Deep Learning

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Content

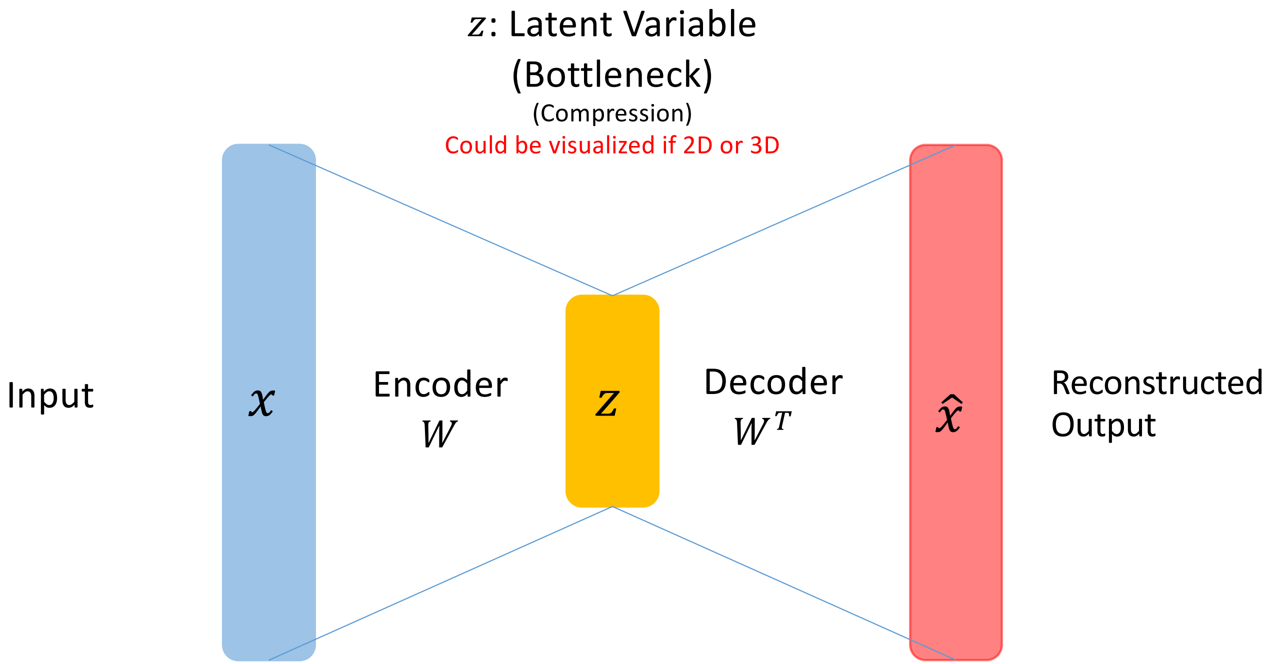
1. Deep Artificial Neural Networks
2. Convolutional Neural Networks
3. Sequence Models
4. **Generative Models**

Generative Models

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

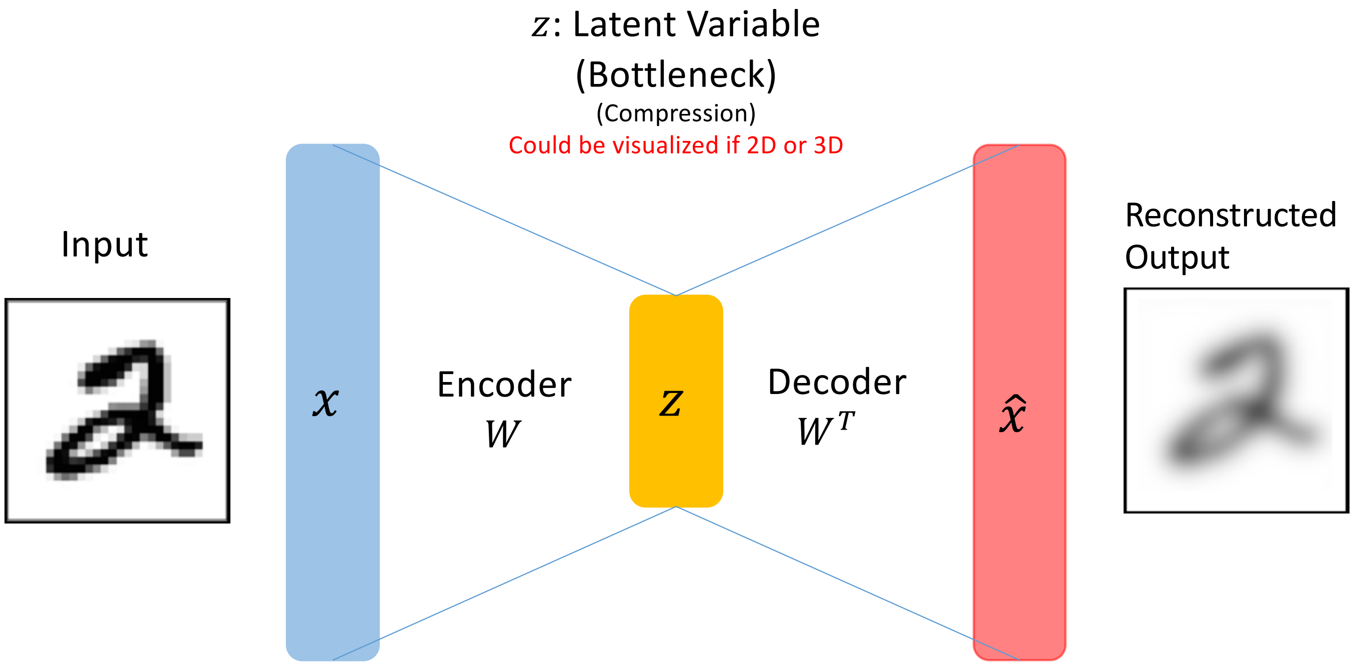
Unsupervised

Auto-Encoders (Shallow)

