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# Investigating Prompt Engineering in Diffusion Models

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## Abstract

With the spread of the use of Text2Img diffusion models such as DALL-E 2, Imagen, Mid Journey and Stable Diffusion, one challenge that artists face is selecting the right prompts to achieve the desired artistic output. We present techniques for measuring the effect that specific words and phrases in prompts have, and (in the Appendix) present guidance on the selection of prompts to produce desired effects.

## 1 Introduction & Related Works

The use of diffusion models for text guided image generation has become an important paradigm in the last year with the introduction of models such as GLIDE (Nichol et al. [2022]), DALL-E 2 (Ramesh et al. [2022]), Imagen (Saharia et al. [2022]) and Latent Diffusion (Rombach et al. [2022]).

In early work, Diffusion models were often conditioned on dataset such as Imagenet (Deng et al. [2009]). Recent models Ramesh et al. [2022], Saharia et al. [2022] have moved away from classifier guidance (Ho et al. [2020]) to guiding their output via the embeddings resulting from text input to language models such as CLIP (Radford et al. [2021]).

The Stable Diffusion model (released under a permissive license in August 2022) is a Latent Diffusion Model (Rombach et al. [2022]) trained on 512x512 images from the LAION Aesthetics dataset of 2 Billion images (a subset of the LAION-5B database Schuhmann et al. [2022]).

## 2 Methodology

In the following, we divide the textual prompt into its two main components : (a) The physical and factual content of the image (eg. “A MaineCoon cat kneeling”); and (b) the stylistic considerations in the way the physical content is displayed (eg. lighting, and other descriptors of style of the image).

Our experiments show that it is possible to measure which words and phrases are likely to fall into each of the categories and then measure the effect of these words and phrases on the generated image.

### 2.1 Probing Images and Prompts

Given a specific random seed for the initial diffusion latents, and a consistent scheduler, images can be produced deterministically by the Stable Diffusion model for a given prompt. By keeping the same random seed and scheduler but changing the prompt slightly, we are able to produce images which visually show the difference between the 2 prompts.

To measure similarity between generated images, we experimented with LPIPS (Zhang et al. [2018]) perceptual loss (Johnson et al. [2016]), and Watson DFT (Czolbe et al. [2020]) measures.

Prompt Collection	LPIPS	VGG	CLIP
Descriptors	0.664	0.646	0.839
Nouns	0.512	0.513	0.200
Artists	0.465	0.530	0.627

Table 1: Image and Text average similarity

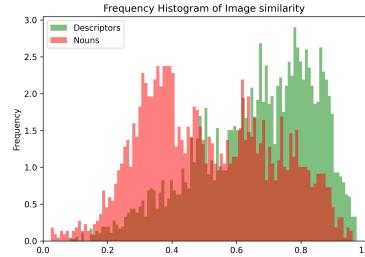


Figure 1: Descriptor vs Noun Distributions

The CLIP model outputs a 768-d embedding tensor each of its 77 input tokens (including padding). We measured the semantic difference between prompts by flattening the overall embedding out and using cosine similarity.

In addition, we measured prompt similarity using Sentence Transformers (Reimers and Gurevych [2019]) as the text similarity measure, since these are known to be effective in pure NLP settings.

### 3 Experiments & Observations

The Stable Diffusion model, supplemented with our chosen metrics, was evaluated on over 15,000 image generations. Over 2,000 prompt variations were used, and this enabled us to observe a number of interesting phenomena when the prompt styles were isolated, and the base prompt kept constant:

- Different linguistic categories (such as adjectives, nouns and proper nouns) tended to influence the image generation in different, but consistent, ways
- Simple adjectives (Descriptors) such as descriptions of qualities, changes in detail or more ethereal words, have a relatively small impact on the generated image
- Nouns (on the other hand) tend to dramatically shift the images as they introduce new content and act as more than just modifiers
- The most extreme examples of this can be seen in using the names of artists (e.g. “in the style of Leonardo da Vinci”) which, while describing a style, usually end up dramatically changing the constitution of the image itself and therefore making the image much further away from the original when measured by image similarity.

Indicative average results, and distributions across a wide range of prompts are illustrated in Table 1 and Figure 1. Further experimental results are given in the Appendix.

