
Exploring Attribute Variations in Style-based GANs using Diffusion Models

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Abstract

Existing attribute editing methods treat semantic attributes as binary, resulting in a single edit per attribute. However, attributes such as eyeglasses, smiles, or hairstyles exhibit a vast range of diversity. In this work, we formulate the task of *diverse attribute editing* by modeling the multidimensional nature of attribute edits. This enables users to generate multiple plausible edits per attribute. We capitalize on disentangled latent spaces of pretrained GANs and train a Denoising Diffusion Probabilistic Model (DDPM) to learn the latent distribution for diverse edits. Specifically, we train DDPM over a dataset of edit latent directions obtained by embedding image pairs with a single attribute change. This leads to latent subspaces that enable diverse attribute editing. Applying diffusion in the highly compressed latent space allows us to model rich distributions of edits within limited computational resources. Through extensive qualitative and quantitative experiments conducted across a range of datasets, we demonstrate the effectiveness of our approach for diverse attribute editing. We also showcase the results of our method applied for 3D editing of various face attributes.

1 Introduction

The recent emergence of deep generative models employing GANs Goodfellow et al. [2014], Karras et al. [2020a], Chan et al. [2022] has significantly transformed image generation and editing. Various methods have been proposed that leverage disentangled latent space of GANs for attribute editing in 2D Shen et al. [2020], Härkönen et al. [2020], Patashnik et al. [2021], Abdal et al. [2021] and in 3D Frühstück et al. [2023], Li et al. [2023]. Existing methods treat semantic attributes as binary and are limited to generating a single edit for a given attribute. However, most *attributes are multidimensional* in nature, e.g., smiles, eyeglasses, and hairstyles. To this end, we explore a new perspective for attribute editing and propose to learn the distribution over plausible attribute edits. This enables users to generate multiple edit variations for a given attribute and select the best one. E.g., it can allow a user to generate diverse eyeglass styles and identify the most fitting option. In this work, we formulate the task of *diverse attribute editing* and propose a method to generate multiple attribute edit variations.

Style-based GAN models have semantically rich and disentangled $\mathcal{W}/\mathcal{W}+$ latent spaces. This is proven by the existence of linear latent directions in StyleGANs that control a single attribute Shen et al. [2020], Shen and Zhou [2021] in the generated image. Leveraging this, current attribute editing methods Patashnik et al. [2021], Shen et al. [2020], Abdal et al. [2021], Härkönen et al. [2020] treat attributes as unidirectional and discover a single linear direction in the latent space to modify these attributes. For instance, they obtain a single direction to add a smile or eyeglasses. However, the representation of diverse edits for smiles or eyeglasses using a single edit direction is restrictive, given the wide range of variations in these attributes. Motivated by this, we propose to train a generative model over the distribution of edit directions for each attribute (Fig. 1).

As the distribution of attributes is extremely rich and contain a large range of variations in appearance and structure, eg., eyeglasses have variations in frames shapes, lens shape, material and colors. To this end, we propose to used diffusion model (implemented as a small MLP) in the latent space due to their excellent mode coverage capabilities. The motivation to apply diffusion in GAN latent space is two folds: 1) *it enables us to exploit attribute disentanglement properties in the space for diverse attribute editing*; 2) *diffusion model training and inference in the compressed latent space is computationally inexpensive*. More specifically, we acquire a dataset of edit directions in the compressed latent space space for training a DDPM Ho et al. [2020] model.

In summary, our contributions are as follows:

1. A novel method to learn the space of diverse attribute variations with Diffusion Model in the latent space of pretrained style-based GANs.
2. State-of-the-art results in generating diverse attribute edit variations on multiple attributes and datasets and comprehensive analysis of different model components.
3. Generalization of the proposed method for editing in 3D and out-of-domain images.

2 Methodology

Approach Overview. The proposed method for diverse attribute variations includes three main steps (illustrated in Fig. 2). Firstly, we generate a dataset of image pairs, each with a single attribute change, and derive a set of edit directions from the difference between corresponding latent codes (Sec. 2.1). Secondly, we use the dataset of edit directions to train a DDPM Ho et al. [2020] model to capture the space of diverse attribute edits (Sec. 2.2). Lastly, during inference, we obtain a new edit direction from the trained model and combine it with the source latent code to produce an edited image (Sec. 2.3). We provide a detailed explanation of each of these steps in the following sections. In our experiments, we explore $\mathcal{W}/\mathcal{W}+$, latent spaces of the style-based GANs for obtaining editing directions.

