

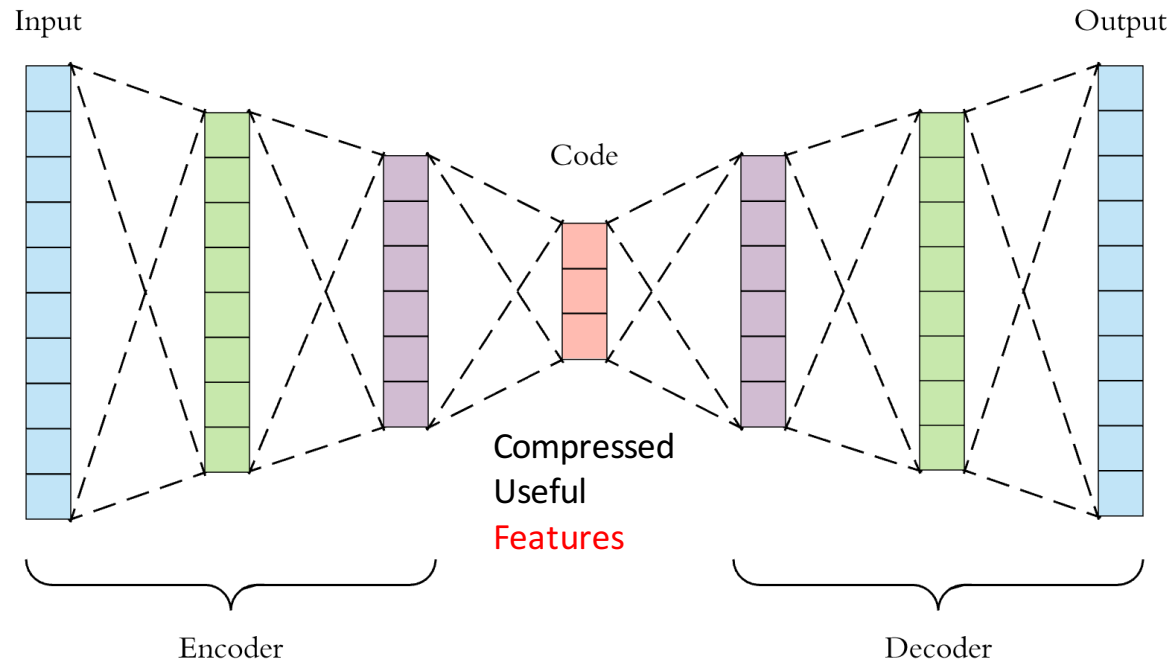
CSCSE 636 Neural Networks (Deep Learning)

Lecture 16: Auto-Encoder

Anxiao (Andrew) Jiang

Based on the interesting lecture of Prof. Hung-yi Lee “Unsupervised Learning: Deep Auto-Encoder”
https://www.youtube.com/watch?v=Tk5B4seA-AU&list=PLJV_el3uVTsPy9oCRY30oBPNLCo89yu49&index=25

Auto-Encoder



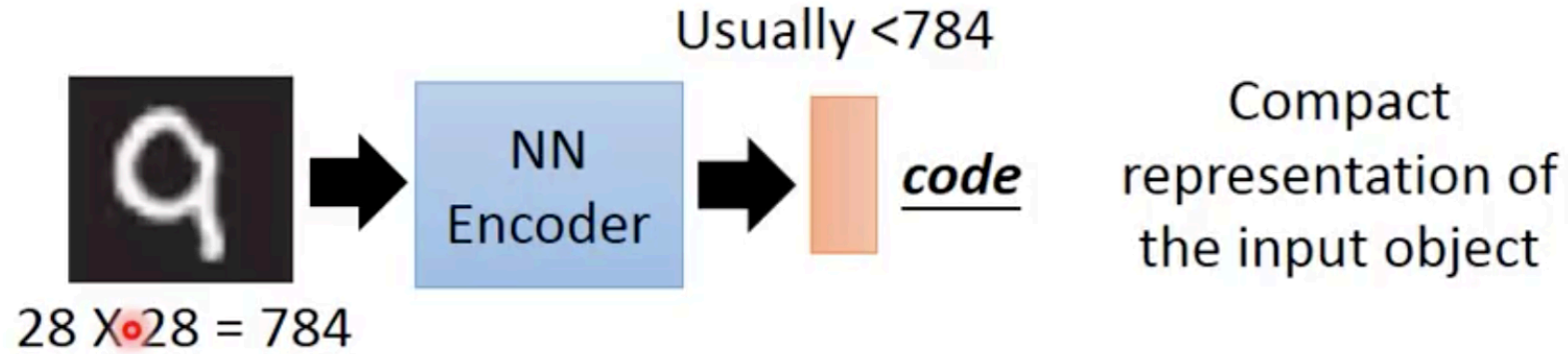
- Methods: (1) Make output data be as close to input data as possible
(2) Limit the size of the encoder's output

Use of encoder: it can extract useful features from input data; the useful features can be used by many applications.

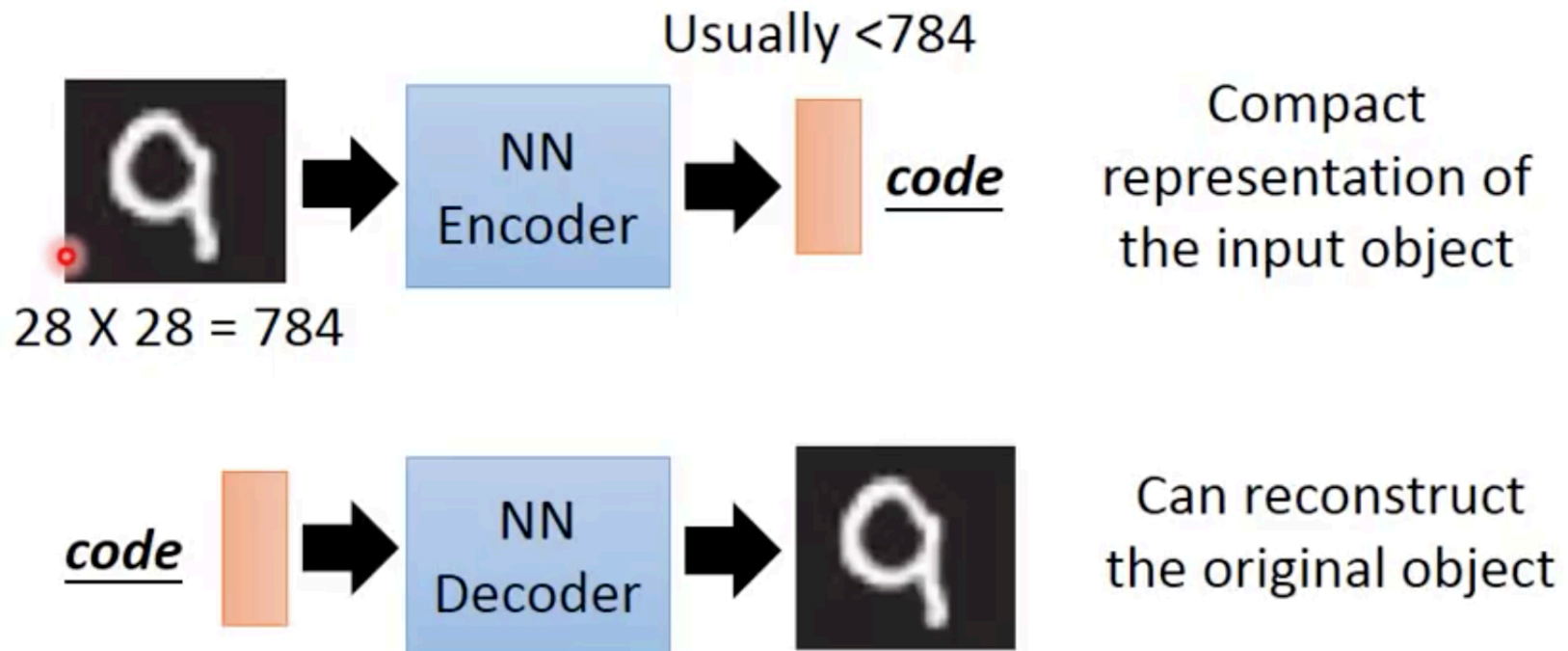
Use of decoder: it can generate realistic data from random inputs.

Nice property of auto-encoder: it can be trained without labels for data.

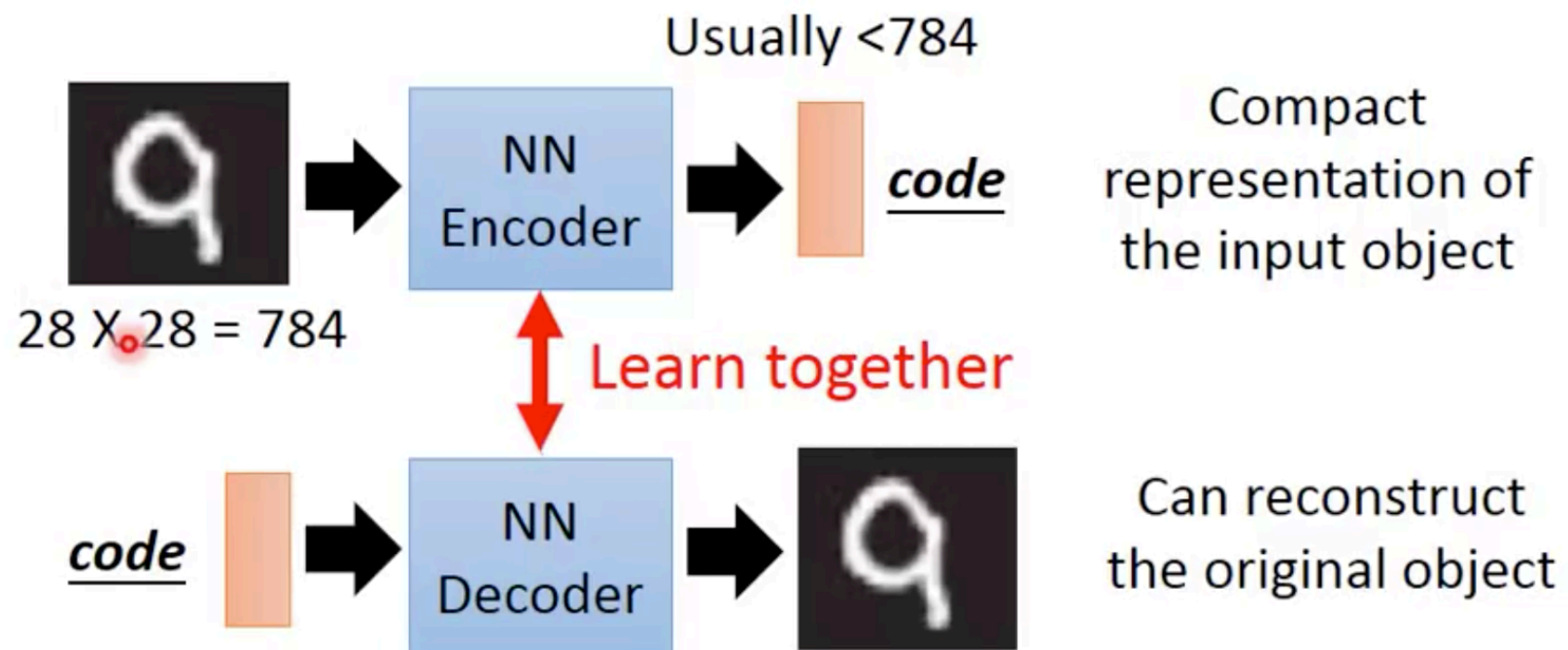
Auto-encoder



Auto-encoder

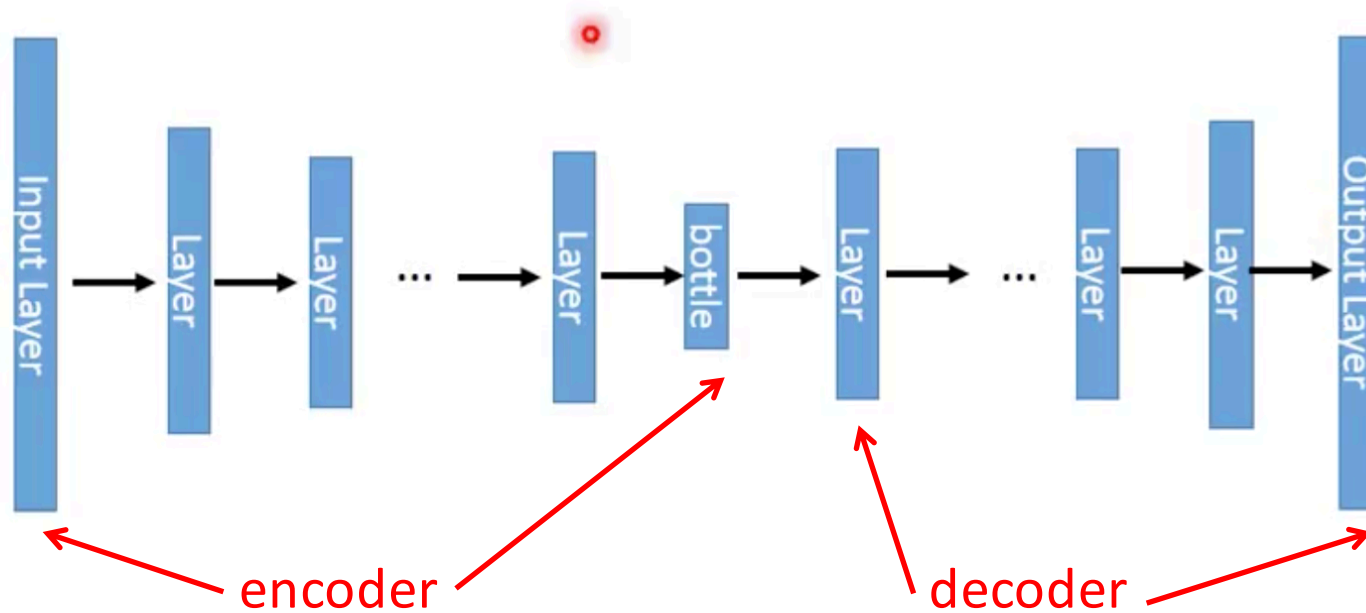


Auto-encoder



Deep Auto-encoder

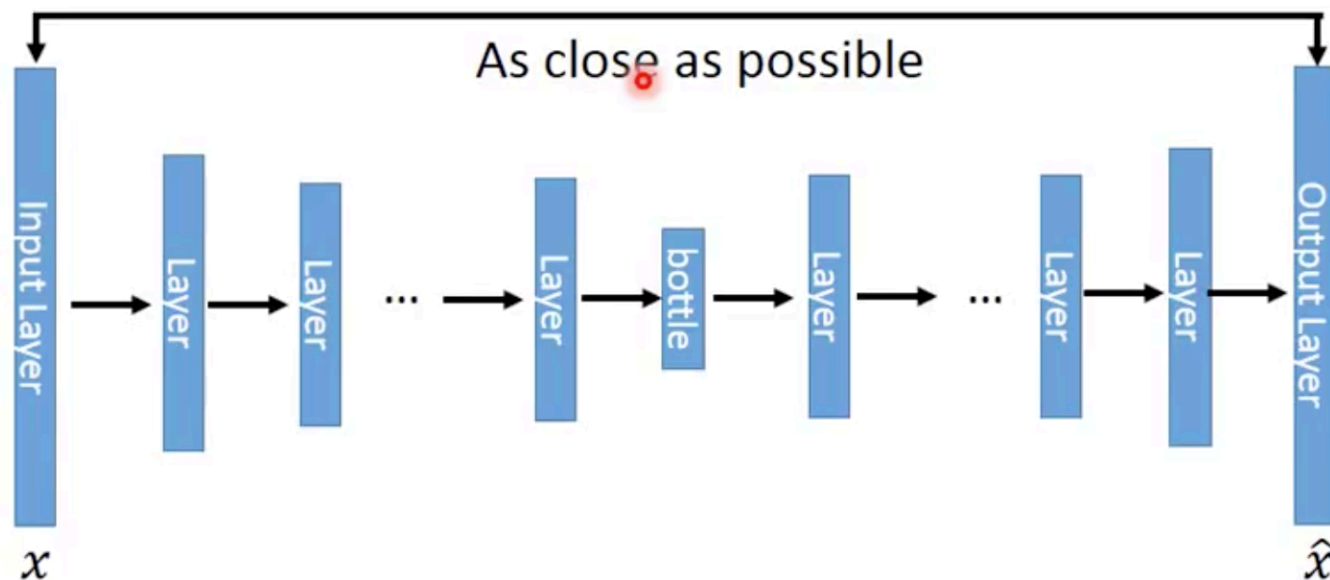
- Of course, the auto-encoder can be deep



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

Deep Auto-encoder

- Of course, the auto-encoder can be deep

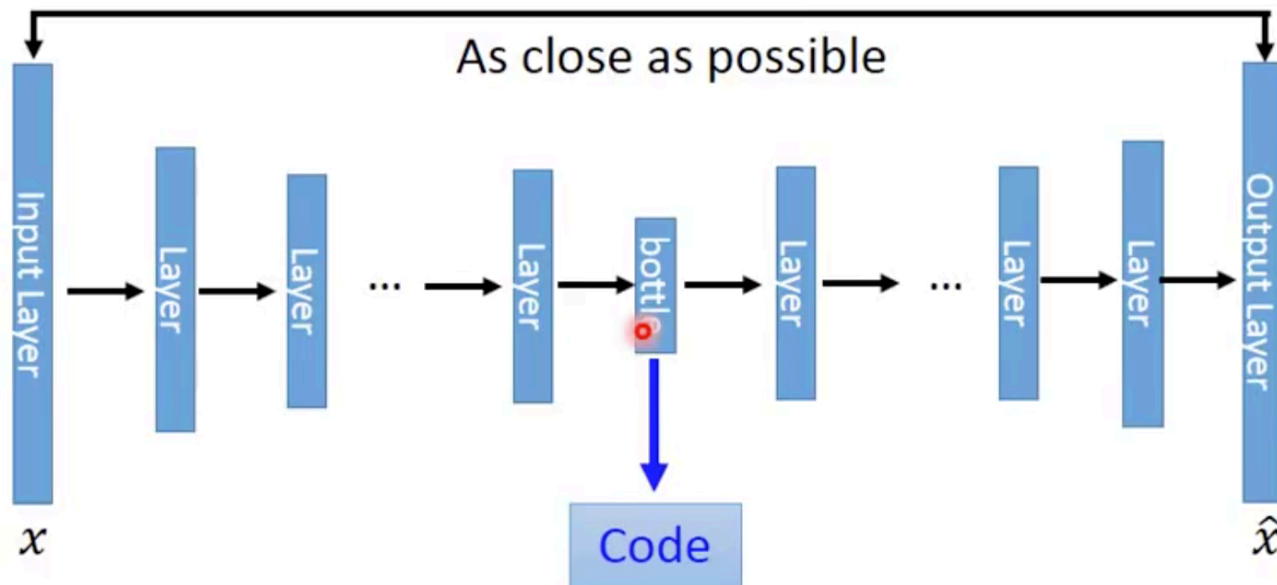


Reference: Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." *Science* 313.5786 (2006): 504-507

