



# Statistical Methods in AI (CSE/ECE 471)

Representation Learning (Siamese Network, Autoencoders)



Ravi Kiran ([ravi.kiran@iiit.ac.in](mailto:ravi.kiran@iiit.ac.in))

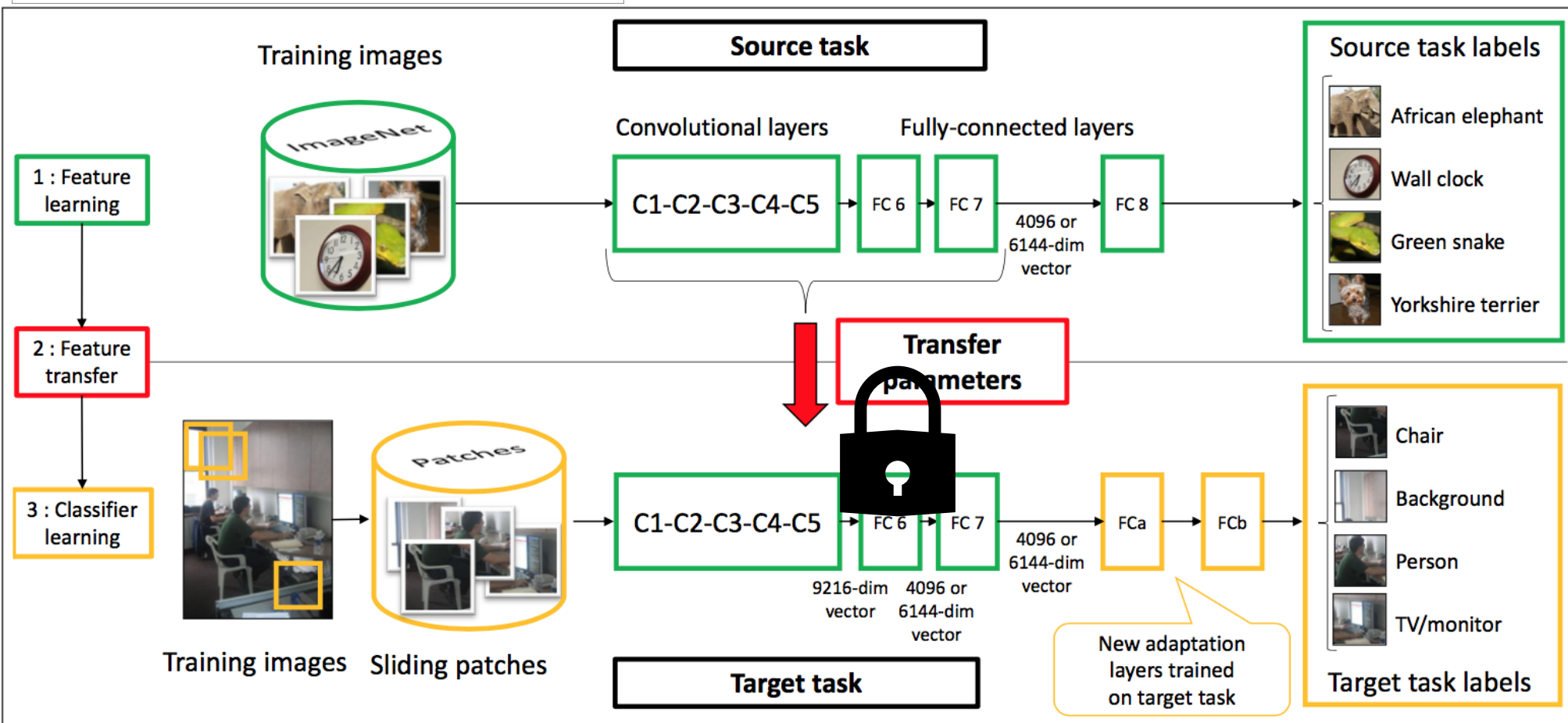
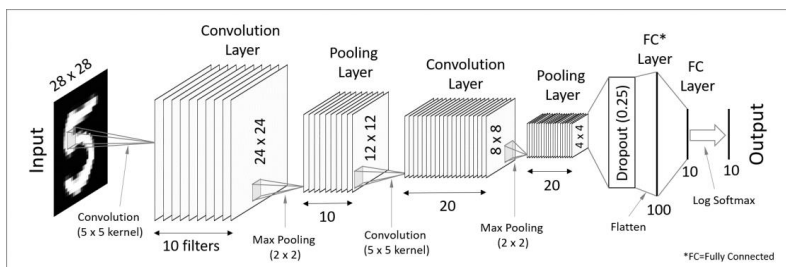
Vineet Gandhi ([v.gandhi@iiit.ac.in](mailto:v.gandhi@iiit.ac.in))



Center for Visual Information Technology (CVIT)  
IIIT Hyderabad

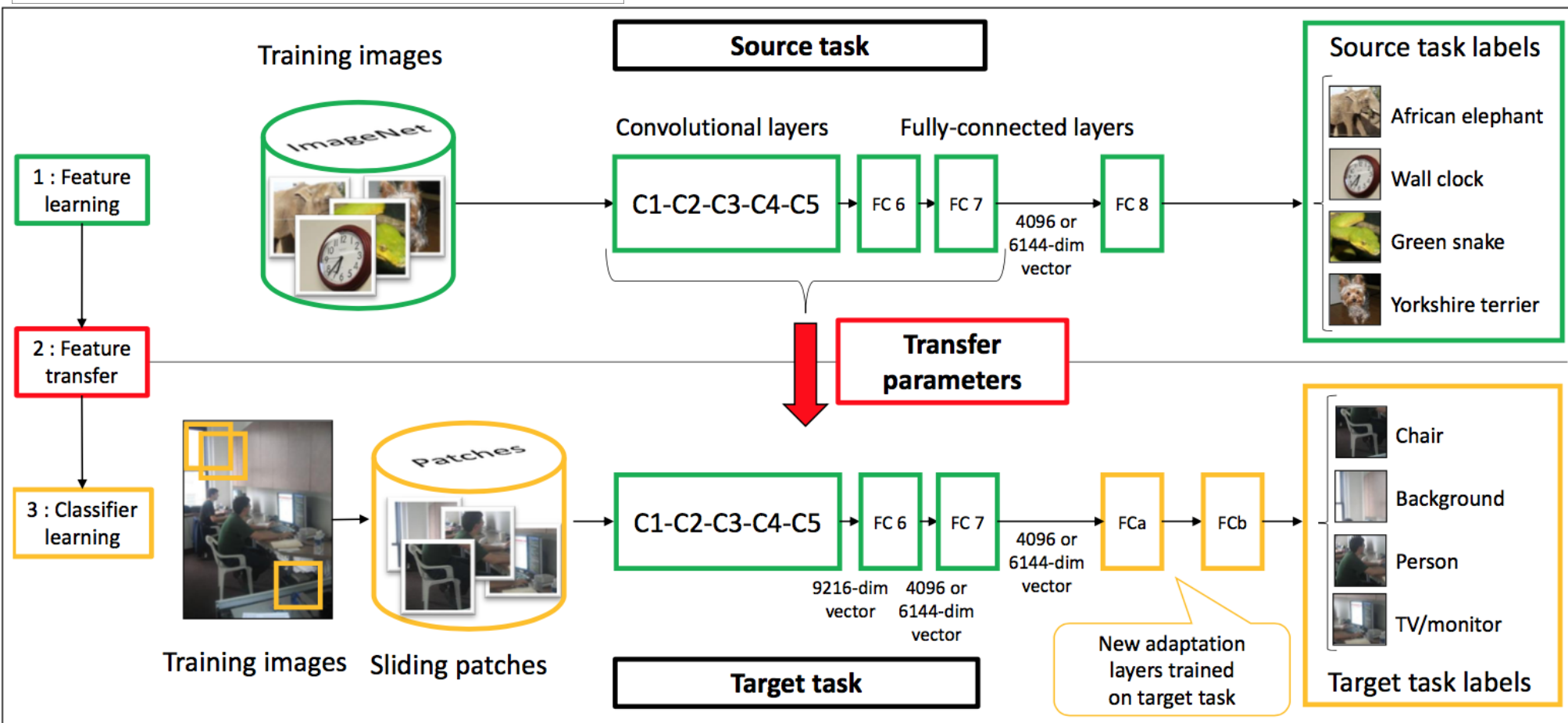
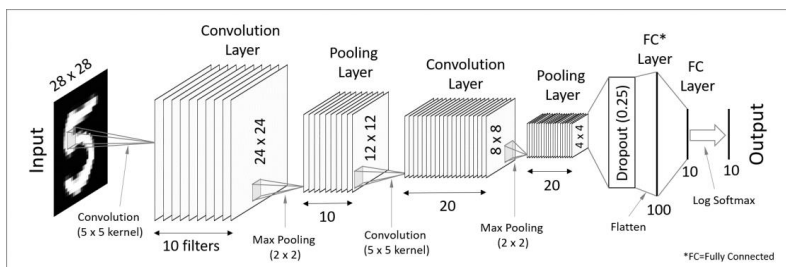


# Transfer Learning : Approach-1



- Learn only weights for newly added layers.
- Ideal when 'new domain' data is small in quantity

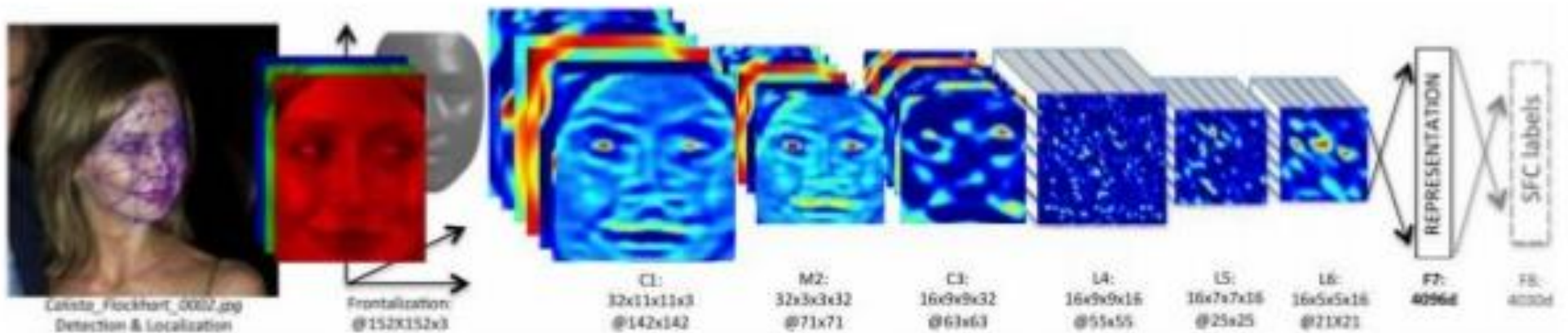
# Transfer Learning : Approach-2



- LR for new layer weights =  $10 * \text{source\_lr}$  (for bias,  $20 * \text{source\_lr}$ )
- Ideal when 'new domain' data is reasonably large or domain shift is significant

# Classification

Face Identification/Recognition (1:N matching)

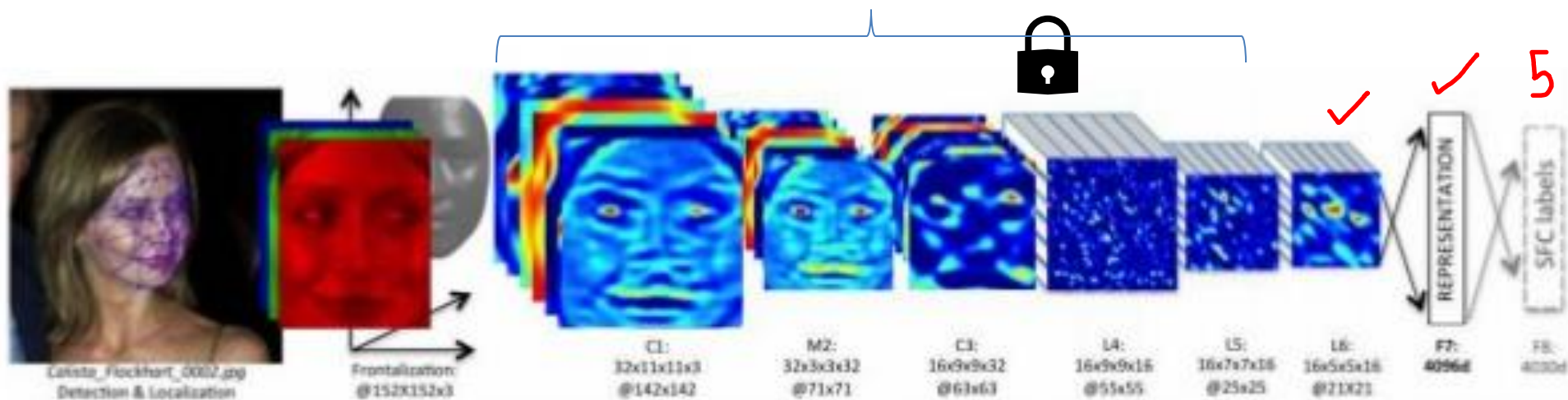


How to reuse DeepFace (trained on celebrities) for another face dataset ?

# Classification

## Classification

### Face Identification/Recognition (1:N matching)



How to reuse DeepFace (trained on celebrities) for another face dataset ?

