BeautifulPrompt: Towards Automatic Prompt Engineering for Text-to-Image Synthesis

Tingfeng Cao[1,2,3,*]**, Chengyu Wang**[2,†]**, Bingyan Liu**[1,2]**, Ziheng Wu**[2]**,**
Jinhui Zhu[1,3†]**, Jun Huang**[2]

[1]South China University of Technology, China
[2]Alibaba Group, China
[3]Key Laboratory of Big Data and Intelligent Robot (South China University of Technology)
Ministry of Education, China
{setingfengcao, eeliubingyan}@mail.scut.edu.cn, csjhzhu@scut.edu.cn
{chengyu.wcy, zhoulou.wzh, huangjun.hj}@alibaba-inc.com

Abstract

Recently, diffusion-based deep generative models (e.g., Stable Diffusion) have shown impressive results in text-to-image synthesis. However, current text-to-image models often require multiple passes of prompt engineering by humans in order to produce satisfactory results for real-world applications. We propose *BeautifulPrompt*, a deep generative model to produce high-quality prompts from very simple raw descriptions, which enables diffusion-based models to generate more beautiful images. In our work, we first fine-tuned the *BeautifulPrompt* model over low-quality and high-quality collecting prompt pairs. Then, to ensure that our generated prompts can generate more beautiful images, we further propose a Reinforcement Learning with Visual AI Feedback technique to fine-tune our model to maximize the reward values of the generated prompts, where the reward values are calculated based on the PickScore and the Aesthetic Scores. Our results demonstrate that learning from visual AI feedback promises the potential to improve the quality of generated prompts and images significantly. We further showcase the integration of *BeautifulPrompt* to a cloud-native AI platform to provide better text-to-image generation service in the cloud. [1]

1 Introduction

Text-to-Image Synthesis (TIS) is one of the most spectacularly developed and widely applied techniques in generative Artificial Intelligence (AI), aiming to create realistic images with texts as input. Recently, with the advance of the modeling power of large models, TIS is undergoing a revolution. Large-scale TIS models, such as DALLE (Ramesh et al., 2021), DALLE-2 (Ramesh et al., 2022), latent diffusion models (Rombach et al., 2022) and Imagen (Saharia et al., 2022), significantly improve the state-of-the-art performance and allow users without artistic expertise to create unprecedented images through personal imagination.

Yet, TIS models require users to write text prompts before model inference (e.g., "A majestic sailing ship"). Writing such prompts that meet the designer's or art worker's needs is full of uncertainty, like opening a surprise box (Oppenlaender, 2022; Liu and Chilton, 2022). This is due to the quality of the training data, leading to the need for detailed descriptions to produce high-quality images. In real-world scenarios, non-experts often find it difficult to write these prompts, and need to do iterative modification through trials and errors to re-generate the images, leading to a significant loss of time and computing resources.

Prompt engineering is an emerging research field, aiming to explore how to provide prompts for deep generative models and improve the efficiency of direct interaction between humans and AI (Oppenlaender, 2022). For example, a user can give a task-oriented prompt and ask Chat-GPT (OpenAI, 2023) to generate texts according to the prompt. For TIS, the user can write a simple prompt and then ask ChatGPT to supplement the contents. However, directly using ChatGPT to write prompts falls into the dilemma of generating irrelevant and plausible images. Hence, the generated prompts can be better in quality if the underlying language model is optimized for the task. We can see that fine-tuning a language model such as (Brown et al., 2020; Scao et al., 2022; Touvron et al., 2023) for TIS prompt generation will be a more worthwhile exploration.

Astronaut rides horse → Astronaut riding a horse, fantasy, intricate, elegant, highly detailed, artstation, concept art, smooth, sharp focus, illustration

A majestic sailing ship → A massive sailing ship, by Greg Rutkowski, highly detailed, stunning beautiful photography, unreal engine, 8K
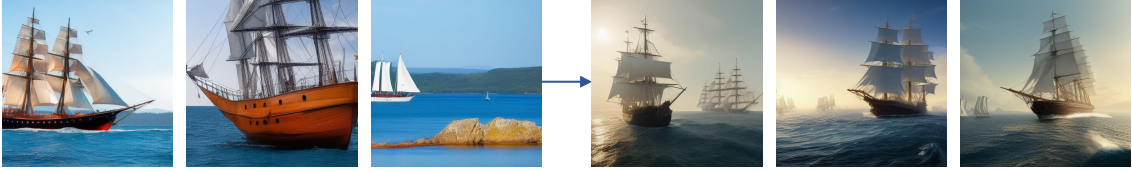
Figure 1: Comparing the qualities of images generated from the original prompts (left) with those from the prompts generated by *BeautifulPrompt* (right). The underlying TIS model is Stable Diffusion 1.5.

