

On Leveraging Pretrained GANs for Generation with Limited Data

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Motivation



Generated from BigGAN



Generated from StyleGAN

GANs can generate highly realistic fake images

- not contained in training datasets
- ➤ potential generalization of GANs

Limited-data applications <⬅ synthetic augmentation

However, to train a GAN on limited data is challenging

- limited data ➤ overfitting or training/mode collapse

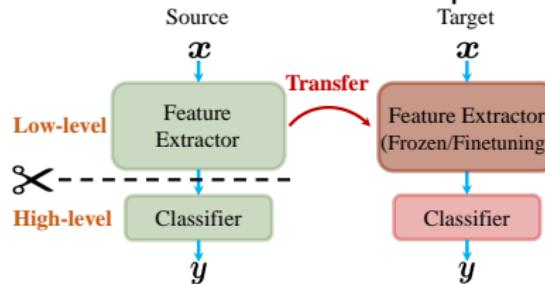
We propose to transfer additional information to facilitate limited-data generation.

- Specifically, the valuable common knowledge within released GANs pretrained on large-scale datasets

Motivation

Key observations associated with common knowledge:

- For classification models pretrained on large-scale datasets
 - lower-level filters (those close to the observation x) are fairly general/transferable (like Gabor)
 - higher-level filters are more task-specific classifier



- For pretrained GAN generators
 - lower-level layers portray generally-applicable local patterns
 - higher-level layers represent more specific semantic objects or object parts
- It's data-demanding to train well-behaved low-level filters
 - transfer often delivers better efficiency and performance

Our Contributions

To better transfer common knowledge for limited-data generation

- from GANs pretrained on large-scale source datasets

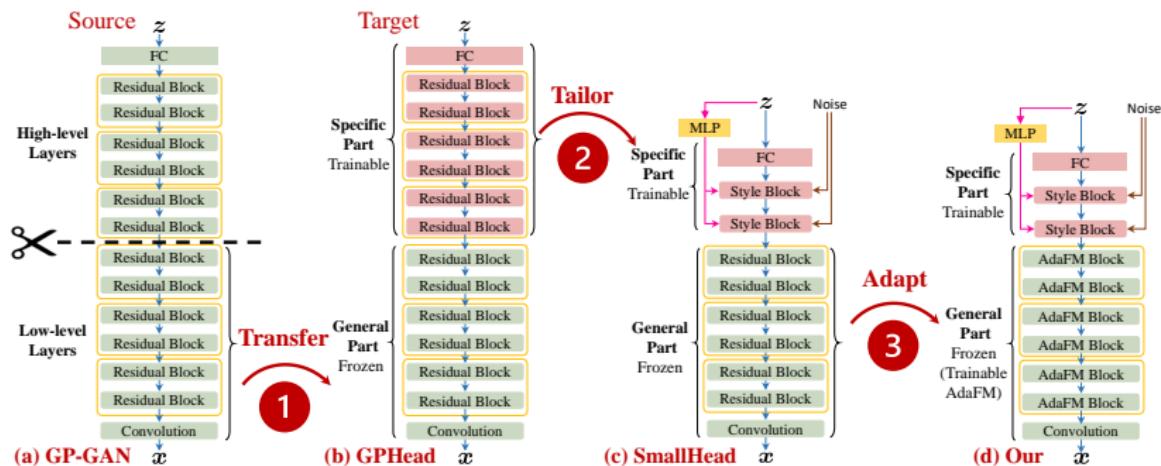


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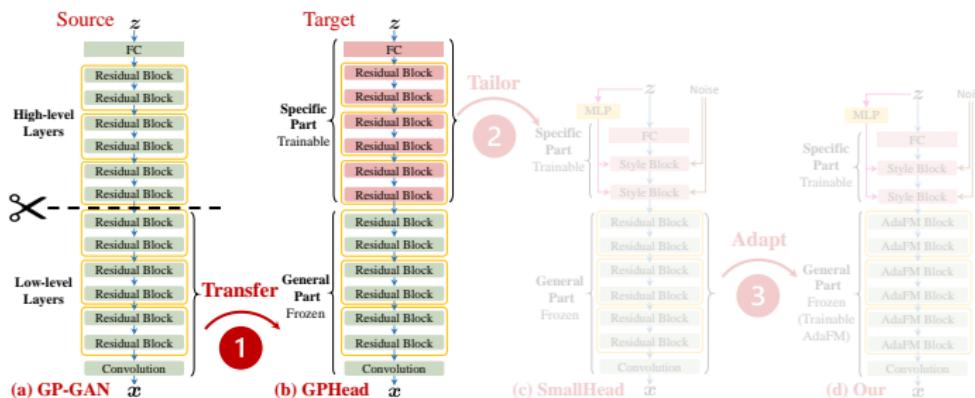
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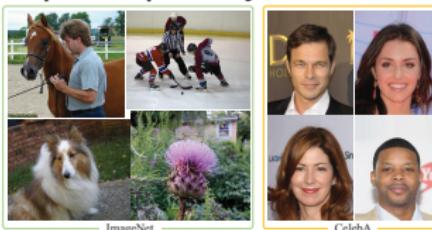
4 Experiments

