NeuroPrompts: An Adaptive Framework to Optimize Prompts for Text-to-Image Generation

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Abstract

Despite impressive recent advances in text-to-image diffusion models, obtaining high-quality images often requires *prompt engineering* by humans who have developed expertise in using them. In this work, we present NeuroPrompts, an adaptive framework that automatically enhances a user's prompt to improve the quality of generations produced by text-to-image models. Our framework utilizes constrained text decoding with a pre-trained language model that has been adapted to generate prompts similar to those produced by human prompt engineers. This approach enables higher-quality text-to-image generations and provides user control over stylistic features via constraint set specification. We demonstrate the utility of our framework by creating an interactive application for prompt enhancement and image generation using Stable Diffusion. Additionally, we conduct experiments utilizing a large dataset of human-engineered prompts for text-to-image generation and show that our approach automatically produces enhanced prompts that result in superior image quality. We make our code[1] and a screencast video demo[2] of NeuroPrompts publicly available.

1 Introduction

Text-to-image generation has recently become increasingly popular as advances in latent diffusion models have enabled widespread use. However, these models are sensitive to perturbations of the prompt used to describe the desired image, motivating the development of *prompt engineering* expertise by users to increase the quality of the resulting images generated by the model.

Prompt design is crucial in ensuring that the model accurately comprehends the user's intent. Text-to-image models face a significant challenge in this aspect as their text encoders have limited capacity, which can make it difficult to produce aesthetically pleasing images. Additionally, as empirical studies have shown, common user input may not be enough to produce satisfactory results. Therefore, developing innovative techniques to optimize prompt design for these models is crucial to improving their generation quality.

To address this challenge, we introduce NeuroPrompts, a novel framework which automatically optimizes user-provided prompts for text-to-image generation models. A key advantage of our framework is its ability to automatically adapt a user's natural description of an image to the prompting style which optimizes the quality of generations produced by diffusion models. We achieve this automatic adaptation through the use of a language model trained with Proximal Policy Optimization (PPO) (Schulman et al., 2017) to generate text in the style commonly used by human prompt engineers. This results in higher quality images which are more aesthetically pleasing, as the prompts are automatically optimized for the diffusion model. Furthermore, our approach allows the user to maintain creative control over the prompt enhancement process via constrained generation with Neurologic Decoding (Lu et al., 2021b), which enables more personalized and diverse image generations.

Our NeuroPrompts framework is integrated with Stable Diffusion (Rombach et al., 2022) in an interactive application for text-to-image generation. Given a user-provided prompt, our application automatically optimizes it similar to expert human prompt engineers, while also providing an interface to control attributes such as style, format, and artistic similarity. The optimized prompt produced by our framework is then used to generate an image with Stable Diffusion, which is presented to the user along with the optimized prompt.

We validate the effectiveness of NeuroPrompts by using our framework to produce optimized

[1] https://github.com/IntelLabs/multimodal_cognitive_ai/tree/main/Demos/NeuroPrompts
[2] https://youtu.be/Cmca_RWYn2g

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prompts and images for over 100k baseline prompts. Through automated evaluation, we show that our optimized prompts produce images with significantly higher aesthetics than un-optimized baseline prompts. The optimized prompts produced by our approach even outperform those created by human prompt engineers, demonstrating the ability of our application to unlock the full potential of text-to-image generation models to users without any expertise in prompt engineering.

2 NeuroPrompts Framework

Given an un-optimized prompt provided by a user, which we denote as x_u, our NeuroPrompts framework generates an optimized prompt x_o to increase the likelihood that text-to-image diffusion models produce an aesthetically-pleasing image when prompted with x_o. We specifically consider the case where x_u is the prefix of x_o and produce the enhanced prompt via a two-stage approach. First, we adapt a language model (LM) to produce a text which is steered towards the style of prompts produced by human prompt engineers. We then generate enhanced prompts via our steered LM using a constrained text decoding algorithm (NeuroLogic), which enables user customizability and improves the coverage of image enhancement keywords.

2.1 LM Adaptation for Prompt Enhancement

To adapt LMs for prompt engineering, we use a combination of supervised fine-tuning followed by reinforcement learning via the PPO algorithm.

2.1.1 Supervised fine-tuning (SFT)

First, we fine-tune a pre-trained LM to adapt the LM's generated text to the style of language commonly used by human prompt engineers. We use a pre-trained GPT-2 LM throughout this work due to its demonstrated exceptional performance in natural language processing tasks. However, our framework is broadly compatible with any autoregressive LM. To fine-tune the LM, we use a large corpus of human-created prompts for text-to-image models, which we describe subsequently in Section 3.1.