In this paper, we propose a new generative model that can write high-quality prompts for diffusion-based models, named *BeautifulPrompt*. For better user experience, it re-writes and optimizes the original, low-quality prompts into high-qualities ones to generate better images. It also provides a good source of inspiration for further manual prompt editing. Specifically, we first collect a dataset for training *BeautifulPrompt* using an automated data collection pipeline based on existing AI models. The dataset is used for supervised fine-tuning. We further propose a Reinforcement Learning with Visual AI Feedback (RLVAIF) technique to maximize the reward values of the generated prompts, which are determined by a couple of trained reward models based on visual signals. The gradient update process of RLVAIF makes the generated prompts more compatible with human preferences without any manual labeling. A simple comparison of prompts and the resulting images are shown in Figure 1. In summary, the main contributions of this study are as follows:

- We release a new dataset containing 143k prompt pairs and 2k test prompts, enabling researchers to develop prompt engineering models for their TIS applications.

- We propose *BeautifulPrompt*, a novel generative model that can write high-quality prompts for diffusion-based TIS models. A Reinforcement Learning with Visual AI Feedback training scheme is further proposed for better visual alignment without human labeling.

- Extensive experimental results show the superiority of *BeautifulPrompt* over strong baselines. We further showcase the integration of *BeautifulPrompt* to an industrial product to provide better image generation service.

2 Related Work

2.1 Text-to-Image Synthesis (TIS)

TIS is a multi-modal task of generating images conditioned on texts. In the early years, popular image generation networks were mainly based on Generative Adversarial Network (GAN) (Goodfellow et al., 2014; Reed et al., 2016). Recently, diffusion models (Ho et al., 2020; Sohl-Dickstein et al., 2015; Liu et al., 2023), such as DALLE-2 (Ramesh et al., 2022), Imagen (Saharia et al., 2022), and Stable Diffusion (Rombach et al., 2022) have achieved remarkable results. Yet, the qualities of generated images depend on prompts. In this paper, we propose a prompt generation model, dedicated to optimizing input prompts to generate more beautiful images.

2.2 TIS Evaluation

There are several metrics for evaluating TIS. CLIP score (Radford et al., 2021) measures the similarity between generated images and prompts. Aesthetic score (Schuhmann et al., 2022) evaluates the aesthetic quality of individual images. There are also metrics trained to align with human preferences, such as HPS (Wu et al., 2023), Image Reward (Xu et al., 2023), and PickScore (Kirstain et al., 2023). Human preferences can be complex and may involve various dimensions, including the similarity

between text and images, as well as image fidelity, aesthetics, and other factors. These evaluation metrics can all serve as visual feedback to optimize the training of prompt engineering models. Among the human preference metrics, PickScore stands out due to its stable scoring and larger, more diverse training datasets, which includes a wider range of implementations (e.g., model size, backbone, hyperparameters) (Kirstain et al., 2023). These factors can potentially contribute to more stable training and facilitate easier extension to other TIS models.

2.3 Prompt Engineering for TIS

Due to the extraordinary potential of TIS, there is a surge of interest in prompt engineering (i.e., creating good prompts). Liu and Chilton (2022) conduct a series of experiments and propose several design guidelines for text-to-image prompt engineering. Oppenlaender (2022) identifies six types of prompt modifiers through a three-month ethnographic study of the online generative art community. However, these studies are limited to the long and tedious manual prompt engineering.

BestPrompt (Pavlichenko and Ustalov, 2022) uses a genetic algorithm to detect keywords to form prompts in order to achieve the best images aesthetically. MagicPrompt[2] is a popular automatic prompt completion model trained from good prompts collected from the Internet. But these models only serve to complete the prompts. *BeautifulPrompt*, on the other hand, can re-write the original prompts to give users a good source of inspiration and generate more beautiful images.

3 Dataset Creation

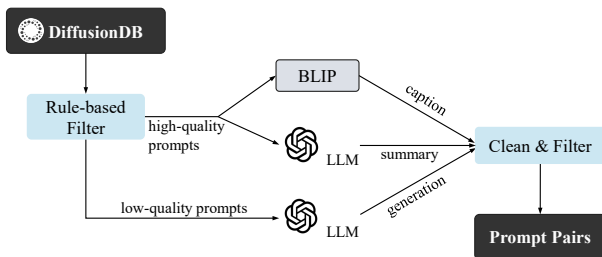In this section, we show the detailed data collection process for *BeautifulPrompt* training.

