



# **BIG DATA and AI for business**

**Auto-encoder**

**Decisions, Operations & Information Technologies  
Robert H. Smith School of Business  
Fall, 2020**



# Unsupervised Learning

- “We expect unsupervised learning to become far more important in the longer term. Human and animal learning is largely unsupervised: we discover the structure of the world by observing it, not by being told the name of every object.”  
– LeCun, Bengio, Hinton, Nature 2015

- Yann LeCun, March 14, 2016

- “Pure” Reinforcement Learning (cherry)

- ▶ The machine predicts a scalar reward given once in a while.
    - ▶ **A few bits for some samples**

- Supervised Learning (icing)

- ▶ The machine predicts a category or a few numbers for each input
    - ▶ Predicting human-supplied data
    - ▶ **10→10,000 bits per sample**

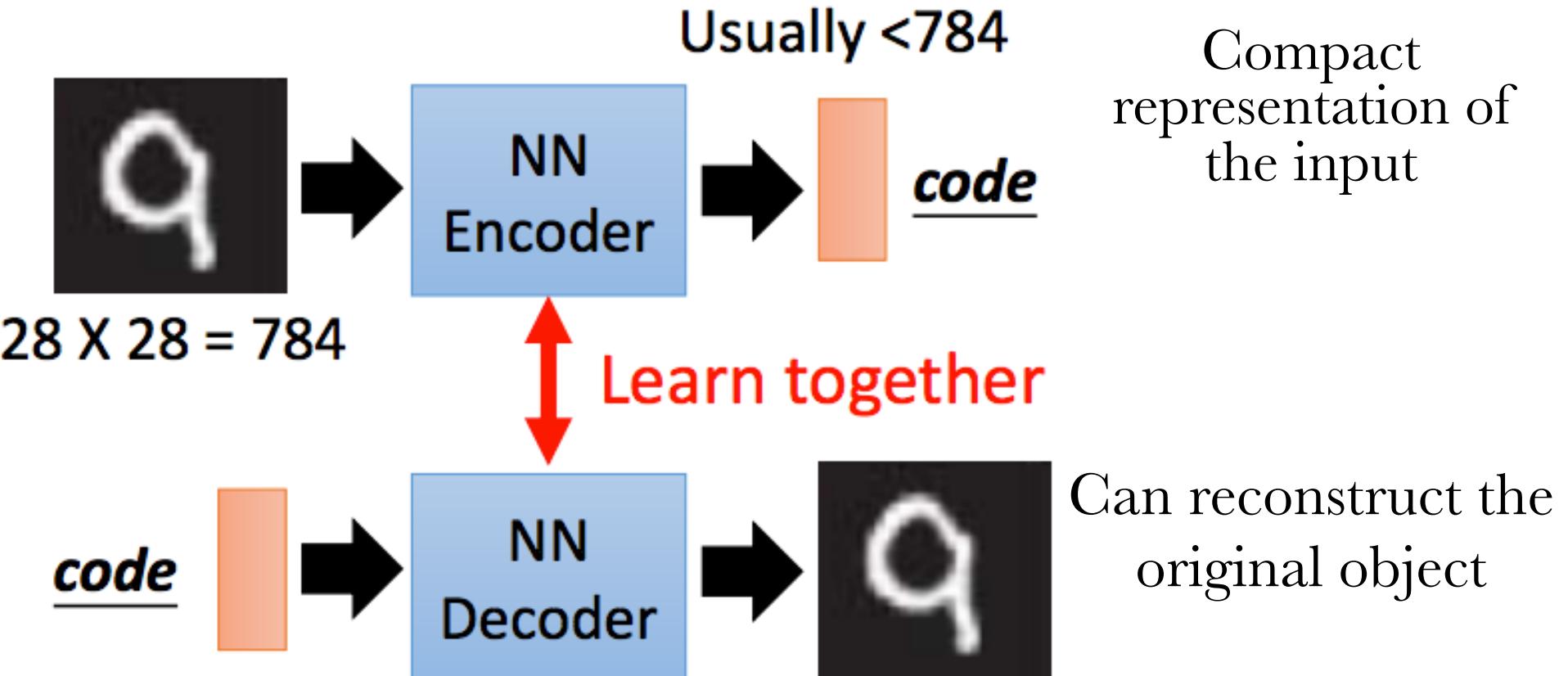
- Unsupervised/Predictive Learning (cake)

- ▶ The machine predicts any part of its input for any observed part.
    - ▶ Predicts future frames in videos
    - ▶ **Millions of bits per sample**

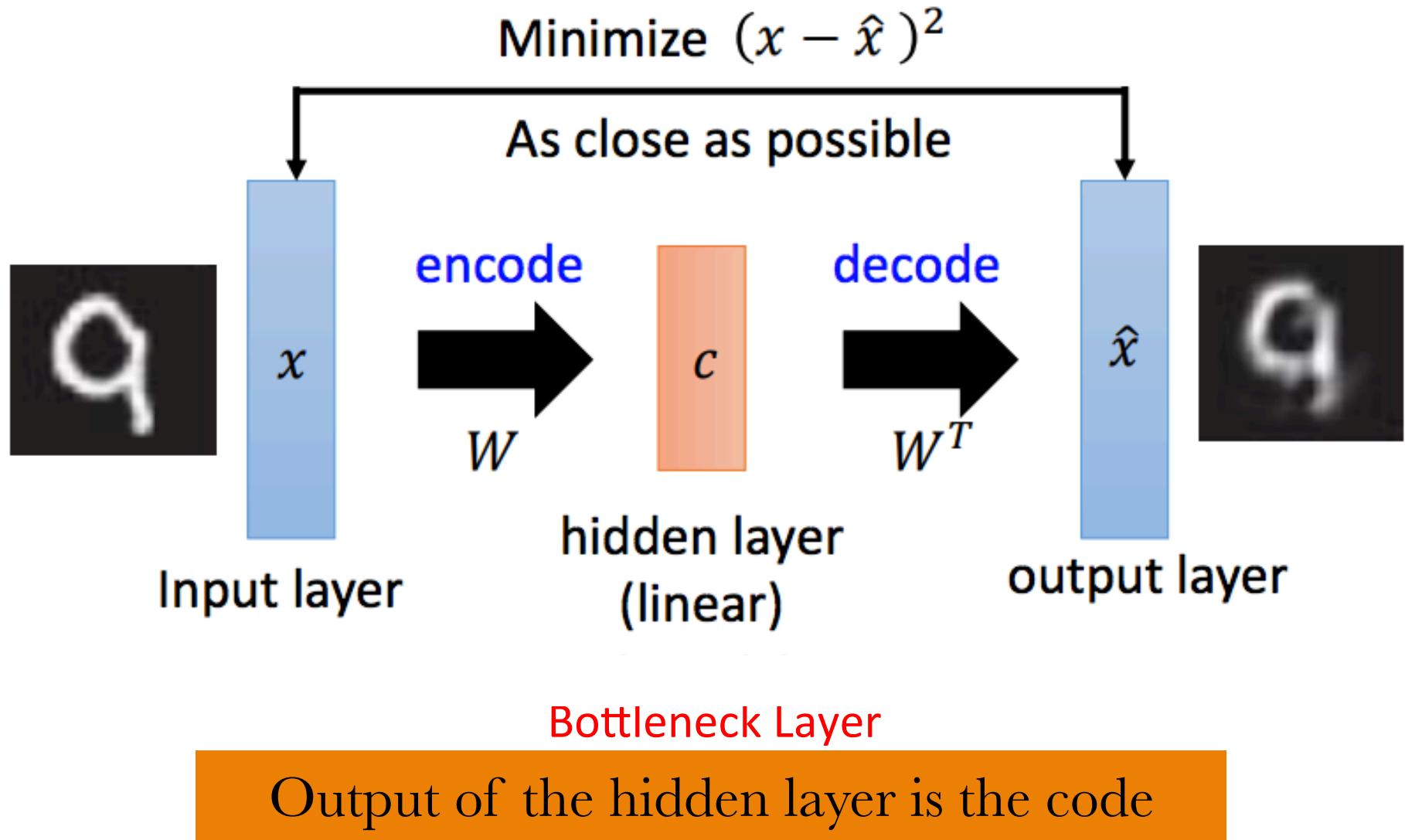
- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)



# Auto-encoder



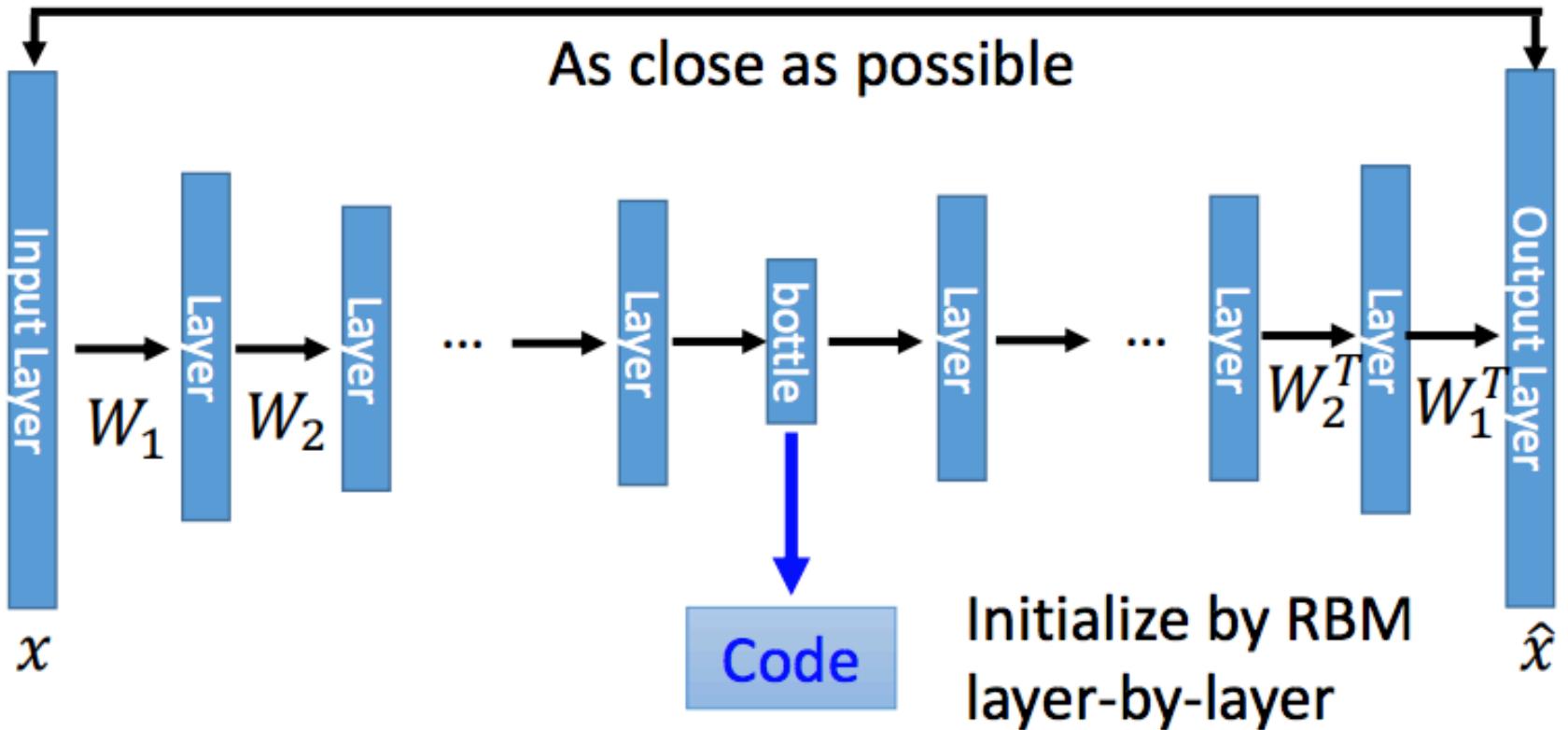
# Recap: PCA



# Deep Auto-encoder

Symmetry is not necessary

- Of course, the auto-encoder can be deep



Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." Science 313.5786 (2006): 504-507

