Object Detection
Lecture 10.3 - Introduction to deep learning (CNN)

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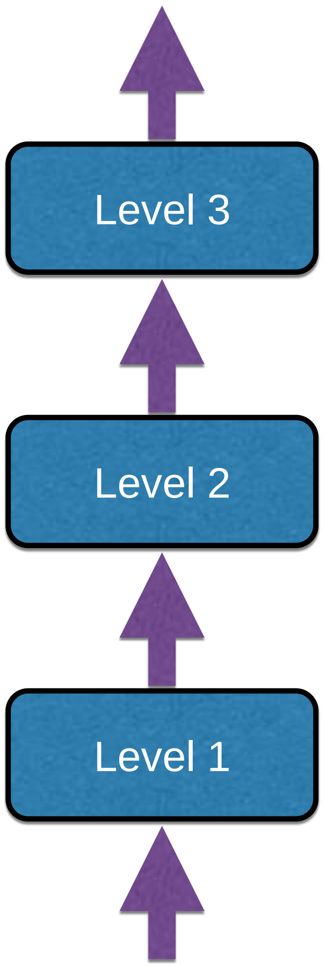
Deep Learning

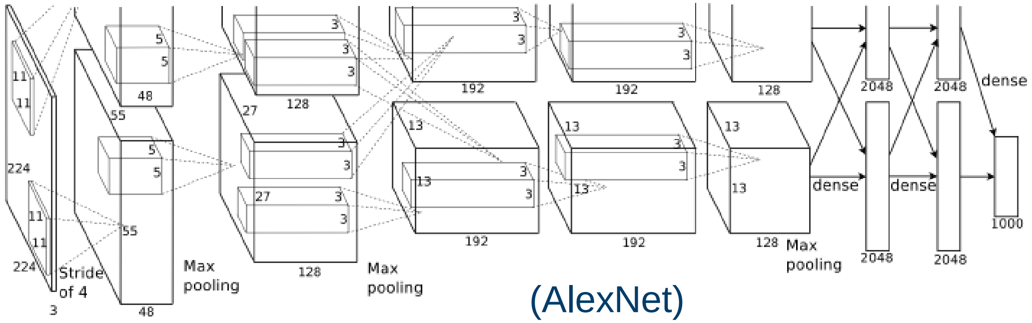
- Computational models composed of multiple processing layers (non-linear transformations)
- Used to learn representations of data with multiple levels of abstraction:
  - Learning a hierarchy of feature extractors
  - Each level in the hierarchy extracts features from the output of the previous layer (pixels $\longrightarrow$ classes)
- Deep learning has dramatically improved state-of-the-art in:
  - Speech and character recognition
  - Visual object detection and recognition
- Convolutional neural nets for processing of images, video, speech and signals (time series) in general
- Recurrent neural nets for processing of sequential data (speech, text).

Labels



Raw data (images, video, signals)

Deep Learning for Object Recognition



(AlexNet)

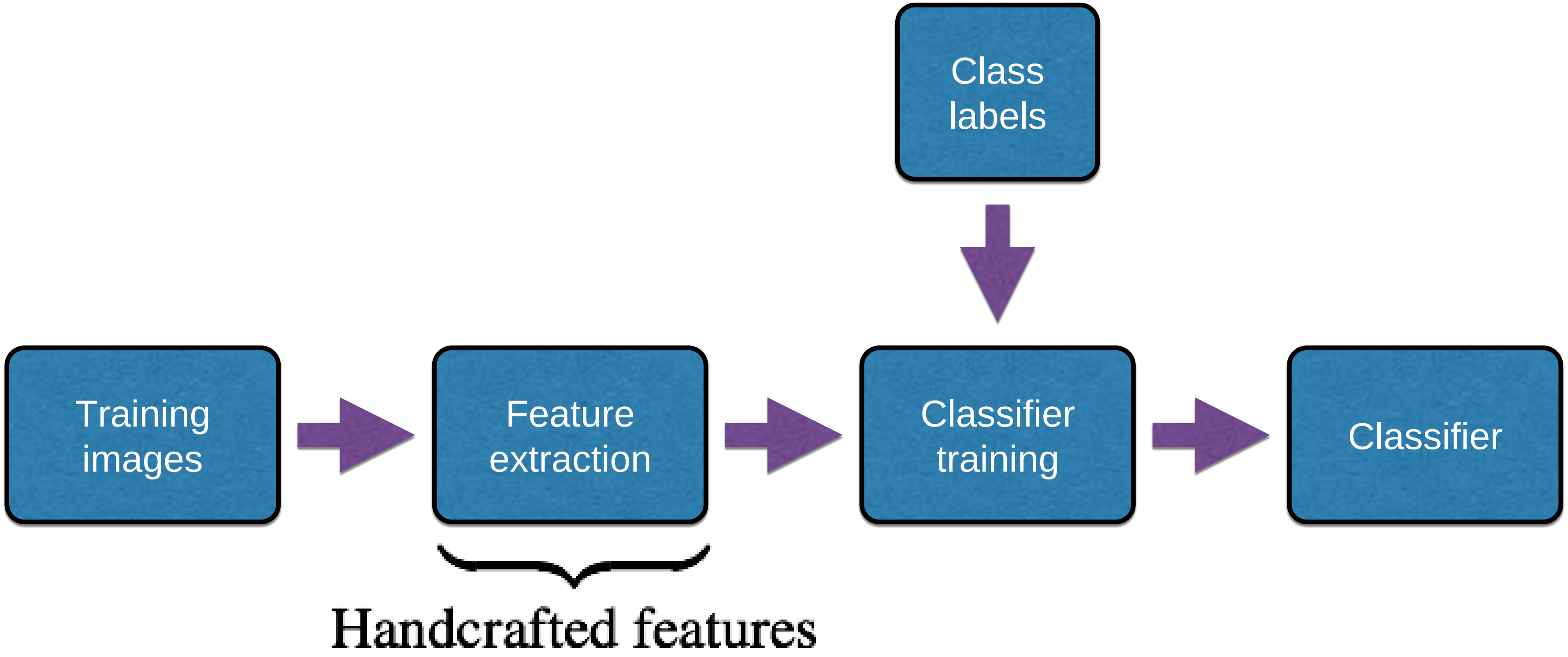
«Ship»