Figure 2: The data collection process.

Collection of Prompt Pairs. The goal of this

step is collecting pairs of high-quality and low-quality prompts with similar semantics. As shown in Figure 2, the original data source is DiffusionDB (Wang et al., 2022b), which contains unpaired prompts only. Heuristically, we split the prompts into low-quality and high-quality ones according to the length of the prompts, the certain tags contained in the prompts, etc. Next, we i) use BLIP (Li et al., 2022) to caption the images associated with high-quality prompts and treat the results as the corresponding low-quality prompts, as the captions are shorter and lack details; ii) use ChatGPT to summarize the high-quality prompts and treat the summaries as low-quality prompts; iii) use ChatGPT to generate better prompts from low-quality prompts; the results are considered high-quality prompts.[3] Through the above three approaches, we obtain a large number of prompt pairs; however, the quality of these prompt pairs cannot be guaranteed. Hence, we need to do further data cleaning and filtering.

Post-processing. We first filter out the examples that are non-English and NSFW (Not Safe For Work). Next, we filter out examples of images generated from high-quality prompts with low aesthetic scores (Schuhmann et al., 2022). For the prompt pairs generated by the mentioned Approaches i) and ii), we use the aesthetic score model (Schuhmann et al., 2022) to score the images, as DiffusionDB already contains the images corresponding to the high-quality prompts. For high-quality prompts generated by the mentioned Approach iii), we use the reward model r_{aes} in Section 4.2 to compute the scores.

We also consider prompts' consistency, calculate the text similarity (Reimers and Gurevych, 2019) between low-quality and high-quality prompts in a pair, and filter out examples with low similarity. More details can be found in the Appendix B.

Statistics. We finally collect 143k prompt pairs as our training set. In addition, we randomly extract 2k entries from low-quality prompts as our testing set. For the training set, the average lengths of low-quality and high-quality prompts are 40.3 and 197.8, respectively, indicating that high-quality prompts contain more descriptions of details. More statistics can be found in Table 1.

Split	Source	Num	Aesthetic	PC	ALLP	ALOP
Train	All	143k	6.22	0.71	40.3	197.8
	Summary	134k	6.23	0.71	39.8	194.5
	Generation	2k	5.70	0.76	52.4	501.4
	Caption	7k	6.23	0.67	44.9	177.7
Test	-	2k	-	-	36.7	-

Table 1: Dataset statistics. Note that, PC, ALLP and ALHP denote the prompt consistency (i.e., text similarity), the average lengths of low-quality and the high-quality prompts, respectively.

4 The *BeautifulPrompt* Model

Inspired by InstructGPT (Ouyang et al., 2022) and ChatGPT, in this section, we introduce the *BeautifulPrompt* training scheme in detail, which contains three stages (Supervised Fine-tuning, Reward Modeling training and Reinforcement Learning), as shown in Figure 3.
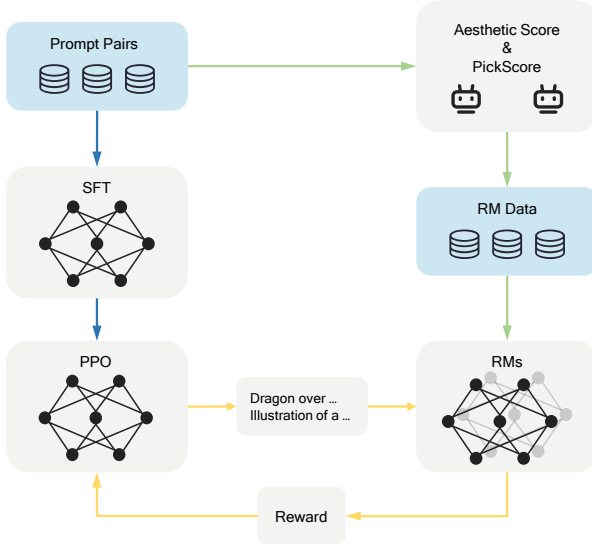
Figure 3: The three steps of training *BeautifulPrompt*. The color of the arrows indicates three different stages.

