ClsGAN: Selective Attribute Editing Based On Classification Adversarial Network

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Abstract

Attribution editing has shown remarkable progress by the incorporating of encoder-decoder structure and generative adversarial network. However, there are still some challenges in the quality and attribute transformation of the generated images. Encoder-decoder structure leads to blurring of images and the skip-connection of encoder-decoder structure weakens the attribute transfer ability. To address these limitations, we propose a classification adversarial model (Cls-GAN) that can balance between attribute transfer and generated photo-realistic images. Considering that the transfer images are affected by the original attribute using skip-connection, we introduce upper convolution residual network (Tr-resnet) to selectively extract information from the source image and target label. Specially, we apply to the attribute classification adversarial network to learn about the defects of attribute transfer images so as to guide the generator. Finally, to meet the requirement of multimodal and improve reconstruction effect, we build two encoders including the content and style network, and select a attribute label approximation between source label and the output of style network. Experiments that operates at the dataset of CelebA show that images are superiority against the existing state-of-the-art models in image quality and transfer accuracy. Experiments on wikiart and seasonal datasets demonstrate that ClsGAN can effectively implement style transfer.

1. Introduction

Attribute editing aims to change an or more attributes of images (e.g., hair color, sex, age, style) and preserve other unchanging attributes. The key of transfer images is to keep high quality and accuracy of target attribute images. The presentation of generative adversarial network (GAN) \cite{5} greatly promotes the development of attribute editing projects. The results range from local changes, e.g., changing hair color, adding accessories (glasses, hats) and altering facial expressions, to overall changes such as converting gender, age and style.

On attribute transfer, \cite{19, 11, 21} take images and labels as inputs of generator and discriminator to realize the attribute transfer, and the loss function is only to train the performance of verifying the authenticity of the images in discriminator. However, the images contain many attributes, and some of them are correlated with each other, i.e., there are complex relationships. So it is not enough to implement the attribute transfer only by the inputting label. As a solution to the problem, \cite{3, 6, 17, 27, 15, 20} put forward the attribute classification restriction, which independently train attribute classification. Therefore greatly enhances the performance of attribute transformation. However, these models still exist problem of low transfer accuracy in some special attribute conversion.

Encoder-decoder structure \cite{7} is also introduced to realize the attribute conversion conveniently in some models, whereas the bottleneck layer of the structure will result in poor image quality (e.g., blurring or artifacts). To address this issue, \cite{6, 17} apply skip-connection to the encoder-decoder architecture to improve image quality. However, skip-connection leads to a trade-off between image quality and accuracy \cite{17}, i.e., it generates high quality images at the cost of low attribute accurate.

We investigate the shortages of skip-connection are mainly due to the source attribute and details of the images being both transmitted into the decoder. Though skip-connection is beneficial to improvement of image quality, it
also enhances the attributes information of the source image and reduces the target attribute information. In order to deal with this question and inspired by the residual neural network \[28\], we introduce the upper convolution residual network(Tr-resnet) to enhance the target attribute information in decoder. Tr-resnet can selectively acquire source image information and target label information by combining a certain encoding layer information, the decoding layer inputs and outputs information.

Through the deep understanding of the GAN \[4\], we find the reason that original and generated images are both inputted to the discriminator instead of original images is to make the discriminator learn about the defects of the generated images during training discriminator. Then the discriminator enhances the generator in a certain direction. Recently proposed models \[3, 6, 17, 27, 15\] mostly take the original images as input of discriminator to train the attribute classifier. Nevertheless, these methods do not take the effect of generating images into account to improve generator performance. ACGAN \[20\] also takes generated image as an auxiliary source when training classifier, but the attribute class of generated image is identified as the true category, which weakens classifier training due to the poor quality of the generated images. In this paper, a attribute classification adversarial network is proposed to enhance the classification accuracy. In the training classifier stage, the original image and the generated image are inputted to the classifier where we specify that the attributes of the generated image are indistinguishable and set the attribute values to none.

