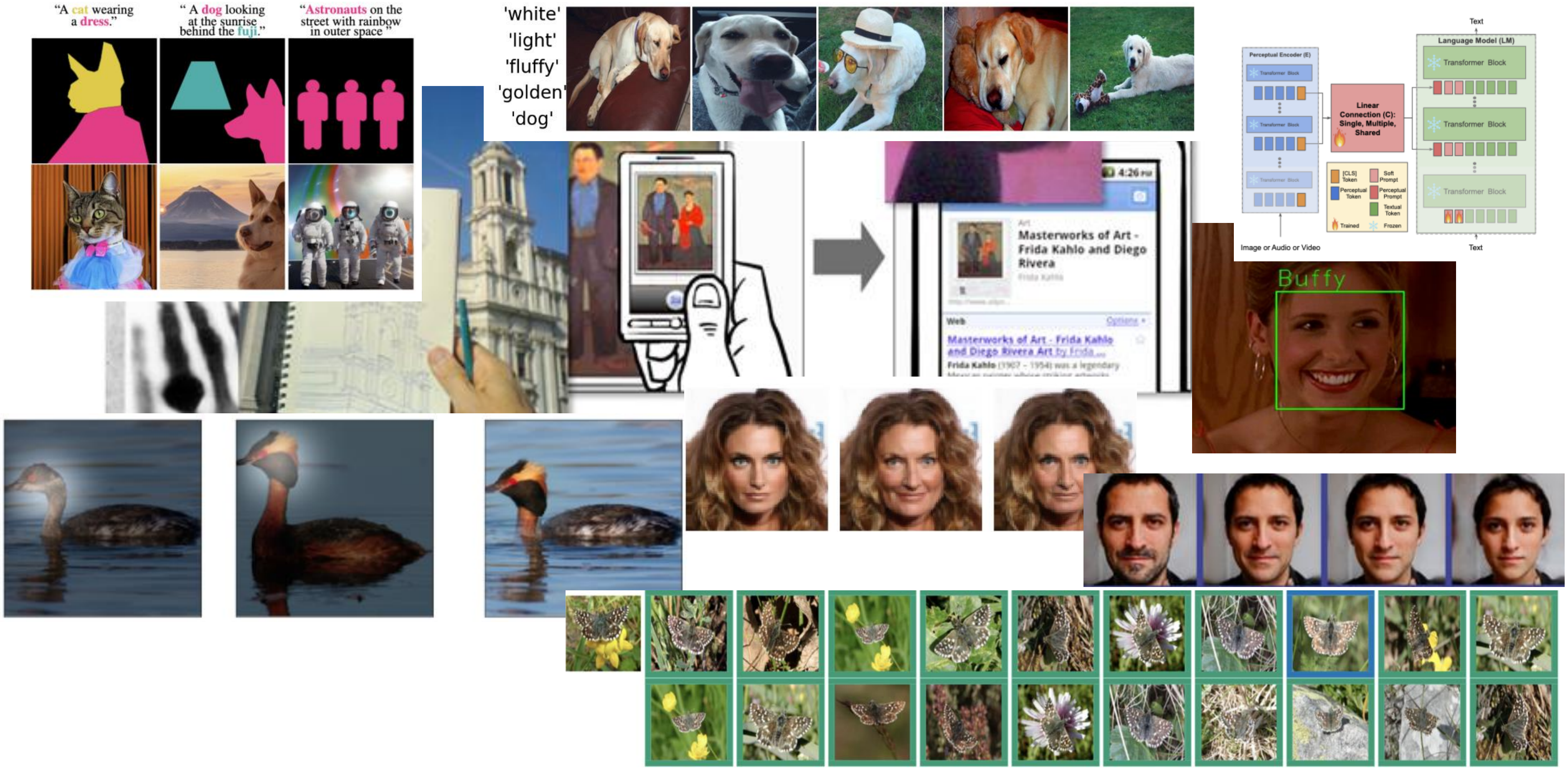


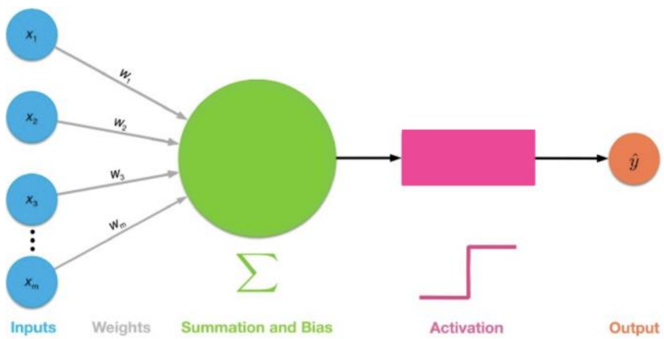
COURS RDFIA deep Image

https://cord.isir.upmc.fr/teaching-rdfia/

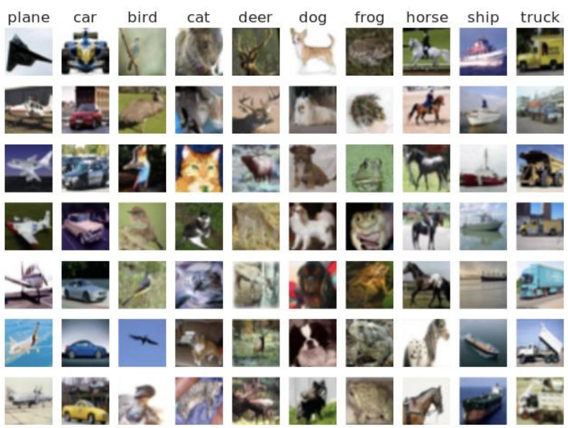
Outline
Convolutional Nets for visual classification

1. **Recap MLP**
2. Convolutional Neural Networks

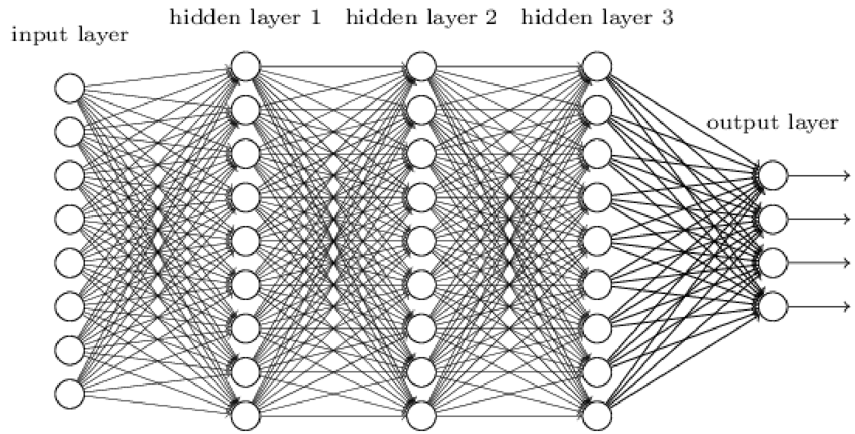
Recap MLP



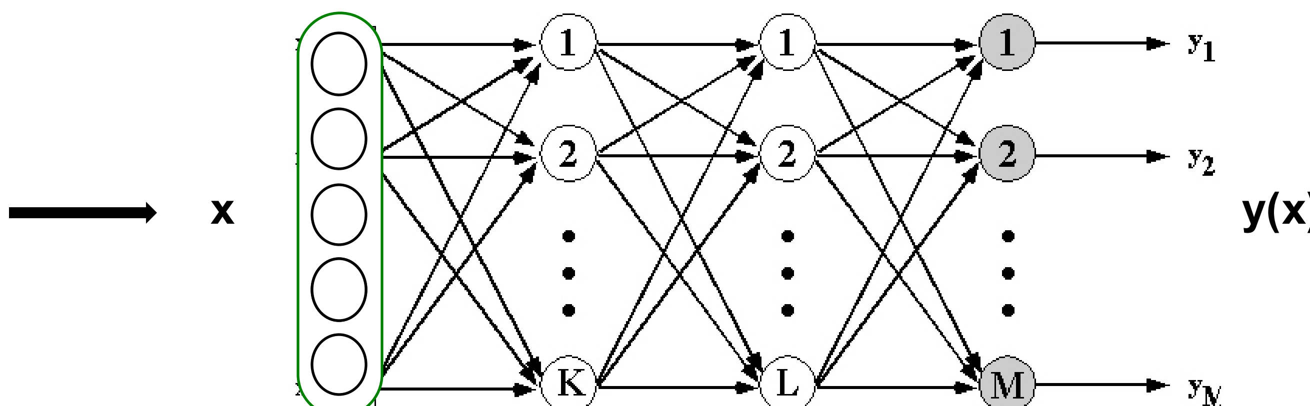
Inputs
Weights
Summation and Bias
Activation
Output



plane car bird cat deer dog frog horse ship truck

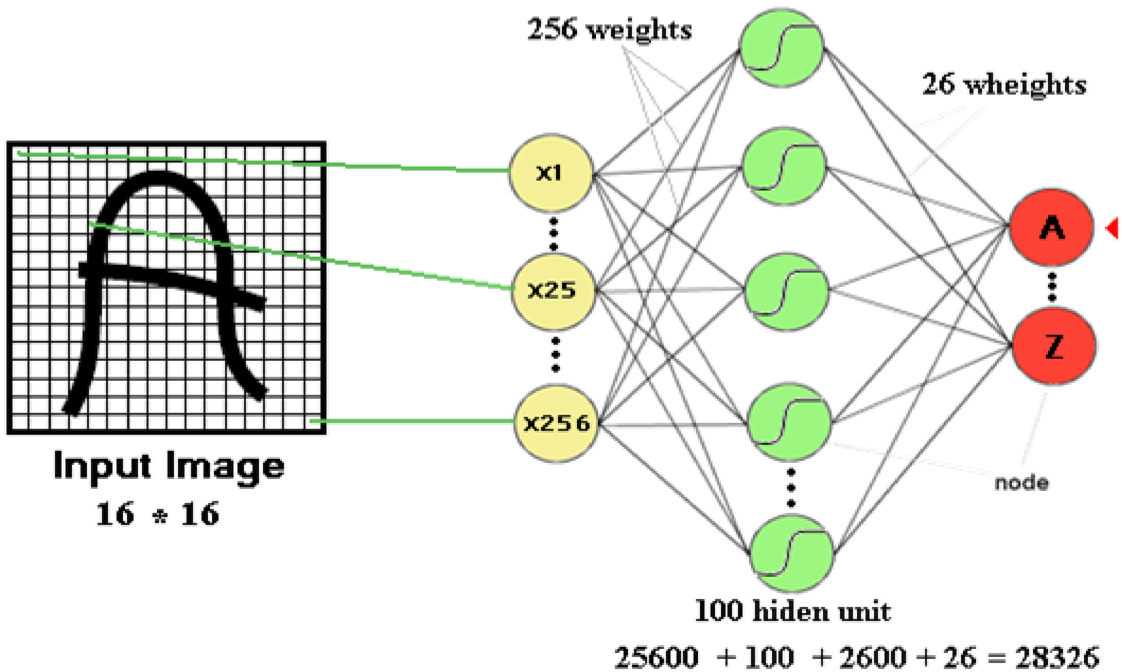


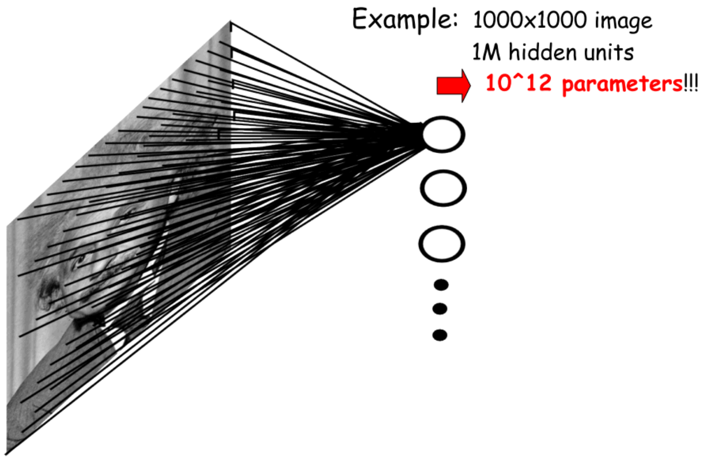
input layer
hidden layer 1
hidden layer 2
hidden layer 3
output layer



x
1
2
K
1
2
L
1
2
M
y_1
y_2
y_M
y(x)

MLP example: brute force connection





First Pb: Scalability

Large images => extremely large number of trainable parameters

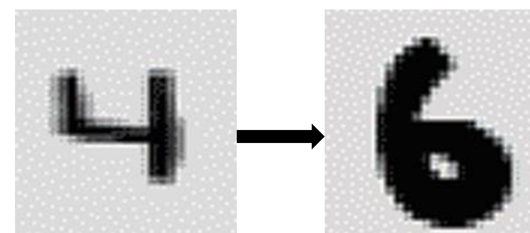
MLP example: brute force connection

2d Pb: *Stability* of the representation

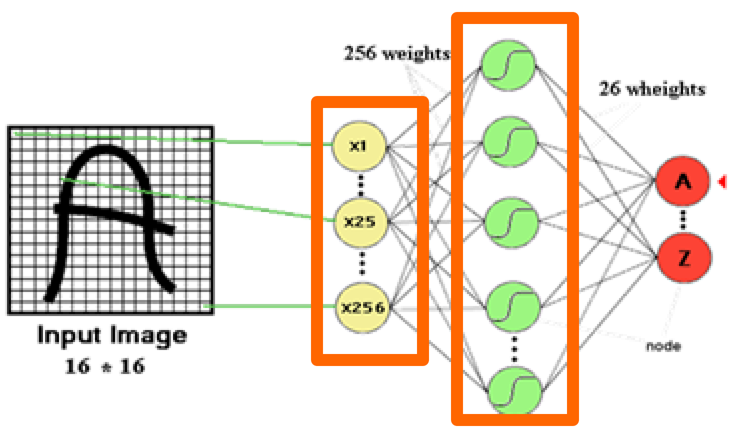
Expectation:

– *Small deformation in the input space*
  => similar representations

– *Large (or unexpected) transfo in the input space*
  => very dissimilar representations

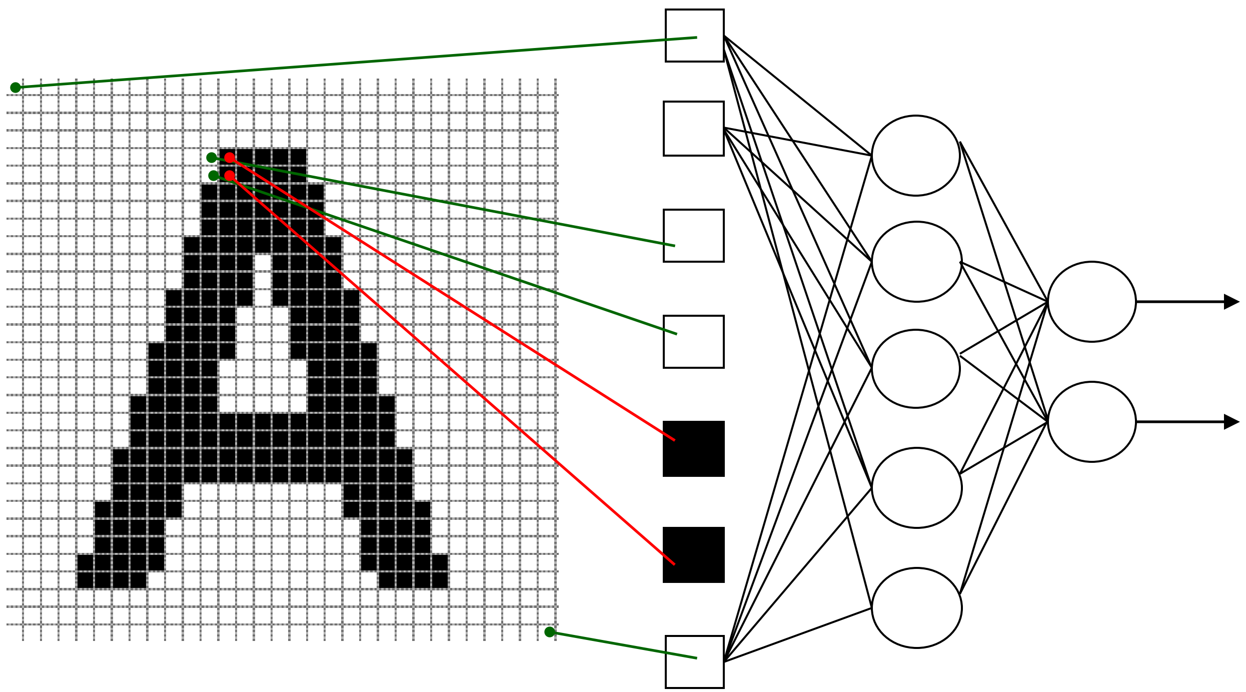


Representations:



