Artificial and robotic vision

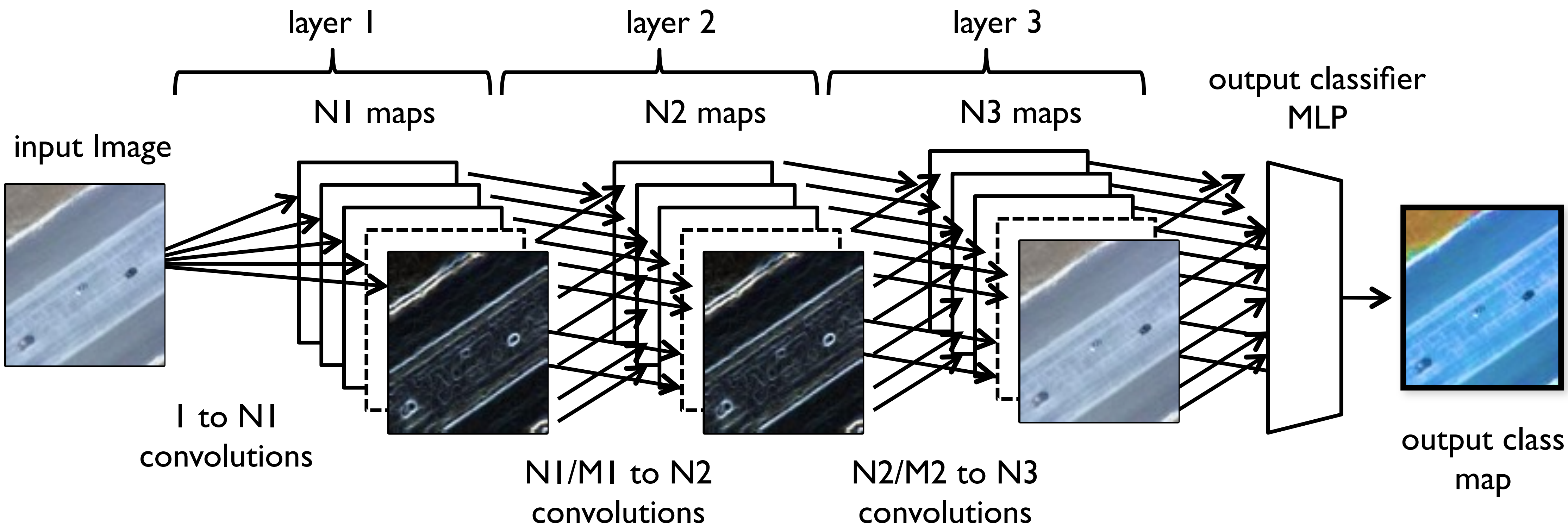
Spring 2013

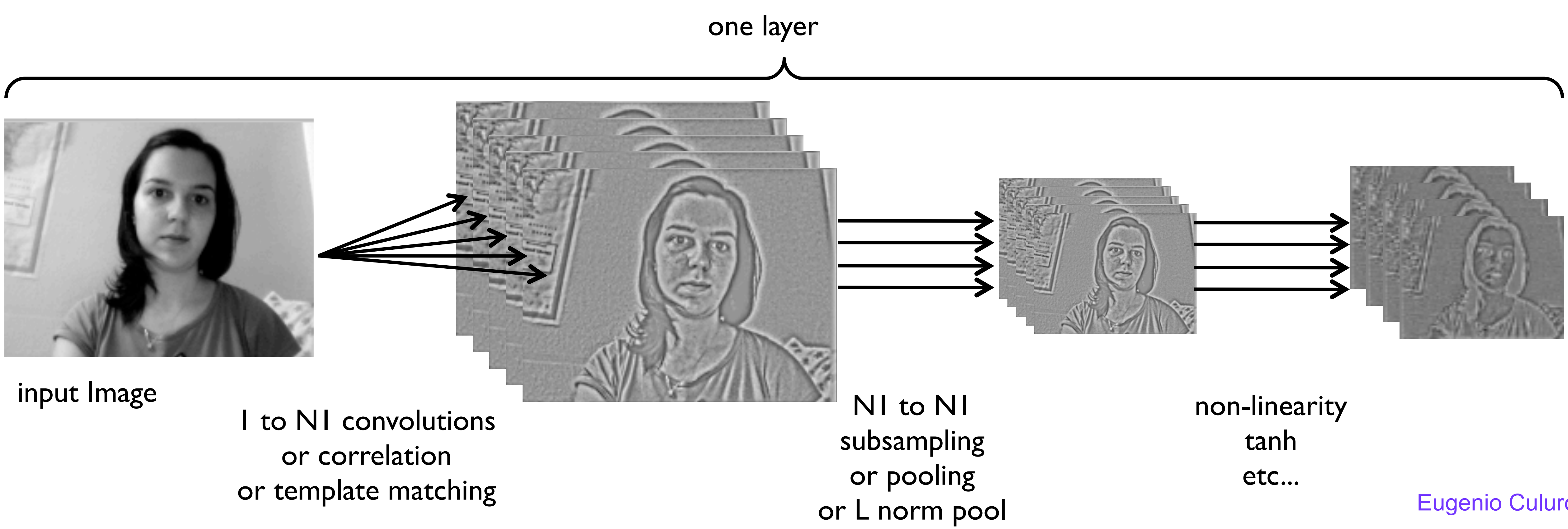
Lecture 6: unsupervised learning

e-Lab

Eugenio Culurciello

deep networks





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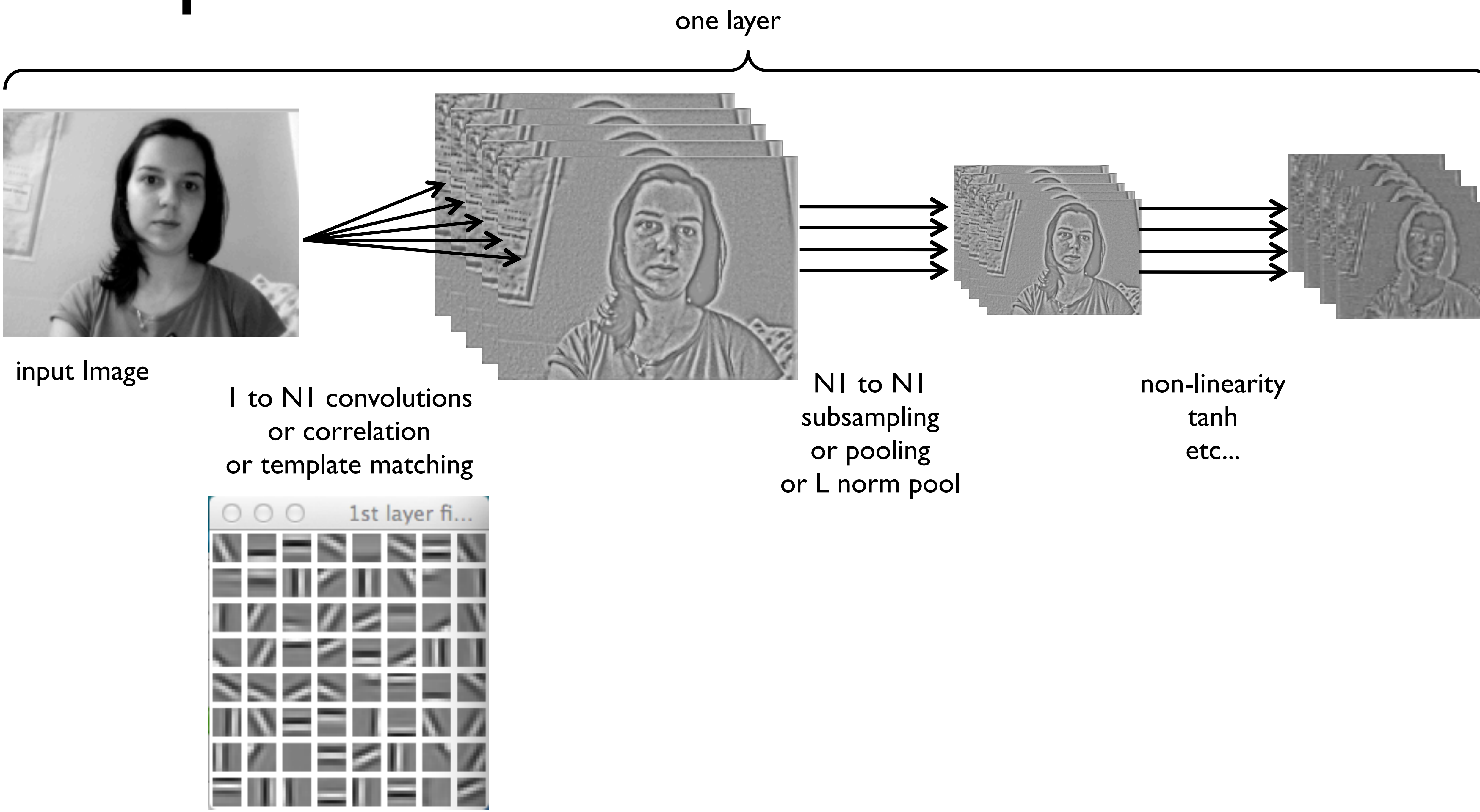
deep networks



How do we compute these filters?

