StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation

实现一对多条件转换

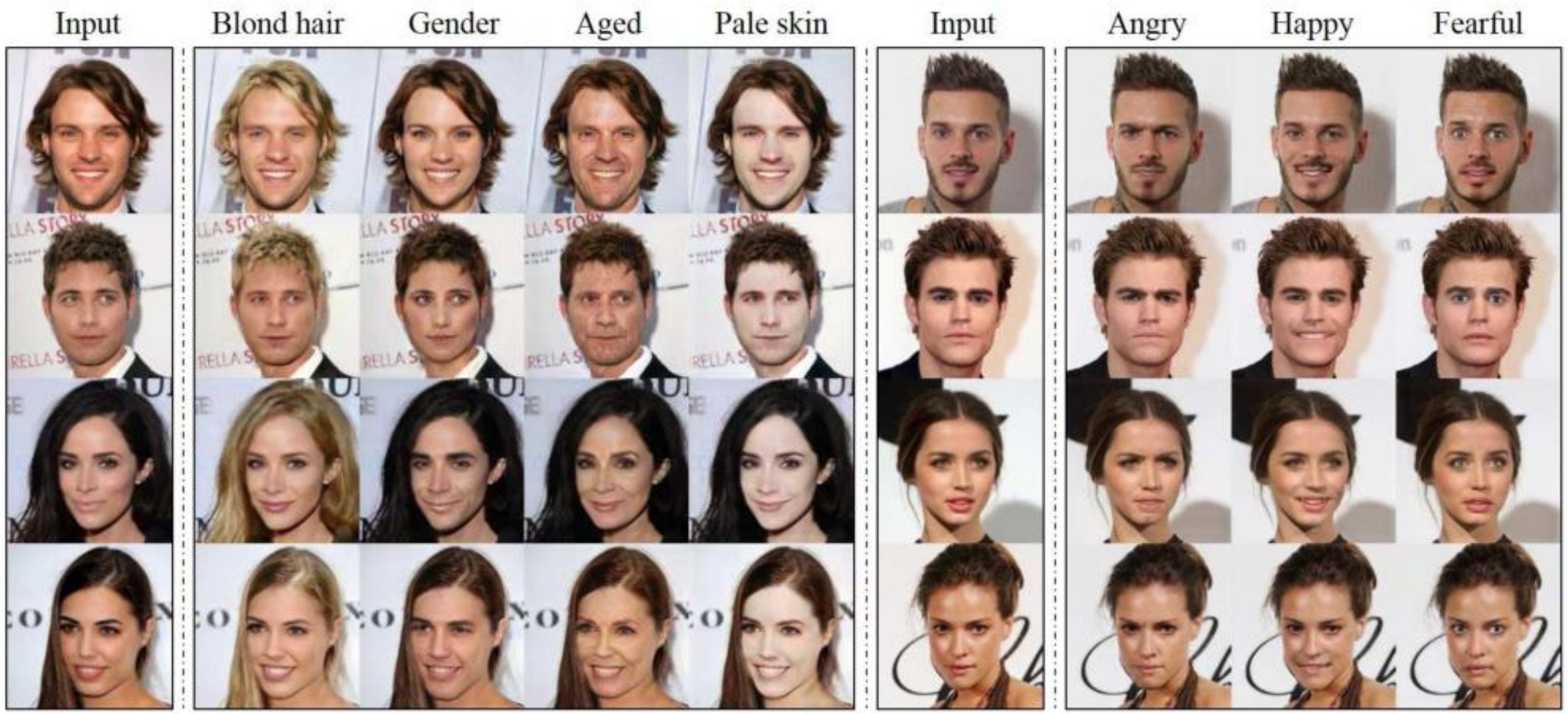
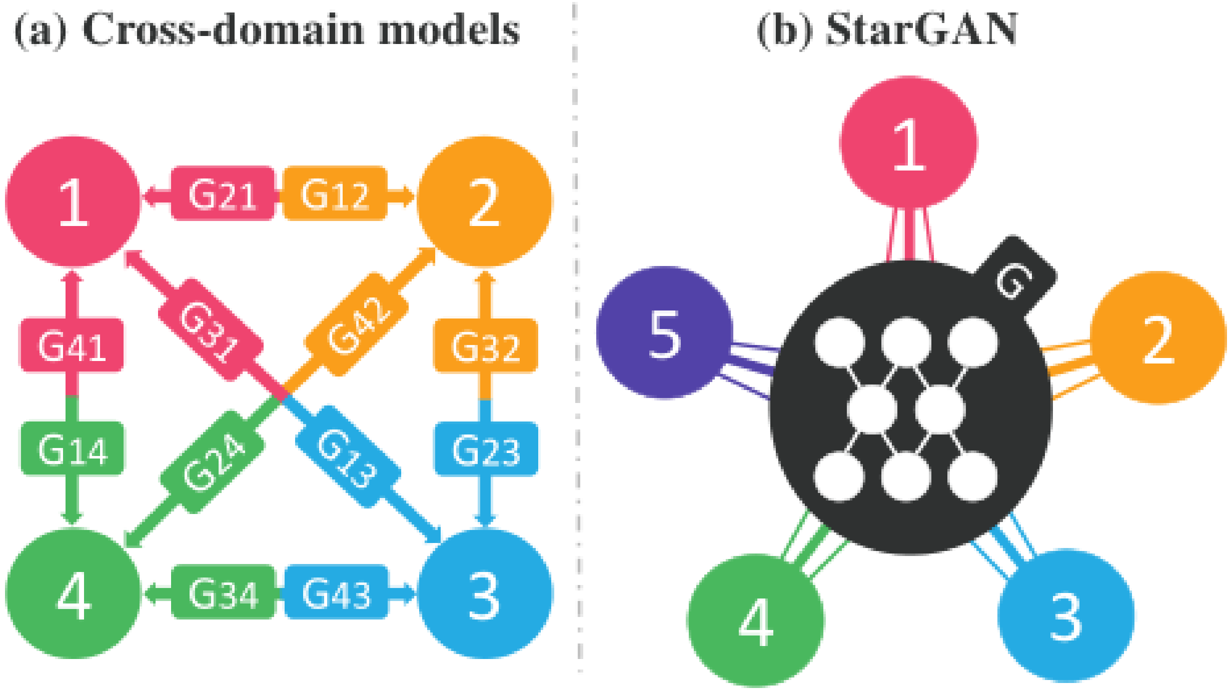


