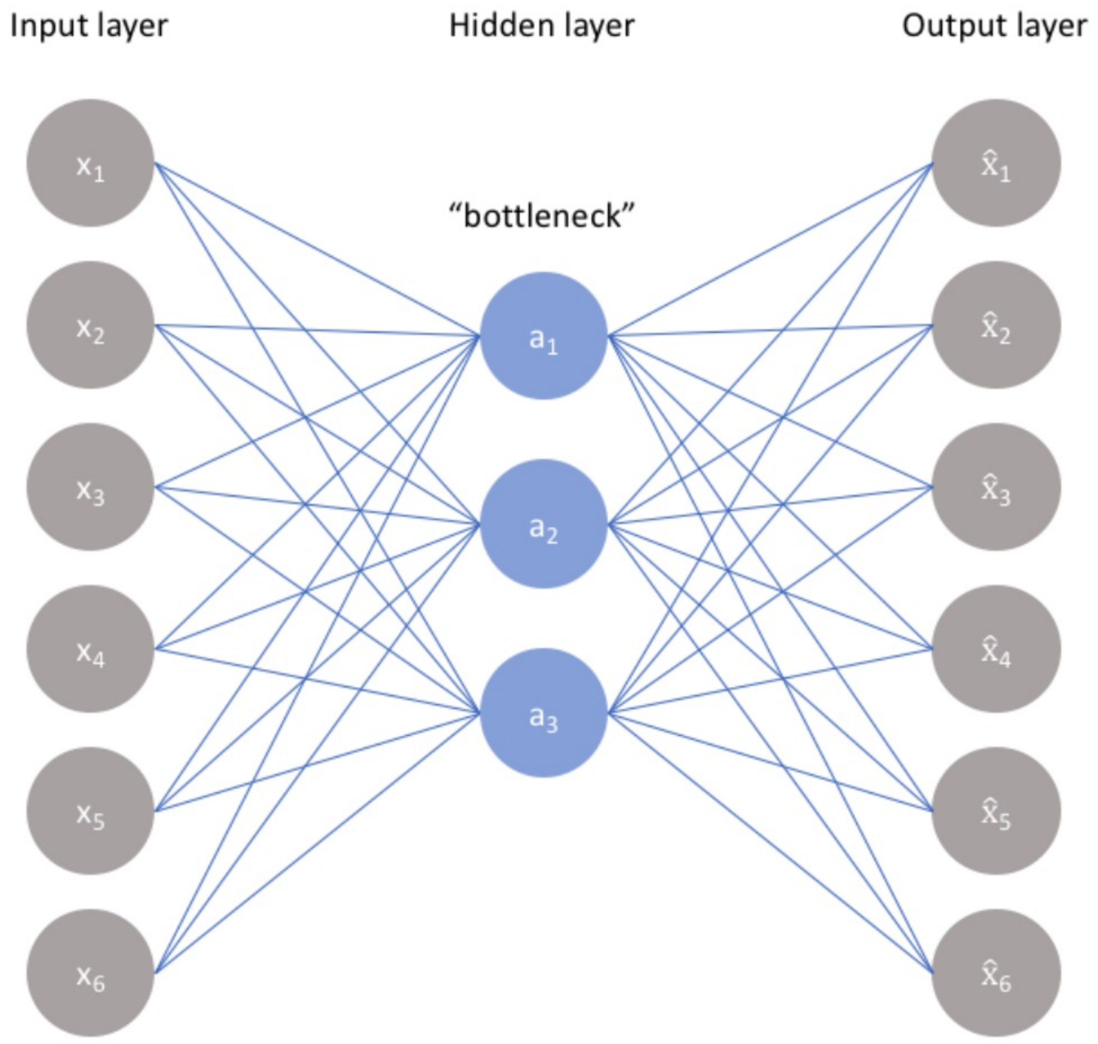
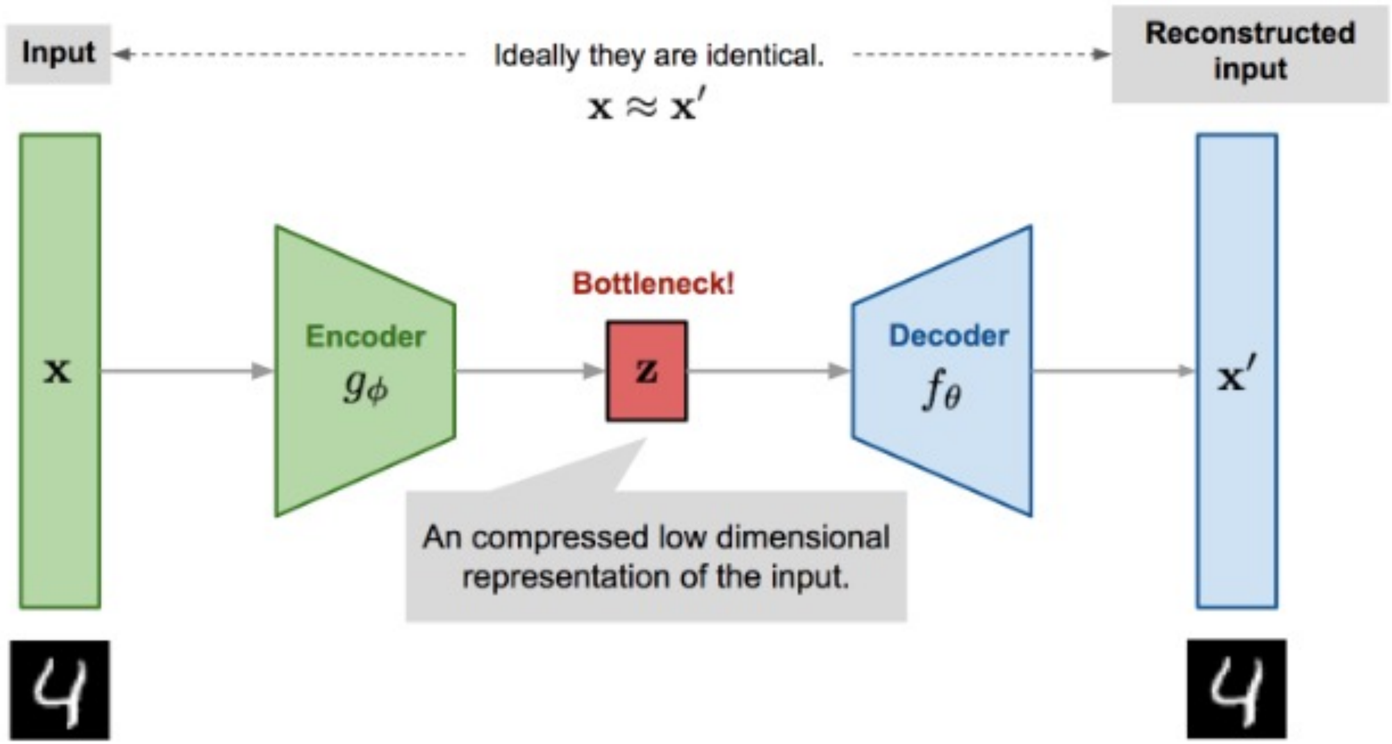
DEEP LEARNING FOR COMPUTER VISION

