

Neural Network & Deep Learning

Deep AE

CSE & IT Department
School of ECE
Shiraz University

AutoEncoder

(AE)

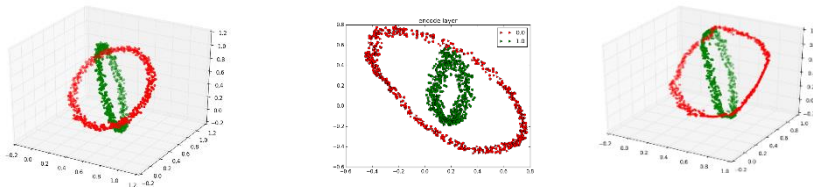
- A **neural network** trained to attempt to **copy** its input to its output
- Typically used in **dimensionality reduction**
 - Works only if the inputs are correlated
- Used for **image denoising** wherein a clear noise-free image could be generated using a noisy one
- Recently, widely used for learning **generative models**
- By adding **regularization**, it will be able to play with the **architecture** instead of only the **depth**

AE Usage

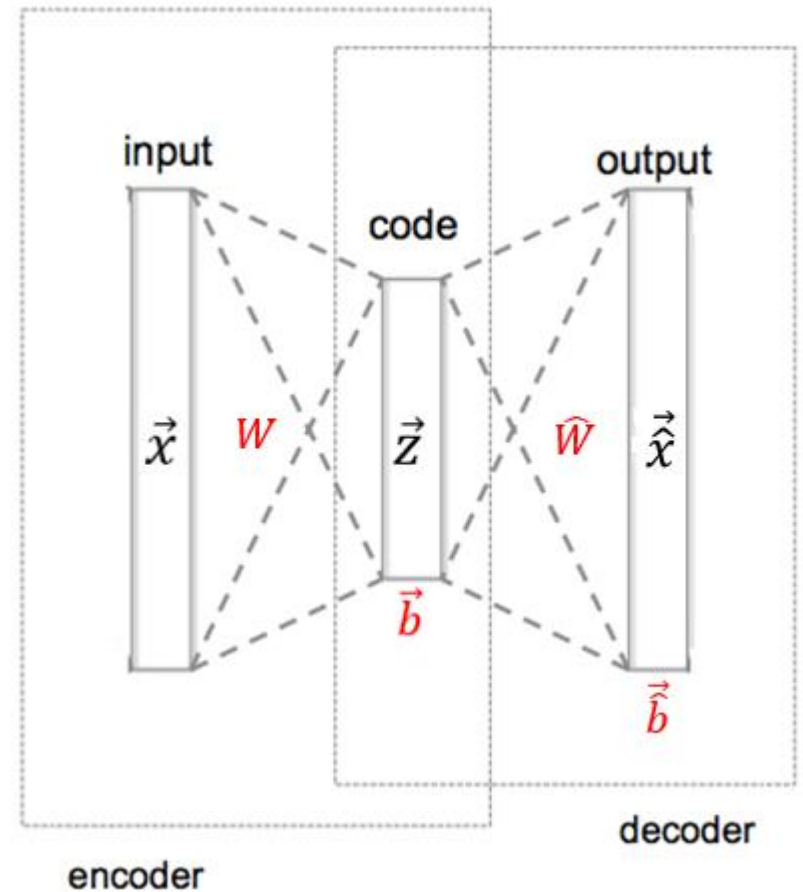
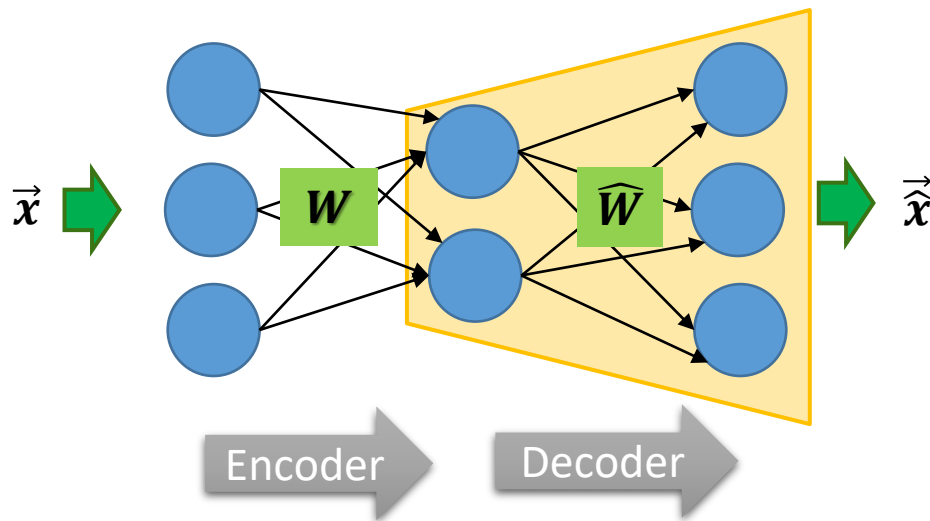


- Compression
 - **Not** popular as compression algorithms still perform **better**
- Denoising
 - Using **noisy** images as input of **AE** while trying to minimize difference between **reconstructed** output and original **clean** image
- Dimensionality reduction
 - Using **output** layer of Encoder with **fewer** dimensions than input to represent data in lower dimensions **non-linearly**
 - In contrast to **PCA** which does **linearly**
- Generating new data via generative models