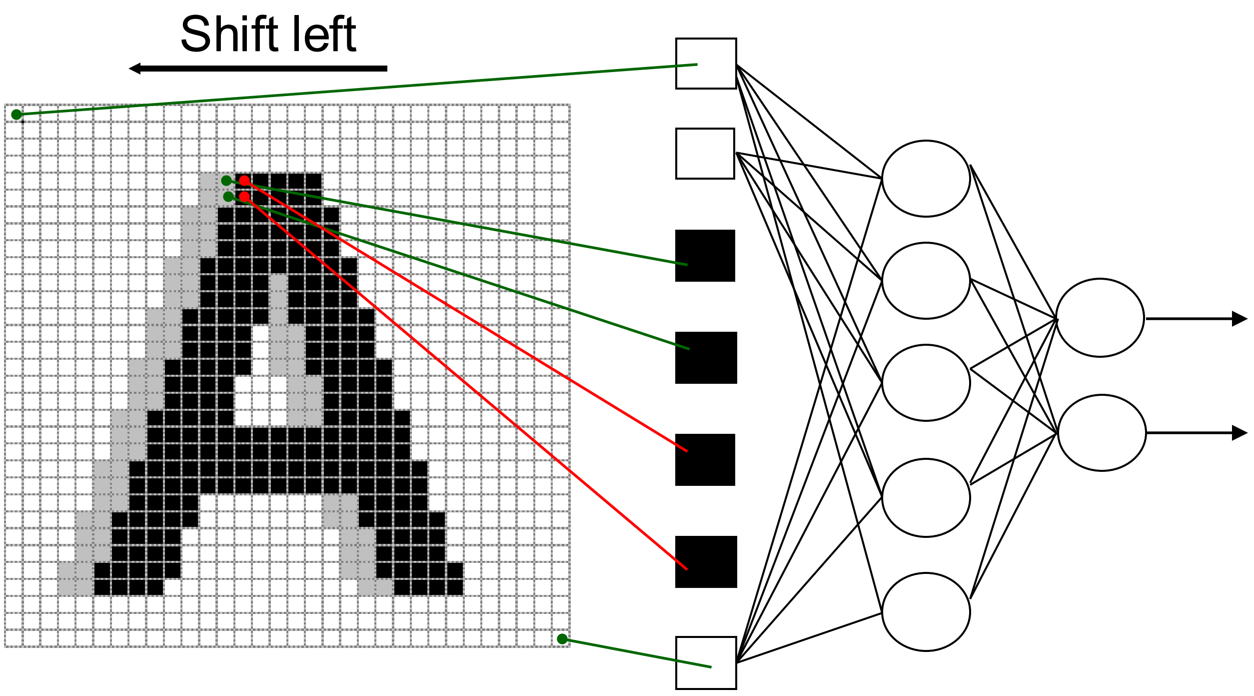
MLP example: brute force connection

Stability: Invariance/Robustness to (local) shifting, scaling, and other forms of (small) distortions?

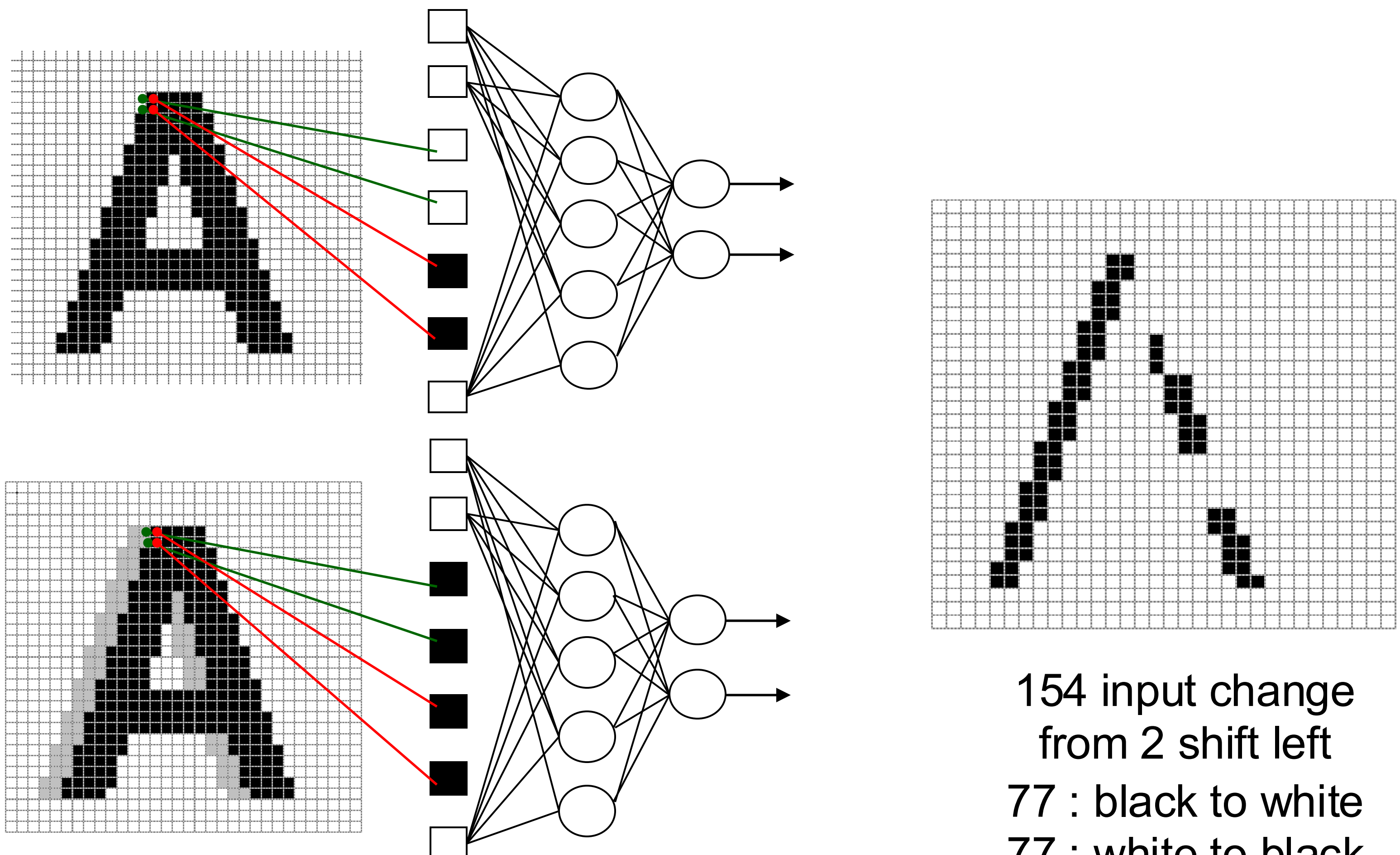


MLP example: brute force connection

Little or no invariance to shifting, scaling, and other forms of distortion



MLP example: brute force connection



154 input change
from 2 shift left
77 : black to white
77 : white to black

@LeCun

MLP example: brute force connection

Scaling and other forms of distortions => same pb

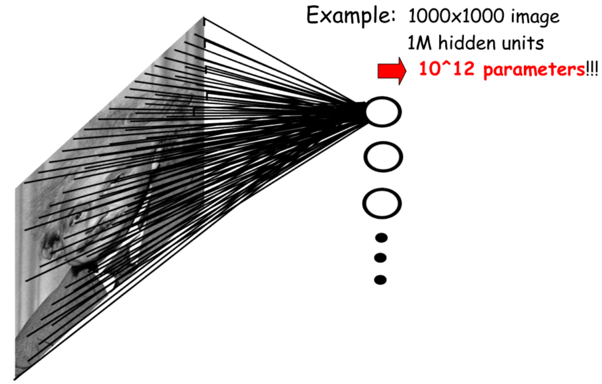
Conclusion of MLP on raw data

Brute force connection of images as input of MLP NOT a good idea

- No Invariance/Robustness of the representation because topology of the input data completely ignored
- Nb of weights grows largely with the size of the input image

How keep spatial topology?

How to limit the weight number?



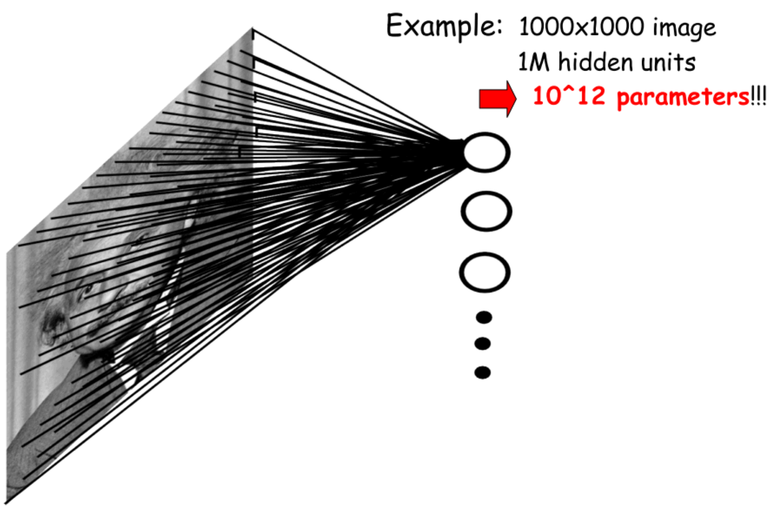
Outline
Convolutional Nets for visual classification

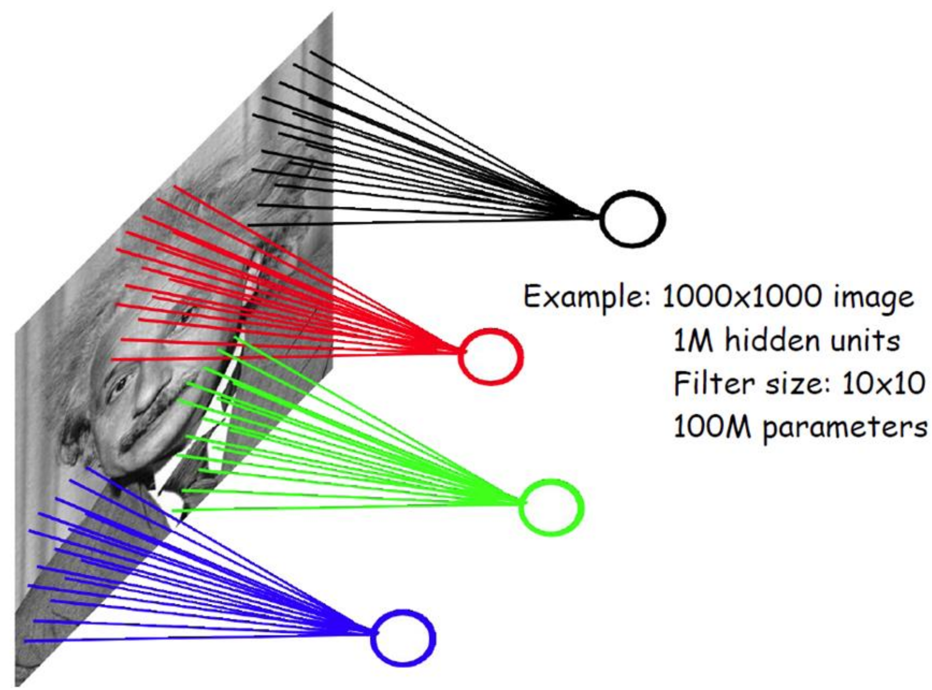
1. Recap MLP
2. **Convolutional Neural Networks**

How to limit the weight numbers?

1/ Locally connected neural networks

- **Sparse connectivity**: a hidden unit is only connected to a local patch (weights connected to the patch are called filter or kernel)
- Inspired by biological systems, where a cell is sensitive to a small sub-region of the input space, called a receptive field. Many cells are tiled to cover the entire visual field

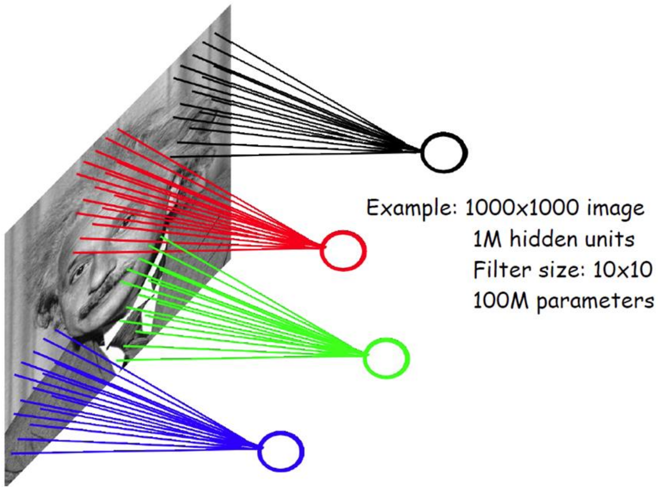


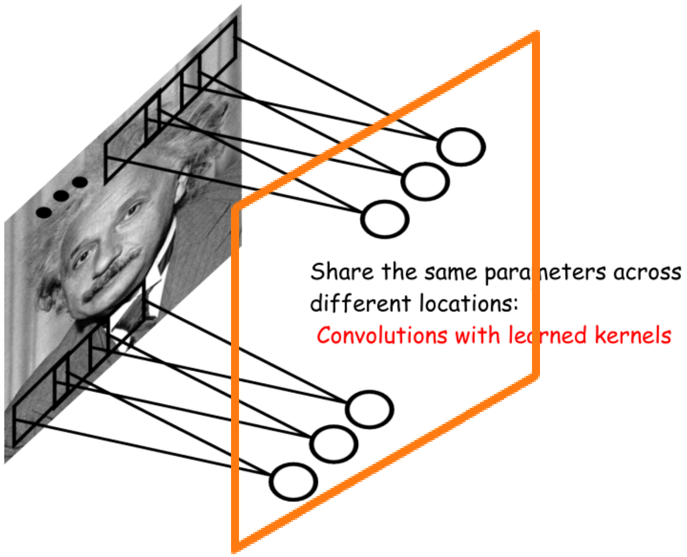


How to limit the weight numbers?