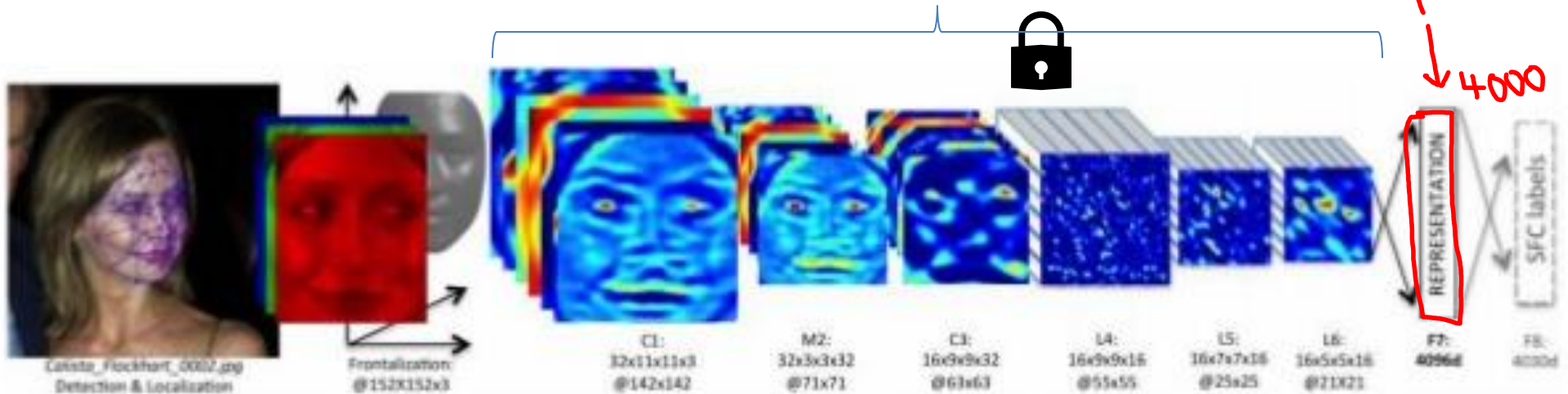
Ans: Fine-tuning



# No-finetuning Classification

Classification

Face Identification/Recognition (1:N matching)



How to reuse DeepFace (trained on celebrities) for another face dataset (without any training)?  
 Ans: Use CNN as feature extractor. k-NN on feature representations

# Verification

Face Authentication/Verification (1:1 matching)

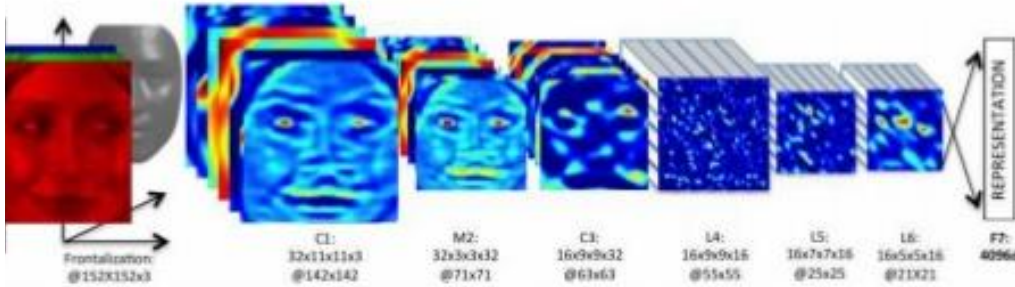
g ✓



d ✓

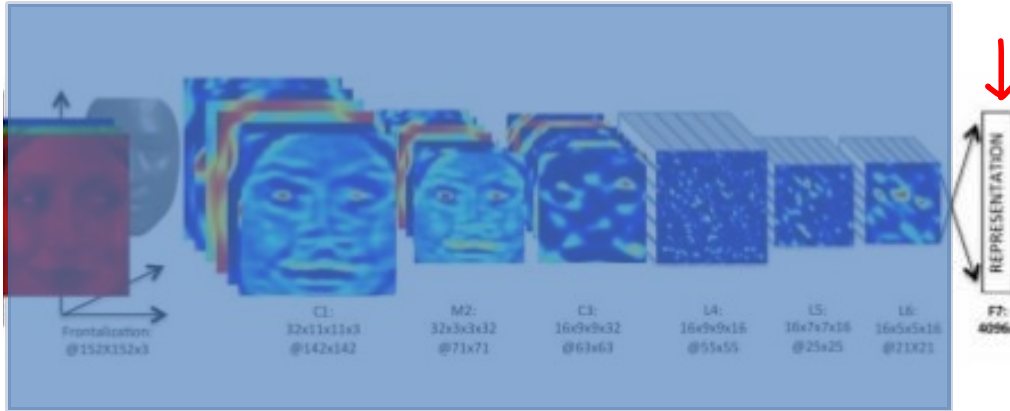


# Feature Extraction





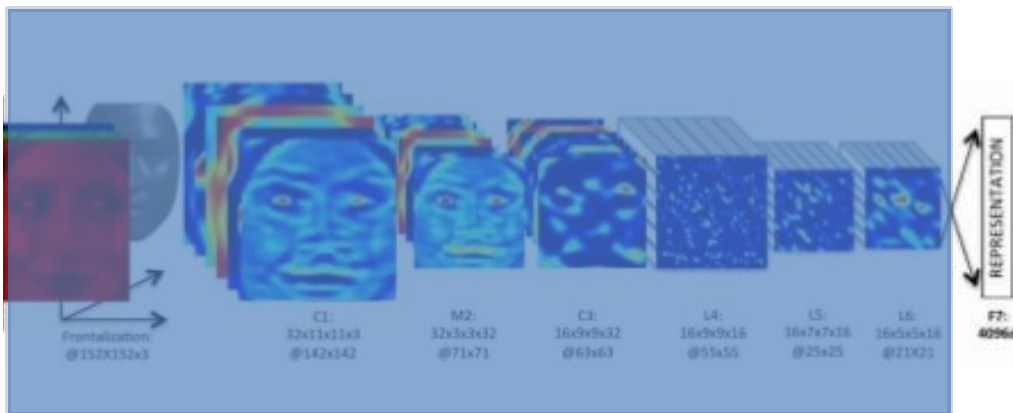
# Feature Extraction



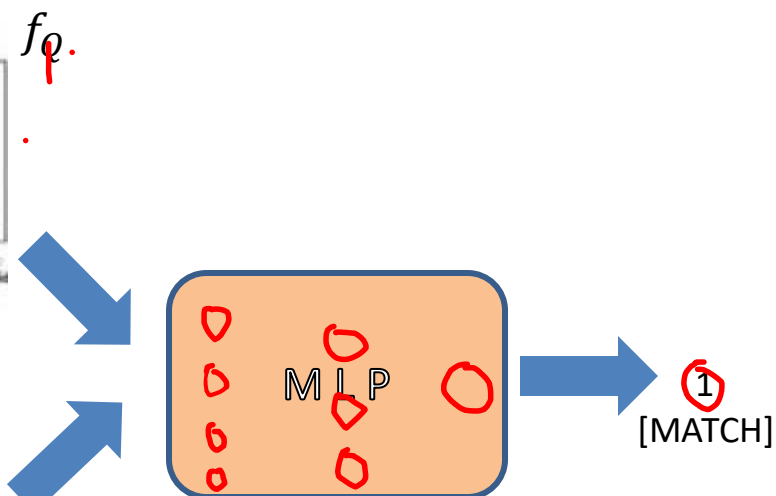
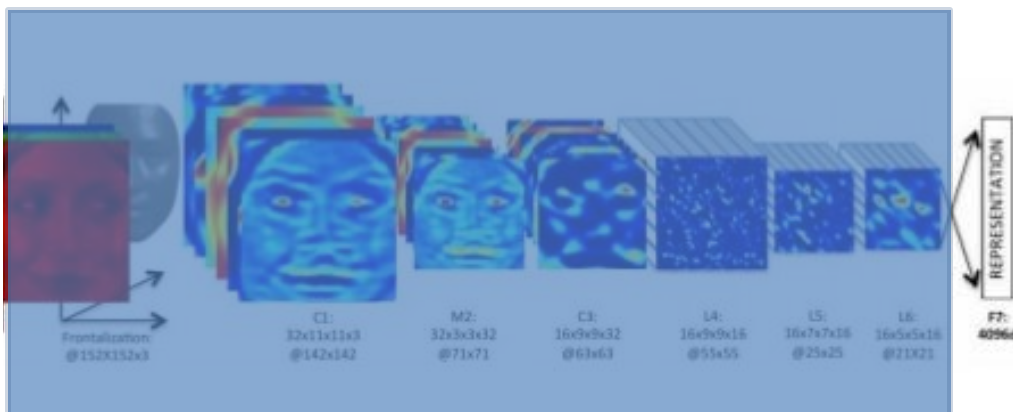
# Verification: Approach - 1



DB image



DB image



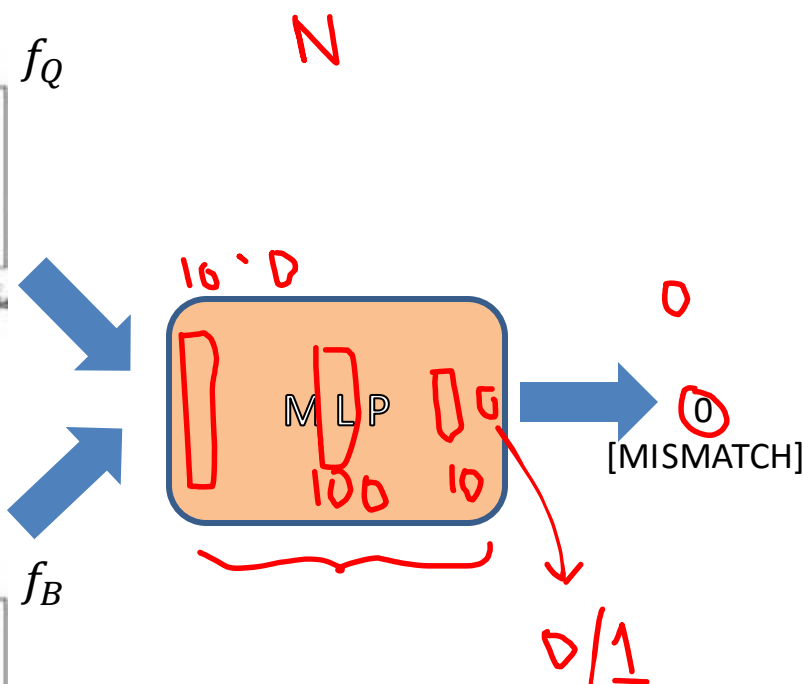
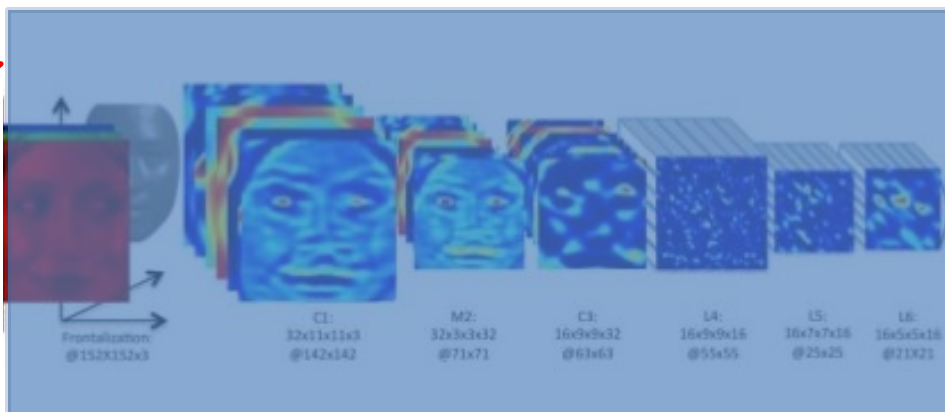
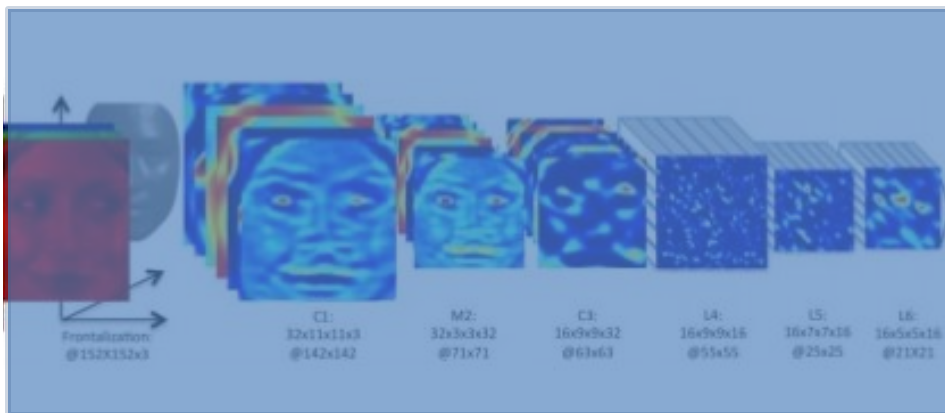
# Verification: Approach - 1



~~DB image~~



DB image

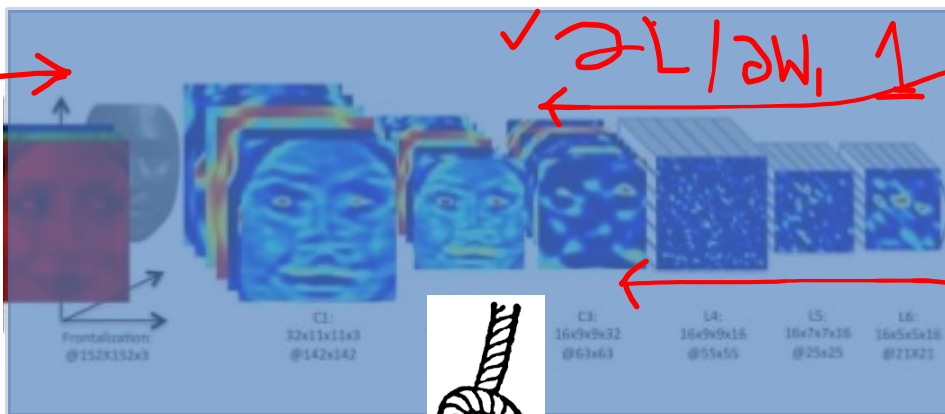




# Verification: Approach – 1B



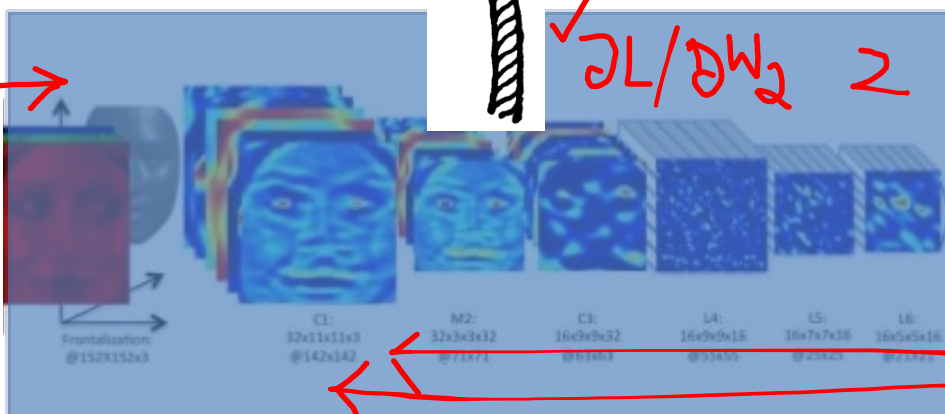
DB-image



Tied weights

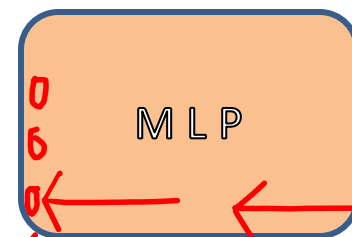


DB image



$f_Q$

$f_B$



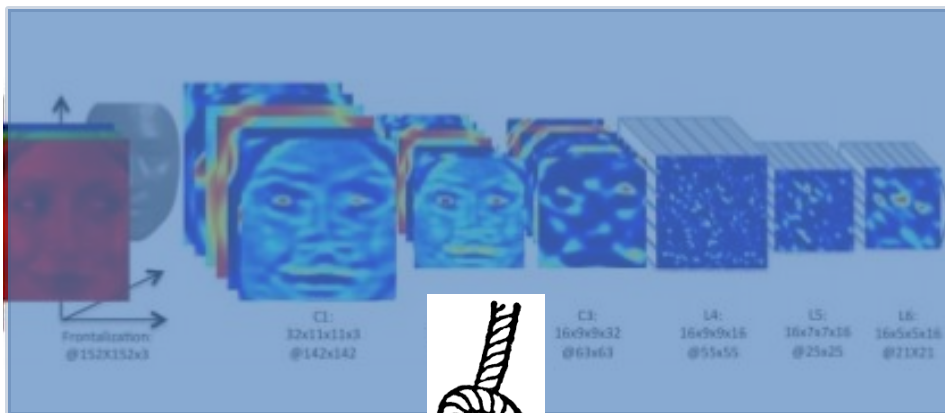
0  
[MISMATCH]

