A Creative Industry Image Generation Dataset Based on Captions and Sketches

Yuejia Xiang*†
xiangyuejia@bytedance.com

Chuanhao Lv*
2001782@stu.neu.edu.cn

Qingdazhu Liu
787673451@qq.com

Xiaocui Yang
yangxiaocui@stumail.neu.edu.cn

Bo Liu
736343658@qq.com

Meizhi Ju†
meizhi.ju@outlook.com

Abstract

Most image generation methods are difficult to precisely control the properties of the generated images, such as structure, scale, shape, etc., which limits its large-scale application in creative industries such as conceptual design and graphic design, and so on. Using the prompt and the sketch is a practical solution for controllability. Existing datasets lack either prompt or sketch and are not designed for the creative industry. Here is the main contribution of our work. a) This is the first dataset that covers the 4 most important areas of creative industry domains and is labeled with prompt and sketch. b) We provide multiple reference images in the test set and fine-grained scores for each reference which are useful for measurement. c) We apply two state-of-the-art models to our dataset and then find some shortcomings, such as the prompt is more highly valued than the sketch.

1. Introduction

Recently, image generation methods have drawn much attention from the community [20, 24, 49]. But the controllability of these methods still improvements and the generated pictures often deviate from the expectation of art creators in the creative industry domain [6, 48] (cf. Section 3.1). Therefore, art creators need to make heavy modifications of the generated image to meet the required object, shape, color, structure, and atmosphere. The controllability limits the widespread application of image generation methods in the creative industry domain [3, 29]. To address the controllability of image generation, many methods have been proposed by previous work, such as prompt, sketch, segment, style picture, etc. [11, 22, 33, 42]. After careful consideration, we chose only prompt and sketch to control image generation with the following reasons: a) prompt and sketch are the most understandable and most accessible material for art creators, b) prompt and sketch can represent the art creator’s intention relatively completely [14, 25].

Existing datasets [2, 9, 10, 13, 27, 30, 41, 44, 45, 50] lack either prompt or sketch and they are not designed for the creative industry domain, where the data is classified into 4 classes: concept design, graphic design, 3D-CG, and outdoor design. To solve these problems, we build an image generation dataset: a) Selecting images that belong to the creative industry domain from text-visual datasets such as CC12M [10]. b) Generating sketches for the images by CLIPasso [47]. c) Providing multiple sketches for each image and manually removing sketches of substandard quality. Note that if N sketches are kept for one image, then N cases are constructed, each of which contains one sketch. As shown in Table 1, our dataset is more suitable for the creative industry domain compared to previous work.

To more accurately measure the effect of the image generation model on our dataset, as shown in Fig 1, we enhance the test set: a) Inspired by Blue [36], we provide

Table 1. Comparing our dataset with previous work. PDID means the Percentage of Data in the creative Industry Domain. NICC means the Number of creative Industry Category Coverage. Although tags are a type of prompt, to distinguish tags from long text descriptions, we mark the dataset with only tags as No Prompt in this table.

| Dataset          | Prompt | Sketch | PDID | NICC |
|------------------|--------|--------|------|------|
| CIFAR-10 [2]     | N      | N      | 2%   | 4    |
| ImageNet [13]    | N      | N      | 1%   | 4    |
| Danbooru2021 [5] | N      | N      | 100% | 1    |
| CC12M [10]       | Y      | N      | 1%   | 4    |
| COYO-700M [9]    | Y      | N      | 1%   | 4    |
| LAION-400M [44]  | Y      | N      | 1%   | 4    |
| Photo-Sketching [30] | N   | Y      | 1%   | 1    |
| Sketchy [41]     | N      | Y      | 3%   | 4    |
| MM-CelebA-HQ [27] | Y    | Y      | 0%   | 0    |
| M2C-Fashion [50] | Y      | Y      | 100% | 1    |
| Our              | Y      | Y      | 100% | 4    |

*These authors contributed equally to this work.
†Corresponding authors.
Figure 1. An example of the test data. Each case in the test data generally has 5 to 20 reference images, which consist of one original image used to generate the sketch (named the golden reference image, which is the reference image located at the top left corner) and several images generated by SD [39] and NovelAI [4]. All fine-grained scores (PCS, SCS, VES) for the golden reference image were set to 1.0, and the other reference images were obtained by manual annotation. Finally, a composite score (CS) is calculated by weighted average.

