Paint by Word

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Figure 1: Paint by word. Our method enables a user to create a scene by painting with words. The user selects any visual concept using free text, and then applies that concept to an arbitrary region. The mask and word are used together with a semantic similarity network to guide a generative model to create a realistic modification to the synthesized image.

Abstract

We investigate the problem of zero-shot semantic image painting. Instead of painting modifications into an image using only concrete colors or a finite set of semantic concepts, we ask how to create semantic paint based on open full-text descriptions: our goal is to be able to point to a location in a synthesized image and apply an arbitrary new concept such as “rustic” or “opulent” or “happy dog.” To do this, our method combines a state-of-the-art generative model of realistic images with a state-of-the-art text-image semantic similarity network. We find that, to make large changes, it is important to use non-gradient methods to explore latent space, and it is important to relax the computations of the GAN to target changes to a specific region. We conduct user studies to compare our methods to several baselines.

1. Introduction

A writer can create vivid verbal imagery using just a few carefully-chosen words, but written scenes are abstract, without any specific physical form. In this paper, we ask how to enable an artist to use words to build an image concretely, painting textually described visual concepts [32] at specific locations in a scene. Our work is inspired and enabled by recent dramatic progress in text-to-image generation [38, 35]. However, rather than having the AI compose the whole image, we ask how large models can be used collaboratively to let a person apply words as a paintbrush. We wish to enable a user to paint brushstrokes on specific objects and regions within a generated image, then restyle, alter, or insert new objects by describing the desired visual concept with words.

The current work introduces the problem of zero-shot se-
2. Related Work

Our application is inspired by recent progress in the text-to-image synthesis problem [37, 35] as well as paint-based semantic image manipulation methods [4, 33, 32].

**Text-to-image synthesis.** Synthesizing an image based on a text description is an ambitious problem that has attracted a variety of proposed solutions: initial RNN-based generators [13, 27] have been followed by a series of by GAN-based [12] methods that have produced increasingly plausible images. The GAN methods have adopted two distinct approaches to generating realistic images from text. One is to generate images corresponding to text by sampling GAN latents that match semantics according to a separately trained image-text matching model [39]; this idea can be refined by viewing the sampling as an energy-based modeling procedure [31]. The second approach is to train a conditional generator that explicitly takes a language embedding as input [39]: the image quality of this approach can be improved using multi-stage generators [51, 52, 54], and semantic consistency can be improved through careful design of architectures and training losses [48, 58, 34, 49, 25, 43]. As an alternative approach, generating images from scene graphs instead of sentences [21] can allow a generator to exploit logical structure explicitly. Recent work stands apart by eschewing the use of GANs: the DALL-E [37] model generates images from text autoregressively using a transformer [44] based on GPT-3 [8] to jointly generate natural text and image tokens using a VQ-VAE encoding [38]; outputs are sampled to maximize semantic consistency via a state-of-the-art image-text matching model CLIP [35]. Artist Murdock has observed that CLIP can be used as a source of gradients to guide a generator [29, 28, 30]. The current paper is different from prior text-to-image work, because our goal is not to generate an image from text, but to define a paintbrush using text that enables a user to manipulate a semantics of a generated image at a specific painted location.

**Semantic image painting.** Our work is also inspired by a series of methods that have enabled users to construct realistic images by painting a finite selection of chosen concepts...
We must achieve semantic consistency. That is, we must be able to encode a given image in the latent representation of a GAN. Therefore, in order to apply GAN manipulation methods on real user-provided images, one must solve GAN inversion. While these methods enable a user to paint images using a finite vocabulary of semantic concepts, the goal of the current work is to enable a user to paint an unlimited vocabulary of visual concepts, specified by free text.

