
Autoencoder

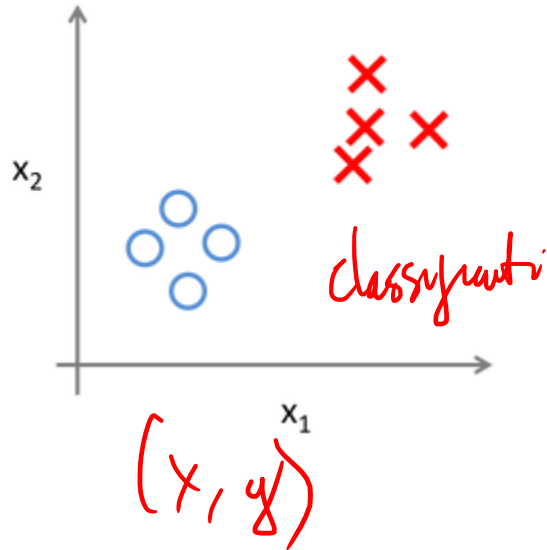
— Tuan Nguyen - AI4E —

Outline

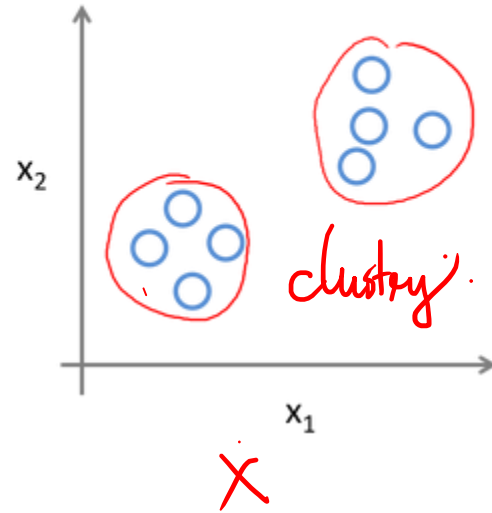
- Unsupervised Learning (Introduction)
- Autoencoder (AE)
- Autoencoder application
- Convolutional AE
- Denoising AE

Supervised vs Unsupervised

Supervised Learning



Unsupervised Learning



Supervised Learning

- Data: (X, Y)
- Goal: Learn a Mapping Function f where:

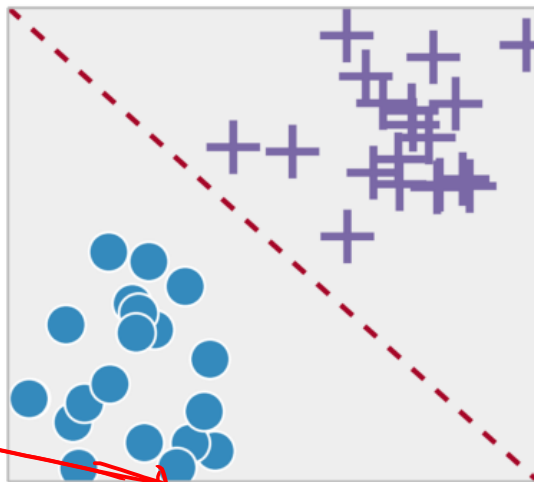
$$f(X) = Y$$

$$f(x) = ax + b$$

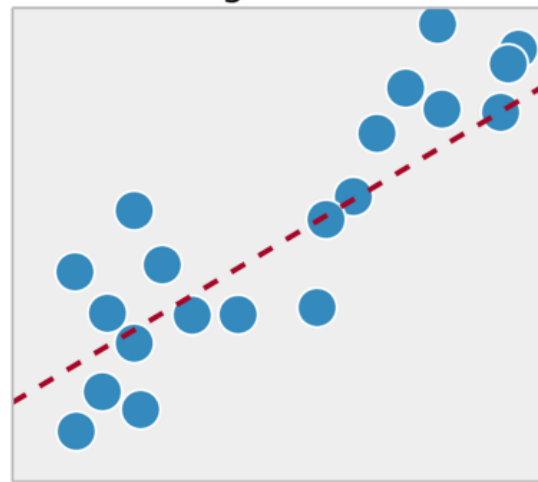
$$f(x) = f_1(f_2(\dots f_n(x)))$$

$$f(x) = \text{conv}(\text{pool}(\dots f(f \dots (x))))$$

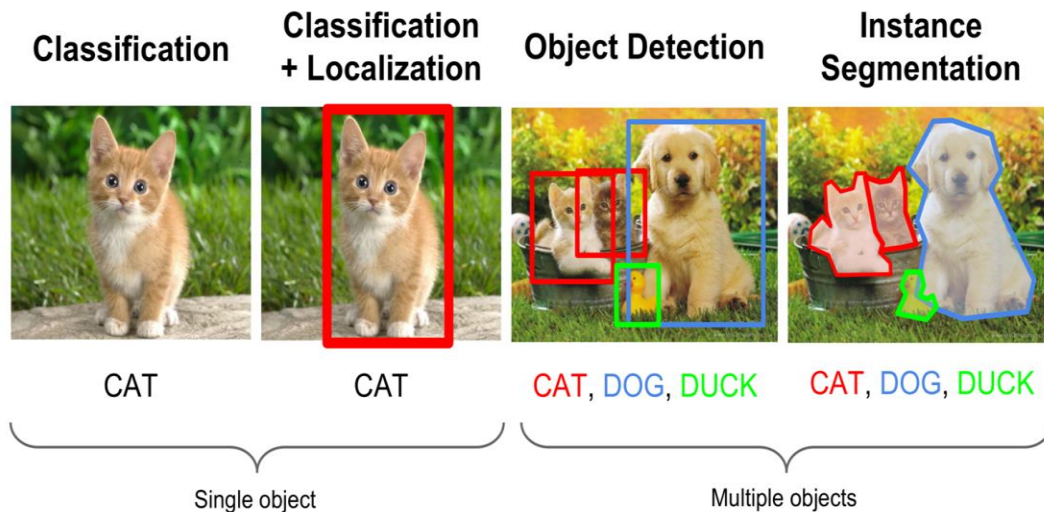
Classification



Regression



Supervised Learning



Label data?

01

What happens
when our labels
are noisy?

- Missing values.
- Labeled incorrectly.

02

What happens
where we don't
have labels for
training **at all**?

Unsupervised Learning

Up until now we have encountered in this course mostly **Supervised Learning** problems and algorithms.