Shallow AE

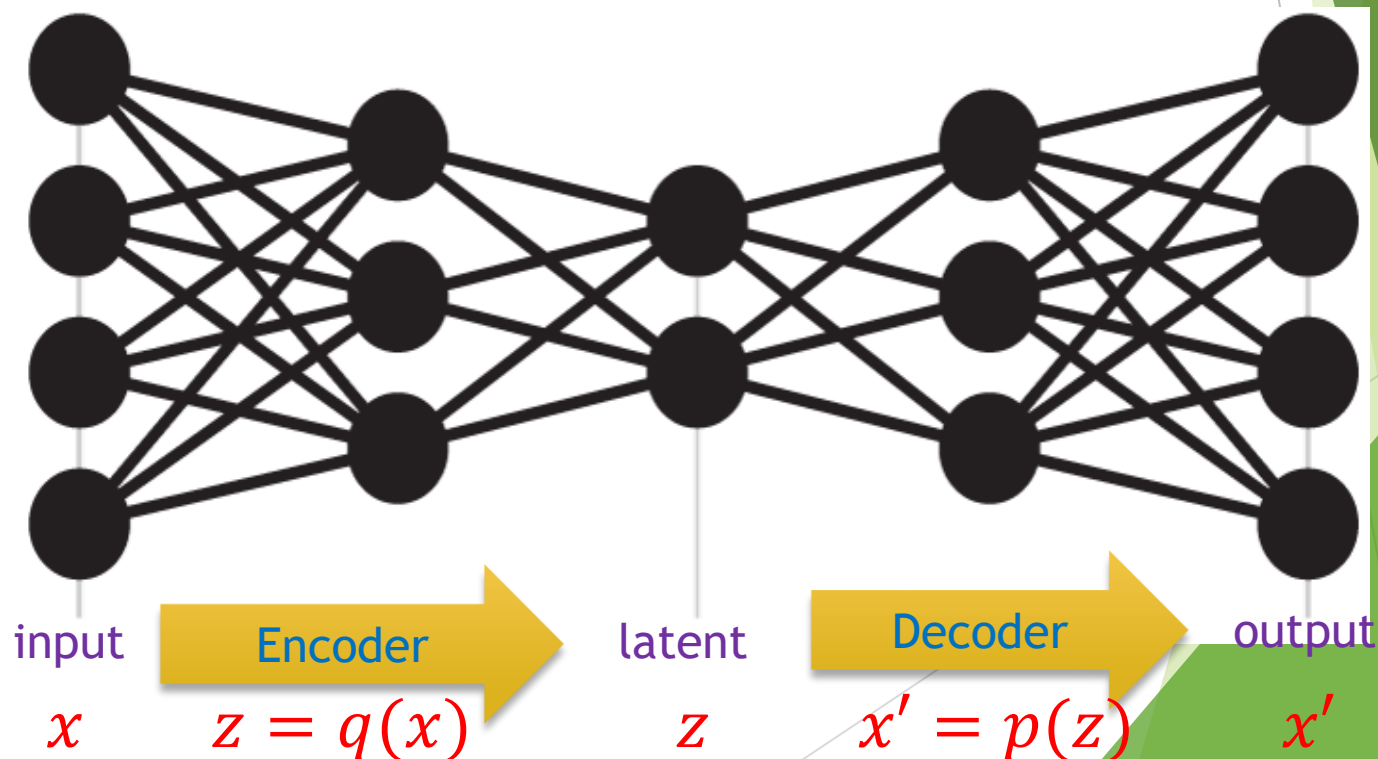


Input layer Code layer Output layer



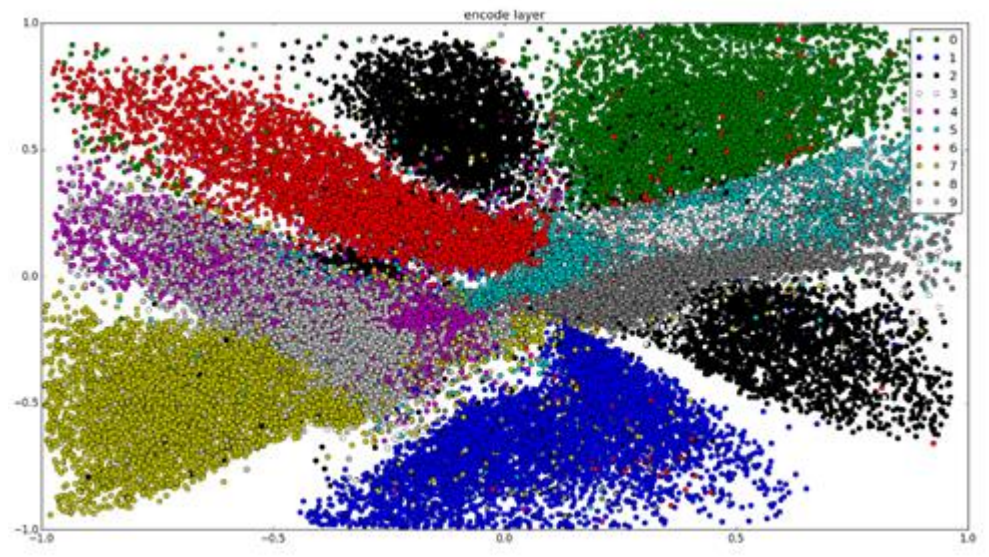
Deep MLP-AE

- **AE**: a neural network trained to attempt to copy its input to its output
- Deep **MLP-AE** has **several** hidden layers in its **encoder** and **decoder**



