Deep Learning

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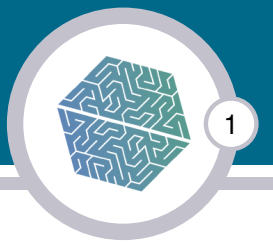
May 25, 2016

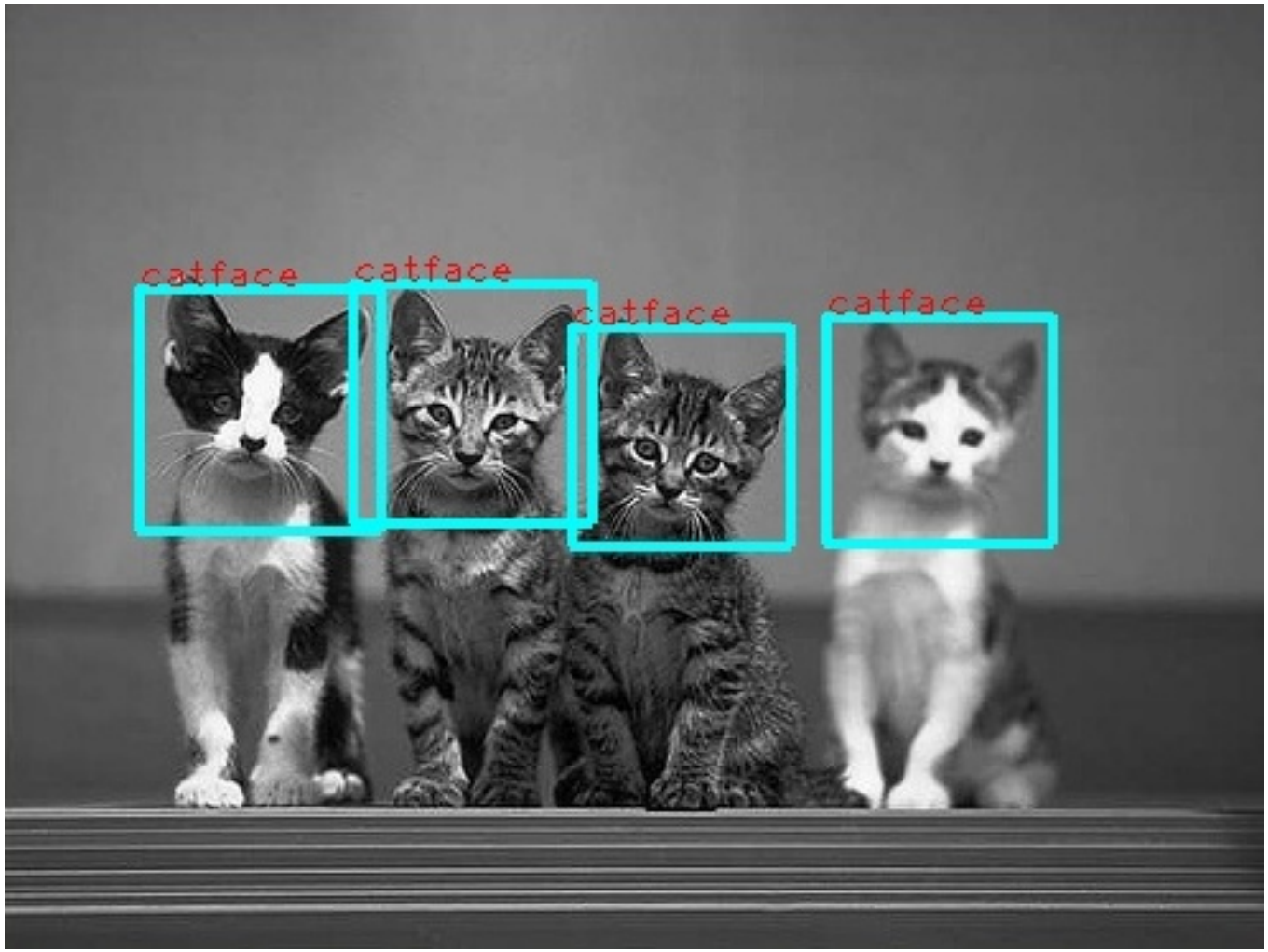
Outline



- Recall machine learning
- Support Vector Machine (SVM) with hand-designed image features
- Convolutional Neural Networks