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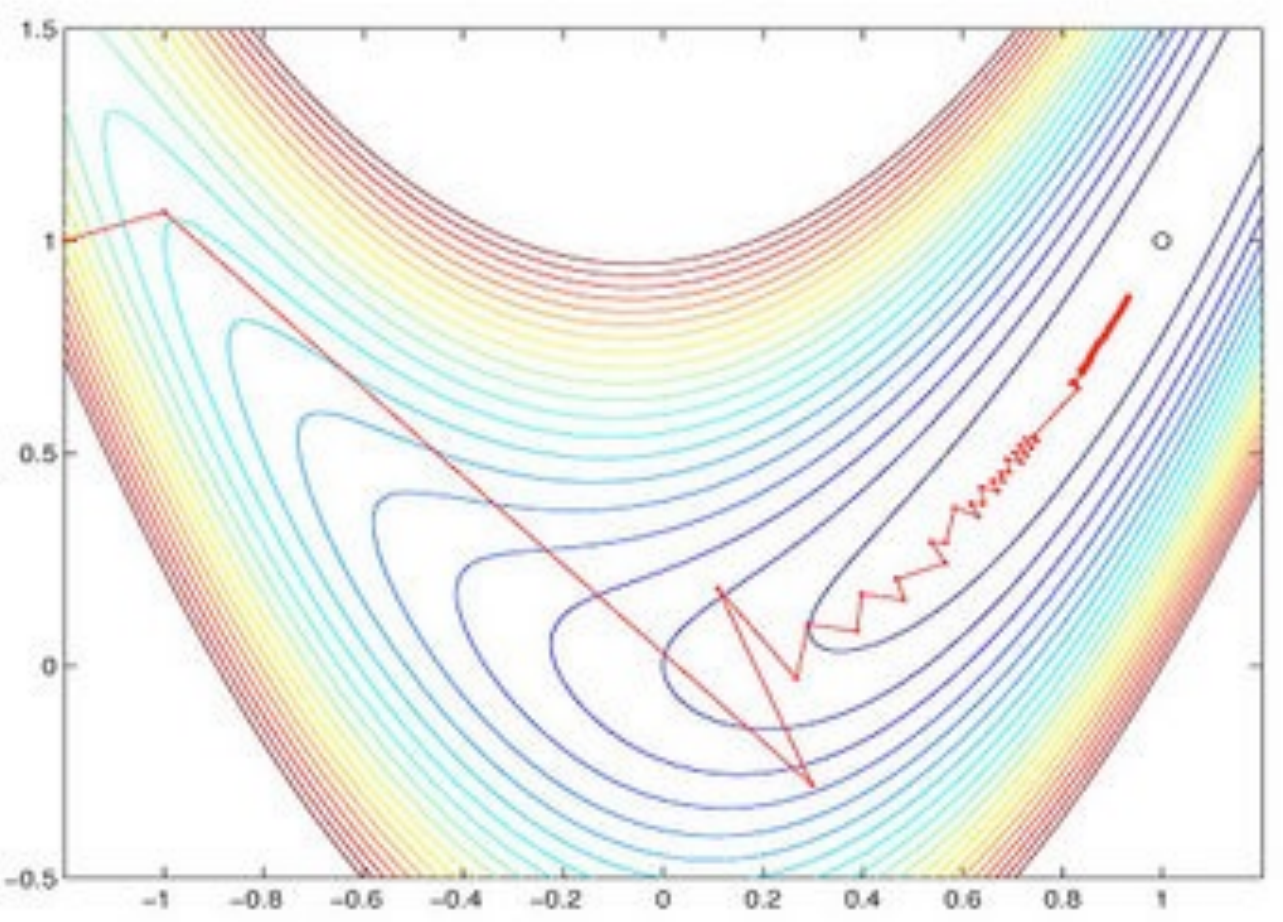
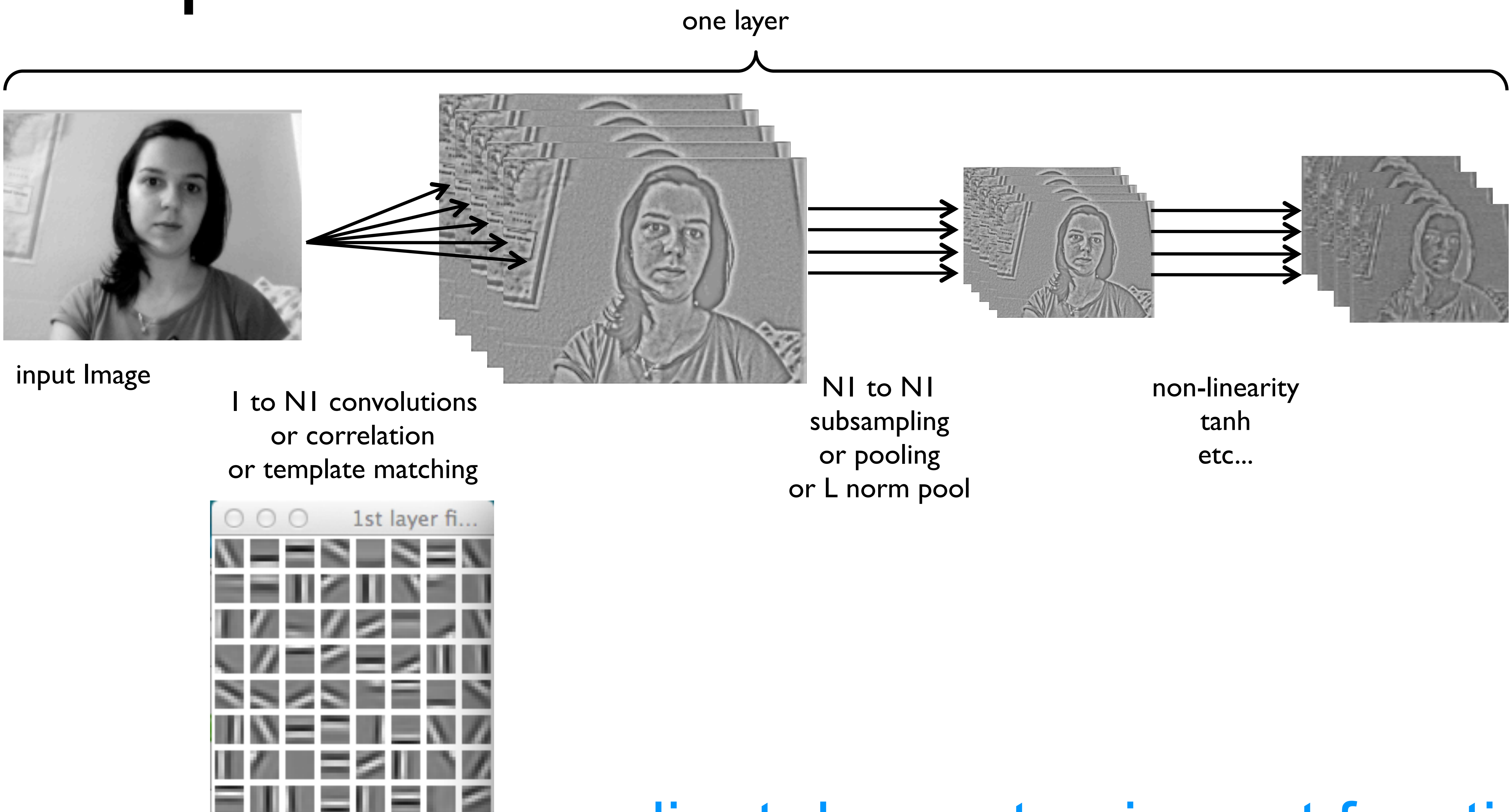
supervised training

dataset



stochastic gradient descent

deep networks



gradient descent, min cost function

$$\underset{W}{\text{minimize}} \quad \lambda \sum_{t=1}^{N-1} \|\mathbf{p}^{(t)} - \mathbf{p}^{(t+1)}\|_1 + \sum_{t=1}^{N} \|\mathbf{x}^{(t)} - W^T W \mathbf{x}^{(t)}\|_2^2 \quad + \gamma \sum_{t=1}^{N} \|\mathbf{p}^{(t)}\|_1$$

p = features, x = input

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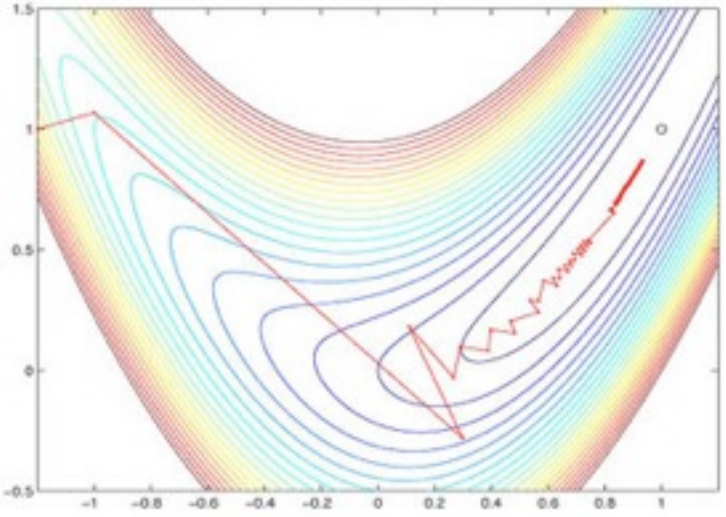
supervised training issues:

- need labeled data!
- takes a long time
- lots of effort
- in videos it is crazy
- we cannot scale up!

