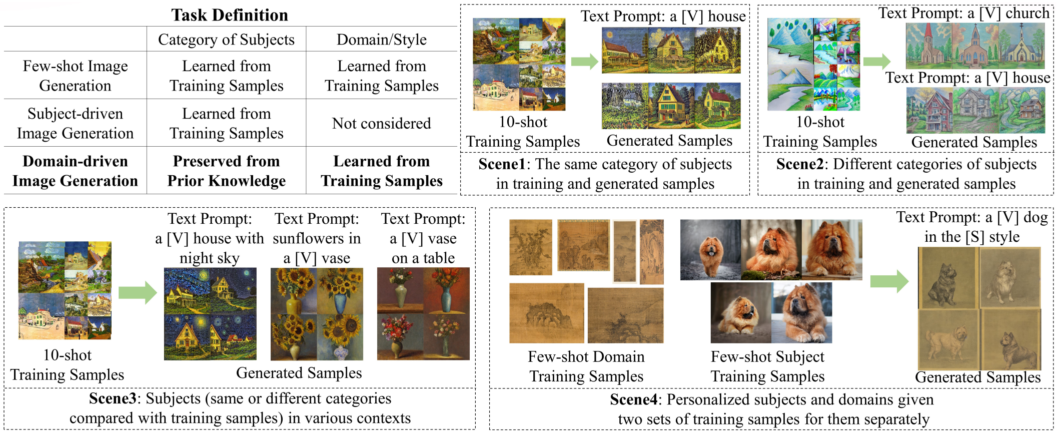
DomainStudio: Fine-Tuning Diffusion Models for Domain-Driven Image Generation using Limited Data

Anonymous authors
Paper under double-blind review



Task Definition		
	Category of Subjects	Domain/Style
Few-shot Image Generation	Learned from Training Samples	Learned from Training Samples
Subject-driven Image Generation	Learned from Training Samples	Not considered
Domain-driven Image Generation	**Preserved from Prior Knowledge**	**Learned from Training Samples**

Text Prompt: a [V] house
10-shot Training Samples
Generated Samples
Scene1: The same category of subjects in training and generated samples
Text Prompt: a [V] church
Text Prompt: a [V] house
10-shot Training Samples
Generated Samples
Scene2: Different categories of subjects in training and generated samples
Text Prompt: a [V] house with night sky
Text Prompt: sunflowers in a [V] vase
Text Prompt: a [V] vase on a table
10-shot Training Samples
Generated Samples
Scene3: Subjects (same or different categories compared with training samples) in various contexts
Text Prompt: a [V] dog in the [S] style
Few-shot Domain Training Samples
Few-shot Subject Training Samples
Generated Samples
Scene4: Personalized subjects and domains given two sets of training samples for them separately

Figure 1: We introduce a DDPM-based AI image creation approach named DomainStudio for domain-driven image generation, which preserves subjects provided by prior knowledge and adapts them to the domains (e.g., styles) learned from training samples. It tackles a task different from few-shot or subject-driven generation. The key difference is that the category of subjects in the generated samples is preserved from prior knowledge (e.g., pre-trained models) and can be different from the subjects in training samples in domain-driven generation. DomainStudio is compatible with both unconditional and text-to-image generation and only needs few-shot training data, extending DDPMs to produce compelling results in various application scenarios as shown above.

Abstract

Denoising diffusion probabilistic models (DDPMs) have been proven capable of synthesizing high-quality images with remarkable diversity when trained on large amounts of data. Unfortunately, they are still vulnerable to overfitting when fine-tuned on extremely limited data. Existing works have explored subject-driven generation with text-to-image (T2I) models using a few samples. However, there still lack effective data-efficient methods to synthesize images in specific domains (e.g., styles), which remains challenging due to ambiguities inherent in natural language and out-of-distribution effects. This paper introduces a few-shot fine-tuning approach named DomainStudio to realize domain-driven image generation, which is defined as retaining the subjects from prior knowledge provided by pre-trained models and adapting them to the domain extracted from training data, pursuing high quality and great diversity like prior few-shot generation methods. We propose to keep the image-level relative distances between adapted samples and enhance the learning of high-frequency details from both pre-trained models and training samples. DomainStudio is compatible with both unconditional and T2I DDPMs. This work makes the first attempt to achieve unconditional DDPM-based image generation using limited data, achieving better visual effects than current GAN-based approaches under the same task settings. For T2I generation, DomainStudio is qualified for synthesizing samples in domains characterized by few-shot training data. It extends the applicable scenarios of modern large-scale T2I diffusion models, which are insufficient to be handled with existing few-shot fine-tuning methods of T2I DDPMs like Textual Inversion and DreamBooth.

1 Introduction

Deep generative models (Goodfellow et al., 2014; Karras et al., 2020b; Kingma & Welling, 2013; Ho et al., 2020) have made significant progress in synthesizing high-quality and diverse images over past years. DDPMs (Sohl-Dickstein et al., 2015) have become the most prevailing approach amongst all of them with their outstanding performance and usability under various conditions (Nichol & Dhariwal, 2021; Li et al., 2023; Zhang & Agrawala, 2023; Rombach et al., 2022).

Despite the remarkable success, DDPMs are heavily dependent on large-scale training data (Schuhmann et al., 2022; Van den Oord et al., 2016; Yu et al., 2015) and vulnerable to overfitting when trained on limited data (Moon et al., 2022) like other generative models. A series of methods have been proposed (Wang et al., 2018; Karras et al., 2020a; Mo et al., 2020; Wang et al., 2020; Li et al., 2020; Ojha et al., 2021; Zhao et al., 2022b;a; 2023) to address such problems for GANs by transferring knowledge from pre-trained models to target domains. However, they are completely unconditional and still get limited fidelity influenced by unexpected blurs and deformations.

Existing data-efficient methods based on DDPMs like LoRA (Hu et al., 2021), Textual Inversion (Gal et al., 2022), and DreamBooth (Ruiz et al., 2023) mainly focus on subject-driven generation which aims to preserve the key features of customized subjects and synthesize novel scenes, poses, and views. It remains challenging to synthesize samples in specific domains (e.g., styles) even with powerful large-scale T2I diffusion models (Saharia et al., 2022; Ramesh et al., 2022; Rombach et al., 2022). Firstly, it is difficult to describe domains with text prompts accurately for T2I models due to the ambiguities in natural language. Besides, even if pre-trained models have captured typical domains owing to the presence of corresponding samples in their training data, they may still produce biased results influenced by the out-of-distribution effects. For example, there exist different styles in Van Gogh's paintings. Given a text prompt of "Van Gogh style", T2I models may choose a certain style randomly or mix some of them, leading to unsatisfactory outputs.

