Generative Adversarial Networks (GANs) have shown remarkable performance in image synthesis tasks, but typically require a large number of training samples to achieve high-quality synthesis. This paper proposes a simple and effective method, Few-Shot GAN (FSGAN), for adapting GANs in few-shot settings (less than 100 images). FSGAN repurposes component analysis techniques and learns to adapt the singular values of the pre-trained weights while freezing the corresponding singular vectors. This provides a highly expressive parameter space for adaptation while constraining changes to the pretrained weights. We validate our method in a challenging few-shot setting of 5-100 images in the target domain. We show that our method has significant visual quality gains compared with existing GAN adaptation methods. We report qualitative and quantitative results showing the effectiveness of our method. We additionally highlight a problem for few-shot synthesis in the standard quantitative metric used by data-efficient image synthesis works. Code and additional results are available at http://e-271.github.io/few-shot-gan.
Figure 1: **Few-shot image generation.** Our method generates novel and high-quality samples in a new domain with a small amount of training data. **(Top)** Diverse random samples from adapting a FFHQ-pretrained StyleGAN2 to toddler images from the CelebA dataset (with **only 30 images**) using our method. **(Bottom)** Smooth latent space interpolation between two random seeds shows that our method produces novel samples instead of simply memorizing the 30 images. Please see the supplementary video for more results.

applies singular value decomposition (SVD) to the network weights of a pretrained GAN (generator + discriminator). We then adapts the singular values using GAN optimization on the target few-shot domain, with fixed left/right singular vectors. We show that varying singular values in the weight space corresponds to semantically meaningful changes of the synthesized image while preserving natural structure. Compared with methods that finetune all weights of the GAN (Wang et al., 2018), individual layers (Mo et al., 2020), or only adapt batch norm statistics (Noguchi & Harada, 2019), our method demonstrates higher image quality after adaptation. We additionally highlight problems with the standard evaluation practice in the low-shot GAN setting.

2 **BACKGROUND**

Generative Adversarial Networks (GANs) GANs (Goodfellow et al., 2014) use adversarial training to learn a mapping of random noise to the distribution of an image dataset, allowing for sampling of novel images. GANs optimize a competitive objective where a generator \(G(Z)\) maximizes the classification error of a discriminator \(D(X)\) trained to distinguish real data \(p(X)\) from fake data \(G(Z)\).

The GAN (Goodfellow et al., 2014) objective is expressed formally as:

\[
\max_G \min_D \mathbb{E}_{x \sim p(x)} \left[ \log D(x) \right] - \mathbb{E}_{z \sim G(z)} \left[ 1 - \log D(x) \right]
\]

Recent research reformulated this objective to address instability problems (Arjovsky et al., 2017; Heusel et al., 2017a; Gulrajani et al., 2017). Improved architecture and training has led to remarkable performance in synthesis (Karras et al., 2020; Brock et al., 2019). Compared to pixel-reconstruction losses (Kingma & Welling, 2014; Higgins et al., 2017; Bojanowski et al., 2018) GANs typically produce sharper images, although strong priors over the latent space can offer competitive quality (Razavi et al., 2019). A high-quality generation has relied on large datasets of high-quality images (>10K) that may be expensive or infeasible to collect in many scenarios. Additionally, GANs can suffer from a lack of diversity, even when large training sets are used because the objective does not penalize the absence of outlier modes (Poole et al., 2016). Data-efficient GAN methods are, therefore, of great utility.