Created with EverCa

Deep Auto-encoder

- Of course, the auto-encoder can be deep



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

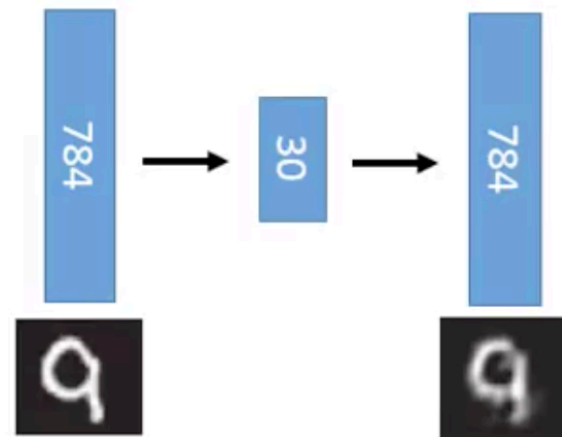
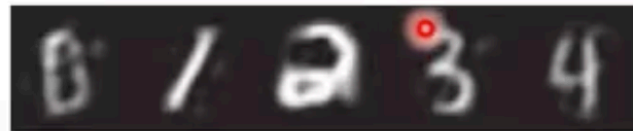
Created with EverC

Deep Auto-encoder

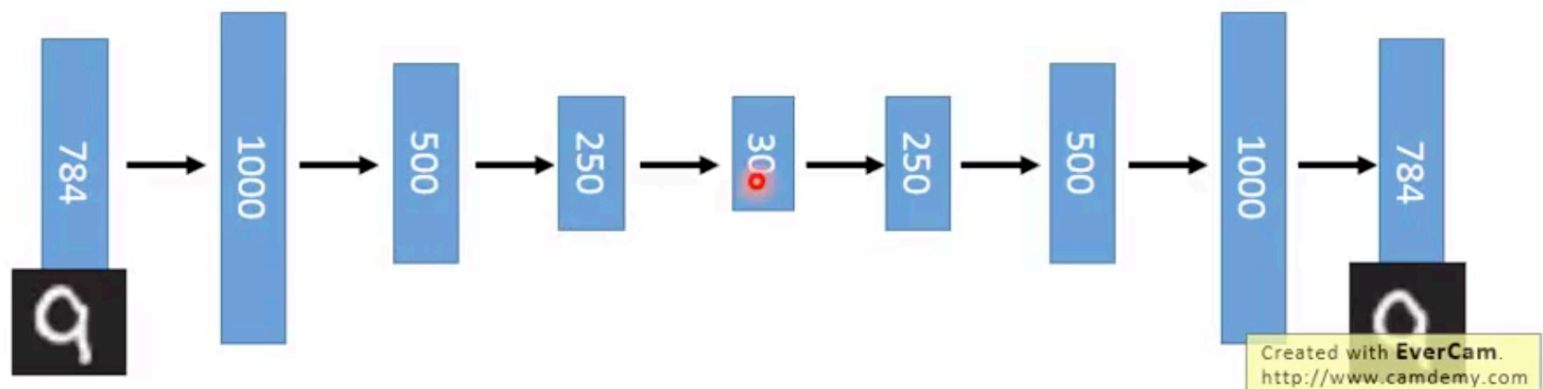
Original Image

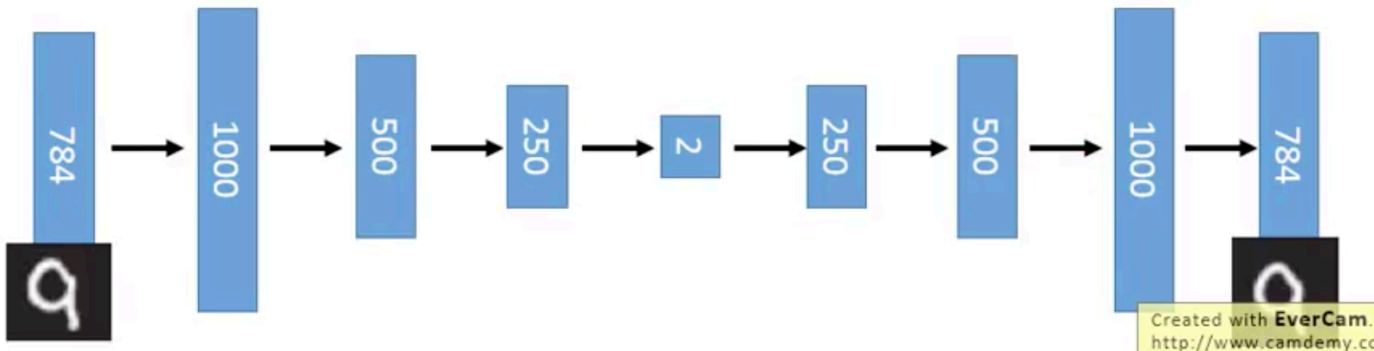


PCA

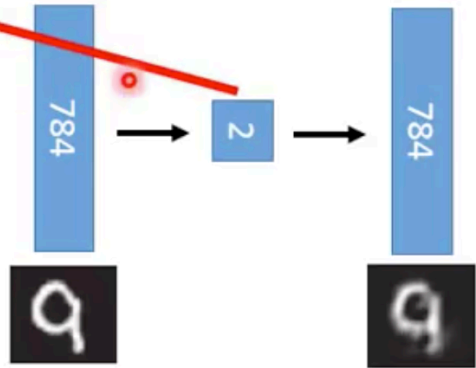
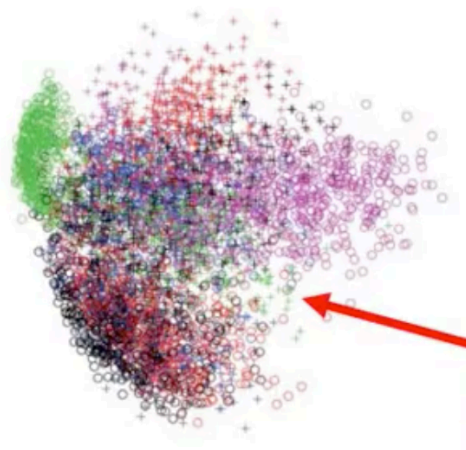


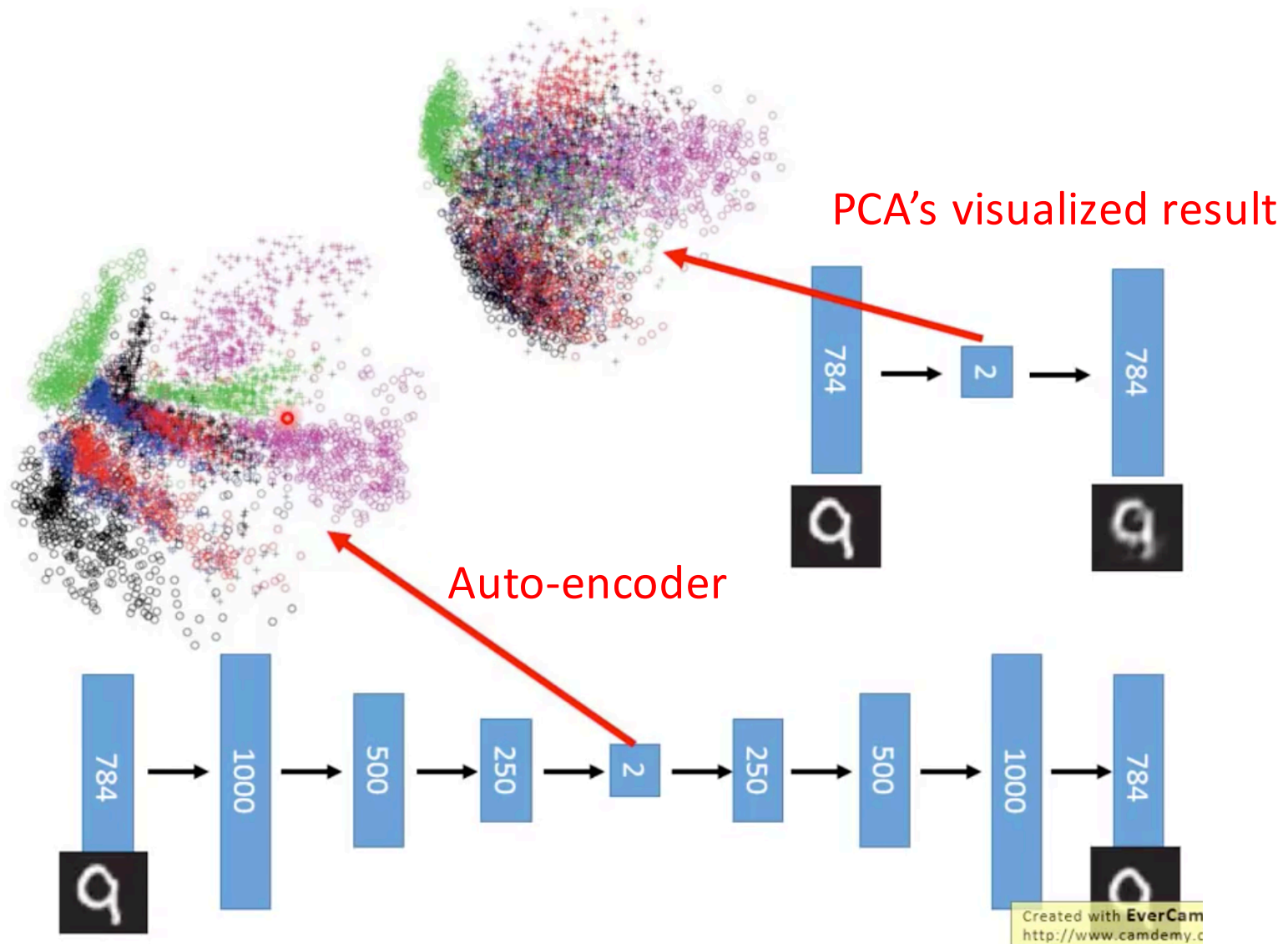
Deep Auto-encoder





PCA's visualized result

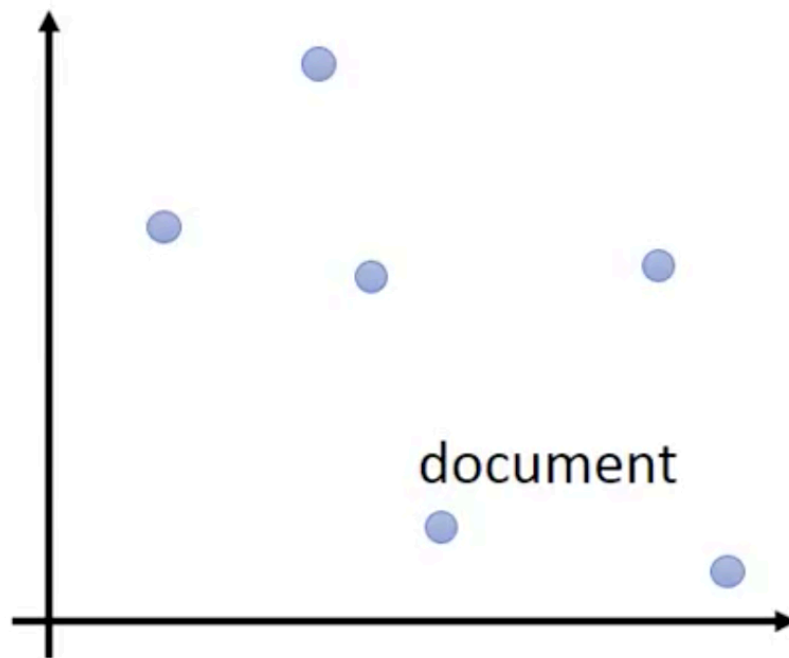




Auto-encoder – Text Retrieval

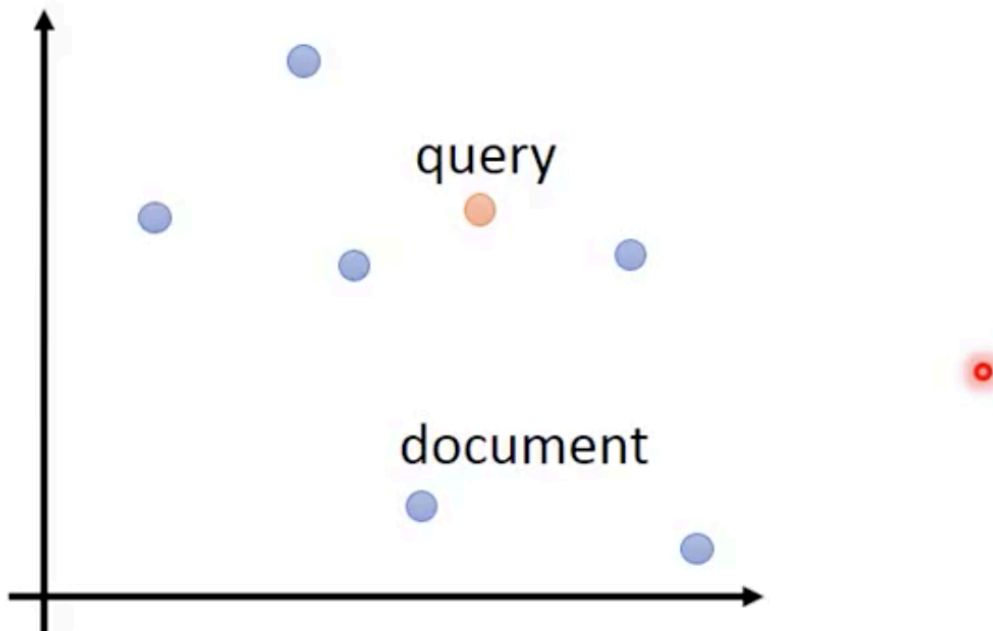
Auto-encoder – Text Retrieval

Vector Space Model



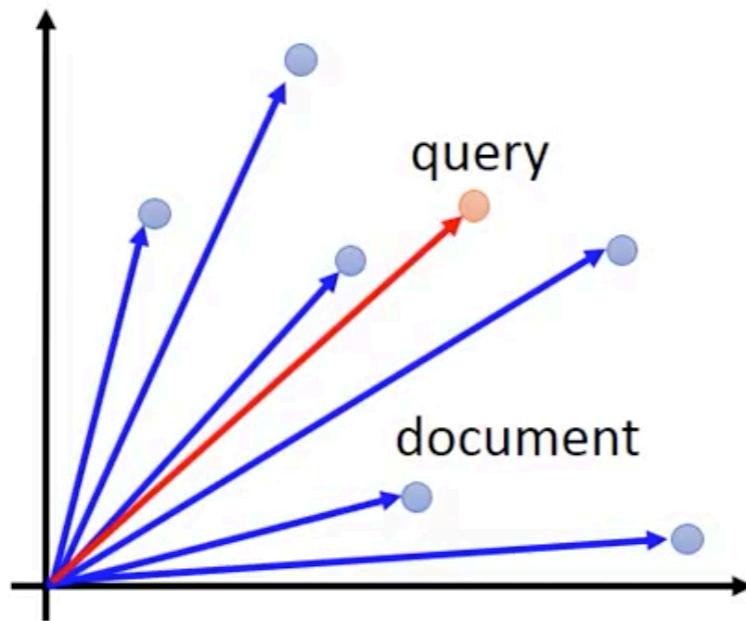
Auto-encoder – Text Retrieval

Vector Space Model



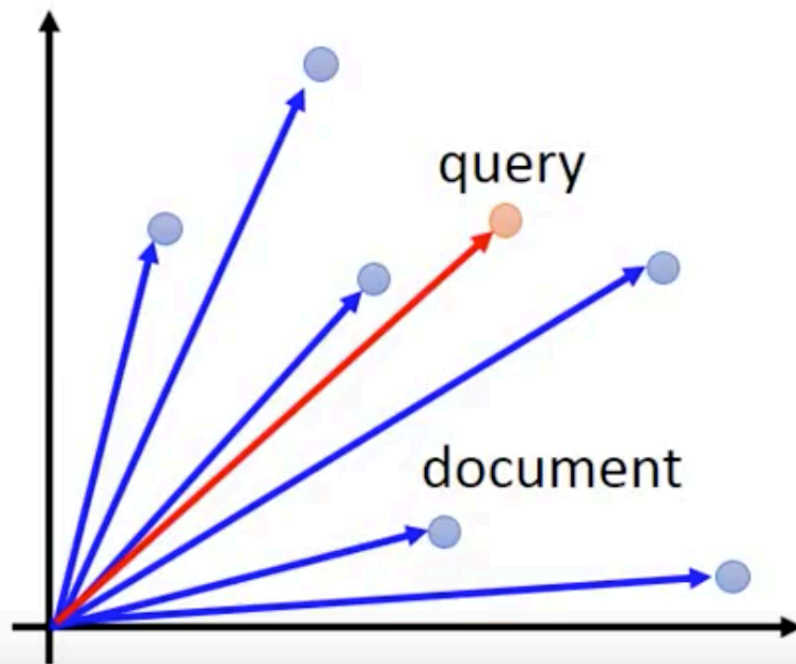
Auto-encoder – Text Retrieval

Vector Space Model



Auto-encoder – Text Retrieval

Vector Space Model



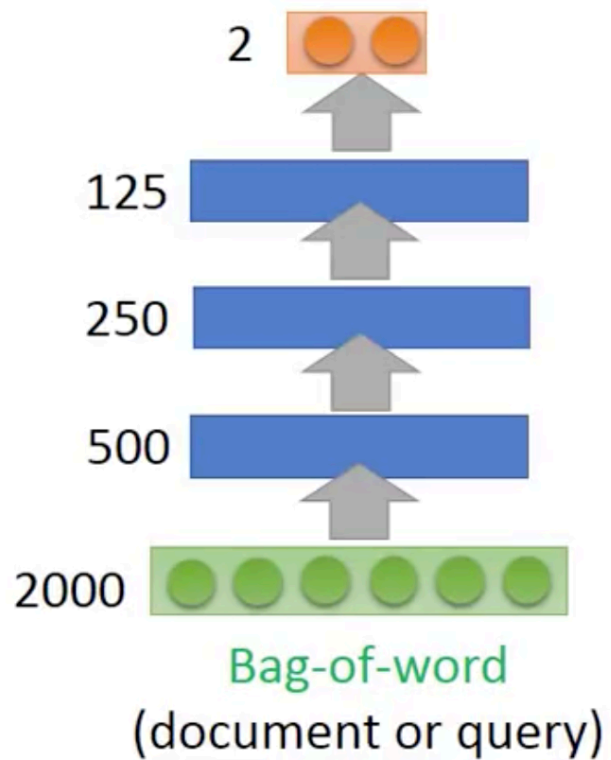
Bag-of-words

word string:
"This is an apple"

