

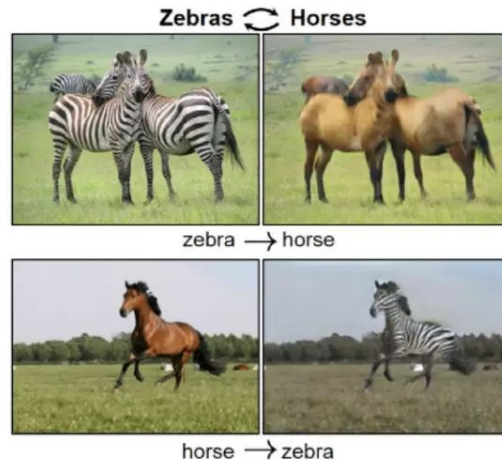
Variational Autoencoder

Do you recognize these people?



Applications

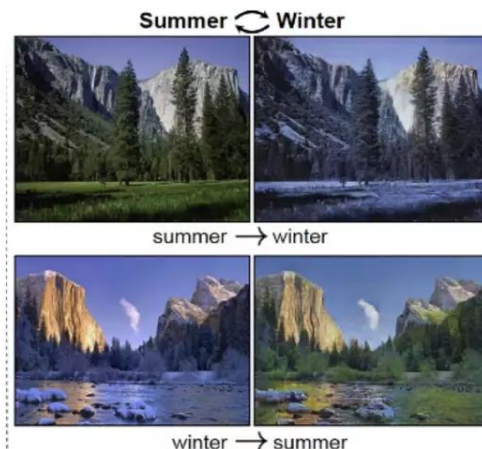
- Image editing



From “Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks,” <https://arxiv.org/abs/1703.10593>

Applications

- Style transfer



From “Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks,” <https://arxiv.org/abs/1703.10593>

Applications

- Pose interpolation



Input



Generated

From “Representation Learning by Rotating Your Faces,”

<https://arxiv.org/abs/1705.11136>

Applications

- Pose interpolation



Input



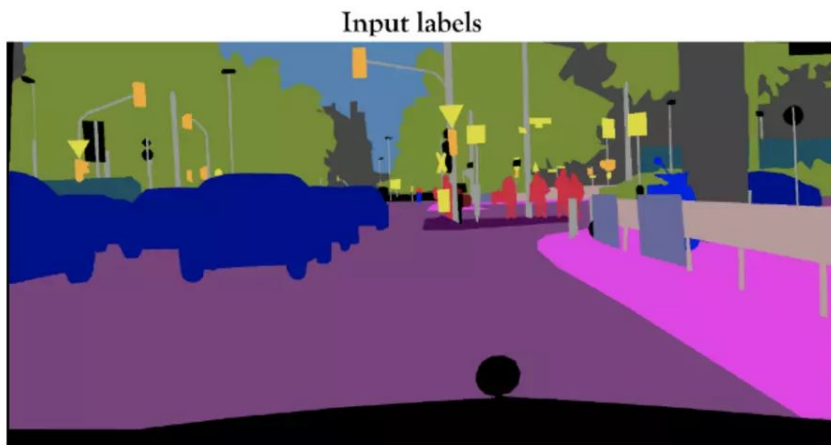
Generated

From “Representation Learning by Rotating Your Faces,”