2/ Shared Weights

- Hidden nodes at different locations share the same weights
    - greatly reduces the number of parameters to learn
- Keep spatial information in a 2D feature map (hidden layer map)





⇒ Computing responses at hidden nodes equivalent to convoluting input image with a linear filter (learned)

⇒ A learned filter as a feature detector

Recap (1D/2D) convolution

1D discrete convolution of input signal x[n], with filter impulse response h[n], and output y[n]:

$$y[n] = x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[n-k]$$

2D discrete convolution of input signal x[m,n], with filter impulse response h[m,n] (*kernel*), and output y[m,n]:

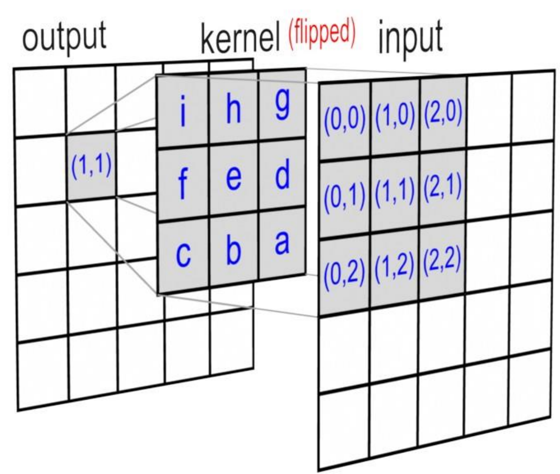
$$y[m,n] = x[m,n] * h[m,n] = \sum_{j=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} x[i,j] \cdot h[m-i, n-j]$$

Example with impulse response (kernel) 3x3, and it's values are a, b, c, d,... : (0,0) located in the center of the kernel

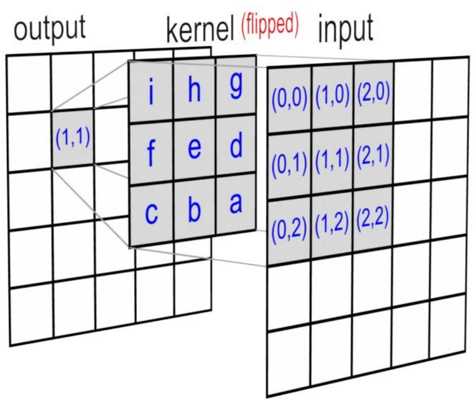
n \ m	-1	0	1
-1	a	b	c
0	d	e	f
1	g	h	i

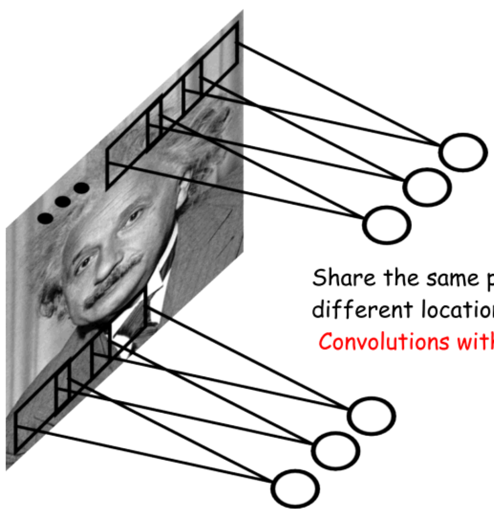
$$y[1,1] = \sum_{j=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} x[i,j] \cdot h[1-i, 1-j]$$

$$\begin{aligned} = \quad & x[0,0] \cdot h[1,1] \quad + x[1,0] \cdot h[0,1] \quad + x[2,0] \cdot h[-1,1] \\ & + x[0,1] \cdot h[1,0] \quad + x[1,1] \cdot h[0,0] \quad + x[2,1] \cdot h[-1,0] \\ & + x[0,2] \cdot h[1,-1] + x[1,2] \cdot h[0,-1] + x[2,2] \cdot h[-1,-1] \end{aligned}$$



Ex. of convolution operator



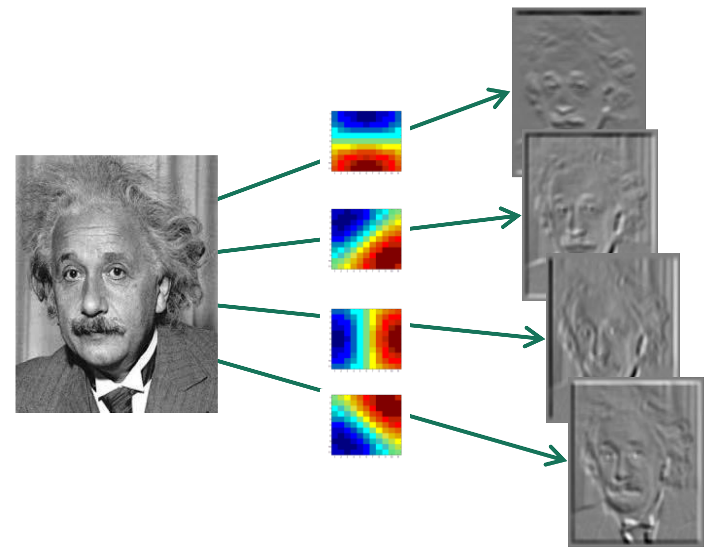


Share the same parameters across different locations:
Convolutions with learned kernels

Convolution

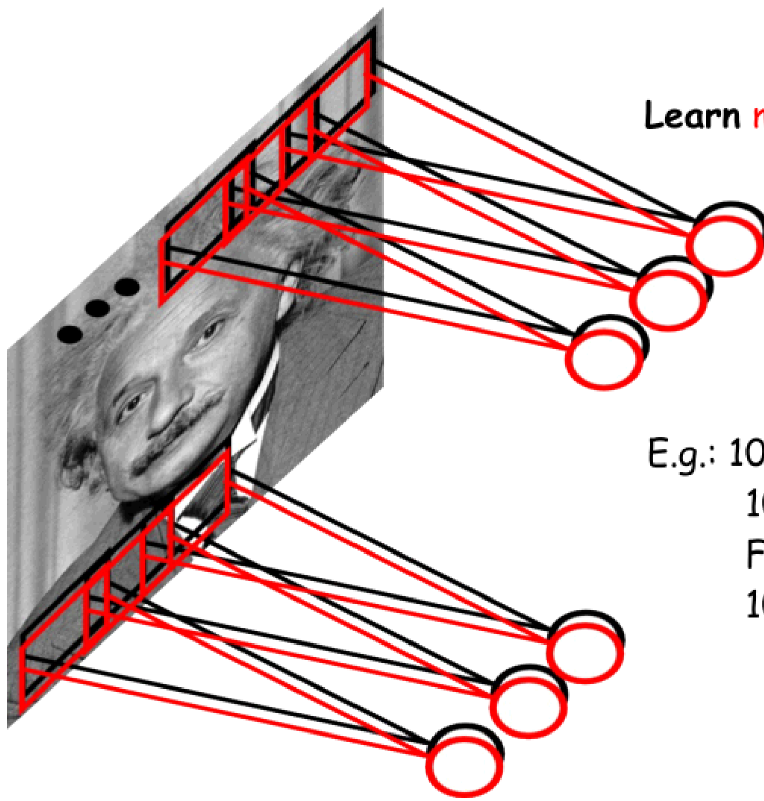
2D

$$\begin{bmatrix} 35 & 40 & 41 & 45 & 50 \\ 40 & 40 & 42 & 46 & 52 \\ 42 & 46 & 50 & 55 & 55 \\ 48 & 52 & 56 & 58 & 60 \\ 56 & 60 & 65 & 70 & 75 \end{bmatrix} \times \begin{bmatrix} & & & & \\ & 0 & 1 & 0 & \\ & 0 & 0 & 0 & \\ & 0 & 0 & 0 & \\ & & & & \end{bmatrix} = \begin{bmatrix} & & & & \\ & & & & \\ & & 42 & & \\ & & & & \\ & & & & \end{bmatrix}$$



From one to many filters

1 filter => 1 feature map (corresponding to 1 visual pattern)
To detect spatial distributions of multiple visual patterns: Multiple filters
M filters => M feature maps!   Get richer description



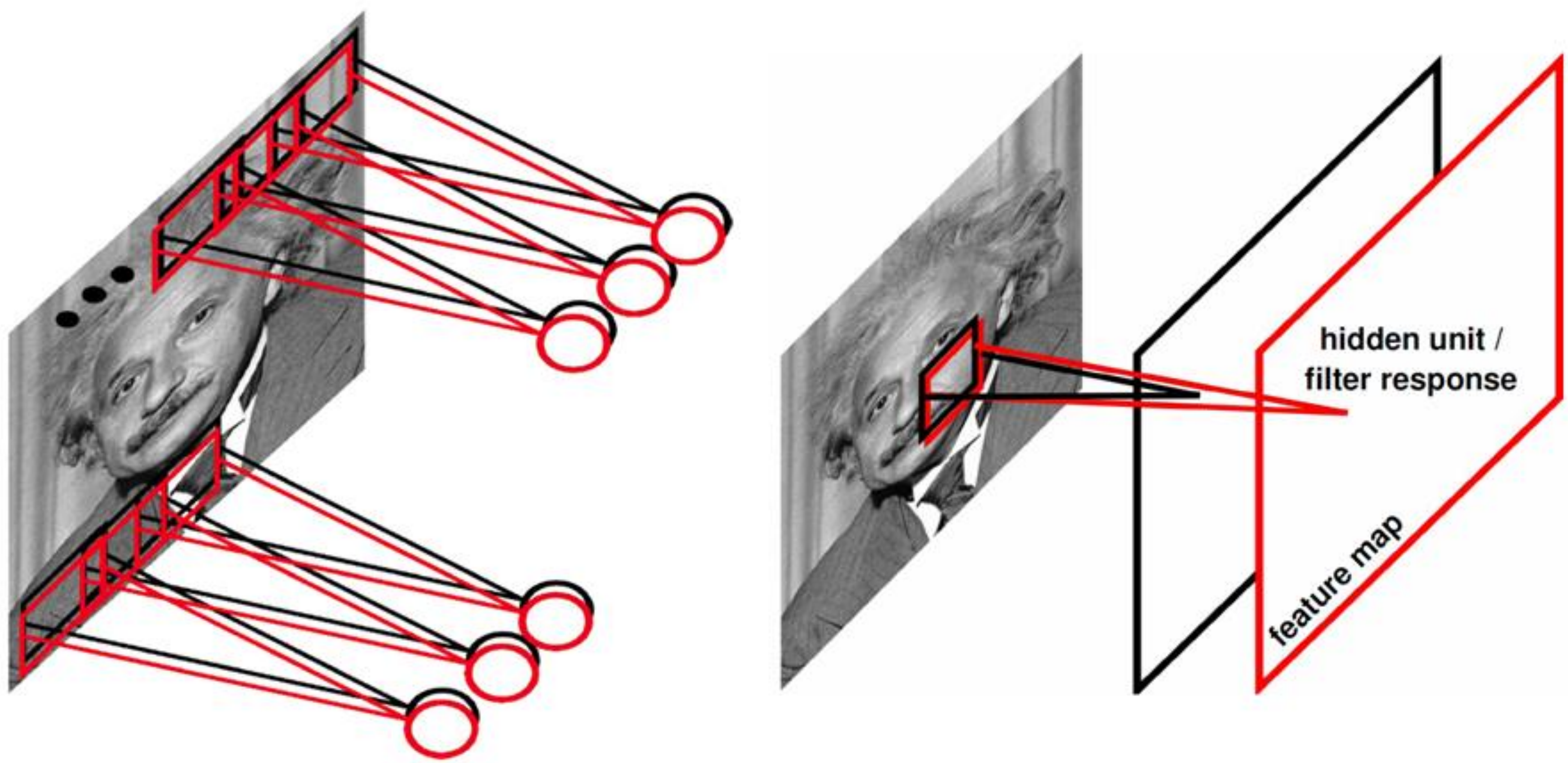
Learn multiple filters.

E.g.: 1000x1000 image
100 Filters
Filter size: 10x10
10K parameters

Not a big deal!
Many filters => still few parameters

From one to many filters

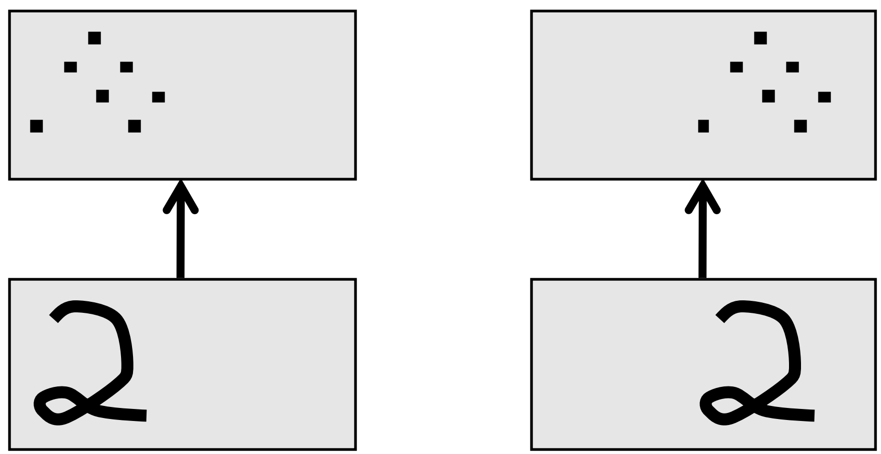
M filters => M feature maps



Rq: not many weights but many neurons! => memory issues will appear

What does replicating the feature detectors achieve?

- Equivariant activities (Hinton Ex): Replicated features do not make the neural activities invariant to translation. The activities are equivariant.



⇒How to get invariance to 2D spatial transformation of the input?

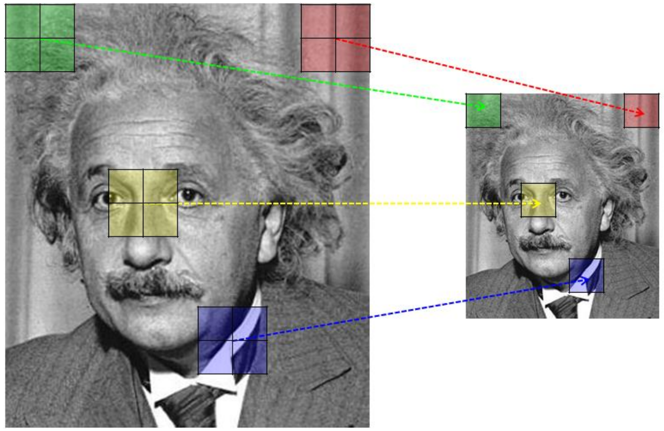
Getting (more) local Invariance

(local) spatial **POOLING** of the outputs of replicated feature detectors:

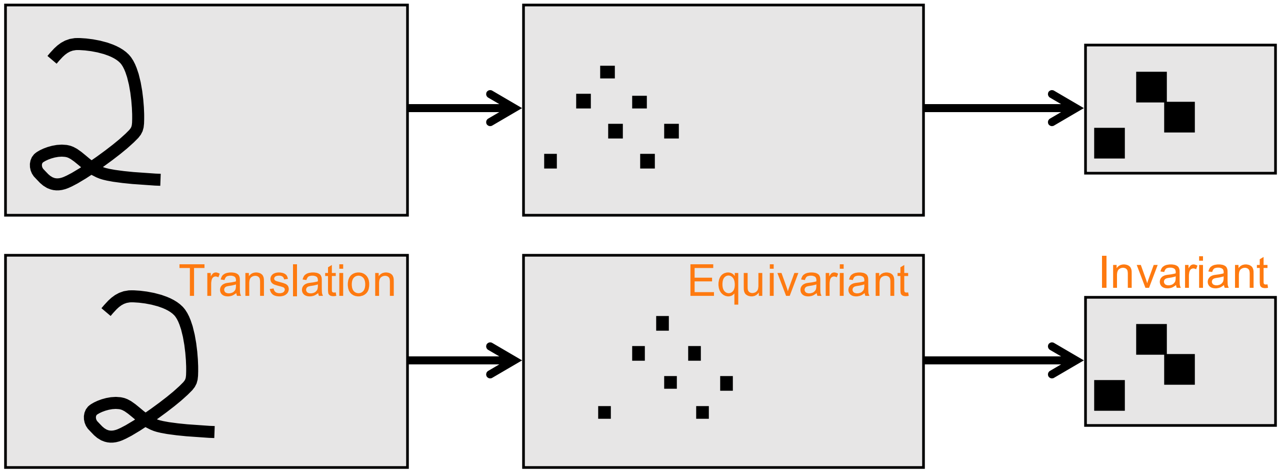
- Averaging neighboring replicated detectors to give a single output to the next level
- Max pooling: Taking the maximum in a neighboring

