

# DIFFUSIONDB: A Large-scale Prompt Gallery Dataset for Text-to-Image Generative Models

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## Abstract

With recent advancements in diffusion models, users can generate high-quality images by writing text prompts in natural language. However, generating images with desired details requires proper prompts, and it is often unclear how a model reacts to different prompts and what the best prompts are. To help researchers tackle these critical challenges, we introduce DIFFUSIONDB, the first large-scale text-to-image prompt dataset. DIFFUSIONDB contains 2 million images generated by Stable Diffusion using prompts and hyperparameters specified by real users. We analyze prompts in the dataset and discuss key properties of these prompts. The unprecedented scale and diversity of this human-actuated dataset provide exciting research opportunities in understanding the interplay between prompts and generative models, detecting deepfakes, and designing human-AI interaction tools to help users more easily use these models. DIFFUSIONDB is publicly available at: <https://poloclub.github.io/diffusiondb>.

## 1 Introduction

Recent diffusion models have gained immense popularity by enabling high-quality and controllable image generation based on text prompts written in natural language (Rombach et al., 2022; Ramesh et al., 2022; Saharia et al., 2022). Since the release of these models, people from different domains have quickly applied them to create award-winning artworks (Roose, 2022), synthetic radiology images (Chambon et al., 2022), and even hyper-realistic videos (Ho et al., 2022).

However, generating images with desired details is difficult, as it requires users to write proper prompts specifying the exact expected results. Developing such prompts requires trial and error, and can often feel random and unprincipled (Liu and Chilton, 2022). Willison et al. (2022) analogize writing prompts to wizards learning “magical

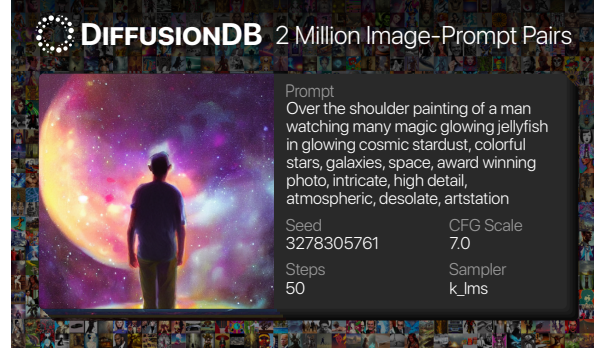


Fig. 1: DIFFUSIONDB is the first large-scale dataset containing **2 million** Stable Diffusion images and their text prompts and hyperparameters. This dataset provides exciting research opportunities in prompt engineering, deepfake detection, as well as understanding and debugging large text-to-image generative models.

spells”: users do not understand why some prompts work, but they will add these prompts to their “spell book.” For example, to generate highly-detailed images, it has become a common practice to add special keywords such as “trending on artstation” and “unreal engine” in the prompt.

Prompt engineering has become a field of study in the context of text-to-text generation, where researchers systematically investigate how to construct prompts to effectively solve different downstream tasks (Branwen, 2020; Reynolds and McDonnell, 2021). As large text-to-image models are relatively new, there is a pressing need to understand how these models react to prompts, how to write effective prompts, and how to design tools to help users generate images (Liu and Chilton, 2022).

To help researchers tackle these critical challenges, we present DIFFUSIONDB (Fig. 1), the first large-scale prompt dataset with 2 million real prompt-image pairs. In this work, we make three major **contributions**:

- **DIFFUSIONDB, the first large-scale prompt dataset**, containing **2 million** images generated

by Stable Diffusion (Rombach et al., 2022) and their prompts and hyperparameters specified by real users. We construct this dataset by collecting images shared on the Stable Diffusion public Discord server (§ 2). We release DIFFUSIONDB with a CC0 1.0 license, allowing users to flexibly share and adapt the dataset for their use. In addition, we open-source our code<sup>1</sup> that collects and processes the images and prompts.

- **Revealing new prompt patterns.** The unprecedented scale of DIFFUSIONDB paves the path for researchers to systematically investigate diverse prompts and associated images that were previously not possible. Through analyzing the linguistic patterns of prompts, we discover the common prompt patterns and tokens (§ 3).
- **Providing new research directions.** As the first-of-its-kind text-to-image prompt dataset, DIFFUSIONDB opens up unique opportunities for researchers from both machine learning (ML) and human-computer interaction (HCI) communities. The scale and diversity of this human-actuated dataset will provide new research opportunities in better tooling for prompt engineering, detecting deepfakes, as well as debugging and explaining large generative models (§ 4).

We hope DIFFUSIONDB will serve as an important resource for researchers to study the roles of prompts in text-to-image generation and design next-generation human-AI interaction tools.

## 2 Constructing DIFFUSIONDB

We construct DIFFUSIONDB by scraping user-generated images on the official Stable Diffusion Discord server. We choose Stable Diffusion because it is currently the only open-source large text-to-image generative model, and all generated images have a CC0 1.0 Universal Public Domain Dedication license that waives all copyright and allows uses for any purpose (StabilityAI, 2022b). We choose the official Stable Diffusion Discord server because it is public, and it has strict rules against generating and sharing illegal, hateful, or NSFW (not suitable for work, such as sexual and violent content) images. The server also disallows users to write or share prompts with personal information (StabilityAI, 2022a).