Millions of images

Millions of parameters

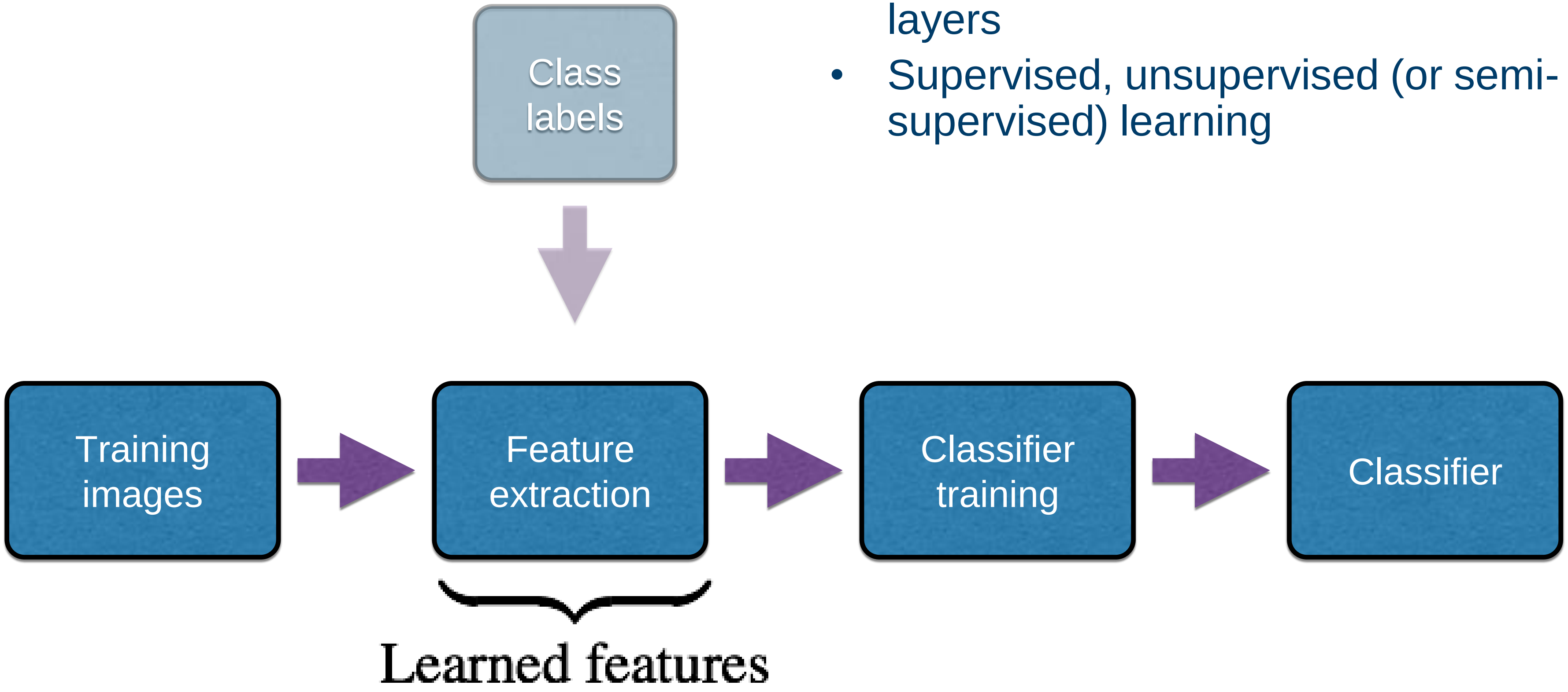
Thousands of classes

Traditional supervised learning

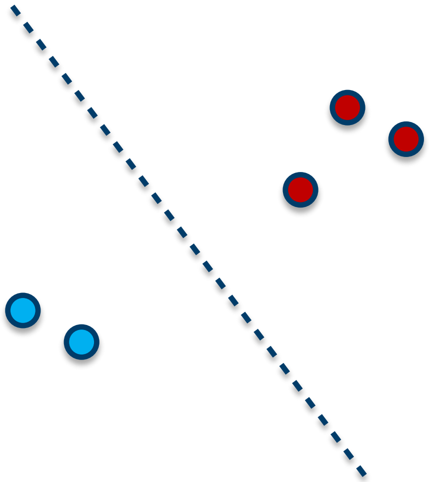


Deep learning

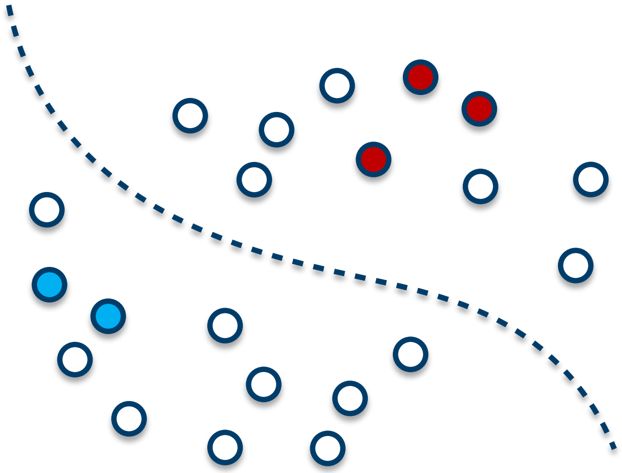
- Learning of weights in the processing layers
- Supervised, unsupervised (or semi-supervised) learning



Semi-supervised learning



Labeled samples and (trained) linear decision boundary



Labeled and unlabeled samples and non-linear decision boundary

Artificial Neural Network (ANN)

Used in Machine Learning and Pattern Recognition:

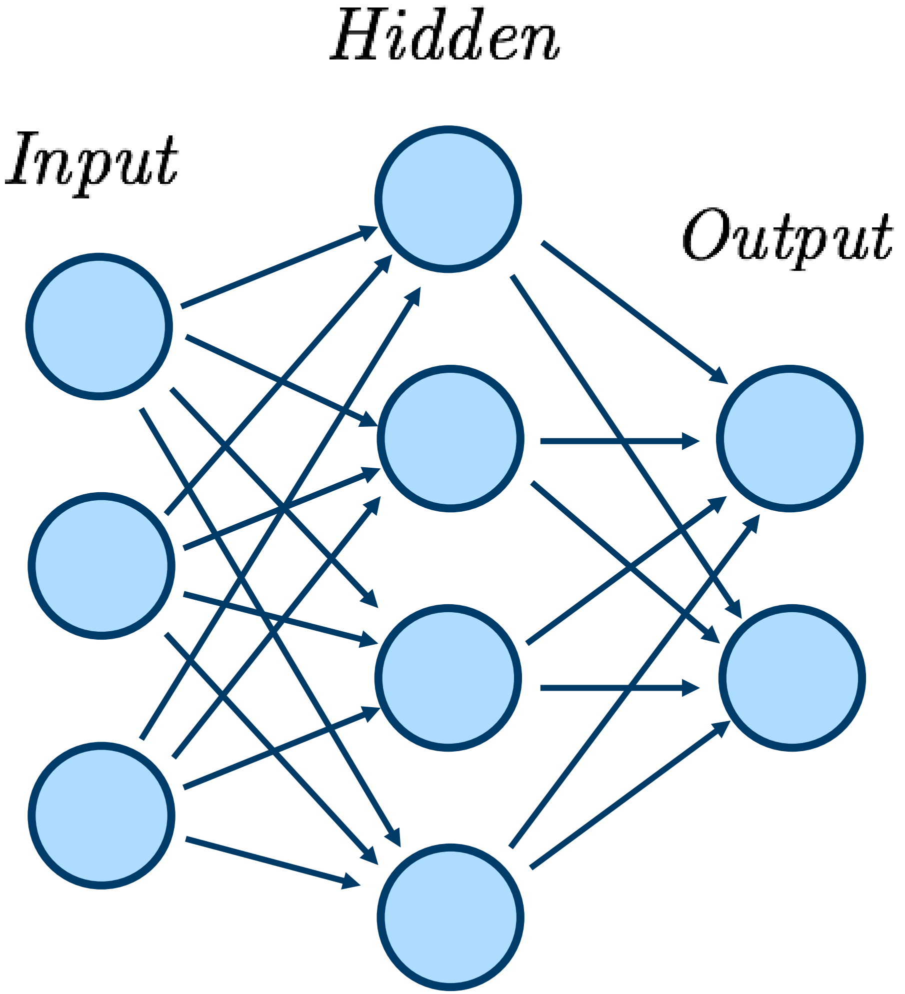
- Regression
- Classification
- Clustering
- …

Applications:

- Speech recognition
- Recognition of handwritten text
- Image classification
- …

