

# Appendix for "Symmetric Variational Autoencoder and Connections to Adversarial Learning"

## 1 Model Architectures

Table 1: Architecture of the models for sVAE-r on MNIST. BN denotes batch normalization.

Encoder X to z	Decoder z to X	Discriminator
Input $28 \times 28$ Gray Image	Input latent code z	Input two $28 \times 28$ Gray Image
$5 \times 5$ conv. 16 ReLU, stride 2, BN $5 \times 5$ conv. 32 ReLU, stride 2, BN MLP output 784, BN	MLP output 1024, BN MLP output 3136, BN $5 \times 5$ deconv. 64 ReLU, stride 2, BN	$5 \times 5$ conv. 32 ReLU, stride 2, BN $5 \times 5$ conv. 64 ReLU, stride 2, BN $5 \times 5$ conv. 128 ReLU, stride 2, BN input z through MLP output 1024, ReLU
MLP output dim of z	$5 \times 5$ deconv. 1 ReLU, stride 2, sigmoid	MLP output 1

Table 2: Architecture of the models for sVAE on CelebA. BN denotes batch normalization. lReLU denotes Leaky ReLU.

Encoder X to z	Decoder z to X	Discriminator
Input Image X concat with noise	Input z concat with noise	Input X
$4 \times 4$ conv. 32 lReLU, stride 2, BN $4 \times 4$ conv. 64 lReLU, stride 2, BN $4 \times 4$ conv. 128 lReLU, stride 2, BN $4 \times 4$ conv. 256 lReLU, stride 2, BN $4 \times 4$ conv. 512 lReLU, stride 2, BN MLP output 512, lReLU MLP output dim of z, tanh	concat random noise MLP output 1024, lReLU, BN MLP output 8192, lReLU, BN $5 \times 5$ deconv. 256 lReLU, stride 2, BN $5 \times 5$ deconv. 128 lReLU, stride 2, BN $5 \times 5$ deconv. 64 lReLU, stride 2, BN $5 \times 5$ deconv. 3 tanh, stride 2, BN	$5 \times 5$ conv. 64 ReLU, stride 2, BN $5 \times 5$ conv. 128 ReLU, stride 2, BN $5 \times 5$ conv. 256 ReLU, stride 2, BN $5 \times 5$ conv. 512 ReLU, stride 2, BN Input z through MLP, output 2046, ReLU concat two features from X and z
		MLP output 1

Table 3: Architecture of the models for sVAE-r on CIFAR. BN denotes batch normalization. lReLU denotes Leaky ReLU. *Dim* denotes the number of attributes.

Encoder X to z	Decoder z to X	Discriminator
Input Image X concat with noise	Input z	Input X
$5 \times 5$ conv. 32 lReLU, stride 2, BN $5 \times 5$ conv. 64 lReLU, stride 2, BN $5 \times 5$ conv. 128 lReLU, stride 2, BN $5 \times 5$ conv. 256 lReLU, stride 2, BN MLP output 512, lReLU MLP output dim of z, tanh	concat random noise MP output 8192, lReLU, BN $5 \times 5$ deconv. 256 ReLU, stride 2, BN $5 \times 5$ deconv. 128 ReLU, stride 2, BN $5 \times 5$ deconv. 3 tanh, stride 2	$5 \times 5$ conv. 64 ReLU, stride 2, BN $5 \times 5$ conv. 128 ReLU, stride 2, BN $5 \times 5$ conv. 256 ReLU, stride 2, BN $5 \times 5$ conv. 512 ReLU, stride 2, BN, avg pooling Input z through MLP, output 512, ReLU concat two features from X and z MLP output 1