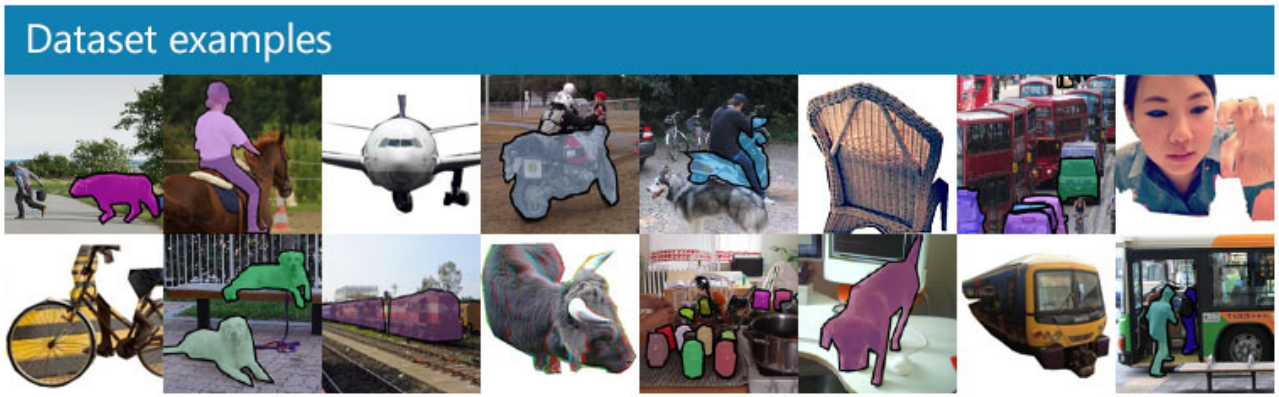
Machine learning

- Object detection



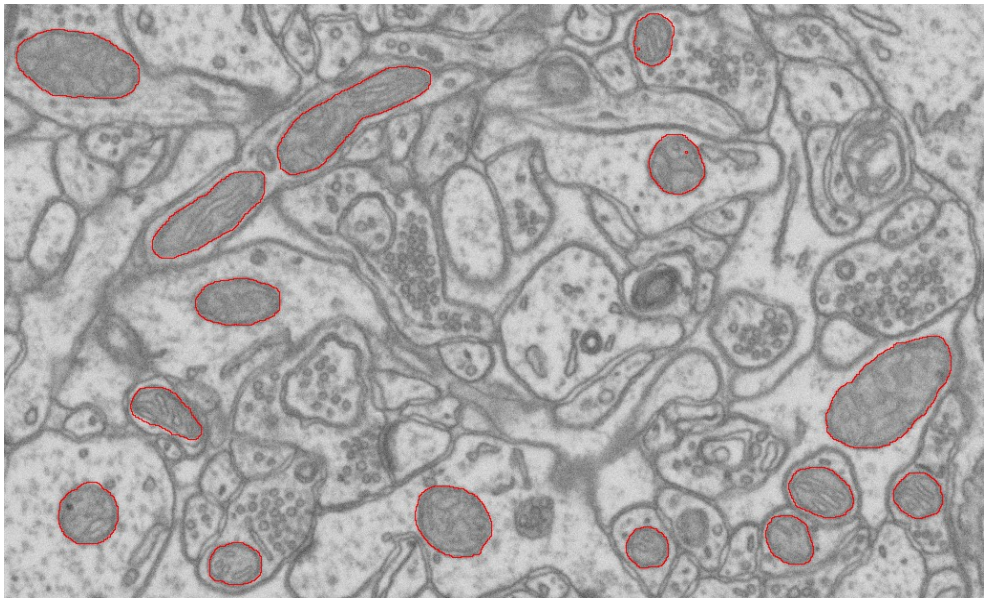
Machine learning

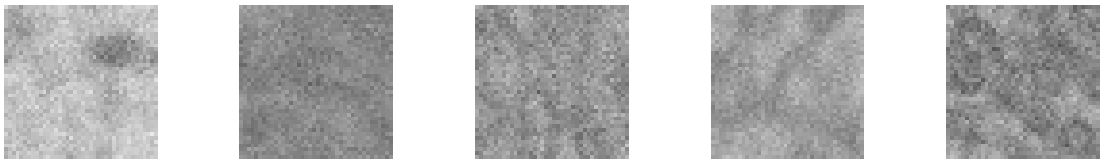
- Image segmentation



Machine learning

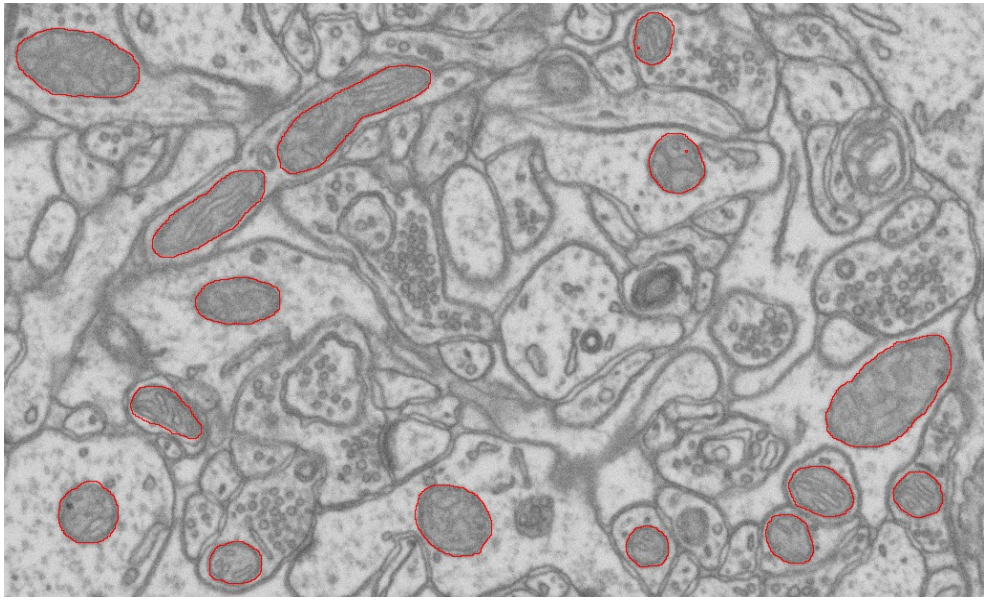
- Can you find the mitochondria in this image?

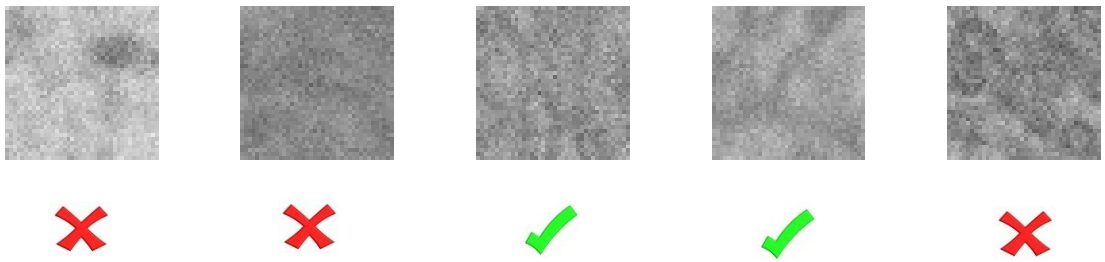




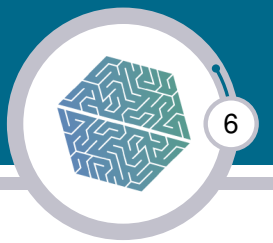
Machine learning

- Can you find the mitochondria in this image?





Machine learning - more formally



- Given a dataset $\{\boldsymbol{x}, \boldsymbol{y}\} = \{(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_n, y_n)\}$
  - $\boldsymbol{x}_i \in \mathbb{R}^d$ = feature vector
  - $y_i \in \{0, 1\}$ = label (binary classification)
- Consider $\boldsymbol{w} \in \mathbb{R}^d$ to be a vector of parameters
- Seek a function $f(\boldsymbol{x}; \boldsymbol{w}) : \mathbb{R}^d \to \mathbb{R}$ to model the data

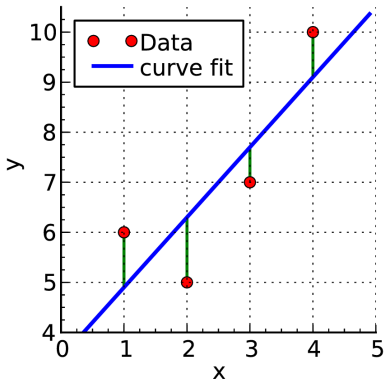
Machine learning - more formally

Open questions:

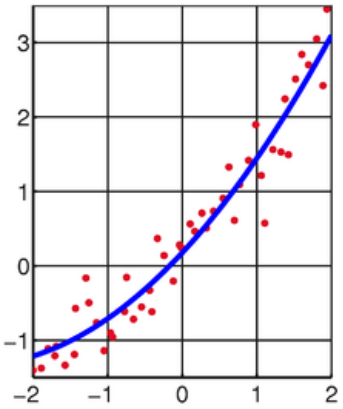
- What features $\boldsymbol{x}$ should I extract?
- What function $f(\boldsymbol{x}; \boldsymbol{w})$ should we pick?

Machine learning - more formally

- Function $f(\boldsymbol{x}; \boldsymbol{w})$ found by minimizing a loss function $L(\boldsymbol{x}; \boldsymbol{w})$
  - Simplest function: $f(\boldsymbol{x}; \boldsymbol{w}) = \boldsymbol{w}^\top \boldsymbol{x}$
  - Linear least-squares, $L(\boldsymbol{x}; \boldsymbol{w}) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \boldsymbol{w}^\top \boldsymbol{x}_i)^2$



Linear fit

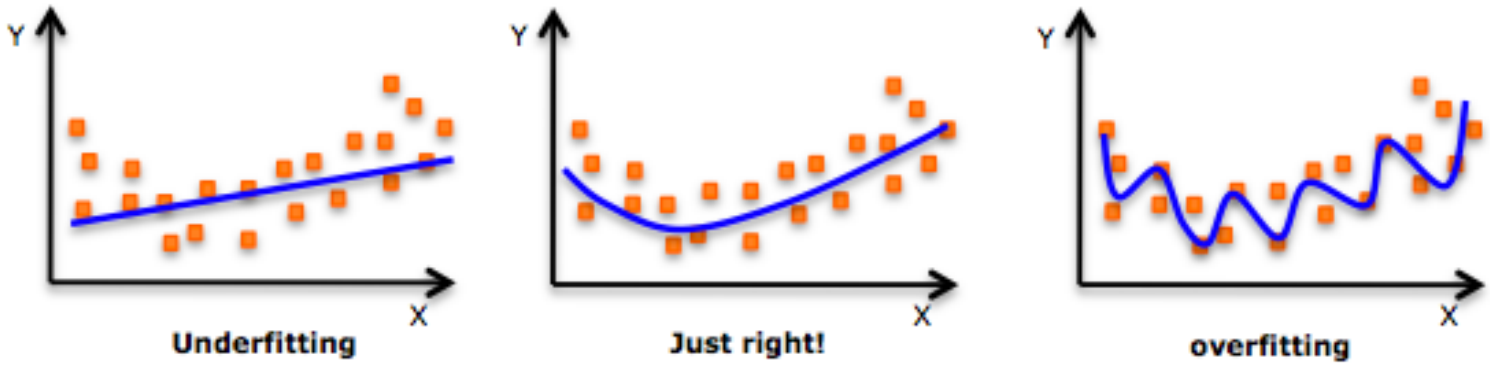


Quadratic fit

Machine learning - more formally

- Consider regularizing in order not to overfit, e.g. ℓ_2 norm

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} L(\boldsymbol{x}; \boldsymbol{w}) + \frac{1}{2}\|\boldsymbol{w}\|^2$$