2.1.2 Reinforcement Learning via PPO

Following SFT, we further train our LM by formulating a reward model based on predicted human preferences of images generated by enhanced prompts. We then use our reward model to further train the LM via the PPO algorithm.

Extracting prefixes from human prompts In order to emulate the type of prompts that a non-expert user might enter into our application for enhancement, we created a dataset of un-optimized prompts which is derived from human-authored prompts. Human prompt engineers commonly optimize prompts by adding a comma-separated list of keywords describing artists, styles, vibes, and other artistic attributes at the end of the prompt. Thus, we truncate each of the human-authored prompts in our training dataset to contain only the substring prior to the first occurrence of a comma. We refer to the resulting prompts as *prefixes*.

Image generation with Stable Diffusion Let x_u hereafter denote a prompt prefix, which we utilize as a proxy for an un-optimized prompt provided by a user. For each x_u derived from our training dataset, we create a corresponding optimized prompt x_o using our SFT-trained LM. Given the prefix, the SFT model generates a continuation of it, leveraging the prompt distribution it has learned from the training dataset (e.g., incorporating modifiers). We employ beam search with a beam size of 8 and a length penalty of 1.0 for this stage of SFT. We then use Stable Diffusion to generate images y_u and y_o for prompts x_u and x_o, respectively.

Reward modeling (RM) We evaluate the effectiveness of our SFT LM at optimizing prompts using PickScore (Lu et al., 2021b), a text-image scoring function for predicting user preferences. PickScore was trained on the Pick-a-Pic dataset, which contains over 500k text-to-image prompts, generated images, and user-labeled preferences.

PickScore utilizes the architecture of CLIP; given a prompt x and an image y, the scoring function s computes a d-dimensional vector representation of x and y using a text and image decoder (respectively), returning their inner product:

$$g_{pick}(x, y) = E_{txt}(x) \cdot E_{img}(y)^T \quad (1)$$

where $g_{pick}(x, y)$ denotes the score of the quality of a generated image y given the prompt x. A higher PickScore indicates a greater likelihood that a user will prefer image y for prompt x.

Reinforcement learning (RL) We further train our LM using PPO (Schulman et al., 2017). Given the images generated previously for the optimized prompt and prompt prefix, we use PPO to optimize the reward determined by the PickScore:

$$\mathrm{R}\,(x, y) = E_{(x,y_u,y_o)\sim D}[g_{pick}\,(x, y_o) - g_{pick}\,(x, y_u)]$$

where $g_{pick}(x, y)$ is the scalar output of the PickScore model for prompt x and image y, y_u is the image generated from the un-optimized prompt, y_o is the image generated from the optimized prompt, and D is the dataset. This phase of training with PPO further adapts the LM by taking into consideration the predicted human preferences for images generated by the optimized prompts.

2.2 Constrained Decoding via NeuroLogic

After training our LM via SFT and PPO, we generate enhanced prompts from it at inference time using NeuroLogic Decoding (Lu et al., 2021b). NeuroLogic is a constrained text decoding algorithm that enables control over the output of autoregressive LMs via lexical constraints. Specifically, NeuroLogic generates text satisfying a set of clauses $\{C_i \mid i \in 1, \cdots m\}$ consisting of one or more predicates specified in conjunctive normal form:

$$\underbrace{(D_1 \vee D_2 \cdots \vee D_i)}_{C_1} \wedge \cdots \wedge \underbrace{(D_k \vee D_{k+1} \cdots \vee D_n)}_{C_m}$$

where D_i is a predicate representing a constraint $D(\mathbf{a}_i, \mathbf{y})$ which evaluates as true if the subsequence $\mathbf{a}_i$ appears in the generated sequence $\mathbf{y}$. NeuroLogic also supports negation of predicates (i.e., $\neg D_i$), specifying the minimum and/or maximum number of predicates within a clause which can be used to satisfy it, and enforcement of clause satisfaction order (Howard et al., 2023).

We use a curated set of prompt enhancement keywords[3] to formulate clauses which must be satisfied in the optimized prompt. Specifically, we create six clauses consisting of keywords for styles, artists, formats, perspectives, boosters, and vibes (see Table 3 of Appendix A.2 for details). Each clause is satisfied when the generated sequence contains one of the keywords from each category. By default, a clause contains five randomly sampled keywords from its corresponding category. However, our application allows users to manually specify which keywords can satisfy each clause to provide more fine-grained control over the optimized prompt.