To this end, we introduce DomainStudio to enable domain learning of both unconditional and T2I DDPMs through few-shot fine-tuning with extremely limited data (e.g., 10 images). We propose to preserve the subjects from pre-trained source models, adapt them to the domain extracted from training samples, and define this task as domain-driven generation. It differs from few-shot image generation (Wang et al., 2018), which learns subject and domain knowledge from training samples, and subject-driven generation, which learns customized subjects and ignores domain knowledge. It is worth noting that "the preserved subjects" in domain-driven generation refer to a category of subjects including diverse individualities (e.g., a dog, a house) instead of specific subjects learned in subject-driven generation. We first propose an image-level pairwise similarity loss for DDPMs to keep the relative distances between adapted samples similar to source samples for the preservation of subject distributions and greater diversity. Then we design a high-frequency details enhancement method from two perspectives, including preserving more details provided by source models and learning more details from limited data for finer quality. As illustrated in Fig. 1, DomainStudio is qualified for a series of domain-driven tasks. Our main contributions are concluded as follows:

- We propose to synthesize samples in specific domains characterized by few-shot data by preserving subjects from source models and learning domain knowledge from training samples.
- We design a domain-driven DomainStudio approach compatible with both unconditional and T2I DDPMs to maintain the distributions of subjects and enhance high-frequency details learning.
- The effectiveness of DomainStudio is demonstrated qualitatively and quantitatively on a series of few-shot domain-driven tasks. For unconditional generation, DomainStudio achieves better diversity and visual effects than current state-of-the-art GAN-based approaches. For T2I generation, DomainStudio achieves compelling results in several scenes which existing few-shot fine-tuning methods of T2I diffusion models cannot handle.

2 Related Work

DDPMs (Sohl-Dickstein et al., 2015) define a forward noising (diffusion) process adding Gaussian noises ϵ to training samples x_0 and employ a UNet-based neural network ϵ_θ to approximate the reverse distribution, which can be trained to predict the added noises or the denoised images. Ho et al. (2020) demonstrates that predicting ϵ performs well and achieves high-quality results for unconditional image generation using a reweighted loss function:

$$\mathcal{L}_{simple}^{unc} = E_{t,x_0,\epsilon}\left[||\epsilon - \epsilon_\theta(x_t, t)||\right]^2, \tag{1}$$

where t and x_t represent the diffusion step and corresponding noised image. DDPMs have achieved competitive unconditional generation results on typical large-scale datasets (Krizhevsky et al., 2009; Yu et al., 2015; Van den Oord et al., 2016). Besides, classifier guidance is added to realize DDPM-based conditional image generation (Dhariwal & Nichol, 2021). Latent diffusion models (Rombach et al., 2022) employ pre-trained autoencoders to compress images into the latent space and achieve high-quality conditional generation using inputs such as text, images, and semantic maps.

T2I Generation (Crowson et al., 2022; Ding et al., 2021; Gafni et al., 2022; Jain et al., 2022; Hinz et al., 2020; Li et al., 2019b;a; Qiao et al., 2019a;b; Ramesh et al., 2021; Tao et al., 2020; Zhang et al., 2018b) has achieved great success based on GANs (Brock et al., 2019; Karras et al., 2019; 2020b; 2021), transformers (Vaswani et al., 2017), and diffusion models (Ho et al., 2020) with the help of image-text representations like CLIP (Radford et al., 2021). Large-scale T2I generative models including Imagen (Saharia et al., 2022), DALL-E2 (Ramesh et al., 2022), and Stable Diffusion (Rombach et al., 2022) further expand application scenarios and improve generation quality. Subject-driven fine-tuning methods like Textual Inversion (Gal et al., 2022) and DreamBooth (Ruiz et al., 2023) realize the personalization of T2I diffusion models using limited data. Custom Diffusion (Kumari et al., 2023) and MixofShow (Gu et al., 2023) explore multi-concept customization of T2I diffusion models. These subject-driven methods ignore the learning of domains. Our work makes up for gaps by tackling the domain-driven task based on DDPMs. Contemporary works (Sohn et al., 2023b;a) based on MaskGIT (Chang et al., 2022) and MUSE (Chang et al., 2023) tackle similar tasks of generating images containing different subjects and learning the style from training samples. Our approach is compatible with both unconditional and T2I DDPMs for domain-driven generation.

Few-shot Image Generation aims to achieve high-quality generation with great diversity using limited data. Existing approaches are GAN-based and unconditional. Most works follow TGAN (Wang et al., 2018) to adapt GANs pre-trained on large source datasets to target domains. Following methods can be roughly divided into data augmentation approaches (Tran et al., 2021; Zhao et al., 2020a;b; Karras et al., 2020a), trainable parameters fixing (Noguchi & Harada, 2019; Mo et al., 2020; Wang et al., 2020), and model regularization (Li et al., 2020; Ojha et al., 2021; Zhao et al., 2022b; Zhu et al., 2022; Xiao et al., 2022). AdAM (Zhao et al., 2022a) and RICK (Zhao et al., 2023) explore knowledge transfer between source/training datasets with large gaps. The proposed DomainStudio follows similar strategies to adapt pre-trained source models to target domains but keeps subjects in source samples. It is compatible with both unconditional and T2I DDPMs. Suppose training samples share the same category of subjects with source samples produced by pre-trained models, the domain-driven DomainStudio shares the same target with few-shot image generation. Otherwise, DomainStudio preserves subjects in source samples and learns domain knowledge.

High-frequency Components (HFC) in GANs have been proven to bias the generation quality (Schwarz et al., 2021). Prior GAN-based methods add skip connections of the HFC in features of generators (Yang et al., 2022; Wang et al., 2022), employ additional discriminators for HFC (Wang et al., 2022; Huang et al., 2022), and build HFC alignment between features in generators and discriminators (Wang et al., 2022) to improve generation quality given limited data. Our approach maintains the distributions of the relative distances between image-level HFC in source samples and learns more HFC from limited data, aiming for finer quality in few-shot fine-tuning of DDPMs.

Neural Style Transfer (NST) (Gatys et al., 2015; Ghiasi et al., 2017; Deng et al., 2022; Park & Kim, 2022; Tumanyan et al., 2022) transfers an input image to the style prompted by another image while maintaining the input contents. NST methods are designed to disentangle content and style information. Although NST and our work synthesize images in specific styles, they have different targets and cannot be compared directly. NST is image-level while our approach is model-level and aims to obtain adapted models synthesizing diverse samples in target domains.

3 Method

This section introduces the DomainStudio approach in detail. We propose to preserve the distributions of subjects during domain adaptation by keeping the image-level relative pairwise distances between adapted samples similar to source samples (Sec 3.1). Besides, we guide adapted models