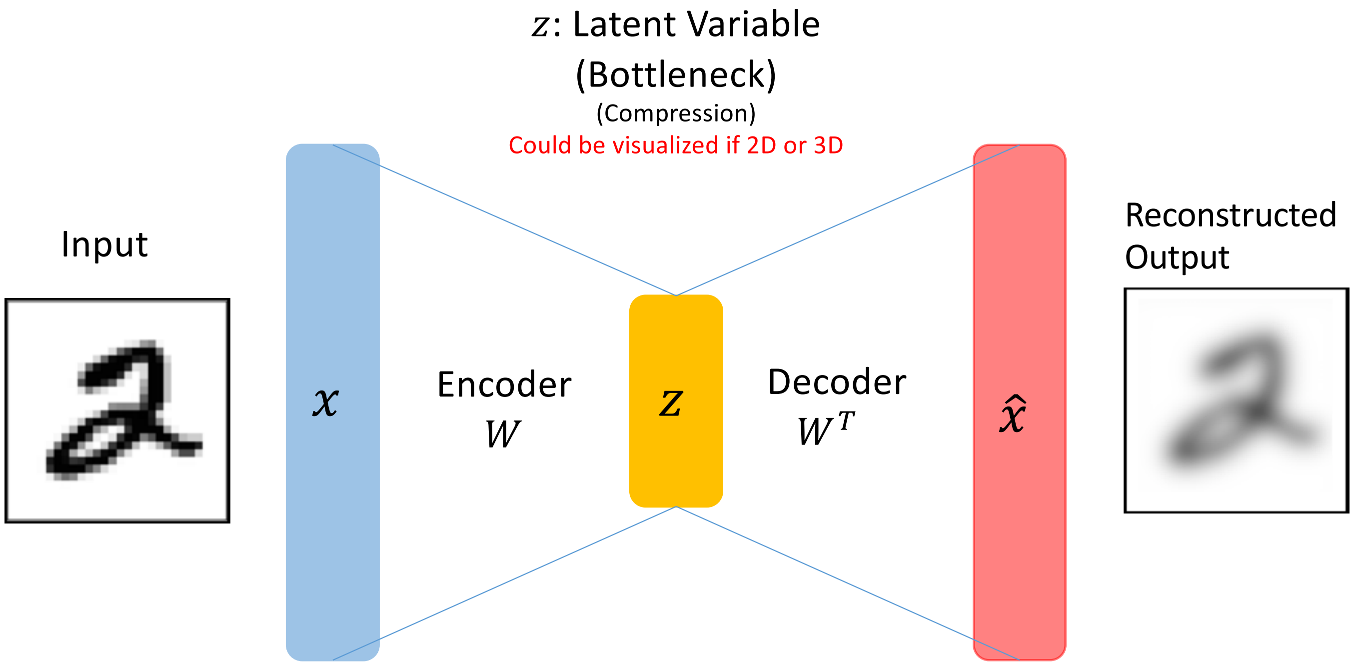


Learn how the data is structured

Auto Encoders (Shallow) : Example



Auto Encoders (Shallow) : Similar to PCA

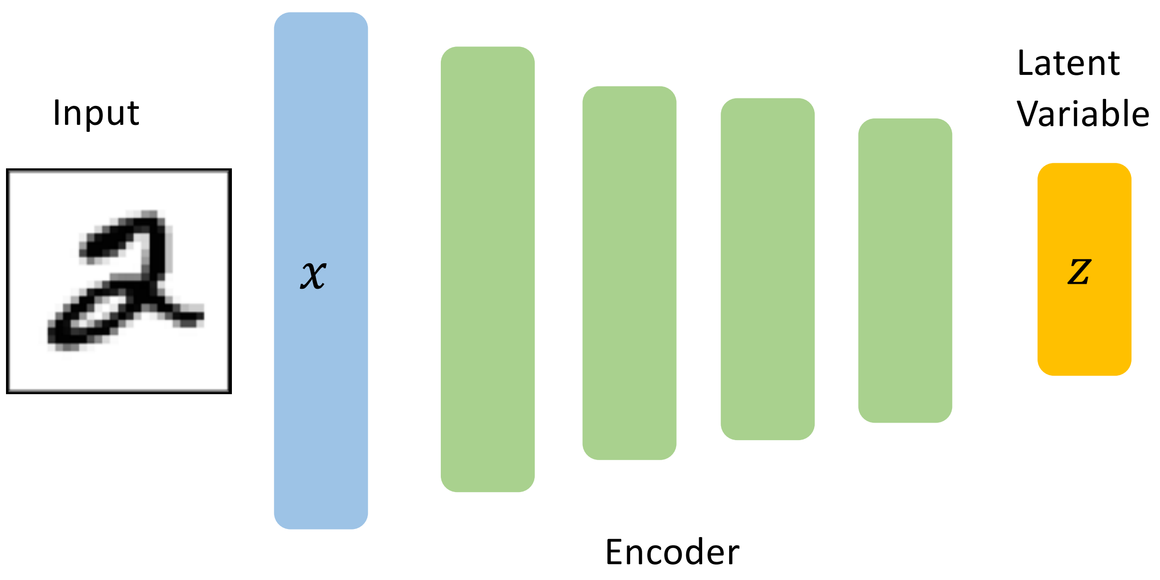


Similar to PCA

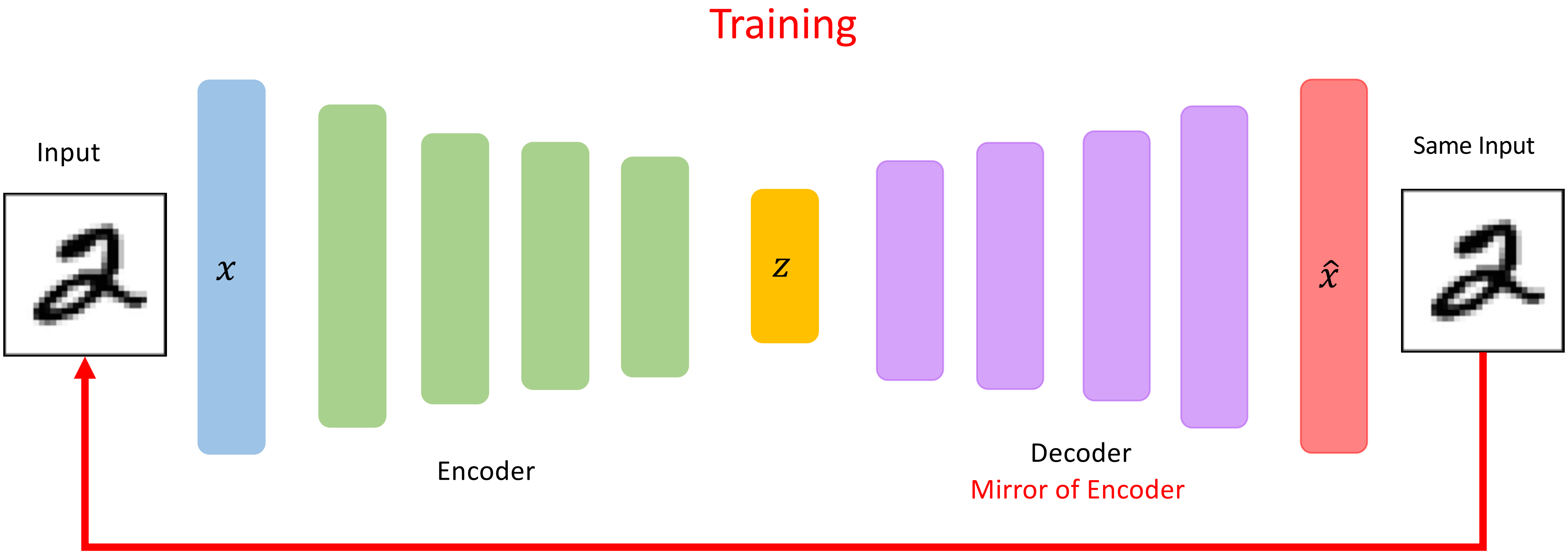
But PCA (linear function) can do better job !

→ Use Deep Auto-Encoders

Auto-Encoders (Deep): Encoder

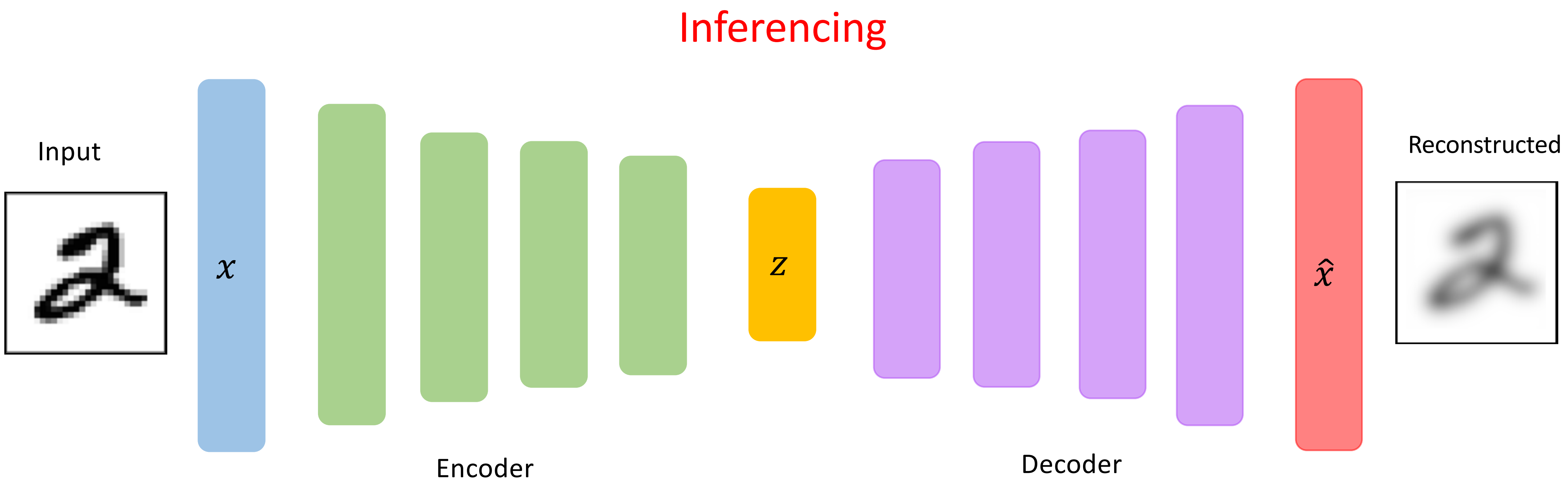


Auto-Encoders: Training (Encoder-Decoder)