<https://arxiv.org/abs/1705.11136>

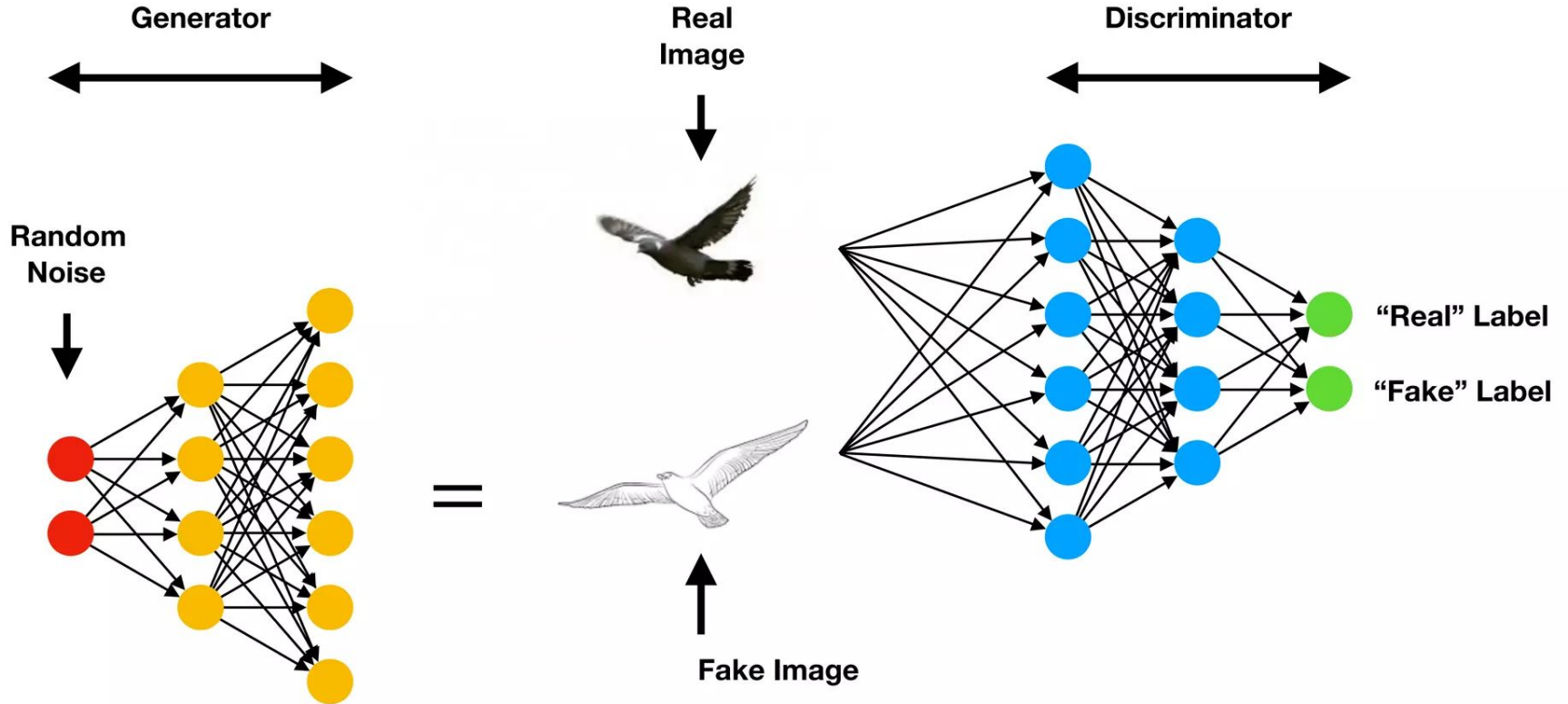
Applications

- Image synthesis



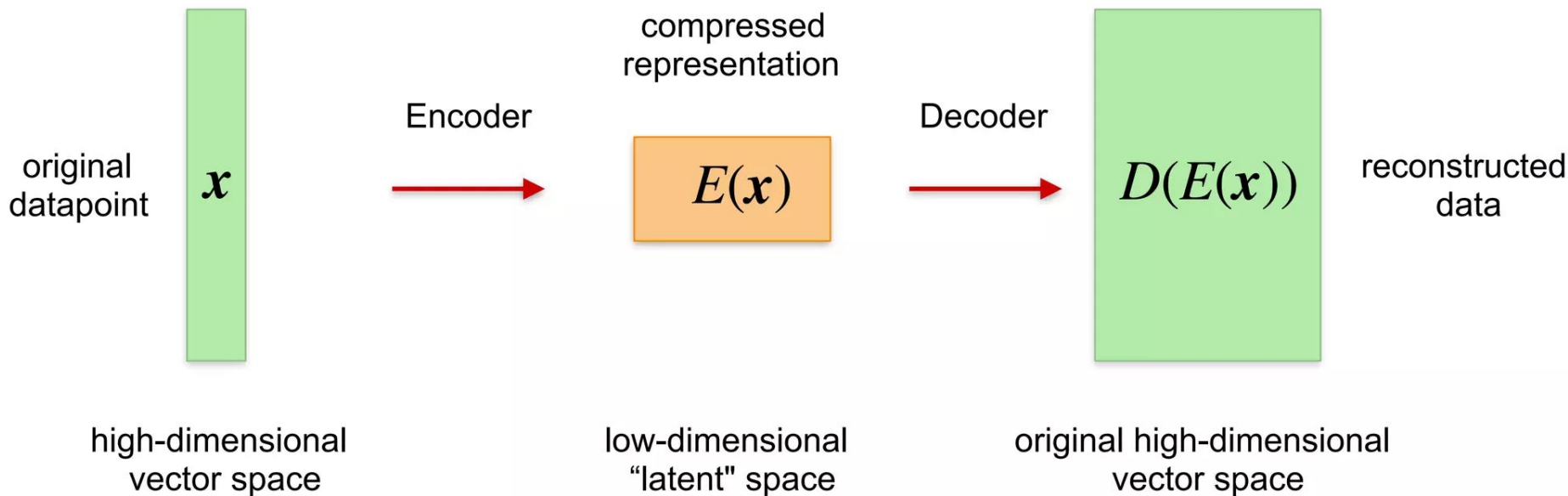
From “High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs,” <https://arxiv.org/abs/1711.11585>