Sample-efficient Image Synthesis Sample-efficient image synthesis methods encourage diverse and high-quality generation in the low-data regime, most commonly through pretraining (Wang et al., 2018; Noguchi & Harada, 2019) or simultaneous training (Yamaguchi et al., 2019) on large image datasets. The main differences among these methods lie in the choice of learnable parameters used for adaptation. Examples include adapting all weights of the generator and discriminator (Wang et al., 2018), freezing only lower layers of the discriminator (Mo et al., 2020), or changing only channel-wise batch statistics (Noguchi & Harada, 2019). Flow-based methods (Gambardella et al., 2019) show promising results in few-shot adaptation, but their architecture is compute- and memory-intensive and requires latent space of the same dimensionality as the data. Our method uses a smaller but more expressive set of parameters (Figure 2), resulting in more natural adapted samples.
Our goal is to improve GAN finetuning on small image domains by discovering a more effective and constrained parameter space for adapting the pretrained weights. We are inspired by prior work in GAN adaptation showing that constraining the space of trainable parameters can lead to improved performance on target domain (Rebuffi et al., 2017; Mo et al., 2020; Noguchi & Harada, 2019). In contrast to identifying the parameter space within the model architecture, we propose to discover a constrained parameter space for adapting the pretrained weights. Specifically, we apply singular value decomposition to the pretrained weights and uncover a basis representing orthogonal directions of maximum variance in the parameter space. To explore the interpretation of the SVD representation, we visualize the top three singular values of synthesis and style layers of StyleGAN2 (Karras et al., 2020). We observe that varying the singular values corresponds to natural and semantically-meaningful changes in the latent space. To further enhance the interpretability of the SVD, we propose to discover a set of orthogonal directions in the weight space that are semantically meaningful and can be used for domain adaptation. Our work differs as we transfer knowledge from a pretrained GAN to a new domain and, therefore, can generate drastically more diverse samples.

### 3.Few-Shot GAN

#### 3.1 OVERVIEW

Our goal is to improve GAN finetuning on small image domains by discovering a more effective and constrained parameter space for adapting the pretrained weights. We are inspired by prior work in GAN adaptation showing that constraining the space of trainable parameters can lead to improved performance on target domain (Rebuffi et al., 2017; Mo et al., 2020; Noguchi & Harada, 2019). In contrast to identifying the parameter space within the model architecture, we propose to discover a parameter space based on the pretrained weights. Specifically, we apply singular value decomposition to the pretrained weights and uncover a basis representing orthogonal directions of maximum variance in the weight space. To explore the interpretation of the SVD representation, we visualize the top three singular values of synthesis and style layers of StyleGAN2 (Karras et al., 2020). We observe that varying the singular values corresponds to natural and semantically-meaningful changes in the output image as shown in Figure 3. Changing the singular values can be interpreted as changing the entanglement between orthogonal factors of variation in the data (singular vectors), providing an

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**Table 2:** Comparing methods for GAN adaptation. Learnable parameters are denoted in red. (a) TransferGAN (TGAN for simplicity) (Wang et al., 2018) and FreezeD (Mo et al., 2020) retrain all weights W in a layer. SSGAN (Noguchi & Harada, 2019) and FSGAN train significantly fewer parameters per layer. Note FSGAN adapts both conv and FC layers, while SSGAN adapts only conv layers. #params is the number of learnable parameters per conv layer; Count gives parameter counts over the full StyleGAN2 generator and discriminator. (b) FSGAN (ours) adapts singular values Σ = {σ₁, ..., σₙ} of pretrained weights W₀ to obtain adapted weights W₂.

| Method       | Conv layer | #params | Count |
|--------------|------------|---------|-------|
| Pretrain     | conv(x, W₀) | --      | --    |
| TGAN         | conv(x, W) | κ²cᵢcₒuₜ | 59M   |
| FreezeD      | conv(x, W) | κ²cᵢcₒuₜ | 47M   |
| SSGAN        | conv(x, W₀) + β | 2cₒuₜ | 23K   |
| FSGAN (Ours) | conv(x, W₂) | cₒuₜ | 16K   |

**Figure 2:** Comparing methods for GAN adaptation. Learnable parameters are denoted in red. (a) TransferGAN (TGAN for simplicity) (Wang et al., 2018) and FreezeD (Mo et al., 2020) retrain all weights W in a layer. SSGAN (Noguchi & Harada, 2019) and FSGAN train significantly fewer parameters per layer. Note FSGAN adapts both conv and FC layers, while SSGAN adapts only conv layers. #params is the number of learnable parameters per conv layer; Count gives parameter counts over the full StyleGAN2 generator and discriminator. (b) FSGAN (ours) adapts singular values Σ = {σ₁, ..., σₙ} of pretrained weights W₀ to obtain adapted weights W₂.
3.2 Adaptation Procedure