GAN latent space methods. Semantic manipulations in GAN latent spaces have been explored from several other perspectives. Early work on GANs observed the presence of some latent vector directions corresponding to semantic concepts [36], and further explorations have developed methods to identify interesting vector directions that steer latent space by using reconstruction losses [19, 41] or by learning from classification losses [10, 11, 32]. One disadvantage of this approach is that a semantic direction can only be found if we train a model to look for it in advance. On the other hand, it has been observed that interior latents in GANs are partially disentangled [5]. So recent work has developed unsupervised methods for identifying disentangled interpretable directions in these interior latents [17, 47]. Our approach differs from the above because our method for identifying latent manipulations is supervised neither by a set of finite classes nor does it rely on disentanglement; rather it identifies semantic latent changes in a zero-shot manner using full-text image semantic similarity.

GAN inversion methods. We note that the leading state-of-the-art generative models are not trained with an encoder. Therefore, in order to apply GAN manipulation methods on real user-provided images, one must solve GAN inversion. That is, we must be able to encode a given image in the latent space of the GAN. Because several powerful editing methods are enabled by GAN latent manipulation, the problem of inverting a GAN is of widespread interest and is the subject of an active line of ongoing research [57, 26, 6, 1, 2, 14, 40, 56, 59, 16]. The GAN inversion problem is complementary to our work. In this paper, we shall assume that the image to be edited is represented in the latent space of the generator.

3. Method

There are two challenging problems that must be simultaneously solved in order to implement paint-by-word: first, we must achieve semantic consistency, altering the painted part of the image to match the text description given by the user; and second, we must achieve realism: the altered part of the image should have a plausible appearance. In particular, the newly painted content should be consistent with the context of the rest of the image in terms of pose, color, lighting, and style.

We adopt a framework that addresses these two concerns using two separately trained networks: the first is a semantic similarity network $C(x, t)$ that scores the semantic consistency between an image $x$ and a text description $t$. This network need not be concerned with the overall realism of the image. The second is a convolutional generative network $G(z)$ that is trained to synthesize realistic images given a random $z$; this network enforces realism. Given $G$ and $C$, we can formulate the following optimization to generate a realistic image $G(z^*)$ that matches descriptive text $t$:

$$z^* = \arg\max_z C(G(z), t)$$

$$\text{(1)}$$
This simple approach factors the problem into two models that can be trained at large scale without any awareness of each other, and we shall use it as a starting point. It allows us to take advantage of recent progress in state-of-the-art models that can be used for $G$ and $C$ (Such as StyleGAN [23, 22], BigGAN [7], CLIP [35], and ALIGN [20]). Because our method allows the direct use of such large-scale models, this simple architecture is a promising approach for generating images from a text description even without any spatial conditions. We study this approach empirically in Section 4.1.

### 3.1. Semantic consistency in a region

When providing semantic paint, the method of Equation 1 is not sufficient, because it does not direct changes specifically towards a user’s chosen painted area. To focus effects on to one area, we direct the matching network $C$ to attend only to the region of the user’s brushstroke instead of the whole image. This can be done in a straightforward way: given a user-supplied mask $m$, we define a masked semantic similarity model

$$C_{t,m}(x) = C(x \odot m, t) \tag{2}$$

Here $x \odot m$ is a projection that zeroes the components of $x$ outside the region of the mask $m$.

By hiding the regions outside the mask from the semantic similarity model, the masked model $C_{t,m}(x)$ focuses the optimization on the selected region. However, in practice we find that this is not enough to direct changes to only a single object. Figure 3(c) shows the effect of optimizing $\arg\max_x C_{t,m}(G(z))$ to match a text description in a StyleGAN2 [23] model. Although no gradients pass from $C$ to $G$ outside the masked region, $G$ has a computational structure that links the appearance of objects outside the mask to objects within the mask.

In order to allow a user to edit a single object, we must obtain a generative model that allows the region inside of the mask to be unlinked. Interestingly, this can be done without training a new large-scale model from scratch.