Get a small amount of translational invariance at each level

Reducing the number of inputs to the next layer of feature extraction

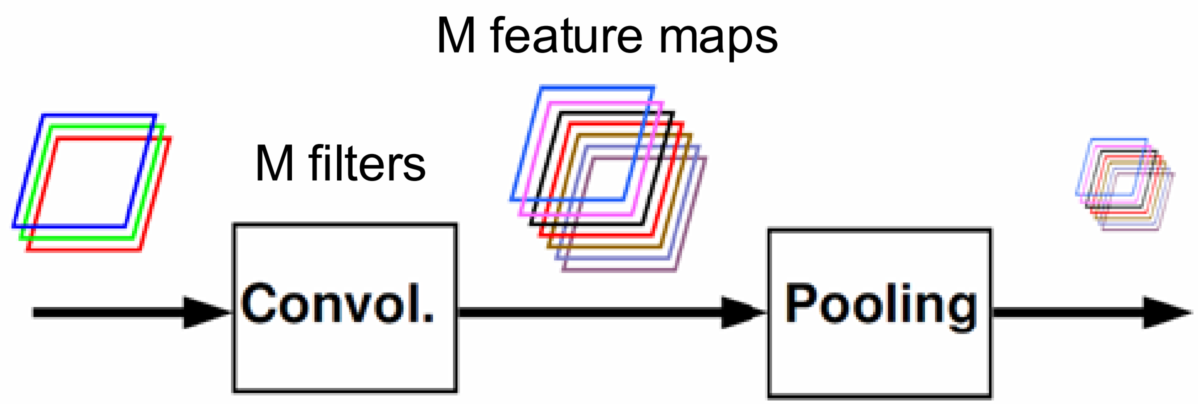


$$y_{ij} = \frac{1}{4}\left(x_{2i,2j} + x_{2i+1,2j} + x_{2i,2j+1} + x_{2i+1,2j+1}\right)$$



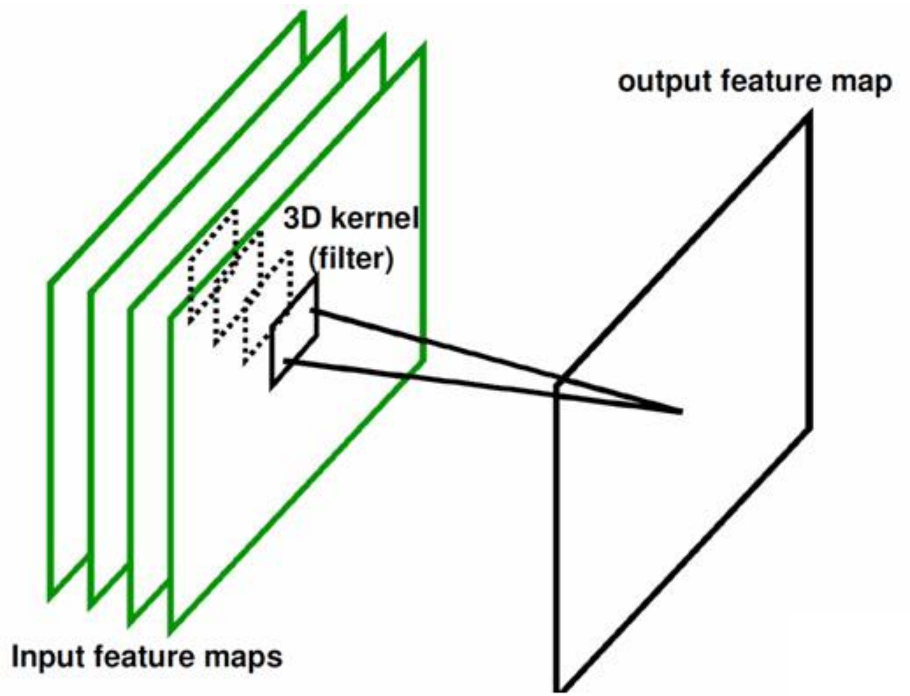
=> Stability OK (at least for local shift) for Convolutional Net!

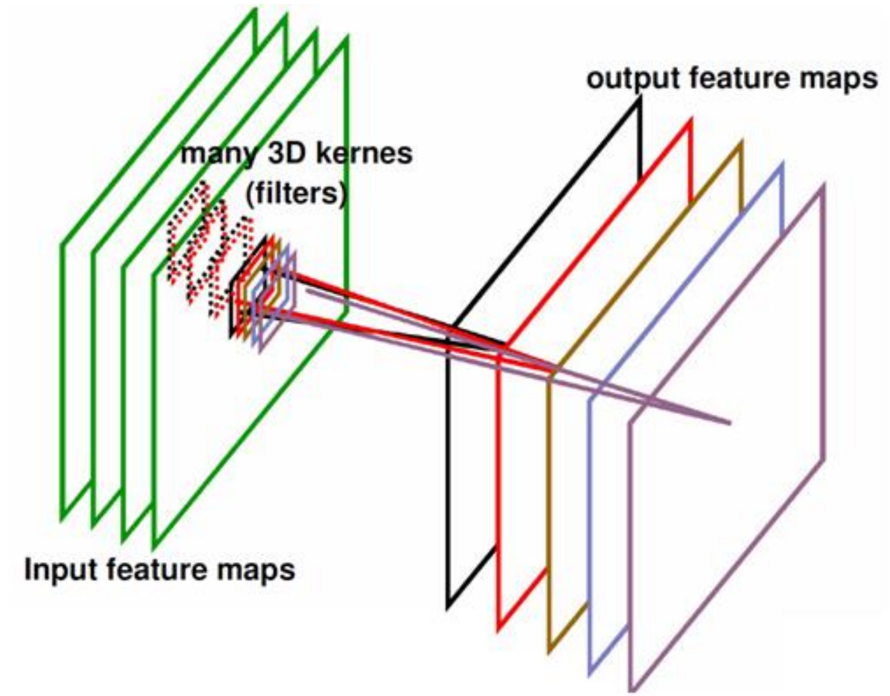
To sum up:



Color images: 3D kernels for filtering

mxnxd parameters per filter
Idem for any layer i to layer i+1

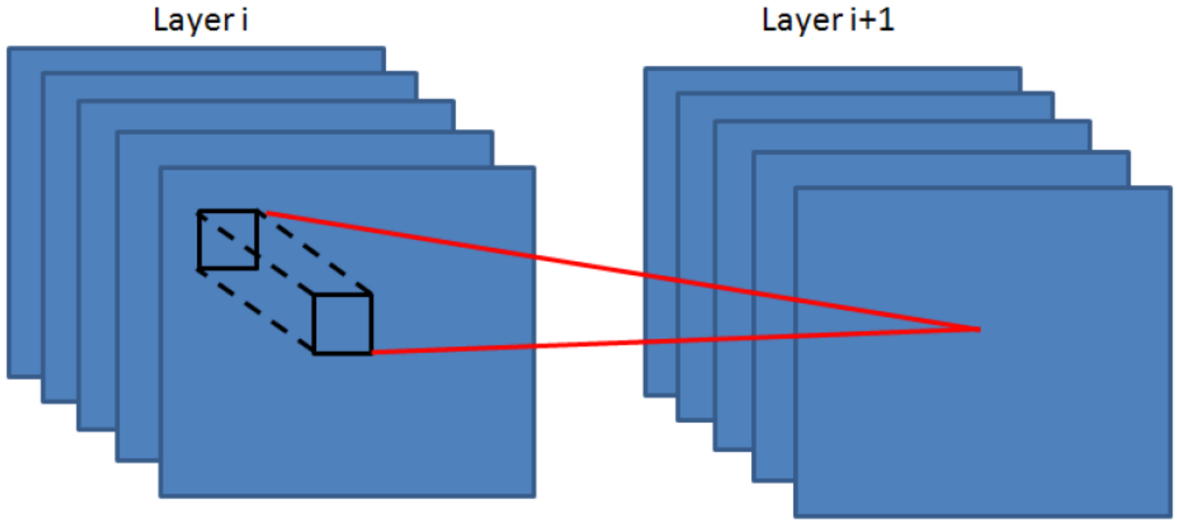




LCN: Local Contrast Normalization

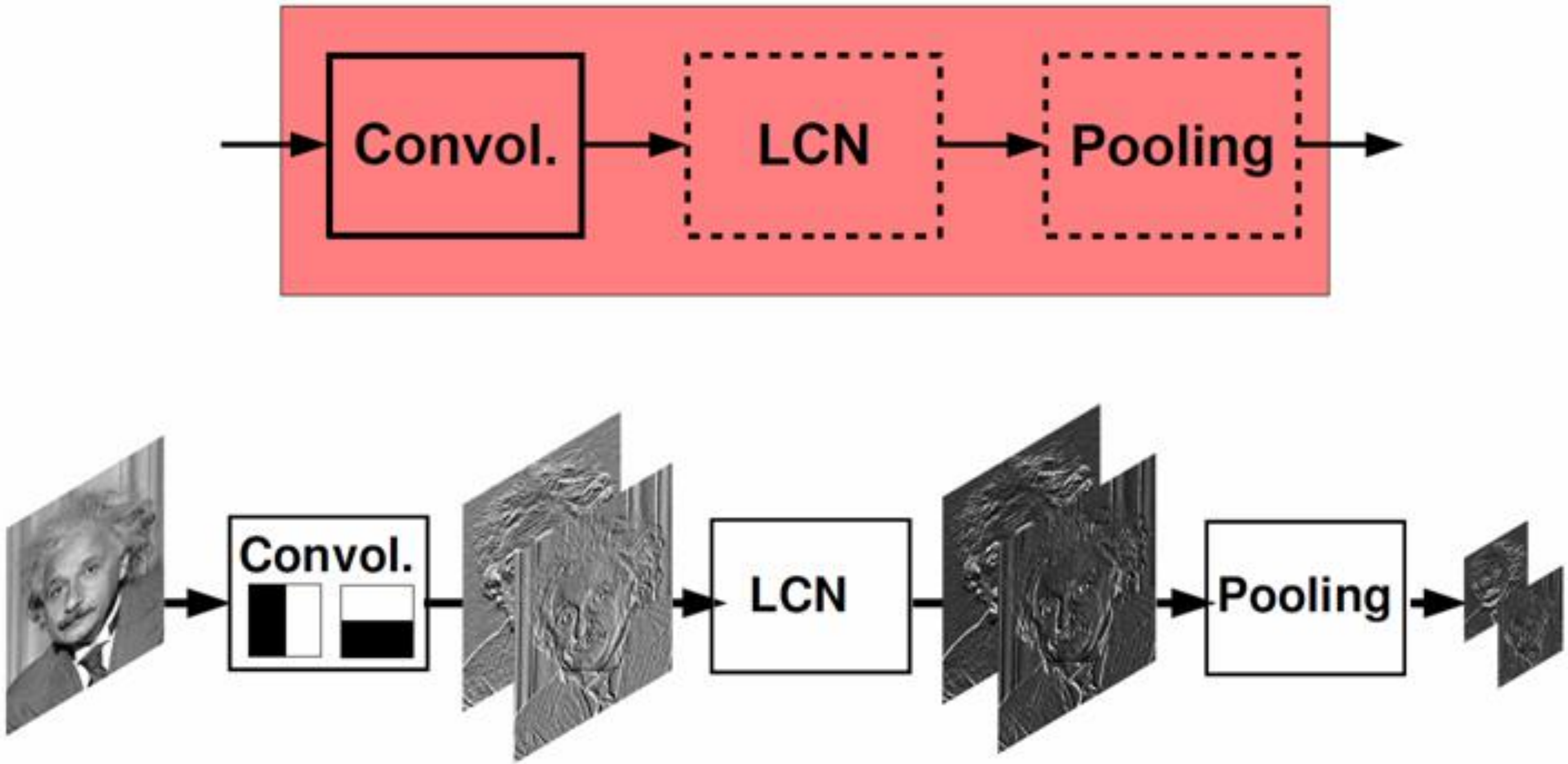
Normalization within a neighborhood along both spatial and feature dimensions

$$h_{i+1,x,y,k} = \frac{h_{i,x,y,k} - m_{i,N(x,y,k)}}{\sigma_{i,N(x,y,k)}}$$



=> Very important for training large nets to carefully consider normalization within mini-batchs [S. Ioffe, C. Szegedy 2015]