4.1 Supervised Fine-tuning (SFT)

Given a dataset of prompt pairs $D = \{(\mathbf{x}, \mathbf{y})\}$, containing pairs of low-quality prompts $\mathbf{x}$ and high-quality prompts $\mathbf{y}$, we fine-tune a decoder-only language model to output a high-quality prompt of tokens $\mathbf{y} = \{y_1, ..., y_n\}$ with a given instruction and a low-quality prompt $\mathbf{x}$. We use the auto-regressive language modeling objective to maximize the following likelihood (Radford et al., 2019):

$$\mathcal{L}_{sft} = -\sum_i \log P(y_i \mid \mathbf{x}, y_1, ..., y_{i-1}).$$

4.2 Reward Modeling (RM)

Human feedback instructs the training of Large Language Models (LLMs) with promising results (Ouyang et al., 2022). However, this requires extensive and tedious labor efforts. Bai et al. (2022) propose to use AI models to instruct the training of LLMs. Taking inspiration from this and considering that our final generated prompts $\mathbf{y}$ are used for drawing, we propose RLVAIF: a method that incorporates visual feedback into the training of language models, thereby avoiding the cost of expensive human labeling.

We focus on the quality of the final generated image and its similarity to the low-quality prompt $\mathbf{x}$. Therefore, we consider PickScore (Kirstain et al., 2023) and the aesthetic score (Schuhmann et al., 2022) as our visual AI feedback to train reward models to fit these scores.

Briefly, PickScore (Kirstain et al., 2023) is a preference model trained on a large dataset of text-to-image prompts and real user preferences. In order to reduce the impact of random seeds on the quality of the images generated by the TIS model, we use 8 different random seeds to generate images and average the results. The calculated averaged PickScore $\mathbb{PS}$ is used as the ground truth to train the reward model. The loss function is:

$$\mathcal{L}_{ps} = -\frac{1}{N} \sum_i^N \text{MSE}(r_{ps}(\mathbf{x}, \mathbf{y}), \mathbb{PS}),$$

where $r_{ps}(\mathbf{x}, \mathbf{y})$ is the scalar output of the reward model for the prompt pair $(\mathbf{x}, \mathbf{y})$. MSE is the Mean Squared Error. N is the total number of samples.

The aesthetic score model (Schuhmann et al., 2022) is trained to predict the rating that people give when asked "how much do you like this image on a scale from 1 to 10". Similarly, a reward model is trained to fit the corresponding prompts from the images to the aesthetic scores $\mathbb{AES}$:

$$\mathcal{L}_{aes} = -\frac{1}{N} \sum_i^N \text{MSE}(r_{aes}(\mathbf{y}), \mathbb{AES}),$$

where $r_{aes}(\mathbf{y})$ is the scalar output of the reward model. Finally, we use α as a balancing factor to combine the scores of the two reward models as the final reward $r(\mathbf{x}, \mathbf{y})$:

$$r(\mathbf{x}, \mathbf{y}) = \alpha \cdot r_{ps}(\mathbf{x}, \mathbf{y}) + (1 - \alpha) \cdot r_{aes}(\mathbf{y}).$$

Method	PickScore	Aesthetic Score	HPS	CLIP Score	Avg. Score
Original	20.74	5.50	0.197	**0.27**	0.57
MagicPrompt	20.11	5.79	0.193	0.22	0.07
ChatGPT	20.73	5.92	0.198	0.25	0.59
BeautifulPrompt (SFT only)	20.42	6.03	0.197	0.23	0.39
BeautifulPrompt (Full implementation)	**20.84**	**6.52**	**0.203**	0.24	**0.85**

Table 2: Results on the testing set. The average score is calculated with all scores normalized into [0,1]. "Original" refers to the method that directly sends the original prompts to Stable Diffusion without modification.

4.3 Reinforcement Learning

As the collected dataset inevitably contains some noise, for example, the consistency between low-quality prompts and the corresponding high-quality prompts is relatively low, the performance of the supervising trained model ρ can be unsatisfactory. To further improve the model performance, we initialize a policy $\pi = \rho$, and then fine-tune π to perform the task using reinforcement learning. We leverage the Proximal Policy Optimization (PPO) (Schulman et al., 2017) algorithm to directly optimize the expected reward:

$$\mathbb{E}_\pi[r] = \mathbb{E}_{\mathbf{x} \sim D, \mathbf{y} \sim \pi(\cdot|\mathbf{x})}[r(\mathbf{x}, \mathbf{y}) - \beta \cdot \log \frac{\pi(\mathbf{y} \mid \mathbf{x})}{\rho(\mathbf{y} \mid \mathbf{x})}],$$

where β is the Kullback-Leibler (KL) penalty coefficient. It prevents the policy from moving too far from ρ. Following Ziegler et al. (2019), we adopt an adaptive KL penalty here.