## 2 More Result

### 2.1 CIFAR-10 result

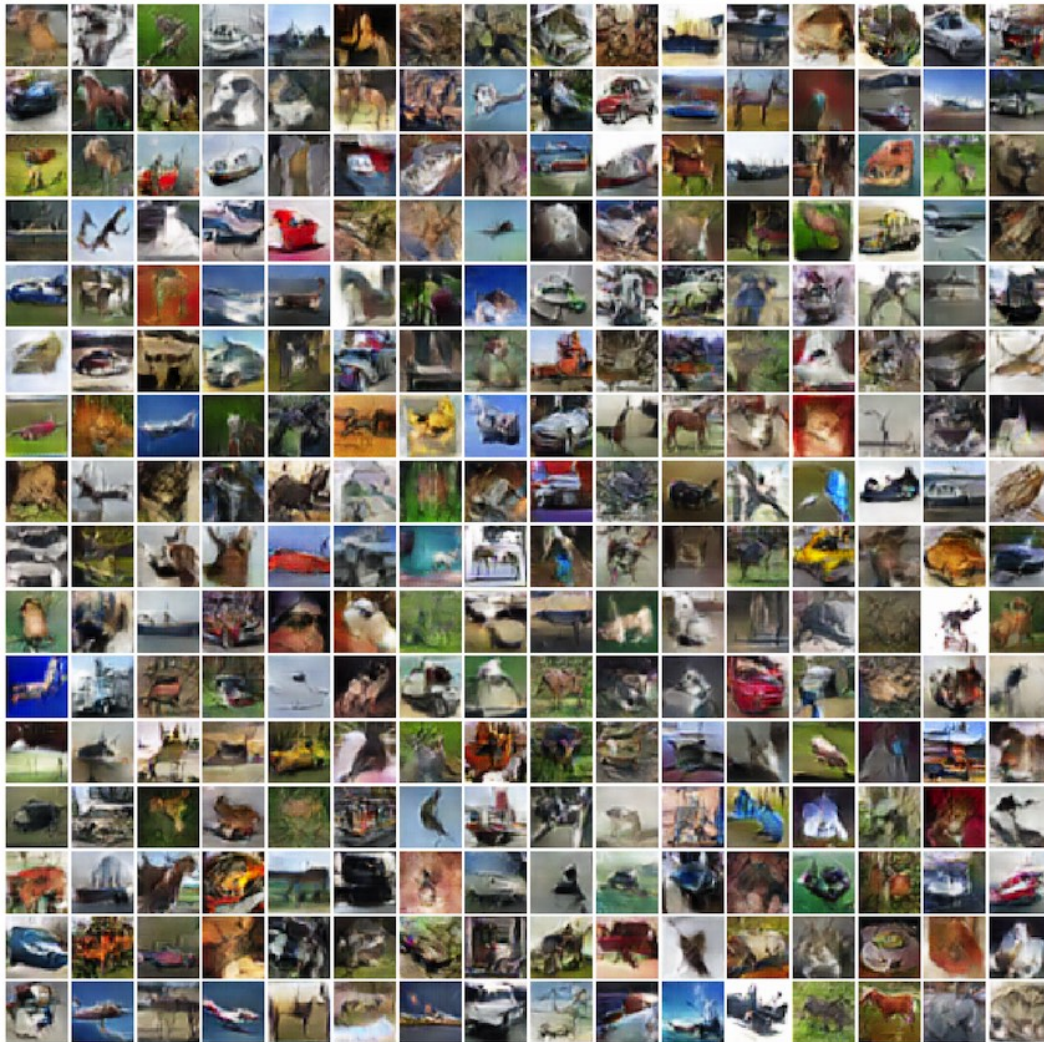


Figure 1: sVAE CIFAR unsupervised generation results with  $\lambda = 0.1$ .

### 2.2 CelebA result

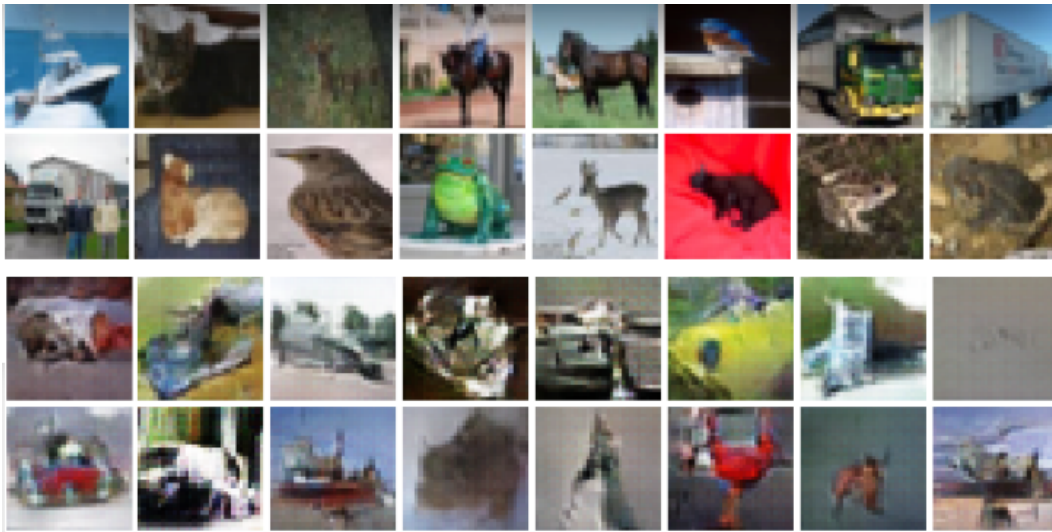


Figure 2: sVAE CIFAR unsupervised reconstruction. First two rows are original images, and the last two rows are the reconstructions