$$W = \frac{G_1 + G_2}{2}$$

# Verification: Approach – 1C



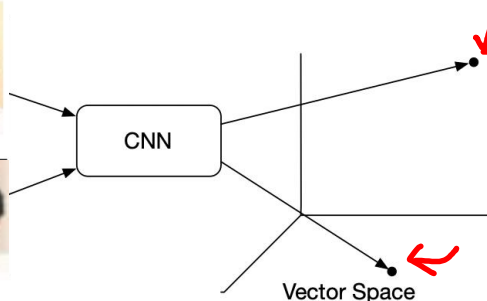
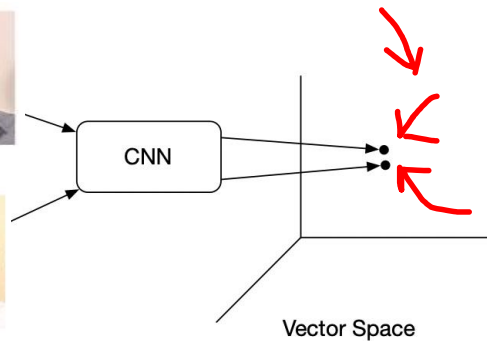
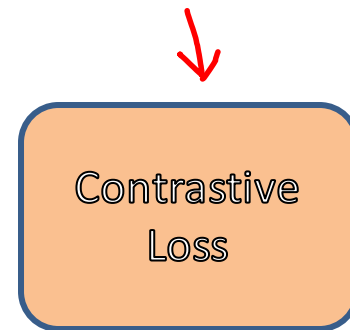
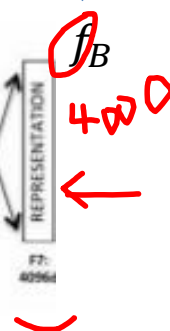
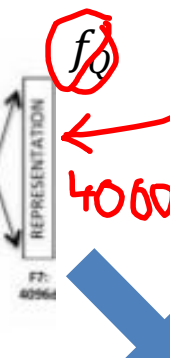
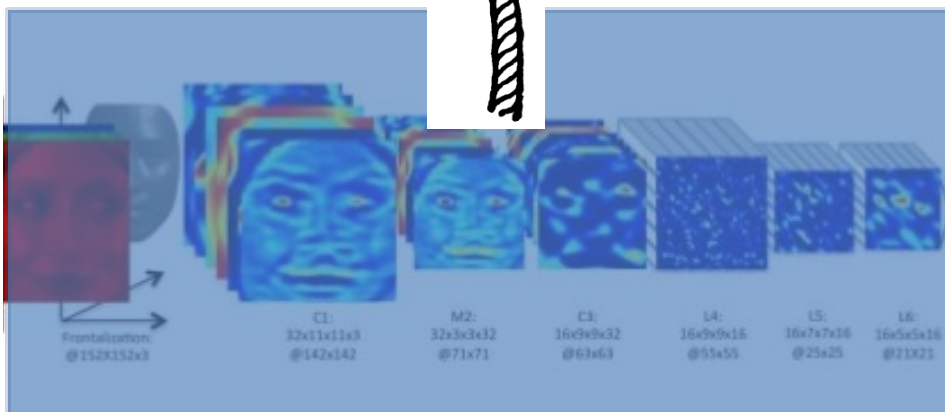
DB-image



Tied weights



DB image



Contrastive Loss:

Learn  $f_Q, f_B$  such that:

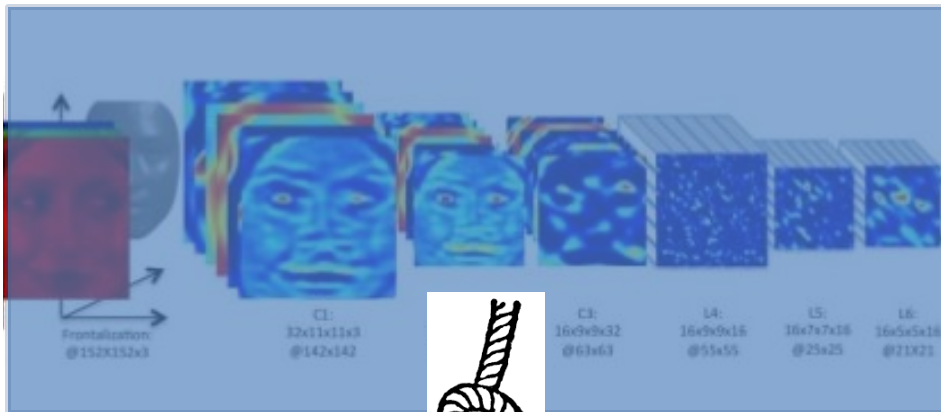
- $\text{dist}(f_Q, f_B)$  is large when ids mismatch
- $\text{dist}(f_Q, f_B)$  is small when ids match



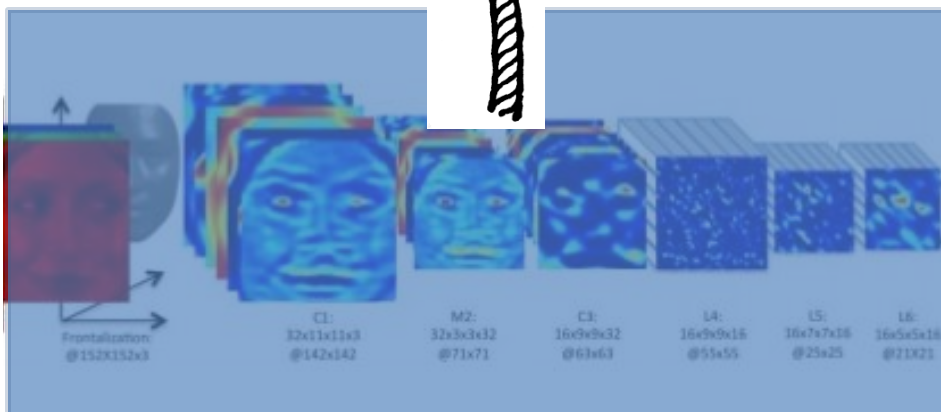
# Verification: Approach – 1C



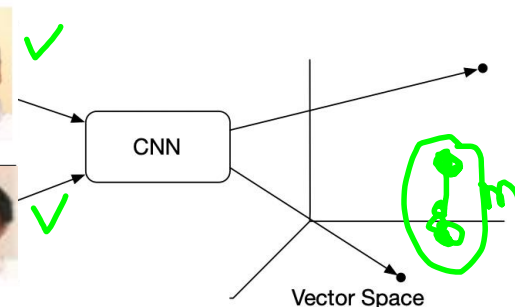
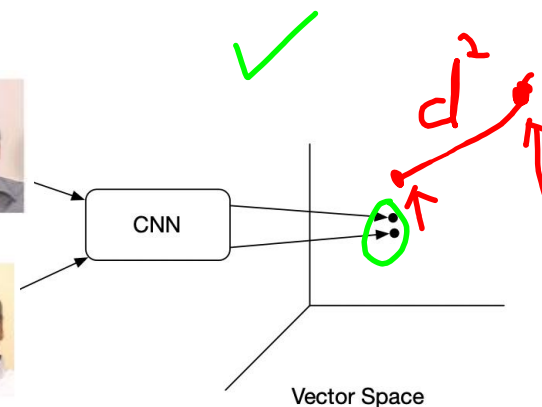
Query



DB image



$f_Q$   $f_B$



Contrastive Loss:  $y d^2 + (1 - y) \max(\text{margin} - d, 0)^2$

Learn  $f_Q, f_B$  such that:

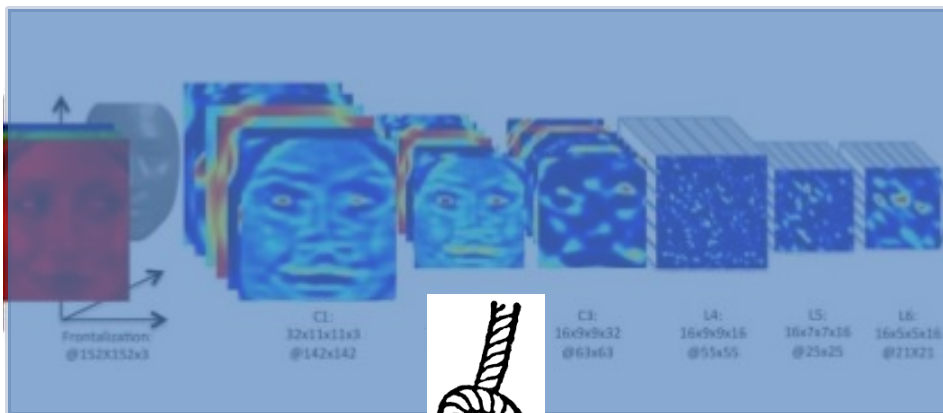
- $d = \text{dist}(f_Q, f_B)$  is large when ids mismatch ( $y=0$ )
- $d = \text{dist}(f_Q, f_B)$  is small when ids match ( $y=1$ )

$d < m$

# Verification: Approach – 1C



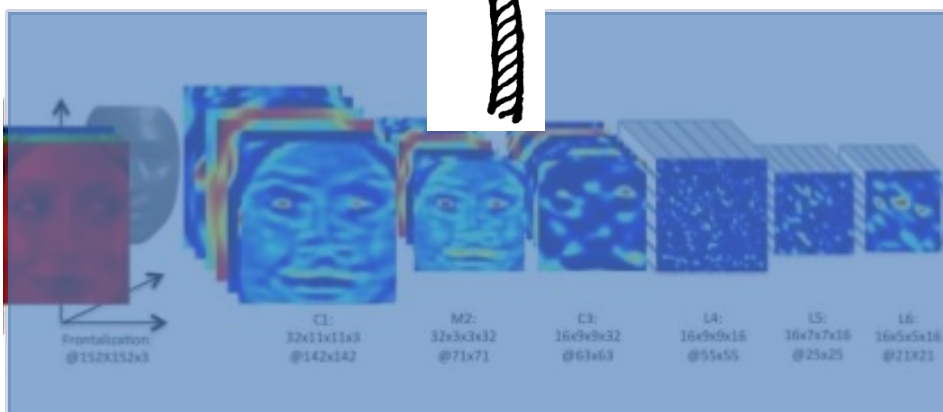
Query



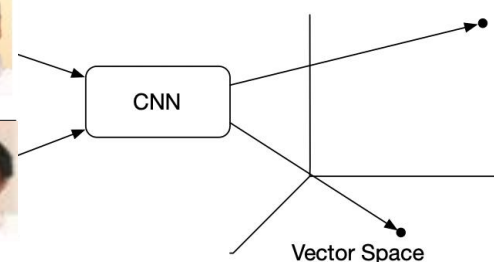
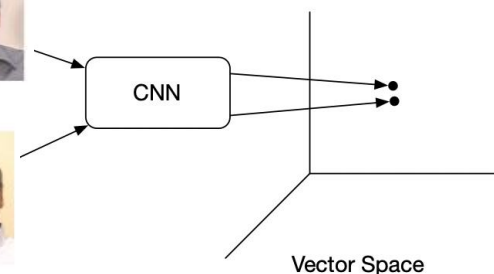
Tied weights



DB image



Learning a similarity function



Contrastive Loss:  $y d^2 + (1 - y) \max(\text{margin} - d, 0)^2$

Learn  $f_Q, f_B$  such that:

- $d = \text{dist}(f_Q, f_B)$  is large when ids mismatch ( $y=0$ )
- $d = \text{dist}(f_Q, f_B)$  is small when ids match ( $y=1$ )

# Verification Approach 2

MATCH (1)



3



DB image



Query

3

MISMATCH (0)



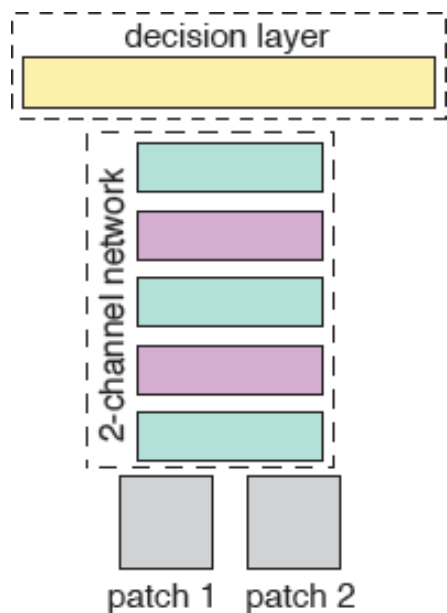
DB image



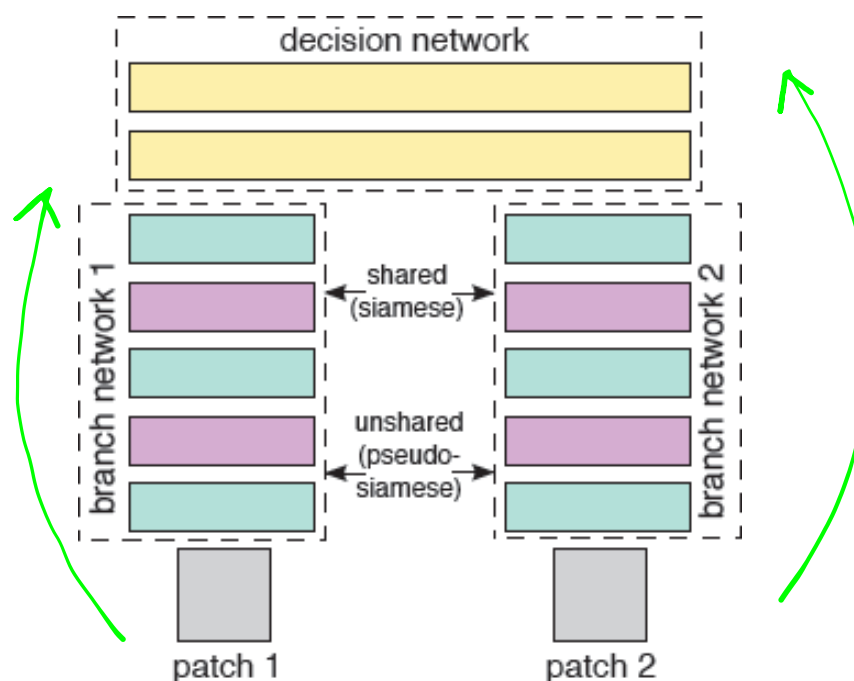
Query

# Popular Architecture Varieties

- No one “architecture” fits all!
- Design largely governed by what performs well empirically on the task at hand.



