misinformation, privacy, and the ethical use of AI-generated content. It is important for the research community to address these issues and to develop ethical guidelines and best practices for the use of such technologies.

Acknowledgments

This work is supported by Quan Cheng Laboratory (Grant No. QCLZD202301).

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A Appendix

A.1 Comparison with ReFL

PRIP enhances input prompts for text-to-image generation systems, while alternative approaches like ReFL directly finetune the diffusion models themselves. Both utilize similar reward scores and reinforcement learning techniques.

Method	Average on Four Datasets				
	ImageReward	HPSv2	Relevance	Win	Win+Tie
ReFL	0.421	27.64	1.42	0%	**100%**
SD1.4+**PRIP**	0.404	27.77	**1.45**	53%	80%
ReFL+**PRIP**	**0.640**	**28.14**	1.44	**64%**	89%

Table 6: Comparison with ReFL, a SD1.4 model finetuned with user preference. Win ratio shows preference against ReFL. Results highlight that PRIP outperforms ReFL in manual evaluations and that integrating PRIP with ReFL yields further enhancements.

Quantitative Analysis: Table 6 details a comparison of their performance. The automated metrics suggest that PRIP, despite only adjusting the input,

rivals the performance of ReFL that finetunes the entire model. By feeding PRIP's refined prompts to ReFL during inference, we observe further improvements, implying that the strengths of the two methods are complementary. From the perspective of human evaluation, images generated by PRIP are notably preferred, a finding that diverges from the ImageReward scores. Considering that ReFL's training utilizes ImageReward, ReFL may adversarially attack this metric (Akhtar and Mian, 2018), resulting in seemingly high but perhaps not genuine scores. PRIP, while also trained with ImageReward, operates under strict constraints imposed by a fixed text-to-image model, thereby avoiding potential attack to the reward model.

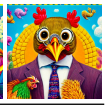
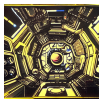
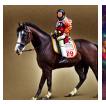
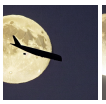
User Prompt	SD1.4	ReFL	SD1.4+PRIP	ReFL+PRIP
A digital art depicting a chicken wearing a suit.				
The interior of a spaceship orbiting alpha centauri.				
A horse and astronaut in one image.				
A plane flies in the sky passing over the moon.				

Table 7: Examples of PRIP and ReFL: The table showcases the user prompts in the first column, followed by images generated using different methods in the subsequent columns. Both ReFL and PRIP enhance the performance of SD1.4 individually, and their combination yields even better outcomes.

Image Examples: Table 7 showcases the images generated by ReFL and PRIP. We can see that both ReFL and PRIP enhance the generation quality of SD1.4. For instance, the first and third examples illustrate that ReFL and PRIP align the generated images more closely with the prompts and that their combination achieves even better images. This observation is consistent with our quantitative findings.

A.2 Human Annotation Process

We recruit annotators to manually evaluate the output images from different generation systems. We recruit five annotators in total, from different backgrounds. The annotator is paid for 30$ per hour. Each data item is labeled by three annotators, and the median value is used as the final label.

The annotators are informed about the intended usage of the data: "The data annotated is used for scientific research, and does not involve any personal privacy. The annotation process will not have any physical or psychological impact on the subjects. The results of this research may be published in academic conferences/journals/books, or used for teaching. The dataset may be made public, but it is only for research by the academic community, and your name or other information that may identify you will not appear in any published or teaching materials."

We provide the instructions for the Preference Annotation task and the Relevance Annotation Task in the following.

