
TWIGMA: A dataset of AI-Generated Images with Metadata From Twitter

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Abstract

Recent progress in generative artificial intelligence (gen-AI) has enabled the generation of photo-realistic and artistically-inspiring photos at a single click, catering to millions of users online. To explore how people use gen-AI models such as DALLE and StableDiffusion, it is critical to understand the themes, contents, and variations present in the AI-generated photos. In this work, we introduce TWIGMA (TWItter Generative-ai images with MetadatA), a comprehensive dataset encompassing over 800,000 gen-AI images collected from Jan 2021 to March 2023 on Twitter, with associated metadata (e.g., tweet text, creation date, number of likes). Through a comparative analysis of TWIGMA with natural images and human artwork, we find that gen-AI images possess distinctive characteristics and exhibit, on average, lower variability when compared to their non-gen-AI counterparts. Additionally, we find that the similarity between a gen-AI image and natural images (i) is inversely correlated with the number of likes; and (ii) can be used to identify human images that served as inspiration for the gen-AI creations. Finally, we observe a longitudinal shift in the themes of AI-generated images on Twitter, with users increasingly sharing artistically sophisticated content such as intricate human portraits, whereas their interest in simple subjects such as natural scenes and animals has decreased. Our analyses and findings underscore the significance of TWIGMA as a unique data resource for studying AI-generated images.

1 Introduction

Recent advancements in text-to-image generation models, such as DALLE [33] and StableDiffusion [36], have revolutionized the creation of realistic and visually captivating images. The ability to generate artistically inspiring images at the click of a button has attracted millions of daily active users. However, the surge in popularity has also given rise to intriguing questions about the boundaries of human and model creativity, as well as the diversity in topics and styles of the generated images. For instance, let’s consider the StableDiffusion model: it passes the user-specified text input (known as *prompts*) into a text encoder CLIP [32] to obtain an encoding that captures the essence of the prompt. Next, the model utilizes a latent diffusion model that takes the text embedding as input and stochastically generates an image guided by the text encoding. Therefore, the output image is influenced by both the user’s input prompt and the complex diffusion process. Consequently, the stochasticity and black-box nature of the diffusion process led to extensive practice and research in the field of prompt engineering, where content creators iteratively refine their text prompts to generate images that align closely with their desired targets [23, 28]. Similar to other emerging technologies with significant capabilities, generative image models have given rise to a plethora of intricate legal and ethical challenges. These include concerns such as the proliferation of AI-generated NSFW

(Not-Safe-For-Work, which broadly includes offensive, violent, and pornographic topics) images, the dissemination of fake news, and controversies surrounding copyright.

Given the ever-increasing popularity and controversy surrounding AI-generated images, understanding their themes, content, and variations is increasingly crucial. However, existing datasets available for research purposes do not sufficiently address these specific inquiries, as many of them were created for specialized investigations (e.g., fake art detection [41, 48]) and image quality evaluation [37]), resulting in limited content diversity. Some recent exceptions include the Kaggle dataset on Midjourney prompts [3] and DiffusionDB [49], two large-scale datasets compiled from Discord for Midjourney and StableDiffusion models, respectively. However, these pioneering datasets are limited in terms of model variations, user distribution, and relatively short data collection periods.

To address these limitations, we present TWIGMA (Twitter Generative-AI Images with MetadatA) — a large-scale dataset encompassing 800,000 AI-generated images from diverse models. Spanning January 2021 to March 2023, TWIGMA covered an extended timeframe and included valuable metadata, such as inferred image subjects and number of likes. To the best of our knowledge, TWIGMA is the *first* AI-generated image dataset with substantial time span and rich metadata, enabling analysis of temporal trends in human-AI generated image content. Moreover, we leverage unsupervised learning techniques and inferred image captions to understand themes of AI-generated images. By contrast, previous studies predominantly focused on the topics and contents of logged prompts [49, 50], which may not accurately represent the output images due to prompt engineering practices. We demonstrate the value and the type of insights TWIGMA enables by using it to characterize the underlying themes and novel aspects of AI-generated images.

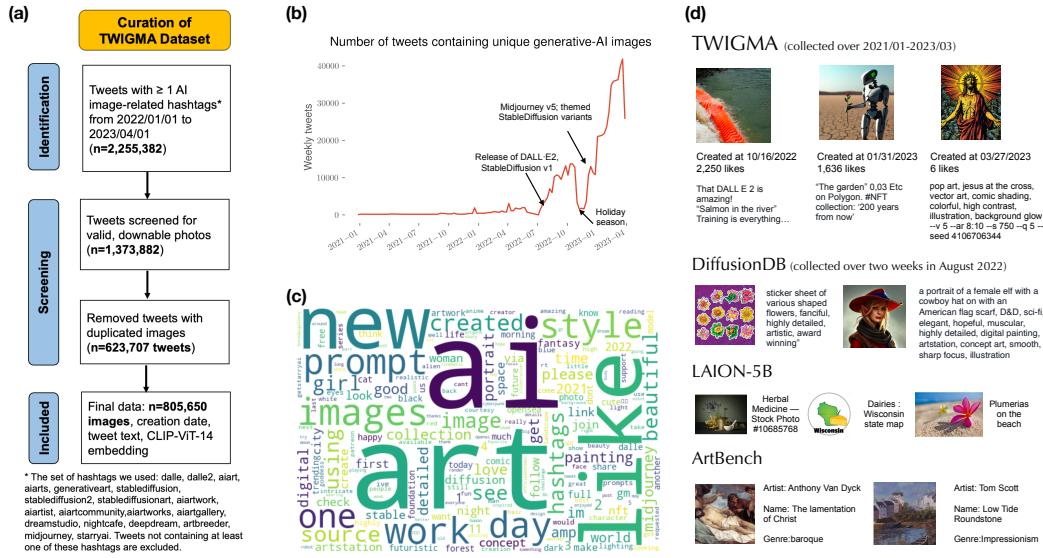


Figure 1: Creation process and content overview of TWIGMA. (a): Curation process of the TWIGMA dataset, resulting in approximately 800,000 images posted from 2021 to March 2023. **(b):** Steady growth in the count of tweets featuring generative AI images over time. **(c):** Wordcloud showcasing the prevalent keywords extracted from the tweets; popular words include new, AI, art, and prompts. **(d):** Schematic depiction of the data and metadata incorporated in our analyses.