Let's talk about **Unsupervised Learning**

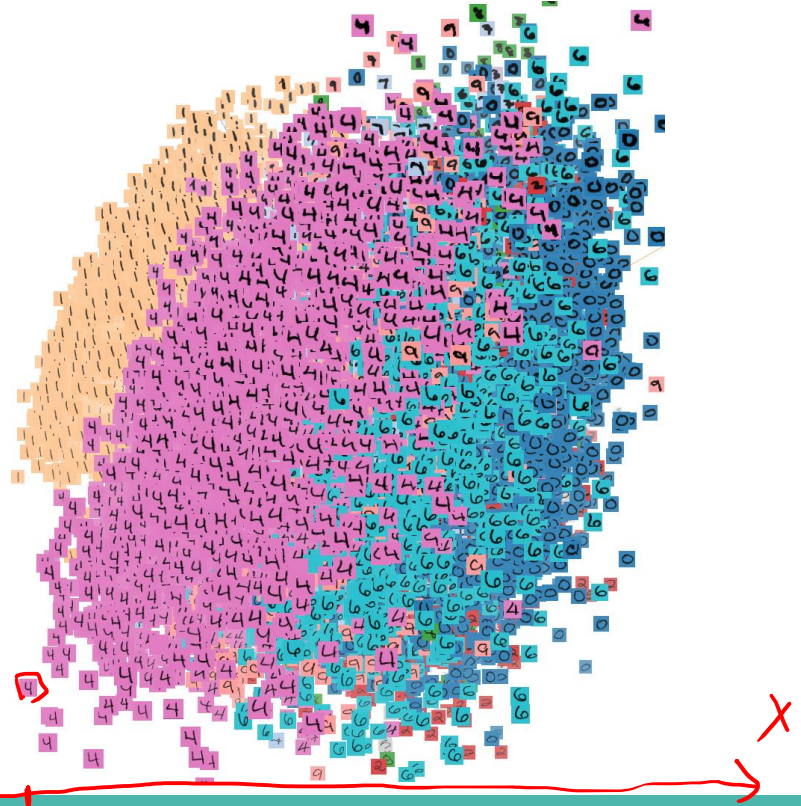
Unsupervised Learning

$$u \frac{1}{u} \rightarrow \frac{1}{2} : \text{unsupervised..}$$

Unsupervised Learning

Data: X no label

Goal: Learn the structure
of the data learn
correlations between
features



Unsupervised Learning

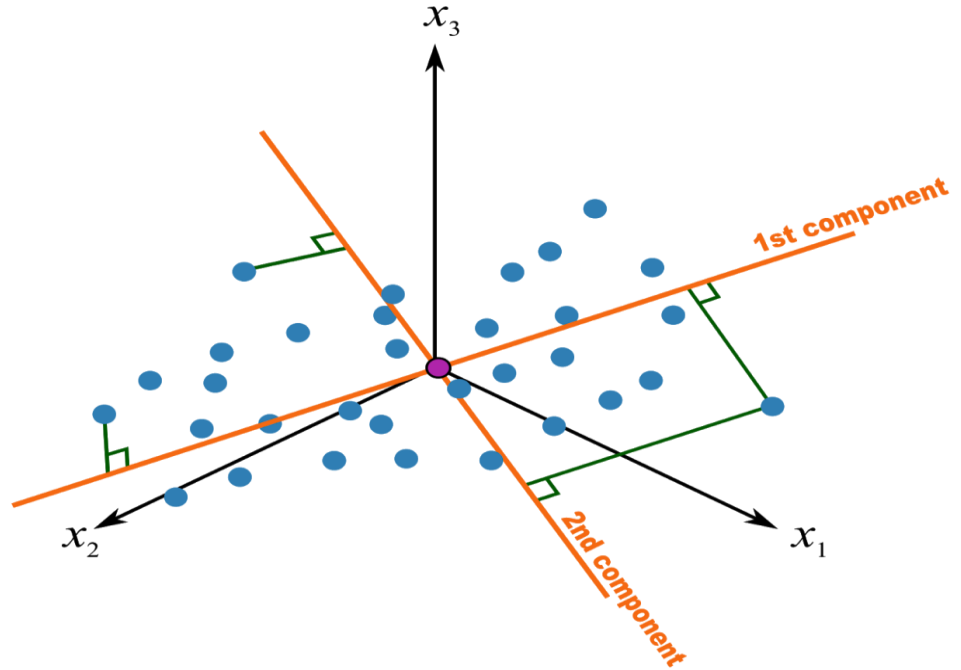
Examples: Clustering, Compression, Feature & Representation learning, Dimensionality reduction, Generative models, etc.

GAN(s). VAE(s)

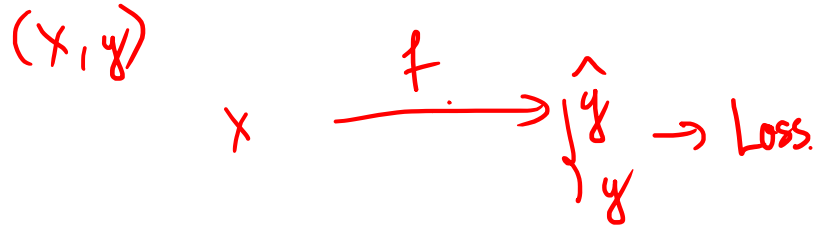
PCA – Principal Component analysis



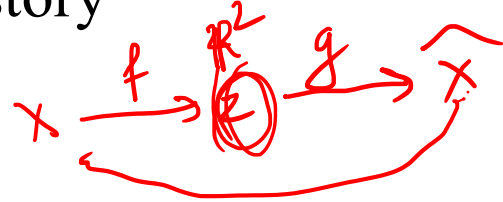
- Statistical approach for data compression and visualization
- Invented by Karl Pearson in 1901
- Weakness: linear components only.



Autoencoder



- The autoencoder idea was a part of NN history for decades (LeCun et al, 1987).
- Traditionally an autoencoder is used for dimensionality reduction and feature learning.
- Recently, the connection between autoencoders and latent space modeling has brought autoencoders to the front of generative modeling.



Simple Idea

- Given data x (no labels) we would like to learn the functions f (encoder) and g (decoder) where:

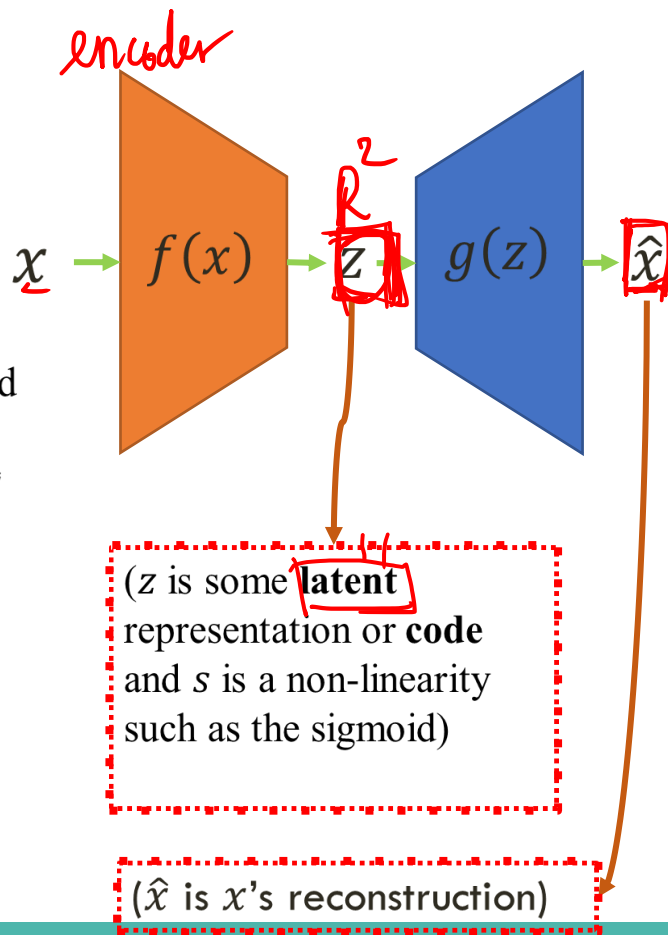
$$f(x) = s(wx + b) = z$$

and

$$g(z) = s(w'z + b') = \hat{x}$$

$$\text{s.t } h(x) = g(f(x)) = \hat{x}$$

where h is an **approximation** of the identity function.



