

Deep Learning

Abdelhak Mahmoudi
abdelhak.mahmoudi@um5.ac.ma

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Content

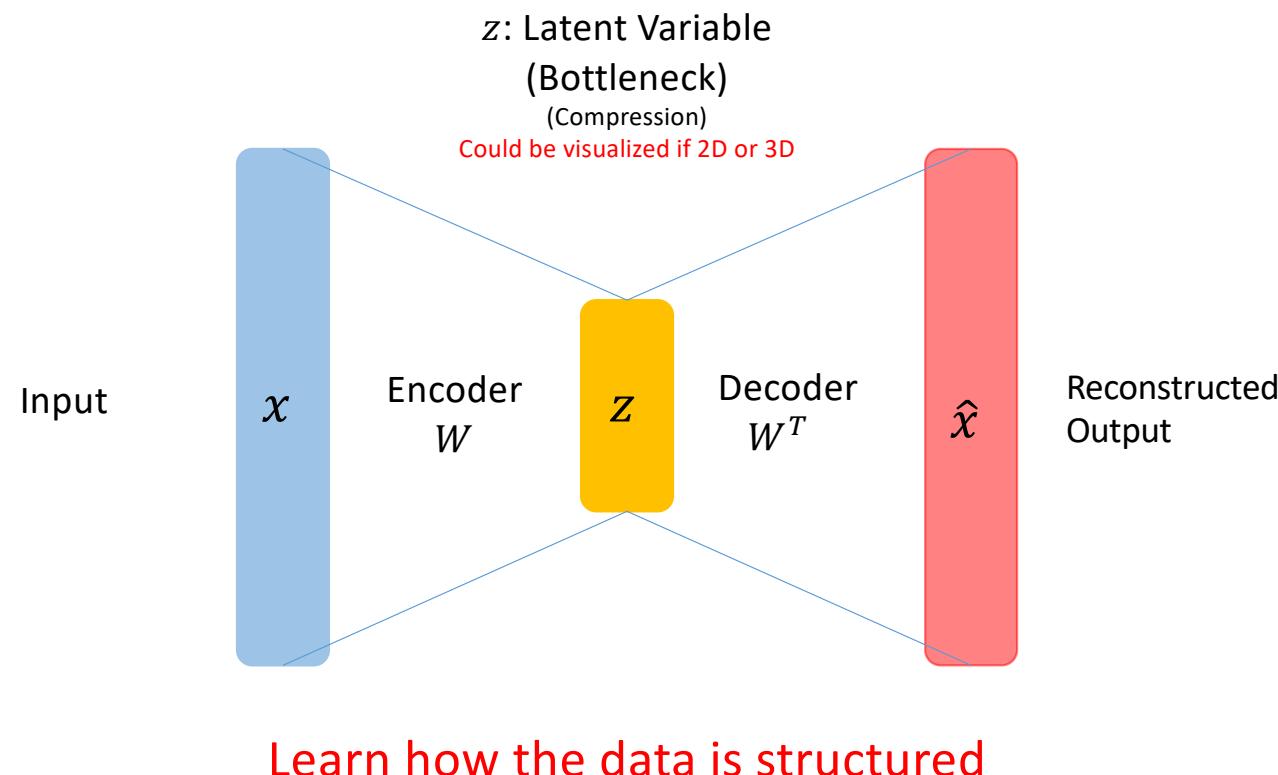
1. Deep Artificial Neural Networks
2. Convolutional Neural Networks
3. Sequence Models
- 4. Generative Models**

Generative Models

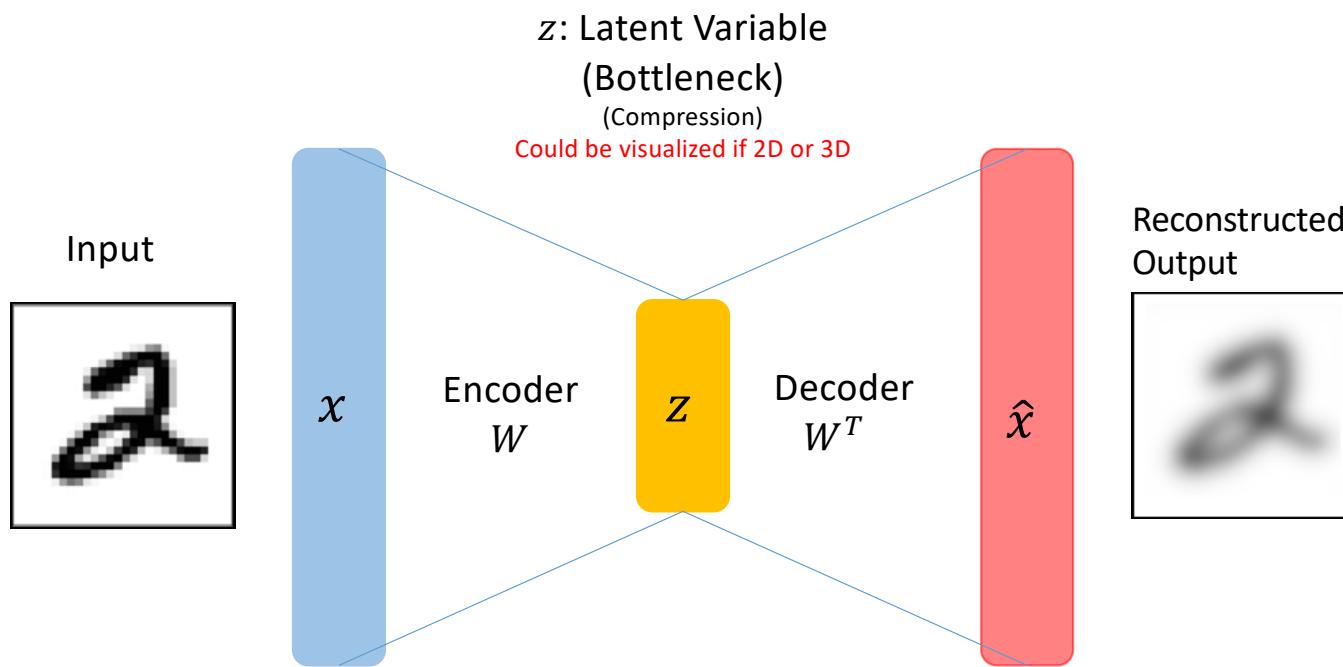
- Auto-Encoders
- Variational Auto-Encoders
- Generative Adversarial Networks



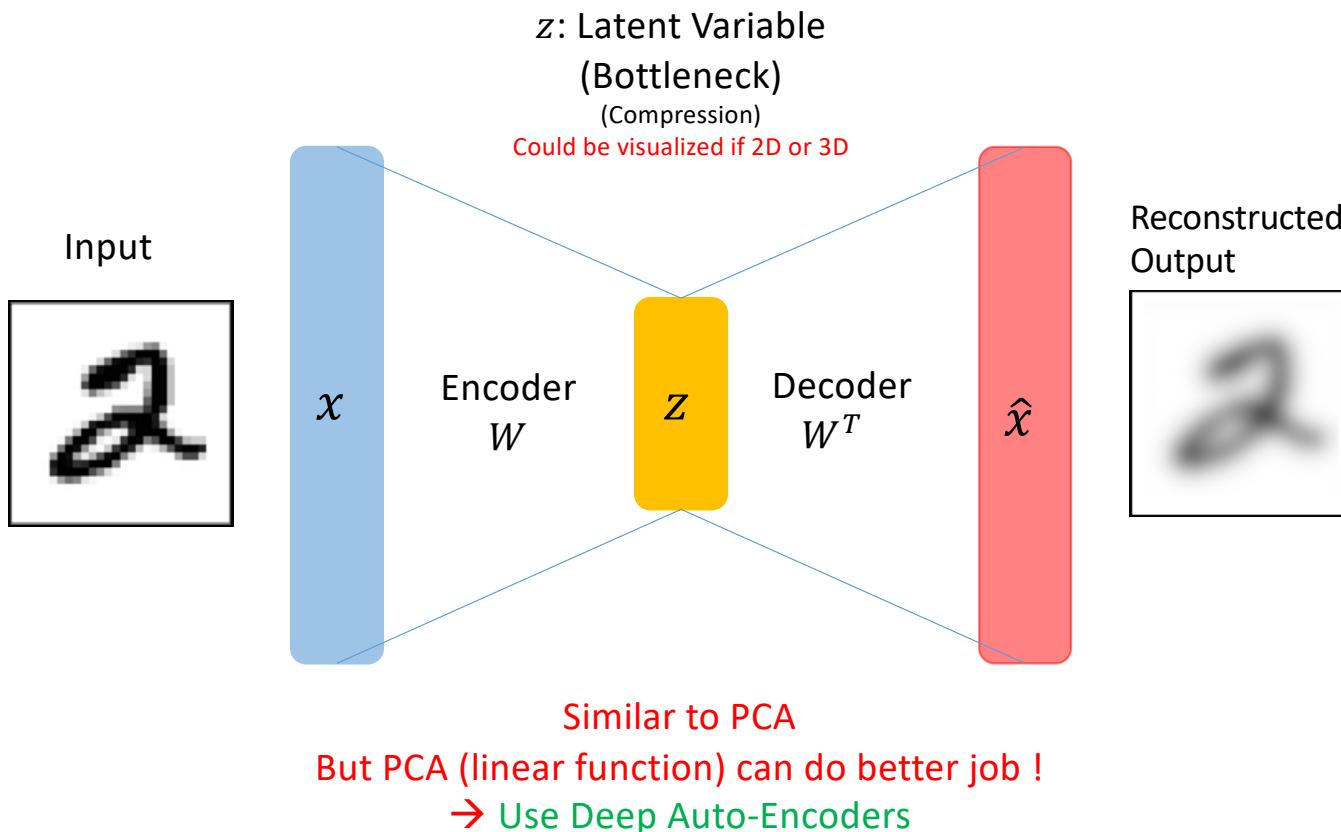
Auto-Encoders (Shallow)