Figure 1. Multi-domain image-to-image translation results on the CelebA dataset via transferring knowledge learned from the RaFD dataset. The first and sixth columns show input images while the remaining columns are images generated by StarGAN. Note that the images are generated by a single generator network, and facial expression labels such as angry, happy, and fearful are from RaFD, not CelebA.

StarGAN与CycleGAN的不同



StarGAN结构

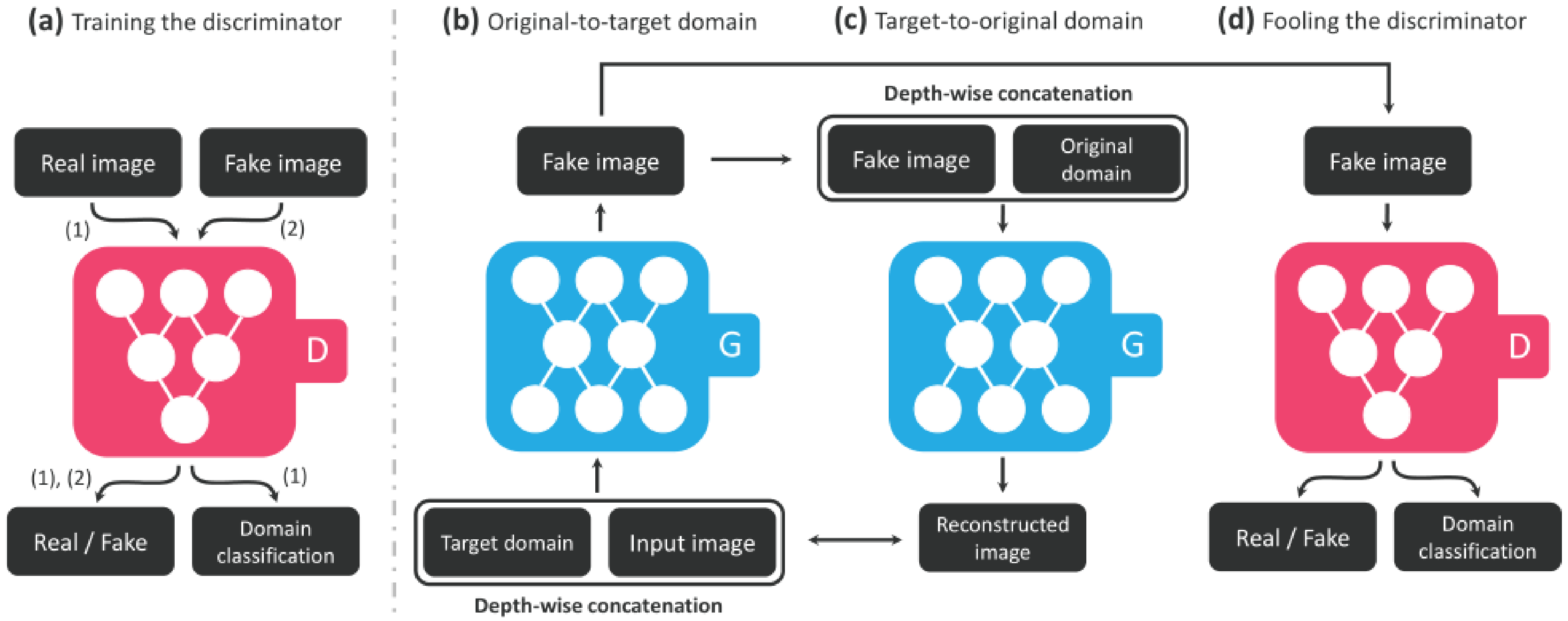


Figure 3. Overview of StarGAN, consisting of two modules, a discriminator D and a generator G. **(a)** D learns to distinguish between real and fake images and classify the real images to its corresponding domain. **(b)** G takes in as input both the image and target domain label and generates an fake image. The target domain label is spatially replicated and concatenated with the input image. **(c)** G tries to reconstruct the original image from the fake image given the original domain label. **(d)** G tries to generate images indistinguishable from real images and classifiable as target domain by D.

损失函数

- Adversarial Loss

$$\mathcal{L}_{adv} = \mathbb{E}_x\left[\log D_{src}(x)\right] + \mathbb{E}_{x,c}[\log(1 - D_{src}(G(x,c))], \quad (1)$$

- Domain Classification Loss

$$\mathcal{L}^r_{cls} = \mathbb{E}_{x,c'}[-\log D_{cls}(c'|x)], \quad (2)$$

$$\mathcal{L}^f_{cls} = \mathbb{E}_{x,c}[-\log D_{cls}(c|G(x,c))]. \quad (3)$$

损失函数

- Reconstruction Loss

$$\mathcal{L}_{rec} = \mathbb{E}_{x,c,c'}[||x - G(G(x,c),c')||_1], \tag{4}$$

- Full Objective

$$\mathcal{L}_D = -\mathcal{L}_{adv} + \lambda_{cls}\,\mathcal{L}_{cls}^{r}, \tag{5}$$

$$\mathcal{L}_G = \mathcal{L}_{adv} + \lambda_{cls}\,\mathcal{L}_{cls}^{f} + \lambda_{rec}\,\mathcal{L}_{rec}, \tag{6}$$

