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AE-StyleGAN: Improved Training of Style-Based Auto-Encoders

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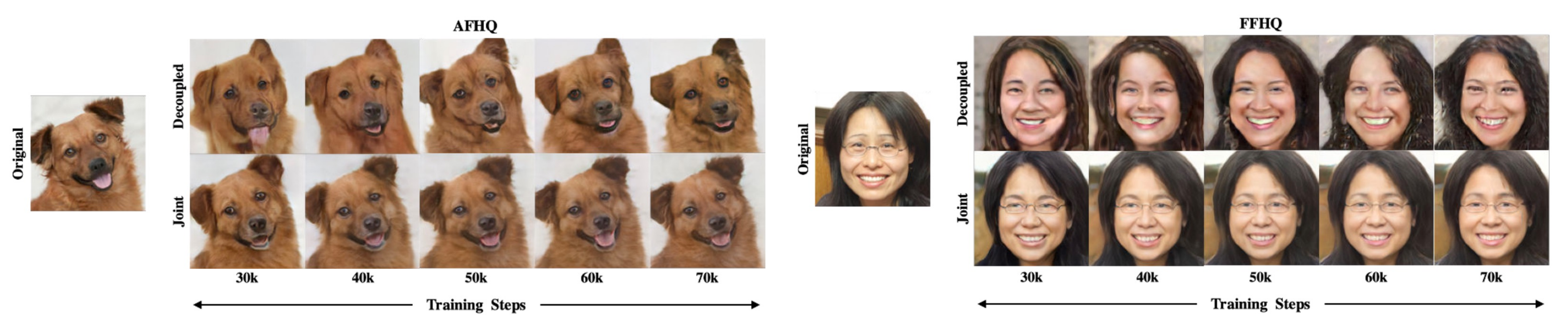
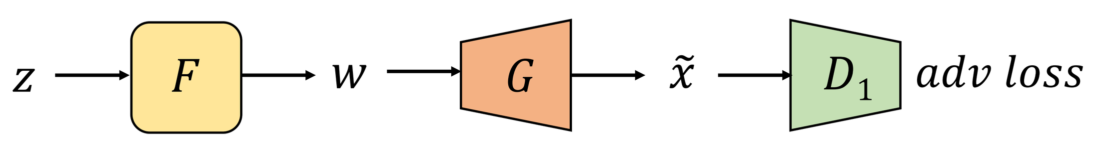
WACV
WAIKOLOA, HAWAII
JANUARY 4-8, 2022