Week7

Dr. Tuchsanai. PloySuwan

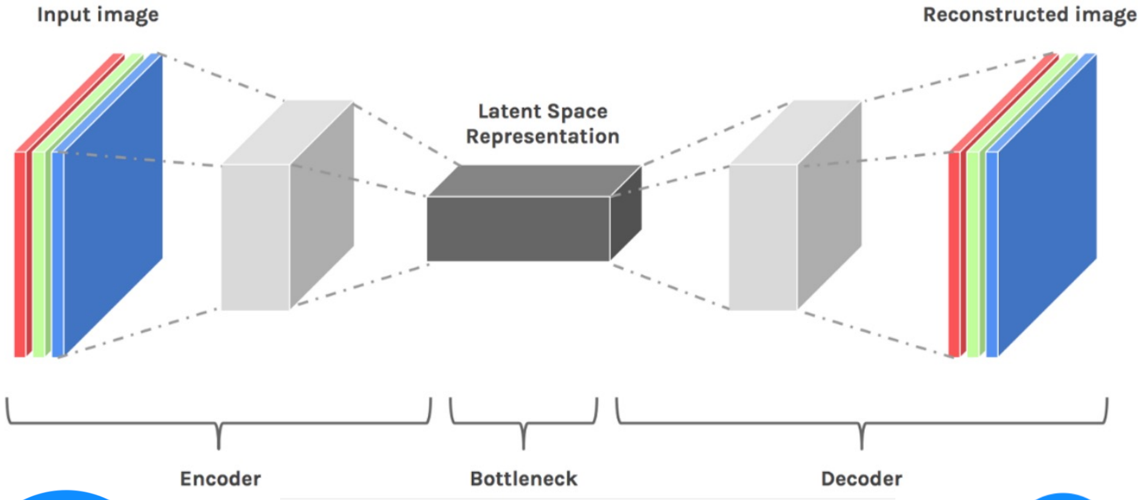
Autoencoders

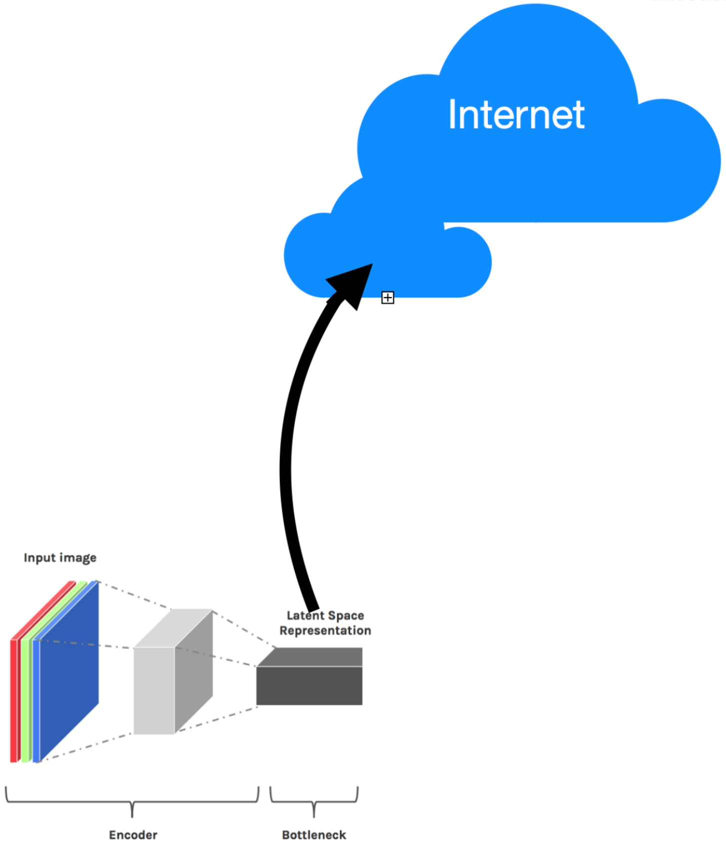

Input layer
Hidden layer
Output layer
"bottleneck"
x_1
x_2
x_3
x_4
x_5
x_6
a_1
a_2
a_3
$\hat{x}_1$
$\hat{x}_2$
$\hat{x}_3$
$\hat{x}_4$
$\hat{x}_5$
$\hat{x}_6$

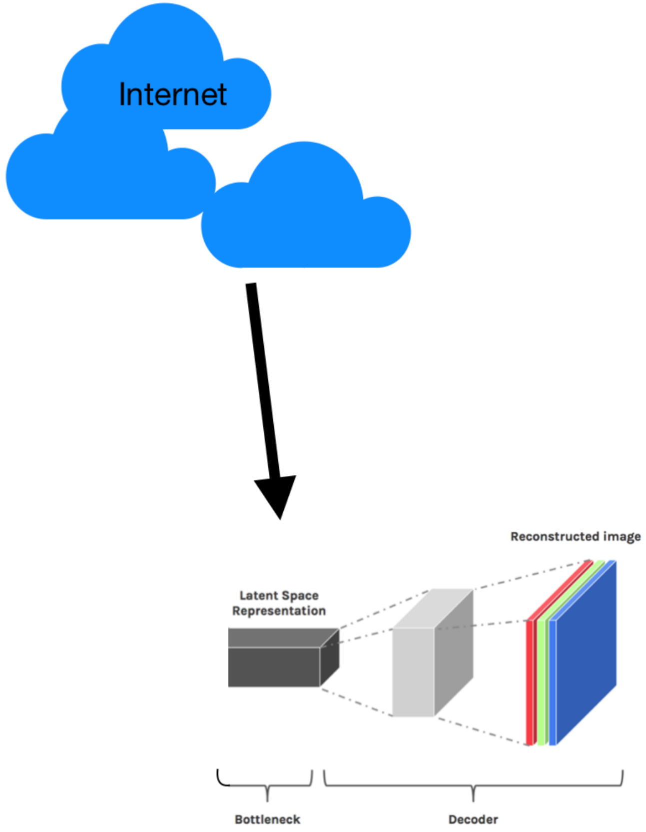


$$L_{\mathrm{AE}}(\theta, \phi) = \frac{1}{n} \sum_{i=1}^{n} (\mathbf{x}^{(i)} - f_\theta(g_\phi(\mathbf{x}^{(i)})))^2$$