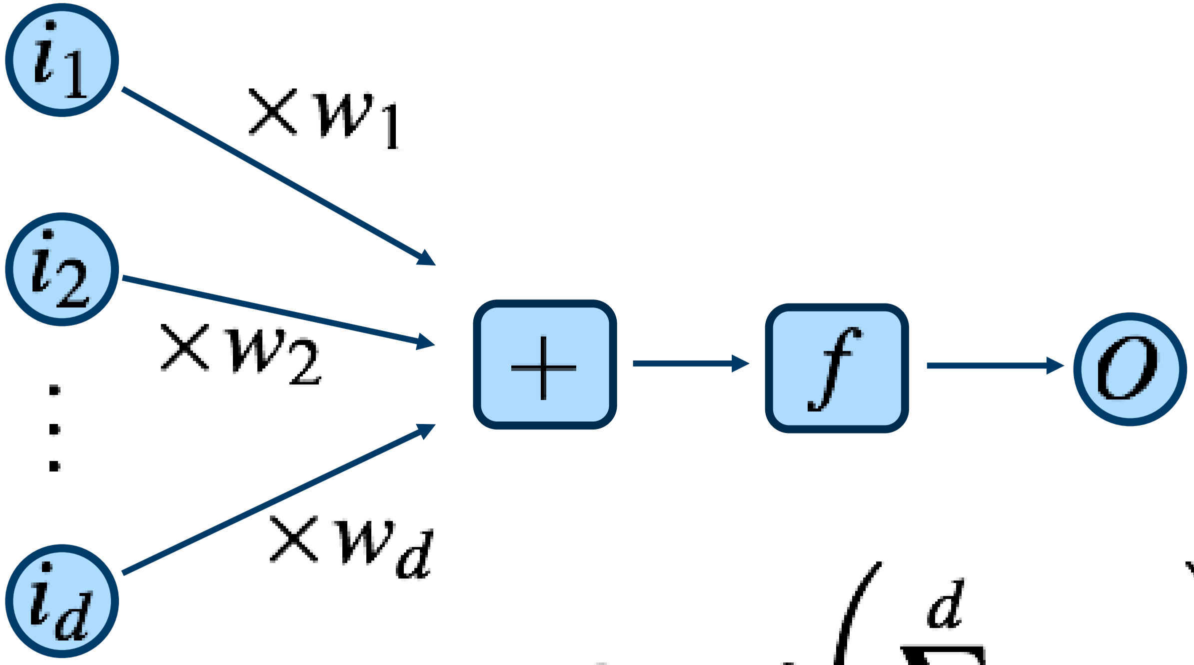
Network types:

- Feed-forward neural networks
- Recurrent neural networks (RNN)
- …

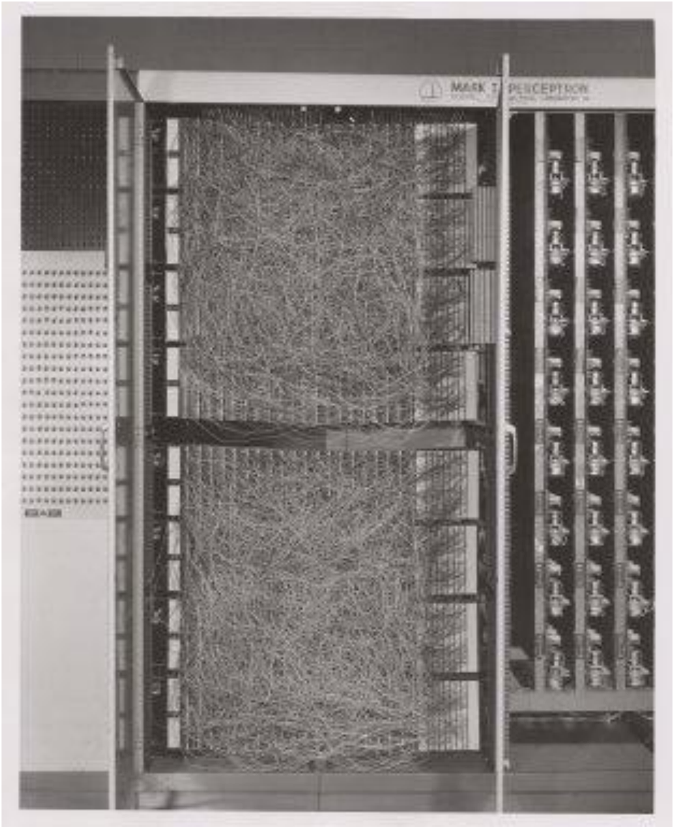


Feed-forward ANN (non-linear classifier)

Mark 1 Perceptron (Rosenblatt, 1957-59)



$$o = f\left(\sum_{k=1}^{d} i_k w_k\right)$$



(Cornell Aeronautical Laboratory)

Activation functions

- Sigmoid (logistic function):

$$f(x) = \frac{1}{1+e^{-x}}$$

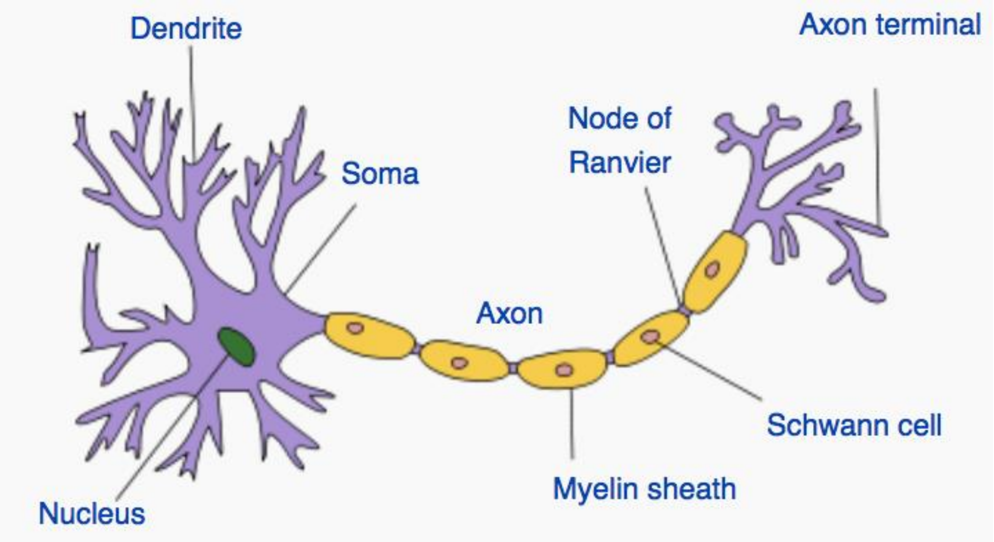
- Hyperbolic tangent:

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

- Rectified linear unit (ReLU):

