다중 도메인으로의 적대적 생성 신경망의 동적 퓨샷 적응*

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DynaGAN: Dynamic Few-shot Adaptation of GANs to Multiple Domains

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Figure 1: (a) For a source image, we show the successful adapted results: (b) cartoon, (c) painting, and (d) statue

Abstract

Few-shot domain adaptation of GANs to multiple domains is a task to learn a complex distribution of multiple domains with just few images, starting from a pre-trained GAN model. A naïve solution is to adapt a separate model to each domain by few-shot domain adaptation methods. However, it takes a lot of space unnecessarily. To tackle this, we propose DynaGAN adapting a single GAN model to multiple domains dynamically. We design an efficient adaptation module, which is a hyper-network that adapts a GAN to multiple domains. Moreover, our contrastive-adaptation loss reflects the unique attributes of each target domain. DynaGAN allows GANs to generate images of diverse domains in an efficient way.

1. Introduction

Generative adversarial networks (GANs)[1] have enabled high-quality image generation and have made great contributions in various fields. However, they require a large amount of training data. Few-shot domain adaptation methods reduce the data requirement by adapting the pre-trained GAN model to another domain through fine-tuning GAN parameters. Unfortunately, adapting to multiple domains often fails due to its complex distribution to be learned. However, it is inefficient to train multiple separate models for each domain to handle various domains.

We propose DynaGAN, which successfully achieves few-shot domain adaptation to multiple domains. Our hyper-network-based adaptation module extends the expression power of GANs to multiple domains efficiently. We also propose a contrastive-adaptation loss to better reflect the unique attributes of each domain. DynaGAN shows that a single GAN model can handle multiple domains and supports the image-to-image translation of real images.

2. DynaGAN

2.1. Adaptation Module

For successful adaptation to multiple domains, GAN models should have different parameters for each domain. To achieve this, we introduce an adaptation module dynamically adapting the pre-trained StyleGAN2[2] generator to multiple domains. The adaptation module takes a domain condition vector as input and estimates modulation parameters of each convolutional layer weights as shown in Figure 2. However, naïve estimation poses a huge burden in memory. To tackle this issue, we adopt rank-1 tensor decomposition for the light-weight adaptation module.

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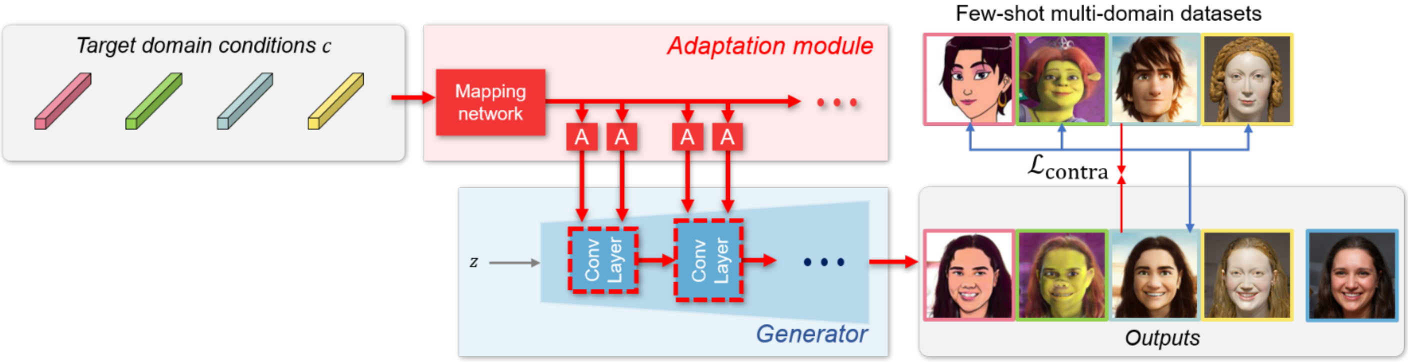

Figure2: DynaGAN overall framework. The adaptation module modulates the convolutional layer weights of the pre-trained generator. Our contrastive-adaptation loss $\mathcal{L}_{contra}$ results in better adaptation.

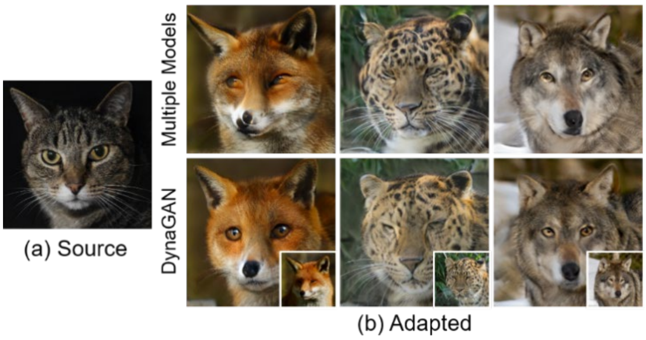

Figure 3: Comparison with multiple separate models

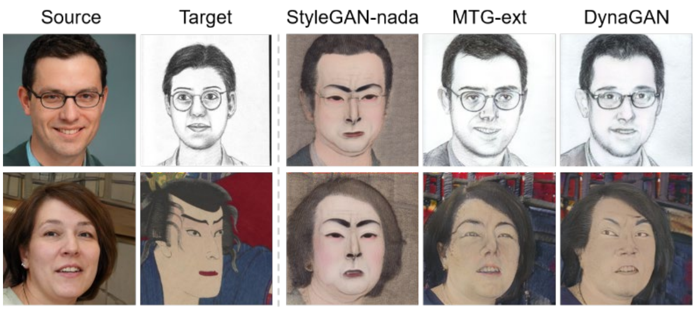

Figure 4: Qualitative comparison with previous few-shot domain adaptation methods: StyleGAN-nada[4] and MTG-ext[3]

2.2. Contrastive-adaptation loss

Our contrastive-adaptation loss guides the adapted image close to the corresponding target domain images and far from the different domain images. It can reflect unique characteristics that are distinguished from other domains. The total training loss consists of our contrastive-adaptation loss and our baseline loss[3]. We update the adaptation module while keeping the StyleGAN2 generator intact.

3. Results

Figure 1 shows synthesized images by DynaGAN. DynaGAN can generate images in various domains by dynamically adapting the generator at the inference time.

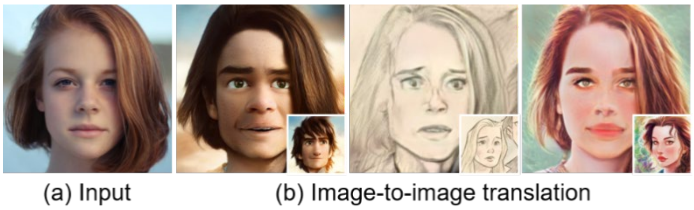

Figure 4: Image-to-image translation results of real images

Thanks to our adaptation module and contrastive-adaptation loss, DynaGAN has superior performance than multiple adapted models as shown in Figure 3. Moreover, DynaGAN shows better adaptation results than previous methods as shown in Figure 4.
DynaGAN supports image-to-image translation of the real input image through GAN inversion. Figure 4 is the results of image-to-image translation.

4. Conclusion

In this paper, we introduce DynaGAN to express multiple domains with few images. Our adaptation module dynamically adapts GANs to multiple domains by modulating the pre-trained generator parameters. Rank-1 based estimation reduces the size of the adaptation module significantly. Through contrastive-adaptation loss, the adapted images have distinct attributes of different domains. We show that DynaGAN results in better domain adaptation and is applicable to image-to-image translation.

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