# Deep Auto-encoder

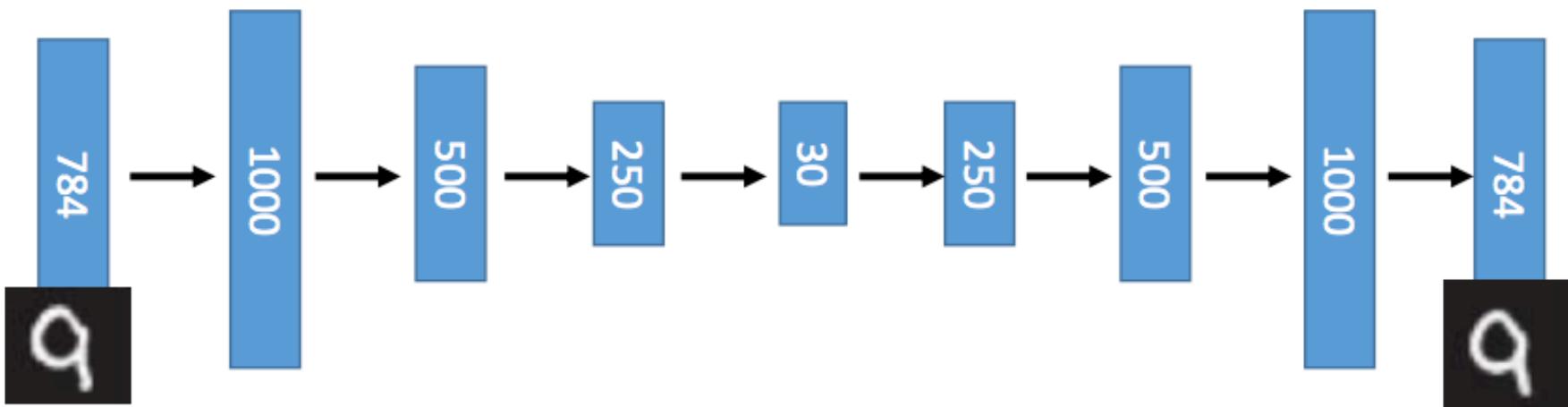
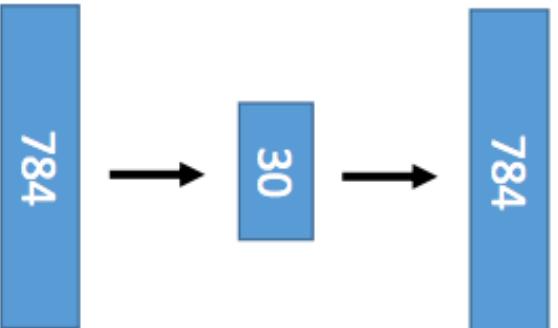
Original  
Image