Training Autoencoder

Using **Gradient Descent** we can simply train the model as any other FC NN with:

- Traditionally with squared error loss function

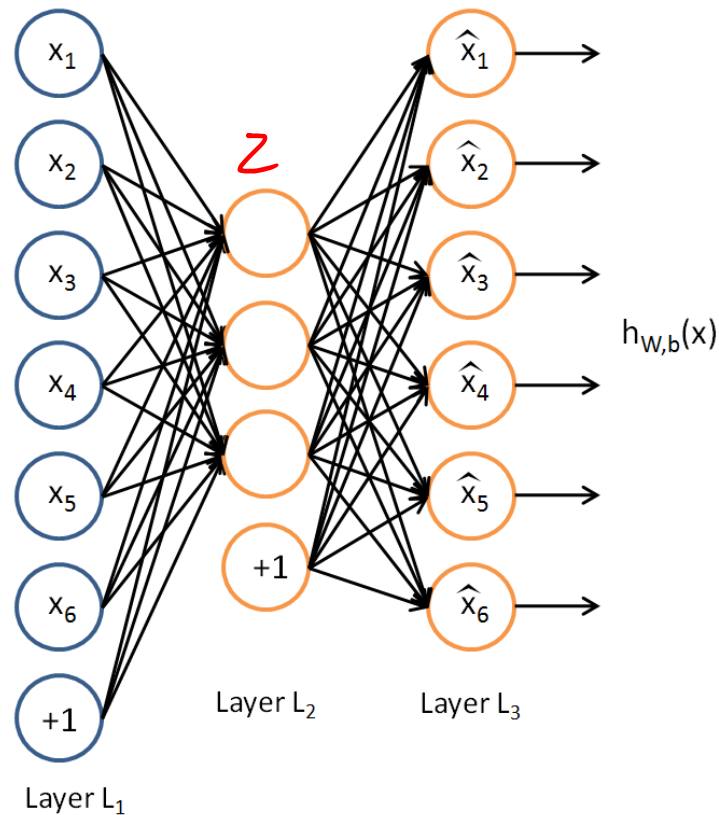
$$L(x, \hat{x}) = \|x - \hat{x}\|^2$$

or.

- If our input is interpreted as bit vectors or vectors of bit probabilities the cross entropy can be used

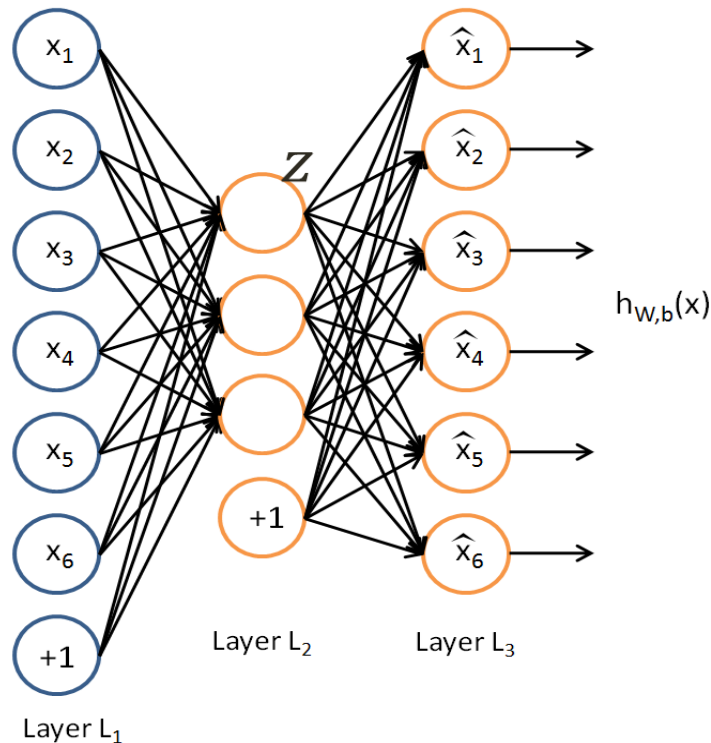
$$H(p, q) = - \sum_x p(x) \log q(x)$$

Traditional Autoencoder

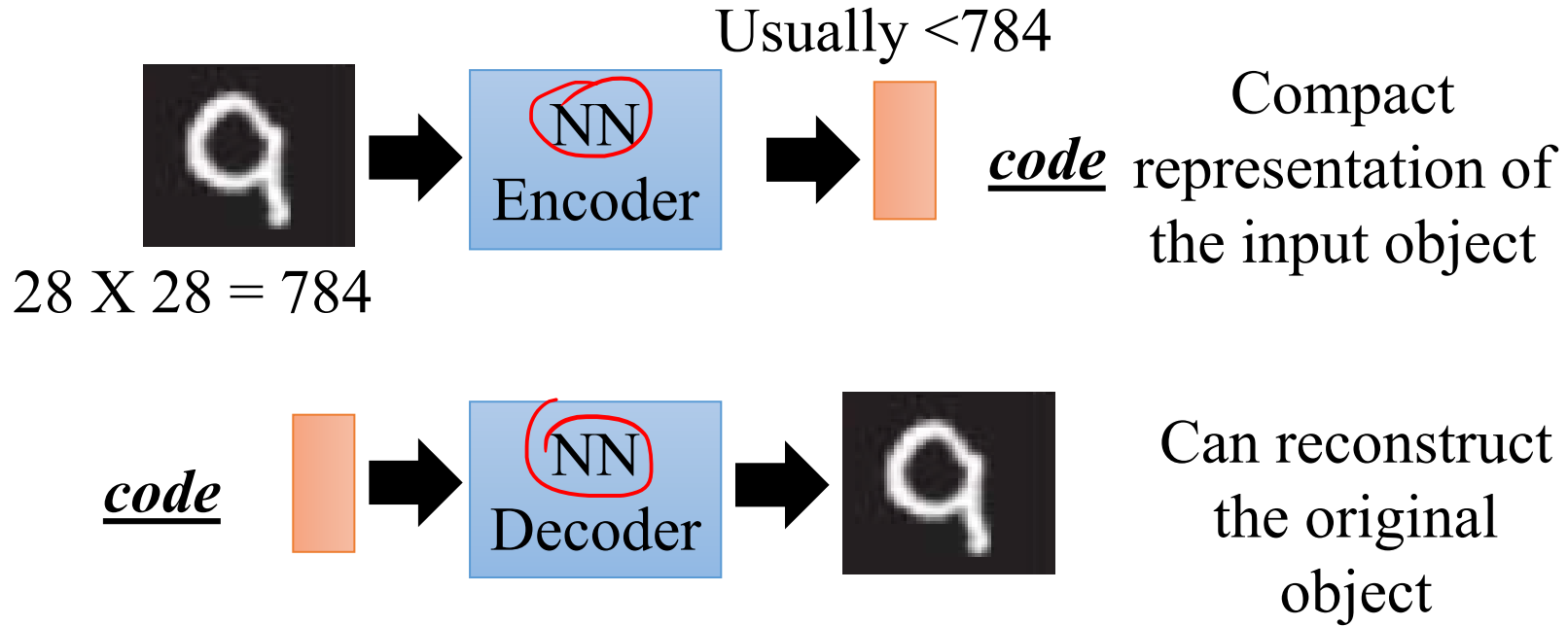


Traditional Autoencoder

- Unlike the **PCA** now we can use activation functions to achieve non-linearity.
- It has been shown that an AE without activation functions achieves the **PCA** capacity.