Our method first performs SVD on both the generator and discriminator of a pretrained GAN and adapts the singular values to a new domain using standard GAN training objectives. A generator layer \( G^{(l)} \) or a discriminator layer \( D^{(l)} \) may consist of either 2D (\( c_{in} \times c_{out} \)) fully-connected weights or 4D (\( k \times k \times c_{in} \times c_{out} \)) convolutional filter weights. We apply SVD separately at every layer of the generator \( G^{(l)} \) and discriminator \( D^{(l)} \). Next, we describe the decomposition process for a single layer of pretrained weights \( W_0^{(l)} \). For fully-connected layer \( W_0^{(l)} \), we can apply SVD directly on the weight matrix. For 4D convolution weights \( W_0^{(l)} \in \mathbb{R}^{k \times k \times c_{in} \times c_{out}} \) this is not feasible because SVD operates only on a 2D matrix. We therefore reshape the 4D tensor by flattening across the spatial and input feature channels before performing SVD to obtain a 2D matrix \( W_0^{(l)} \in \mathbb{R}^{k^2 c_{in} \times c_{out}} \). Our intuition is that the spatial-feature relationship in the pretrained model should be preserved during the adaptation. We apply SVD over each set of flattened convolutional weights or fully convolution weights to obtain the decomposition:

\[
W_0^{(l)} = (U_0 \Sigma_0 V_0^T)^{(l)}.
\]

After decomposing the pretrained weights, we perform domain adaptation by freezing pretrained left/right singular vectors in \((U_0, V_0)^{(l)}\) and optimizing the singular values \( \Sigma = \lambda \Sigma_0 \) using a standard GAN objective to obtain transferred weights (Figure 2):

\[
W_2^{(l)} = (U_0 \Sigma V_0^T)^{(l)}.
\]
We adapt a pretrained model to a new target domain using only 5-100 target images, as we focus on scenarios with 1-2 orders fewer number of training samples than standard data-efficient GAN adaptation methods (Wang et al., 2018; Mo et al., 2020; Noguchi & Harada, 2019). As discussed in Section 3.4, we find that the FID score is unsuitable in the low-shot regime due to overfitting bias. However, we still report the FID scores of our experiments for completeness. In addition, we report additional quality metrics and extensive qualitative results in the low-shot setting. In high-data settings, a very large number of parameters would be required to memorize the images, so this problem is less likely to occur. Based on these observations, throughout our evaluation, we limit training timesteps rather than select the step with the best FID as we find the latter approach gives more inferior qualitative results.

### 3.4 Evaluation in Few-Shot Synthesis

A common adverse outcome in few-shot image generation is overfitting to the target set, such that all generated images look similar to the training data. Evaluation metrics should reflect the diversity of generated images, so that memorization is penalized. The standard evaluation practice used in prior low-shot GAN adaptation work (Wang et al., 2018; Noguchi & Harada, 2019; Mo et al., 2020) is to estimate FID (Heusel et al., 2017b) using a large held-out test set with 1K+ images, from which the low-shot training set was sampled. Standard GAN evaluation typically measures FID with respect to the training set, but in the low-shot setting, this is not desirable because the generator may simply memorize the training set. However, we find that even when measuring FID against a held-out test set, this evaluation still favors overfitted or poor-quality models, as shown in Figure 4. FID between real and fake images is calculated as the Frechet distance between perceptual features $p_r(X)$ and $p_f(Z)$:

$$||\mu_r - \mu_f||^2 + \text{Tr}(C_r + C_f - 2\sqrt{C_rC_f}).$$

(4)