5 Experiments

Training Settings. We use the pre-trained checkpoint of BLOOM (Scao et al., 2022) (1.1B parameters with 24 transformer layers) as the backbone.[4] The BFLOAT16 formats are leveraged to save GPU memory and speed up training. For the SFT and RM stages of training, we set the batch size to 64, the maximum length to 384, and the learning rate to 1e-5 with warmup and cosine decay. We find that proper over-fitting benefits PPO training, so we set the SFT training epoch to 4 and the weight decay to 0. For PPO training, we set the learning rate to 5e-6, α to 0.7, the batch size to 32, the initial KL coefficient to 0.05, the training step to 5000, and freeze two-thirds of the parameters. All the

experiments are implemented in PyTorch and run on a single server with NVIDIA Tesla A100 GPUs.
Baselines. We consider two strong baselines: MagicPrompt and ChatGPT. MagicPrompt is a popular automatic prompt completion model trained from 80,000 pieces of data crawls from Lexica.ai (refer to related work). ChatGPT is almost the most powerful general-purpose LLM and serves as a human-level prompt engineer here.

Evaluation Protocols. Systematically evaluating the goodness of a prompt engineer is a challenging task. One of the most straightforward methods is to evaluate the images generated by the prompts that models produce. We use Stable Diffusion 1.5[5] to generate images and calculate PickScore (Kirstain et al., 2023), the aesthetic score (Schuhmann et al., 2022), HPS (Wu et al., 2023) and CLIP score (Radford et al., 2021) for the images and the original prompts. In addition, we conduct a human evaluation experiment on 200 randomly selected examples from the testing set. Given the raw prompts, we ask 10 human experts to pick the most desirable images generated by the different methods and report the win rates of *BeautifulPrompt* compared against other methods. [6]

5.1 Overall Results

From Table 2, our method consistently outperforms the other baselines in most scores. As the CLIP score reflects the semantic consistency between the text and image, it is natural that sending the original prompts to Stable Diffusion unchanged obtains the highest score. Our method does not decrease the CLIP score to a large extent, showing that *BeautifulPrompt* well preserves the semantics of the original input prompts. As shown in Figure 4, the human evaluation experiment shows the superiority of our approach, with a win rate of over

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[4]We choose a relatively small version of BLOOM as the backbone to ensure the high inference speed of online deployment to support real-world applications. In addition, we find that the 1.1B model is sufficiently large to accomplish our task effectively with good results.

[5]https://huggingface.co/runwayml/stable-diffusion-v1-5
[6]Refer to the user interface in Appendix C.
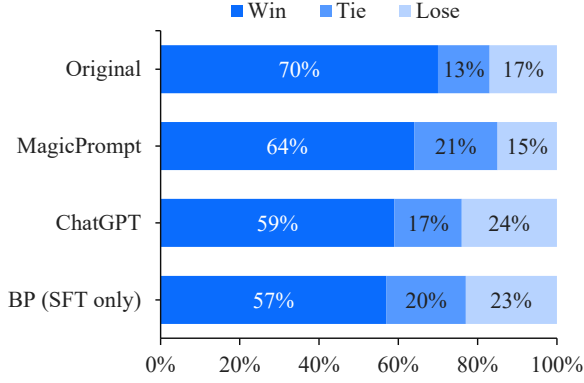
Figure 4: Results of human preference evaluation (i.e., win/lose/tie rates of our method against others). "BP" is short for *BeautifulPrompt*.
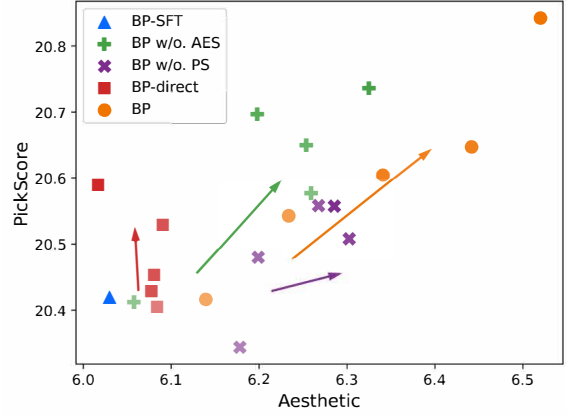

Figure 5: Aesthetic-PickScore plot for *BeautifulPrompt* and its variants. "BP" is short for *BeautifulPrompt*. We visualize checkpoints every 1000 training steps. The color gradually darkens as the number of training steps increases and the arrows indicate the training direction. For both scores, higher numbers are better.