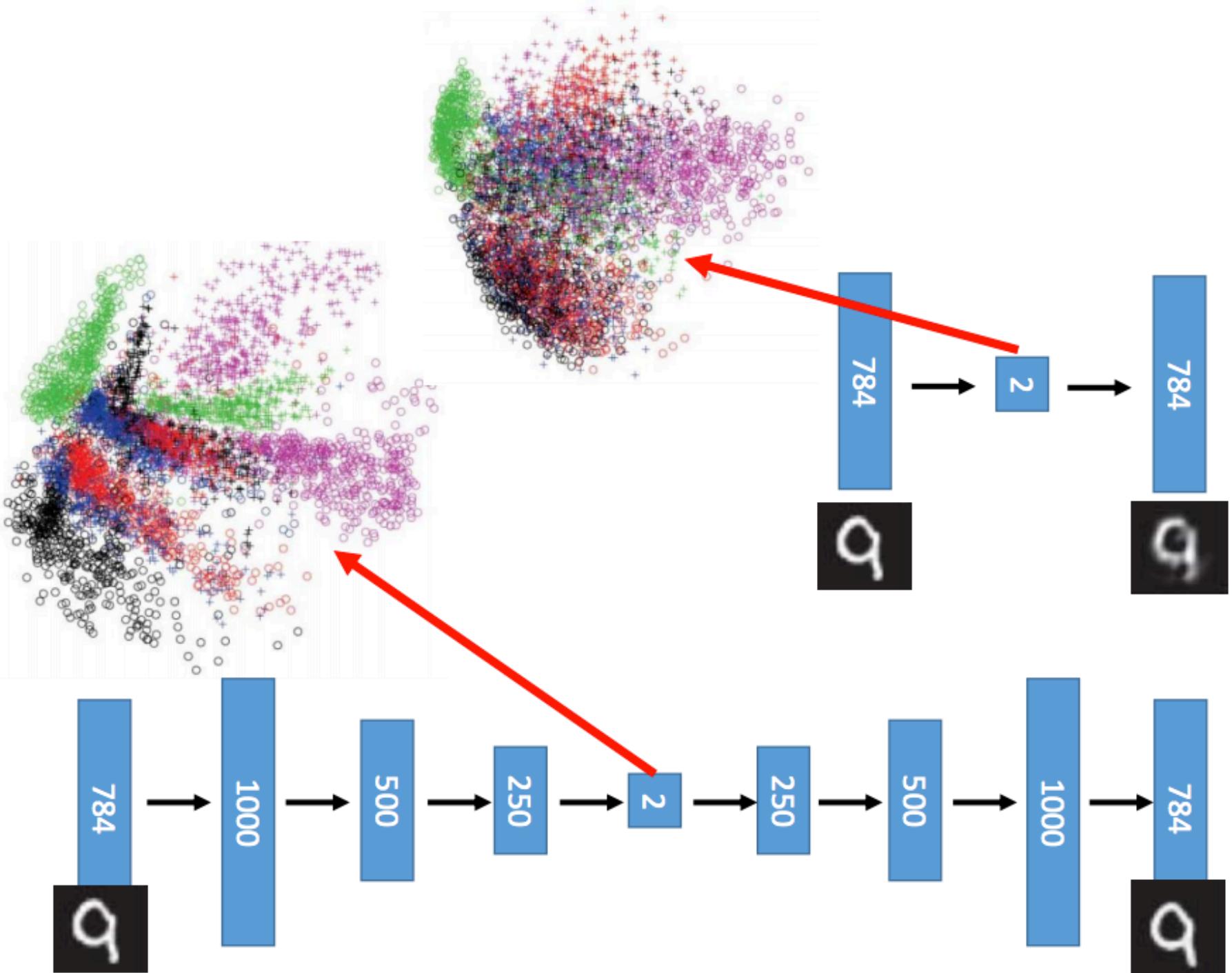


PCA



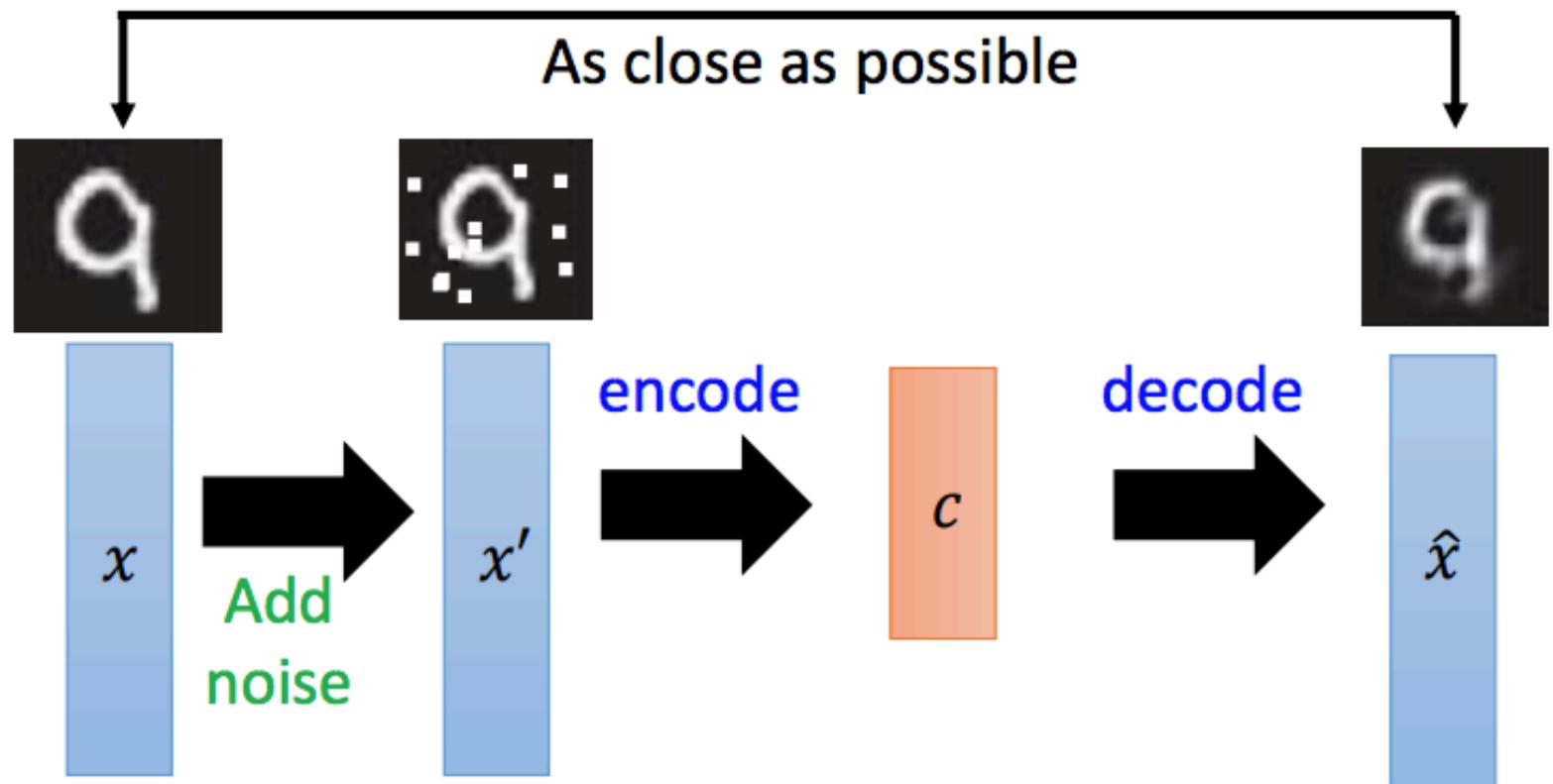
Deep  
Auto-encoder





# Deep Auto-encoder

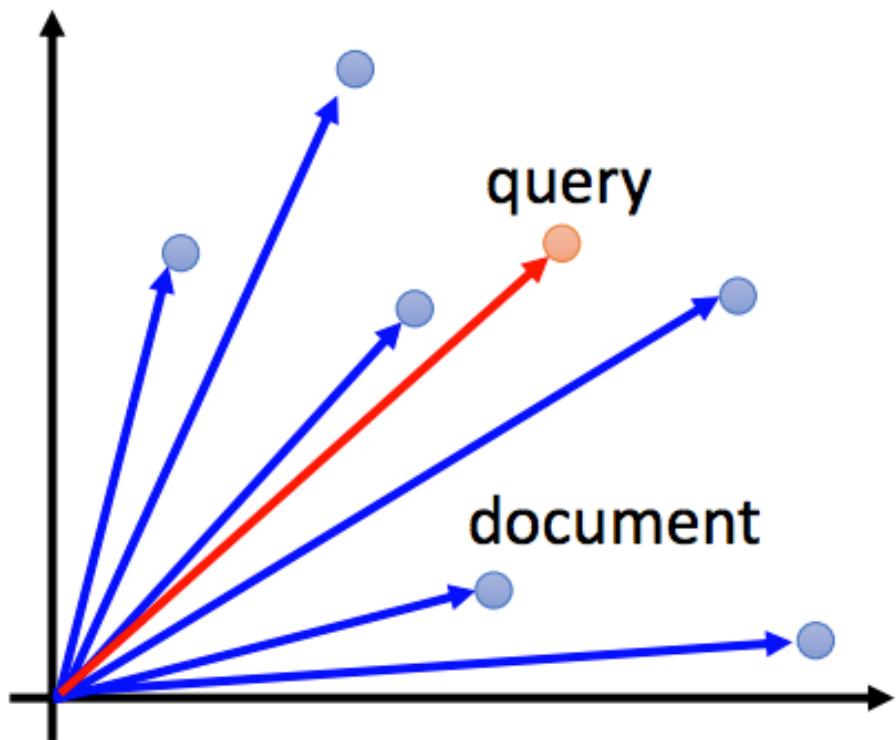
- De-noising auto-encoder



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

# Auto-encoder - Text Retrieval

## Vector Space Model



## Bag-of-word

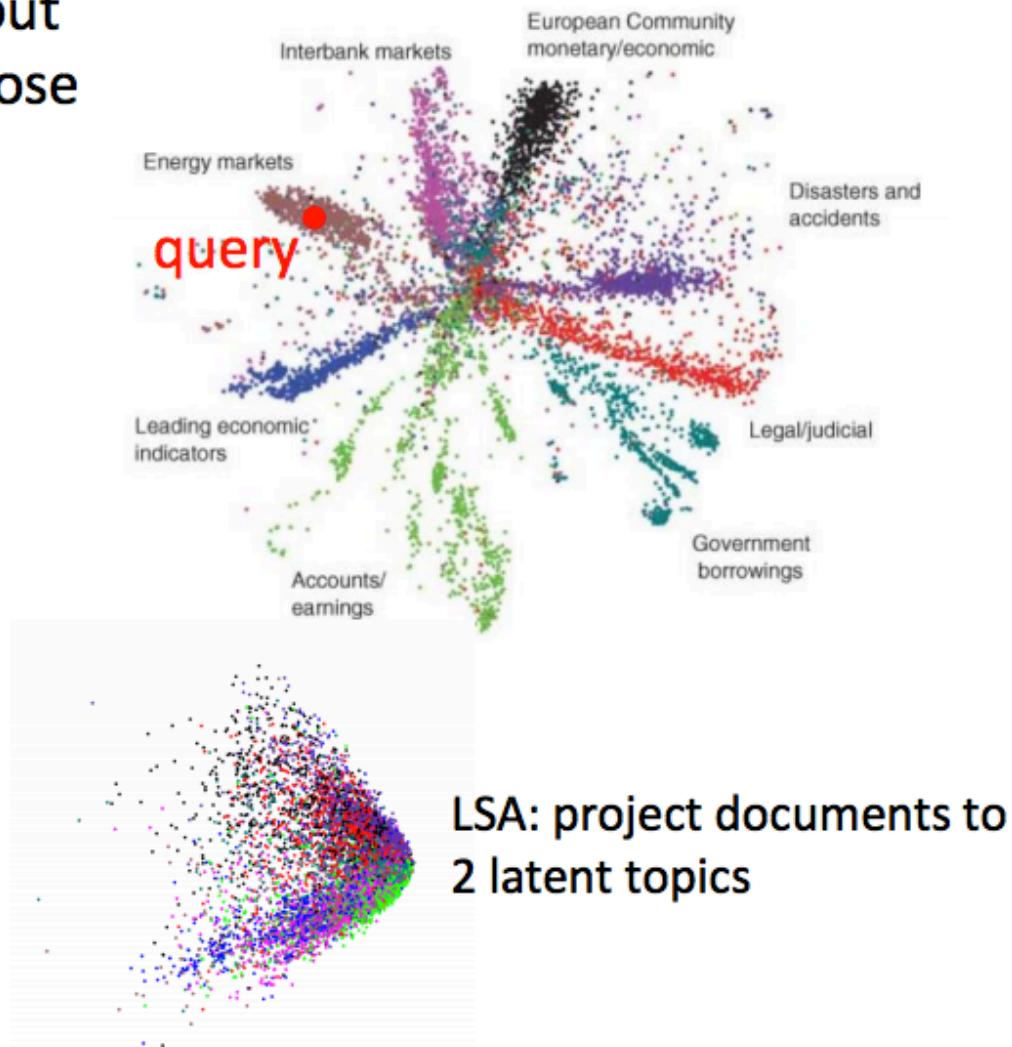
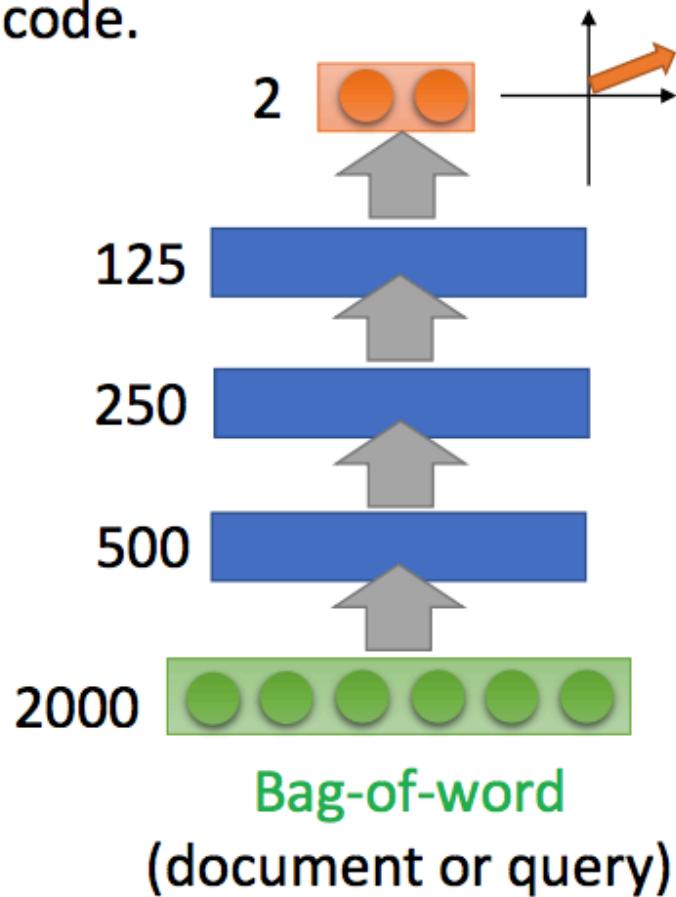
word string:  
“This is an apple”

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

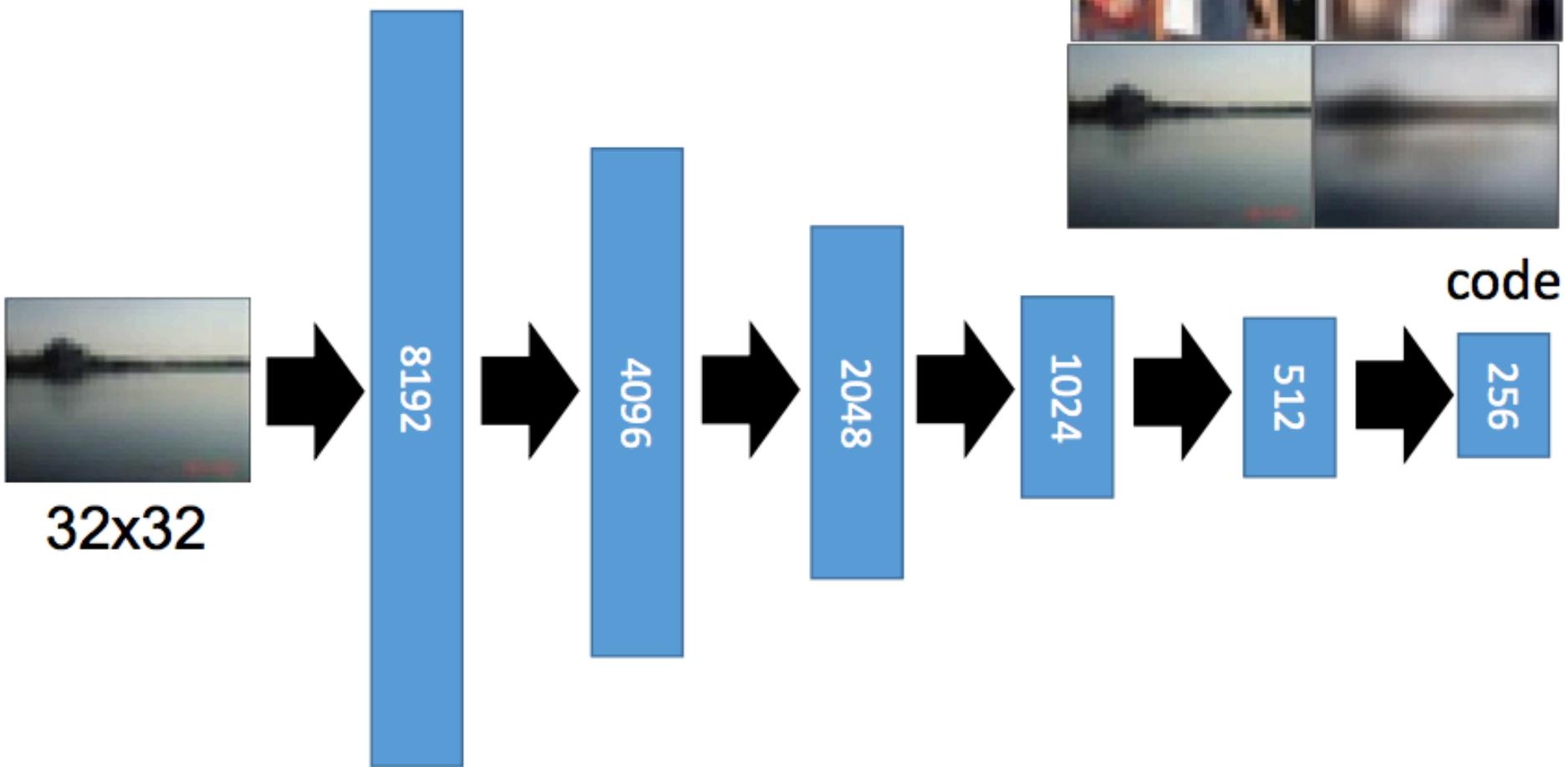
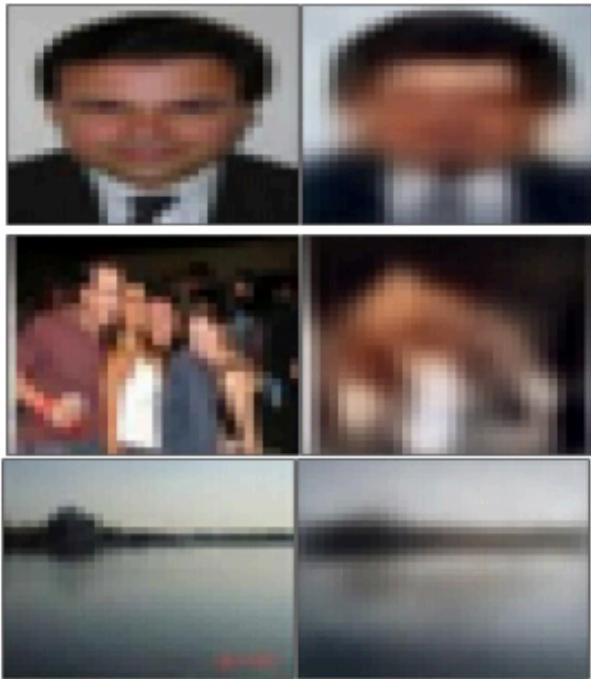
Semantics are not considered.