The rest of the paper is organized as follows. We review image datasets and evaluation metrics for model novelty and variation in Section 2. The data collection and analysis process are outlined in Section 3. Section 4 presents empirical results addressing our research questions. Finally, Section 5 discusses limitations, safety and ethics concerns, and future research directions.

2 Relevant work

AI-generated image dataset: The creation of large-scale image-text datasets has rapidly evolved, transitioning from carefully annotated datasets relying on human labels [17, 22] to vast collections of image-text pairs gathered from the web [32, 36, 44]. As text-to-image models continue to demonstrate

unprecedented capabilities in generating images based on user prompts, researchers have started curating similar datasets featuring images generated by these models. For example, DiffusionDB and Midjourney Kaggle provide large-scale datasets (14 millions and 250,000, respectively) with prompts and images generated by StableDiffusion and Midjourney, respectively. However, these pioneering, general-purpose datasets are limited in terms of style (as they originate from a single model variation), user distribution (restricted to Discord users of specific channels), and relatively short data collection periods (one month in 2022 for both datasets). Researchers have also constructed datasets of AI-generated images for specialized use, such as detecting generated art images [43, 48], evaluating qualities of specific contents such as human portraits [7, 19], investigating safety filters and hidden vocabularies [27, 34], and evaluating potential biases [25]. Given the problem-oriented nature, these datasets are often limited in size and skewed in themes. Recognizing the gap between existing datasets and our research questions on novelty, themes, and variation of AI-generated images, we curated TWIGMA to demonstrate its potential to answer intriguing research inquiries.

Novelty and variation of AI-generated images: Many text-to-image models rely on continuous training with a substantial amount of human artistic artifacts sourced from datasets such as LAION [39], which includes images from platforms such as Wikiart and Pinterest, and potentially copyrighted or proprietary contents [31, 34, 41]. Users have also fine-tuned the open-sourced StableDiffusion model on additional samples from specific artists or art genres, such as anime, to generate AI-generated art imitating those styles [5, 9, 24]. While prior research has examined the reproduction of training data in AI-generated art settings [43, 48] and from the perspective of adversarial attack [8, 27], large-scale empirical results comparing AI- and non-AI-generated images are relatively limited. This prompts our first research question (RQ) to investigate the novelty of AI-generated images:

RQ1: How different are AI-generated images from non-AI-generated images?

Furthermore, the stochastic nature of many text-to-image models has sparked inquiries about the variability of their generated image outputs. In a notable court case, a judge determined that AI-generated images do not qualify for copyright protection, citing the significant disparity between the user’s intended prompts for Midjourney and the resulting visual material it produced. Recent research has explored the variation within the prompt space [23, 49, 50], and our second RQ builds upon these findings, aiming to supplement them by investigating the variation in the image space:

RQ2: How do AI-generated image variations compare to non-AI-generated counterparts?

Lastly, we leverage the extended time span offered by TWIGMA to explore our final RQ:

RQ3: How do the content and theme of AI-generated images change over time?

By answering RQ1–3, our paper makes the following contributions to the literature: Firstly, we utilize metrics proposed in generative model evaluation to demonstrate the distinctiveness of AI-generated images compared to real images, providing evidence of the novelty embedded in the underlying models. Moreover, we find that the distance between AI-generated and human images (i) correlates with the number of likes received; and (ii) can be leveraged to identify human images that served as inspiration for AI-generated creations. Secondly, we introduce quantitative measures to establish that (i) images from generative models exhibit less diversity than real images; and (ii) a substantial portion of variations in the image space can be attributed to the variation in user prompts. Finally, we observed a shift in the preferences for generative models and image topics among Twitter users: they are increasingly sharing artistically sophisticated or distinct content, such as intricate human portraits and anime, while interest in simpler subjects like natural scenes and animals has declined.

3 Methods

Curating the TWIGMA dataset: To curate the TWIGMA dataset, we began with the initial filtering of available tweets using hashtags commonly associated with AI-generated images, such as #dalle, #stablediffusion, and #aiart. We then proceeded to iteratively refine the set of hashtags by incorporating new hashtags that co-occur with the existing ones and contain highly relevant tweets with AI-generated images. We evaluated the quality of these new hashtags based on the first 20 tweets returned by the hashtag search. This iterative process allowed us to create a final set of 19 hashtags, encompassing both generic community descriptions (e.g., #aiart, #generativeart) and specific models (e.g., #midjourney, #dalle2); please refer to Figure 1(a) for the complete list of hashtags.

Next, we utilized the official Twitter API to scrape tweets containing at least one of the identified hashtags. This process encompassed the time frame from January 1st, 2021 to March 31st, 2023, resulting in approximately 2.2 million tweets. Out of these potentially duplicated tweets, around 1.3 million contained downloadable photos as of April 2023. To ensure data quality, we conducted a two-step deduplication process. Firstly, we utilized the media ID in Twitter to retain only one image in cases where the same tweet was associated with multiple hashtags. Secondly, we computed CLIP-ViT-L-14 embeddings [32] to remove images with identical embeddings. This deduplication step resulted in a dataset of 623,707 tweets and 805,650 images in TWIGMA.

Furthermore, we extracted comprehensive metadata for each image in the TWIGMA dataset, including original tweet texts, engagement metrics such as likes, as well as user-related information such as follower counts. Recognizing that tweet texts may not always accurately describe the image content, we also generated captions for each image in TWIGMA using the BLIP model [20]. We release TWIGMA at <https://yiqunchen.github.io/TWIGMA/>. This dataset includes our curated metadata pertaining to the image creation date, number of likes, assigned cluster membership obtained through k-means clustering, and the inferred BLIP captions. Additionally, we provide a list of Twitter IDs and the necessary code to retrieve images and metadata using the Public Twitter API.

In this paper, we conduct a series of analyses to showcase the fascinating insights that TWIGMA can offer into human-AI generated images. Our approaches represent an initial exploration effort, and numerous other intriguing questions can be addressed using TWIGMA.