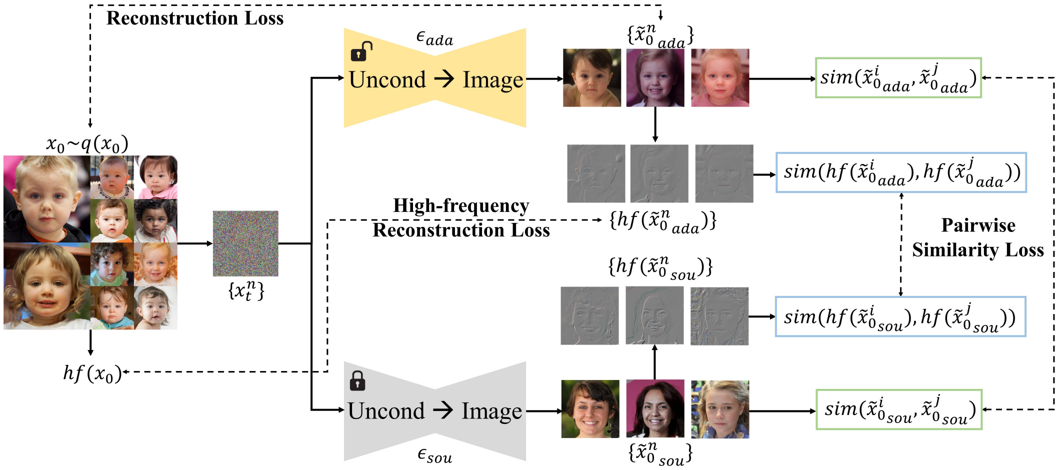

Reconstruction Loss
ϵ_{ada}
Uncond → Image
$\{\tilde{x}_{0\ ada}^{n}\}$
$sim(\tilde{x}_{0\ ada}^{i}, \tilde{x}_{0\ ada}^{j})$
$sim(hf(\tilde{x}_{0\ ada}^{i}), hf(\tilde{x}_{0\ ada}^{j}))$
$x_0 \sim q(x_0)$
High-frequency Reconstruction Loss
$\{hf(\tilde{x}_{0\ ada}^{n})\}$
Pairwise Similarity Loss
$\{x_t^n\}$
$\{hf(\tilde{x}_{0\ sou}^{n})\}$
$sim(hf(\tilde{x}_{0\ sou}^{i}), hf(\tilde{x}_{0\ sou}^{j}))$
$hf(x_0)$
Uncond → Image
$sim(\tilde{x}_{0\ sou}^{i}, \tilde{x}_{0\ sou}^{j})$
ϵ_{sou}
$\{\tilde{x}_{0\ sou}^{n}\}$

Figure 2: **Overview of DomainStudio on unconditional DDPMs.** We introduce an image-level pairwise similarity loss to maintain the diverse distributions of subjects and guide adapted models to learn knowledge of target domains. We also apply it to high-frequency components for better preservation of high-frequency details and guide adapted models to learn more high-frequency details from limited data with the reconstruction loss between high-frequency components extracted from few-shot data and adapted samples.

to learn more high-frequency details from limited training data and source samples (Sec 3.2). Our approach fixes source DDPMs ϵ_{sou} as reference for adapted DDPMs ϵ_{ada}. The pre-trained autoencoders ($\mathcal{E}$ + D) and text encoders Γ used in T2I generation are fixed as well. Adapted models are initialized to source models and adapted to target domains. Overviews of DomainStudio for unconditional and T2I generation are illustrated in Fig. 2 and 3, respectively.

For T2I generation, we define source and adapted samples using text prompts P_{sou} and P_{tar}. To avoid using the prior knowledge of target domains provided by the large T2I model, we employ a unique identifier [V] to represent target domains. For example, we define the source and adapted samples with text prompts “a house” and “a [V] house” in Fig. 3. Subjects in source and adapted samples share the same category but can be different from subjects in training samples. The source and target text prompts P_{sou} and P_{tar} are encoded by pre-trained text encoder Γ to conditioning vectors c_{sou} and c_{tar}. The adapted models are guided to learn from training samples with the reconstruction loss:

$$\mathcal{L}_{simple}^{text} = \mathbb{E}_{t,z_t,c_{tar},\epsilon}||\epsilon_{ada}(z_t, t, c_{tar}) - \epsilon||^2, \tag{2}$$

where z_t represents the latent codes z compressed from training samples added with noises.

3.1 Subject Distributions Preservation

We design an image-level pairwise similarity loss to maintain the relative pairwise distances between adapted samples for subject distributions preservation during domain adaptation. To construct N-way probability distributions for each sample in unconditional image generation, we sample a batch of noised images $\{x_t^n\}_{n=0}^N$ by randomly adding Gaussian noises to training samples $x_0 \sim q(x_0)$ following $x_t = \sqrt{\overline{\alpha}_t}x_0 + \sqrt{1-\overline{\alpha}_t}\epsilon$, where $\overline{\alpha}_t := \prod_{s=0}^t (1-\beta_s)$ and $\beta_s \in (0,1)$ represents the variance at diffusion step t. Then both source and adapted models are applied to predict the fully denoised images $\{\tilde{x}_0^n\}_{n=0}^N$. We have the prediction of $\tilde{x}_0$ in terms of x_t and $\epsilon_\theta(x_t, t)$ as follows:

$$\tilde{x}_0 = \frac{1}{\sqrt{\overline{\alpha}_t}}x_t - \frac{\sqrt{1-\overline{\alpha}_t}}{\sqrt{\overline{\alpha}_t}}\epsilon_\theta(x_t, t). \tag{3}$$

Cosine similarity is employed to measure the relative distances between the predicted images $\tilde{x}_0$. The probability distributions for $\tilde{x}_0^i$ $(0 \leq i \leq N)$ in source and adapted models are as follows:

$$p_{sou}^{unc,i} = sfm(\Big\{sim(\tilde{x}_{0_{sou}}^i, \tilde{x}_{0_{sou}}^j)\Big\}_{\forall i \neq j}), \quad p_{ada}^{unc,i} = sfm(\Big\{sim(\tilde{x}_{0_{ada}}^i, \tilde{x}_{0_{ada}}^j)\Big\}_{\forall i \neq j}), \tag{4}$$

where sim and sfm denote cosine similarity and softmax function, respectively. However, it's difficult to build correspondence for T2I generation with fixed noise inputs since the source and

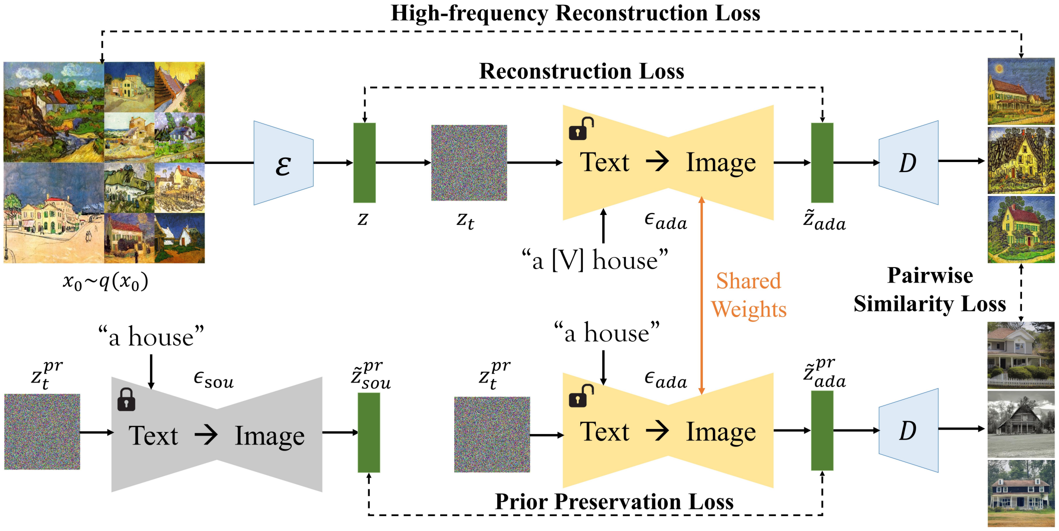


Figure 3: **Overview of DomainStudio on T2I DDPMs.** DomainStudio on unconditional DDPMs can be directly generalized to T2I DDPMs for domain-driven generation since it only uses image-level information for additional optimization. Prior preservation loss is used to preserve source samples during domain adaptation.