Inputs are merged right at the onset



Inputs are first embedded independently, then merged.



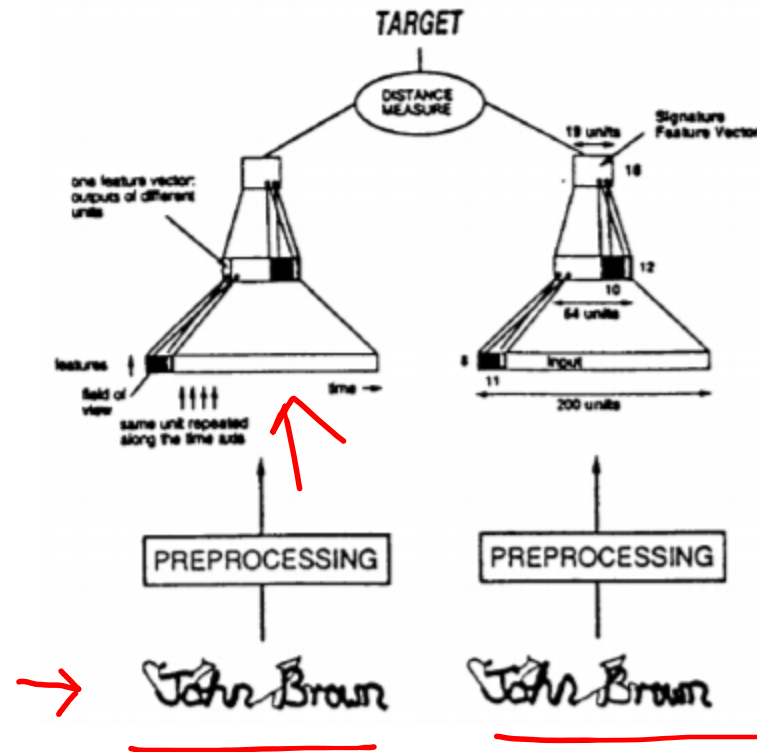
# Siamese Network

## Application in Signature Verification

- The input is 8(feature) x 200(time) units.
- The cosine distance was used, (1 for genuine pairs, -1 for forgery pairs)

$$\cos(f_1, f_2)$$

-1 ← → +1

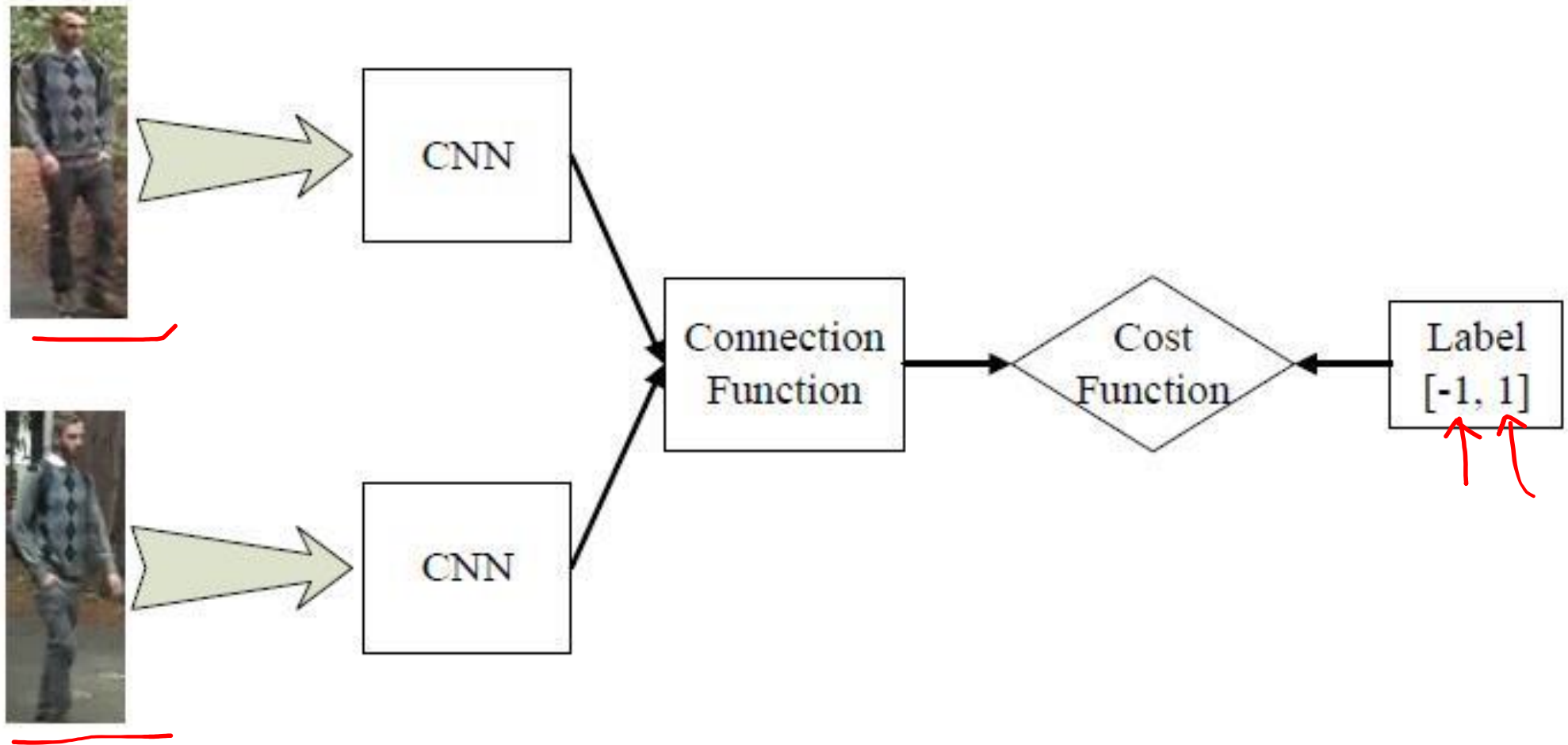


Bromley J, Guyon I, Lecun Y, et al. Signature Verification using a "Siamese" Time Delay Neural Network, NIPS Proc. 1994



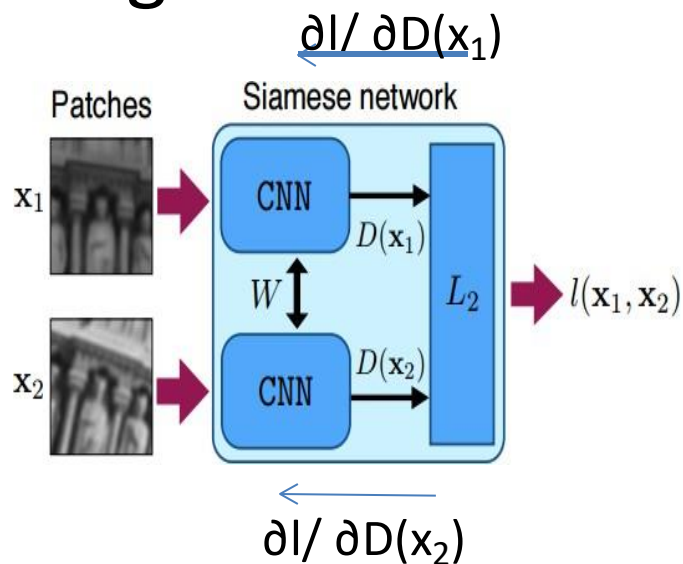


# Siamese Network (Person re-id)



# Siamese CNN – Training

- Update each of the two streams independently and then average the weights.

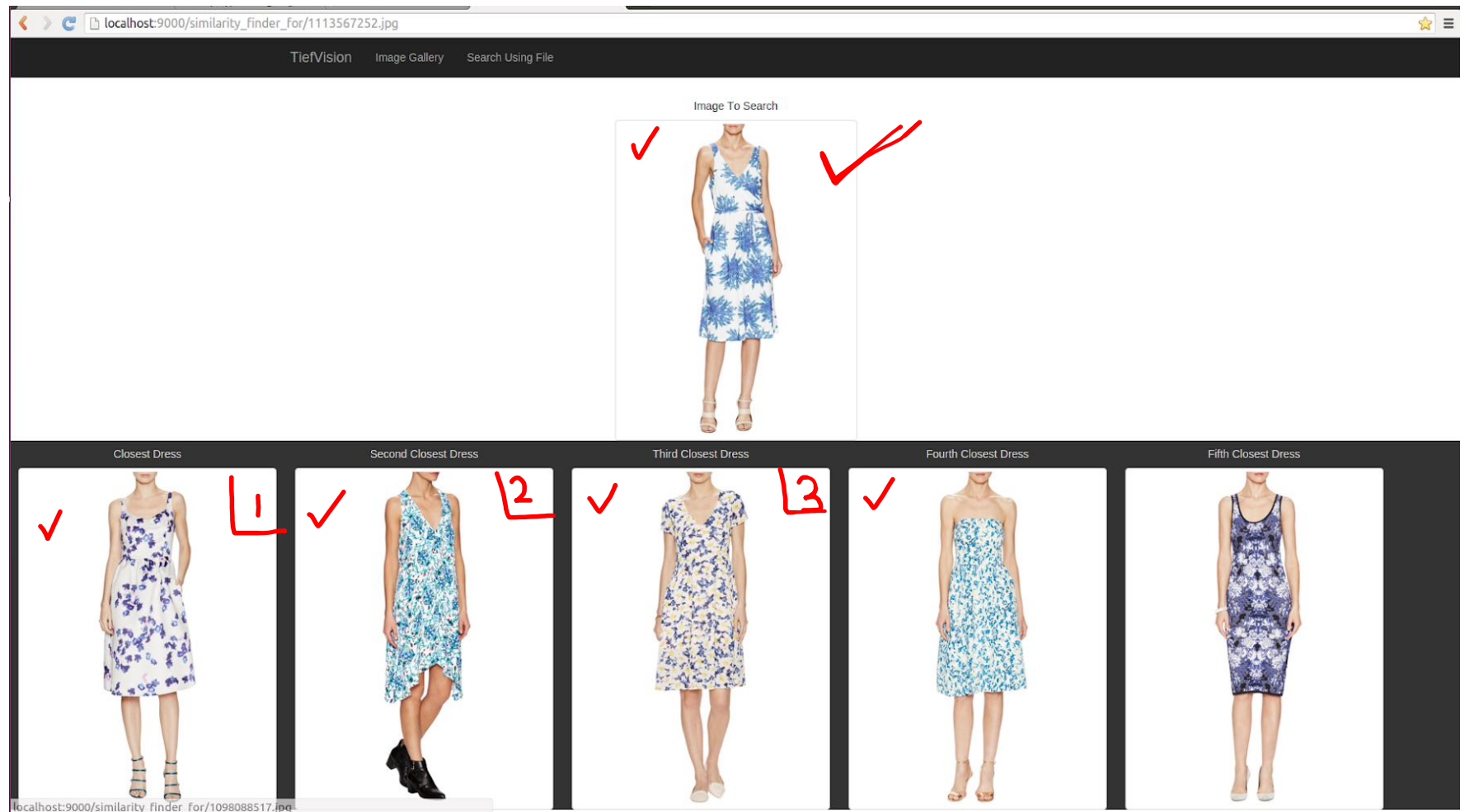




# Applications

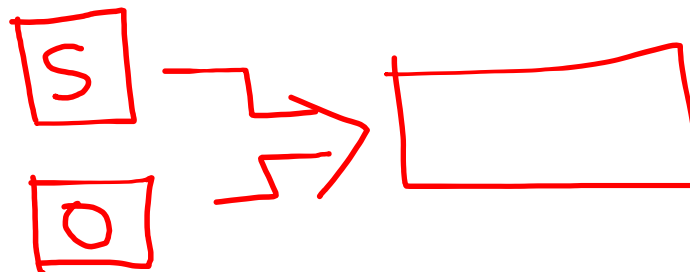
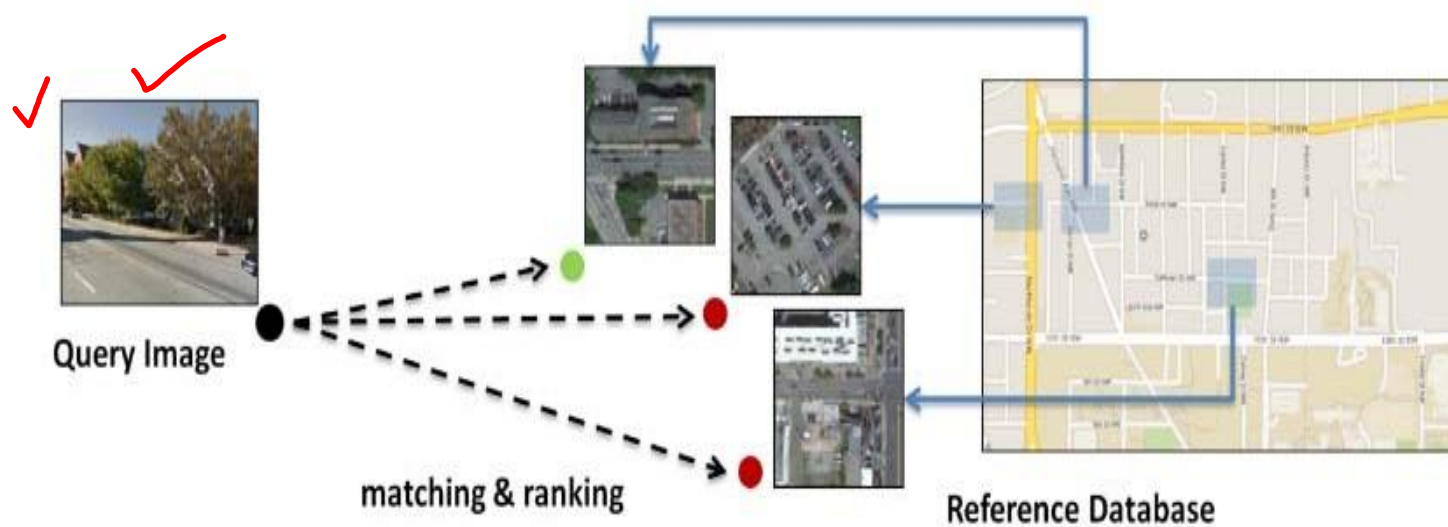
Retrieval