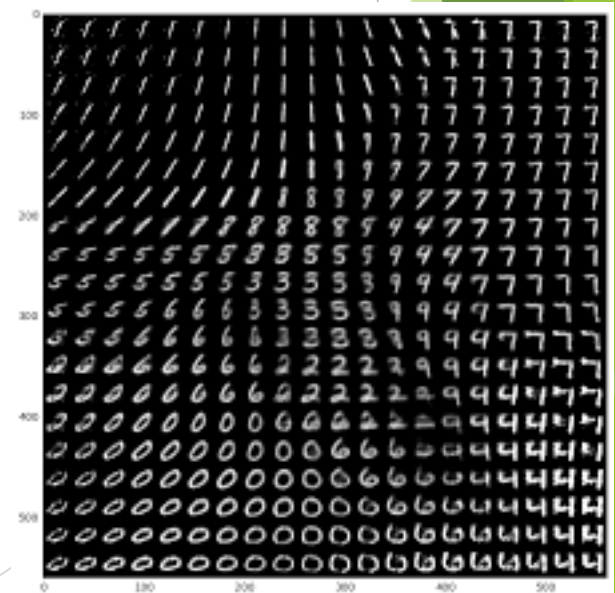
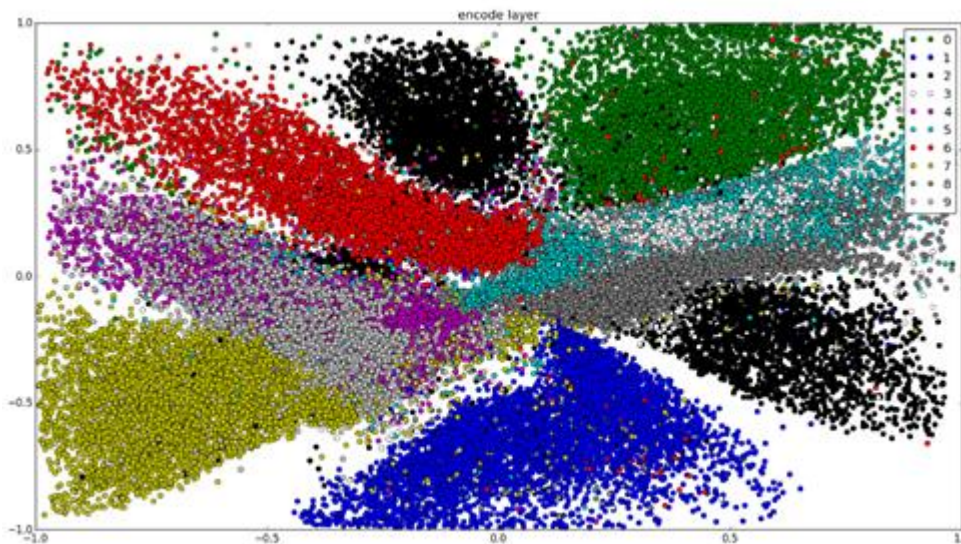
Deep AE Properties

- AE can find an abstract representation of data in its encode layer which contains most information of original representation of data in a lower dimension
- Results on MNIST dataset



Deep AE Properties

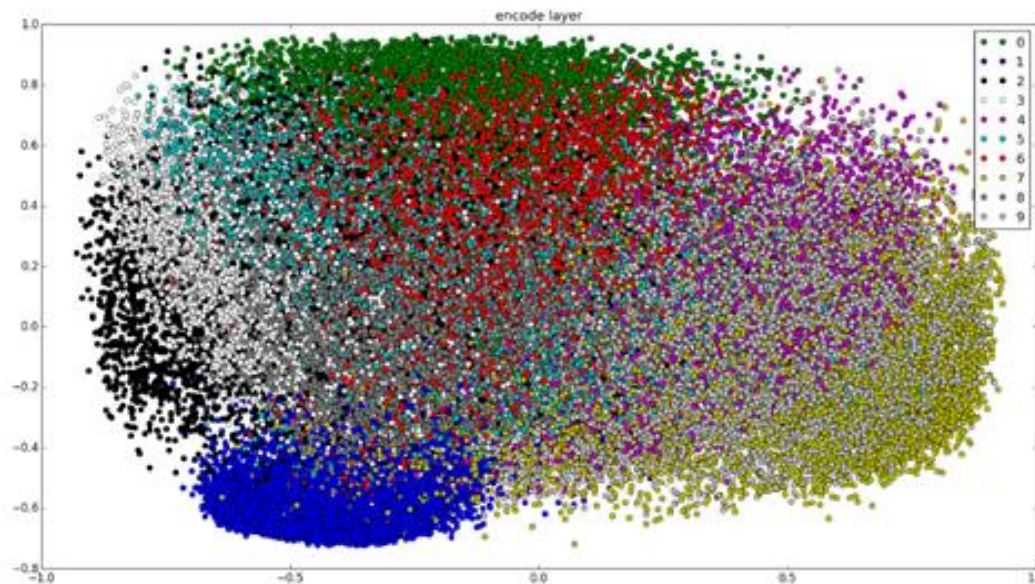
- AE is a **generative** model
- By generating random samples in **encode** layer of a trained AE, its **decoder** can map them to **new** data samples in original data space