Measuring novelty of AI-generated images: To enable efficient computational evaluation without relying on human ratings, we operationalize the concept of “novelty” as the difference between the distribution Q of a generative model (e.g., images generated by StableDiffusion in TWIGMA) and the distribution P of real data (e.g., real images in LAION); we then leverage recent advances in metrics proposed for quantifying the difference between two distributions.

Our analysis incorporates a diverse range of image datasets, including AI-generated images from TWIGMA and DiffusionDB, as well as human images from LAION [39] and ArtBench [21]. ArtBench features 60,000 high-quality, genre-annotated images of artwork spanning ten different art genres from the 14th century to the 21st century; and LAION encompasses CLIP-similarity-filtered image-text pairs sourced from the Common Crawl.

To investigate the novelty of AI-generated images, we first employ two-dimensional UMAP [26] in the CLIP embedding space to visualize the differences in distributions between AI-generated and non-AI-generated images. Additionally, we employ k-means clustering using the efficient implementation in FAISS [13] and compute Kullback-Leibler (KL) divergence among pairs of image distributions via the quantization approach outlined in Pillutla et al. [30]. In essence, their approach converts distributions P and Q into two multinomial distributions using k-means clustering; KL divergence can then be efficiently estimated from the multinomial distributions using plug-in estimators.

Measuring the variation of AI-generated images: Quantifying the variation of distributions is a well-studied topic [6, 10, 14, 18, 35, 45]. In our analysis, we employed the following metrics to capture different aspects of variations: (i) pairwise distance, computed as $\sum_{i \neq j} \|x_i - x_j\|_2 / N(N-1)$, where x_i, x_j are embeddings of randomly sampled images; this metric is equivalent to cosine distance when x_i and x_j have unit ℓ_2 norms; (ii) inverse of explained variance (IEV) by the largest singular value [51], $\sum_{i=1}^d \sigma_d / \sigma_1$, where σ_i denotes the i th-largest singular value of the embedding matrix; (iii) product of marginal variances (PMV) [18], $\left(\prod_{i=1}^d \hat{s}_i\right)^{1/d}$, where \hat{s}_i denotes the sample standard deviation of the i th feature; and (iv) entropy estimated using the multinomial distributions [35] from the aforementioned quantization approach. We adjusted the original definitions slightly for some measures to ensure that a *higher* value always indicates *greater variability* in the data.

4 Results

4.1 Quantified novelty and variations of AI-generated images

In this section, we present our analysis of the novelty and variations of AI-generated images. Figure 2 displays different approaches we used to compare AI-generated and non-AI-generated images. The UMAP density plot in Figure 2(a) reveals minimal overlap between sampled LAION, TWIGMA,

and ArtBench images, whereas the overlap between TWIGMA and DiffusionDB is substantial. We note a distinct density peak of TWIGMA images absent in DiffusionDB, primarily representing a subset of images generated in specific styles (such as anime) and often of NSFW nature (see Figure 4 for more details). This distinction is further confirmed by estimated k -means clusters and KL divergence between image distributions, as shown in panels (b) and (c) of Figure 2. Specifically, cluster 1 primarily consists of LAION images, while AI-generated images are present in clusters 2–4. Additionally, the estimated KL divergence between AI-generated and non-AI-generated data pairs tend to much larger compared to the divergence between DiffusionDB and TWIGMA.

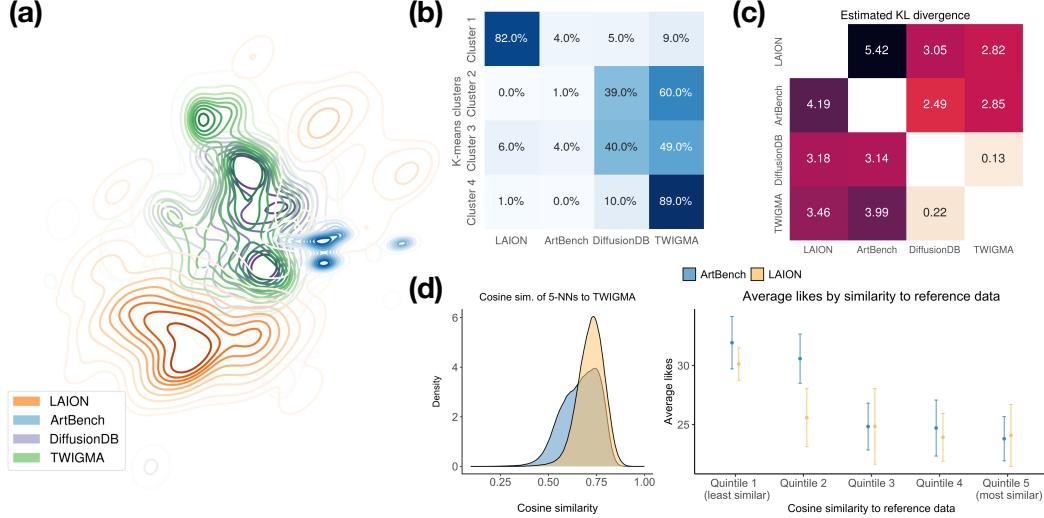


Figure 2: Comparing AI-generated and non-AI-generated images. (a): Kernel density plot of the 2D-UMAP embedding of randomly-sampled images from TWIGMA, LAION, DiffusionDB, and ArtBench. (b): K-means clustering (with $k = 4$) separates AI-generated and non-AI-generated images. (c): Estimated KL divergence of pairs of image distributions using the quantization approach (with 10 clusters) outlined in Section 3. Each entry in the table represents the KL divergence between the row and column distributions, e.g., the 5.42 entry is the KL divergence between LAION and ArtBench, defined as $\sum_x p_{\text{LAION}}(x) \log(p_{\text{LAION}}(x)/p_{\text{ArtBench}}(x))$. (d): (Left) Average cosine similarity of the five nearest neighbors in LAION/ArtBench for TWIGMA images. (Right) Average number of likes per similarity quintile, with error bars representing 95% confidence intervals. On average, TWIGMA images least similar to LAION/ArtBench receive the most likes.

