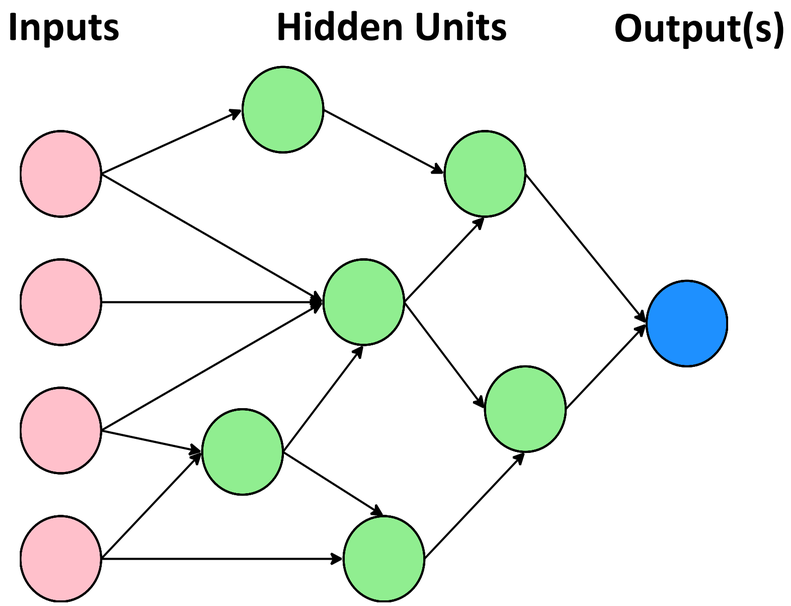
Neural Networks 2
Convolutional Networks

(Some slide credits to CMU 16-720 Fall 2014)

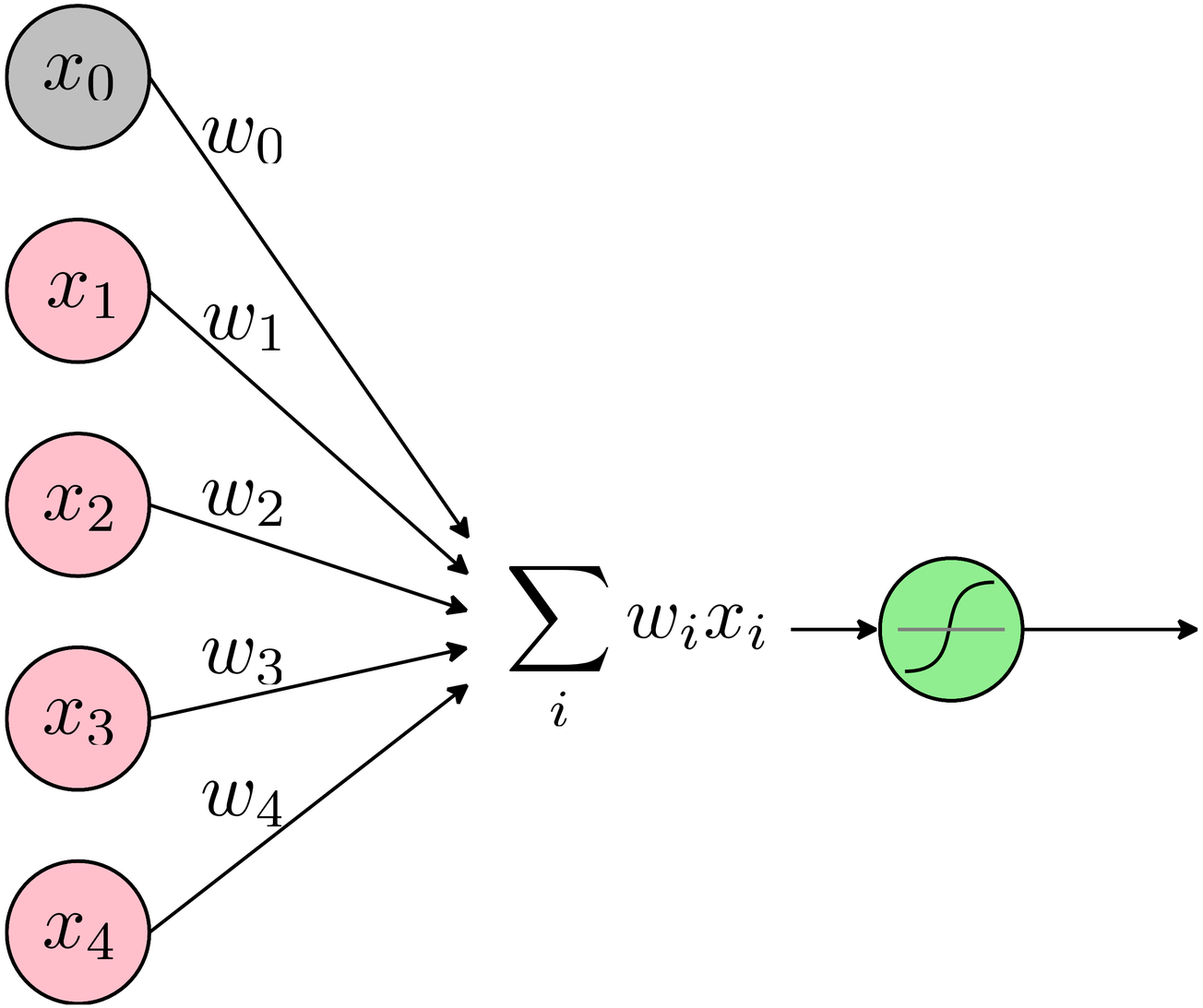
Gary Overett

Neural Network Questions

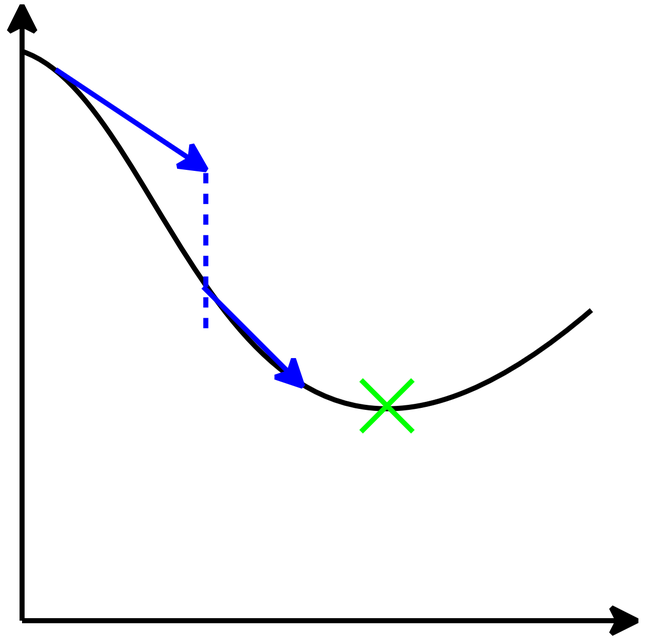
- What structure to use?
- What non-linearity's to adopt?
- Size/Depth of the network
- HOW TO DETERMINE (LEARN) THE WEIGHTS???
- How to use and arrange data?