Generative Adversarial Network (GAN)



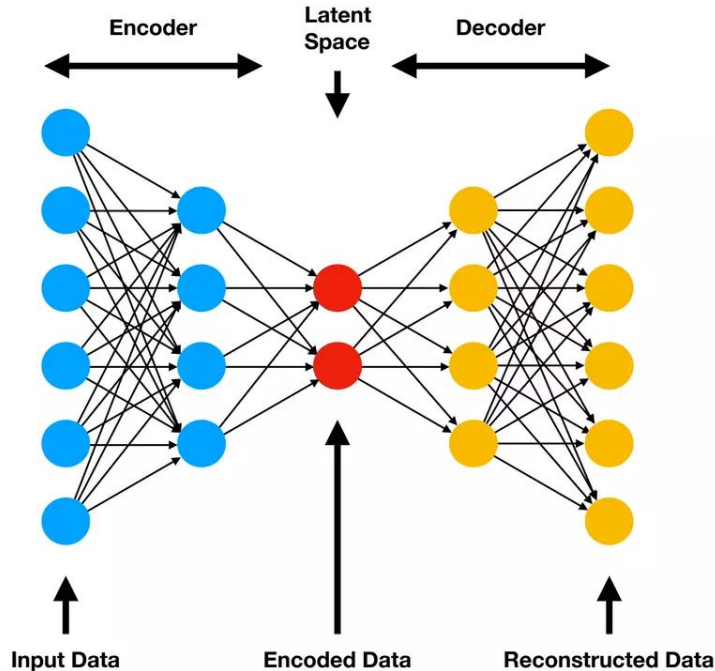
The autoencoder (AE)

- Learn a low-dimensional representation of high-dimensional data.
- Macro-architecture comprises an encoder followed by a decoder.



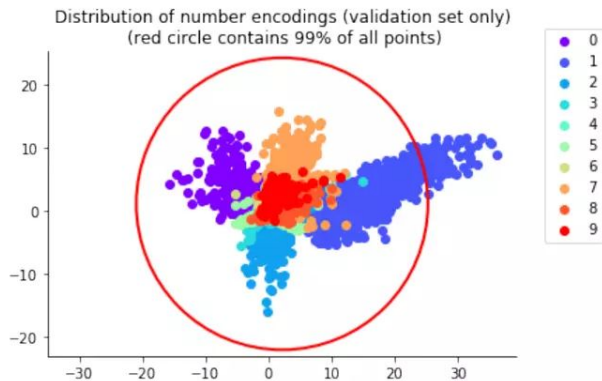
AE microarchitecture

- The encoder and decoder are usually neural networks:
- Layers are often fully connected or convolutional (for image data):

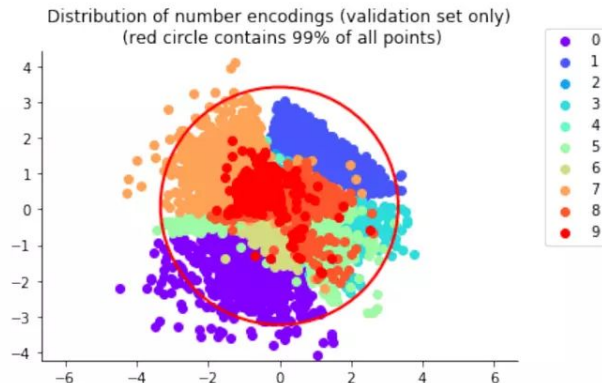


AE limitations

- Encoded representations optimize for data reconstruction, not generation.
- Encoding clusters have irregular shape, which make them hard to sample.
- As a result, random generation of good imitation data is hard to do.



