

ELEGANT: Exchanging Latent Encodings with GAN for Transferring Multiple Face Attributes

Taihong Xiao, Jiapeng Hong & Jinwen Ma

Department of Information Sciences, School of Mathematical Sciences and LMAM, Peking University

xiaotaihong@pku.edu.cn, jphong@pku.edu.cn, jwma@math.pku.edu.cn



Introduction

There are many approaches to transferring face attributes. However, most of them suffer from one or more following limitations:

1. Incapability of generating image by exemplars;
2. Being unable to transfer multiple face attributes simultaneously;
3. Low quality of generated images, such as low-resolution or artifacts.

Here are our intuitions to address the above three limitations.

1. To generate images by exemplars, a model must receive a reference for conditional image generation.
2. For manipulating multiple attributes simultaneously, the latent encodings of an image can be divided into different parts, where each part encodes information of a single attribute.
3. To improve the quality of generated images, we adopt the idea of residual learning and multi-scale discriminators.

Model

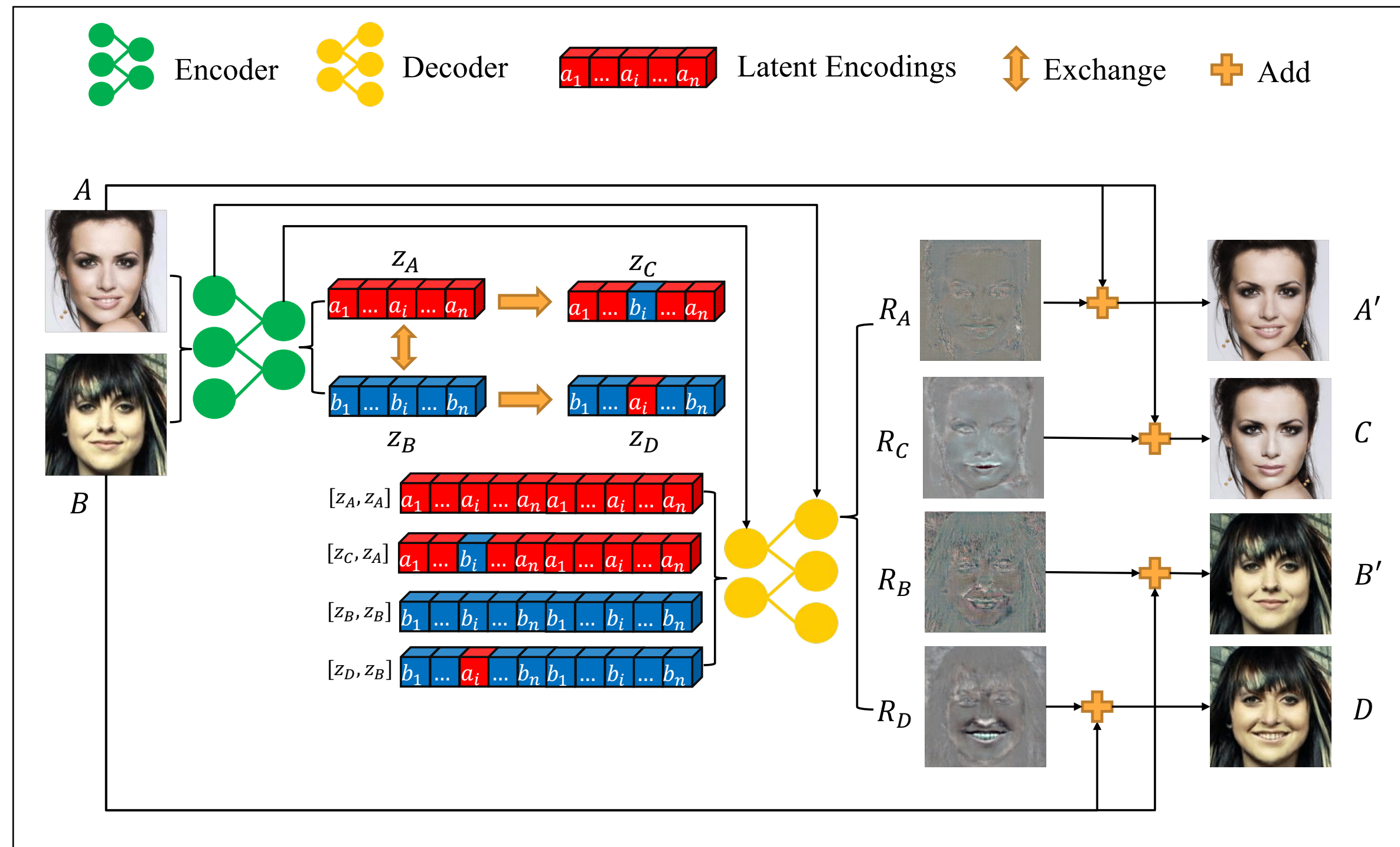


Figure 1: The ELEGANT model architecture.

- Two input images batches of opposite attribute. Formally, the attribute labels of A and B are required to be in this form $Y^A = (y_1^A, \dots, 1_i, \dots, y_n^A)$ and $Y^B = (y_1^B, \dots, 0_i, \dots, y_n^B)$.
- An encoder was used to obtain the disentangled latent encodings for different attributes,

$$z_A = \text{Enc}(A) = [a_1, \dots, a_i, \dots, a_n], \quad z_B = \text{Enc}(B) = [b_1, \dots, b_i, \dots, b_n] \quad (1)$$

where a_i and b_i are the smiling feature tensors.

- Exchanging latent encodings so as to swap face attribute,

