

# Autoencoders in a nutshell

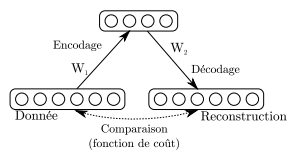
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## Autoencoder

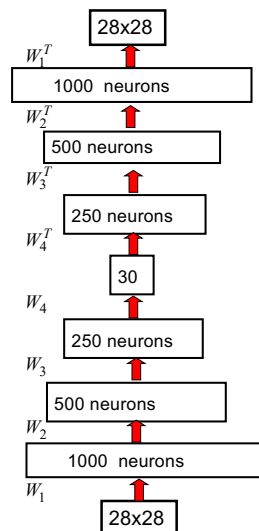
- What's the objective of AE?
  - extract low-dimensional representation
- How ?
  - reconstruct (decode) data from the internal (latent) code
- Some features
  - PCA can be seen as a linear AE  
(see: <https://arxiv.org/pdf/1804.10253.pdf>)
  - possibility to stack encoding layers
  - improve the latent space (c.f., VAE)

### Architecture of AE (1)

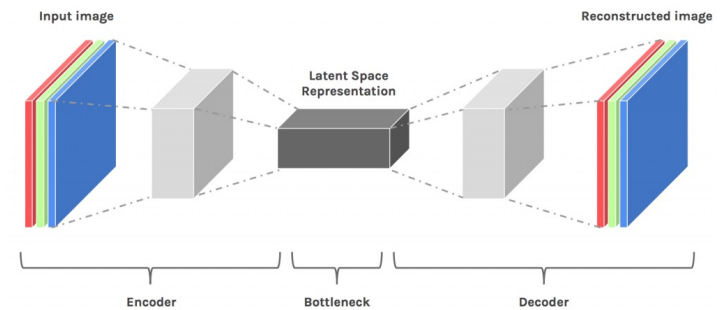


encoder :  $p_{\text{encode}}(h|x)$   
decoder :  $p_{\text{decode}}(x|h)$

make is deep ->

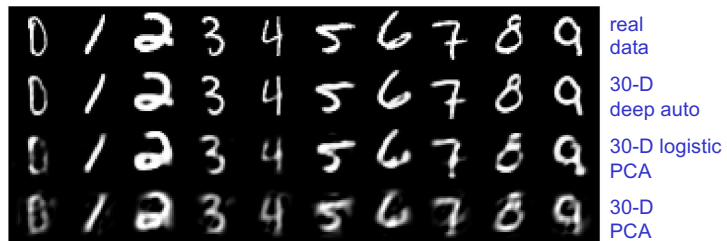


### Architecture of AE (2)

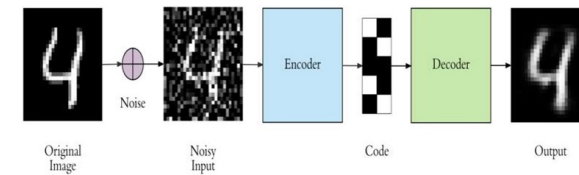


## Comparison

taken from CSC2535: 2013 (G. Hinton)



## Denoising AE



source: <https://medium.com/@harishr2301/denoising-autoencoders-996e866e5cd0>

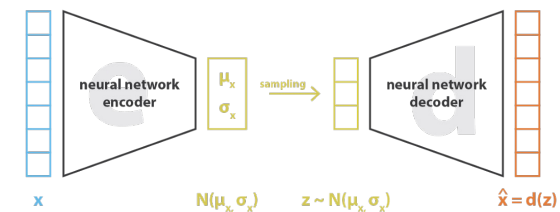
## Sparse autoencoder

Adding a penalty on the code  $\mathbf{h}$  :

$$L(x, g(f(x))) + \Omega(h)$$

For instance,  $\Omega(h) = \lambda \sum_i |h_i|$

## Variational AE



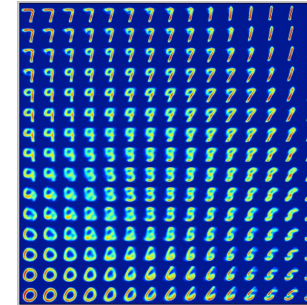
$$\text{loss} = ||x - \hat{x}||^2 + \text{KL}[N(\mu_x, \sigma_x), N(0, I)] = ||x - d(z)||^2 + \text{KL}[N(\mu_x, \sigma_x), N(0, I)]$$

source: <https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73>

## VAE (con't)

- Solution to get better latent spaces therefore better generation
- Two parts of the architecture:
  - encoder:  $p(z|x)$
  - decoder:  $p(x|z)$
- Optimization based on Variational Inference (VI)
- Implemented with the « reparametrization trick »
- The internal code (z) should follow a « simple » law (e.g., Gaussian)

## VAE (con't)



source: <https://blog.keras.io/building-autoencoders-in-keras.html>