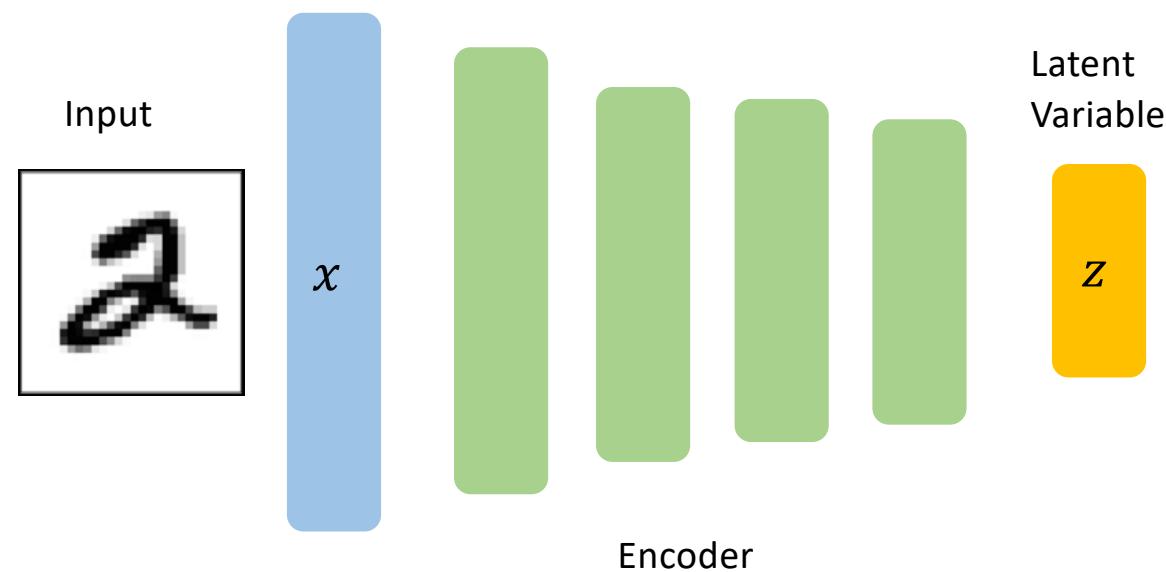
Auto Encoders (Shallow) : Example



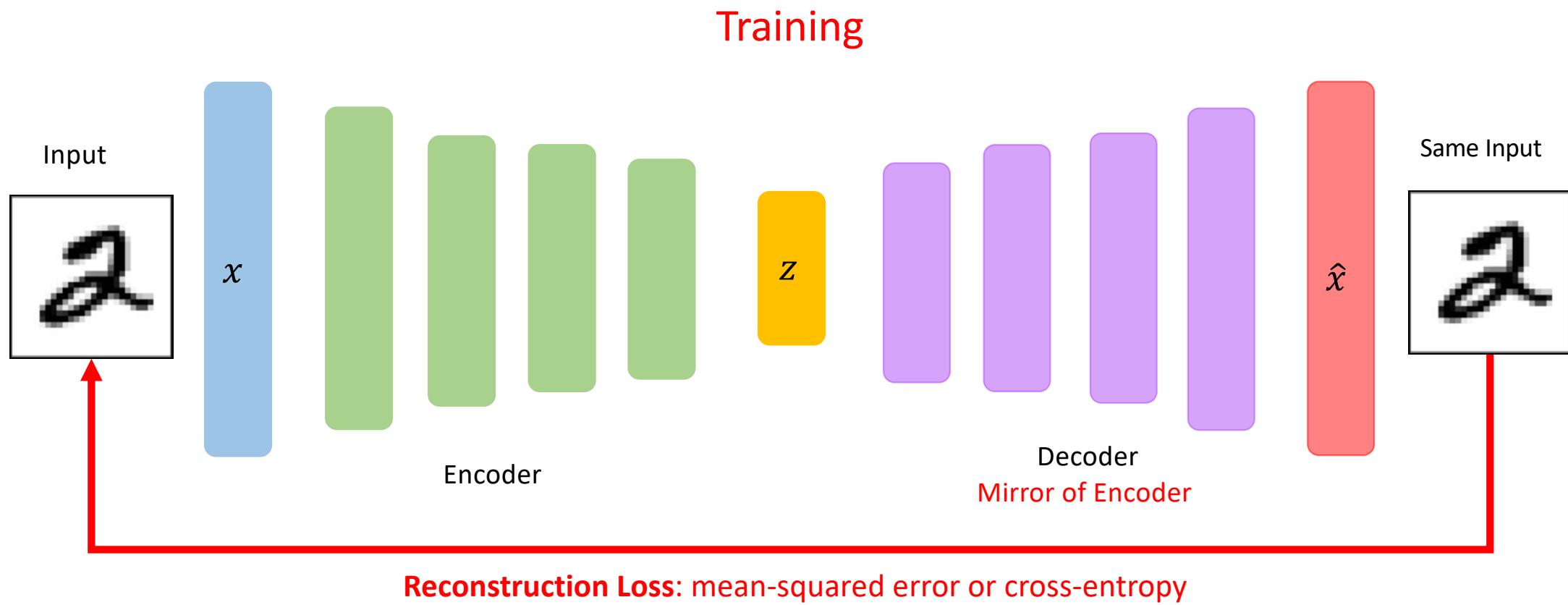
Auto Encoders (Shallow) : Similar to PCA