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

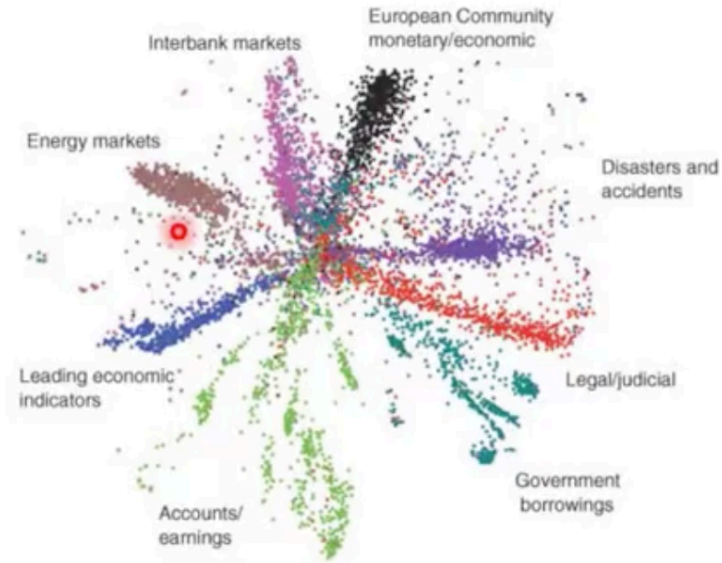
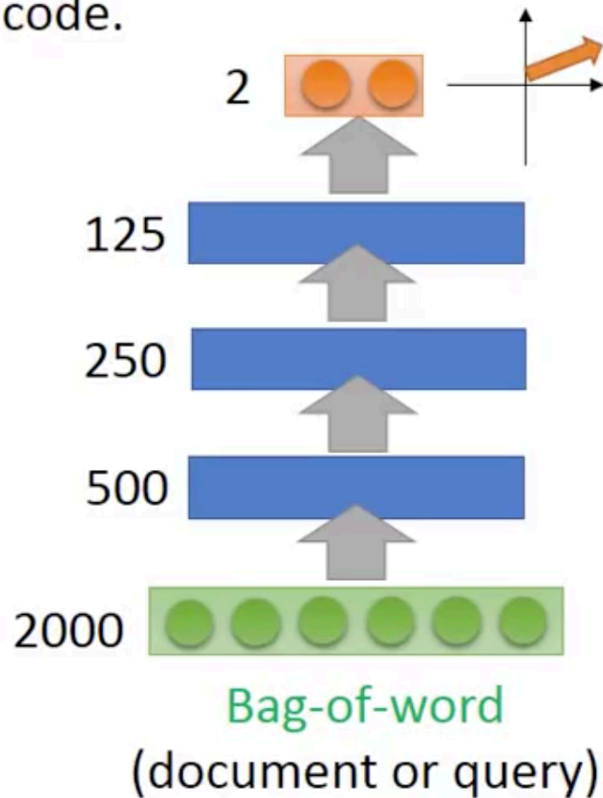
Auto-encoder – Text Retrieval

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



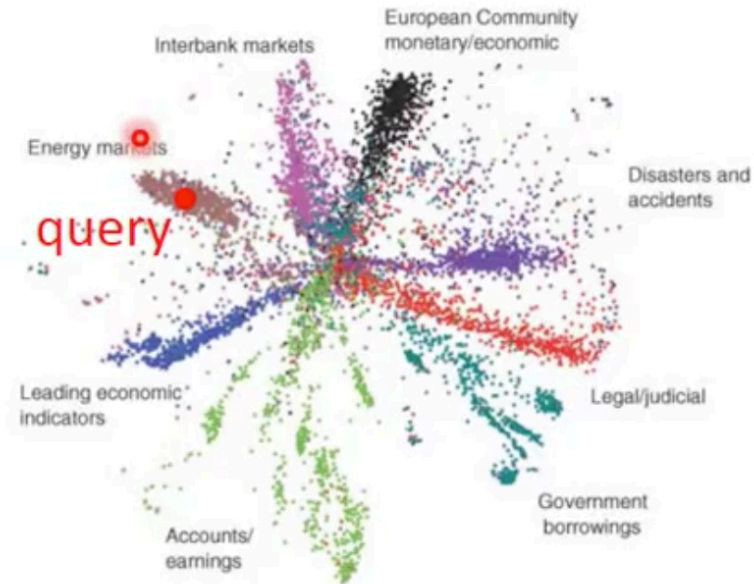
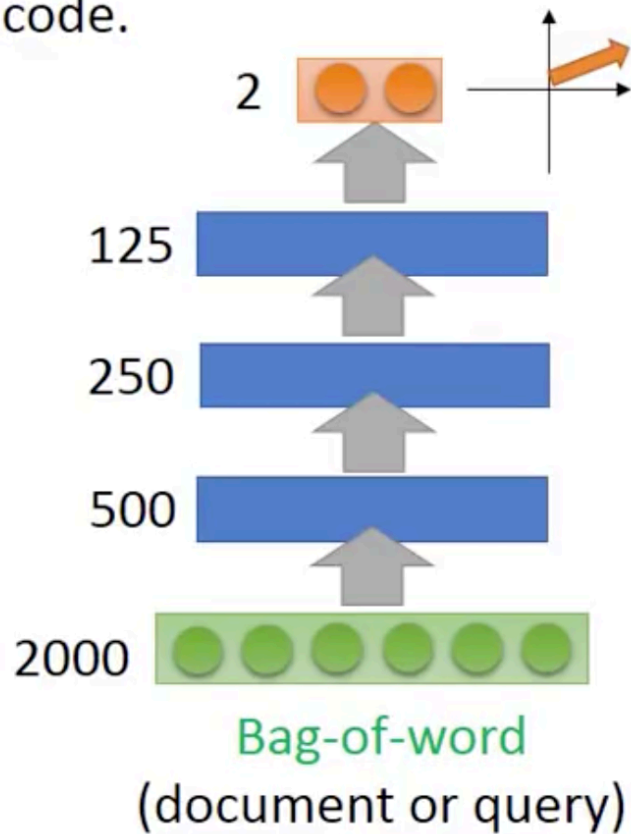
Auto-encoder – Text Retrieval

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



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

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

Created with E
<http://www.ca>

Auto-encoder – Similar Image Search

Retrieved using Euclidean distance in pixel intensity space

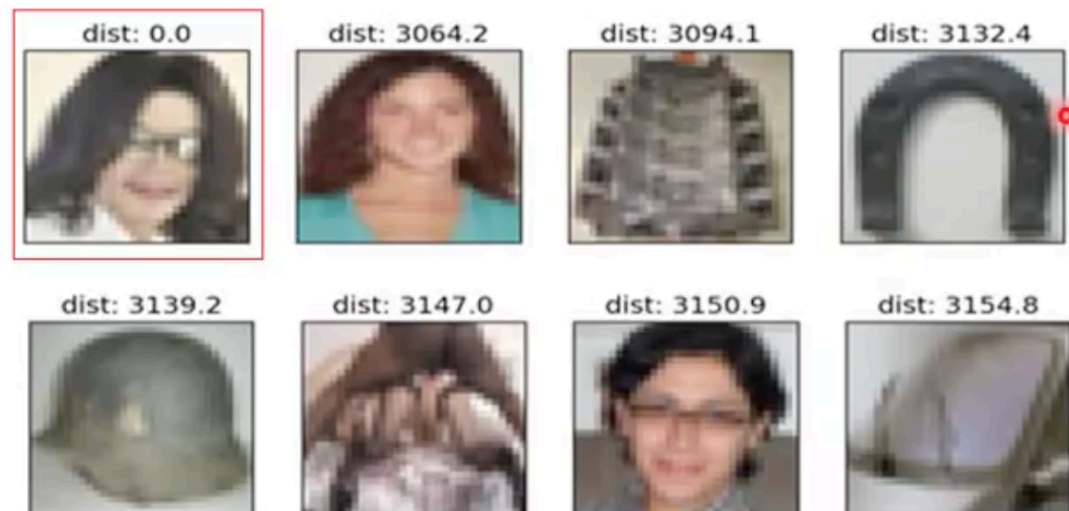


(Images from Hinton's slides on Coursera)

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

Auto-encoder – Similar Image Search

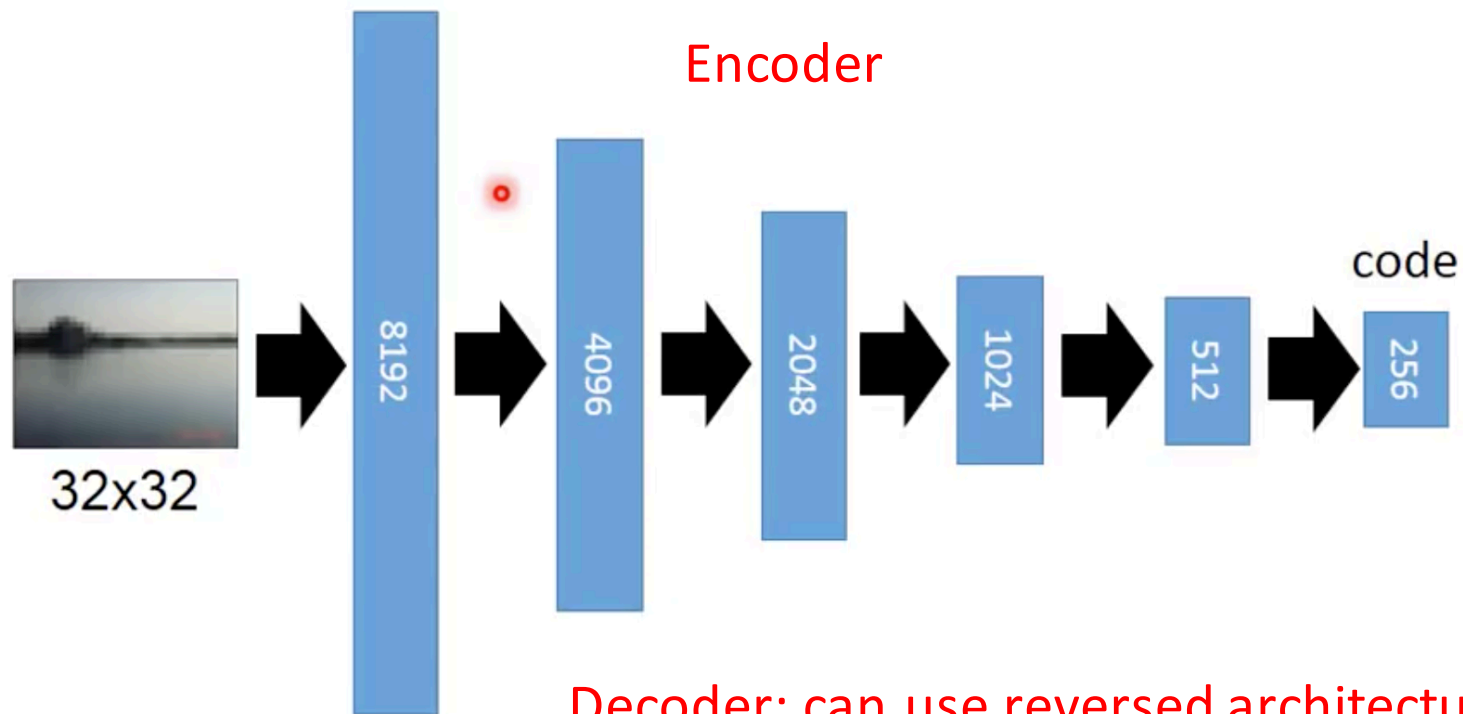
Retrieved using Euclidean distance in pixel intensity space



(Images from Hinton's slides on Coursera)

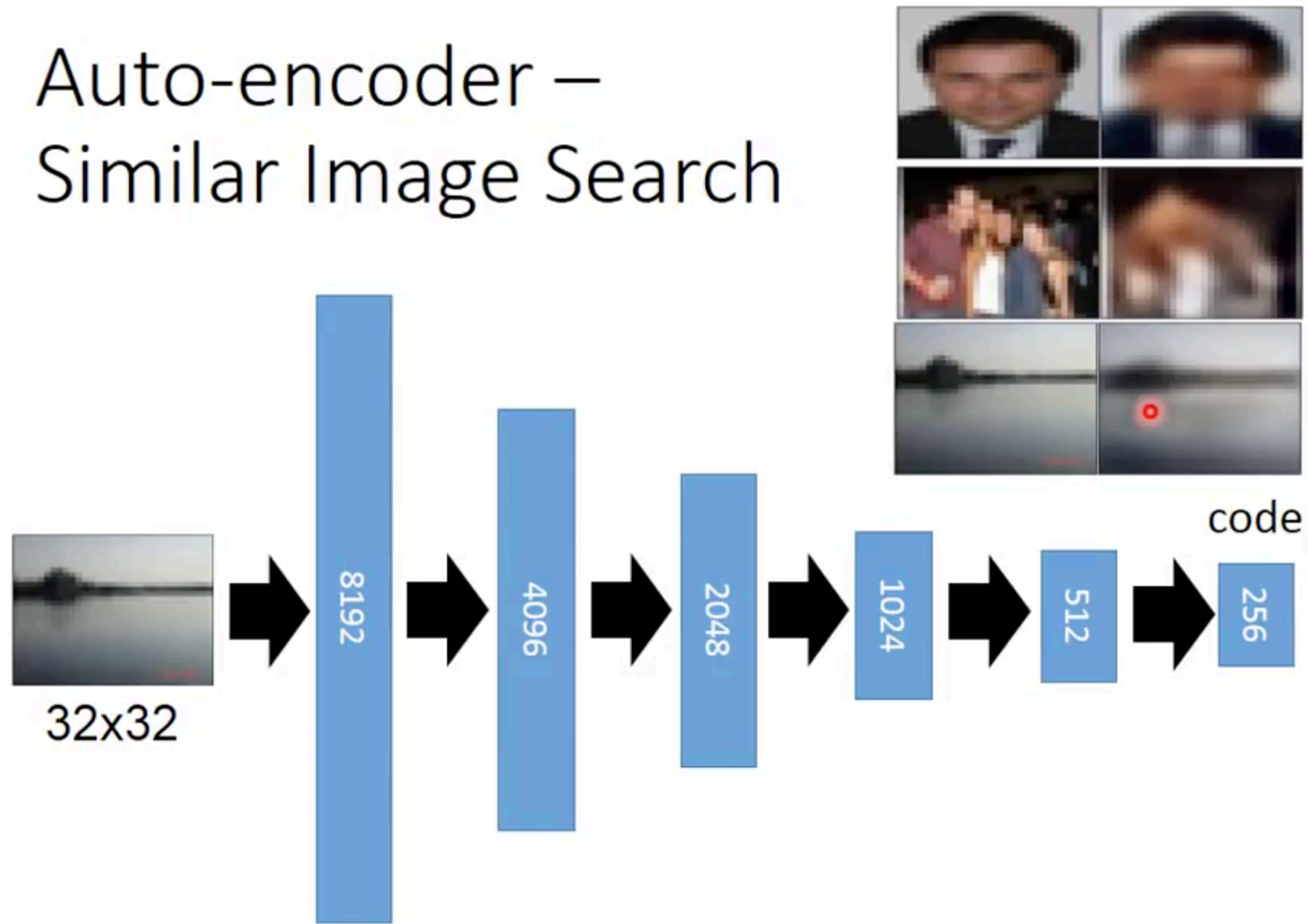
Reference: Krizhevsky, Alex, and Geoffrey E. Hinton. "Using very deep autoencoders for content-based image retrieval." *ESANN*. 2011.

Auto-encoder – Similar Image Search



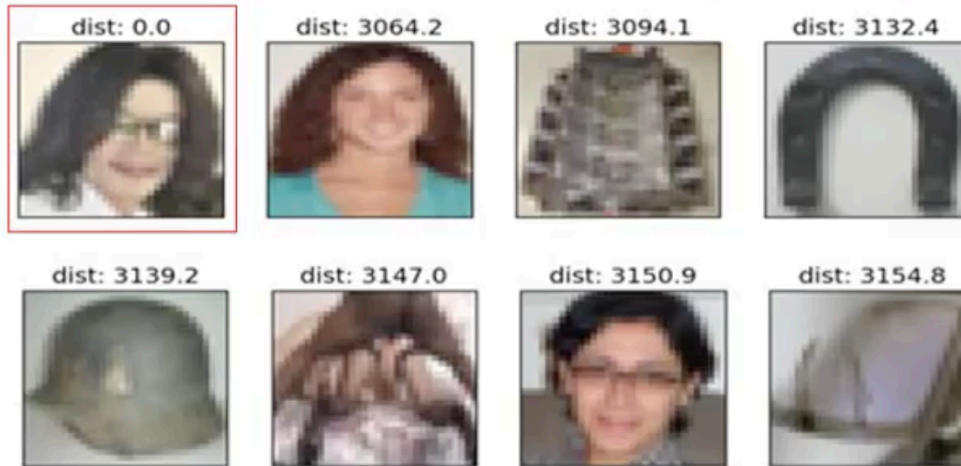
Decoder: can use reversed architecture
(crawl millions of images from the Internet)

Auto-encoder – Similar Image Search



(crawl millions of images from the Internet)