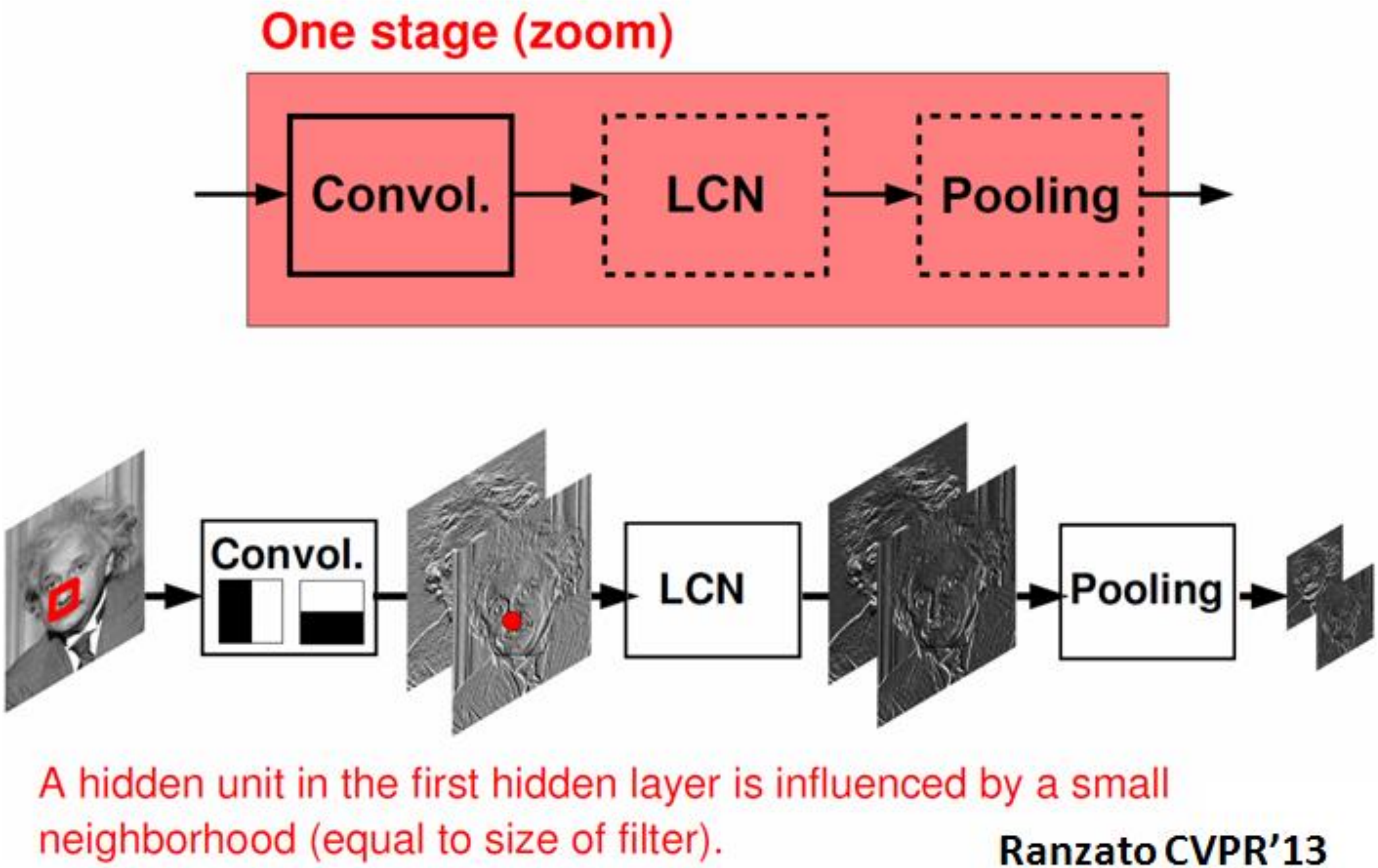
1stage of convolutional neural networks



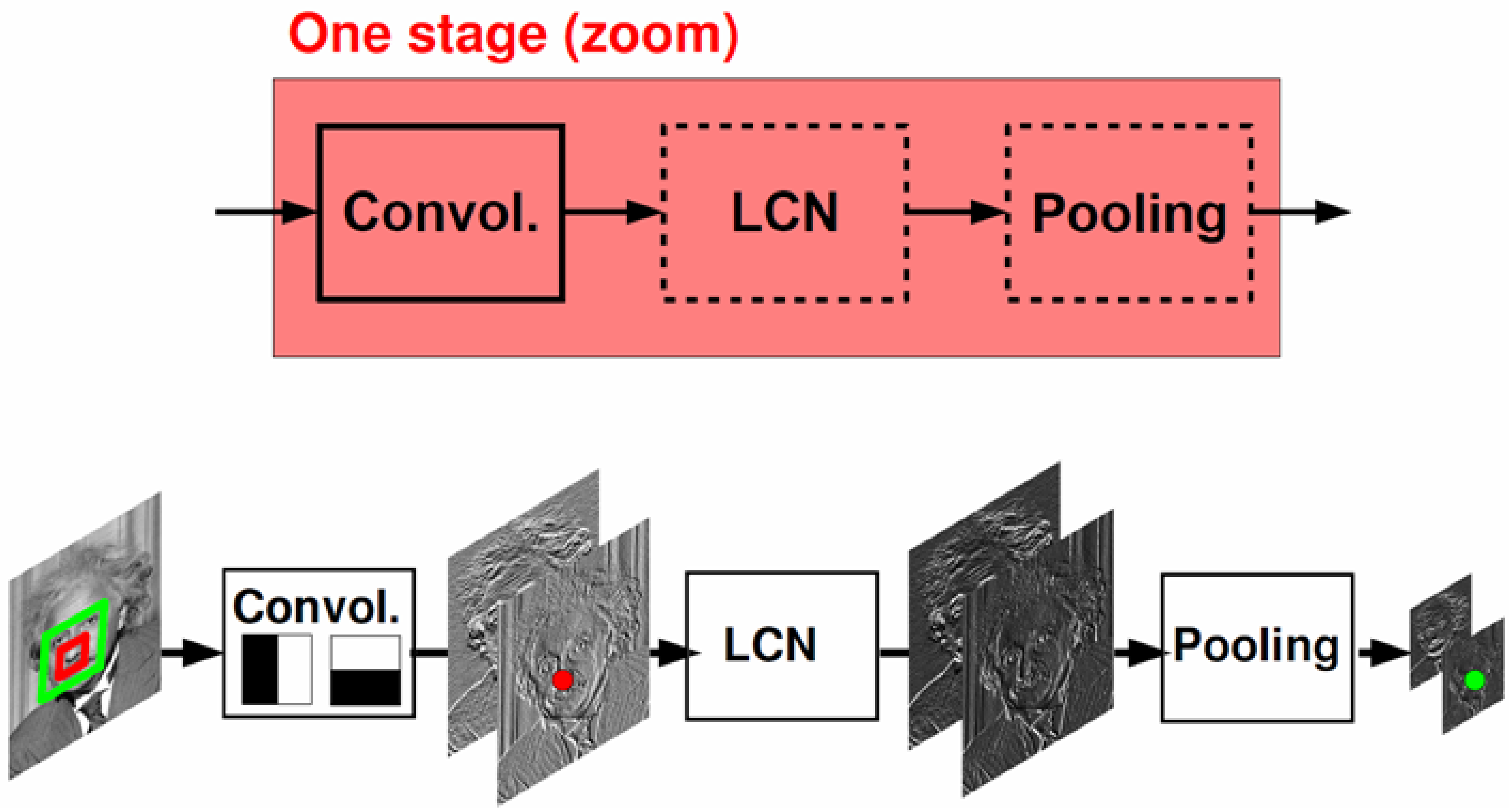
Example with only two filters.

Ranzato CVPR'13

1stage of convolutional neural networks



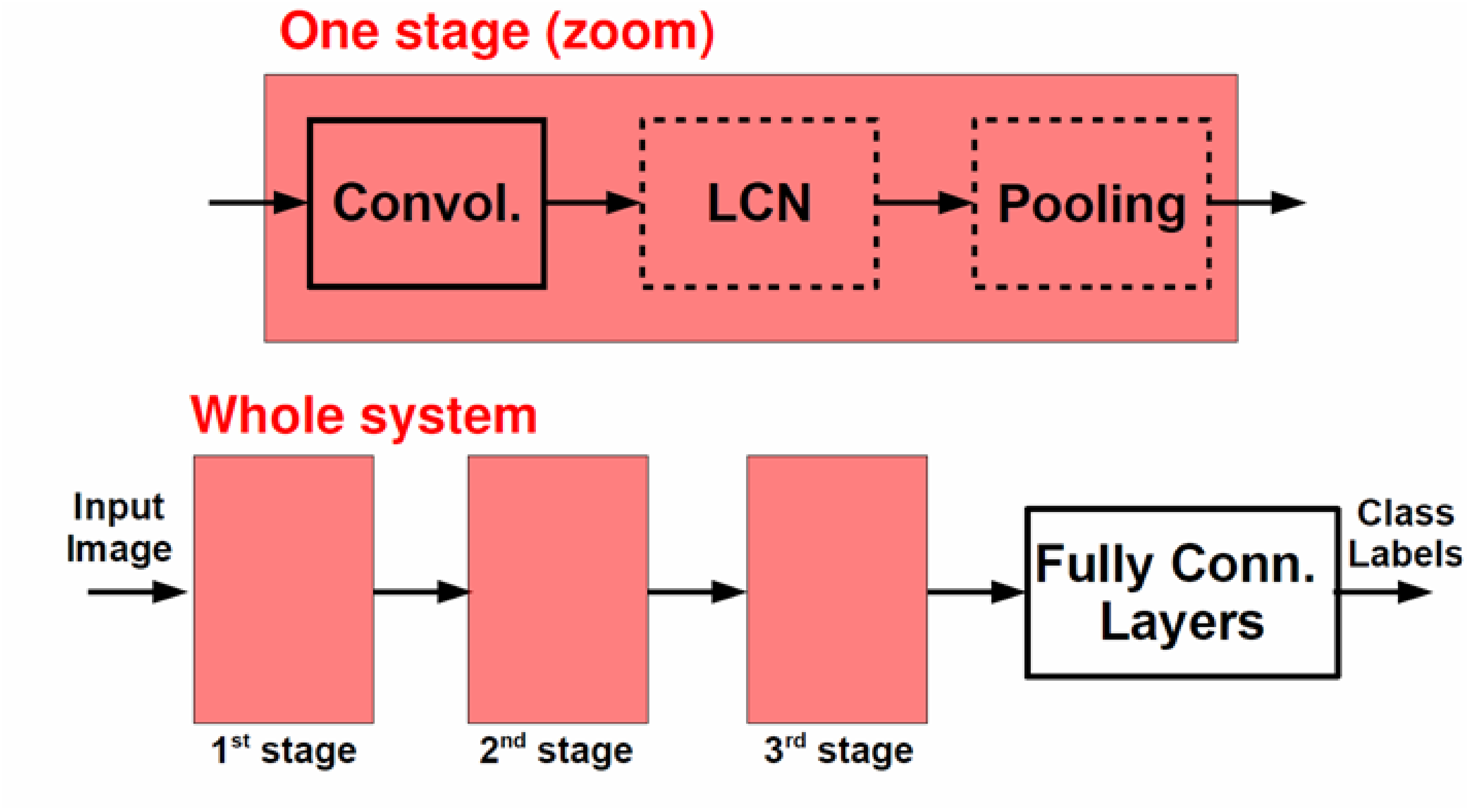
1stage of convolutional neural networks



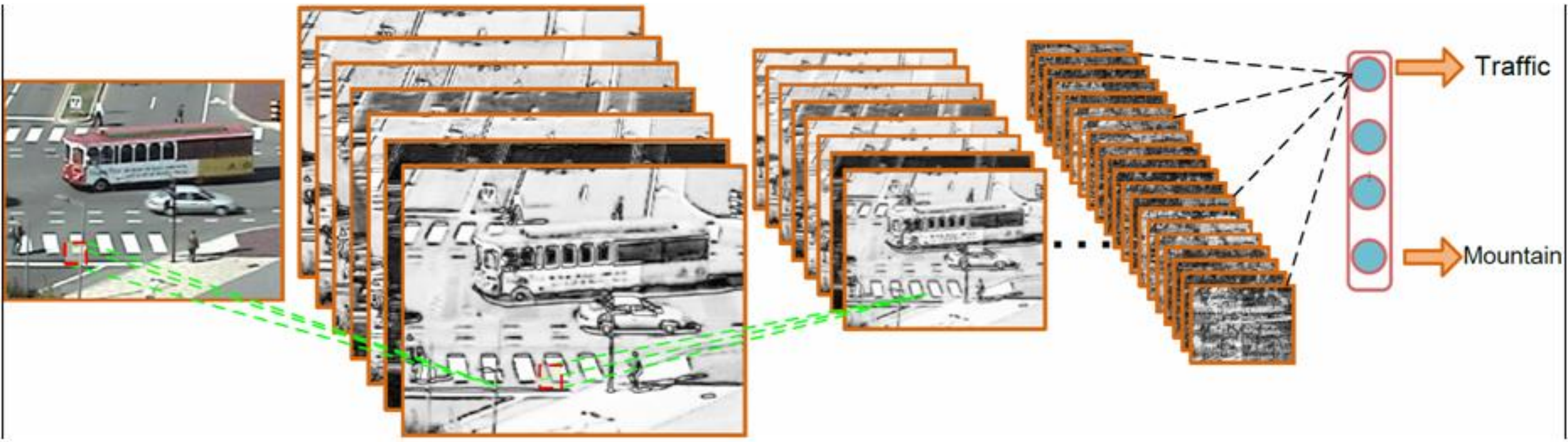
A hidden unit after the pooling layer is influenced by a larger neighborhood (it depends on filter sizes and the sizes of pooling regions)

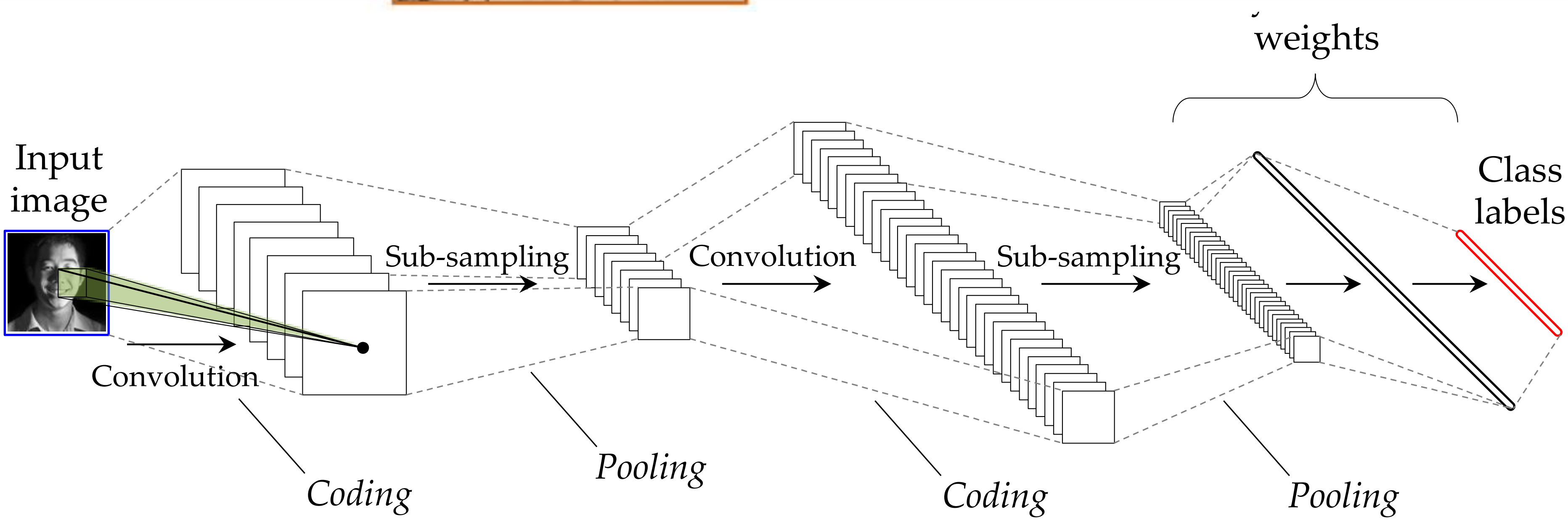
Ranzato CVPR'13

Full ConvNet architecture



To sum up: Full ConvNet architecture





To sum up: Full ConvNet architecture

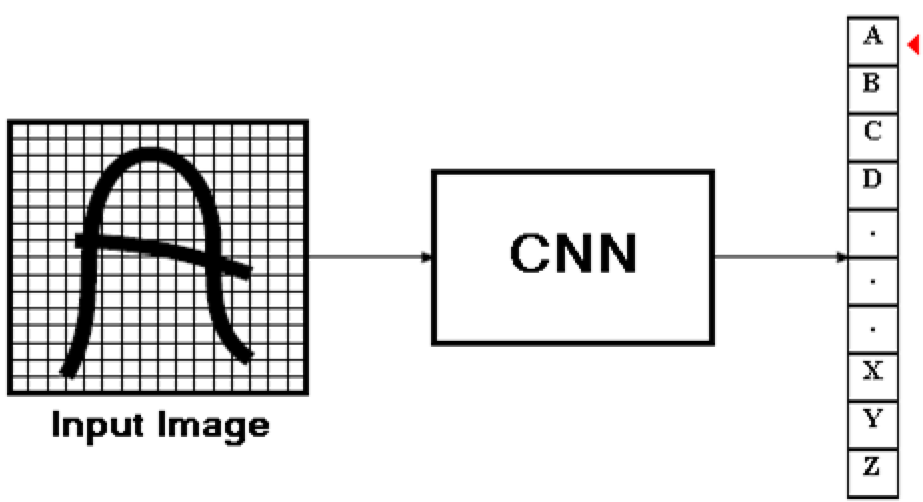
ConvNet (CNN): feed-forward network with

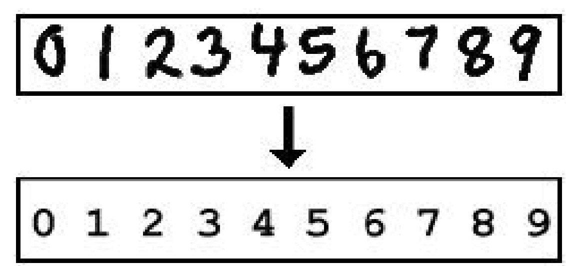
-- ability to extract topological properties from image