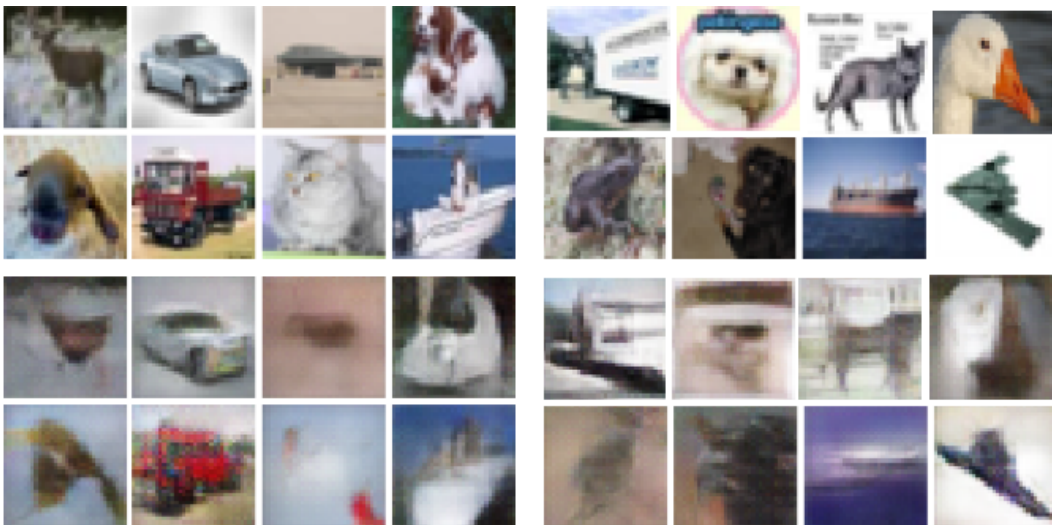


Figure 3: sVAE-r CIFAR unsupervised reconstruction. First two rows are original images, and the last two rows are the reconstructions





Figure 4: sVAE-r CelebA generations results with different  $\lambda$

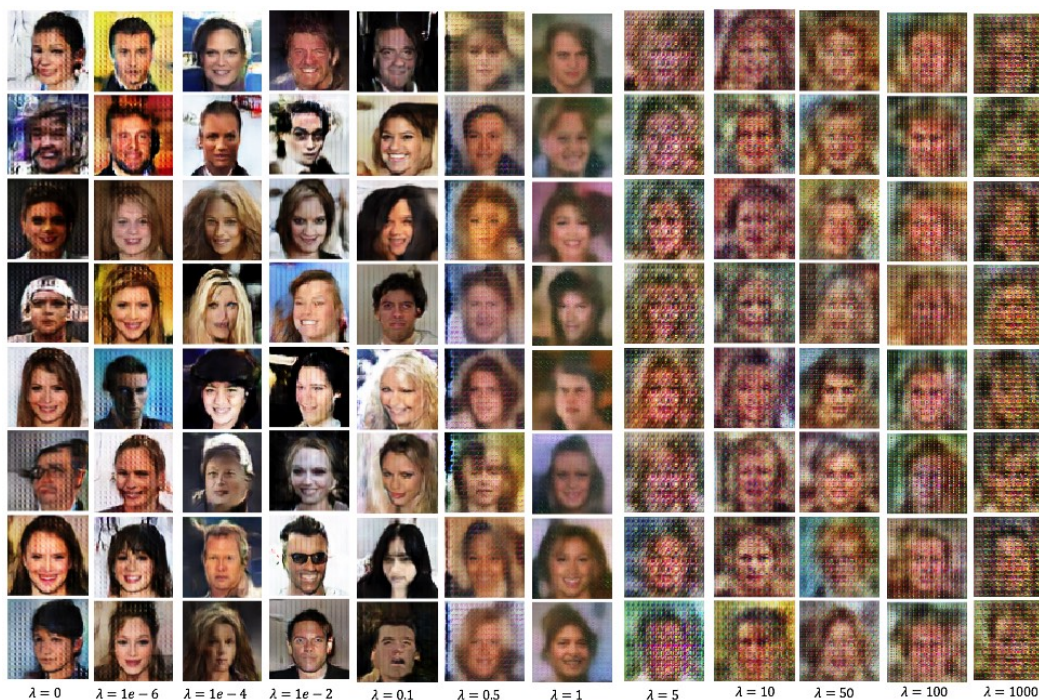


Figure 5: ALICE CelebA generations results with different  $\lambda$





Figure 6: ALICE CelebA reconstructions with different  $\lambda$ .



Figure 7: ALICE CelebA reconstructions with different  $\lambda$ .