Retrieved using Euclidean distance in pixel intensity space

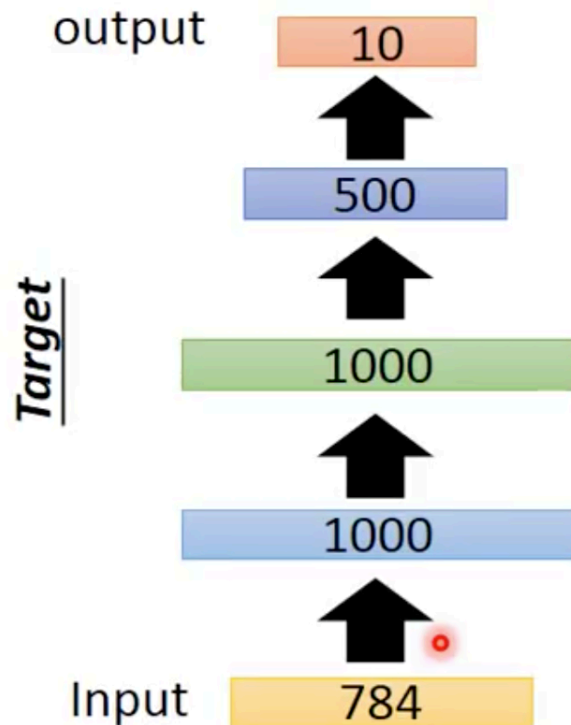


retrieved using 256 codes of auto-encoder



Auto-encoder – Pre-training DNN

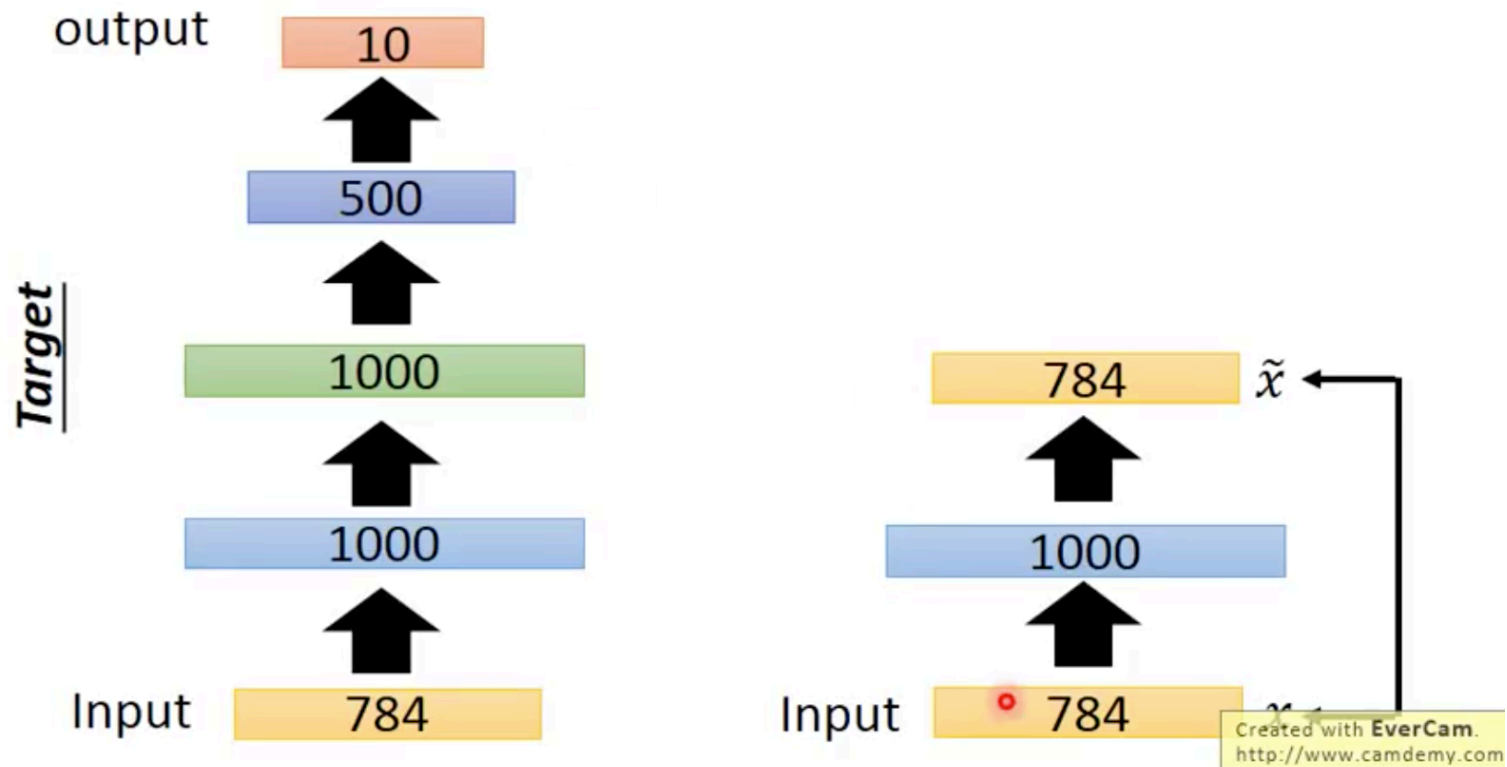
- Greedy Layer-wise Pre-training *again*