- ~all use gradient descent
- not related to learning in the brain
- use global error propagation
- not local err. prop.
- math-heavy techniques
- they take a long time to compute



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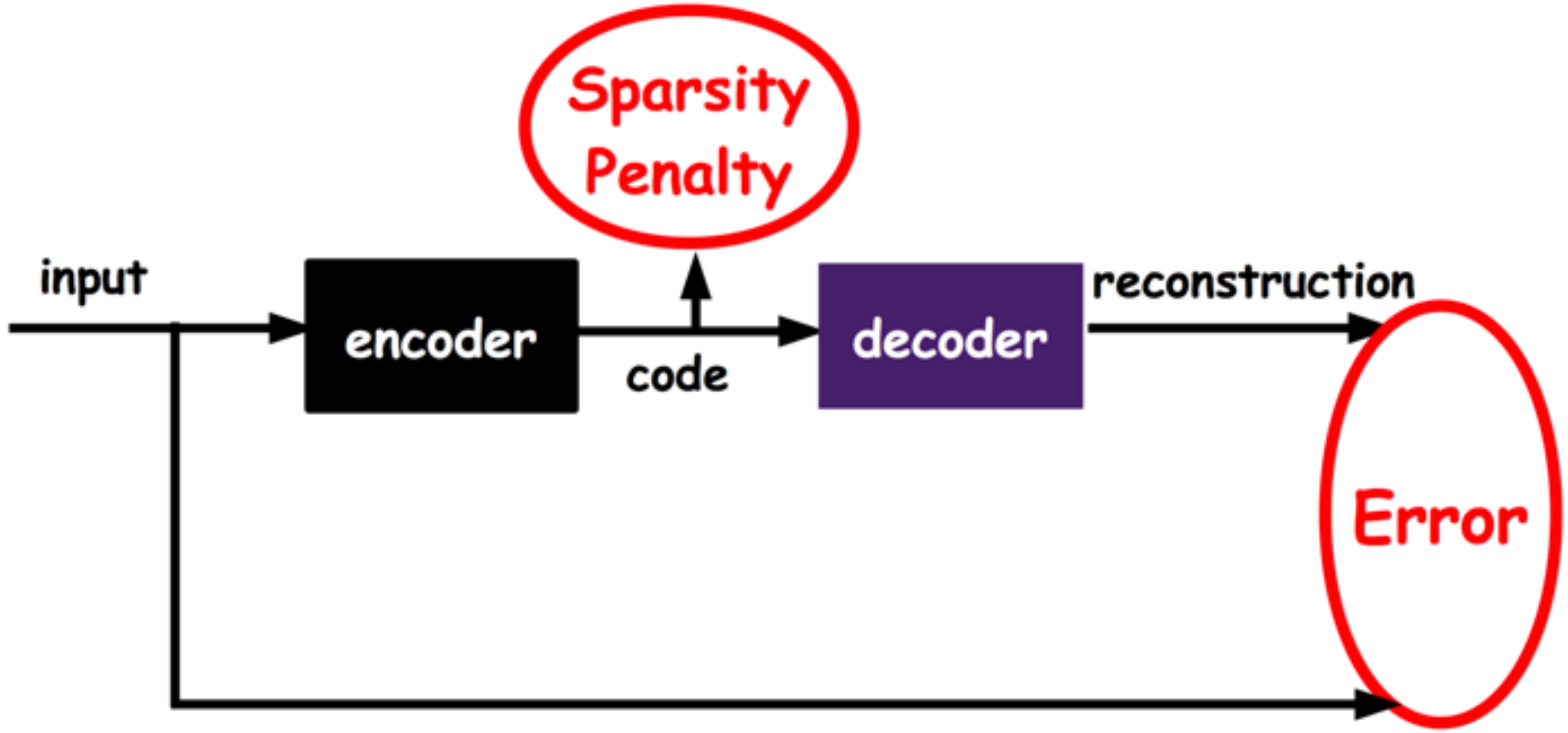
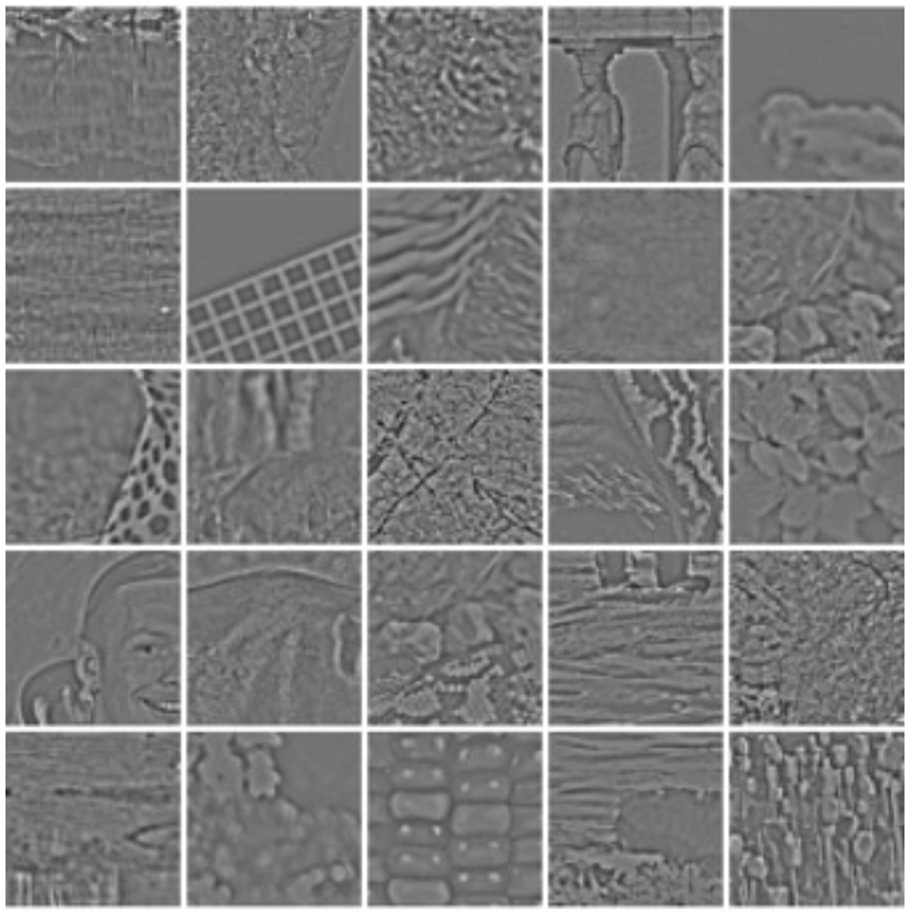
unsupervised training: autoencoders