"Old" pipeline

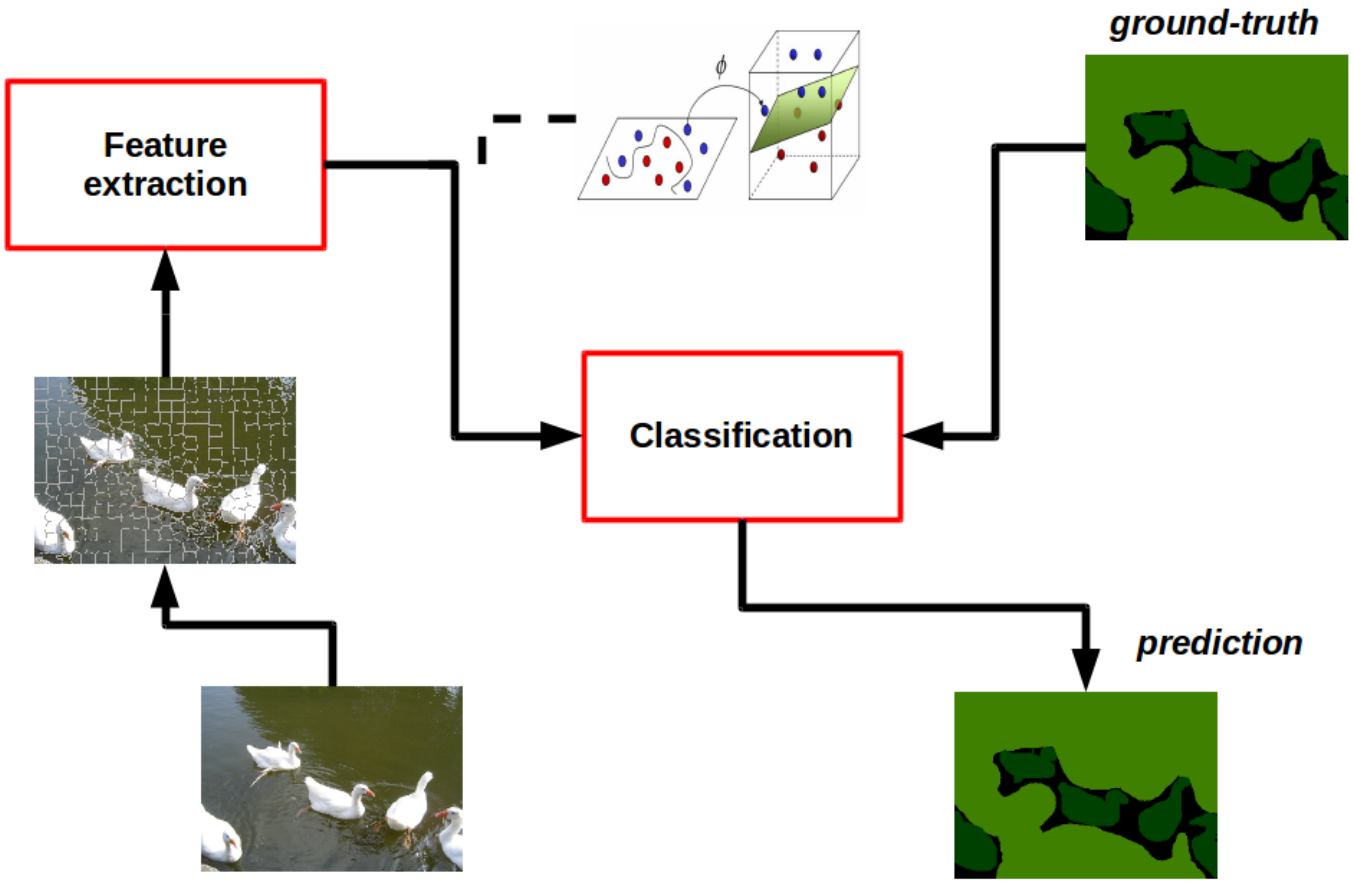


Image features

- **Color histogram**

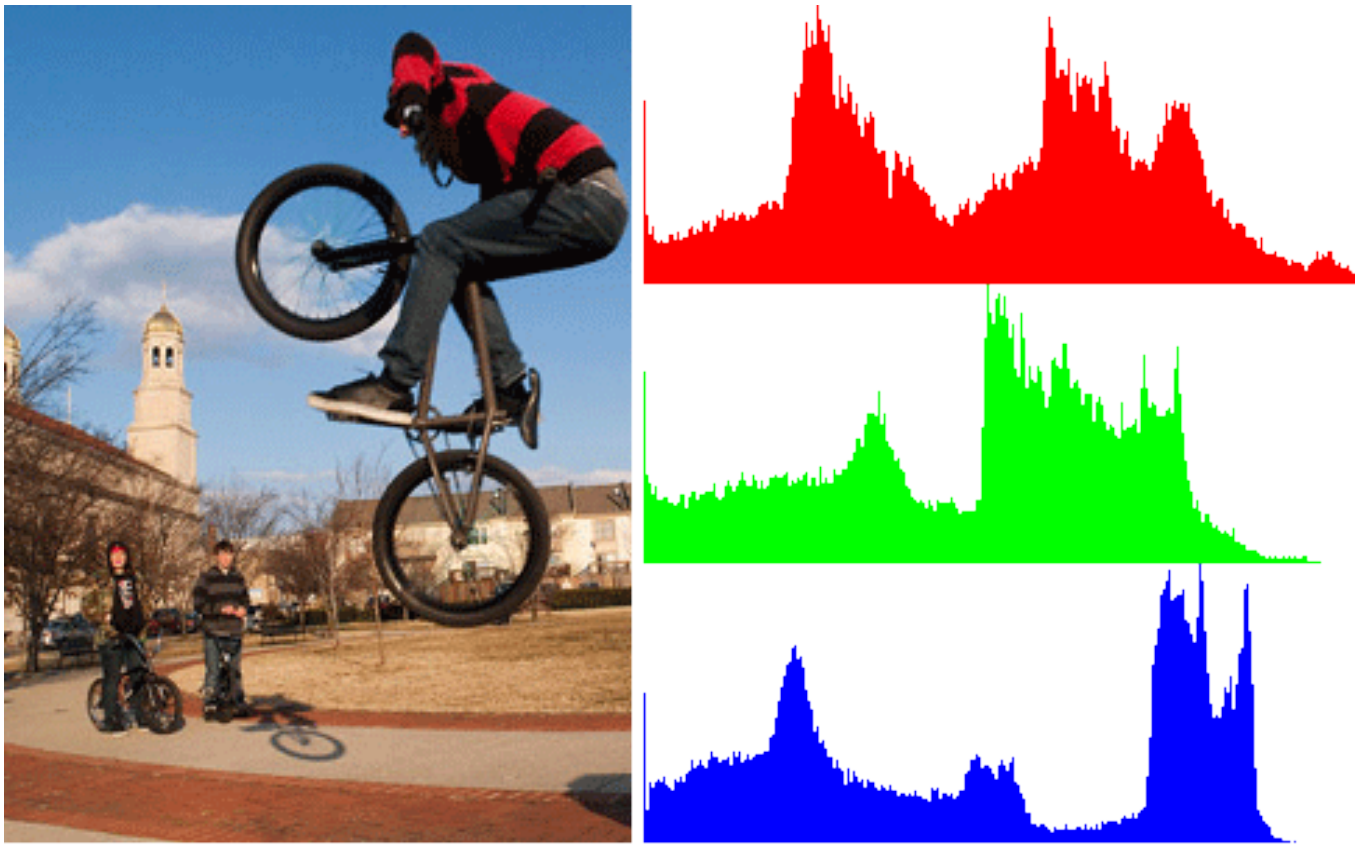