Pre-training:
find good initial values for weights

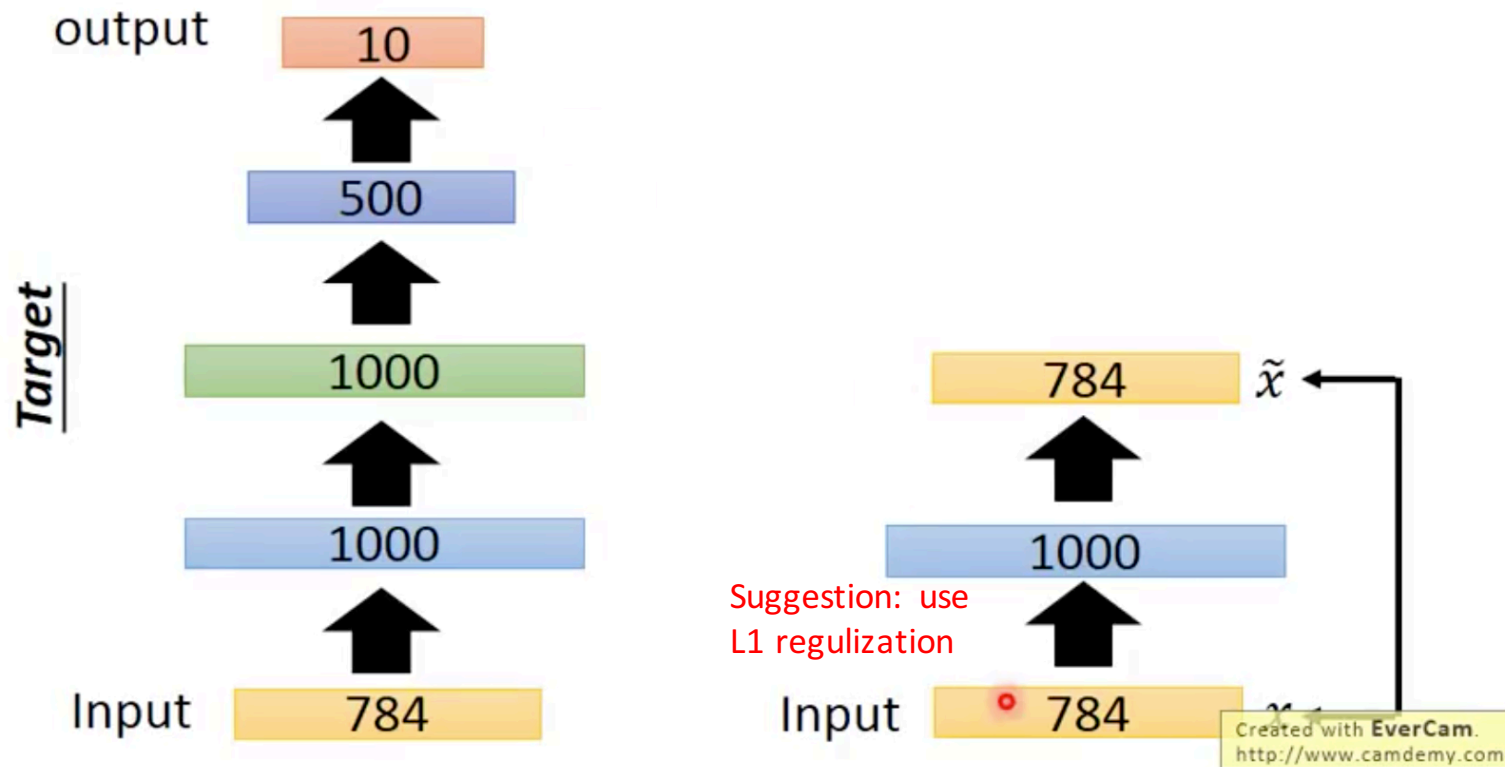
Auto-encoder – Pre-training DNN

- Greedy Layer-wise Pre-training *again*



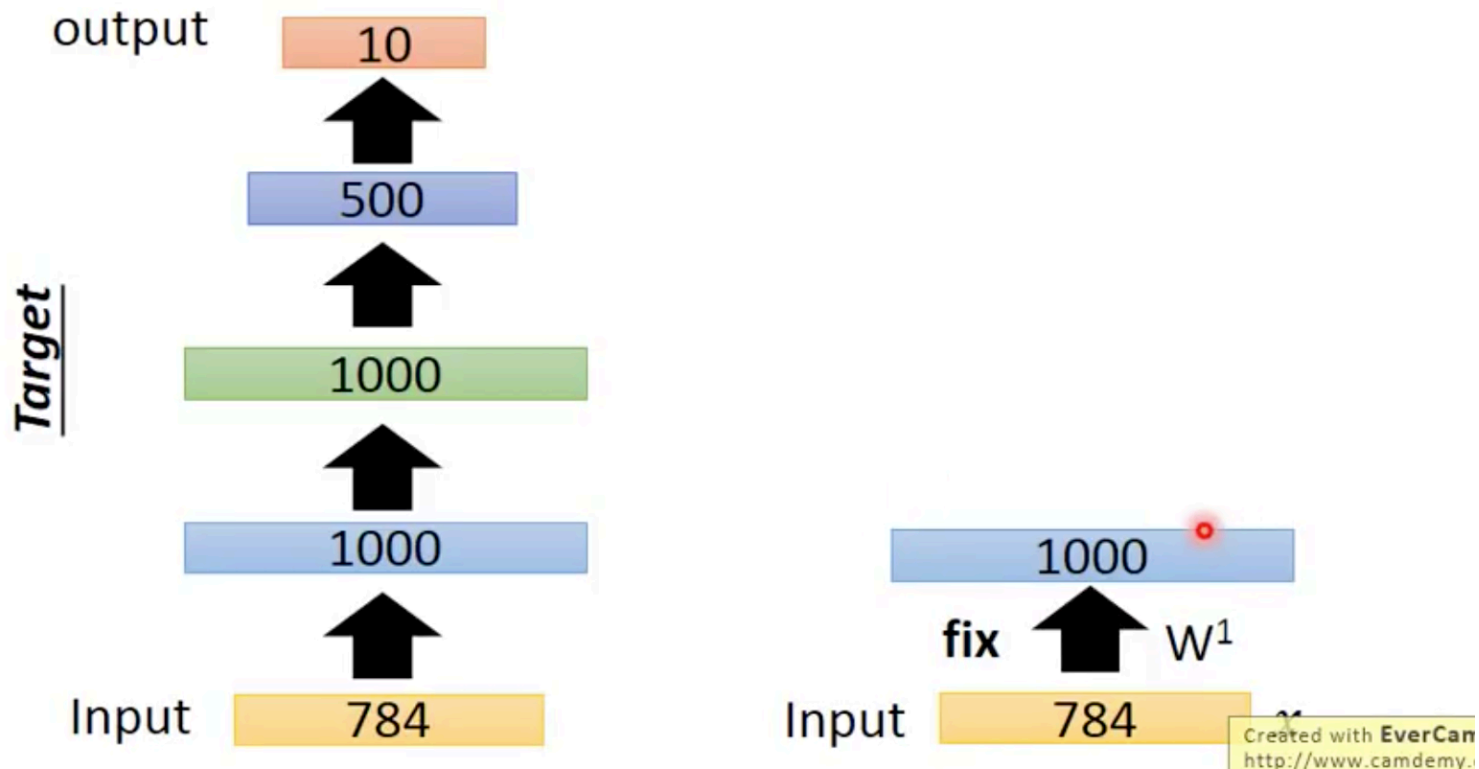
Auto-encoder – Pre-training DNN

- Greedy Layer-wise Pre-training *again*



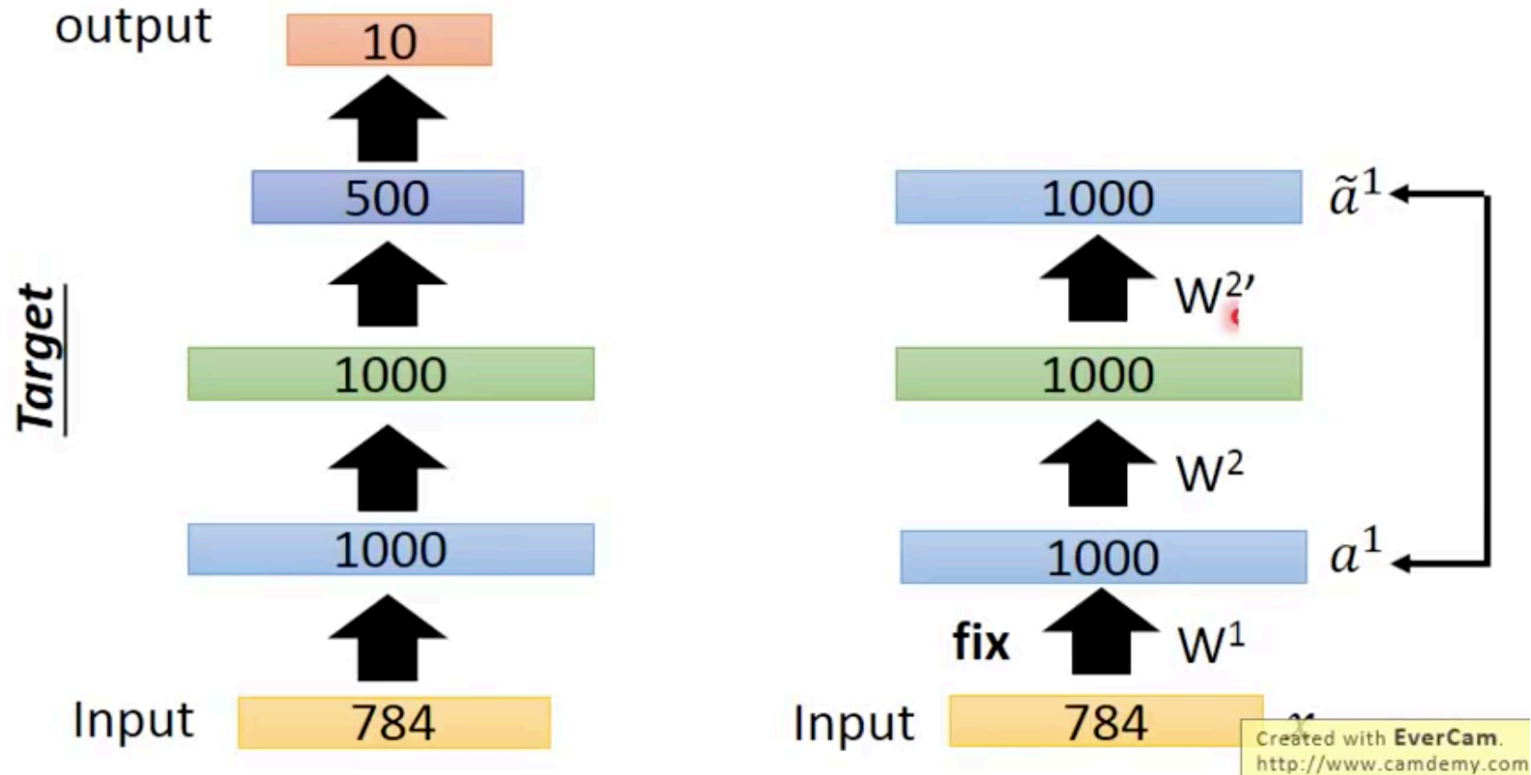
Auto-encoder – Pre-training DNN

- Greedy Layer-wise Pre-training *again*



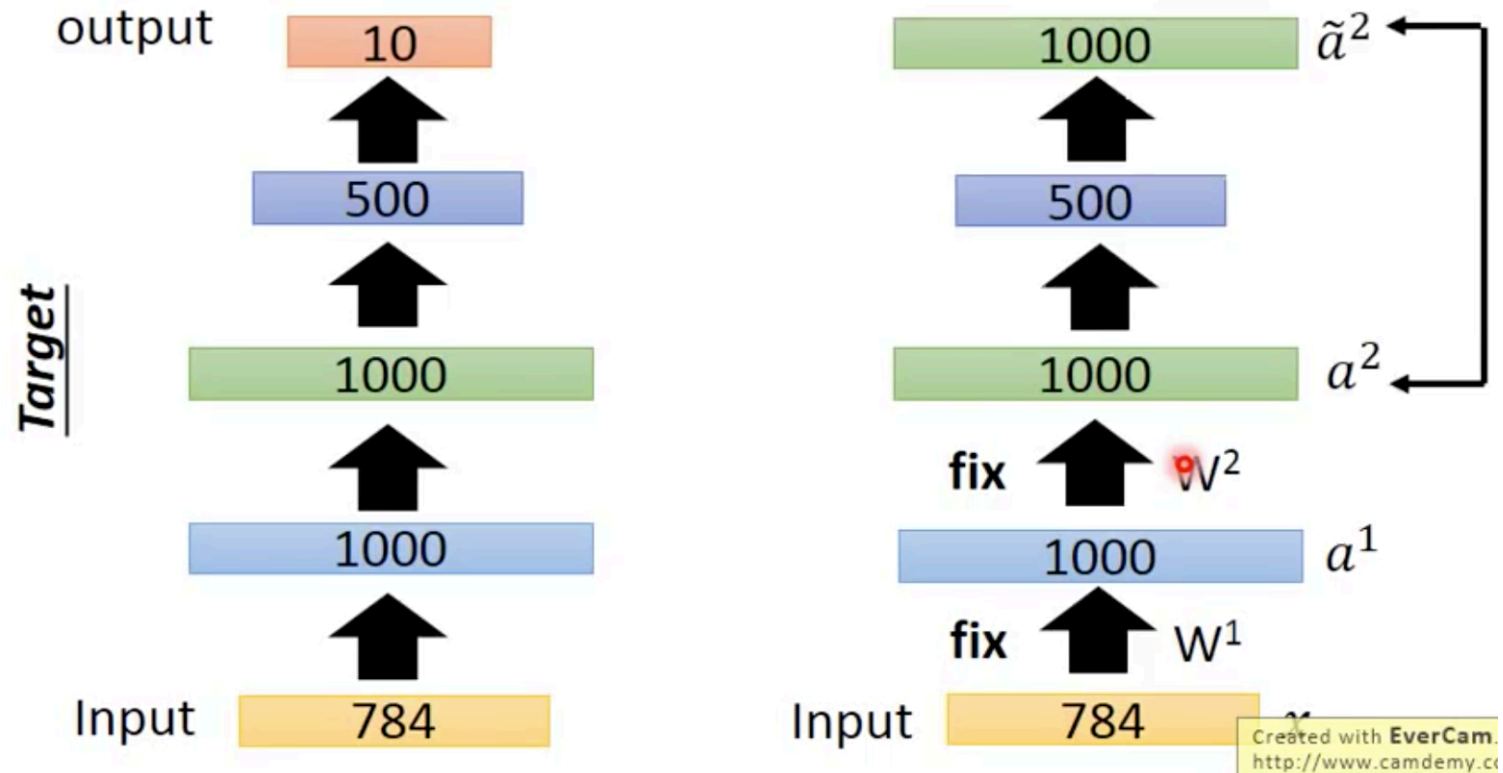
Auto-encoder – Pre-training DNN

- Greedy Layer-wise Pre-training *again*



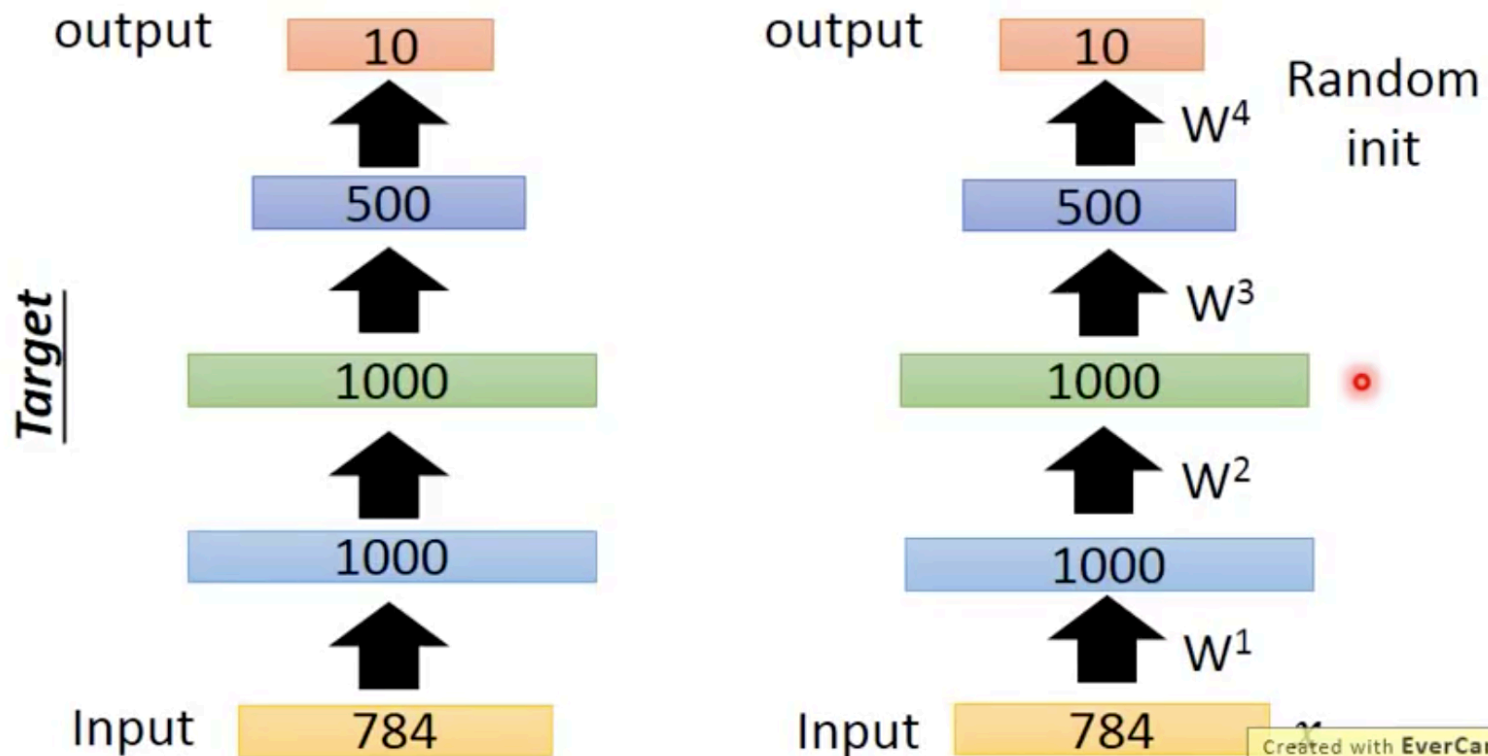
Auto-encoder – Pre-training DNN

- Greedy Layer-wise Pre-training *again*



Auto-encoder – Pre-training DNN

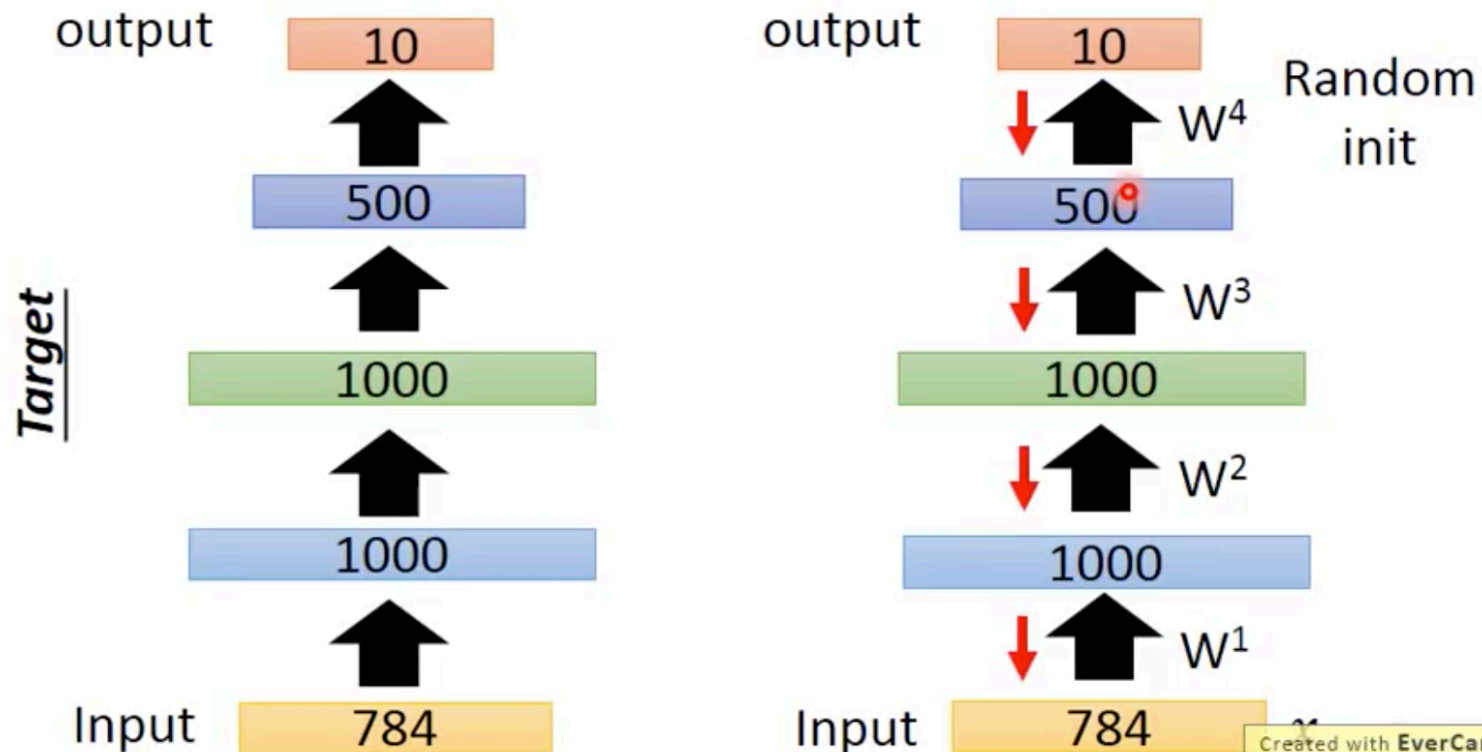
- Greedy Layer-wise Pre-training *again*



Auto-encoder – Pre-training DNN

- Greedy Layer-wise Pre-training *again*

Find-tune by backpropagation

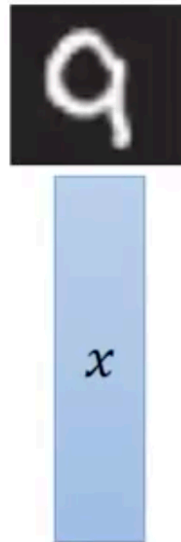


Pre-training is used much less often than before,
Because today we have back-propagation algorithms that can train
very deep networks.

However, if we have a large set of un-labelled data and only a small set of
labelled data, we can use the large set of un-labelled data to pre-train all
the layers other than the last layer, and then use the small set of labelled
data to train the last layer and fine tune weights in all layers.

Auto-encoder

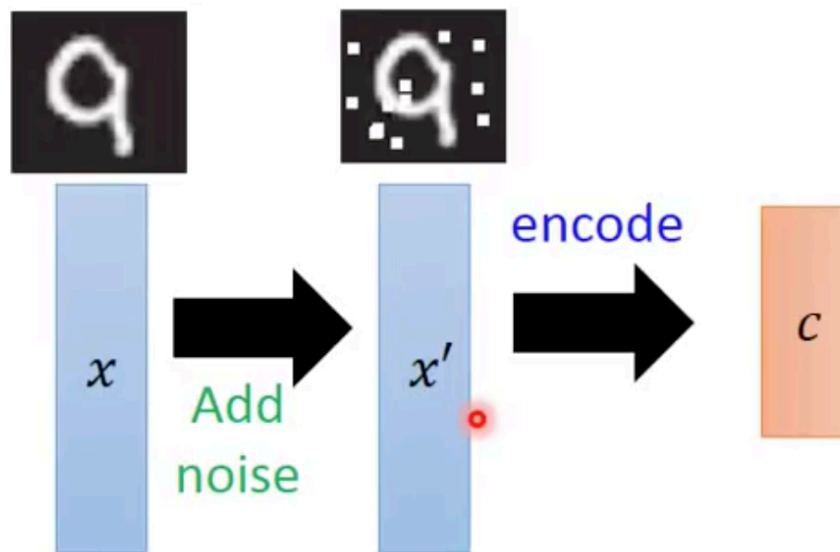
- De-noising auto-encoder



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

Auto-encoder

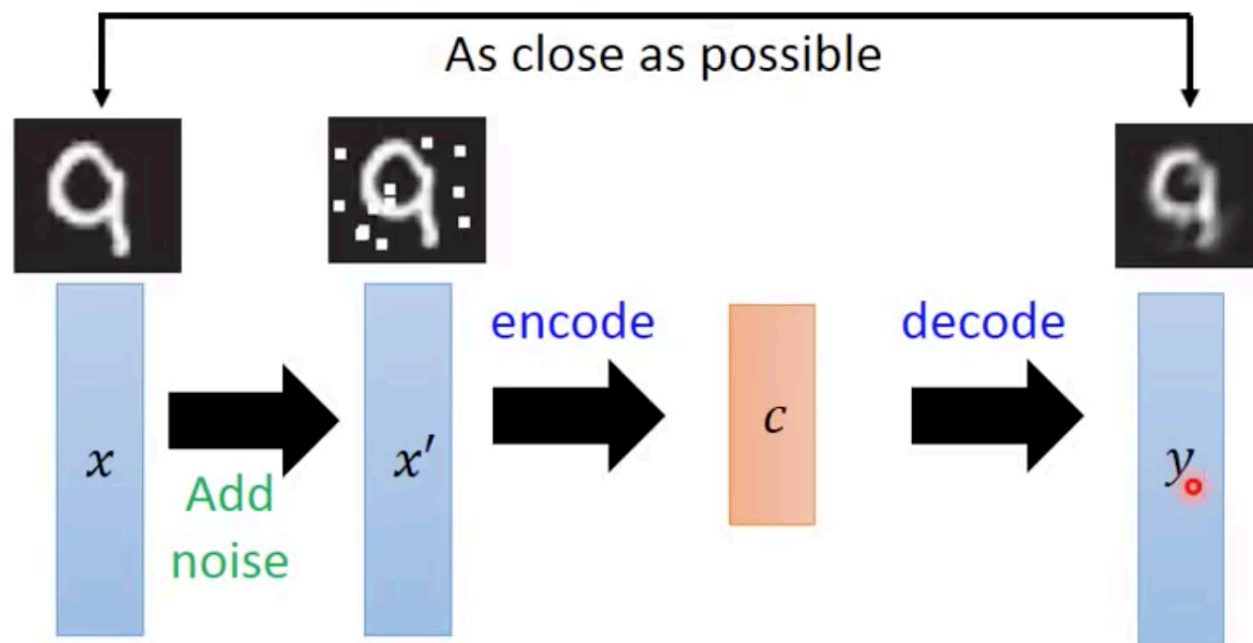
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Vincent, Pascal, et al. "Extracting and composing robust features with denoising autoencoders." *ICML*, 2008.

Auto-encoder

- De-noising auto-encoder



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

Learning More Methods for non-linear dimension-reduction

- Restricted Boltzmann Machine

- Neural networks [5.1] : Restricted Boltzmann machine – definition
 - https://www.youtube.com/watch?v=p4Vh_zMw-HQ&index=36&list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH
- Neural networks [5.2] : Restricted Boltzmann machine – inference
 - https://www.youtube.com/watch?v=lekCh_i32iE&list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH&index=37
- Neural networks [5.3] : Restricted Boltzmann machine - free energy
 - https://www.youtube.com/watch?v=e0Ts_7Y6hZU&list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH&index=38

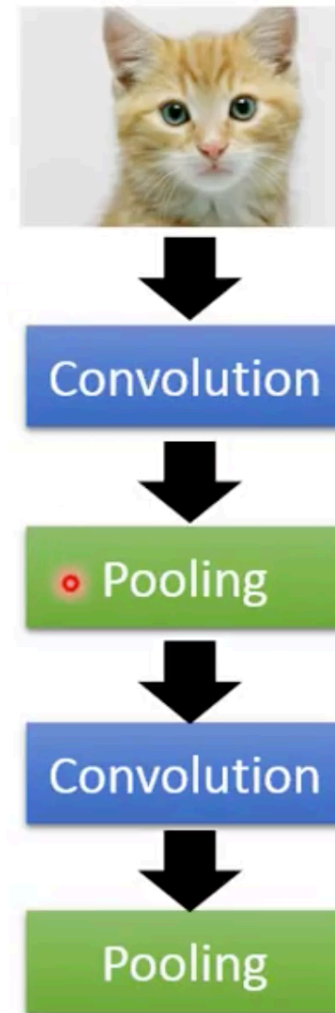
Learning More

Graphical Model

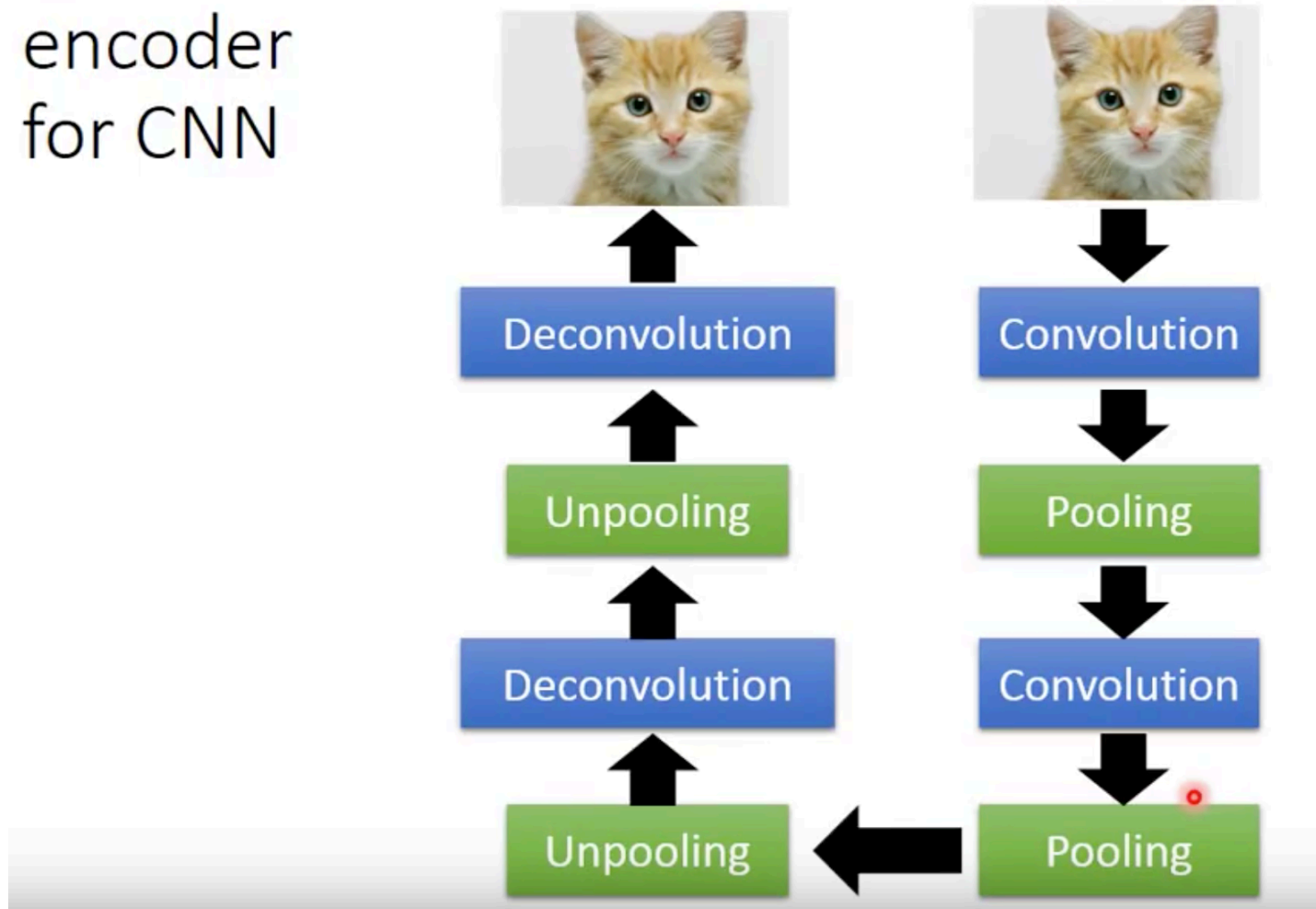
- Deep Belief Network

- Neural networks [7.7] : Deep learning - deep belief network
 - <https://www.youtube.com/watch?v=vkb6AWYXZ5I&list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH&index=57>
- Neural networks [7.8] : Deep learning - variational bound
 - <https://www.youtube.com/watch?v=pStDscJh2Wo&list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH&index=58>
- Neural networks [7.9] : Deep learning - DBN pre-training
 - <https://www.youtube.com/watch?v=35MUIYCColk&list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH&index=59>

