Semi-Latent GAN: Learning to generate and modify facial images from attributes

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Abstract
Generating and manipulating human facial images using high-level attributal controls are important and interesting problems. The models proposed in previous work can solve one of these two problems (generation or manipulation), but not both coherently. This paper proposes a novel model that learns how to both generate and modify the facial image from high-level semantic attributes. Our key idea is to formulate a Semi-Latent Facial Attribute Space (SL-FAS) to systematically learn relationship between user-defined and latent attributes, as well as between those attributes and RGB imagery. As part of this newly formulated space, we propose a new model – SL-GAN which is a specific form of Generative Adversarial Network. Finally, we present an iterative training algorithm for SL-GAN. The experiments on recent CelebA and CASIA-WebFace datasets validate the effectiveness of our proposed framework. We will also make data, pre-trained models and code available.

1. Introduction
Analysis of faces is important for biometrics, non-verbal communication, and affective computing. Approaches that perform face detection [3, 21], facial recognition [1, 33, 41], landmark estimation [2, 44], face verification [36, 37] and action coding have received significant attention over the past 20+ years in computer vision. However, an important problem of generation (or modification) of facial images based on high-level intuitive descriptions remains largely unexplored. For example, it would be highly desirable to generate a realistic facial composite based on eyewitness’ high level attributal description (e.g., young, male, brown hair, pale skin) of the suspect. Further, modifying facial attributes of a given person can help to inform criminal investigation by visualizing how a suspect may change certain aspects of their appearance to avoid capture. In more innocuous use cases, modifying facial attributes may help a person visualize what he or she may look like with a different hair color, style, makeup and so on.

In this paper, we are interested in two related tasks: (i) generation of facial images based on high-level attribute descriptions and (ii) modifying facial images based on the high-level attributes. The difference in the two tasks is important, for generation one is interested in generating (a sample) image from a distribution of facial images that con-
tain user-specified attributes. For modification, we are interested in obtaining an image of the pre-specified subject with certain attributes changed. In both cases, one must take care to ensure that the resulting image is of high visual quality; in the modification case, however, there is an additional constraint that identity of the person must be maintained. Intuitively, solving these two tasks requires a generative model that models semantic (attributal) space of faces and is able to decouple identity-specific and identity-independent aspects of the generative process.

Inspired by [10], we formulate the Semi-Latent Facial Attribute Space (SL-FAS) which is a composition of two, user-defined and latent, attribute subspaces. Each dimension of user-defined attribute subspace corresponds to one human labeled interpretable attribute. The latent attribute space is learned in a data-driven manner and learns a compact hidden structure from facial images.

The two subspaces are coupled, making learning of SL-FAS challenging. Recently, in [42], attribute-conditioned deep variational auto-encoder framework was proposed that can learn latent factors (i.e. attributes) of data and generate images given those attributes. In [42], only the latent factors are learned and the user-defined attributes are given as input. Because of this, they can not model the distribution of user-defined attributes for a given an image; leading to inability to modify the image using semantic attributes. Inspired by InfoGAN [4], we propose a network that jointly models the subspace of user-defined and latent attributes.

In this paper, to jointly learn the SL-FAS, we propose a Semi-Latent Generative Adversarial Network (SL-GAN) framework which is composed of three main components, namely, (i) encoder-decoder network, (ii) GAN and (iii) recognition network. In encoder-decoder network, the encoder network projects the facial images into SL-FAS and the decoder network reconstructs the images by decoding the attribute vector in SL-FAS. Thus the decoder network can be used as a generator to generate an image if given an attribute vector. The GAN performs the generator and discriminator min-max game to ensure the generated images are of good quality, by ensuring that generated images cannot be discriminated from the real ones. Recognition network is the key recipe of jointly learning user-defined and latent attributes from data. Particularly, the recognition network is introduced to maximize the mutual information between generated images and attributes in SL-FAS. Figure 1 gives the examples of generating and modifying the facial attributes. As shown in the first and third rows of modification Figure 1 (b), our SL-GAN can modify the attributes of facial images in very noisy background.

Contributions. (1) To the best of our knowledge, there is no previous work that can do both generation and modification of facial images using visual attributes. Our framework only uses high-level semantic attributes to modify the facial images. (2) Our SL-GAN can systematically learn the user-defined and latent attributes from data by formulating a semi-latent facial attribute space. (3) A novel recognition network is proposed that is used to jointly learn the user-defined and latent attributes from data. (4) Last but not the least, we propose an iterative training algorithm to train SL-GAN in order to solve two related and yet different tasks at the same time.