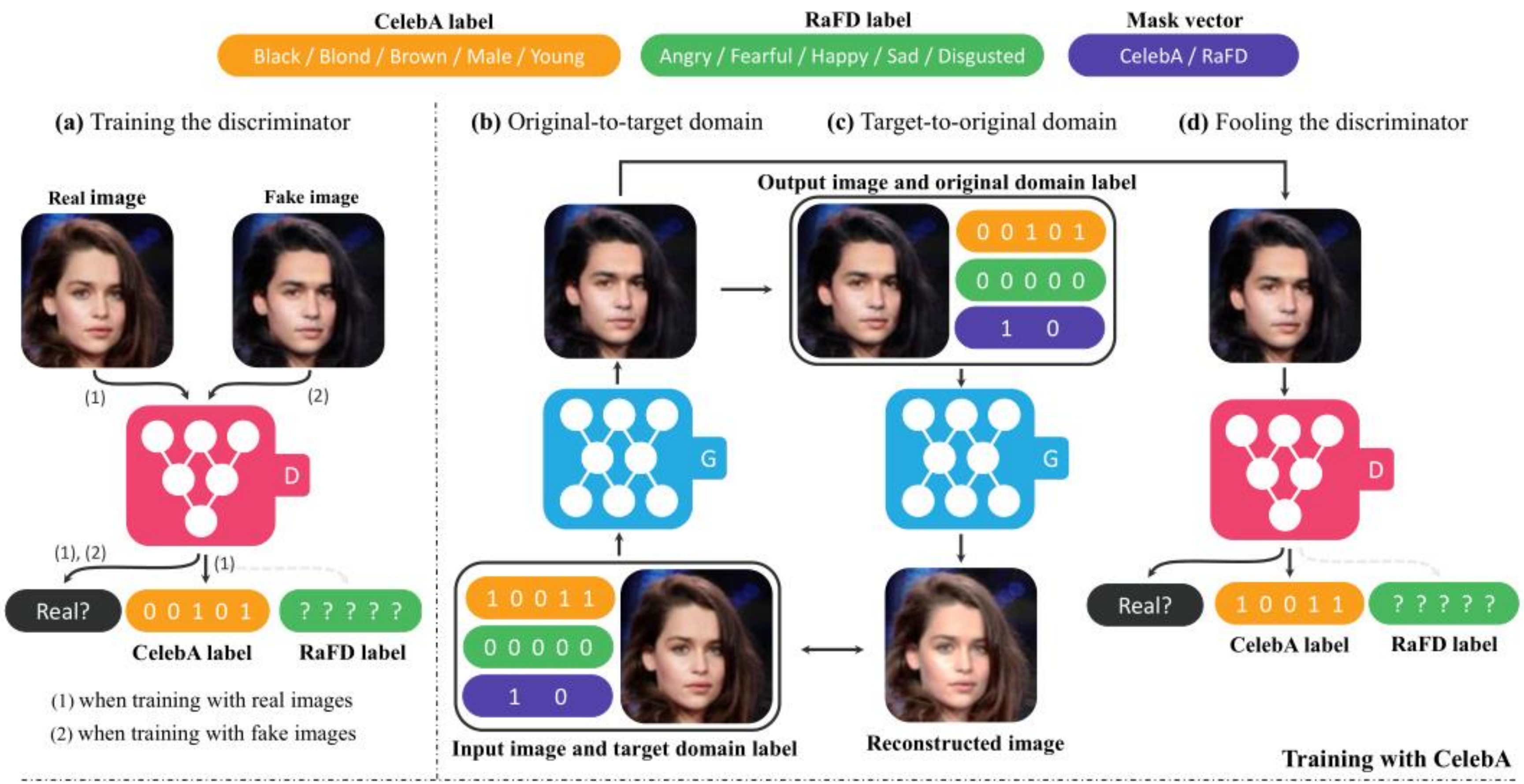
Mask vector

In StarGAN, we use an n-dimensional one-hot vector to represent m, with n being the number of datasets. In addition, we define a unified version of the label as a vector:

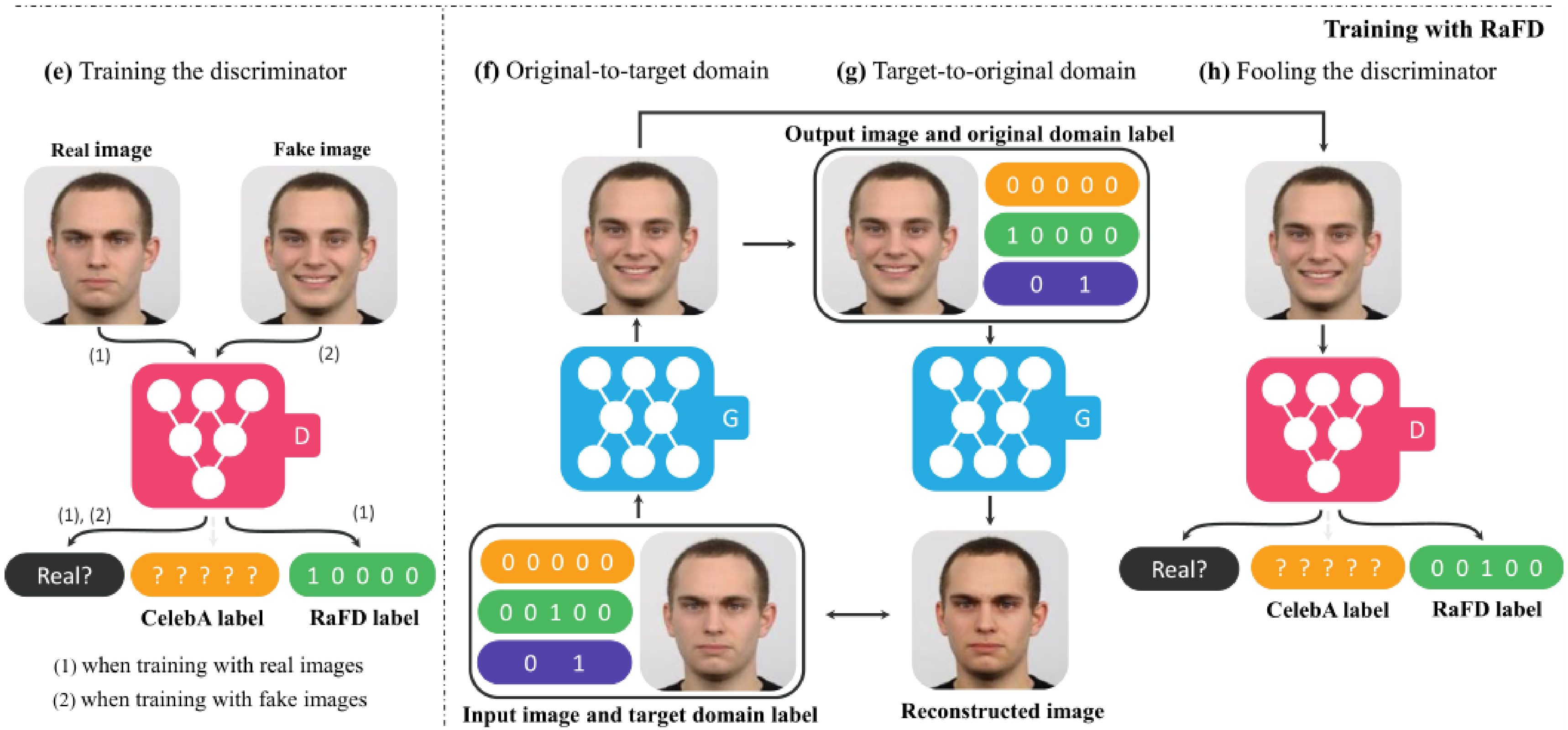
$$\tilde{c} = [c_1, ..., c_n, m], \tag{7}$$

where [·] refers to concatenation, and c_i represents a vector for the labels of the i-th dataset. In our experiments, we utilize the CelebA and RaFD datasets, where n is 2.