adapted samples have different conditions. We find that keeping similar distributions of relative pairwise distances for randomly generated source and adapted samples also maintains the distributions of subjects well for T2I generation. Given batches of noised source latent codes $\{z_t^{pr,n}\}_{n=0}^{N}$ and target latent codes $\{z_t^{n}\}_{n=0}^{N}$, we build probability distributions for source and adapted samples as follows:

$$p_{sou}^{text,i} = sfm(\left\{sim(D(\tilde{z}_{ada}^{pr,i}), D(\tilde{z}_{ada}^{pr,j})\right\}_{\forall i\neq j}), \quad p_{ada}^{text,i} = sfm(\left\{sim(D(\tilde{z}_{ada}^{i}), D(\tilde{z}_{ada}^{j}))\right\}_{\forall i\neq j}), \tag{5}$$

where $\tilde{z}_{ada}^{pr}$ and $\tilde{z}_{ada}$ are denoised source and target latent codes produced by adapted models. The image-level pairwise similarity loss for unconditional and T2I generation are as follows:

$$\mathcal{L}_{img}^{unc} = \mathbb{E}_{t,x_0,\epsilon} \sum_i D_{KL}(p_{ada}^{unc,i} \,||\, p_{sou}^{unc,i}), \tag{6}$$

$$\mathcal{L}_{img}^{text} = \mathbb{E}_{t,z_t,z_t^{pr},\epsilon,\epsilon^{pr}} \sum_i D_{KL}(p_{ada}^{text,i} || p_{sou}^{text,i}), \tag{7}$$

where D_{KL} represents KL-divergence and z_t^{pr} represents the source latent codes added with noises ϵ^{pr}. $\mathcal{L}_{img}$ prevents adapted samples from being too similar to each other or replicating training data. It encourages adapted models to keep the distributions of subjects in adapted samples similar to source samples and learns domain knowledge from training samples for domain-driven generation.

We are inspired by CDC (Ojha et al., 2021), which builds pairwise similarity loss based on features in certain layers of the generator in StyleGAN2 (Karras et al., 2020b) to preserve cross-domain similarity. DDPMs are trained to predict noises with multiple steps in synthesizing images. It is difficult to find proper features to represent generated samples. As a result, we directly build image-level pairwise similarity with the completely denoised samples, which makes our approach compatible with DDPMs. Besides, our method is designed for domain-driven generation to preserve the basic distributions of subjects, which take up most parts of the generated samples, instead of building one-to-one correspondence across domains like CDC. We use various noise inputs for source and adapted samples in T2I generation but still achieve the preservation of subject categories.

3.2 High-frequency Details Enhancement

To begin with, we employ the typical Haar wavelet transformation (Daubechies, 1990) to disentangle images into multiple frequency components. Haar wavelet transformation decomposes inputs into the low-frequency component LL and high-frequency components LH, HL, and HH. We define hf as the sum of all high-frequency components needing enhancement: $hf = LH + HL + HH$.

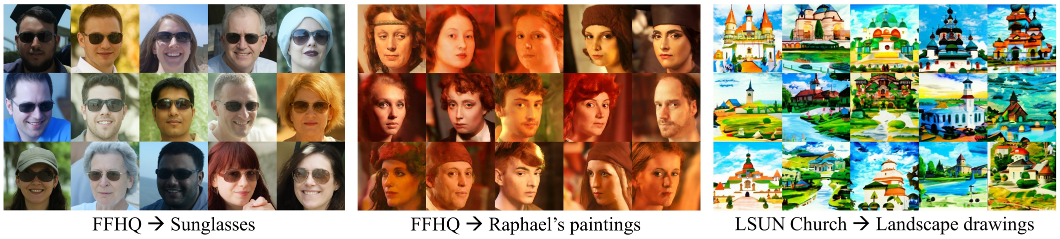


Figure 4: DomainStudio generation samples under several 10-shot unconditional adaptation setups.

We implement high-frequency details enhancement from two perspectives. Firstly, we use the proposed pairwise similarity loss to preserve high-frequency details learned from source samples. The probability distributions for the high-frequency components of generated samples of source and adapted models for unconditional and T2I generation are as follows ($i \neq j$):

$$pf_{sou}^{unc,i} = sfm(\left\{sim(hf(\tilde{x}_{0_{sou}}^{i}), hf(\tilde{x}_{0_{sou}}^{j}))\right\}), pf_{ada}^{unc,i} = sfm(\left\{sim(hf(\tilde{x}_{0_{ada}}^{i}), hf(\tilde{x}_{0_{ada}}^{j}))\right\}), \quad (8)$$

$$pf_{sou}^{text,i} = sfm(\left\{sim(hf(D(\tilde{z}_{ada}^{pr,i})), hf(D(\tilde{z}_{ada}^{pr,j}))\right\}), \quad (9)$$

$$pf_{ada}^{text,i} = sfm(\left\{sim(hf(D(\tilde{z}_{ada}^{i})), hf(D(\tilde{z}_{ada}^{j})))\right\}). \quad (10)$$

Similar to the image-level losses shown in Eq. 6 and 7, the pairwise similarity loss for the high-frequency components in unconditional and T2I generation are defined as follows:

$$\mathcal{L}_{hf}^{unc} = \mathbb{E}_{t,x_0,\epsilon} \sum_i D_{KL}(pf_{ada}^{unc,i} \,||\, pf_{sou}^{unc,i}), \quad (11)$$

$$\mathcal{L}_{hf}^{text} = \mathbb{E}_{t,z_t,z_t^{pr},\epsilon,\epsilon^{pr}} \sum_i D_{KL}(pf_{ada}^{text,i} || pf_{sou}^{text,i}). \quad (12)$$

Secondly, we propose high-frequency reconstruction loss to guide adapted models to learn more high-frequency details from limited training data by minimizing the mean squared error (MSE) between the high-frequency components in adapted training samples, which can be expressed for unconditional and T2I generation as follows:

$$\mathcal{L}_{hfmse}^{unc} = \mathbb{E}_{t,x_0,\epsilon}\left[||hf(\tilde{x}_{0_{ada}}) - hf(x_0)||\right]^2, \quad (13)$$

$$\mathcal{L}_{hfmse}^{text} = \mathbb{E}_{t,x_0,z_t,\epsilon}||hf(D(\tilde{z}_{ada})) - hf(x_0)||^2. \quad (14)$$

3.3 Overall Optimization Target

The overall optimization target of DomainStudio combines all the methods proposed above to realize the preservation of subject distributions and high-frequency details enhancement. The loss function for unconditional and T2I generation are expressed in Eq. 15 and 16 respectively:

$$\mathcal{L}^{unc} = \mathcal{L}_{simple}^{unc} + \lambda_{11}\mathcal{L}_{vlb} + \lambda_2\mathcal{L}_{img}^{unc} + \lambda_3\mathcal{L}_{hf}^{unc} + \lambda_4\mathcal{L}_{hfmse}^{unc}, \quad (15)$$

$$\mathcal{L}^{text} = \mathcal{L}_{simple}^{text} + \lambda_{12}\mathcal{L}_{pr} + \lambda_2\mathcal{L}_{img}^{text} + \lambda_3\mathcal{L}_{hf}^{text} + \lambda_4\mathcal{L}_{hfmse}^{text}. \quad (16)$$

We set the weight λ_{11} of the variational lower bound loss $\mathcal{L}_{vlb}$ (Nichol & Dhariwal, 2021) as 0.001 and the weight λ_{12} of the prior preservation loss $\mathcal{L}_{pr}$ (Ruiz et al., 2023) as 1 (see more details in Appendix B). We empirically find λ_2, λ_3 ranging between 0.1 and 1.0 and λ_4 ranging between 0.01 and 0.08 to be effective for most unconditional adaptation setups and λ_2, λ_3 ranging between 100 and 500 and λ_4 ranging between 0.1 and 1.0 to be effective for most T2I adaptation setups.