### 4 Discussion

The technique outlined in this paper allows the changes made to text prompts to be quantified in conjunction with their effect on the generated images.

We have established that words and phrases can be categorised, with each category having a different degree of effect on the overall image. While the exact effect of each word or phrase may change from model to model, the process for doing this should be robust enough to work on various types of models and only require an evaluation to establish baselines for that model going forward.

### 5 Future Work

This work suggests that the similarity of images and their CLIP vectors could be used as a form of guidance in image generation in the future, potentially being incorporated as part of the loss in the training of these models . There is also the intriguing possibility that the generative abilities of these kinds of multi-modal models could be used to develop and train novel similarity metrics.

## 6 Ethical Implications

Generative models such as Stable Diffusion have the potential for both good or bad depending on how they are used. The models themselves contain various biases towards various groups that occur from the images they were trained on and their training procedures. This can be seen clearly in experiments on images based on styles from various artists and should be taken into account when evaluating these models and their datasets.

By documenting these experiments and providing techniques to measure the changes, we aim to make it possible to see natural biases in these generative models.

## 7 Acknowledgments

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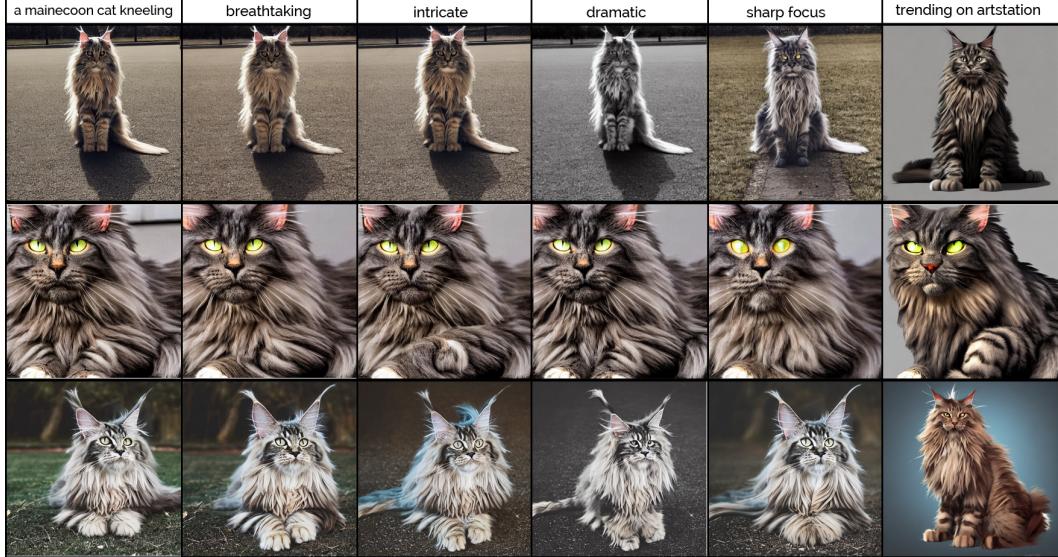


Figure 2: Overview of different image modifiers (base prompt on left)

## Appendices

### A Additional Experiments

In this section of the Appendix, we give illustrative results from our experiments using various types of modifiers added to a basic text prompt to measure the impact on the image by comparing image similarity to the image made with a base prompt (examples are shown in Figure 2).

We also tested additional factors, such as adding repeating words, lighting phrases, and creating images in the style of a particular artist, to see the change they create compared to a base image made with the same seed.

#### A.1 Repeating Words

One technique that has been reported to improve prompts is that of repeating words. We analysed repeating modifiers from the descriptor class to compare the effects of having the modifier once, and also repeated two, three and five times. Please see Figure 3. An example of repeating words changing an image can be seen in adding the word “minimalist” to the prompt. Repetition appears to have the effect of removing details from the background and eventually (with five occurrences of the word) starts to affect the actual subject of the image. Overall, though, we found that while having multiple occurrences of a word can change the image it often has no effect at all or has an effect that is not a desired semantic effect the word might be expected to contribute.