2.1 Data Generation

We generate a synthetic dataset of image pairs to obtain a dataset of disentangled edit directions for a given attribute a . These image pairs consist of a positive and a negative image, where the positive image I_p^a has the attribute a , and the negative image I_n^a does not. We create these image pairs such that all the other attributes and identity are unchanged in I_p^a and I_n^a . To obtain an edit direction d_a , we first encode the image pairs into the $\mathcal{W}+$ latent space using e4e Tov et al. [2021] encoder model \mathcal{E} and take a difference between them. As the image pairs have modifications in only a single attribute, the difference vector d_a captures transformation corresponding to only attribute a .

$$d_a = \mathcal{E}(I_p^a) - \mathcal{E}(I_n^a) \quad (1)$$

We make a dataset $\mathcal{D}_a = \{d_a^i\}$ of N edit directions for attribute a by accumulating these edit directions. To obtain the dataset of disentangled image pairs with a single attribute change, we use off-the-shelf attribute editing methods Patashnik et al. [2021], Alaluf et al. [2021a] for hairstyles and age attributes. For eyeglass and smile attributes, we use the method proposed in Parihar et al. [2022]. Further details about the dataset creation are provided in the supplementary document. We generate

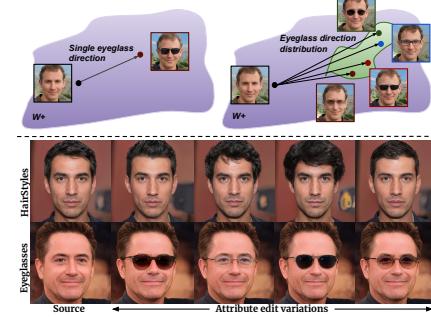


Figure 1: Existing methods consider attributes as binary and obtain a single attribute edit direction, our proposed method generates a distribution over edit directions, allowing for multiple attribute variations

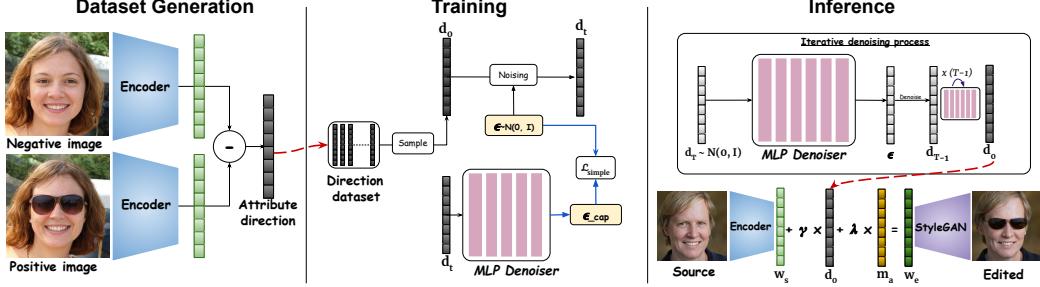


Figure 2: Our methodology for diverse attribute editing comprises three major stages: 1) **Dataset Generation**. We create a dataset of edit directions by embedding negative and positive image pairs into the latent space and computing the difference between these directions. 2) **Training**. We train a DDPM model over the dataset of edit directions for the given attribute employing a denoising objective. 3) **Inference**. To edit a new image, we first encode it into the latent space and then add an edit direction sampled with iterative denoising in the reverse diffusion process.

a dataset of image pairs for each attribute with $30K$ source images from CelebA-HQ Karras et al. [2017] dataset. Next, we encode the image pairs and obtain the edit direction using Eq. 1.

2.2 Diffusion model training

Diffusion models (DM) being likelihood models, are shown to learn complex image distributions with excellent mode coverage ability in the data distribution. Latent DMs Rombach et al. [2022] train DM on features and we go further by modeling over the \mathcal{W}^+ space of StyleGAN models as an image representation, because of its high compression. We train a DDPM on the \mathcal{W}^+ space to model the multimodality in the attribute variations.