To construct DIFFUSIONDB, we first collect images shared on the Discord server (§ 2.1), then we

link these images to their prompts and hyperparameters (§ 2.2). We design a flexible and modularized file structure to organize 2 million images (§ 2.3). We make the dataset publicly available to anyone and provide a way to enable users to flag images for removal (§ 2.4). We discuss DIFFUSIONDB’s limitations and broader impacts in its Data Sheet (Geburu et al., 2020) (§ A) and § 6.

### 2.1 Collecting User Generated Images

We first download chat messages and images from the Stable Diffusion Discord channels with DiscordChatExporter (Holub, 2017). This tool saves chat messages as HTML files. In this version of DIFFUSIONDB, we focus on channels where users can request a bot run Stable Diffusion to generate images. In these channels, a user can type a prompt, hyperparameters, and the number of images, and then a bot would reply the user with generated images along with used random seeds.

### 2.2 Processing Images & Extracting Metadata

After collecting chat messages and images, we use Beautiful Soup (Richardson, 2007) to parse the message HTML files to map each generated image with its prompt, hyperparameters, seed, and the requester’s Discord username. Many generated images are collages, where the bot has composited  $n$  generated images into a grid (e.g., a  $3 \times 3$  grid of  $n = 9$  images). These  $n$  images have the same prompt and hyperparameters but different random seeds. We use Pillow (Clark, 2015) to split a collage into  $n$  individual images. To save storage, for each collage, we randomly select one out of  $n$  images to include in this version of DIFFUSIONDB. All images are stored as PNG files.

### 2.3 Organizing DIFFUSIONDB

We design a modularized file structure to organize DIFFUSIONDB. We first use the Universally Unique Identifier (UUID, Version 4) (Leach et al., 2005) to assign each image a unique filename. Then, we organize images into 2,000 sub-folders where each folder includes 1,000 images. In each sub-folder, we create a JSON file that contains 1,000 key-value pairs mapping an image name to its prompt, seed, CFG scale, and sampler. An example of this image-prompt pair can be seen in Fig. 1. The seed, CFG scale, and sampler are hyperparameters that can be configured by the users. This modularized file structure enables researchers to

<sup>1</sup>Code: <https://github.com/poloclub/diffusiondb>

flexibly download a subset of DIFFUSIONDB instead of the entire 2 million images.

At the top level folder, we include a metadata table stored as an Apache Parquet file (Apache, 2013); the table has six columns: unique image name, image path, prompt, seed, CFG scale, and sampler, and each row represents an image. We choose Parquet because it is column-based: researchers can efficiently query individual columns (e.g., prompts) without reading the entire table.

## 2.4 Distribution and Expansion

To distribute DIFFUSIONDB, we compress each image sub-folder as a Zip file and follow the same modularized file structure (§ 2.3). Note that we have collected the Discord usernames of image creators (§ 2.2); however, we decide not to include these usernames in our dataset distribution (§ 2.3). We decide to anonymize the dataset because some prompts might include sensitive information: explicitly linking them to their creators can cause harm to creators. Finally, we host the dataset at Hugging Face Datasets,<sup>2</sup> a popular website where ML researchers share and find datasets.

We discuss the limitations of DIFFUSIONDB in the Data Sheet (Gebru et al., 2020) (§ A) and § 6. To mitigate the potential harms of our dataset, the DIFFUSIONDB website links to a Google Form where anyone can report harmful and sensitive prompts or images. In addition, image creators can also use this form to notify us if they do not want to have their images included in DIFFUSIONDB by providing their Discord usernames. We will periodically monitor this form and remove reported images and prompts from the dataset.

Despite DIFFUSIONDB’s unprecedented size, it is the first step to studying large text-to-image generative models. To help researchers make strides in exciting research directions (§ 4), we will continue expanding this dataset by including more split images (§ 2.2) and collecting new images from other sources and generative models.

## 3 Prompt Analysis

DIFFUSIONDB is a constantly growing dataset as more image-prompt pairs are scraped from user creations. As such, we perform a brief summary of prompt composition on a subset consisting of 1.5 million prompts from DIFFUSIONDB. The nature

<sup>2</sup>Hugging Face Dataset: <https://huggingface.co/datasets/poloclub/diffusiondb>

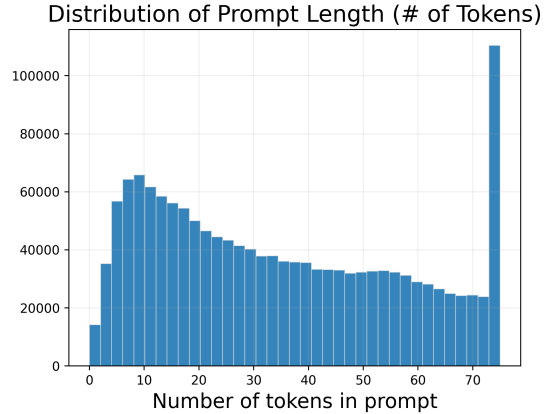


Fig. 2: A distribution of prompts in the dataset binned by the length of their tokens. All prompts are truncated to the model default number of tokens (75), explaining the spike in the final bin.