Figure 3: Repetitions of an image modifier (base prompt on left)

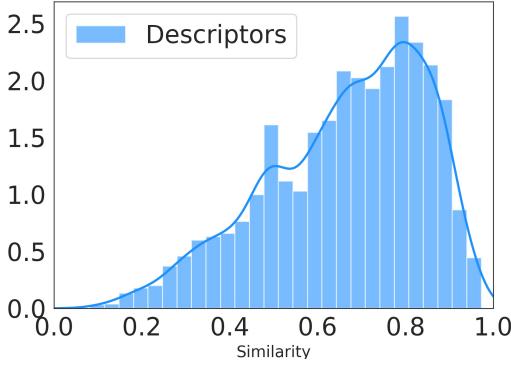


Figure 4: Descriptors Distribution

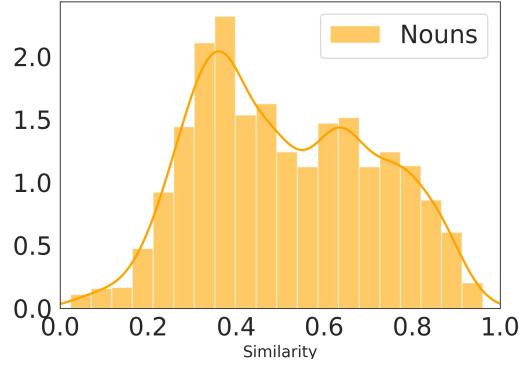


Figure 5: Nouns Distribution

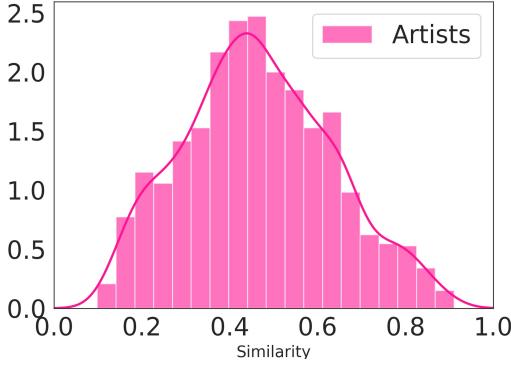


Figure 6: Artists Distribution

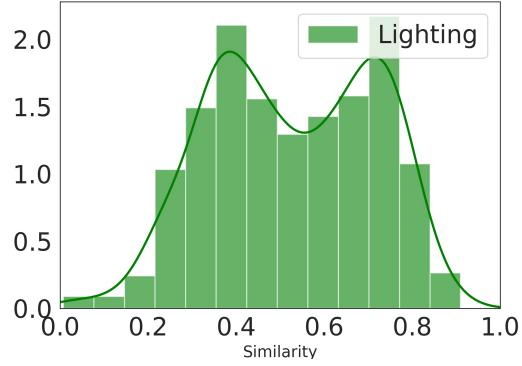


Figure 7: Lighting Distribution

## A.2 Categories of Styles

As outlined in the main paper, the content of the style section of a prompt can be viewed within categories. Figures 4 - 7 show the distribution of similarity *changes* in LPIPS scores for the different categories of style prompt additions.

As can be seen, adding Descriptors (roughly adjectives or adjectival phrases) affects the image less than adding Nouns, Artists or Lighting. These latter two categories are discussed below.

## A.3 Adding ‘Lighting’ Words



Figure 8: Comparing lighting modifiers (base prompt on left)

Words and phrases that describe lighting effects are unusual in that they can have either the properties of descriptors (which we have found don’t change generated images much) or they can act as nouns (which we observe to make larger changes in the actual content of the image).

This bimodal behaviour can be seen from the plot of the distribution of the image similarities in Figure 7, which shows 2 clear spikes in the distribution. One of these spikes being close to the that of descriptors and the other spike being similar to the distribution of nouns.

We also can clearly see this in the images in Figure 8 where we see that phrases such as “ambient lighting” can change the content significantly, whereas a phrase such as “beautiful volumetric lighting” has relatively little impact on the generated image. Lighting phrases can often change the look of the subject, the mood of the image and often just adding lighting information will also change the background of the image.



Figure 9: Examples of lighting prompts added to a single base image

#### A.4 Comparing CLIP to LPIPS

As mentioned in the main paper, we examined the relationship between the image similarity measured by comparing the images using LPIPS and the text similarity of the prompt. Figure 10 illustrates how semantic differences in the textual embeddings (measured using CLIP cosine distance) correspond to differences in the images as measured by LPIPS.

