A Closer Look at Few-shot Image Generation

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Figure 1. Upper Left: Transferring a GAN pretrained on a large-scale source domain (FFHQ [24]) to 10-shot Amedeo Modigliani’s paintings [55]. Right: During adaptation, we randomly select four fixed noise input and visualize the generated images with different existing methods. We observe that all methods including those with disproportionate focus on diversity preserving achieve similar quality after convergence (evaluated by our proposed realism classifier in Sec. 4.2). Therefore, the better methods are those that can slow down diversity degradation (Bottom Left, evaluated by intra-LPIPS in Sec. 4.3). We perform a rigorous study and show quantitative results in Sec. 4.5.

Abstract

Modern GANs excel at generating high quality and diverse images. However, when transferring the pretrained GANs on small target data (e.g., 10-shot), the generator tends to replicate the training samples. Several methods have been proposed to address this few-shot image generation task, but there is a lack of effort to analyze them under a unified framework. As our first contribution, we propose a framework to analyze existing methods during the adaptation. Our analysis discovers that while some methods have disproportionate focus on diversity preserving which impede quality improvement, all methods achieve similar quality after convergence. Therefore, the better methods are those that can slow down diversity degradation. Furthermore, our analysis reveals that there is still plenty of room to further slow down diversity degradation.

Informed by our analysis and to slow down the diversity degradation of the target generator during adaptation, our second contribution proposes to apply mutual information (MI) maximization to retain the source domain’s rich multi-level diversity information in the target domain generator. We propose to perform MI maximization by contrastive loss (CL), leverage the generator and discriminator as two feature encoders to extract different multi-level features for computing CL. We refer to our method as Dual Contrastive Learning (DCL). Extensive experiments on several public datasets show that, while leading to a slower diversity-degrading generator during adaptation, our proposed DCL brings visually pleasant quality and state-of-the-art quantitative performance. Project Page: yunqing-me.github.io/A-Closer-Look-at-FSIG.

1. Introduction

Powerful Generative Adversarial Networks (GANs) [4, 15, 25] have been built in recent years that can generate images with high fidelity and diversity [7, 46]. Unfortunately,
these GANs often require large-scale datasets and computational expensive resources to achieve good performance. For example, StyleGAN [24] is trained on Flickr-Faces-HQ (FFHQ) [24], which contains 70,000 images, with almost 56 GPU days. When the dataset size is decreased, however, the generator often tends to replicate the training data [12].

Would it be possible to generate sufficiently diverse images, given only limited training data? For example, with 10-shot sketch style human faces [47], could we generate diverse face sketch paintings? This few-shot image generation task is important in many real-world applications with limited data, e.g., artistic domains. It can also benefit some downstream tasks, e.g., few-shot image classification [3, 6].

1.1. A Closer Look at Few-shot Image Generation

To address this few-shot image generation task, instead of training from scratch [44, 53], recent literature focus on transfer learning [2, 36, 52] based ideas, i.e., leveraging the prior knowledge of a GAN pretrained on a large-scale, diverse dataset of the source domain and adapting it to a small target domain, without access to the source data. The early method is based on fine-tuning [49]. In particular, starting from the pretrained generator $G_s$, the original GAN loss [15] is used to adapt the generator to the new domain:

$$\min_{G_t} \max_{D_t} \mathcal{L}_{adv} = \mathbb{E}_{x \sim p_{data}(x)} [\log D_t(x)] + \mathbb{E}_{z \sim p_z(z)} [\log (1 - D_t(G_t(z)))]_1$$

where $z$ is sampled from a Gaussian noise distribution $p_z(z)$, $p_{data}(x)$ is the probability distribution of the real target domain data $x$, $G_t$ and $D_t$ are generator and discriminator of the target domain, and $G_t$ is initialized by the weights of $G_s$. This GAN loss in Eqn. 1 forces $G_t$ to capture the statistics of the target domain data, thereby to achieve both good quality (realisticness w.r.t. target domain data) and diversity, the criteria for a good generator.

However, for few-shot setup (e.g. only 10 target domain images), such approach is inadequate to achieve diverse target image generation as very limited samples are provided to define $p_{data}(x)$. Recognizing that, recent methods [29, 34] have focused disproportionately on improving diversity by preserving diversity of the source generator during the generator adaptation. In [29], Elastic Weight Consolidation (EWC) [26] is proposed to limit changes in some important weights to preserve diversity. In [34], an additional Cross-domain Correspondence (CDC) loss is introduced to preserve the sample-wise distance information of source to maintain diversity, and the whole model is trained via a multi-task loss with the diversity loss $\mathcal{L}_{dist}$ as an auxiliary task to regularize the main GAN task with loss $\mathcal{L}_{adv}$:

$$\min_{G_t} \max_{D_t} \mathcal{L}_{adv} + \mathcal{L}_{dist}. \quad (2)$$

In [34], a patch discriminator [21, 61] is also used to further improve the performance in $\mathcal{L}_{adv}$. Details of $\mathcal{L}_{dist}$ in [34].

Diversity preserving methods [29, 34] have demonstrated impressive results based on Fréchet Inception Distance (FID) [19] which measures the quality and diversity of the generated samples simultaneously. However, second thoughts about these methods reveal some questions:

- With disproportionate focus on diversity preserving in recent works [29, 34], will quality of the generated samples be compromised? For example, in Eqn. 2, $\mathcal{L}_{adv}$ is responsible for quality improvement during adaptation, but $\mathcal{L}_{dist}$ may compete with $\mathcal{L}_{adv}$, as it has been observed in multi-task learning [13, 41]. We note that this has not been analyzed thoroughly.

- With recent works’ strong focus on diversity preserving [29, 34], will there still be room to further improve via diversity preserving? How could we know when the gain of diversity preserving approaches become saturated (without excessive trial and error)?

