

AE GAN

S.Lan

AutoEncoder (AE)

Generative Adversarial Networks (GAN)

# Lecture 10 AutoEncoders (AE) and Generative Adversarial Networks (GAN)

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STP598 Machine Learning and Deep Learning Fall 2021



### **Table of Contents**

ΑE S.Lan

AutoEncoders (AE)

AutoEncoders (AE)



#### **AutoEncoder**

AE GAN S.Lan

AutoEncoders (AE)

Generative Adversarial Networks (GAN

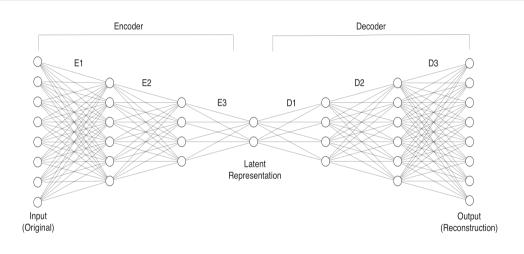


Figure: A typical architecture of autoencoder (AE) neural network.



#### **AutoEncoders**

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AutoEncoders (AE)

Generative Adversarial Networks (GAN)

- An autoEncoder (AE) is a neural network that is trained to attempt to copy its input to its output.
- The network consists of two parts:

**① encoder**:  $f: x \mapsto h$ 

**2** decoder:  $g: h \mapsto r$ 

- The network is trrained to approximately recover (copy) x, i.e. " $r \approx x$ ".
- The goal of AE is not to perfectly copy, but rather to learn useful (latent) properties of the data!



#### **AutoEncoders**

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Networks (GAN

- If the hidden (latent) dimension is smaller than the input dimension, then the AE is called *undercomplete*; otherwise, it is called *overcomplete*.
- The learning process involves minimizing a loss function as follows

$$\min L(x, g(f(x))) \tag{1}$$

where L is the loss penalizing g(f(x)) deviating from x, e.g. mean squared error.

- When the decoder is linear and L is the mean squared error, an undercomplete AE is equivalent to PCA (latent space is spanned by principal directions).
- When f, g are allowed to be nonlinear without constraint, the latent space can be meaningless.



#### Regularized AutoEncoders

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- **Sparse AE** adds sparsity penalty  $\Omega(h)$  to the loss:  $L(x, g(f(x))) + \Omega(h)$ .
- Typical choice of  $\Omega(h)$  could be from Laplace prior  $p(h; \lambda) = \lambda/2 \exp(-\lambda |h|)$ :  $\Omega(h) = -\log p(h; \lambda) = \lambda \sum_i h_i$ .
- **Denoising AE** minimizes  $L(x, g(f(\tilde{x})))$  with  $\tilde{x}$  being a copy of x corrupted by some noise and tries to undo such corruption.
- **Contractive AE** regularizes AE with a penalty on the gradients of decoder to learn the distribution of training data:

$$L(x,g(f(x))) + \Omega(h,x), \quad \Omega(h,x) = \lambda \sum_{i} \|\nabla_{x} h_{i}\|^{2}.$$
 (2)



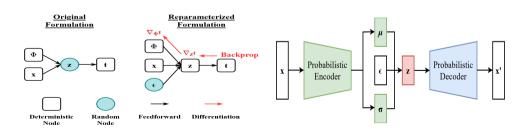
# Variational AutoEncoder (VAE)

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Generative Adversarial Networks (GAN)

- Variational AutoEncoder (VAE) (Kingma and Welling 2014) is probabilistic model for variational Bayesian inference.
- The goal is to approximate posterior distribution  $p_{\theta}(z|x)$  with  $q_{\Phi}(z|x)$  (part of VAE) by minimizing evidence lower bound (ELBO) loss (variation of Kullback–Leibler divergence).
- It reduces to construct a probabilistic encoder  $q_{\Phi}(z|x)$  and a probabilistic decoder  $p_{\theta}(x|z)$ .