While panels (a)–(c) in Figure 2 focused on examining whether AI-generated and non-AI-generated images are distinct, we additionally investigated whether image distances contain useful information about an image’s likability. Figure 2(d) presents the analysis results for TWIGMA data (limited to the subset for which we were able to obtain likes data using Twitter API): On the left side, we present the average similarities of the five nearest neighbors in LAION and ArtBench, determined using cosine similarities, for the images in TWIGMA. On the right side, we plot the average likes for each quintile of similarities, where quintiles 1 and 5 represent the least and most similar images to LAION or ArtBench, respectively. There is some evidence suggesting that AI-generated images that are less similar to their non-AI-generated counterparts receive more likes. For instance, quintile 1 images for LAION and Artbench received, on average, 30.1 (95% CI: [28.8, 31.5]) and 31.9 (95% CI: [29.7, 34.1]) likes, respectively, compared to 23.8 (95% CI: [21.9, 25.7]) and 24.1 (95% CI: [21.5, 26.7]) likes in quintile 5. However, it’s important to note that the number of likes for a tweet is influenced by various factors, such as a user’s social networks [12, 47]. To account for these factors, we used the following Poisson regression that incorporates the number of followers and similarity quintiles:

$$\log(\mathbb{E}(\text{Likes}|X)) = \alpha + \beta_1 \mathbf{1}(500-5,000 \text{ followers}) + \beta_2 \mathbf{1}(>5,000 \text{ followers}) + \sum_{i=1}^4 \gamma_i \mathbf{1}(\text{Quintile } i). \quad (1)$$

The regression model in (1) shows that within the same follower count category (i.e., < 500 , $500 - 5,000$, or $> 5,000$ followers), compared to TWIGMA images most similar to their ArtBench neighbors (quintile 5), images in quintile 1 receive, on average, 19% more likes (95% CI: [18%, 19%], $p < 0.0001$); similar trends are observed for images in quintile 2 (12% more likes; 95% CI:

[11%, 12%]; $p < 0.0001$), while the differences are less pronounced for more similar quintiles (0.8% fewer likes in quintile 3 and 2% more likes in quintile 4). Comparable results are found for LAION neighbors as well, where images in quintiles 1 and 2 receive, on average, 10% (95% CI: [9%, 10%], $p < 0.0001$) and 2% more (95% CI: [2%, 3%], $p < 0.0001$) likes, respectively, compared to quintile 5 images posted by accounts with the same follower categories. Upon further investigation, we observe that many of the highly-liked images that stand out from the non-AI-generated images are often anime-style NSFW photos. This observation highlights the need for caution when interpreting the number of likes as an additional indicator of aesthetic and creative value for an image.

Next, we explore image variations across distributions (see Figure 3(a)–(b)). On average, LAION images exhibit the highest variability, followed closely by ArtBench, DiffusionDB, and TWIGMA, which show similar variation distributions based on pairwise Euclidean distance. Notably, ArtBench shows reduced variation when conditioned on image pairs from the same artist. Similarly, conditioning on prompts in DiffusionDB reduces around 50% of the variation in generated images, measured by the average distance between two image embeddings; that is, the average distance between images in DiffusionDB with the same prompt is roughly half that between randomly selected images with different prompts. Additional variation metrics in Figure 3(b) align with pairwise distance. The lower estimated entropy for ArtBench may be due to its smaller sample size compared to the other datasets.

Given the observation that a substantial portion of the variations in the image output space is explained by the variation in the input prompts, we further analyzed the latter in Figure 3(c)–(d). Specifically, in (c), we plotted the average pairwise distance of images with the same prompt as a function of the number of words in the prompts. Each dot represents a unique prompt, and we observe that, on average, longer prompts with more details lead to reduced variations in the output images (Kendall’s τ : -0.1, p -values: 0.01). Furthermore, to calibrate the variation of the prompt variations, we compared the pairwise distance of CLIP embeddings from different text input sources with similar word counts to the DiffusionDB prompts. These sources included real image captions [42], English Haikus [1], Twitter text (after removing hyperlinks and hashtags), CNN news summarization [40], and a book chapter [52]. We found that image captions exhibit similar variation to DiffusionDB prompts and Twitter texts, indicating higher variability. In contrast, as expected, texts with unified styles and themes, such as Haikus and book chapters, show significantly lower variation. Overall, our analysis suggests a wide range of topics covered by the DiffusionDB prompts.

4.2 Themes of AI-generated images on Twitter

Here, we examine the themes and their longitudinal changes for images in the TWIGMA dataset. In Figure 4(a), we display the creation-date color-coded two-dimensional UMAP of TWIGMA image embeddings, suggesting a shift in the image distribution over time in our Twitter dataset. To investigate this qualitative observation further, we applied k -means clustering to the TWIGMA data with $k = 10$ and plotted the change of cluster membership over time. We note substantial changes in cluster memberships: clusters 1, 3, and 4 have experienced a steady decline over time, while clusters 8 and 9 showed a consistent increase. Here, the choice of $k = 10$ was motivated by the observation in Figure 3(a), which indicated that TWIGMA exhibits comparable variation to ArtBench, a dataset with 10 distinct art styles (sensitivity analysis using other values of k yielded similar results).

Due to the lack of direct access to the prompts used for generating every image in TWIGMA, as well as the distance between the input prompt and the resulting output, we used BLIP [20] to caption the images in TWIGMA and visualized the resulting caption concepts in Figure 4(c). Prominent themes we observed include painting, woman, man, and hair, aligning with the known interest of users in generating detailed human portraits in various styles using text-to-image models [16, 46, 50].

We further visualized each cluster along with the most frequent topics derived using BLIP captions in Figure 4(d), with emojis representing the relative trends over time. Our findings indicate a shift in preferences for image topics among Twitter users. There is a growing interest in sharing artistically sophisticated or distinct content, such as intricate human portraits, while interest in simpler themes such as natural scenes has declined. In addition, clusters 5 and 8 notably contain a substantial number of images with increasing popularity but also significant amounts of NSFW, pornographic, and nude content. This observation aligns with recent studies that highlight the rapid growth of online communities focused on generating these models, which are relatively less regulated [15, 34, 38]. This is confirmed by experimental results using a pre-trained NSFW detector [4] in Figure 4(e), revealing a substantial number of likely NSFW images in both TWIGMA and LAION datasets.