57% against all other baselines.

5.2 Detailed Analysis

Ablation Study. Figure 5 illustrates the training process using one reward model alone, two reward models, and directly using existing models to score the images as the reward. Using r_{ps} alone can drive an increase in aesthetic score, while using r_{aes} alone does not drive an increase in PickScore. This is consistent with the finding that PickScore reflects real human preferences, incorporating various factors such as image aesthetics, text-image matching, etc (Kirstain et al., 2023). Combining the two rewards allows for more rapid and stable growth of both metrics and makes the training process more stable. The training process is unstable and the gains obtained are small when we directly use the models (Schuhmann et al., 2022; Kirstain et al., 2023) to compute rewards on the generated images instead of additionally training the reward models. Consistent with Ziegler et al. (2019), we observe that reward models need to understand languages to better guide training.

Is *BeautifulPrompt* Transferable? We further explore the transferability of *BeautifulPrompt* to the other diffusion-based TIS models. Consider the popular model Deliberate[7]. As shown in Figure 6, although Deliberate already performs well in most vanilla prompts, *BeautifulPrompt* is still able to make Deliberate generate more beautiful images in most cases. This shows *BeautifulPrompt* can also be applied to other TIS models. More examples can be found in the Appendix D.

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[7] https://huggingface.co/XpucT/Deliberate

6 Industrial Application

In this section, we briefly discuss how our model benefits users in real-world applications. Currently, we have integrated *BeautifulPrompt* into a cloud-native AI platform (Platform of Artificial Intelligence, Alibaba Cloud[8]) to assist users (especially designers and art workers) to create and edit artistic images based on a variety of Stable Diffusion-style models, together with other modules such as LoRA (Hu et al., 2021) and ControlNet (Zhang et al., 2023). Users can freely perform any types of image generation and editing operations through WebUI. During any operation, users can invoke a *BeautifulPrompt* helper plug-in to assist the design or art creation process. In addition, based on the Query Per Second (QPS) requirements and the system workload, our inference service can automatically scale to an adjustable number of machines on GPU clusters.

7 Conclusion

We propose a deep generative model named *BeautifulPrompt* to create high-quality prompts, which can be feed to Stable Diffusion-style models to produce more beautiful images. Specifically, we collect and release a new dataset for training prompt engineering models. A Reinforcement Learning with Visual AI Feedback technique is introduced

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[8] https://www.alibabacloud.com/product/machine-learning

A phoenix flying above a rugged mountain peak silhouetted by the sunrise. → The phoenix fly high above the mountains. The sharp light of the sun rising highlights his wings. Epic, fantasy art, trending on Artstation
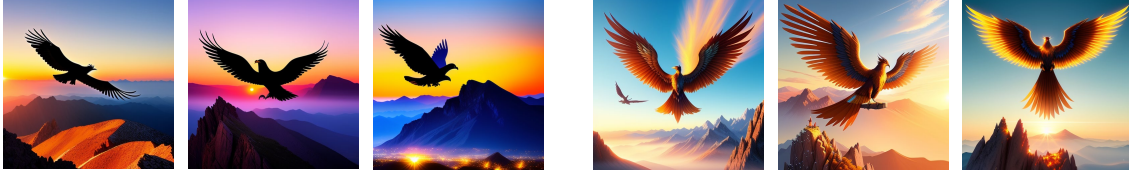
A cute girl → a portrait of an extremely cute and adorable girl, intricate, elegant, digital painting, concept art, artstation, 8k
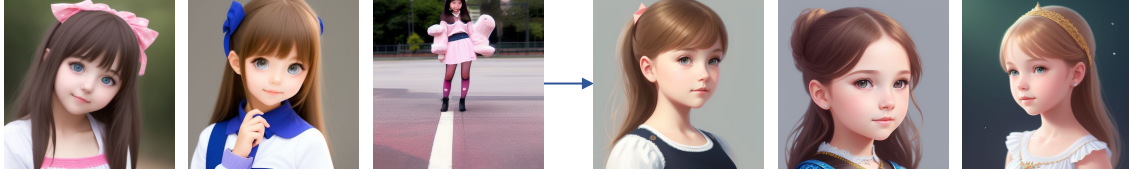