Table 2. Count the number of metadata of each type in the train set and the test set of our dataset.

| Metadata                  | Train Set | Test Set |
|---------------------------|-----------|----------|
| Image                     | 23155     | 500      |
| De-duplicated Images      | 13227     | 293      |
| Prompt                    | 23155     | 500      |
| Sketch                    | 23155     | 500      |
| Reference                 | 23155     | 6928     |
| Fine-Grained Score        | 0         | 27712    |

Table 2. Count the number of metadata of each type in the train set and the test set of our dataset.

Our Contribution

- This is the first dataset that covers the 4 most important areas of creative industry domains and is labeled with prompt and sketch. We choose prompt and sketch because prompt and sketch are the most understandable and accessible material for art creators. And we ensure that every sketch in the dataset is high quality by manual annotation. We believe that our dataset can strongly contribute to the controllability of image generation methods in creative industry domains.

- For a more effective metric, we provide multiple reference images in the test set and each reference image has fine-grained scores.

- We apply two state-of-the-art models to our dataset and then find some valuable phenomena that we believe can guide the direction of subsequent research.

2. Related work

Datasets. a) Datasets with neither prompt nor sketch. The CIFAR-10 [2] dataset consists of 60000 32x32 color images in 10 classes, with 6000 images per class. ImageNet [13] is an image dataset organized according to the WordNet [34] hierarchy, with 14 million images and 21841 synsets. b) The dataset with prompt only. CC [45] present a dataset of image caption annotations, which contains 3 million images and represents a wider variety of both images and image caption styles. CC12M [10] introduce a vision-and-language pre-training resource obtained by leveraging noisy Web-scale image-text pairs. COYO-700M [9] collecting many informative pairs of alt-text and its associated image in HTML documents which contains 747M image-text pairs. LAION-400M [44] and LAION-5B [43] are datasets with CLIP-filtered 400 million and 5 billion image-text pairs respectively, their CLIP embeddings and kNN indices that allow efficient similarity search.
Figure 2. Both prompt and sketch can be used to control image generation. In this figure, we control the material by prompt and the shape by sketch. For each pair composed of one prompt and one sketch we show 9 images, of which 3 are manually selected, 3 are generated by the Stable Diffusion (SD) [39] model, and 3 are generated by the NovelAI [4] model. It can be found that these two models follow the prompt constraint better but follow the sketch constraint worse.

Danbooru2021 [5] is a large-scale anime image database with 4.9m+ images annotated with 162m+ tags. c) The dataset with sketch only. Photo-Sketching [30] use a crowdsourcing platform to collect 5000 high-quality drawings on outdoor images. Sketchy [41] ask crowd workers to sketch particular photographic objects sampled from 125 categories and acquire 75471 sketches of 12500 objects.

d) The dataset with both prompt and sketch. Multi-Modal CelebA-HQ [27] is a large-scale face image dataset that has 30,000 high-resolution face images, each having a high-quality segmentation mask, sketch, and descriptive text. M2C-Fashion [50] is a multi-modal large-scale clothing dataset.

Prompt. Danbooru2021 [8] is an anime image database with 4.9 million images annotated with 162 million tags which associate several tags to one image. CC12M [10] is a dataset with 12 million image-text pairs which provide one caption to one image. MS-COCO [32] contains 328000 images which provide five written caption descriptions for each image.

Sketch. Boundary Detection [18] is a joint probability distribution for the array of pixel gray levels and an array of labels. Photo-Sketching [30] collect a new dataset of contour drawings and propose a learning-based method that resolves diversity in the annotation and, unlike boundary detectors, can work with imperfect alignment of the annotation and the actual ground truth. SketchyScene [52] is created through a novel and carefully designed crowdsourcing pipeline, enabling users to efficiently generate large quantities of realistic and diverse scene sketches. SketchyScene contains more than 29,000 scene-level sketches, 7,000+ pairs of scene templates and photos, and 11,000+ object sketches.