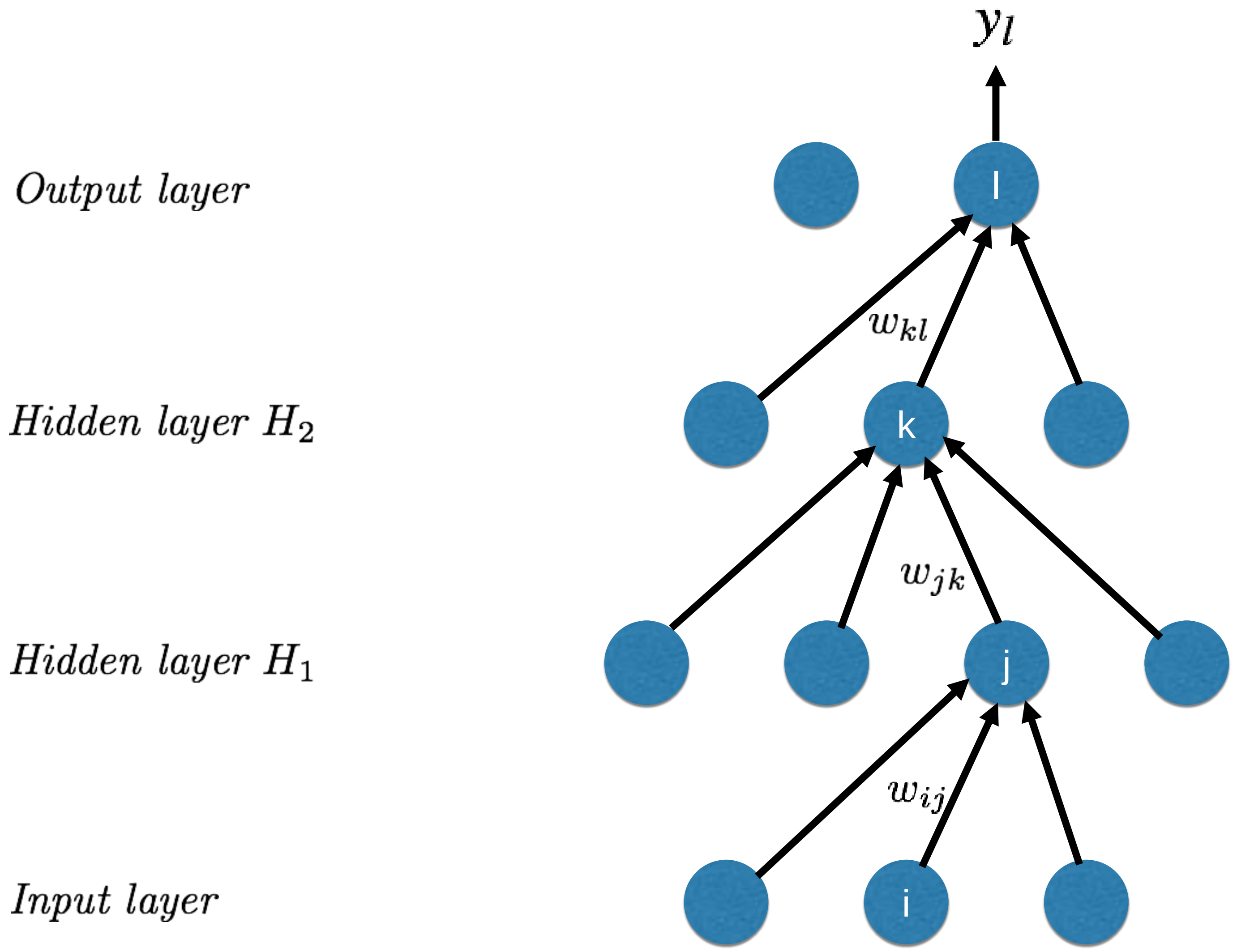
$$f(x) = \max(x, 0)$$

Biological neuron:



(Quasar Jarosz, English Wikipedia)

Feed-forward neural network

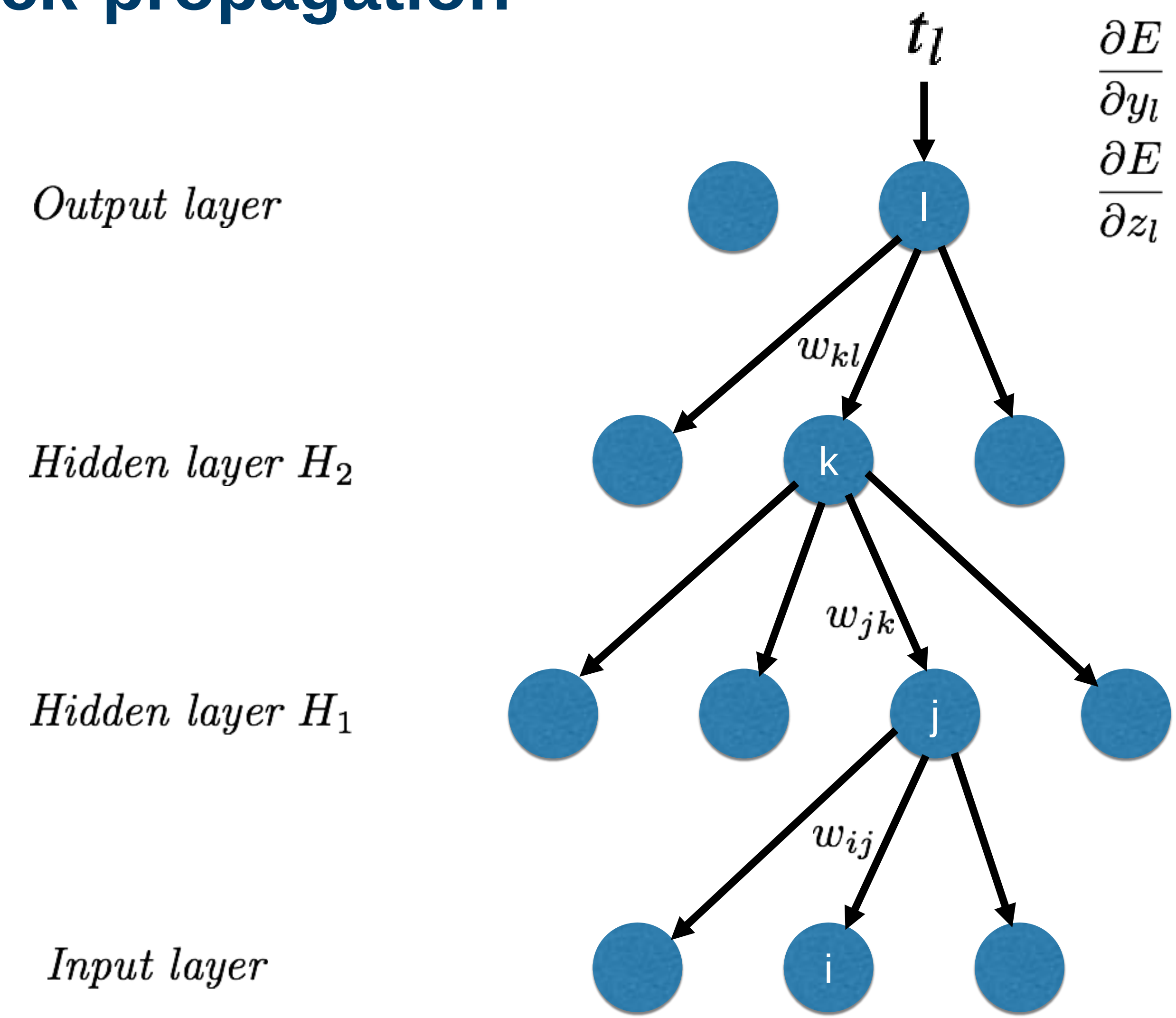


$$y_l = f(z_l)$$
$$z_l = \sum_{k \in H_2} w_{kl} x_k$$

$$y_k = f(z_k)$$
$$z_k = \sum_{j \in H_1} w_{jk} x_j$$

$$y_j = f(z_j)$$
$$z_j = \sum_{i \in Input} w_{ij} x_i$$

Back-propagation



$$\frac{\partial E}{\partial y_l} = y_l - t_l$$

$$\frac{\partial E}{\partial z_l} = \frac{\partial E}{\partial y_l}\frac{\partial y_l}{\partial z_l}$$

$$E(\boldsymbol{w}) = \sum_{k=1}^{n}(t_i - y_i)^2$$

$$\frac{\partial E}{\partial y_k} = \sum_{l \in Output} w_{kl}\frac{\partial E}{\partial z_l}$$

$$\frac{\partial E}{\partial z_k} = \frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial z_k}$$

$$\frac{\partial E}{\partial y_j} = \sum_{k \in H_2} w_{jk}\frac{\partial E}{\partial z_k}$$

$$\frac{\partial E}{\partial z_j} = \frac{\partial E}{\partial y_j}\frac{\partial y_j}{\partial z_j}$$