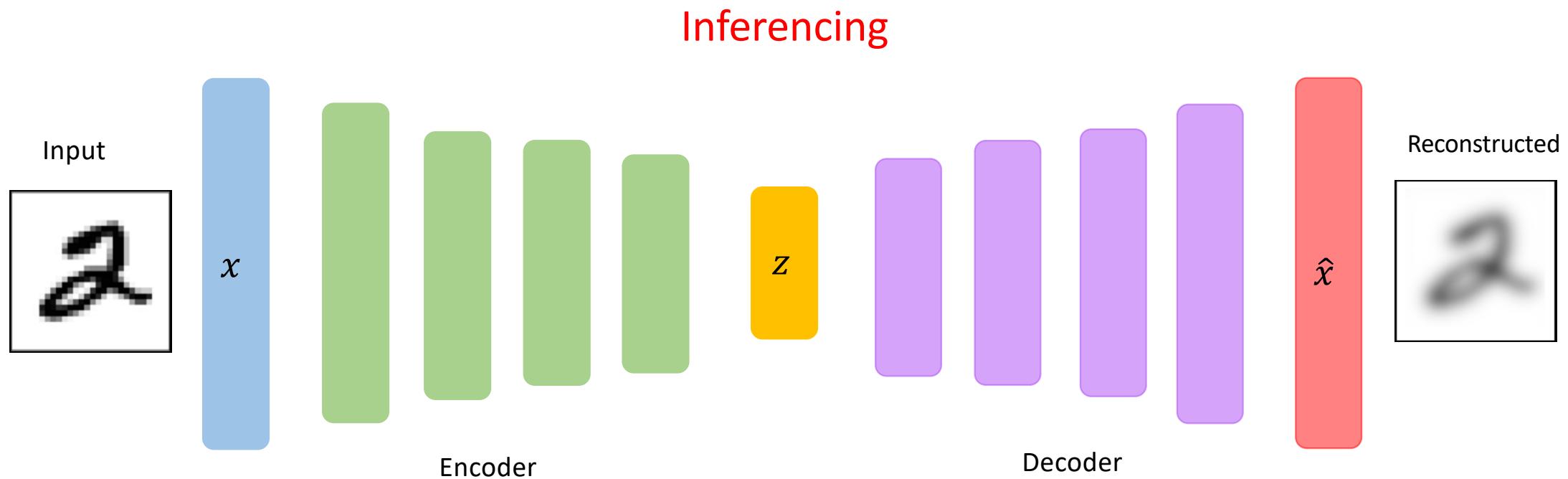
Auto-Encoders (Deep): Encoder



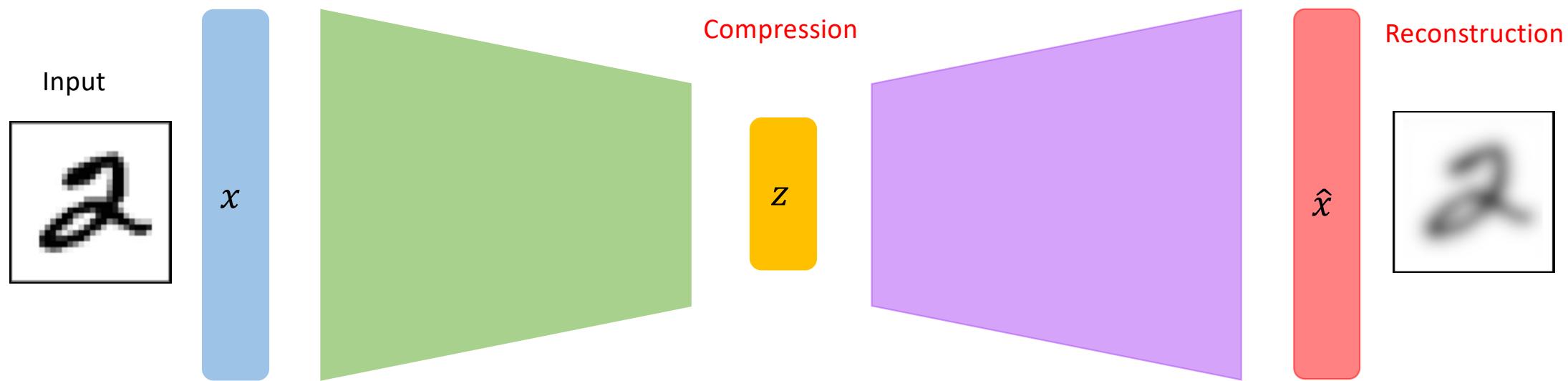
Auto-Encoders: Training (Encoder-Decoder)



Auto-Encoders: Inferencing

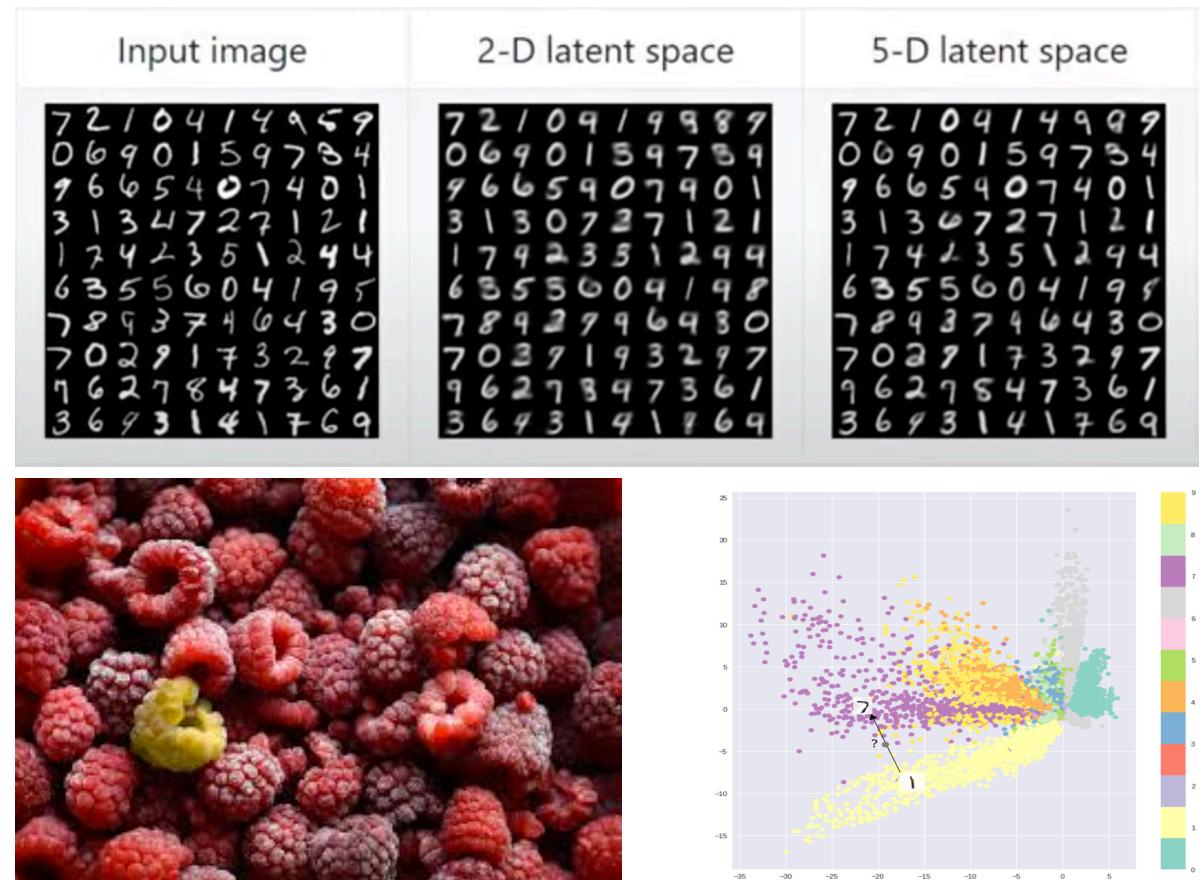


Auto-Encoders: Compression/Construction



Auto-Encoders Usage

- Bigger latent space
 - Better results
- AE are Data-specific
- Reconstruction
 - Always loosing information
- Visualization
 - t-SNE after AE
- Use case
 - Anomaly Detection



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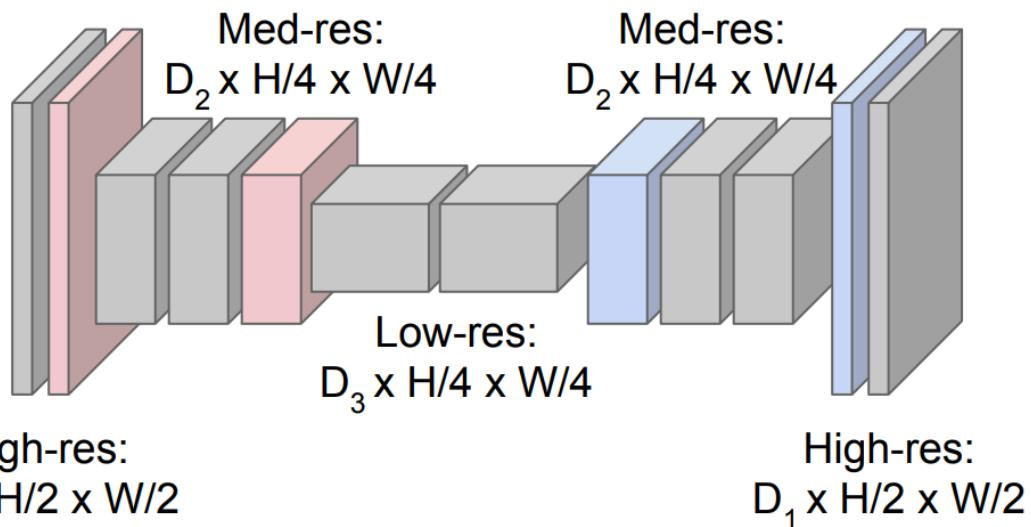
Convolutional Auto-Encoders