We also performed a comparison of the prompts using Sentence transformers Reimers and Gurevych [2019], a popular method for text similarity. By comparing Figure 11 to Figure 10, it can be seen that the sentence transformer model had a relatively weaker correlation to the LPIPS image changes. This is most likely due to the fact that the CLIP model has been used in the training of the overall model and so its representations are naturally aligned to match the generation of images.

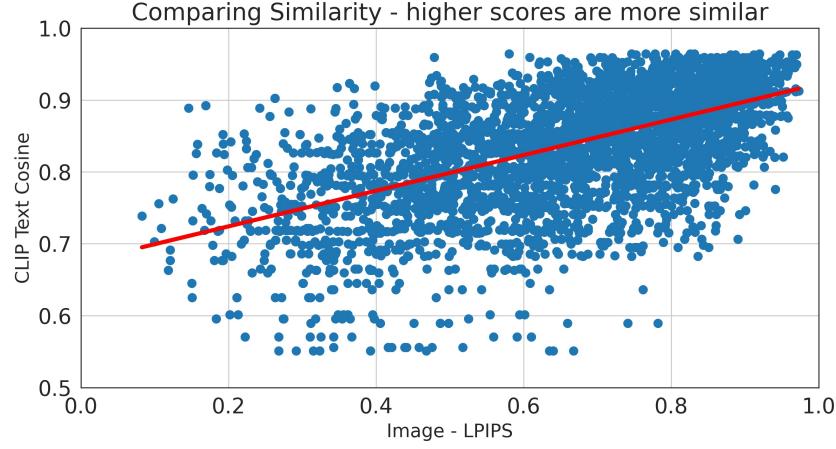


Figure 10: CLIP Text vs Image score differences for modifiers

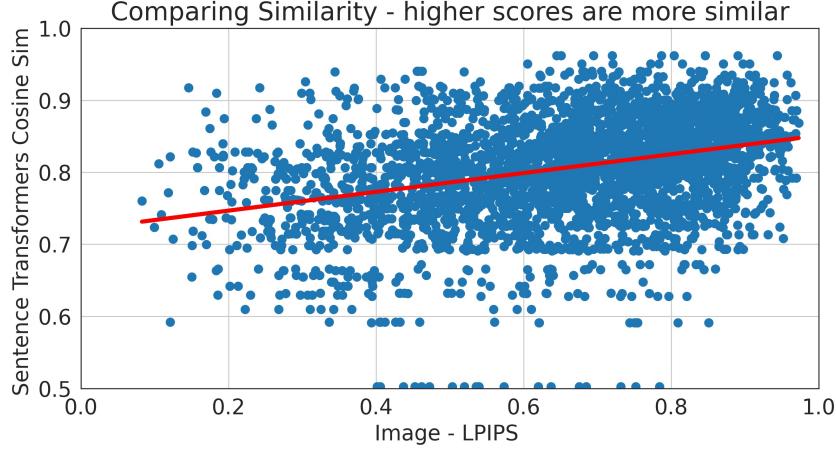


Figure 11: S-BERT Sentence Embeddings vs Image score differences for modifiers

### A.5 Styled by Artist

We examined the effect of adding the prompt “in the style of” along with an artist’s name to the original prompt with an extensive set of artist names.

Qualitatively, we found that including an artist’s name in the prompt can lead to image generation changes on multiple levels, with the artist’s name alone potentially informing the image generation as to the art medium (photo, oil paint, water color etc), the color palette and often the racial qualities of the subject.

Please see Figure 12 for an illustration of the range of effects seen.