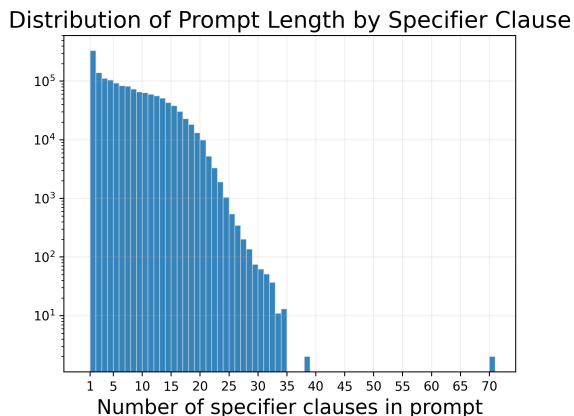
by which we construct DIFFUSIONDB means that many prompts in the dataset are not unique. Users can submit the same prompt multiple times, often trying different seeds, guidance scales, and sampling methods (all of which are also included in DIFFUSIONDB § 2.3). Our subset of 1.5 million images contains about 1.1 million unique prompts.

### 3.1 Prompt Lengths

We tokenize every prompt in DiffusionDB using the tokenizer included with the Stable Diffusion v1.4 pretrained weights and code distributed by Huggingface Diffusers (von Platen et al., 2022; Rombach et al., 2022) using default tokenization configuration. Note that the default configuration truncates tokenized prompts at 75 tokens.

We measure the length of each prompt according to its tokenized length (excluding special tokens like `<|startoftext|>` and `<|endoftext|>`). We show a distribution of the token lengths of prompts in this dataset in Fig. 2. The spike at 75 indicates that many users submitted prompts that are longer than that taken by the model.

Many users submit prompts containing many comma-delimited phrases that apply desirable constraints to their prompt. We refer to each subphrase as a “specifier clause”; the first of these typically refers to the desired object or scene, and subsequent clauses describe the style or constraints. It has been shown that these additional clauses can create significant improvement in the generation of desired images. The following is an example of a typical prompt with several specifier clauses:



A cavalier knight approaching a castle, future, render of dreamy beautiful landscape, fantasy dreamy, artgerm, large scale, details, vintage, photo, hyper realistic, ultra realistic, photography, unreal engine, high detailed, 8 k

To compute the number of specifier clauses we first truncate each prompt to the maximum token length and split each prompt by the common delimiters `{, ; |}`. In the above prompt, there are 15 specifier clauses and only the first clause describes the scene. In Fig. 3, we show the distribution of prompts according to the number of specifier clauses.

### 3.2 Most Common Tokens

We collect the frequencies of each token in DIFFUSIONDB’s prompts and present the top 40 most popular tokens (after filtering special tokens, punctuation, stop words, and subtokens that are difficult to assign to a single concept). In certain cases, a most frequent token is part of a longer token (e.g., the tokens `art` and `station</w>` are common subtokens that combine to form the word “art-station” in the majority of cases). When applicable, we use our discretion to combine these. In Fig. 4, these most frequent tokens are presented as a word cloud (Griffiths et al., 2003).

## 4 Enabling New Research Directions

The unprecedented scale and diversity of DIFFUSIONDB bring new exciting research opportunities for both NLP and HCI communities. Below, we

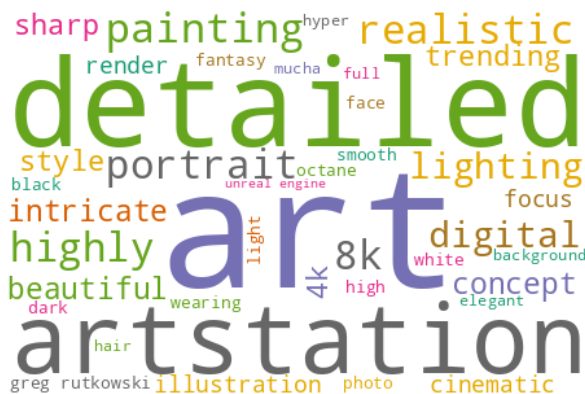


Fig. 4: A word cloud representing the top 40 most frequent and yet meaningful tokens in DIFFUSIONDB. Each token is sized by its relative frequency; i.e., art is the most frequent, and hyper is the 40th most frequent.

### 4.1 Prompt Autocomplete

With DIFFUSIONDB, researchers can develop an autocomplete system to help users construct prompts. For example, one can use the prompt corpus to train an  $n$ -gram model to predict the words that are most likely to occur following a prompt part. A more sophisticated approach is to use *semantic autocomplete* (Hyvönen and Mäkelä, 2006): researchers can first categorize prompt keywords into “ontological categories”, such as subject, style, quality, repetition, and magic terms (Oppenlaender, 2022). Then, a semantic autocomplete model can suggest related keywords from unspecified categories. For example, when a user writes “a dog resting on the grass,” the system can suggest a style keyword “depth of field” and a magic keyword “award-winning” to improve the quality of generated images.