Image Generation methods a) Support neither prompt nor sketch. StyleGAN [28] propose an alternative generator architecture for generative adversarial networks, borrowing from style transfer literature. CycleGAN [51] present an approach for learning to translate an image from a source domain X to a target domain Y in the absence of paired examples. b) Support only prompt. Make-A-Scene [17] propose a novel text-to-image method that enables a simple control mechanism complementary to text in the form of a scene. DALL·E [38] based on a transformer that autoregressively models the text and image tokens as a single stream of data. c) Support only sketch. SketchyGAN [12] propose a novel Generative Adversarial Network (GAN) approach that synthesizes plausible images from 50 categories including motorcycles, horses, and couches. Interactive Sketch [19] propose an interactive GAN-based sketch-to-image translation method that helps novice users easily create images of simple objects. d) Support both prompt and sketch. PoE-GAN [23] is a product-of-experts generative adversarial networks framework, which can synthesize images conditioned on multiple input modalities or any subset of them, even the empty set. M6-UFC [50] propose a new two-stage architecture to unify any number of multi-modal controls, in which both the diverse control signals and the synthesized image are uniformly represented as a sequence of discrete tokens to be processed by Transformer. Stable Diffusion (SD) [39] apply diffusion model training in the latent space of powerful pretrained autoencoders and achieve a new state of the art for image inpainting and highly competitive performance on various tasks. NovelAI [4] is a production focused on anime art generation based on stable diffusion method.

Evaluation Methods. Inception Score [40] (IS) evaluates GANs by using the KL divergence between properties captured by a pre-trained network (InceptionNet [46], trained
on the ImageNet [13] dataset). Fréchet Inception Distance (FID) [21] evaluates the generated data and real data by the Fréchet distance between two continuous multivariate Gaussian distributions constructed from the mean and variance of the feature of InceptionNet.

3. Image Collection

In order to build a dataset for the creative industry domain, we need to solve the following problems: a) What is the creative industry domain? b) How to get the images belonging to the creative industry domain? c) How to get prompts and sketches?

3.1. Creative Industry Domain

Due to the lack of a comprehensive and credible classification system for the creative industrial domain, we divide the creative industry domain into 4 categories by the suggestion made by an art professional who is inspired by the classification system of art-pro websites [15,37]. As shown in Table 3 and Fig. 3, the 4 categories are Concept Design (CD), Graphic Design (GD), 3D-CG, and Outdoor Design (OD).

3.2. Image Source

Since a large number of datasets with prompt already exist, we directly select the images belonging to the creative industry domain from the existing datasets CC12M [10] and Danbooru2021 [5], thus reusing the prompts from the previous datasets. Since the images in Danbooru2021 have only tags, we splice the tags together to construct a sentence as its prompt.

3.3. Image Selection

We only select images that match the creative industry domain by manual annotation. Images that do not belong to these categories will not be selected. We employ 5 annotators and train them until the accuracy of their annotation is higher than 99.0%. The distribution of categories is shown in Table 4. Each image in the dataset is labeled with the category it belongs to.

4. Prompt and Sketch

We need to give each image a prompt and a sketch. As the images were selected from CC12M and Danbooru2021, they all have a prompt. Therefore, we only need to generate a sketch for each image. Considering that some art creators sketch with just a few strokes, while some art creators sketch in great detail, we should provide sketches made up of different numbers of strokes.

4.1. Sketch Annotation Rules

To assess the quality of the sketch, the following two evaluation dimensions were developed: shape fidelity and line quality (cf. Appendix E). Note that whether a sketch has only a few strokes or a lot of strokes does not affect the evaluation of the quality of the sketch, i.e. the number of strokes in the sketch does not matter. This principle ensures that our dataset does not prefer simple sketches or prefer complex sketches. Figure 1 shows examples of sketches with their evaluation score.

4.2. Method of Obtain Sketch

Due to the high cost of sketch annotation, we use a model named CLIPasso [47] to obtain sketches at a low cost. It has been proven that method CLIPasso is better than competing methods such as BCDE (A) Kampelmuhler and Pinz [26], (B) Li et al. [31], (C) Li et al. [30], and CLIPDraw [16]. A case study is shown in Fig. 5. Furthermore, as examples shown in Fig. 6, CLIPasso is proven superior on generate sketches with different levels of abstraction. See Appendix H for details of the parameter setting of CLIPasso.