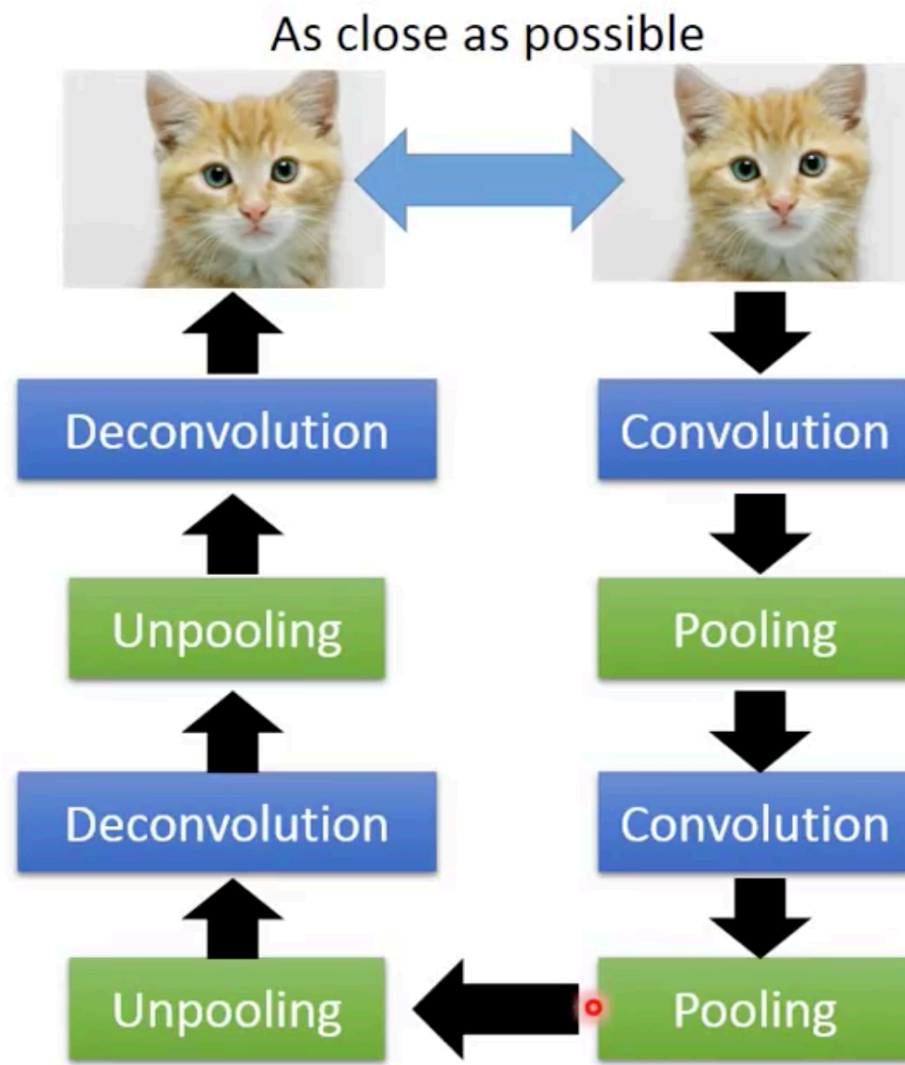
Auto- encoder for CNN



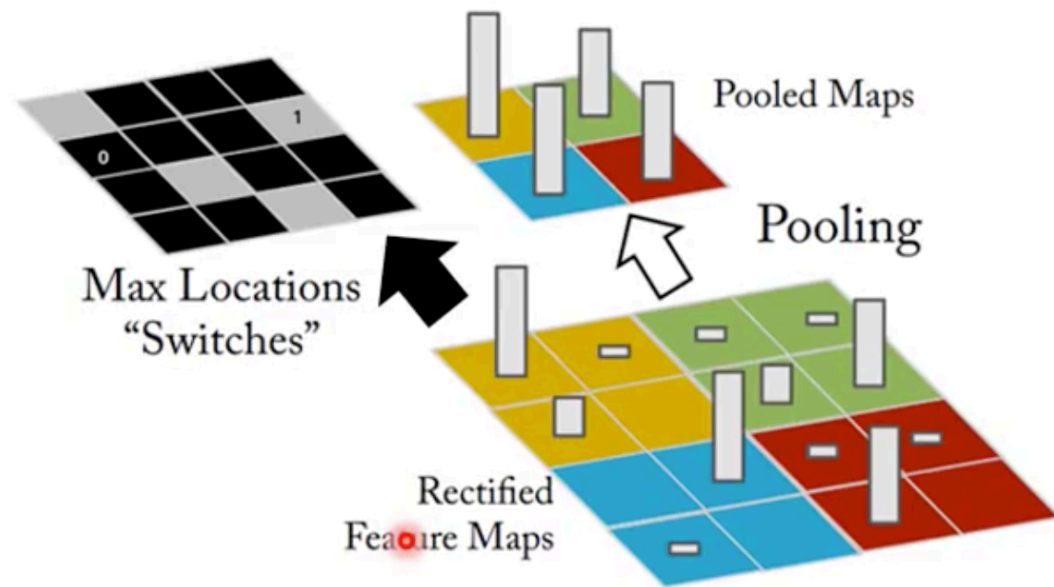
Auto-encoder for CNN



Auto- encoder for CNN



CNN -Unpooling

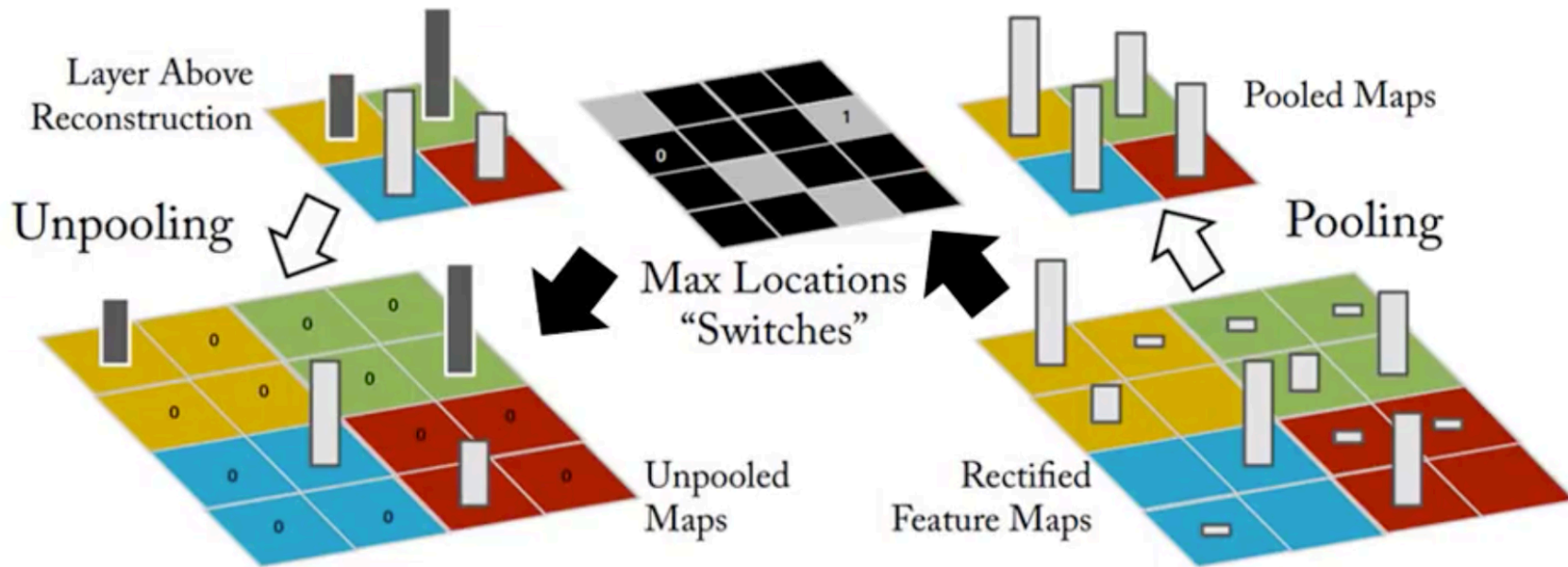


Source of image :

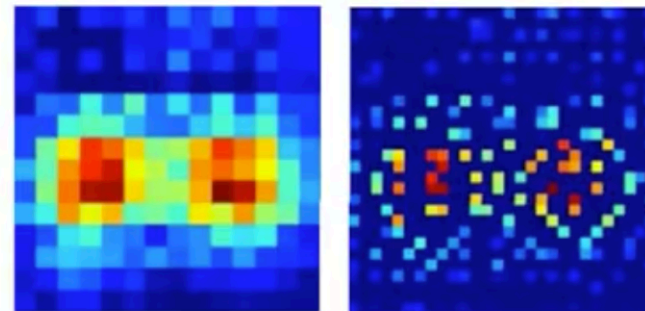
https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/image_segmentation.html

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

CNN -Unpooling

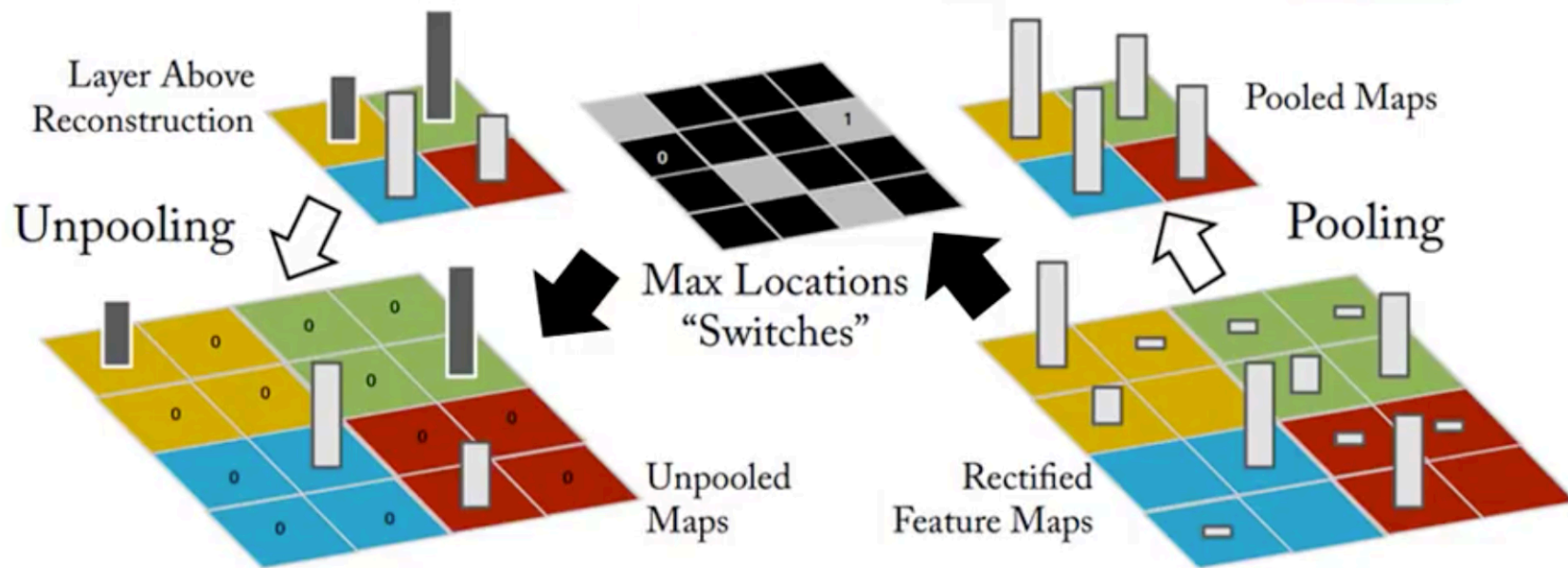


CNN -Unpooling

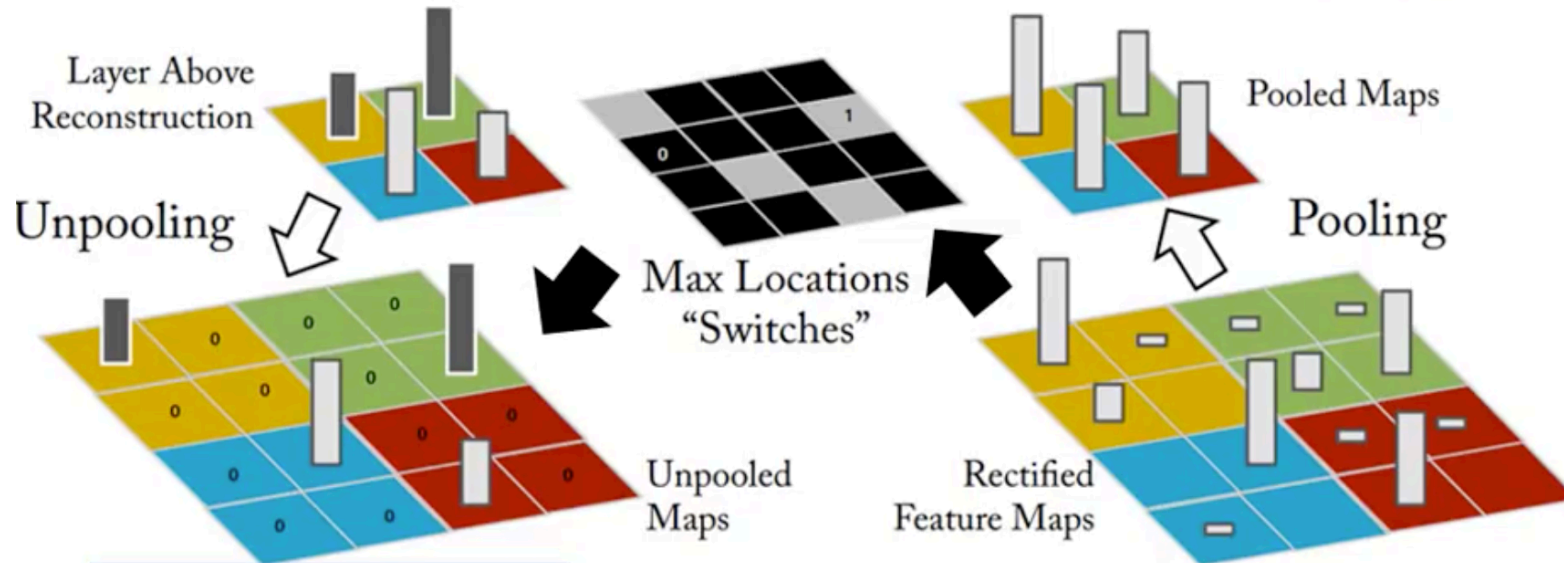
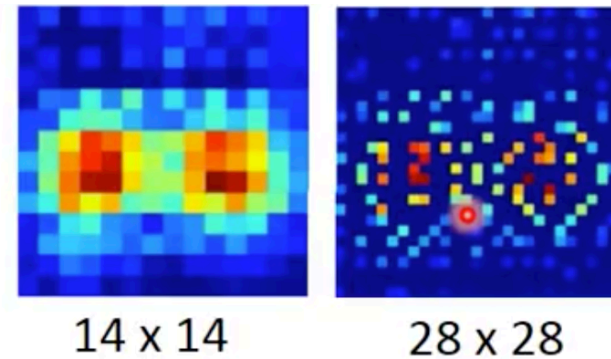


14 x 14

28 x 28



CNN -Unpooling



Keras

Alternative: simply repeat the values

No need to remember "Max locations"

Source of image : https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/image_segmentation.html

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

CNN

- Deconvolution

CNN

- Deconvolution

Actually, deconvolution is convolution.

Actually, deconvolution is convolution.

CNN

- Deconvolution



Example: 1-dimensional convolution

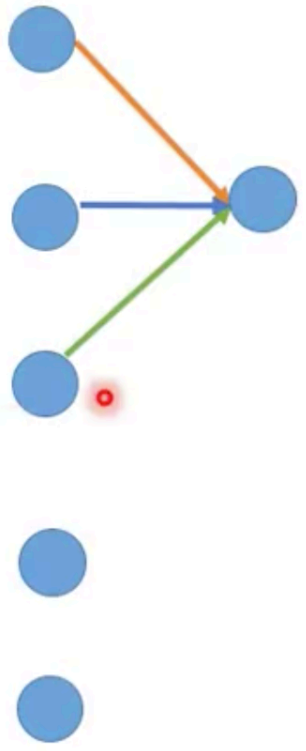


Actually, deconvolution is convolution.

CNN

- Deconvolution

convolution



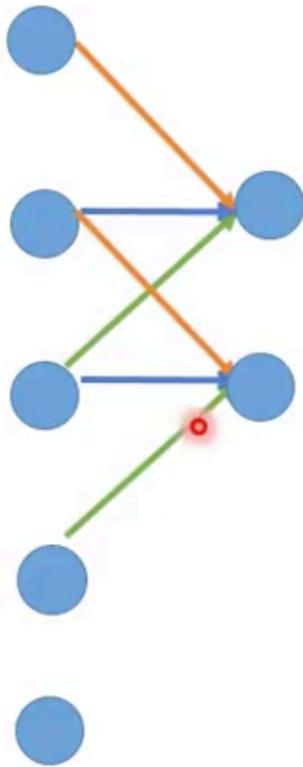
Filter size: 3

Actually, deconvolution is convolution.

CNN

- Deconvolution

convolution

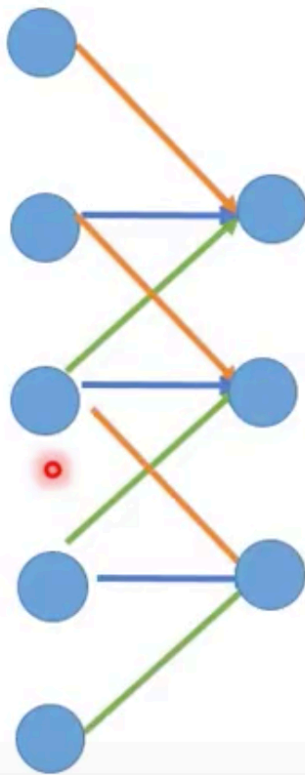


Actually, deconvolution is convolution.

CNN

- Deconvolution

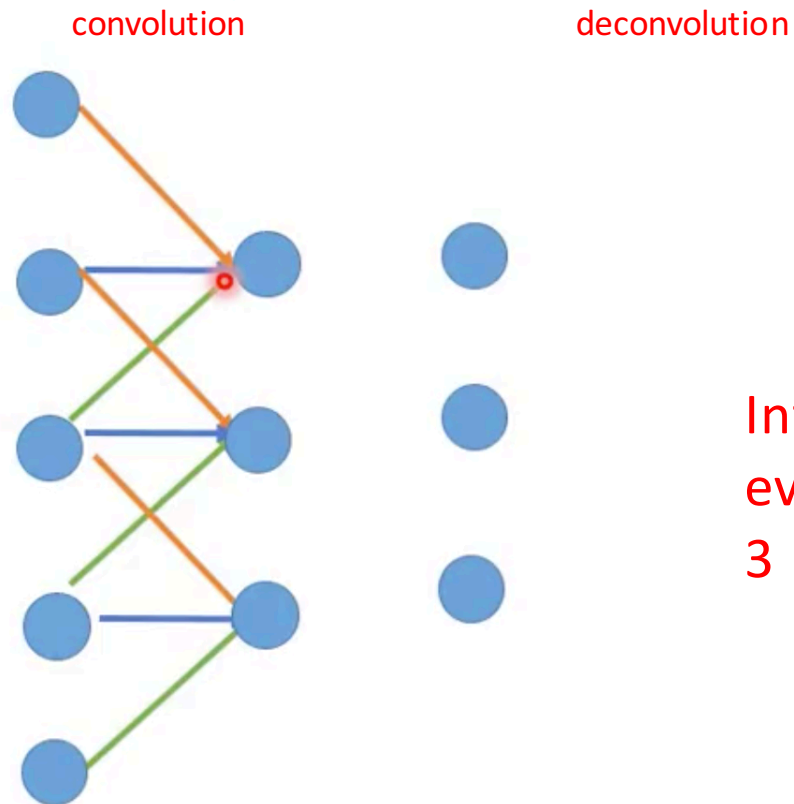
convolution



CNN

Actually, deconvolution is convolution.