# Auto-encoder - Text Retrieval

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



# Auto-encoder – Similar Image Search



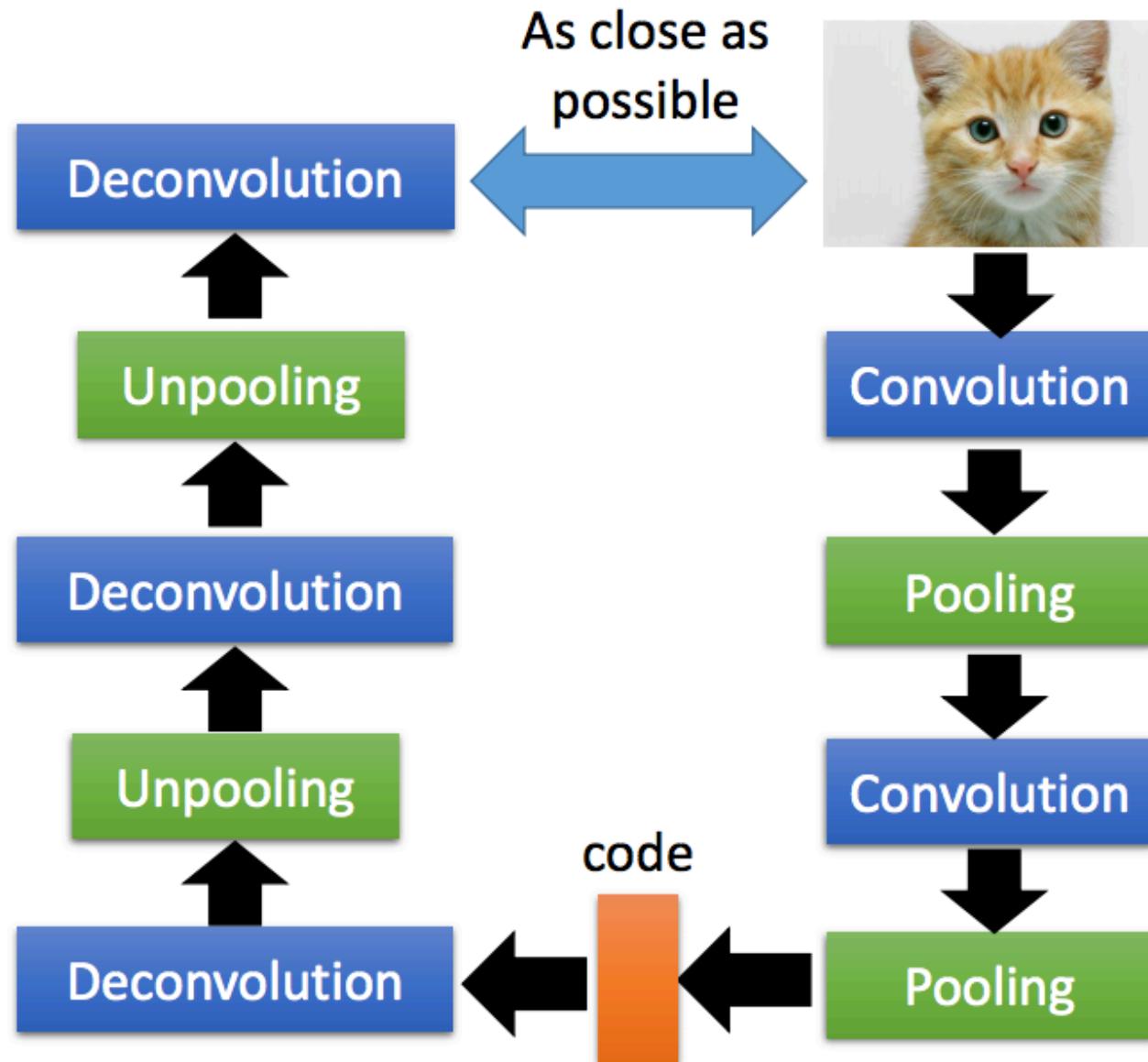
## Retrieved using Euclidean distance in pixel intensity space



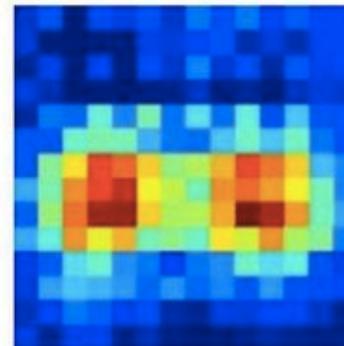
retrieved using 256 codes



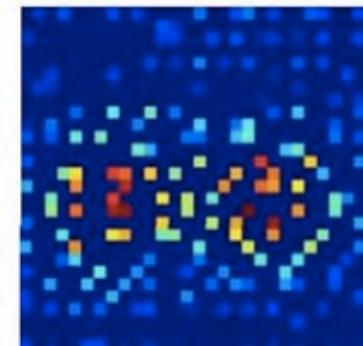
# Auto-encoder - CNN



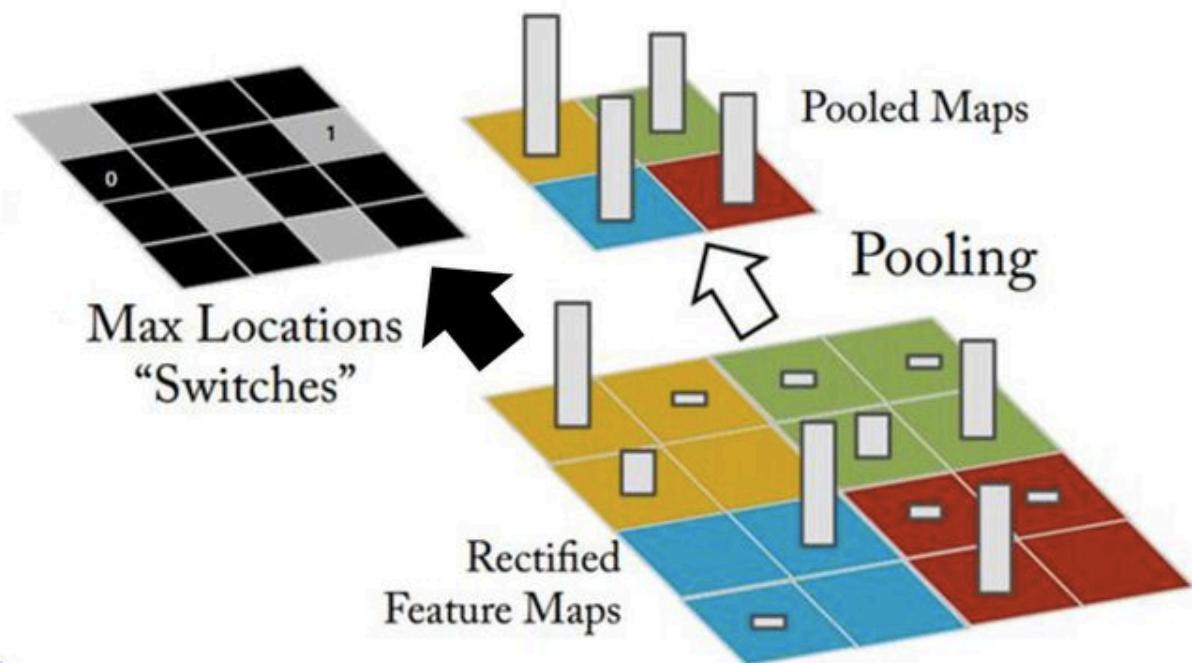
# CNN -Unpooling



14 x 14



28 x 28



Alternative: simply repeat the values

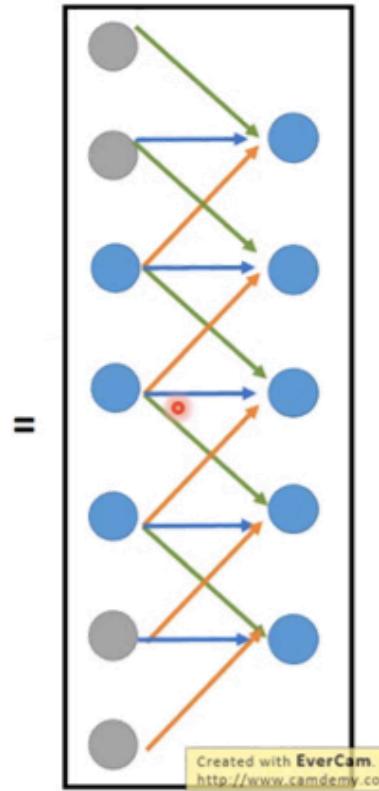
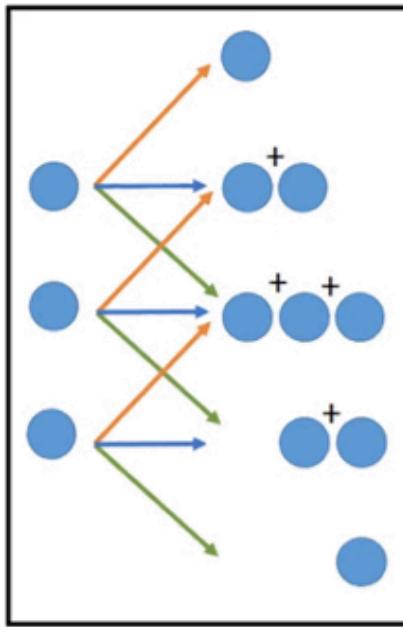
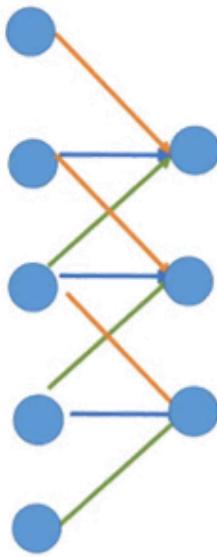
Source of image :

[https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/image\\_segmentation.html](https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/image_segmentation.html)

# CNN

## - Deconvolution

Actually, deconvolution is convolution.



$W^T$

Created with EverCam.  
<http://www.camdemyc.com>

$W$   
 $conv(W)$

$deconv(W)$

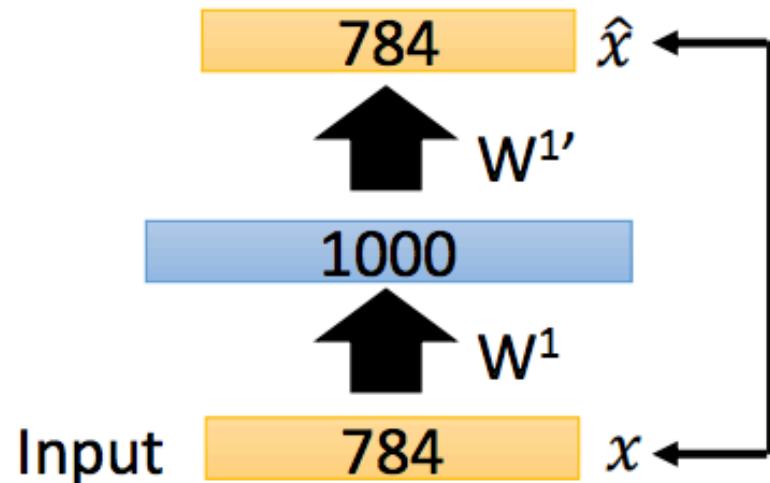
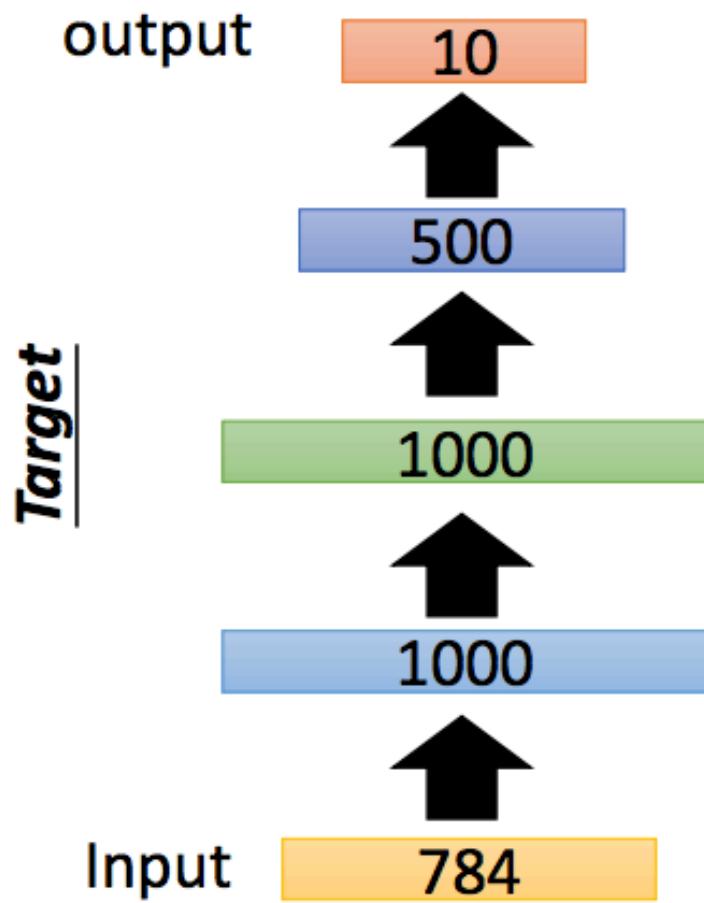
$conv(W^T)$