The encodings we got.

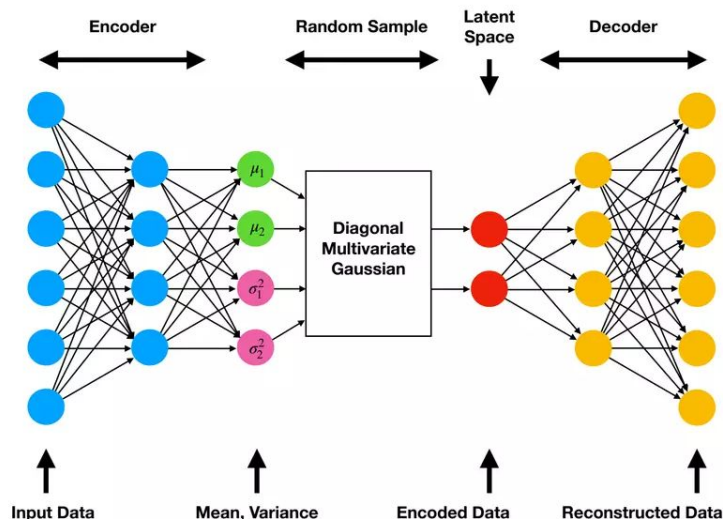


The encodings we want.

Variational autoencoders (VAE)

A variational autoencoder (VAE) is an AE with two adaptations.

- Encoder maps datapoints to probability distributions.

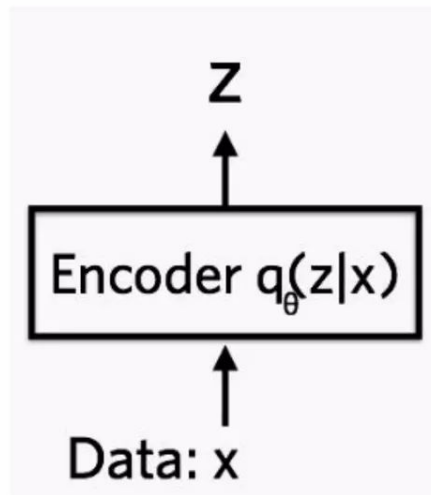


- Add a new “KL-divergence” term to the loss function during training.

Variational Auto-Encoder

Neural network prespective

The approximated function starts to shape up as a neural encoder, going from training datapoints \mathbf{x} to the likely \mathbf{z} points following $Q(z|X)$, which in turn is similar to the real $P(z|X)$.

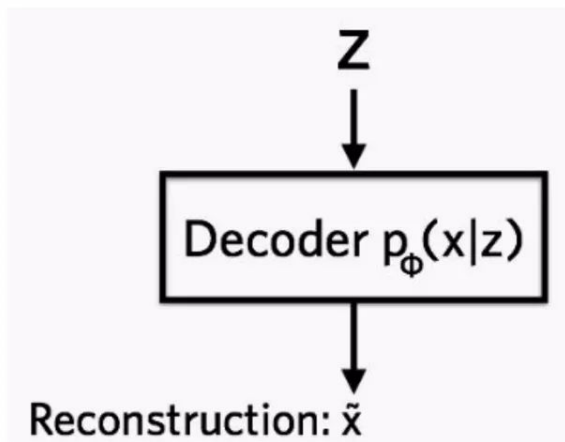


Credit: Altosaar

Variational Auto-Encoder

Neural network prespective

The (latent→ data) mapping starts to shape up as a neural decoder, where we go from our sampled \mathbf{z} to the reconstruction, which can have a very complex distribution.



Credit: Altosaar

VAE learning objective

- KL-divergence measures “distance” between two probability distributions.

$$L = \frac{1}{|T|} \sum_{x \in T} d(x, D(E(x))) + \text{KL}(\mathcal{N}(\boldsymbol{\mu}(x), \boldsymbol{\sigma}(x)^2) || \mathcal{N}(0,1))$$

The KL term in L encourages datapoints to map near to unit-Gaussians.

- Update weights in the encoder E and decoder D via gradient descent.