Semantic Segmentation with **Fully Conv Nets**



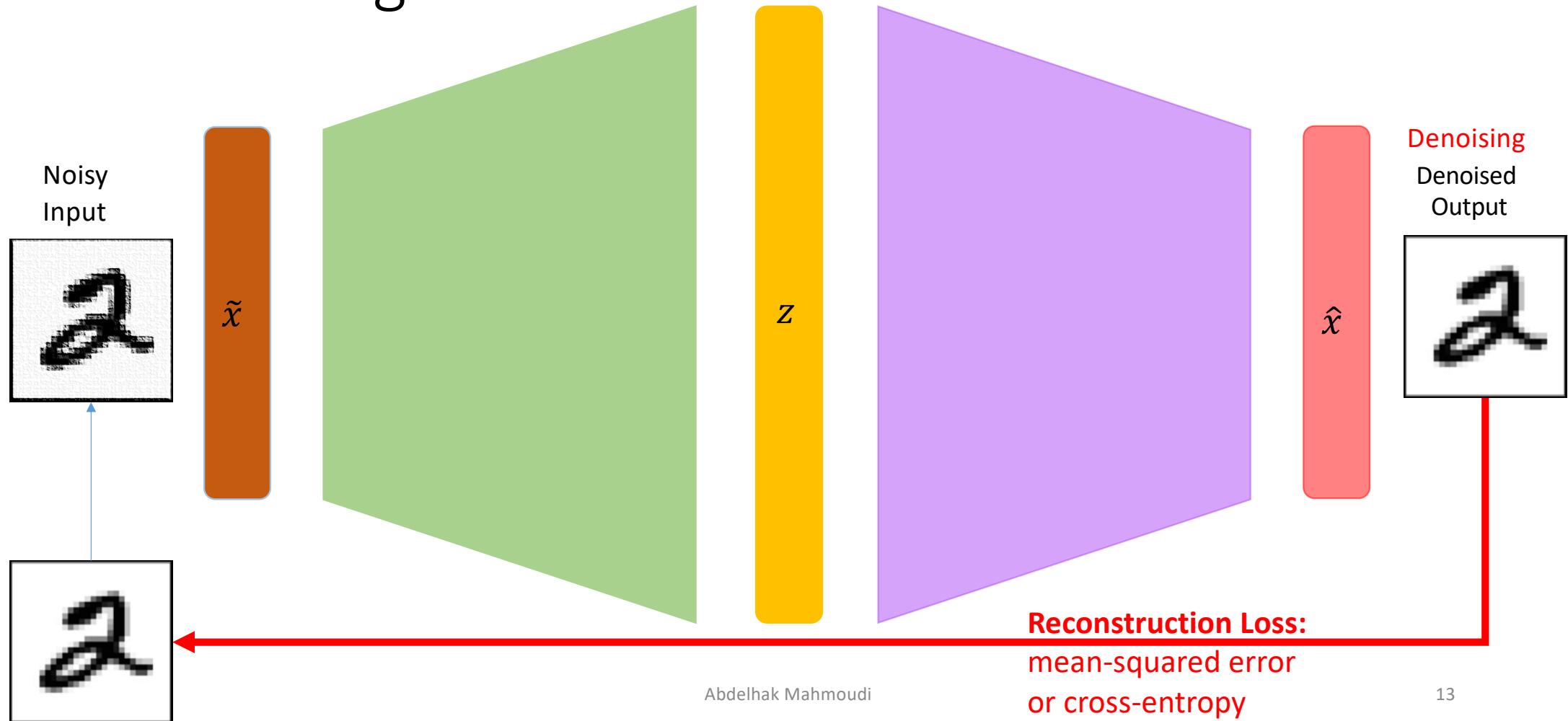
Input:
 $3 \times H \times W$

High-res:
 $D_1 \times H/2 \times W/2$



Predictions:
 $H \times W$

Denoising with Auto-Encoders



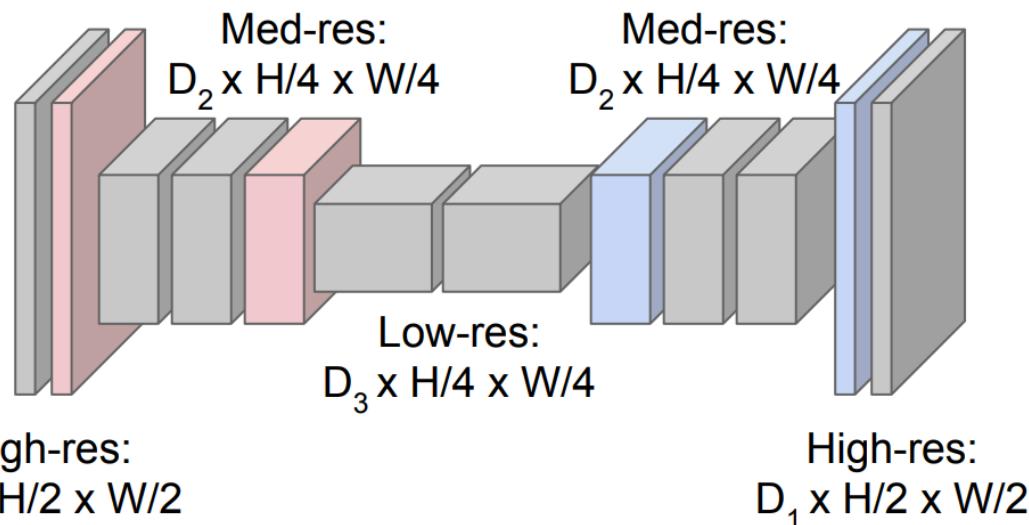
Inpainting with Auto-Encoders

Remove Inpainting, Watermark, etc.



Input:
 $3 \times H \times W$

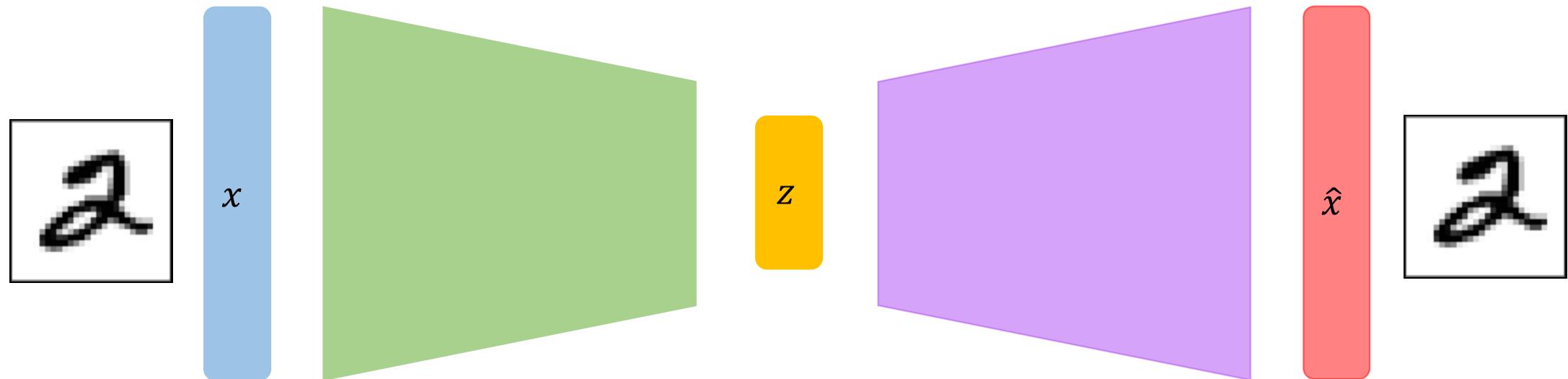
High-res:
 $D_1 \times H/2 \times W/2$



Predictions:
 $H \times W$

Auto-Encoders: not for generation !