# Demonstration: Banana-Biscuit-Doughnut distribution

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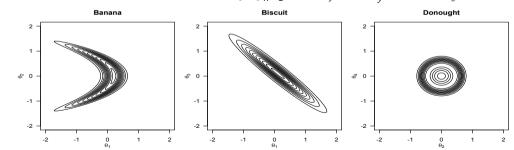
# AutoEncoders (AE)

Generative Adversarial Networks (GAN • Denote parameters  $\theta = (\theta_1, \cdots, \theta_D)$ . Consider

$$y|oldsymbol{ heta} \sim \mathcal{N}(\mu_y, \sigma_y^2), \quad \mu_y := \sum_{k=1}^{\lceil D/2 \rceil} heta_{2k-1} + \sum_{k=1}^{\lfloor D/2 \rfloor} heta_{2k}^2$$

$$heta_i \stackrel{\mathit{iid}}{\sim} \mathcal{N}(0, \sigma_{ heta}^2), \quad i = 1, \cdots, D$$

• Generate N=100 data points  $\{y_n\}_{n=1}^N$  with  $\mu_y=1, \sigma_y^2=4$  and  $\sigma_\theta^2=1$ .





#### **Autoencoder HMC Demonstration**

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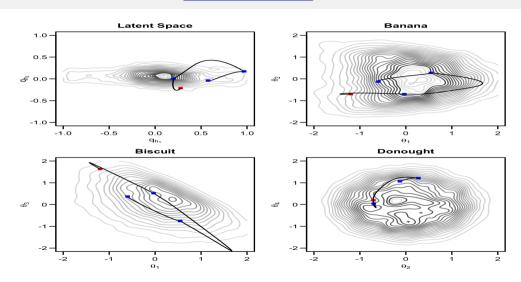


Figure: Top left: HMC trajectory in the latent space (2-dimensional); the red square is the initial position, and the blue squares are HMC proposals. The others: Trajectories



#### **Table of Contents**

AE GAN S.Lan

AutoEncode (AE)

Generative Adversarial Networks (GAN)

1 AutoEncoders (AE)

② Generative Adversarial Networks (GAN)



# Generative Adversarial Networks (GAN)

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(AE) Generative

Networks (GAN)

 A generative adversarial network (GAN) (Goodfellow et al 2014) is a class of machine learning frameworks to generate artificial data that mimic the original data.

- A GAN consists of two neural networks contesting with each other in a zero-sum game (one agent's gain is another agent's loss):
  - **1** generator:  $G_{\theta}(z)$
  - **2** discriminator:  $D_{\omega}(x)$
- Training a GAN reduces to a min-max problem  $\inf_{\theta} \sup_{\omega} L(\theta, \omega)$ . For example, Goodfellow et al (2014) propose the following loss

$$L(\theta,\omega) = \mathbb{E}_{X \sim P_r}[\log D_{\omega}(X)] + \mathbb{E}_{Z \sim P_Z}[\log (1 - D_{\omega}(G_{\theta}(Z)))]$$
(3)

$$= \mathbb{E}_{X \sim P_r}[\log D_{\omega}(X)] + \mathbb{E}_{X \sim P_{G_{\theta}}}[\log (1 - D_{\omega}(X))], \tag{4}$$

 GANs have achieved numerous interesting applications in science, video games, fashion and art, etc..

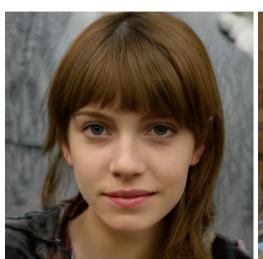


## **Generative Adversarial Networks (GAN)**

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AutoEncode

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## More Reading

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AutoEncode

Generative Adversarial Networks (GAN

#### AE

- https://sci2lab.github.io/ml\_tutorial/autoencoder/
- https://towardsdatascience.com/generating-images-with-autoencoders-77fd3a8dd368
- https://www.tensorflow.org/tutorials/generative/autoencoder

#### GAN

- https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/
- https://wiki.pathmind.com/generative-adversarial-network-gan
- https://www.tensorflow.org/tutorials/generative/dcgan