2. Related Work

Attribute Learning. Attribute-centric semantic representations have been widely investigated in multi-task [31] and transfer learning [19]. Most early works [19] had assumed a space of user-defined namable properties as attributes. User-defined facial attributes [5, 9, 30, 40, 45, 18] had also been explored. These attributes, however, is hard and prohibitively expensive to specify, due to the manual effort required in defining the the attributal set and annotating images with that set. To this end, latent attributes [10] have been explored for mining the attributes directly from data. It is important to note that user-defined and latent attributes are complementary to one another and can be used and learned simultaneously, forming a semi-latent attribute space. Our SL-GAN model is a form of semi-latent attribute space specifically defined for generation and modification of facial images.

Deep Generative Image Modeling. Algorithmic generation of realistic images has been the focus of computer vision for some time. Early attempts along these lines date back to 2006 with Deep Belief Networks (DBNs) [13]. DBNs were successful for small image patch generation, but failed to generalize to larger images and more holistic structures. Recent models that address these challenges, include auto-regressive models [16, 38, 39], Variational Auto-Encoders (VAEs) [20, 35, 42], Generative Adversarial Networks (GANs) [4, 6, 7, 8, 11, 14, 17, 24, 27, 28, 29], and Deep Recurrent Attention Writer (DRAW) [12]. InfoGAN [4] and stackGAN [14] utilized the recognition network to model the latent attributes, while our SL-GAN extends the recognition network to jointly model user-defined and latent attributes and thus our framework can both generate and modify the facial images using attributes.

Semantic Image Generation. More recently, there has been a focus on generating images conditioned on semantic information (e.g., text, pose or attributes). Reeds et al. [28] studied the problem of automatic synthesis of realistic images from text using deep convolutional GANs. Yan et al. [42] proposed an attribute-conditioned deep variational auto-encoder framework that enables image generation from visual attributes. Mathieu et al. [23] learned the hidden factors within a set of observations in the conditional generative model. However, their frameworks can only gen-
erate the images rather than modifying an existing image based on attributes or other form of semantic information.

**Image Editing and Synthesis.** Our work is also related to previous work on image editing [15, 26, 34, 46]. The formulation in [47] also enables task of image editing using GAN, where the user strokes are used to specify the attributes being changed. In contrast, our SL-GAN does not need user strokes as input. Very recently, two technical reports [26, 34] can also enable modifying the attribute of facial images. [34] proposed a GAN-based image transformation networks for face attribute manipulation. In [34], one trained model can only modify one type attribute in facial images; in contrast, our SL-GAN can learn to generate or modify many attributes simultaneously. In fact, our models on CelebA dataset can generate or modify 17 different facial attributes all at ones.

### 3. Semi-Latent GAN (SL-GAN)

#### 3.1. Background

GAN [11] aims to learn to discriminate real data samples from generated samples; training the generator network \( G \) to fool the discriminator network \( D \). GAN is optimized using the following objective,

\[
\min_{G} \max_{D} \mathcal{L}_{GAN} = \mathbb{E}_{x \sim p_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_{prior}(z)} [\log (1 - D(G(z))]),
\]

where \( p_{data}(x) \) is the distribution of real data; \( p_{prior}(z) \) is a zero-mean Gaussian distribution \( \mathcal{N}(0, 1) \). The parameters of \( G \) and \( D \) are updated iteratively in training. The loss function for generator and discriminator are \( \mathcal{L}_{D} = \mathcal{L}_{GAN} \) and \( \mathcal{L}_{G} = -\mathcal{L}_{GAN} \) respectively. To generate an image, generator draws a sample \( z \sim p_{prior}(z) = \mathcal{N}(0, 1) \) from prior (a.k.a., noise distribution) and then transforms that sample using a generator network \( G \), i.e., \( G(z) \).

InfoGAN [4] decomposes the input noise of GAN into latent representation \( y \) and incompressible noise \( z \) by maximizing the mutual information \( I(y; G(z, y)) \) and it ensures no loss information of latent representation during generation. The mutual information term can be described as the recognition loss,

\[
\mathcal{L}_{rg} = -\mathbb{E}_{x \sim p_{data}(x)} \left[ \mathbb{E}_{y \sim p_{data}(y|x)} [\log Q(y|x)] \right]
\]

where \( Q(y|x) \) is an approximation of the posterior \( p_{data}(y|x) \). Thus the parameters of the generator \( G \) can thus be updated as \( \mathcal{L}_{G_{InfoGAN}} = \mathcal{L}_{G} - \mathcal{L}_{rg} \). InfoGAN can learn the disentangled, interpretable and meaningful representations in a completely unsupervised manner.