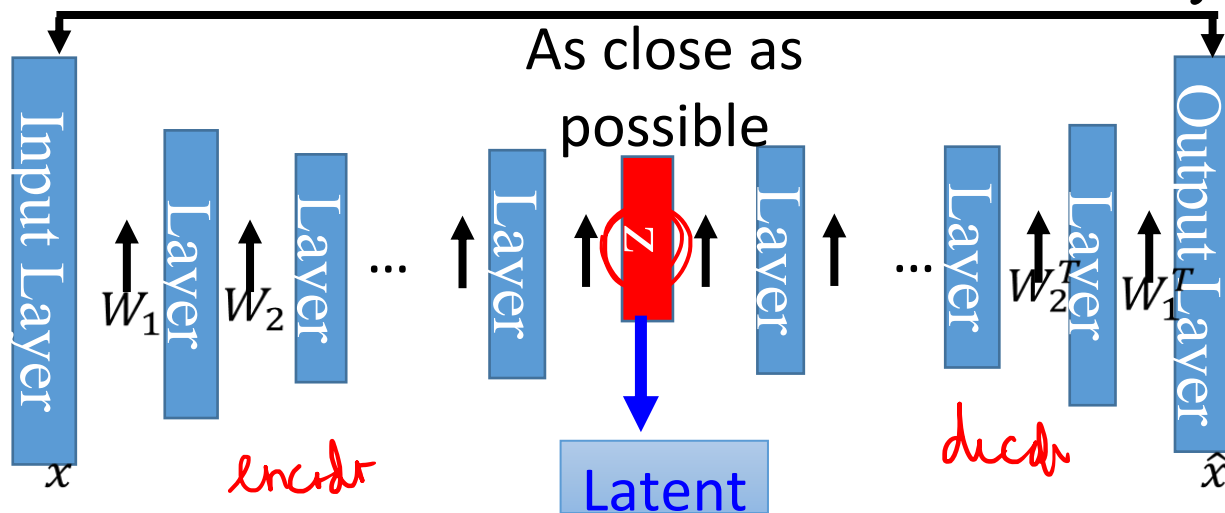
Auto-encoder



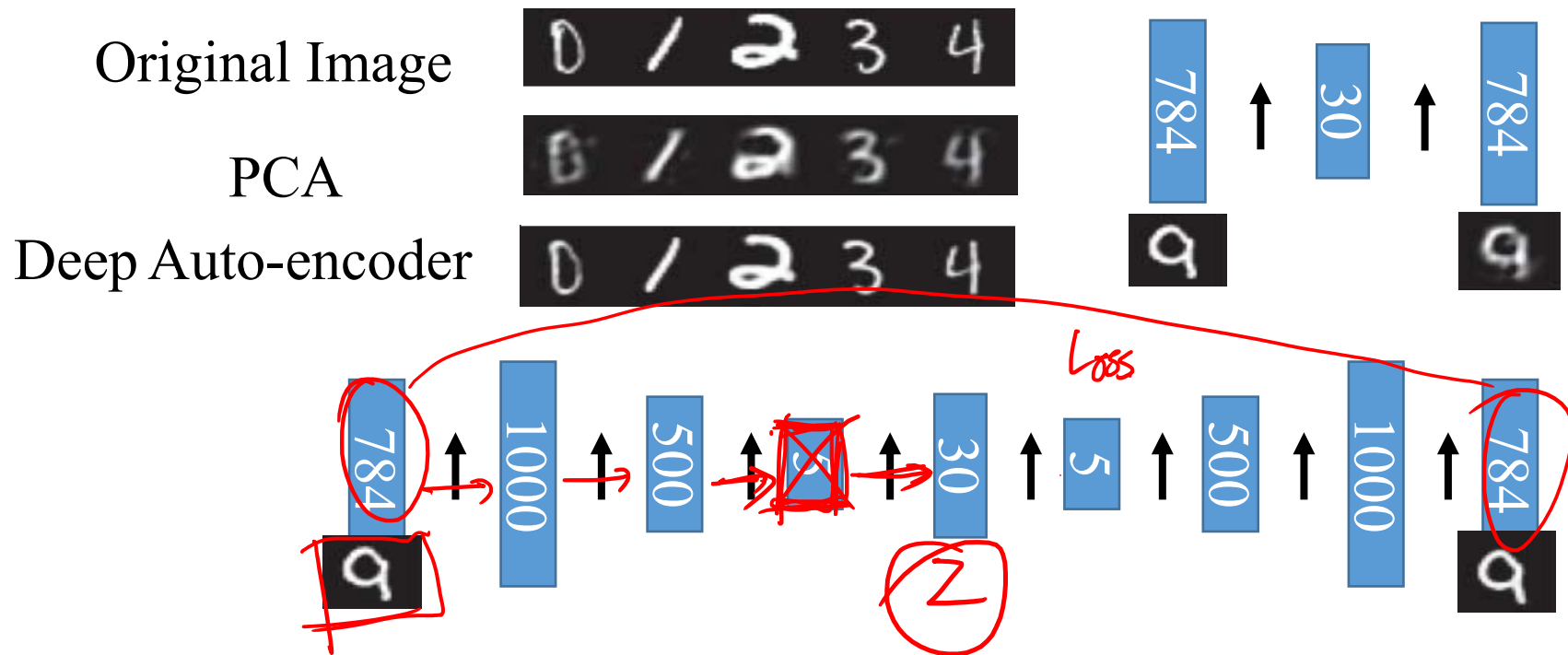
Deep Autoencoder

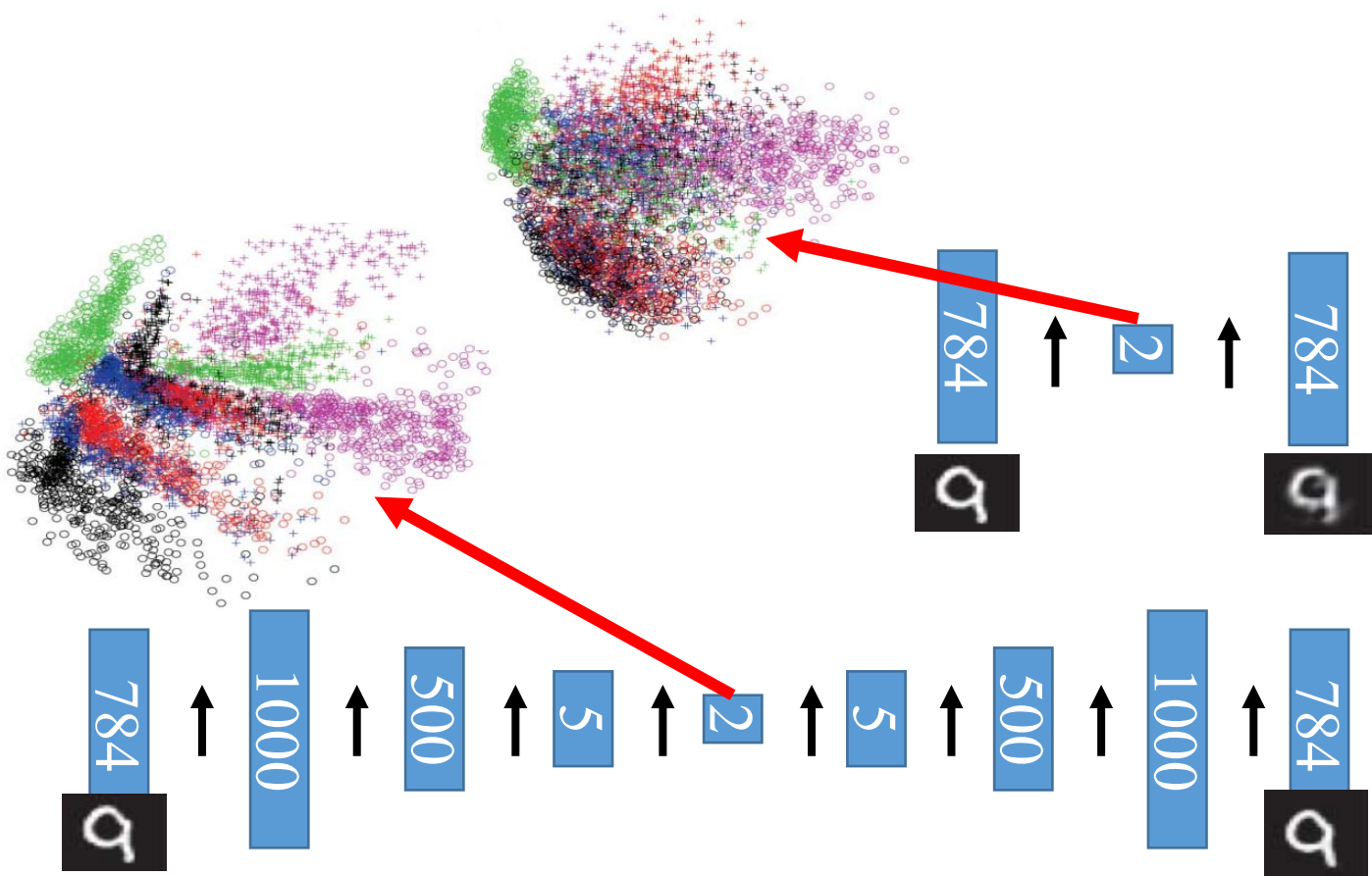
Of course, the auto-encoder can be deep

Symmetric is not necessary.