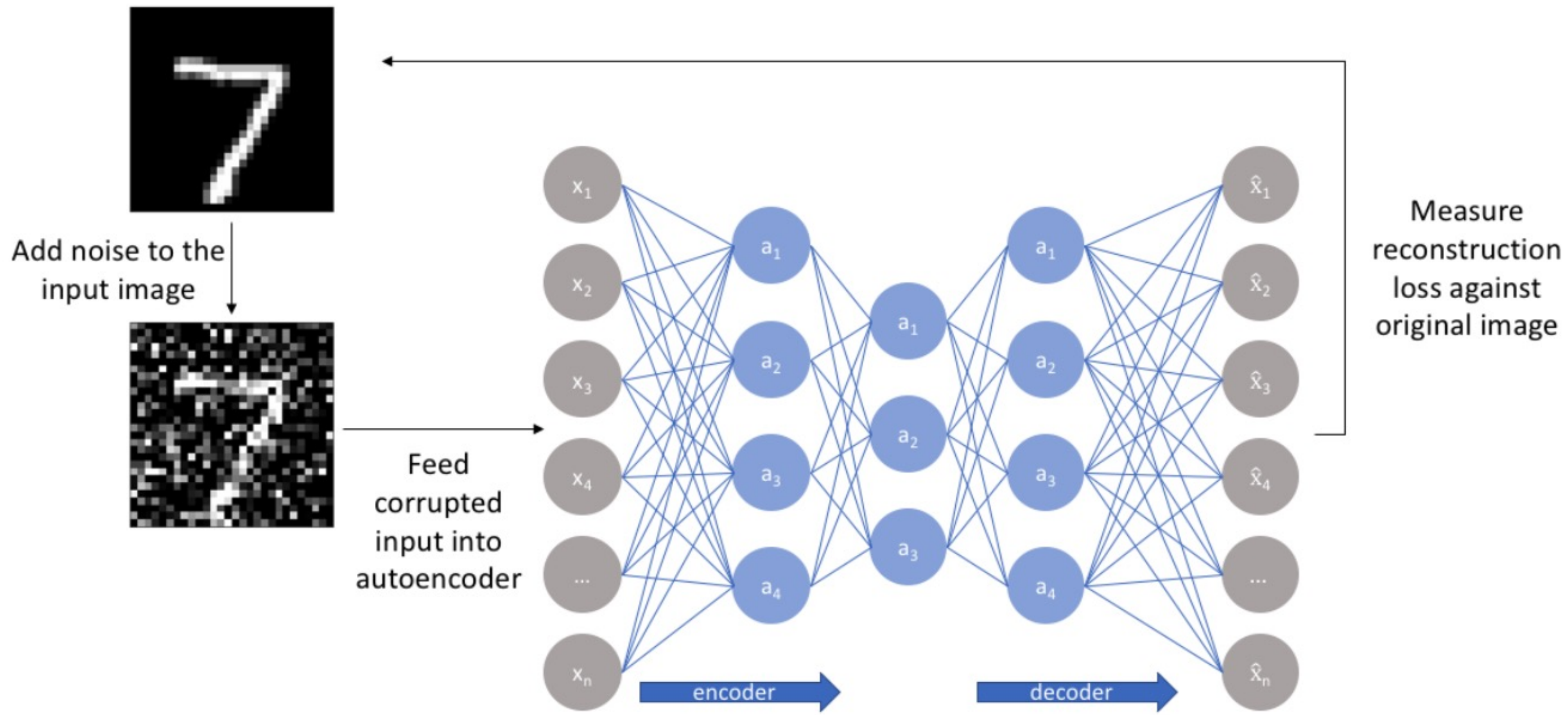
Data compression

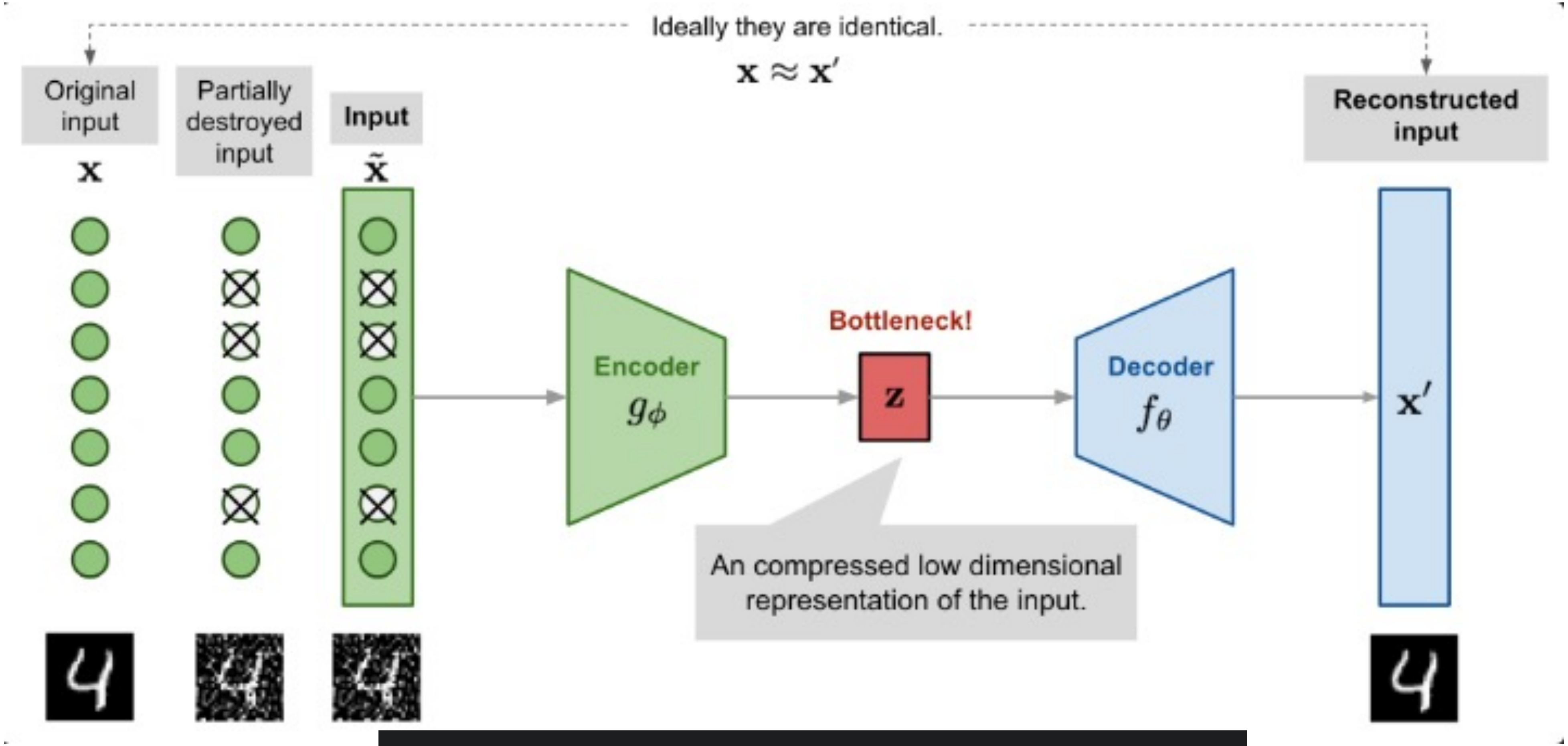






Denoising data





$$\tilde{\mathbf{x}}^{(i)} \sim \mathcal{M}_{\mathcal{D}}(\tilde{\mathbf{x}}^{(i)} | \mathbf{x}^{(i)})$$

$$L_{\text{DAE}}(\theta, \phi) = \frac{1}{n} \sum_{i=1}^{n} (\mathbf{x}^{(i)} - f_\theta(g_\phi(\tilde{\mathbf{x}}^{(i)})))^2$$