In addition to autocomplete, researchers can also study prompt *auto-replace*. Previous research has shown that two semantically similar prompts can yield images with different qualities (Liu and Chilton, 2022). Therefore, one can use DIFFUSIONDB to distill effective prompt patterns and create a “translation” model that replaces weaker prompt keywords with more effective keywords. For example, the model can translate “Cool image of a flying dragon in fantasy art style” to “Flying dragon, Greg Rutkowski, trending



on artstation.” In this example, Greg Rutkowski is a famous fantasy artist, and adding his name to a prompt can significantly improve the generated image quality (Heikkilä, 2022).

## 4.2 Generating Images through Search

As DIFFUSIONDB contains 2 million images, this dataset might have already included images with a user’s desired effects. Therefore, a user can quickly search images in DIFFUSIONDB instead of running Stable Diffusion, which can be slow and costly. Lexica (Shameem, 2022), an AI start-up, provides such a search engine, where users can search Stable Diffusion images by natural language or images. In addition to searching images, users can also use a search engine for educational purposes—browsing related images and prompts to learn how to write effective prompts. To better support Stable Diffusion learners, researchers can construct a structured index of images and prompts, such as building a *semantivisual image hierarchy* of images (Li et al., 2010), or a *hierarchical topic model* of prompts (Griffiths et al., 2003). This hierarchical index can then help learners easily discover images with similar and different styles.

## 4.3 Debugging Image Generation

With DIFFUSIONDB, a large and diverse collection of Stable Diffusion usage logs, researchers can detect weak points and failure modes of Stable Diffusion. For example, we expect prompts and their associated images to have similar semantic meanings—researchers can compare the joint text-image embedding, such as CLIP (Radford et al., 2021), between prompts and images to detect misalignments. A misalignment example can be a dog prompt resulting in a cat image. Researchers can also use separate text and image embedding spaces to detect potential model failures. For example, we expect similar prompts to yield similar images. Therefore, researchers can compute and compare the embedding distances of images whose prompts are similar to each other. This approach can potentially reveal sensitive keywords that do not significantly change a prompt’s meaning but could lead to a drastic change in the generated images.

## 4.4 Enabling Explainable Image Generation

As generative models have been gaining immense popularity, there is a call for transparent creativity (Llano et al., 2022). Researchers argue that explanations of how a model generates text and

images can help users construct mental models and better use these models. There is a growing body of research in explainable AI (Mittelstadt et al., 2019). However, this line of research currently focuses on predictive models instead of generative models. Many popular explanation techniques rely on input permutation: one can compute feature attribution scores by running a model several times on slightly-modified input values (Ribeiro et al., 2016; Lundberg and Lee, 2017). DIFFUSIONDB contains 2 million prompts including similar prompts with minor differences, such as “a happy dog” and “a sad dog”. Therefore, researchers can leverage DIFFUSIONDB’s “naturally permuted” prompts and their associated images to investigate how individual keywords affect the generation process. DIFFUSIONDB can save significant time and cost, as researchers no longer need to permute prompts and run Stable Diffusion themselves.

## 4.5 Deepfake Detection

Recent breakthroughs in large text-to-image generative models have raised concerns about using them for deepfake generation (Wiggers, 2022). Deepfakes refer to fake imagery of real individuals for unethical and malicious applications (Korshunov and Marcel, 2018). As these image generative models have become more and more accessible, it has never been more important to study how to detect and mitigate deepfakes. For example, Emad Mostaque, the founder of Stability AI that created Stable Diffusion, has also acknowledged the urgency of counterbalance deepfakes and stated that Stability AI has a \$200,000 prize to award the best open-source deepfake detector (Roose et al., 2022).

The state-of-art methods to detect deepfakes focus on artifact detection and undirected detection (Mirsky and Lee, 2022). DIFFUSIONDB is extremely valuable for both approaches. For example, with this large-scale collection of images generated by the cutting-edge model, researchers can identify synthetic artifacts and train ML models or use forensic analysis to detect these artifacts. Similarly, researchers can use DIFFUSIONDB and LAION-5B (Schuhmann et al., 2022) (the training data of Stable Diffusion) to train a classifier that classifies synthetic images from real images.

## 5 Related Work

**Text-to-text Prompting.** Since the introduction of large language models, such as GPT-3 (Brown

et al., 2020), researchers have been studying prompt engineering for text-to-text generation (e.g., Liu et al., 2022; Lu et al., 2022; Rubin et al., 2022). In particular, researchers have introduced PromptSource (Bach et al., 2022), a dataset of 2k text prompts along with a framework that helps practitioners create and share their prompts. The PromptSource dataset has enabled researchers to create interactive tools to facilitate prompt construction (Strobelt et al., 2022). In contrast, our work focuses on text-to-image prompting, and DIFFUSIONDB has an unprecedented scale of 2 million real prompt-image pairs.

**Text-to-image Prompting.** Despite the relatively short history of large text-to-image generative models, such as Stable Diffusion (Rombach et al., 2022), there is an explosion of interest in text-to-image prompt engineering research from both ML and HCI communities (e.g., Qiao et al., 2022; Pavlichenko and Ustalov, 2022). For example, Openlaender (2022) identifies six types of prompt modifiers through a 3-month ethnographic study with online generative art communities. Similarly, Liu and Chilton (2022) proposes design guidelines for text-to-image prompt engineering by experimenting with 1,296 prompts. Closest in spirit to DIFFUSIONDB is Lexica (Shameem, 2022), a start-up that allows users to search over 5 million Stable Diffusion images with their prompts. However, Lexica does not release its internal database. In comparison, DIFFUSIONDB is open-source and publicly available to everyone.