1.2. Our Contributions

In this paper, we take the first step to address these research gaps for few-shot image generation. Specifically, as our first contribution, we propose to independently analyze the quality and diversity during the adaptation. Using this analysis framework, we obtain insightful information on quality/diversity progression. In particular, on one hand, it is true that strong diversity preserving methods such as [34] indeed impede the progress of quality improvement. On the other hand, interestingly, we observe that these methods can still reach high quality rather quickly, and after quality converges they have no worse quality compared to other methods such as [49] which uses simple GAN loss (Eqn. 1). Therefore, methods with disproportionate focus on preserving diversity [34] stand out from the rests as they can produce slow diversity-degrading generators, maintaining good diversity of generated images when their quality reaches the convergence. Furthermore, our analysis reveals that there is still plenty of room to further slow down the diversity degradation across several source $\rightarrow$ target domain setups.

Informed by our analysis, our second contribution is to propose a novel strong regularization to take a further step in slowing down the diversity degradation, with the understanding that it is unlikely to compromise quality as observed in our analysis. Our proposed regularization is based on the observation that rich diversity exists in the source images at different semantic levels: diversity in middle levels such as hair style, face shape, and that in high levels such as facial expression (smile, grin, concentration). However, such source diversity can be easily ignored in the images produced by target domain generators. Therefore, to preserve source diversity information, we propose to maximize the mutual information (MI) between the source/target image features originated from the same latent code, via contrastive loss [35] (CL). To compute CL, we leverage the generator and discriminator as two feature encoders to extract image features
at multiple feature scales, such that we can preserve diversity at various levels. By combining the two feature encoders (generator and discriminator), we gain additional feature diversity. We show that our proposed Dual Contrastive Learning (DCL) outperforms the previous work in slowing down the diversity degradation without compromising the image quality on the target domain, and hence achieving the state-of-the-art performance.

2. Related Work

Conventional few-shot learning [11,14,40] aims at learning a discriminative classifier [1, 17, 30, 40, 42]. In contrast, generative few-shot learning [29,34,51,54] often follows a transfer learning [36] pipeline to adapt a pretrained GAN on a small target domain, without access to the source data. Specifically, our analysis and comparison in this paper mainly focus on the following recent baseline models:

- Transferring GAN [49] (TGAN): directly fine-tune all parameters of both the generator and the discriminator on the target domain;
- Adaptive Data Augmentation (ADA) [32]: apply data augmentation [43,59,60] during adaptation which does not leak to the generator;
- BSA [33]: only update the learnable scale and shift parameters of the generator during adaptation;
- FreezedD [32]: freeze a few high-resolution layers of the discriminator, during the adaptation process;
- MineGAN [48]: use additional modules between the noise input and the generator. It aims at matching the target distribution before input to the generator;
- Elastic Weight Consolidation (EWC) [29]: apply EWC loss to regularize GAN, preventing the important weights from drastic changes during adaptation;
- Cross-domain Correspondence (CDC) [34]: preserve the distance between different instances in the source.

We firstly take a rigorous study of the above methods under the same setup. Then, motivated by our findings, we aim to address this few-shot image generation task.

Our proposed method is related to contrastive learning [5,9,16,18,35,57]. Contrastive learning for unsupervised instance discrimination aims at learning invariant embeddings with different transformation functions of the same object [18,22,31], which can benefit the downstream tasks. To slow down the diversity degradation during few-shot GAN adaptation, we present a simple and novel method via contrastive loss [35,50]: we hypothesize that, the same noise input could be mapped to fake images in the source and target domains with shared semantic information [38]. In experiments, we demonstrate convincing and competitive results of our approach for few-shot GAN adaptation, with sufficiently high quality and diversity.

3. Preliminary

Given a GAN pretrained on the source domain, we denote the generator as $G_s$. In the adaptation stage, the target generator $G_t$ and the discriminator $D_t$ can be obtained by fine-tuning the pretrained GAN on the target domain via Eqn. 1. We follow the settings of the prior work [34,48,49]: during adaptation, there is no access to the abundant source data, and we can only leverage the pretrained GAN and target data for transfer learning.

For the target data size, some recent work [23,49] applies more than 1,000 images in adaptation, and show satisfied results. In contrast, we focus on the challenging case: fine-tune the pretrained GAN with only few-shot (e.g., 10-shot) data.

4. Revisit Few-Shot GAN Adaptation

4.1. Motivation

While a few recent works [29,34] propose different ideas, including to inherit the diversity during adaptation, to our knowledge, no effort attends to analyze the underlying mechanism of this problem. The specific issues concerning this study are as follows: will quality be compromised due to the disproportionate focus on diversity preserving? will there still be room to further improve via diversity preserving? We study these concerns from a novel perspective: compare different methods by visualizing and quantifying the few-shot adaptation process. In particular, we decouple their performance by evaluating the quality and diversity on the target domain separately, under a unified framework.

4.2. Binary Classification for Quality Evaluation

The probability output of a classifier indicates the confidence of how likely an input sample belongs to a specific class [8,20]. Therefore, we employ the probability output of a binary classifier to assess to what extent the generated images belong to the target domain. In particular, we train a convolutional network $C$ on two sets of real images (from source and target, excluded during adaptation). Then, we apply $C$ to the synthetic images from the adapted generator $G_t$ during adaptation. The soft output of $C$ are $p_t$, predicted probability of input belonging to the target domain, and $(1-p_t)$, that of not belonging to the target domain. Therefore, we take $p_t$ as an assessment of the realisticness of the synthetic images on the target domain:

$$p_t = E_{z ~ p_s(z)} \left[ C(G_t(z)) \right].$$ (3)

$z$ is a batch of random noise input (size=1,000) fixed during adaptation, which is a proxy to indicate the quality and realisticness evolution process of different methods.