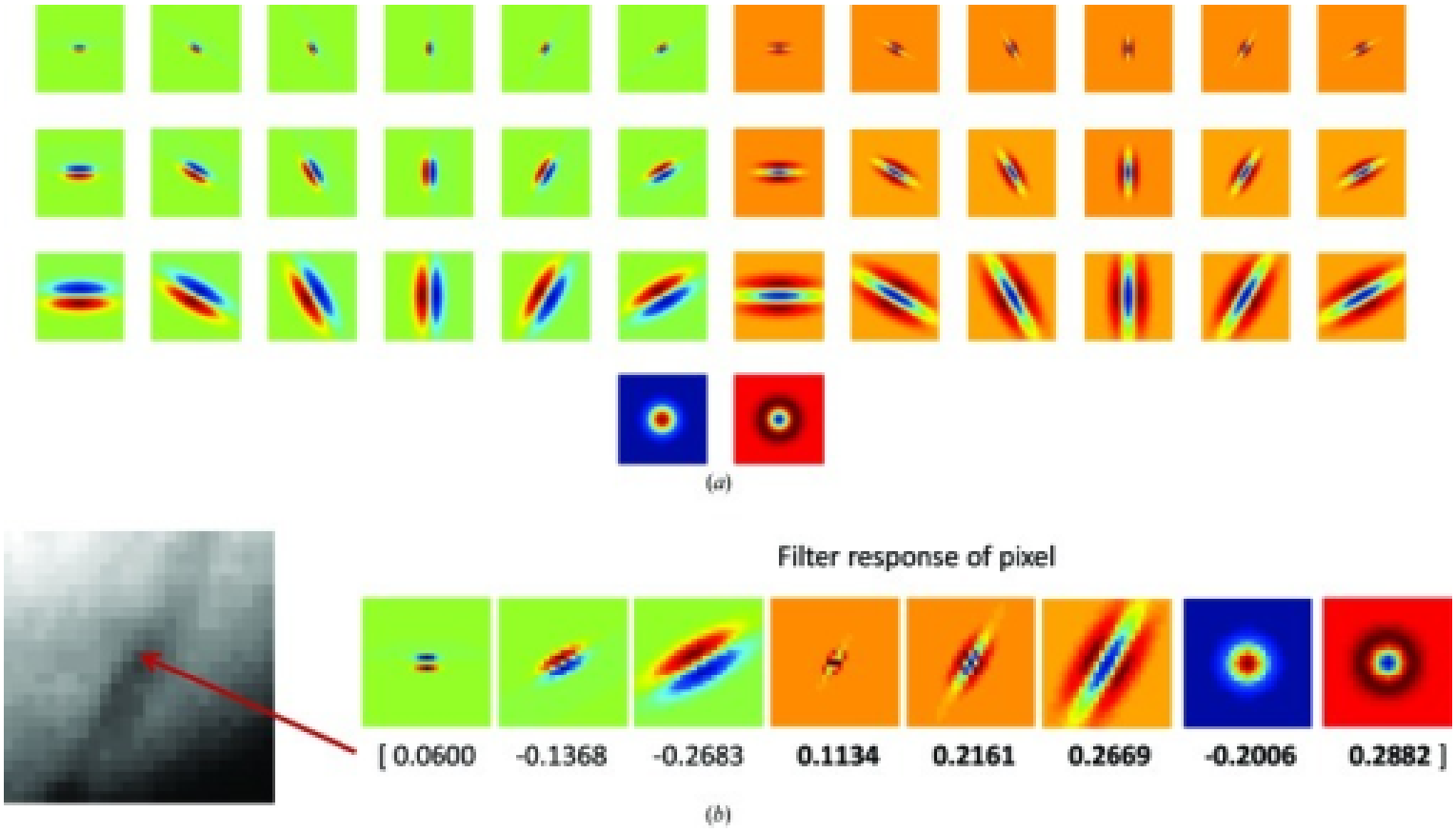


Image features

- **Edge filters**

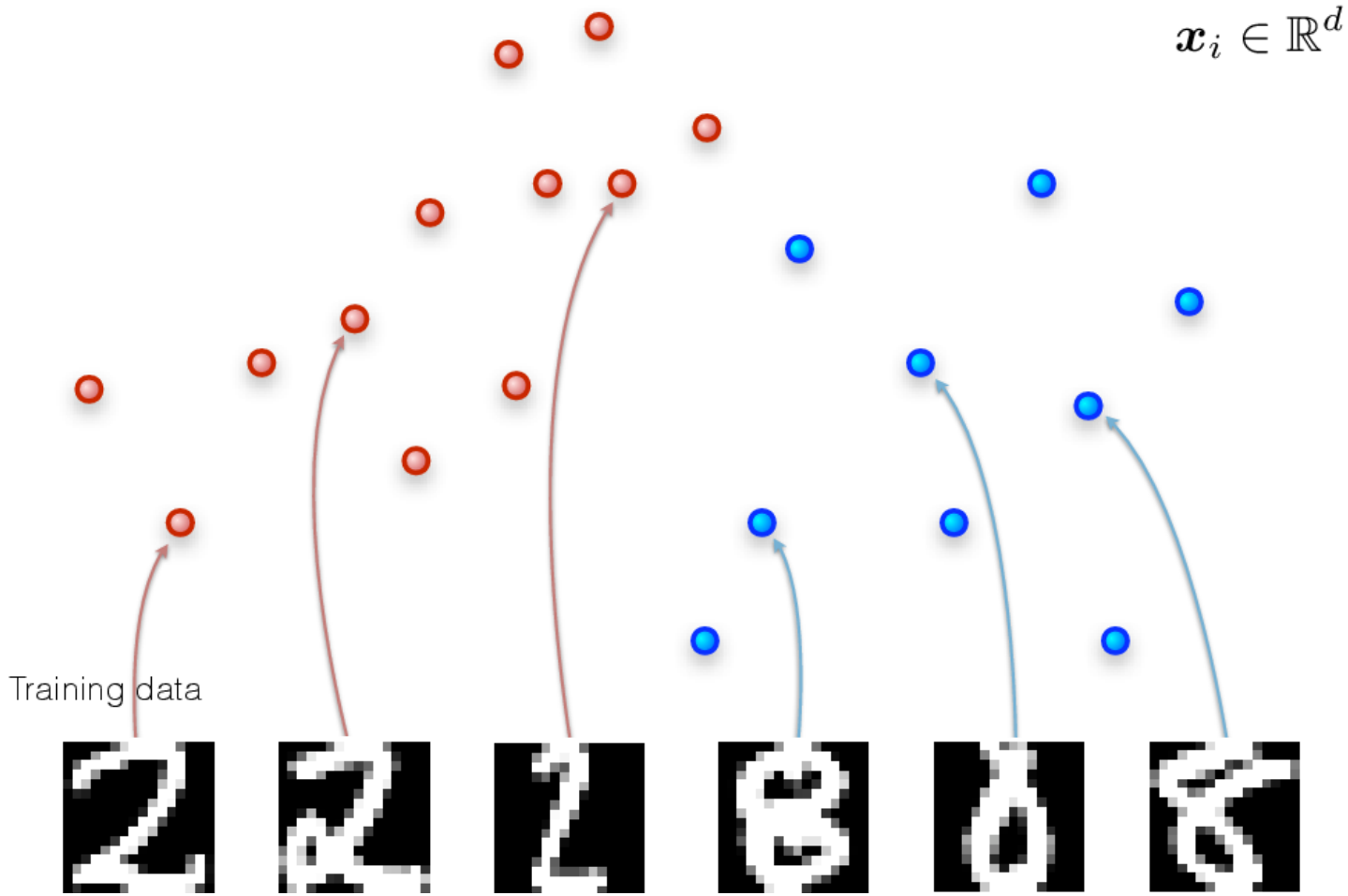


SVM (Support Vector Machine)

