Best Prompts for Text-to-Image Models and How to Find Them

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Figure 1: Comparison of Stable Diffusion model-generated images using popular and custom keywords. Two pairs of images are shown, with each pair consisting of an image generated with the top-15 most popular keywords (left) and an image generated with keywords found by our method (right). The left pair of images depicts the “interior of an alien spaceship,” while the right pair depicts “daenerys targaryen queen.” Descriptions are cherry-picked.

ABSTRACT
Advancements in text-guided diffusion models have allowed for the creation of visually appealing images similar to those created by professional artists. The effectiveness of these models depends on the composition of the textual description, known as the prompt, and its accompanying keywords. Evaluating aesthetics computationally is difficult, so human input is necessary to determine the ideal prompt formulation and keyword combination. In this study, we propose a human-in-the-loop method for discovering the most effective combination of prompt keywords using a genetic algorithm. Our approach demonstrates how this can lead to an improvement in the visual appeal of images generated from the same description.

CCS CONCEPTS
• Human-centered computing → Empirical studies in visualization; • Information systems → Query reformulation; Image search.

KEYWORDS
human feedback, text-to-image generation, genetic optimization, aesthetics evaluation

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1 INTRODUCTION
Recent progress in computer vision and natural language processing has enabled a wide range of possible applications to generative models. One of the most promising applications is text-guided image generation (text-to-image models). Solutions like DALL-E 2 [14] and Stable Diffusion [16] use the recent advances in joint image and text embedding learning (CLIP [13]) and diffusion models [19] to produce photo-realistic and aesthetically-appealing images based on a textual description.

However, in order to ensure the high quality of generated images, these models need a proper prompt engineering [7] to specify the exact result expected from the generative model. In particular, it became a common practice to add special phrases (keywords) before or after the image description, such as “trending on artstation,” “highly detailed,” etc. Developing such prompts requires human intuition, and the resulting prompts often look arbitrary. Another problem is the lack of evaluation tools, so practically, it means that the user subjective judges the quality of a prompt by a single generation or on a single task. Also, there is currently no available analysis on how different keywords affect the final quality of generations and which ones allow to achieve the best images aesthetically.

In this work, we want to bridge this gap by proposing an approach for a large-scale human evaluation of prompt templates
using crowd workers. We apply our method to find a set of keywords for Stable Diffusion that produces the most aesthetically appealing images. Our contributions can be summarized as follows:

- We introduce a method for evaluating the quality of generations produced by different prompt templates.
- We propose a set of keywords for Stable Diffusion v1.4 and experimentally show that it improves the aesthetics of the generated images.
- We release all the data and code that allow to reproduce our results and build solutions on top of them, such as finding even better keywords and finding them for other models.

2 PROMTS AND HOW TO EVALUATE THEM

Consider a standard setup for generative models with text inputs. A model gets as an input a natural language text called prompt and outputs a text completion in the case of the text-to-text generation or an image in the case of text-to-image generation. Since specifying the additional information increases the quality of the output images [7], it is common to put specific keywords before and after the image description:

prompt = [kw₁, ..., kwₘ] [description] [kwₘ, ..., kwₙ].

Consider a real-world example when a user wants to generate an image of a cat using a text-to-image model. Instead of passing a straightforward prompt a cat, they use a specific prompt template, such as Highly detailed painting of a calico cat, cinematic lighting, dramatic atmosphere, by dustin nguyen, akihiko yoshida, greg tocchini, greg rutkowski, cliff chiang, 4k resolution, luminous grassy background. This example text is often used as a standard test prompt.