4.3. Intra-Cluster Diversity Evaluation

To evaluate the diversity, we introduce a Learned Perceptual Image Patch Similarity (LPIPS) [58] based metric, intra-cluster LPIPS (intra-LPIPS) [34], to identify the similarity
Figure 2. Analysis of existing few-shot GAN adaptation methods under a unified setup (see Sec. 4.4). **Observation 1**: While methods such as CDC [34] have disproportionate focus on diversity preserving which impedes quality improvement, all methods we have evaluated achieve similar quality/realisticness after convergence. **Observation 2**: Different methods exhibit substantially dissimilar diversity degrading rates. Combined the results in Figure 2a and 2b: since the achieved quality is similar, the better methods are those that can slow down diversity degradation. We summarize our findings in Sec. 4.5, which motivate our proposed method in Sec. 5. Best viewed in color.

between the generated images and the few-shot target samples during adaptation. The **standard** LPIPS evaluates the perceptual distance between two images, and it is empirically shown to align with human judgements [58]. **Intra-LPIPS** is a variation of the standard LPIPS: We firstly generate abundant (size=1,000) images, then assign each of them to one of the \(M\) target samples (with lowest standard LPIPS), and form \(M\) clusters. The intra-LPIPS is obtained by computing the average standard LPIPS for random paired images within each cluster, then average over \(M\) clusters. We provide the pseudo-code in Supp.

Ideally, we hypothesize that the highest diversity knowledge is achieved by the generator pretrained on the large source domain, and it will degrade during the few-shot adaptation. In the worst case, the adapted generator simply replicates the target images, and intra-LPIPS will be zero. To justify our conjecture, we sample the target generator at different adaptation iterations, then apply intra-LPIPS to assess the diversity of the generated images.

**4.4. Experiment settings**

**Basic setup**: For all methods: We follow the previous work [29, 34] to use StyleGAN-V2 [25] with default hyper-parameters. We use AlexNet [28] as the binary classifier. We fine-tune the pretrained GAN on the target domain with batch size 4 and 3,000 iterations, on a Tesla V100 GPU.

**Source \(\rightarrow\) target adaptation**: Training the binary classifier requires rich data on both source and target domains. Therefore, we transfer the model pretrained on FFHQ [24] (70,000 images) to 10-shot samples from target domains that contain abundant data originally: Sketches, Babies, and Sunglasses (roughly 300, 2500, 2700 images, respectively). To obtain unbiased classifiers, we form each dataset by keeping the source and target training data balanced.

**Evaluation**: The baseline methods for evaluation are introduced in Sec. 2. In this section, we do not include BSA [33] and MineGAN [48]: BSA applies a different GAN architecture (BigGAN [4]), and MineGAN employs additional training modules during adaptation, and it is time-consuming for training. We include the results of these two models in Sec. 6. To compute the intra-LPIPS, we follow [34] to use the base implementation from [58].

**4.5. Empirical Analysis Results**

The analysis results are shown in Figure 1 and Figure 2. Generally, our observations can be stated as follows:

- **Image quality/realisticness (Observation 1)**: As shown in Figure 2a, strong diversity preserving methods such as CDC [34] (and ours, to be discussed in Sec. 5) indeed impede the progress of quality improvement, most noticeable in FFHQ \(\rightarrow\) Babies. This is because additional regularization for diversity preserving (e.g. [https://github.com/richzhang/PerceptualSimilarity](https://github.com/richzhang/PerceptualSimilarity))
**Image diversity (Observation 2):** In Figure 1 and Figure 2b, we demonstrate the qualitative and quantitative results of the diversity change during few-shot adaptation. While different methods can achieve similar quality on the target domain, their diversity-degrading rates vary drastically. For example, in Figure 1, TGAN [49] immediately loses the diversity and the generator replicates the target samples at the early adaptation stage. Since the achieved quality is similar for all these methods, the better methods are those that do not suffer from rapid diversity degradation.

As shown in Figure 2b, for all existing methods, the loss of diversity is inevitable in adaptation. On the other hand, since all methods achieve similar realism after the quality converges, the better generators are those that can slow down the diversity degradation, and the worse ones are those that lose diversity rapidly before the convergence of the quality improvement. Recalling the concerns we raise in Sec. 4.1: we show that, there is still plenty of room to further reduce the rate of diversity degradation, besides, the gain of diversity preservation becomes saturated only until the rate of diversity degradation is much reduced. These findings motivate our proposed method in the next section to further slow down diversity degradation.

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**5. Dual Contrastive Learning**

**5.1. Overall Framework**

Rich diversity exists in the source images $G_s(z)$ at different semantic levels: middle levels such as different hair style, high levels such as different facial expression. To preserve source images’ diversity information in the target domain generator, we propose to maximize the mutual information (MI) between the source/target image features originated from the same input noise. In particular, for an input noise $z_i$, we seek to maximize:

$$\text{MI}(\pi^l(G_t(z_i)); \pi^l(G_s(z_i))),$$

where $G_t(z_i), G_s(z_i)$ are generated images by the target / source generators respectively, and $\pi^l(\cdot)$ is a feature encoder to extract $l$-th level features (to be further discussed). As $G_s$ is fixed during adaptation, the MI maximization enables $G_t$ to learn to generate images that include source images’ diversity at various semantic levels (with the use of multiple $l$ during adaptation). Furthermore, in GAN, we have $G_t$ and $D_t$, and we take advantage both of them to use as the feature encoders $\pi^l(\cdot)$ to extract different features. As directly maximizing MI is challenging [37], we apply contrastive learning [35] to solve Eqn. 4.

Specifically, we propose Dual Contrastive Learning (DCL) for few-shot GAN adaptation, as Figure 3. There are several goals for DCL: i) Maximize the MI between generated images on the source/target domain originated from the same noise input; ii) push away the generated images on the source and target domain that use different noise input; iii) push away the generated target images and the real target images, to prevent collapsing to the few-shot target set. To achieve these goals, we let the generating and the discriminating views using the same noise input, on source and target, as the positive pair, and maximize the agreement between them. Concretely, DCL includes two parts.

