

# *Autoencoder*

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# Embedding

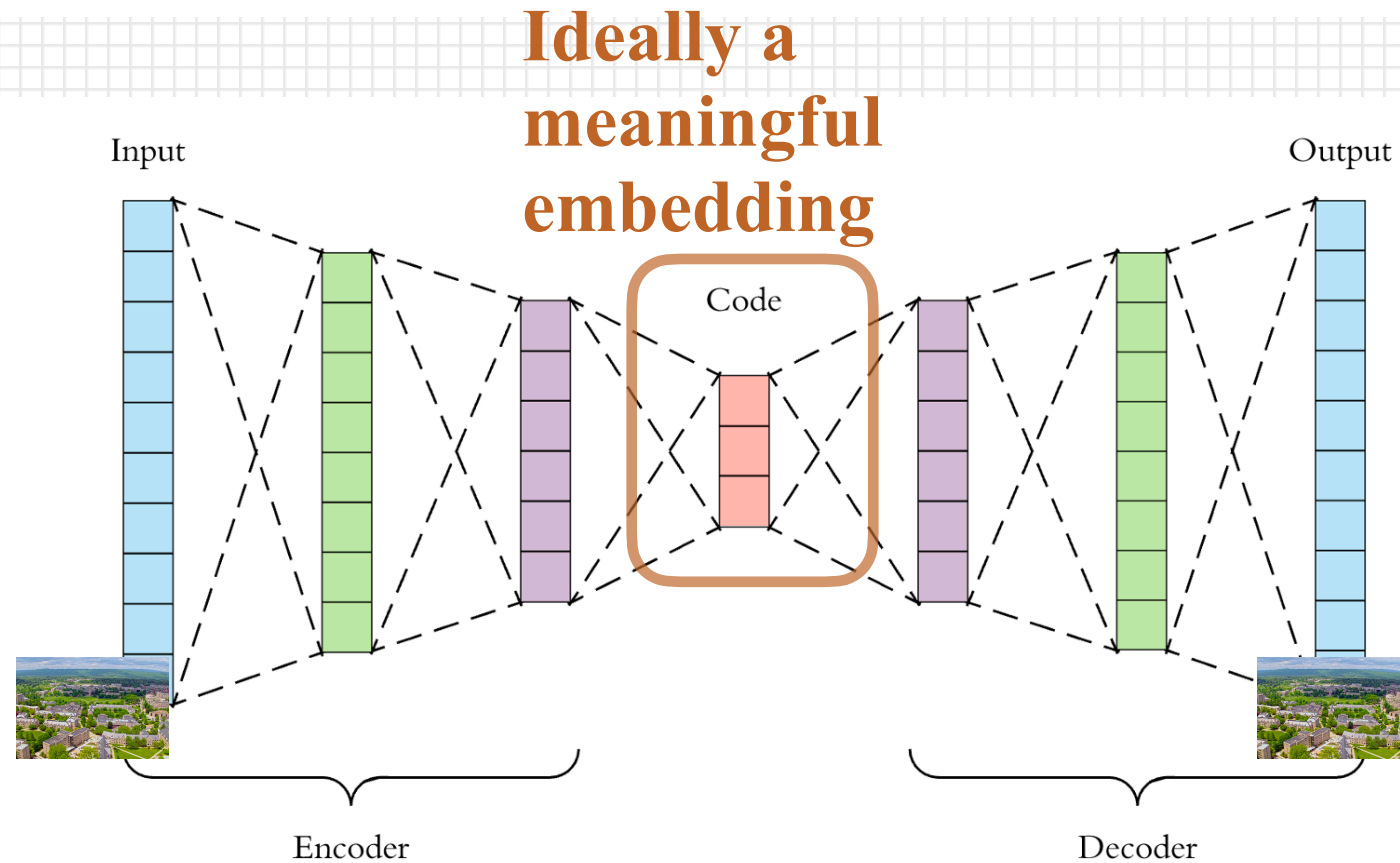
- Represent higher dimensional data in a lower dimensional data while still containing useful information
- Embed this picture?
- Depending on tasks



Photo credits: [VT](#)

# Autoencoder

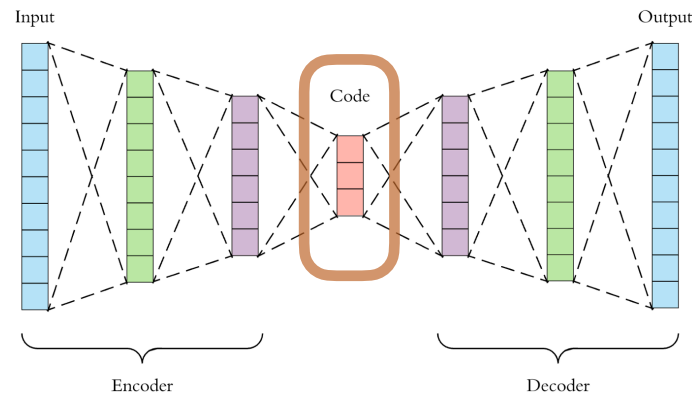
- 'Auto' means self



- A bottleneck shape neural networks
- Retrieve hidden state values as embeddings

# Advantages of autoencoder

- Parameter savings, fewer dimensions
- Compression
- Denoising
- Data generation
  - Manipulate the input to the decoder part