## 6 Limitations

We conclude by acknowledging three main limitations of our work.

- **Possible inclusion of harmful images and prompts.** We collect images and their prompts from the Stable Diffusion Discord server (§ 2). The Discord server has rules against users generating or sharing harmful or NSFW (not suitable for work, such as sexual and violent content) images. The Stable Diffusion model used in the server also has an NSFW filter that blurs the generated images if it detects NSFW content. However, it is still possible that some users had generated harmful images that were not detected by the NSFW filter or removed by the server moderators. Therefore, DIFFUSIONDB can potentially contain these images. To mitigate the potential

harm, we provide a Google Form on the DIFFUSIONDB website where users can report harmful or inappropriate images and prompts. We will closely monitor this form and remove reported images and prompts from DIFFUSIONDB.

- **Potential biases of the data source.** The 2 million images in DIFFUSIONDB have diverse styles and categories. However, Discord can be a biased data source. Our images come from channels where early users could use a bot to use Stable Diffusion before release. As these users had started using Stable Diffusion before the model was public, we hypothesize that they are AI art enthusiasts and are likely to have experience with other text-to-image generative models. Therefore, the prompting style in DIFFUSIONDB might not represent novice users. Similarly, the prompts in DIFFUSIONDB might not generalize to domains that require specific knowledge, such as medical images (Chambon et al., 2022).
- **Generalizability.** Previous research has shown a prompt that works well on one generative model might not give the optimal result when used in other models (Borji, 2022). Therefore, different models can need users to write different prompts. For example, many Stable Diffusion prompts use commas to separate keywords, while this pattern is less seen in prompts for DALL-E 2 (Ramesh et al., 2022) or Midjourney (Holz, 2022). Thus, we caution researchers that some research findings from DIFFUSIONDB might not be generalizable to other text-to-image generative models.

## 7 Conclusion

In this paper, we present DIFFUSIONDB, the first large-scale text-to-image prompt dataset. The dataset contains 2 million images with their text prompts collected from the Stable Diffusion discord server. We release the dataset with a CC0 1.0 license and open source all collection and analysis code, broadening the public’s access to cutting-edge AI technologies. We discuss our findings regarding the prompt and image patterns. We hope our work will serve as a cornerstone for the future development of large text-to-image generative modes and tools that help users use these modes.

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## References

- Apache. 2013. [Apache Parquet: Open Source, Column-oriented Data File Format Designed for Efficient Data Storage and Retrieval](#).
- Stephen Bach, Victor Sanh, Zheng Xin Yong, Albert Webson, Colin Raffel, Nihal V. Nayak, Abheesht Sharma, Taewoon Kim, M Saiful Bari, Thibault Fevry, Zaid Alyafeai, Manan Dey, Andrea Santilli, Zhiqing Sun, Srulik Ben-david, Canwen Xu, Gunjan Chhablani, Han Wang, Jason Fries, Maged Alshaibani, Shanya Sharma, Urmish Thakker, Khalid Almubarak, Xiangru Tang, Dragomir Radev, Mike Tian-jian Jiang, and Alexander Rush. 2022. [Prompt-Source: An Integrated Development Environment and Repository for Natural Language Prompts](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*.
- Ali Borji. 2022. [Generated Faces in the Wild: Quantitative Comparison of Stable Diffusion, Midjourney and DALL-E 2](#). *arxiv:2210.00586*.
- Gwern Branwen. 2020. [GPT-3 Creative Fiction](#).
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. [Language models are few-shot learners](#). In *Advances in Neural Information Processing Systems*, volume 33.
- Pierre Chambon, Christian Bluethgen, Curtis P. Langlotz, and Akshay Chaudhari. 2022. [Adapting Pre-trained Vision-Language Foundational Models to Medical Imaging Domains](#). *arxiv:2210.04133*.
- Alex Clark. 2015. [Pillow: Python Imaging Library \(Fork\)](#).
- Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé III, and Kate Crawford. 2020. [Datasheets for Datasets](#). *arXiv:1803.09010 [cs]*.
- Thomas Griffiths, Michael Jordan, Joshua Tenenbaum, and David Blei. 2003. [Hierarchical topic models and the nested chinese restaurant process](#). In *Advances in Neural Information Processing Systems*, volume 16.
- Melissa Heikkilä. 2022. [This Artist is Dominating AI-generated Art. And He’s Not Happy about It](#).
- Jonathan Ho, William Chan, Chitwan Saharia, Jay Whang, Ruiqi Gao, Alexey Gritsenko, Diederik P. Kingma, Ben Poole, Mohammad Norouzi, David J. Fleet, and Tim Salimans. 2022. [Imagen Video: High Definition Video Generation with Diffusion Models](#). *arxiv:2210.02303*.
- Oleksii Holub. 2017. [DiscordChatExporter: Exports Discord Chat Logs to a File](#).
- David Holz. 2022. [Midjourney: Exploring New Mediums of Thought and Expanding the Imaginative Powers of the Human Species](#).
- Eero Hyvönen and Eetu Mäkelä. 2006. [Semantic Autocompletion](#). In *The Semantic Web – ASWC 2006*, volume 4185.
- Pavel Korshunov and Sebastien Marcel. 2018. [DeepFakes: A New Threat to Face Recognition? Assessment and Detection](#). *arxiv:1812.08685*.
- P. Leach, M. Mealling, and R. Salz. 2005. [A Universally Unique Identifier \(UUID\) URN Namespace](#). Technical report, RFC Editor.
- Li-Jia Li, Chong Wang, Yongwhan Lim, David M. Blei, and Li Fei-Fei. 2010. [Building and using a semantivisual image hierarchy](#). In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*.
- Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2022. [Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing](#). *ACM Computing Surveys*.
- Vivian Liu and Lydia B Chilton. 2022. [Design Guidelines for Prompt Engineering Text-to-Image Generative Models](#). In *CHI Conference on Human Factors in Computing Systems*.
- Maria Teresa Llano, Mark d’Inverno, Matthew Yee-King, Jon McCormack, Alon Ilsar, Alison Pease, and Simon Colton. 2022. [Explainable Computational Creativity](#). *arxiv:2205.05682*.
- Yao Lu, Max Bartolo, Alastair Moore, Sebastian Riedel, and Pontus Stenetorp. 2022. [Fantastically Ordered Prompts and Where to Find Them: Overcoming Few-Shot Prompt Order Sensitivity](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*.
- Scott M. Lundberg and Su-In Lee. 2017. [A unified approach to interpreting model predictions](#). In *Proceedings of the 31st International Conference on Neural Information Processing Systems, NIPS’17*.