3 Experiments

3.1 Dataset

For supervised fine-tuning and reinforcement learning, we utilize the DiffusionDB dataset (Wang et al., 2022), a large dataset of human-created prompts.

[3]From prompt engineering templates

Model	Aesthetics Score
Original prefix	5.64
Original (human) prompt	5.92
SFT only	6.02
NeuroPrompts w/o PPO	6.05
NeuroPrompts w/o NeuroLogic	6.22
NeuroPrompts	6.27

Table 1: Aesthetics scores calculated for images generated by NeuroPrompts and baseline methods

In the reinforcement learning stage, we truncate the prompt to contain only the substring before the first occurrence of a comma, as previously described in Section 2.1.2. This allows for improved exploration of paraphrasing (see App. A.1 for details).

3.2 Experimental setting

To adapt GPT-2 to the style of prompts created by human prompt engineering, we train it on 600k prompts sampled from DiffusionDB. Specifically, we fine-tune the model for 15,000 steps with a learning rate of 5e-5 and batch size of 256. We then further train our SFT LM with PPO for 10k episodes using a batch size of 128, a minibatch size of one, four PPO epochs per batch, and a constant learning rate of 5e-5. We used a value loss coefficient of 0.1 and a KL reward coefficient of 0.2. This stage of training was conducted using the PPO implementation from (von Werra et al., 2020).

We use two metrics to evaluate the benefits of our prompt adaptation for text-to-image models: aesthetics score and PickScore. Aesthetics score is a measure of the overall quality of the generated image and is computed by a model[4] trained on LAION (Schuhmann et al., 2022) which predicts the likelihood that a human would find the image aesthetically pleasing. As detailed in Section 2.1.2, PickScore measures how likely a human would prefer the generated image using a fine-tuned clip model. We use a different set of 100k prompts (non-overlapping with our 600k training set) sampled from DiffusionDB for this evaluation and compare the performance of our prompt optimization method to three baselines: (1) the original human-authored prompt from DiffusionDB; (2) the prefix extracted from human-authored prompts, which we consider a proxy for user-provided prompts; and (3) prompts enhanced only using our LM trained with supervised fine-tuning (i.e., without PPO training).