Shallow AE

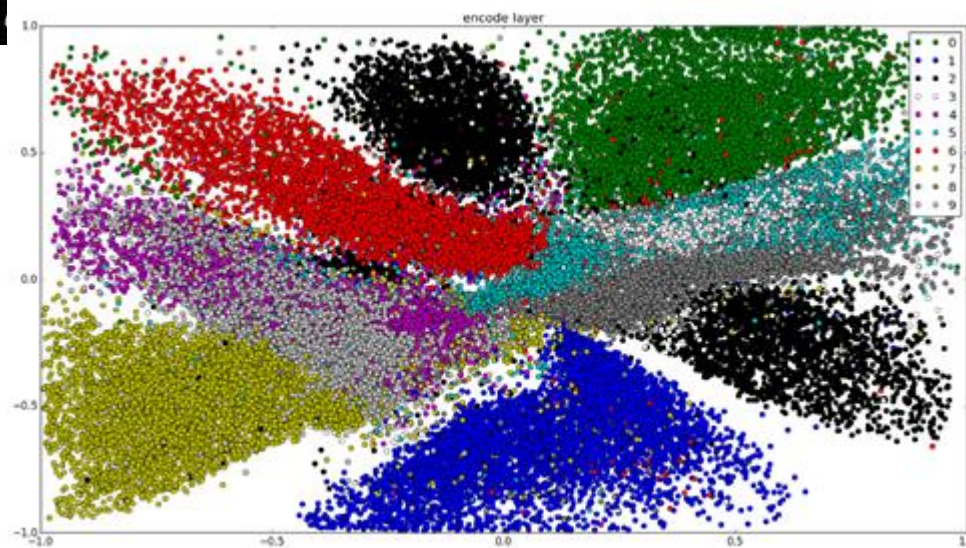
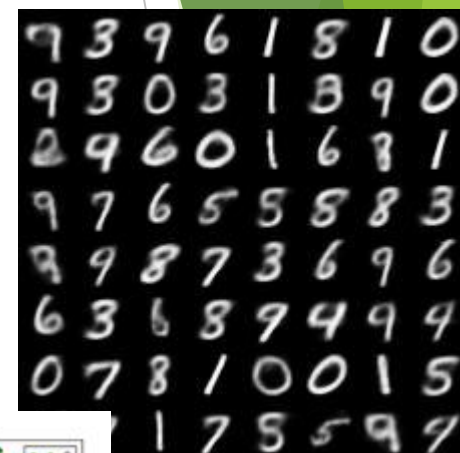