Figure 6: Comparing the qualities of images generated from the original prompts (left) with those from the prompts generated by *BeautifulPrompt* (right). The underlying TIS model is Delibrate.
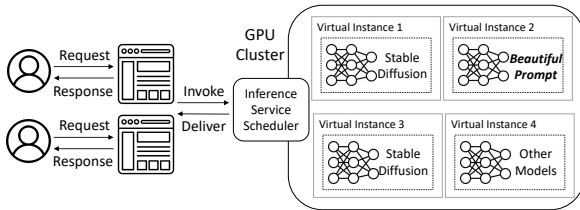
Figure 7: Architecture of online deployment with *BeautifulPrompt* for text-to-image generation service.

to fine-turn the LLMs based on our dataset. Extensive experimental results show that *BeautifulPrompt* outperforms existing methods in terms of both automatic and human evaluation.

Limitations

Although *BeautifulPrompt* can generate more aesthetically pleasing images, limited by the training data, it sometimes ignores part of the information in the original prompts or generates meaningless prompts. In a few cases, the generated images can be semantically inconsistent with the original prompts, due to the auto-regressive and generative nature of language models. These improvements are left to our subsequent work. In addition, multiple open-source models are used in our training data construction, and model training process, which may cause some degree of bias as well as error accumulation.

Ethical Considerations

The techniques for training the *BeautifulPrompt* model presented in this work are fully methodological. Hence, there are no direct negative social impacts of our method. As for the model, to ensure that the generated contents are suitable for public release, we have also filtered out NSFW prompts from our training data. However, since the generative process is difficult to control, it is possible (although not likely) for our model to create toxic contents. We suggest that in our case, *BeautifulPrompt* should not be used to generate offensive or inappropriate images for people intentionally. Users should carefully deal with the potential risks for online deployment.

Acknowledgements

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A ChatGPT Templates

Figure 8 and Figure 9 show examples of using ChatGPT to generate part of the training set.
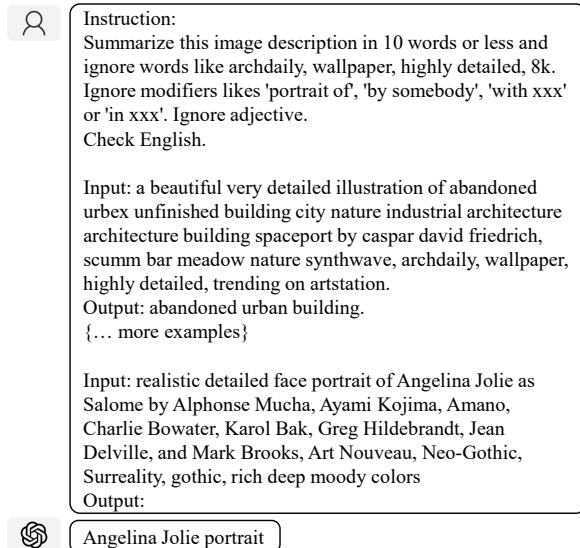
Figure 8: An example of "ChatGPT summary" for data collection.

B Data Post-processing Details

For NSFW filtering, we use a trained NSFW classifier[9]. For consistency filtering, we first use the trained sentence encoder[10] to obtain sentence representations and then compute their cosine similarity:

$$\text{cos\_sim}(\mathbf{r}_x, \mathbf{r}_y) = \frac{\mathbf{r}_x^\top \mathbf{r}_y}{\| \mathbf{r}_x \| \cdot \| \mathbf{r}_y \|},$$

where $\mathbf{r}_x$ and $\mathbf{r}_y$ are sentence representations of low- and high-quality prompts.

C Human Preference Evaluation

Figure 10 shows a screenshot of the human evaluation experiment.

D More Cases

In Figure 11, we apply *BeautifulPrompt* to more Stable Diffusion-style models (i.e., Stable Diffusion 1.5, Delibrate, Dreamlike[11] and Realistic[12]).

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[9] https://huggingface.co/michellejieli/NSFW_text_classifier