Training with Multiple Datasets



Training with Multiple Datasets



网络结构

Part	Input → Output Shape	Layer Information
Down-sampling	$(h, w, 3+n_c) \rightarrow (h, w, 64)$	CONV-(N64, K7x7, S1, P3), IN, ReLU
	$(h, w, 64) \rightarrow (\frac{h}{2}, \frac{w}{2}, 128)$	CONV-(N128, K4x4, S2, P1), IN, ReLU
	$(\frac{h}{2}, \frac{w}{2}, 128) \rightarrow (\frac{h}{4}, \frac{w}{4}, 256)$	CONV-(N256, K4x4, S2, P1), IN, ReLU
Bottleneck	$(\frac{h}{4}, \frac{w}{4}, 256) \rightarrow (\frac{h}{4}, \frac{w}{4}, 256)$	Residual Block: CONV-(N256, K3x3, S1, P1), IN, ReLU
	$(\frac{h}{4}, \frac{w}{4}, 256) \rightarrow (\frac{h}{4}, \frac{w}{4}, 256)$	Residual Block: CONV-(N256, K3x3, S1, P1), IN, ReLU
	$(\frac{h}{4}, \frac{w}{4}, 256) \rightarrow (\frac{h}{4}, \frac{w}{4}, 256)$	Residual Block: CONV-(N256, K3x3, S1, P1), IN, ReLU
	$(\frac{h}{4}, \frac{w}{4}, 256) \rightarrow (\frac{h}{4}, \frac{w}{4}, 256)$	Residual Block: CONV-(N256, K3x3, S1, P1), IN, ReLU
	$(\frac{h}{4}, \frac{w}{4}, 256) \rightarrow (\frac{h}{4}, \frac{w}{4}, 256)$	Residual Block: CONV-(N256, K3x3, S1, P1), IN, ReLU
	$(\frac{h}{4}, \frac{w}{4}, 256) \rightarrow (\frac{h}{4}, \frac{w}{4}, 256)$	Residual Block: CONV-(N256, K3x3, S1, P1), IN, ReLU
Up-sampling	$(\frac{h}{4}, \frac{w}{4}, 256) \rightarrow (\frac{h}{2}, \frac{w}{2}, 128)$	DECONV-(N128, K4x4, S2, P1), IN, ReLU
	$(\frac{h}{2}, \frac{w}{2}, 128) \rightarrow (h, w, 64)$	DECONV-(N64, K4x4, S2, P1), IN, ReLU
	$(h, w, 64) \rightarrow (h, w, 3)$	CONV-(N3, K7x7, S1, P3), Tanh

Table 1. Generator network architecture

网络结构

Layer	Input → Output Shape	Layer Information
Input Layer	$(h, w, 3) \rightarrow (\frac{h}{2}, \frac{w}{2}, 64)$	CONV-(N64, K4x4, S2, P1), Leaky ReLU
Hidden Layer	$(\frac{h}{2}, \frac{w}{2}, 64) \rightarrow (\frac{h}{4}, \frac{w}{4}, 128)$	CONV-(N128, K4x4, S2, P1), Leaky ReLU
Hidden Layer	$(\frac{h}{4}, \frac{w}{4}, 128) \rightarrow (\frac{h}{8}, \frac{w}{8}, 256)$	CONV-(N256, K4x4, S2, P1), Leaky ReLU
Hidden Layer	$(\frac{h}{8}, \frac{w}{8}, 256) \rightarrow (\frac{h}{16}, \frac{w}{16}, 512)$	CONV-(N512, K4x4, S2, P1), Leaky ReLU
Hidden Layer	$(\frac{h}{16}, \frac{w}{16}, 512) \rightarrow (\frac{h}{32}, \frac{w}{32}, 1024)$	CONV-(N1024, K4x4, S2, P1), Leaky ReLU
Hidden Layer	$(\frac{h}{32}, \frac{w}{32}, 1024) \rightarrow (\frac{h}{64}, \frac{w}{64}, 2048)$	CONV-(N2048, K4x4, S2, P1), Leaky ReLU
Output Layer (D_{src})	$(\frac{h}{64}, \frac{w}{64}, 2048) \rightarrow (\frac{h}{64}, \frac{w}{64}, 1)$	CONV-(N1, K3x3, S1, P1)
Output Layer (D_{cls})	$(\frac{h}{64}, \frac{w}{64}, 2048) \rightarrow (1, 1, n_d)$	CONV-(N(n_d), K$\frac{h}{64}$x$\frac{w}{64}$, S1, P0)