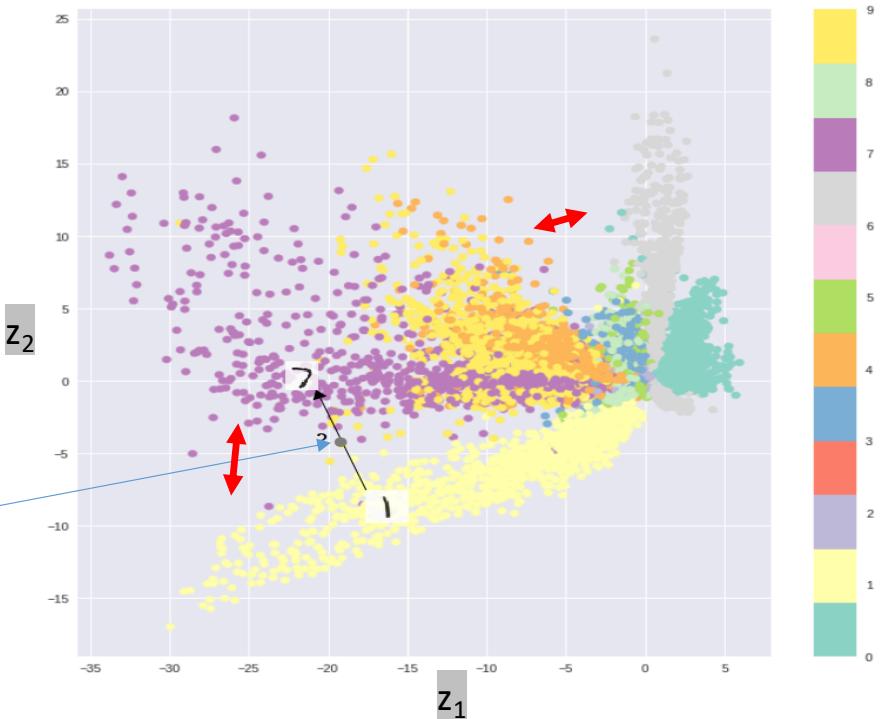
But How can we generate data ?



Auto-Encoders: not for generation !

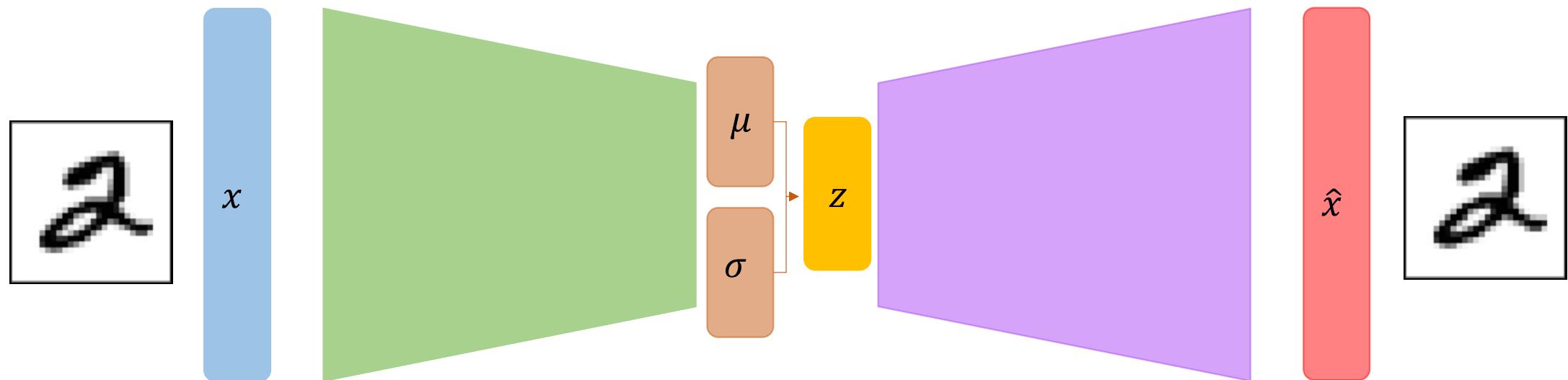
- Discrete latent space !
 - Ok for replicating the same examples
 - Not for generating new examples

↔ Discontinuities
This will generate random noise



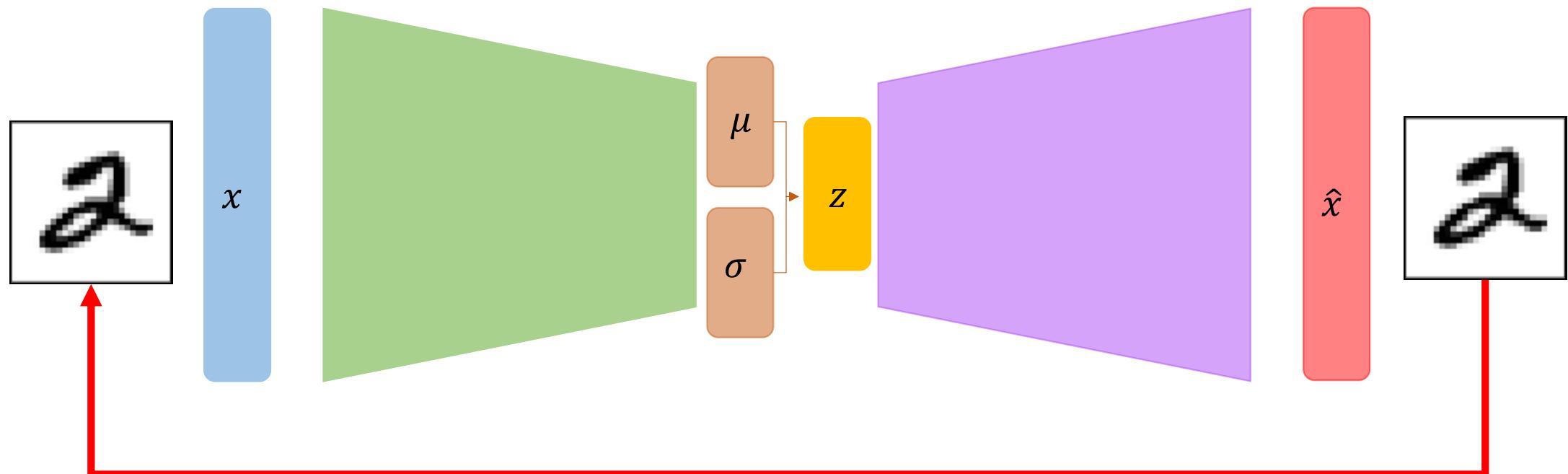
Variational Auto-Encoders

Learn a distribution (μ, σ) instead of latent variable



Variational Auto-Encoders: KL Divergence Loss

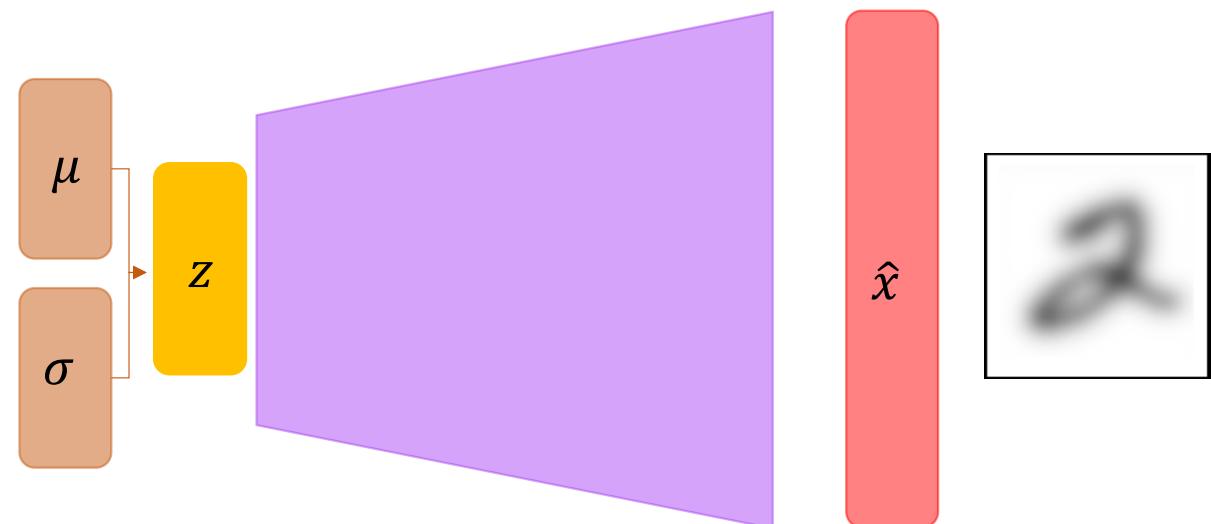
Learn a distribution (μ, σ) instead of latent variable