[10] https://huggingface.co/sentence-transformers/all-mpnet-base-v2

[11] https://huggingface.co/dreamlike-art/dreamlike-photoreal-2.0

[12] https://huggingface.co/SG161222/Realistic_Vision_V1.4
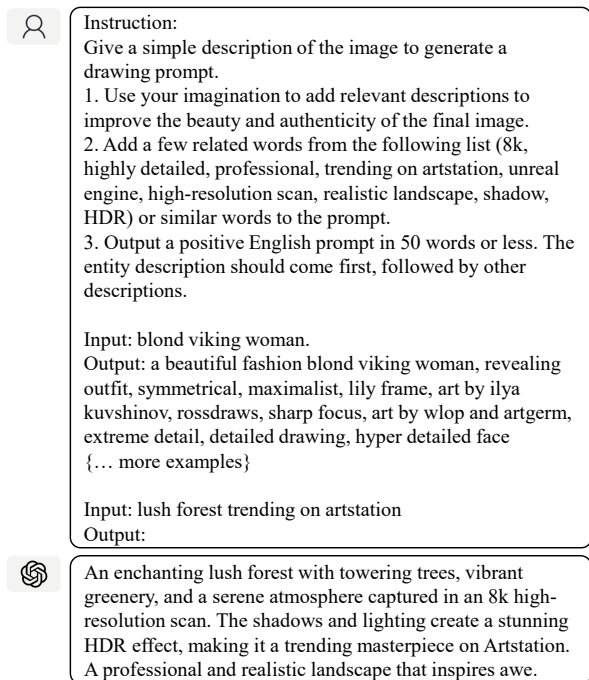
Figure 9: An example of "ChatGPT prompt generation" for data collection.
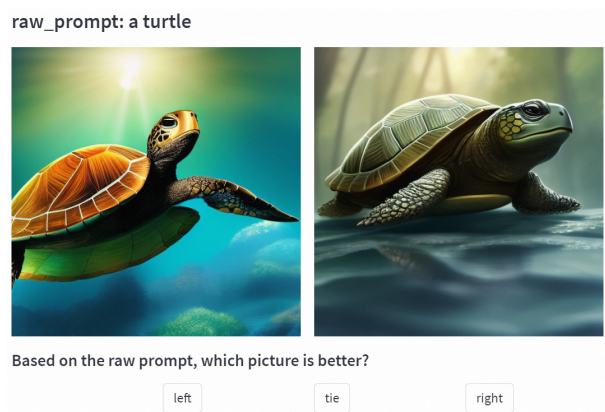
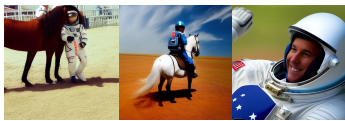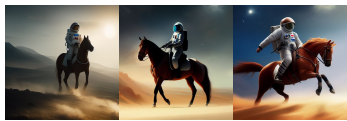Figure 10: Screenshot of the user inferface for the human evaluation experiment.
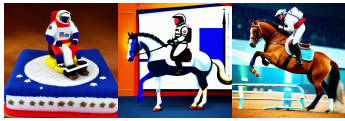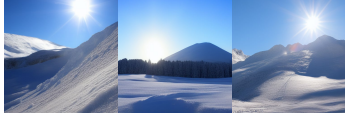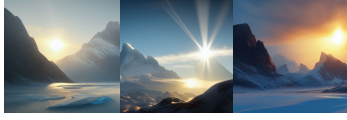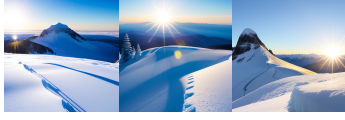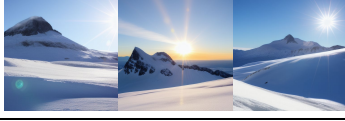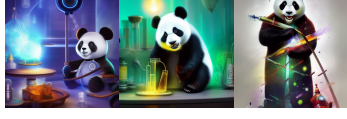
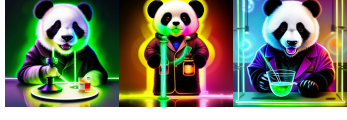| Raw Prompt & Generated Prompt	TIS	Raw Image	Optimized Image
Astronaut rides horse

Astronaut riding a horse, fantasy, intricate, elegant, highly detailed, artstation, concept art, smooth, sharp focus, illustration | Stable Diffusion 1.5 | | |
	Delibrate		
	Dreamlike		
	Realistic		
Sunshine on iced mountain

photo of sun rays coming from melting iced mountain, by greg rutkowski, 4 k, trending on artstation | Stable Diffusion 1.5 | | |
	Delibrate		
	Dreamlike		
	Realistic		
panda mad scientist mixing sparkling chemicals

panda as a mad scientist, lab coat, mixing glowing and disinertchemicals, fantasy, intricate, elegant, highly detailed, digital painting, artstation, concept art, smooth, sharp focus, illustration | Stable Diffusion 1.5 | | |
	Delibrate		
	Dreamlike		
	Realistic		

Figure 11: Examples of images generated by various Stable Diffusion-style models w/ and w/o *BeautifulPrompt*.