where it is assumed features are Gaussian i.e., $p_f(Z) = N(\mu_f, C_f)$ and $p_r(X) = N(\mu_r, C_r)$. In the few-shot setting, our n-shot training set $T = (x_1, x_2, ..., x_n)$ is sampled from our test set $p_r(X)$. Assuming $T$ is chosen at random, its sample mean and variance $\mu_r, \sigma_r^2$ are unbiased estimators of $\mu_r, C_r$. Therefore if the generator memorizes $T$, its statistics approximate $\mu_r, C_r$. This artificially decreases the FID of an overfit model (Figure 4). Consequently, we suggest that FID should be supplemented with additional metrics and extensive qualitative results in the low-shot setting. In high-data settings, a very large number of parameters would be required to memorize the images, so this problem is less likely to occur. Based on these observations, throughout our evaluation, we limit training timesteps rather than select the step with the best FID as we find the latter approach gives more inferior qualitative results. To address the limitations of standard metrics for GAN evaluation, we also report sharpness (Kumar et al., 2012) and face quality index (Hernandez-Ortega et al., 2019) for human face transfer.

### 4 Experiments

#### 4.1 Settings

We adapt a pretrained model to a new target domain using only 5-100 target images, as we focus on scenarios with 1-2 orders fewer number of training samples than standard data-efficient GAN adaptation methods (Wang et al., 2018; Mo et al., 2020; Noguchi & Harada, 2019). As discussed in Section 3.4, we find that the FID score is unsuitable in the low-shot regime due to overfitting bias. However, we still report the FID scores of our experiments for completeness. In addition, we report additional quality metrics and extensive qualitative results.

**Adaptation Methods.** We compare the proposed FSGAN with Transfer GAN (TGAN) (Wang et al., 2018), FreezeD (FD) (Mo et al., 2020), and the Scale & Shift GAN (SSGAN) baseline of Noguchi & Harada (2019). For a fair comparison in the GAN setting, we choose the GAN baseline of SSGAN (Noguchi & Harada, 2019) instead of their GLO-based variant. We implement all methods using the
StyleGAN2 (Karras et al., 2020) codebase. We follow the training setting of StyleGAN, but change the learning rate to 0.003 to stabilize training and reduce the number of training steps to prevent overfitting in the low-shot setting. Figures 4, 7 show comparisons of different training times.

![Figure 5: Close-domain adaptation (FFHQ→CelebA). Models adapted from a pretrained StyleGAN2 using ~30 target images (left-most column) of (a) CelebA ID 4978 and (b) CelebA ID 3719. The proposed FSGAN generates more natural face images without noticeable artifacts. Comparison methods include TGAN (Wang et al., 2018), FD (Mo et al., 2020), SSGAN (Noguchi & Harada, 2019), trained with a limited number of timesteps to prevent overfitting or degradation.](image)

Table 1: Quantitative comparisons in three metrics: FID (Heusel et al., 2017b), Face Quality Index (FQI) (Hernandez-Ortega et al., 2019), and sharpness (Kumar et al., 2012). See Fig 5 for illustrations. FQI and Sharpness are evaluated on 1,000 images randomly generated with the same set of seeds. Bracketed/bold numbers indicated the best/second best results, respectively.

| Method         | CelebA 4978 | CelebA 3719 |
|---------------|------------|------------|
|               | FID        | FQI        | Sharpness | FID        | FQI        | Sharpness |
| Pretrain      | –          | 0.40±0.11  | 0.91±0.06 | –          | 0.37±0.12  | 0.92±0.06 |
| TransferGAN   | 75.41      | 0.30±0.07  | 0.61±0.05 | 178.31     | 0.26±0.09  | 0.61±0.04 |
| FreezeID      | 75.30      | 0.33±0.09  | 0.58±0.04 | 143.83     | 0.27±0.09  | 0.56±0.05 |
| SSGAN         | 87.79      | 0.32±0.08  | [0.67±0.05] | 147.14     | 0.27±0.10  | 0.58±0.05 |
| FSGAN (ours)  | 78.90      | [0.36±0.07] | 0.65±0.05 | 170.00     | 0.27±0.08  | [0.68±0.07] |