### 3.2. Generative modeling in a region

To create a generative model that decouples the region inside and outside the mask, we exploit the convolutional structure of $G$. We work with an intermediate latent representation of the image $w$ that has a spatial structure over the field of the image. To access this structure, we express $G$ as two steps:

$$x = G(z) = h(f(z)) \tag{3}$$

$$w = f(z) \tag{4}$$

Given a mask $m$ provided by the user’s brushstrokes, we then decompose $w$ into a portion outside the mask $w_0$ and a portion inside the mask $w_1$, as follows:

$$w = w_0 + w_1 \tag{5}$$

$$w_1 = w \odot m \tag{6}$$

Here $w \odot m$ is a projection that zeroes the components of $w$ outside the region of the mask $m$. In practice, we downsample $m$ to the relevant feature map resolution(s) of $w$, and use the Hadamard product to zero the outside components.

For a given original image $G(z)$ we can fix the original $w_0 = w - w \odot m$ while allowing $w_1$ to vary. This split gives us a new generative model, where the representation outside the mask $m$ is fixed as $w_0$, while the representation inside the mask is parameterized by $w$:

$$G_{z,m}(w) = h(w_0 + w \odot m) \tag{7}$$

Splitting $w_0$ and $w$ in this way relaxes the problem, and allows $G_{z,m}(w)$ to generate images that the original model $G(z)$ could not generate.

In BigGAN, we use as $w$ the featuremap output of a layer of the network. This featuremap has a direct natural spatial structure, and $w \odot m$ simply zeros the featuremap locations outside the mask. In our BigGAN experiments we split the featuremap output of the first convolutional block of the generative network.

In StyleGAN, the natural interior latent, the $w$ vector, modulates featuremaps by changing channel normalizations uniformly across the spatial extent of the featuremap at all layers. In our formulation, we split the $w$ style latent vector spatially by applying a one style modulation outside the user-specified mask, fixed as $w_0$, and another style modulation

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**Figure 4:** Avoiding adversarial examples when optimizing an image to match the description “A photo of a yellow bird flying through the air.” The gradient descent method (Adam) obtains good scores while yielding an unrealistic image that looks neither like it is flying, nor like a real bird. In practice, we obtain better results by using the non-gradient sampling method (CMA-ES). Although samples do not achieve scores that are as good, the generated samples avoid becoming adversarial, and user studies (Section 4.1) show that results are both more realistic and accurate in practice.
this is a speckle black white and yellow bird with a yellow patch on its head

a white bird with black spots all over its wings and flanks and red brow and malar stripe

this little bird has a white belly and breast with a brown superciliary and brown striped crown

a tiny bird with a tiny head and bill brown coverts white secondaries a black back grey outer retices and a white breast

small beige colored bird with brown and white stripes on his wings and tail back is orange and pointy black eyes

a bird with a gray body gray wings with yellow coverts yellow crown black cheek patch and throat

this bird is a deep yellow almost orange color from the crown to the nape of the neck as well as its breast and belly leaving only its wings and tail black with the addition of white wingbars

Figure 5: Qualitative comparison of a handful of birds from the user study conducted in Section 4.1. Our method (third row) is applied to synthesizing full images based on description of birds. It is compared to an ablation where the Adam optimizer is used alone instead of CMA-ES; and we also compare our method to DALL-E [38]. Note that images from our method tend to be more realistic more often when compared to the other implementations.
and yet has many artifacts that look obviously synthetic. It does not resemble a photo of a bird.

One way to think about the problem is that our networks $C$ and $G$ were trained for optimal expected behavior over a distribution, not worst-case behavior for every individual. So when optimizing a single instance it is not hard to find an individual point at which both models misbehave.

We solve this problem by switching optimization strategies. Instead of seeking out a single optimal image, we use the Covariance Matrix Adaptation evolution strategy (CMA-ES) [15], which is a non-gradient method that aims to optimize a Gaussian distribution to have minimal loss when random samples are drawn from the distribution. Although CMA-ES may not achieve individual point losses that are as low as a gradient method like Adam, we find that in practice, the images that it obtains match modeled semantics very well, while remaining more realistic than the images produced by gradient descent: Figure 4(c) shows a typical image from the distribution after running CMA optimization for an equivalent amount of time as Adam. In Section 4.1 we compare CMA-ES to Adam in a human evaluation.