main idea: learn to reconstruct the input with some sparse base functions

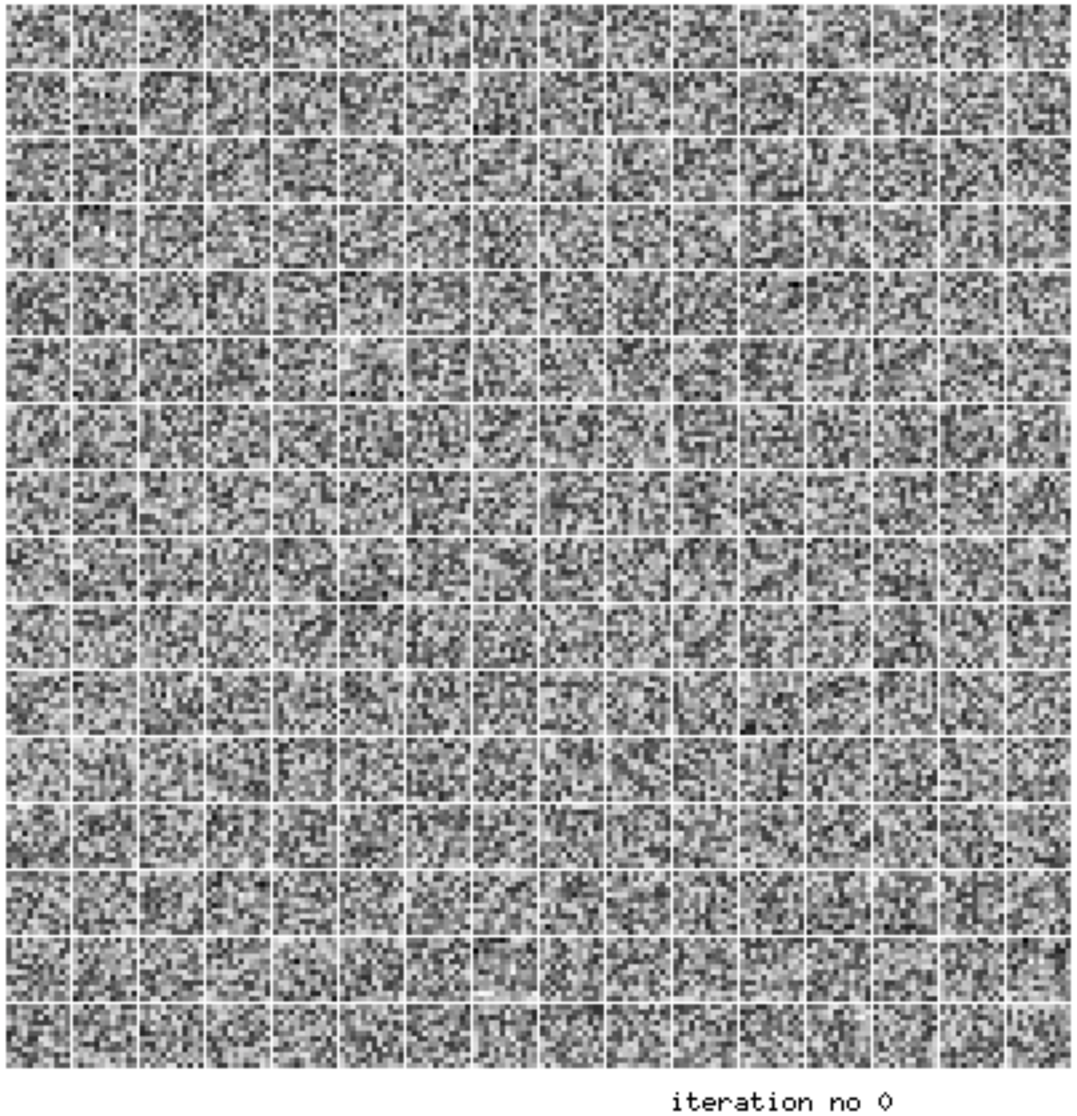


Karol Gregor, Marc'Aurelio Ranzato, Koray Kavukcuoglu, Yann LeCun

unsupervised training: autoencoders



the dataset is just unlabeled data!
of any form: video, frames, etc
easy to get!
easy to consume

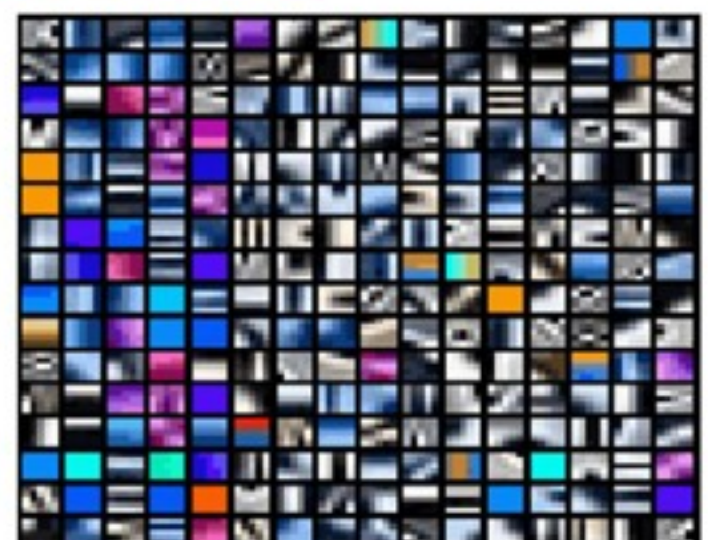


train by finding base-functions
or the basic blocks of images

unsupervised training: autoencoders

related to:
vector quantization
clustering

used for:
compression
de-noising



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sparse coding

Sparse coding (Olshausen & Field,1996). Originally developed to explain early visual processing in the brain (edge detection).