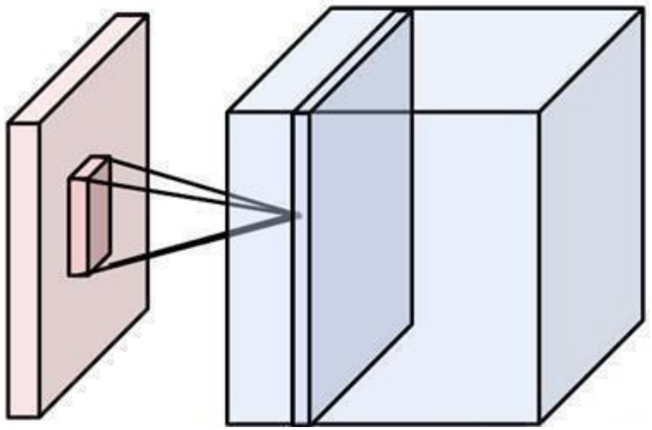
Convolutional Neural Network (CNN)

Used in Machine Vision and Image Analysis:

- Speech Recognition
- Image Recognition
- Video Recognition
- Image Segmentation
- …

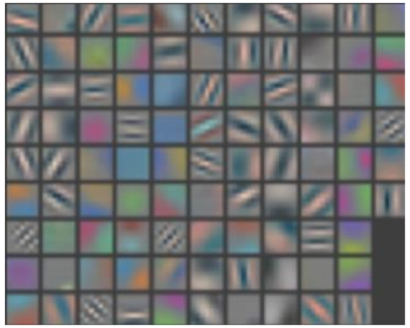
Convolutional neural network:

- Multi-layer feed-forward ANN
- Combinations of *convolutional* and fully connected layers
- Convolutional layers with *local* connectivity
- *Shared* weights across spatial positions
- Local or global pooling layers

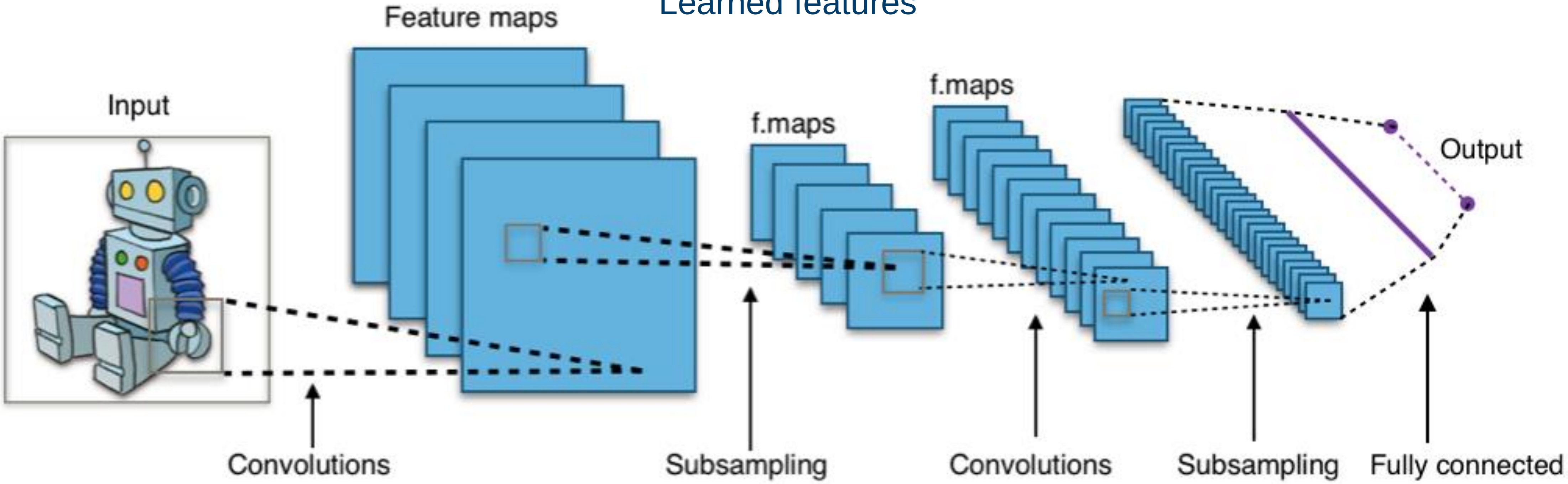


(A. Karpathy)

Typical CNN



Learned features

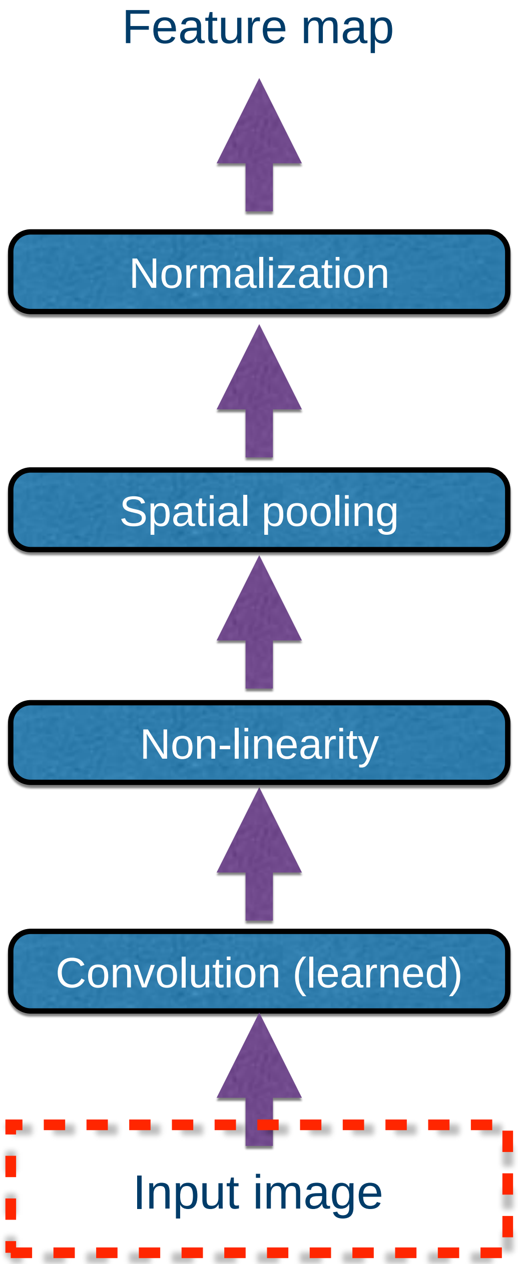


(Aphex34)