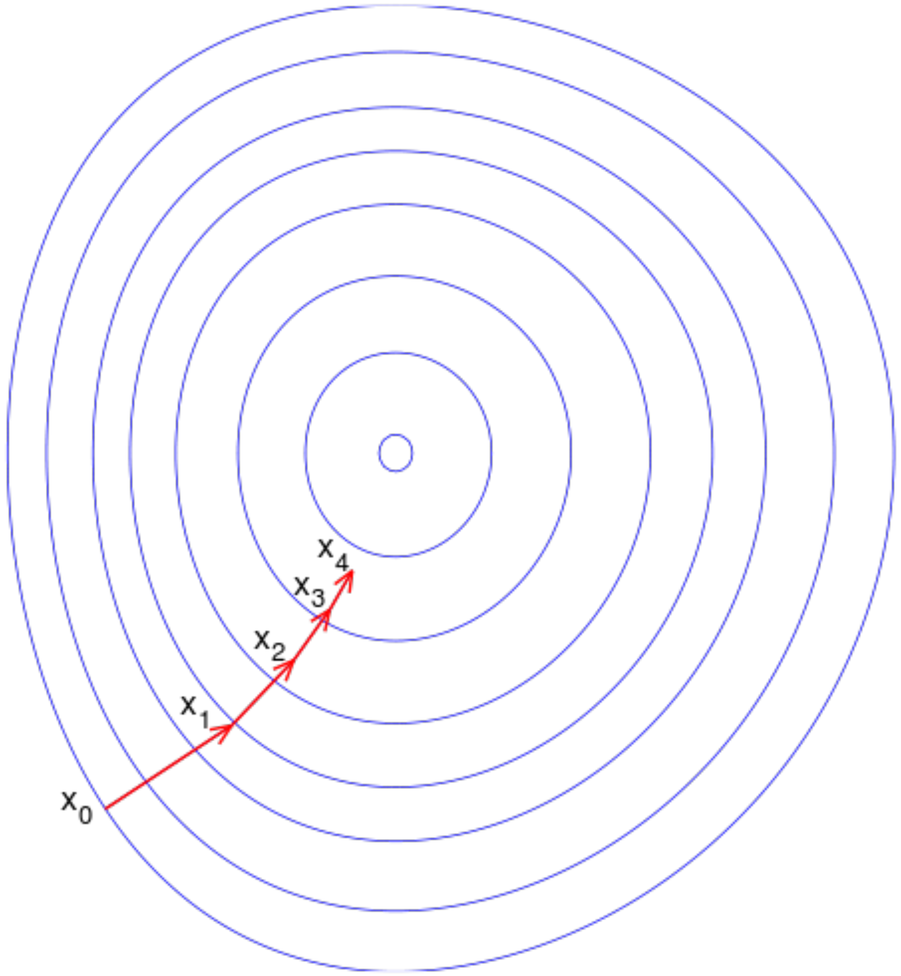


A Neuron

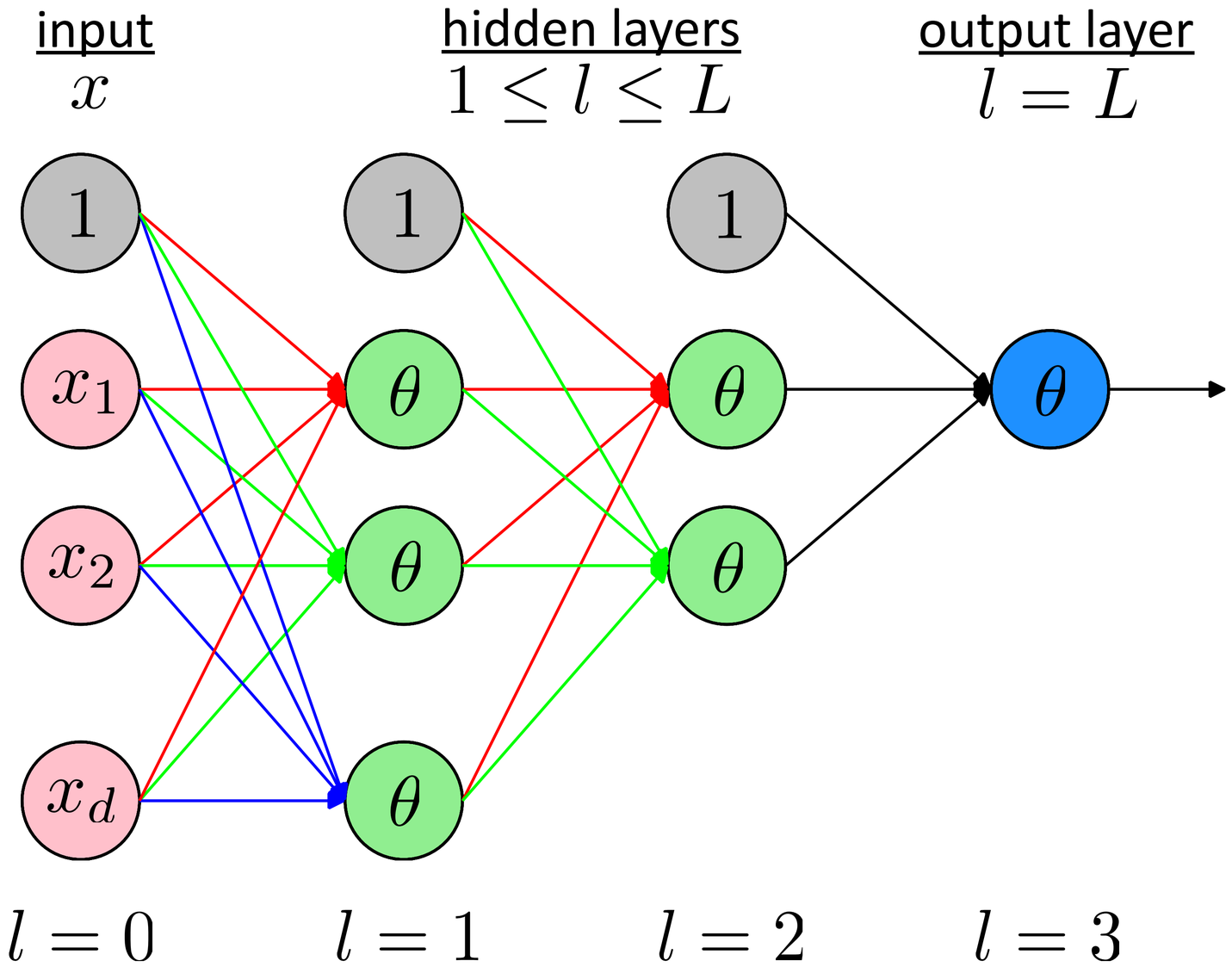


Gradient Descent





Neural Network Notation



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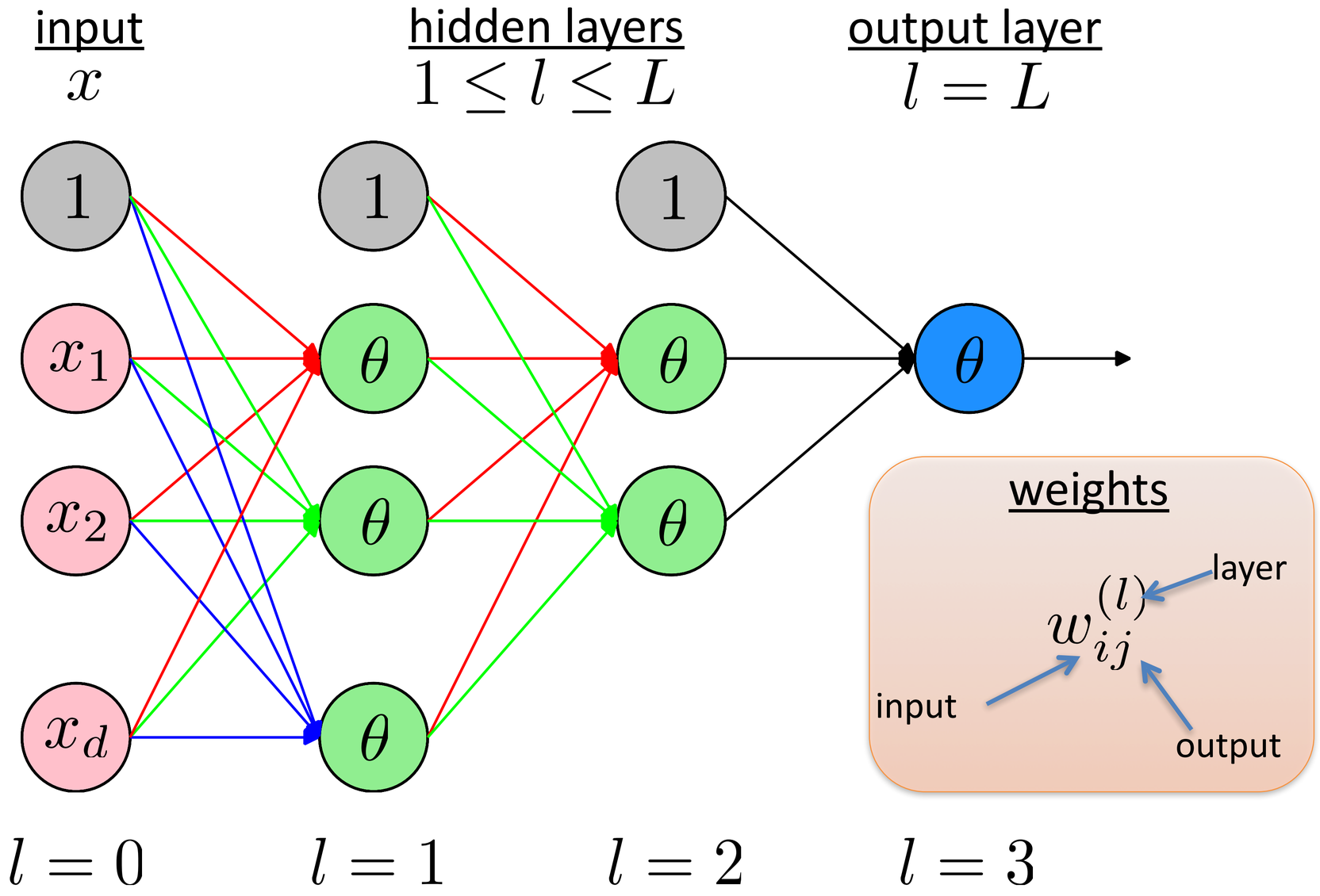
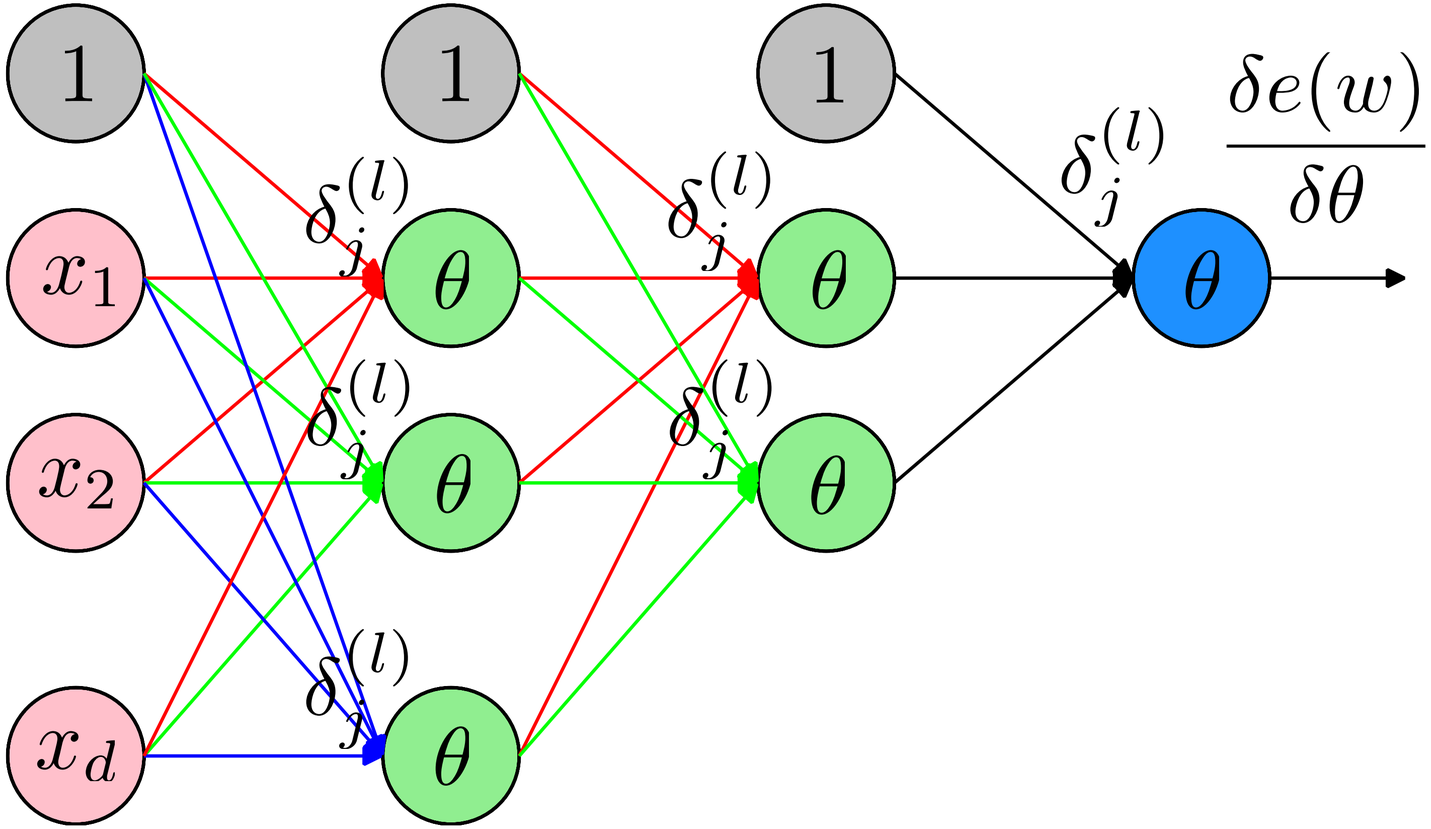
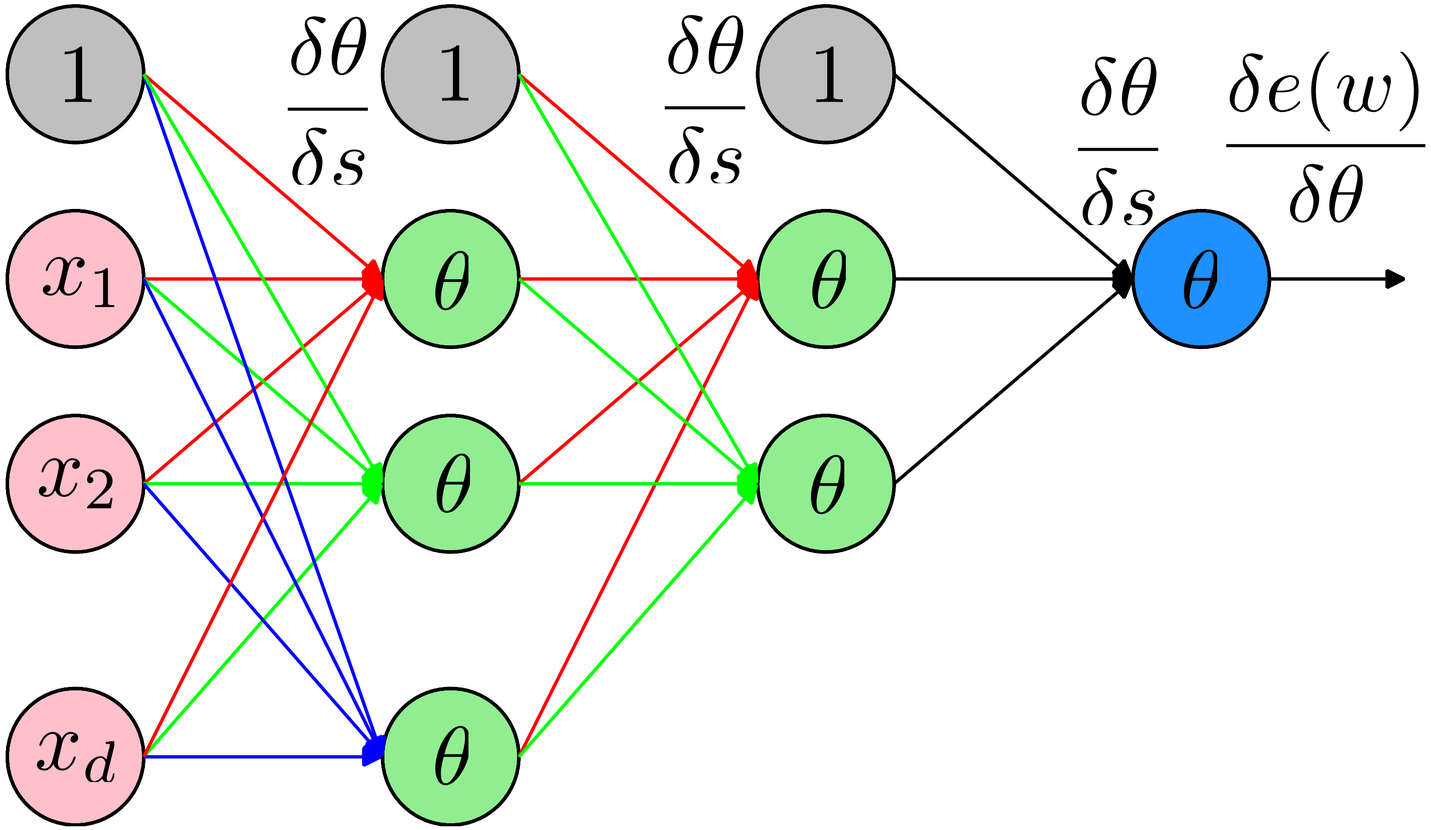


Computing the “Delta’s” Recursively

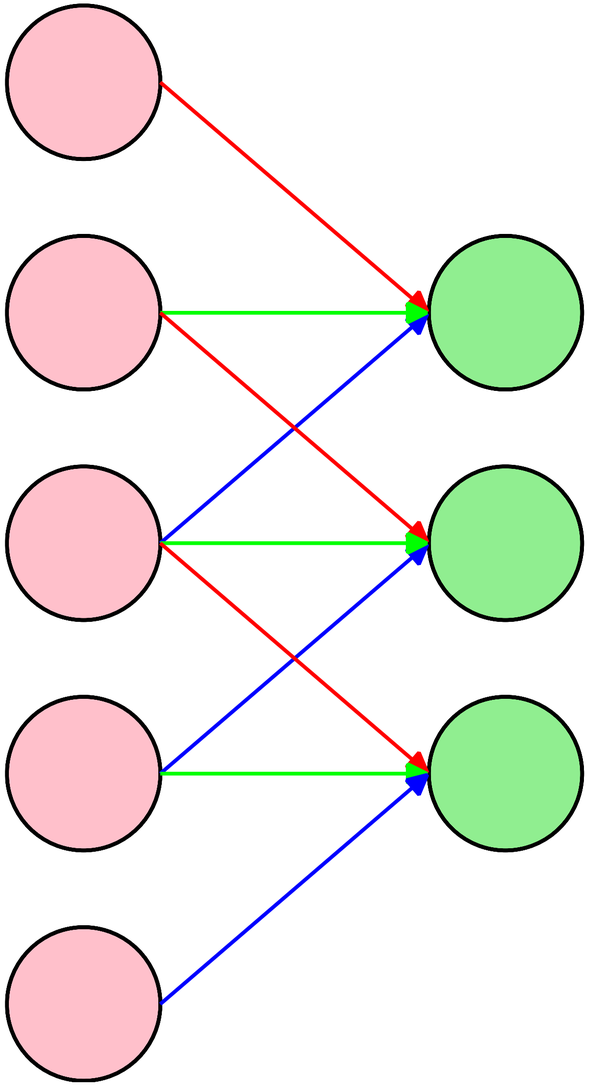


Chain Rule Magic

$$\frac{\delta e(w)}{\delta w_{ij}^{(1)}} = \frac{\delta e(w)}{\delta \theta}\frac{\delta \theta}{\delta s}\frac{\delta s}{\delta \theta}\frac{\delta \theta}{\delta s}\frac{\delta s}{\delta \theta}\frac{\delta \theta}{\delta s}\frac{\delta s}{\delta w}$$

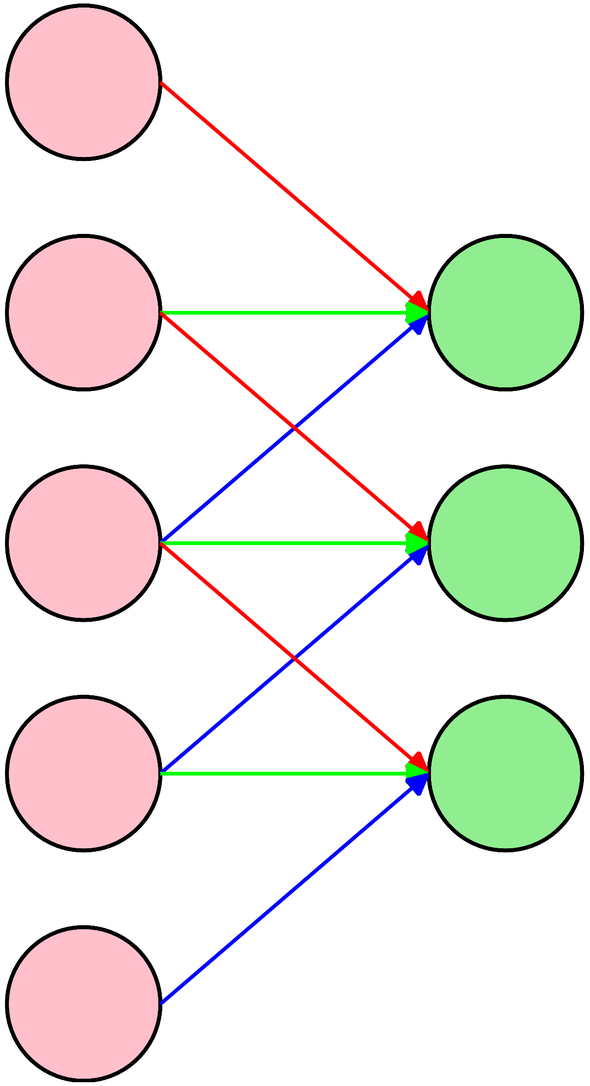


Convolutional Neural Networks



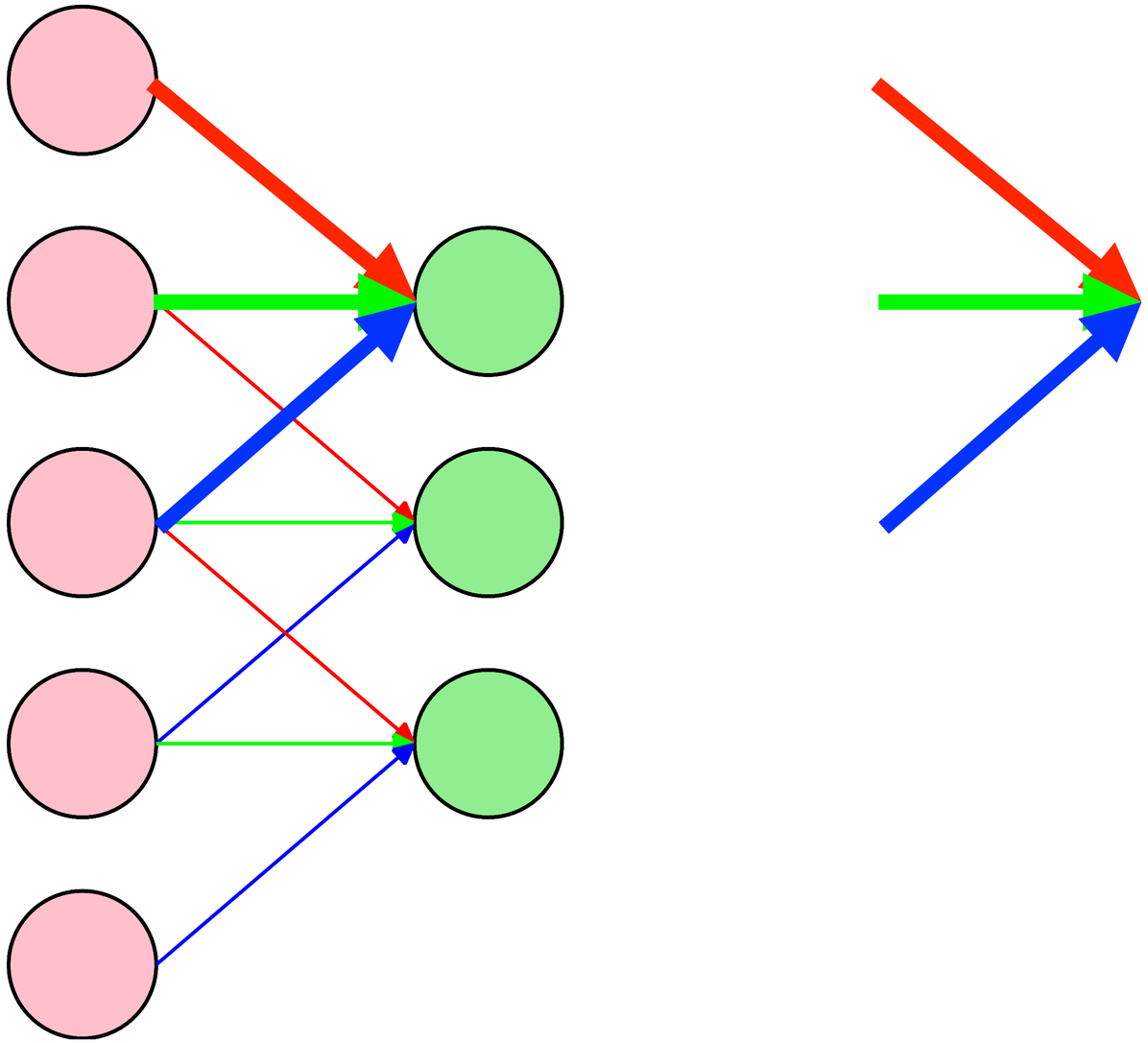
- Shared weights used across network
- May mimic a behavior of particular importance to the visual cortex of the brain