Training: given a set of random patches x, learning a dictionary of bases [$\Phi_{1,}$ $\Phi_{2,}$ …]

$$\min_{a,\phi} \sum_{i=1}^{m} \left\| x_i - \sum_{j=1}^{k} a_{i,j}\phi_j \right\|^2 + \lambda \sum_{i=1}^{m} \sum_{j=1}^{k} |a_{i,j}|$$

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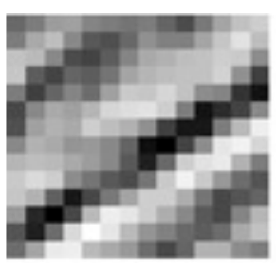
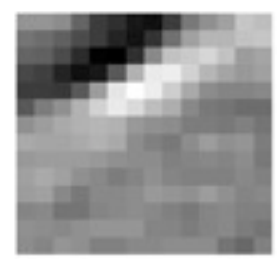
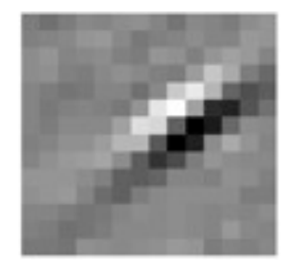
sparse coding

Input: Novel image patch x (in R^d) and previously learned ϕ_i's

Output: Representation $[a_{i,1}, a_{i,2}, \ldots, a_{i,\kappa}]$ of image patch x_i.

$$\min_a \sum_{i=1}^{m} \left\| x_i - \sum_{j=1}^{k} a_{i,j} \phi_j \right\|^2 + \lambda \sum_{i=1}^{m} \sum_{j=1}^{k} |a_{i,j}|$$

 $\approx 0.8 *$  $+ 0.3 *$  $+ 0.5 *$ 

Represent x_i as: a_i = [0, 0, …, 0, **0.8**, 0, …, 0, **0.3**, 0, …, 0, **0.5**, …]