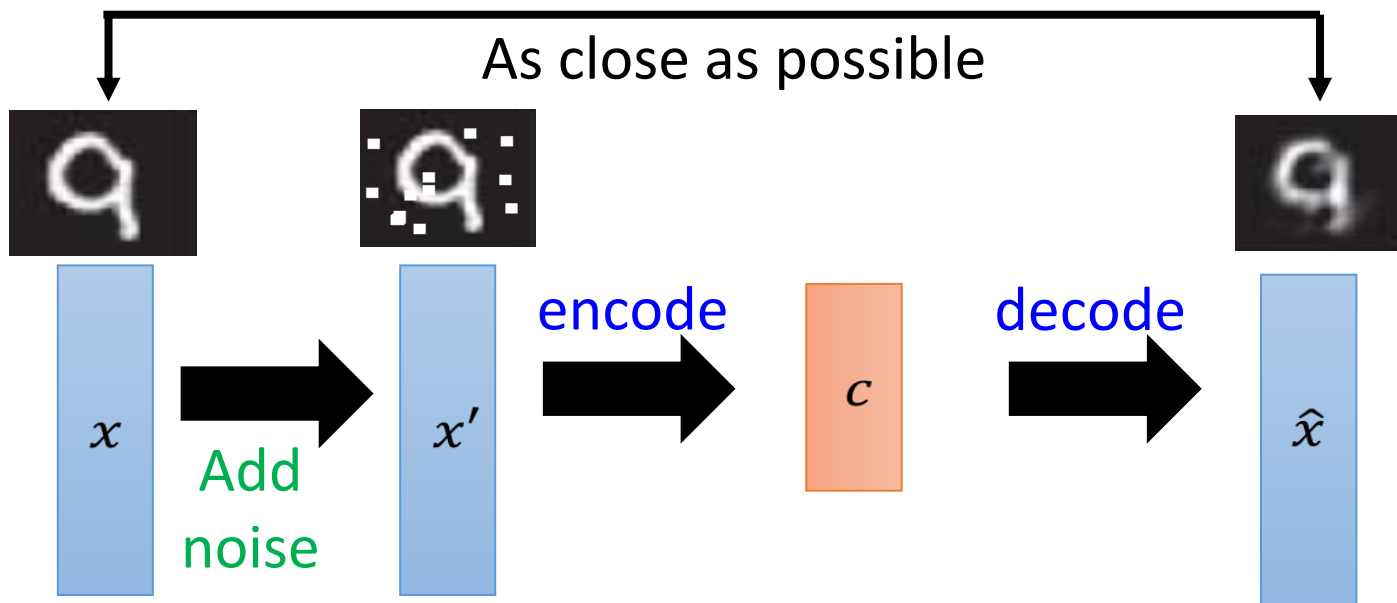


Deep Autoencoder





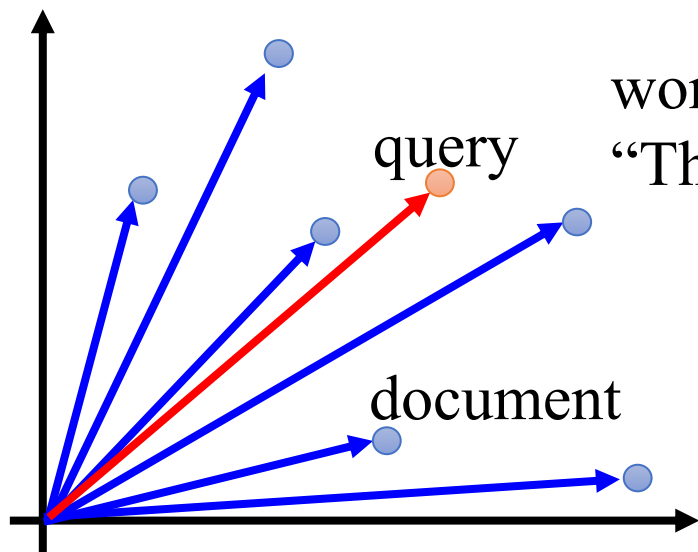
Denoise



Vincent, Pascal, et al. "Extracting and composing robust features with denoising autoencoders." *ICML*, 2008.

Text Retrieval

Vector Space Model



word string:

“This is an apple”

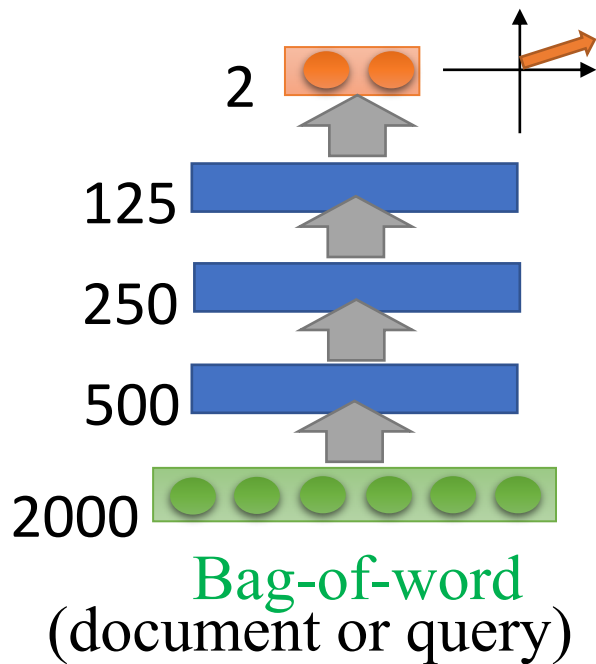
Bag-of-words

this	●	1
is	●	1
a	●	0
an	●	1
apple	●	1
pen	●	0
⋮	●	

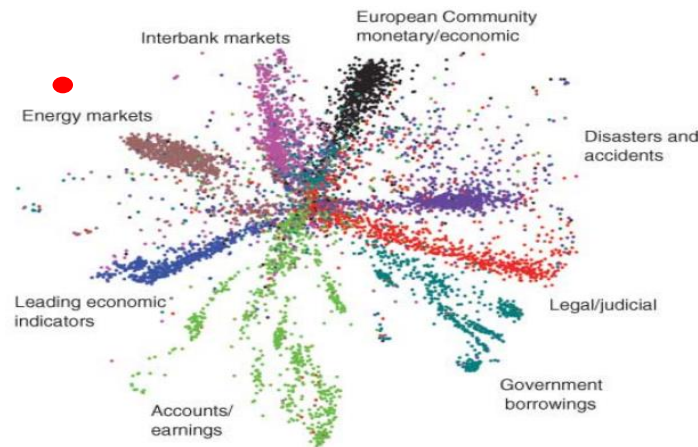
Semantics are not
considered.