Meanwhile, drawing on the practices of \[27, 15\], ClsGAN inputs images into two encoders to decouple entanglement between the attributes and unchanged content. What's more, we approach the encoded attribute and reference labels to keep labels continuous. From Figure 1 ClsGAN generates high-quality images with high attribute accuracy.

In conclusion, our contributions are as follows:

1. We propose ClsGAN which has significant improvement in image resolution and attribute classification accuracy. For improve image quality and accurate, we introduce the upper convolution residual network which combined up-sampling with skip-connection technique. This network avoids the drawbacks of a single skip-connection.

2. Influenced by the idea of GAN, we introduce the method of attribute classification adversarial network which applies classifier to guide the generator in certain directions and greatly improve the accuracy of image attributes. At the same time, in order to keep the continuity of attribute label, we approximate the style encoded output to the target label. And ClsGAN designs two encoders to decouple image attribute and content.

3. We propose quantitative and qualitative experimental results in face attribute editing to demonstrate its superiority over the basic model. Art style and season transformation also be used to test the effects of ClsGAN model.

2. Related works

Generative adversarial network GAN \[4\] consists of two parts: generator and discriminator. The generator generates an image as photo-realistic as possible to make it difficult for discriminator to distinguish, while discriminator tries to distinguish the generated image from the original image. In order to maintain stability during training, DCGAN \[22\] applies convolutional neural net(CNN) and batch normalization into the model. \[13\] propose Wasserstein-1 distance and Gradient penalty function to enhance training stability and avoid model crash. CGAN \[19\] takes the reference label as inputs of generator and discriminator to produce specific images that are consistent with the label. GAN has received significant attention since it was proposed, and has been applied to many aspects of the computer field, e.g., image production \[4, 22, 13, 5, 2\], image style transfer \[19\].
Figure 2. The structure of ClsGAN, which mainly includes the structure of generator (a) and discriminator (c). The generator is composed of two encoders and a decoder, which consist of a series of convolution layer and upper convolution residual layer(b) respectively. Discriminator is composed of classifier and adversarial network, whose parameters are Shared.

8, 31, 9], super resolution image [13] and facial attribute transfer [14, 29, 11, 24] to realize the mutual transformation between two domains. With the increase of domains, the number of models increases exponentially, which is not universal and leads to model overfitting and poor generalization ability.

Face attribute editing is an image transformation operation between multiple domains. 8, 6, 17, 27, 15, 16, 30, 25 introduce the attribute classification constraint to discriminator to control the model autonomous implementing attribute classification. StarGAN [3] takes both labels and images as input to control the specific attribute images transfer. AttGAN [6] adds skip-connection based on the structure of encoder-decoder which improve the image quality. 17, 25 both take difference attribute labels as the input. STGAN [17] improves the skip-connection method called STU to auto-selective information between reference images and target label. RelGAN [25] presents matching-aware discriminator and interpolation discriminator to guarantee the attribute transfer and interpolation quality. AMEGAN [27] separates the input images into image attribute part and image background part on manifolds. Then it enforces attribute latent variables to Gaussian distributions and background latent variables to uniform distributions respectively to achieve attribute transfer procedure controllable. AGUIT [15] utilizes a novel semi-supervised learning process. Then it decomposes image representation into domain-invariant content code and domain-specific style code to handle multi-modal and multi-domain tasks of un-
paired image-to-image translation jointly. In [16], multi-path consistency loss is introduced to evaluate the differences between direct and indirect translation to regularize training. UGAN [30] employs a source classifier in discriminator to determine whether the translated image still holds the features of the source domain, so that remove the irrelevant source features. In ACGAN [20], transfer images are also used as an auxiliary source to train classifier training. In this paper, we propose ClsGAN, which applies Tr-resnet and attribute classification adversarial network to improve image quality and attribute accuracy.