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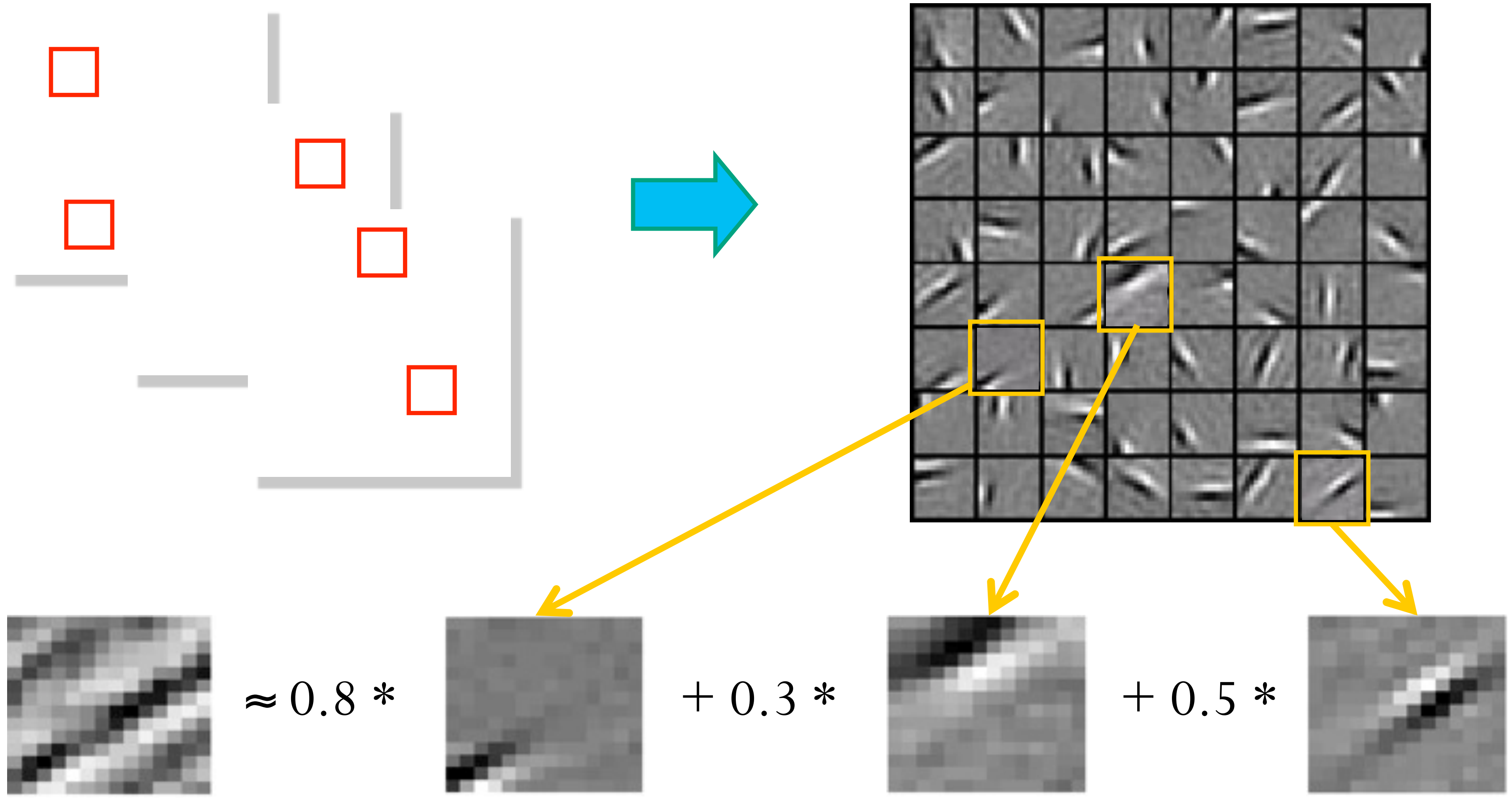
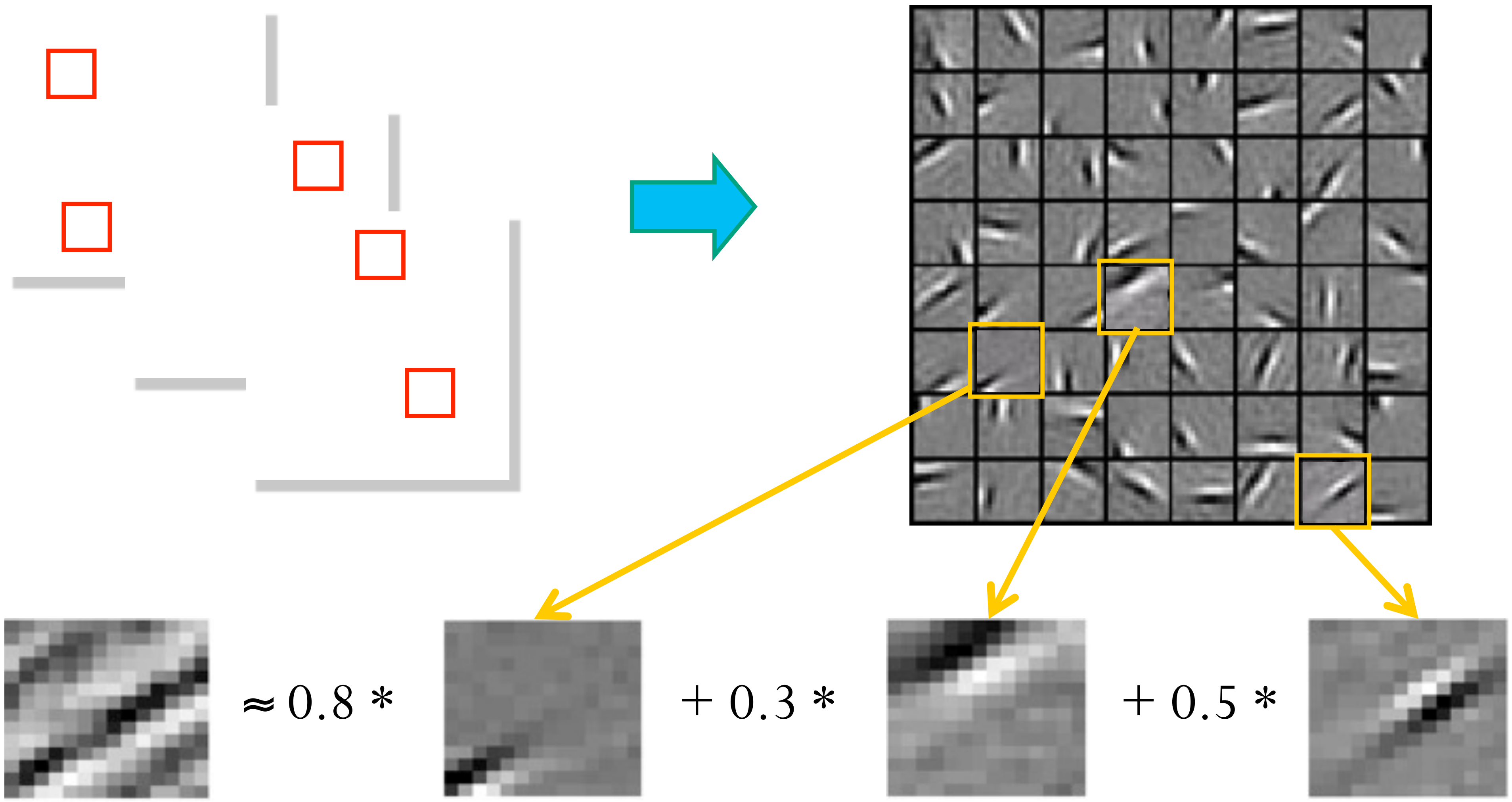


Slide credit: Andrew Ng

sparse coding