A.2.1 Preference Annotation

The instruction for the Preference Annotation task is mainly the same as Wu et al. (2023): " We will provide a prompt that describes the image the user wants to draw. You will see two images, which are generated from two different AI models. Please consider the prompt and choose the better image from the perspectives of universal and personal aesthetic appeal. This task mainly involves two aspects: text-image alignment and image quality. Although we encourage and value personal preference, it's important to consider the following fundamental principles when balancing the two aspects or facing a dilemma: (1) When Image (A) surpasses Image (B) in terms of aesthetic appeal and fidelity, or Image (B) suffers from severe distortion and blurriness, if Image (B) aligns only slightly better with the prompt, Image (A) should take precedence over Image (B). (2) When facing a dilemma that images are relatively similar in terms of aesthetics and personal preference, please carefully read and consider the prompt for sorting based more on the text-image alignment. (3) It is crucial to pay special attention to the capitalized names. If there is any term or content you are not familiar with, we recommend you to search for sample images and explanations online. "

A.2.2 Relevance Annotation

We will provide a prompt that describes the image the user wants to draw. You will see one image, which is generated from an AI system. Please consider the prompt and choose how relevant the image is to the prompt.

- 0: The image is completely irrelevant to the

given prompt. The image does not contain any of the key entities mentioned in the prompt. This also applies if the image only matches the prompt in style or detail, but does not contain the corresponding key entities.

- 1: The image is partially relevant to the given prompt. The image contains some of the key entities mentioned in the prompt, but may differ in style, action, or detail.
- 2: The image is perfectly relevant to the given prompt. The subject, style, and details of the image are all consistent with the prompt.

A.3 Datasheet

In this paper, we use two public datasets, namely DiffusionDB (Wang et al., 2023) for training and HPSv2 benchmark (Wu et al., 2023) for evaluation.

- License: The DiffusionDB dataset is under "CC0 1.0 License" license. The HPSv2 benchmark is under 'Apache-2.0 license'.
- Intended use: our use is consistent with the dataset creators' intended use. For DiffusionDB, the authors stated that the dataset can help "design human-AI interaction tools to help users more easily use these models.". The HPSv2 benchmark is exactly proposed to evaluate text-to-image generation performance.
- Content Processing: Since we directly use the two public datasets and do not preprocess the datasets, we also inevitably use the potentially harmful content from the two datasets. According to both creators, the data is filtered by NSFW classifiers but still may contain a small portion of harmful content.
- Coverage: The two datasets cover a wide range of topics, including anime, concept art, paintings, and realistic photos. The languages are mainly English, and also include other languages like Japanese and Chinese.
- Train/Val/Test: We use DiffusionDB for training and validation. We construct 300k image preference pairs and 900k system language prompts for training. We randomly sample 1,000 prompts from DiffusionDB for validation. HPSv2 is used as the test set. It contains four categories, each consisting of 800 prompts.

A.4 Computational Experiments

Preference Encoder is initialized from Flan-T5-Large (Chung et al., 2022) and is of 738M parameters. Prompt Decoder is initialized from Llama 2 7B (Touvron et al., 2023) and is of 7B parameters. We use Transformers library (Wolf et al., 2020) for training and inference. User-pivot warmup, pivot-system warmup and RL takes 24, 144, and 384 GPU hours on A100 devices.

We empirically tune the training hyper-parameters such as learning rate to minimize the validation loss on a held-out set. During warmup, Preference Encoder is trained for 3 epochs with a learning rate of 0.001, and Prompt decoder is trained for 2 epochs and a learning rate of 2×10^{-5}. During user-pivot-system RL training, we use ImageReward and HPSv2 to output preference scores, and train PRIP for $1,000$ steps with a batch size of 512 and a constant learning rate of 0.001

A.5 PRIP Model Card

The two components of PRIP, namely the Preference Encoder and the Prompt Decoder, share the same model architecture with Flan-T5-Large (Chung et al., 2022) and Llama 2 (Touvron et al., 2023), respectively.

Preference Encoder	
Initialization	Flan-T5-Large
Input	Text
Output	$\mathbb{R}^{32\times768}$
Prompt Decoder	
Initialization	Llama 2
Input	$\mathbb{R}^{32\times768}$
Output	Text

Table 8: PRIP Model Card.

A.6 Use of AI Assistant

We used AI assistant tools such as ChatGPT for polishing. However, AI-generated text is only used for reference in writing and is added to the article after careful consideration and modification. The help of AI lies in providing suggestions to make the paper more readable. We do not directly copy large chunks of text generated by ChatGPT into our paper without checking or modification.