Datasets. We used FFHQ (Karras et al., 2019a) and LSUN Churches (Yu et al., 2015) pretrained checkpoints from StyleGAN2 (Karras et al., 2019b), and transferred to few-shot single-ID CelebA (30 or 31 images) (Liu et al., 2015), Portraits (5-100 images) (Lee et al., 2018), Anime ID “Rem” (25 images) 2, and Van Gogh landscapes (25 images) (Zhu et al., 2017). We evaluate FID against a large test set (10K for CelebA) following the evaluation method of Wang et al. (2018). We also evaluate face quality index (Hernandez-Ortega et al., 2019) and image sharpness (Kumar et al., 2012) for face domain adaptation, using 1000 images from each method generated using identical seeds. Full few-shot target sets are shown in Figures 5 & 6, and we will make all few-shot sets available online.

1 https://github.com/NVlabs/stylegan2
2 https://www.gwern.net/Danbooru2019
4.2 Near-domain adaptation

We first show a near domain transfer setting (adapting FFHQ to single-ID CelebA dataset (Liu et al., 2015)). As both source and target domains contain faces, the pretrained model has useful features for the transfer domain. Figure 5 shows that existing GAN adaptation methods produce artifacts around the eyes/chin and low overall structural consistency. In contrast, our method generates more natural face images with characteristics similar to the training samples (e.g., the head size, position of the faces). Comparing Figure 5 and Table 1 shows that the FID correlates poorly with qualitative evaluation for this setting. In light of this, we report additional metrics of face quality (Hernandez-Ortega et al., 2019) and sharpness (Kumar et al., 2012). On these metrics, our method achieves competitive performance across adaptation settings.

4.3 Far-domain adaptation

We show far-domain 25-shot transfer, where we define “far” as differing significantly in the distribution of image features such as textures, proportions, and semantics. 1) LSUN Churches → Van Gogh paintings: The two domains differ in the foreground, building shapes, and textural styles. 2) FFHQ → Art portraits: The main differences between the two domains are low-level styles and facial features. 3) FFHQ → Anime Rem ID: A challenging setting with exaggerated facial proportions and lack of texture details. Figure 6 shows visual comparisons with three state-of-the-art methods. We
find that the proposed FSGAN can adapt the model to produce more dramatic changes to match the target distributions in terms of semantics, proportions, and textures while maintaining image quality.

4.4 N-shot Settings

We test the sensitivity of both FSGAN (ours) and FreezeD (Mo et al., 2020) to differing n-shot settings and show the results in Figure 7. We find that FSGAN is more robust to n-shot setting compared to FreezeD. To show this better, we compare two variations of FreezeD. The first FreezeD variant (FD) is limited in timesteps (20K images / 16K on 5-shot) to match FSGAN and the results reported in Figures 5 & 6. Limiting timesteps prevents degradation that occurs at later iterations in the few-shot settings. However, the time-limited FD produces low quality and limited adaptation of textures and semantic features. The second FreezeD variant (FD-FT) is trained for longer (60K images) to demonstrate (1) degradation in fewer n-shot and (2) improvements in quality/adaptation in higher n-shot as seen in (Mo et al., 2020). In contrast, our method (FSGAN) effectively transfers semantic features while preserving quality across all n-shot settings tested in Figure 7. We note variance across n-shot settings for all methods as the data distribution changes.

5 Conclusions

We presented Few-Shot GAN, a simple yet effective method for adapting a pre-trained GAN based model to a new target domain where the number of training images is scarce. Our core idea lies in factorizing the weights of convolutional/fully-connected layers in a pretrained model using SVD to identify a semantically meaningful parameter space for adaptation. Our strategy preserves the capability of generating diverse and realistic samples while provides the flexibility for adapting the model to a target domain with few examples. We demonstrate the effectiveness of the proposed method with close-domain and far-domain adaptation experiments and across various n-shot settings. We show favorable results compared with existing data-efficient GAN adaptation methods.
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