$$z_C = [a_1, \dots, b_i, \dots, a_n], \quad z_D = [b_1, \dots, a_i, \dots, b_n] \quad (2)$$

- Residual learning: the input of the decoder is the concatenation (or difference) of the source and target encodings, and the output of the decoder is the residual image.

$$\text{Dec}([z_A, z_A]) = R_A, \quad A' = A + R_A \quad \text{Dec}([z_C, z_A]) = R_C, \quad C = A + R_C \quad (3)$$

$$\text{Dec}([z_B, z_B]) = R_B, \quad B' = B + R_B \quad \text{Dec}([z_D, z_B]) = R_D, \quad D = B + R_D \quad (4)$$

- Multi-scale discriminators: two discriminators having identical network structures whereas operating at different image scales. D_1 has a smaller receptive field compared with D_2 . Therefore, D_1 is specialized in guiding the Enc and Dec to produce finer details, whereas D_2 is adept in handling the holistic image content so as to avoid generating grimaces.

Loss Functions

- The multi-scale discriminators D_1 and D_2 receive the standard adversarial loss

$$L_{D_1} = -\mathbb{E}(\log(D_1(A|Y^A))) - \mathbb{E}(\log(1 - D_1(C|Y^C))) - \mathbb{E}(\log(D_1(B|Y^B))) - \mathbb{E}(\log(1 - D_1(D|Y^D))) \quad (5)$$

$$L_{D_2} = -\mathbb{E}(\log(D_2(A|Y^A))) - \mathbb{E}(\log(1 - D_2(C|Y^C))) - \mathbb{E}(\log(D_2(B|Y^B))) - \mathbb{E}(\log(1 - D_2(D|Y^D))) \quad (6)$$

$$L_D = L_{D_1} + L_{D_2} \quad (7)$$

- As for the Enc and Dec, there are two types of losses. The first type is the reconstruction loss,

$$L_{reconstruction} = \|A - A'\| + \|B - B'\| \quad (8)$$

and the second type is the standard adversarial loss

$$L_{adv} = -\mathbb{E}(\log(D_1(C|Y^C))) - \mathbb{E}(\log(D_1(D|Y^D))) - \mathbb{E}(\log(D_2(C|Y^C))) - \mathbb{E}(\log(D_2(D|Y^D))) \quad (9)$$