4 Experiments

We evaluate DomainStudio with a series of domain-driven generation tasks using extremely limited data ($\leq$ 10 images). It is compared with directly fine-tuned DDPMs, GAN-based few-shot image generation methods, and few-shot fine-tuning methods of large-scale T2I models on generation quality and diversity qualitatively and quantitatively. Ablation analysis is discussed in Sec. 4.3.

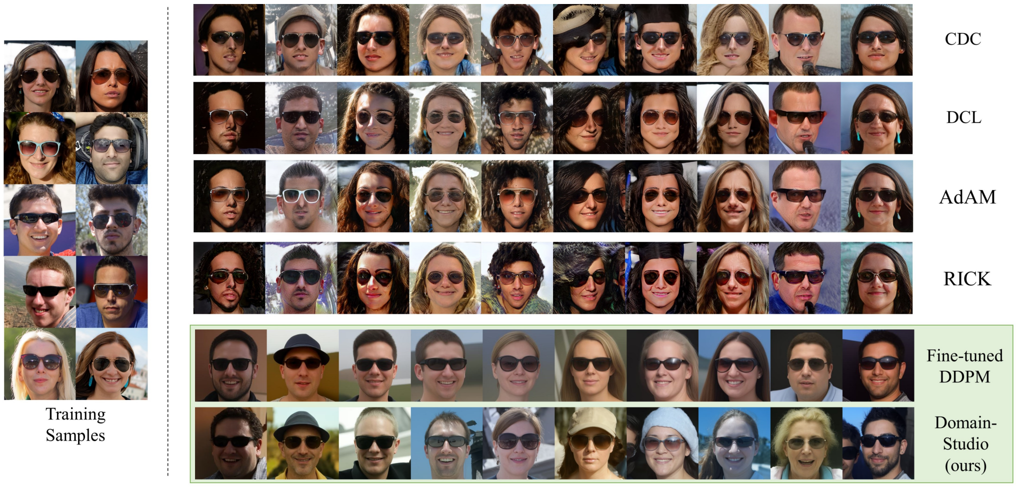


Figure 5: 10-shot unconditional image generation samples on FFHQ → Sunglasses. All the samples of GAN-based approaches are synthesized from fixed noise inputs (rows 1-4). Samples of the directly fine-tuned DDPM and DomainStudio are synthesized from fixed noise inputs as well (rows 5-6). Our approach generates high-quality results with fewer blurs and artifacts and achieves considerable generation diversity.

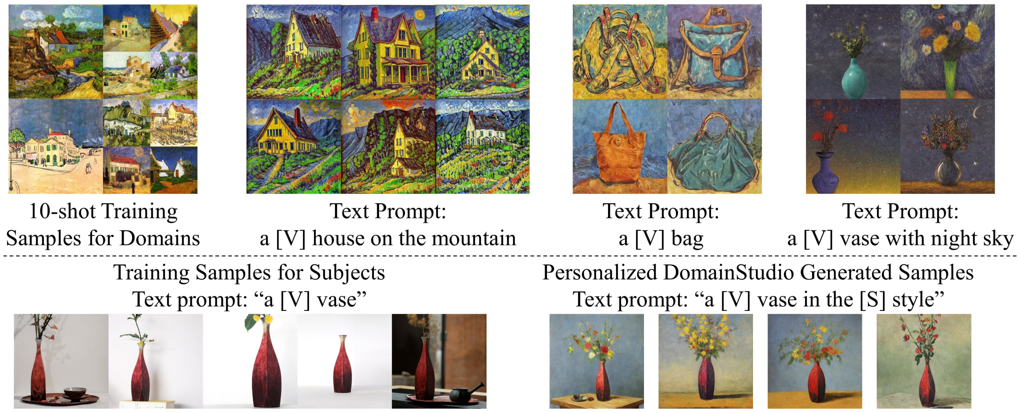

10-shot Training
Samples for Domains
Text Prompt:
a [V] house on the mountain
Text Prompt:
a [V] bag
Text Prompt:
a [V] vase with night sky
Training Samples for Subjects
Text prompt: “a [V] vase”
Personalized DomainStudio Generated Samples
Text prompt: “a [V] vase in the [S] style”

Figure 6: Given 10-shot training samples to characterize the target domain, DomainStudio can synthesize samples in target domains with diverse contexts, different categories of subjects or personalized subjects.

Basic Setups We train DDPMs from scratch on FFHQ (Karras et al., 2020b) and LSUN Church (Yu et al., 2015) as source models for unconditional generation. Stable Diffusion (Rombach et al., 2022) v1.4 is employed as the source model for T2I generation. Several datasets containing less than 10 samples are used as training datasets. More details of implementation are added in Appendix H.

Baselines Since few prior works realize DDPM-based few-shot image generation unconditionally, we employ several GAN-based baselines sharing similar targets with us on subject-consistent source/training datasets: CDC (Ojha et al., 2021), DCL (Zhao et al., 2022b), AdAM (Zhao et al., 2022a), and RICK (Zhao et al., 2023). All the GAN-based methods are implemented based on StyleGAN2 (Karras et al., 2020b). The StyleGAN2 models and unconditional DDPMs trained on the large source datasets share similar generation quality and diversity (see more details in Appendix I). Modern few-shot fine-tuning methods Textual Inversion (Gal et al., 2022) and DreamBooth (Ruiz et al., 2023) are used as baselines for T2I generation. Textual Inversion is trained to learn styles.

Evaluation Metrics We follow CDC to employ Intra-LPIPS for diversity evaluation and FID (Heusel et al., 2017) for quality evaluation. As for T2I generation, we employ CLIP (Radford et al., 2021) to measure the textual alignment with text prompts using CLIP-Text, which is the average pairwise cosine similarity between the CLIP embeddings of text prompts and generated samples and evaluates the preservation of subjects. More details of metrics are added in Appendix C.

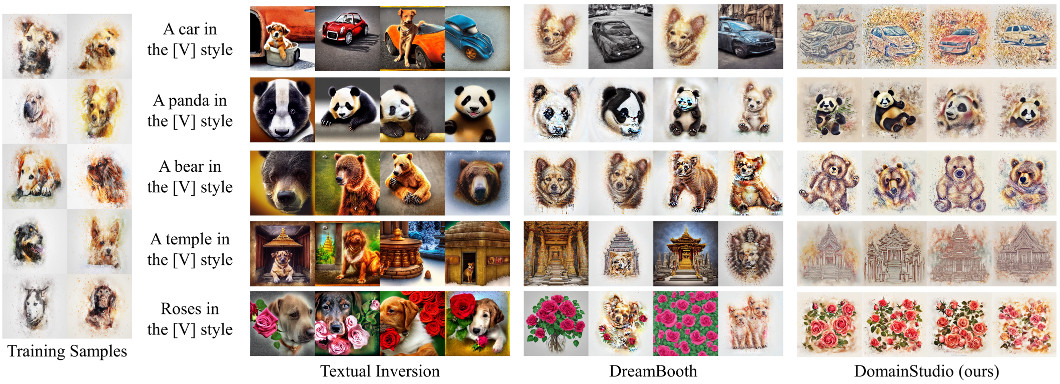


Figure 7: 10-shot T2I generation samples trained on Watercolor dogs. DomainStudio produces samples containing diverse subjects consistent with text prompts and sharing the same style with training data.