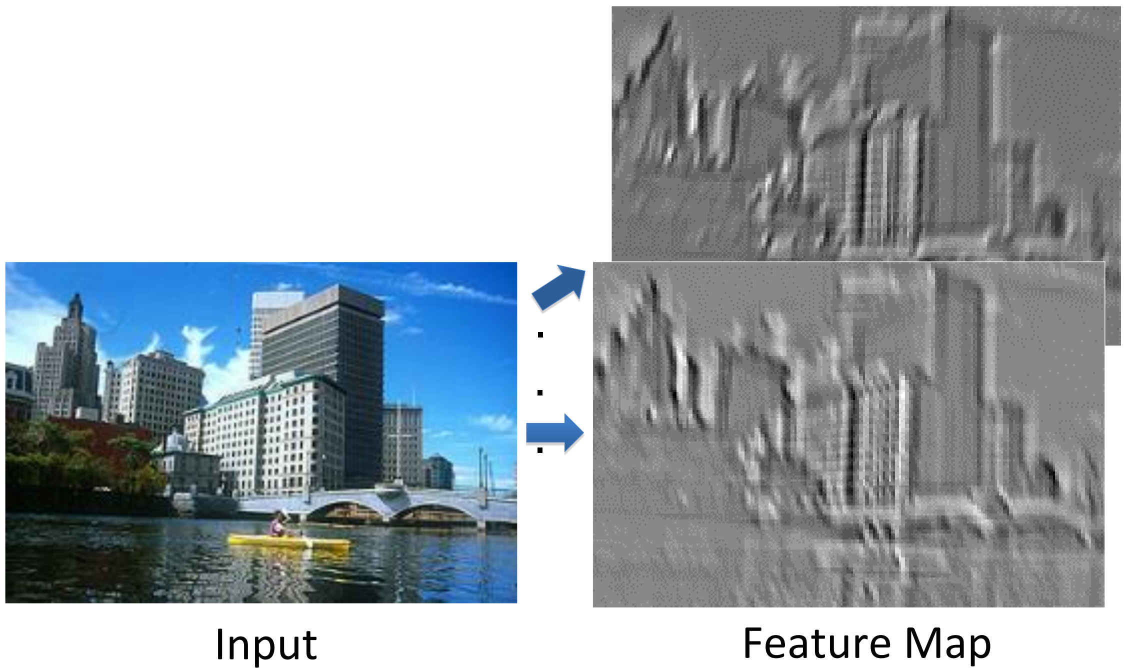
Convolutional neural net

Input image

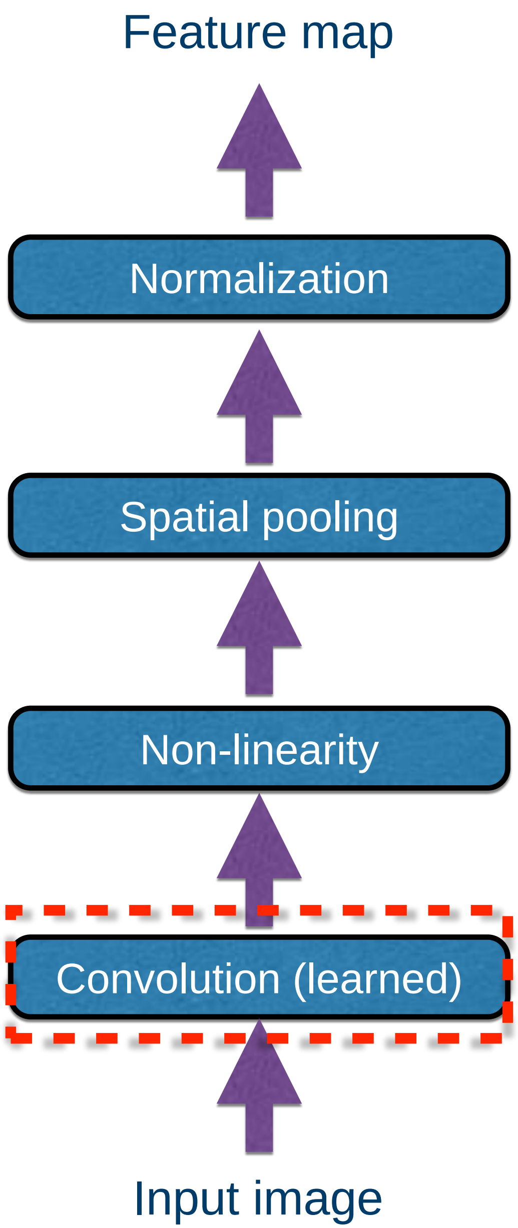
(credit: S. Lazebnik)



Convolutional neural net

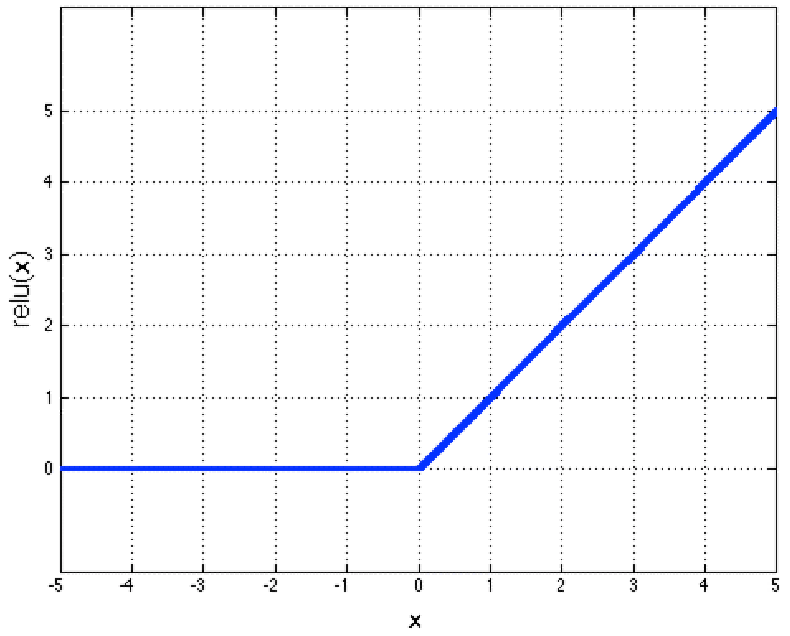


(credit: S. Lazebnik)