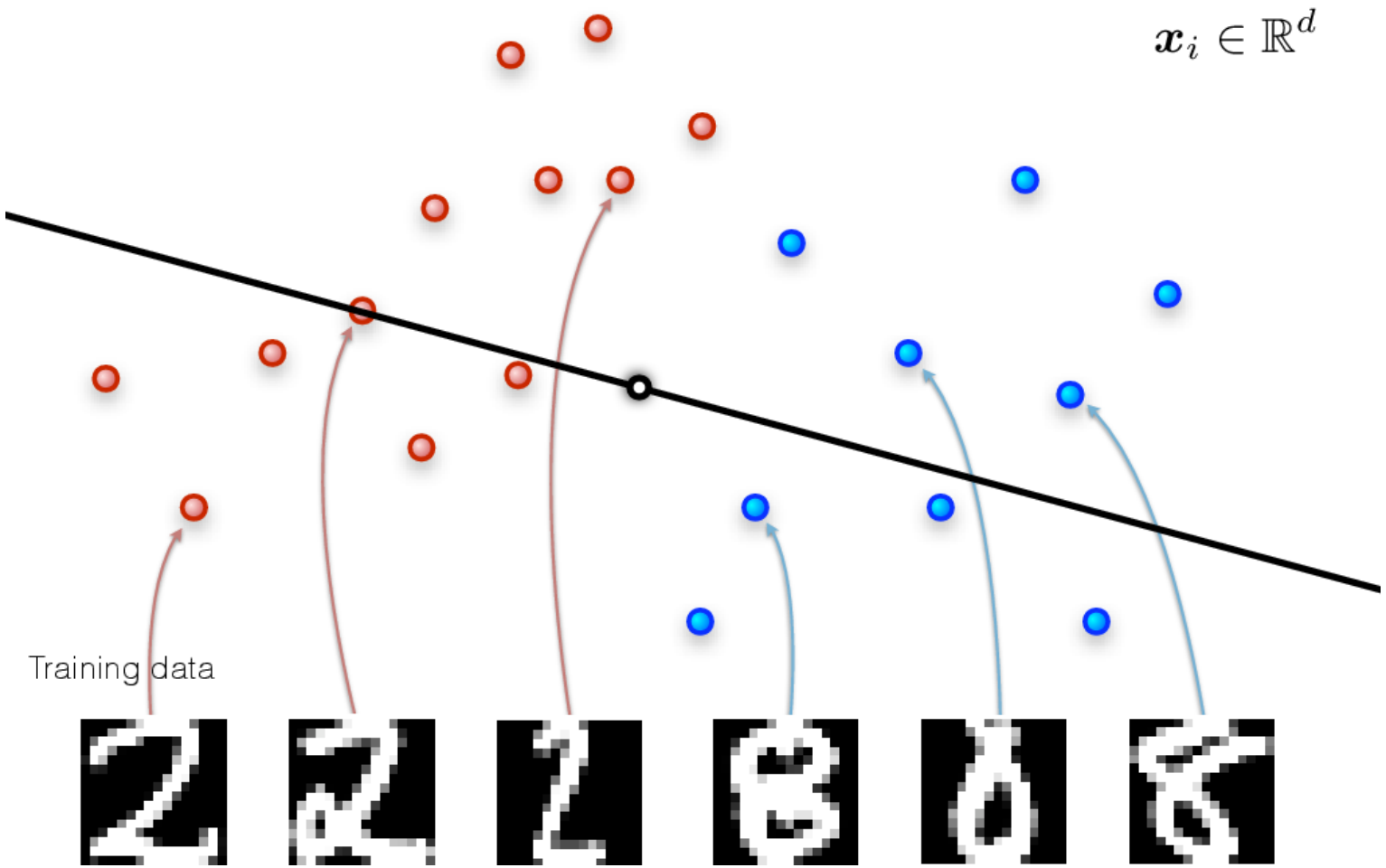
$$\boldsymbol{x}_i \in \mathbb{R}^d$$

Training data

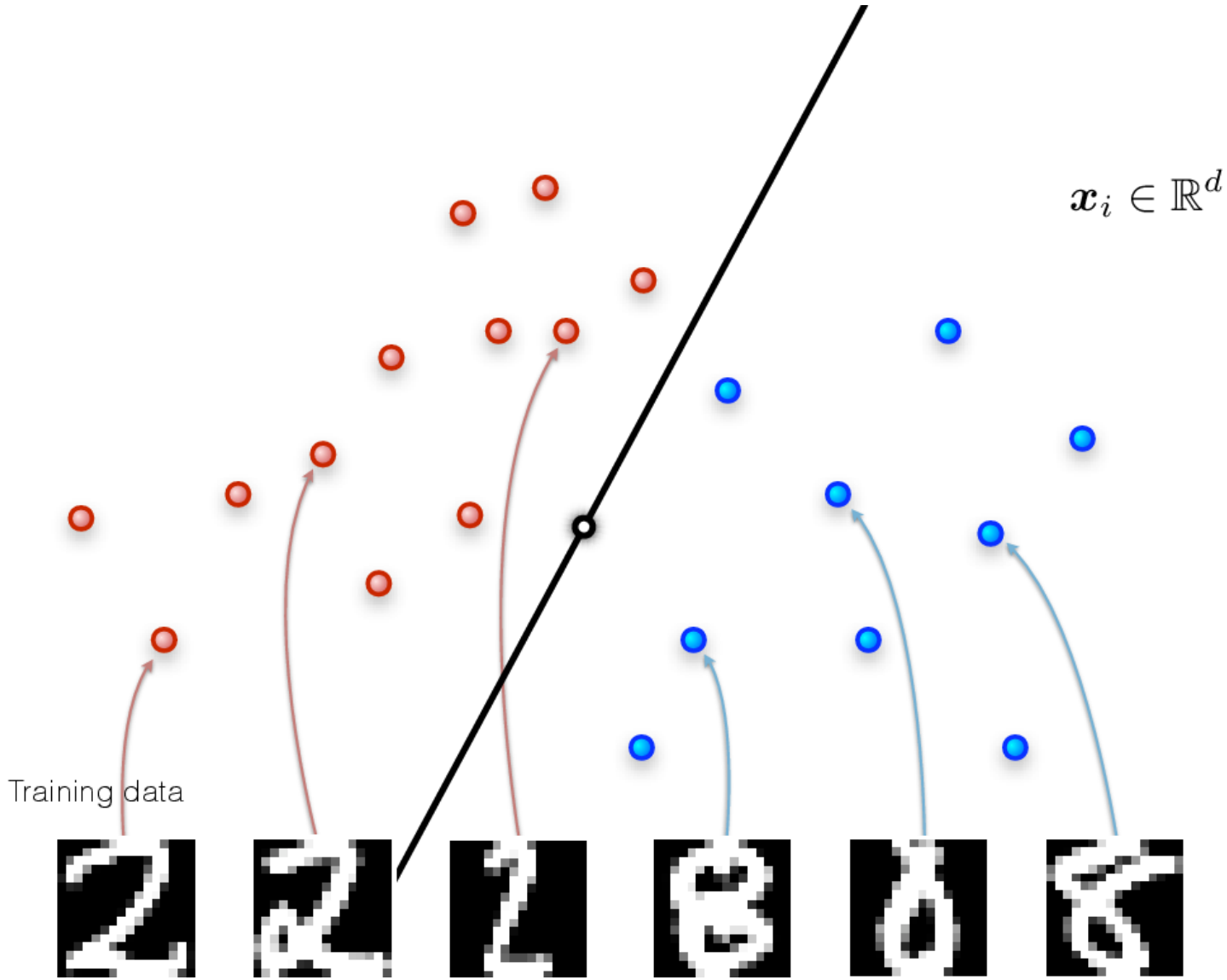
SVM



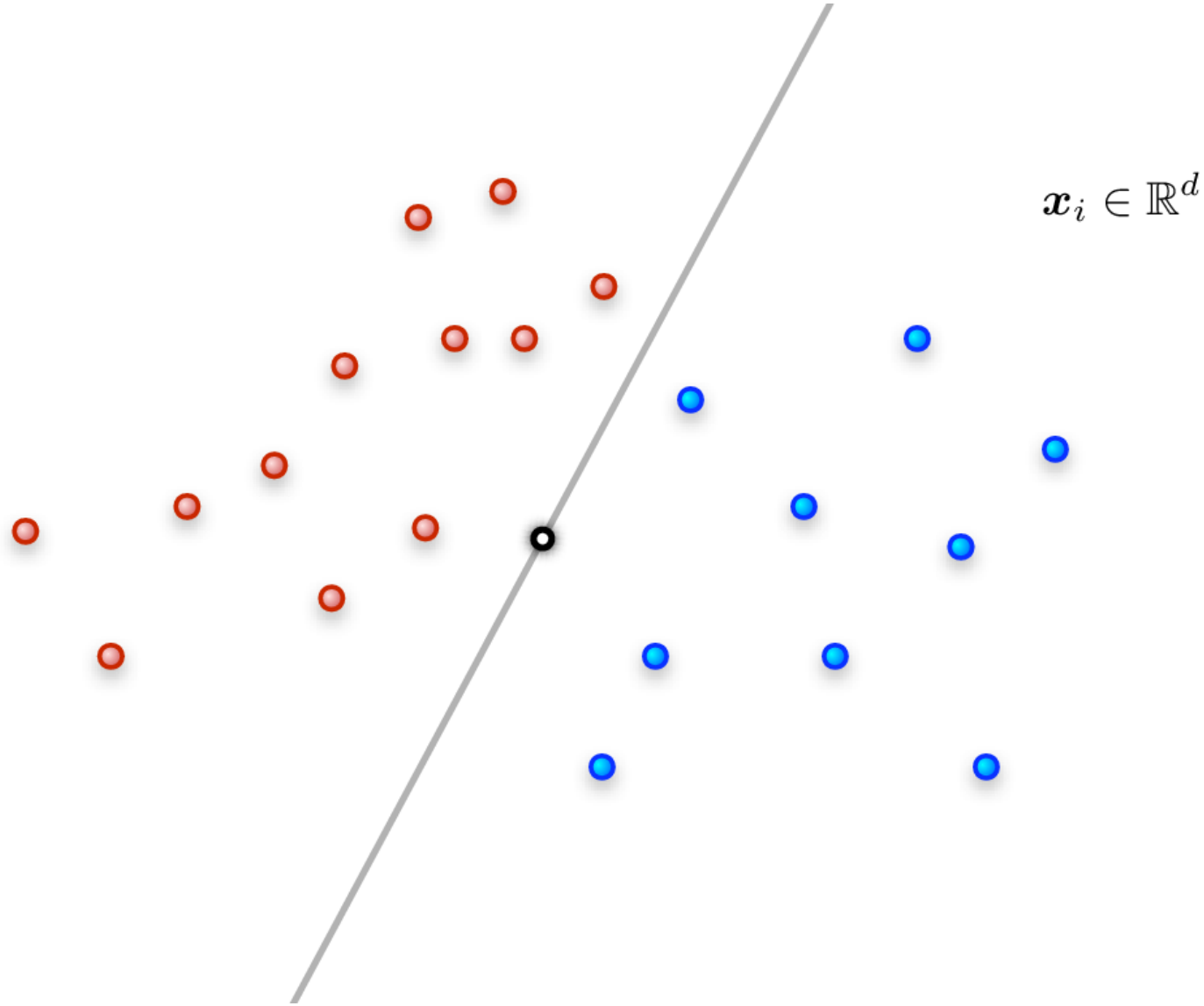
SVM



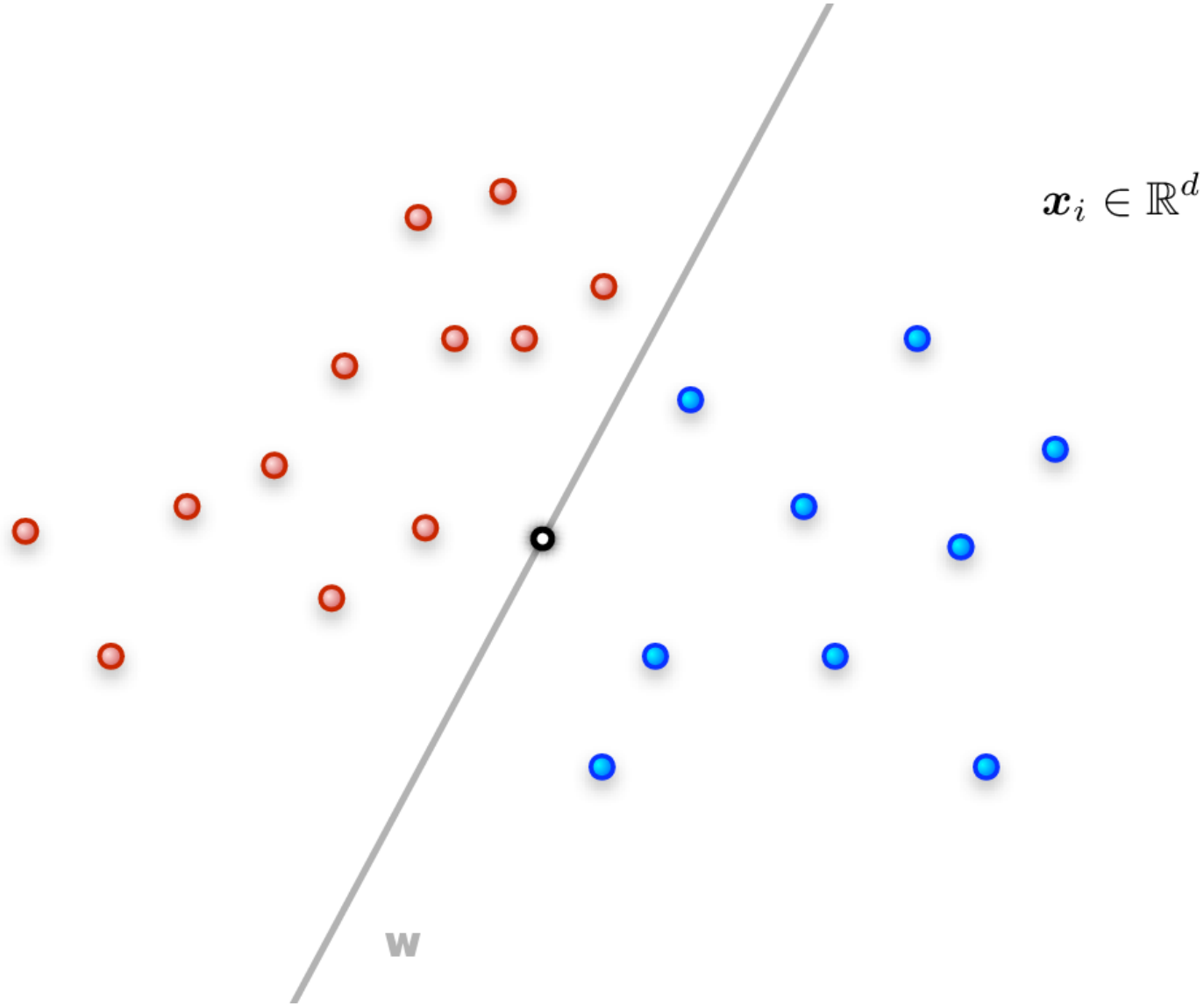
SVM



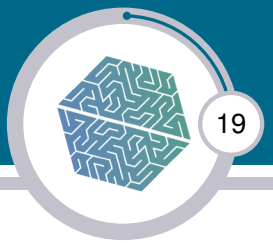
SVM



SVM



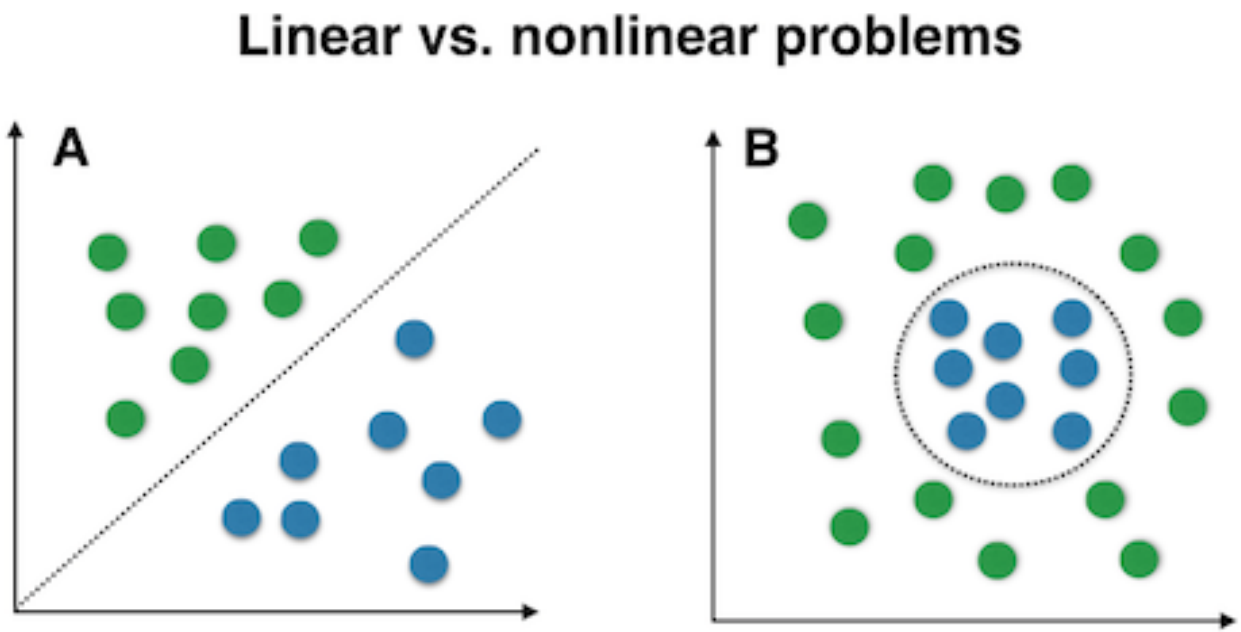
Questions?



- Why just using linear classifiers?