784 \longrightarrow 2 \longrightarrow 784



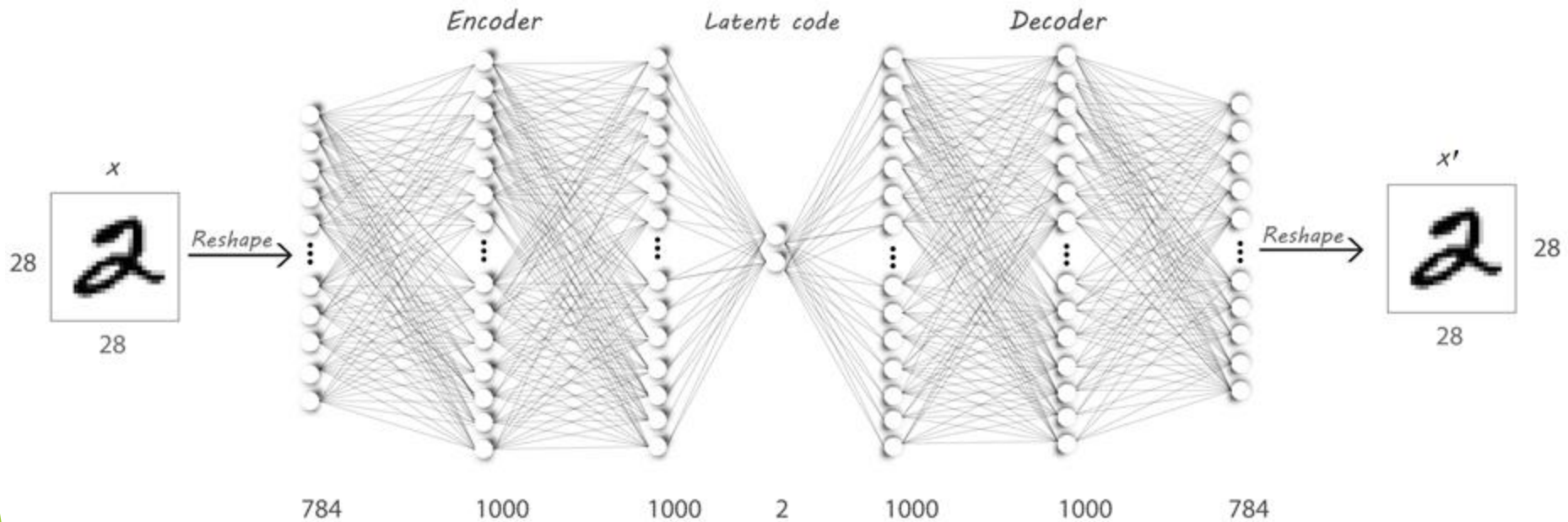
Deep AE

784 -> 512 -> 256 -> 128 -> 32 -> 2 -> 32 -> 128 -> 256 -> 512 -> 784

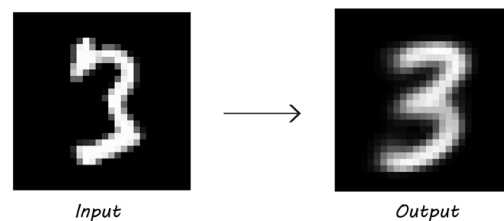


AE for MNIST Dataset

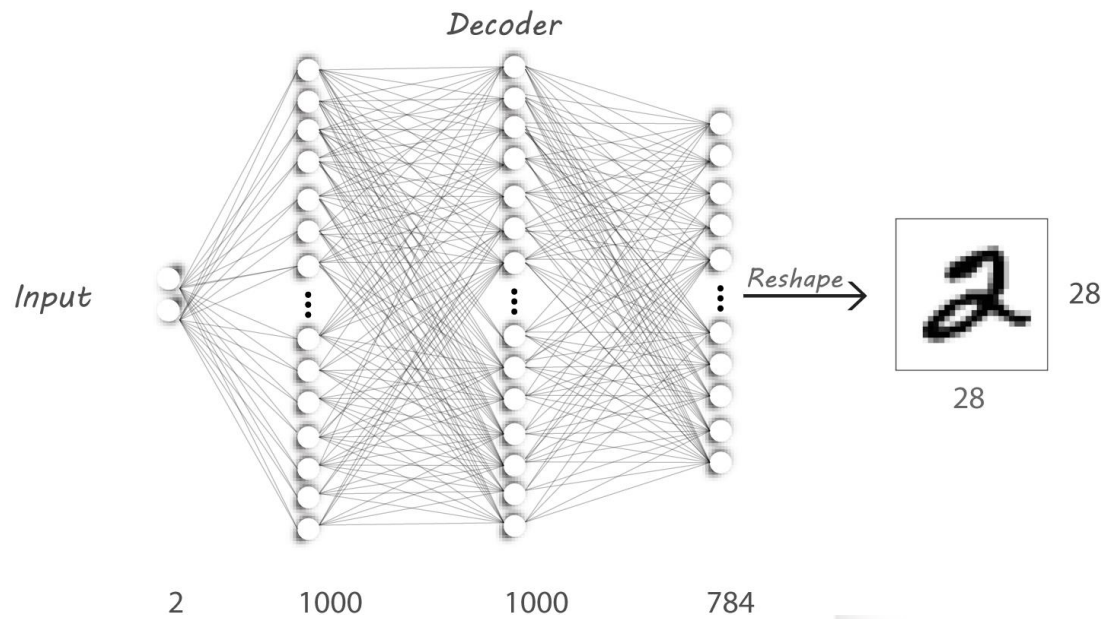
Training phase



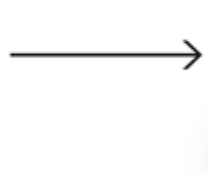
Test phase



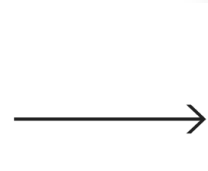
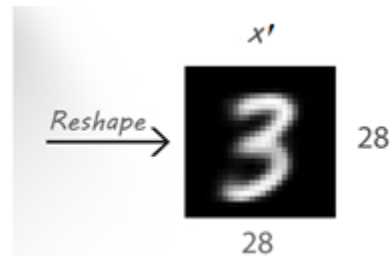
Decoder of AE as Generator



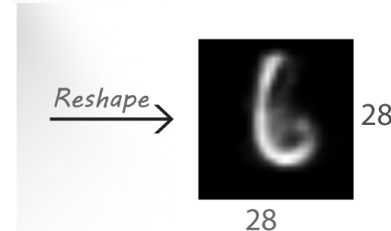
$$\begin{bmatrix} .13 \\ .18 \end{bmatrix}$$

$$\begin{bmatrix} .0 \\ .0 \end{bmatrix}$$


Decoder



Decoder



12 Blurry image ---> encoder output (latent code) not follow any distribution

Variational AutoEncoder

(VAE)

Why Variational?

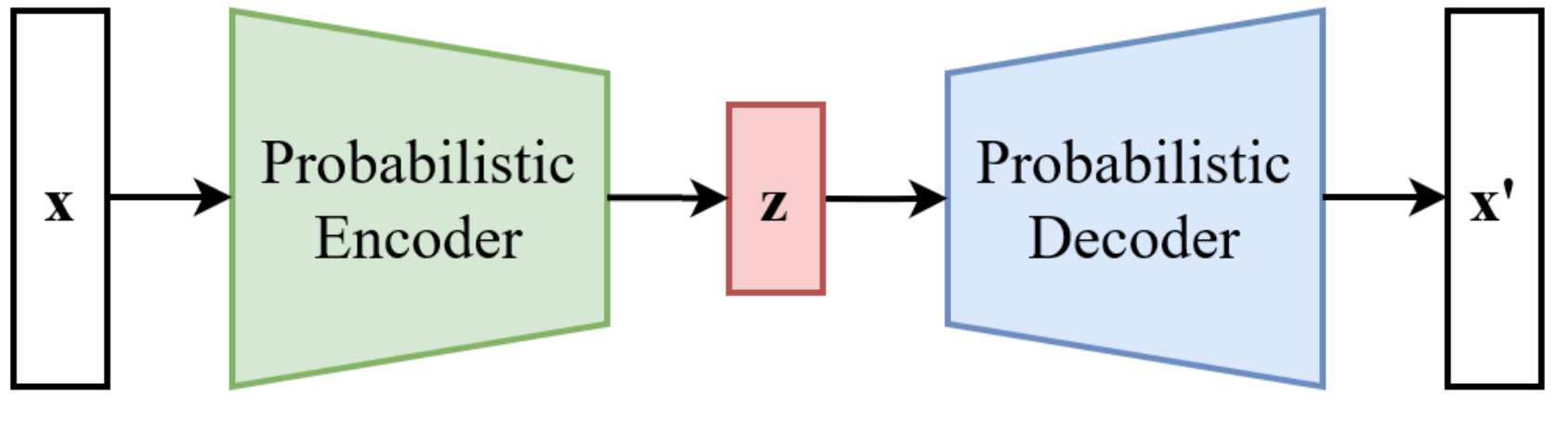


- In AE,
 - latent vectors, generated by encoder, tends to be irregular, unorganized, or uninterpretable as
 - it only aims to reconstruct input as similar as possible without any constraint on latent space
- We would like latent space to be continuous but separated which allow interpolation between different attributes