**Generator CL:** Given a batch of noise input $\{z_0, z_1, ..., z_{N-1}\}$, we obtain images $\{G_s(z_0), G_s(z_1), ..., G_s(z_{N-1})\}$.
and \( \{G_t(z_0), G_t(z_1), ..., G_t(z_{N-1})\} \), generated on the source and the target domain, respectively. Considering an anchor image \( G_t(z) \), we optimize the following object:

\[
L_{CL1} = -\log \frac{f(G_t^i(z_i), G_t^j(z_j))}{\sum_{j=0}^{N-1} f(G_t^i(z_i), G_t^j(z_j))}
\]

which is an \( N \)-Way categorical cross-entropy loss to classify the positive pair \((G_t^i(z_i), G_t^j(z_j))\) at \( l \)-th layer correctly. \( \frac{f(G_t^i(z_i), G_t^j(z_j))}{\sum_{j=0}^{N-1} f(G_t^i(z_i), G_t^j(z_j))} \) is the prediction probability and

\[
f(G_t^i(z_i), G_t^j(z_j)) = \exp(CosSim(G_t^i(z_i), G_t^j(z_j))/\tau)
\]

for \( i \in \{0, 1, ..., N - 1\} \) is the exponential of the cosine similarity between \( l \)-th layer features of the generated images on source and target, scaled by a hyperparameter temperature \( \tau = 0.07 \) and passed as logits [18, 38].

**Discriminator CL:** We focus on the view of the discriminator \( D_t \). Given the generated images by the source and target generator and real data \( x \) as input to \( D_t \), we maximize the agreement between the discriminating features of the generated images on source and target, using the same noise \( z \). To prevent replicating the target data, we regularize the training process by pushing away discriminating features of the generated target images and the real target data at different scales. We optimize the following object:

\[
L_{CL2} = -\log \frac{f(D_t^i(G_t(z_i)), D_t^j(G_s(z_j)))}{f(D_t^i(G_t(z_i)), D_t^j(G_s(z_j))) + \Delta},
\]

where \( \Delta = \sum_{j=1}^{M} f(D_t^i(G_t(z_i)), D_t^j(x_j)) \) and \( M \) is the number of real target images. The final objective of DCL in our work is simply:

\[
\min_G \max_D L_{adv} + \lambda_1 L_{CL1} + \lambda_2 L_{CL2}.
\]

In practice, we find \( \lambda_1 = 2 \) and \( \lambda_2 = 0.5 \) work well. In each iteration, we randomly select different layers of \( G_t \) and \( D_t \) to perform DCL with multi-level features.

### 5.2. Design Choice

The design choice of DCL is intuitive: DCL takes the advantage of \( G_s = G_t \) before adaptation. Our idea is to reuse the highest diversity knowledge from the source as the strong regularization to slow down the inevitable diversity degradation, before the quality improvement converges. The Generator CL and Discriminator CL are similar in idea, while they constraint different parts for GAN adaptation: Generator CL requires the adapted generator \( G_t \) to generate features at different scales that are similar to that of the source generator (with the same noise input). Differently, Discriminator CL regularizes the adversarial training: while fitting to the target domain, the generated target images are encouraged to be pushed away from the real data at different feature scales.

| Dataset (source) | FFHQ → Babies | FFHQ → Sunglasses | FFHQ → Sketches |
|------------------|----------------|-------------------|------------------|
| TGAN [49]        | 0.51 ± 0.02    | 0.52 ± 0.04       | 0.46 ± 0.03      |
| TGAN+ADA [23]    | 0.54 ± 0.02    | 0.57 ± 0.03       | 0.48 ± 0.04      |
| BSA [53]         | 0.46 ± 0.02    | 0.45 ± 0.02       | 0.44 ± 0.03      |
| FreezeD [12]     | 0.54 ± 0.03    | 0.45 ± 0.02       | 0.50 ± 0.05      |
| MineGAN [48]     | 0.53 ± 0.04    | 0.44 ± 0.06       | 0.49 ± 0.02      |
| EWC [29]         | 0.56 ± 0.03    | 0.58 ± 0.06       | 0.43 ± 0.02      |
| CDC [34]         | 0.63 ± 0.03    | 0.60 ± 0.04       | 0.52 ± 0.04      |
| DCL (Ours)       | 0.66 ± 0.02    | 0.63 ± 0.01       | 0.55 ± 0.02      |

Table 1. For target domains that contain rich data, we follow [34] to compare FID\(^2\) [19] with different adaptation setups. We firstly generate 5,000 fake images using the adapted generator, then compare them with the real target data (excluded during adaptation). The standard derivations is computed by 5 different runs.

| Dataset (source) | FFHQ → Otto’s Paintings | Church → Haunted House | Cars → Abandoned Cars |
|------------------|-------------------------|------------------------|-----------------------|
| TGAN [49]        | 0.51 ± 0.02              | 0.52 ± 0.04             | 0.46 ± 0.03           |
| TGAN+ADA [23]    | 0.54 ± 0.02              | 0.57 ± 0.03             | 0.48 ± 0.04           |
| BSA [53]         | 0.46 ± 0.02              | 0.45 ± 0.02             | 0.44 ± 0.03           |
| FreezeD [12]     | 0.54 ± 0.03              | 0.45 ± 0.02             | 0.50 ± 0.05           |
| MineGAN [48]     | 0.53 ± 0.04              | 0.44 ± 0.06             | 0.49 ± 0.02           |
| EWC [29]         | 0.56 ± 0.03              | 0.58 ± 0.06             | 0.43 ± 0.02           |
| CDC [34]         | 0.63 ± 0.03              | 0.60 ± 0.04             | 0.52 ± 0.04           |
| DCL (Ours)       | 0.66 ± 0.02              | 0.63 ± 0.01             | 0.55 ± 0.02           |

Table 2. For target domains containing only 10-shot data, we evaluate the diversity of the adapted generator. We firstly generate 5,000 fake images, then we compute intra-cluster LPIPS\(^+\) with few-shot target samples. The standard derivation is computed across 10-shot clusters (see details in Sec. 4.3).