1. On Specifying the General-Part for Transfer



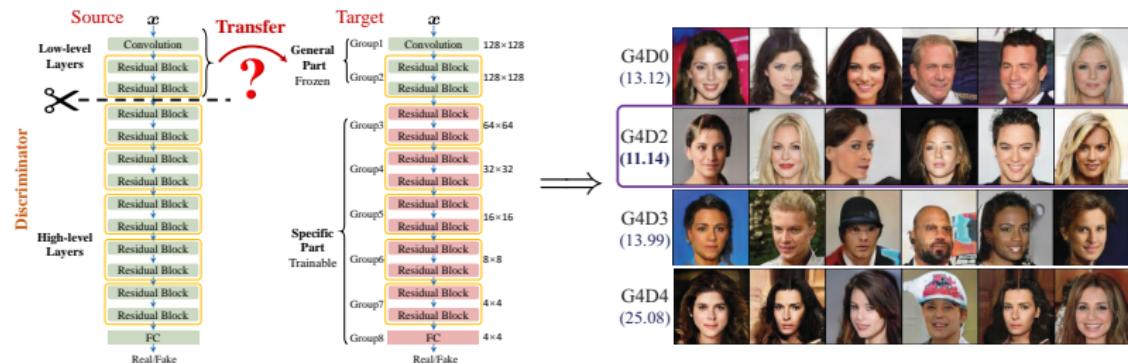
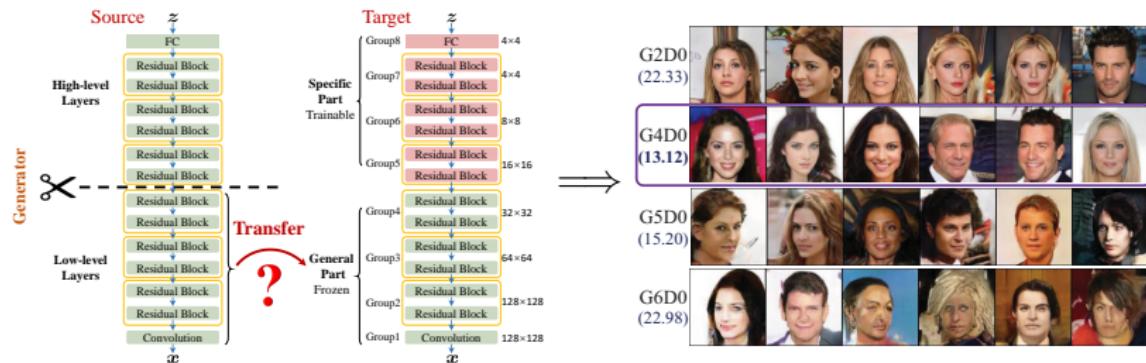
Source model: the GP-GAN¹ pretrained on ImageNet