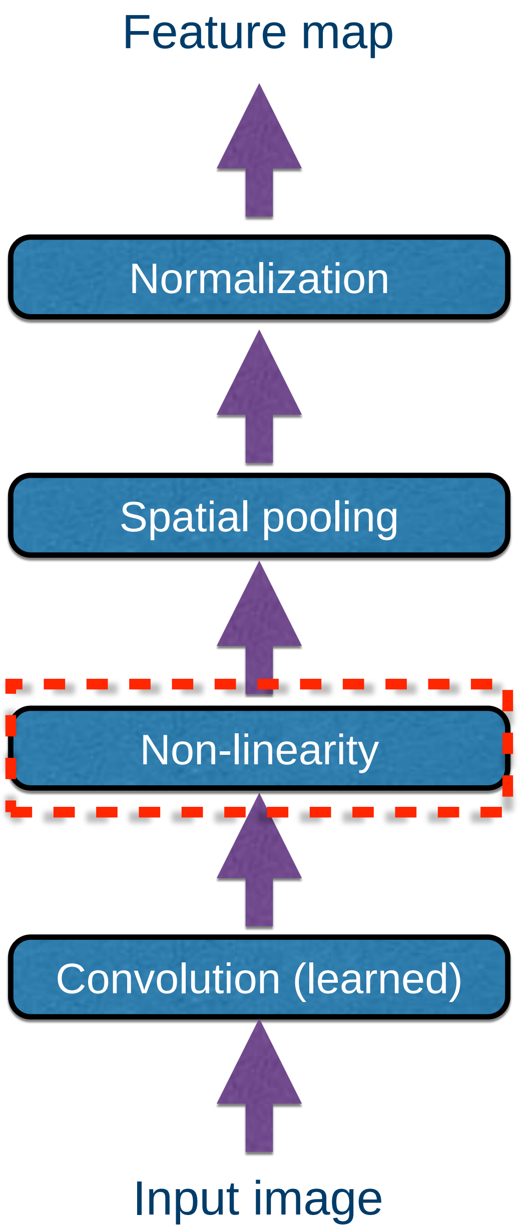


Convolutional neural net

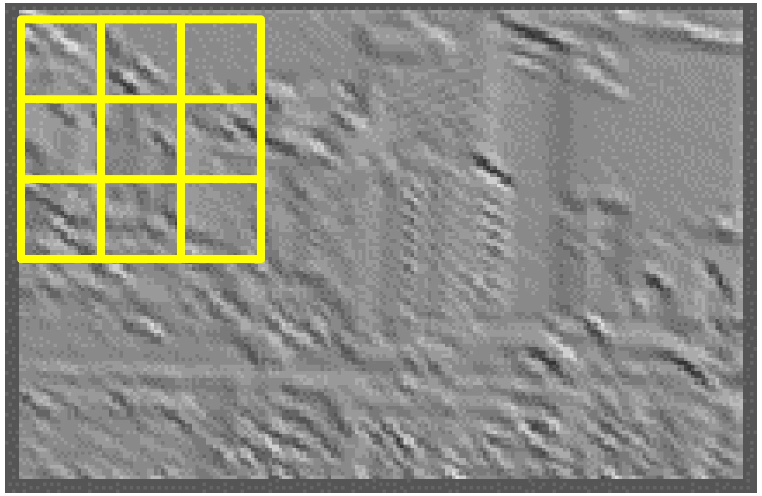
Rectified Linear Unit (ReLU)



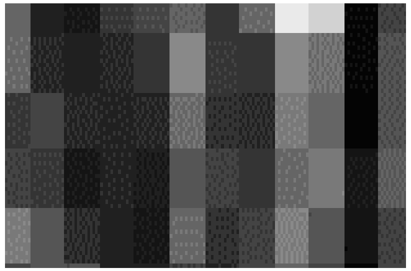
(credit: S. Lazebnik)



Convolutional neural net



Max pooling



Feature map

Normalization

Spatial pooling

Non-linearity

Convolution (learned)

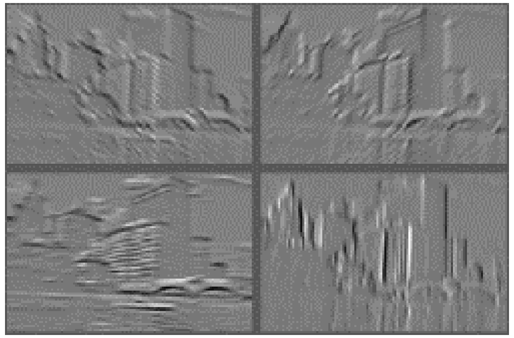
Input image

Max-pooling: a non-linear down-sampling

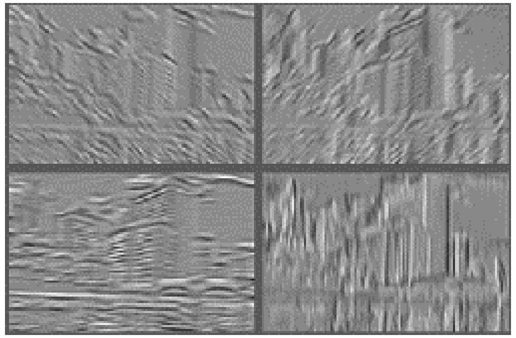
Provide *translation invariance*

(credit: S. Lazebnik)

Convolutional neural net

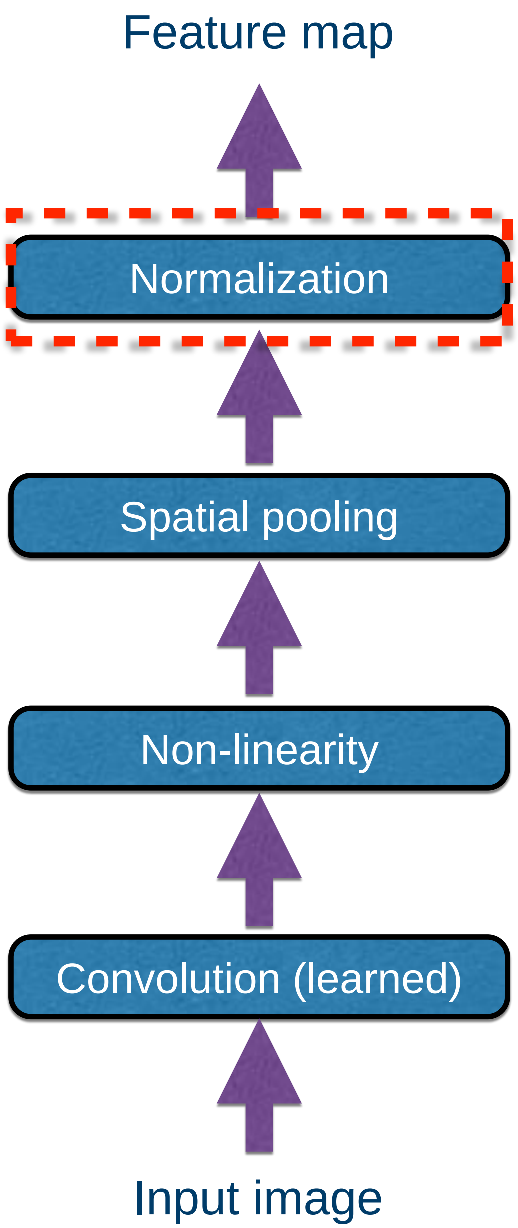


Feature Maps

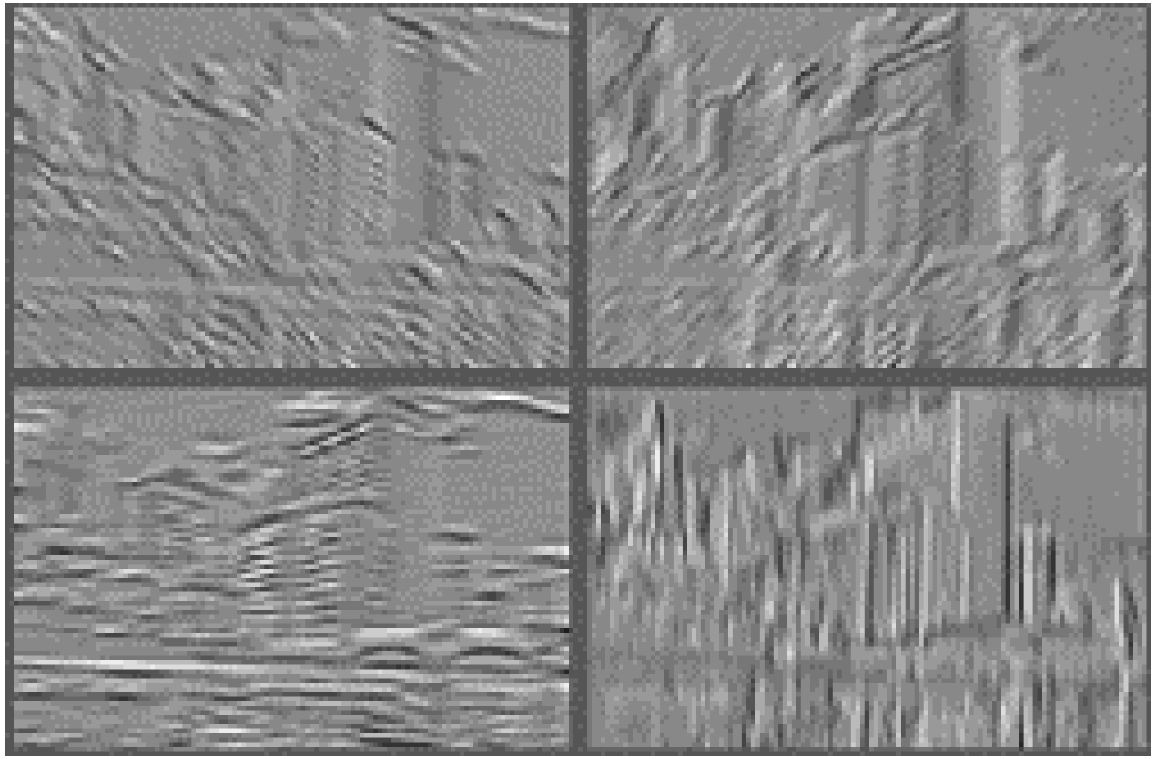


Feature Maps
After Contrast
Normalization

(credit: S. Lazebnik)