-- designed to recognize visual patterns

Working directly from pixel images with (no/minimal) preprocessing

Trained with back-propagation





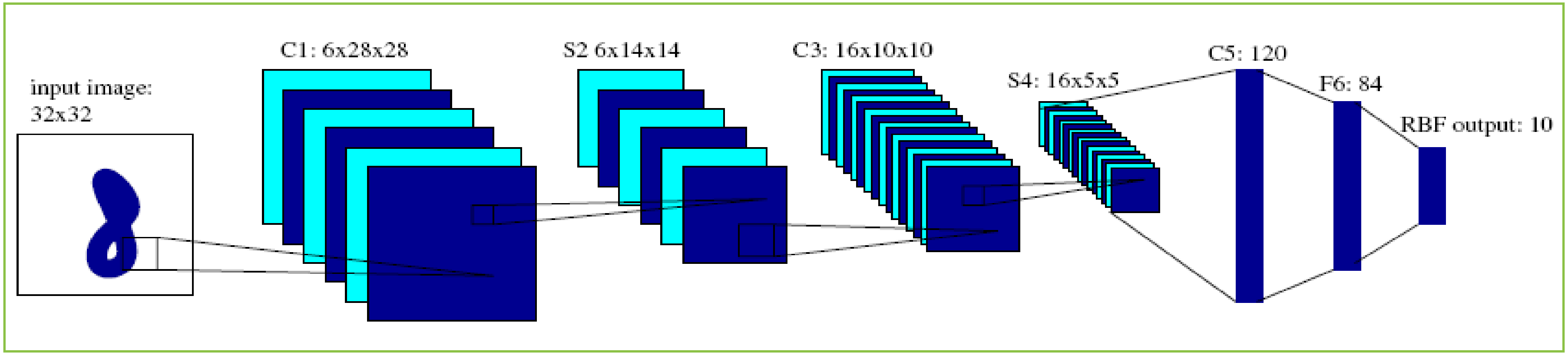
Outline
Convolutional Nets for visual classification

1. Recap MLP
2. Convolutional Neural Networks
3. **Examples: LeNet5, AlexNet**

Example: LeNet5

Introduced by Y. LeCun

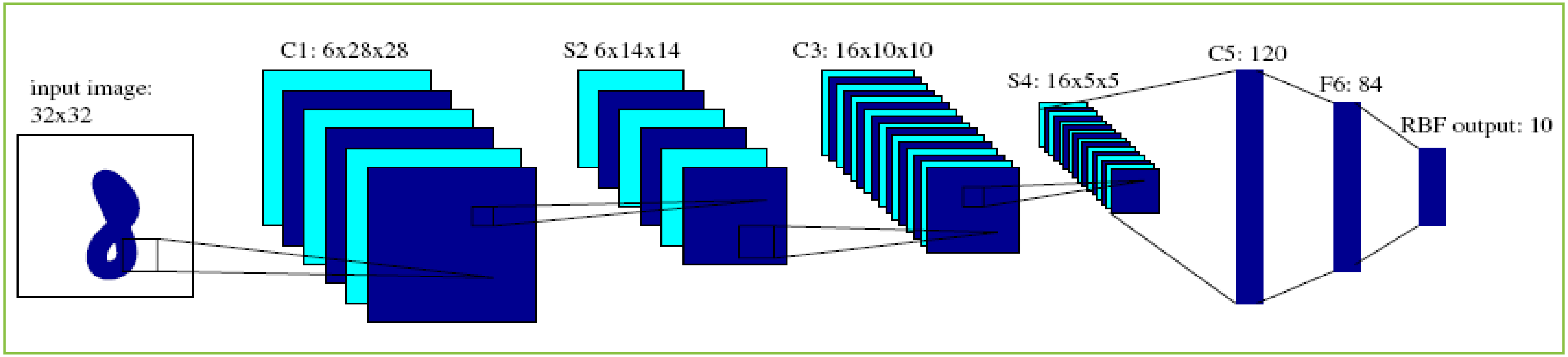
Raw image of 32 × 32 pixels as input



Example: LeNet5

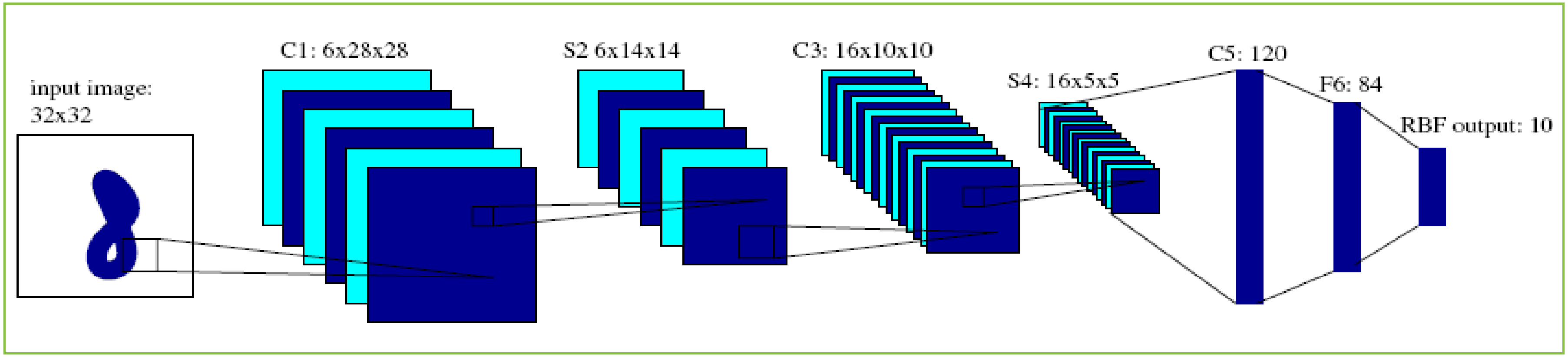
- C1,C3,C5 : Convolutional layer
- 5 × 5 Convolution matrix
- S2 , S4 : Subsampling layer = Pooling+stride s=2

  => Subsampling by factor 2
- F6 : Fully connected layer

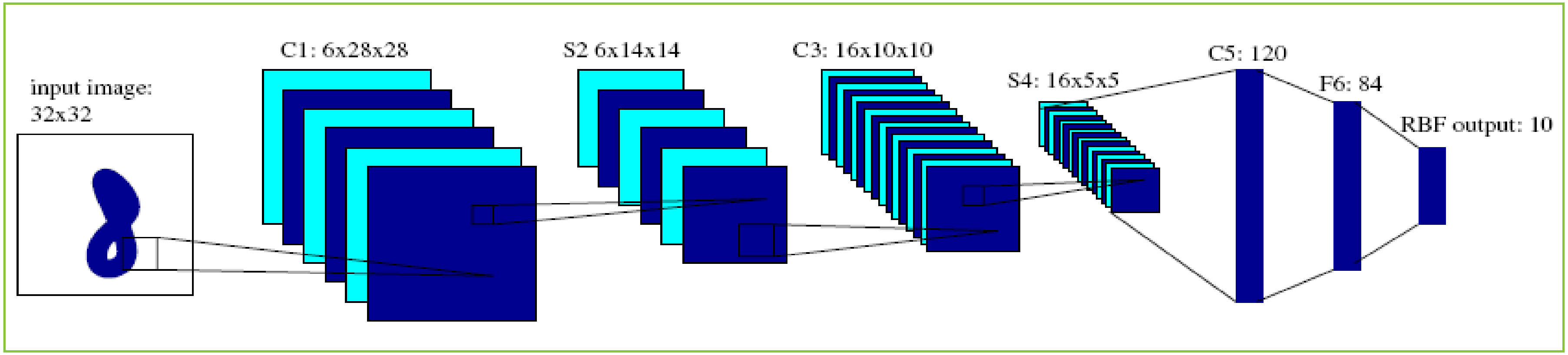


LeNet5

All the units of the layers up to F6 have a sigmoidal activation function

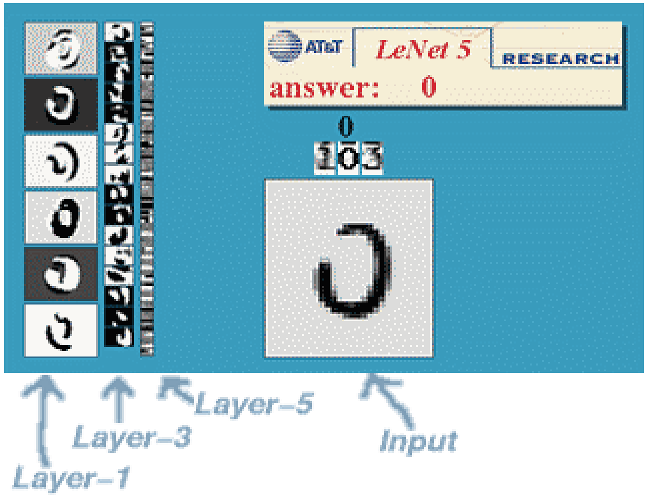


LeNet5

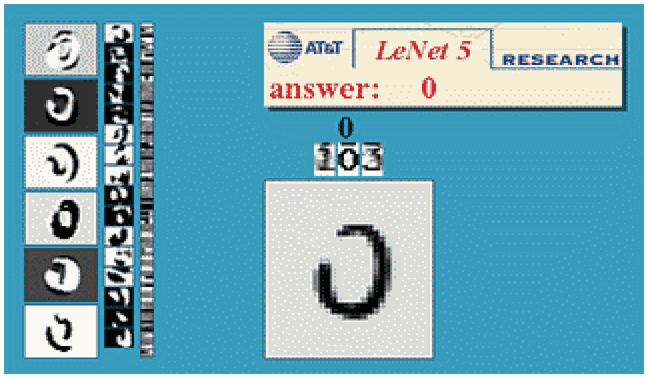


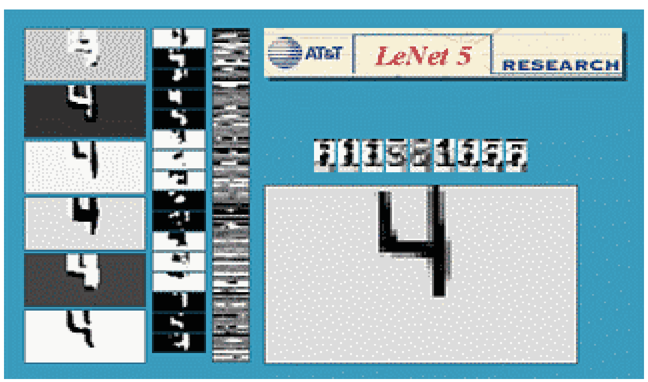
About 187,000 connections

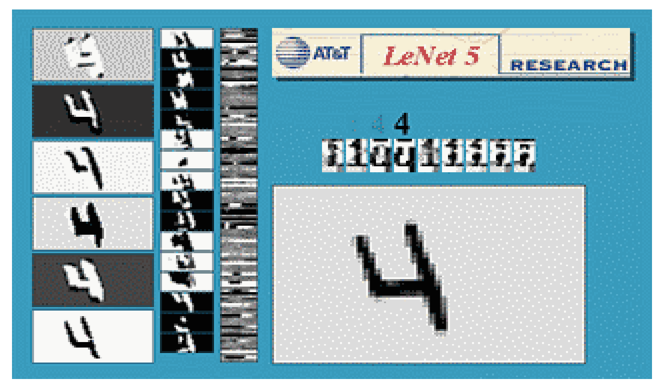
About 14,000 trainable weights



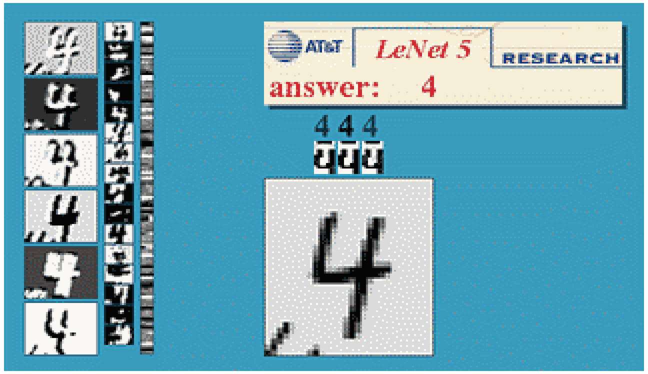
LeNet5 (@LeCun)

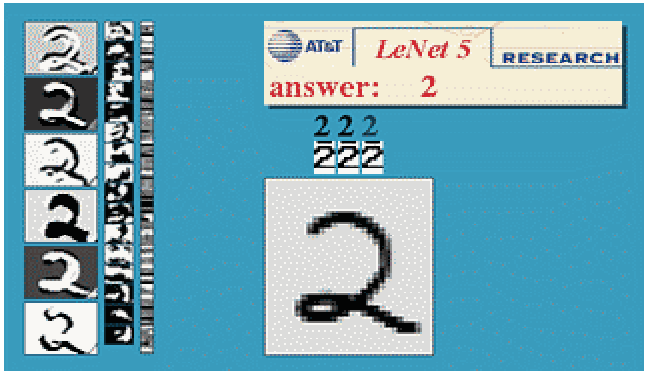


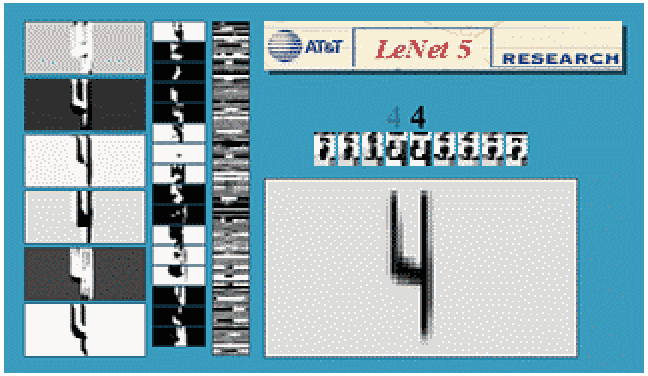


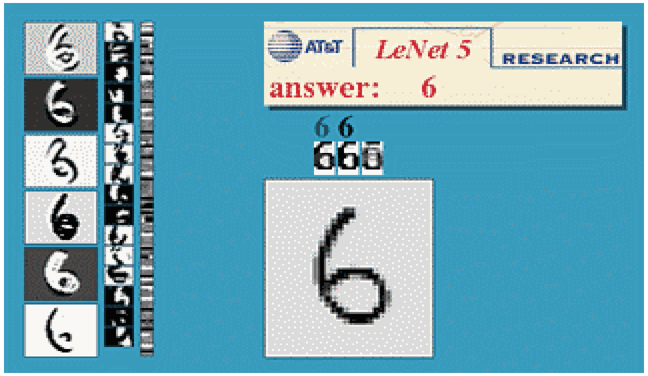


LeNet5 (@LeCun)