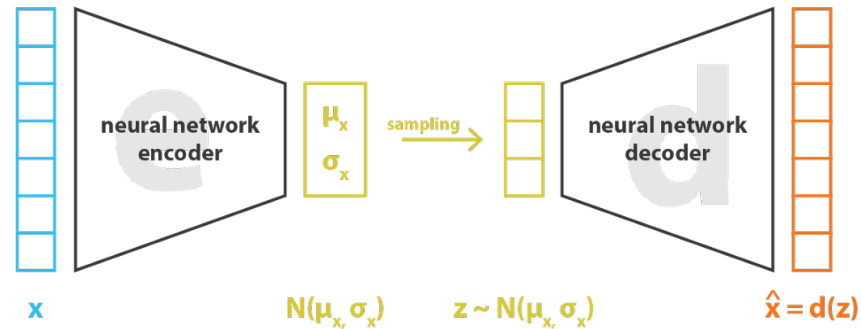
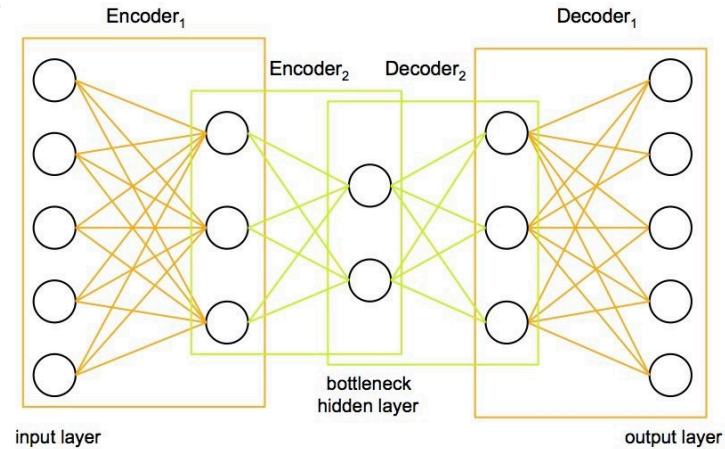


# *Autoencoder with Maths*

- Encoder:  $f(\cdot)$
- Decoder:  $g(\cdot)$
  
- Autoencoder  $g(f(\mathbf{x})) = \mathbf{x}$
- For a training sample  $(x^l, y^l)$ ,  $y^l = x^l$ 
  - Thus, auto

# Autoencoder Variants

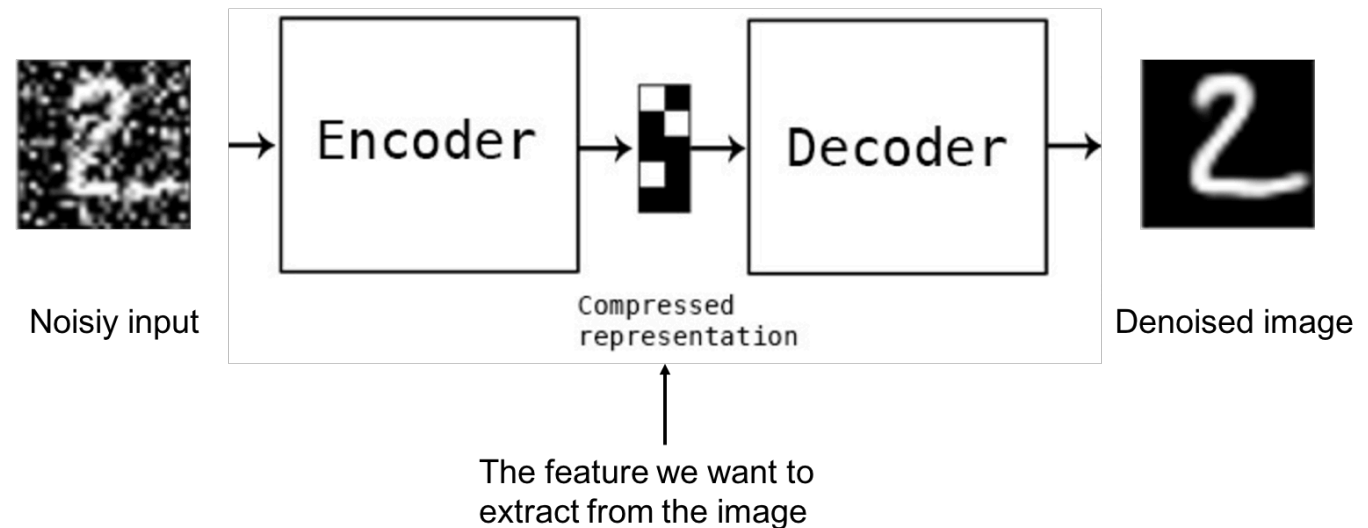
- Deep
- Stacked
  
- Variational
  
- And more?



$$\text{loss} = \|x - \hat{x}\|^2 + \text{KL}[N(\mu_x, \sigma_x), N(0, I)] = \|x - d(z)\|^2 + \text{KL}[N(\mu_x, \sigma_x), N(0, I)]$$

# Denoising Autoencoder

- Intentionally add noise to input
  - $\tilde{x} = x + \mathcal{N}(0, \sigma)$
- Output remains the same
  - $y = x$



# *More on Dimension Reduction*

- Principle Component Analysis (PCA)
- Singular-value Decomposition (SVD)
  
- Both are deterministic and do not need extra parameters or external training