4. Results

To understand the strengths and weaknesses of our method, we conduct user studies in two problem settings. Then we explore the types of new image manipulations that are enabled by paint-by-word.

4.1. Testing full image generation

Without a user-provided mask, our method is a simple factorization of the text-conditional image generation problem (Equation 1). We wish to understand if this straightforward split of the problem has disadvantages compared to other approaches that explicitly condition image generation, so we begin by evaluating this architecture in comparison to a state-of-the-art model.

For $G$ we train a 256-pixel StyleGAN2 [23] with Adaptive Data Augmentation [22] on the CUB birds data set [45]. Standard training settings are used: the generator is unconditional, so no bird class labels nor text descriptions are revealed to the network during training. For $C$ we use an off-the-shelf CLIP [35] model, using the pretrained ViT-B/32 weights; this model was trained on an extensive proprietary data set of 400 million image/caption pairs. We generate images using two different techniques to maximize $C(G(z), t)$. As a simple baseline we optimize $z$ using first-order gradient descent (Adam [24]). Then we also optimize $z$ using CMA [15] followed by Adam.

To evaluate our method, we generate images from 500 descriptions of birds from a test dataset also used for evaluation of DALL-E in [38]. To compare the images generated by our method to images generated by DALL-E, we conduct a user study on Amazon Mechanical Turk [3] in which workers are asked to choose which of a pair of images are more realistic, and in a separately asked question, which of a pair more closely resemble a given text description.

The results are shown in Figure 6. We find that, for this test setting, our method gives competitive results. The CMA optimization process is able to steer $G$ to generate an image that is found to be a better fit for the description than the DALL-E method 65.4% of the time, and more realistic 89% of the time. The CMA method is also better than Adam alone, more accurate in 66.2%; more realistic in 75.2%.

This experiment is not intended to show that our simple method is superior to DALL-E: it is not. Our network is trained only on birds; it utterly fails to draw any other type of subject. Because of this narrow focus, it is unsurprising that it might be better at drawing realistic bird images than the DALL-E model, which is trained on a far broader variety of unconstrained images. Nevertheless, this experiment demonstrates that it is possible to obtain state-of-the-art semantic consistency, at least within a narrow image domain, without explicitly training the generator to take information about the textual concept as input.
4.2. A large scale user study of bedroom image edits

Next, we conduct a large-scale user study on localized editing of objects in bedroom scenes. For this study, we sample 300 images generated by StyleGAN2 [23] trained on LSUN bedrooms [50] and manually paint a single bed in each image. Then for each image we perform 10 paint-by-word tests by applying one of a set of 50 text descriptions of colors, textures, styles, states, and shapes. Humans compare each of the 3000 edited images to the corresponding original image: they evaluate whether one image is better described by the text description than the other, and separately whether one image is more realistic than the other. Each comparison is done without revealing which image is the original. Each comparison is evaluated by two people.

Results are tabulated by category in Table 1, and charted by word in Figure 8. Our method can decisively edit a range of colors and textures, but it is also effective for a range of other visual classes to a lesser degree. In all tested categories, most visual words can have some positive effect discerned by raters, however our method is weakest at being able to alter the shapes of objects. Examples of success and failure cases from the test are shown in Figure 7.