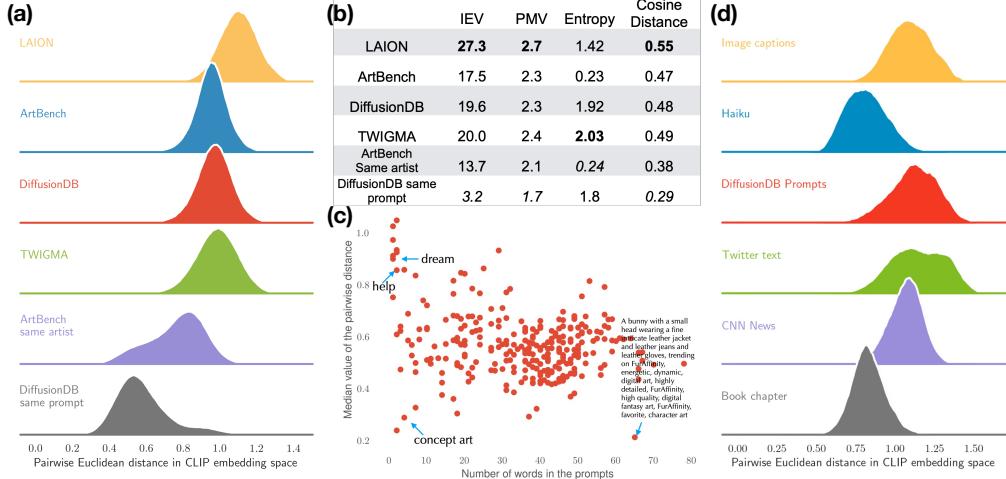


Figure 3: **Comparing variations of AI-generated and non-AI-generated images.** (a): Pairwise Euclidean distance of randomly-sampled, ℓ_2 -normalized image embeddings from LAION, ArtBench, DiffusionDB, TWIGMA, paintings by the same artists in ArtBench, and DiffusionDB images with identical prompts. (b): Additional variation metrics (see Section 3 for details) for the dataset mentioned in (a); larger values of these metrics correspond to a more variable dataset. Metric values for the most and least variable dataset are in **bold** and *italic*, respectively. (c): Average pairwise Euclidean distance of ℓ_2 -normalized embeddings in DiffusionDB with identical prompts (each dot is a unique prompt); on average, longer and more detailed prompts correspond to reduced variations in output images. (d): Similar analysis as in (a), but with sampled text embedding data from real image captions, English Haikus, DiffusionDB prompts, Tweets, CNN news, and a book chapter.

Lastly, as a proof-of-concept analysis to explore the possibility of using similarity measures to detect non-AI-generated images that may have been used as training data for the text-to-image models, we employed cosine similarity to extract the nearest neighbors of TWIGMA images. In Figure 4(f), we displayed pairs with a high likelihood that the neighbors from ArtBench and LAION served as potential inspirations (i.e., training data) for the text-to-image models. Notably, this analysis revealed striking similarities between some of these neighbor pairs, confirming concerns of copyright issues and the potential for identifying such pairs using a similarity-measure-based approach.

5 Discussion

Recent advancements in generative AI have revolutionized text-to-image generation, empowering users to create millions of captivating images. Our work explores themes and variations in AI-generated images. To facilitate this investigation, we introduce TWIGMA, an extensive dataset comprising 800,000 gen-AI images, associated tweets, and metadata collected from Twitter between January 2021 and March 2023. Our analysis characterizes distinctiveness, variation, and longitudinal shift of themes of gen-AI images shared on Twitter. The analysis in this paper are not meant to be exhaustive but rather to illustrate the types of interesting questions that TWIGMA can help to answer, opening the door to investigating various facets of human-AI art generation.

Limitations: It is important to note the limitations in our work, primarily due to the large-scale nature of the datasets employed, which makes a comprehensive examination of all aspects impractical. One limitation stems from the scope and quality of the datasets utilized in our analysis. Although we made efforts to select representative data sources from both AI-generated and non-AI-generated image spaces, the content within the final datasets used in our paper imposes certain constraints: ArtBench primarily consists of the most popular art genres in WikiArt [2], resulting in limited coverage of non-European, non-Japanese, modern, techno arts, as well as works from lesser-known independent artists. Consequently, this might lead to an underestimate of the similarity between human art images and AI-generated art images. Similarly, LAION data has undergone filtration based on text-image pair similarity [39], and around 10% of Twitter images are not available through the official Twitter