Under mild assumptions, DCL maximizes the MI (Eqn. 4) between the generated samples using the same input noise, on source and target, e.g., for \( L_{CL1} \): \( \text{MI}(G_t^i(z_i); G_t^j(z_j)) \geq \log[N] - L_{CL1} \) [35]. In the next, we show the effectiveness of DCL in experiments.

### 6. Experiments

#### 6.1. Implementation Details

In this section, we discuss our main experiments. Additional analysis and discussion is included in Supp.

**Basic setups:** We mostly follow the experiment setups as Ojha et al. [34], including the non-saturating GAN loss \( \mathcal{L}_{adv} \) in Eqn. 2, the same pretrained GAN and 10-shot target samples, with no access to the source data. We employ StyleGAN-V2 [25] as the GAN architecture for pretraining and few-shot adaptation, with an image/patch level discriminator [34]. We fine-tune with batch size 4 on a Tesla V100 GPU. The baseline methods are introduced in Sec. 2.

**Datasets:** We use models pretrained on different source domains: i) FFHQ [24] ii) LSUN Church and iii) LSUN Cars [56]. We transfer the pretrained model to the following target domains: i) Sketches [47] ii) Face paintings by Amedeo and Otto Dix [55] iii) FFHQ-Babies iv) FFHQ-Sunglasses v) Haunted houses vi) Wrecked cars. Images for training and evaluation are interpolated to the resolution of 256 × 256.

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\(^2\)Our implementation is based on [https://github.com/mseitzer/pytorch-fid](https://github.com/mseitzer/pytorch-fid).
Figure 4. **Left:** Transferring a GAN pretrained on FFHQ to 10-shot target samples. We fix the noise input by each column to observe the relationship of generated images before and after adaptation. **Mid:** We observe that, most of existing methods lose diversity quickly before the quality improvement converges, and tend to replicate the training data. Our method, in contrast, slows down the loss of diversity and preserves more details. For example: In red frames (Upper), the hair style and hat are better preserved. In pink frames (Bottom), the smile teeth are well inherited from the source domain. We also outperform others in quantitative evaluation (Right). See details in Sec. 6.2.

### 6.2. Comparison with State-of-the-art Methods

**Qualitative results.** In Figure 4, we visualize the generated images with different methods after adaptation on few-shot target samples. In Figure 5, we show more results with different source → target adaptation setups. Regularized by DCL, the adapted target generator needs to retain the connection to the generated images on source, a slow diversity degradation is thus achieved. We show that, the refined details, e.g., the smile teeth, hairline or structure appearance are well preserved, while the style and texture features are fitted to the target domain. Compared with recent state-of-the-art methods, these semantic meaningful features in the source domain are well inherited by DCL.

**Quantitative comparison.** We mainly focus on two metrics to evaluate our method. i) For datasets which contain a lot of real data, e.g., FFHQ-Babies, FFHQ-Sunglasses, we apply the widely used Fréchet Inception Distance (FID) [19] to evaluate the generated fake images. ii) For those datasets
which contain only few-shot real data, FID becomes tricky and unstable, since it summarizes the quality and diversity to a single score. Therefore, we use intra-LPIPS (see Sec. 4.3) to measure the diversity of generated images. The better diversity comes with a higher score. As shown in Table 1 and Table 2, our method outperforms the baseline methods. This indicates that the target generator we obtain can cover a wide range of modes, and the loss of diversity is further reduced.

6.3. Analysis

Effect of our methods. The goal of our proposed binary classifier is to detect if an input image is “non-target” or “target”. In Figure 6 (left), we replace the source with equally sampled images from {FFHQ, ImageNet [10], CUB [45], Cars [27]} as “non-target” and Sketches as “target”, and we observe the similar results, compared to Figure 2a. We also show that both Generator CL and Discriminator CL can slow down the diversity degradation, and the better results are achieved when combined together. This further confirms our observations in Sec. 4: the slower diversity degradation leads to the better target generator for few-shot adaptation.

Effect of target data size. In this work, we mainly focus on 10-shot adaptation, similar to the prior literature [29, 34]. We further perform ablation study on 5-shot and 1-shot adaptation, use the same setup as Sec. 4 and Sec. 6. As results in Supp., we have the similar qualitative and quantitative observations, which confirms our findings stated in Sec. 4.5.

7. Conclusion

Focusing on few-shot image generation, our first contribution is to analyze existing few-shot image generation methods in a unified framework to gain insights on quality/diversity progress during adaptation. Of surprise is that the achieved quality is similar for different existing methods despite some of them have disproportionate focus on preserving diversity. Of interest is that the different rates of diversity degradation is the main factor for different performances. Informed by our analysis, as our second contribution we propose a mutual information based method to slow down degradation of diversity during adaptation. We connect the source and the target generators through the latent code, and construct positive-negative pairs to facilitate the contrastive learning. Our proposed method shows successful results both visually and quantitatively. Our study provides concrete information that future work could continue to focus on reducing the rate of diversity degradation in order to further improve few-shot image generation.

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Overview of Appendix

This Supplementary provides additional experiments and results to further support our main finding and proposed method for few-shot image generation. The Supplementary materials are organized as follows:

- Section A: Limitations
- Section B: Potential Social/Ethic Impacts
- Section C: Additional Details for Binary Classifier
- Section D: Pseudo-code for Intra-LPIPS
- Section E: Additional Training Details for DCL
- Section F: Proof of MI Maximization
- Section G: Additional Evaluation Metric
- Section H: Additional Results for Source $\mapsto$ Target Adaptation
- Section I: Effect of Unrelated Source $\mapsto$ Target Adaptation
- Section J: Effect of the Target Data Size
- Section K: Discussion of the Design Choice of DCL
- Section L: Does our realisticness classifier learn meaningful attributes?

A. Limitations

We follow exactly previous work (e.g., [34]) in the choices of domains and datasets for fair comparison. However, given the extremely wide range of domains to which few-shot image generation can be applied, it is not feasible for us to validate our findings for all possible domains. On the other hand, our comprehensive qualitative and quantitative experiment results supported by our analysis provide supportive evidence that our findings could be generalized for other domains.