Introduction to Autoencoders for Anomaly Detection

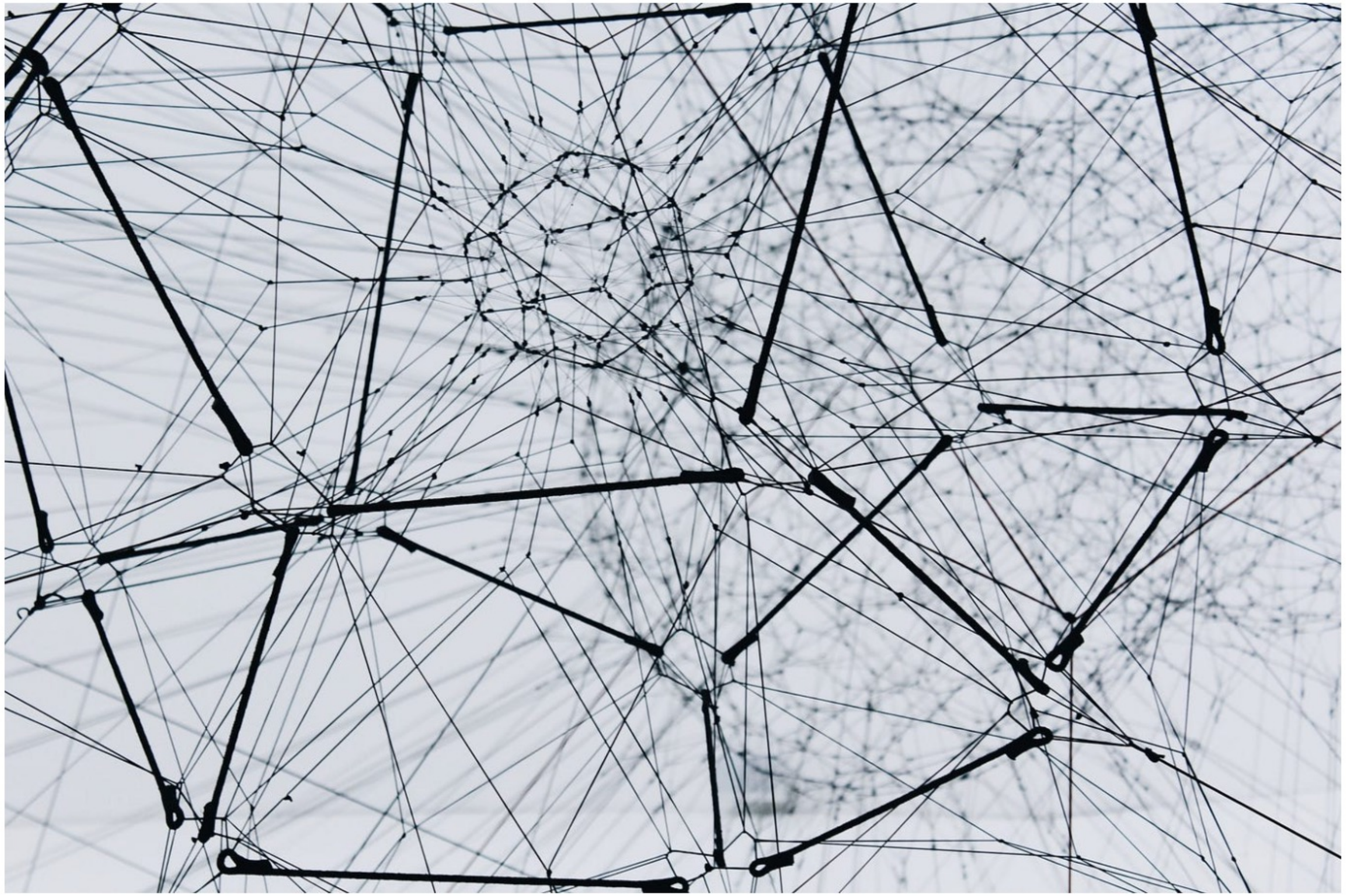


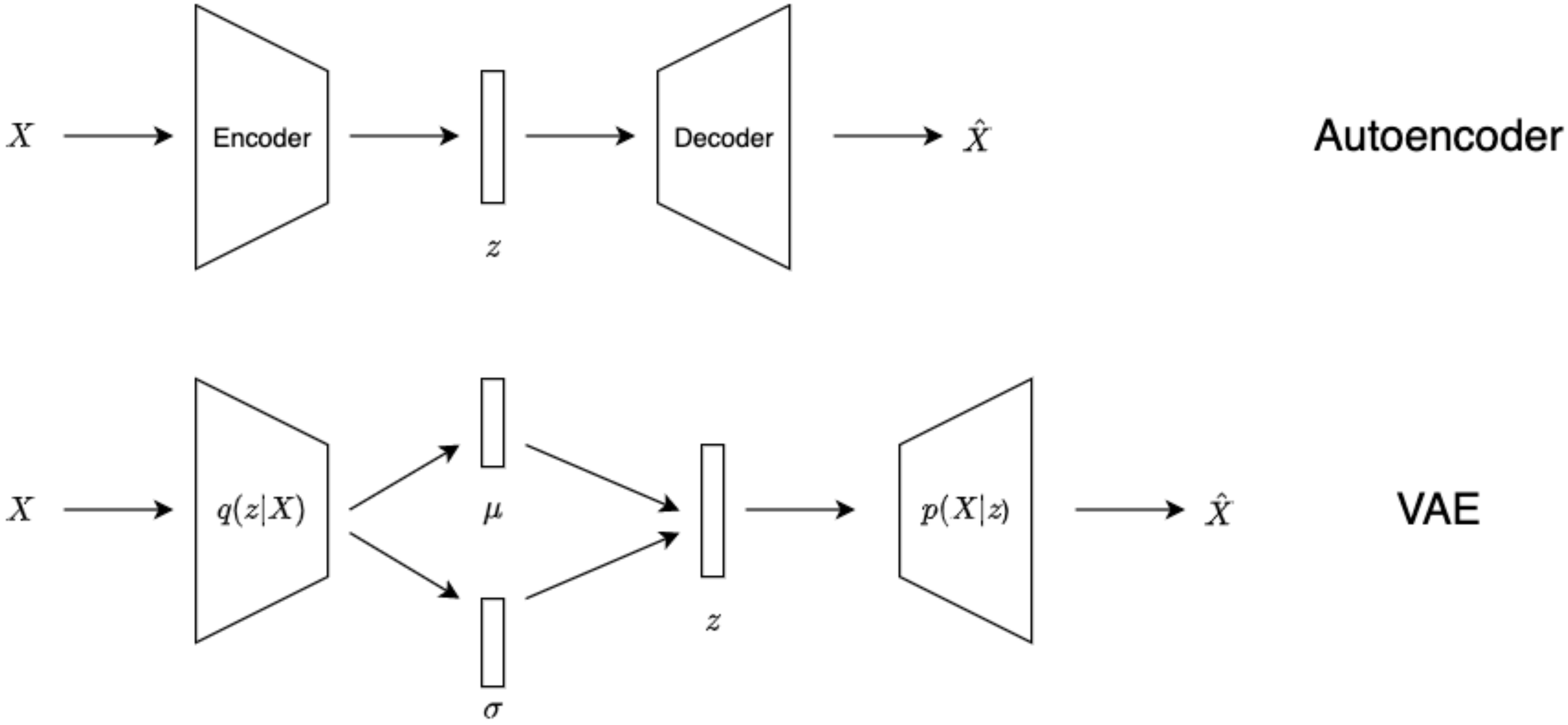
Photo by Alina Grubnyak / Unsplash

https://medium.com/artificialis/introduction-to-autoencoders-for-anomaly-detection-a9897591cc72

