The Supplementary Materials for Dynamic Prompt Optimizing for Text-to-Image Generation

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In this appendix, we provide additional information and materials to complement our research, including training samples, more qualitative results, additional experimental details, and discussion.

A. Examples of training data

We utilize a diverse range of text-image pairs sourced from public datasets and online communities. As shown in Fig. A4, we present some prompts that are included in our training data. These prompts have undergone filtration and construction following the automated process described in Sec. 3.3 of the main manuscript. The short prompts s primarily describe the subject matter of the images, while the modifiers (highlighted in gray) provide additional details and enhance the aesthetic appeal of the images. In the figure, the term "Aes" denotes the aesthetic score, and "CLIP" quantifies the semantic relevance of the generated image to the short prompt. We can see that the generated images I' corresponding to the original prompt s' are more visually effective than the generated images I corresponding to the short prompt s.

Lexica.art	Aes	CLIP
Short Prompt	5.58	0.28
+ "artstation"	5.83	0.26
+ "concept art"	5.68	0.30
+ "digital painting"	5.79	0.30
+ "sharp focus"	5.60	0.28
+ "highly detailed"	5.64	0.29

Table A1. The effect of different words on generating images.

B. More detailed statistical analysis

Fig. A1 indicates a predominance of shorter token sequences in model predictions, implying that adding a few modifiers can significantly enhance an image's visual appeal without altering the original prompt's meaning. Fig. 5 (b-d) of the main manuscript show frequently generated modifiers, most of which are trends, styles, and texture terms. We also conduct experiments to analyze word impact. As shown in Tab. A1, "artstation" boosts Aesthetic

scores at the cost of text-image similarity, whereas styles and texture modifiers slightly increase Aesthetic scores while preserving alignment.

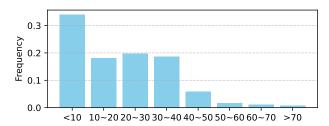


Figure A1. Frequency of the number of predicted word tokens.

C. Enhanced text encoder for DF-prompt

In Stable Diffusion, the text encoder is modified to achieve fine-grained control over the generated effects. These modifications involve two key aspects:

• We introduce weights for each word embedding, representing the impact of a word or phrase on the resulting image. To accomplish this, we apply a weighting operation to each word's embedding by multiplying it with a specific weight. Subsequently, we normalize the entire set of text embeddings, ensuring that the overall mean value remains consistent with the original text embeddings. This normalization step is crucial for maintaining numerical stability. Our technique yields results similar to the existing prompt weighting method (Fig. A2 (b)) but having dynamic time-range control. The pseudo-code for weighting tokens is below.

```
# Given text_embs:[77x768], weights:[77,]
previous_mean = text_embs.mean() # float
text_embs *= weights
current_mean = text_embs.mean()
text_embs *= previous_mean / current_mean
```

Listing 1. Python pseudo code for weighting tokens.

The injection time steps are regulated using a dictionary.
 This dictionary maps each word or phrase to a designated time step, which determines when to initiate and conclude the injection of that specific word or phrase during the image generation process. By manipulating the time steps in

Method	Training		Inference (per prompt)		T2I Pipeline (per image)	
Method	Stage 1	Stage 2	Ours	Promptist	Vanilla SD	Dynamic SD
GPU Times	18 hours	3 days	0.73s	0.69s	5.64s	5.71s

Table A2. Experiment on an A800 (80GB) GPU.

the dictionary, precise control over the duration of different concepts within the generated image can be achieved. These modifications empower the text encoder to exert more precise control over the effects within the Stable Diffusion framework. As a result, more personalized and user-specific image-generation outcomes can be attained.

Method (+"DSLR")	FID (↓)
Promptist	70.80
PAE (Ours)	69.84

Table A3. Quantitative comparison of image quality between our method and Promptist, measured using the FID metric.

D. More experimental details

For the evaluation process, we use a maximum new token length of 75 for all evaluated models. We use a temperature of 0.9 during the evaluation and apply a top-k sampling strategy with a k-value of 200. To ensure consistency, we use the same seed in all quantitative evaluation experiments.

E. More qualitative results

In this section, we present more qualitative results, as depicted in Figs. A5 and A6. We compare the images $\mathbf{I}^{\mathrm{DFP}}$ generated using DF-Prompts with the images \mathbf{I} generated using the short prompts. For example, in Fig. A5, we observe that the images corresponding to DF-Prompts, $\mathbf{I}^{\mathrm{DFP}}$, exhibit more vibrant details and aesthetically pleasing color combinations compared to the images \mathbf{I} generated from the short prompts. Some specific examples include "symmetry!! portrait of a warrior transformers robot", "a symmetrical portrait of a beautiful menacing lilith", "commission of a fit male anthro albino lion holding a sword" and "glowwave portrait of dark batman from overwatch". We ensure fairness and consistency by generating the columns corresponding to \mathbf{I} and $\mathbf{I}^{\mathrm{DFP}}$ using the same seed.