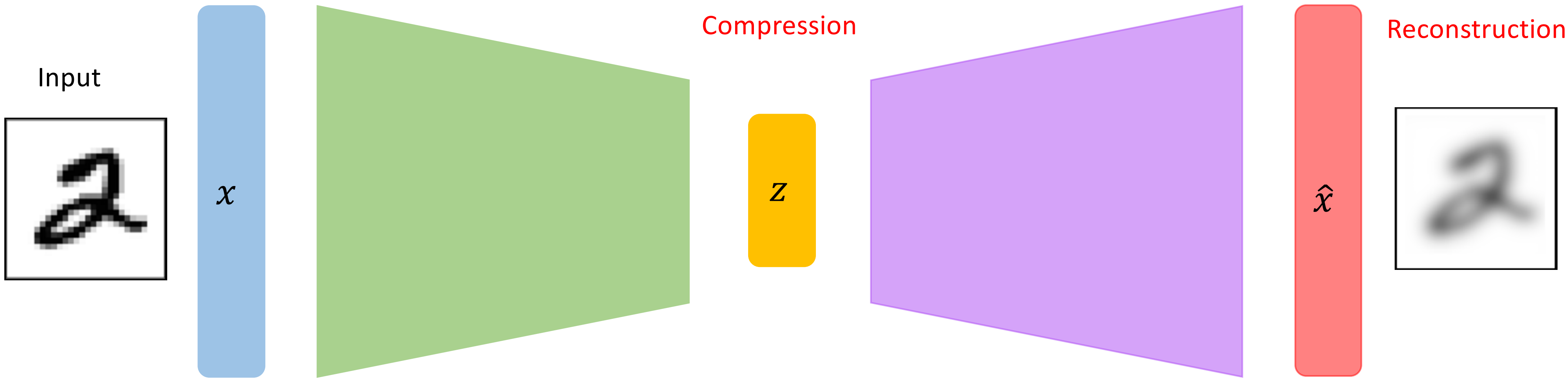


Reconstruction Loss: mean-squared error or cross-entropy

Auto-Encoders: Inferencing

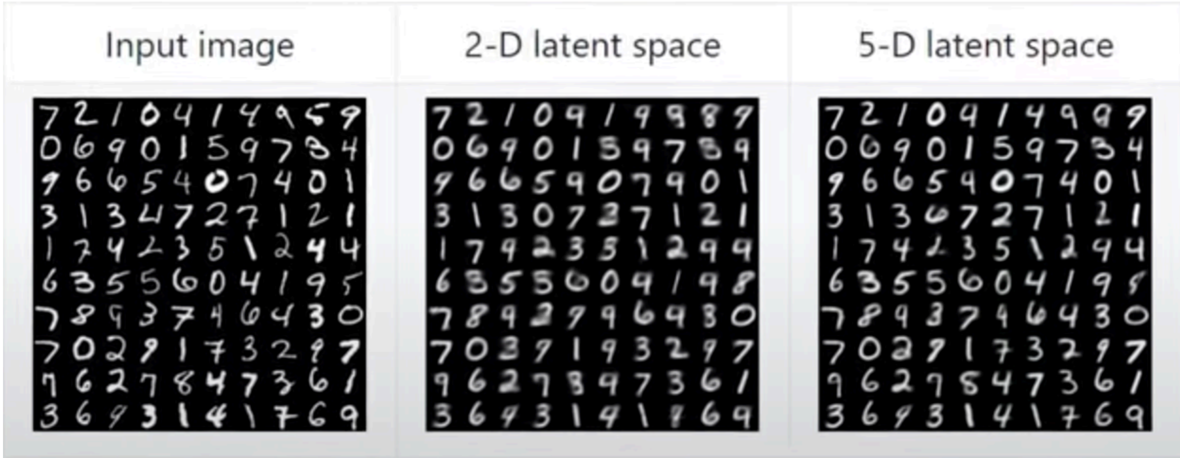


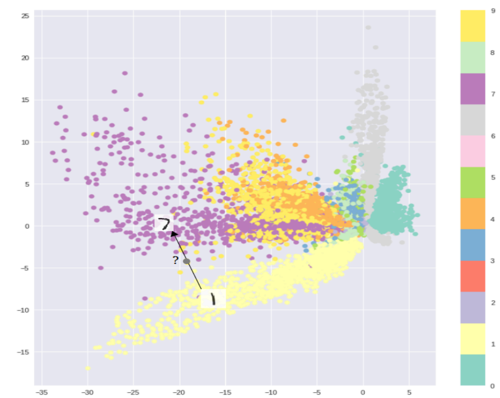
Auto-Encoders: Compression/Construction



Auto-Encoders Usage

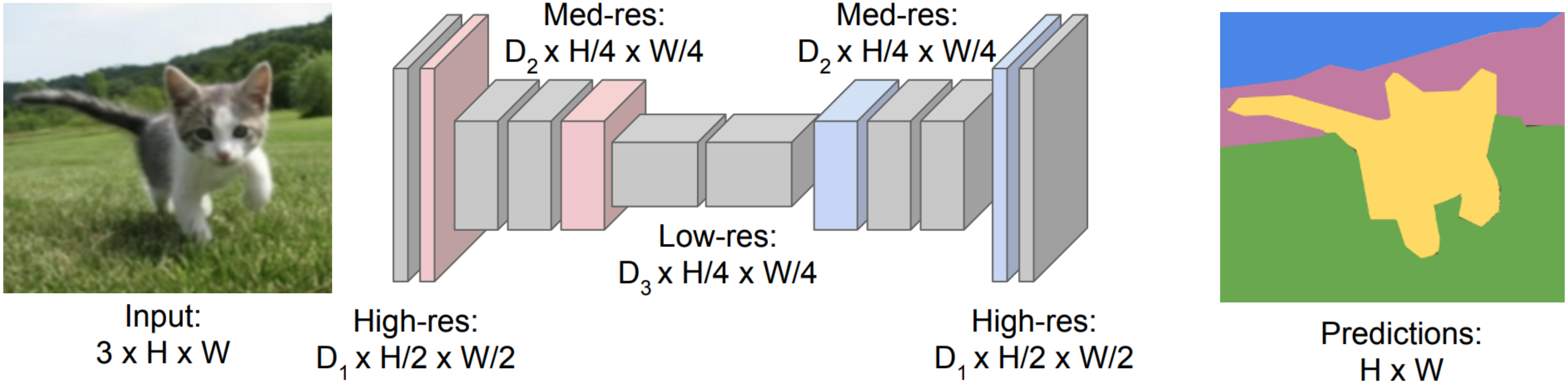
- Bigger latent space
  - Better results
- AE are Data-specific
- Reconstruction
  - Always loosing information
- Visualization
  - t-SNE after AE
- Use case
  - Anomaly Detection