Target dataset: the perceptually-distinct CelebA

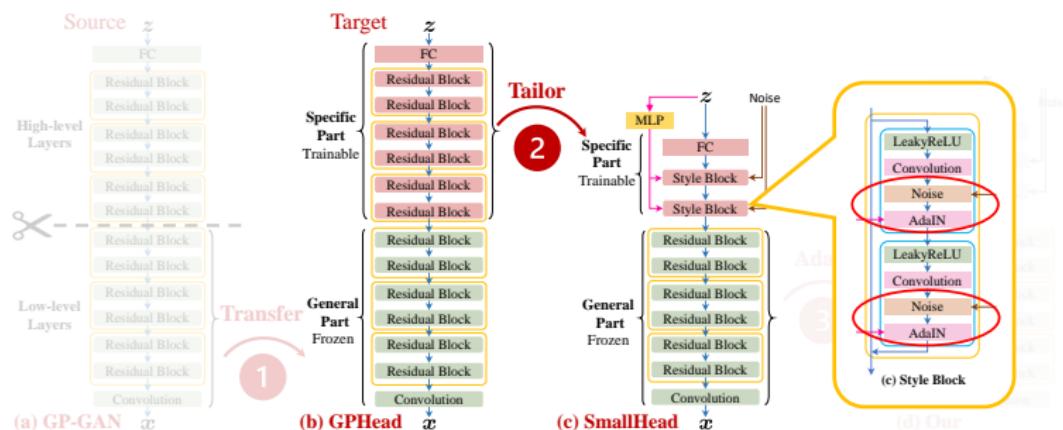


¹ Which training methods for GANs do actually converge? ICML 2018.

1. On Specifying the General-Part for Transfer



2. On Tailoring the High-Level Specific-Part



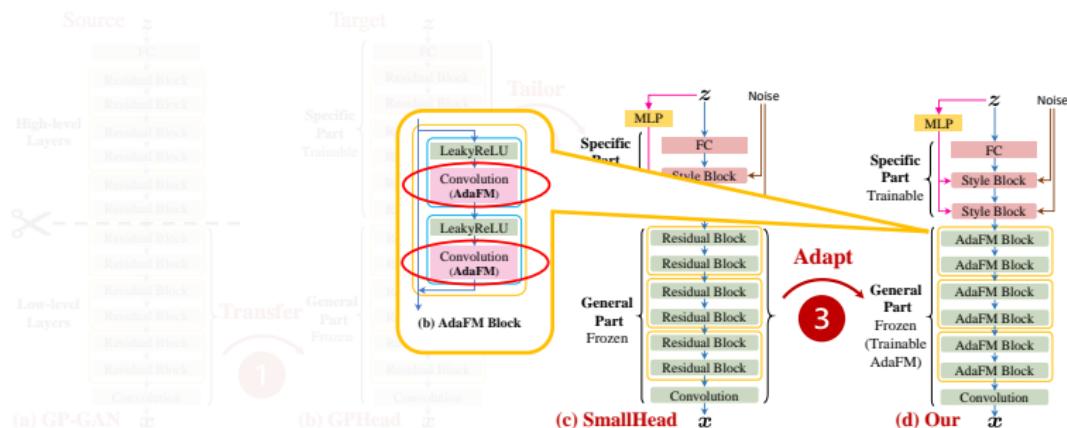
Even with the G4D2 general-part, mode collapse may still happen on small data (Flowers 8,189).

Style blocks deliver

- disentangled high-level attributes \Rightarrow efficient exploration of underlying data manifold \Rightarrow better generative quality
- style mixing
- cheaper computation



3. On Better Adaption of the Transferred General-Part



We introduce the **adaptive filter modulation (AdaFM)** to

- better adapt the transferred general-part to target domains
- relax the requirements for the general-part

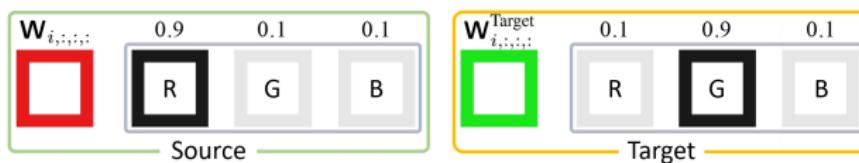
Given a Conv filter $\mathbf{W} \in \mathbb{R}^{C_{\text{out}} \times C_{\text{in}} \times K_1 \times K_2}$, AdaFM uses learnable $\gamma \in \mathbb{R}^{C_{\text{out}} \times C_{\text{in}}}$ and $\beta \in \mathbb{R}^{C_{\text{out}} \times C_{\text{in}}}$ to modulate its statistics

$$\mathbf{W}_{i,j,:,:}^{\text{AdaFM}} = \gamma_{i,j} \mathbf{W}_{i,j,:,:} + \beta_{i,j} \quad (1)$$

3. On Better Adaption of the Transferred General-Part

The underlying assumption is

- basic shape/pattern within $\mathbf{W}_{i,j,:,:}$ \Rightarrow generally applicable
- statistics/correlation among i,j -channels \Rightarrow target-specific
- empirically verified in the experiments



- Source and target filters share the same basic shape/pattern but with different among-channel correlations.
- AdaFM learns $\gamma_{i,:} = [1/9, 9, 1]$ to adapt source $\mathbf{W}_{i,:,:,:}$ to target $\mathbf{W}_{i,:,:,:}^{\text{Target}}$.