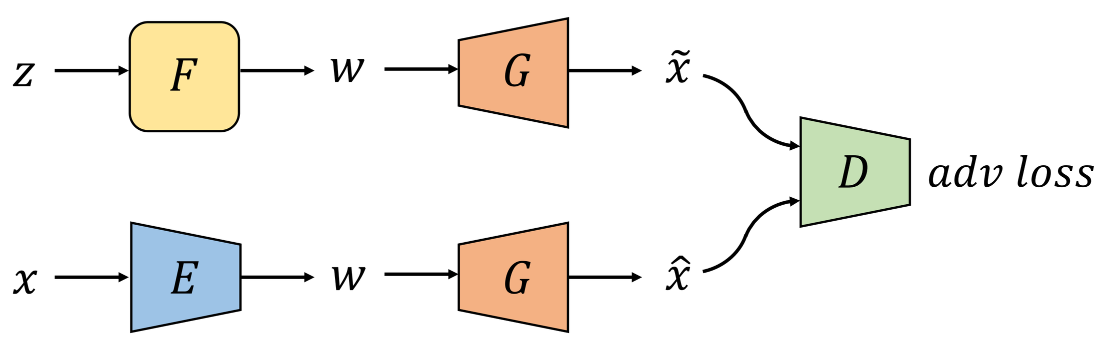
Introduction

Decoupled AE-StyleGAN



Decoupled AE-StyleGAN

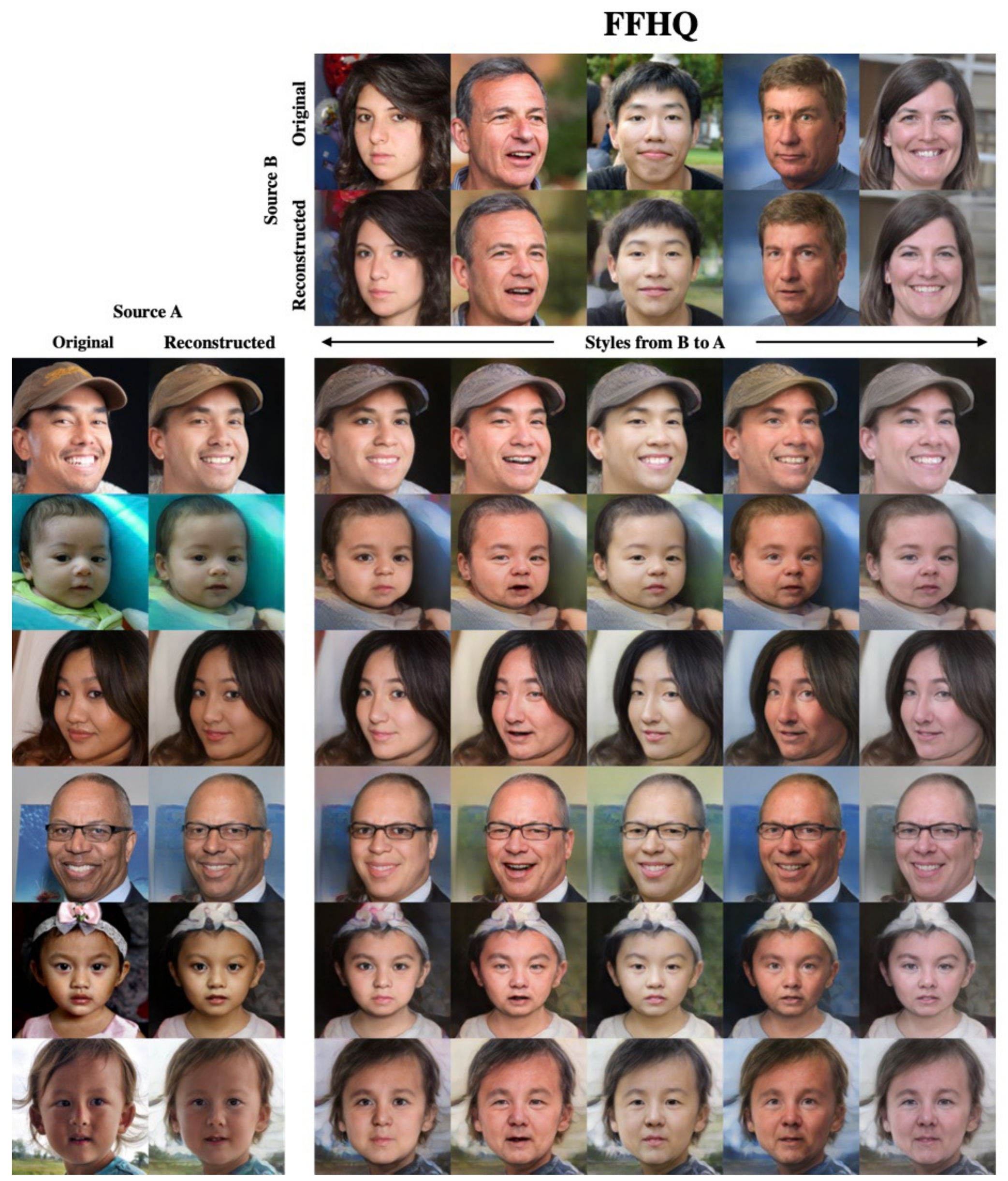
Joint AE-StyleGAN

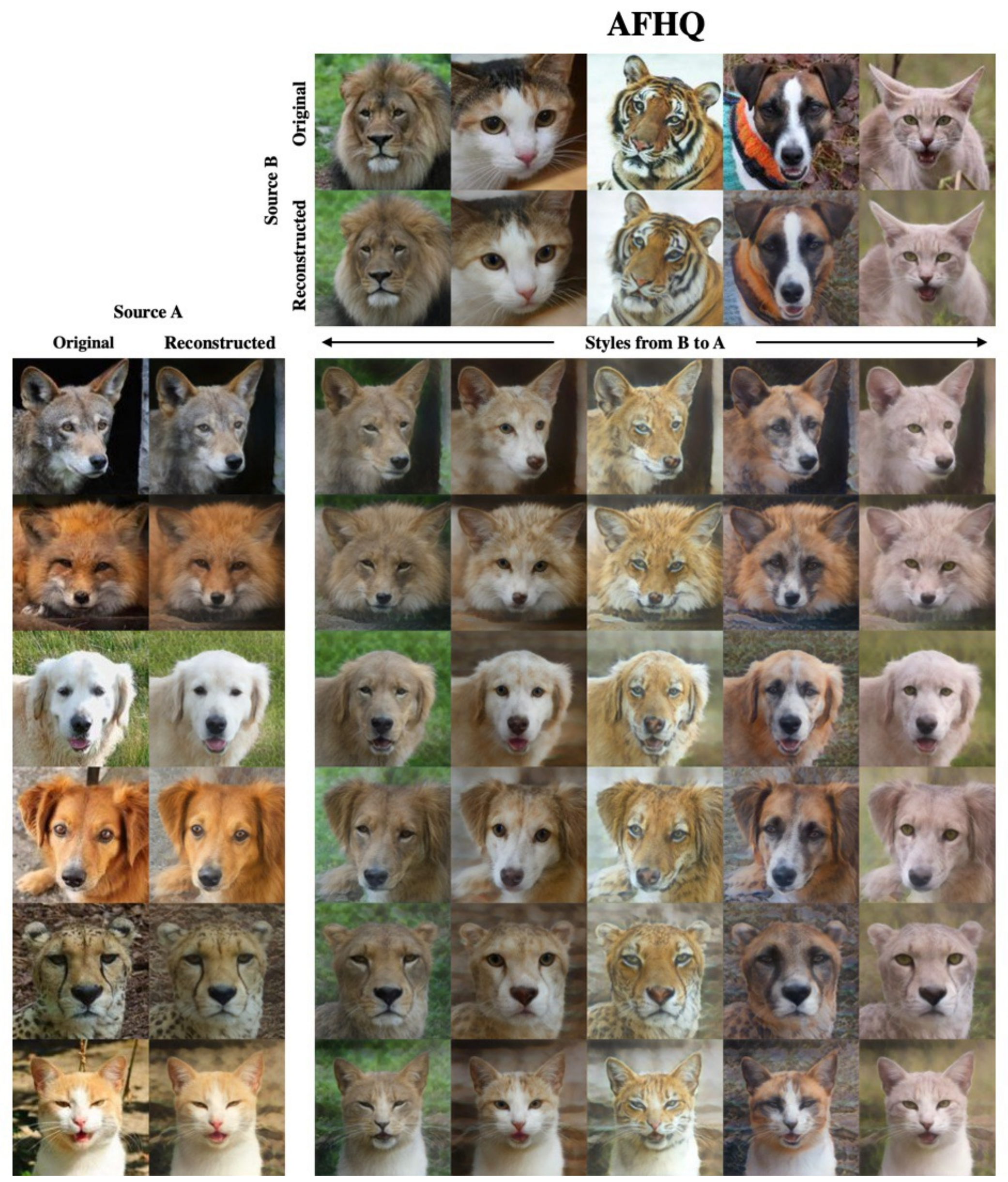


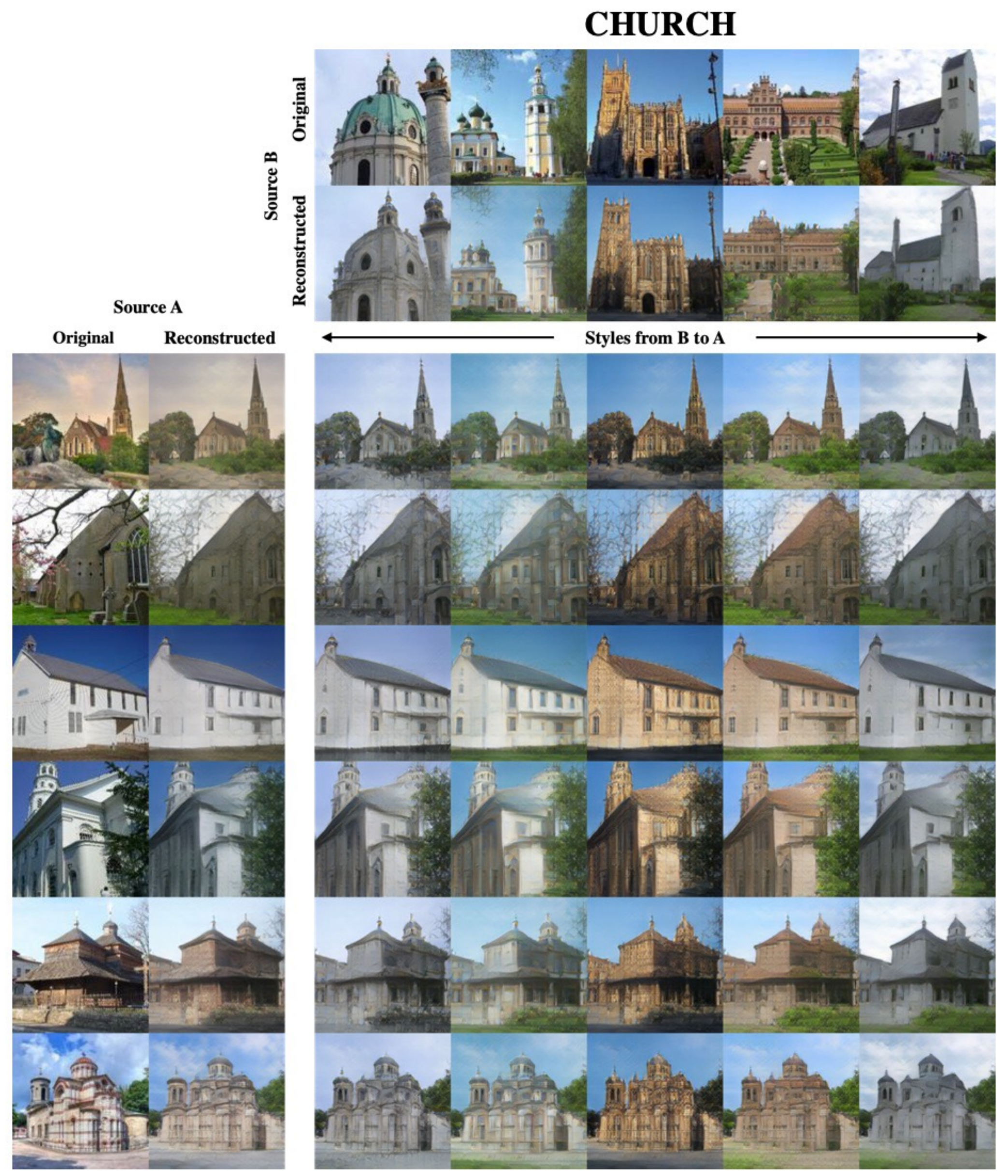
Joint AE-StyleGAN

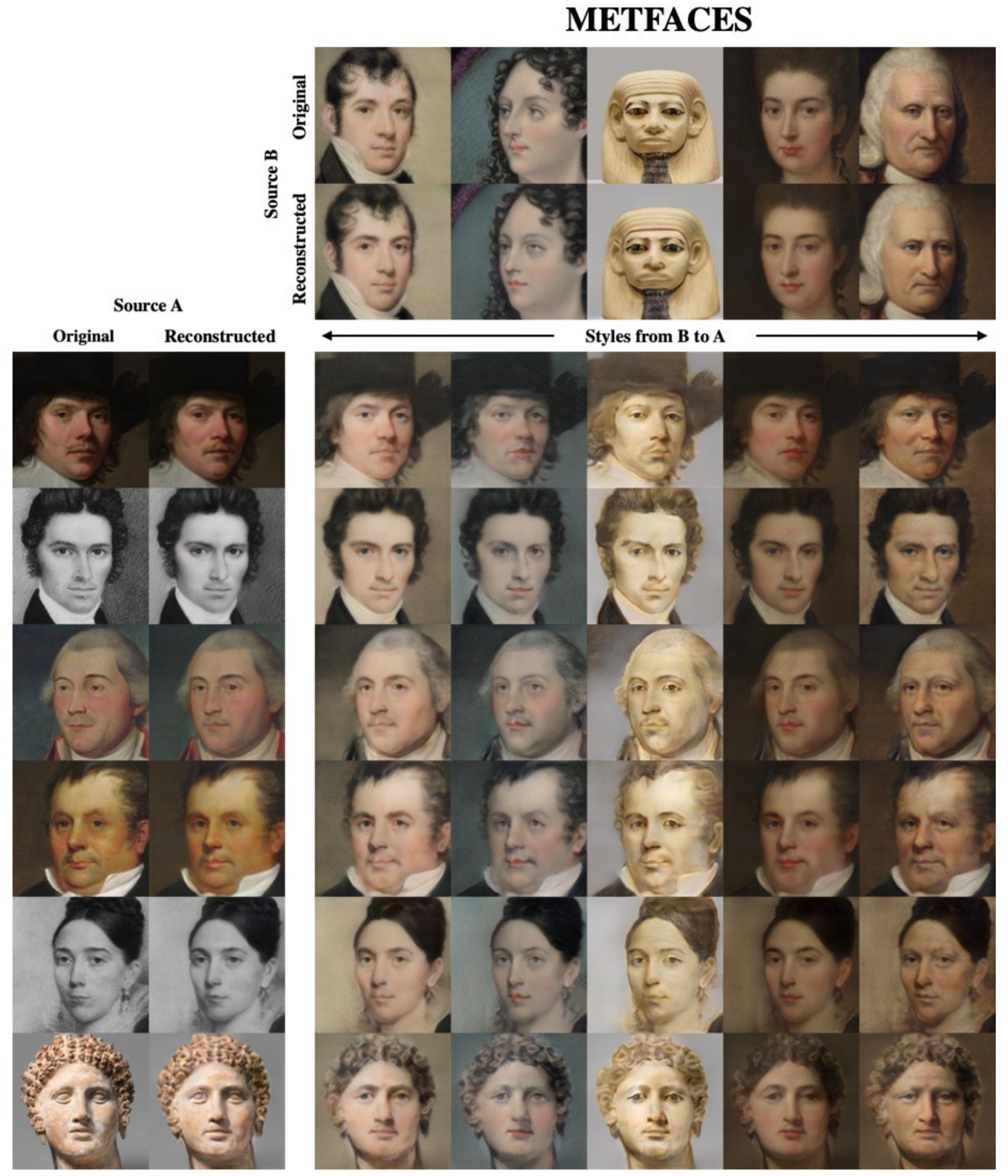
Experiments

- FFHQ, AFHQ, CHURCH, METFACES – Reconstructions & Style Transfers









Method

- Loss Functions

$$V_{\text{GAN}}(G \circ F, D) = -\mathbb{E}_{x\sim P_X}\mathcal{A}(-\tilde{D}(x)) - \mathbb{E}_{z\sim P_Z}\mathcal{A}(\tilde{D}(G(F(z)))) \quad (1)$$