Furthermore, similar to existing work [29, 34], our main focus is on related source/target domains, while we also discuss some analysis on unrelated source/target domains, e.g., see details in Figures A9.

B. Potential Social/Ethic Impacts

In this work, we adhere to the general ethical conducts and guidelines, including that we use the publicly available datasets to conduct all of our experiments, without any personally identifiable information or sensitive identifiable information (e.g., name of the human data). However, since real images are used for transfer learning, we hope the community could take the privacy issue carefully and seriously.

C. Additional Details for Binary Classifier

In this section, we provide more details of how to build the binary classifier $C$ (see Sec. 4.2 in the main paper) for quality/realisticness evaluation for different methods, during the few-shot adaptation.

Dataset. As mentioned in the main paper, we aim to build the unbiased binary classifier $C$ by keeping the training data of the source and the target domain balanced. Note that the data used for training the binary classifier is unseen during few-shot adaptation. We summarize the dataset setups and the data link in Table A3.

Optimization. In the training phase of $C$, we randomly initialize the AlexNet with official Pytorch implementation, and we employ the Adam optimizer with binary cross-entropy loss to optimize the weights. We train it until convergence on each dataset.

Table A3. We provide the training data of different source $\mapsto$ target adaptation setups for training the binary classifier $C$.

| Source $\mapsto$ Target | Source data | Target data | Size  |
|------------------------|-------------|-------------|-------|
| FFHQ $\mapsto$ Sketches| Link        | Link        | $\sim$ 300 |
| FFHQ $\mapsto$ Babies  | Link        | Link        | $\sim$ 2700 |
| FFHQ $\mapsto$ Sunglasses| Link       | Link        | $\sim$ 2500 |

D. Pseudo-code for Intra-LPIPS

Intra-LPIPS [34] evaluates to what extent the generated images collapse to the few-shot target data. The detailed text description of Intra-LPIPS can be found in Sec. 4.3 in the main paper. In this section, we provide the pseudo-code to compute the intra-LPIPS for evaluating the diversity-degradation during few-shot adaptation, as Algorithm 1.

Algorithm 1 Pseudo-code of Intra-LPIPS

```python
# Input: 1. Generated images X=[x1, ..., xn]; # 2. Cluster center: c0, c1; # Output: Avg Intra-LPIPS over 2 clusters # ------------------------------------------- # Step 0. Define the LPIPS function
lpips_fn = lpips.LPIPS(net='vgg')

# Step 1. Assign images to the closet center
for X[i] in X:
    dist0 = lpips_fn(X[i], c0)
    dist1 = lpips_fn(X[i], c1)
    if dist0 < dist1:
        Cluster_0.append(X[i])
    else:
        Cluster_1.append(X[i])

# Step 2. Compute Intra-LPIPS
lpips_dist = []
while not done:
    for img_i, img_j in Cluster_0:
        lpips_dist.append(lpips_fn(img_i, img_j))
    for img_i, img_j in Cluster_1:
        lpips_dist.append(lpips_fn(img_i, img_j))
return lpips_dist.mean() # ------------------------------------------- #
```
E. Additional Training Details for DCL

We follow the previous work [29, 32, 34] to use the architecture of StyleGAN-V2 with pytorch implementation. We use Adam optimizer to optimize the generator and the discriminator, and use the same hyperparameters and settings in [34], including the non-saturating loss $L_{adv}$. For the image resolution applied in this work, except for the adaptation setup "Cars → Wrecked cars", in which we adopts the 512 × 512 (this is because the GAN pretrained on LSUN Cars adopts the 512 × 512 image resolution), we use 256 × 256 for other adaptation setups in both the pretraining and the adaptation stage. We run our experiments (including those in Sec. 4) on a single Tesla V100 GPU.

\[ L_{C_{L1}} = E_X - \log \frac{f(G_i(z_i), G_s(z_i))}{\sum_{j=1}^{N} f(G_i(z_i), G_s(z_i))} \] (9)

To make it concise, in this section we omit the layer index $l$ used in the main paper. We let $X = \{G_i(z_1), G_i(z_2), \ldots, G_i(z_N)\}$. Follow [35], we write the optimal probability of this objective function (Eqn. 9) as $p(d = i | X, G_s(z_i))$ where $d = i$ indicates that the sample $X_i$ is the ‘positive’ sample $G_i(z_i)$ that corresponds to $G_s(z_i)$. The probability of the generated image which is sampled from $p(G_i(z_i) | G_s(z_i))$, rather than the random generated image distribution, can be shown as follows:

\[
p(d = i | X, G_s(z_i)) = \frac{p(d = i, X|G_s(z_i))}{\sum_{j=1}^{N} p(d = j, X|G_s(z_i))} \]

\[ = \frac{p(X_i|G_s(z_i)) \prod_{k \neq i} p(X_k)}{\sum_{j=1}^{N} p(X_i|G_s(z_i)) \prod_{k \neq j} p(X_k)} \]

\[ = \frac{p(X_i|G_s(z_i))}{\sum_{j=1}^{N} \frac{p(X_j|G_s(z_i))}{p(X_j)}}. \] (12)

Therefore, $f(X_i, G_s(z_i))$ is proportional to $\frac{p(X_i|G_s(z_i))}{p(X_i)}$. Then, we argue that DCL is a lower bound of the MI between $G_s(z_i)$ from the source generator, and $G_t(z_i)$ from the target generator, which adopt the same noise vector $z_i$. This can be shown as follows.