Convolutional Neural Networks



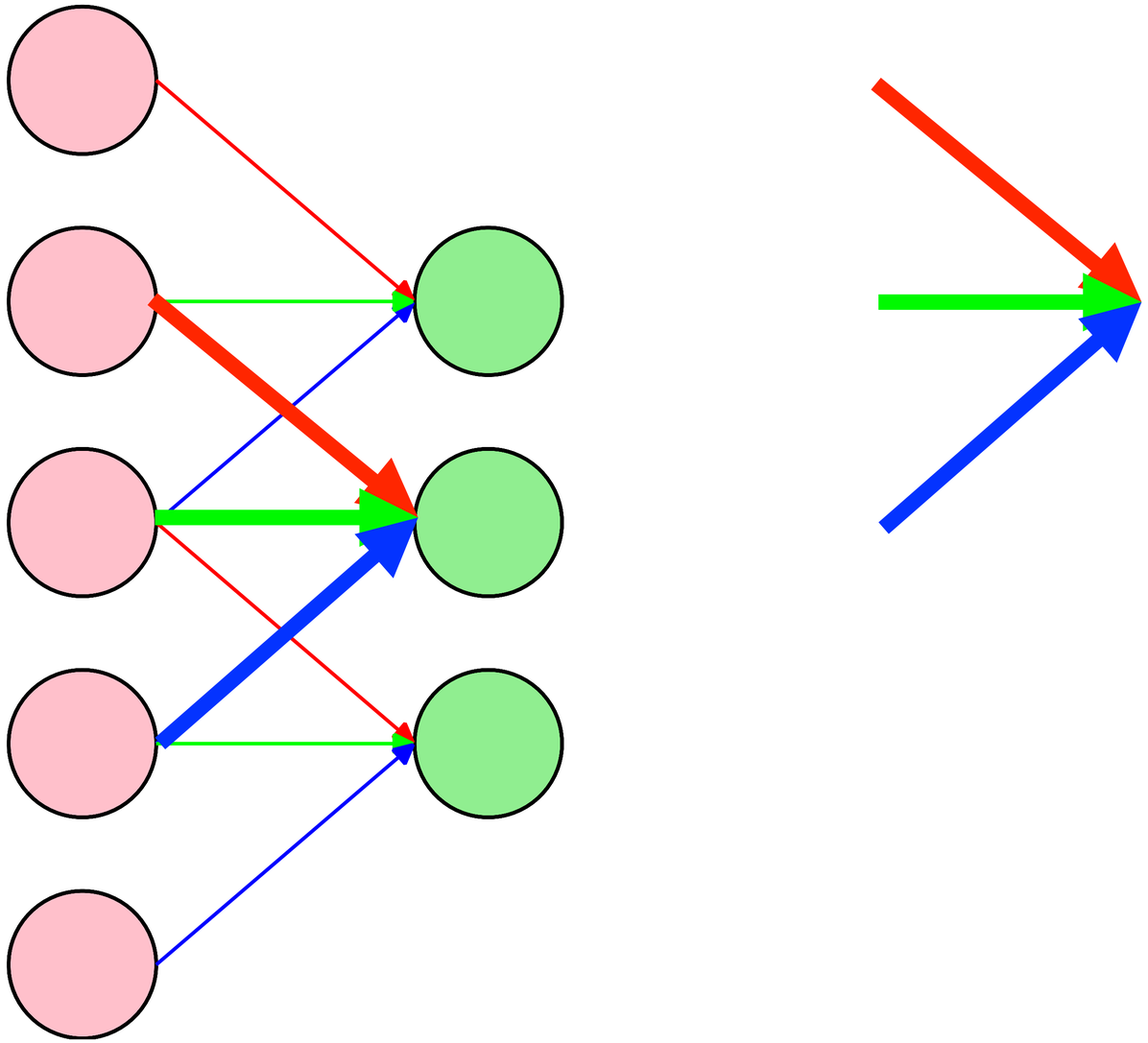
- Shared weights used across network
- May mimic a behavior of particular importance to the visual cortex of the brain
- Note that we have lost a degree of freedom. All those weights of the **same** color must now have the same weight
- We also reduce memory, computation and optimization problem size :)

Convolutional Neural Networks



- Think of these 3 weights as a **kernel** being applied by **convolution** over the input **spatially**

Convolutional Neural Networks



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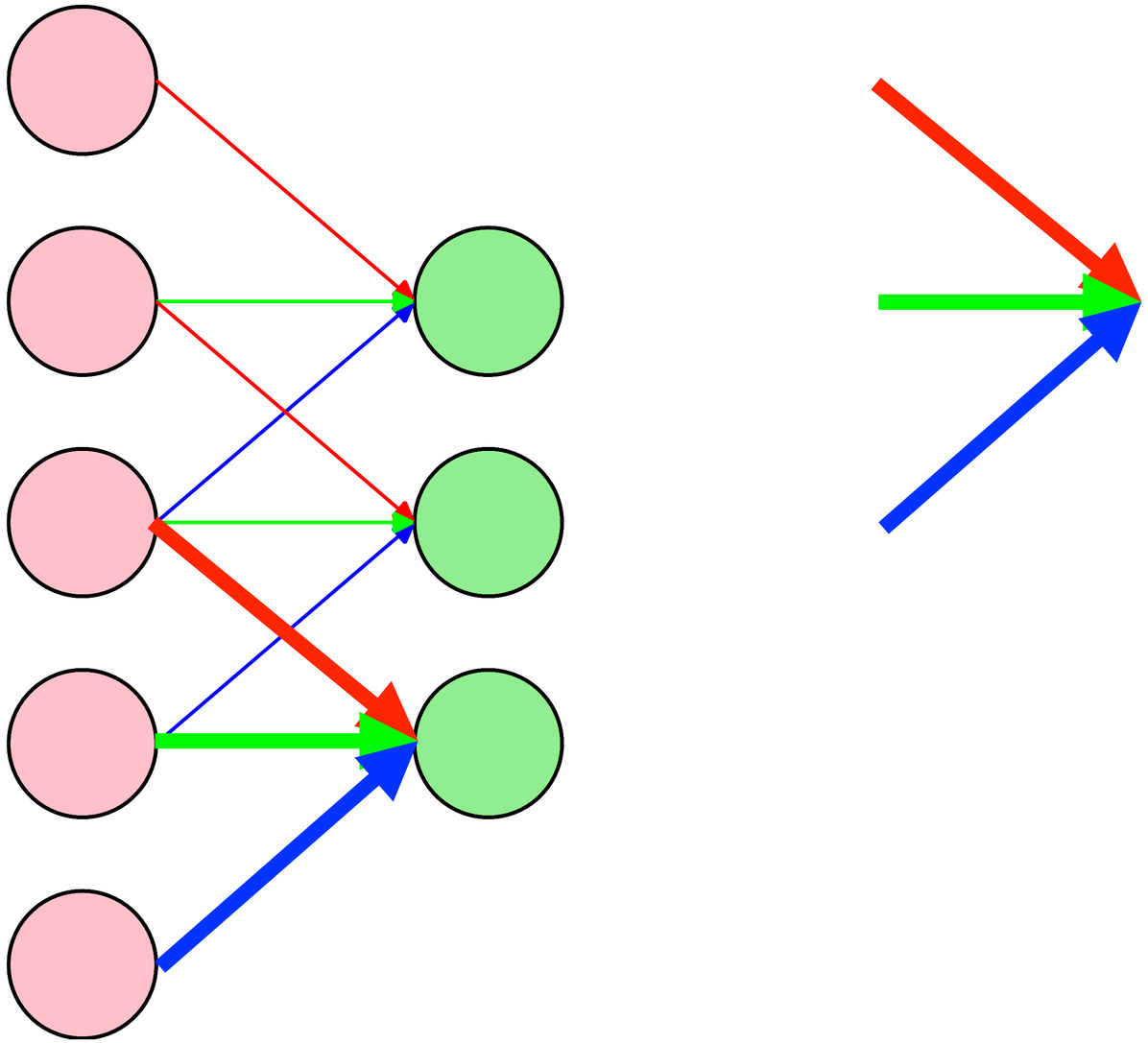
Convolutional Neural Networks



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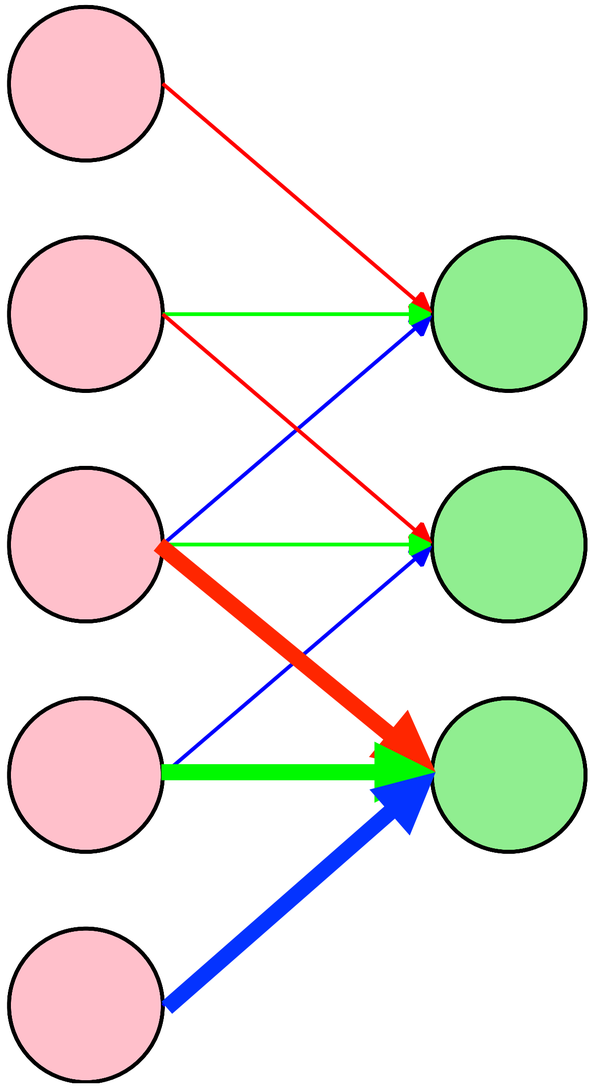
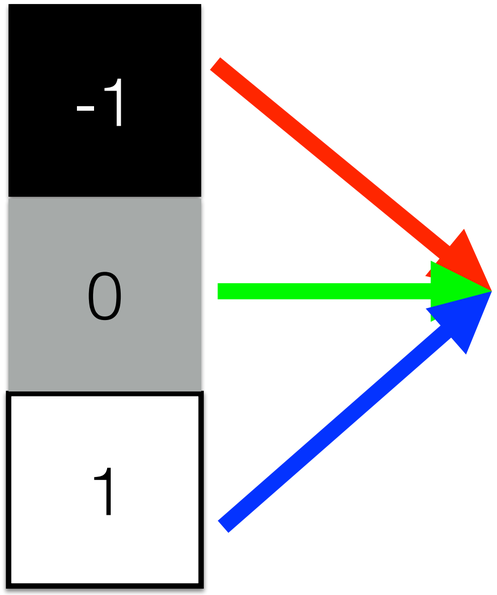
CNN Kernel's as "Features"





Example Edge Detection Kernel

- Each CNN Kernel can be thought of as a convolution filter or **feature**
- Only, we do not design it! Gradient descent will determine what is 'learnt'.
- Low level features tend to resemble popular features such as; gradients, edges, corners, centre-surround features and so on…

What is the purpose of image features?

- Encapsulate Prior Knowledge : e.g. symmetry, texture
- Statistical Invariance : e.g. illumination invariance, scale invariance etc.
- Simplification : e.g. Haar Wavelets
- Computational Optimization : e.g. integral images, LiteHOG, etc.
- Dimensionality reduction : raw pixels suffer the curse of dimensionality : e.g. SVM & HOG pedestrian detection (Dalal & Triggs)

Impressive Results

- Classifying handwritten digits (MNIST)
  - Better than humans
- Chinese character recognition
- Traffic Sign Recognition 99% accurate
  - Better than humans
- Winning entries for ImageNet Challenge

Learning Feature Representations

- In computer vision Deep Learning is very much about learning good feature representations (and its very impressive at learning these!)
  - w/ some qualification
  - needs lots of data
  - longer training times (than say SVM + <your fav. feature>)
  - really needs GPU compute power

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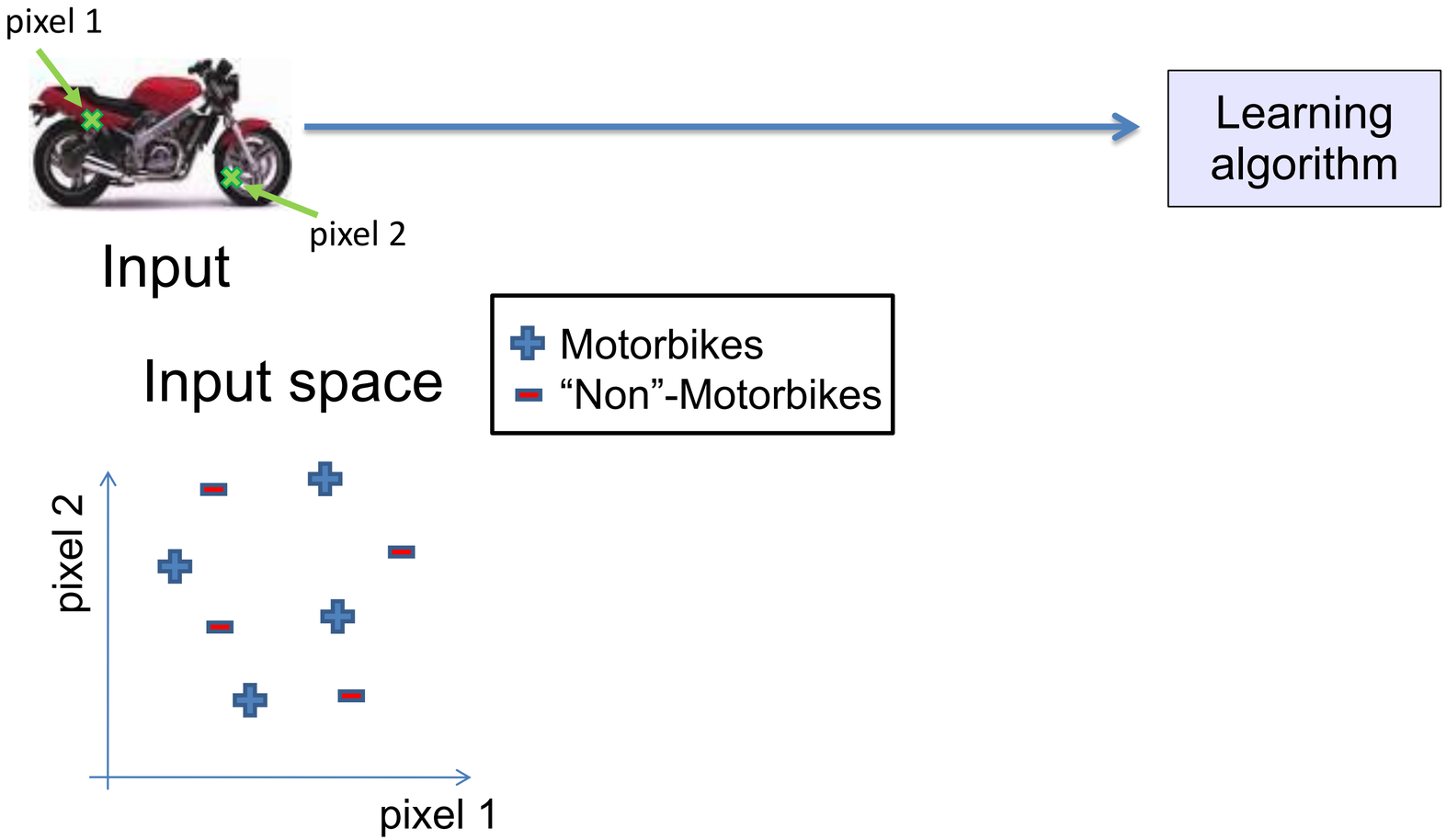
Feature representations