Text Retrieval

The documents talking about the same thing will have close code.



query



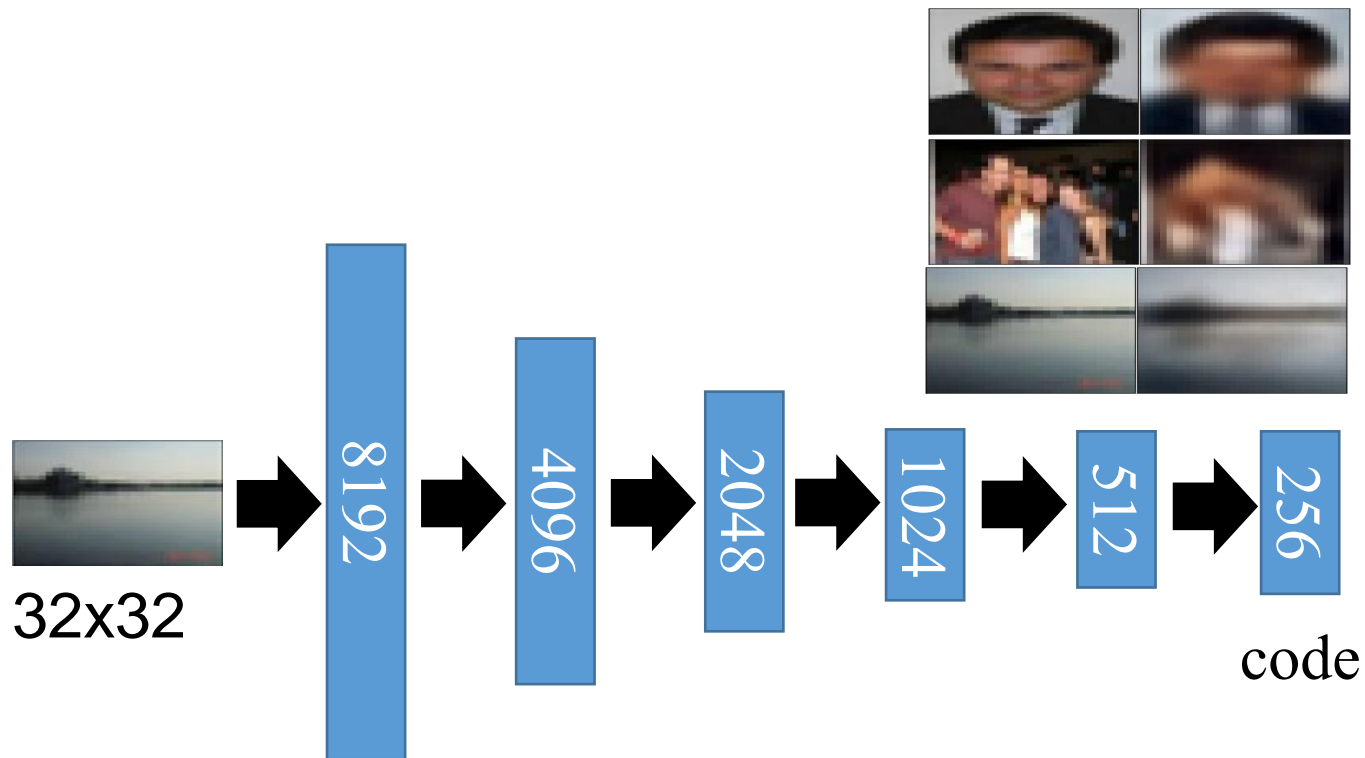
Similar image search

Retrieved using Euclidean distance in pixel intensity



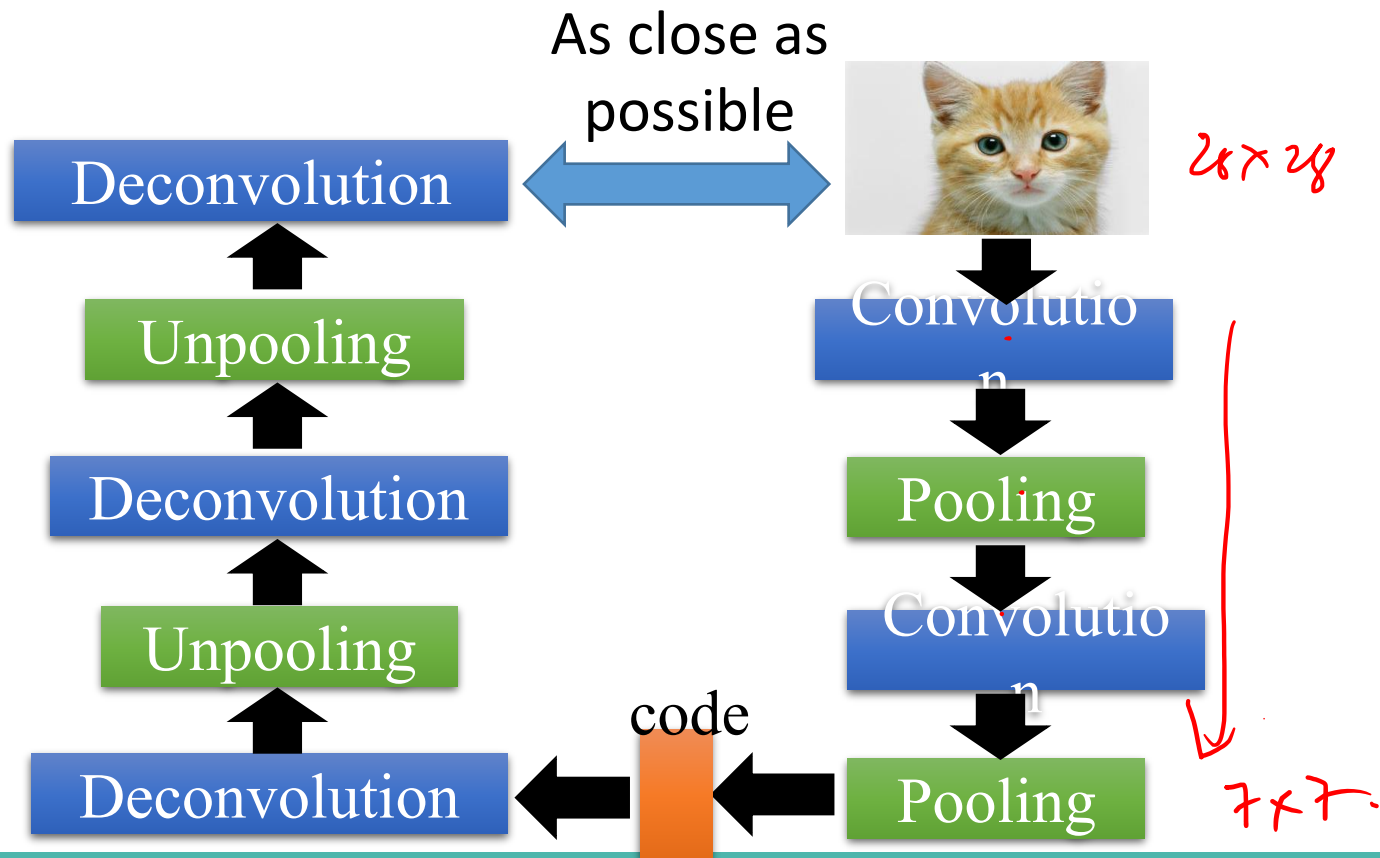
Reference: Krizhevsky, Alex, and Geoffrey E. Hinton. "Using very deep autoencoders for content-based image retrieval." *ESANN*. 2011.

Similar image search



Auto-encoder for CNN

max pooling, Conv $s=2$.