[4]We use Improved Aesthetic Predictor

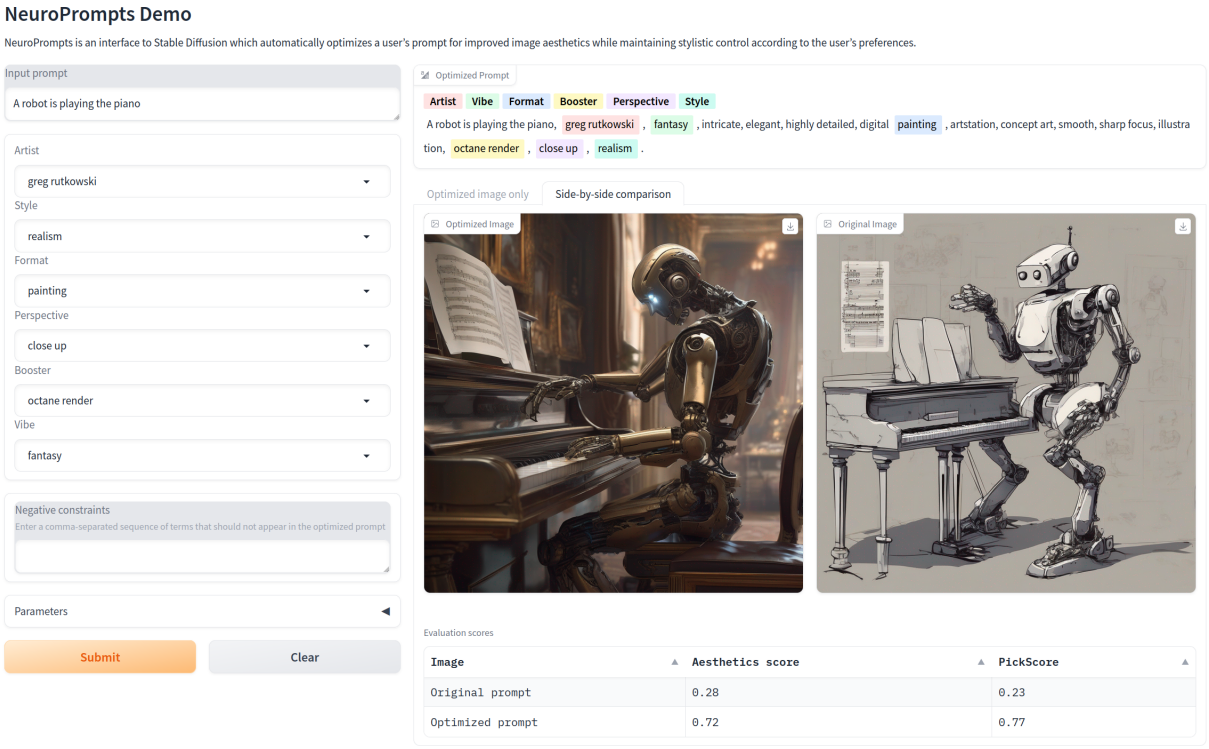


Figure 1: The interface of NeuroPrompts in side-by-side comparison mode

3.3 Results

Optimized prompts produce images with higher aesthetics score Table 1 provides the mean aesthetic scores of images produced by our optimized prompts as well as other baseline methods. NeuroPrompts outperforms all other baselines, achieving an average aesthetics score of 6.27, which is an absolute improvement of 0.63 over images produced by un-optimized prompt prefixes. NeuroPrompts even outperform human-authored prompts by a margin of 0.35, which could be attributed to how our method learns the relationship between prompt enhancement keywords and image aesthetics across a large dataset of human-authored prompts. These results demonstrate our framework's effectiveness at generating prompts that produce aesthetically pleasing images.

To analyze the impact of different components of our framework, Table 1 provides results for variations without PPO training and constrained decoding. PPO training significantly outperforms approaches that only utilize our SFT LM, improving the aesthetics score by approximately 0.2 points. Constrained decoding with NeuroLogic further improves the aesthetics of our PPO-trained model by 0.05, which could be attributed to greater coverage of prompt enhancement keywords. Beyond improvements in aesthetics score, NeuroLogic also enables user control over prompt enhancement.

Optimized prompts achieve higher PickScores We further investigated the effect of NeuroPrompts on the predicted PickScore of generated images. Specifically, for each prompt in our DiffusionDB evaluation set, we calculated the PickScore using images generated for the prompt prefix and our optimized prompt. Our optimized prompts consistently achieve a higher PickScore than prompt prefixes, with NeuroPrompts having an average PickScore of 60%. This corresponds a 20% absolute improvement in the predicted likelihood of human preference for our optimized images relative to those produced by prompt prefixes.

Discussion Our experiments demonstrate that NeuroPrompts consistently produce higher-quality images, indicating that our framework can be used as a practical tool for artists, designers, and other creative professionals to generate high-quality and personalized images without requiring specialized prompt engineering expertise.

4 NeuroPrompts

The user interface of NeuroPrompts is depicted in Figure 1. The application's inputs include the ini-

tial prompt as well as selection fields for specifying the clauses used to populate constraints for style, artist, format, booster, perspective, and vibe. Additionally, a negative constraints input allows the user to specify one or more phrases which should be excluded from the optimized prompt. While the initial prompt is required, all other fields are optional; if left unselected, clauses for each constraint set will be automatically populated as described previously in Section 2.2. This functionality allows the user to take control of the constrained generation process if desired or simply rely on our framework to optimize the prompt automatically.

After clicking the submit button, the optimized prompt is displayed at the top of the screen. If constraints were selected by the user, the optimized prompt will appear with color-coded highlighting to show where each constraint has been satisfied in the generated sequence. The image produced by Stable Diffusion for the optimized prompt is displayed directly below the optimized prompt in the center of the interface. If the user selects the side-by-side comparison tab, an image generated for the original prompt is also displayed to the right of the optimized image. Additionally, the application calculates PickScore and a normalized aesthetics score for the two images, which is displayed in a table below the images. This side-by-side comparison functionality allows the user to directly assess the impact of our prompt optimizations on the quality of images generated by Stable Diffusion.

Examples of images generated from original and optimized prompts To further illustrate the impact of NeuroPrompts on image quality, Table 2 provides examples of images generated from original prompts and our optimized prompts. Each row of the table provides an original (un-optimized) prompt along with images generated by Stable Diffusion for the original prompt (center) and an optimized prompt produced by NeuroPrompts (right). These examples illustrate how NeuroPrompts consistently produces a more aesthetically-pleasing image than un-optimized prompts.