- Deconvolution

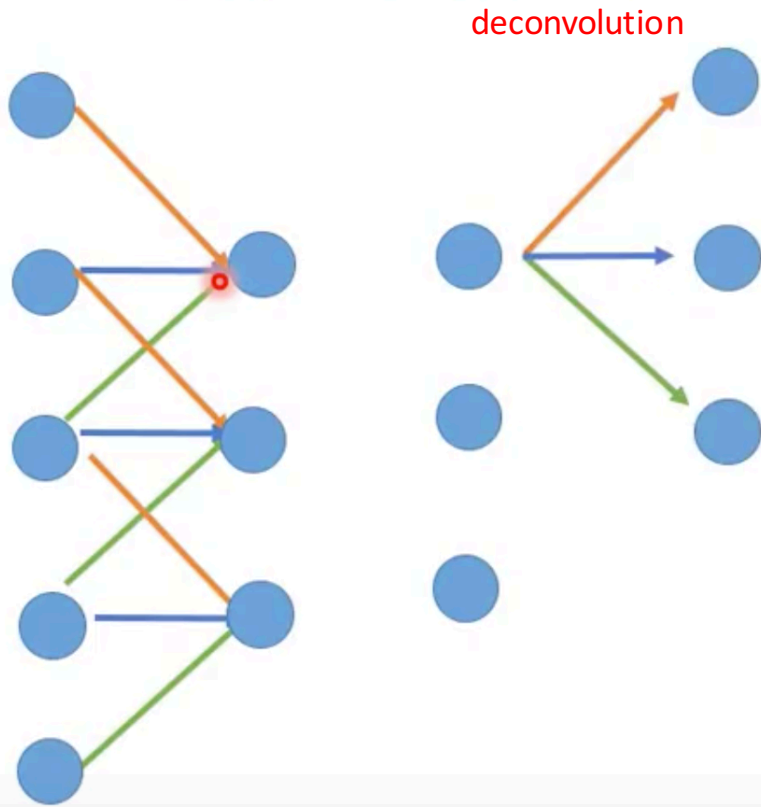


Intuitively, in deconvolution, every left node should correspond to 3 right node.

CNN

Actually, deconvolution is convolution.

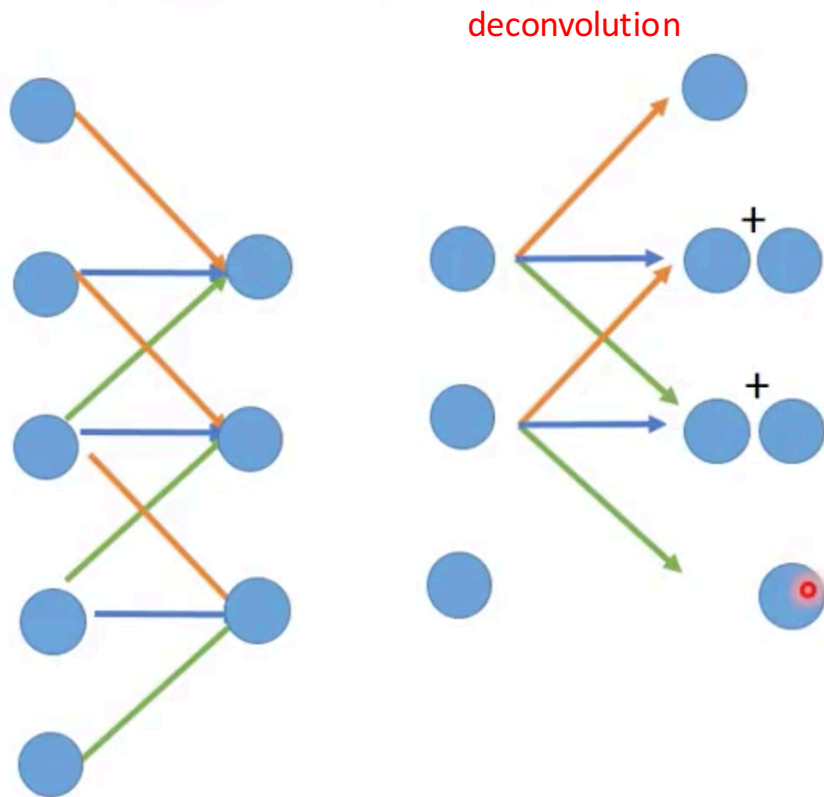
- Deconvolution



CNN

Actually, deconvolution is convolution.

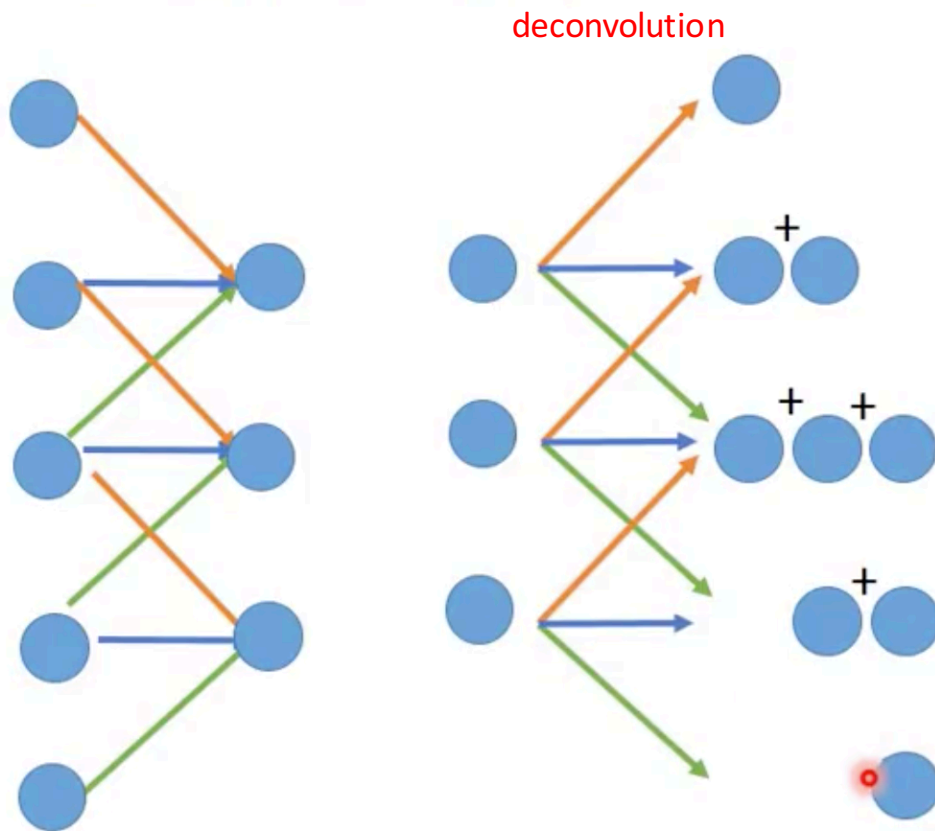
- Deconvolution



Actually, deconvolution is convolution.

CNN

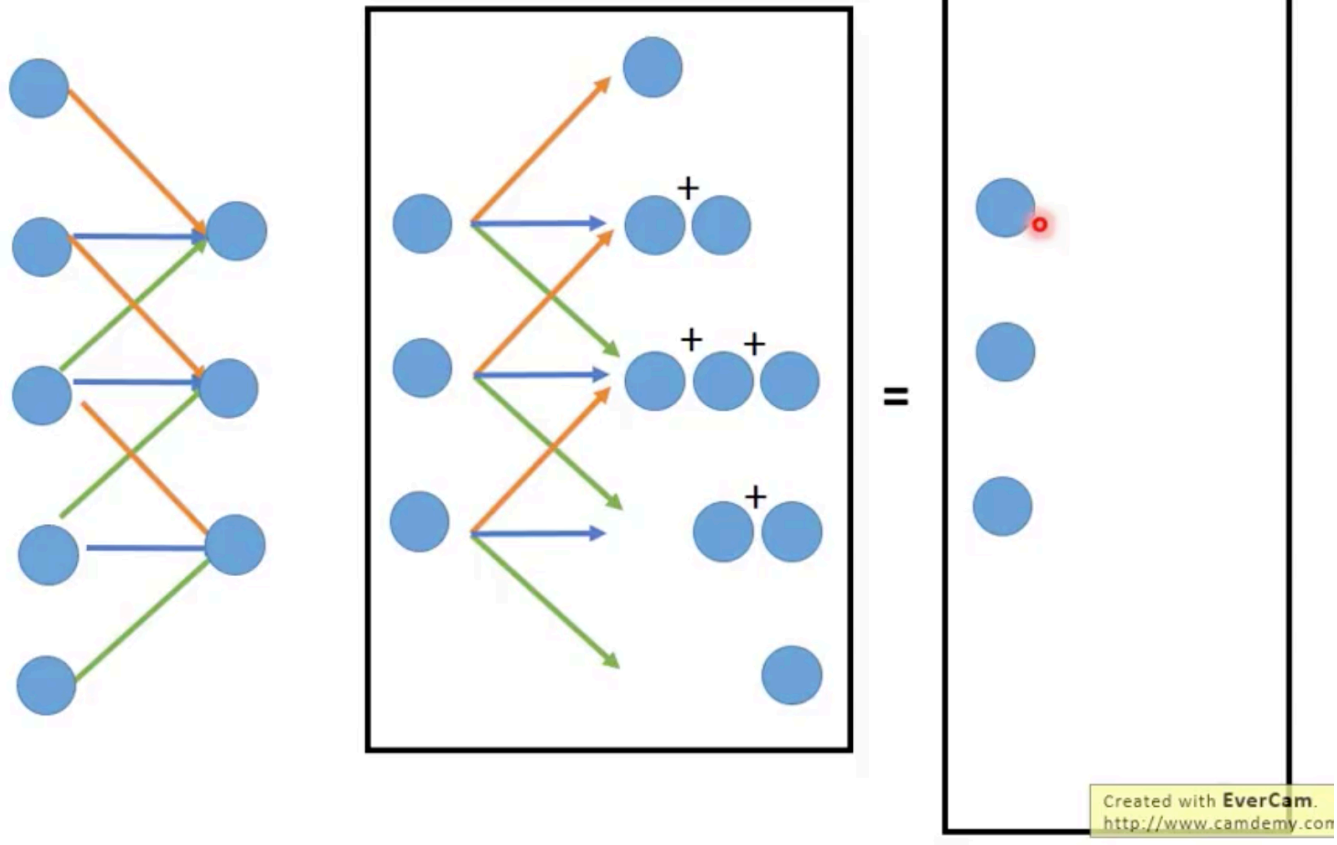
- Deconvolution



Actually, deconvolution is convolution.

CNN

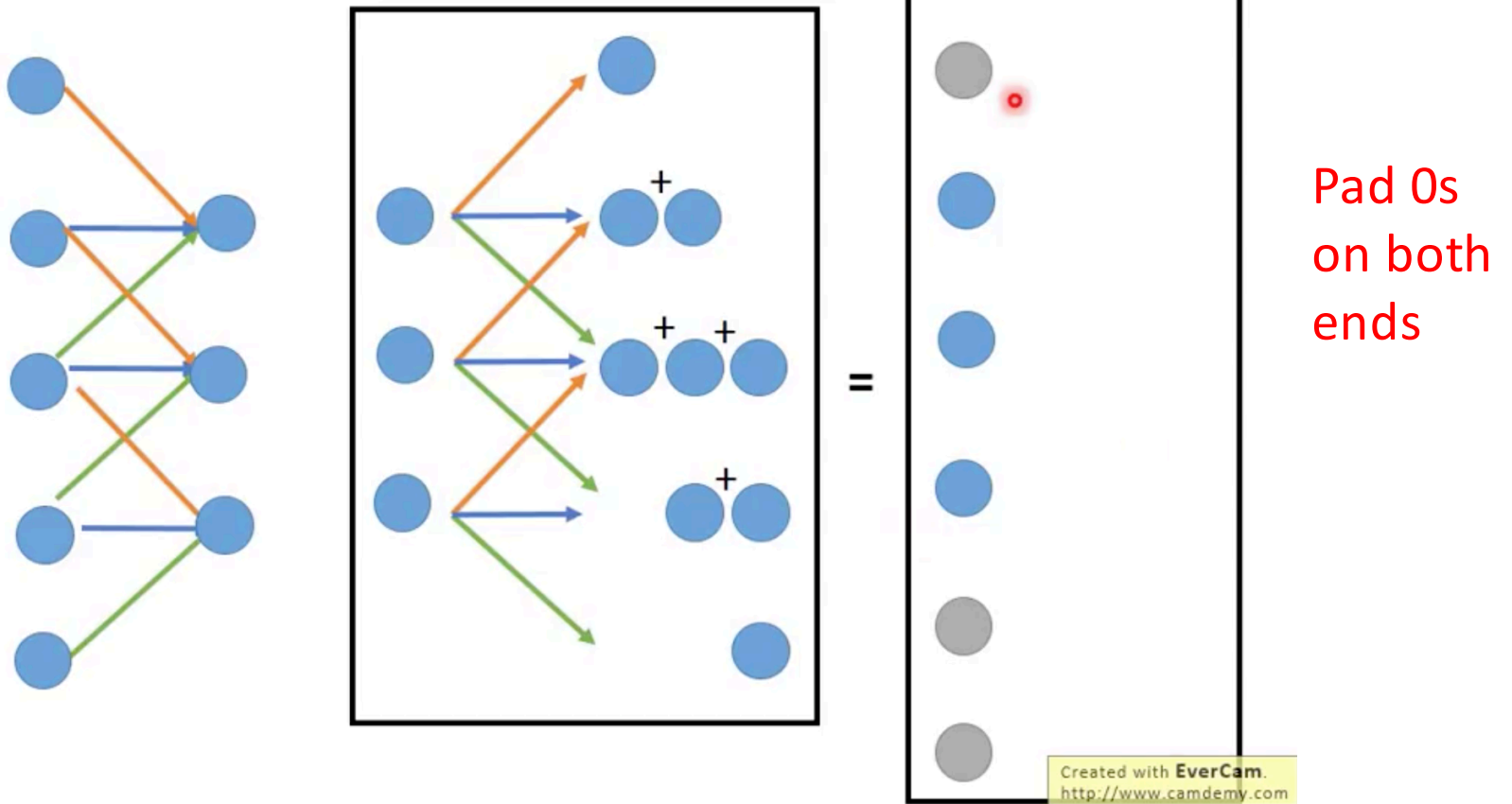
- Deconvolution



CNN

- Deconvolution

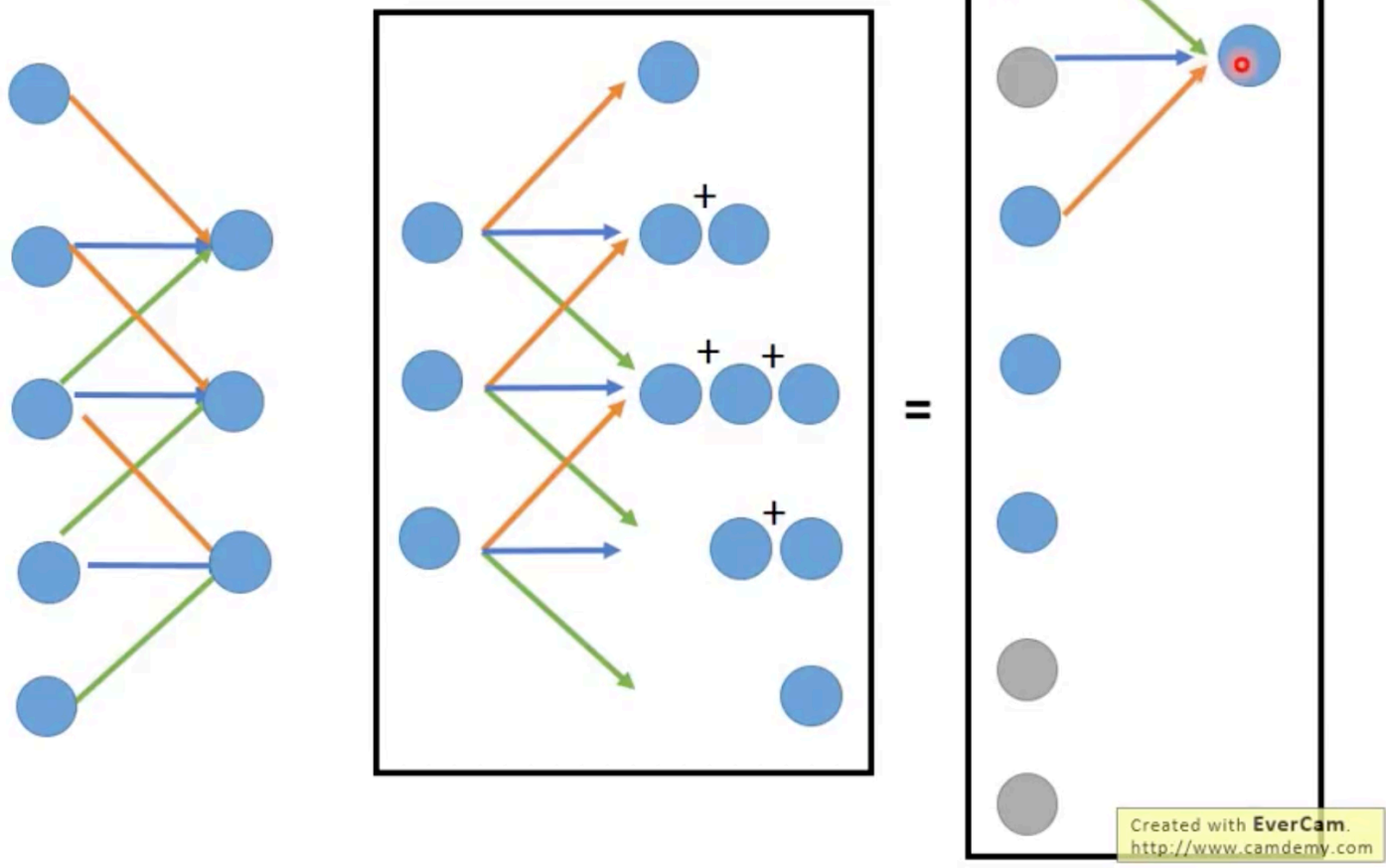
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Actually, deconvolution is convolution.