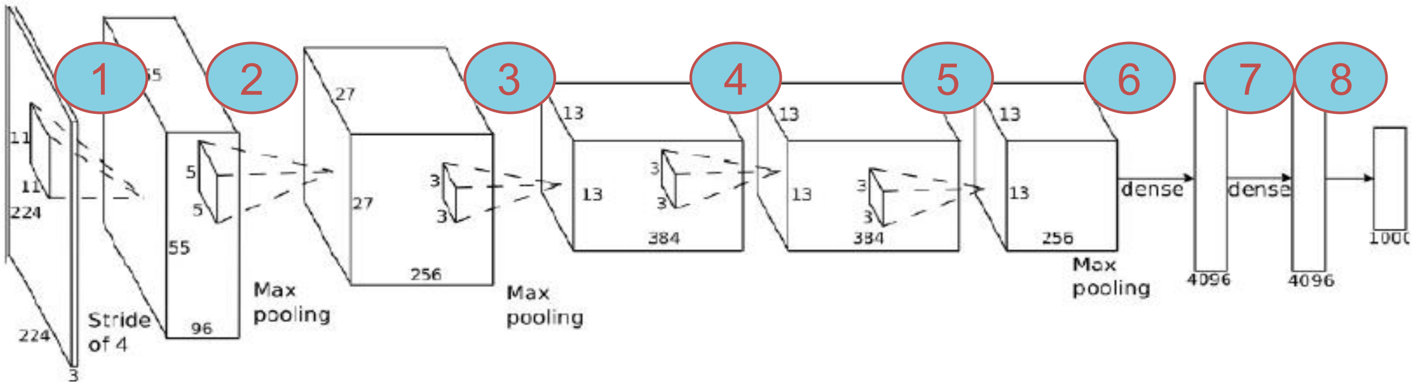




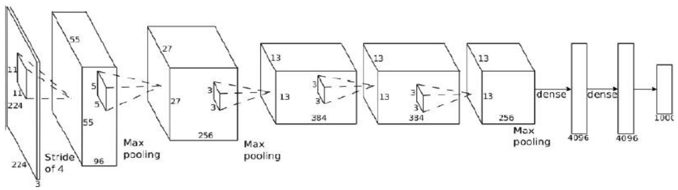


AlexNet 2012

- Same model as LeCun'98 but:
  - Bigger model (8 layers)
  - More data (10^6 vs 10^3 images)
  - GPU implementation (50x speedup over CPU)
  - Better regularization (DropOut)



AlexNet 2012

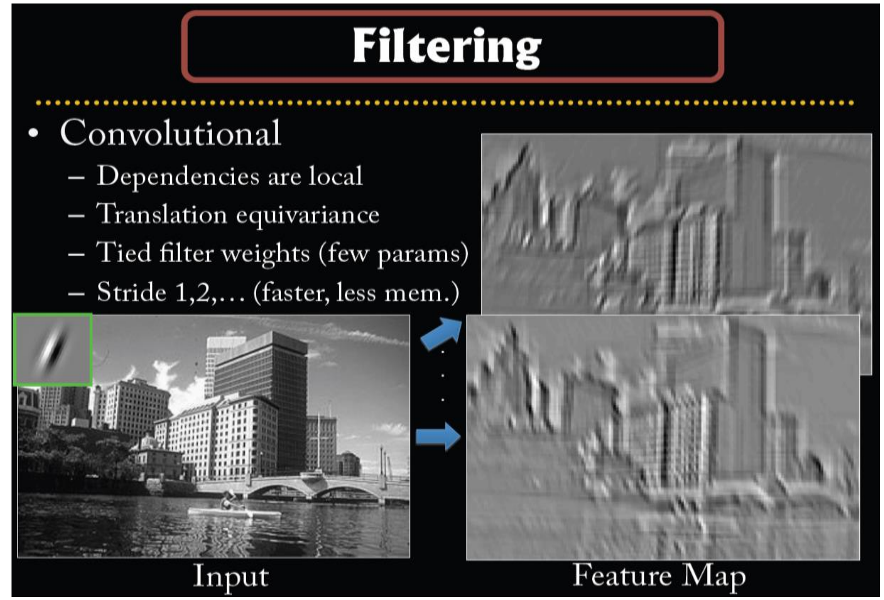


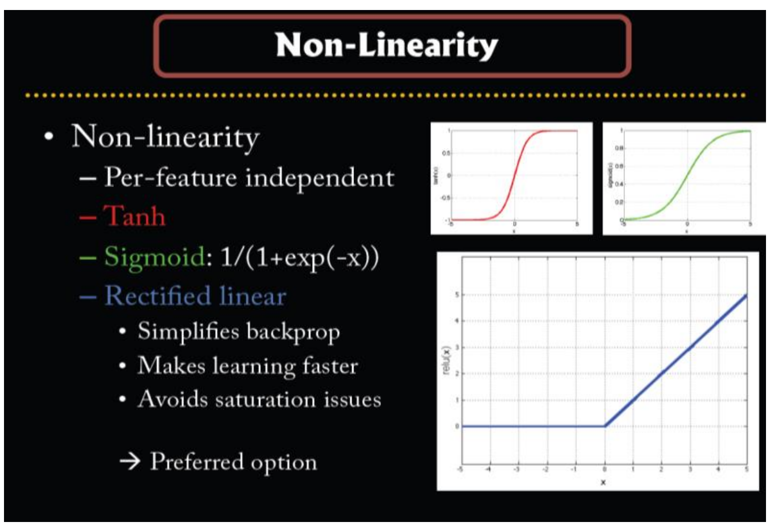
Same type of convnet with

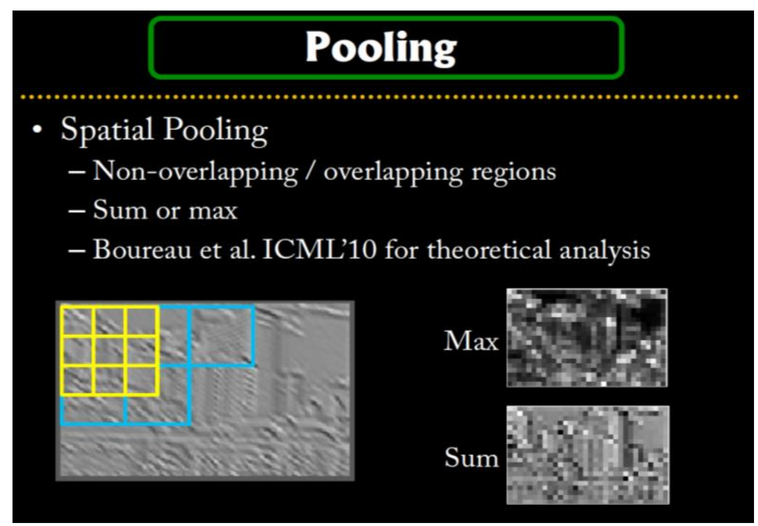
- Filtering (convolution)
- Non-Linearity
- Pooling

8 layers but 224x224 input images => much biger model:

- 650,000 neurons
- 60,000,000 weights!



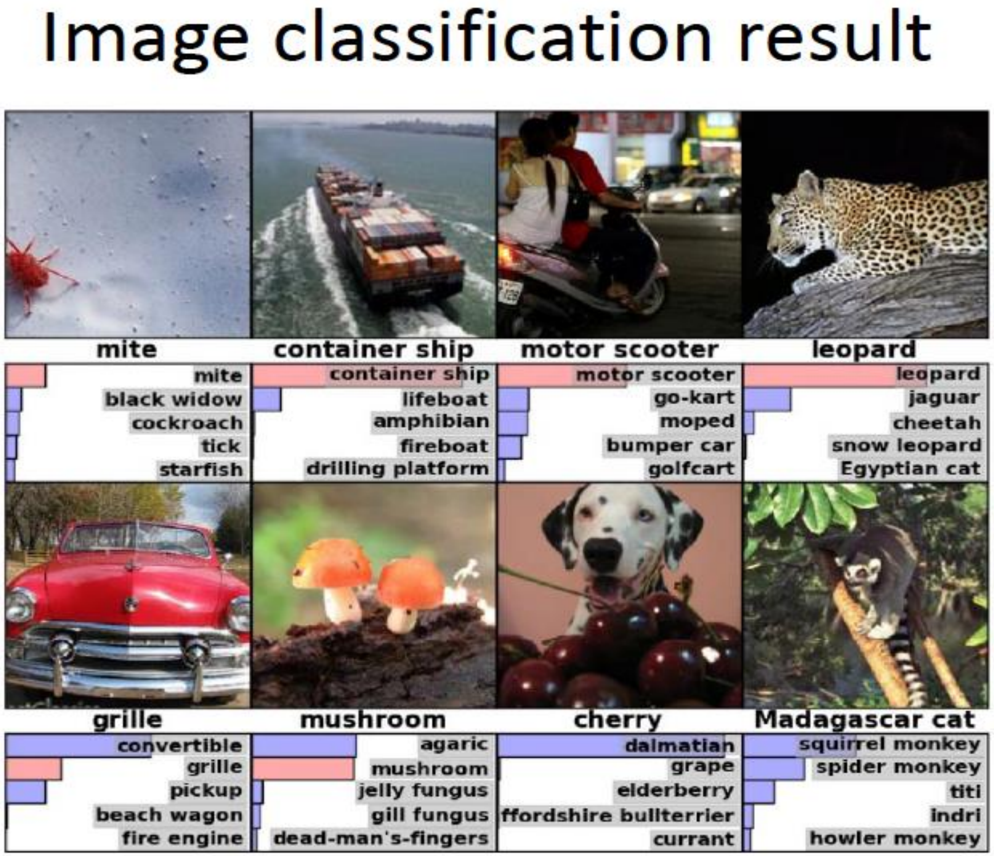




More data for supervised training

ImageNet 2012: the (deep) revolution

- 1.2 million labeled images
- 1000 classes
- Mono-class
- TOP5



Learning the AlexNet

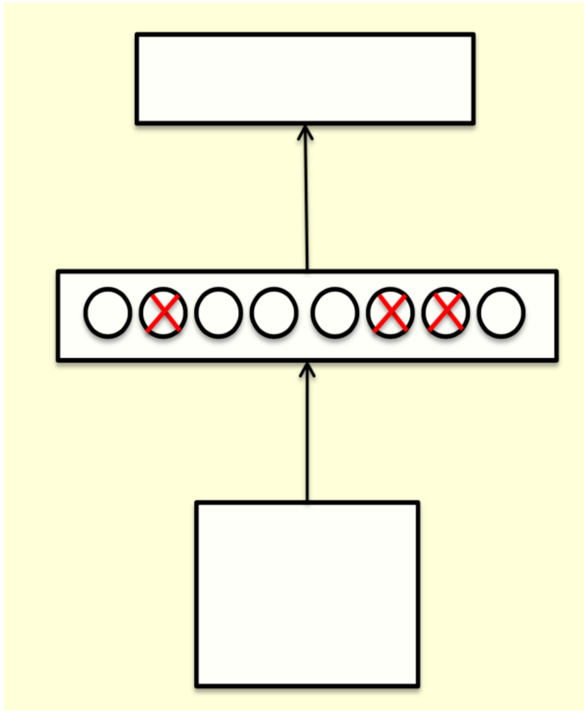
- Basics:
  - SGD, Backprop
  - Cross Validation
  - Grid search
- “New”
  - Huge computational resources (GPU)
  - Huge training set (1 million images)
  - Data augmentation - Pre-processing
  - Dropout
  - ReLu
  - *Contrast normalization*

Data Augmentation

lots of jittering, mirroring, and color perturbation of the original images generated on the fly to increase the size of the training set

Crop, flip,.. in train / in test

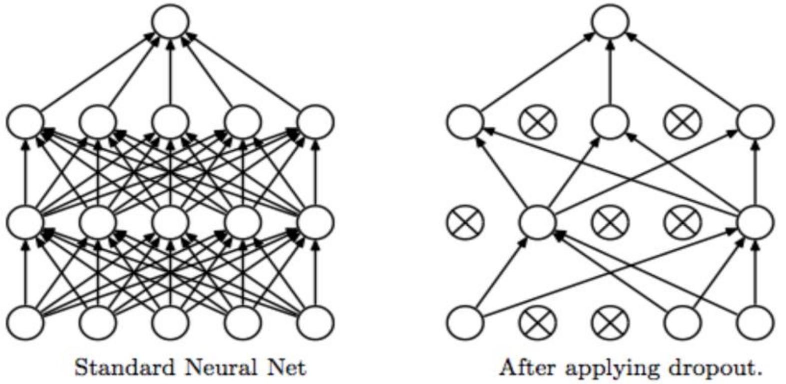
Dropout: an efficient way to average many large neural nets



For each training example, randomly omit each hidden unit with probability 0.5

Due to sharing of weights, model strongly regularized

- Pulls the weights towards what other models want.
- Better than L2 and L1 regularization that pull weights towards zero



@Hinton, NIPS 2012

Dropout: what do we do at test time?

Option 1:

Sample many different architectures and take the geometric mean of their output distributions

Option 2: (Faster way)

Use all the hidden units

but after **halving their outgoing weights**

Rq: In case of single hidden layer, this is equivalent to the geometric mean of the predictions of all models

For multiple layers, it’s a pretty good approximation and its fast

How well does dropout work?

Improving generalization:

- For very deep nets, or at least when there are huge fully connected layers (eg. AlexNet first FC layer, VGG next, …)
- Less useful for fully convolutional nets

Useful to prevent feature co-adaptation (feature only helpful when other specific features present)

Later in course

$\Rightarrow$**Dropout as a Bayesian Approximation**

$\Rightarrow$**Representing Model Uncertainty in Deep Learning**

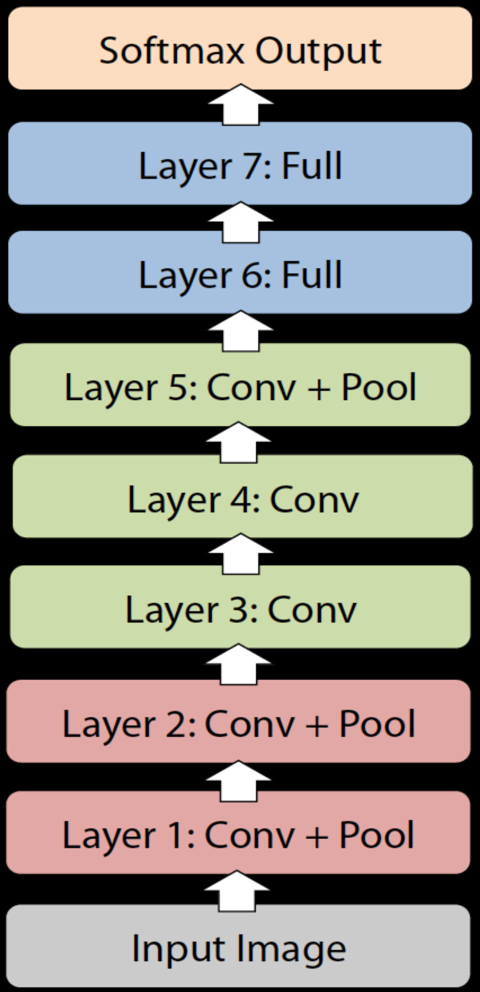
AlexNet 2012

Ablation study

1. **Number of layers**
2. ***Tapping off features at each layer***
3. **Transfo Robustness vs layers**

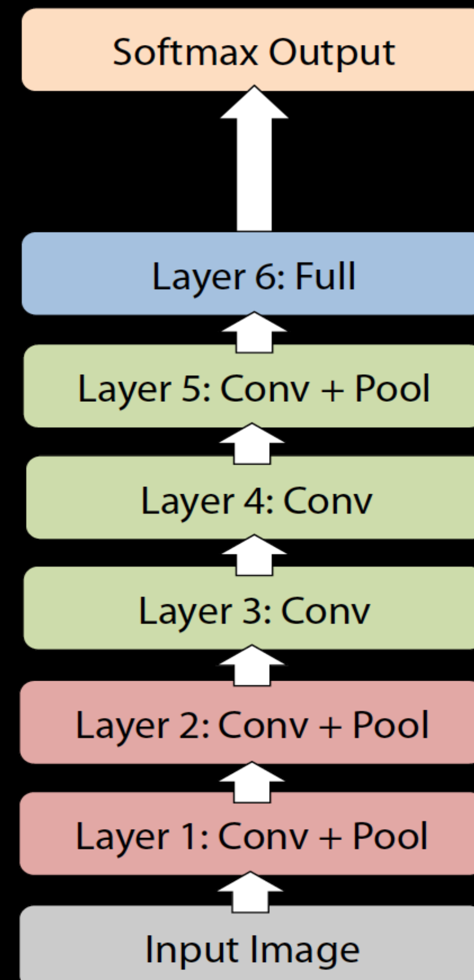
Architecture of Krizhevsky et al.