Empirical evidence shows that our method not only creates aesthetically pleasing images but also caters precisely to user queries, such as achieving photorealism with "DSLR" or creating 3D-rendered effects with "3D blender" in user prompts (Fig. A2 (a)). Our method shows adaptability when integrating detailed modifiers like "DSLR" and achieves competitive Frechet Inception Distance (FID) [1] (Tab. A3). This adaptability is critical in practical applications.

The time cost of each stage is shown in Tab. A2. As for inference, the average time is marginally higher than that of Promptist (+0.04 s). Moreover, our Dynamic Stable Diffusion (Dynamic SD) method is slightly slower than the Vanilla SD method, but the difference is minimal.

F. Discussion

The significant enhancement in image quality and text alignment observed in Fig. 3 of the main manuscript for the case "cats in suits smoking cigars together" can be attributed to our model's reward mechanism. Specifically, we incorporate the Aes score to encourage actions that improve aesthetic features and the CLIP score to ensure semantic coherence. Additionally, our reward function introduces the PickScore, which allows for more diverse prompt modifiers and ultimately leads to improved image quality. In Fig. 3 of the main manuscript, the inclusion of new semantic elements like "on a ship deck" alongside other modifiers contributes significantly to the visual appeal of the generated output.

Differences among PAE, Promptist, hugging face weighting prompt method (WP)¹ lie in that Promptist focuses solely on prompt expansion, while WP manipulates the likelihood of certain phrases appearing in images by artificially setting their weights. PAE, on the other hand, innovatively introduces dynamic prompts, and dynamically adjusts the weights of different phrases during various stages of image denoising, thus achieving more granular control over the image generation process. Additionally, PAE introduces a richer set of reward metrics (aligning closely with user preferences), without the need for manual intervention, resulting in visually striking and semantically consistent images.

As shown in Figs. A5 and A6, the generated image I^{DFP} maintains the identity consistency of the image I produced by the short prompt s when using the same seed. Meanwhile, it incorporates additional image details that enhance visual appeal. This is evident in Fig. A5 with the example of a "commission of a fit male anthro albino lion holding a sword," and in Fig. A6 with "Grimes with elf ears." This capability can be further developed to ensure consistent role generation. To further enhance our model, it is advantageous to incorporate more comprehensive reward considerations. For instance, evaluating generated images based

 $^{^{1} \}verb|https://huggingface.co/docs/diffusers/using-diffusers/weighted_prompts$

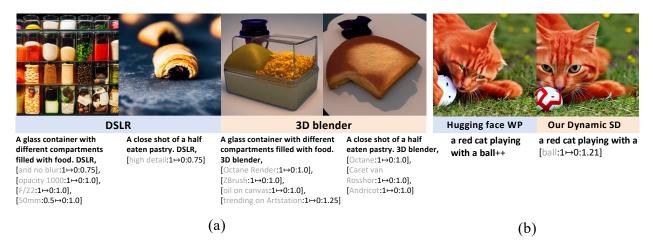


Figure A2. (a) Examples of practicability. (b) Weight methods.

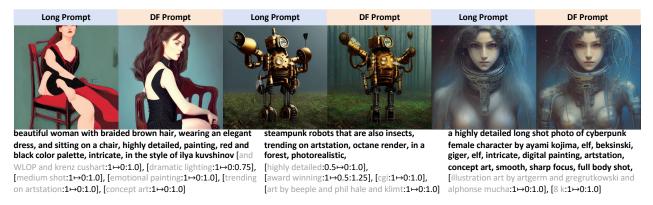


Figure A3. The input long prompts are in bold.

on factors such as high resolution and proportional composition can contribute to their overall quality and realism. Furthermore, to address issues such as attribute leakage and missing objects observed in the original Stable Diffusion method, advanced control techniques can be explored. One potential approach involves incorporating control attention maps into the action space. By selectively directing attention to specific regions in the input image, the model gains finer control over the generation process. Consequently, issues related to attribute leakage can be mitigated, and the preservation of important elements can be ensured. By exploring these possibilities and developing more sophisticated control mechanisms, we can enhance the capabilities of our model and overcome the limitations observed in its current implementation.

References

[1] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two

time-scale update rule converge to a local nash equilibrium. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, pages 6626–6637, 2017. 2