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Feature representations

Input

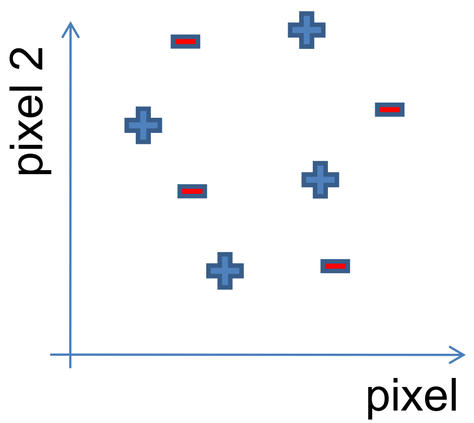
Feature representation

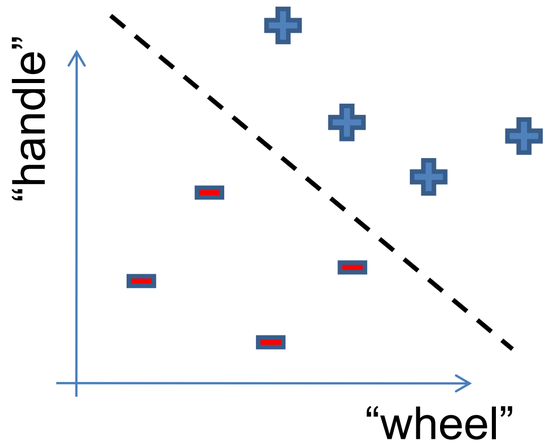
Learning algorithm

Input space

Motorbikes
"Non"-Motorbikes

Feature space





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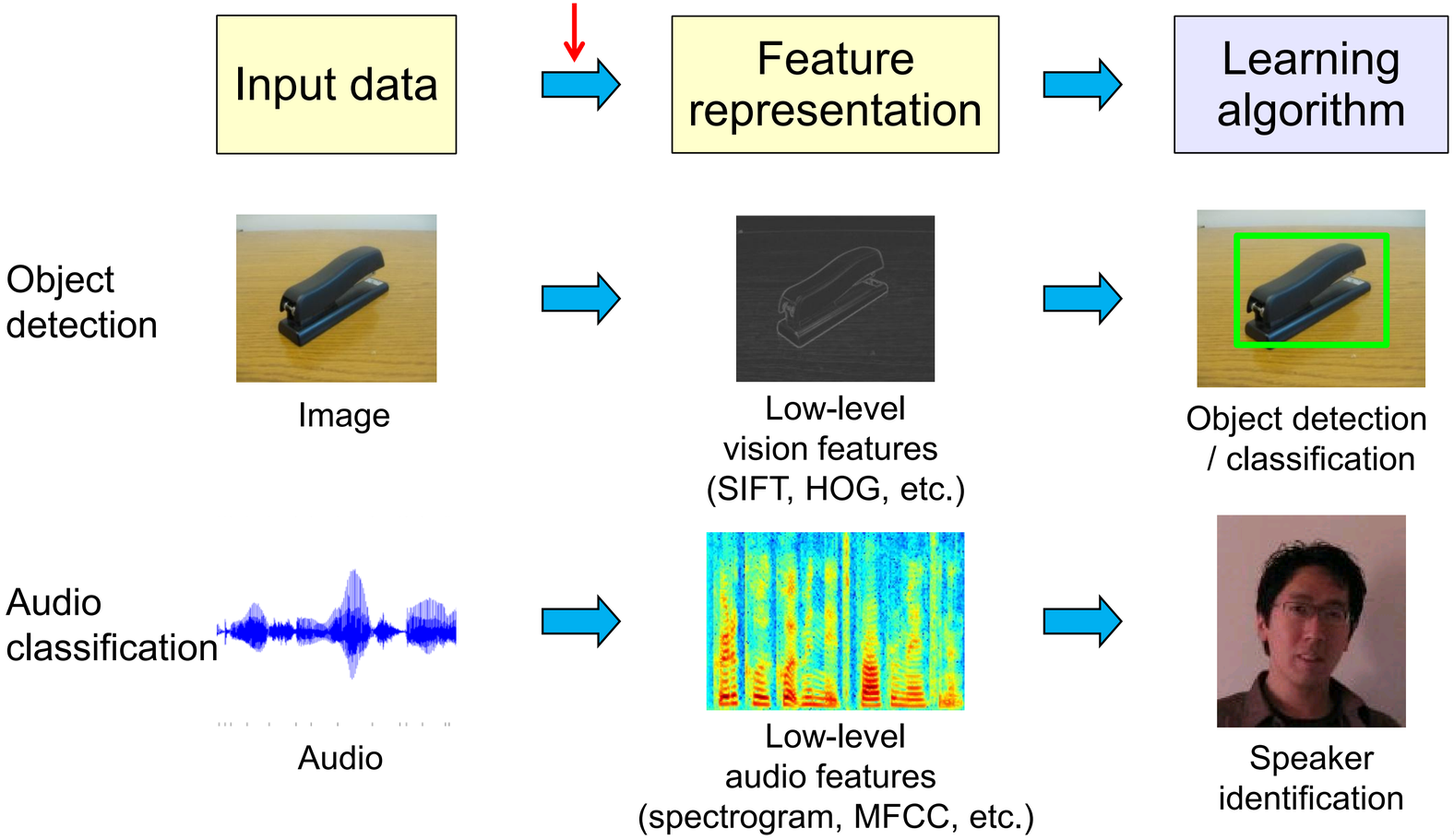
How is computer perception done?

State-of-the-art:
"hand-crafting"



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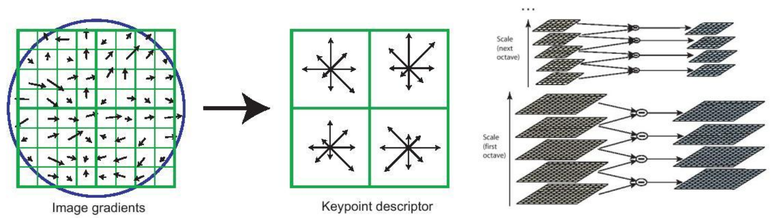
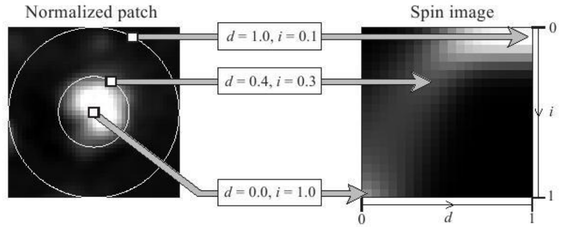
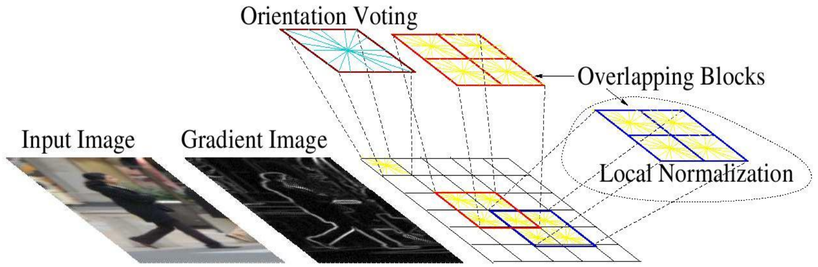
Computer vision features



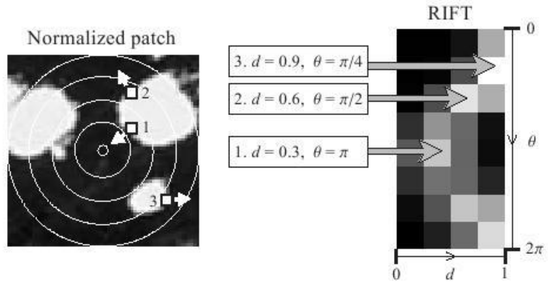
SIFT



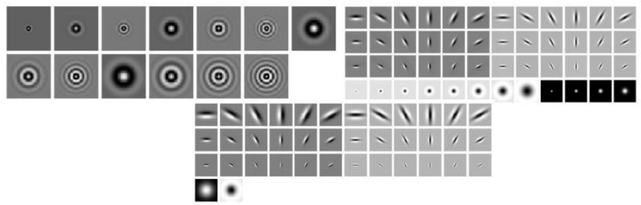
Spin image



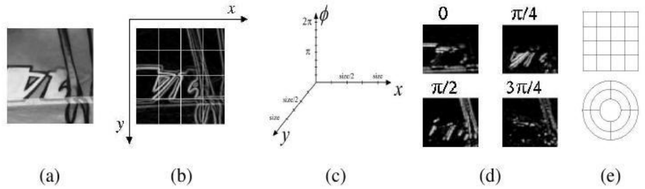
HoG



RIFT



Textons



GLOH

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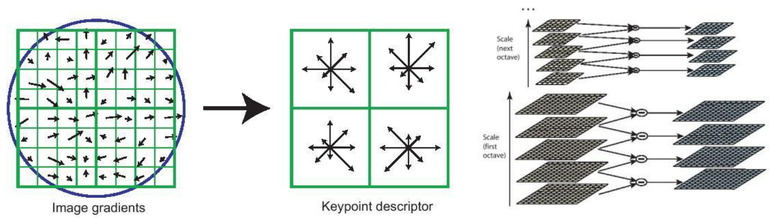
Computer vision features



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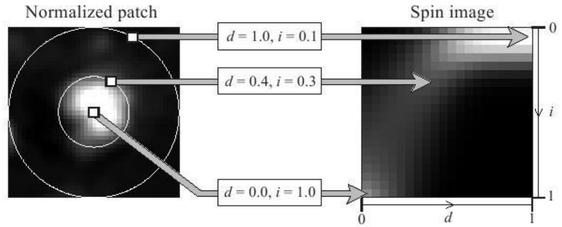

Spin image

Hand-crafted features:

1. Needs expert knowledge
2. Requires time-consuming hand-tuning
3. (Arguably) one of the limiting factors of computer vision systems

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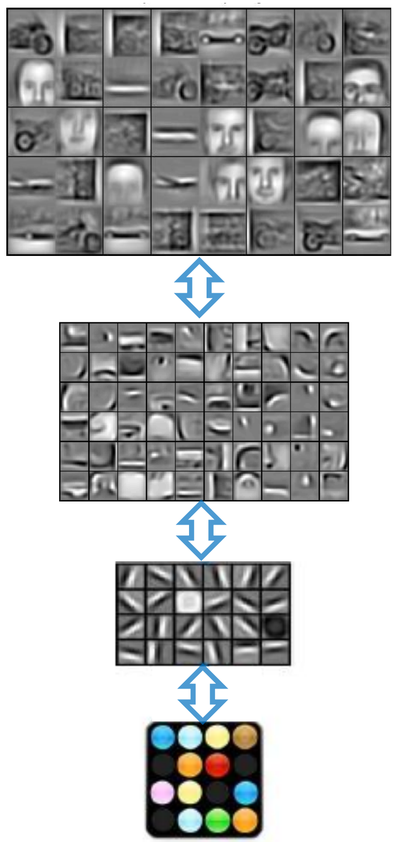
Learning Feature Hierarchy

- Deep Learning
  - Deep architectures can be representationally efficient.
  - Natural progression from low level to high level structures.
  - Can share the lower-level representations for multiple tasks.



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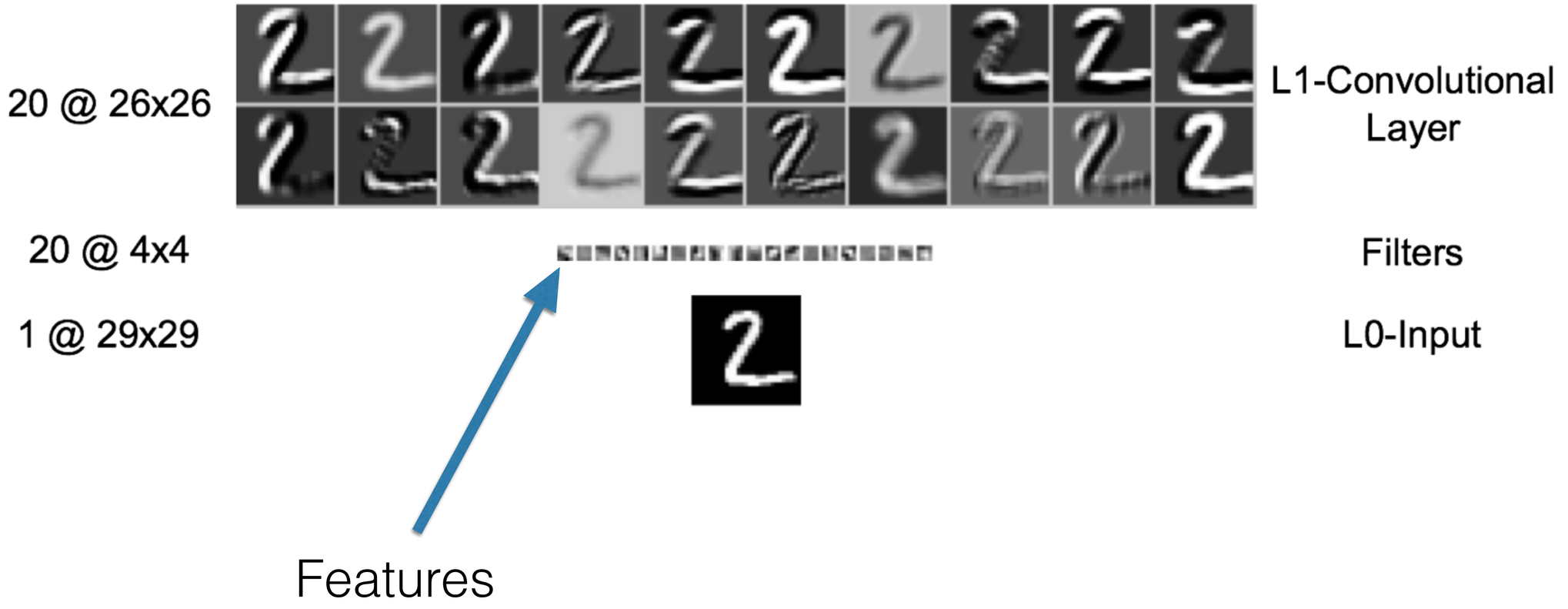
MNIST Example : Initial Layer



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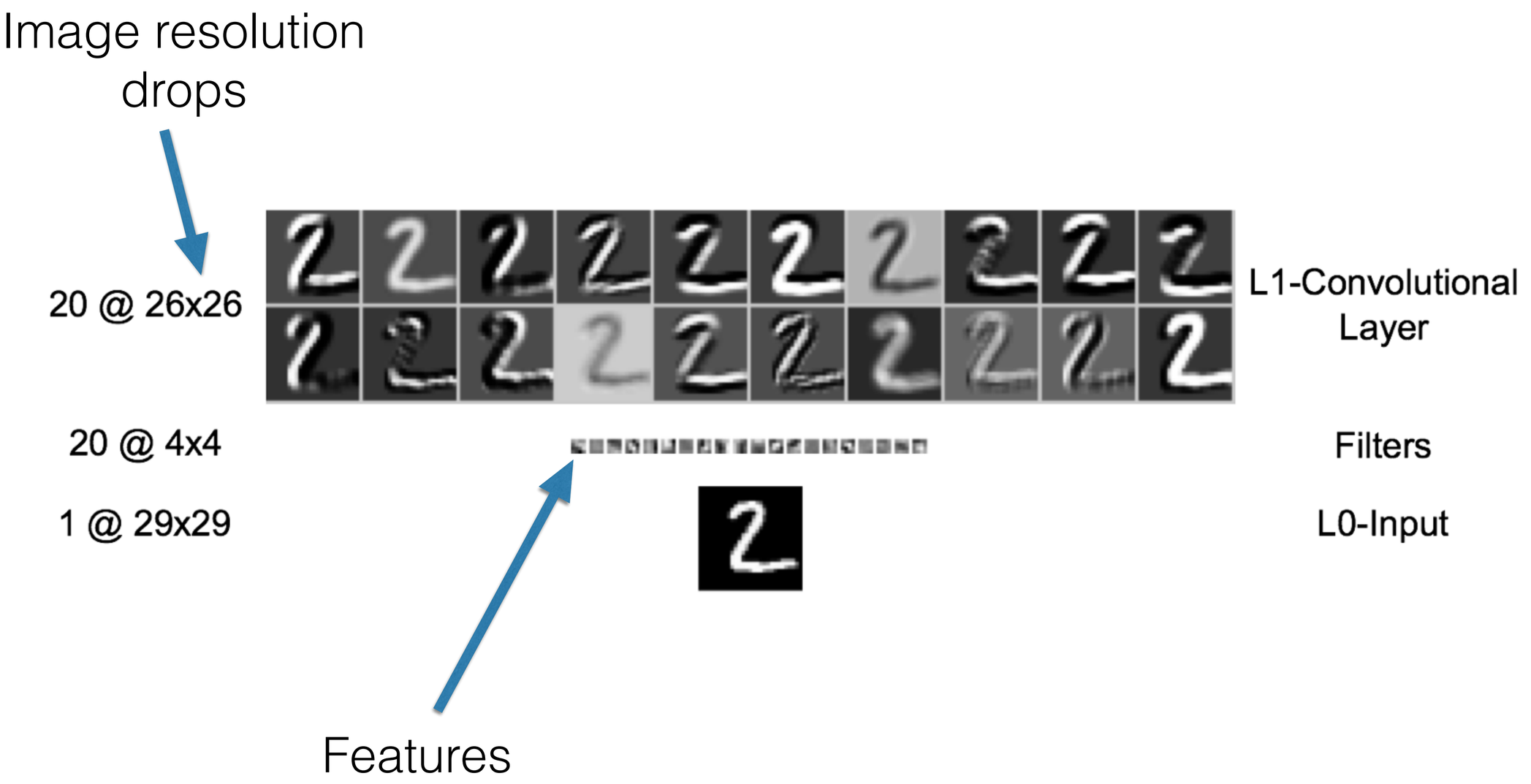


MNIST Example : Initial Layer

Image resolution drops

Exploding Data!