Specifically, given a dataset of diverse attribute edit directions \mathcal{D}_a , we train a DDPM model to learn the distribution over edit directions. The goal is to sample a new edit direction from the DDPM model that models a novel and realistic transformation only in the attribute a . During training, we randomly sample an edit direction d from \mathcal{D}_a , and corrupt it with a gaussian noise $\epsilon \sim \mathcal{N}(0, I)$. Following the convention, we denote the selected sample as \mathbf{d}_0 : $\mathbf{d}_t = \sqrt{\bar{\alpha}_t} \mathbf{d}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$ with $\bar{\alpha} = \prod_{i=1}^T \alpha_i$, and $0 = \alpha_T < \alpha_{T-1} < \dots < \alpha_0 = 1$, being hyperparameter of diffusion schedule. We implement the denoiser network $\epsilon_\theta(\mathbf{d}_t, t)$ as a time-conditioned Multi-Layer Perceptron (MLP) network. To train the denoising network, we use the simple loss Ho et al. [2020], between added noise ϵ and $\epsilon_\theta(d_t, t)$ as $\mathcal{L}_{\text{simple}} = \mathbb{E}_{\mathbf{d}_0, t, \epsilon} [\|\epsilon - \epsilon_\theta(\mathbf{d}_t, t)\|_2^2]$. As a normalization step, we subtract the mean direction \mathbf{m}_a of the dataset \mathcal{D}_a from the vectors \mathbf{d}_a and normalize them to unit length before training.

2.3 Diverse attribute editing

Given a DDPM model on edit directions, we show how to use it to edit a given source image I_s diversely. To perform diverse attribute editing, we first map it to its corresponding latent code w_s , where $w_s = \mathcal{E}(I_s)$. To obtain a new edit attribute direction \mathbf{d}_0 , we first sample a noised direction $\mathbf{d}_T \sim \mathcal{N}(0, I)$, and iteratively denoise it using trained MLP denoiser ϵ_θ . Finally, we scale and shift the sampled latent direction (\mathbf{d}_0) as $\mathbf{d}' = \gamma * \mathbf{d}_0 + \lambda * \mathbf{m}_a$, before finally adding it to the source latent code (w_s) as $w_e = w_s + \mathbf{d}'$. The edited latent code w_e is then passed through the pre-trained StyleGAN2 model \mathcal{G} to obtain the edited image I_e , where $I_e = \mathcal{G}(w_e)$, diversity parameter γ and scale parameter λ are the hyperparameters, and \mathbf{m}_a is the mean edit direction for attribute a . We find that the hyperparameter γ controls the diversity in the edits and λ controls the strength of the edit, as supported by the analysis in the supp. mat..

3 Experiments

We provide extensive experiments and ablations to evaluate our model for diverse attribute editing. First, we explain the datasets used, followed by results on diverse attribute editing for faces. Further, we present results for attribute editing on out-of-domain face images from Metfaces Karras et al. [2020b], cars, and church datasets Yu et al. [2015]. Finally, we present results for 3D-aware attribute editing on EG3D Chan et al. [2022]. Please check the supplementary for more visual results.

3.1 Diverse attribute editing

We present results for hairstyle, smile, eyeglass, and age attribute variations generated by our method in Fig. 3. Our method generates different hairstyles - bangs, mohawks, curls, and short hairs while

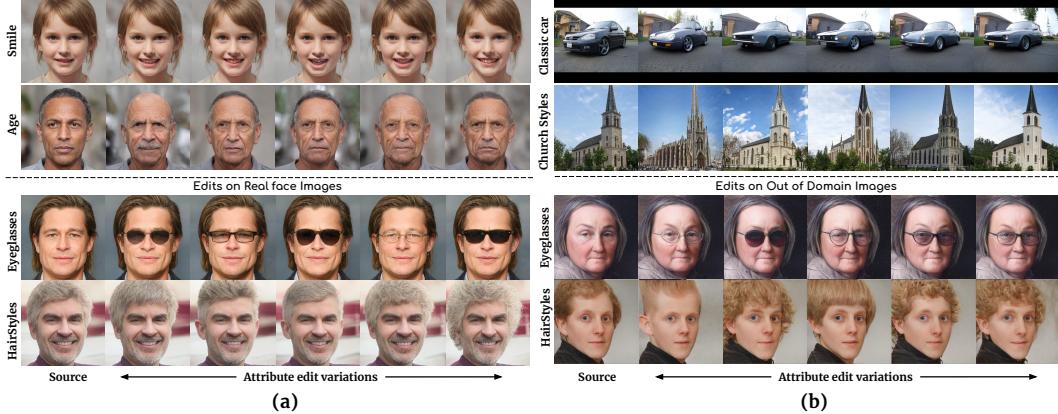


Figure 3: **a)** Diverse attribute editing on (Top) synthetic faces and (Bottom) real face images. The model generates diverse edit directions that are disentangled and preserve the subjects’ identity. **b)** Diverse attribute variations for *classic car* and *church styles* (Top) and diverse attribute editing on out-of-domain painting images from Metfaces.