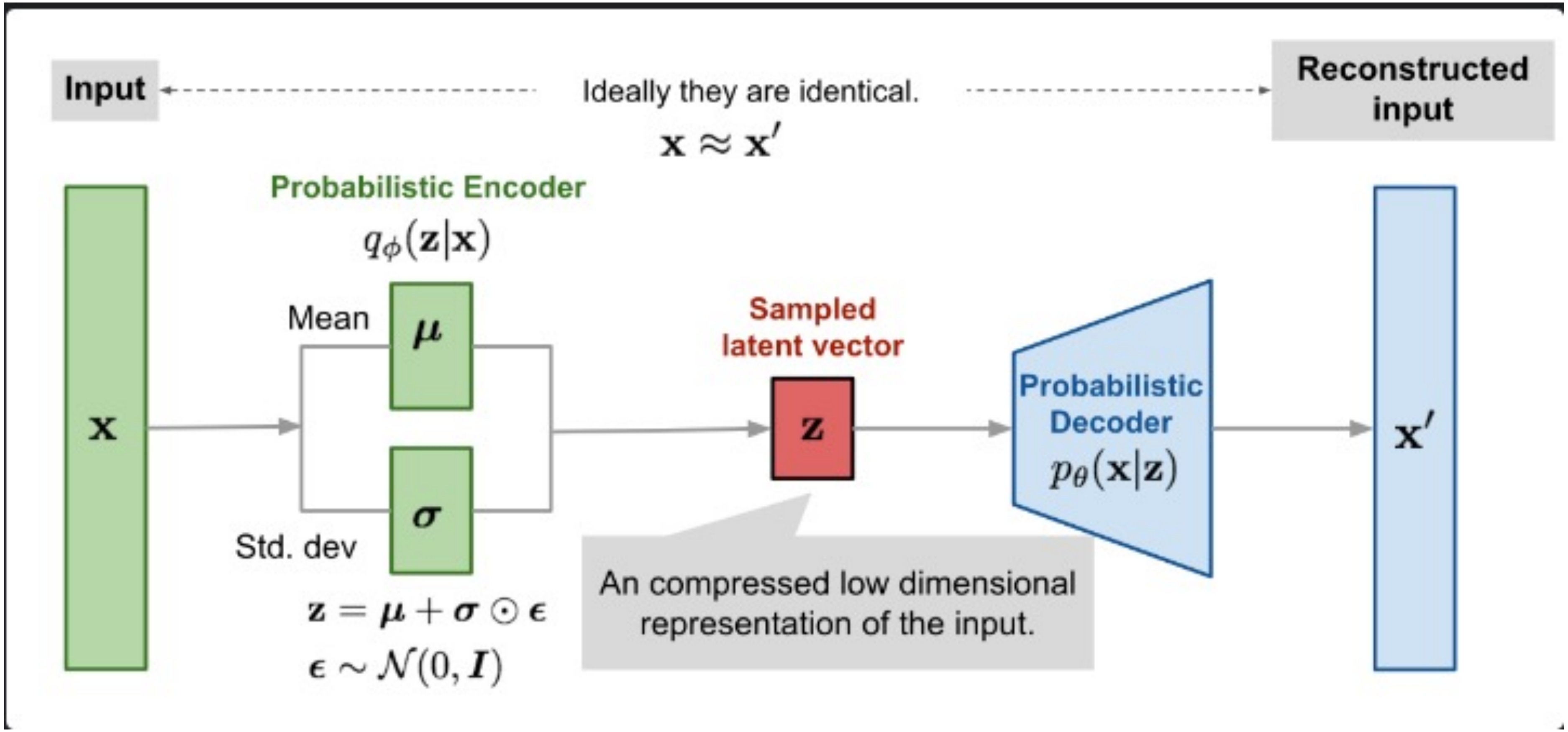
https://towardsdatascience.com/anomaly-detection-with-autoencoder-b4cdce4866a6

https://medium.com/georgian-impact-blog/time-series-anomaly-detection-the-detectives-toolbox-9ef131dddaf9