In Table 1, we note that ratings of realism of edited images are worst in the same categories where the strength of the semantic consistency is best. Some of the loss of realism is due to visible artifacts such as the blurred colors seen in Figure 7(e). However, other cases without noticeable visual artifacts are rated as less realistic by raters as in Figure 7(c,d),

Table 1: User study of edits, by semantic category. Percentages shown include only cases where both evaluations agree. “Accurate” counts cases where the edited image is a better match for the text. “Realistic” counts cases where the edited image is more realistic than the original. In both cases the opposite counts are also shown.

| color   | texture | state | style | shape |
|---------|---------|-------|-------|-------|
| accurate (2/2) | 72.8    | 46.5  | 40.6  | 37.2  | 31.7  |
| not accurate (0/2) | 3.9     | 13.2  | 20.0  | 20.4  | 22.8  |
| realistic (2/2) | 13.1    | 18.2  | 21.7  | 26.1  | 25.4  |
| not realistic (0/2) | 48.8    | 34.1  | 30.0  | 27.8  | 27.2  |

Figure 7: Representative successes and failures in a large-scale user study of image edits. 3000 edits were made on 300 randomly sampled StyleGAN2 bedroom outputs, and the edited image was compared to the original by crowdsourced workers. In cases a-e, 2/2 workers rated the modified image as a better match to the word than the original, and in case (f), both workers rated the modified image as a worse match to the word. In case (a) 2/2 workers rated the edited image as more realistic than the original, in cases (b) and (f) the two workers split on realism, and in cases c-e, both workers rated the edited image as less realistic than the original.

Figure 8: A detailed breakdown of user edits that were considered accurate by 2/2 workers, according to individual word. The most accurate edits among those we tested are for the color orange; and the least accurate are for the word “Scandinavian”. Edits that were considered less realistic than the original are shown in orange.
including many of the most interesting edits in the study. In these cases, the new painted styles are noticeable and stand out as less realistic than the original because the painted object now has an atypical style for the context - such as a gold bed in a cream-colored room, or an ugly bed in a hotel room. The portion of effective edits that are rated as unrealistic is shown as orange bars in Figure 7.  

4.3. Demonstrating paint-by-word on a broader diversity of image domains

To demonstrate the usefulness of our method beyond the narrow domains of birds and bedrooms, we apply our method on BigGAN models [7]. We apply two BigGAN models. First, we apply a BigGAN model trained on MIT Places [55]; and then we apply a BigGAN model trained on Imagenet [9].

Because the BigGAN models are trained on broad distributions of images, these generative models allow us to experiment with a wide variety of different editing operations. In Figure 9, We demonstrate our method’s ability to alter the style of buildings outdoors (a); we also demonstrate the ability to add new objects that did not previously exist in the scene (b). Both (a) and (b) demonstrate the potential of of BigGAN trained on Places to be used to manipulate general scene images. On BigGAN Imagenet, we discover the ability to change whether a dog is happy or sad (c-d). We can also add new objects to an appropriate context (e). A challenging task is to force the model to synthesize objects outside its training domain. Although the Imagenet training data contains no blue firetrucks, we can use language to specify that we wish for the model to render a firetruck as blue (f). Using our method, it can create blue parts of a vehicle, but the out-of-domain task of creating a whole blue firetruck remains difficult and introduces distortions.

5. Discussion

We have introduced the problem of paint-by-word, a human-AI collaborative task which enables a user to edit a generated image by painting a semantic modification specified by any text description, to any location of the image. Our work is enabled by the recent development of large-scale high-performance networks for realistic image generation and accurate text-image similarity matching. We have shown that a natural combination of these powerful components can work well enough to enable paint-by-word. Our user studies and demonstrations of effective edits have taken a first step in characterizing the opportunities, challenges and potential utility in this new application.

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Author Contributions Alex Andonian contributed to developing the method, creating data sets, implementing and running experiments, analyzing results, and writing. Sabrina Osmany developed the concept and prototype for abstract words like minimal, rustic, etc, including data sets, experiments, analysis. Audrey Cui contributed to developing the method, implemented experiments. YeonHwan Park contributed to implementing experiments, graphing and comparing results with other techniques. Ali Jahanian contributed to developing the method, implementing experiments, and writing. David Bau contributed to developing the method, created data sets, implemented experiments, analyzed results, and writing.