\[
L_{C_{L1}} = E_X - \log \left\{ \frac{p(X_i|G_s(z_i))}{\sum_{j=1}^{N} \frac{p(X_j|G_s(z_i))}{p(X_j)}} \right\} \]

\[ = E_X - \log \left\{ \frac{p(X_i|G_s(z_i))}{p(X_i) + \sum_{x \in Neg} p(X_i|G_s(z_i))} \right\} \] (14)

\[ = E_X \log \left\{ 1 + \frac{p(X_i)}{p(X_i|G_s(z_i))} \sum_{x \in Neg} p(X_i|G_s(z_i)) \right\} \] (15)

\[ = E_X \log \left\{ 1 + \frac{p(X_i)}{p(X_i|G_s(z_i))} \right\} \] (16)

\[ = E_X \log \left\{ 1 + \frac{p(X_i)}{p(X_i|G_s(z_i))} \right\} (N - 1) \] (17)

\[ = E_X \log \left\{ 1 + \frac{p(X_i)}{p(X_i|G_s(z_i))} \right\} \] (18)

\[ = E_X \log \left\{ N \frac{p(X_i)}{p(X_i|G_s(z_i))} \right\} \] (19)

\[ = \log [N] - \frac{1}{2} \sum_{i=1}^{N} \frac{1}{p(X_i|G_s(z_i))} \] (20)

Therefore, we have $MI(G_s(z_i); G_t(z_i)) \geq \log [N] - L_{C_{L1}}$, which means the Eqn. 9 is a lower bound of the mutual information between $G_s(z_i)$ and $G_t(z_i)$.

F. Proof of MI Maximization

Under mild assumptions, our proposed DCL (see Sec. 5) maximizes the lower bound of mutual information (MI) between generated samples with the same noise input, of the source and the target generator, respectively [35].

In this section, we show the proof of this statement in the main paper. We use $L_{C_{L1}}$ (with expectation) for example and show that, $MI(G_t(z_i); G_s(z_i)) \geq \log [N] - L_{C_{L1}}$, where

\[
L_{C_{L1}} = E_X - \log \frac{f(G_i(z_i), G_s(z_i))}{\sum_{j=1}^{N} f(G_i(z_i), G_s(z_j))} \] (9)

G. Additional Evaluation Metric

Standard LPIPS. In the main paper, we use intra-LPIPS [34] to evaluate the diversity (degradation) of the target generator for different methods. Here, we provide the standard LPIPS (↑) results in order to have a comprehensive comparison. In Table A4, we show that, we still outperform other models. Different from intra-LPIPS, the standard LPIPS only evaluate if the generated images are different from each other, and does not evaluate if they collapse to the few-shot training samples, hence we do not include the result of standard LPIPS in the main paper.

H. Additional Results of Source \(\mapsto\) Target Adaptation

In this section, we perform additional source \(\mapsto\) target adaptation experiments to visualize the effectiveness of our method. In Figure A8, compared to the source domain images, the generated samples on the target domain preserve rich semantic features (e.g., hair style, hat, building structure) on the source, but capture the style (and accessories) of the few-shot target set, which further confirm our ideas proposed in this work.
Table A4. Standard Pair-wise LPIPS distance (↑) of generated fake images. We firstly generate abundant data using the adapted generator on the target domain, then we compute the average perceptual distance between randomly paired images [38].

|                              | FFHQ → Church | FFHQ → Haunted house | FFHQ → Amedeo’s paintings | FFHQ → Sketches |
|------------------------------|---------------|-----------------------|---------------------------|-----------------|
| TGAN [69]                   | 0.57 ± 0.06   | 0.58 ± 0.12           | 0.44 ± 0.09               |
| TGAN+ADA [23]               | 0.60 ± 0.05   | 0.61 ± 0.11           | 0.45 ± 0.08               |
| BSA [33]                    | 0.47 ± 0.05   | 0.45 ± 0.07           | 0.32 ± 0.05               |
| Freezed [31]                | 0.55 ± 0.08   | 0.55 ± 0.13           | 0.42 ± 0.09               |
| MineGAN [48]                | 0.56 ± 0.10   | 0.59 ± 0.12           | 0.46 ± 0.09               |
| EWC [29]                    | 0.59 ± 0.06   | 0.60 ± 0.09           | 0.45 ± 0.06               |
| CDC [34]                    | 0.61 ± 0.03   | 0.62 ± 0.06           | 0.47 ± 0.05               |
| DCL (Ours)                  | 0.63 ± 0.03   | 0.64 ± 0.06           | 0.51 ± 0.05               |

I. Effect of Unrelated Source → Target Adaptation

Background. In this work, we mainly focus on the few-shot image generation (with GAN adaptation) where the source domain and the target domain are related, similar to all existing methods [29, 32, 34, 49]. However, the case where the source and the target domain are unrelated should be included in the discussion, e.g., transferring from FFHQ (human face) to Haunted Houses.

Experiments. In this section, we compare with other methods (see related works in the main paper) with the setup that the source domain and the target domain are unrelated. Note that all other settings are identical to Sec. 6 in the main paper. In Figure A9, we adapt two source domains (FFHQ, LSUN Church) to three different target domains (Haunted house, Amedeo’s paintings and Van Gogh’s house). The differences between these methods are more obvious, as discussed in Figure A9.

Nevertheless, these methods cannot accurately capture the target domain distribution with much diversity knowledge, as what we expect when the source domains and the target domains are related. To the best of our knowledge, there is no existing work that focus on this issue and we leave this open problem as our future work.

J. Effect of the Target Data Size

In the main paper, we mainly focus on the 10-shot adaptation setups, in both Sec. 4 and Sec. 6. Here, we extend our analysis to 5-shot and 1-shot setups. As Figure A10 and Figure A11, we show that, our main analysis is still hold for 1-shot and 5-shot adaptation case: while some methods have disproportionate focus on diversity preserving which impede quality improvement, they will achieve almost the identical realtisticness on the target domain, even for 1-shot and 5-shot adaptation. Therefore, we argue that the main focus of few-shot image generation method should be on reducing the diversity degradation during few-shot adaptation.

K. Discussion of the Design Choice of DCL

Choice of coefficients. In Eqn. 8 in the main paper, there are two coefficients: λ1 and λ2 in the loss term of DCL. We perform a grid search to tune these hyperparameters, depending on the performance on diversity and FID score. In experiments, we empirically find that the setting λ1 = 2, λ2 = 0.5 achieves the best result.