**VAE [20]** combines the VAE into GAN and replaces the element-wise errors of GAN with feature-wise errors of VAEGAN in the data space. Specifically, it encodes the data sample \( x \) to latent representation \( z: z \sim Enc(x) = p_{enc}(z|x) \) and decodes the \( z \) back to data space: \( \tilde{x} \sim Dec(x|z) = p_{dec}(x|z) \). We can define the loss functions of the regularization prior as \( \mathcal{L}_{prior} = KL(q_{enc}(z|x) \| p_{prior}(z)) \), \( q_{enc}(z|x) \) is the approximation to the true posterior \( p_{dec}(z|x) \). The reconstruction error is \( \mathcal{L}_{recon} = -\mathbb{E}_{q_{enc}(z|x)} \left[ \log p_{dec}(D_{l}(x|z)) \right] \) where \( D_{l}(x) \) is hidden representation of \( l \)-th layer of the discriminator. Thus this loss minimizes the sum of the expected log likelihood of the data representation of \( l \)-th layer of discriminator. Thus the loss function of VAEGAN is

\[
\mathcal{L}_{VAE} = \mathcal{L}_{GAN} + \mathcal{L}_{recon} + \mathcal{L}_{prior}
\]

However the latent representation \( z \) is totally unsupervised; there is no way to explicitly control the attributes over the data or modify facial images using attributes.

**CVAE** [42, 35] is the conditional VAE. The independent attribute variable \( y \) is introduced to control the generating process of \( x \) by sampling from \( p(x|y,z) \); where \( p(y,z) = p(y)p(z) \). The encoder and decoder networks of CVAE are thus \( z \sim Enc(x) = q_{enc}(z|x) \) and \( \tilde{x} \sim Dec(z,y) = p_{dec}(x|z,y) \). The variable \( y \) is introduced to control the generate process of \( x \) by sampling from \( p(x|y,z) \); where \( p(y,z) = p(y)p(z) \). Nevertheless, \( y \) is still sampled from data, rather than being directly optimized and learned from the data as our SL-GAN. Thus \( y \) can be used to modify the attributes similar to proposed SL-GAN.

#### 3.2. Semi-Latent Facial Attribute Space

The input noise of GAN can be further decomposed into two parts: (1) User-defined attributes \( y \) are the manually annotated attributes of each image \( x \), i.e. \( y \sim p_{data}(y|x) \); (2) Latent attributes \( z_{la} \) indicate the attributes that should be mined from the data\(^1\) in a data-driven manner, i.e., \( z_{la} \sim p_{data}(z_{la}|x) \).

Mathematically, the \( y \) and \( z_{la} \) can be either univariate or multivariate; and these attributes are mutual independent, i.e., \( p(y, z_{la}) = p(y)p(z_{la}) \). Each dimension of \( y \)

\(^1\)Note that the latent attribute \( z_{la} \) also includes the incompressible noise, which is not explicitly modelled due to less impact to our framework.
is clipped with one type of facial attribute annotated in real images; our SL-GAN train $y$ in a supervised manner. In contrast, each dimension of $z_{la}$ is trained totally unsupervised. We define semi-latent facial attribute space to combine both $y$ attributes and the latent $z_{la}$ attributes.

With the decomposed input noise, the form of generator is $G(z_{la}, y)$ now. Directly learning $z_{la}$ from input data will lead to the trivial solution that the generator is inclined to ignore the latent attributes as $p_G(x \mid z_{la}, y) = p_G(x \mid y)$. In contrast, we maximize the mutual information between the attributes $z_{la}$ and the generator distribution $G(z_{la}, y)$, which can be simplified as minimizing the recognition loss for the attribute $y$ and $z_{la}$.

It is important to jointly learn the attributes $y$ and $z_{la}$; and make sure that $z_{la}$ can represent un-modeled aspects of the input facial images rather than re-discovering $y$. The “re-discovering” means that some dimensions of $z_{la}$ have very similar distribution as the distribution of $y$ over the input images, i.e., the same patterns in $y$ repeatedly discovered from latent attributes $z_{la}$.