Deconvolution:

$n \times n$
 14×14

$\text{conv} \xrightarrow{s=2, p=1} 7 \times 3$

$\text{deconv} \xrightarrow{s=2, p=1} m \times m$
 28×28

$n. 14 \times 14$

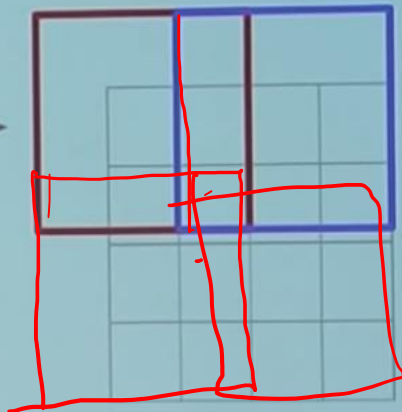
Learnable Upsampling: "Deconvolution"

3 x 3 "deconvolution", stride 2 pad 1



Input gives
weight for
filter

Input: 2 x 2



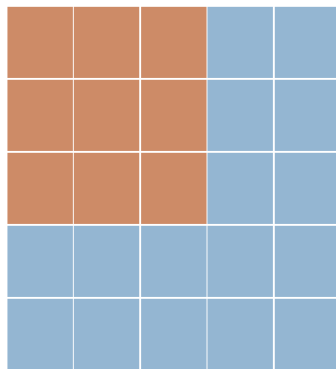
Output: 4 x 4

$\times \xrightarrow{\text{conv}} \times$
 s, p, W

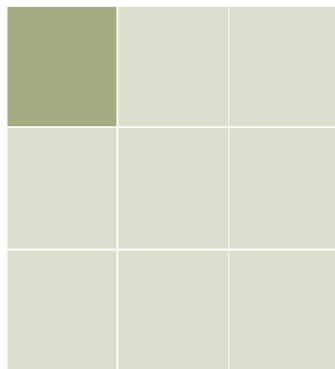
$\gamma \xrightarrow{\text{deconv}} \times$
 s, p, W