The total loss for the generator is

$$L_G = L_{reconstruction} + L_{adv}. \quad (10)$$

Experiments

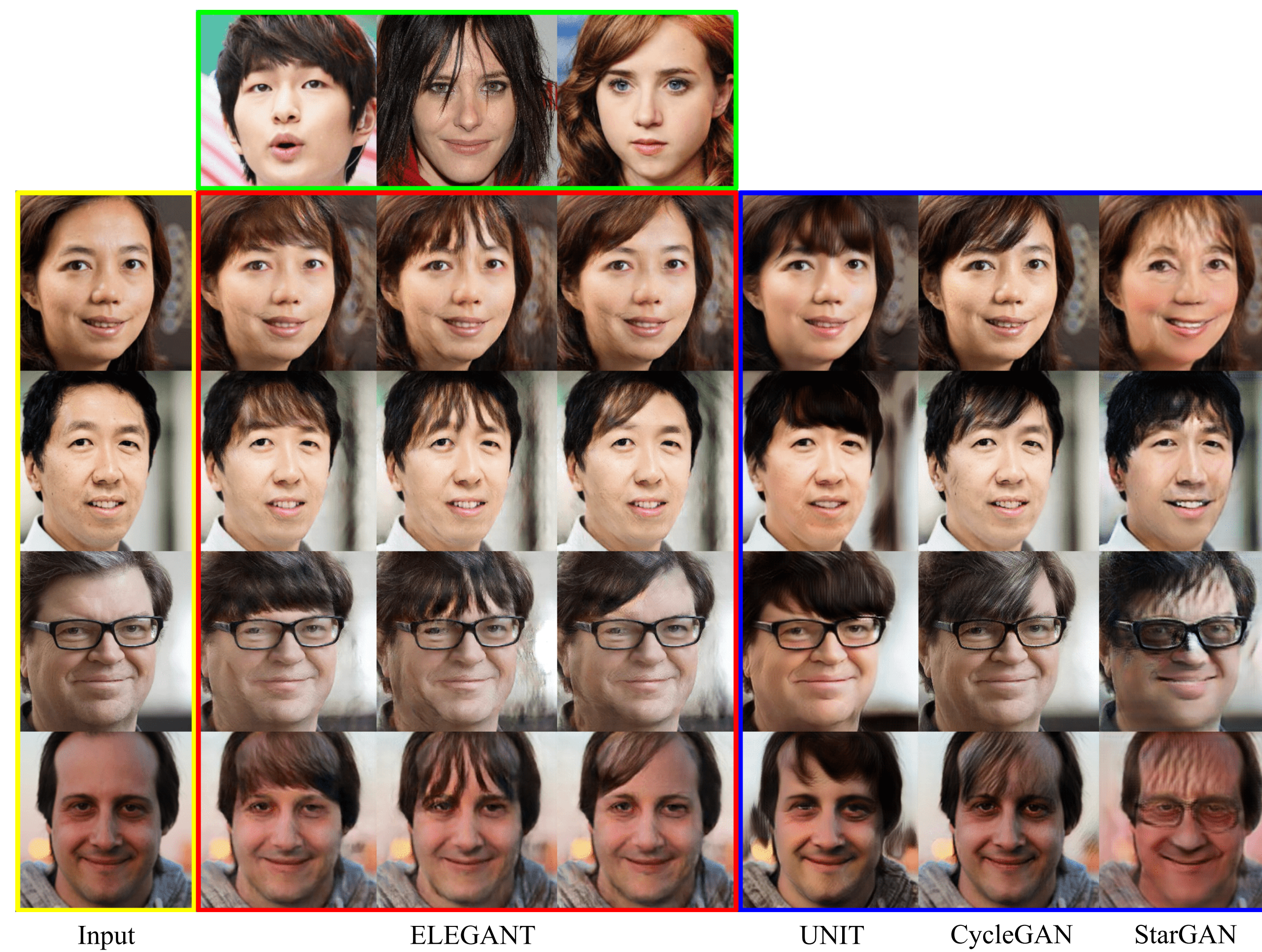


Figure 2: Face image generation by exemplars.



Figure 3: Interpolation of different types of bangs.