In Tensorflow

$= conv\_transpose(W)$

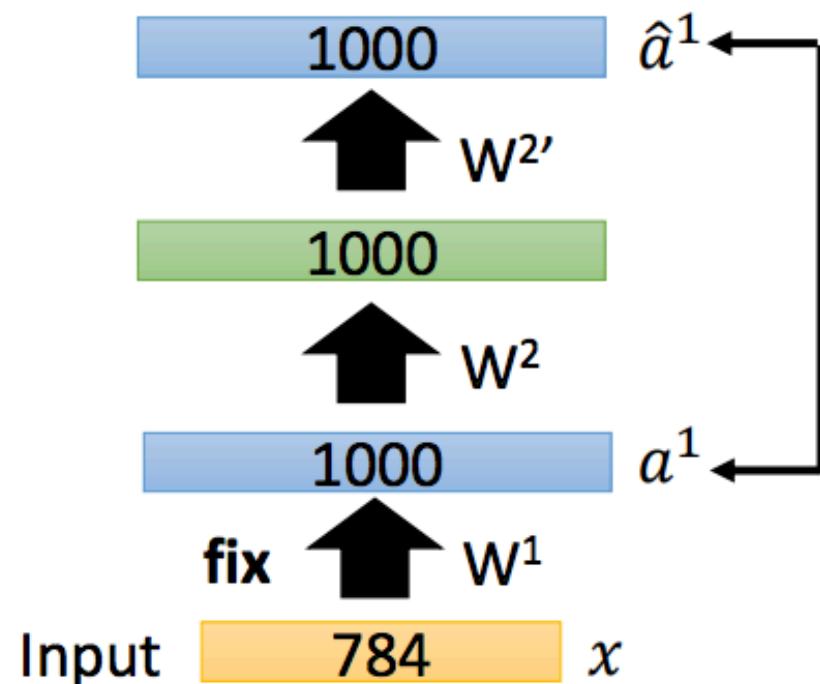
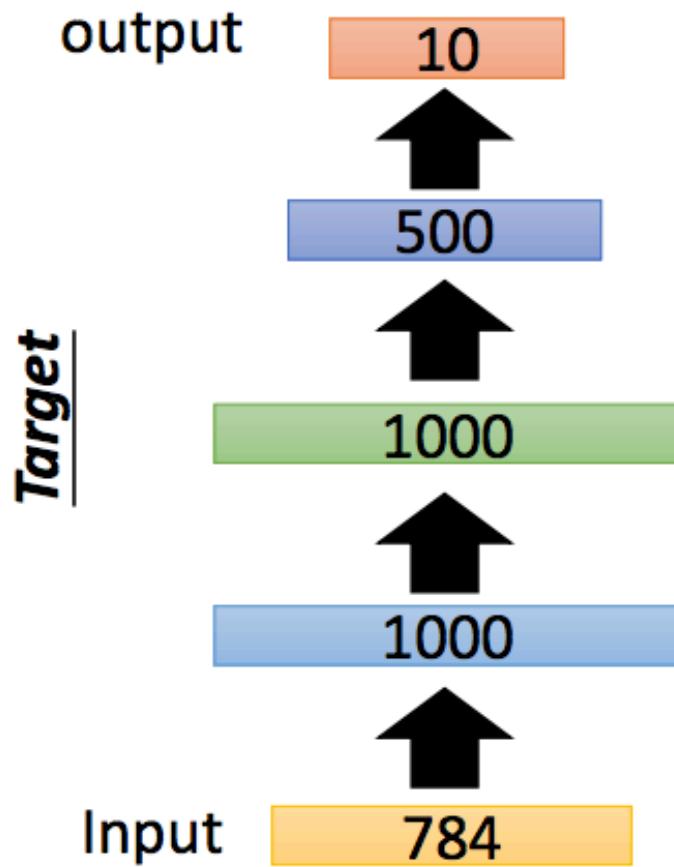
# Auto-encoder – Pre-training

- Greedy layer-wise pre-training



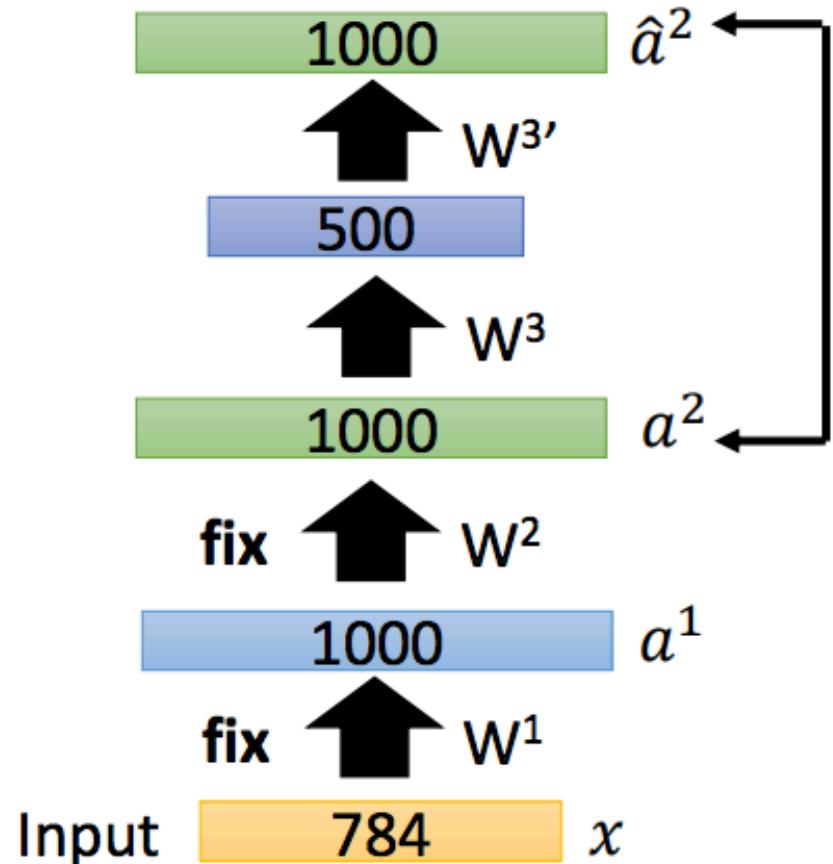
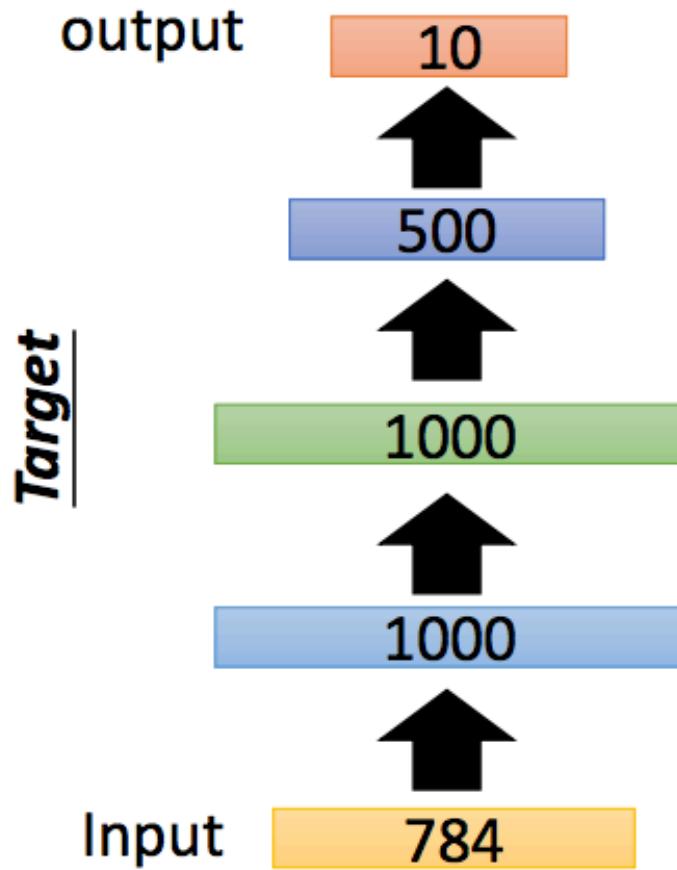
# Auto-encoder – Pre-training

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# Auto-encoder – Pre-training