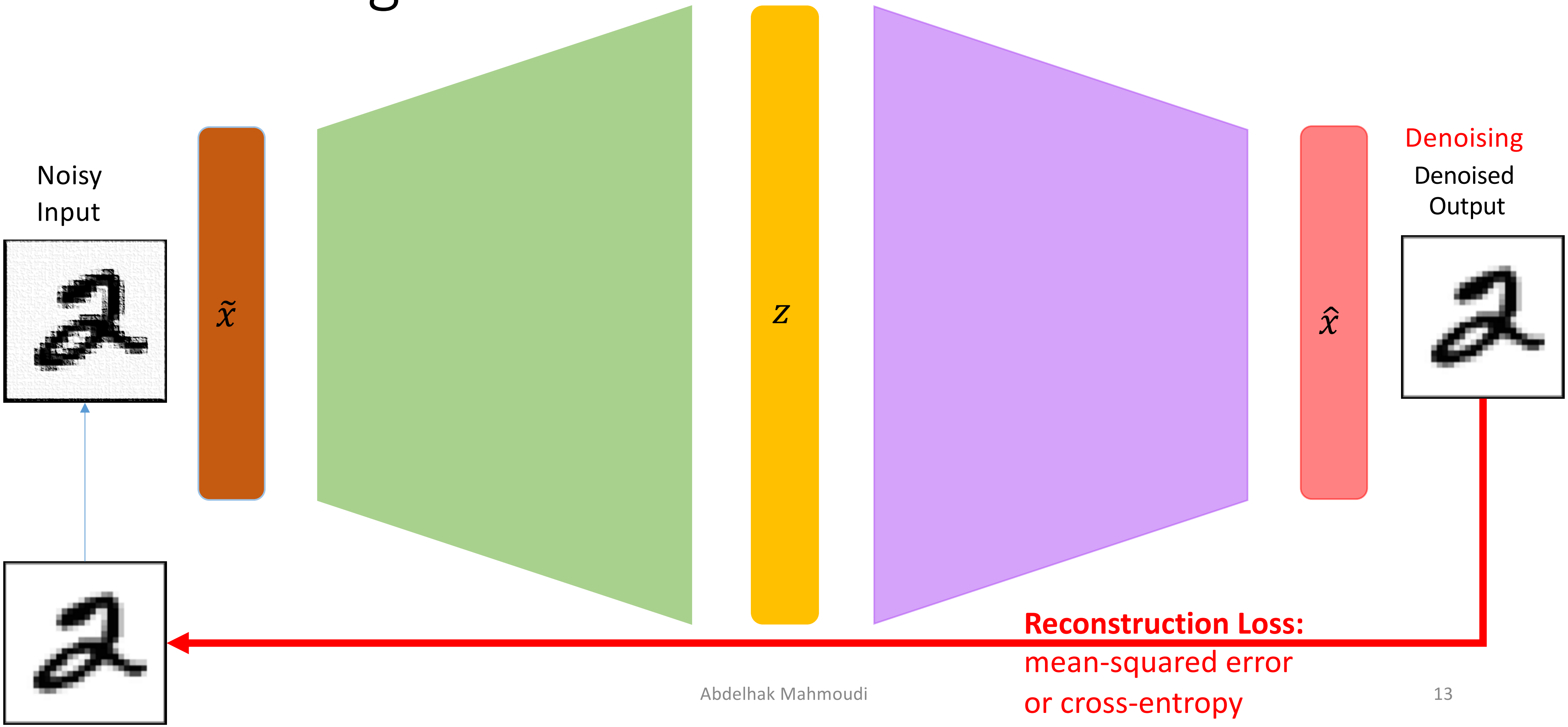


Convolutional Auto-Encoders

Semantic Segmentation with **Fully Conv Nets**

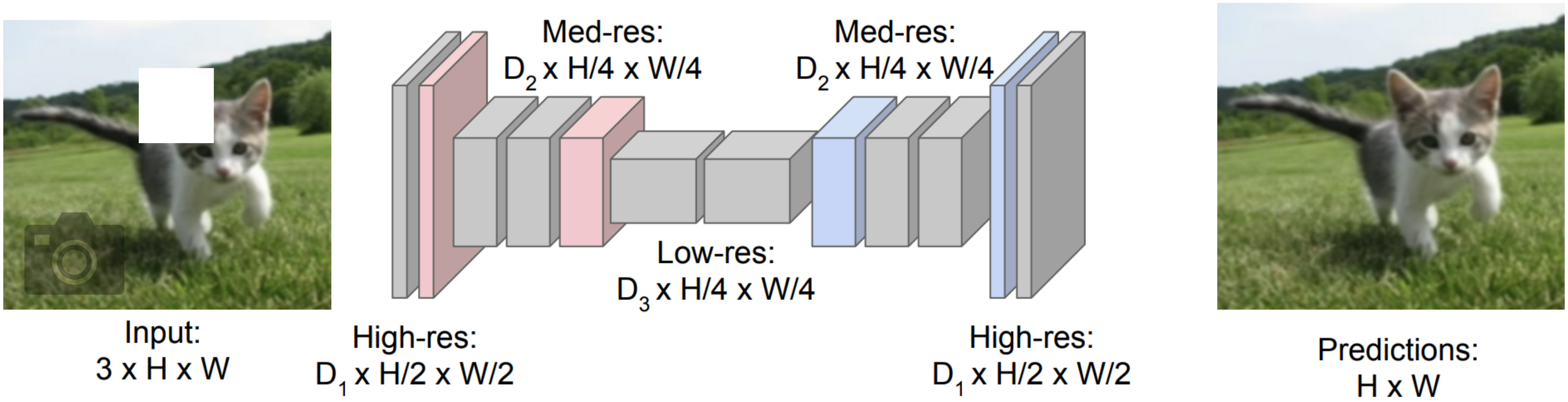


Denoising with Auto-Encoders



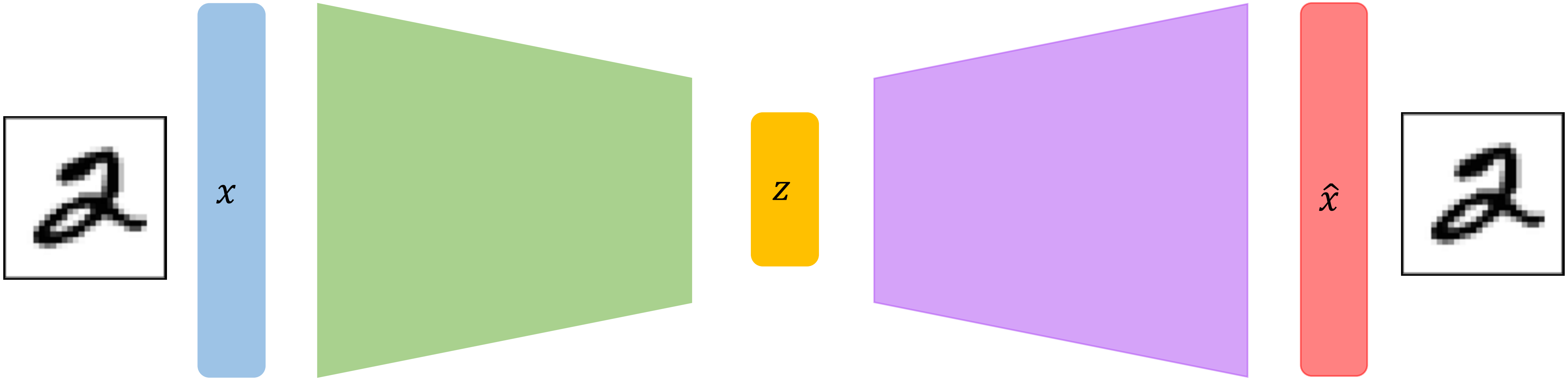
Inpainting with Auto-Encoders

Remove Inpainting, Watermark, etc.



Auto-Encoders: not for generation !

But How can we generate data ?

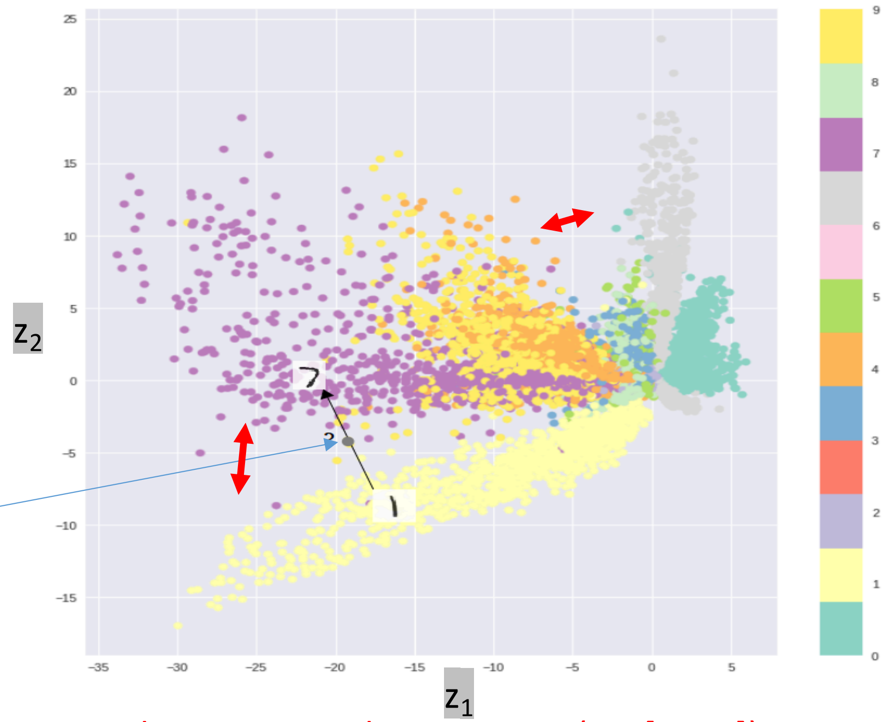


Auto-Encoders: not for generation !