Variational autoencoders



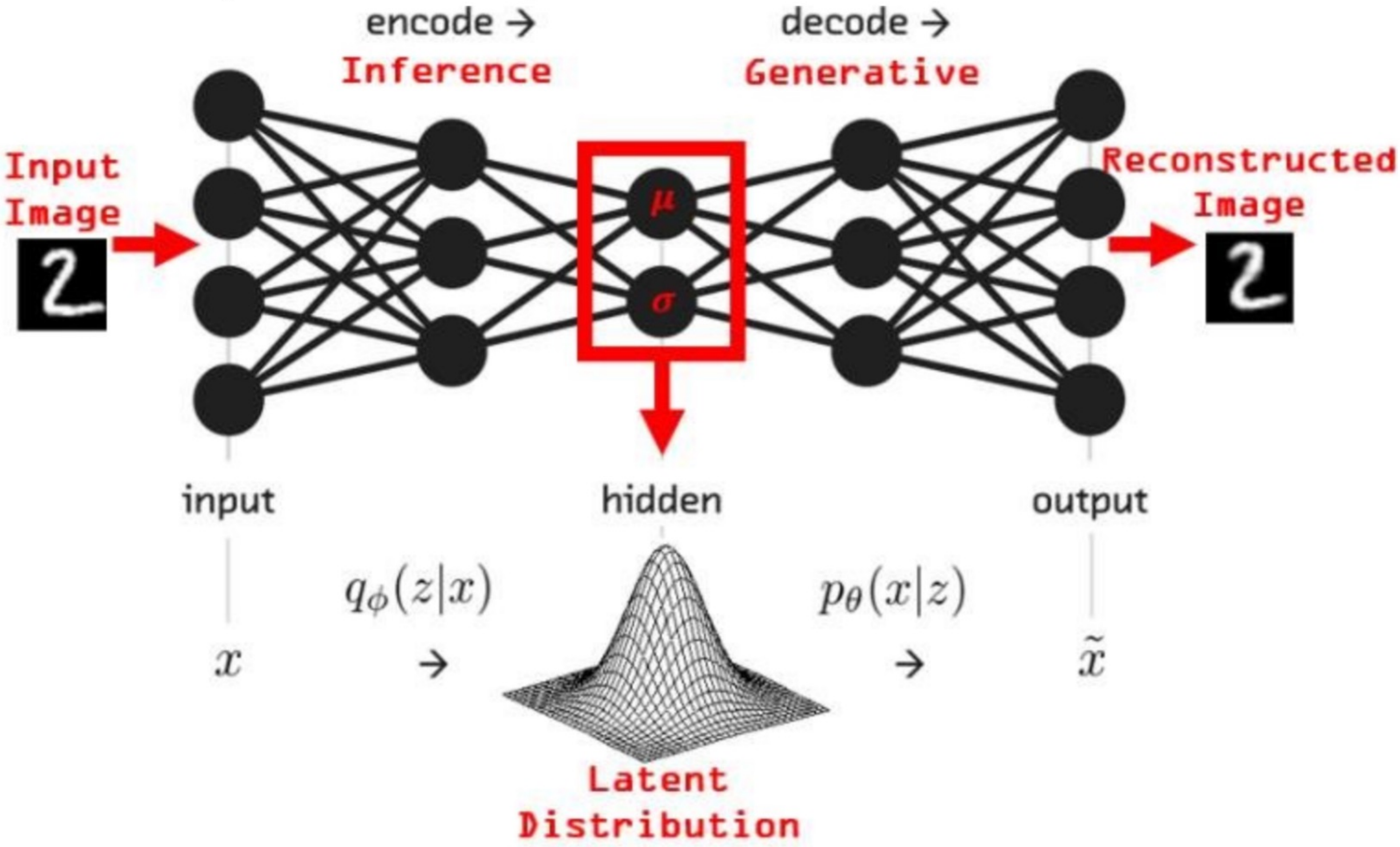
X
Encoder
z
Decoder
$\hat{X}$
Autoencoder
X
$q(z|X)$
μ
σ
z
$p(X|z)$
$\hat{X}$
VAE