Since aesthetics are difficult to evaluate computationally, we propose a human-in-the-loop method for evaluating the keyword sets. Our method takes as an input a set of textual image descriptions D, a set of all possible keywords K, and a set of the keyword set candidates S and outputs a list of keyword sets sⱼ ⊆ K, sⱼ ∈ S in the increasing order of their aesthetic appeal to humans. Since the setting is challenging for annotators to directly assign scores for images or rank them, we run pairwise comparisons of images generated from a single description but with different keyword sets and then infer the ranking from the annotation results. Our algorithm can be described as follows:

1. For each pair of a description dᵢ ∈ D and a keyword set sⱼ ∈ S, generate four images 𝐼ᵢⱼ = {𝑖ⱼ₁, ..., 𝑖ⱼₖ}.
2. For each image description dᵢ ∈ D, sample nk log₂(n) pairs of images (𝑖ⱼ₁, 𝑖ⱼₖ) generated with different keyword sets, where n is the number of keyword sets to compare, and k is the number of redundant comparisons to get the sufficient number of comparisons [9].
3. Run a pairwise comparison crowdsourcing task in which the workers are provided with a description and a pair of images, and they have to select the best image without knowing the keyword set.
4. For each description dᵢ ∈ D, aggregate the pairwise comparisons using the Bradley-Terry probabilistic ranking algorithm [1], recovering a list rᵢ = s₁ < ... < sᵢₙ of keyword sets ordered by their visual appeal to humans.
5. For each keyword set, compute the average rank in the lists recovered for the descriptions.

As a result, we quantify the quality of a keyword set as its rank averaged per description.

3 ITERATIVE ESTIMATION OF THE BEST KEYWORD SET

One of the advantages of our approach is that the keywords can be evaluated iteratively. Once we have compared a number of keyword sets, we can request a small additional number of comparisons to evaluate the new set of keywords. This allows us to apply discrete optimization algorithms, such as a genetic algorithm, to retrieve from a large pool of keywords the most influential keywords.

Figure 2 represents a scheme of our approach. We pick a set of keyword sets for initialization, rank the keywords using the approach in Section 2, and use it as an initial population for the genetic algorithm. Then we repeat the following steps multiple times to obtain the best-performing keyword set.

1. Obtain the next candidate keyword set sⱼ based on quality metrics of currently evaluated keyword sets using the genetic algorithm. We present the details on a particular variation of a genetic algorithm we use in Section 4.1.
2. For each image description dᵢ ∈ D, sample k (n + 1) log₂(n + 1) − n log₂ n pairs (𝑖ⱼ₁, 𝑖ⱼₖ) of images generated using keywords from the new candidate set and already evaluated keyword sets. We do this to sustain kn log₂ n comparisons in total.
3. Evaluate the quality of the obtained keyword set (steps 3-5 in Section 2).

4 EXPERIMENT

We perform an empirical evaluation of the proposed prompt keyword optimization approach in a realistic scenario using the publicly available datasets.

4.1 Setup

To construct a set of possible keywords, we have parsed the Stable Diffusion Discord and took the 100 most popular keywords. For image descriptions, we decided to choose prompts from six categories: portraits, landscapes, buildings, interiors, animals, and other. We took twelve prompts for each category from Reddit and https://lexica.art/ and manually filtered them to obtain only raw descriptions without any keywords.

We use a simple genetic algorithm to find the optimal prompt keyword set. The algorithm was initialized with two keyword sets: one is an empty set, and another set contained the 15 most popular keywords that we retrieved before. We limited the maximum number of output keywords by 15 as otherwise, the resulting prompts became too long.
which is then evaluated according to scheme (a). The process is repeated for the pre-determined number of iterations.

\( n \) was generated with the Stable Diffusion model [16] with 50 diffusion steps and 7.5 classifier-free guidance scale using the DDIM scheduler [20]. Then, we run crowdsourcing annotation on the Toloka platform.\(^3\) After the annotation is completed, we run the Bradley-Terry [1] aggregation from the Crowd-Kit [21] library for Python to obtain a ranked list of keyword sets for each image description. The final evaluation metric used in the genetic algorithm to produce the new candidate sets is the average rank of a keyword set (as described in Section 2). We use 60 image descriptions for optimization (ten from each category) and 12 for the validation of the optimization results.

For the keywords optimization, we use a genetic algorithm as follows. We parameterized every keyword set by a binary mask of length 100, indicating whether the keyword should be appended to the prompt. We initialized the algorithm with all zeros and the mask follows. We parameterized every keyword set by a binary mask of length 100, indicating whether the keyword should be appended to the prompt. We initialized the algorithm with all zeros and the mask including the 15 most popular keywords. At the selection step, we chose the keyword sets with the highest rank and perform crossover and mutation to obtain a new candidate, which is then evaluated according to scheme (a). The process is repeated for the pre-determined number of iterations.