3. Proposed Method

This section presents the ClsGAN model for arbitrary attribute editing. Firstly, we build the generator framework of ClsGAN by introducing upper convolution residual network and attribute continuity processing. Then, ClsGAN puts forward an adversarial network about attribute classification in discriminator to enhance the accuracy of attribute. Finally, the network structure and model target of ClsGAN are proposed.

3.1. Upper convolution residual network (Tr-resnet)

STGAN [17] proves that skip-connection in AttGAN [6] is beneficial to improvement of image quality at the cost of attribute classification accuracy, so STGAN modifies skip-connection called STU. However, it requires more parameters than AttGAN, and the process is relatively complex. In this paper we propose the upper convolution residual network which has the same effect as STU, simple procedure and few parameters. The Tr-resnet structure is shown in Figure 2(b).

In deep learning, the phenomenon of gradient vanishing will become more obvious as the number of layers deepens. Therefore, Kaiming He et al. [17] propose ResNet to avoid gradient vanishing. Inspired by this idea, we introduce the upper convolution residual network in the decoder to evade loss of original image and target label information. What’s more, for the sake of selective use of resource image and target attribute information, we apply weights to the resource image information in encoder, the current layer and the upper-layer information of decoder. Specific operations are as follows:

\[ y_l^* = Ty_l \]  (1)

\[ f_{l+1} = \begin{cases} 
\alpha \cdot y_l^* + (1 - \alpha) \cdot y_{l+1} & (l \neq 3) \\
\alpha \cdot y_3^* + (1 - \alpha) \cdot y_4 + \beta \cdot x_2 & (l = 3) 
\end{cases} \]  (2)

Where \( y_l \) denotes the decoder feature of \( l \)-th layer, \( T \) denotes transposed convolution operation. \( x_2 \) denotes the encoder feature of 2-th layer, \( f_l \) denotes the output of \( l \)-th of decoder. In formula (2), when \( l = 3 \), the model weights and sums about the 2-th layer feature graph information of the encoder, the 4-th layer input and output information of the decoder as the output of the 4-th layer of decoder. When \( l \neq 3 \), the output of decoder is the weighted sum of information the input and output of \( l \)-th layer. We initialize \( \alpha = (a_1, a_2, ..., a_s) \), \( \beta = (b_1, b_2, ..., b_a) \), where \( a_i, b_i \sim \text{uniform}(0, 1) \) and \( s \) equals the number of feature map in \( y_{l+1} \) or \( x_2 \).

3.2. Attribute consistency processing

StarGAN [3] and STGAN [17] generate a transfer image with a specific attribute value (0 or 1), but such an image is relatively single and discontinuous about attribute. AttGAN [6] employs an style controller to realize multi-modal for a specific attribute on the basis of source model. In order to control the attribute value continuously, the attribute value obtained by the attribute encoder is approximated to the real attribute value in this paper. The optimization formula is as follows:

\[ L_a = ||t_r - E_a(x_r)||_1 \]  (3)

Where \( t_r \) denotes reference label of source image. \( E_a \) denotes attribute encoder in generator. \( || \cdot ||_1 \) denotes \( l_1 \) loss.

3.3. Attribute classified adversarial network

GAN [4] updates the generator according to the deficiency of generated image which is learned about by the discriminator. Based on this idea, we apply the adversarial method to classification attributes. [3, 6, 17] take real images as the input of classifier, and then use the optimized classifier to improve the generator. However, it is difficult for classifier to discover the difference between the generated images and source images.

In our model, the classifier is designed as an adversarial network. The source image and the generated image are fed into the classifier to optimize classifier simultaneously, and then the classifier trains the generator according to the defects in the generated image. When training classifier about source images, the category is required to be separable and the value is defined as 1(true) at the same time the attribute value is correct. So the classifier needs to optimize the whole attribute evaluation values for the source images. In contrast, classifier only needs to assume that it is inseparable for generated images and the value is 0(false), so the remaining classification attribute values are not considered needlessly. The detailed operation is shown in (c) in Figure 2. Meanwhile, in order to maintain the stability of the model, ClsGAN adds a penalty function for classification loss. The concrete operation is shown in the loss function. We define the loss function of training generator
and classifier about classification adversarial net as follows:

\[ R_a = \frac{1}{n} \sum_{i=1}^{n} \left[ t_r^{(i)} l(s(C^{(i)}(x_r))) + (1 - t_r^{(i)}) l(1 - s(C^{(i)}(x_r))) \right] \]

\[ F_a = t_f^{(i)} l(s(C^{(1)}(x_f))) + (1 - t_f^{(i)}) l(1 - s(C^{(1)}(x_f))) \]

\[ \max_C L_{Cd} = R_a + F_a + \lambda E_{x^*} \left[ ||\nabla x^* C(x^*)||_2 - 1 \right]^2 \]

\[ \max_C L_{Cg} = \frac{1}{n} \sum_{i=1}^{n} \left[ t_r^{(i)} l(s(C^{(i)}(x_r))) + (1 - t_r^{(i)}) l(1 - s(C^{(i)}(x_r))) \right] \]

\[ \max_C L_{Cg} = \frac{1}{n} \sum_{i=1}^{n} \left[ t_f^{(i)} l(s(C^{(1)}(x_f))) + (1 - t_f^{(i)}) l(1 - s(C^{(1)}(x_f))) \right] \]

Where \( L_{Cd} \) and \( L_{Cg} \) denote the loss functions when training classifier \( C \) and generator about attributes. \( R_a, F_a \) represent classification losses in source and transfer images respectively. \( E_{x^*} \) denotes gradient penalty term about \( x^* \) which is obtained by line sampling between the original and the generated images. \( x_r \) and \( x_f \) are source and transfer images. \( t_r \) and \( t_f \) are both the vector with \( n+1 \)-dimensions, where the first dimension is used to determine whether the attribute is separable or not, define \( t_r^{(1)} = 1, t_f^{(1)} = 0, \) and
the remaining n-dimensions vector represents the values of the image’s difference attributes. \( l \) and \( s \) denote log function and sigmoid function respectively. \( t_{r/f}^{(i)}/C^{(i)}(x_{r/f}) \) represents \( i \)-th attribute value in target label \( t_{r/f} \) or evaluate label \( C(X_{r/f}) \).

### 3.4. Network structure

Fig. 2 shows the frame diagram of the network structure, in which the generator includes two encoders and a decoder. The encoder consists two convolutional neural networks \( E_c, E_a \), which operate about image contents and attributes respectively. \( E_c \) extracts high-level semantic features about image content from source image and obtains feature vectors of size \( 512 \times 16 \times 16 \). An image attribute feature is extracted by \( E_a \) from the original image to obtain a vector with the same dimension as the reference label.

The decoder \( E_d \) concatenates the content features from \( E_c \) and attribute feature from \( E_a \) (or the reference label) which extends to the same size as the content feature to construct a whole feature vector. Then decoder \( E_d \) takes the whole feature vector as input to generate reconstructed images or images with specific attributes. For purpose of selective use of attribute information and original image information, the decoder \( E_d \) that consists of a series of up-sampled convolutional layers applies the structure of upper residual network. The specific structure is shown in Figure 2(b).

The discriminator \( D \) consists of a series of convolution layers, and it shares parameters with the classifier \( C \) which has the same structure with \( D \) (except for the last layer). The source image and generated image are used as the input of discriminator and classifier. It is assumed that the image attribute dimension is \( n \) dimension. So the output dimension of classifier is \( n + 1 \) dimension. The first dimension is used to distinguish whether the attribute is separable or not and the remaining \( n \) dimension vector correspond to the \( n \)-dimensional attributes of the images. By referring to the method of loss function in target detection \([23]\), the classification vector of the generated image only takes the first dimension for loss function operation, and the other dimensions are expressed as none in the training classifier stage. The specific method is shown in Figure 2(c).