- Yisroel Mirsky and Wenke Lee. 2022. [The Creation and Detection of Deepfakes: A Survey](#). *ACM Computing Surveys*, 54.
- Brent Mittelstadt, Chris Russell, and Sandra Wachter. 2019. [Explaining Explanations in AI](#). In *Proceedings of the Conference on Fairness, Accountability, and Transparency*.
- Jonas Oppenlaender. 2022. [A Taxonomy of Prompt Modifiers for Text-To-Image Generation](#). *arxiv:2204.13988*.
- Nikita Pavlichenko and Dmitry Ustalov. 2022. [Best Prompts for Text-to-Image Models and How to Find Them](#). *arxiv:2209.11711*.
- Han Qiao, Vivian Liu, and Lydia Chilton. 2022. [Initial Images: Using Image Prompts to Improve Subject Representation in Multimodal AI Generated Art](#). In *Creativity and Cognition*.
- Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. [Learning transferable visual models from natural language supervision](#). In *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*.
- Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. 2022. [Hierarchical Text-Conditional Image Generation with CLIP Latents](#). *arxiv:2204.06125*.
- Laria Reynolds and Kyle McDonell. 2021. [Prompt Programming for Large Language Models: Beyond the Few-Shot Paradigm](#). In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*.
- Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. ["Why Should I Trust You?": Explaining the Predictions of Any Classifier](#). In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.
- Leonard Richardson. 2007. [Beautiful Soup Documentation](#).
- Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. 2022. [High-resolution image synthesis with latent diffusion models](#). In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*.
- Kevin Roose. 2022. [An A.I.-Generated Picture Won an Art Prize. Artists Aren't Happy](#).
- Kevin Roose, Casey Newton, and Emad Mostaque. 2022. [Generative A.I. Is Here. Who Should Control It?](#)
- Ohad Rubin, Jonathan Herzig, and Jonathan Berant. 2022. [Learning To Retrieve Prompts for In-Context Learning](#). In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*.
- Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily Denton, Seyed Kamyar Seyed Ghasemipour, Burcu Karagol Ayan, S. Sara Mahdavi, Rapha Gontijo Lopes, Tim Salimans, Jonathan Ho, David J. Fleet, and Mohammad Norouzi. 2022. [Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding](#). *arxiv:2205.11487*.
- Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, Patrick Schramowski, Srivatsa Kundurthy, Katherine Crowson, Ludwig Schmidt, Robert Kaczmarczyk, and Jenia Jitsev. 2022. [LAION-5B: An open large-scale dataset for training next generation image-text models](#). *arxiv:2210.08402*.
- Sharif Shameem. 2022. [Lexica: Building a Creative Tool for the Future](#).
- StabilityAI. 2022a. [Stable Diffusion Discord Server Rules](#).
- StabilityAI. 2022b. [Stable Diffusion Dream Studio beta Terms of Service](#).
- Hendrik Strobelt, Albert Webson, Victor Sanh, Benjamin Hoover, Johanna Beyer, Hanspeter Pfister, and Alexander M. Rush. 2022. [Interactive and Visual Prompt Engineering for Ad-hoc Task Adaptation With Large Language Models](#). *IEEE Transactions on Visualization and Computer Graphics*.
- Patrick von Platen, Suraj Patil, Anton Lozhkov, Pedro Cuenca, Nathan Lambert, Kashif Rasul, Mishig Davaadorj, and Thomas Wolf. 2022. [Diffusers: State-of-the-art diffusion models](#). <https://github.com/huggingface/diffusers>.
- Kyle Wiggers. 2022. [Deepfakes for all: Uncensored AI art model prompts ethics questions](#).
- Simon Willison, Adam Stacoviak, and Jerod Stacoviak. 2022. [Stable Diffusion Breaks the Internet](#).