Convolution

Type: conv - Stride: 1 Padding: 0

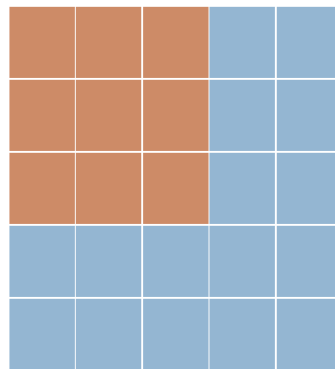


Input

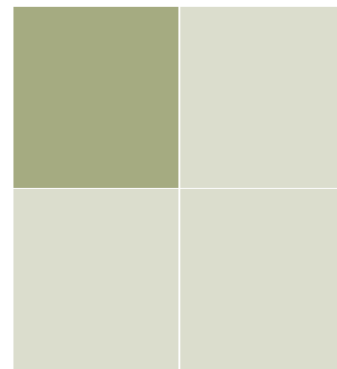


Output

Type: conv - Stride: 2 Padding: 0

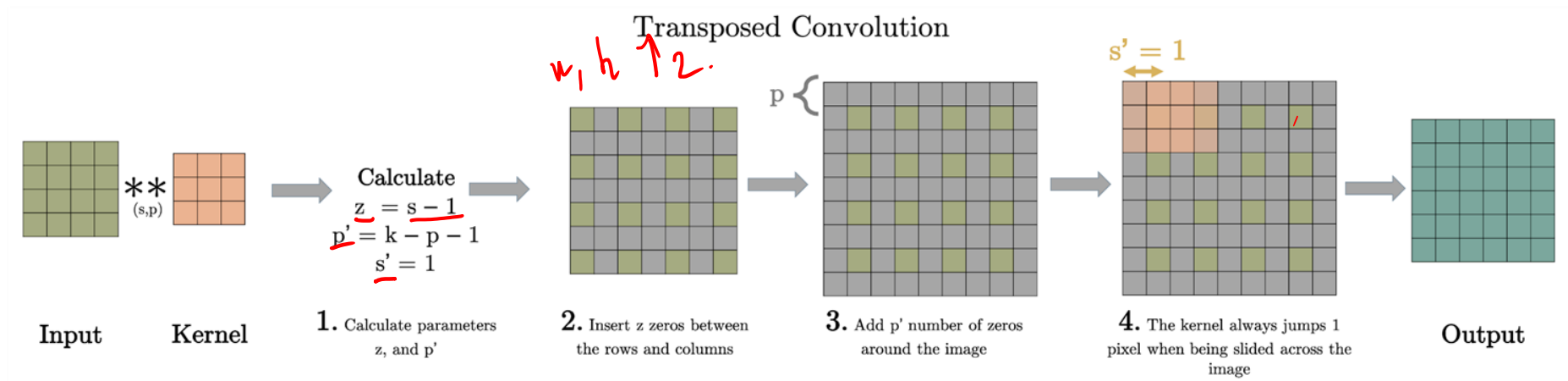


Input



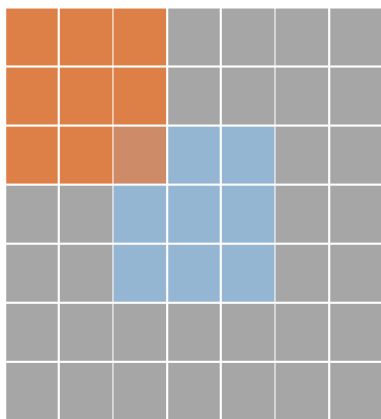
Output

Transposed convolution

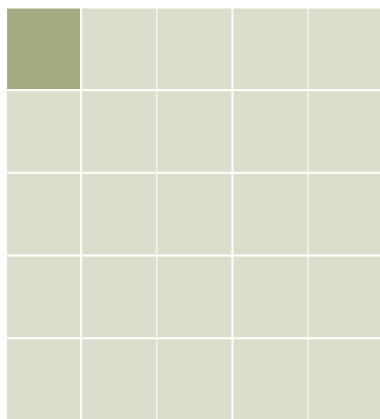


Transposed convolution

Type: transposed'conv - Stride: 1 Padding: 0

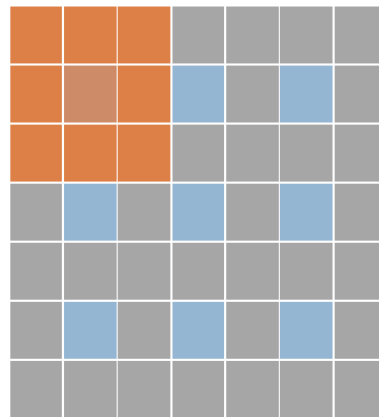


Input

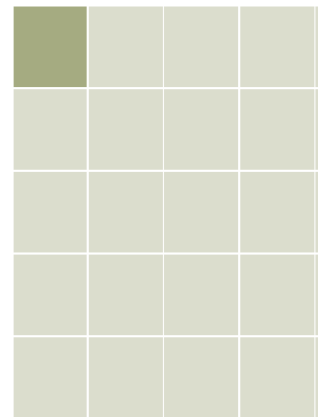


Output

Type: transposed'conv - Stride: 2 Padding: 1

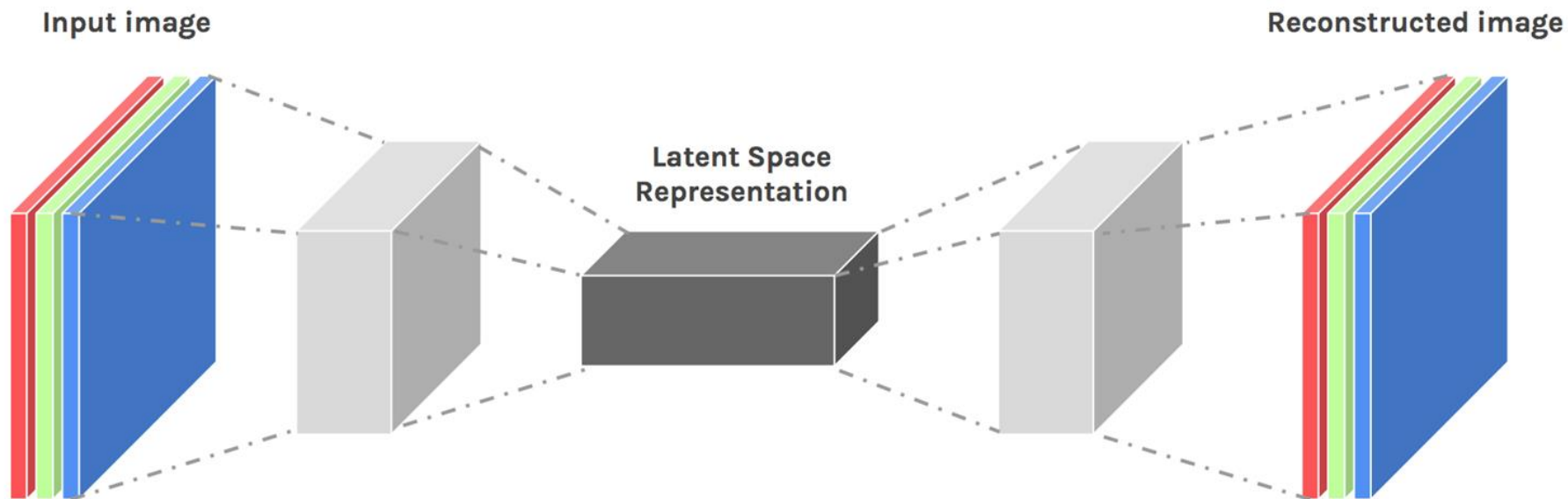


Input

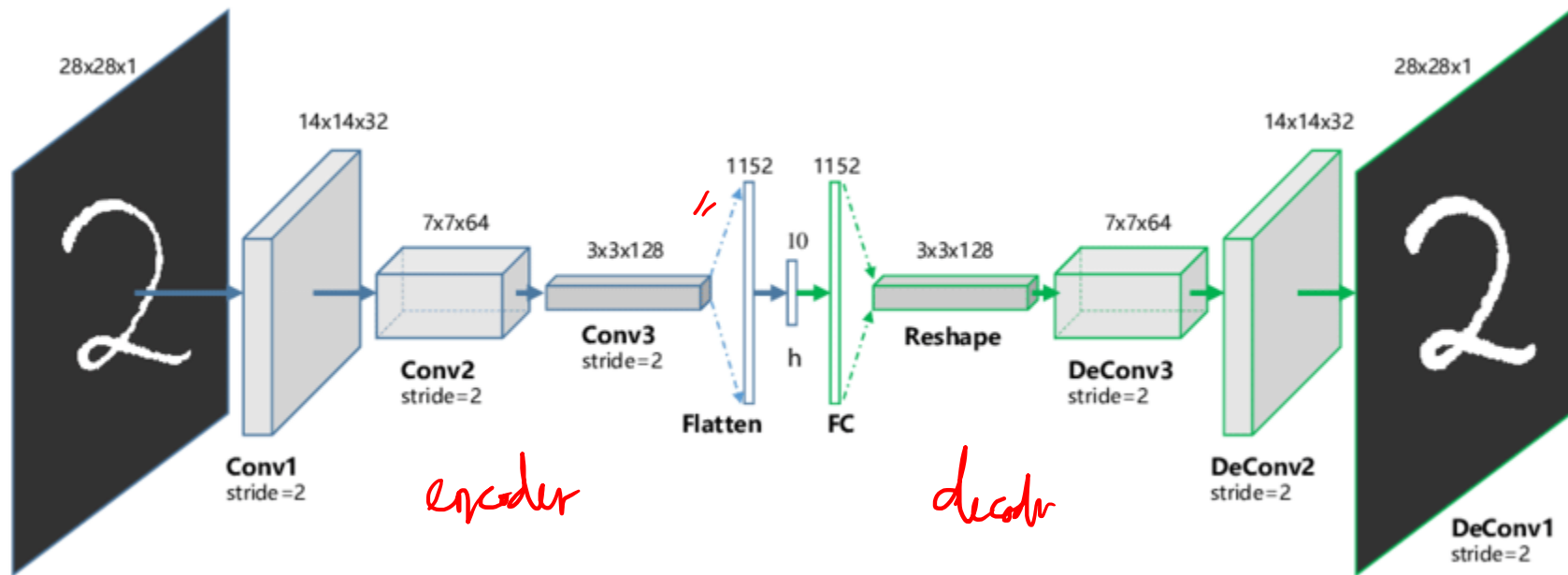


Output

Convolutional AE



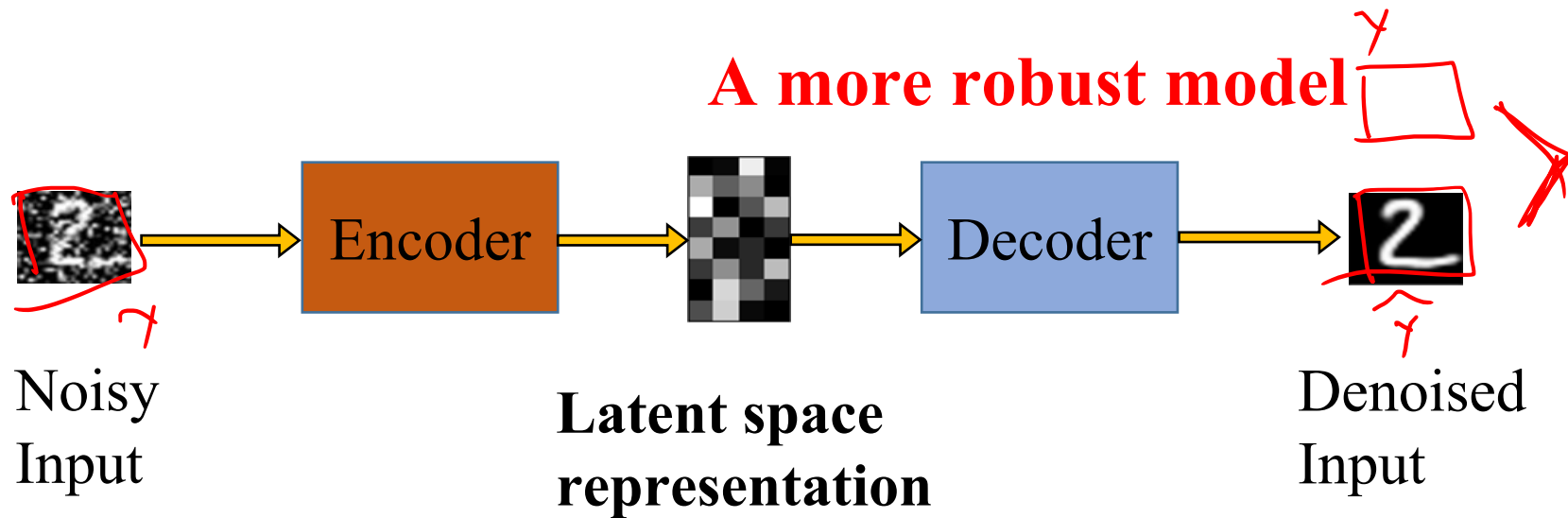
Convolutional AE



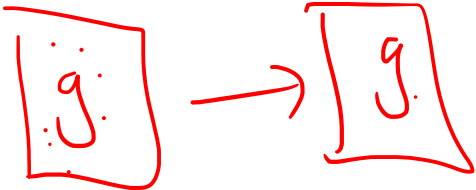
Denoising AE

Intuition:

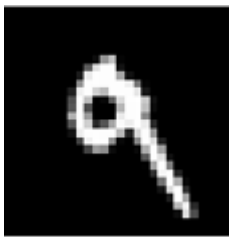
- We still aim to encode the input and to NOT mimic the identity function.
- We try to undo the effect of *corruption* process stochastically applied to the input.



Process

denoise:  supervised.

Taken some input x



x

Apply Noise



\tilde{x}



\tilde{x}

Q&A