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

Discontinuities

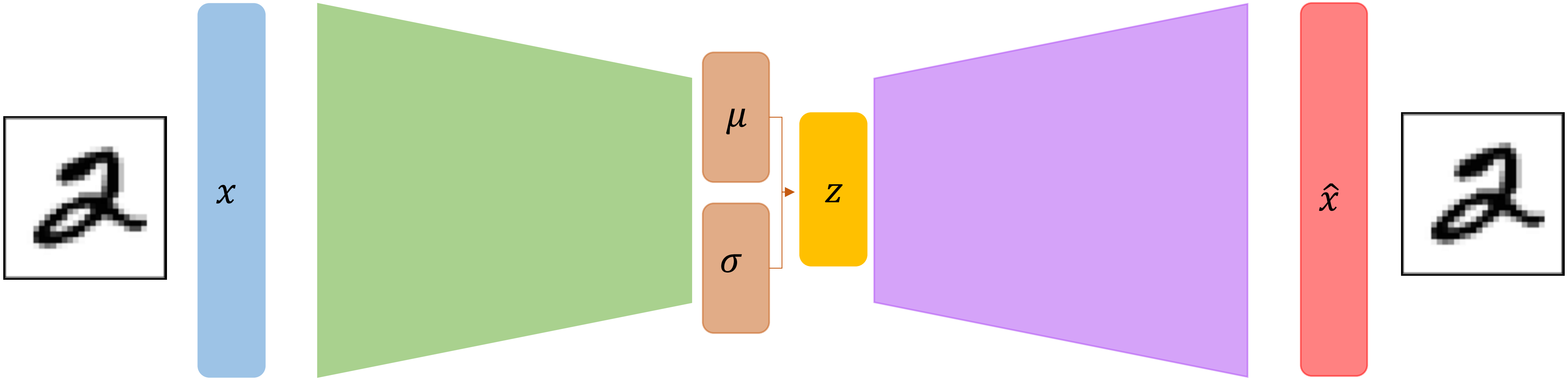
This will generate random noise



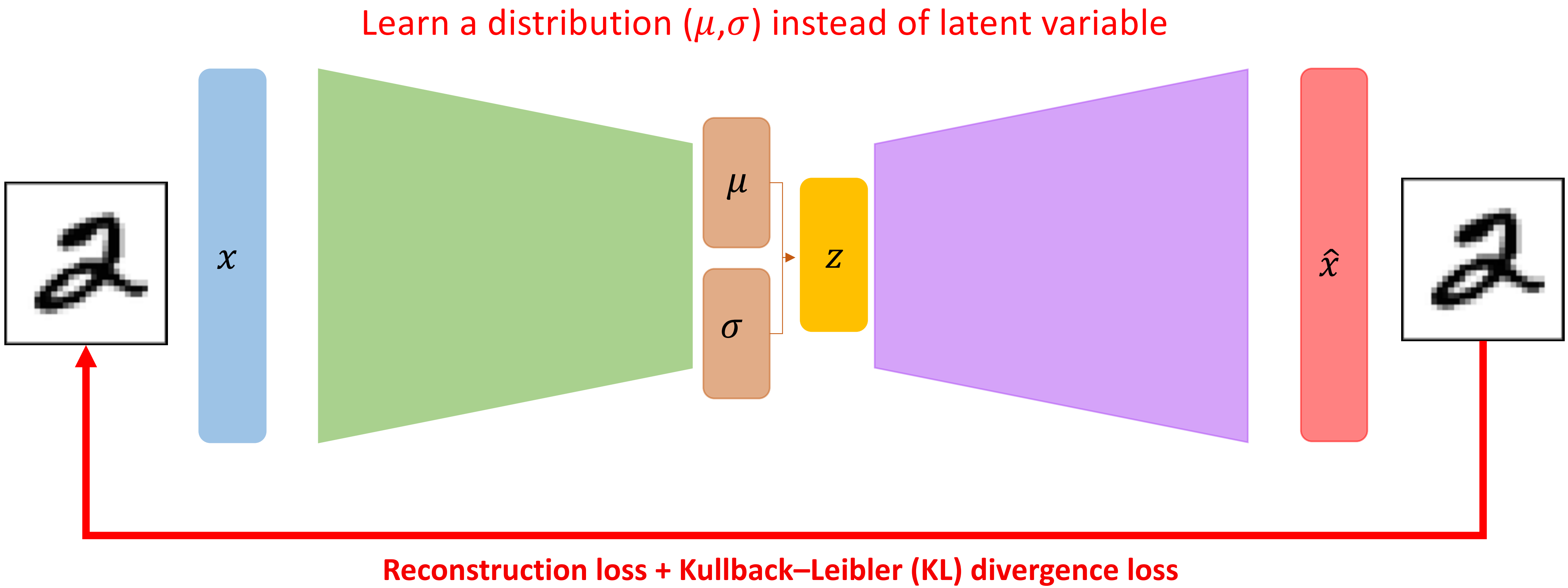
Visualization in 2D latent space ($z = [z_1, z_2]$)