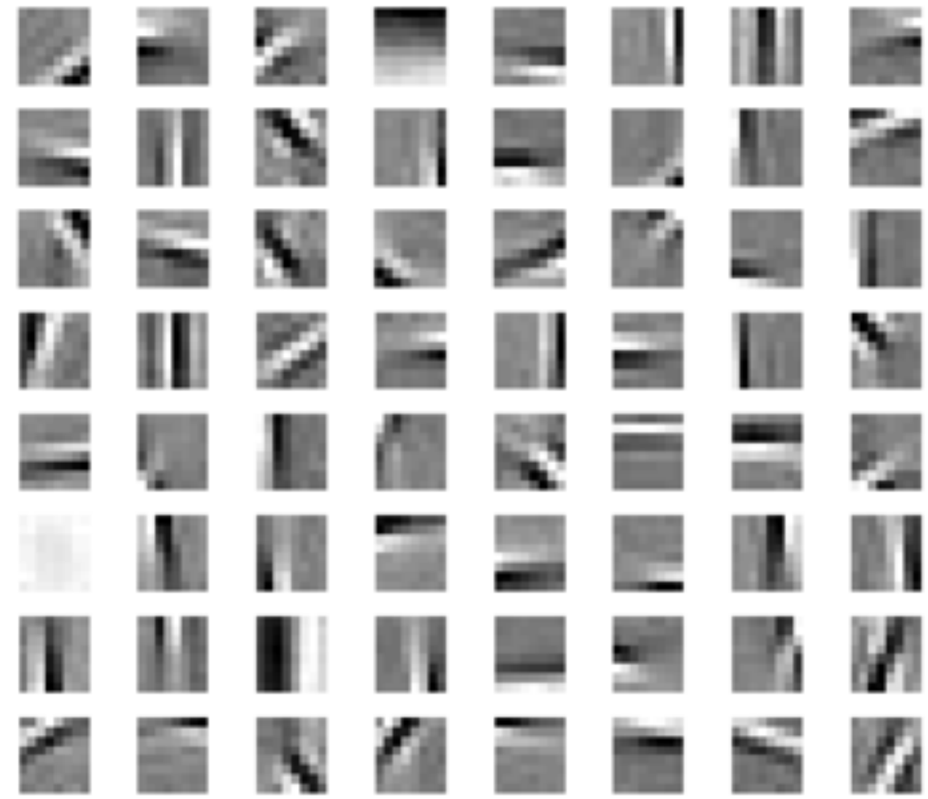


$[a_1, \ldots, a_{64}] = [0, 0, \ldots, 0, \mathbf{0.8}, 0, \ldots, 0, \mathbf{0.3}, 0, \ldots, 0, \mathbf{0.5}, 0]$
(feature representation)