5 Related Work

Text-to-image generation. Recent advances in text-to-image generation have led to the release of a variety of models which can translate text prompts into high quality images, including Glide (Nichol et al., 2021), DALL-E (Ramesh et al., 2022), ImageGen (Saharia et al., 2022), and Stable Diffusion (Rombach et al., 2022). Text-to-image diffusion models such as Stable Diffusion encode text prompts using CLIP (Radford et al., 2021). Images are then generated via a diffusion process by conditioning on the representation of the text encoding in the latent space of an autoencoder.

Prompt engineering. Previous studies have demonstrated the superior performance of models trained on manually designed prefix prompts (Brown et al., 2020). However, these models are heavily dependent on the prompt components (Liu et al., 2021). Research on text-to-image models has focused on proposing keywords (Oppenlaender, 2022) and design guidelines (Liu and Chilton, 2022). Additionally, prior studies have explored the enhancement of LM prompts through differentiable tuning of soft prompts (Lester et al., 2021; Qin and Eisner, 2021). Similar to our approach, Hao et al. (2022) proposed an automatic prompt engineering scheme via reinforcement learning. In contrast to this prior work, NeuroPrompts preserves user interpretabilty and control over the prompt optimization process via the use of symbolic constraints.

Learning from human preference. Human feedback has been used to improve various machine learning systems, and several recent investigations into reinforcement learning from human feedback (RLHF) have shown encouraging outcomes in addressing machine learning challenges. These studies include applications to instruction following (Ouyang et al., 2022), summarization (Stiennon et al., 2020) and text-to-image models (Lee et al., 2023). While Hao et al. (2022) also leverage RLHF for the purpose of prompt engineering, our approach uses a different reward function based on human preferences for images (PickScore) while providing user control via constrained decoding.

NeuroLogic Decoding NeuroLogic Decoding (Lu et al., 2021b) has been extended and applied to various use cases, including A* search (Lu et al., 2021a) counterfactual generation (Howard et al., 2022), inductive knowledge distillation (Bhagavatula et al., 2022), and the acquisition of comparative knowledge (Howard et al., 2023). To the best of our knowledge, our work is the first to explore the applicability of constrained text generation with NeuroLogic to prompt optimization.

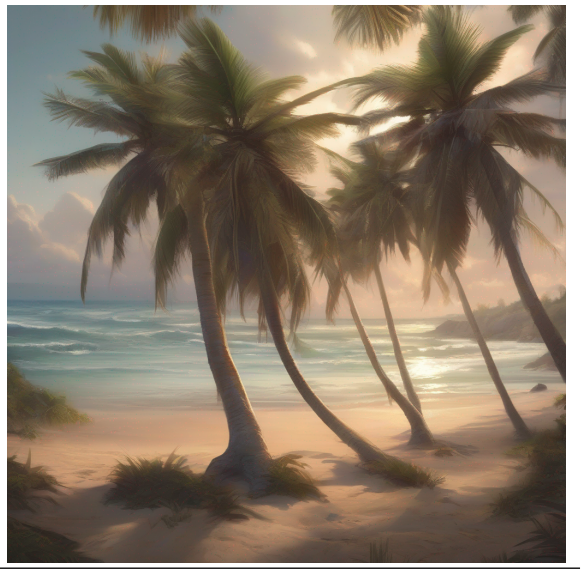
	Original Image	NeuroPrompts Optimized Image
A boy on a horse		
A tropical beach with palm trees		
Two women working in a kitchen		

Table 2: Examples of images generated from original prompts and our optimized prompts. The original (un-optimized) prompt is shown in rotated text to the left of each image pair

6 Conclusion

We presented NeuroPrompts, an application which automatically optimizes user prompts for text-to-image generation. NeuroPrompts unlocks the full potential of text-to-image diffusion models to users without requiring any training in how to construct an optimal prompt for the model. Therefore, we expect it to increase the accessibility of such models while improving their ability to be deployed in a more automated fashion. In future work, we would like to extend NeuroPrompts to video generation models and other settings which can benefit from automated prompt engineering.

Limitations

While NeuroPrompts is broadly compatible with any text-to-image generation model, we only evaluated its use with Stable Diffusion in this work due to limited computational resources. Images generated from Stable Diffusion have been shown to exhibit societal biases (Luccioni et al., 2023); therefore, it is expected that images generated using NeuroPrompts will also exhibit similar biases. The automated nature of our prompt enhancement and image generation framework introduces the possibility of content being generated which may be considered offensive or inappropriate to certain individuals. Consequently, user discretion is advised when interacting with NeuroPrompts.