Ranking



<https://github.com/paucarre/tiefvision>

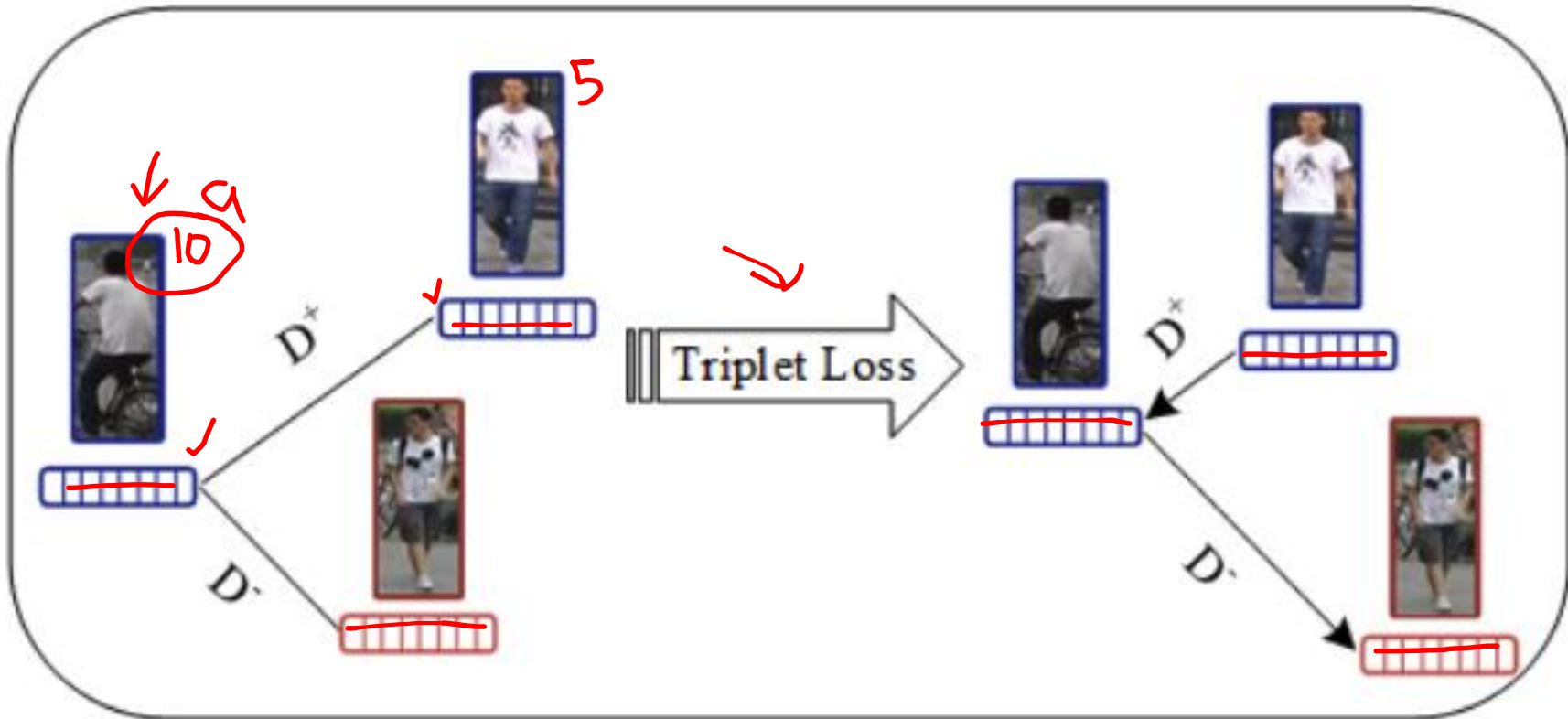
# Street-View to Overhead-View Image Matching



✓ Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

# Many variants exist

- Popular Loss Function – Triplet Loss







---

# Code Reference

<https://medium.com/@prabhnoor0212/siamese-network-keras-31a3a8f37d04>

# Unsupervised Learning:

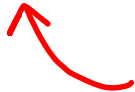
## Deep Auto-encoder



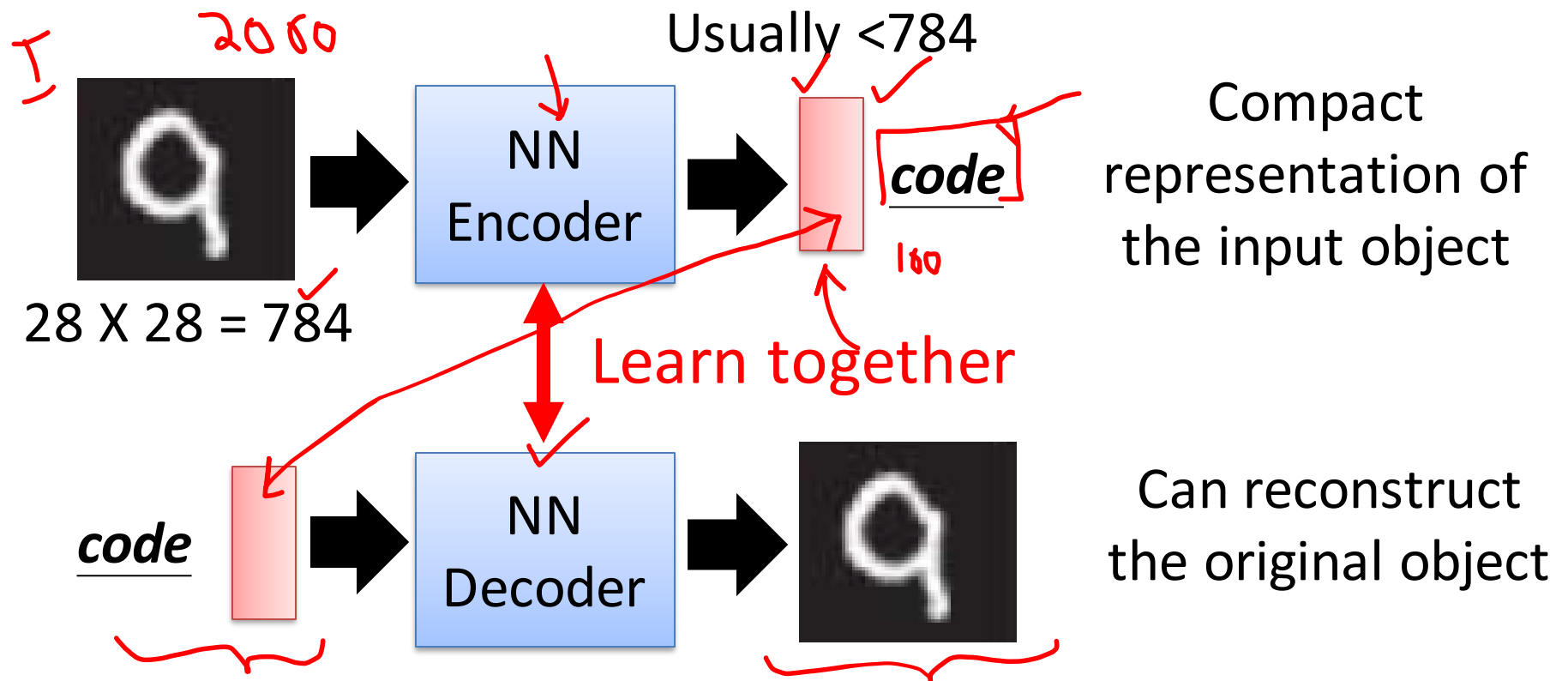
# Unsupervised Learning

“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



# Auto-encoder



# Deep Auto-encoder

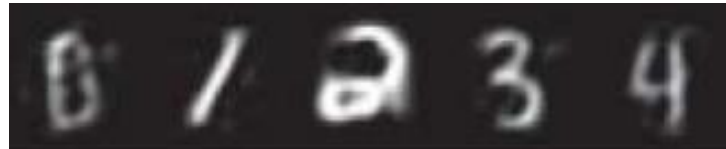


$$d(x, \hat{x})$$

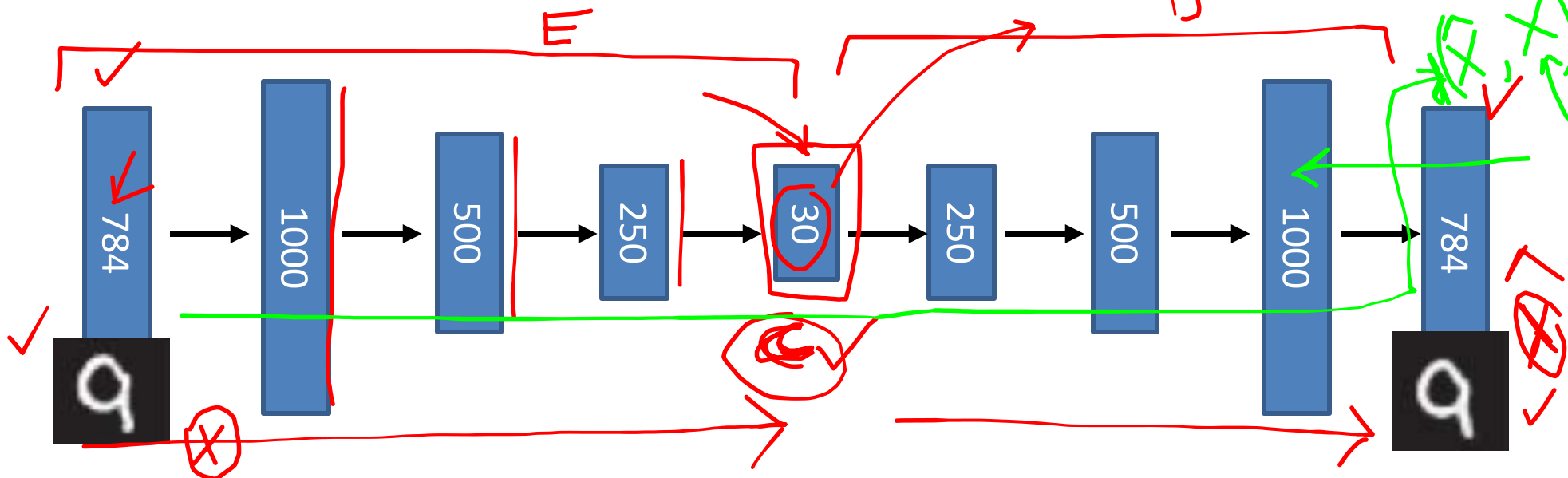
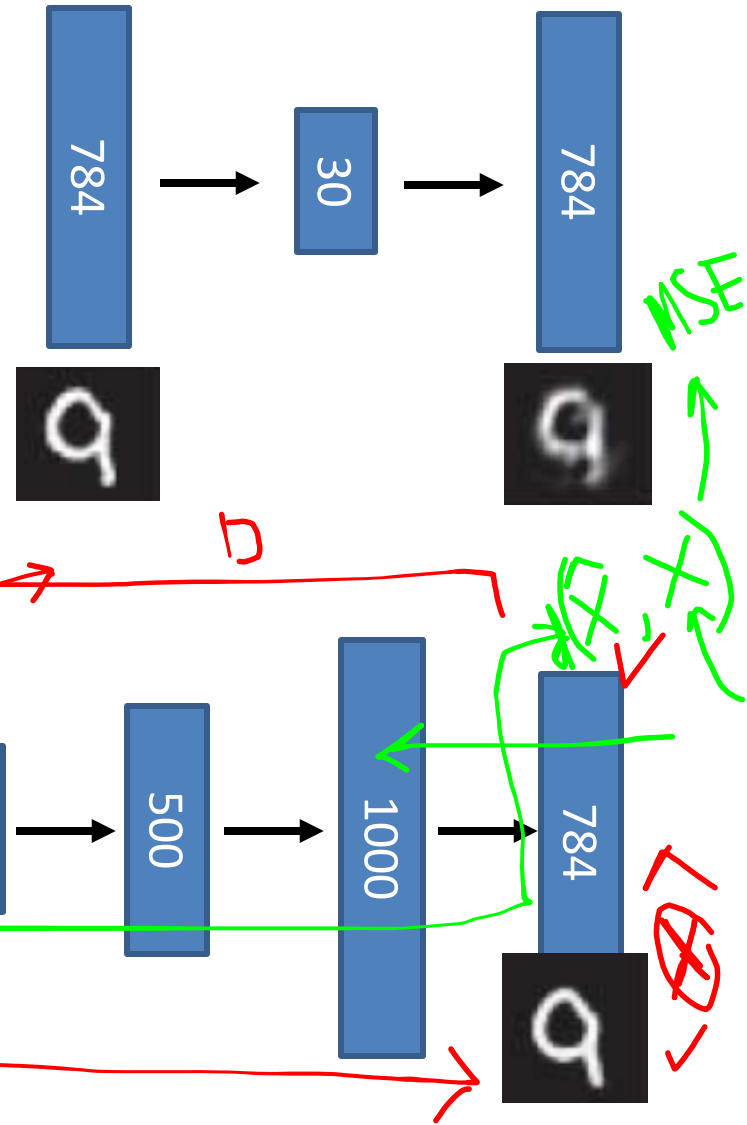
Original Image