L1-Convolutional Layer

20 @ 26x26

But I have grown by a factor of 20
20 - “Feature Maps”

20 @ 4x4

Filters

1 @ 29x29

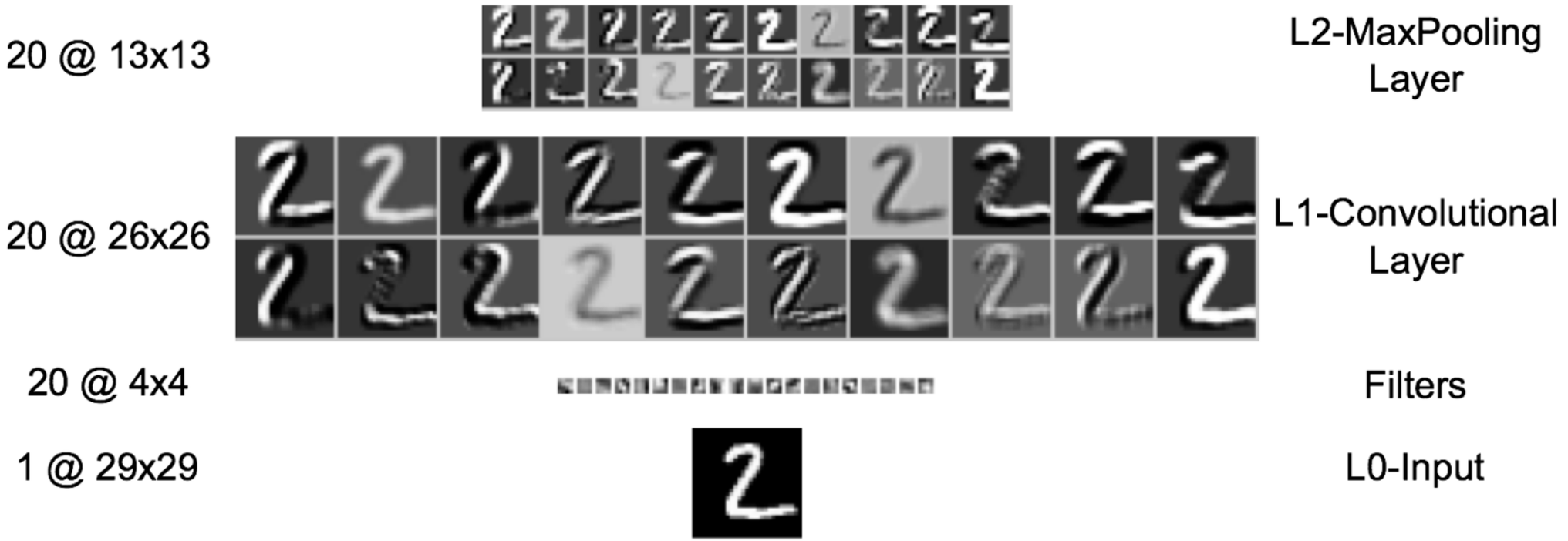
L0-Input

Features

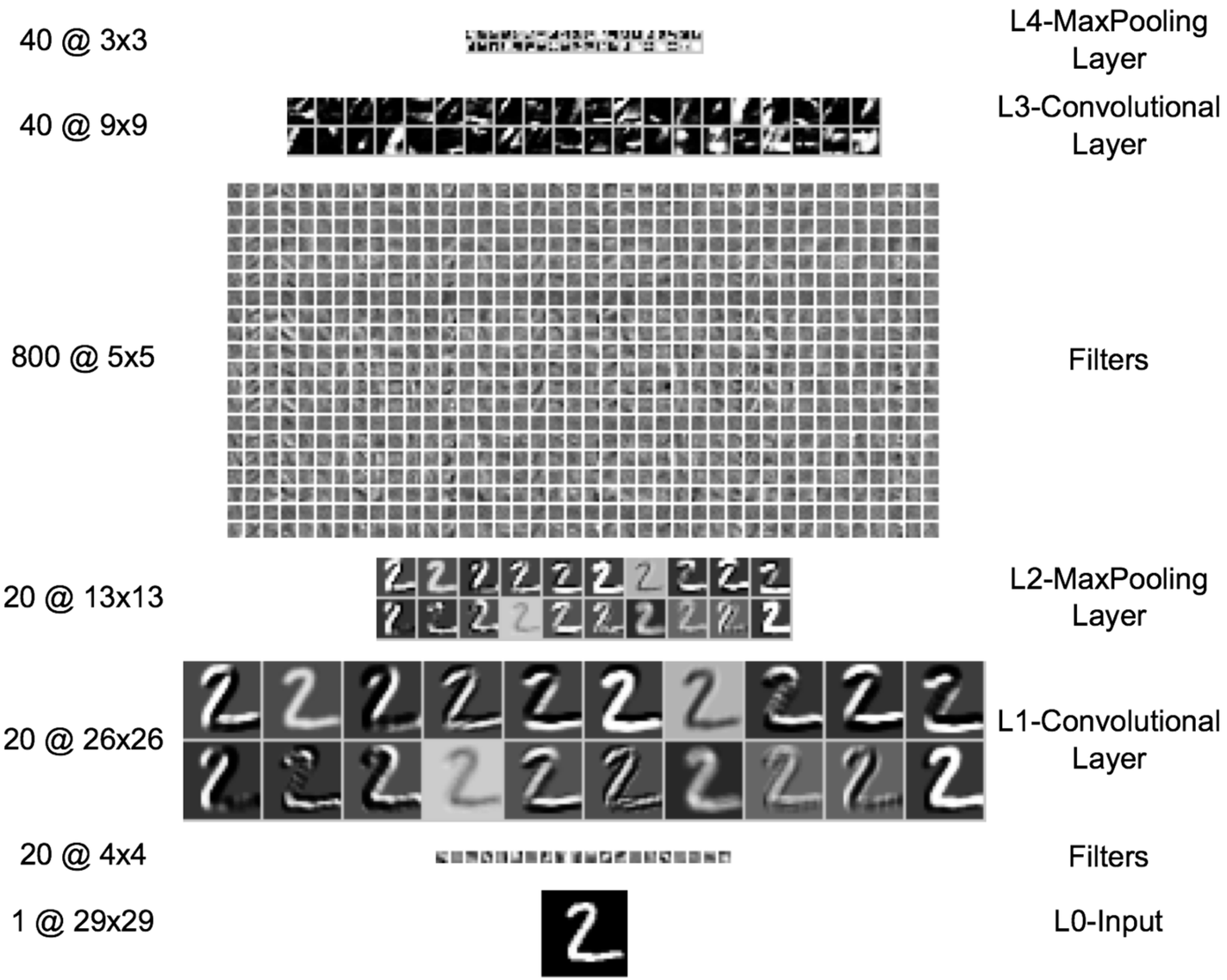
Pooling as Data Reduction

- The use of multiple filters leads to an explosive growth in the amount of data being pushed forward through the network.
- Therefore we use “Pooling” methods to reduce (or summarize) the data. There are many kinds of pooling:
  - Average Pooling - just scale the output e.g. 2x2 “pixel” region -> 1x1
  - Max Pooling - pass forward the strongest response e.g. strongest response in a 2x2 “pixel”

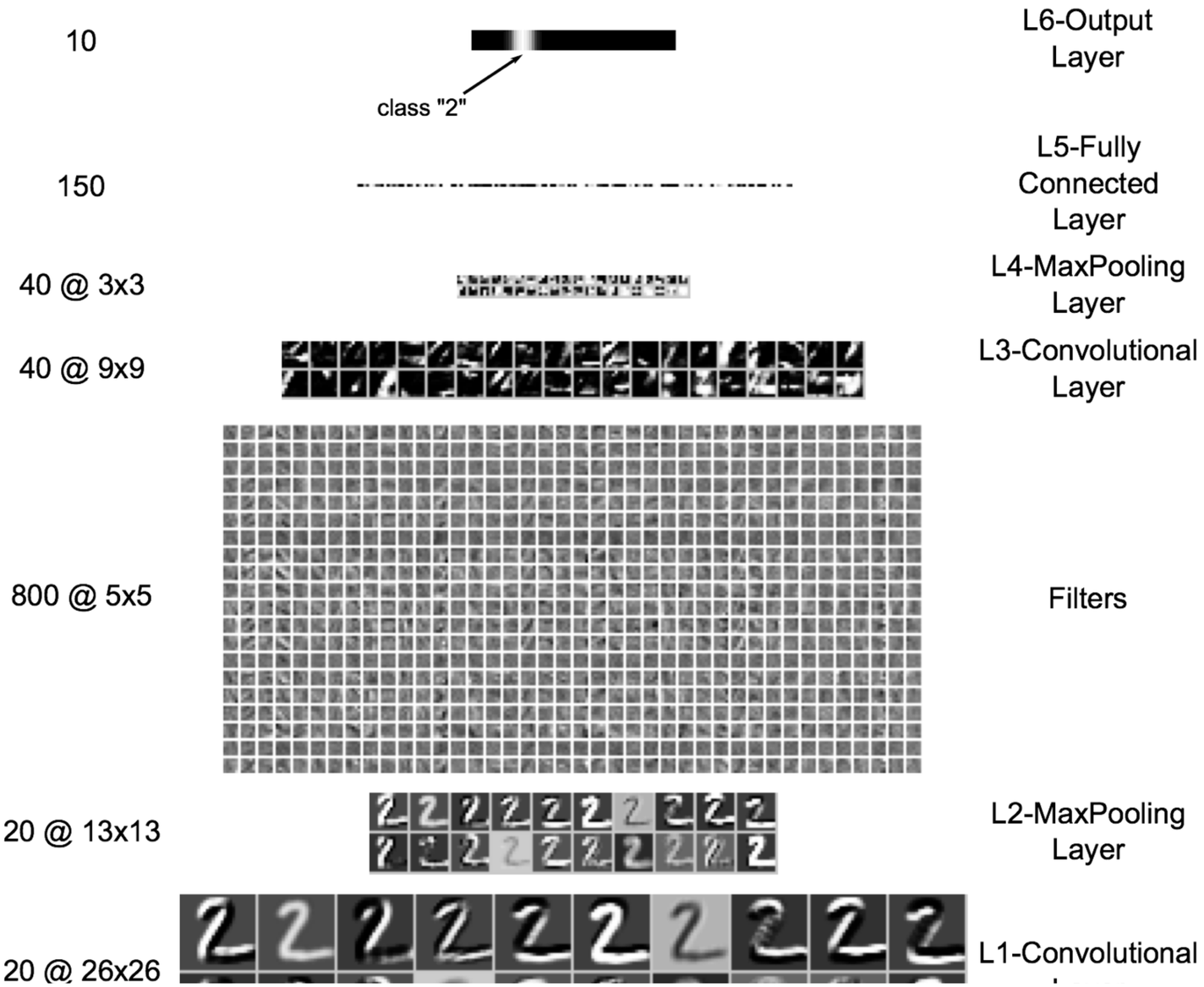
Pooling


20 @ 13x13
L2-MaxPooling Layer
20 @ 26x26
L1-Convolutional Layer
20 @ 4x4
Filters
1 @ 29x29
L0-Input

Alternating Feature & Pooling Layers



Fully Connected Final Layer

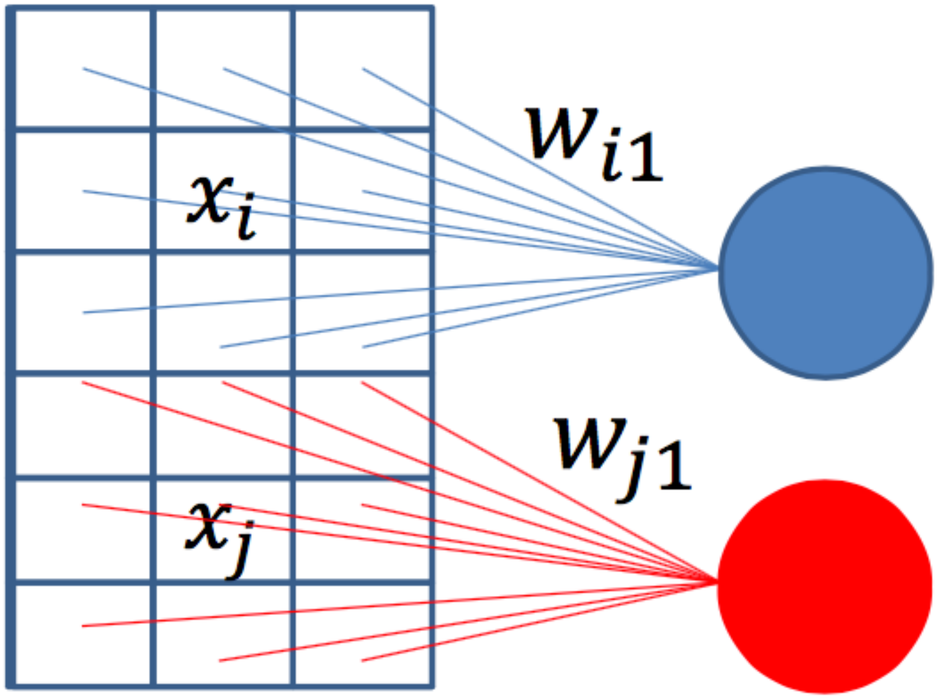


Different Types of Hidden Nodes

- Feature Convolutional Nodes
- Pooling Nodes
- Fully Connected Layers

Convolutional Nodes : 3x3 example

Same weights for i and j: $W_{ik} = W_{jk} = W_k$

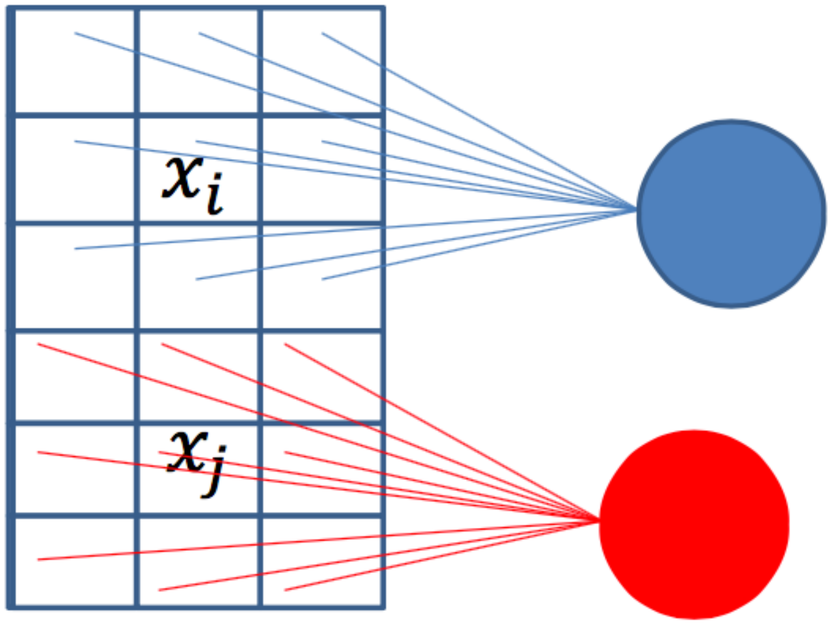


$$y_i = \phi\left(\sum_{k \in N(i)} w_k x_k\right)$$

$$y_j = \phi\left(\sum_{k \in N(j)} w_k x_k\right)$$

Pooling Nodes

- Combines the values of nodes from the previous layers without computing new features
- Example: Max pooling:
  - Take the max of the nodes from the previous layers in $K \times K$ neighborhood N . .
  - Reduce the number of nodes
- Others: L2 pooling, ...