References

[1] Rameen Abdal, Yipeng Qin, and Peter Wonka. Image2stylegan: How to embed images into the stylegan latent space? In ICCV, 2019. 3
[2] Rameen Abdal, Yipeng Qin, and Peter Wonka. Image2stylegan++: How to edit the embedded images? In CVPR, 2020. 3
[3] Jeff Barr and Luis Felipe Cabrera. Ai gets a brain: New technology allows software to tap real human intelligence. Queue, 4(4):24–29, 2006. 6
[4] David Bau, Hendrik Strobelt, William Peebles, Jonas Wulff, Bolei Zhou, Jun-Yan Zhu, and Antonio Torralba. Semantic photo manipulation with a generative image prior. ACM Transactions on Graphics, 38(4):1–11, 2019. 2, 3
[5] David Bau, Jun-Yan Zhu, Hendrik Strobelt, Bolei Zhou, Joshua B. Tenenbaum, William T. Freeman, and Antonio Torralba. Gan dissection: Visualizing and understanding generative adversarial networks. In ICLR, 2019. 3
[6] David Bau, Jun-Yan Zhu, Jonas Wulff, William Peebles, Hendrik Strobelt, Bolei Zhou, and Antonio Torralba. Inverting layers of a large generator. In ICLR Debugging Machine Learning Models Workshop, 2019. 3
[7] Andrew Brock, Jeff Donahue, and Karen Simonyan. Large scale gan training for high fidelity natural image synthesis. In ICLR, 2018. 2, 4, 8
[8] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. In NeurIPS, 2020. 2
[9] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In CVPR, pages 248–255, 2009. 8
[10] Emily Denton, Ben Hutchinson, Margaret Mitchell, and Timnit Gebru. Detecting bias with generative counterfactual face attribute augmentation. In Fairness, Accountability,
Figure 9: Exploring edits using our method with BigGAN. Because BigGAN models have been pretrained on very broad distributions, they provide an opportunity to experiment with a broad range of types of edits.

Transparency and Ethics in Computer Vision Workshop (in conjunction with CVPR), 2019.

[11] Lore Goetschalckx, Alex Andonian, Aude Oliva, and Phillip Isola. Ganalyze: Toward visual definitions of cognitive image properties. In CVPR, pages 5744–5753, 2019.

[12] Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C Courville, and Yoshua Bengio. Generative adversarial nets. In Neural Information Processing Systems, 2014.

[13] Karol Gregor, Ivo Danihelka, Alex Graves, Danilo Rezende, and Daan Wierstra. Draw: A recurrent neural network for image generation. In International Conference on Machine Learning, pages 1462–1471. PMLR, 2015.

[14] Shanyan Guan, Ying Tai, Bingbing Ni, Feida Zhu, Feiyue Huang, and Xiaokang Yang. Collaborative learning for faster stylegan embedding. \textit{arXiv preprint arXiv:2007.01758}, 2020.

[15] Nikolaus Hansen. The cma evolution strategy: A tutorial. \textit{arXiv preprint arXiv:1604.00772}, 2016.

[16] Minyoung Huh, Richard Zhang, Jun-Yan Zhu, Sylvain Paris, and Aaron Hertzmann. Transforming and projecting images to class-conditional generative networks. In ECCV, 2020.

[17] Erik Härkönen, Aaron Hertzmann, Jaakko Lehtinen, and Sylvain Paris. Ganspace: Discovering interpretable gan controls. In NeurIPS, 2020.

[18] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In CVPR, pages 1125–1134, 2017.

[19] Ali Jahanian, Lucy Chai, and Phillip Isola. On the” steerability” of generative adversarial networks. In ICLR, 2019.

[20] Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc V Le, Yunhsuan Sung, Zhen Li, and Tom Duerig. Scaling up visual and vision-language representation learning with noisy text supervision. \textit{arXiv preprint arXiv:2102.05918}, 2021.