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A Appendix

A.1 Dataset

To train and evaluate our adaptive framework for prompt enhancement in text-to-image generation, we utilized the DiffusionDB dataset (Wang et al., 2022), a large dataset of human-created prompts. We use a subset of 600k prompts from this dataset to conduct supervised fine-tuning of our LM. For the reinforcement learning stage of training, we use a different subset of 400k prompts from DiffusionDB. For each of the 400k prompts, we truncate the prompt to contain only the substring before the first occurrence of a comma, assuming that modifiers generally appear after the first comma. This approach allows for improved exploration of paraphrasing by our policy. We filtered examples with a significant overlap between the prefix and the entire prompt. To achieve this, we used a sentence similarity threshold of 0.6 overlap and excluded cases which exceeded this threshold.

A.2 Prompt enhancement keywords

Table 3 provides the complete set of prompt enhancement keywords utilized in our constraint sets.

Style	Artist	Format	Boosters	Vibes	Perspective
expressionism	pablo picasso	watercolor painting	trending on artstation	control the soul	long shot
suminagashi	edvard munch	crayon drawing	octane render	futuristic	plain background
surrealism	henri matisse	US patent	ultra high poly	utopian	isometric
anime	thomas cole	kindergartener drawing	extremely detailed	dystopian	panoramic
art deco	mark rothko	cartoon	very beautiful	blade runner	wide angle
photorealism	alphonse mucha	in Mario Kart	studio lighting	cinematic	hard lighting
cyberpunk	leonardo da vinci	pixel art	fantastic	fantasy	knolling
synthwave	claude monet	diagram	postprocessing	elegant	shallow depth of field
realism	james gurney	album art cover	well preserved	magnificent	extreme wide shot
pop art	toshi yoshida	under an electron microscope	4k	retrofuturistic	drone
pixar movies	zdzislaw beksinski	photograph	arnold render	awesome	from behind
abstract organic	gustave doré	pencil sketch	detailed	transhumanist	landscape
dadaism	georges braque	stained glass window	hyperrealistic	bright	1/1000 sec shutter
neoclassicism	bill watterson	advertising poster	rendering	wormhole	from below
ancient art	michelangelo	mugshot	vfx	eclectic	head-and-shoulders shot
baroque	greg rutkowski	cross-stitched sampler	high detail	epic	from above
art nouveau	vincent van gogh	illustration	zbrush	tasteful	oversaturated filter
impressionist	caravaggio	pencil and watercolor drawing	70mm	gorgeous	aerial view
symbolism	diego rivera	in Fortnite	hyper realistic	opaque	telephoto
hudson river school	dean cornwell	line art	8k	old	motion blur
suprematism	ralph mcquarrie	product photography	professional	lsd trip	85mm
rococo	rené magritte	in GTA San Andreas	beautiful	lo-fi	viewed from behind
pointillism	john constable	news crew reporting live	trending on artstation	emo	through a porthole
vaporwave	gustave dore	line drawing	stunning	lucid	dark background
futurism	jackson pollock	courtroom sketch	contest winner	moody	fisheye lens
skeumorphism	hayao miyazaki	on Sesame Street	wondrous	crystal	through a periscope
ukiyo-e	lucian freud	wikiHow	look at that detail	melancholy	white background
medieval art	johannes vermeer	daguerreotype	highly detailed	cosmos	on canvas
corporate memphis	hieronymus bosch	3d render	4k resolution	faded	tilted frame
minimalism	hatsune miku	modeling photoshoot	rendered in unreal engine	uplight	framed
fauvism	utagawa kuniyoshi	one-line drawing	photorealistic	concept art	low angle
renaissance	roy lichtenstein	charcoal drawing	blender 3d	atmospheric	lens flare
constructivism	yoji shinkawa	captured on CCTV	digital art	dust	close face
cubism	craig mullins	painting	vivid	particulate	over-the-shoulder shot
memphis design	claude lorrain	macro 35mm photograph	wow	cute	close up
romanticism	funko pop	on America's Got Talent	high poly	stormy	extreme close-up shot
hieroglyphics	katsushika hokusai	pastel drawing	unreal engine	magical	midshot

Table 3: Prompt enhancement keywords utilized in constraint sets