- Can we learn features from data instead of hand-designing them?

Machine learning

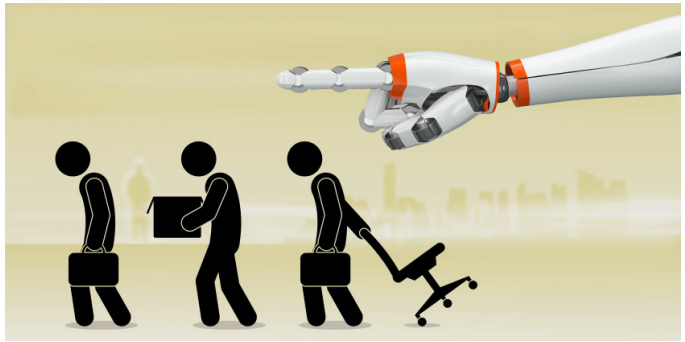
- **Linear classifiers**: Logistic regression, Support Vector Machine, ...
- **Non-linear classifiers**: Decision trees, (Deep) neural networks



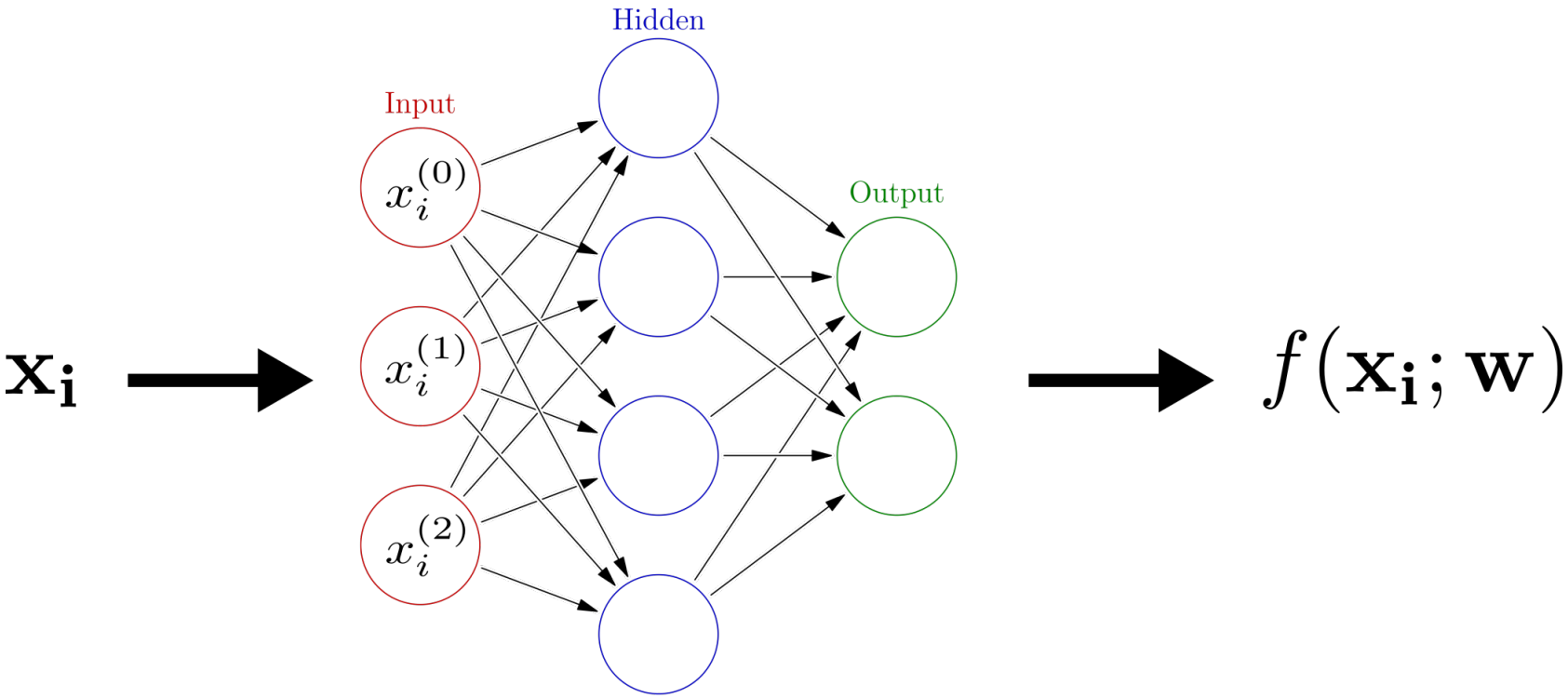
source: `http://sebastianraschka.com`

Neural networks

- Can we learn features from data instead of hand-designing them?