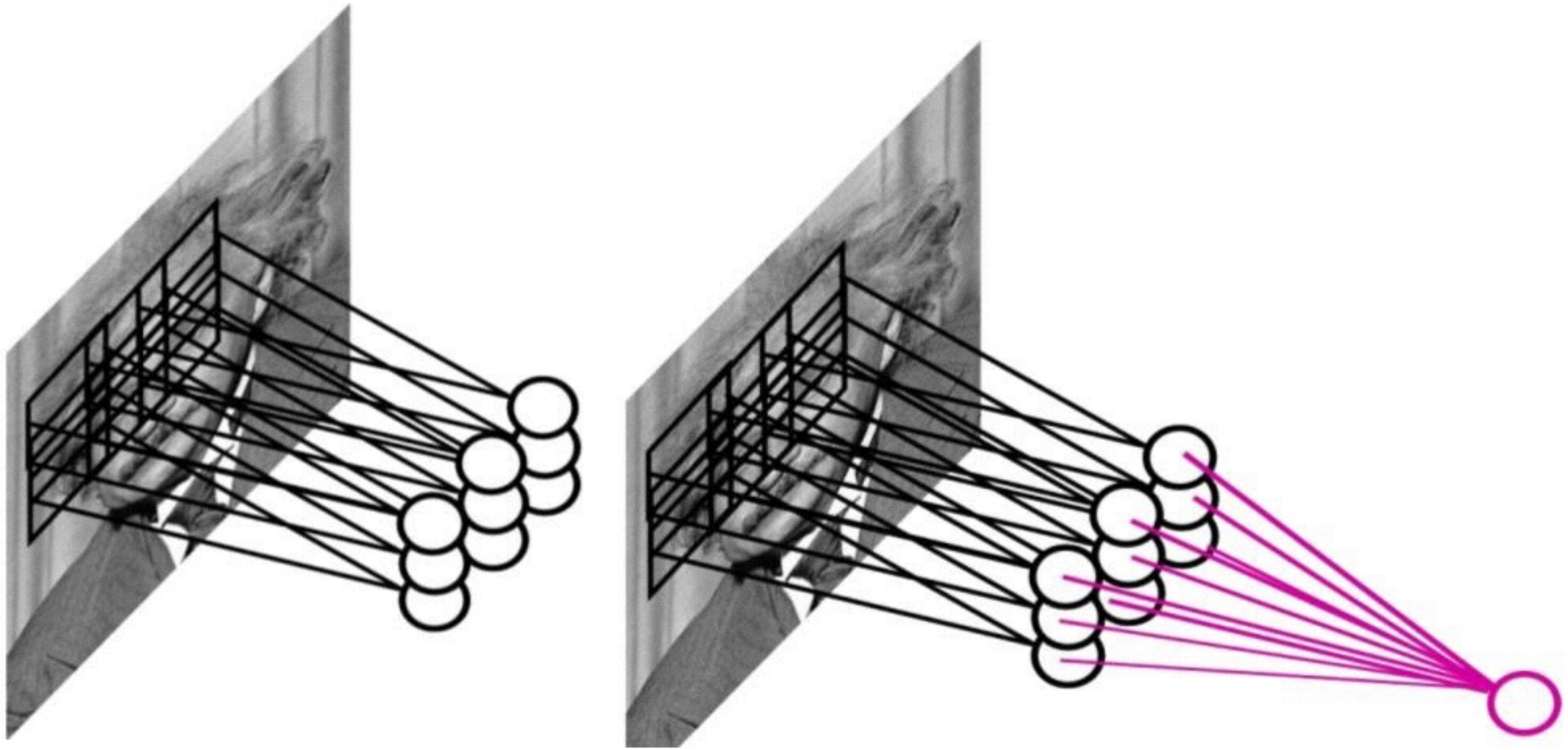
$$y_i = \max_{k \in N(i)} x_k$$

$$y_j = \max_{k \in N(j)} x_k$$

Example: R Fergus

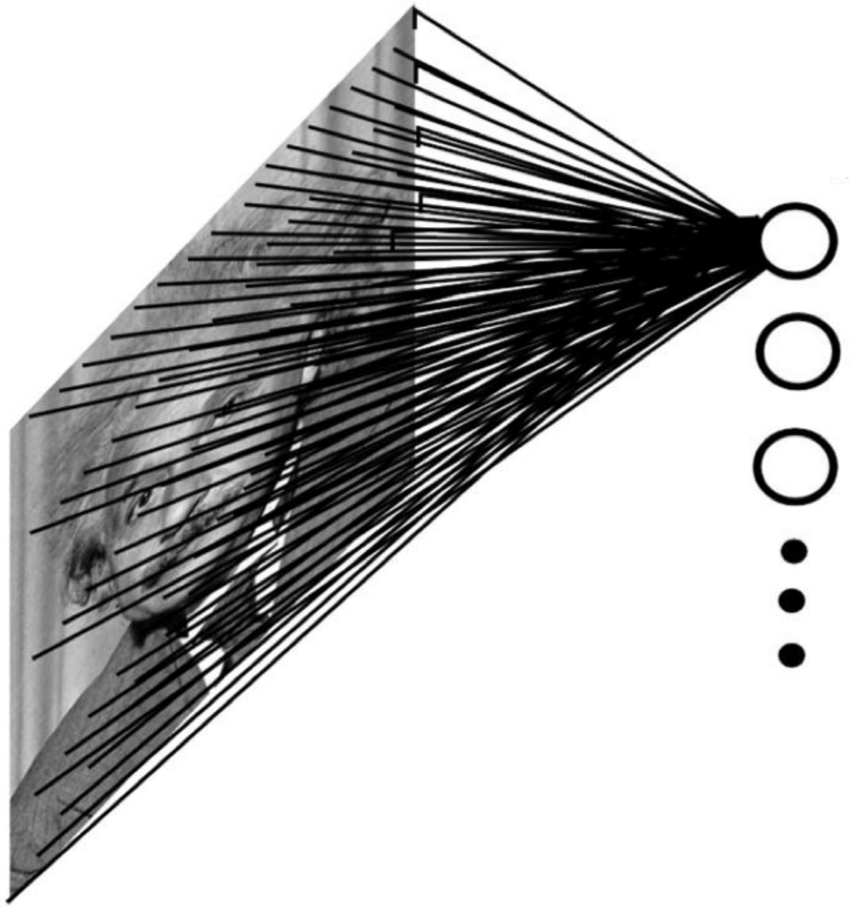
Convolution

Pooling



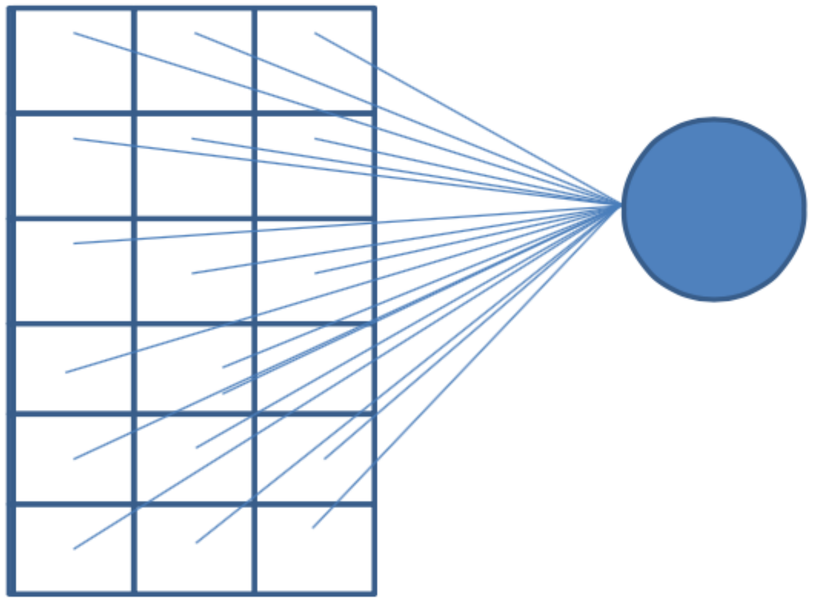
Example: R Fergus

Fully Connected



Fully Connected Node

- All the nodes from the previous layer are connected to the hidden units
- All with different weights
- Very large number of connections (N x M): This is used only in the last levels when the “image” has been reduced sufficiently



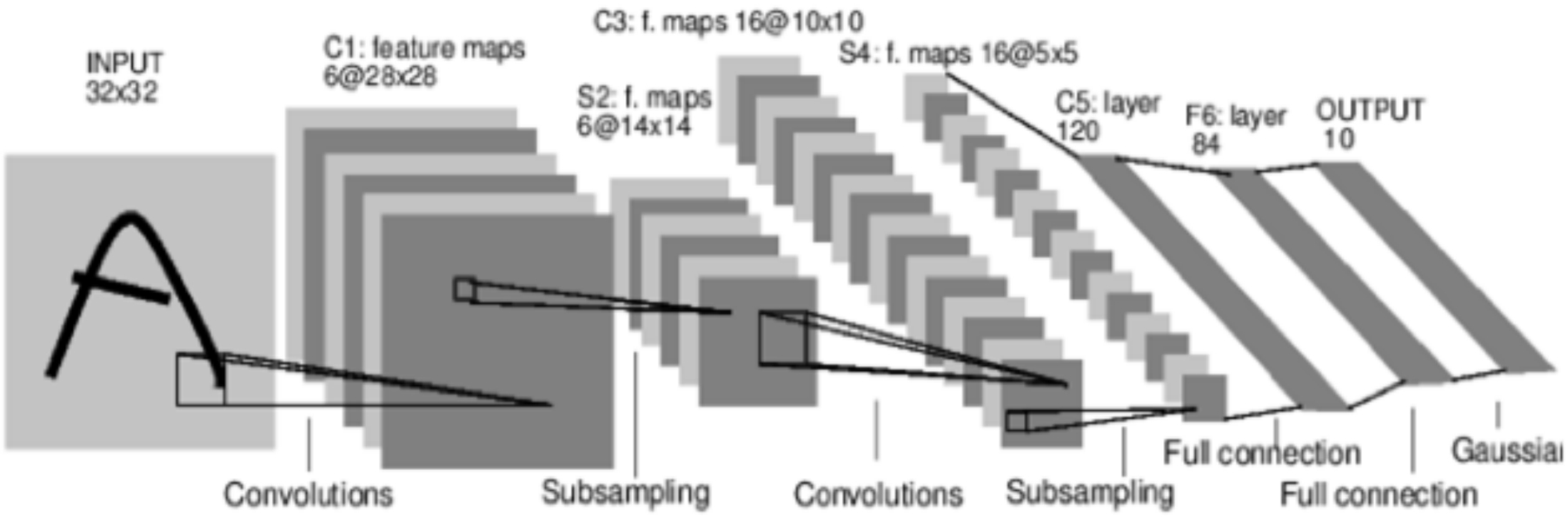
$$y_i = \phi\left(\sum_k w_k x_k\right)$$

Training

- Learn weights by minimizing error (or maximizing similarity) on training sample
- Output z is function of input x and W = vector of weights
- Minimize loss between output z and true value of training sample $L(z(x, W), \hat{z})$
- Backpropagation:
  - Estimate change on weights ΔW from first order derivative
    $\Delta L(z(x, W), \hat{z}) \approx \cdots \frac{\partial z(x,W)}{\partial W} \Delta W$
  - (Complicated) derivative computed with repeated chain rule
- Stochastic gradient:
  - We should use the sum over all the samples:
    $L(W) = \sum_x L(z(x, W), \hat{z}) \qquad W \leftarrow W - \alpha \nabla L(W)$
  - Intractable because of number of samples
  - Instead update on samples chosen randomly:

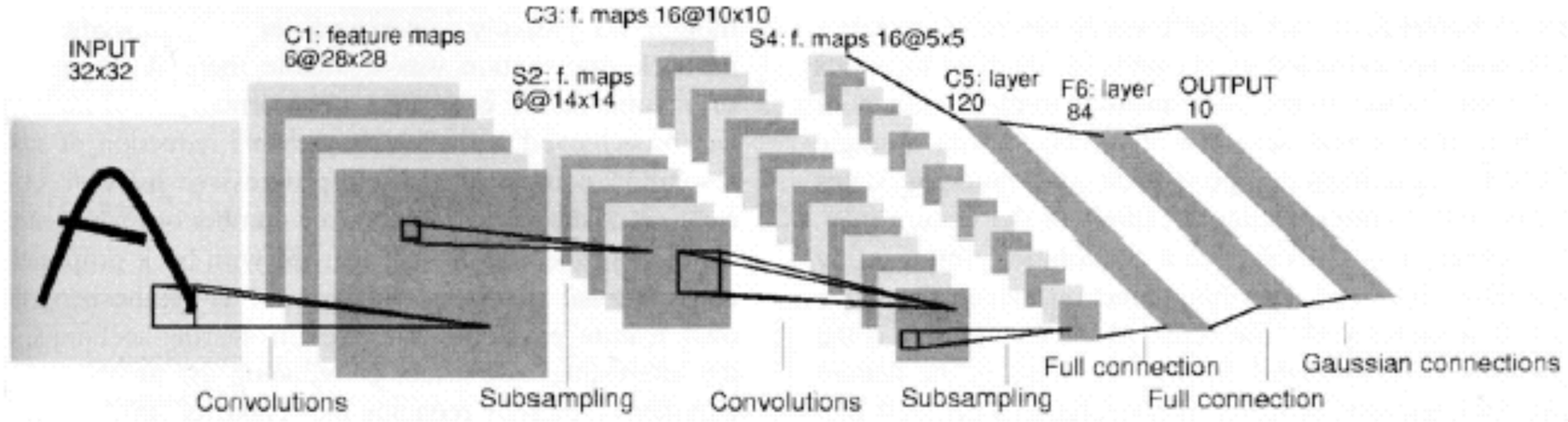
$$W \leftarrow W - \alpha \nabla L(z(x, W), \hat{z})$$