## A Data Sheet for DIFFUSIONDB

### Motivation

**For what purpose was the dataset created?** Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

The DIFFUSIONDB project was inspired by important needs in research focused on diffusion models and prompt engineering. As large text-to-image models are relatively new, there is a pressing need to understand how these models work, how to write effective prompts, and how to design tools to help users generate images. To tackle these critical challenges, we present DIFFUSIONDB, the first large-scale prompt dataset with 2 million real prompt-image pairs.

**Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?**

The dataset was created by Zijie J. Wang, Evan Montoya, David Munechika, Haoyang Yang, Benjamin Hoover, and Duen Horng Chau at the Georgia Institute of Technology.

**Who funded the creation of the dataset?** If there is an associated grant, please provide the name of the grantor and the grant name and number.

Funded in part by J.P. Morgan PhD Fellowship, NSF grants IIS-1563816, DARPA GARD, and gifts from Intel, Cisco, NVIDIA, Bosch, Google.

**Any other comments?**

None.

### Composition

**What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)?** Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.

Each instance consists of an image generated by the Stable Diffusion model and the prompt as well as parameters that were input into the model to generate the image. The input parameters include seed, CFG scale, and sampler.

**How many instances are there in total (of each type, if appropriate)?**

There are 2 million instances in total in the dataset.

**Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set?** If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).

The dataset is a sample of instances. It represents a sample of images from the Stable Diffusion discord server. No tests were run to determine representativeness.

**What data does each instance consist of?** “Raw” data (e.g., unprocessed text or images) or features? In either case, please provide a description.

Each instance consists of the image generated by the Stable Diffusion model (with a unique id), along with the prompt used to generate the image and the model parameters as a JSON file.

**Is there a label or target associated with each instance?** If so, please provide a description. The labels associated with each image are the prompt and other input parameters.

**Is any information missing from individual instances?** If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.

Everything is included. No data is missing.

**Are relationships between individual instances made explicit (e.g., users’ movie ratings, social network links)?** If so, please describe how these relationships are made explicit.

Not applicable.

**Are there recommended data splits (e.g., training, development/validation, testing)?** If so, please provide a description of these splits, explaining the rationale behind them.

No. This dataset is not for ML model benchmarking. Researchers can use any subsets of it.

**Are there any errors, sources of noise, or redundancies in the dataset?** If so, please provide a description.

No. All images and prompts are extracted as is from the Discord chat log.

**Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)?**

The dataset is entirely self-contained.

**Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' nonpublic communications)?** If so, please provide a description.

Unknown to the authors of the datasheet.

It is possible that some prompts contain sensitive information. However, it would be rare, as the Stable Diffusion Discord has rules against writing personal information in the prompts, and there are moderators removing messages that violate the Discord rules.

**Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?** If so, please describe why.

We collect images and their prompts from the Stable Diffusion discord server. Even though the discord server has rules against users sharing any NSFW (not suitable for work, such as sexual and violent content) and illegal images, it is possible that some discord users had posted harmful images that were not removed by the server moderators.

**Does the dataset identify any subpopulations (e.g., by age, gender)?** If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

No.

**Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset?** If so, please describe how.

No.

**Any other comments?**

None.

## Collection

**How was the data associated with each instance acquired?** Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If the data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

The data was directly observed from the Stable Diffusion Discord Channel. It was gathered from channels where users can generate images by interacting with a bot, which consisted of messages of user generated images and the prompts used to generate those images.

**What mechanisms or procedures were used to collect the data (e.g., hardware apparatuses or sensors, manual human curation, software programs, software APIs)?** How were these mechanisms or procedures validated?

The data was gathered using a DiscordChatExporter (Holub, 2017), which collected images and chat messages from each channel specified. We then extracted and linked prompts to images using Beautiful Soup (Richardson, 2007). Random images and prompts were selected and manually verified to validate the prompt-image mapping.

**If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?**

For certain messages, there would exist a collage of  $n$  images (e.g.,  $n = 2, 4, 9$ ) with identical prompts consolidated into a single image. These images were split and a single image would be randomly selected from  $n$  images with equal probability of any image being selected. This saved space and prioritized unique prompts.

**Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?**

Students conducted the data collection process and

were compensated with stipend or course credits.

**Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)?** If not, please describe the timeframe in which the data associated with the instances was created.

All messages were generated in August 2022 and messages were collected between October 18th and 24th 2022.

**Were any ethical review processes conducted (e.g., by an institutional review board)?** If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.

There were no ethical review processes conducted.

**Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?**

The data was directly obtained from individual messages in the Discord server.

**Were the individuals in question notified about the data collection?** If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.

Users of the channel were not notified about this specific gathering of data but agree to forfeit any intellectual property rights claims by using Stable Diffusion. In addition, users are instructed that the images are public domain and can be used by anyone for any purpose. The exact language is as follows (StabilityAI, 2022b):

Note, that while users have forfeited copyright (and any/all intellectual property right claims) on these images, they are still public domain and can be used by anyone for any purpose, including by the user. Feel free to use images from DreamStudio Beta and the Stable Diffusion beta Discord service for anything, including commercial purposes.

**Did the individuals in question consent to the collection and use of their data?** If so, please describe (or show with screenshots or other infor-

mation) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.