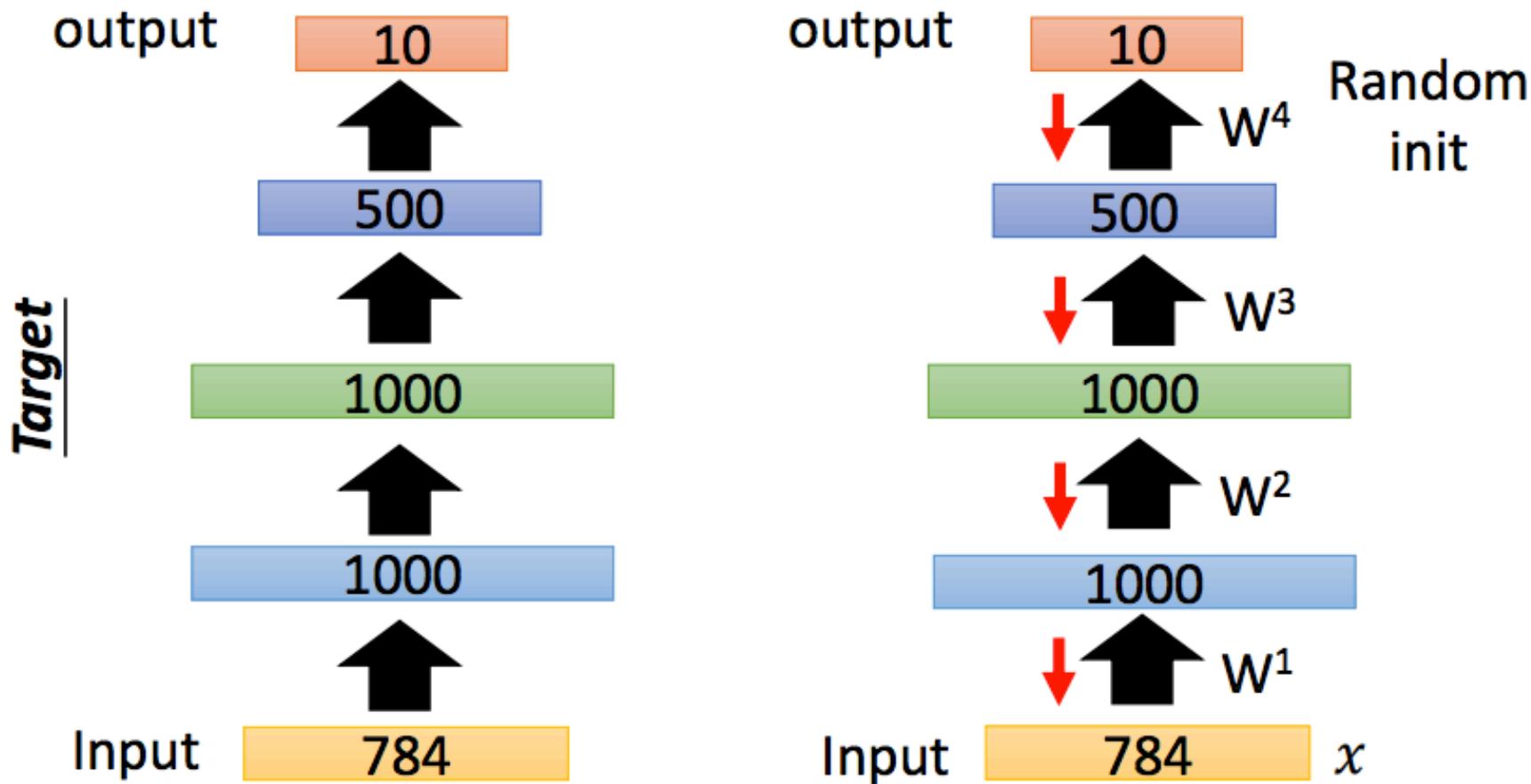
- Greedy layer-wise pre-training



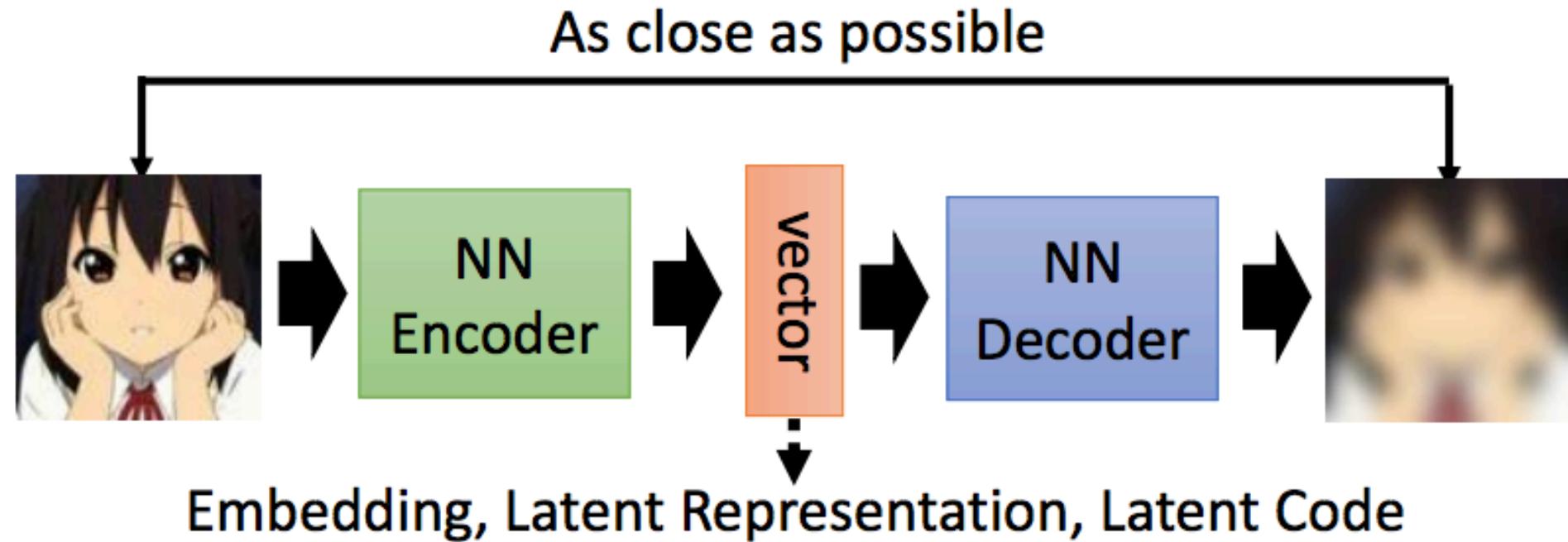
# Auto-encoder – Pre-training

- Greedy layer-wise pre-training

Find-tune by  
backpropagation



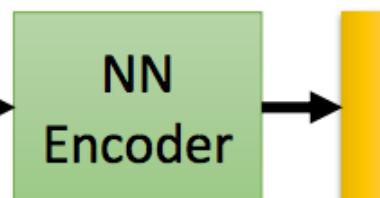
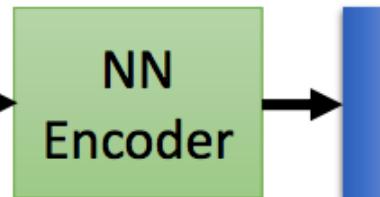
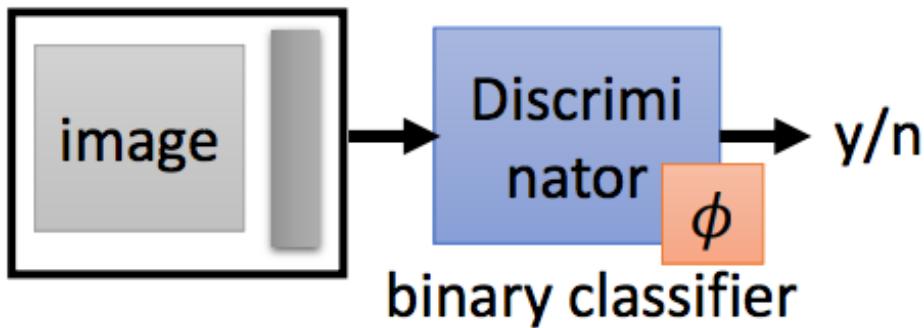
# More about Auto-encoder



- More than minimizing reconstruction error
- More interpretable embedding

# 1. Beyond Reconstruction

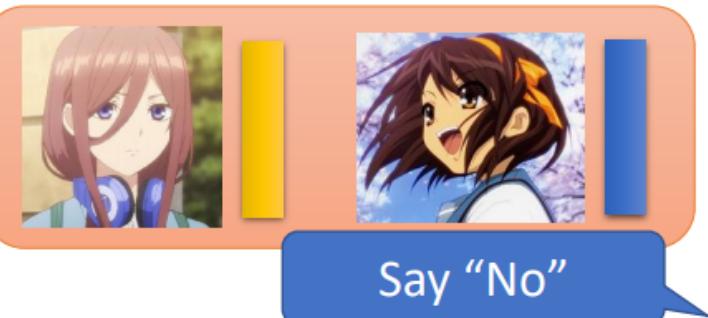
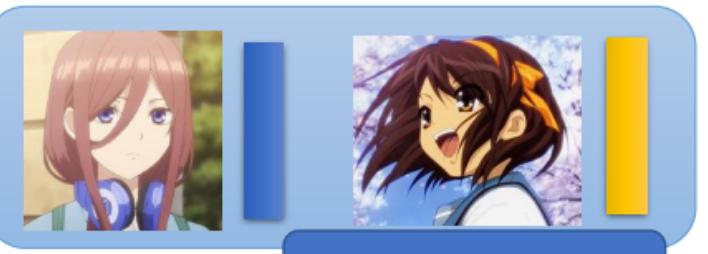
- How to evaluate an encoder?
  - Loss of the classification task is  $L_D$



Train  $\phi$  to minimize  $L_D$   
$$L_D^* = \min_{\phi} L_D$$

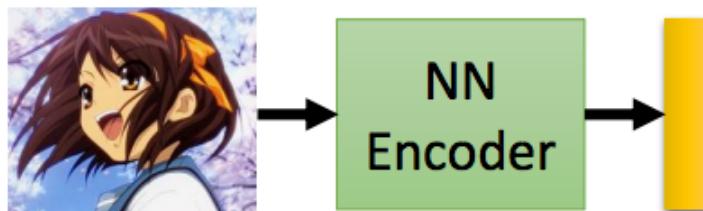
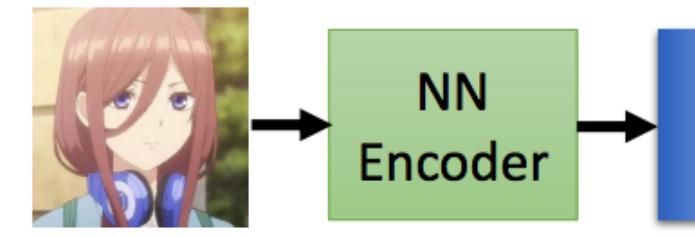
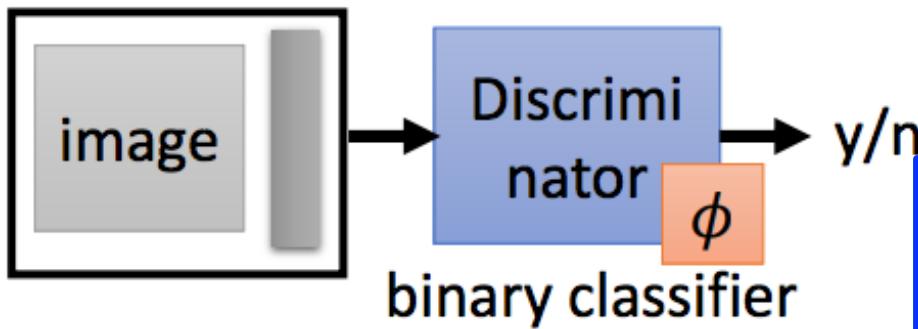
Small  $L_D^*$  → The embeddings are representative.

Large  $L_D^*$  → Not representative



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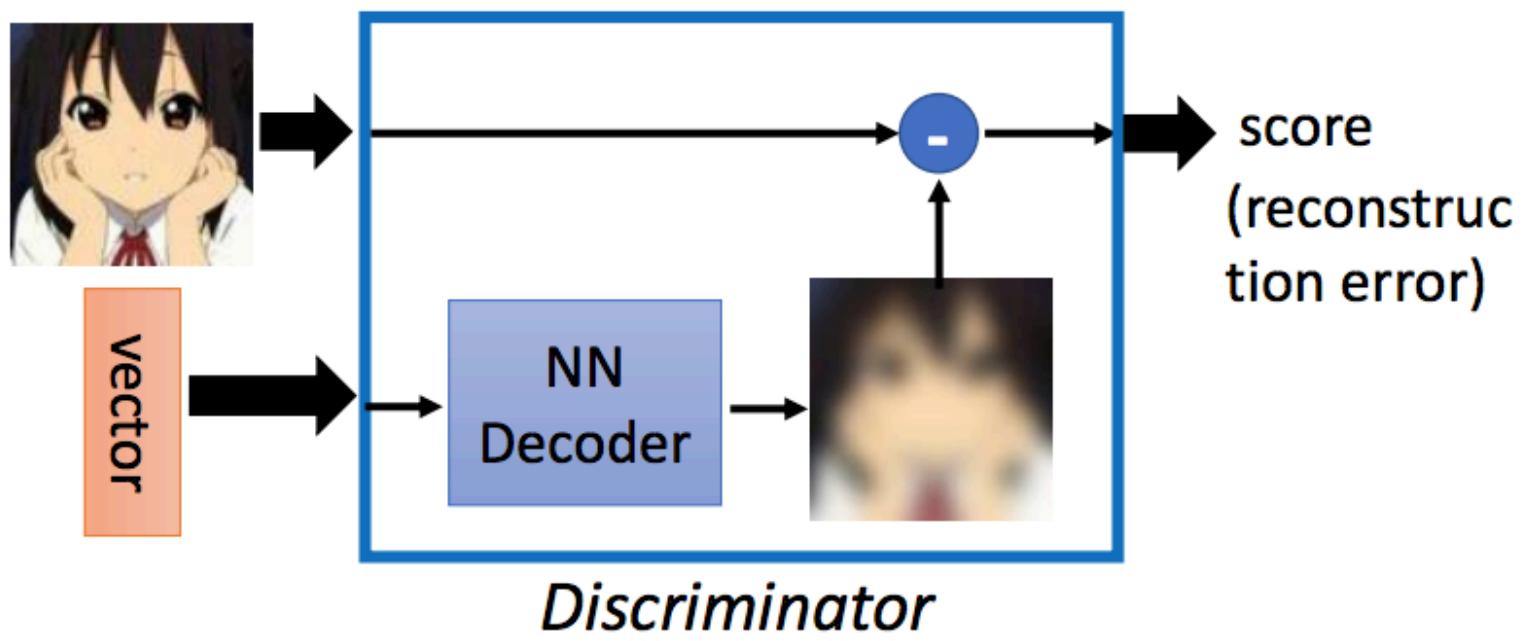
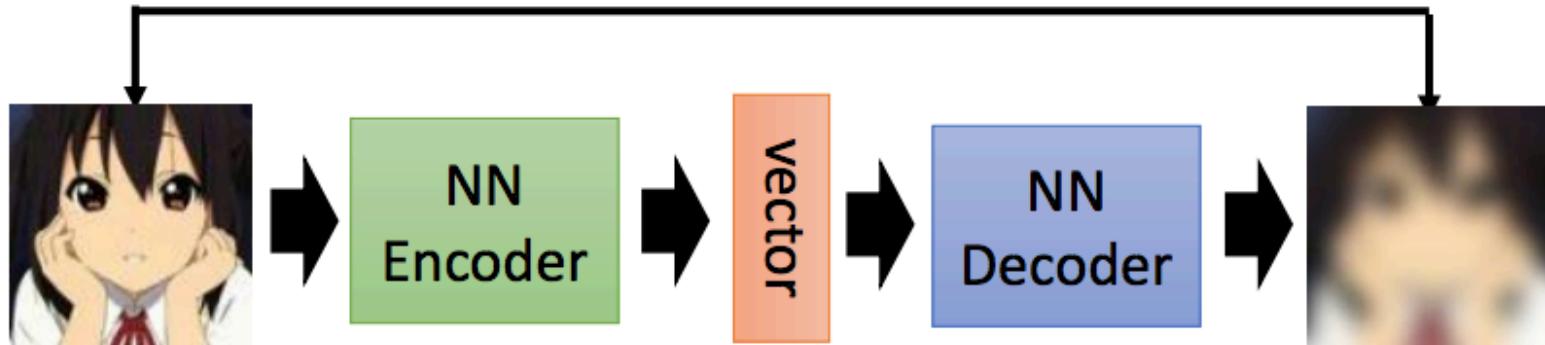
Train  $\theta$  to minimize  $L_D^*$   
 $\theta^* = \arg \min_{\theta} L_D^*$   
 $= \arg \min_{\theta} \min_{\phi} L_D$