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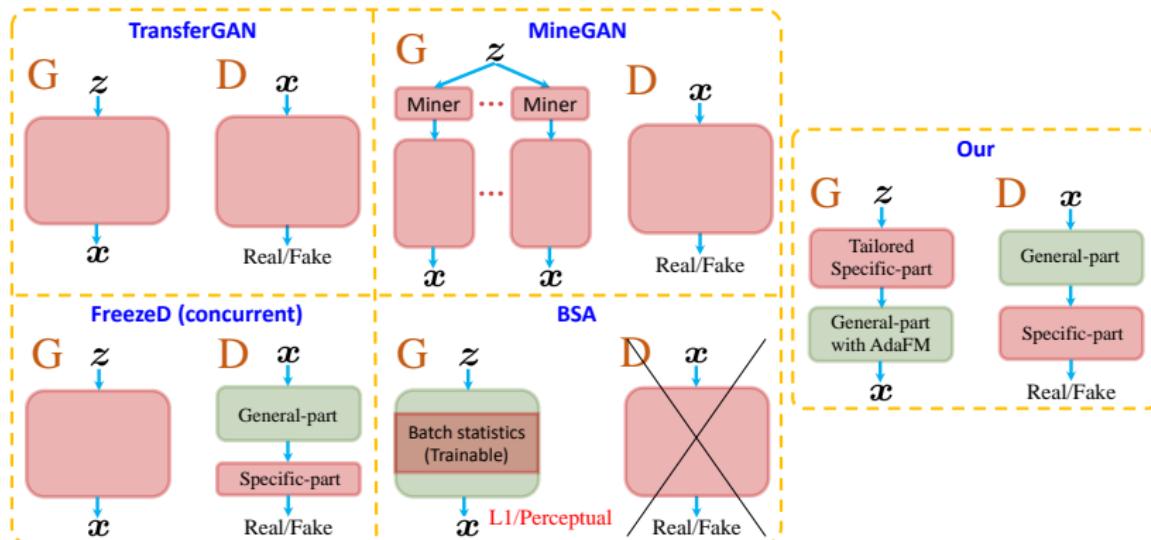
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Related Work

Exploit GANs to transfer knowledge for limited-data generation.



TransferGAN: Transferring GANs: generating images from limited data. ECCV 2018.

BSA: Image generation from small datasets via batch statistics adaptation. ICCV 2019.

MineGAN: MineGAN: effective knowledge transfer from GANs to target domains with few images. CVPR 2020.

FreezeD: Freeze discriminator: A simple baseline for fine-tuning GANs. arXiv 2020.

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Experiments

Comparisons with existing/naive methods on

1. moderate or small datasets
2. limited datasets with 1,000 images
3. extremely limited datasets with 25 images

Analysis of the proposed techniques

1. ablation study of our method
2. modulations from AdaFM
3. style augmentation/mixing with the tailored specific-part

Comparisons with Existing/Naive Methods

1. On moderate or small datasets

CelebA (202,599), Flowers (8,189), Cars (8,144), Cathedral (7,350)

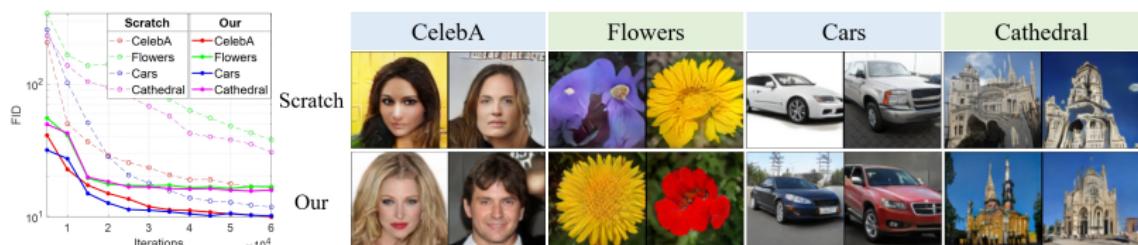


Figure 8. FID scores (left) and generated images (right) of Scratch and Our method on 4 target datasets. The transferred general-part dramatically accelerates the training, leading to better performance.

Table 2. FID scores of the compared methods after 60,000 training iterations. Lower is better. “Failed” means training/mode collapse.