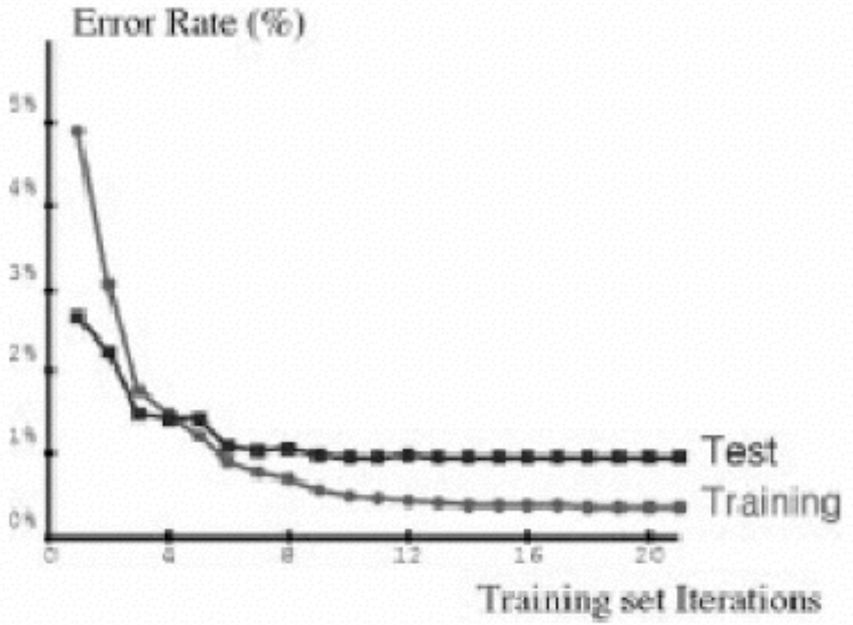
Example : Lecun Digit Recognition



~350,000 connections total 60,000 parameters

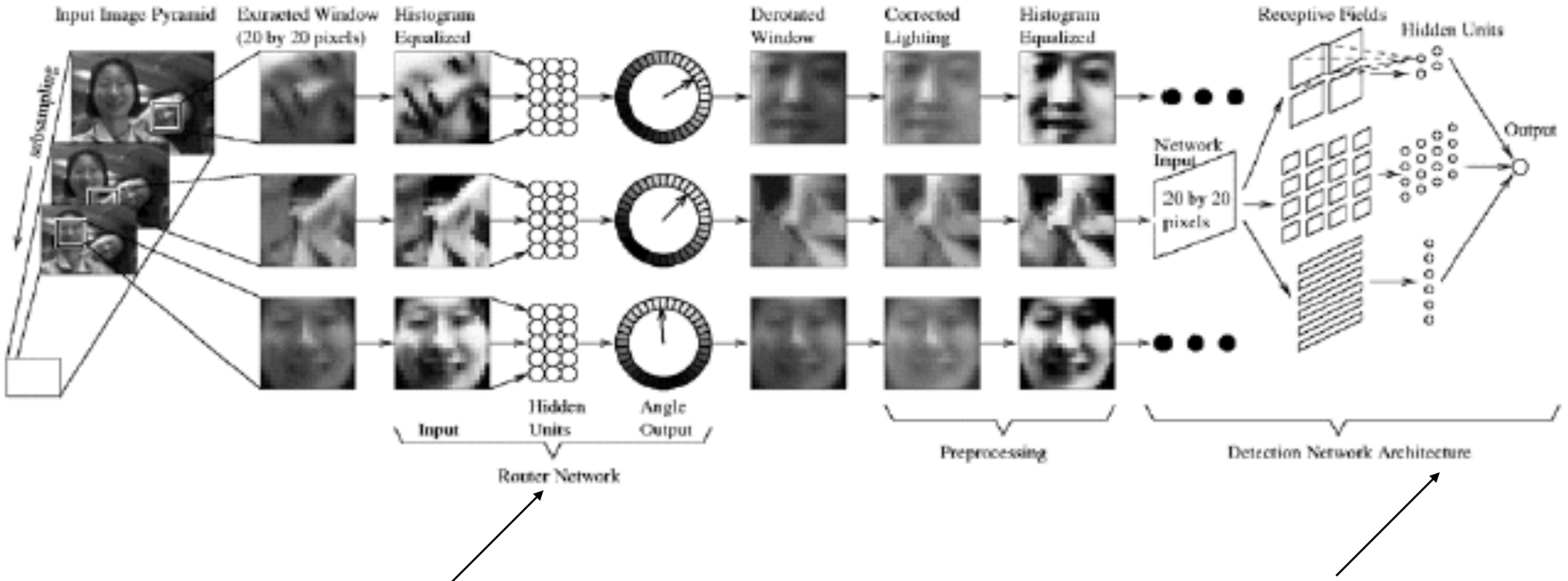
Example : Lecun Digit Recognition





Convolutional Networks: Lecun et al.
http://yann.lecun.com/exdb/lenet/

(Classic) Example: Face detection



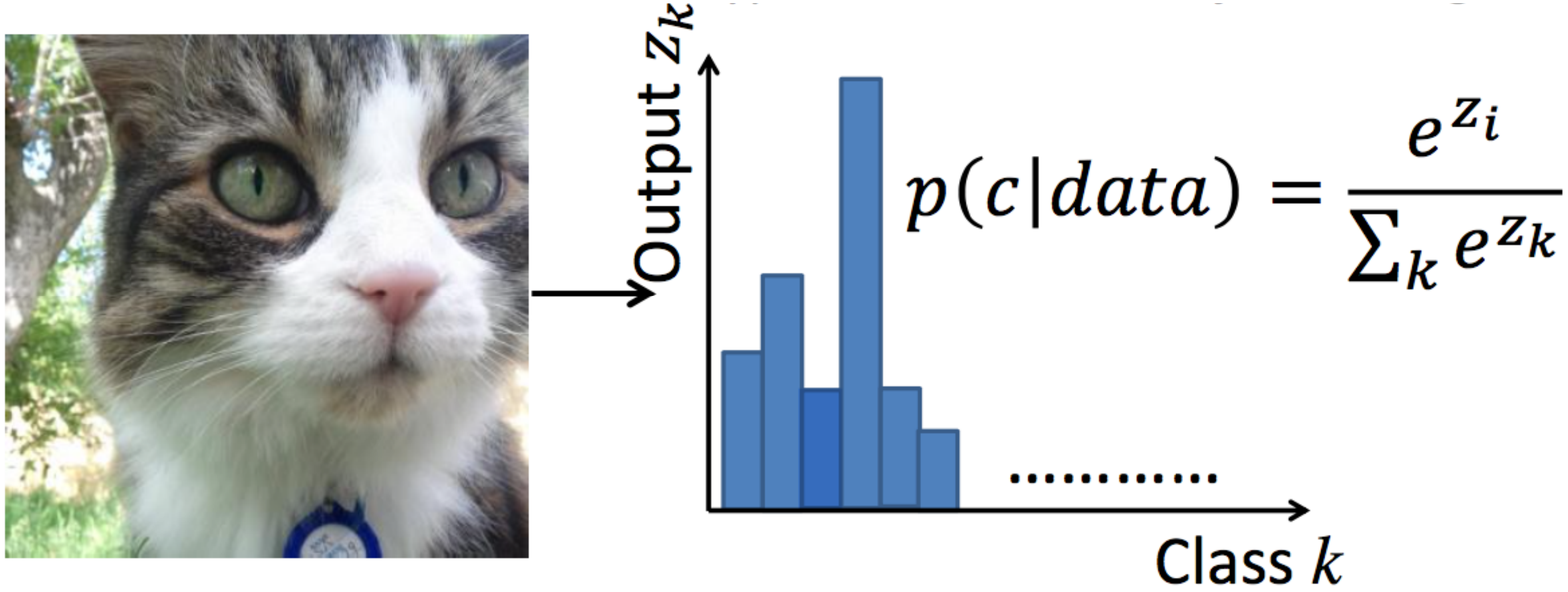
f(x) = orientation of template sampled at 10° intervals

f(x) = face detection posterior

Example from Rowley et al.

ImageNet Classification

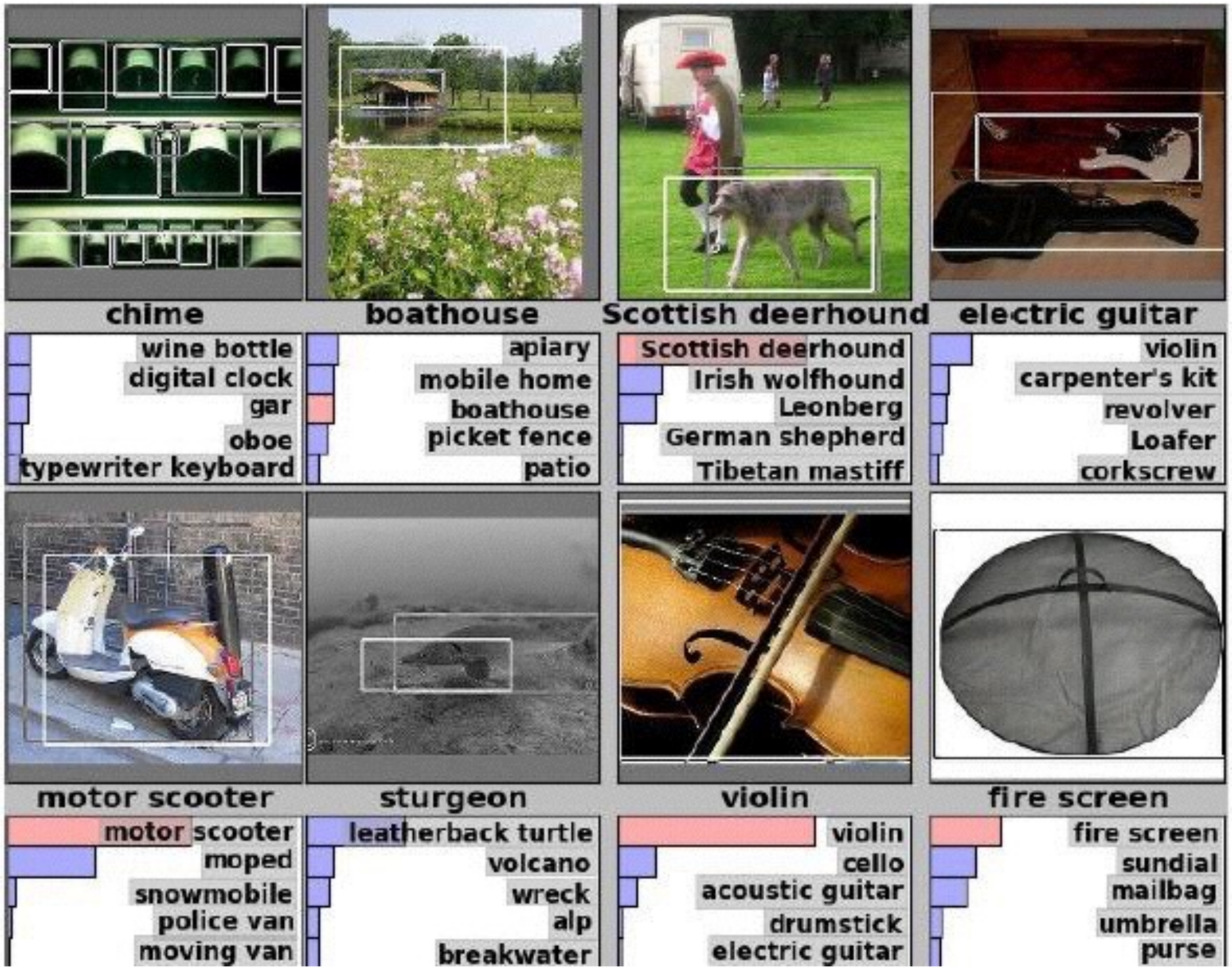
- Imagenet dataset (1000 classes!)
- Input: Image, output: Probability of object type in image (logistic model)
- Classification: Classify image type
- Localization/detection: Find type and location of object in image



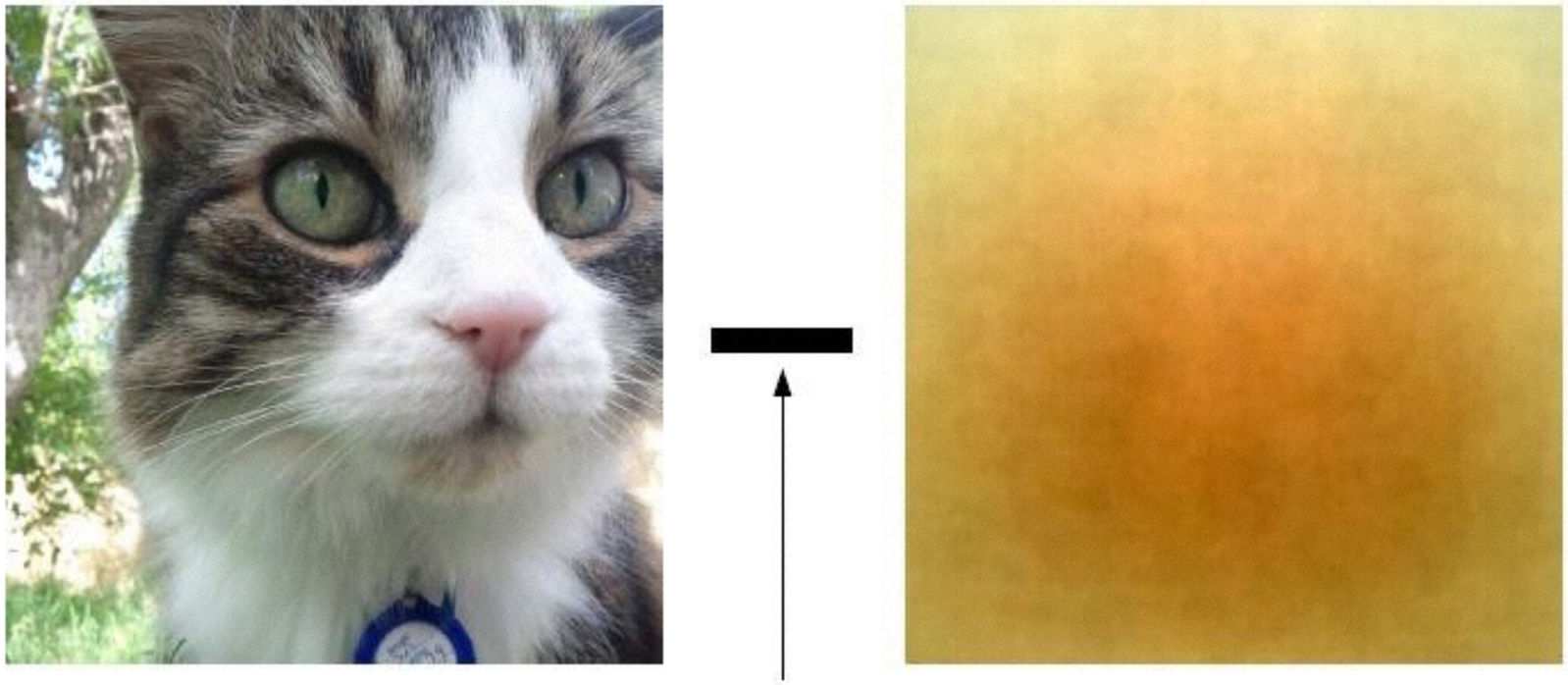
Krizhevsky, A., Sutskever, I. and Hinton, G. E. ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.