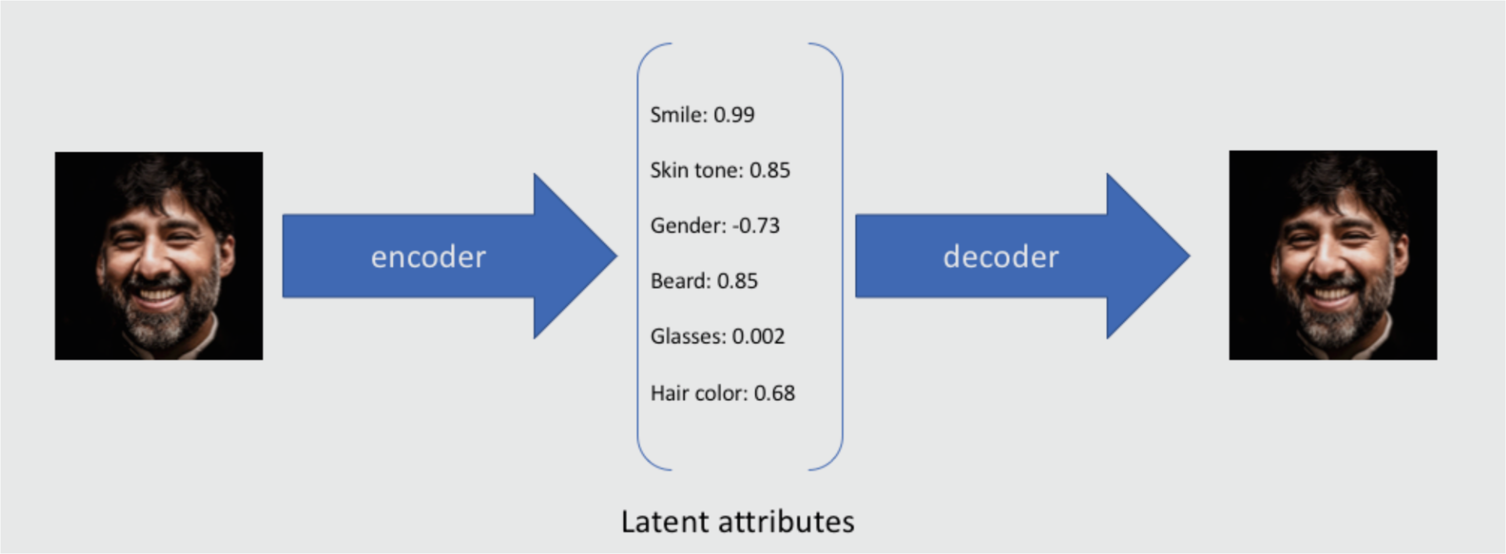


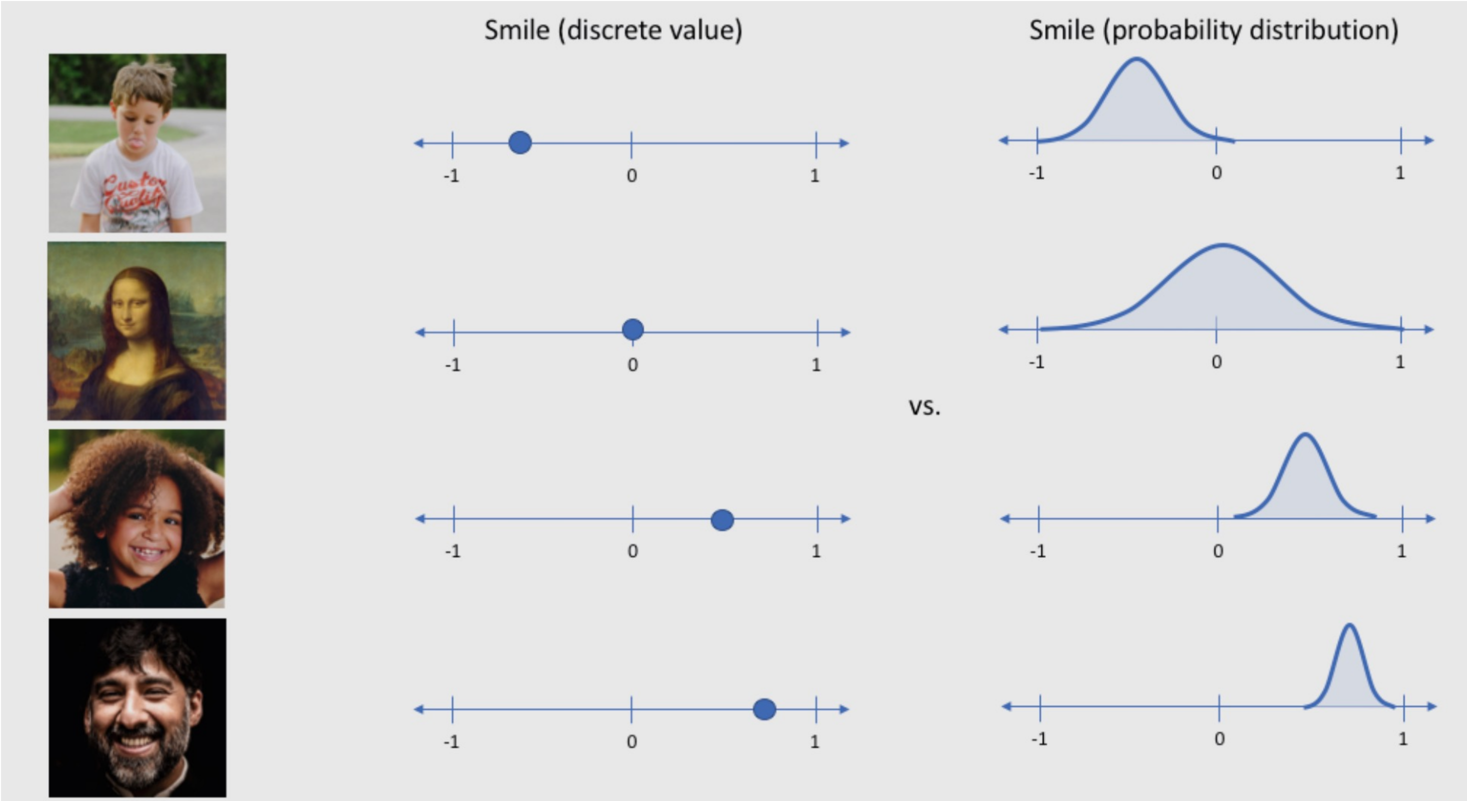
Input
Ideally they are identical.
$\mathbf{x} \approx \mathbf{x}'$
Reconstructed input
Probabilistic Encoder
$q_\phi(\mathbf{z}|\mathbf{x})$
Mean
$\boldsymbol{\mu}$
Std. dev
$\boldsymbol{\sigma}$
$\mathbf{x}$
Sampled latent vector
$\mathbf{z}$
Probabilistic Decoder
$p_\theta(\mathbf{x}|\mathbf{z})$
$\mathbf{x}'$
$\mathbf{z} = \boldsymbol{\mu} + \boldsymbol{\sigma} \odot \boldsymbol{\epsilon}$
$\boldsymbol{\epsilon} \sim \mathcal{N}(0, \boldsymbol{I})$
An compressed low dimensional representation of the input.

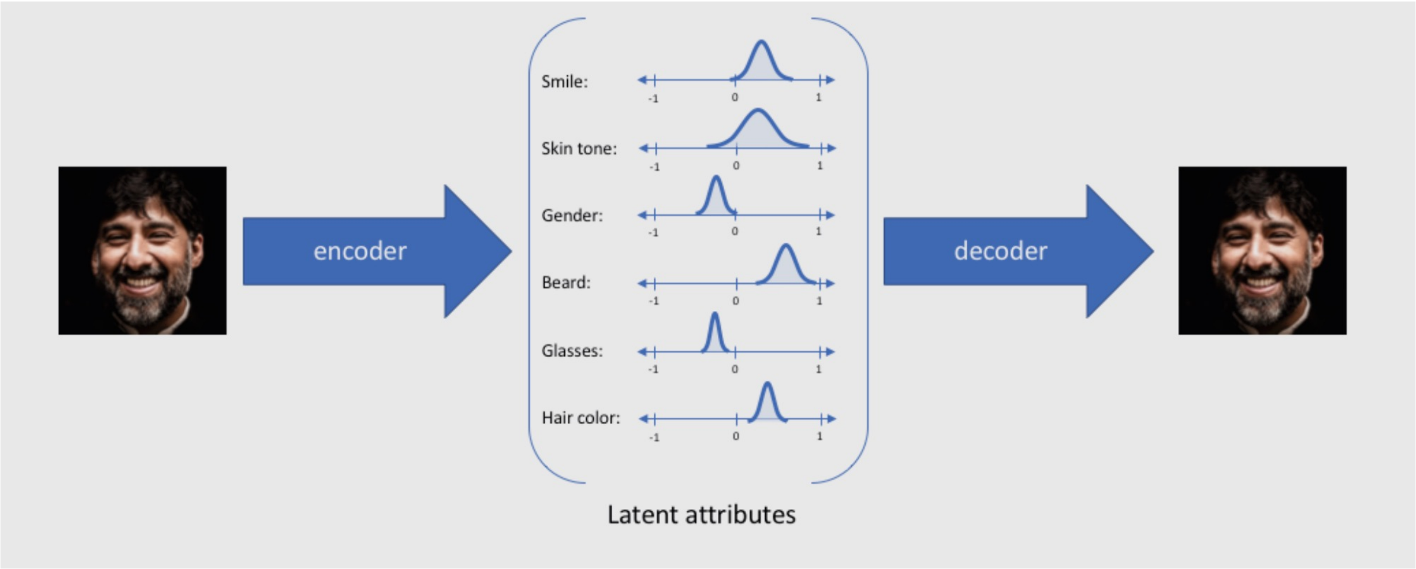
What is Variational AutoEncoder?