Train the encoder  $\theta$  and discriminator  $\phi$  to minimize  $L_D$

Deep InfoMax (DIM)  
(c.f. training encoder and decoder to minimize reconstruction error)

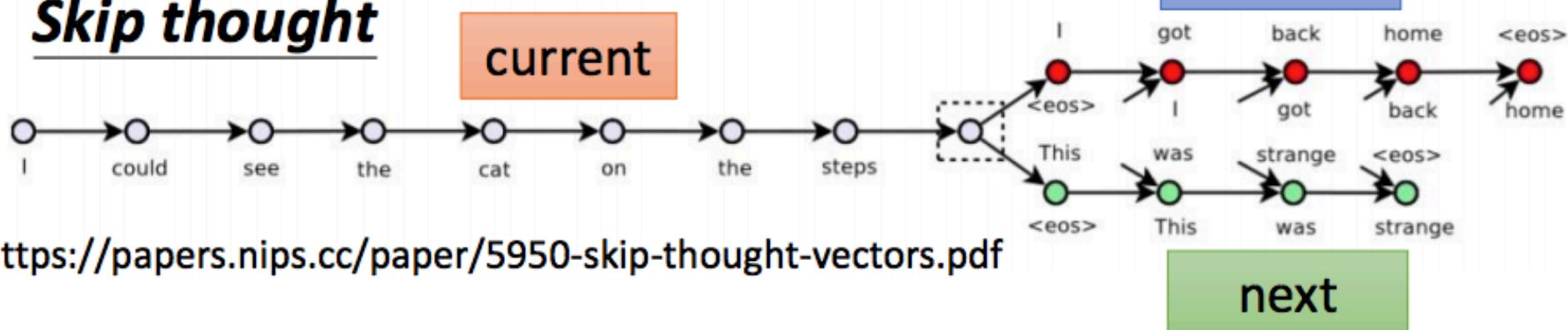
# 1. Beyond Reconstruction

As close as possible



# 2. Sequential Data

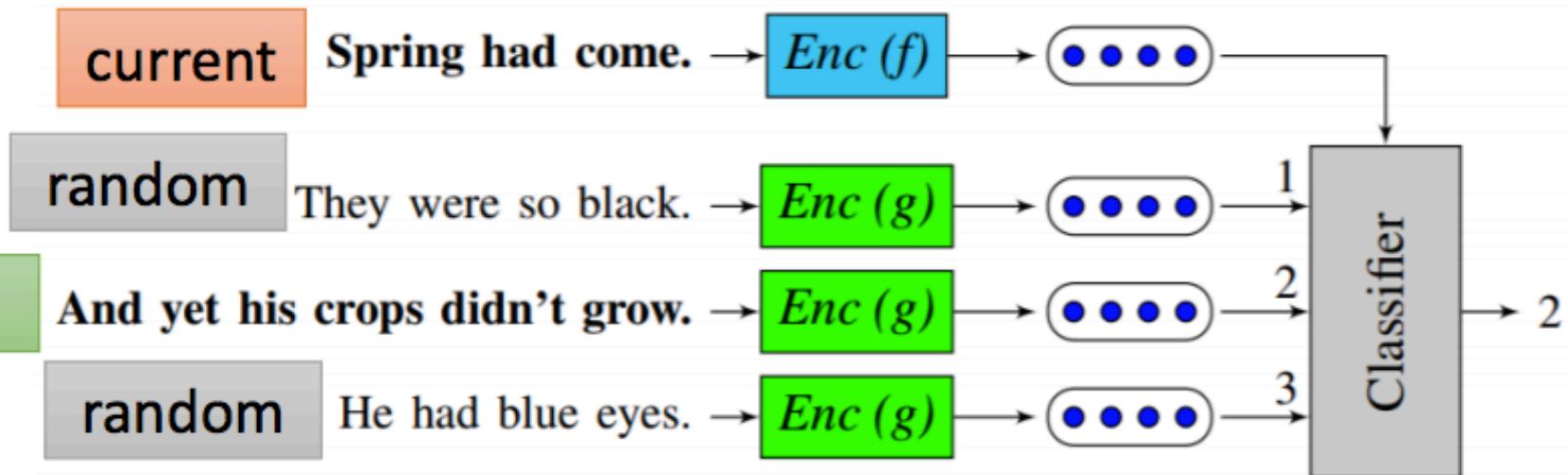
## Skip thought



<https://papers.nips.cc/paper/5950-skip-thought-vectors.pdf>

# 2. Sequential Data

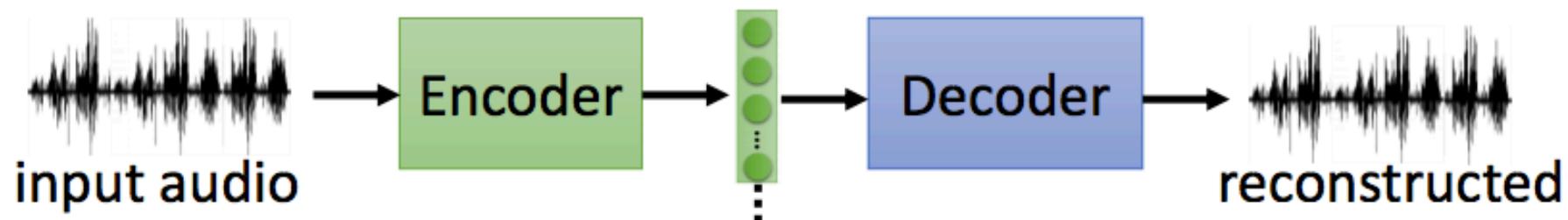
## Quick thought



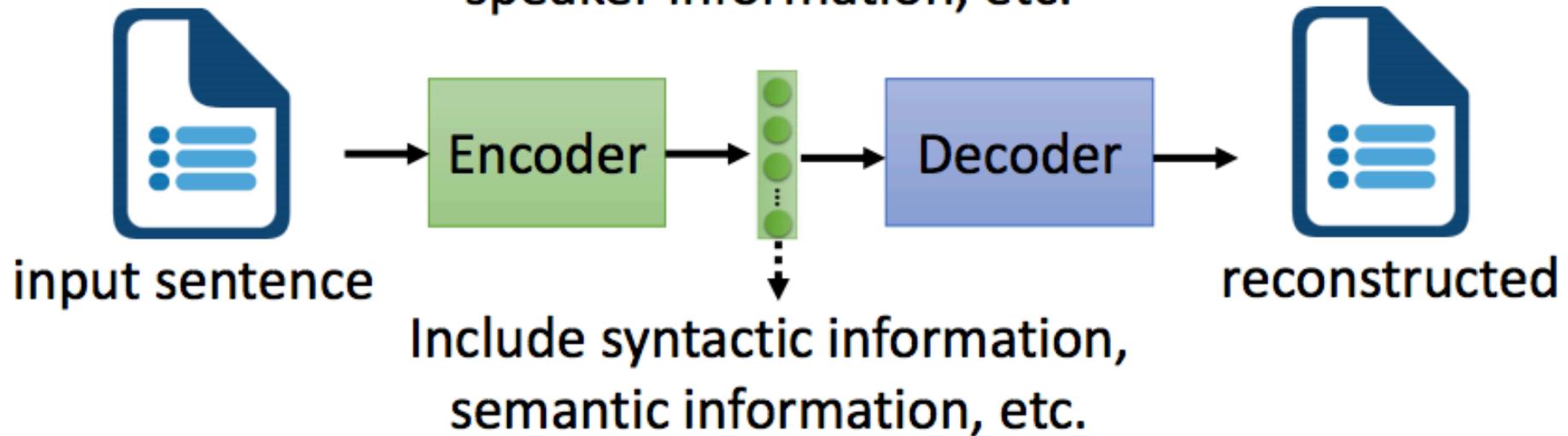
<https://arxiv.org/pdf/1803.02893.pdf>

### 3. Feature Disentangle

- An object contains multiple aspect information

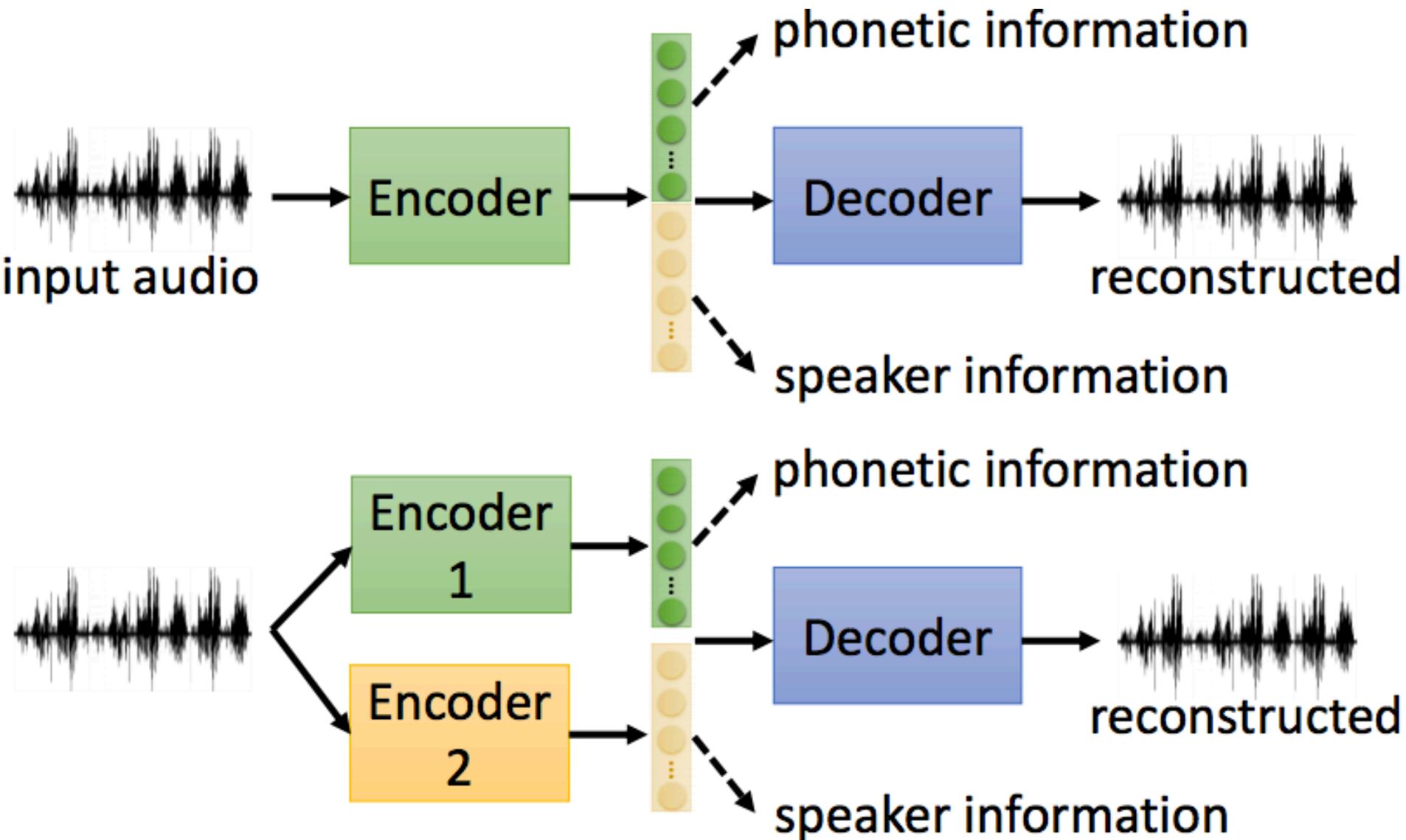


Include phonetic information,  
speaker information, etc.