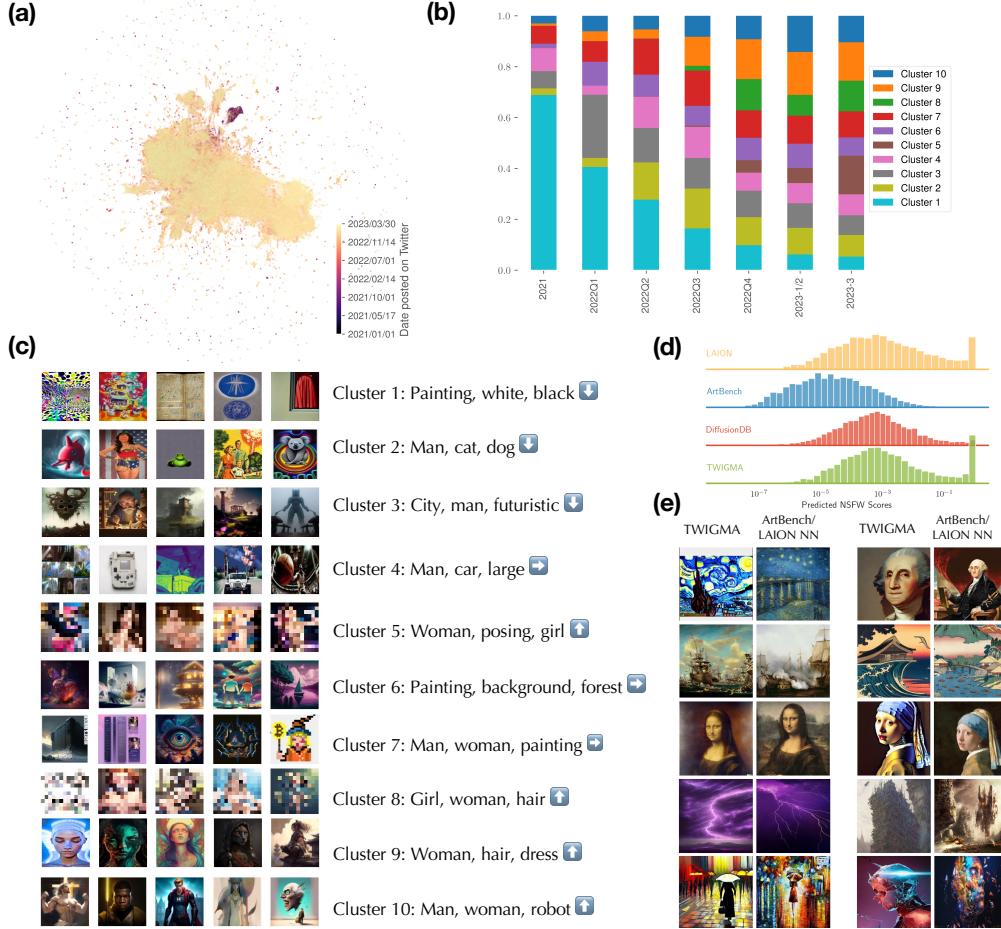


Figure 4: Themes and longitudinal trends of images in TWIGMA. **(a):** Two-dimensional UMAP embedding of TWIGMA images, color-coded based on their creation dates on Twitter. **(b):** Composition of image clusters (estimated using k -means clustering with $k = 10$) over time. We observe notable changes in cluster membership and underlying themes of TWIGMA images from 2021 to 2023. **(c):** Randomly sampled images from the 10 clusters identified in (b). Clusters 5 and 8 predominantly contain NSFW photos and have been pixelated accordingly. Cluster annotations are provided using the most frequent words in associated BLIP-inferred captions, with up arrow, down arrow, and right arrow emojis indicating increasing, decreasing, or unchanged trends over time, respectively. **(d):** Predicted NSFW scores from a pre-trained CLIP-based NSFW detector. Noteworthy presence of NSFW photos is observed in both TWIGMA and LAION datasets. **(e):** TWIGMA images and their nearest neighbors in terms of image embedding cosine similarities from ArtBench or LAION. These images from ArtBench and LAION serve as potential inspirations (i.e., training data) for the text-to-image model, indicating the possibility of identifying such pairs using a similarity-measure-based approach.

API at the time of our study, due to the deletion or removal of tweets. Additionally, it is possible that a small proportion of images within TWIGMA are non-AI-generated, as users sometimes share relevant non-AI-generated content, such as real images closely resembling AI-generated outputs or screenshots from model websites or APIs. All of the aforementioned data issues could bias our findings in Section 4.1, though we estimate the bias from non-AI-generated images in TWIGMA to be quite small based on inspections of random samples of the data.

Future work: There are several promising avenues for future research. Firstly, the inclusion of more contemporary and modern art forms, particularly illustration art and anime, along with the identification of non-AI-generated images in TWIGMA, would strengthen the robustness of our findings. Furthermore, conducting a follow-up analysis using state-of-the-art methods [8, 43] to identify AI-generated images and their non-AI-generated nearest neighbors would help identify potential instances of copyrighted materials used in training. Finally, while our focus has primarily been on variations in the CLIP latent space, exploring other dimensions of variation and diversity [25, 29] is crucial. For instance, examining the presence of stereotypical associations between output images and societal representations in human images, such as whether the female portraits in TWIGMA resemble a specific racial, ethnic, or societal group, would provide valuable insights.

Safety and ethical concerns: One challenging aspect of text-to-image generative models is the generation of NSFW content. Our data analysis revealed a substantial subset of explicit images posted on Twitter, even among those with high likes and retweets. While some generative models like DALLE2 and StableDiffusion have built-in safety filters that block generated NSFW images, these filters can still be circumvented through prompt engineering [34, 38]. Moreover, there is a subcategory of models and online communities specifically dedicated to generating NSFW content. These observations serve as a cautionary tale for large-scale studies involving AI-generated content, as NSFW content is likely to be present and popular among certain subsets of followers due to the relatively low regulation in the current landscape. Additionally, our analysis also highlighted some AI-generated images that bear a striking resemblance to images found in human image and art datasets. These findings bear implications for potential copyright violations if training images were used without explicit consent, especially when the outputs are essentially reproductions or minor edits of memorized training examples. Finally, there is a risk of perpetuating stereotypical representations if AI-generated images tend to resemble specific groups based on demographic identities. Similar observations, discussions, and potential mitigations have been noted in other recent works [11, 25].

6 Conclusion

Understanding themes, contents, and user interests of AI-generated images is a critical topic that requires data beyond the currently available prompt and output image pairs datasets. We introduced TWIGMA, an extensive dataset comprising 800,000 gen-AI images, tweets, and associated metadata from Twitter (Jan 2021–March 2023). Our contribution is two-fold: Firstly, TWIGMA enables analysis of AI-generated image content and evolution across models and time on Twitter. Additionally, our analysis highlights the distinctiveness and variation of AI-generated images when compared to non-AI-generated content. We hope that our dataset and analysis will contribute to the broader discourse on the safety, novelty, and sociological/legal challenges posed by AI-generated images.

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A Details for dataset distribution

We have provided additional details regarding TWIGMA on our website at <https://yiqunchen.github.io/TWIGMA/>. The dataset used for analysis can be downloaded from <https://zenodo.org/record/8031785>. Additionally, readers may find our interactive introduction at <https://huggingface.co/spaces/yiqunchen/TWIGMA> informative. We confirm that as authors of TWIGMA, we will provide necessary maintenance, such as addressing questions and investigating potential bugs related to the dataset.