4.3. Sketch selection

The quality of the sketches generated by CLIPasso varies. In order to improve the quality of sketches in our dataset, we asked the annotators to evaluate all sketches according to sketch annotation rules and remove all sketches with shape fidelity less than 0.5 or line quality less than 0.2.

5. Reference Images and Fine-Grained Scores

Since our dataset focuses on the prompt and the sketch, we wonder whether the generated results satisfy the requirements of the prompt and the sketch. The previous evaluation methods cannot meet our needs, because they have two shortcomings: a) There is no standard answer for the image generation task, and using only one golden reference image limits the accuracy of the evaluation. b) It is difficult to assess the similarity between the image and prompt or sketch. To alleviate these problems, we enhance the test set with multiple reference images and fine-grained scores. And then we propose a new evaluation method.

5.1. Generate Reference Images

We use two state-of-the-art image generation models SD [39] and NovelAI [4] that support both prompt and sketch to generate candidate reference images. For detail, we input prompt and sketch to the two models and ask each model to generate 10 images. We call these 20 generated images candidate reference images. See Appendix G for details of the parameter setting of these models.
Table 3. The classification of the creative industry.

| Name            | Describe                                                                 |
|-----------------|--------------------------------------------------------------------------|
| concept design  | game concept design, film concept design, cartoon animation, illustration, costume |
| graphic design  | posters, packaging, product design, publications                         |
| 3D-CG           | 3D modeling, 3D animation, visual effects design, CG environment, renderings |
| outdoor design  | architecture, garden, landscape, outdoor environment, sculpture           |

Figure 3. Examples of images in each category in the creative industry domain.

Table 4. Selected image category distribution.

| label | CD | GD | 3D-CG | OD |
|-------|----|----|-------|----|
| Percent | 42.5 | 33.9 | 17.5 | 6.1 |

Figure 4. Examples of sketches with their evaluation score.

5.2. Reference Image Annotation Rules

To annotate the level of consistency of a reference image and a condition consisting of one prompt and one sketch, fine-grained image annotation rules (cf. Appendix F) are designed by an art professional (cf. Appendix A). As shown in Fig.1, the fine-grained score contains PSC, SCS, VES, and CS.

Figure 5. Comparison to competitor methods. Left to right: (A) Kampelmuhler and Pinz [26], (B) Li et al. [31], (C) Li et al. [30], and CLIPDraw [16]. Our16 and Our8 refer to the sketches generated by CLIPasso model with strokes of 16 and 8 respectively.

Data Split. We randomly selected 500 images from the training set as the test set and the rest images as the Train...
Figure 6. Levels of Abstraction Comparison. In the top and left parts are comparisons to Muhammad et al. [35] and in the right bottom part is a comparison to Berger et al. [7]. The leftmost column shows the input image, and the next four columns show different levels of abstraction.

Image Selection. We obtain 20 generated image candidate reference images for each image in the test set. Then we annotate all the candidate reference images and delete the images of which the Composite Score (CS) is lower than 0.7.

Statistic. Some statistic of our dataset is shown in Fig. 7.  

Table 5. An comparison of human score, FID score, and wFID score.

| Case | C | G | B | F | A | H | E | J | D | I |
|------|---|---|---|---|---|---|---|---|---|---|
| Human| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10|
| FID  | 6 | 10| 7 | 9 | 2 | 4 | 6 | 1 | 3 | 8 |
| wFID | 2 | 4 | 1 | 3 | 10| 6 | 8 | 7 | 5 | 9 |

We sorted the 10 generated images by each evaluation method and found that the agreement rate between manual score and wFID score is higher than that of FID score.

ATTENTION: the wFID is only one of the many possible ways to utilize our test set. We believe that the value of Multiple Reference Images and Fine-Graied scores has not been fully exploited.

6. Discussion

We found some phenomena of the current SOTA model on our dataset. Note that we did not fine-tune these models.