Compact & easily interpretable

Slide credit: Andrew Ng

sparse coding: example



64 bases functions of 8x8 pixels

The bases seem to capture the intrinsic structure of the building elements, that are mainly composed of vertical, horizontal, slanting edges and corners.

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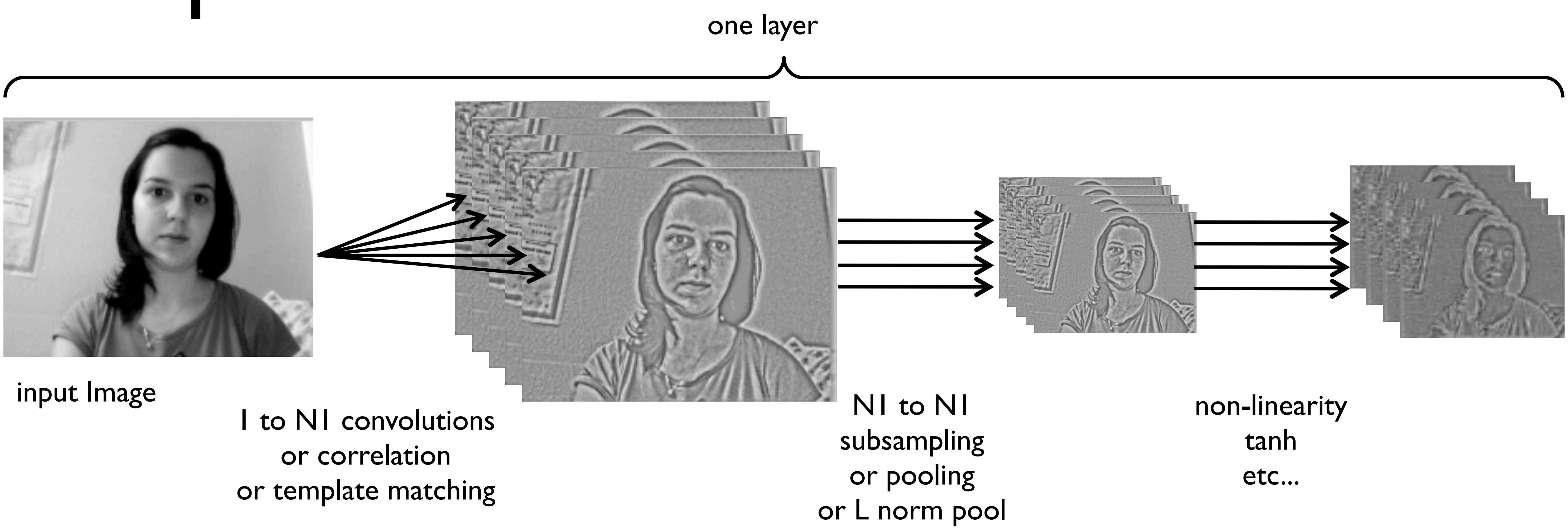
deep networks



Multiple layers of deep network:

Repeat for each layer:

1- sample output of previous layer (new input)

2- learn dictionary of inputs = filters

3- use filters to generate outputs

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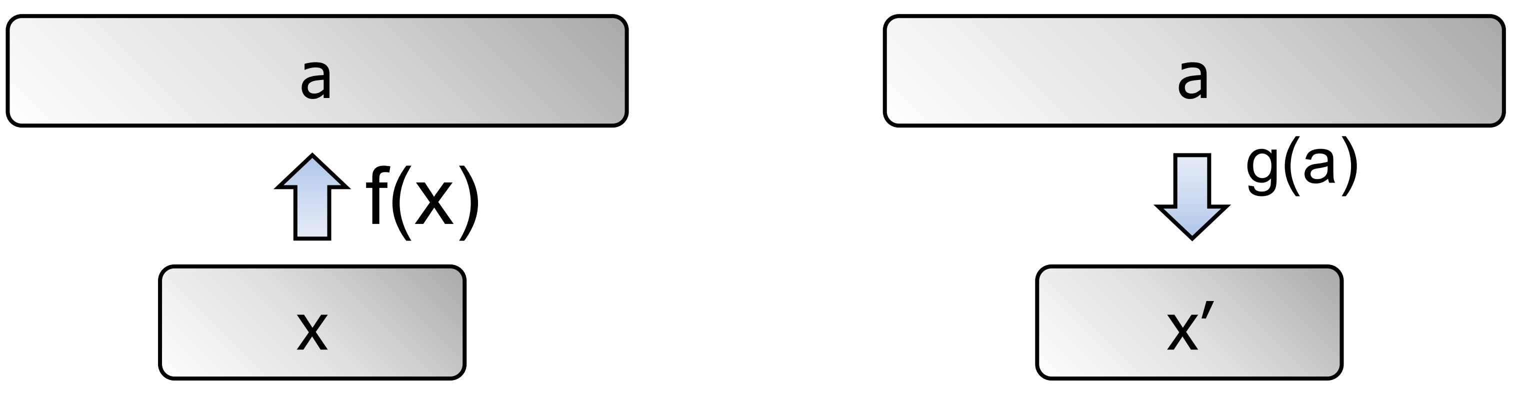
sparse coding: deep networks

Any feature mapping from x to a, i.e. a = f(x), where

-a is sparse (and often higher dim. than x)

-f(x) is nonlinear

-reconstruction x'=g(a) , such that x'≈x



Therefore, sparse RBMs, sparse auto-encoder, even VQ can be viewed as a form of sparse coding.