### 3.3. Semi-Latent GAN

Our SL-GAN is illustrated in Fig. 2; it is composed of three parts, namely, encoder-decoding network, GAN and recognition network. The user-defined and latent attributes are encoded and decoded by the encoder-decoder network. Recognition network helps learn the SL-FAS from data. In our SL-GAN, the recognition network and discriminator shares the same network structure and have different softmax layer at the last layer. The loss functions of the generator $G_{SL-GAN}$ and discriminator $D_{SL-GAN}$ are thus,

$$
\mathcal{L}_{G_{SL-GAN}} = \mathcal{L}_G + \lambda_1 (\mathcal{L}_{rgy} + \mathcal{L}_{rgy-D}) + \lambda_2 \mathcal{L}_{recon} \tag{3}
$$

$$
\mathcal{L}_{D_{SL-GAN}} = \mathcal{L}_D + (\mathcal{L}_{rgy-D} + \mathcal{L}_{rgy}) \tag{4}
$$

where $\mathcal{L}_{rgy}$ is the recognition loss on $z_{la}$. For recognition loss on $y$, we use $\mathcal{L}_{rgy-D}$ and $\mathcal{L}_{rgy}$ as the loss for the discriminator and generator respectively. We also define the decoder loss as $\mathcal{L}_{dec} = \mathcal{L}_{G_{SL-GAN}}$ and the encoder loss as $\mathcal{L}_{enc} = \mathcal{L}_{VAE}$.

**Encoder loss** $\mathcal{L}_{enc}$ is the sum of reconstruction error of the variational autoencoder and a prior regularization term over the latent distribution $z_{la}$; thus it is defined as $\mathcal{L}_{VAE} = \mathcal{L}_{prior} + \mathcal{L}_{recon}$ and the $\mathcal{L}_{prior} = KL(q_{enc}(z_{la} \mid x) \| p_{prior}(z_{la}))$ measures the KL-divergence between approximate posterior $q_{enc}(z_{la} \mid x)$ and the prior $p_{prior}(z_{la})$. The reconstruction loss $\mathcal{L}_{recon} = -E_{z \sim q_{enc}(z_{la} \mid x), y \sim p_{data}(y \mid x)} \log p_{dec}(x \mid z_{la}, y)$ measures loss of reconstructing generated images by sampling the attributes in SL-FAS. Here, $q_{enc}(z_{la} \mid x)$ is an approximation of $p_{enc}(z_{la} \mid x)$ parameterized by a neural network, e.g., the encoder.

The recognition loss of $z_{la}$ is trained on both generated data and real data. It aims at predicting the values of latent attributes. Suppose the latent $z_{la} \sim p_{enc}(z \mid x)$ is sampled from the distribution of encoder network. The update steps of generator and discriminator use the same recognition loss on $z_{la}$ defined as,

$$
\mathcal{L}_{rgy} = -E_{x \sim p_{data}(x), z \sim p_{enc}(z_{la} \mid x)} \log (Q(x \mid z)) \tag{5}
$$

$$
-\mathcal{L}_{rgy-D} = -E_{x \sim p_{dec}(x \mid z, y) \sim p_{data}(y \mid x), z \sim p_{enc}(z_{la} \mid x)} \log (Q(x \mid z)) \tag{6}
$$

$$
-\mathcal{L}_{rgy} = -E_{x \sim p_{dec}(x \mid z, y) \sim p_{data}(y \mid x), z \sim p_{prior}(z_{la})} \log (Q(x \mid z)) \tag{7}
$$

Note that intrinsically in each term in Eq (5) and (7) could be weighted by a coefficient. Here we omit these coefficients for the ease of notation.
3.4. The training algorithms

Our SL-GAN aims at solving generation and modification of facial images via attributes. The key ingredients are to learn a disentangled representation of data-driven attributes \( z_{la} \) and user-defined attributes \( y \) unified in our SL-GAN framework. Our SL-GAN is composed of three key components and aims at solving two related but yet very different problems – generation and modification of facial images. The conventional way of training GAN does not work in our problem. Thus we propose a new training algorithms to train our SL-GAN. Specifically, one iteration of our algorithm needs to finish the following three stages,

Learning facial image reconstruction. This stage mainly updates the encoder-decoder network and learns to reconstruct the image given corresponding user-defined attributes with the steps of,

- Sampling a batch of images \( x \sim p_{data}(x) \) and attributes \( y \sim p_{data}(y) \), \( z_{la} \sim p_{enc}(z \mid x) \)
- Updating the SL-GAN by minimizing the encoder \( \mathcal{L}_{enc} \), Decoder \( \mathcal{L}_{dec} \) and Discriminator with \( \mathcal{L}_{DSL-GAN} \) iteratively.