6.1. Prompts and Sketches is Effective.

As shown in Fig. 2, we find that both prompt and sketch can control the images generated by models, but images generated by diffusion models have a big gap in prompt consistency compared to the manually selected images. The model currently does not combine the information of prompt and sketch well to generate images, which needs to be improved and is a promising research direction. And the prompt is more highly valued than the sketch in both models.

6.2. The difference among four industry task categories

The images generated by the model [4,39] were analyzed in 4 Industry Task categories scenarios. In the Concept design task, as shown in Fig. 3, the images are mostly in the form of cartoons and animation. This task does not require high details of characters and things in the images. After manual evaluation, the images generated by diffusion models often have a higher CS. As shown in Fig. 3, the Graphic design task compared with the Concept design task requires more details, but most of the images generated by diffusion models are not fine enough, so there are fewer acceptable images. In the 3D-CG task, the objects in the images are not required to conform to common sense logic. For example, a prompt like “a lamp without a light bulb” is acceptable, and the images generated by diffusion models are of low quality. We analyzed this problem in 6.4. In the Outdoor design task, the prompt is mostly a text describing the whole. For example, “a snow-capped mountain.”. The content of the prompt is not much, and the generated images
are more likely to conform to the prompt but are missing a lot of detail compared to the original image. So the images generated by diffusion models have a higher PCS and a lower SCS.

6.3. The competition between prompt and sketch

We analyzed whether there is a competitive relationship between prompt and sketch. We conducted a case study for the following two queries.

1. when the prompt is rich, do the images generated by diffusion models follow the prompt more than the line shape of the sketch?
2. When there is less or no content in the prompt, do the images generated by diffusion models follow the line shape of the sketch more than the prompt?

As shown in Fig. 8, the richness of the prompt has nothing to do with whether the images generated by diffusion models follow the line shape of the sketch more or not, or whether they follow the prompt more.

6.4. The analysis of anti-common sense data

As shown in Fig. 2, in the case where the prompt is “ball”, the PCS of the images generated by diffusion models [4,39] is significantly lower than that of the images generated by diffusion models when the input sketch is an ellipse than when the input sketch is a circle. The same phenomenon is observed in the case where the prompt is “fruit”. We deduce that this phenomenon is caused by the data distribution, which means that most of the fruits and balls in the training set of these models are round, with few oval fruits or oval balls. To verify this conclusion, as shown in Fig. 9, we keep the oval sketch unchanged and changed the prompt to “omelet”. After manual evaluation, diffusion models generate images with a mean PCS value greater than 0.8. Further, we also generate images when the prompt is “wheel” with the input sketch as a square and the prompt is “national flag” with the input sketch as a triangle. After manual evaluation, their mean CS is less than 0.2 and 0.1, respectively. It is reasonable to assume that uncommon combinations of the prompt and the image in the training data will not perform well when inferred.

6.5. Semantic confusion

When a word appears polysemy in a text, the diffusion models [4,39] can not disambiguate the text semantics well. As shown in Fig. 10, “Carnes” is a polysemous word in the prompt “cranes at a high rise development.”.

6.6. The influence of sketch drawing form

As shown in Fig. 8 9 10 12 13, the sketches are in the drawing form of a black line on white background, the images generated by diffusion models [4,39] are also often in the form of black lines on a white background. In order to investigate whether this form of painting leads to a specific style of painting in the images generated by the model, we used the PS tool to modify the black lines and the white background to red respectively. As shown in Fig. 11. We found that the drawing form of the sketch does have a great impact on the generated image. Take the second line of the image as an example, in the case that the background of the sketch is red, there is no way to generate an image with a white background even if the prompt contains a description that modifies the background to white. Moreover, when the line color or background color of the sketch is changed, the SC of the generated images is relatively lower.

6.7. The influence of cfg scale parameter

Stable-diffusion-webui, a tool that generates the images, provides cfg scale parameter, its full name is Classifier Free Guidance Scale, which means how strongly the image should conform to prompt - lower values produce more creative results. [1] When generating images, the cfg scale parameter can be used to adjust the faithfulness. As shown in Fig. 12, this parameter does not make the pictures generated by diffusion models more faithful to the lines of the sketch. Even, too large cfg scale parameter will cause diffusion models to generate bad images.