Decoupled AE-StyleGAN. One straightforward way to train encoder and generator end-to-end is to simultaneously train an encoder with GAN inversion algorithms along with the generator. Here we choose in-domain inversion. To keep the generator's generating ability intact, one can decouple GAN training and GAN inversion training by introducing separate discriminator models D_1 and D_2, and freezing G in inversion step. Specifically, D_1 is involved in $V_{\text{GAN}}(G \circ F, D_1)$ in Equation 1 for GAN training steps, and D_2 is involved in $L_{\text{idinv}}(E, D_2, G)$ in Equation 2. Training of D_2 follows:

$$V_{\text{GAN}}(G \circ F, D_2) = -\mathbb{E}_{x\sim P_X}\mathcal{A}(-\tilde{D}_2(x)) - \mathbb{E}_{x\sim P_X}\mathcal{A}(\tilde{D}_2(G(E(x)))). \quad (4)$$

Joint AE-StyleGAN. The generator of a decoupled AE-StyleGAN would be exactly equivalent to a standard StyleGAN generator, however, we often find the encoder not capable of faithfully reconstruct real images. This phenomenon is illustrated in Figure 5. We hypothesize that with G frozen at inversion step, E cannot catch up with G's update, thus lags behind G. To cope with this issue, we propose to train G jointly with E in the inversion step. We also use a single discriminator for both pathways. For the GAN pathway, the value function is written as:

$$V_{\text{AEGAN}}(G \circ F, D) = -\mathbb{E}_{x\sim P_X}\mathcal{A}(-\tilde{D}(x)) - \lambda_{\text{adv}}\mathbb{E}_{x\sim P_X}\mathcal{A}(\tilde{D}(G(E(x)))) - (1-\lambda_{\text{adv}})\mathbb{E}_{z\sim P_Z}\mathcal{A}(\tilde{D}(G(F(z)))). \quad (5)$$