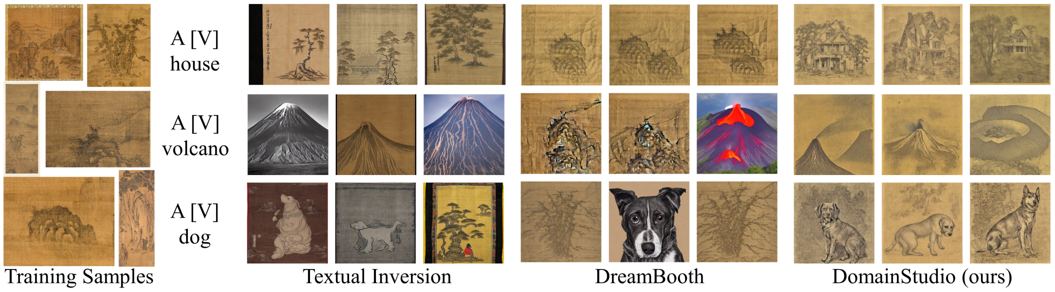


Figure 8: T2I generation samples trained on 6-shot Ink paintings. DomainStudio adapts subjects mentioned in text prompts to target domains naturally while baselines get unrealistic results due to underfitting or overfitting.

4.1 Qualitative Evaluation

Unconditional Image Generation As shown in Fig. 4, DomainStudio adapts source models to target domains naturally and produces diverse samples under several 10-shot adaptation setups. Samples of diverse faces can be found when adapting FFHQ to target domains. The adaptation from LSUN Church to Landscape drawings retains various church structures. Fig. 5 shows samples of DomainStudio and baselines on 10-shot FFHQ → Sunglasses. GAN-based baselines generate some incomplete sunglasses and unnatural blurs and artifacts. Directly fine-tuned DDPM produces smoother results but lacks details like lighting effects and fine hair structures. In contrast, DomainStudio improves generation quality and diversity and achieves more pleasing visual effects.

T2I Generation As illustrated in Fig. 1 and 6, DomainStudio is qualified for domain-driven generation regardless of whether the category of subjects in training samples is consistent with adapted samples. For example, given 10-shot Van Gogh houses as training data, we synthesize samples with text prompts such as “a [V] bag”. Besides, we combine DomainStudio with DreamBooth to realize domain-driven generation with personalized subjects (see more details in Appendix G).

Metrics	FID (↓)		Intra-LPIPS (↑)		
Datasets	Babies	Sunglasses	Babies	Sunglasses	Sketches
CDC	74.39	42.13	0.583 ± 0.014	0.579 ± 0.018	0.454 ± 0.017
DCL	52.56	38.01	0.579 ± 0.018	0.574 ± 0.007	0.461 ± 0.021
AdAM	48.43	28.03	0.573 ± 0.016	0.559 ± 0.017	0.424 ± 0.018
RICK	**39.39**	**25.22**	0.589 ± 0.010	0.591 ± 0.030	0.443 ± 0.025
Fine-tuned DDPMs	114.95	54.47	0.513 ± 0.026	0.527 ± 0.024	0.473 ± 0.022
DomainStudio (ours)	48.92	34.75	$\mathbf{0.599 \pm 0.024}$	$\mathbf{0.604 \pm 0.014}$	$\mathbf{0.495 \pm 0.024}$

Table 1: Quantitative results of unconditional few-shot image generation (source datasets: FFHQ). DomainStudio achieves better generation diversity than directly fine-tuned DDPMs and prior GAN-based methods.

DomainStudio is compared with Textual Inversion and DreamBooth in Fig. 7 and 8. It's difficult for baselines to learn the domain knowledge from few-shot data, especially when the subjects in adapted samples are different from training samples. For instance, when generating temples and roses in the watercolor style, baselines tend to combine the subjects in training samples with the subjects mentioned in text prompts. They lack guidance on what to learn from few-shot data and what to preserve from source models, resulting in overfitting or underfitting results. DomainStudio successfully adapts the subjects mentioned in text prompts to the domain of training samples, achieving high-quality and diverse samples. More visualized results are provided in Appendix M.

4.2 Quantitative Evaluation

We provide the quantitative results of DomainStudio on unconditional and T2I generation in Table 1 and 2. DomainStudio achieves a superior improvement of generation diversity compared with directly fine-tuned DDPMs and outperforms state-of-the-art GAN-based approaches in terms of Intra-LPIPS. Although DomainStudio fails to achieve the best FID, it produces samples in target domains with fewer blurs and artifacts, resulting in better visual effects, as shown in the qualitative results. For T2I generation, DomainStudio achieves state-of-the-art CLIP-Text results, indicating its ability to preserve subjects in domain-driven generation and synthesize images consistent with text prompts while adapting to target domains. More quantitative results and analysis are added in Appendix D.

Methods	Van Gogh houses	Ink painting volcanoes
Textual Inversion	0.259 ± 0.001	0.244 ± 0.001
DreamBooth	0.262 ± 0.002	0.275 ± 0.004
DomainStudio (ours)	$\mathbf{0.276 \pm 0.002}$	$\mathbf{0.301 \pm 0.002}$

Table 2: CLIP-Text (↑) results of DomainStudio on T2I tasks. DomainStudio outperforms baselines on text alignment.

4.3 Ablation Analysis

We ablate our approach to show the roles of two parts. Subject distributions preservation is the basis of DomainStudio, without which mode collapse occurs and leads to blurred and low-quality results. High-frequency details enhancement guides adapted models to generate more details (e.g., house structures and hairstyles). DomainStudio combines them to achieve compelling and diverse results and better metrics. Without these two parts, DomainStudio degrades to DreamBooth and directly fine-tuned models in T2I and unconditional generation. More detailed ablations are provided in Appendix E.

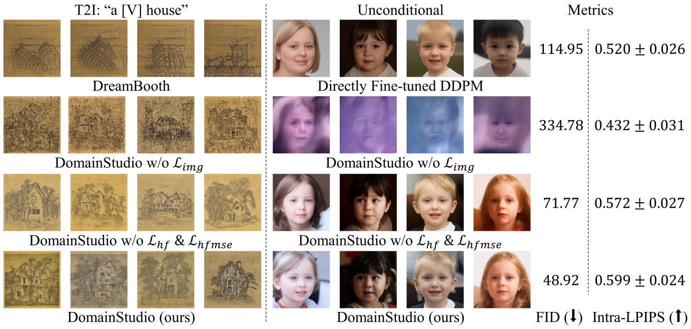


Figure 9: Ablation analysis of DomainStudio on T2I (houses in the ink painting style) and unconditional DDPMs (FFHQ → Babies).

5 Conclusion

We propose DomainStudio, a novel approach to realize few-shot and domain-driven image generation. DomainStudio fills the vacuum of synthesizing samples in specific domains (e.g., styles) with DDPMs. It is compatible with both unconditional and T2I DDPMs. DomainStudio first introduces DDPMs to unconditional image generation given limited data. It produces compelling results with rich details and few blurs, outperforming current state-of-the-art GAN-based methods on visual effects and generation diversity. DomainStudio also performs better than prior few-shot fine-tuning methods in T2I domain-driven generation. It is qualified for domain-driven T2I tasks regardless of the subject gaps between source and training samples. This work takes an essential step toward more data-efficient DDPMs. The limitations and societal impacts are discussed in Appendix F.