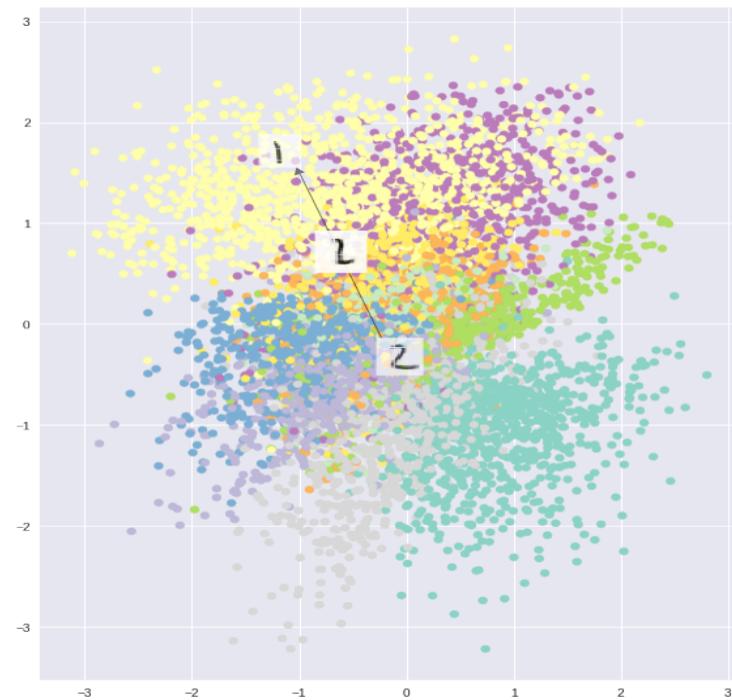
Reconstruction loss + Kullback–Leibler (KL) divergence loss

VAEs: Learn a distribution

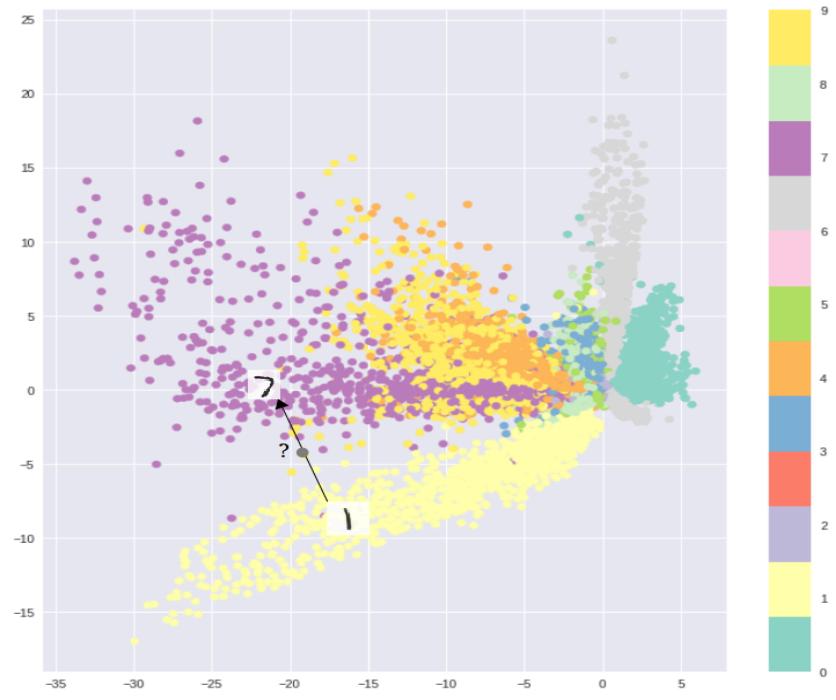
Now we can generate data
from noise distribution with the learned (μ, σ)