### 3.5. Loss function

**Adversarial loss** In order to maintain stability, we follow the loss function defined by WGAN \([11]\) and WGAN-GP \([5]\), and define the loss function of generator and discriminator during training as follows:

\[
\max_D L_D = E_x D(x) - E_{x,c} D(G(x,c)) + \lambda E_x [||\nabla_{x'} D(x')||_2 - 1]^2 \quad (8)
\]

\[
\max_G L_G = E_{x,c} D(G(x,c)) \quad (9)
\]

**Reconstitution loss** StarGAN reconstructs the original images by means of cycle consistency loss, which is not direct enough and will increase the lack of image generation during the cycle. In contrast, ClsGAN uses the attribute encoder to directly encode the input image attributes, and then directly takes the attributes and content features into the decoder to reconstruct the image. The reconstitution loss function is as follows:

\[
L_{\text{rec}} = ||x - E_d(E_c(x), E_a(x))||_1 \quad (11)
\]

Where the \( L_1 \) norm is used to suppress blurring of reconstitution images and to maintain clarity.

**Object model** Considering formula (7),(9), the target loss functions of training discriminator \( D \) and classifier \( C \) can be expressed as:

\[
\min_{C,D} L_{CD} = -L_D - \lambda_1 L_{Ca} \quad (12)
\]

The target function of the generator is:

\[
\min_G L_{\text{alt}} = -L_G - \lambda_2 L_{Cg} + \lambda_3 L_{\text{rec}} + \lambda_4 L_a \quad (13)
\]

Where \( L_{Cg}, L_{Ca} \) denote classification adversarial losses of classifier and generator which is mentioned in section 3.2. \( L_a \) denotes the attribute approximation loss mentioned in section 3.3. \( \lambda_1, \lambda_2, \lambda_3, \lambda_4 \) are model tradeoff parameters.
4. Experiments

We use Adam optimizer to train the model, and its’ parameters are set to $\beta_1 = 0.5, \beta_2 = 0.999$. The learning rate of the first 10 epoch is set as $2 \times 10^{-4}$, and it is linearly attenuated to 0 at the next 10 epoch. In all experiments, the parameter is set as $\lambda_1 = 0.5, \lambda_2 = 1, \lambda_3 = 20$ and $\lambda_4 = 1$. All experiments are both performed in a Pytorch environment, with training on a single GeForce RTX 2080 GPU. Source code can be found at https://github.com/liuying/Cls-GAN.git.

4.1. Dataset

CelebA [18] is used in this paper for training and testing of facial attribute transformation. The CelebA dataset is a large face dataset, which contains more than 200,000 images of celebrities’ faces and 40 facial attributes. In this paper, the last 2000 images of the dataset are used as the test set, and the remaining images are all used as the training set. We perform center cropping the initial $178 \times 218$ size images to $170 \times 170$, then resize them as $128 \times 128$ for training and test images.

13 of the 40 attributes are selected for attribute transfer in the paper, which are "Bald", "Bangs", "Black Hair", "Blond Hair", "Brown Hair", "Bushy Eyebrows", "Eyeglasses", "Gender", "Mouth Open", "Mustache", "No Beard", "Pale Skin" and "Age". These attributes already covers the most prominent of all attributes.

4.2. Image Quality Assessment

The FID method is used to evaluate the image quality. ClsGAN, StarGAN, AttGAN and STGAN models all use the test set of ClsGAN model to generate transformed images. All 13 attribute images corresponding to each source image in test set are randomly selected 5 as the dataset(a total of 10,000 generated images) to evaluate image quality. At the same time, SSIM is adopted to evaluate the similarity between reconstructed images and original images. The specific comparison results are shown in Table 1, from which it can be seen that the method in this paper is superior to other methods in image quality, indicating that the use of upper convolution residual network operation is indeed helpful to improve the quality of generated images. Compared with STGAN, we improved the reconstruction rate by 4 percentage points to 97%.