VAE: Deep Learning + Bayesian Inference



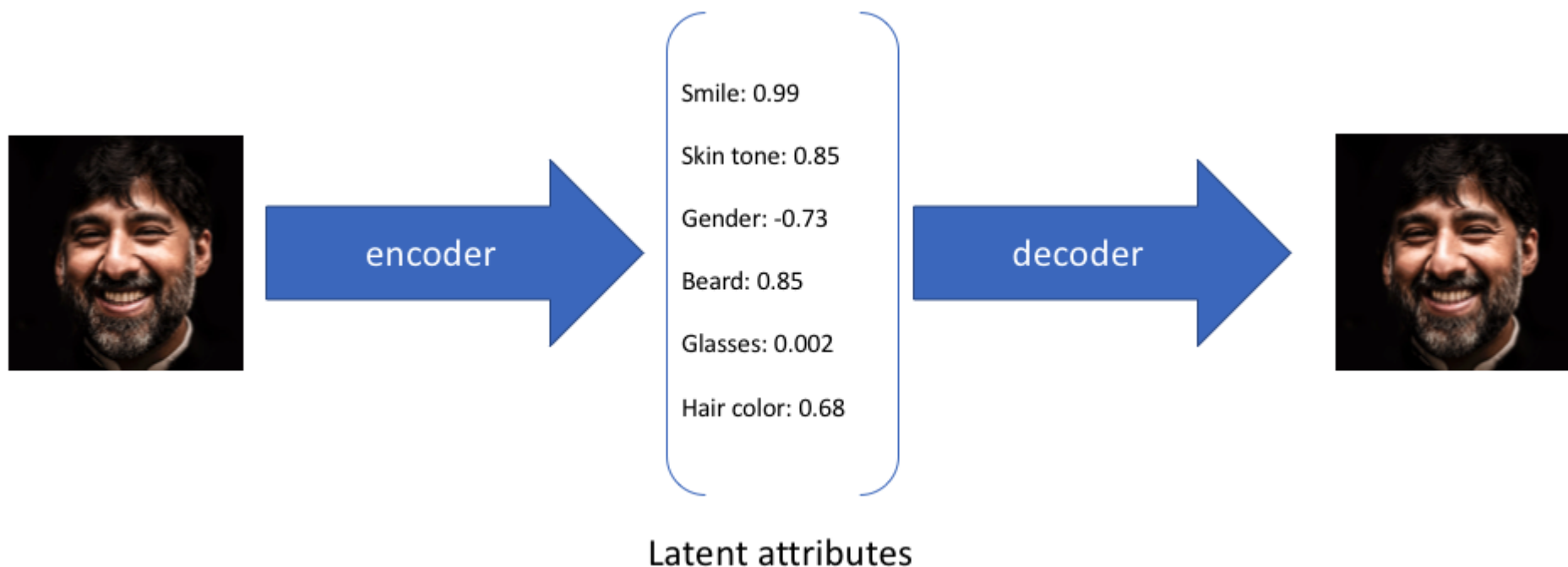
- Combines techniques from **deep learning** and **Bayesian variational inference**
- Provides a **probabilistic** manner for describing an observation in **latent space**



- Its **encoder** describes a **probability distribution** (instead of producing a **single value**) for each latent attribute

VAE Motivation

- Describing **input image** in terms of its **latent attributes** using a **single value** to describe each attribute

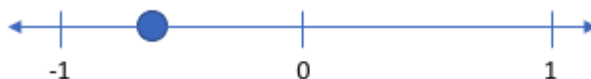


- Preferring to represent **latent attributes** as **range of possible values**

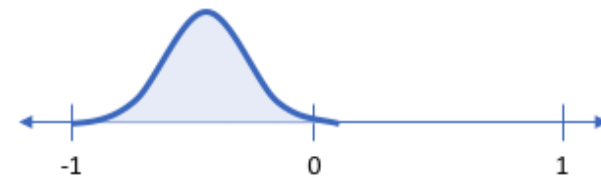
VAE Motivation

Representing latent attributes as a probability distribution

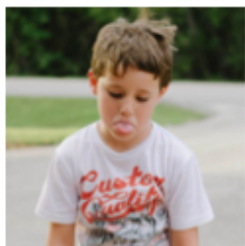
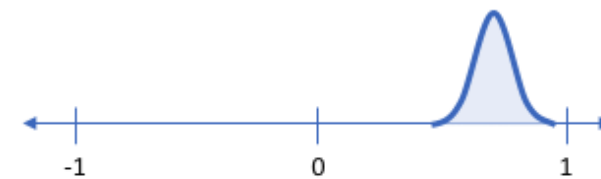
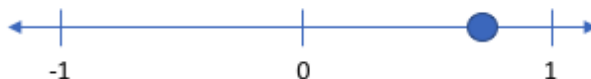
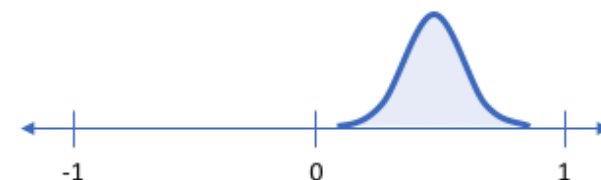
Smile (discrete value)