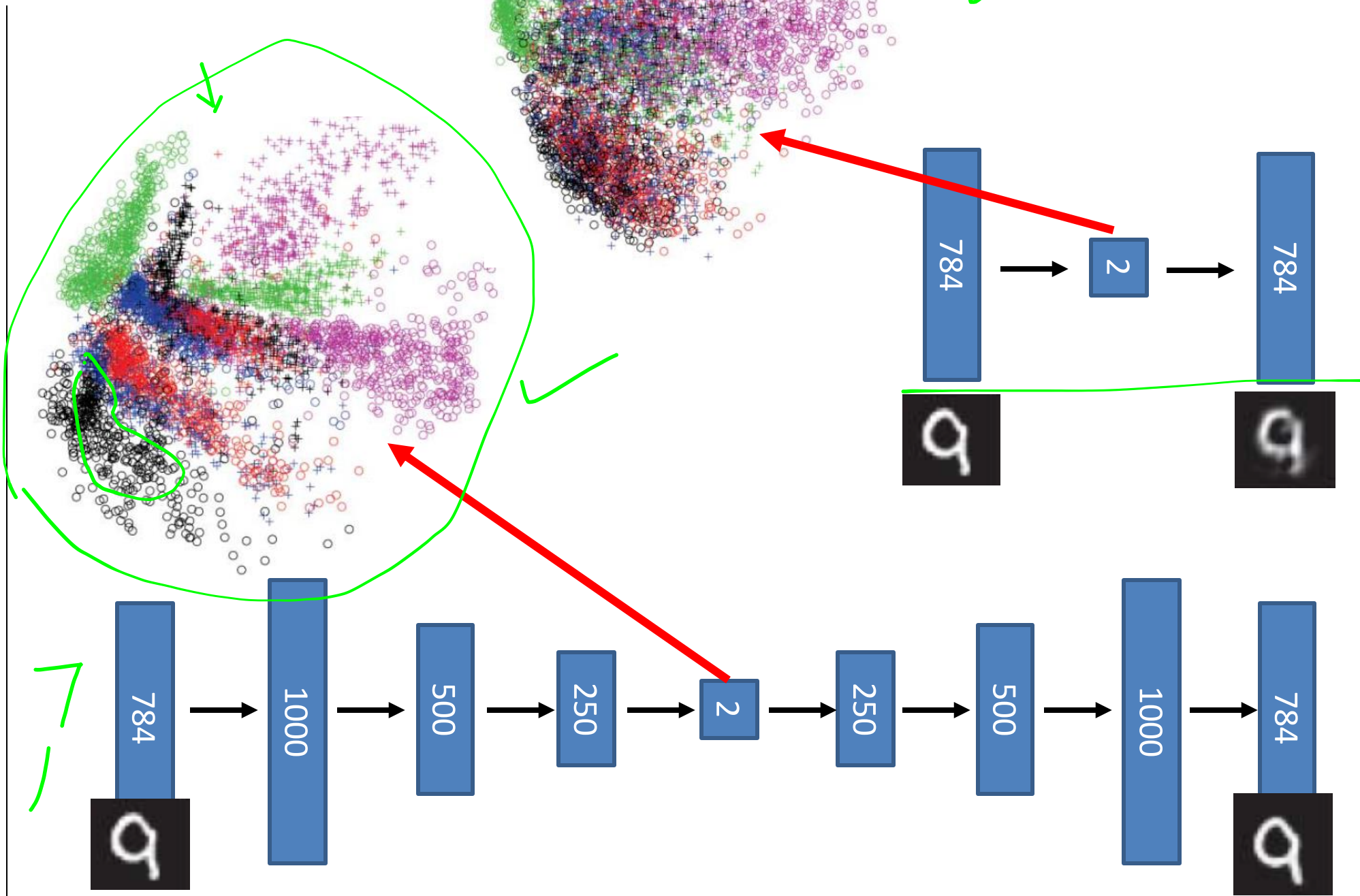
PCA



Deep Auto-encoder

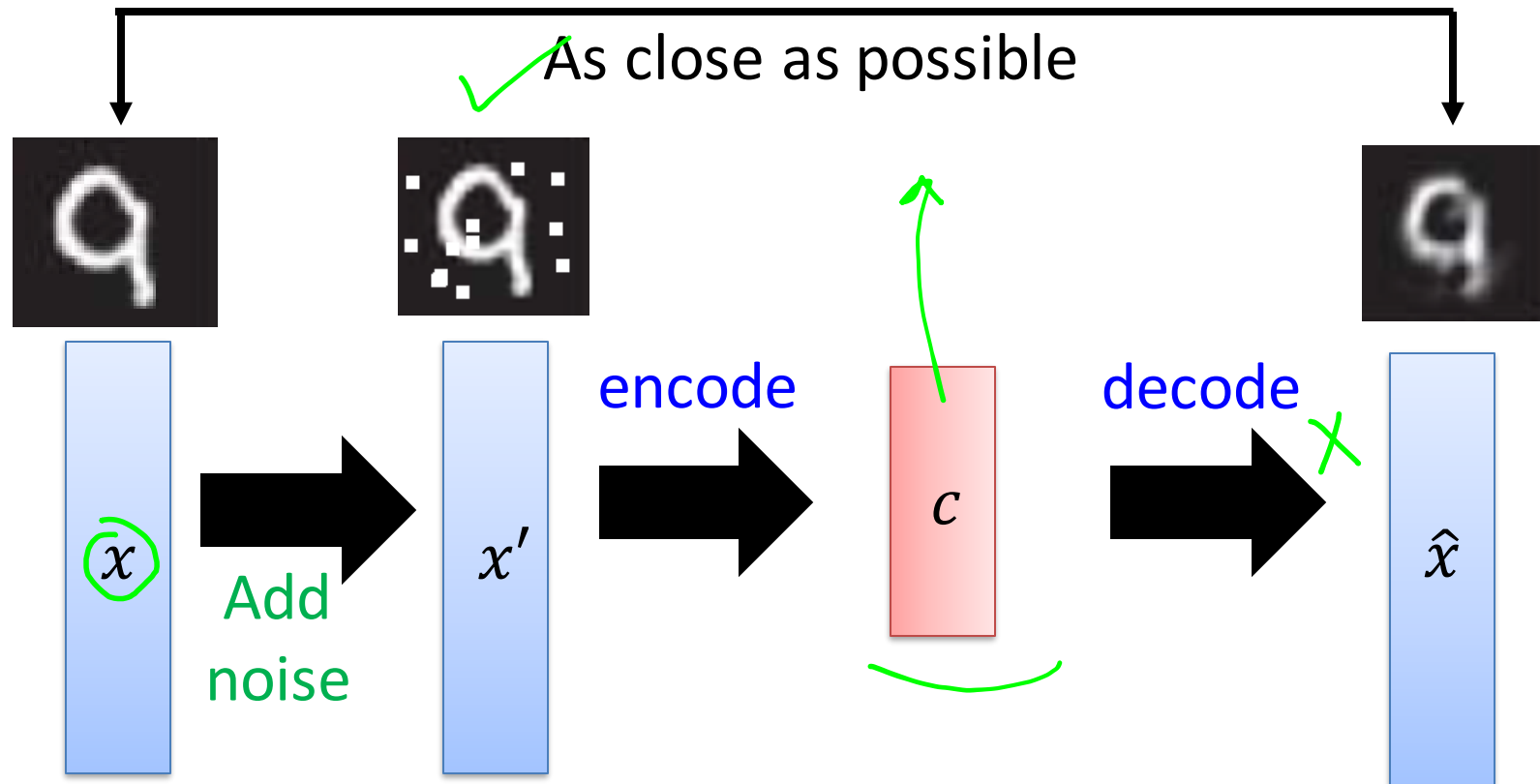






# Auto-encoder

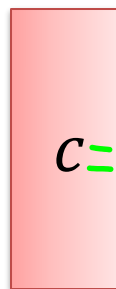
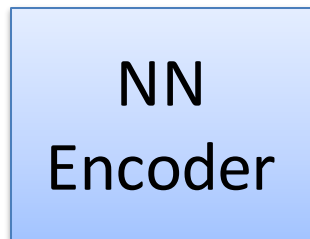
## De-noising auto-encoder



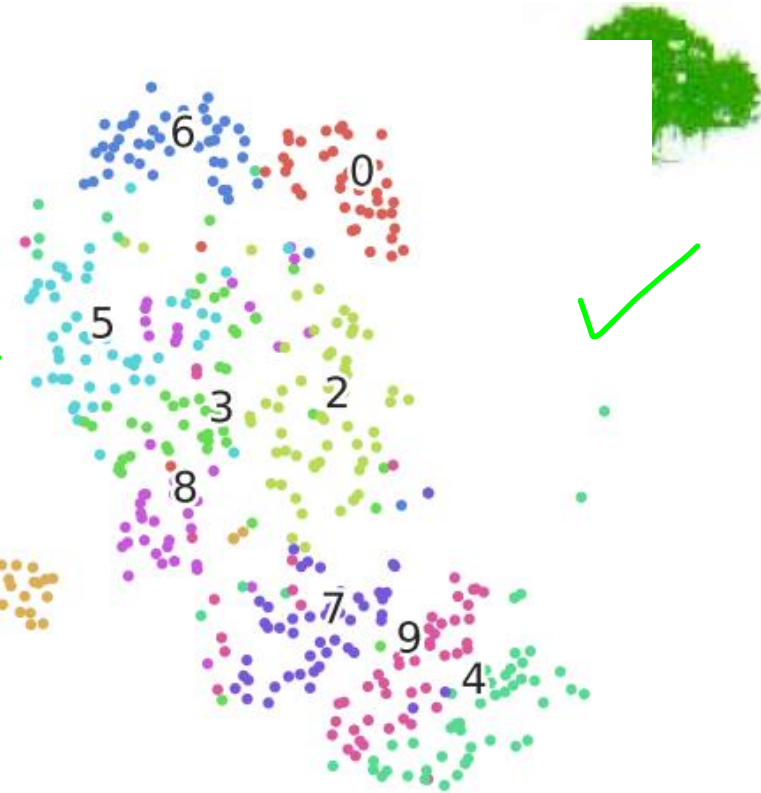
Vincent, Pascal, et al. "Extracting and composing robust features with denoising autoencoders." *ICML*, 2008.



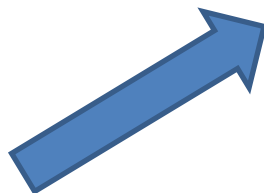
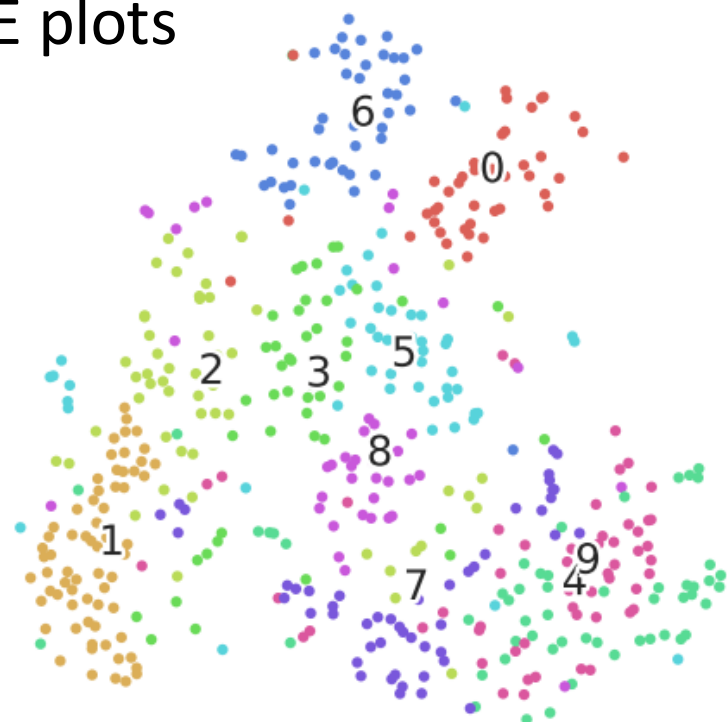
# Deep Auto-encoder - Example



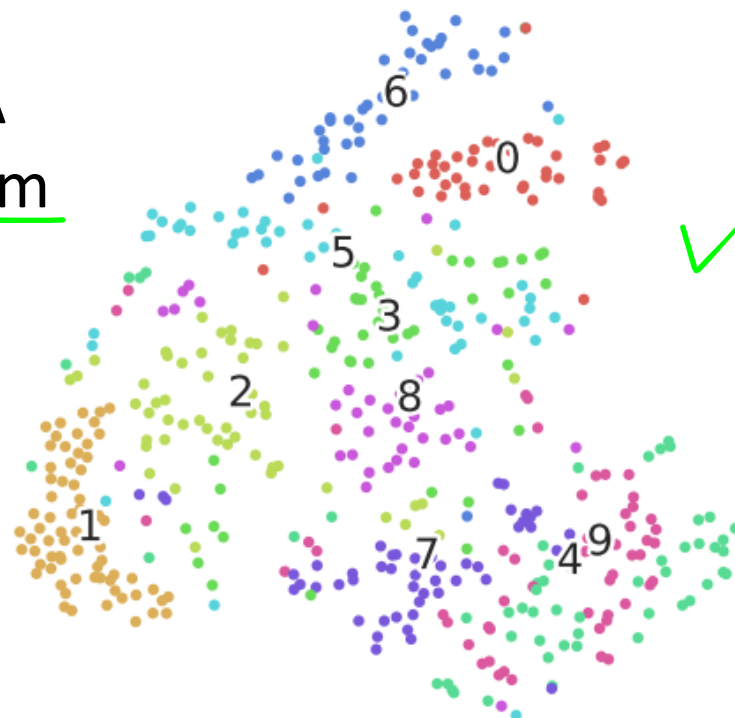
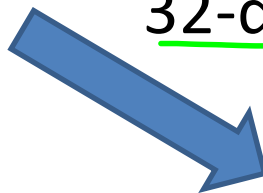
✓