Meanwhile, we also shows the transfer effects and reconstruction effects generated by these four methods. The generated image is almost indistinguishable from the original image in terms of image quality from Figure 1. From Figure 5, ClsGAN has a higher degree of restoration in the aspects of background color and skin color compared with AttGAN and STGAN.

| Method  | StarGAN  | AttGAN  | STGAN   | our      |
|---------|----------|---------|---------|----------|
| F,S     | 7.9/0.56 | 7.1/0.8 | 6.1/0.92| 5.9/0.97 |

Table 1. We use FID(F) and SSIM(S) to evaluate Visual and Reconstruction quality.

![Attribute accuracy](image)

Figure 6. The attribute accuracy about StarGAN,AttGAN,STGAN and ClsGAN

4.3. Image attribute resolution evaluation

In order to evaluate the classification accuracy, we use the training set of CelebA dataset to train a classifier for 13 attributes, and use the same test set with ClsGAN model. The average accuracy of test set is 93%. Similarly, the three comparison models mentioned in 4.1 section are compared in terms of attribute accuracy with our model. For single attribute transfer, it can be seen from Figure 3 that the results of our model have a great improvement on the overall level of attributes.

In order to further compare the transformation ability of each model, we listed the conversion rate of 13 attributes on the test set about four models in the form of a bar chart. From the figure 6, the ‘Bangs’ attribute transfer accuracy is improved by 10 percentage points compared with STGAN, and the ‘Mouthopen’ attribute is improved by 6 percentage points compared with AttGAN.

To show the effects of attribute approximation method, Figure 4 lists the transfer images of the above four models with values attribute label of 0, 0.2, 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6 respectively. We not only test attribute values between 0 and 1, but also values that is bigger than 1, and the performance was still great. It indicates that our model implements the continuity of attributes. We can see that the transformation effect is good on continuity for largely modified information about the source images (such as bangs).

4.4. Seasons and artistic styles transfer

In order to prove the transformation ability, we also use the model to realize the mutual transformation between dif-
different seasons and different artistic styles. The seasonal images are from the unplash website. The number of images of different seasons are: spring (29343), summer (23395), fall (7630) and winter (13433). Images of artistic style mainly come from wikiart website, and ClsGAN realizes the mutual transformation between four styles and photographs. The scale of images is Monet: 1050, Cezanne: 582, VanGogh: 1931, ukiyo-e: 1372, photograph: 4674. The photos are downloaded from Flickr and use landscape labels.

It can be seen from the Figure 7-8 that we realizes the transformation of seasons and styles of images, and the images quality is high, indicating that the model learns the features between different attributes and the unchanged features in the images.

5. Concludes

ClsGAN solves the constraint problem between image attribute and quality caused by skip-connection by introducing the upper convolution residual network (Tr-resnet), which provides the a method for producing high quality and attribute accuracy images. In order to improve the attribute accuracy of the generated image, we propose the classified adversarial network inspired by the generated adversarial network. At the same time, in order to meet the requirement of multimodal, we make an approximation between reference label and attribute feature vector generated by style encoder. Experiments demonstrate the great effectiveness of ClsGAN in face attribute editing, style and season conversion.

References

[1] Martin Arjovsky, Soumith Chintala, and Léon Bottou. Wasserstein generative adversarial networks. In International conference on machine learning, pages 214–223, 2017.
[2] Andrew Brock, Jeff Donahue, and Karen Simonyan. Large scale gan training for high fidelity natural image synthesis. arXiv preprint arXiv:1809.11096, 2018.
[3] Yunjey Choi, Minje Choi, Munyoung Kim, Jung-Woo Ha, Sunghun Kim, and Jaegul Choo. Stargan: Unified generative adversarial networks for multi-domain image-to-image translation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 8789–8797, 2018.
[4] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In Advances in neural information processing systems, pages 2672–2680, 2014.
[5] Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, and Aaron C Courville. Improved training of wasserstein gans. In Advances in neural information processing systems, pages 5767–5777, 2017.
[6] Zhenliang He, Wangmeng Zuo, Meina Kan, Shiguang Shan, and Xilin Chen. Attgan: Facial attribute editing by only changing what you want. IEEE Transactions on Image Processing, 2019.
[7] Geoffrey E Hinton and Richard S Zemel. Autoencoders, minimum description length and helmholtz free energy. In Advances in neural information processing systems, pages 3–10, 1994.
[8] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1125–1134, 2017.
[9] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4401–4410, 2019.
[10] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114, 2013.
[11] Guillaume Lample, Neil Zeghidour, Nicolas Usunier, Antoine Bordes, Ludovic Denoyer, et al. Fader networks:
Manipulating images by sliding attributes. In Advances in Neural Information Processing Systems, pages 5967–5976, 2017.