Smile (probability distribution)

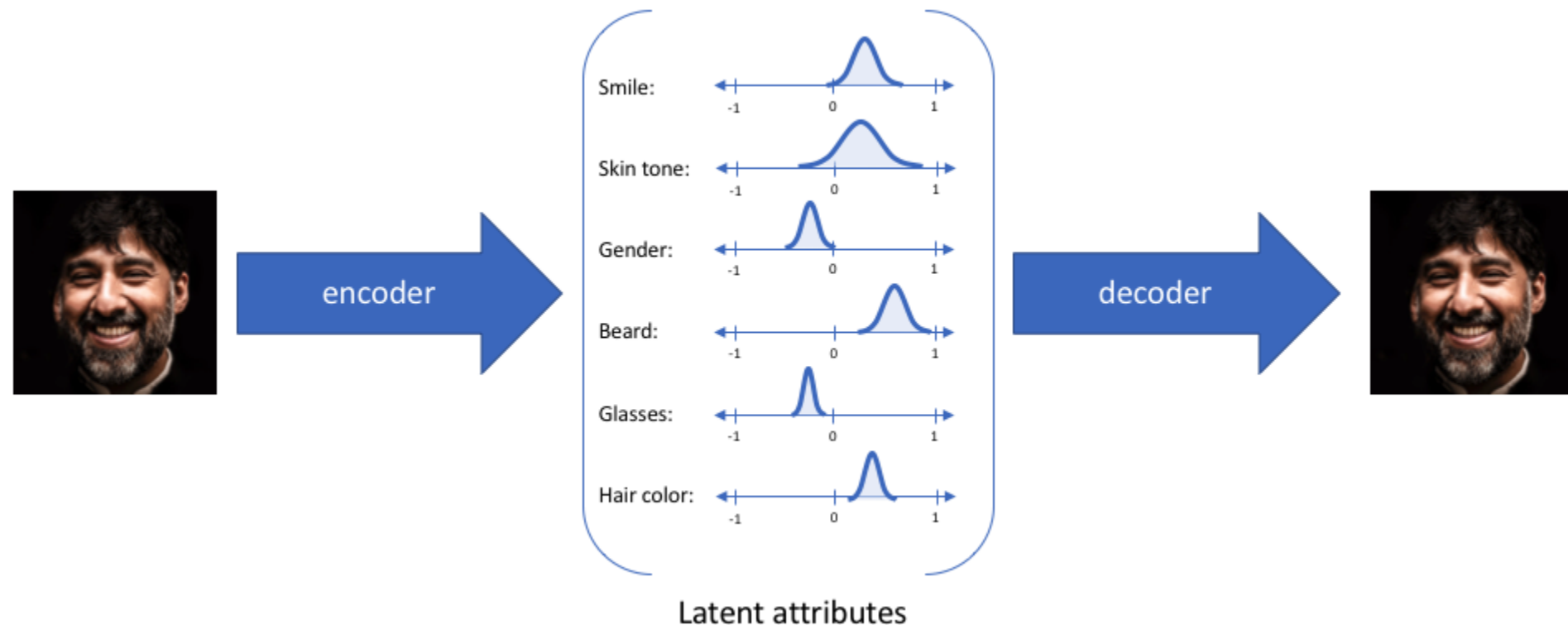


vs.