- Popular solution in the past few years = neural networks
  - Non-linear classifier
  - Neural Networks are modelled as collections of neurons that are connected in an acyclic graph



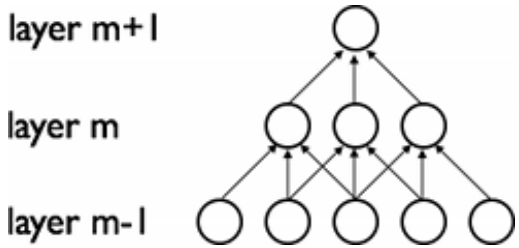
Neural networks



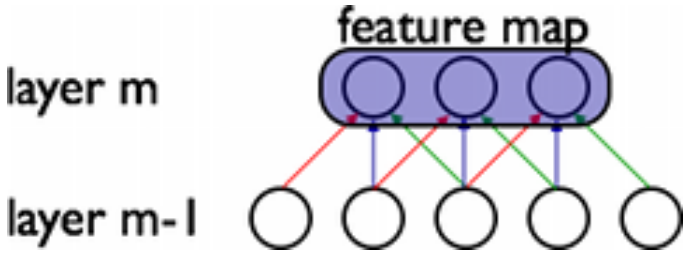
- The vector ***w*** is here represented by the edge weights
- Want to learn ***w*** by minimizing a certain loss function (more on this later)