Choice of batch size. For our proposed DCL, in Generator CL, the batch size depends on how many noise vectors we sample in each iteration. In Discriminator CL, the batch size depends on how many real samples we have in the few-shot adaptation. Therefore, for fair comparison, we sample 4 noise vectors as input in each iteration, which is identical to other methods, while we sample all few-shot real target images (e.g., 10-shot) to perform Discriminator CL.

Choice of negative samples. The negative samples can be selected from various sources for both Generator CL and Discriminator CL. In Generator CL, the negative samples are Gs(zj,i) where zi is used to produce Gzj (Setup A). However, the negative samples can also be Gt(zj,i) to prevent all generated images of the adapted generator collapsing to the same mode (Setup B). Empirically, we find that the both setups has similar performance on reducing the loss of diversity during adaptation, as we show the change of intra-LPIPS in Figure A7.

Figure A7. Transferring from FFHQ → 10-shot Amedeo’s paintings (the same setup as Figure 1 in the main paper). We show that both Setup A and Setup B have similar performance on mitigating the loss of diversity during few-shot adaptation. Note that we do not use Discriminator CL in this ablation study.

For Discriminator CL, we aim to prevent the generated images collapsing to real target data, as observed in other methods (e.g., TGAN). Therefore, we sample discriminatimg features from real target data (i.e., Dt(x)) as negative samples to regularize the few-shot adaptation process. Potentially, the negative samples can also come from the generated images. However, in experiments we do not observe better performance with this setup.
L. Does our realism classifier learn meaningful attributes?

We applied Guided Grad-CAM (GGC) [39] to show pixel-wise explanations and validated that our classifier $C$ (as Sec. 4 in the main paper) indeed learns meaningful semantic features to evaluate the realism of generated images, w.r.t. target domain. The results are in Figure A12. Additional analysis is below:

- We convert real FFHQ images to grey-scale, our $C$ outputs 0.73 of being sketch for 1k images (column 8). The score is not high. We hypothesize that our $C$ learns other features beyond color, e.g. style. In this case, GGC's visualization shows face regions are relevant for decision, which is consistent for color/style features.

- Importantly, we have visually inspected generated sketch images which have high score from $C$, and they resemble real sketch images (column 7). Overall, we believe our $C$ learns other features beyond color, but it remains open problem to validate what DNN has learned. On the other hand, we notice the quick convergence for FFHQ-to-sketch (as in Figure 2 in the main paper). However, it is possible that this is due to easy adaptation: generator only needs to adapt color/style rather than semantic concepts.

- The goals of our $C$ and discriminator are similar, but discriminator is trained with very limited target ("real") samples, preventing it to be used for reliable evaluation. Meanwhile, $C$ is trained with more abundant held-out target samples. Moreover, as our $C$ is trained with real target samples, $C$ should evaluate later part of few-shot adaptation as well.

Overall, with additional analysis and visualization, we are more confident in our realism evaluation in Sec. 4. The results are consistent and supportive for our main takeaway: "...all methods achieve similar quality after convergence. Therefore, the better methods are those that can slow down diversity degradation. ...there is still plenty of room to further slow down diversity degradation."
Figure A9. Generated images with unrelated source $\rightarrow$ target adaptation setups. We show that, TGAN still overfits the few-shot target set regardless of the source domain knowledge; CDC preserves the distance between instances in the source, therefore it captures the part-level correspondence between the source and the target, e.g., the eyes and the teeth are roughly mapped to the doors and windows in the target domain. In contrast, since DCL (Ours) emphasizes on the connection to the generated image on the source domain with the same latent code, our results preserve more refined details (e.g., glasses, hair style) and the structure appearance is not thoroughly destroyed when transferring to the target domain.
Figure A10. Generated images with 1-shot adaptation (the same setup as Section 4 in the main paper), which is an extension to the Figure 2 in the main paper.

Figure A11. Generated images with 5-shot adaptation (the same setup as Section 4 in the main paper), which is an extension to the Figure 2 in the main paper.
| Real FFHQ | Real Babies | FFHQ → Babies | Real Sunglasses | FFHQ → Sunglasses | Real Sketches | FFHQ → Sketches | Real FFHQ (Gray) | Cat → Dog | Dog → Cat |
|-----------|-------------|----------------|----------------|------------------|---------------|----------------|-----------------|-----------|-----------|
| ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) | ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) | ![Image](image10.png) |

$p_{\text{FFHQ}}^{\text{FFHQ}} = 0.99$  
$p_{\text{baby}}^{\text{baby}} = 0.99$  
$p_{\text{baby}}^{\text{baby}} = 0.99$  
$p_{\text{baby}}^{\text{baby}} = 0.99$  
$p_{\text{sketch}}^{\text{sketch}} = 0.99$  
$p_{\text{sketch}}^{\text{sketch}} = 0.99$  
$p_{\text{sketch}}^{\text{sketch}} = 0.99$  
$p_{\text{sketch}}^{\text{sketch}} = 0.99$  
$p_{\text{sketch}}^{\text{sketch}} = 0.73$  
$p_{\text{sketch}}^{\text{sketch}} = 0.39$  
$p_{\text{sketch}}^{\text{sketch}} = 0.48$

Figure A12. We use GGC [39] to show pixel-wise explanations that our $C$ learns meaningful semantic features (not just color) to discriminate between source and target domains. The output probability of $C$ for each sample is indicated. Pixel-wise explanations clearly show that $C$ leverages on substantial amounts of meaningful semantic features in discriminating source and target domains: • FFHQ: jawline/lips; • FFHQ → Babies: eyes/lips • FFHQ → Sunglasses: sunglass/style • FFHQ → Sketches: style (face) • Dogs → Cats: snouts/ears in dogs, whiskers/fur in cats. $p_t$ are output probabilities of $C$. For Dogs ↔ Cats adaptation, we intentionally select bad images at initial iterations (500) of the adaptation, to validate low $p_t$ from $C$. For other adaptations, images at the end are selected. **Best viewed in color and enlarged.**