6.8. The comparison of two diffusion models

The two diffusion models used in our experiment, stable diffusion v1.4 [39] can generate more realistic pictures, and the images generated by novel AI [4] are basically in the form of animation and cartoon. Based on the test set data we provided, the SD model generated realistic images with roughly 9% probability, while the novel AI generated realistic images with roughly 2% probability. As shown in Fig. 13, We show several realistic images generated by stable diffusion v1.4. Besides, As shown in Fig. 8 12, It is worth noting that novel AI is more suitable for the Concept design task because of the high quality of the generated cartoon and anime images.

7. Appendix Overview

A) Train set examples. Show several cases in train set.

B) Test set examples. Show several cases in test set.

C) Educational background of annotators. Detailed information on the educational background of each marker.

D) Training program for annotators. To ensure annotation accuracy of annotators.

E) Scoring criteria of sketch. Details the criteria used by annotators to assess the quality of Sketch.
Figure 8. The case study of the competition between prompt and sketch

| Sketch          | Results of SD | Results of NovelAI |
|-----------------|---------------|--------------------|
| pokemon ~(creature) | ![Images](images/8a.png) | ![Images](images/8b.png) |

Figure 9. Examples of anti-common sense data

| Prompt          | Sketch | Results of SD | Results of NovelAI |
|-----------------|--------|---------------|--------------------|
| omelet          | ![Images](images/9a.png) | ![Images](images/9b.png) | ![Images](images/9c.png) |
| wheel           | ![Images](images/9d.png) | ![Images](images/9e.png) | ![Images](images/9f.png) |
| national flag   | ![Images](images/9g.png) | ![Images](images/9h.png) | ![Images](images/9i.png) |

Figure 10. The animal “crane” and the machine “crane” both appear in the images

| Input          | Results |
|----------------|---------|
| prompt         | ![Images](images/10a.png) | ![Images](images/10b.png) | ![Images](images/10c.png) |
| sketch         | ![Images](images/10d.png) | ![Images](images/10e.png) | ![Images](images/10f.png) |
| reference      | ![Images](images/10g.png) | ![Images](images/10h.png) | ![Images](images/10i.png) |

Figure 11. Examples of three drawing forms

| Input          | Sketch | Results of SD | Results of NovelAI |
|----------------|--------|---------------|--------------------|
| prompt         | ![Images](images/11a.png) | ![Images](images/11b.png) | ![Images](images/11c.png) |
| reference      | ![Images](images/11d.png) | ![Images](images/11e.png) | ![Images](images/11f.png) |

Figure 12. Prompt is “1boy, black hair, brown eyes, brown hair, cross print, curtained hair, fingerless gloves, gloves, jacket, looking at viewer, male focus, parted hair, solo, turtleneck, upper body, white jacket”

Figure 13. Examples of realistic images generated by stable diffusion v1.4

F) Scoring criteria of reference. Details the criteria used by annotators to assess the quality of Sketch.

G) Setting of SD and Noval AI. The setting of SD and Noval AI when generating candidate reference images.
H) Setting of CLIPasso. The setting of CLIPasso when generating sketches.