retaining other features. Similarly, our method can generate diverse smile and age variations in a disentangled manner with identity preservation. Our proposed method can generate diverse eyeglasses with variations in frame shapes, sizes, and colors of frames. Observe that all the edit variations preserve the subject’s identity and other attributes. Our method generates diverse edits on real images as well (Fig. 3 Bottom).

Quantitative comparison. We generate five edits for each attribute for a synthetic test set of 1000 images to evaluate the quality and diversity of the edits. We compute FID, cosine similarity between face embeddings Esler [2021] (CS), improved precision (P), and recall metrics (R) Kynkääniemi et al. [2019]. We compare our method against - 1) Baseline - random edit directions sampled from the training dataset and 2) FLAME Parihar et al. [2022], which is a few-shot method and performs diverse edits. We used the smaller set of 50 edit directions from our training set and obtained edit directions from the FLAME method. Results are shown in Tab. 1. We note that the proposed method performed best in identity preservation and visual quality measured by FID. In most cases, it obtained the highest precision and recall suggesting diversity in the output generations. The superior performance of our method to baseline in identity preservation suggests that the trained DDPM model is robust to outliers.

Generalization and OOD Results. We present results on cars, churches, and out-of-domain painting images from Metfaces Karras et al. [2020b] in Fig. 3. We generate diverse types of "classic cars" with high fidelity. For churches, we change the style of the church keeping while preserving the outer structure. For Metfaces, we generate multiple attribute edit directions from our diffusion models trained with real image pairs as explained in Sec 2.2. We can observe that the generated directions generalize well to the out-of-domain painting images and generate diverse attribute edits. Notably, the styles of the generated edits blend seamlessly with the painting styles.

Editing on 3D aware GANs. Our method generalizes for diverse attribute edits on 3D aware generative model EG3D Chan et al. [2022]. We present the geometry of the edited outputs, where we can clearly observe shape changes associated with eyeglass edits.

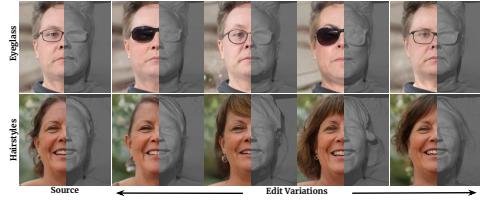


Figure 4: Diverse edits for eyeglass attribute on EG3D in 3D consistent manner. Observe the modified geometry of the eyeglass frames in both outputs.

Table 1: Quantitative comparison for diverse attribute editing.

Attr.	Method	CS ↑	ED ↓	FID ↓	Prec. ↑	Recall ↑
Hairstyle	Baseline	0.869	0.79	41.50	0.62	0.92
	FLAME	0.956	0.45	44.87	0.79	0.97
	Ours	0.973	0.35	39.58	0.91	0.98
Eyeglass	Baseline	0.931	0.53	70.91	0.66	0.28
	FLAME	0.948	0.49	69.50	0.61	0.22
	Ours	0.958	0.41	66.65	0.69	0.35
Smile	Baseline	0.920	0.55	54.44	0.74	0.09
	FLAME	0.953	0.48	53.29	0.73	0.16
	Ours	0.969	0.43	49.51	0.77	0.14

4 Conclusion

This work explores the challenging problem of diverse attribute editing by latent space manipulation in pre trained style-based GANs. Deviating from the existing method that estimates a single edit direction for a given attribute, we learn a diffusion model over the edit directions to learn the multimodal nature of the edits. Extensive results show that the proposed method generates diverse edits for real images, out-of-distribution images and 3D edits. The limitation of our method is reliance on synthetic image pairs to train the model. As a future work, text-driven multimodal editing can be explored. Additionally, a fine-grained control for multimodal attribute editing is interesting.

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