By using the server and tools, users consented to the regulations posed by Stability AI LTD, the company that both made Stable Diffusion and runs the Discord server. This implies consent by using the tool. The exact wording is as follows:

By your use of DreamStudio Beta and the Stable Diffusion, you hereby agree to forfeit all intellectual property rights claims, worldwide, and regardless of legal jurisdiction or intellectual property law applicable therein, including forfeiture of any/all copyright claim(s), to the Content you provide or receive through your use of DreamStudio Beta and the Stable Diffusion beta Discord service.

This message is contained in the rules and terms of service section of the Stable Diffusion Discord (StabilityAI, 2022a,b). In conjunction with the previous statement about images being public domain (CC0 1.0 license), it is established that the images made by using Stable Diffusion can be used for other purposes.

**If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses?** If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate).

Users will have the option to report harmful content or withdraw images they created through a Google Form listed on the DIFFUSIONDB website: <https://github.com/poloclub/diffusiondb>.

**Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted?** If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation.

No analysis has been conducted.

**Any other comments?**

None.

## Preprocessing

**Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)?** If so, please provide a description. If not, you may skip the remaining questions in this section.

The Discord chat logs include collage images, where each collage contains a grid of images that share the same prompt but have different seeds. We use Pillow (Clark, 2015) to split a collage into individual images. Then, among these images sharing the same prompt, we randomly select one to include in DIFFUSIONDB. We sample images to save the dataset storage size.

**Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)?** If so, please provide a link or other access point to the “raw” data.

Raw data was not saved due to high storage requirements.

**Is the software that was used to preprocess/clean/label the data available?** If so, please provide a link or other access point.

All our data collection and preprocessing code is available at: <https://github.com/poloclub/diffusiondb>.

**Any other comments?**

None.

## Uses

**Has the dataset been used for any tasks already?** If so, please provide a description.

No.

**Is there a repository that links to any or all papers or systems that use the dataset?** If so, please provide a link or other access point.

No.

**What (other) tasks could the dataset be used for?**

This dataset can be used for (1) prompt autocomplete, (2) generating images through search, (3) detecting deepfake, (4) debugging image gen-

eration, (5) explaining image generation, and more.

**Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses?**

For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other risks or harms (e.g., legal risks, financial harms)? If so, please provide a description. Is there anything a dataset consumer could do to mitigate these risks or harms?

There is minimal risk for harm: the data were already public. Personally identifiable data (e.g., discord usernames) were removed during the collection/preprocessing phases.

**Are there tasks for which the dataset should not be used?** If so, please provide a description.

All tasks that utilize this dataset should follow the licensing policies and the regulations (StabilityAI, 2022b) posed by Stability AI, the company that both made Stable Diffusion and runs the official Discord server.

**Any other comments?**

None.

## Distribution

**Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created?** If so, please provide a description.

Yes, the dataset is publicly available on the internet.

**How will the dataset will be distributed (e.g., tarball on website, API, GitHub)?** Does the dataset have a digital object identifier (DOI)?

The dataset is distributed on the project website: <https://poloclub.github.io/diffusiondb>.

The dataset shares the same DOI as this paper.

**When will the dataset be distributed?**

The dataset is released on October 25th, 2022.

**Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?** If so, please describe this license and/or



ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.

All images generated by stable diffusion discord services are under the CC0 1.0 License, and therefore so are images in this dataset. In addition, the distribution of the dataset is under the Terms of Use (StabilityAI, 2022b) posed by Stability AI, the company that both made Stable Diffusion and runs the official Discord server.

**Have any third parties imposed IP-based or other restrictions on the data associated with the instances?** If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.

All images in this dataset have a CC0 1.0 License and follows the Stability AI's Terms of Use (StabilityAI, 2022b).

**Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?** If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.

No.

**Any other comments?**

None.

<b>Maintenance</b>
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**Who will be supporting/hosting/maintaining the dataset?**

The authors of this paper will be supporting and maintaining the dataset.

**How can the owner/curator/manager of the dataset be contacted (e.g., email address)?**

The contact information of the curators of the dataset is listed on the project website: <https://poloclub.github.io/diffusiondb>.

**Is there an erratum?** If so, please provide a link or other access point.

There is no erratum for our initial release. Errata will be documented in future releases on the dataset website.

**Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?** If so, please describe how often, by whom, and how updates will be communicated to dataset consumers (e.g., mailing list, GitHub)?

Yes, we will monitor the Google Form where users can report harmful images and creators can remove their images. We will update the dataset bimonthly. Updates will be posted on the project website <https://poloclub.github.io/diffusiondb>.

**If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were the individuals in question told that their data would be retained for a fixed period of time and then deleted)?** If so, please describe these limits and explain how they will be enforced.

People can use a Google Form linked on the project website to remove specific instances from DIFFUSIONDB.

**Will older versions of the dataset continue to be supported/hosted/maintained?** If so, please describe how. If not, please describe how its obsolescence will be communicated to dataset consumers.

We will continue to support older versions of the dataset.

**If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so?** If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to dataset consumers? If so, please provide a description.

Anyone can extend/augment/build on/contribute to DIFFUSIONDB. Potential collaborators can contact the dataset authors.

**Any other comments?**

None.