[12] Anders Boesen Lindbo Larsen, Søren Kaae Sønderby, Hugo Larochelle, and Ole Winther. Autoencoding beyond pixels using a learned similarity metric. arXiv preprint arXiv:1512.09300, 2015.

[13] Christian Ledig, Lucas Theis, Ferenc Huszár, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, et al. Photo-realistic single image super-resolution using a generative adversarial network. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4681–4690, 2017.

[14] Mu Li, Wangmeng Zuo, and David Zhang. Deep identity-aware transfer of facial attributes. arXiv preprint arXiv:1610.05586, 2016.

[15] Xinyang Li, Jie Hu, Shengchuan Zhang, Xiaopeng Hong, Qixiang Ye, Chenglin Wu, and Rongrong Ji. Attribute guided unpaired image-to-image translation with semi-supervised learning. arXiv preprint arXiv:1904.12428, 2019.

[16] Jianxin Lin, Yingce Xia, Yijun Wang, Tao Qin, and Zhibo Chen. Image-to-image translation with multi-path consistency regularization. arXiv preprint arXiv:1905.12498, 2019.

[17] Ming Liu, Yukang Ding, Min Xia, Xiao Liu, Errui Ding, Wangmeng Zuo, and Shilei Wen. Sigan: A unified selective transfer network for arbitrary image attribute editing. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3673–3682, 2019.

[18] Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep learning face attributes in the wild. In Proceedings of the IEEE international conference on computer vision, pages 3730–3738, 2015.

[19] Mehdi Mirza and Simon Osindero. Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784, 2014.

[20] Augustus Odena, Christopher Olah, and Jonathon Shlens. Conditional image synthesis with auxiliary classifier gans. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 2642–2651. JMLR. org, 2017.

[21] Guim Perarnau, Joost Van De Weijer, Bogdan Raducanu, and Jose` M Álvarez. Invertible conditional gans for image editing. arXiv preprint arXiv:1611.06355, 2016.

[22] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434, 2015.

[23] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 779–788, 2016.

[24] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention, pages 234–241. Springer, 2015.

[25] Po-Wei Wu, Yu-Jing Lin, Che-Han Chang, Edward Y Chang, and Shih-Wei Liao. Relgan: Multi-domain image-to-image translation via relative attributes. arXiv preprint arXiv:1908.07269, 2019.

[26] Taihong Xiao, Jiapeng Hong, and Jinwen Ma. Dna-gan: learning disentangled representations from multi-attribute images. arXiv preprint arXiv:1711.05415, 2017.

[27] De Xie, Muli Yang, Cheng Deng, Wei Liu, and Dacheng Tao. Fully-featured attribute transfer. arXiv preprint arXiv:1902.06258, 2019.

[28] Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He. Aggregated residual transformations for deep neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1492–1500, 2017.

[29] Shuchang Zhou, Taihong Xiao, Yi Yang, Dieqiao Feng, Qinyao He, and Weiran He. Genegan: Learning object transfiguration and attribute subspace from unpaired data. arXiv preprint arXiv:1705.04932, 2017.

[30] Defa Zhu, Si Liu, Wentao Jiang, Chen Gao, Tianyi Wu, and Guodong Guo. Ugan: Untraceable gan for multi-domain face translation. arXiv preprint arXiv:1907.11418, 2019.

[31] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE international conference on computer vision, pages 2223–2232, 2017.