Method \ Target	CelebA	Flowers	Cars	Cathedral
TransferGAN	18.69	failed	failed	failed
Scratch	16.51	29.65	11.77	30.59
Our	9.90	16.76	10.10	15.78

- TransferGAN vs Scratch/Our: tailored specific-part \gg overfitting
- Scratch vs Our: (i) the transferred general-part, (ii) AdaFM

Comparisons with Existing/Naive Methods

2. On limited datasets with 1,000 images

Random selection ➤ CelebA-1K, Flowers-1K, and Cathedral-1K

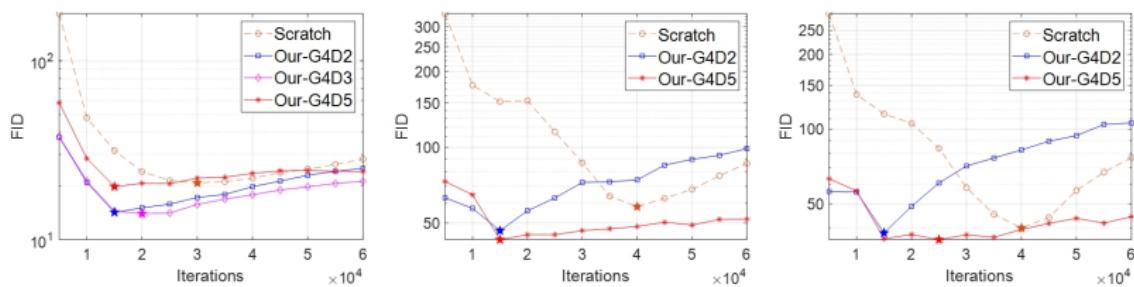


Figure 10. FID scores on CelebA-1K (left), Flower-1K (center), and Cathedral-1K (right). The best FID achieved is marked with a star.

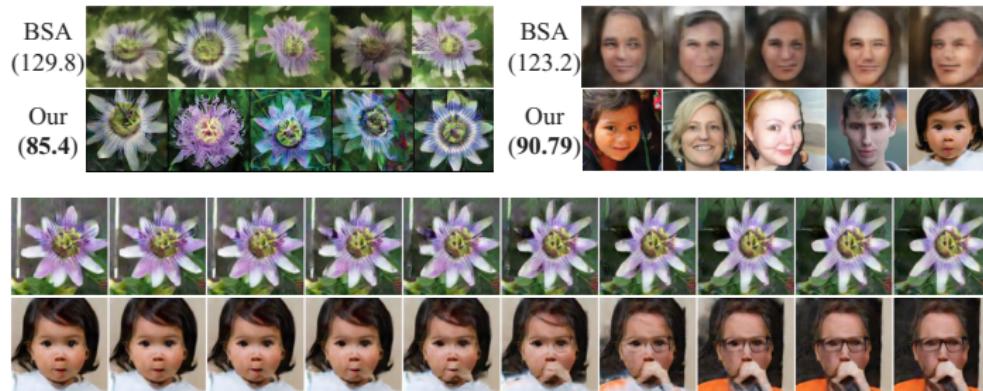
Table 3. The best FID achieved within 60,000 training iterations on the limited-1K datasets. Lower is better.

Method \ Target	CelebA-1K	Flowers-1K	Cathedral-1K
Scratch	20.75	58.18	39.97
Our-G4D2	14.19	46.68	38.17
Our-G4D3	13.99	-	-
Our-G4D5	19.77	43.05	35.88

Comparisons with Existing/Naive Methods

3. On extremely limited datasets with 25 images

Random selection ➤ Flowers-25 and FFHQ-25, following BSA.²



Our: G4D6 general-part, GP on both real and fake samples

- More realistic generation
- Smooth interpolations on the learned data manifold

²

Image generation from small datasets via batch statistics adaptation. ICCV 2019.

Analysis of the Proposed Techniques

1. Ablation Study of Our Method

- GP-GAN: no filters are transferred; baseline for GPHead
- GPHead: GP-GAN architecture + transferred general-part
- SmallHead: transferred general-part + tailored specific-part
- Our: SmallHead + the proposed AdaFM

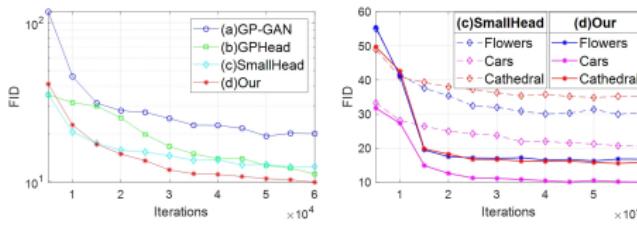


Figure 9. FID scores from the ablation studies of our method on CelebA (left) and the 3 small datasets of Flower, Cars, and Cathedral (right).