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4.2 Results

We ran the optimization for 56 iterations on 60 image descriptions since we have a fixed annotation budget. To ensure that our method did not overfit, we ran the evaluation on another 12 descriptions (validation). Figure 4 shows ranks of tried keyword sets. According to the evaluation results in Table 1, we found that our algorithm was able to find a significantly better set of keywords than the fifteen most popular ones (Top-15). Also, we see that any set of prompt keywords is significantly better than no keywords at all (No Keywords).
Table 1: Average rank of the baseline keywords (top-15 most common on Stable Diffusion Discord) and the ones found by the genetic algorithm. Rank is averaged over 60 prompts on train and over 12 prompts on validation (val); maximal rank is 56.

|          | Train | Validation |
|----------|-------|------------|
| No Keywords | 3.5   | 5.42       |
| Top-15    | 14.25 | 12.50      |
| Best Train | 43.60 | 38.00      |
| Best Val  | 39.32 | 46.00      |

Figure 4: Average ranks of keyword sets tried by the genetic algorithm. There are total 56 keyword sets, so the maximal average rank is 56.

We see that most results hold on the validation set, too, but the metrics have more noise. Overall, the best set of keywords on the training set of 60 prompts is *cinematic, colorful background, concept art, dramatic lighting, high detail, highly detailed, hyper realistic, intricate, intricate sharp details, octane render, smooth, studio lighting, trending on artstation*. An example of images generated with this keyword set is shown in Figure 1.

4.3 Discussion

We show that adding the prompt keywords significantly improves the quality of generated images. We also noticed that the most popular keywords do not result in the best-looking images. To estimate the importance of different keywords, we trained a random forest regressor [2] on the sets of keywords and their metrics that is similar to W&B Sweeps. We found that the most important keywords, in reality, are different from the most widely used ones, such as "trending on artstation." The most important keyword we found was "colorful background."

There are several limitations to our approach. We can not conclude that the found set of keywords is the best one since the genetic algorithm can easily fall into a local minimum. In our run, it tried only 56 keywords out of the 100 most popular ones. Also, our evaluation metrics are based on ranks, not absolute scores, so they are not sensitive enough to determine the convergence of the algorithm.

However, since we release all the comparisons, generated images, and code, it is possible for the community to improve on our results. For instance, one can run a genetic algorithm from a different initialization, for a larger number of iterations, or even with more sophisticated optimization methods. This can easily be done by comparing the new candidates with our images and adding these results to the dataset.

5 RELATED WORK

The aesthetic quality evaluation is one of the developing topics in computer vision. There are several datasets and machine learning methods aiming at solving this problem [18, 22]. However, the available datasets contain human judgments on image aesthetics scaled from 1 to 5. Our experience shows that the pairwise comparisons that we used in this paper are a more robust approach as different humans perceive scales differently and subjectively.

Also, they specify training a model to evaluate the aesthetics but not on the generative models. Large language models, such as GPT-3 [3], have enabled a wide range of research tasks on prompt engineering [5, 6, 8, 10, 12, 15, 17]. Recent papers also discover the possibilities of prompt engineering for text-to-image models and confirm that prompts benefit from the added keywords [7]. To the best of our knowledge, we are the first to apply it to find the best keywords.

6 CONCLUSION

We presented an approach for evaluating the aesthetic quality of images produced by text-to-image models with different prompt keywords. We applied this method to find the best keyword set for Stable Diffusion and showed that these keywords produce better results than the most popular keywords used by the community. Despite the fact that our work focuses on the evaluation of keywords for text-to-image models, it is not limited by this problem and can be applied for an arbitrary prompt template evaluation, for example, in the text-to-text setting. This is a direction for our future work. Last but not least, we would like to encourage the community to continue our experiment and find better keyword sets using our open-source code and data.5

5 [https://docs.wandb.ai/guides/sweeps](https://docs.wandb.ai/guides/sweeps)

5 [https://github.com/toloka/BestPrompts](https://github.com/toloka/BestPrompts)
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