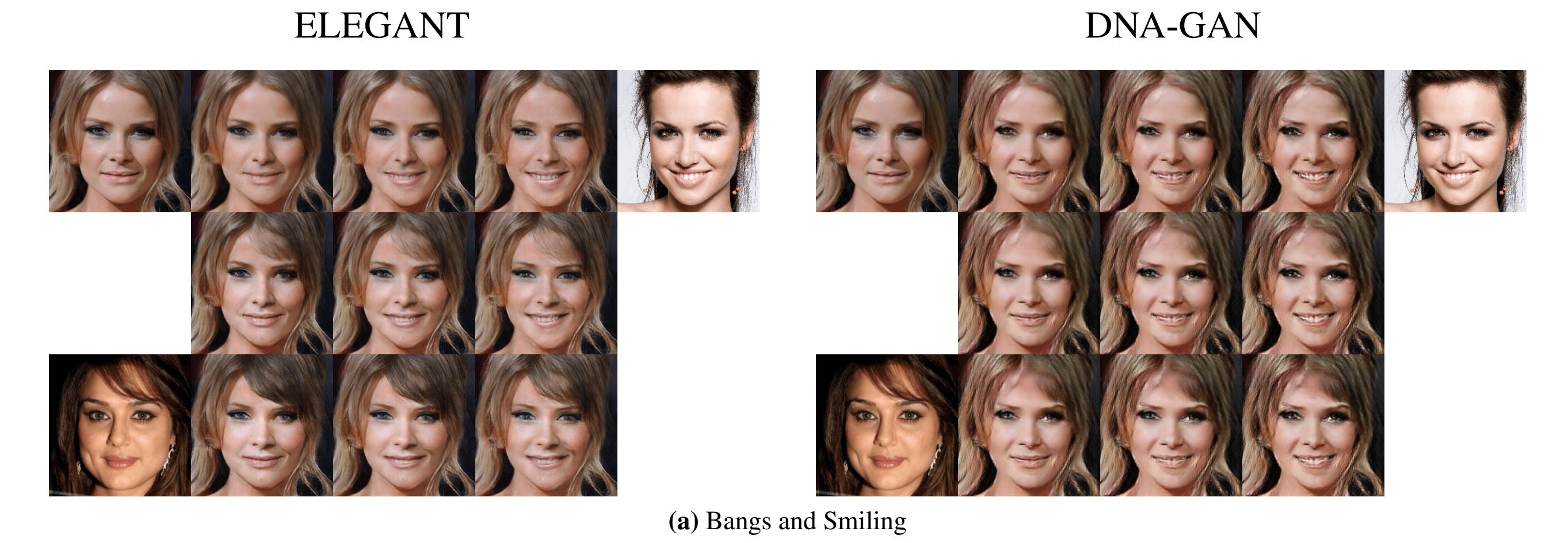
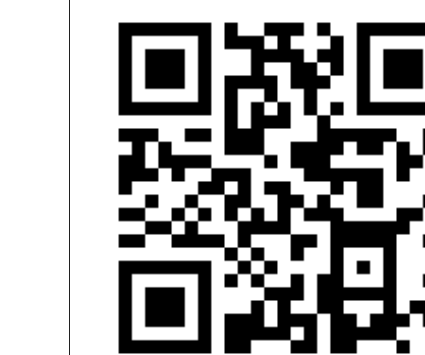


Figure 4: Multiple Attributes Interpolation. Compared with DNA-GAN, ELEGANT preserves the face id without the annihilation operation, and generate visually better images.

Table 1: FID of Different Methods with respect to five attributes. The + (−) represents the generated images by adding (removing) the attribute.

FID	bangs		smiling		mustache		eyeglasses		male	
	+	−	+	−	+	−	+	−	+	−
UNIT	135.41	137.94	120.25	125.04	119.32	131.33	111.49	139.43	152.16	154.59
CycleGAN	27.81	33.22	23.23	22.74	43.58	55.49	36.87	48.82	60.25	46.25
StarGAN	59.68	71.07	51.36	78.87	99.03	176.18	70.40	142.35	70.14	206.21
DNA-GAN	79.27	76.89	77.04	72.35	126.33	127.66	75.02	75.96	121.04	118.67
ELEGANT	30.71	31.12	25.71	24.88	37.51	49.13	47.35	60.71	59.37	56.80



Scan for source code.

<https://github.com/Prinsphield/ELEGANT>