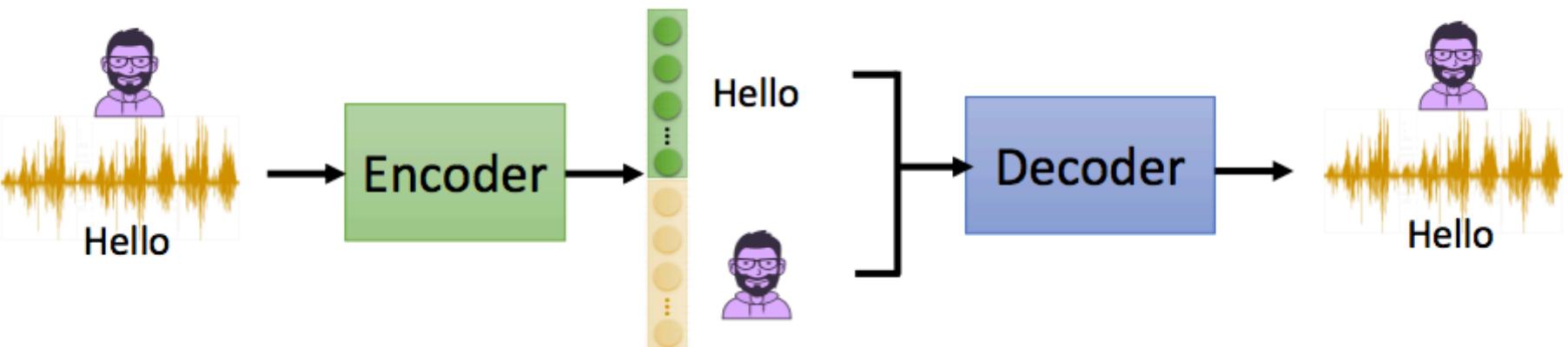
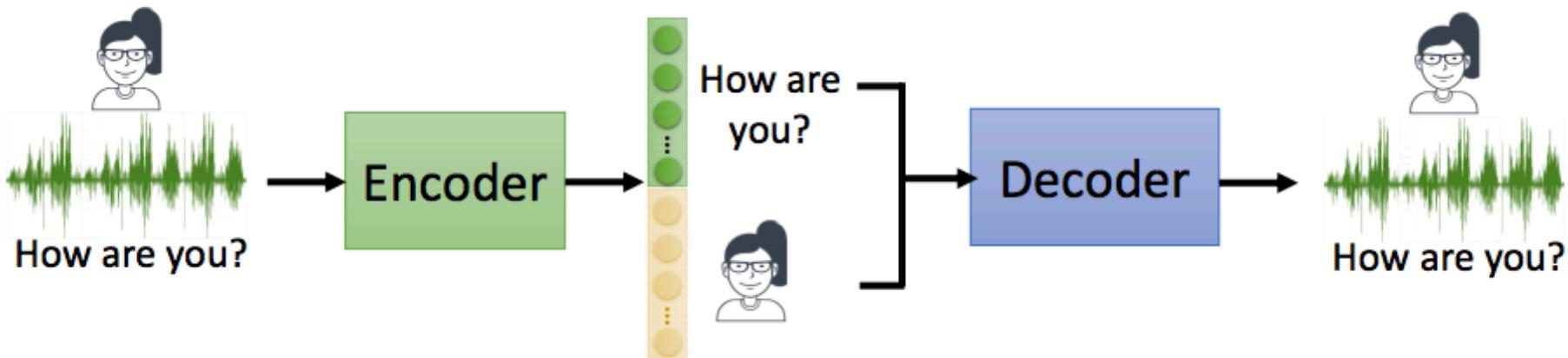
Include syntactic information,  
semantic information, etc.

### 3. Feature Disentangle



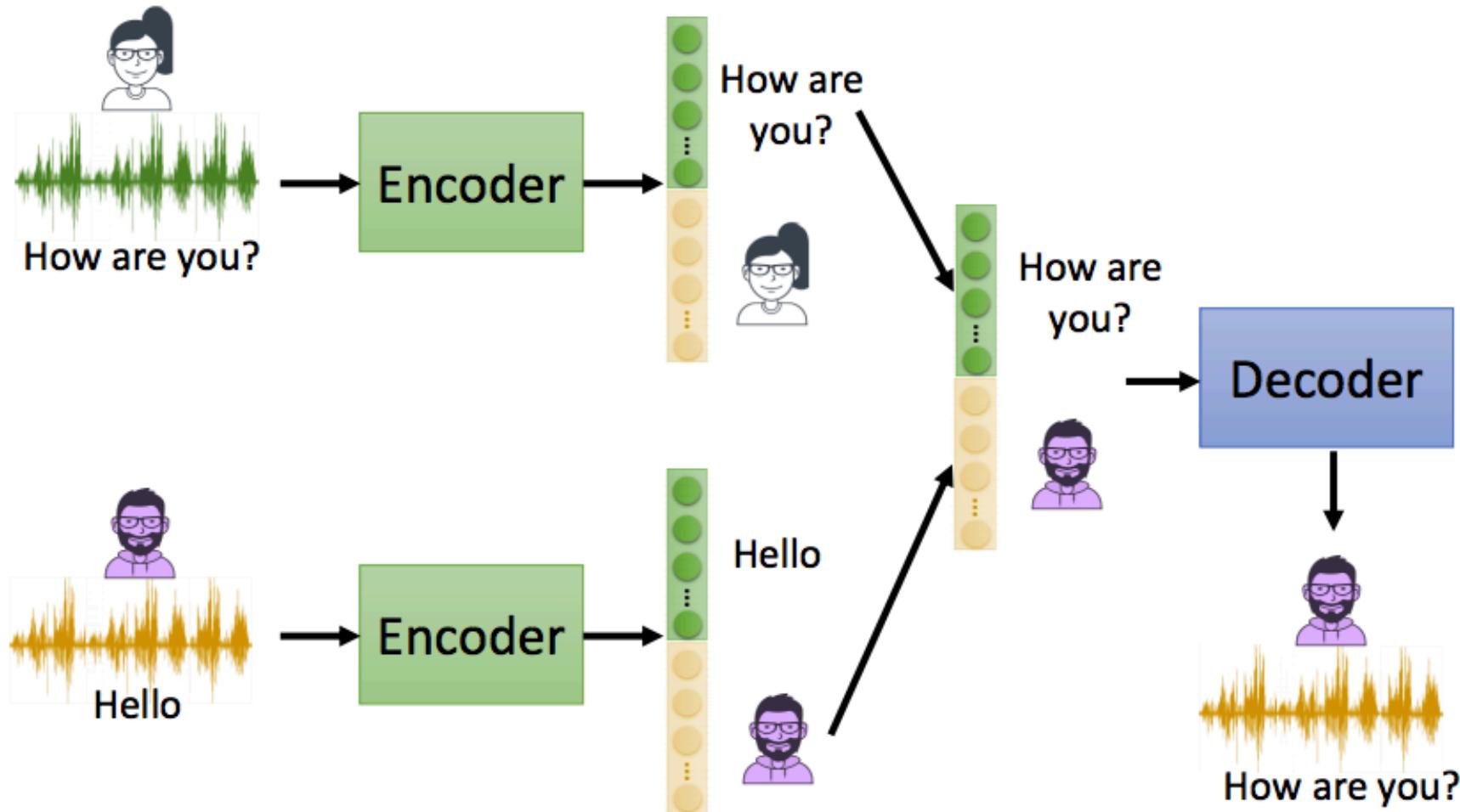
# 3. Feature Disentangle

- Voice conversion



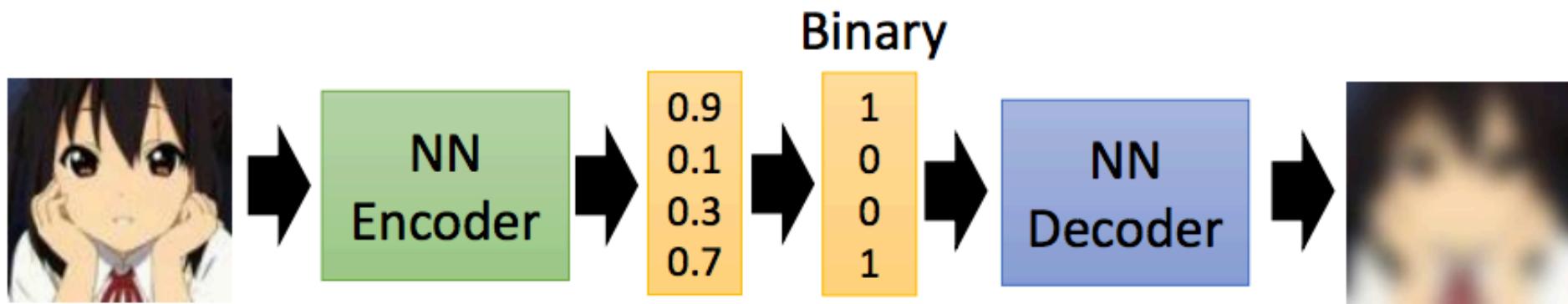
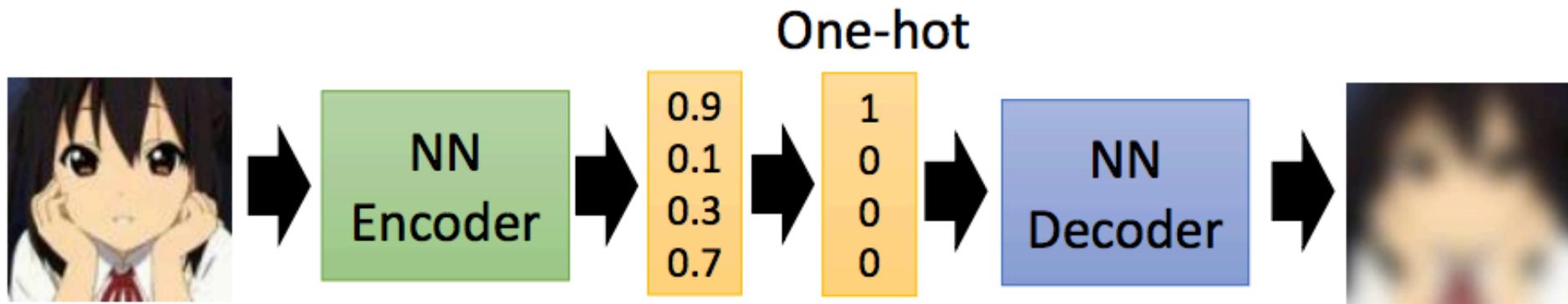
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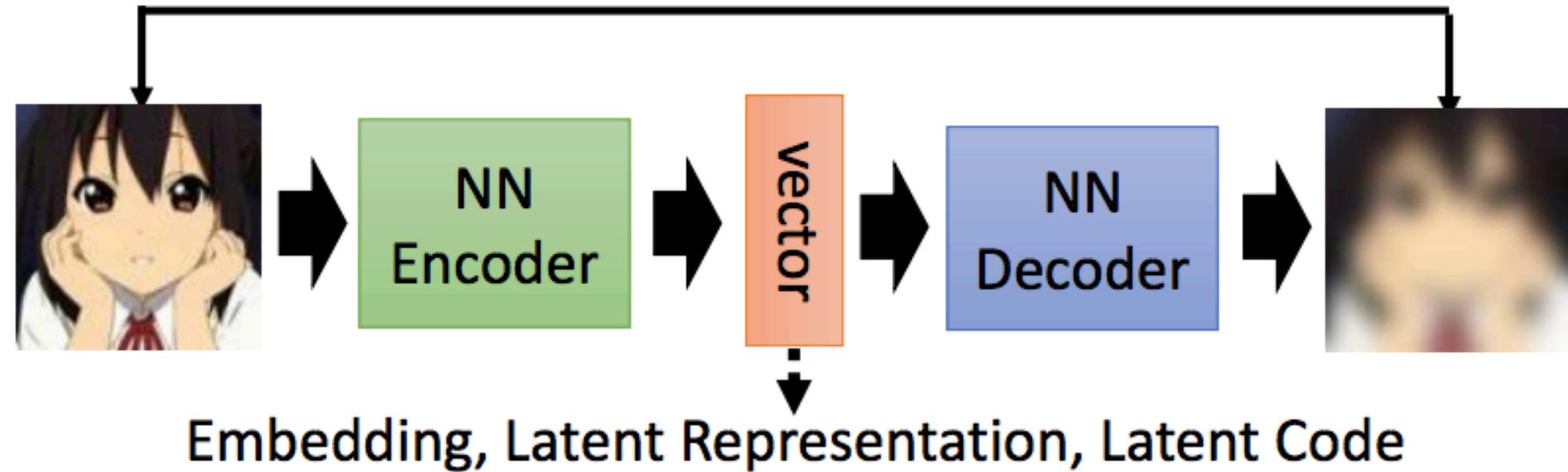
# 4. Discrete Representation

- Easier to interpret or clustering



# Concluding Remarks

As close as possible



- More than minimizing reconstruction error
  - Using discriminator
  - Sequential data
- More interpretable embedding
  - Feature disentangle
  - Discrete representation