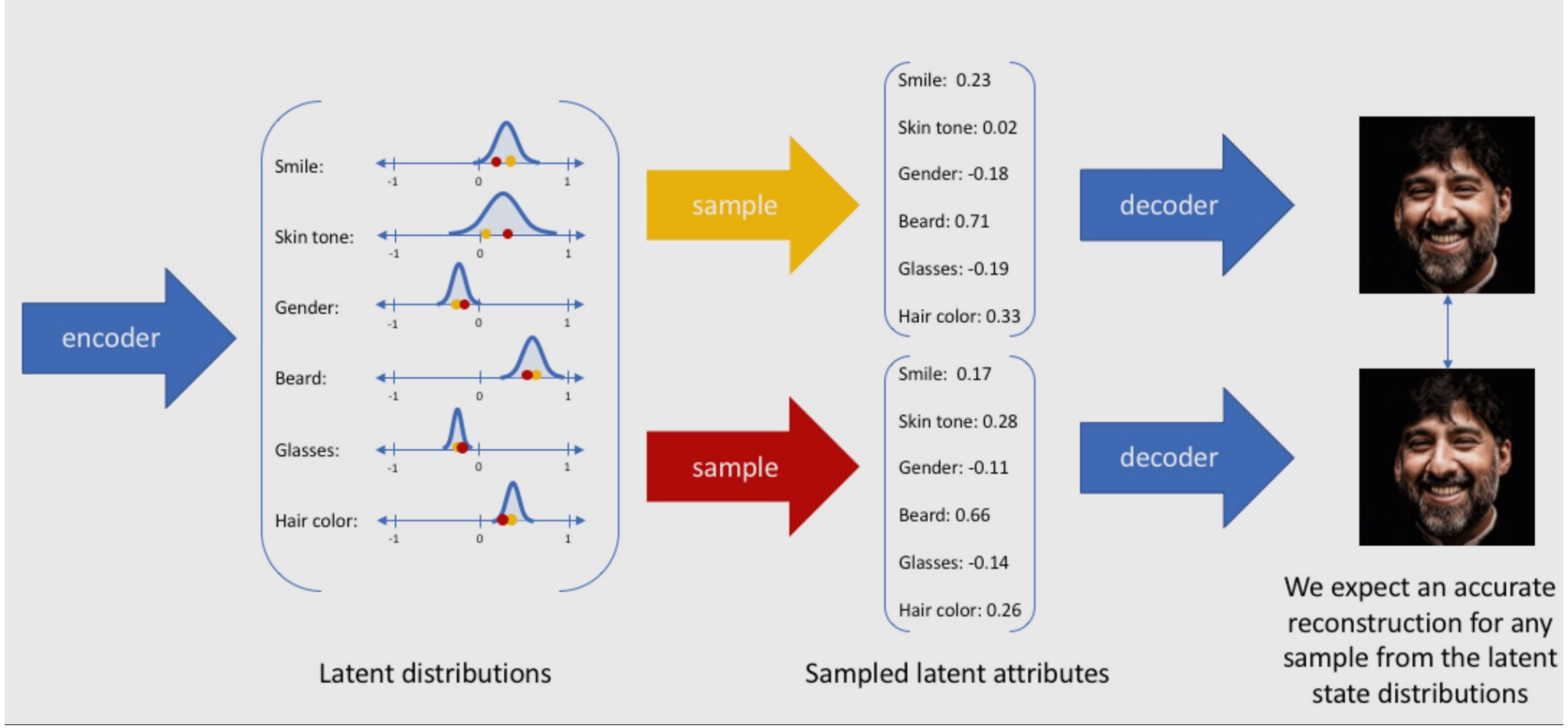
VAE is an autoencoder whose encodings distribution is regularised during the training in order to ensure that its latent space has good properties allowing us to generate some new data. A variational autoencoder (VAE) provides a probabilistic manner for describing an observation in latent space.




encoder
Smile: 0.99
Skin tone: 0.85
Gender: -0.73
Beard: 0.85
Glasses: 0.002
Hair color: 0.68
decoder
Latent attributes


Smile (discrete value)
Smile (probability distribution)
vs.
-1
0
1


encoder
Smile:
Skin tone:
Gender:
Beard:
Glasses:
Hair color:
decoder
Latent attributes


encoder
Smile:
Skin tone:
Gender:
Beard:
Glasses:
Hair color:
sample
sample
Smile: 0.23
Skin tone: 0.02
Gender: -0.18
Beard: 0.71
Glasses: -0.19
Hair color: 0.33
Smile: 0.17
Skin tone: 0.28
Gender: -0.11
Beard: 0.66
Glasses: -0.14
Hair color: 0.26
decoder
decoder
Latent distributions
Sampled latent attributes
We expect an accurate reconstruction for any sample from the latent state distributions

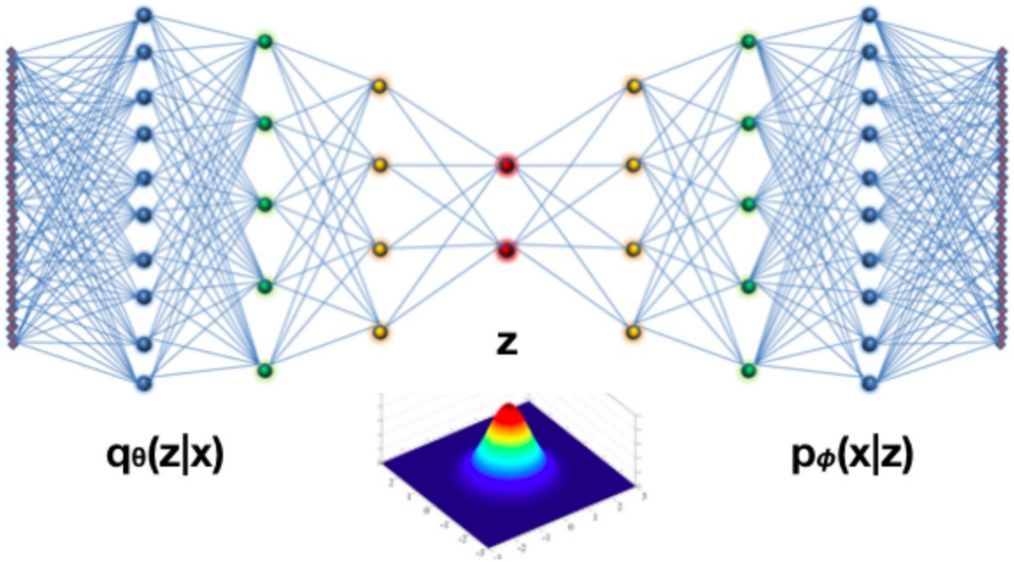


Figure 2: VAE

$$\min KL\left(q\left(z|x\right)||p\left(z|x\right)\right)$$

$$E_{q(z|x)} \log p\left(x|z\right) - KL\left(q\left(z|x\right)||p\left(z\right)\right)$$

The KL divergence between the approximate and the real posterior distributions is given by,

$$D_{KL}\left(q_\theta(z|x_i)||p(z|x_i)\right) = -\int q_\theta(z|x_i)\log\left(\frac{p(z|x_i)}{q_\theta(z|x_i)}\right)dz \geq 0$$

https://medium.com/dataseries/variational-autoencoder-with-pytorch-2d359cbf027b

Variational Autoencoder - dogs generation

https://www.kaggle.com/code/speedwagon/variational-autoencoder-dogs-generation

Mid term ?

Generate music with Variational AutoEncoder

https://www.kaggle.com/code/basu369victor/generate-music-with-variational-autoencoder