Generated Image I' Short Prompt s **Generated Image I** Original Prompt s' An attack plane falling from the sky into the ocean, Battlefield 1, extremely detailed An attack plane falling digital painting, in the style of Fenghua from the sky into the Zhong and Ruan Jia and jeremy lipking and ocean Peter Mohrbacher, mystical colors, rim light, beautiful Lighting, 8k, stunning scene raytracing, octane, trending on artstation Aes: 5.27 CLIP: 0.25 Aes: 5.30 CLIP: 0.25 Aes: 6.46 CLIP: 0.28 Aes: 6.63 CLIP: 0.24 !dream a mad scientist in a back yard laughing happily at the fruits which are !dream a mad scientist in a back yard laughing happily at falling from the sky, made by Stanley the fruits which are falling Artgerm Lau, WLOP, Rossdraws, ArtStation, from the sky CGSociety, concept art, cgsociety, octane render, trending on artstation, artstationHD, artstationHQ, unreal engine, Aes: 5.33 CLIP: 0.26 Aes: 5.55 CLIP: 0.21 4k, 8k, Aes: 6.36 CLIP: 0.28 Aes: 6.92 CLIP: 0.28 A castle made out of white stone covered in A castle made out of white stone fire covered in fire, rising smoke, dark fantasy, nighttime, hyper realistic, by greg rutkowski, trending on artstation Aes: 5.43 CLIP: 0.24 Aes: 6.06 CLIP: 0.29 Aes: 6.30 CLIP: 0.30 Aes: 6.58 CLIP: 0.27 Anime style Tokyo in fog, magic mist, Anime style Tokyo in fog cyberpunk buildings, digital concept art, cityscape, high resolution, trending on artstation, unreal engine Aes: 5.72 CLIP: 0.30 Aes: 6.08 CLIP: 0.28 Aes: 6.13 CLIP: 0.28 Aes: 6.39 CLIP: 0.31 Face portrait of a young handsome Face portrait of a young detective with a black leather coat, handsome detective with yellow eyes, neck chains, short hair , sci-fy, a black leather coat cyber punk, high detail, digital painting, artstation, concept art, sharp focus, illustration, art by greg rutkowski and alphonse mucha Aes: 6.47 CLIP: 0.26 Aes: 6.78 CLIP: 0.26 Aes: 6.89 CLIP: 0.27 Dieselpunk Venice city, steam, dieselpunk **Dieselpunk Venice city** gondola, oil petroleum black rivers, epic composition, intricate, elegant, volumetric lighting, digital painting, highly detailed, artstation, sharp focus, illustration, concept art, ruan jia, steve mccurry Aes: 5.47 CLIP: 0.24 Aes: 6.10 CLIP: 0.24 Aes: 6.47 CLIP: 0.28 Aes: 6.86 CLIP: 0.32 princess elsa gone mental, beautiful shadowing, 3 d shadowing, reflective surfaces, illustrated completely, 8 k beautifully detailed pencil illustration, princess elsa gone extremely hyper - detailed pencil illustration mental intricate, epic composition, masterpiece, bold complimentary colors. stunning masterfully illustrated by artgerm, range murata, alphonse mucha, katsuhiro otomo. 88 CLIP: 0.25 Aes: 5.11 CLIP: 0.26 Aes: 6.14 CLIP: 0.24 Aes: 7.14 CLIP: 0.26 A Titan falling from the sky causing a bright flash, Titanfall 2, extremely detailed A Titan falling from the sky digital painting, in the style of Fenghua causing a bright flash Zhong and Ruan Jia and jeremy lipking and Peter Mohrbacher, mystical colors, rim light, beautiful Lighting, 8k, stunning scene, raytracing, octane, trending on artstation

Figure A4. Some examples of the training data.

Aes: 6.14 CLIP: 0.23 Aes: 6.22 CLIP: 0.22

Aes: 5.60 CLIP: 0.22 Aes: 5.42 CLIP: 0.21



Figure A5. More examples of the generated images.

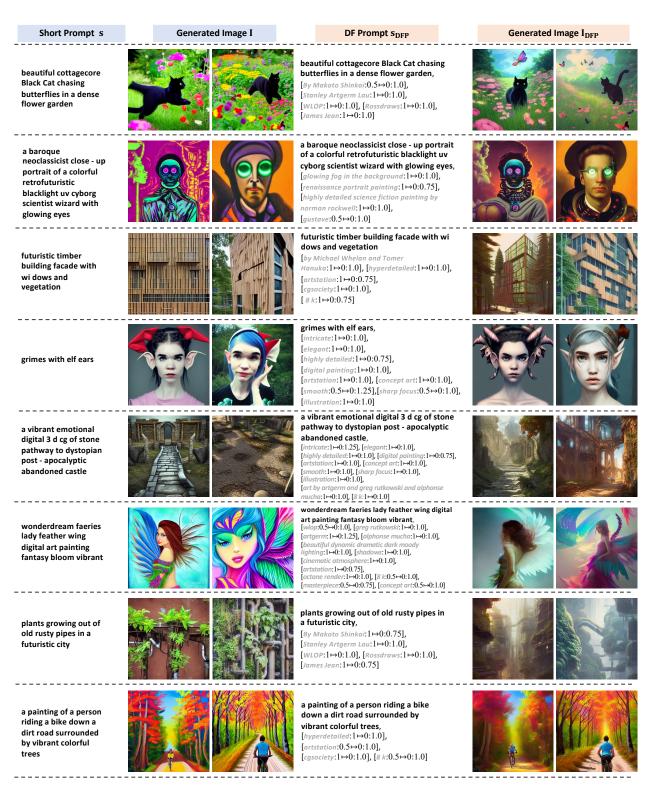


Figure A6. More examples of the generated images.