Classification Examples

Detection/Localization Examples

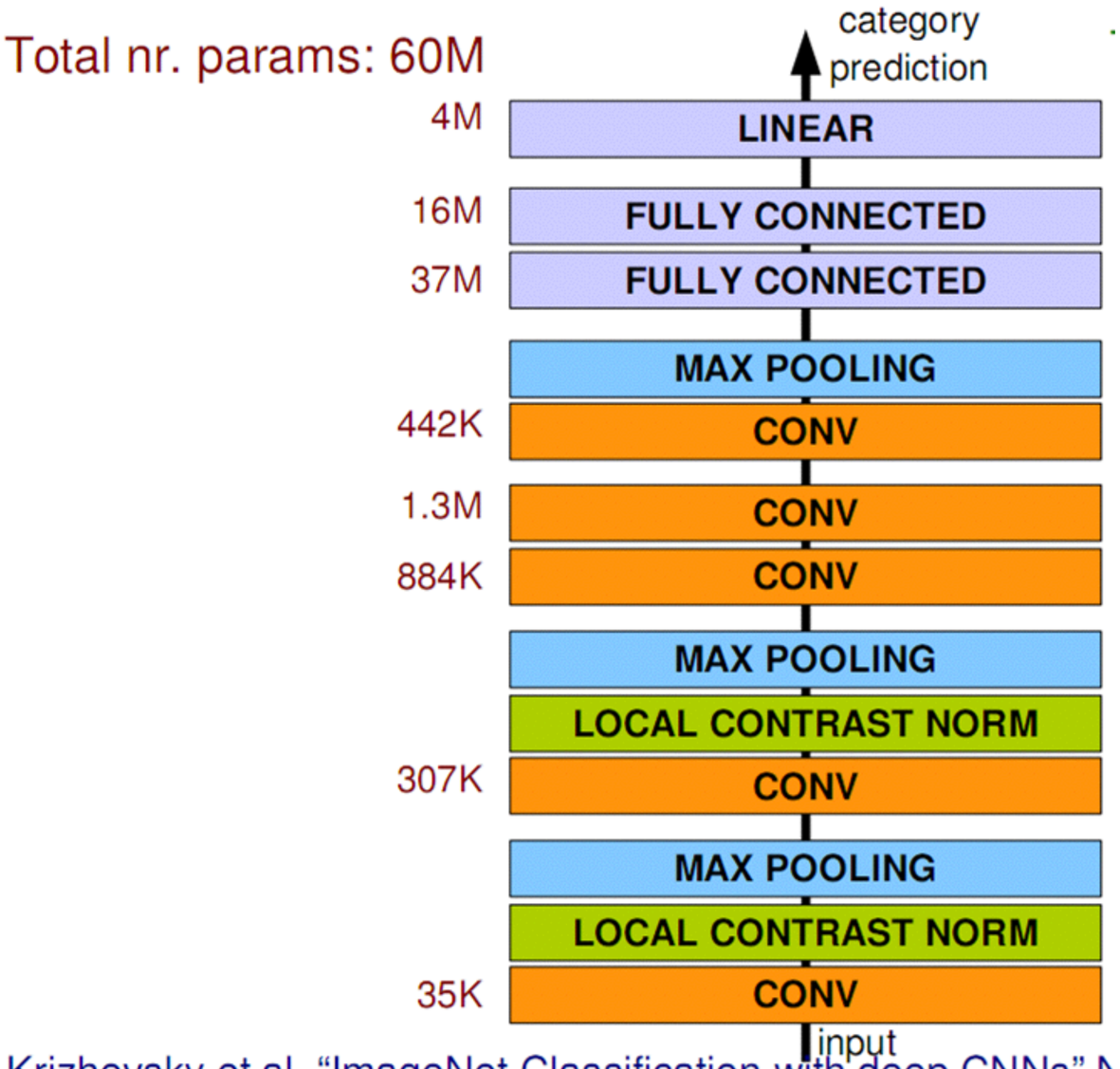


Input Preparation



Normalize Inputs by subtracting the mean of all training images

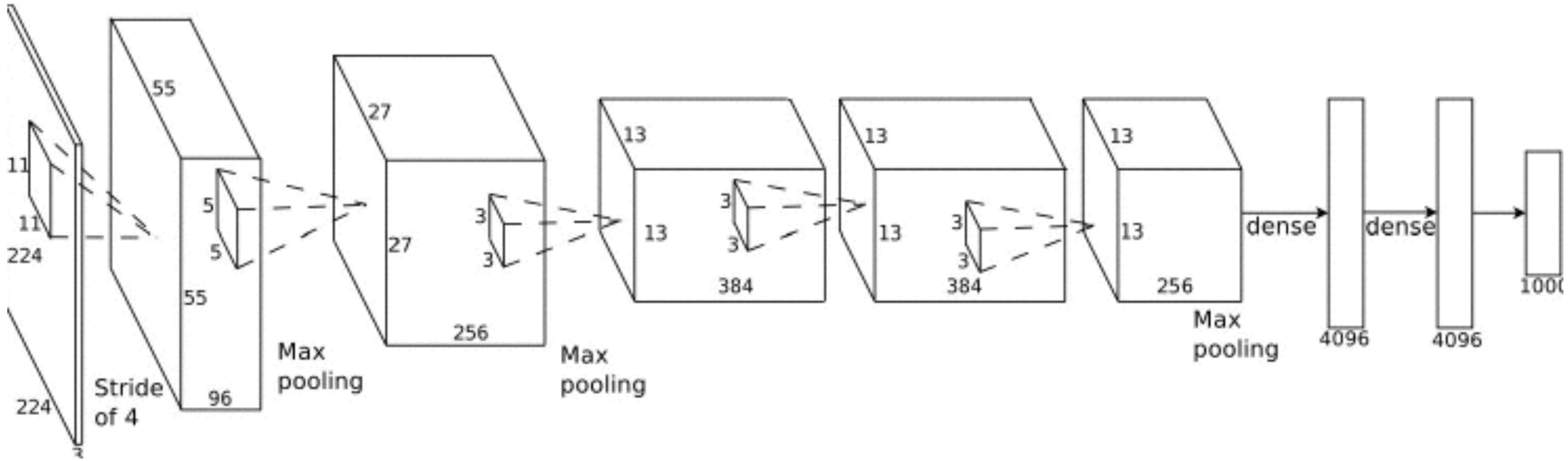
Full Architecture



Krizhevsky et al. “ImageNet Classification with deep CNNs” N

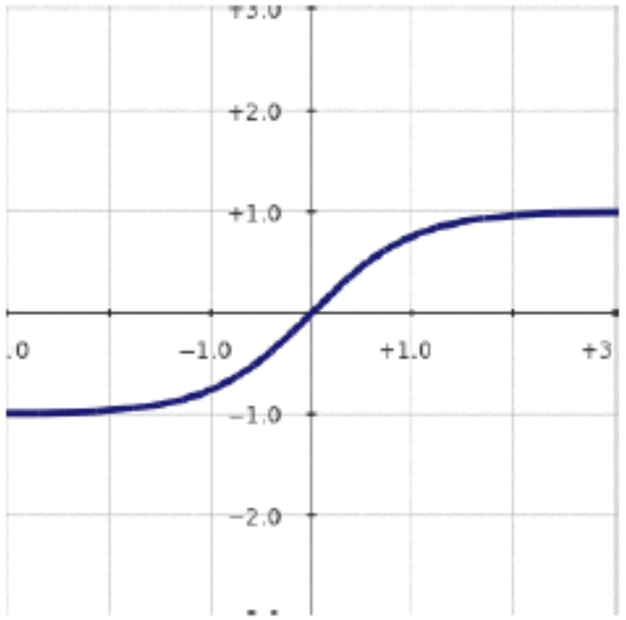
Architecture “AlexNet”

- 5 convolution layer
- 3 max pooling
- 2 fully connected
- Total number of nodes= 253440+186624+64896+64896+43264+4096+4096+10 00=650K
- 630 million connections
- 60 million parameters (!!)

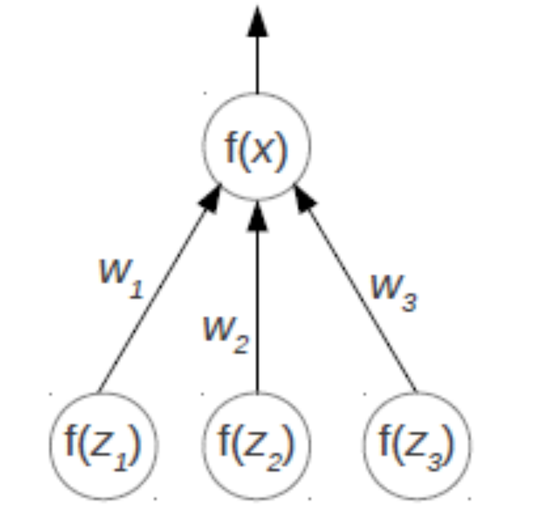


Choice of Non-Linearity

$f(x) = \tanh(x)$



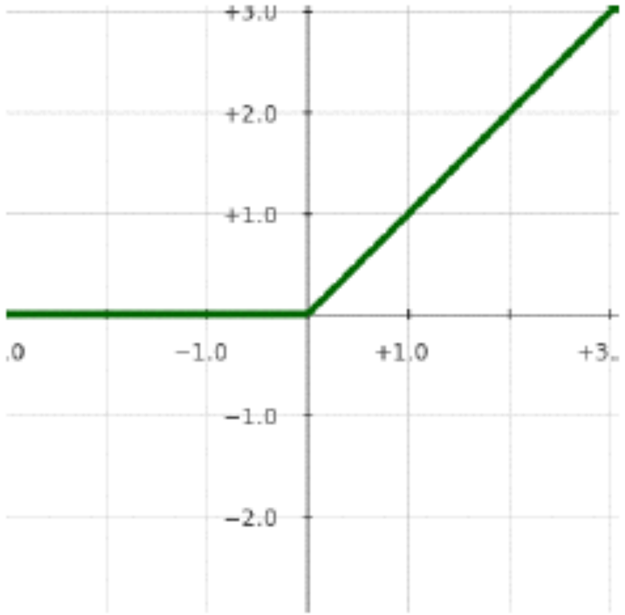
Hard to Train



$x = w_1 f(z_1) + w_2 f(z_2) + w_3 f(z_3)$

x is called the total input to the neuron, and $f(x)$ is its output

$f(x) = \max(0, x)$

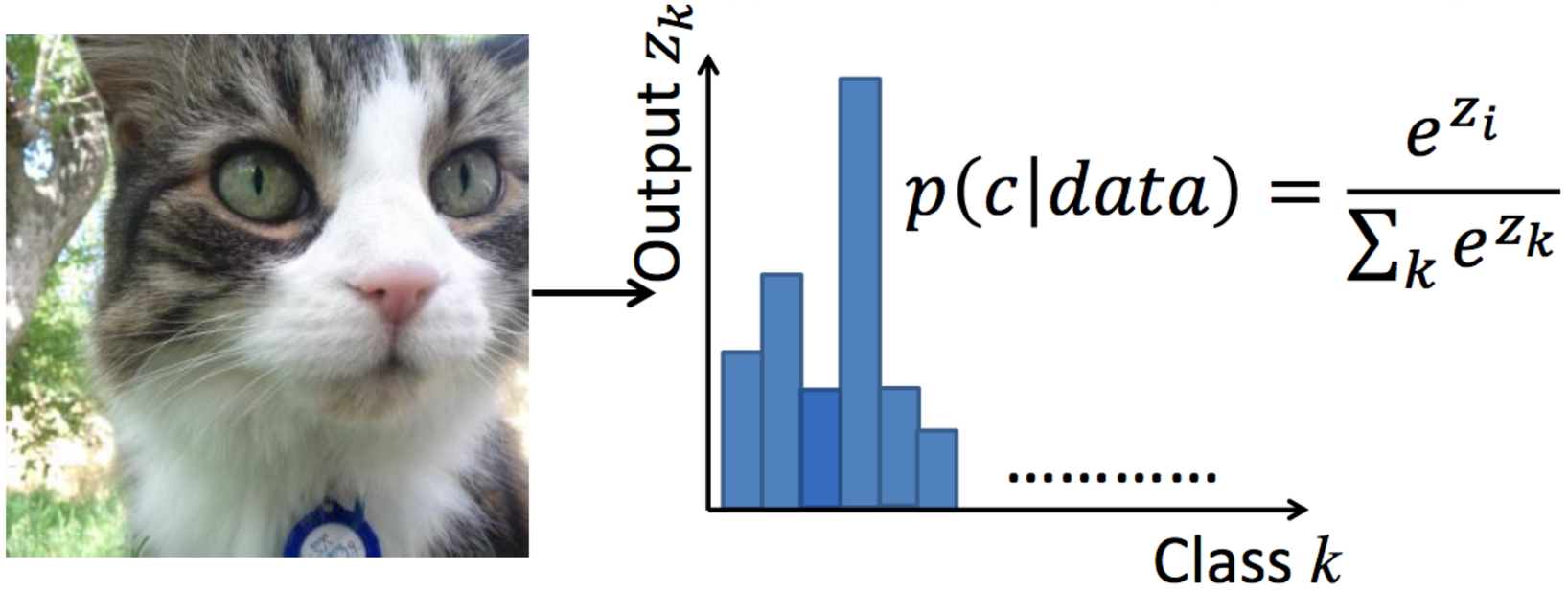


Easy to Train

Empirical “Fact” no real justification!

Training

- Initialization: Random (Gaussian noise) values for the parameters
- Backpropagation to maximize **log probability** of true class
- Stochastic gradient descent



Overfitting Issues

- We need to learn 60 million parameters!!
- Limited training data
- Will lead to massive overfitting
- Two tricks (essential):
  - Data augmentation
  - Dropout

Data Augmentation

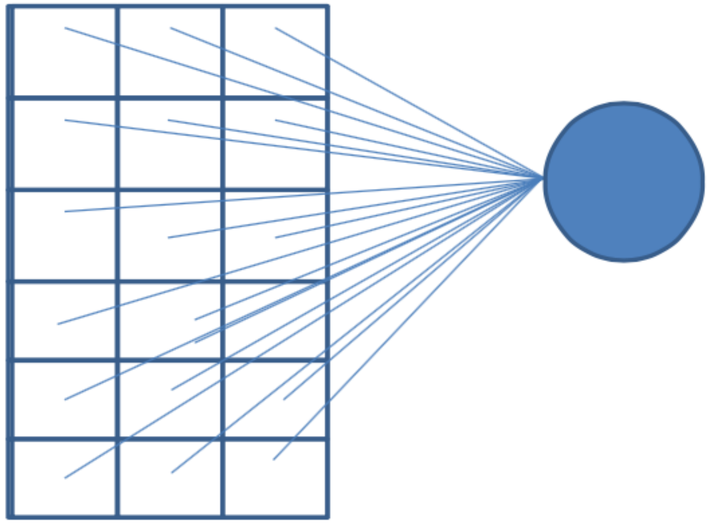
- In all systems: Essential to create additional training data to avoid overfitting to limited samples

- Example:
  – Train on 224x224 patches extracted randomly from 256x256

- images
  – Horizontal reflections

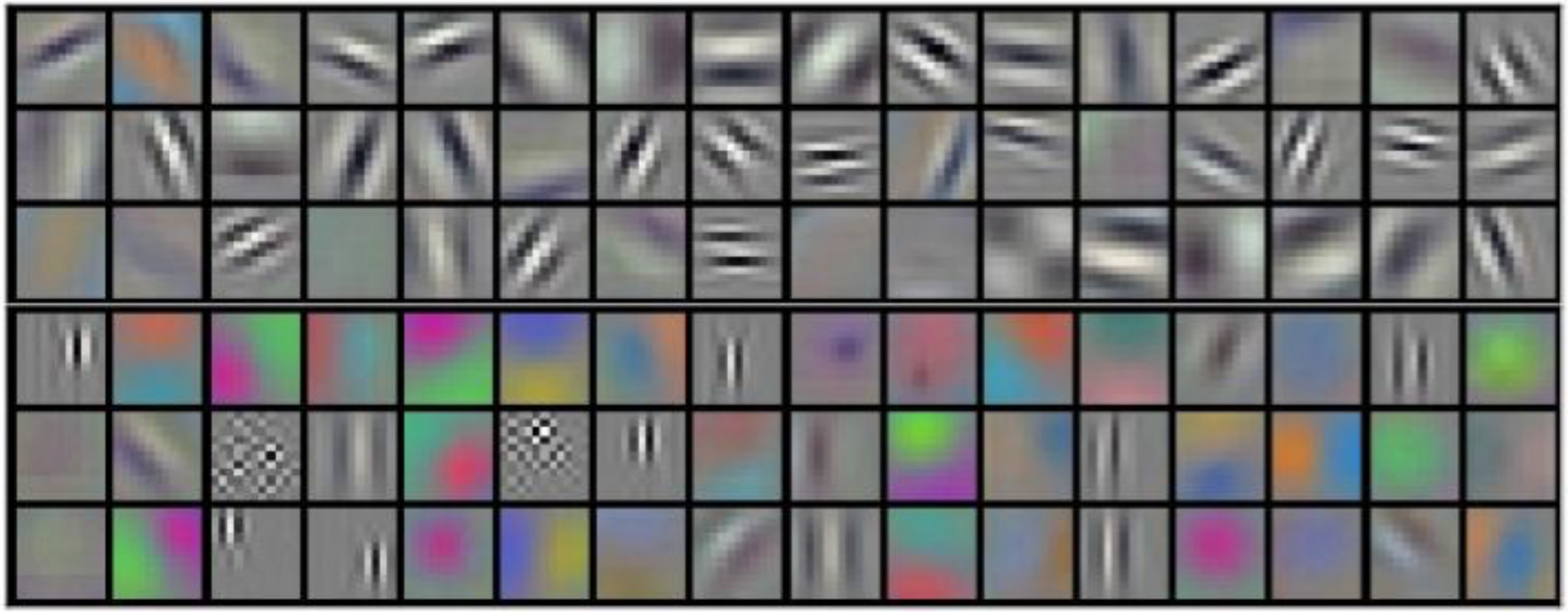
Dropout

- Essential: Randomly drop connections to prevent the network to overfit to a specific configuration of connections
- Example:
  – Independently set each hidden unit activity to zero with 0.5
- probability
  – Done in the two fully-connected hidden layers



$$y_i = \begin{cases} \phi\left(\sum_k w_k x_k\right) \\ 0 \text{ with probability } 0.5 \end{cases}$$

96 1st Layer Convolutional Filters



Retrieval Example