Variational Auto-Encoders

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

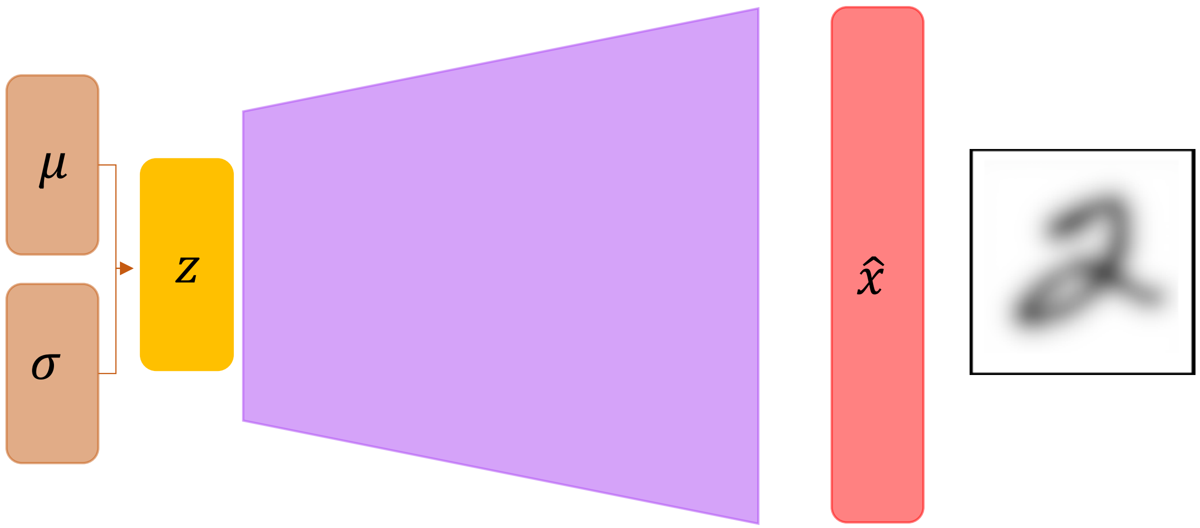


Variational Auto-Encoders: KL Divergence Loss

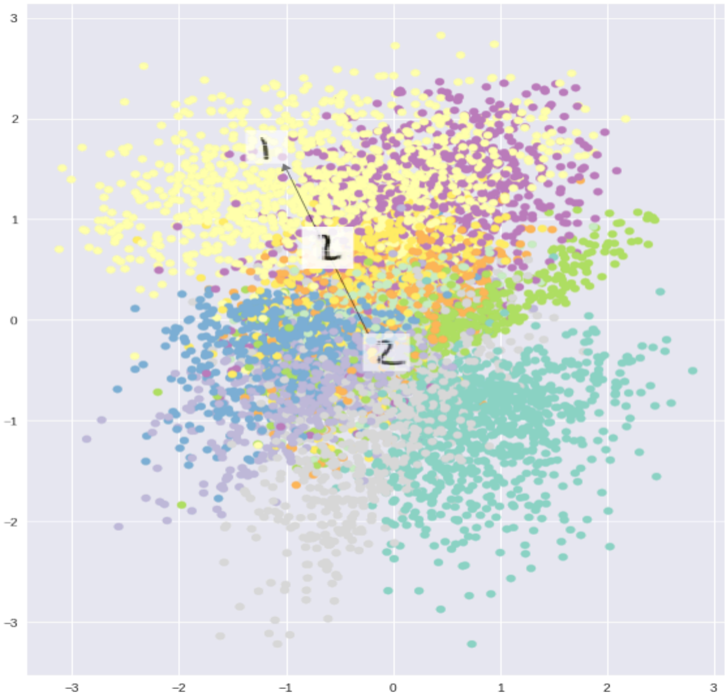


VAEs: Learn a distribution

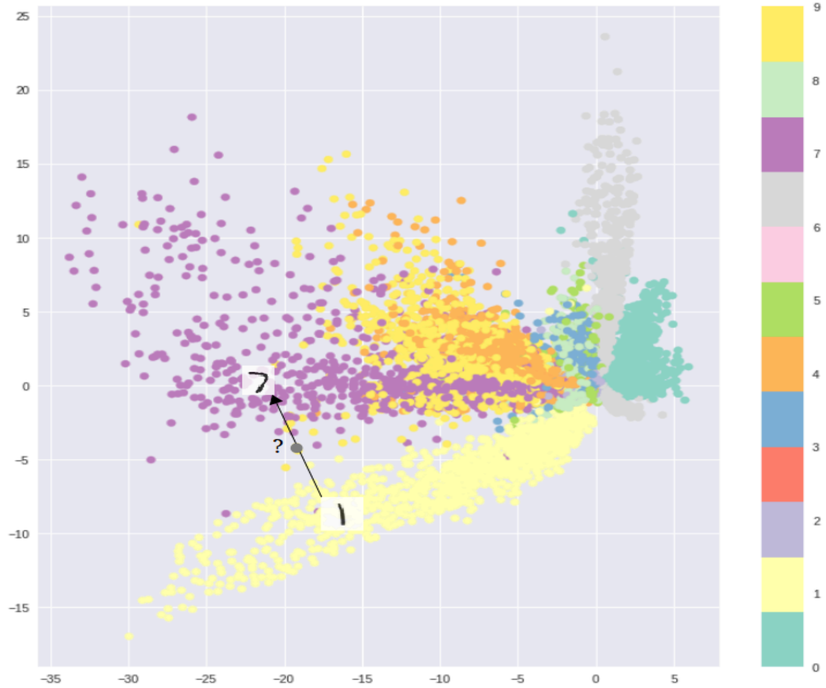
Now we can generate data
from noise distribution with the learned (μ,σ)