[21] Justin Johnson, Agrim Gupta, and Li Fei-Fei. Image generation from scene graphs. In CVPR, pages 1219–1228, 2018.

[22] Tero Karras, Miika Aittala, Janne Hellsten, Samuli Laine, Jaakko Lehtinen, and Timo Aila. Training generative adversarial networks with limited data. In NeurIPS, 2020.
[23] Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, and Timo Aila. Analyzing and improving the image quality of stylegan. *CVPR*, 2020. 2, 3, 4, 5, 6, 7

[24] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *ICLR*, 2015. 5, 6

[25] Wenbo Li, Pengchuan Zhang, Lei Zhang, Qiuyuan Huang, Xiaodong He, Siwei Lyu, and Jianfeng Gao. Object-driven text-to-image synthesis via adversarial training. In *CVPR*, pages 12174–12182, 2019. 2

[26] Zachary C Lipton and Subarna Tripathi. Precise recovery of latent vectors from generative adversarial networks. *arXiv preprint arXiv:1702.04782*, 2017. 3

[27] Elman Mansimov, Emilio Parisotto, Lei Jimmy Ba, and Ruslan Salakhutdinov. Generating images from captions with attention. In *ICLR*, 2016. 2

[28] Ryan Murdock. Aleph2Image. https://colab.research.google.com/drive/1Q-TbVvASMPRMXCOqkJxxf72CXYr8Vp, Feb. 2021. 2

[29] Ryan Murdock. The Big Sleep. https://colab.research.google.com/drive/1NCceX2mbiKOSlAdo7IU7a9UshKN5W8, Jan. 2021. 2

[30] Ryan Murdock. Thoughts on deepdaze, bigsleep, and aleph2image. https://rynmurdock.github.io

[31] Anh Nguyen, Jeff Clune, Yoshua Bengio, Alexey Dosovitskiy, and Jason Yosinski. Plug & play generative networks: Conditional iterative generation of images in latent space. In *CVPR*, pages 4467–4477, 2017. 2

[32] Sabrina Osmany. Visualizing semiotics in generative adversarial networks. *arXiv preprint arXiv:2303.12731*, 2023. 1, 2, 3

[33] Taesung Park, Ming-Yu Liu, Ting-Chun Wang, and Jun-Yan Zhu. Semantic image synthesis with spatially-adaptive normalization. In *CVPR*, pages 2337–2346, 2019. 2, 3

[34] Tingting Qiao, Jing Zhang, Duanqing Xu, and Dacheng Tao. MIRrorgan: Learning text-to-image generation by redescription. In *CVPR*, pages 1505–1514, 2019. 2

[35] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. *arXiv preprint arXiv:2103.00020*, 2021. 1, 2, 4, 5, 6

[36] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. In *ICLR*, 2016. 3

[37] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. *arXiv preprint arXiv:2102.12092*, 2021. 2

[38] Ali Razavi, Aaron van den Oord, and Oriol Vinyals. Generating diverse high-fidelity images with VQ-VAE-2. In *NeurIPS*, 2019. 1, 2, 5, 6

[39] Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran, Bernt Schiele, and Honglak Lee. Generative adversarial text to image synthesis. In *ICML*, pages 1060–1069. PMLR, 2016. 2

[40] Elad Richardson, Yuval Alaluf, Or Patashnik, Yotam Nitzan, Yaniv Azar, Stav Shapero, and Daniel Cohen-Or. Encoding in style: a stylegan encoder for image-to-image translation. *arXiv preprint arXiv:2008.00951*, 2020. 3

[41] Yujun Shen, Jinjin Gu, Xiaouu Tang, and Bolei Zhou. Interpreting the latent space of gans for semantic face editing. In *CVPR*, pages 9243–9252, 2020. 3

[42] Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. *arXiv preprint arXiv:1312.6199*, 2013. 5