tSNE plots

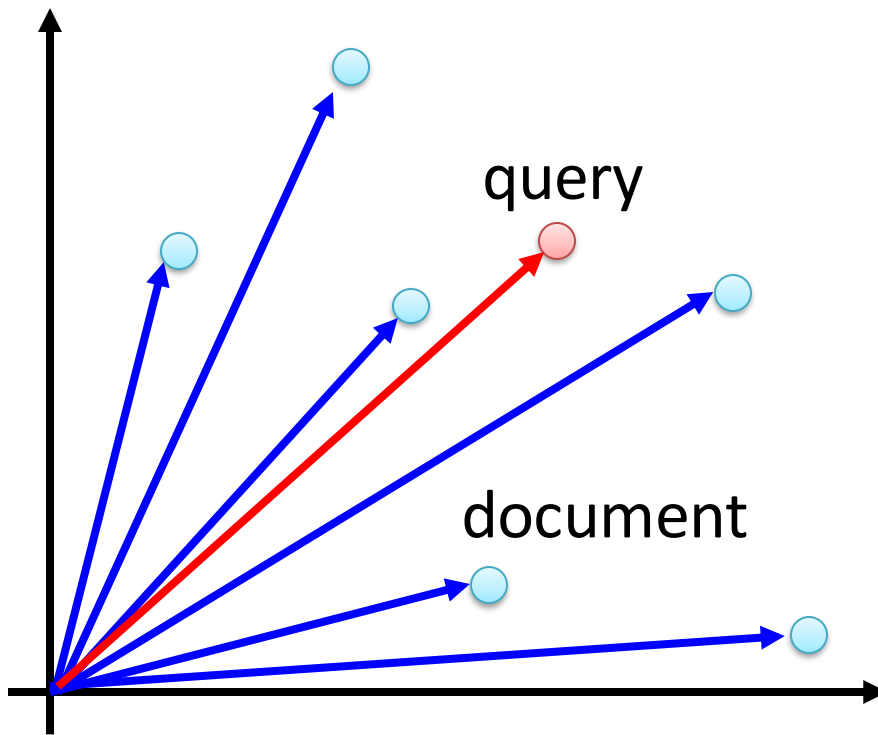


PCA  
32-dim










# Auto-encoder – Text Retrieval

## Vector Space Model



## Bag-of-words

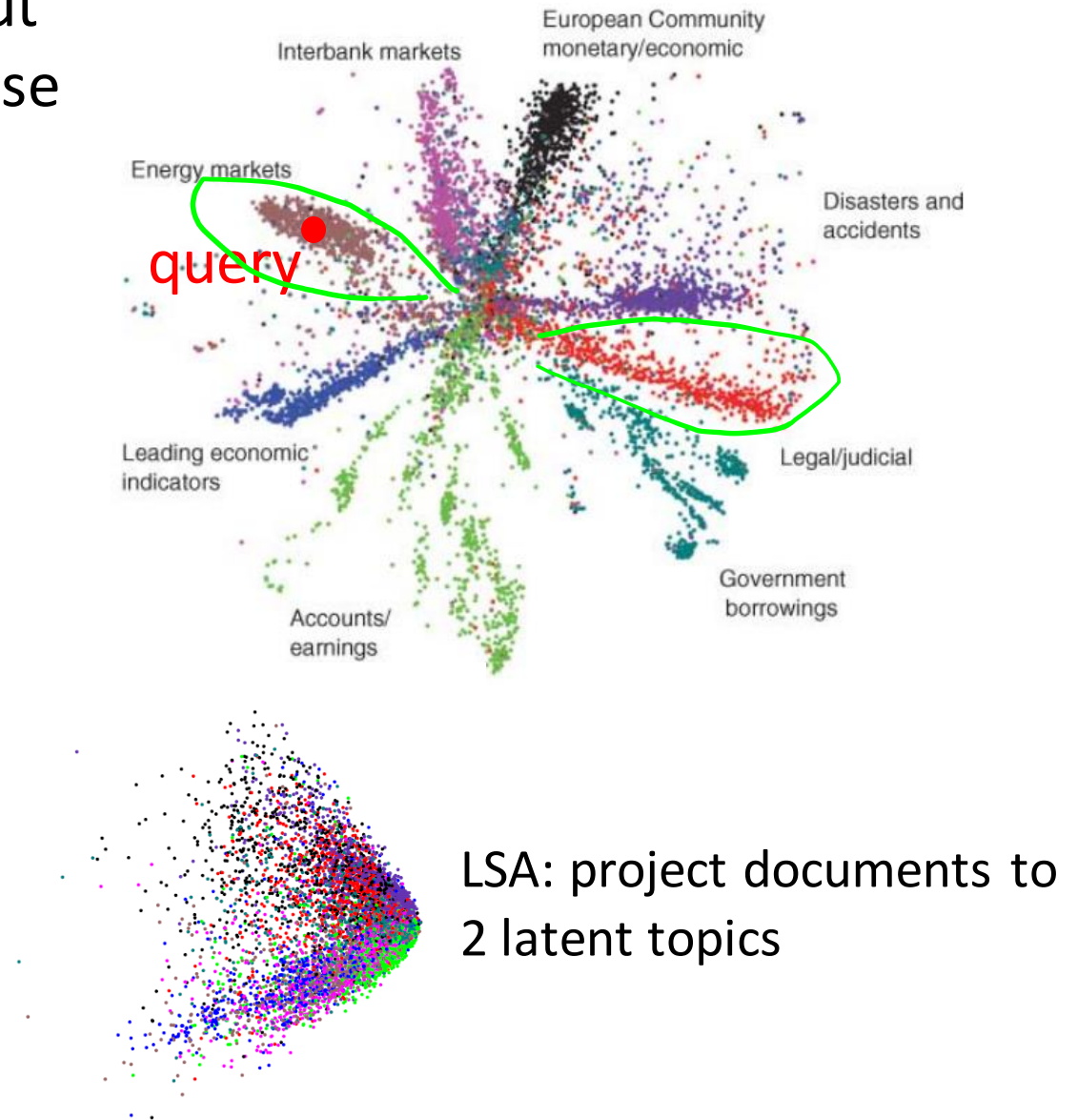
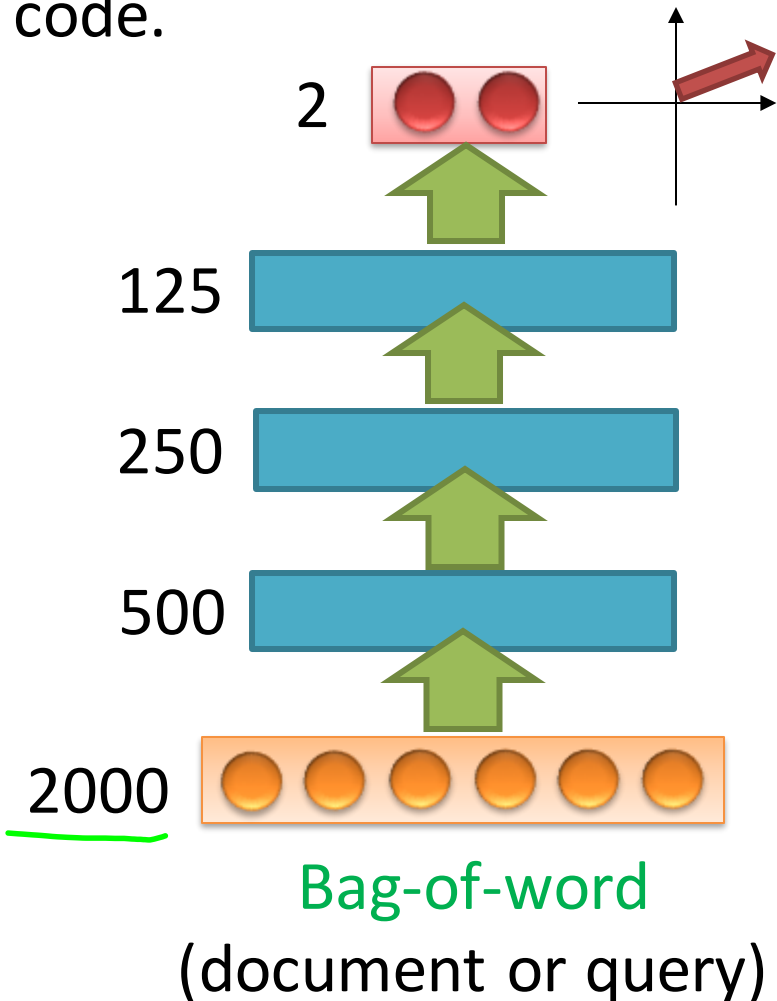
word string:  
"This is an apple"

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

Semantics are not considered.

# Auto-encoder – Text Retrieval

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





# Auto-encoder – Similar Image Search

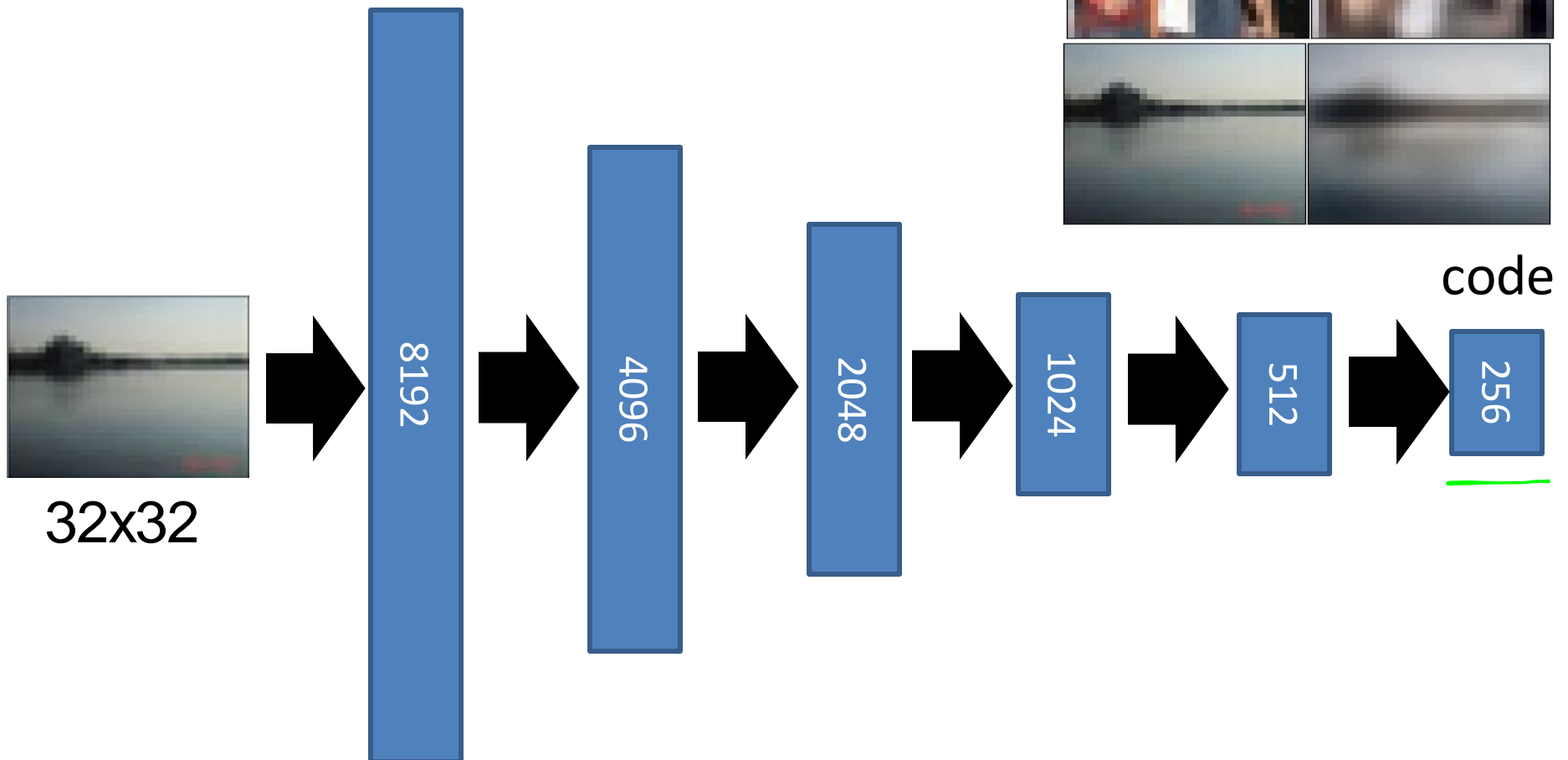
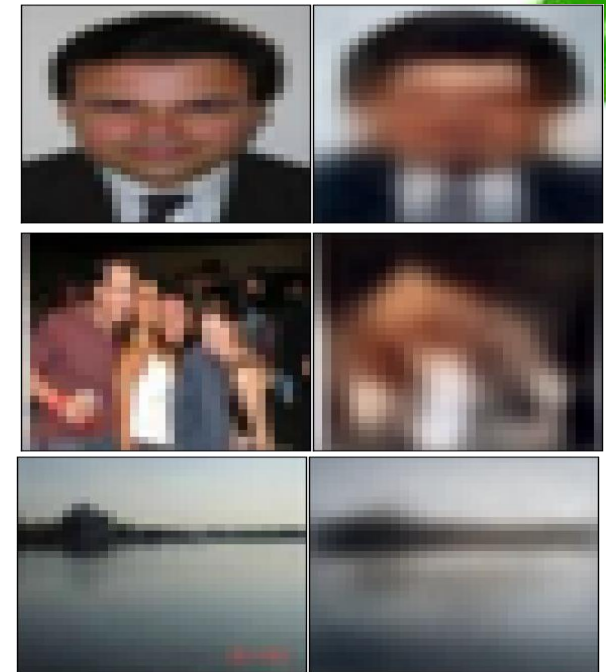
Retrieved using Euclidean distance in pixel intensity space



(Images from Hinton's slides on Coursera)

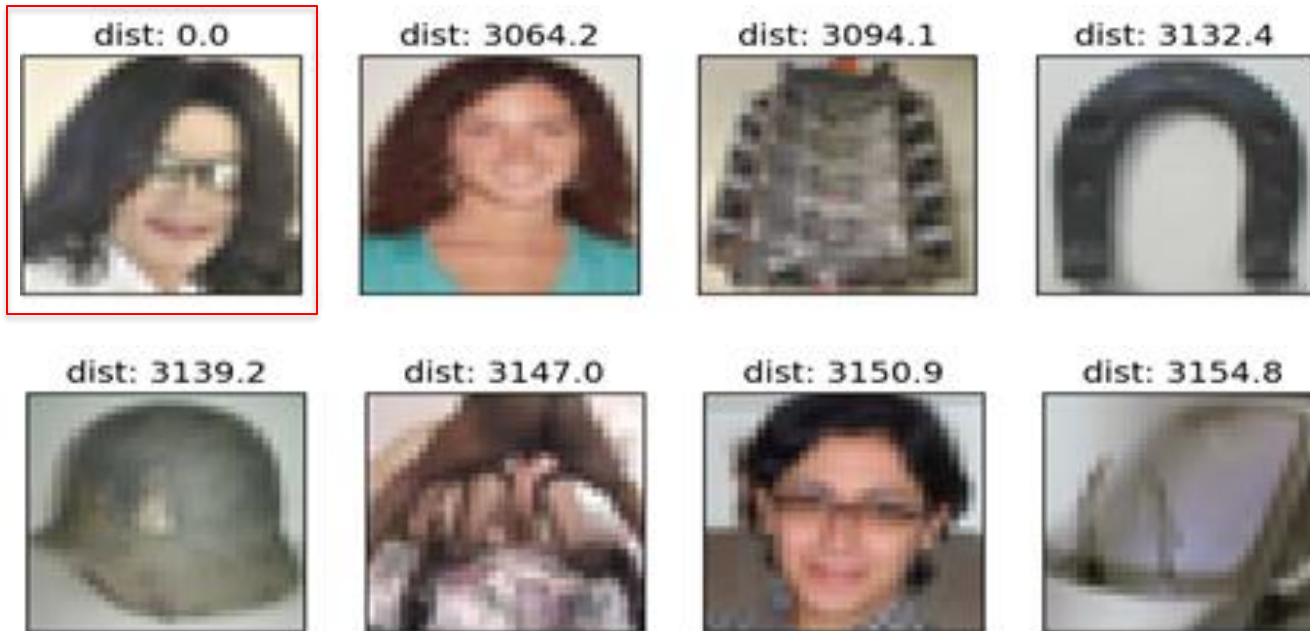
Reference: Krizhevsky, Alex, and Geoffrey E. Hinton. "Using very deep autoencoders for content-based image retrieval." *ESANN*. 2011.