VAEs- vs AEs

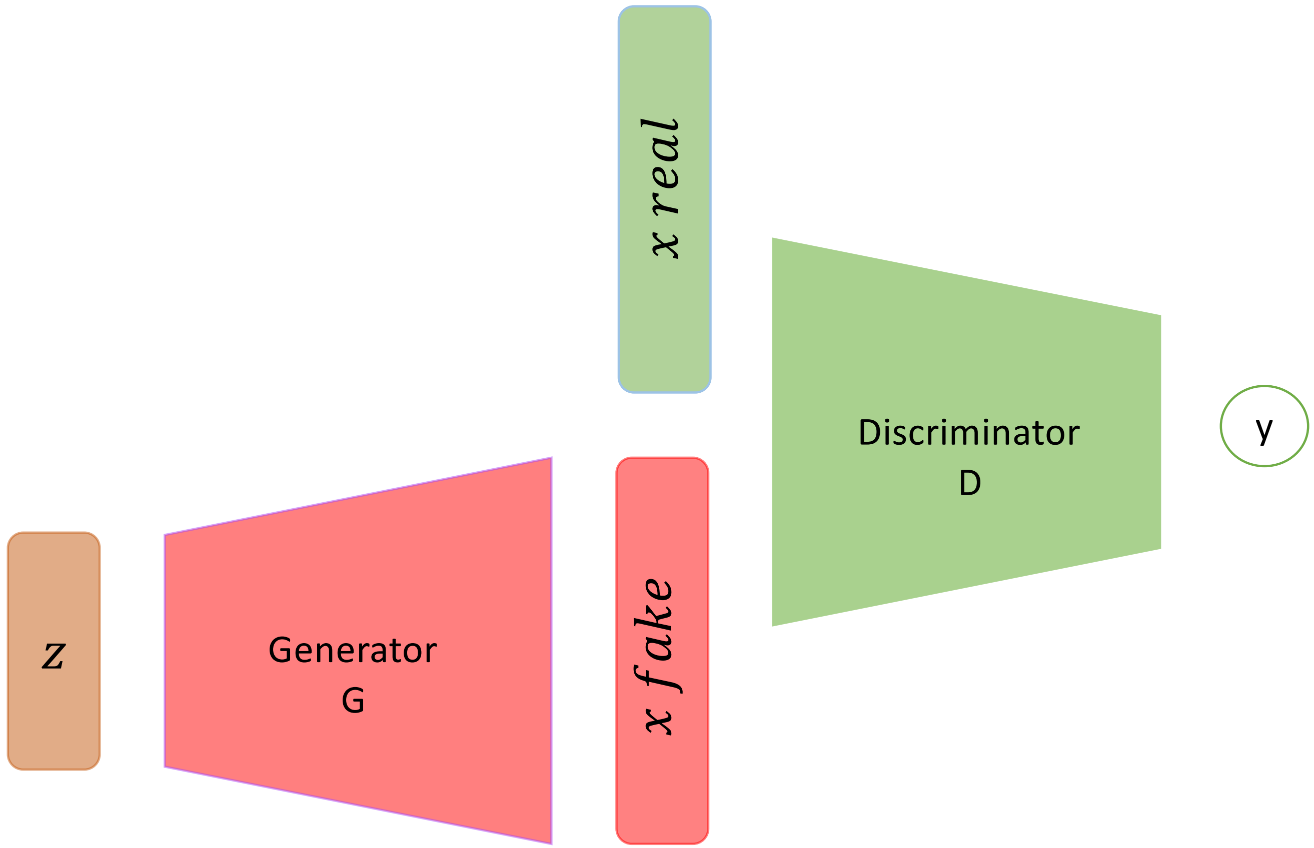


Variational Auto-Encoders



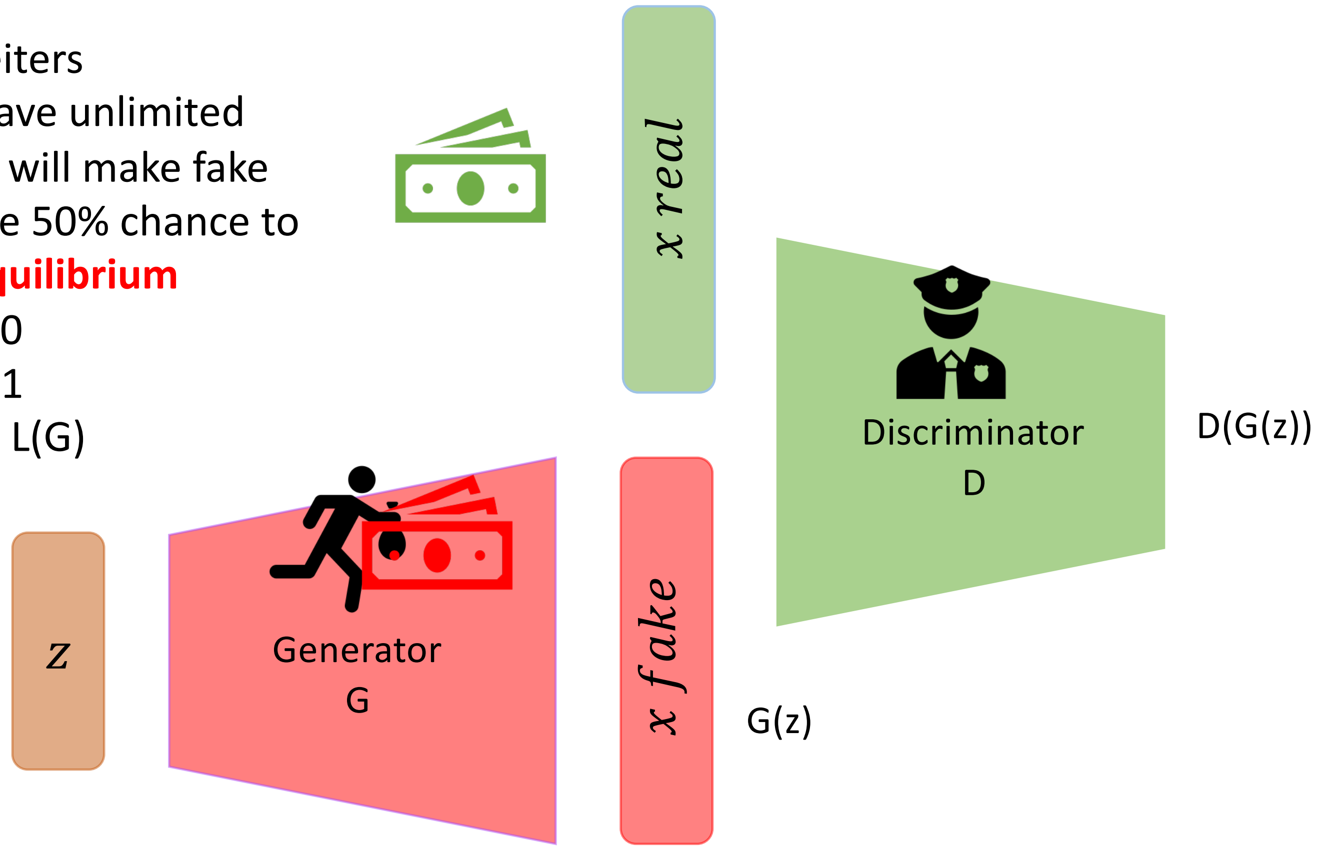
Auto-Encoders

Generative Adversarial Networks

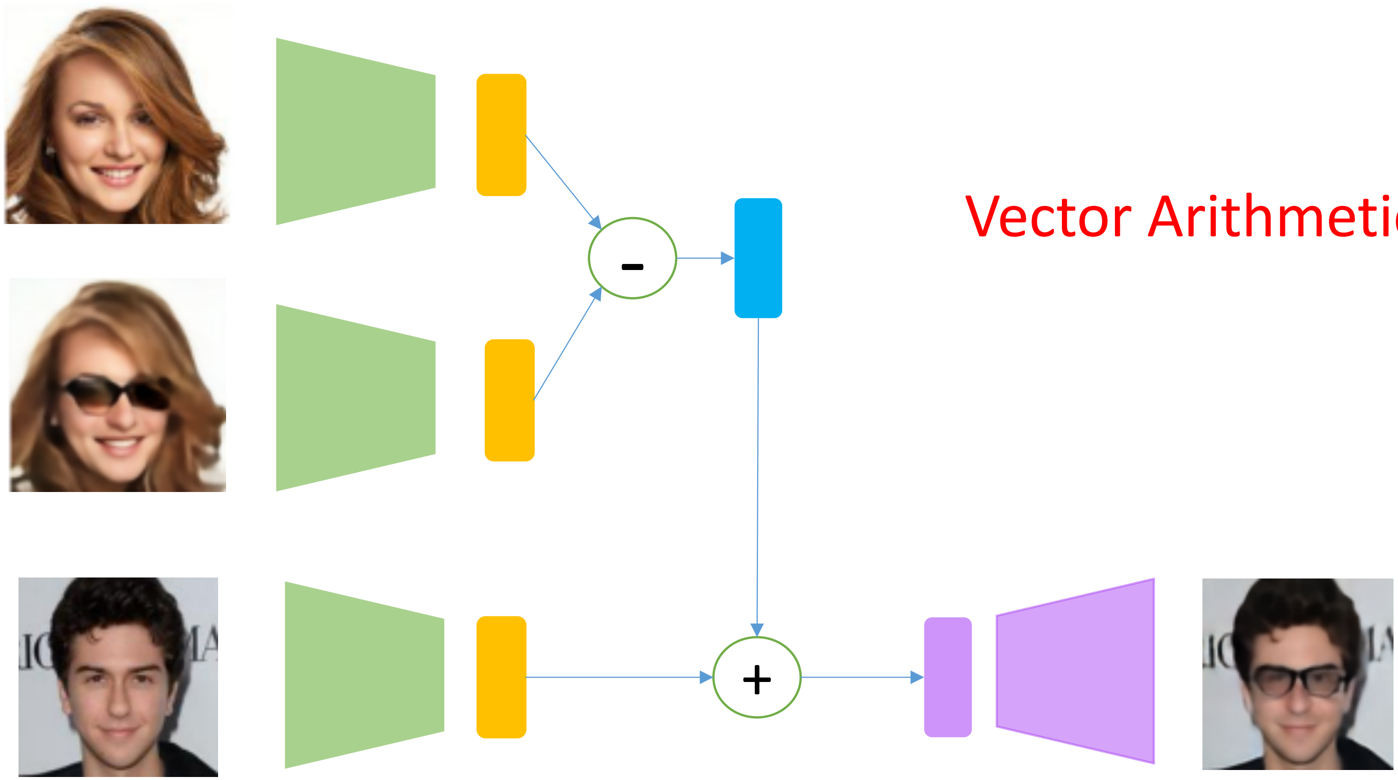


Generative Adversarial Networks

- 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)