VAEs- vs AEs

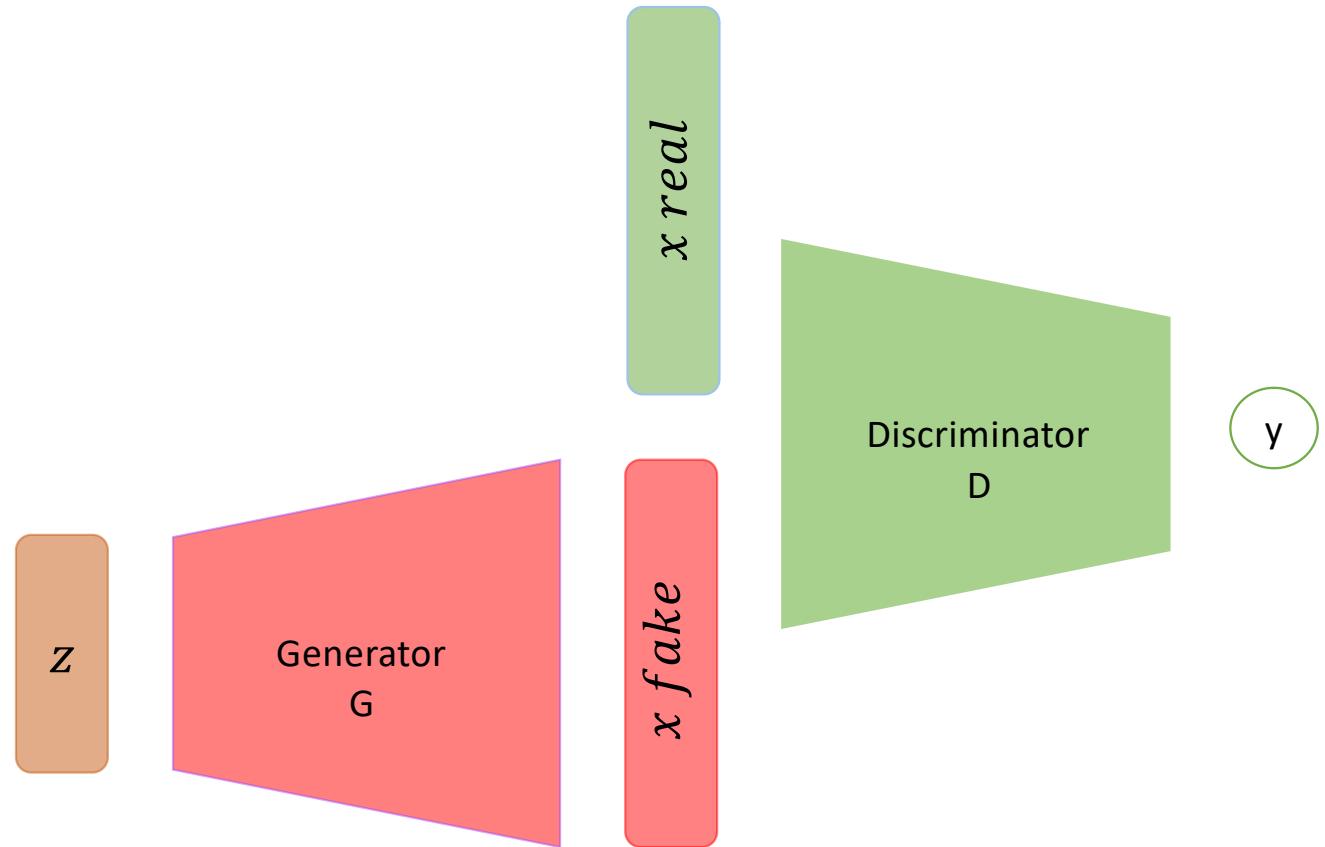


Variational Auto-Encoders



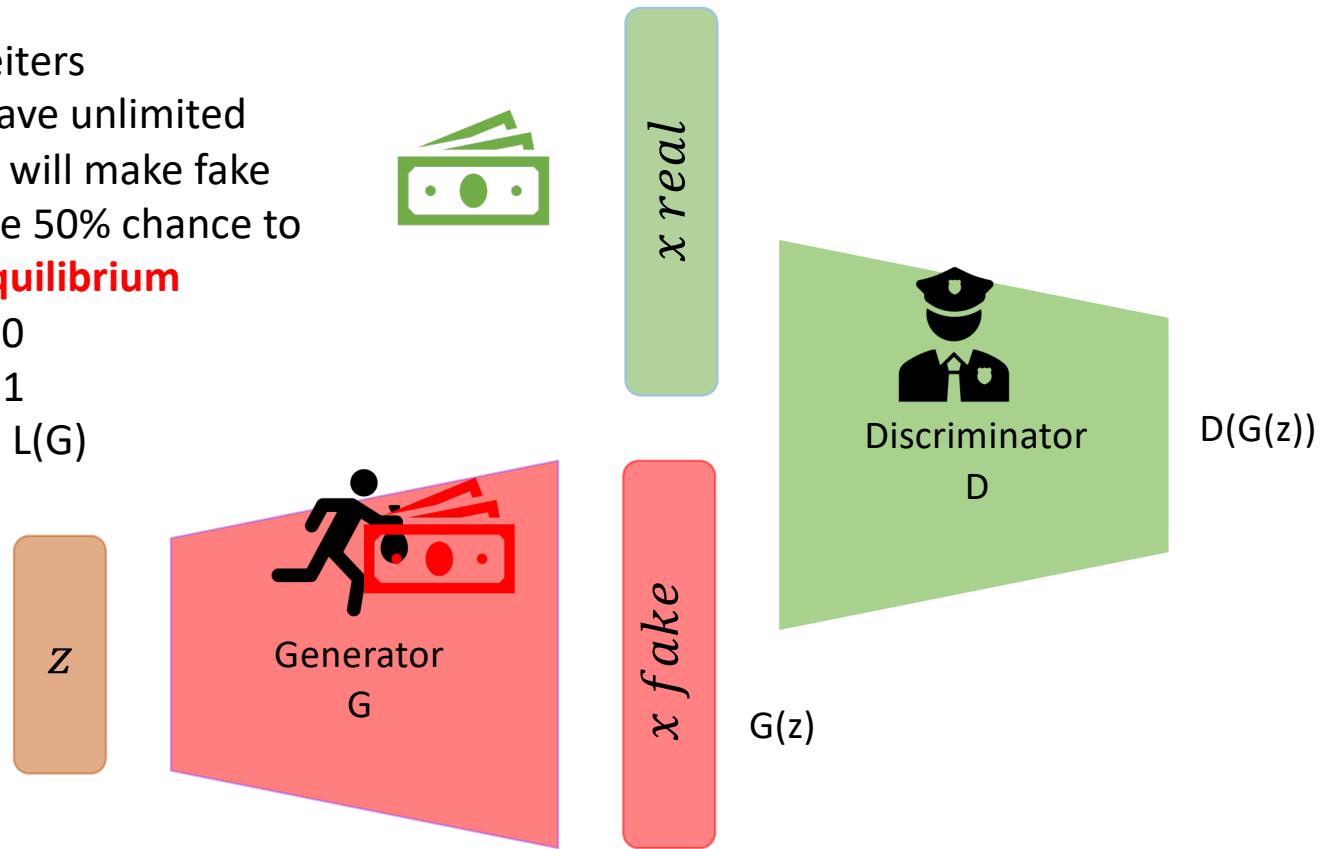
Auto-Encoders

Generative Adversarial Networks

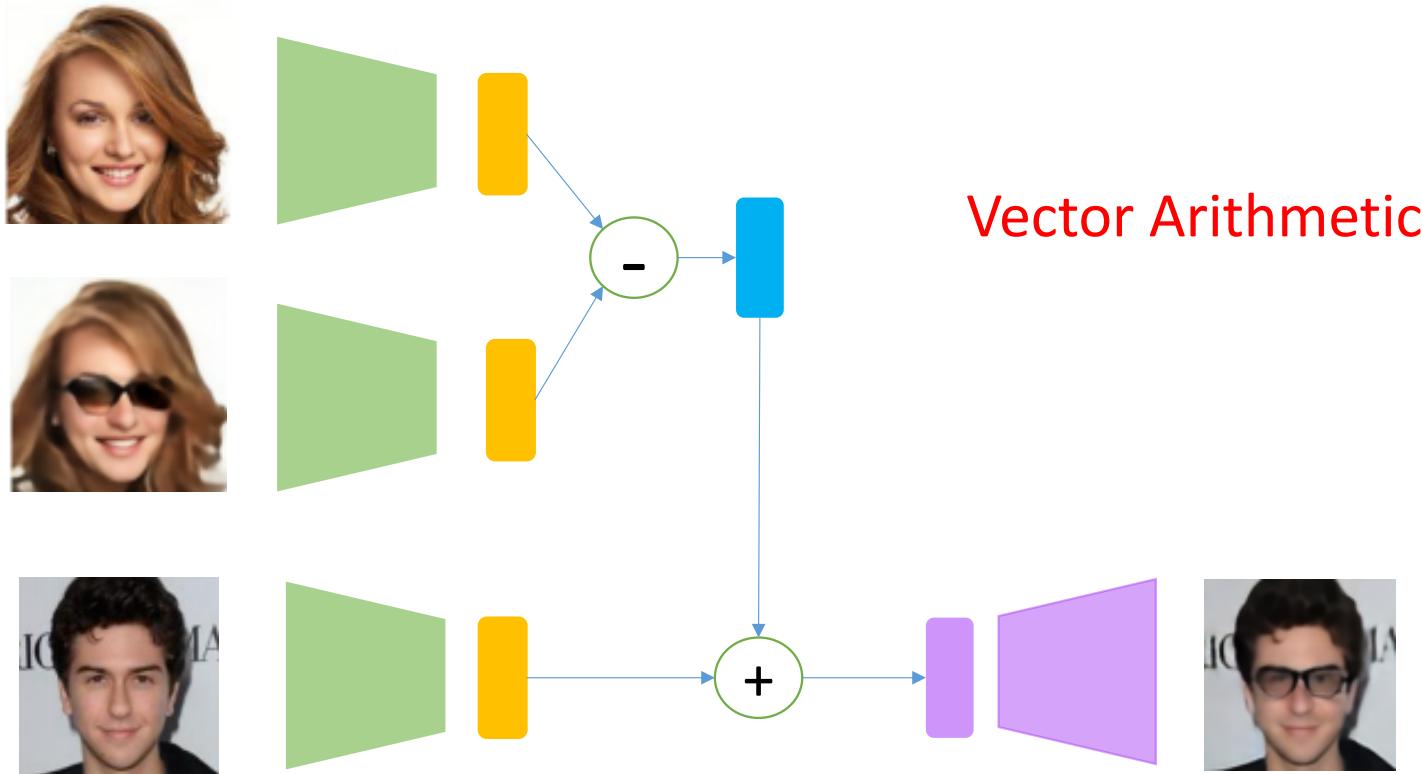


Generative Adversarial Networks

- Think of Police and counterfeiters
- If Police and counterfeiters have unlimited resources, the counterfeiters will make fake money so that the police have 50% chance to recognize it's fake → **Nash Equilibrium**
- D want to make $D(G(z))$ near 0
- G want to make $D(G(z))$ near 1
- 2 losses to minimize $L(D)$ and $L(G)$