Learning to modify the facial image. We sample an image \( x \) and the attribute \( y \) from all data. This stage trains the SL-GAN to be able to modify the image \( x \) by supplying \( y \). Note that the image \( x \) does not necessarily have the attribute \( y \). Another important question here is how to keep the same identity of sampled images when modifying the facial image; two strategies are employed here: first, \( z_{la} \) is sampled from \( p_{enc}(z \mid x) \) parameterized by the encoder network which is not updated in this sub-step; second, our SL-GAN minimizing the \( \mathcal{L}_{recon} \) essentially to guarantee the identity of the same person. Thus this step encourages the generator to learn a disentangled representation of \( y \) and \( z_{la} \).

- Learning to modify the attributes: Sample a batch of images \( x \sim p_{data}(x) \) and the attribute \( y \sim p_{data}(y) \), \( z_{la} \sim p_{enc}(z \mid x) \);
- Update the SL-GAN by minimizing the Decoder \( \mathcal{L}_{dec} \) and Discriminator with \( \mathcal{L}_{DSL-GAN} \) iteratively;

Learning to generate facial images. We sample \( z_{la} \) from their prior distributions and \( y \) from the distribution of data, i.e.

- Sample a batch of latent vectors \( z_{la} \sim p_{prior}(z) \) and attribute vectors \( y \sim p_{data}(y) \).
- Update the SL-GAN by minimizing the Decoder \( \mathcal{L}_{dec} \) and Discriminator with \( \mathcal{L}_{DSL-GAN} \) iteratively;

Once the network is trained, we can solve the task of generation and modification; particularly,

- Generating new facial images with any attributes. This can be achieved by sampling \( z_{la} \) from \( p_{prior}(z) \) and setting \( y \) to any desired attributes. We can then get from the generator the image \( x' \sim G(z_{la}, y) \).
- Modifying the existing images with any attributes. Given an image \( x \) and the desired attribute \( y \), we can sample \( z_{la} \sim p(z \mid x) \). Then the modified image can be generated by \( x' \sim p_{dec}(x \mid z_{la}, y) \).

4. Experiments

4.1. Experimental settings

Dataset. We conduct the experiments on two datasets. The CelebA dataset [22] contains approximately 200k images of 10k identities. Each image is annotated with 5 landmarks (two eyes, the nose tips, the mouth corners) and binary labels of 40 attributes. Since the distribution of the binary annotations of attributes is very unbalanced, we select 17 attributes with relatively balanced annotations for our experiments. We use the standard split for our model: first 160k images are used for training, 20k images for validation and remaining 20k for test. CASIA-WebFace dataset is currently the largest publicly released dataset for face verification and identification tasks. It contains 10,575 celebrities and 494, 414 face images which are crawled from the web. Each person has 46.8 images on average. The CASIA-WebFace [43] does not have any facial attribute labels. We use the 17 attributes of CelebA dataset [22] to train the facial attribute classifier, i.e., MOON model [30]. The trained model can be utilized to predict the facial attributes on the CASIA-WebFace dataset. The predicted results are used as the facial attribute annotation. We will release these annotations, trained models and code upon acceptance.

Evaluation. We employ different evaluation metrics. (1) For the generation task, we utilize inception score and attribute errors. Inception score [32] measures whether varied images are generated and whether the generated images contains meaningful objects. Also, inspired by the attribute similarity in [42], we propose the attribute error. Specifically, we use the MOON attribute [30] models to predict the user-defined attributes of generated images and the predicted attributes are compared against the specified attributes by mean square error. (2) For the modification task, we employ the user-study for the evaluation.

Implementation details. Training converges in 9-11 hours on CelebA dataset on GeForce GTX 1080; our model needs around 2GB GPU memory. The input size of images is 64×64. The methods to which we compare have code available on the web, which we use to directly compare to our results.
Attribute Errors on CelebA dataset

Attribute Errors on CASIA-WebFace dataset

Figure 3. Attribute Errors of user-defined attributes on CelebA and CASIA-WebFace dataset. The lower values, the better results. The attribute names are listed in the X-axis.

Figure 4. Inception Scores on two datasets. The higher values, the better results.

Figure 5. Qualitative results of the generation task.