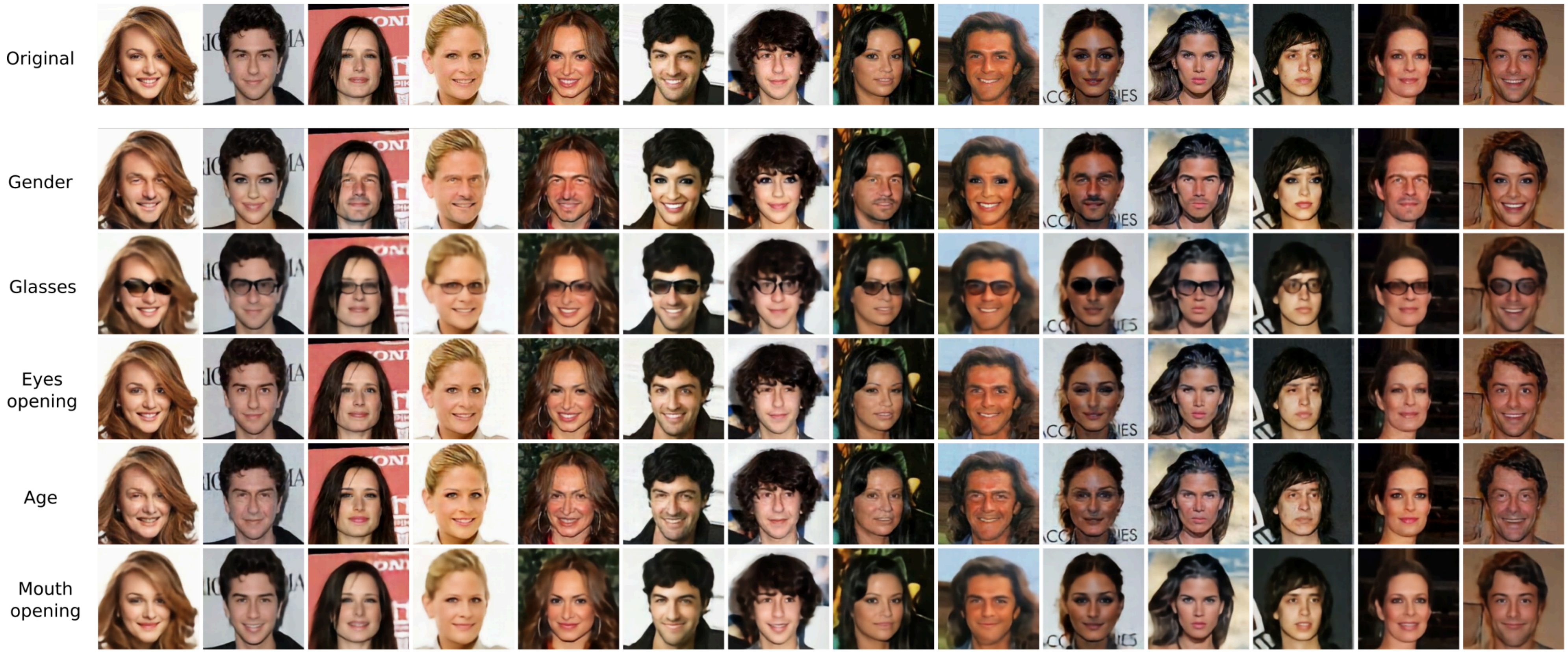


Generative Models: Applications

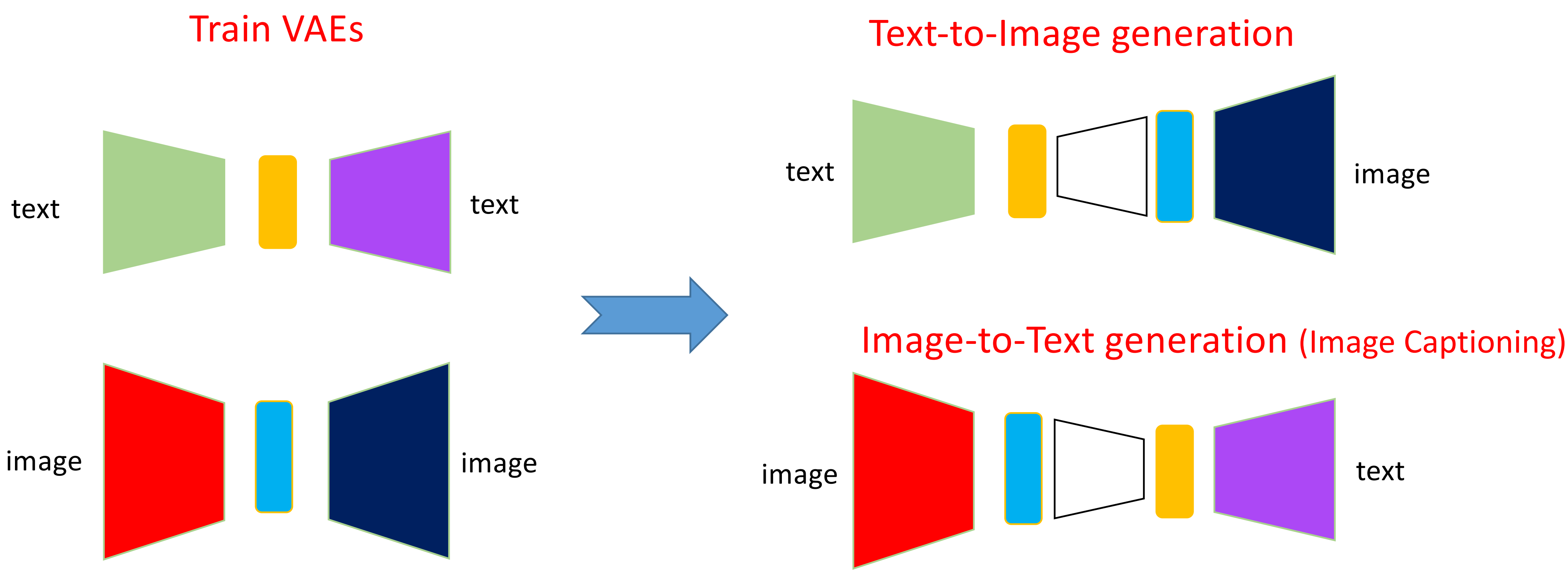


Vector Arithmetic

Generative Models: Applications

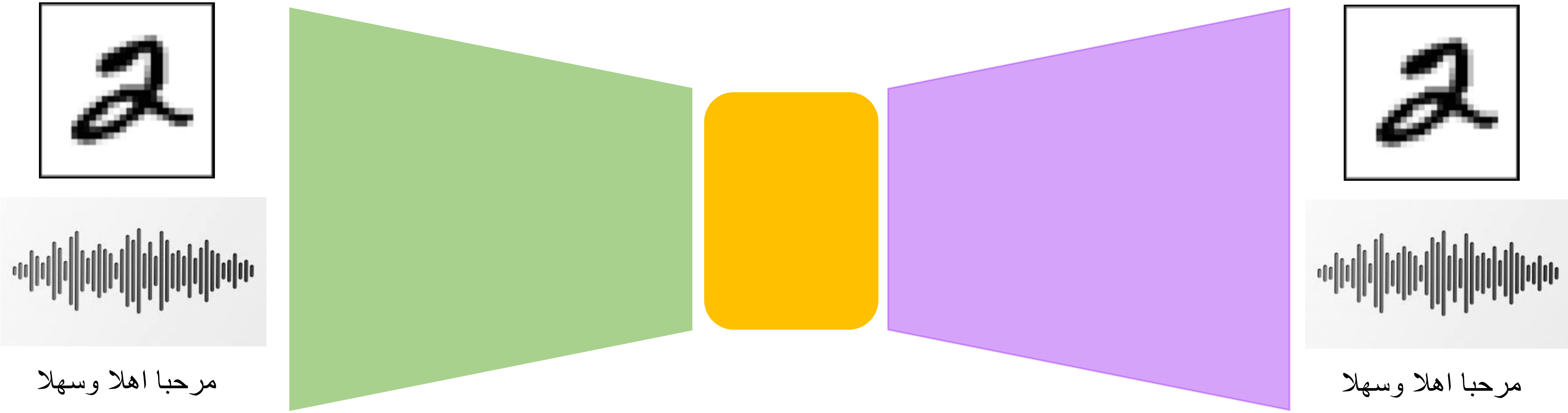


Generative Models: Applications



Generative Models: Different Data Types

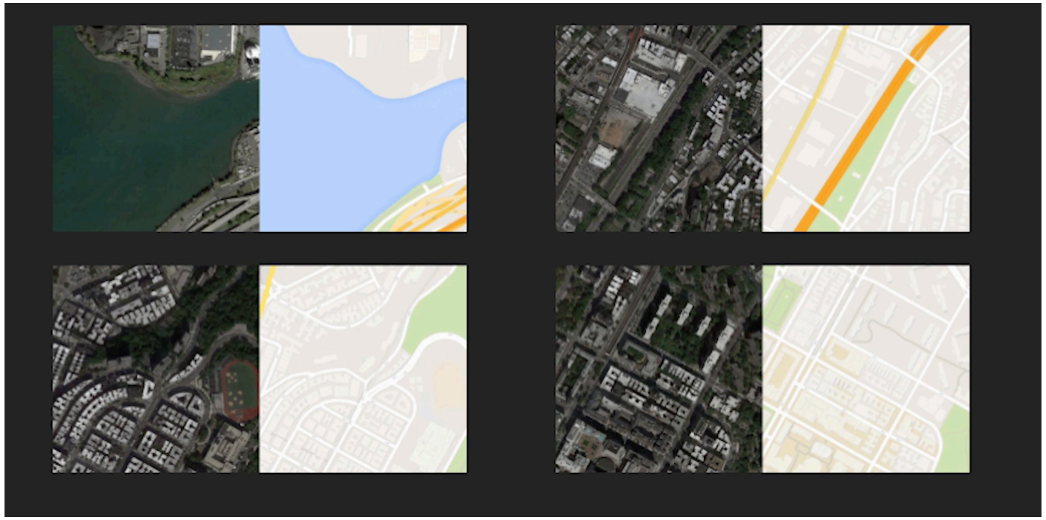
- Sequential or non-sequential,
- Continuous or discrete,
- Labelled or un-labelled



Generative Models: Other Architectures

- Pix2Pix
- BicycleGAN
- CycleGAN
- ...

Paired Images



Unpaired Images