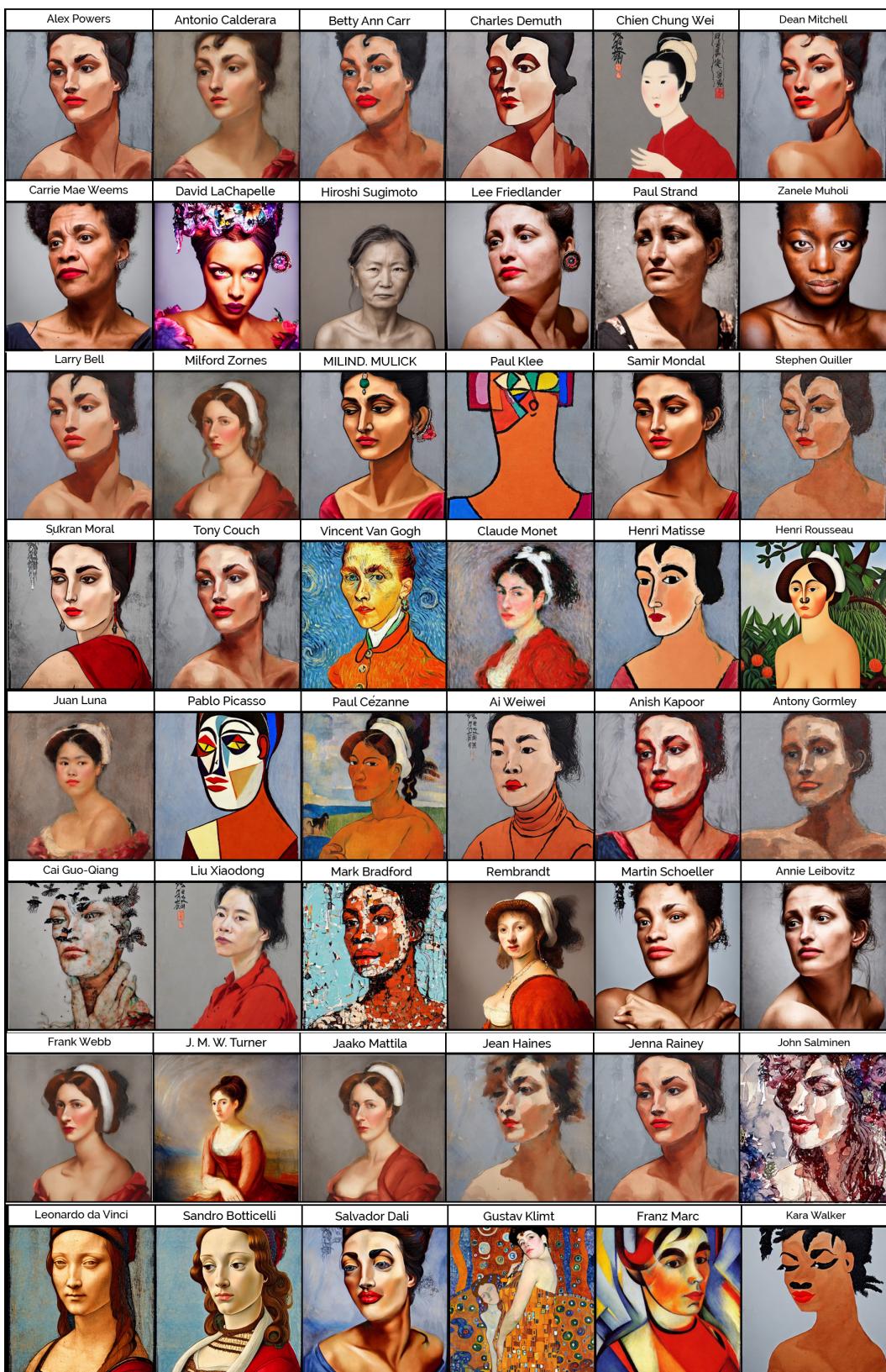


Figure 12: “A portrait of a beautiful woman in the style of ARTIST NAME”

## B Guidance for choosing your Prompts

While creating a prompt to generate an image may initially seem trivial and easy, it very quickly becomes clear to aspiring artists that it is often much harder than it might first appear to create a prompt that produces an output that matches their original intent.

Here we propose a procedure for creating prompts, where each stage builds on the previous ones :

- Start with a clear noun-based statement that contains the main subject you wish to have in the image.
- Be systematic about recording what seeds are effective, since it is easier to iterate on images based on a firm foundation (as can be seen from the samples included in this Appendix).
- The properties of the Stable Diffusion model allow it to be very good at replicating style of various artists. Because of this, it is often beneficial to look for artists and key styles that you would like to emulate and add that to your prompt.
- Finally, experiment with descriptors that you wish to add, considering the importance of (for instance) having a simple or a busy/intricate background. This can be done through adding lighting effects phrases and repeating words.

Overall, the process for ‘Prompt Engineering’ can also be seen as an artistic endeavour, and the techniques required for success must be honed by over time, using experimentation, imagination and creativity.