As per Twitter's official policy on data usage and sharing, we want to emphasize that we have not included any raw Twitter text or media in the dataset. Only the Twitter IDs are provided. If users wish to download and review the original Twitter posts, they should access the source page directly on Twitter and *fully comply* with the rules and regulations outlined in the *official Twitter developer policy*, available at <https://developer.twitter.com/en/developer-terms/policy>. The TWIGMA dataset, which consists of non-personally-identifiable, no-raw-Twitter-content, has been released under a Creative Commons Attribution 4.0 International License.

Lastly, in Section 5 of our paper, we extensively discuss the presence of a significant amount of NSFW (not-safe-for-work) content within the TWIGMA dataset. It includes content that is violent, pornographic, or contains nudity. Since our aim is to explore the content and themes of AI-generated images without filtering, we have included two fields in the final TWIGMA dataset: `possibly_sensitive`, which is a binary indicator of whether Twitter classifies an image as sensitive content, and `nsfw_score`, which represents the predicted NSFW score from a pre-trained CLIP-based NSFW detector (where a score of 1 indicates a higher likelihood of being NSFW). These fields can help identify and handle these types of images appropriately.

B Datasheet for datasets

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.	metadata, enabling analysis of temporal trends in human-AI generated image content.

	Who created this dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?
	The first author of this paper (YC) curated the dataset under the supervision of the senior author (JZ); both authors are affiliated with Stanford University.

	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.
	YC is supported by a Stanford Data Science Postdoctoral Fellowship. JZ is supported by the National Science Foundation (CCF 1763191 and CAREER 1942926), the US National Institutes of Health (P30AG059307 and U01MH098953) and grants from the Silicon Valley Foundation and the Chan-Zuckerberg Initiative.

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.

TWIGMA contains images, texts, and associated metadata from Twitter (Jan 2021–March 2023). However, per data sharing policy from Twitter, we will only be able to include Twitter id and the derived metadata in our final dataset. See details at <https://yiqunchen.github.io/TWIGMA/>.

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

During our analysis, we utilized a total of 805,650 unique images. It is important to acknowledge that due to the dynamic nature of Twitter, certain content may have been deleted or set to private since our analysis was conducted. Consequently, conducting a similar analysis at a later time will naturally result in a reduced number of accessible or downloadable images.

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).

Our objective is to curate a comprehensive dataset of AI-generated images on Twitter by collecting tweets that include at least one of the 19 hashtags listed in Figure 1 of the main text. It is important to note that there is a possibility of omitting some images that were posted without using any of these hashtags.

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

TWIGMA contains images, texts, and associated metadata from Twitter (Jan 2021–March 2023). However, per data sharing policy from Twitter, we will only be able to include Twitter id and the derived metadata in our final dataset. See details at <https://yiqunchen.github.io/TWIGMA/>.

Is there a label or target associated with each instance? If so, please provide a description.

N/A.

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.

Due to the dynamic nature of Twitter, content may have been deleted or set to private during the course of our analysis. Consequently, metadata such as likes is missing for those contents that become unavailable to the public.

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.

N/A.

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.

We do not have recommended splits, but want to mention that we do observe a change in the underlying content temporally.

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

It is possible that a small proportion of images within TWIGMA are non-AI-generated, as users sometimes share relevant non-AI-generated content, such as real images closely resembling AI-generated outputs or screenshots from model websites or APIs. In addition, while we deduplicated our datasets based on media id and image embedding, there still could be a small set of near duplicates of the same images in our dataset.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any

restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.

Due to the official data sharing policy prescribed by Twitter, we cannot share the original content (text and images) from Twitter. Therefore, we expect that a subset of the data included in our data will not be available for retrieval, as users hide and delete their contents (as well as moderation efforts put forth by Twitter). By the time we finalize our study, less than 10% of Twitter images became unavailable through the official Twitter API due to the deletion or removal of tweets. The development of this dataset has been done in compliance with Twitter's policy on data usage and sharing. If users intend to review the original Twitter post, we recommend accessing the source page directly on Twitter and closely adhering to the official Twitter developer policy, available at <https://developer.twitter.com/en/developer-terms/policy>.

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 non-public communications)? If so, please provide a description.

The development of this dataset has been done in compliance with Twitter's policy on data usage and sharing. The use of this dataset is solely at your own risk and should be in accordance with applicable laws, regulations, and ethical considerations. If you intend to review the original Twitter post, we recommend accessing the source page directly on Twitter and closely adhering to the official Twitter developer policy, available at <https://developer.twitter.com/en/developer-terms/policy>.

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

It is important to note that a substantial amount of images in this dataset have been classified as NSFW (not-safe-for-work) by both Twitter and a CLIP-based NSFW model. This includes content that is violent, pornographic, or contains nudity. We have chosen not to exclude these images from the dataset in order to understand the content and themes without filtering. However, we have included two fields in the final TWIGMA dataset

`possibly_sensitive` and `nsfw_score` which can be used to filter out these images.

Does the dataset relate to people? If not, you may skip the remaining questions in this section.

N/A since only Twitter ids are provided.

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.

N/A.

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.

N/A.

Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.

N/A.

Collection Process

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 data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

TWIGMA contains the following fields:

- `id`: This is the Twitter id uniquely identifying each tweet used in this dataset and our analysis;
- `image_name`: This is the media id used to uniquely identify each photo. Leveraging this field is necessary since a tweet can contain multiple images;

- created_at: This is the time of creation corresponding to the Twitter id;
- like_count: This is the number of likes collected from official Twitter API (snapshot: the week of May 29th). Note that some likes are not available because the corresponding tweets have been deleted since we first downloaded the photos;
- quote_count: Same as like_count, but for quotes;
- reply_count: Same as like_count, but for replies;
- all_captions: This is the BLIP-generated (Li et al. 2022) captions for the corresponding image;
- label_10_cluster: This is the assigned k-means cluster ($k=10$ so this number varies from 1 to 10);
- possibly_sensitive: Binary variable indicating whether the media content has been marked as sensitive/NSFW by Twitter;
- nsfw_score: The predicted NSFW from a pre-trained CLIP-based NSFW detector (ranges from 0 to 1; closer to 1 means more likely to be NSFW);
- UMAP_dim_1: The first dimension for a two-dimensional UMAP projection of the CLIP-ViT-L-14 embeddings of the images in TWIGMA.
- UMAP_dim_2: The second dimension for a two-dimensional UMAP projection of the CLIP-ViT-L-14 embeddings of the images in TWIGMA.