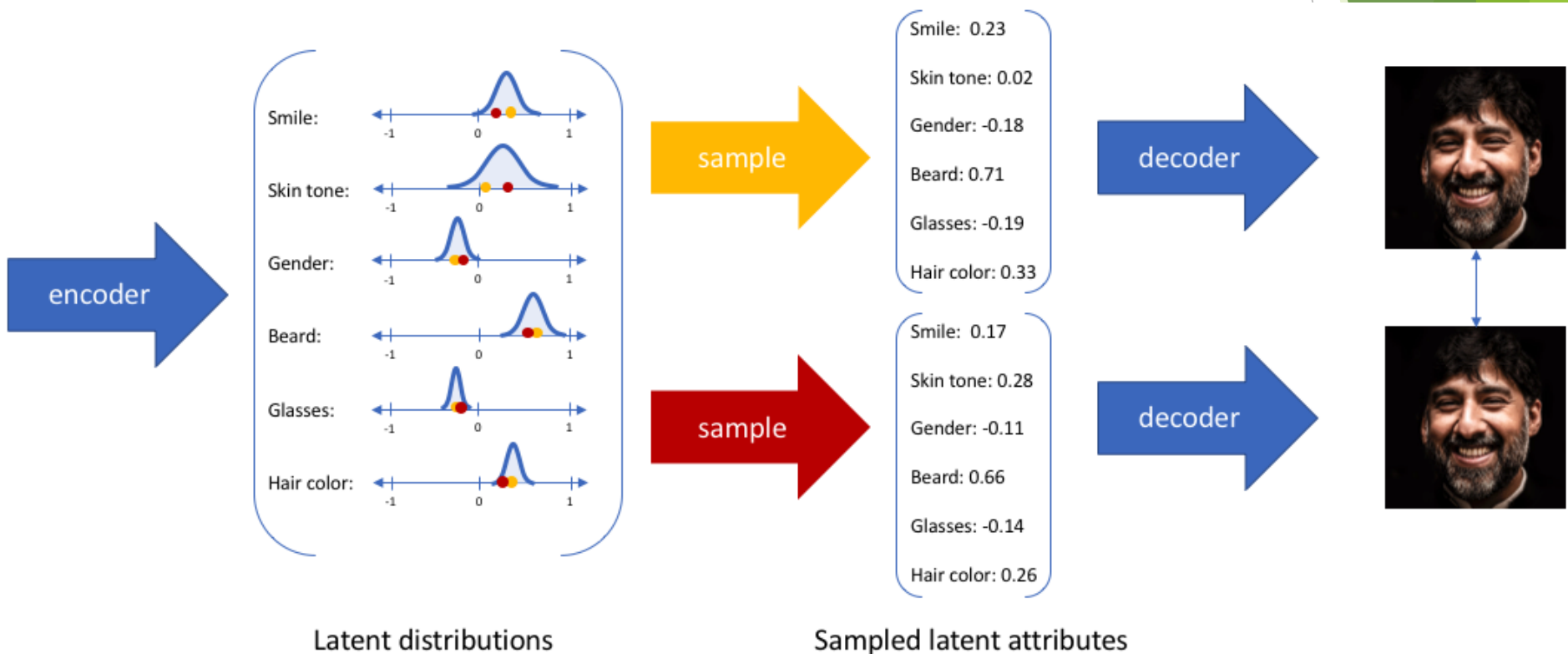
VAE Motivation

Describing **input image** in terms of its **latent attributes** using a **probability distribution** to describe each attribute



VAE Motivation

Expecting an **accurate reconstruction** for any sample from the **latent state distributions**

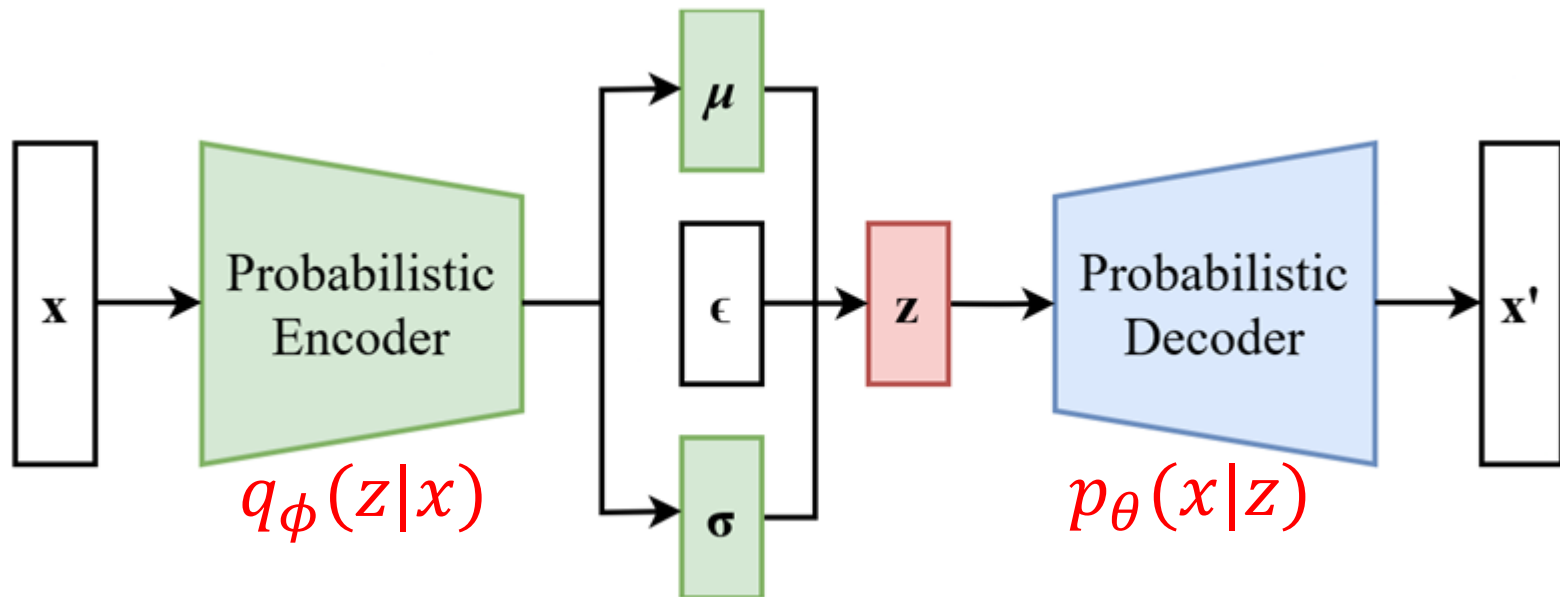


AE vs VAE



- AE is **regular**: each layer represents **encoded data**
- VAE is **Bayesian**: layers represent **distribution of data**
 - Input to Encoder:
 - **Bernoulli distribution** (binary data)
 - **Gaussian distribution** (real-valued data)
 - Latent layer: **Gaussian distribution**
 - Input to Decoder: **samples from Gaussian distribution**
 - Output of Decoder:
 - **Bernoulli distribution** (binary data)
 - **Gaussian distribution** (real-valued data)

VAE Forward Pass



- Encoder $q_{\phi}(z|x)$ approximates posterior distribution $p(z|x)$
 $q_{\phi}(z|x) = \mathcal{N}(z; \mu_{\phi}(x), \text{diag}(\sigma_{\phi}(x)))$
- Decoder carries conditional likelihood distribution $p_{\theta}(x|z)$ to approximate $p(x|z)$
- VAE computes $p(x'|x)$