# Auto-encoder – Similar Image Search



(crawl millions of images from the Internet)

# Retrieved using Euclidean distance in pixel intensity space

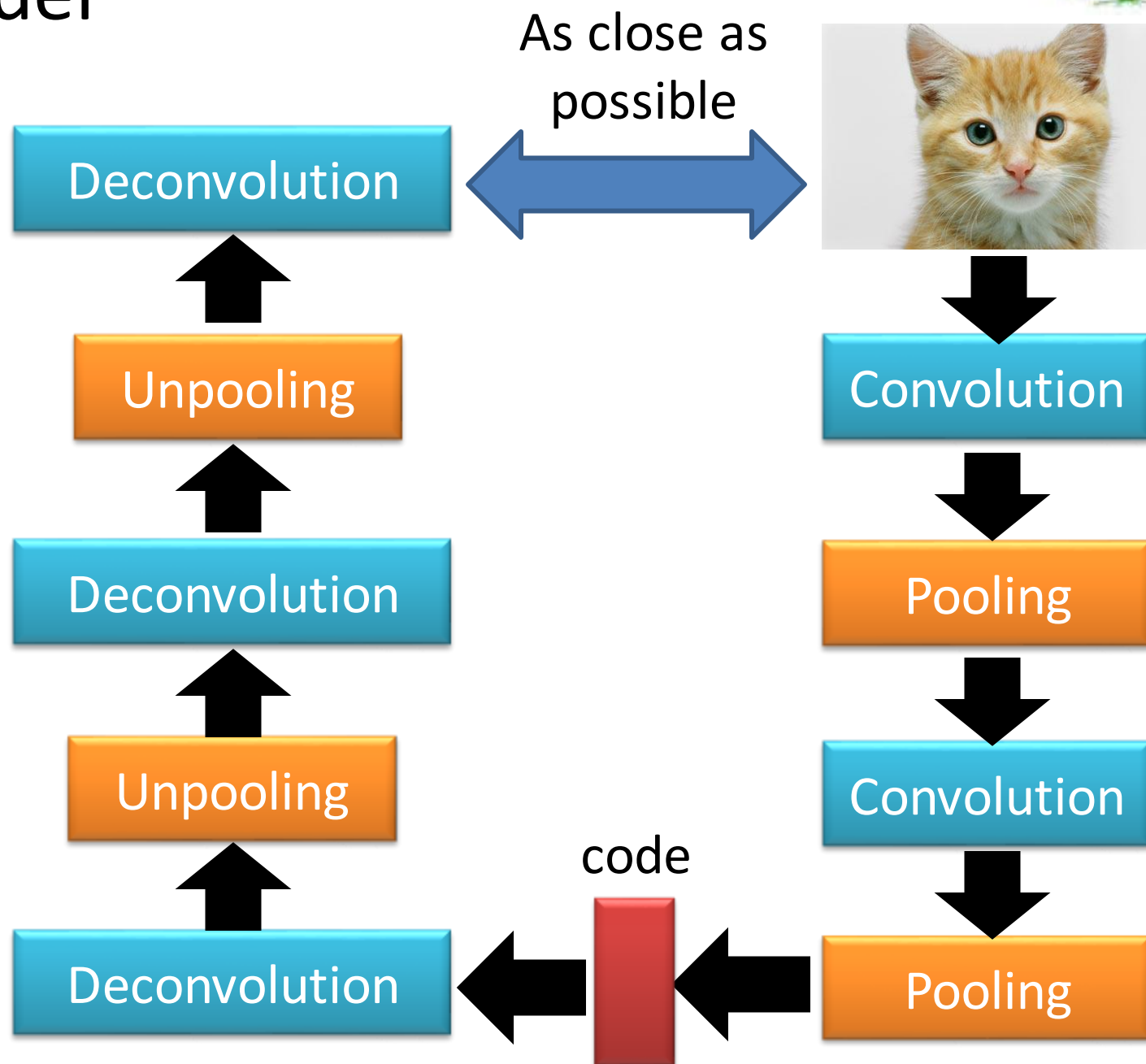


retrieved using 256 codes

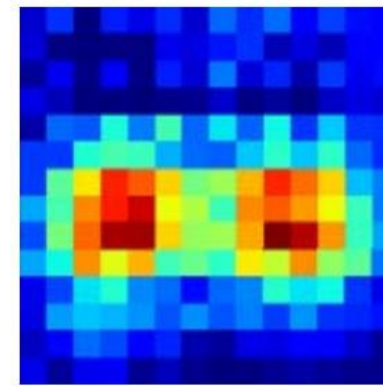




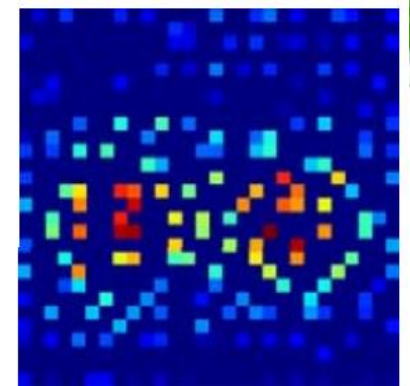
# Auto-encoder for CNN



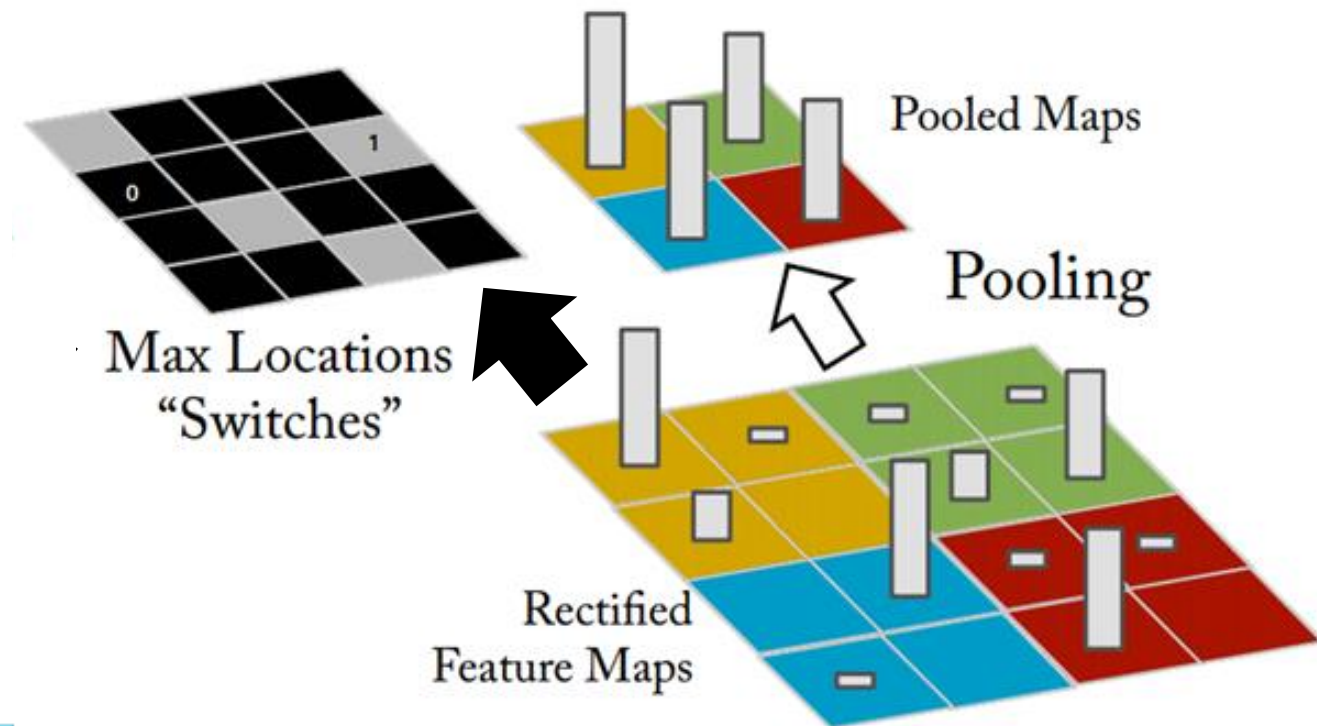
# CNN -Unpooling



14 x 14



28 x 28



Alternative: simply repeat the values

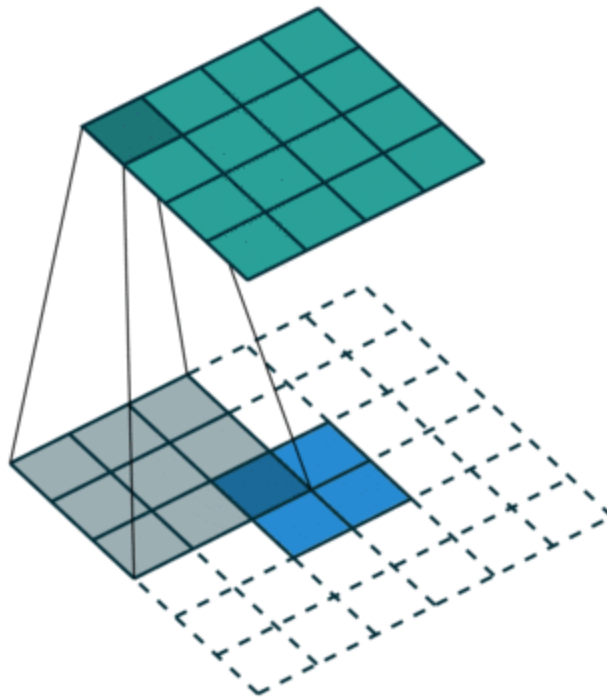
Source of image :  
[https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/image\\_segmentation.html](https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/image_segmentation.html)





# Deconvolution

Actually, deconvolution is convolution.



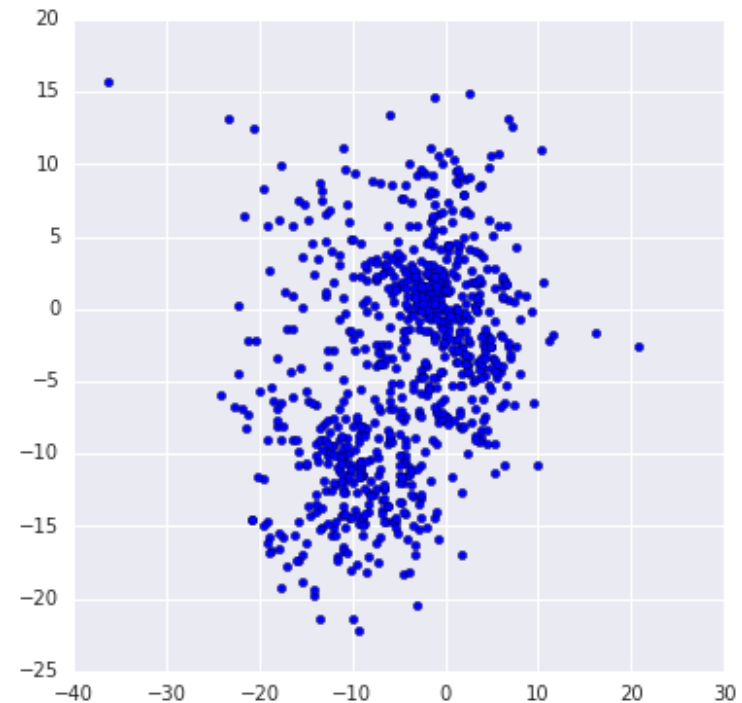
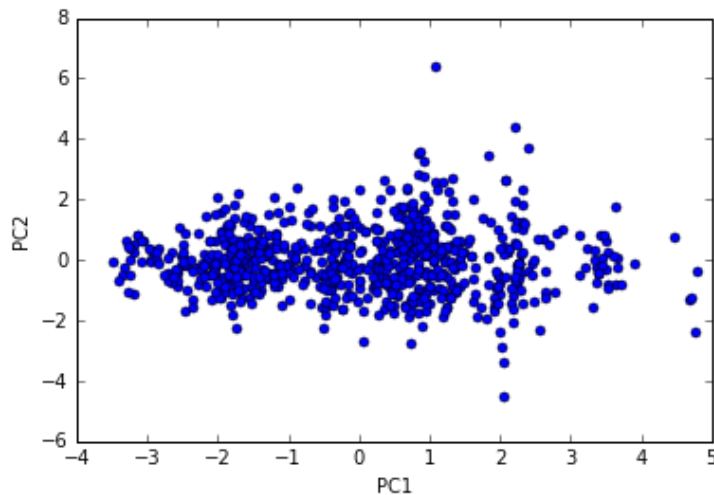
# Pokémon

<http://140.112.21.35:2880/~tlkagk/pokemon/pca.html>

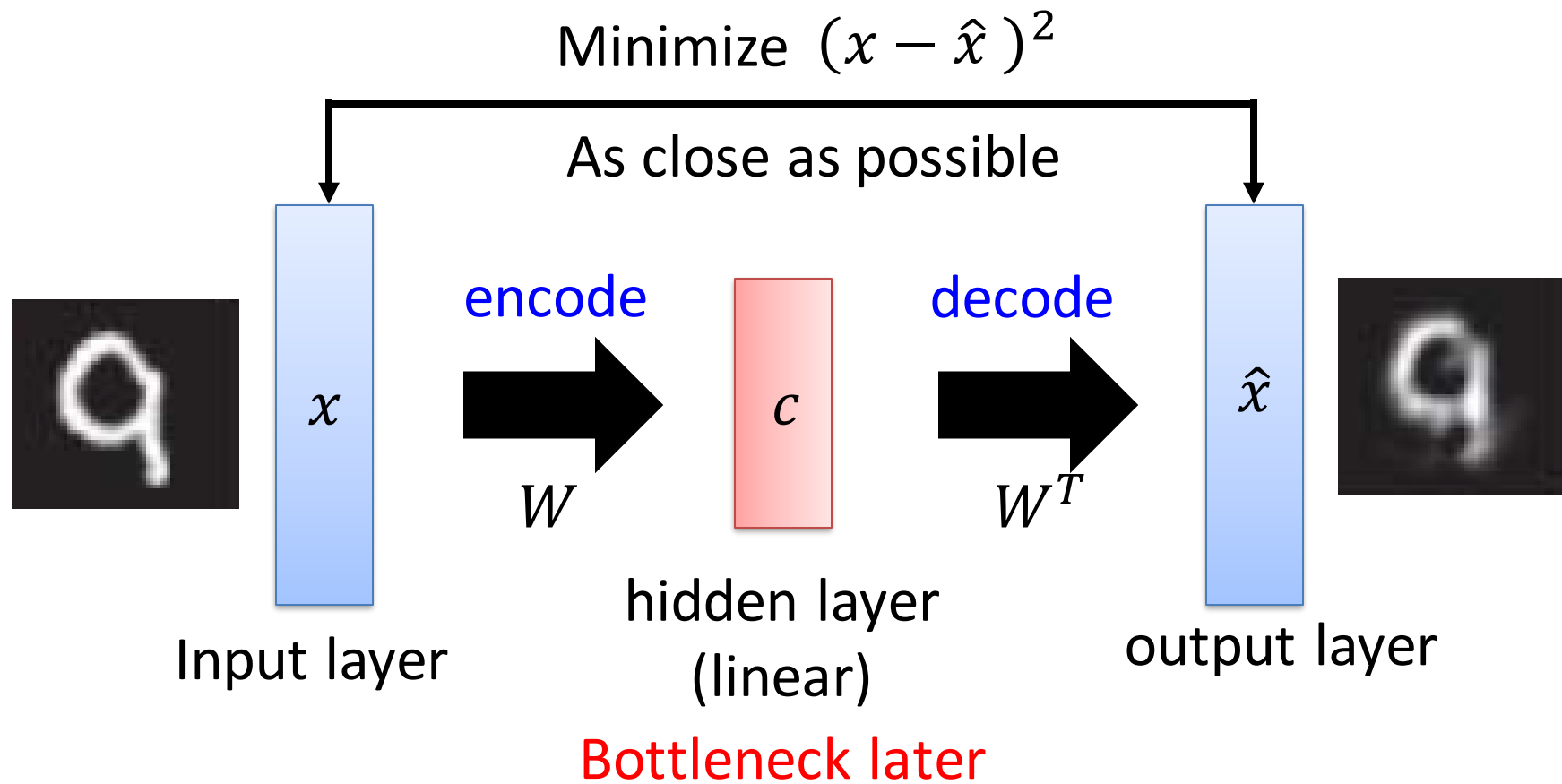
<http://140.112.21.35:2880/~tlkagk/pokemon/auto.html>

The code is modified from

<http://jkunst.com/r/pokemon-visualize-em-all/>



# PCA ~ Autoencoder with linear layers



Output of the hidden layer is the code



---

# Code Reference

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