Out of these fields, `id`, `image_name`, `created_at`, `like_count`, `quote_count` and `reply_count` are directly observable variables from Twitter. On the other hand, `all_captions` is derived from a BLIP (deep learning) model where we validated the outcome by manually inspecting random pairs of images and captions; `possibly_sensitive` and `nsfw_score` are two predicted scores indicating how sensitive/NSFW an image might be. Finally, `label_10_cluster` is derived from k-means clustering and `UMAP_dim_1/2` are derived from a UMAP projection.

What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)?
How were these mechanisms or procedures validated?

We used Twitter API and employed an sequential approach to curate the TWIGMA data (see details in Section 3 of the main text). The image embeddings were performed on a single GPU with 32GB RAM and the UMAP embeddings were performed on multi-core CPUs with 256GB RAM; both are conducted over computing clusters.

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

We performend simple random sampling whenever the analysis of the full data would be too time-consuming and does not add substantial value: UMAP and density visualization, as well as samples of non-AI-generated human images.

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)?

N/A, only the first author was invovled in the data collection process.

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.

Data present in TWIGMA ranged from Jan. 2021 to Mar. 2023. The curation process of this project took place from Jan. to May 2023.

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.

N/A.

Does the dataset relate to people? If not, you may skip the remaining questions in this section.

N/A; only Twitter ids are provided.

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

N/A.

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.

N/A.

Did the individuals in question consent to the collection and use of their data?

If so, please describe (or show with screenshots or other information) 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.

N/A.

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).

N/A.

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.

N/A.

Preprocessing/cleaning/labeling

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 remainder of the questions in this section.

We provide simple deduplication using twitter media id as well as CLIP image embeddings. We did not impute any missing values but simply reported the results after dropping the missing values in our analysis. Images collected in our study are transformed into CLIP image embeddings and many subsequent analyses (including the metadata such as clustering labels and UMAP coordinates) are based on these embeddings.

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.

The raw data containing images and texts are not shared due to Twitter policy. We did not publicly share duplicated tweets and tweets without an image since these are not relevant to our main research questions of interest.

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

They are but we could not provide public access to the raw instances due to data sharing policy of Twitter. However, users can easily retrieve the raw instances using the provided Twitter id.

Uses

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

We performed a comparative analysis of TWIGMA with natural images and human artwork, and found that gen-AI images possess distinctive characteristics and exhibit, on average, lower variability when compared to their non-gen-AI counterparts. We also revealed a longitudinal shift in the themes of images in TWIGMA, with users increasingly sharing artistically sophisticated content such as intricate human portraits, whereas their interest in simple subjects such as natural scenes and animals has decreased. These analyses are detailed in Section 4 of our paper.

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.

We will release our preprint on arXiv and code on GitHub; links will be updated on the project website at <https://yiqunchen.github.io/TWIGMA/>.

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

What we presented in our paper is just an initial exploration of the dataset. Users can further explore the relationship between depicted subject and the number of likes, the underlying real images that inspired the AI-generated images, and so on so forth.

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 future user 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 undesirable harms (e.g., financial harms, legal risks)? If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?

It is possible that the Twitter id and content in this dataset can be used to identify corresponding Twitter accounts that are active in this generative AI space, but we do not see immediate harm as long as these Twitter accounts do not reveal personally identifiable information.

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

We urge that researchers exercise caution and discretion when using this dataset. The development of this dataset has been done in compliance with Twitter's policy on data usage and sharing. The use of this dataset should be in accordance with applicable laws, regulations, ethical considerations, and especially official Twitter developer policy at <https://developer.twitter.com/en/developer-terms/policy>.

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.

We distribute the metadata we collected at <https://zenodo.org/record/8031785>.

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

We release the dataset at <https://zenodo.org/record/8031785>; a detailed introduction to our project and dataset can be accessed at <https://yiqunchen.github.io/TWIGMA/>.

When will the dataset be distributed?

The dataset has been made available since June 12, 2023.

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.

We currently released the metadata under a Creative Commons CC BY 4.0 License; if you plan to get the official Twitter content, please consult the official Twitter policy at <https://developer.twitter.com/en/developer-terms/policy>.

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.

Please exercise caution and discretion when using this dataset. The development of this dataset has been done in compliance with Twitter's policy on data usage and sharing. The use of this dataset is solely at your own risk and should be in accordance with applicable laws, regulations, and ethical considerations. If you intend to review the original Twitter post, we recommend accessing the source page directly on Twitter and closely adhering to the official Twitter developer policy, available at <https://developer.twitter.com/en/developer-terms/policy>.

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. Please exercise caution and discretion when using this dataset. The development of this dataset has been done in compliance with Twitter's policy on data usage and sharing. The use of this dataset is solely at your own risk and should be in accordance with applicable laws, regulations, and ethical considerations. If you intend to review the original Twitter post, we recommend accessing the source page directly on Twitter and closely adhering to the official Twitter developer policy, available at <https://developer.twitter.com/en/developer-terms/policy>.

Maintenance	
Who will be supporting/hosting/maintaining the dataset?	data associated with the instances (e.g., were 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.
The first author, YC, will be hosting and maintaining the dataset.	N/A.
How can the owner/curator/manager of the dataset be contacted (e.g., email address)?	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 users.
yiqun.t.chen@gmail.com	N/A since no new versions are actually being planned.
Is there an erratum? If so, please provide a link or other access point.	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 other users? If so, please provide a description.
N/A.	The users can leave comments as Github issues at https://github.com/yiqunchen/TWIGMA .
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 users (e.g., mailing list, GitHub)?	
We do not have plans to regularly add new instances; but we will review requests and gather feedback from users on a quarterly basis.	
If the dataset relates to people, are there applicable limits on the retention of the	