4.2. Generation by user-defined attributes

Competitors. We compare various open-source methods on this task, including VAE-GAN [20], AC-GAN [25], and Attrb2img [42]. Attrb2img is an enhanced version of CVAE. All the methods are trained with the same settings and have the same number dimensions for attribute representation. For a fair comparison, each method only trains one model on all 17 user-defined attributes.

Attribute errors are compared on CelebA and CASIA-WebFace dataset and illustrated in Fig. 3. Since VAE-GAN does not model the attributes, our model can be only compared against AC-GAN and Attrb2img methods. On most of the 17 attributes, our method has lower attribute errors than the other methods. This indicates the efficacy of our SL-GAN on learning user-defined attributes. In contrast, the relatively higher attribute errors of Attrb2img were largely due to the fact that Attrb2img is based on CVAE and user-defined attributes are only given as the model input, rather than explicitly learned as in our SL-GAN and AC-GAN. The advantages of our SL-GAN results over AC-GAN are in part due to our generator model with feature-wise error encoded by $L_{recon}$ in Eq (3).

Inception scores are also compared on two datasets and shown in Fig. 4. We compare the inception scores on both generated and reconstructed image settings. The differences between generated and reconstructed images lies in how to obtain the attribute vectors: the attribute vectors of reconstructed images is computed by the encoder network, while such vectors of generated images are either sampled from Gaussian prior (for $z_{la}$) or pre-defined (for $y$).

As an objective evaluation metric, inception score, first proposed in [32], was found to correlate well with the hu-
man evaluation of visual quality of samples. Thus higher inference scores can reflect the relatively better visual quality. (1) On generated image setting, we use the same type of attribute vector to generate the facial images for VAEGAN, AC-GAN, and Attrb2img. On both dataset, our SL-GAN has higher inference scores than all the other methods, still thanks to our training algorithm for more efficiently and explicitly learning user-defined and latent attribute in SL-FAS. These results indicate that our generated images in general have better visual quality than those generated by the other methods. We note that AC-GAN has relatively lower inference scores since it does not model the feature-wise error as our SL-GAN. (2) On reconstructed image setting, AC-GAN is not compared since it does not have the encoder-decoder structure to reconstruct the input image. On both dataset, our SL-GAN again outperforms the other baselines, which suggests that the visual quality of our reconstructed images is better than that from the other competitors.

**Qualitative results.** Figure 5 gives some qualitative examples of the generated images by VAEGAN, AC-GAN, Attrb2img and SL-GAN as well as the ground-truth images. For all the methods, the same attribute vectors are used for all methods to generate the images. The generated images are compared against the ground-truth image which is annotated by the corresponding attribute vector. As we can see, samples generated by Attrb2img has successfully generated the images with rich and clear details of human faces and yet very blurred hair styles\(^2\). In contrast, the image generated by AC-GAN can model the details of both human faces and hair styles. However, it has lower visual quality than our SL-GAN, which generates a more consistency and nature style of human faces and hair styles.

### 4.3. Modification by user-defined attributes

**Competitors.** We compare various open source methods on this task, including attrb2img [42] and icGAN [26]. Note that attrb2img can not directly modify the attributes of images. Instead, we take it as an “attribute-conditioned image progression” which interpolates the attributes by gradually changing the values along attribute dimension. We still use the same settings for all the experiments.

**User-study experiments.** We design a user study experiment to compare attrb2img with our SL-GAN. Specifically,

| Metric   | Saliency | Quality | Similarity | Guess   |
|----------|----------|---------|------------|---------|
| Attrb2img| 3.02     | 4.01    | 4.43       | 30.0%   |
| icGAN    | 4.10     | 3.83    | 3.40       | 65.4%   |
| SL-GAN   | 4.37     | 4.20    | 4.45       | 75.0%   |

Table 1. The user-study of modification of user-defined attributes. The “Guess” results are reported as the accuracy of guessing.

\(^2\)This point is also consistency with the example figures given [42] which has blurred hair style details.

\[5\]

In this paper, we introduce a semi-latent facial attribute space to jointly learn the user-defined and latent attributes from facial images. To learn such a space, we propose a unified framework– SL-GAN which for the first time can both learn to generate and modify facial image attributes. Our model is compared against the state-of-the-art methods and achieves better performance.

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Figure 6. Qualitative results of comparing different modification methods. The red box indicates that the attribute modified is inverse to the attribute of each row.

Figure 7. Results of modifying attributes on CelebA dataset. Each column indicates modifying by adding one type of attribute to image, while the red box means the image is modified to not have that attribute.

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