References

[1] A browser interface based on gradio library for stable diffusion. https://github.com/AUTOMATIC1111/stable-diffusion-webui, 2022. 7
[2] Yehya Abouelnaga, Ola S Ali, Hager Rady, and Mohamed Mostafa. Cifar-10: Knn-based ensemble of classifiers. In 2016 International Conference on Computational Science and Computational Intelligence (CSCI), pages 1192–1195. IEEE, 2016. 1, 2
[3] Nantheera Anantrasirichai and David Bull. Artificial intelligence in the creative industries: a review. Artificial Intelligence Review, pages 1–68, 2021. 1
[4] Anlatan. Novalai: Driven by ai, painlessly construct unique stories, thrilling tales, seductive romances, or just fool around. anything goes!. 2022. 2, 3, 4, 6, 7
[5] Anonymous, Danbooru community, and Gwern Branwen. Danbooru2021: A large-scale crowdsourced and tagged anime illustration dataset. https://www.gwern.net/Danbooru2021, January 2022. Accessed: DATE. 1, 3, 4
[6] Mark Banks and Justin O’Connor. After the creative industries. 2009. 1
[7] Itamar Berger, Ariel Shamir, Moshe Mahler, Elizabeth J. Curter, and Jessica K. Hodgins. Style and abstraction in portrait sketching. ACM Trans. Graph., 32(4):55:1–55:12, 2013. 6
[8] Gwern Branwen and A Gokaslan. Danbooru2019: A large-scale crowdsourced and tagged anime illustration dataset, 2019. 3
[9] Minwoo Byeon, Beomhee Park, Haecheon Kim, Sungjun Lee, Woonhyuk Baek, and Saehoon Kim. Coyo-700m: Image-text pair dataset. https://github.com/kakaobrain/coyo-dataset, 2022. 1, 2
[10] Soravit Changpinyo, Piyush Sharma, Nan Ding, and Radu Soricut. Conceptual 12m: Pushing web-scale image-text pre-training to recognize long-tail visual concepts. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 3558–3568, 2021. 1, 2, 3, 4
[11] Shu-Yu Chen, Wanchao Su, Lin Gao, Shihong Xia, and Hongbo Fu. Deepfacedrawing: Deep generation of face images from sketches. ACM Transactions on Graphics (TOG), 39(4):72–1, 2020. 1
[12] Wengling Chen and James Hays. Sketchygan: Towards diverse and realistic sketch to image synthesis. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 9416–9425, 2018. 3
[13] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition, pages 248–255. Ieee, 2009. 1, 2, 4
[14] Stephen Ekwaro-Ostire, Ricardo Cruz-Lozano, Haileyesus B Endeshaw, and João Paulo Dias. Uncertainty in communication with a sketch. Journal of Integrated Design and Process Science, 20(4):43–60, 2016. 1
[15] Inc. Epic Games. Artstation: provides an awesome browsing and discovery experience, enabling you to view thousands of artworks by the world’s best artists., 2022. 4
[16] Kevin Frans, Lisa B. Soros, and Olaf Witkowski. Clipdraw: Exploring text-to-drawing synthesis through language-image encoders. CoRR, abs/2106.14843, 2021. 4, 5
[17] Oran Gafni, Adam Polyak, Oron Ashual, Shelly Sheynin, Devi Parikh, and Yaniv Taigman. Make-a-scene: Scene-based text-to-image generation with human priors. arXiv preprint arXiv:2203.13131, 2022. 3
[18] Donald Geman, Stuart Geman, Christine Graffigne, and Ping Dong. Boundary detection by constrained optimization. IEEE Transactions on pattern analysis and machine intelligence, 12(7):609–628, 1990. 3
[19] Arnav Ghosh, Richard Zhang, Puneet K Dokania, Oliver Wang, Alexei A Efros, Philip HS Torr, and Eli Shechtman. Interactive sketch & fill: Multiclass sketch-to-image translation. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 1171–1180, 2019. 3
[20] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks. Communications of the ACM, 63(11):139–144, 2020. 1
[21] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. Advances in neural information processing systems, 30, 2017. 2, 4
[22] Xun Huang, Arun Mallya, Ting-Chun Wang, and Ming-Yu Liu. Multimodal conditional image synthesis with product-of-experts gans. arXiv preprint arXiv:2112.05130, 3, 2021. 1
[23] Xun Huang, Arun Mallya, Ting-Chun Wang, and Ming-Yu Liu. Multimodal conditional image synthesis with product-of-experts gans. In European Conference on Computer Vision, pages 91–109. Springer, 2022. 3
[24] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1125–1134, 2017. 1
[25] DL Jenkins and RR Martin. The importance of free-hand sketching in conceptual design: automatic sketch input. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, volume 11702, pages 115–128. American Society of Mechanical Engineers, 1993. 1
[26] Moritz Kampelmüller and Axel Pinz. Synthesizing human-like sketches from natural images using a conditional convolutional decoder. In IEEE Winter Conference on Applications of Computer Vision, WACV 2020, Snowmass Village, CO, USA, March 1-5, 2020, pages 3192–3200. IEEE, 2020. 4, 5
[27] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. arXiv preprint arXiv:1710.10196, 2017. 1, 3
[28] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks.