[43] Ming Tao, Hao Tang, Songsong Wu, Nicu Sebe, Fei Wu, and Xiao-Yuan Jing. DF-GAN: Deep fusion generative adversarial networks for text-to-image synthesis. *arXiv preprint arXiv:2008.05865*, 2020. 2

[44] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Neural Information Processing Systems*, 2017. 2

[45] Catherine Wah, Steve Branson, Pietro Perona, and Takeshi Mitra. The Caltech-UCSD Birds-200-2011 Dataset. Technical Report CNS-TR-2011-001, California Institute of Technology, 2011. 6

[46] Ting-Chun Wang, Ming-Yu Liu, Jun-Yan Zhu, Andrew Tao, Jan Kautz, and Bryan Catanzaro. High-resolution image synthesis and semantic manipulation with conditional gans. In *CVPR*, pages 8798–8807, 2018. 3

[47] Zongze Wu, Dani Lischinski, and Eli Shechtman. Stylespace analysis: Disentangled controls for stylegan image generation. *arXiv preprint arXiv:2011.12799*, 2020. 3

[48] Tao Xu, Pengchuan Zhang, Qiuyuan Huang, Han Zhang, Zhe Gan, Xiaolei Huang, and Xiaodong He. AttnGAN: Fine-grained text to image generation with attentional generative adversarial networks. In *CVPR*, pages 1316–1324, 2018. 2

[49] Guojun Yin, Bin Liu, Lu Sheng, Nenghai Yu, Xiaogang Wang, and Jing Shao. Semantics disentangling for text-to-image generation. In *CVPR*, pages 2327–2336, 2019. 2

[50] Fisher Yu, Ari Seff, Yinda Zhang, Shuran Song, Thomas Funkhouser, and Jianxiong Xiao. Lsun: Construction of a large-scale image dataset using deep learning with humans in the loop. *arXiv preprint arXiv:1506.03365*, 2015. 3, 5, 7

[51] Han Zhang, Tao Xu, Hongsheng Li, Shaoting Zhang, Xiaogang Wang, Xiaoou Tang, and Bolei Zhou. Interpreting the latent space of gans for semantic face editing. In *ICLR*, 2018. 2

[52] Han Zhang, Tao Xu, Hongsheng Li, Shaoting Zhang, Xiaogang Wang, Xiaoou Tang, and Dimitris N Metaxas. Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In *CVPR*, pages 5907–5915, 2017. 2

[53] Han Zhang, Tao Xu, Hongsheng Li, Shaoting Zhang, Xiaogang Wang, Xiaoou Tang, and Dimitris N Metaxas. Stackgan++: Realistic image synthesis with stacked generative adversarial networks. *PAMI*, 41(8):1947–1962, 2018. 2

[54] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *CVPR*, 2018. 5

[55] Zizhao Zhang, Yuanpu Xie, and Lin Yang. Photographic text-image synthesis with a hierarchically-nested adversarial network. In *CVPR*, pages 6199–6208, 2018. 2
[55] Bolei Zhou, Agata Lapedriza, Jianxiong Xiao, Antonio Torralba, and Aude Oliva. Learning deep features for scene recognition using places database. In Neural Information Processing Systems, 2014. 8

[56] Jiapeng Zhu, Yujun Shen, Deli Zhao, and Bolei Zhou. Indomain gan inversion for real image editing. In ECCV, 2020. 3

[57] Jun-Yan Zhu, Philipp Krähenbühl, Eli Shechtman, and Alexei A Efros. Generative visual manipulation on the natural image manifold. In ECCV, pages 597–613. Springer, 2016. 3

[58] Minfeng Zhu, Pingbo Pan, Wei Chen, and Yi Yang. Dm-gan: Dynamic memory generative adversarial networks for text-to-image synthesis. In CVPR, pages 5802–5810, 2019. 2

[59] Peihao Zhu, Rameen Abdal, Yipeng Qin, and Peter Wonka. Improved stylegan embedding: Where are the good latents? arXiv preprint arXiv:2012.09036, 2020. 3