Table 2. Discriminator network architecture

实验结果

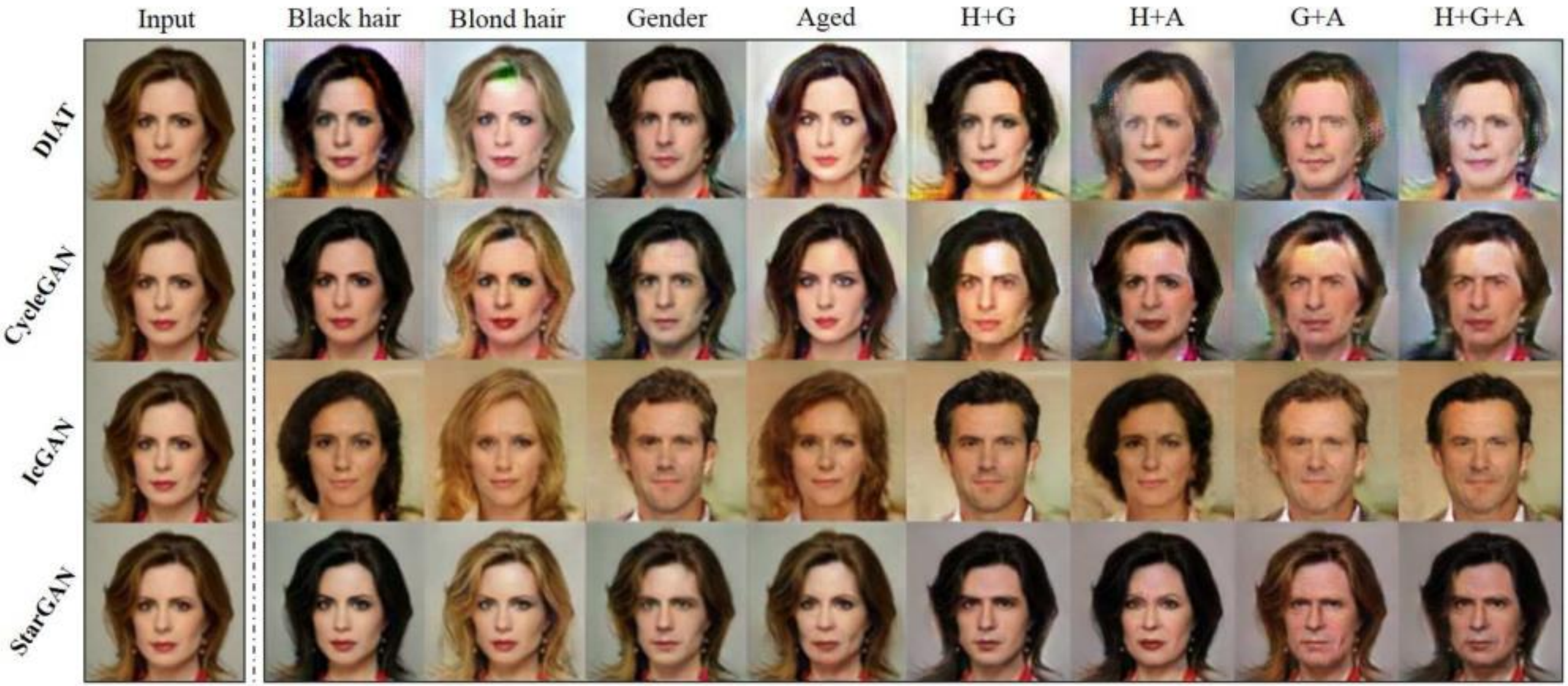


Figure 4. Facial attribute transfer results on the CelebA dataset. The first column shows the input image, next four columns show the single attribute transfer results, and rightmost columns show the multi-attribute transfer results. H: Hair color, G: Gender, A: Aged.

启发

1. 可以生成多不同类别的数据用于训练。
2. 关于生成样本去训练分类器的文章有没有。