REFERENCES

Jacob Austin, Daniel D Johnson, Jonathan Ho, Daniel Tarlow, and Rianne van den Berg. Structured denoising diffusion models in discrete state-spaces. *Advances in Neural Information Processing Systems*, 34:17981–17993, 2021.

Andrew Brock, Jeff Donahue, and Karen Simonyan. Large scale GAN training for high fidelity natural image synthesis. In *International Conference on Learning Representations*, 2019.

Huiwen Chang, Han Zhang, Lu Jiang, Ce Liu, and William T Freeman. Maskgit: Masked generative image transformer. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 11315–11325, 2022.

Huiwen Chang, Han Zhang, Jarred Barber, AJ Maschinot, Jose Lezama, Lu Jiang, Ming-Hsuan Yang, Kevin Murphy, William T Freeman, Michael Rubinstein, et al. Muse: Text-to-image generation via masked generative transformers. *arXiv preprint arXiv:2301.00704*, 2023.

Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In *International Conference on Machine Learning*, pp. 1597–1607. PMLR, 2020.

Ting Chen, Ruixiang Zhang, and Geoffrey Hinton. Analog bits: Generating discrete data using diffusion models with self-conditioning. In *International Conference on Learning Representations*, 2023.

Katherine Crowson, Stella Biderman, Daniel Kornis, Dashiell Stander, Eric Hallahan, Louis Castricato, and Edward Raff. Vqgan-clip: Open domain image generation and editing with natural language guidance. In *Proceedings of the European Conference on Computer Vision*, pp. 88–105. Springer, 2022.

I. Daubechies. The wavelet transform, time-frequency localization and signal analysis. *IEEE Transactions on Information Theory*, 36(5):961–1005, 1990.

Yingying Deng, Fan Tang, Weiming Dong, Chongyang Ma, Xingjia Pan, Lei Wang, and Changsheng Xu. Stytr2: Image style transfer with transformers. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 11326–11336, 2022.

Prafulla Dhariwal and Alexander Nichol. Diffusion models beat gans on image synthesis. *Advances in Neural Information Processing Systems*, 34:8780–8794, 2021.

Ming Ding, Zhuoyi Yang, Wenyi Hong, Wendi Zheng, Chang Zhou, Da Yin, Junyang Lin, Xu Zou, Zhou Shao, Hongxia Yang, et al. Cogview: Mastering text-to-image generation via transformers. *Advances in Neural Information Processing Systems*, 34:19822–19835, 2021.

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. In *Proceedings of the European Conference on Computer Vision*, pp. 89–106. Springer, 2022.

Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. An image is worth one word: Personalizing text-to-image generation using textual inversion. *arXiv preprint arXiv:2208.01618*, 2022.

Leon A Gatys, Alexander S Ecker, and Matthias Bethge. A neural algorithm of artistic style. *arXiv preprint arXiv:1508.06576*, 2015.

Golnaz Ghiasi, Honglak Lee, Manjunath Kudlur, Vincent Dumoulin, and Jonathon Shlens. Exploring the structure of a real-time, arbitrary neural artistic stylization network. *arXiv preprint arXiv:1705.06830*, 2017.

Giorgio Giannone, Didrik Nielsen, and Ole Winther. Few-shot diffusion models. In *NIPS 2022 Workshop*, 2022.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. *Advances in Neural Information Processing Systems*, 27, 2014.

Yuchao Gu, Xintao Wang, Jay Zhangjie Wu, Yujun Shi, Yunpeng Chen, Zihan Fan, Wuyou Xiao, Rui Zhao, Shuning Chang, Weijia Wu, et al. Mix-of-show: Decentralized low-rank adaptation for multi-concept customization of diffusion models. *arXiv preprint arXiv:2305.18292*, 2023.

Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 9729–9738, 2020.

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.

Tobias Hinz, Stefan Heinrich, and Stefan Wermter. Semantic object accuracy for generative text-to-image synthesis. *IEEE transactions on pattern analysis and machine intelligence*, 44(3):1552–1565, 2020.

Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *Advances in Neural Information Processing Systems*, 33:6840–6851, 2020.

Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. Lora: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2021.

Jiaxing Huang, Kaiwen Cui, Dayan Guan, Aoran Xiao, Fangneng Zhan, Shijian Lu, Shengcai Liao, and Eric Xing. Masked generative adversarial networks are data-efficient generation learners. *Advances in Neural Information Processing Systems*, 35:2154–2167, 2022.

Ajay Jain, Ben Mildenhall, Jonathan T Barron, Pieter Abbeel, and Ben Poole. Zero-shot text-guided object generation with dream fields. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 867–876, 2022.

Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In *Proceedings of the European Conference on Computer Vision*, pp. 694–711. Springer, 2016.

Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4401–4410, 2019.

Tero Karras, Miika Aittala, Janne Hellsten, Samuli Laine, Jaakko Lehtinen, and Timo Aila. Training generative adversarial networks with limited data. *Advances in Neural Information Processing Systems*, 33:12104–12114, 2020a.

Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, and Timo Aila. Analyzing and improving the image quality of stylegan. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8110–8119, 2020b.

Tero Karras, Miika Aittala, Samuli Laine, Erik Härkönen, Janne Hellsten, Jaakko Lehtinen, and Timo Aila. Alias-free generative adversarial networks. *Advances in Neural Information Processing Systems*, 34:852–863, 2021.

Tero Karras, Miika Aittala, Timo Aila, and Samuli Laine. Elucidating the design space of diffusion-based generative models. *Advances in Neural Information Processing Systems*, 2022.

Diederik Kingma, Tim Salimans, Ben Poole, and Jonathan Ho. Variational diffusion models. *Advances in Neural Information Processing Systems*, 34:21696–21707, 2021.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. *Master's thesis, University of Tront*, 2009.

Nupur Kumari, Bingliang Zhang, Richard Zhang, Eli Shechtman, and Jun-Yan Zhu. Multi-concept customization of text-to-image diffusion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1931–1941, 2023.

Bowen Li, Xiaojuan Qi, Thomas Lukasiewicz, and Philip Torr. Controllable text-to-image generation. *Advances in Neural Information Processing Systems*, 32, 2019a.

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 *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 12174–12182, 2019b.

Yijun Li, Richard Zhang, Jingwan Lu, and Eli Shechtman. Few-shot image generation with elastic weight consolidation. *Advances in Neural Information Processing Systems*, 33:15885–15896, 2020.

Yuheng Li, Haotian Liu, Qingyang Wu, Fangzhou Mu, Jianwei Yang, Jianfeng Gao, Chunyuan Li, and Yong Jae Lee. Gligen: Open-set grounded text-to-image generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 22511–22521, 2023.

Cheng Lu, Yuhao Zhou, Fan Bao, Jianfei Chen, Chongxuan Li, and Jun Zhu. Dpm-solver: A fast ode solver for diffusion probabilistic model sampling in around 10 steps. *Advances in Neural Information Processing Systems*, 2022a.

Cheng Lu, Yuhao Zhou, Fan Bao, Jianfei Chen, Chongxuan Li, and Jun Zhu. Dpm-solver++: Fast solver for guided sampling of diffusion probabilistic models. *arXiv preprint arXiv:2211.01095*, 2022b.