CNN

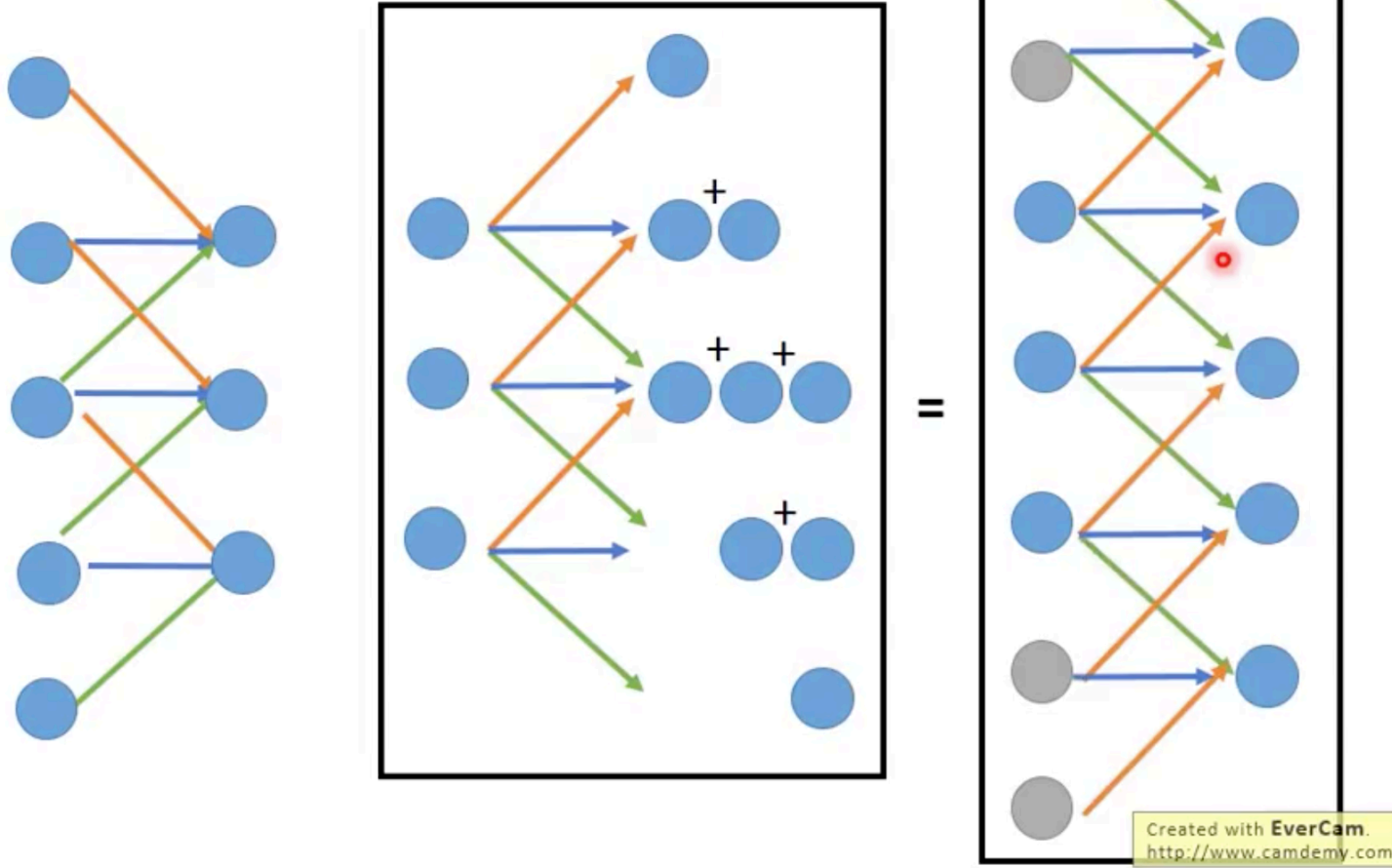
- Deconvolution

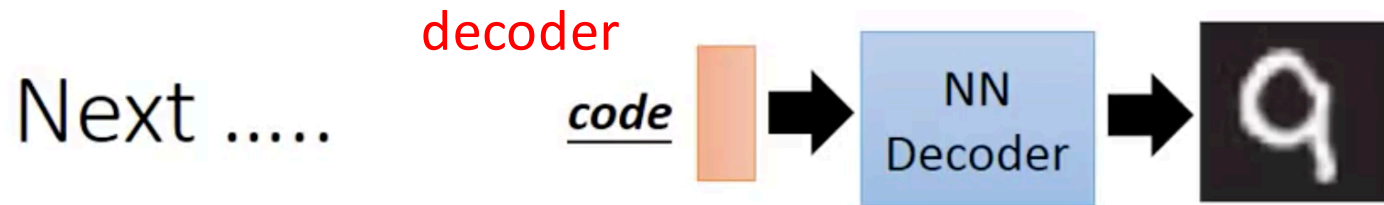


Actually, deconvolution is convolution.

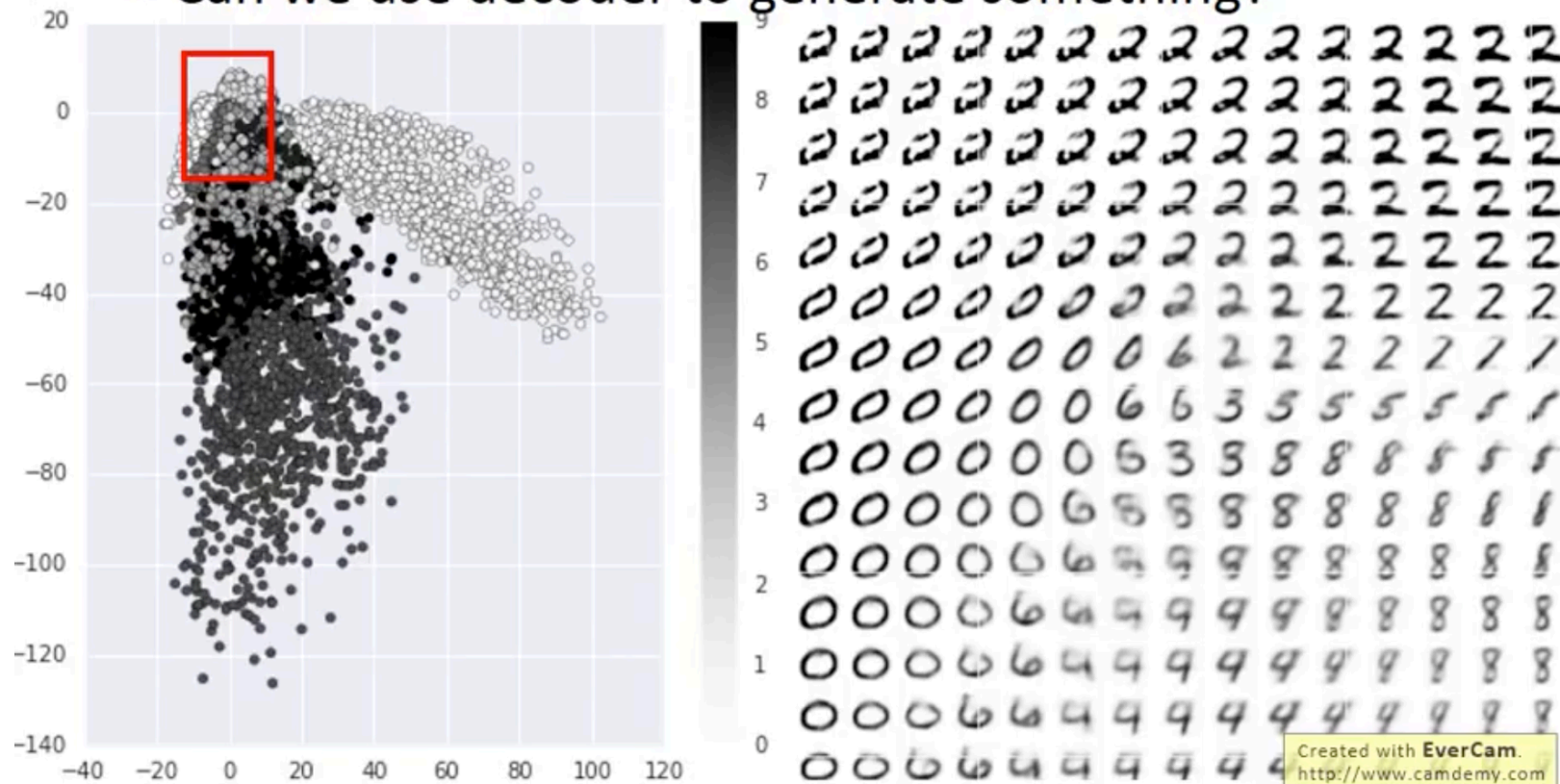
CNN

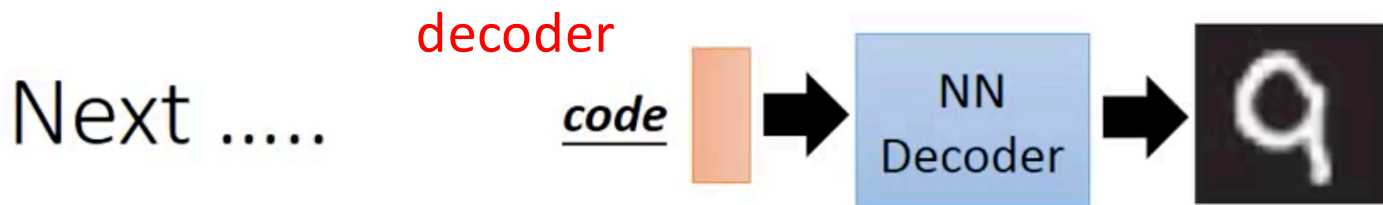
- Deconvolution





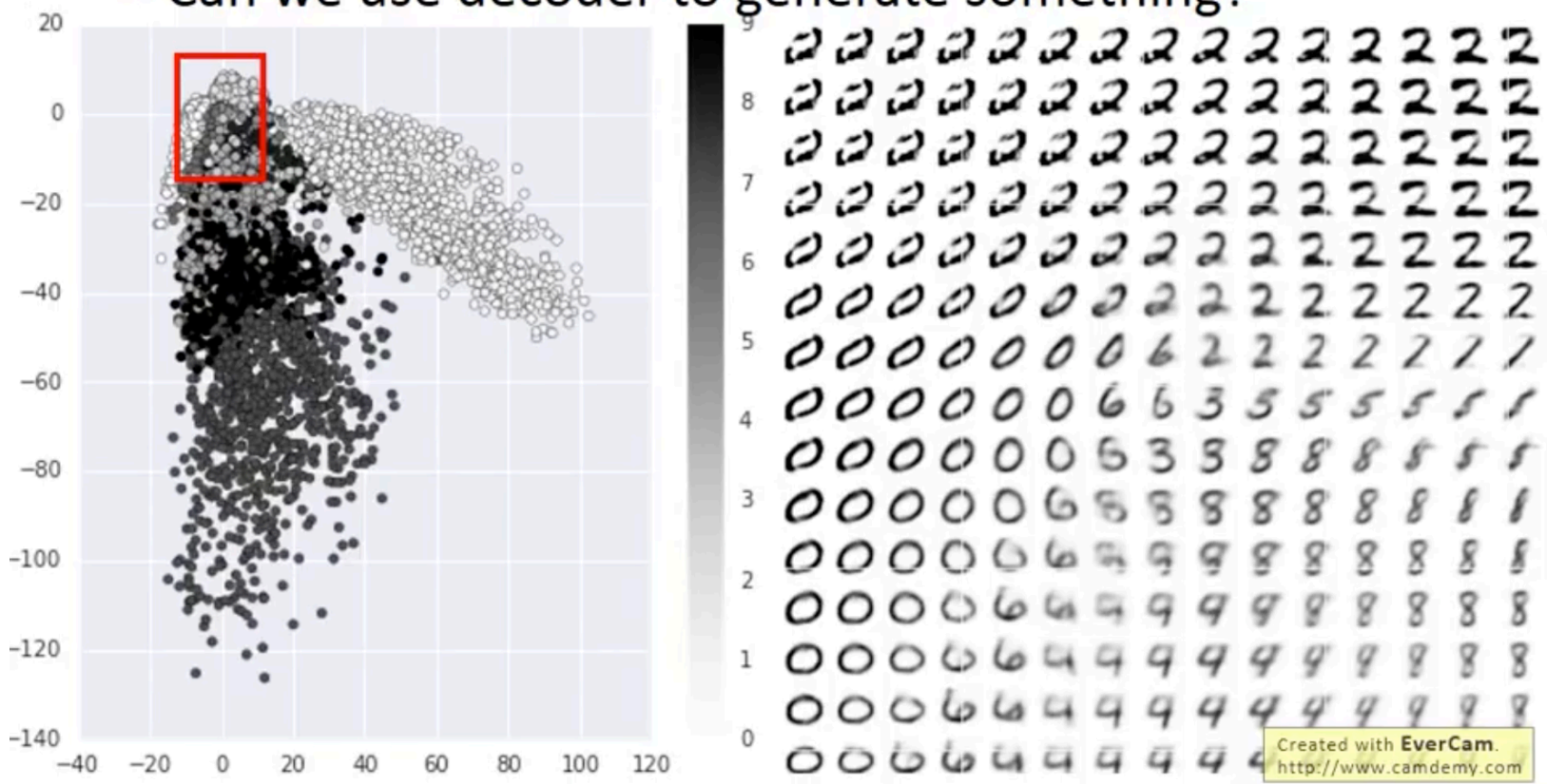
- Can we use decoder to generate something?

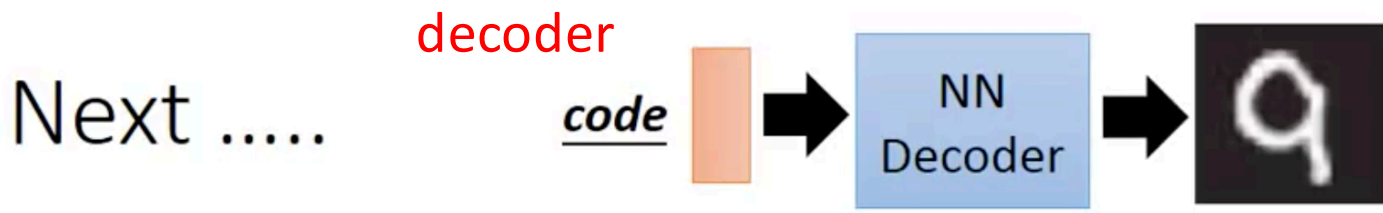




MNIST Dataset: Encoder compresses the $28 \times 28 = 784$ -dimensional input image to 2-dimensional data.

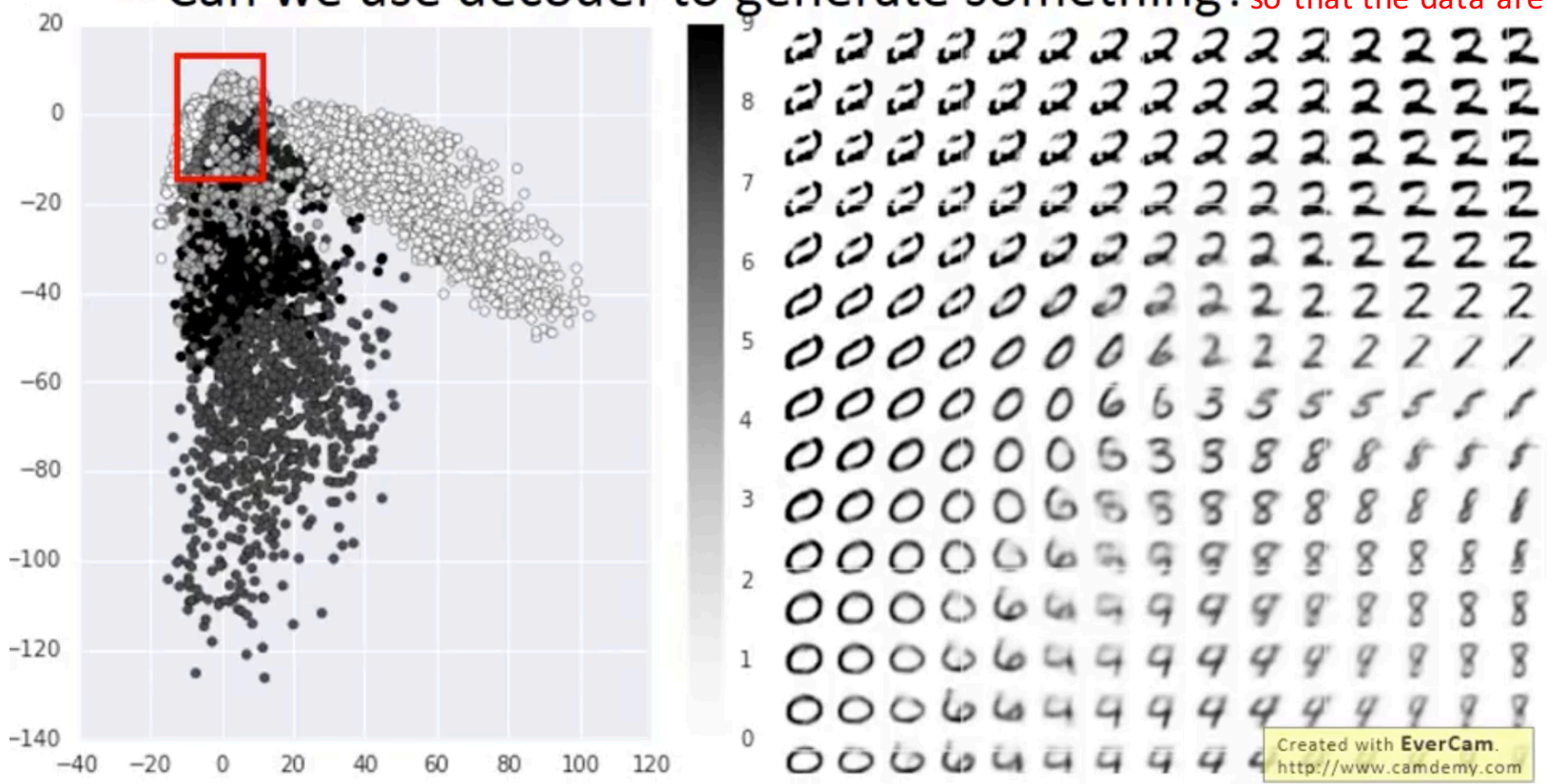
- Can we use decoder to generate something?



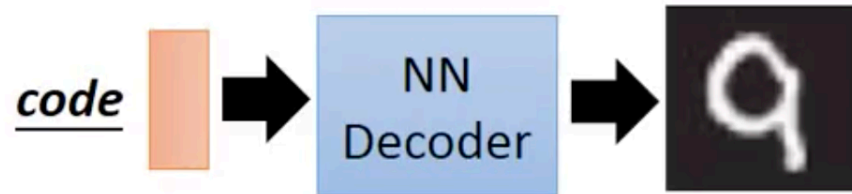


How to know which region to sample, if the code has more than 2 dimensions? We can use L2 regularization during training,

- Can we use decoder to generate something? so that the data are all around 0.



Next



- Can we use decoder to generate something?

Auto-encoder
trained with
L2 regularization