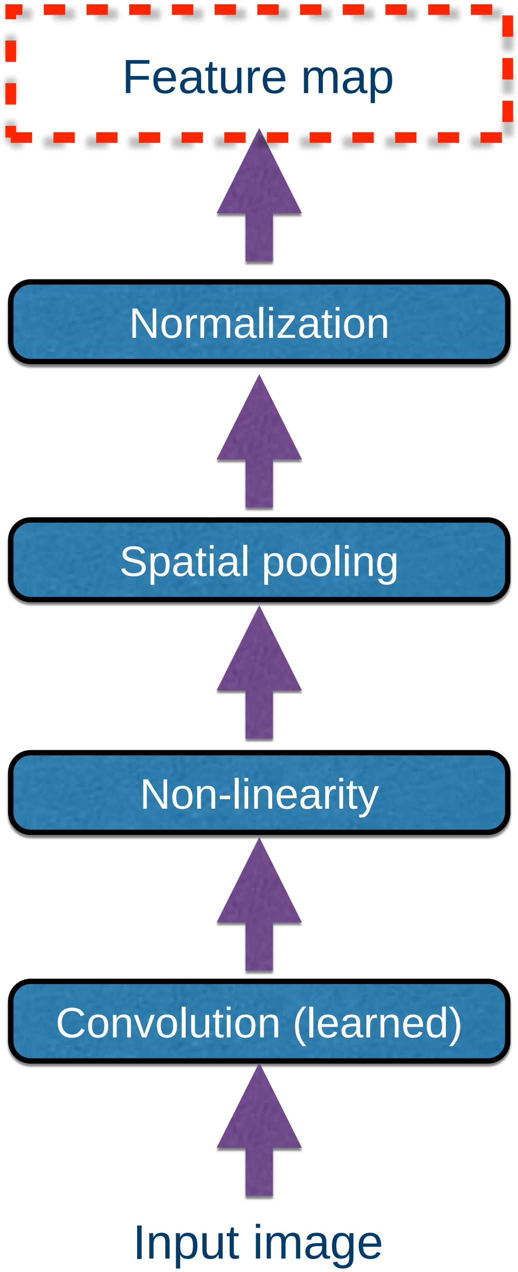


Convolutional neural net



Feature maps after contrast normalization

(credit: S. Lazebnik)

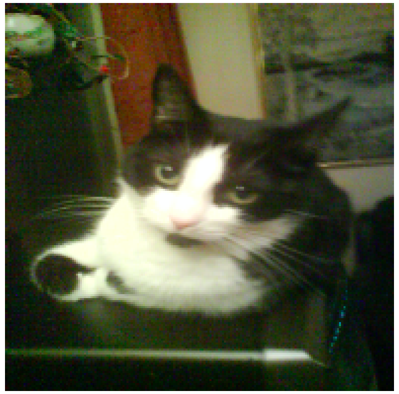


Example - Caffe Demos

The Caffe neural network library makes implementing state-of-the-art computer vision systems easy.

Classification

Click for a Quick Example



Maximally accurate | Maximally specific

Egyptian cat	0.32645
tabby	0.16689
tiger cat	0.10922
Persian cat	0.06203
Siamese cat	0.05992

CNN took 0.112 seconds.

http://demo.caffe.berkeleyvision.org

Caffe Demos

The Caffe neural network library makes implementing state-of-the-art computer vision systems easy.

Classification

Click for a Quick Example

Maximally accurate | Maximally specific

macaw	0.99985
lorikeet	0.00008
crane	0.00002
vulture	0.00002
flamingo	0.00002

CNN took 0.067 seconds.

Caffe Demos

The Caffe neural network library makes implementing state-of-the-art computer vision systems easy.

Classification

Click for a Quick Example

Maximally accurate | Maximally specific

suspension bridge	0.20551
lakeside	0.16864
pier	0.12692
alp	0.05951
radio telescope	0.04751

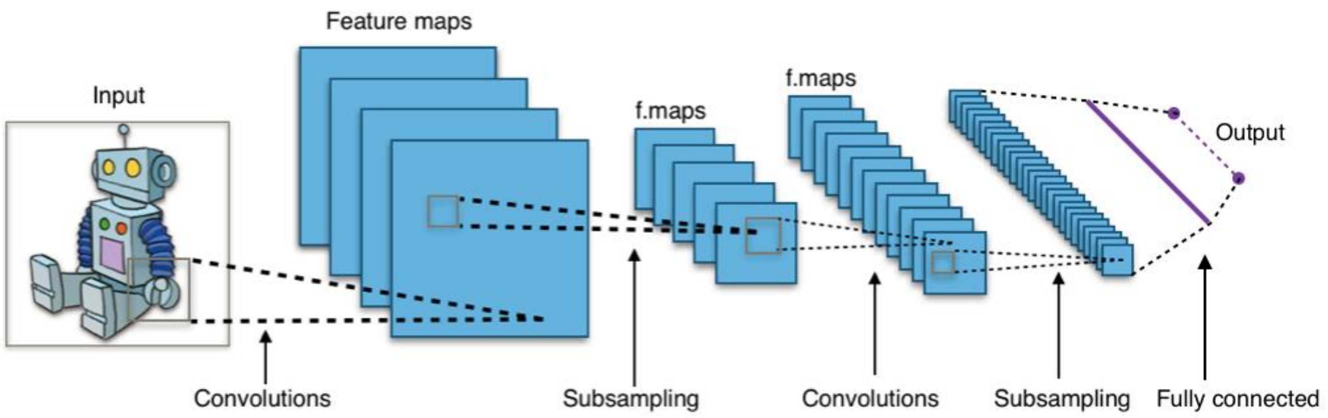
CNN took 0.254 seconds.

Example - Semantic Segmentation (SegNet)

http://mi.eng.cam.ac.uk/projects/segnet/

Summary

Topics covered:
- Deep learning
- Artificial neural networks
- Convolutional neural networks



More information:
- Szeliski, chapter 14
- Yann LeCun ,Yoshua Bengio & Geoffrey Hinton, “Deep learning”, Nature, Vol 521, 28. May 2015.
- Shaohuai Shi, Qiang Wang, Pengfei Xu, Xiaowen Chu, “Benchmarking State-of-the-Art Deep Learning Software Tools”, 2017 (https://arxiv.org/pdf/1608.07249.pdf)

Software:
- Caffe (http://caffe.berkeleyvision.org)
- TensorFlow (https://www.tensorflow.org/)
- MatConvNet (http://www.vlfeat.org/matconvnet)