- 8 layers total
- Trained on Imagenet dataset [Deng et al. CVPR'09]
- 18.2% top-5 error
- Our reimplementation:
  18.1% top-5 error



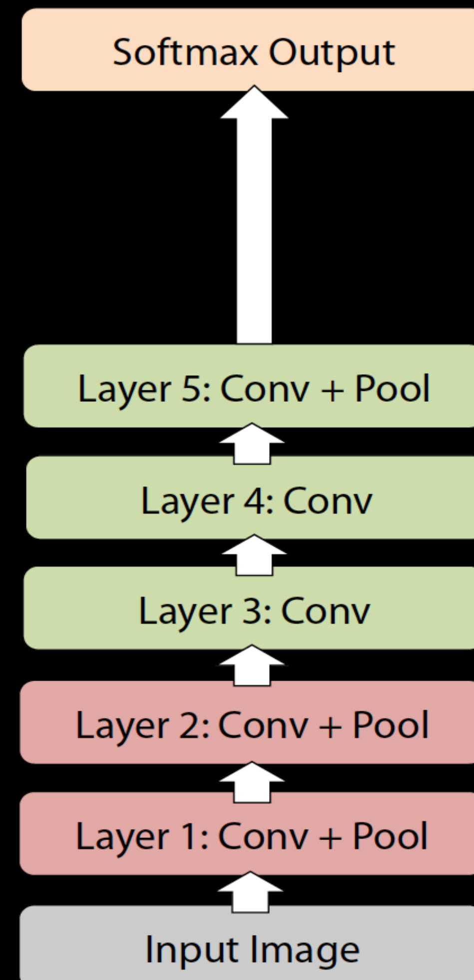
Architecture of Krizhevsky et al.

- Remove top fully connected layer
  - Layer 7
- Drop 16 million parameters
- Only 1.1% drop in performance!



Architecture of Krizhevsky et al.

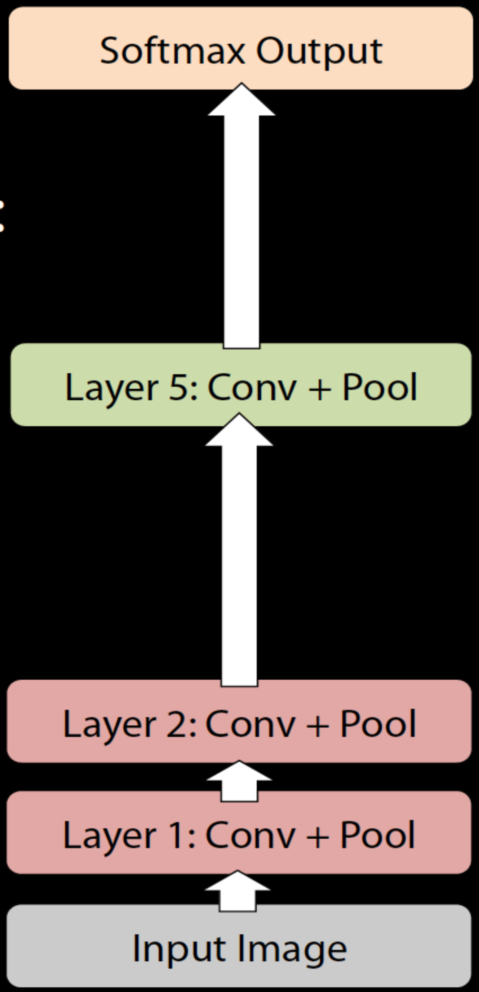
- Remove both fully connected layers
  - Layer 6 & 7
- Drop ~50 million parameters
- 5.7% drop in performance



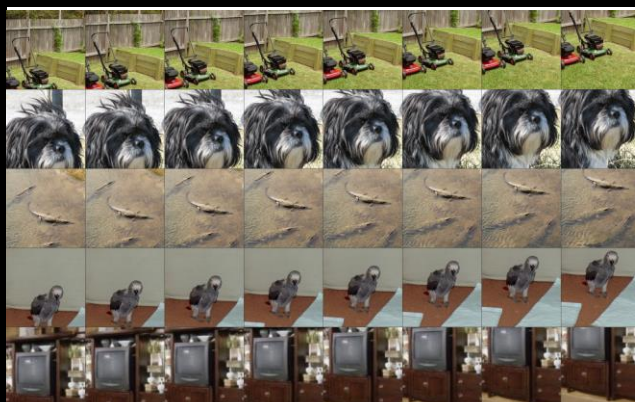
Architecture of Krizhevsky et al.

- Now try removing upper feature extractor layers & fully connected:
  - Layers 3, 4, 6 ,7
- Now only 4 layers
- 33.5% drop in performance

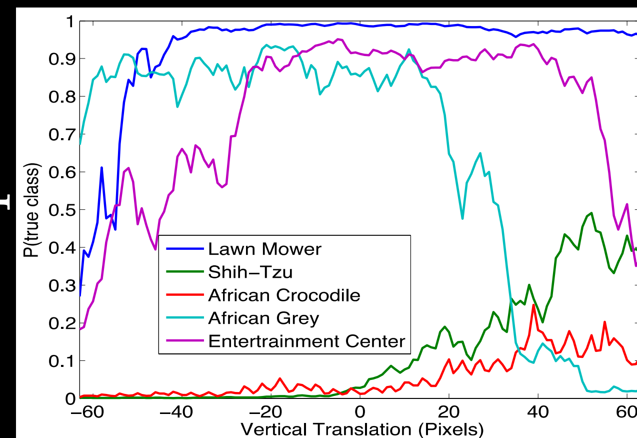
→Depth of network is key



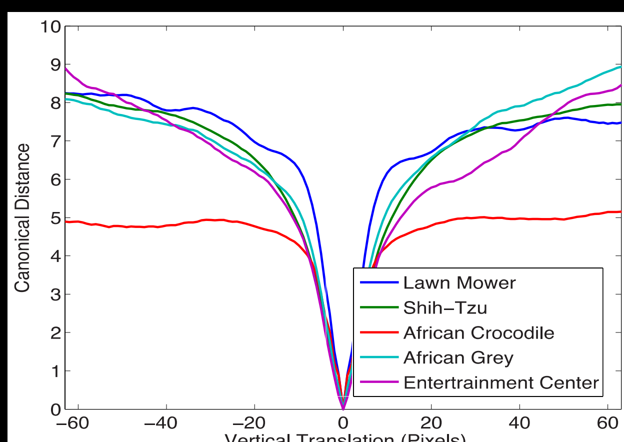
Translation (Vertical)



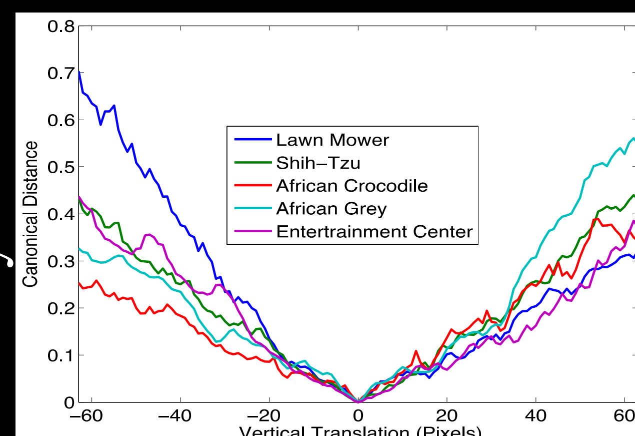
Output



Layer 1

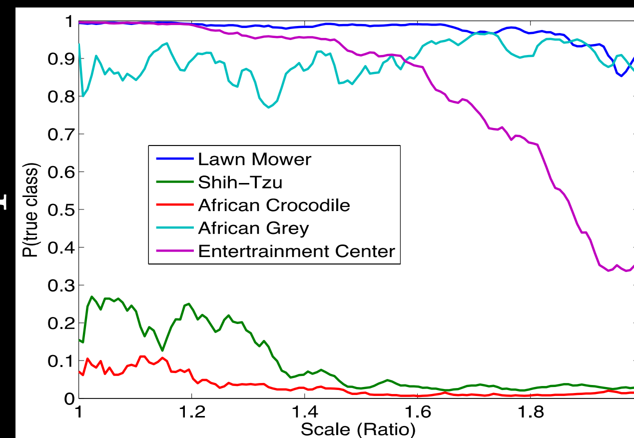


Layer 7

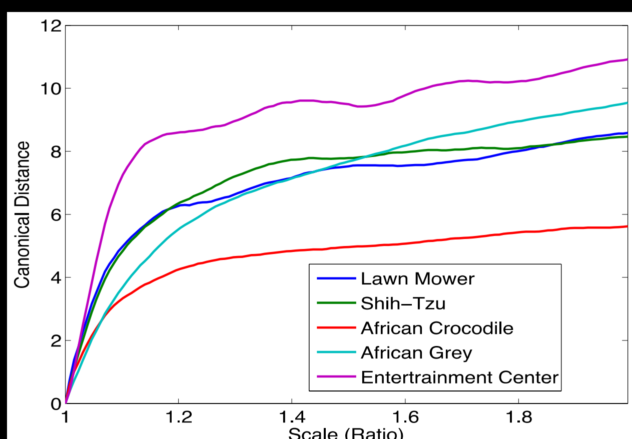


Scale Invariance

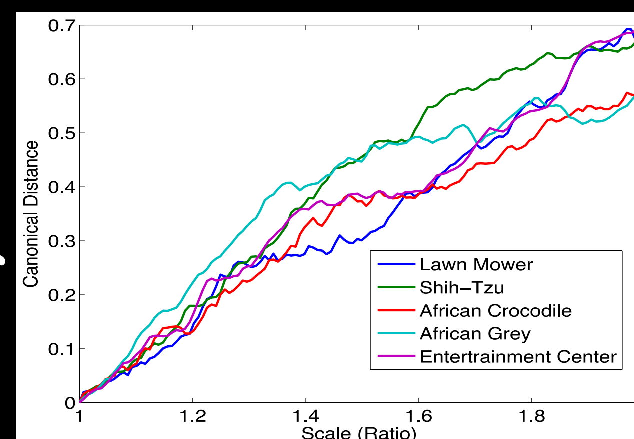
Output



Layer 1

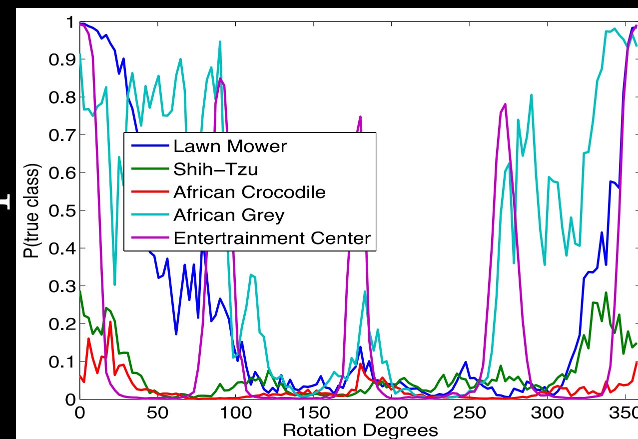


Layer 7

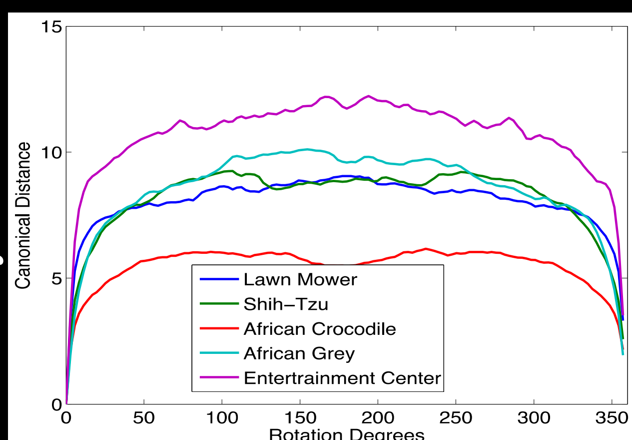


Rotation Invariance

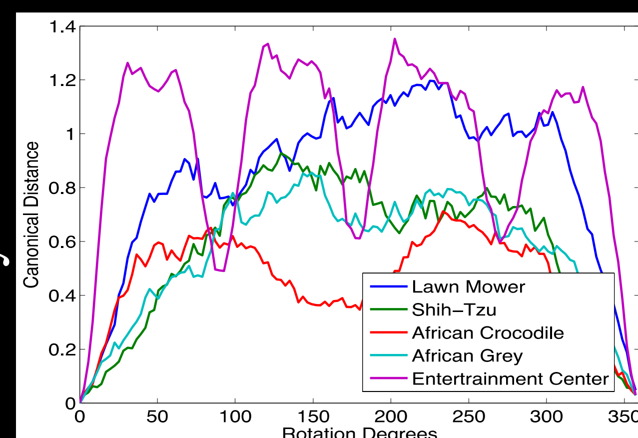
Output



Layer 1

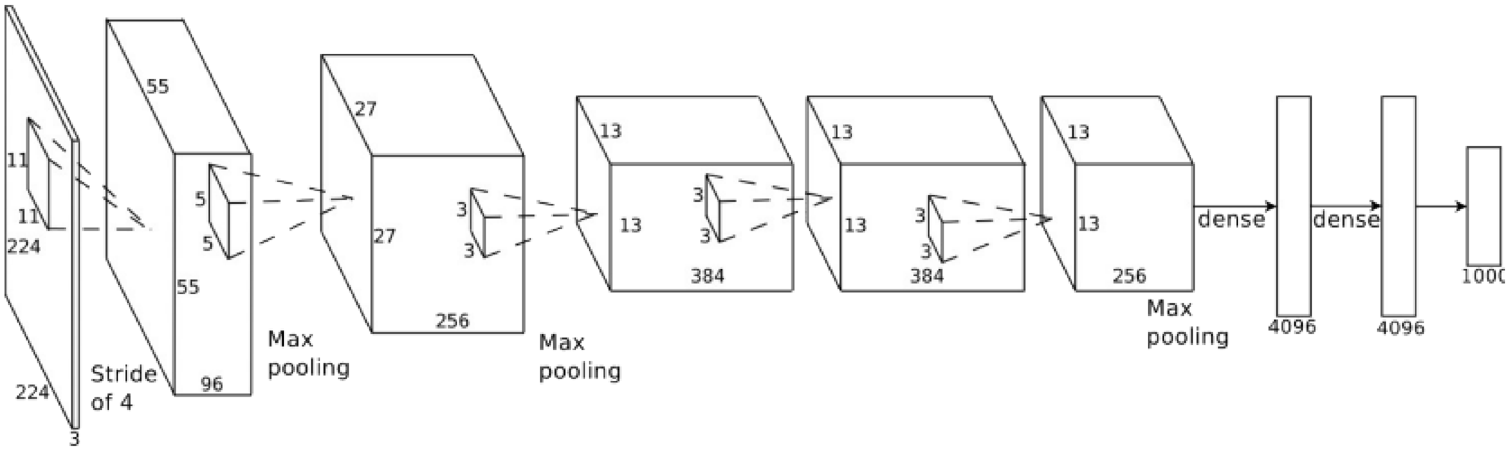


Layer 7



Deep ConvNets for image classification

- AlexNet 8 layers, 62M parameters



Alex Krizhevsky, Ilya Sutskever and Geoffrey Hinton
ImageNet Classification with Deep Convolutional Neural Networks.
In *NIPS*, 2012.