Sangwoo Mo, Minsu Cho, and Jinwoo Shin. Freeze the discriminator: A simple baseline for fine-tuning gans. In *CVPR AI for Content Creation Workshop*, 2020.

Taehong Moon, Moonseok Choi, Gayoung Lee, Jung-Woo Ha, and Juho Lee. Fine-tuning diffusion models with limited data. In *NeurIPS 2022 Workshop on Score-Based Methods*, 2022.

Alexander Quinn Nichol and Prafulla Dhariwal. Improved denoising diffusion probabilistic models. In *International Conference on Machine Learning*, pp. 8162–8171. PMLR, 2021.

Atsuhiro Noguchi and Tatsuya Harada. Image generation from small datasets via batch statistics adaptation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 2750–2758, 2019.

Utkarsh Ojha, Yijun Li, Jingwan Lu, Alexei A Efros, Yong Jae Lee, Eli Shechtman, and Richard Zhang. Few-shot image generation via cross-domain correspondence. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 10743–10752, 2021.

Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*, 2018.

Jeeseung Park and Younggeun Kim. Styleformer: Transformer based generative adversarial networks with style vector. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8983–8992, 2022.

Tingting Qiao, Jing Zhang, Duanqing Xu, and Dacheng Tao. Learn, imagine and create: Text-to-image generation from prior knowledge. *Advances in neural information processing systems*, 32, 2019a.

Tingting Qiao, Jing Zhang, Duanqing Xu, and Dacheng Tao. Mirrorgan: Learning text-to-image generation by redescription. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1505–1514, 2019b.

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. In *International conference on machine learning*, pp. 8748–8763. PMLR, 2021.

Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. In *International Conference on Machine Learning*, pp. 8821–8831. PMLR, 2021.

Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 2022.

Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 10684–10695, 2022.

Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 22500–22510, 2023.

Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al. Photorealistic text-to-image diffusion models with deep language understanding. *Advances in Neural Information Processing Systems*, 35:36479–36494, 2022.

Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. Laion-5b: An open large-scale dataset for training next generation image-text models. *Advances in Neural Information Processing Systems*, 35:25278–25294, 2022.

Katja Schwarz, Yiyi Liao, and Andreas Geiger. On the frequency bias of generative models. *Advances in Neural Information Processing Systems*, 34:18126–18136, 2021.

Jascha Sohl-Dickstein, Eric Weiss, Niru Maheswaranathan, and Surya Ganguli. Deep unsupervised learning using nonequilibrium thermodynamics. In *International Conference on Machine Learning*, pp. 2256–2265, 2015.

Kihyuk Sohn, Nataniel Ruiz, Kimin Lee, Daniel Castro Chin, Irina Blok, Huiwen Chang, Jarred Barber, Lu Jiang, Glenn Entis, Yuanzhen Li, et al. Styledrop: Text-to-image generation in any style. *arXiv preprint arXiv:2306.00983*, 2023a.

Kihyuk Sohn, Albert Shaw, Yuan Hao, Han Zhang, Luisa Polania, Huiwen Chang, Lu Jiang, and Irfan Essa. Learning disentangled prompts for compositional image synthesis. *arXiv preprint arXiv:2306.00763*, 2023b.

Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. In *International Conference on Learning Representations*, 2021.

Ming Tao, Hao Tang, Songsong Wu, Nicu Sebe, Xiao-Yuan Jing, Fei Wu, and Bingkun Bao. Df-gan: Deep fusion generative adversarial networks for text-to-image synthesis. *arXiv preprint arXiv:2008.05865*, 2020.

Ngoc-Trung Tran, Viet-Hung Tran, Ngoc-Bao Nguyen, Trung-Kien Nguyen, and Ngai-Man Cheung. On data augmentation for gan training. *IEEE Transactions on Image Processing*, 30:1882–1897, 2021.

Narek Tumanyan, Omer Bar-Tal, Shai Bagon, and Tali Dekel. Splicing vit features for semantic appearance transfer. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 10748–10757, 2022.

Aaron Van den Oord, Nal Kalchbrenner, Lasse Espeholt, Oriol Vinyals, Alex Graves, et al. Conditional image generation with pixelcnn decoders. *Advances in Neural Information Processing Systems*, 29, 2016.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

Yaxing Wang, Chenshen Wu, Luis Herranz, Joost van de Weijer, Abel Gonzalez-Garcia, and Bogdan Raducanu. Transferring gans: Generating images from limited data. In *Proceedings of the European Conference on Computer Vision*, pp. 218–234, 2018.

Yaxing Wang, Abel Gonzalez-Garcia, David Berga, Luis Herranz, Fahad Shahbaz Khan, and Joost van de Weijer. Minegan: Effective knowledge transfer from gans to target domains with few images. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 9332–9341, 2020.

Zhe Wang, Ziqiu Chi, Yanbing Zhang, et al. Fregan: exploiting frequency components for training gans under limited data. *Advances in Neural Information Processing Systems*, 35:33387–33399, 2022.

Jiayu Xiao, Liang Li, Chaofei Wang, Zheng-Jun Zha, and Qingming Huang. Few shot generative model adaption via relaxed spatial structural alignment. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 11204–11213, 2022.

Mengping Yang, Zhe Wang, Ziqiu Chi, and Wenyi Feng. Wavegan: Frequency-aware gan for high-fidelity few-shot image generation. In *European Conference on Computer Vision*, pp. 1–17. Springer, 2022.

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.

Lvmin Zhang and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. *arXiv preprint arXiv:2302.05543*, 2023.

Qinsheng Zhang and Yongxin Chen. Fast sampling of diffusion models with exponential integrator. In *NIPS 2022 Workshop*, 2022.

Qinsheng Zhang, Molei Tao, and Yongxin Chen. gddim: Generalized denoising diffusion implicit models. In *The Eleventh International Conference on Learning Representations*, 2022.

Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 586–595, 2018a.

Zizhao Zhang, Yuanpu Xie, and Lin Yang. Photographic text-to-image synthesis with a hierarchically-nested adversarial network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 6199–6208, 2018b.

Shengyu Zhao, Zhijian Liu, Ji Lin, Jun-Yan Zhu, and Song Han. Differentiable augmentation for data-efficient gan training. *Advances in Neural Information Processing Systems*, 33:7559–7570, 2020a.

Yunqing Zhao, Keshigeyan Chandrasegaran, Milad Abdollahzadeh, and Ngai-Man Cheung. Few-shot image generation via adaptation-aware kernel modulation. *Advances in Neural Information Processing Systems*, 2022a.

Yunqing Zhao, Henghui Ding, Houjing Huang, and Ngai-Man Cheung. A closer look at few-shot image generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 9140–9150, 2022b.

Yunqing Zhao, Chao Du, Milad Abdollahzadeh, Tianyu Pang, Min Lin, Shuicheng YAN, and Ngai-Man Cheung. Exploring incompatible knowledge transfer in few-shot image generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023.

Zhengli Zhao, Zizhao Zhang, Ting Chen, Sameer Singh, and Han Zhang. Image augmentations for gan training. *arXiv preprint arXiv:2006.02595*, 2020b.

Jingyuan Zhu, Huimin Ma, Jiansheng Chen, and Jian Yuan. Few-shot image generation via masked discrimination. *arXiv preprint arXiv:2210.15194*, 2022.