Results

	StyleGAN		ALAE		AE-StyleGAN ($\mathcal{W}$)		AE-StyleGAN ($\mathcal{W}^+$)	
	FID ↓	LPIPS ↑	FID ↓	LPIPS ↑	FID ↓	LPIPS ↑	FID ↓	LPIPS ↑
FFHQ	**7.359**	0.432	12.574	0.438	8.176	**0.448**	**7.941**	**0.451**
AFHQ	**7.992**	0.496	21.557	0.508	15.655	**0.522**	**10.282**	**0.518**
MetFaces	**29.318**	0.465	41.693	0.462	29.710	**0.469**	**29.041**	**0.471**
LSUN Church	**27.780**	0.520	29.999	0.552	29.387	**0.603**	**29.358**	**0.592**

	StyleGAN		ALAE		AE-StyleGAN ($\mathcal{W}$)		AE-StyleGAN ($\mathcal{W}^+$)	
	Full	End	Full	End	Full	End	Full	End
FFHQ	**173.09**	**173.68**	192.60	193.94	181.03	180.23	**166.70**	**165.85**
AFHQ	244.83	240.68	**229.54**	**232.53**	247.75	248.75	**233.86**	**231.91**
MetFaces	**231.40**	**232.77**	**235.39**	237.63	238.84	238.60	240.01	**235.41**
LSUN Church	245.22	**239.62**	298.06	295.01	**241.46**	231.73	**240.01**	**231.49**

Algorithm

Algorithm 1 Decoupled AE-StyleGAN Training

$\theta_E, \theta_{D_1}, \theta_{D_2}, \theta_F, \theta_G \leftarrow$ Initialize network parameters
while not converged **do**
  $x \leftarrow$ Random mini-batch from dataset
  $z \leftarrow$ Samples from $\mathcal{N}(0, I)$
  Step I. Update D_1, D_2
  $L_D \leftarrow -V_{\text{GAN}}(G \circ F, D_1) - V_{\text{GAN}}(G \circ E, D_2)$ in 1
  $\theta_{D_1}, \theta_{D_2} \leftarrow \text{ADAM}(\nabla_{\theta_{D_1}, \theta_{D_2}} L_D, \theta_{D_1}, \theta_{D_2})$
  Step II. Update E
  $L_E \leftarrow L_{\text{idinv}}(E, D_2, G)$ in 2 or 6
  $\theta_E \leftarrow \text{ADAM}(\nabla_{\theta_E} L_E, \theta_E)$
  Step III. Update F, G
  $L_G \leftarrow V_{\text{GAN}}(G \circ F, D_1)$ in 1
  $\theta_F, \theta_G \leftarrow \text{ADAM}(\nabla_{\theta_F, \theta_G} L_G, \theta_F, \theta_G)$
end while

Algorithm 2 Joint AE-StyleGAN Training

$\theta_E, \theta_D, \theta_F, \theta_G \leftarrow$ Initialize network parameters
while not converged **do**
  $x \leftarrow$ Random mini-batch from dataset
  $z \leftarrow$ Samples from $\mathcal{N}(0, I)$
  Step I. Update D
  $L_D \leftarrow -V_{\text{AEGAN}}(G \circ F, D)$ in 5
  $\theta_D \leftarrow \text{ADAM}(\nabla_{\theta_D} L_D, \theta_D)$
  Step II. Update E, G
  $L_E \leftarrow L_{\text{idinv}}(E, D, G)$ in 2 or 6
  $\theta_E, \theta_G \leftarrow \text{ADAM}(\nabla_{\theta_E, \theta_G} L_E, \theta_E, \theta_G)$
  Step III. Update F, G
  $L_G \leftarrow V_{\text{AEGAN}}(G \circ F, D)$ in 5
  $\theta_F, \theta_G \leftarrow \text{ADAM}(\nabla_{\theta_F, \theta_G} L_G, \theta_F, \theta_G)$
end while

Summary

In this paper, we proposed AE-StyleGAN, a novel algorithm that jointly trains an encoder with a style-based generator. With empirical analysis, we confirmed that this methodology provides an easy-to-invert encoder for real image editing. Extensive results showed that our model has superior image generation and reconstruction capability than baselines. We have explored the problem of training an end-to-end autoencoder. With improved generation fidelity and reconstruction quality, the proposed AE-StyleGAN model can serve as a building-block for further development and applications.