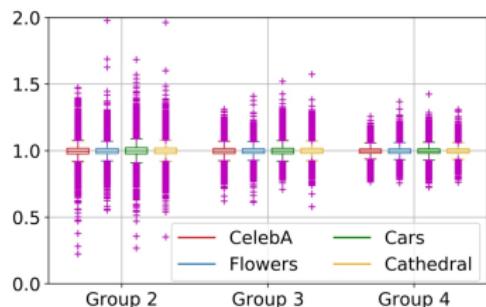
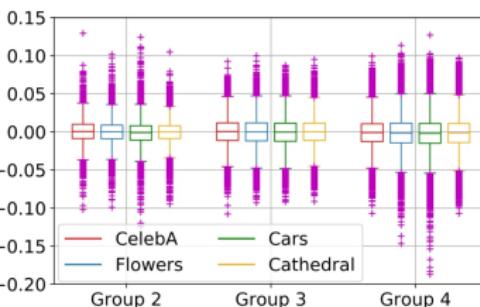
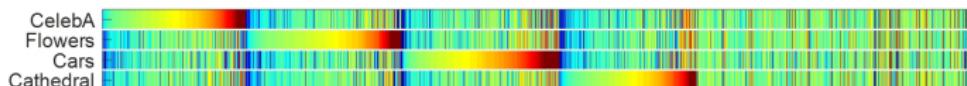
Table 1. FID scores from ablation studies on our method after 60,000 training iterations. Lower is better.

Method \ Target	CelebA	Flowers	Cars	Cathedral
(a)GP-GAN	19.48	failed	failed	failed
(b)GPHead	11.15	failed	failed	failed
(c)SmallHead	12.42	29.94	20.64	34.83
(d)Our	9.90	16.76	10.10	15.78

Analysis of the Proposed Techniques

2. Modulations from AdaFM

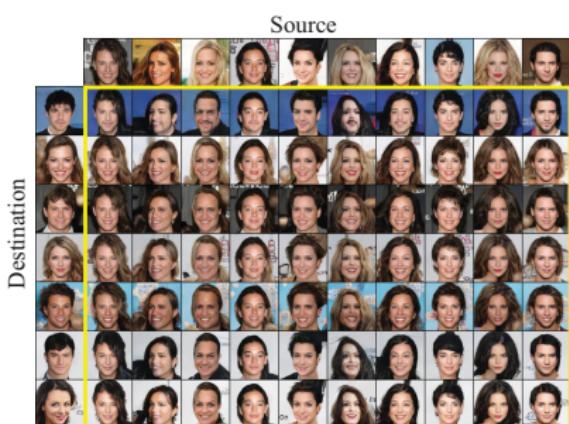
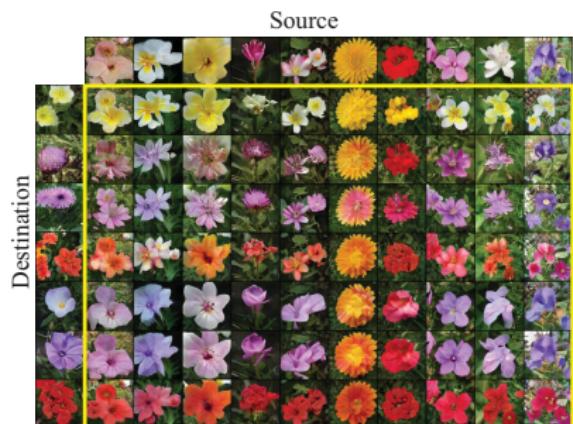
Boxplots of the learned scale γ and shift β on target datasets

(a) Scale γ (b) Shift β (c) γ in Group 2

- All filters are used in target domains but with modulations
- Different target datasets prefer different modulations

Analysis of the Proposed Techniques

3. Style Mixing/Augmentation with the Tailored Specific-Part



Style mixing is extremely appealing for limited-data applications

- Vast novel generation via style/attribute combinations
- Diverse synthetic augmentation

Thank you!