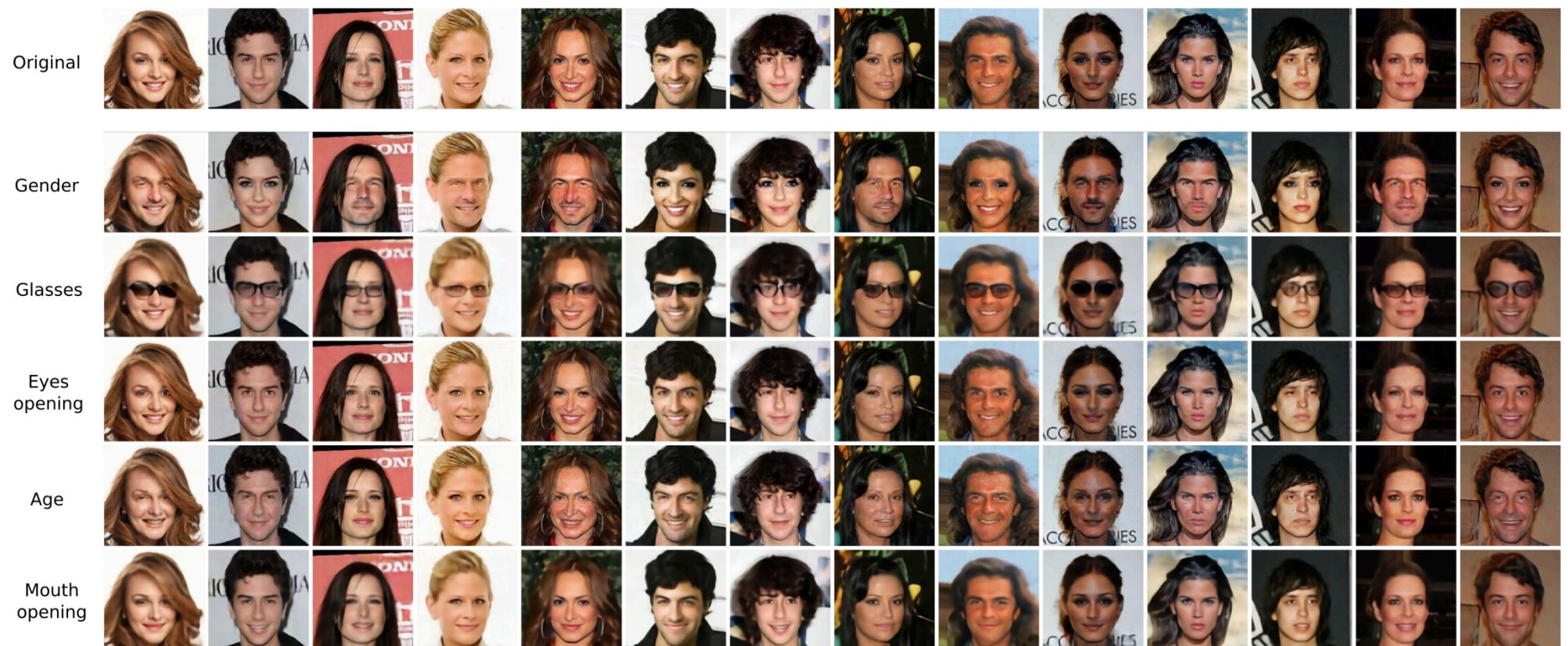
Generative Models: Applications



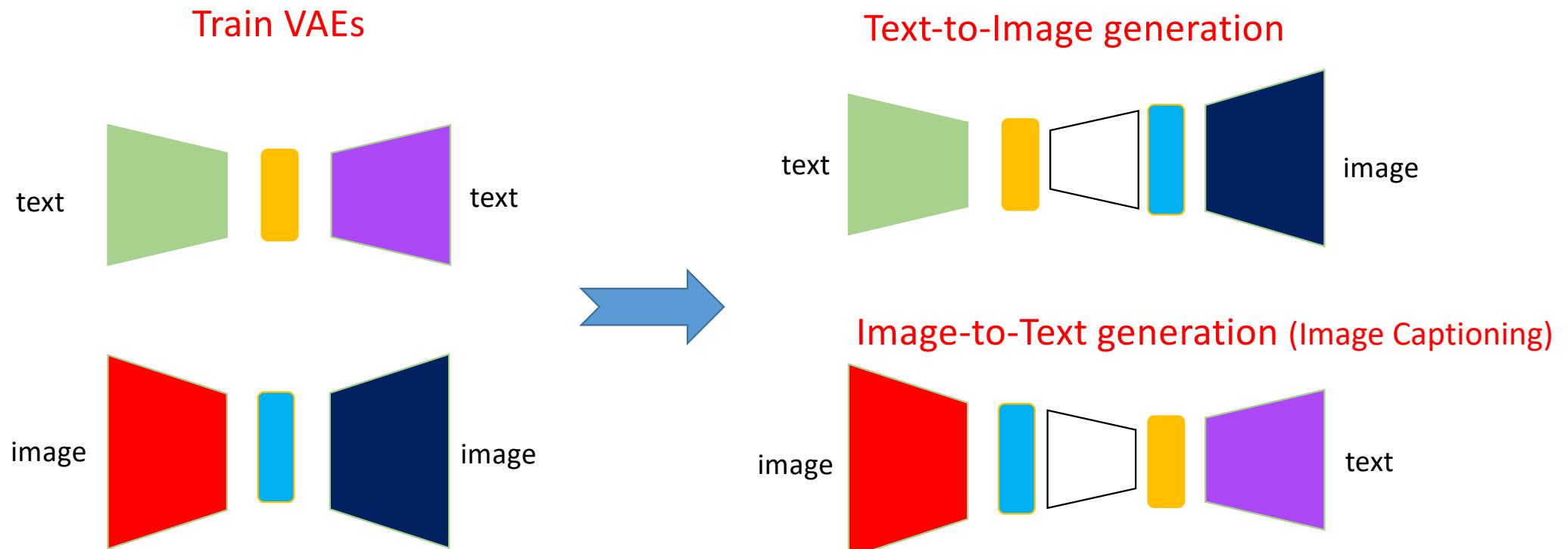
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Generative Models: Applications



Generative Models: Applications

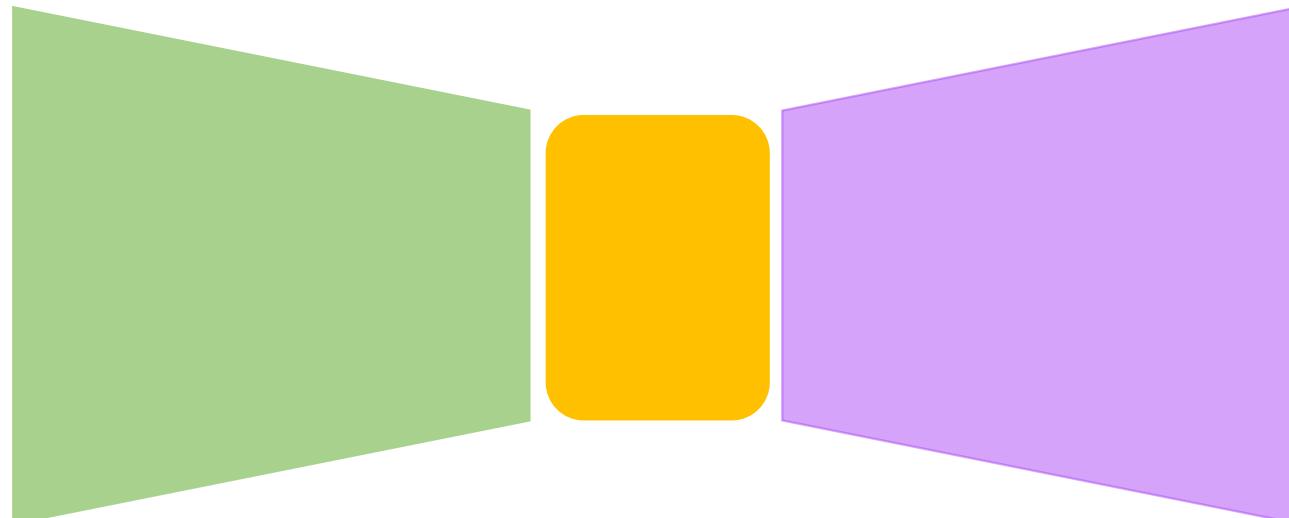


Generative Models: Different Data Types

- Sequential or non-sequential,
- Continuous or discrete,
- Labelled or un-labelled



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