Neural Networks

- **Sparse connectivity**: exploit spatially-local correlation by enforcing a local connectivity pattern between neurons of adjacent layers
- **Weight sharing**



Sparse connectivity

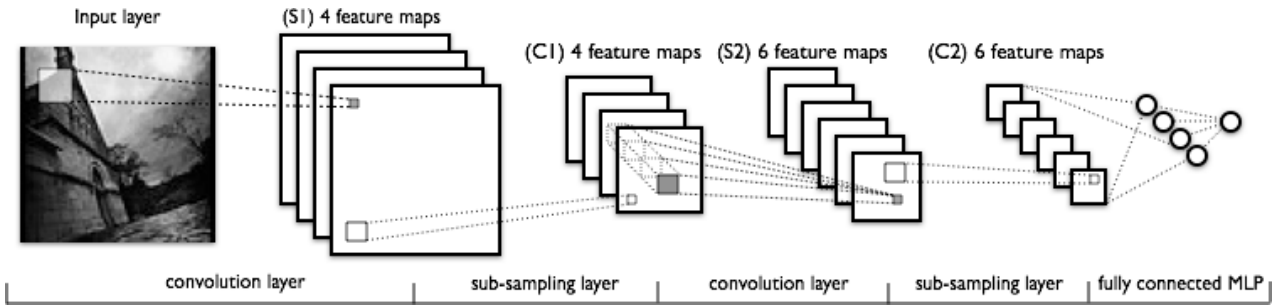


Weight sharing

source: `http://deeplearning.net/tutorial/lenet.html`

Neural Networks for Images

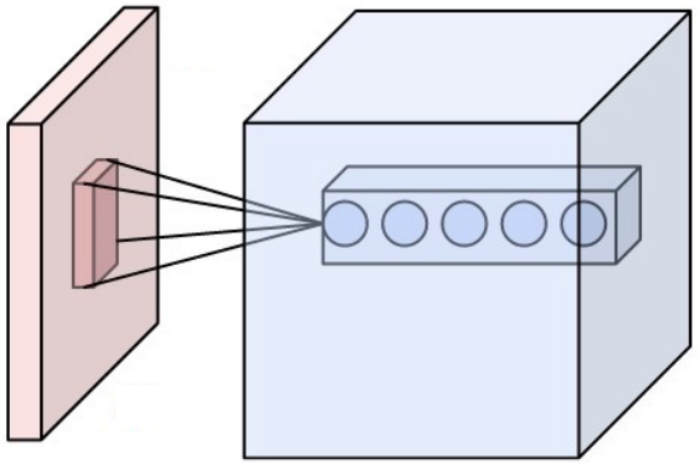
- Convolutional Neural Network = Feed-forward neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex.
- Three building blocks (more on this later)



Neural Networks for Images: Receptive Fields

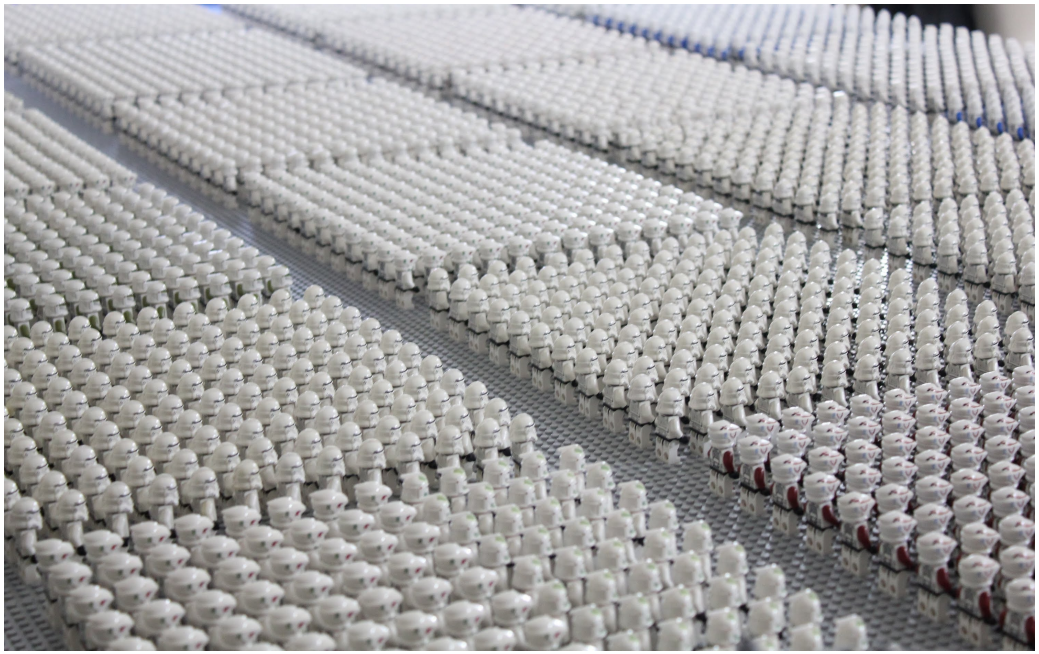
- Topological connectivity
  - encourage network to first extract localized features
  - subsequent layers: less and less localized features

- Receptive field
  - inputs that can affect a neuron (other weights = 0)
  - small images patches as receptive fields
  - can have multiple channels (in figure: 5)

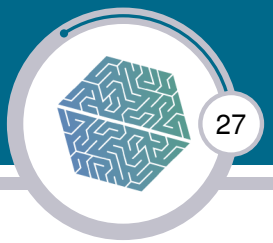


Neural Networks for Images: Translation Invariance

- Translation invariance of images
  - image patches look the same, irrespective of their location
  - idea: extract translation invariant features
  - what does that mean for a neural network?

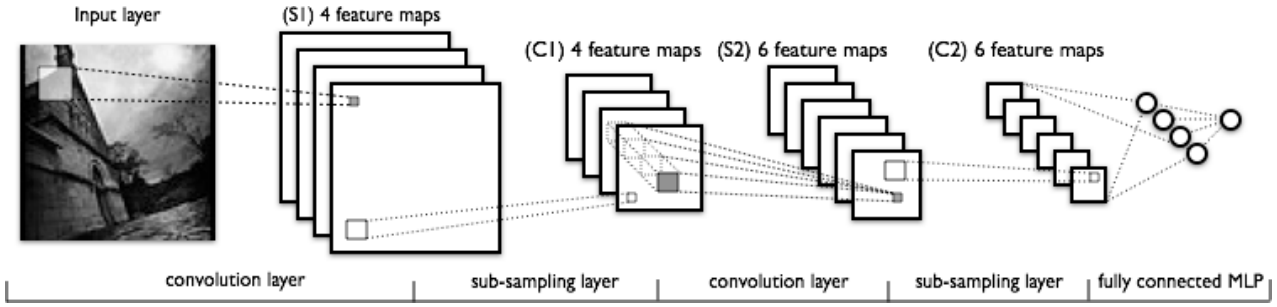


Neural Networks for Images: Weight Sharing



- Weight Sharing
  - neurons share the same weights = compute same function
  - differ in location of their receptive field = different input
  - mirrors what has been done in image processing (manually)
- Shift-invariant Filters
  - layers learn shift-invariant filters
  - weights define a filter mask (e.g. 3x3 or 5x5)
  - typically as many neurons as inputs (border padding etc.)
    - e.g. 64x64 pixel per image $\Rightarrow$ 64x64 neurons per channel
  - color images: 3 color channels, 3-dimensional filter mask
  - nice demo at `cs231n.github.io/assets/conv-demo/index.html`

CNN: Buildings blocks



- **Three building blocks:**
  - Convolutional layer
  - Pooling layer
  - Fully-connected layer

Convolutional Layers

- **Convolution:**
  - Mathematical operation on two functions (f and g)
  - It produces a third function that is typically viewed as a modified version of one of the original function
  - This operation can be used to detect edges in an image

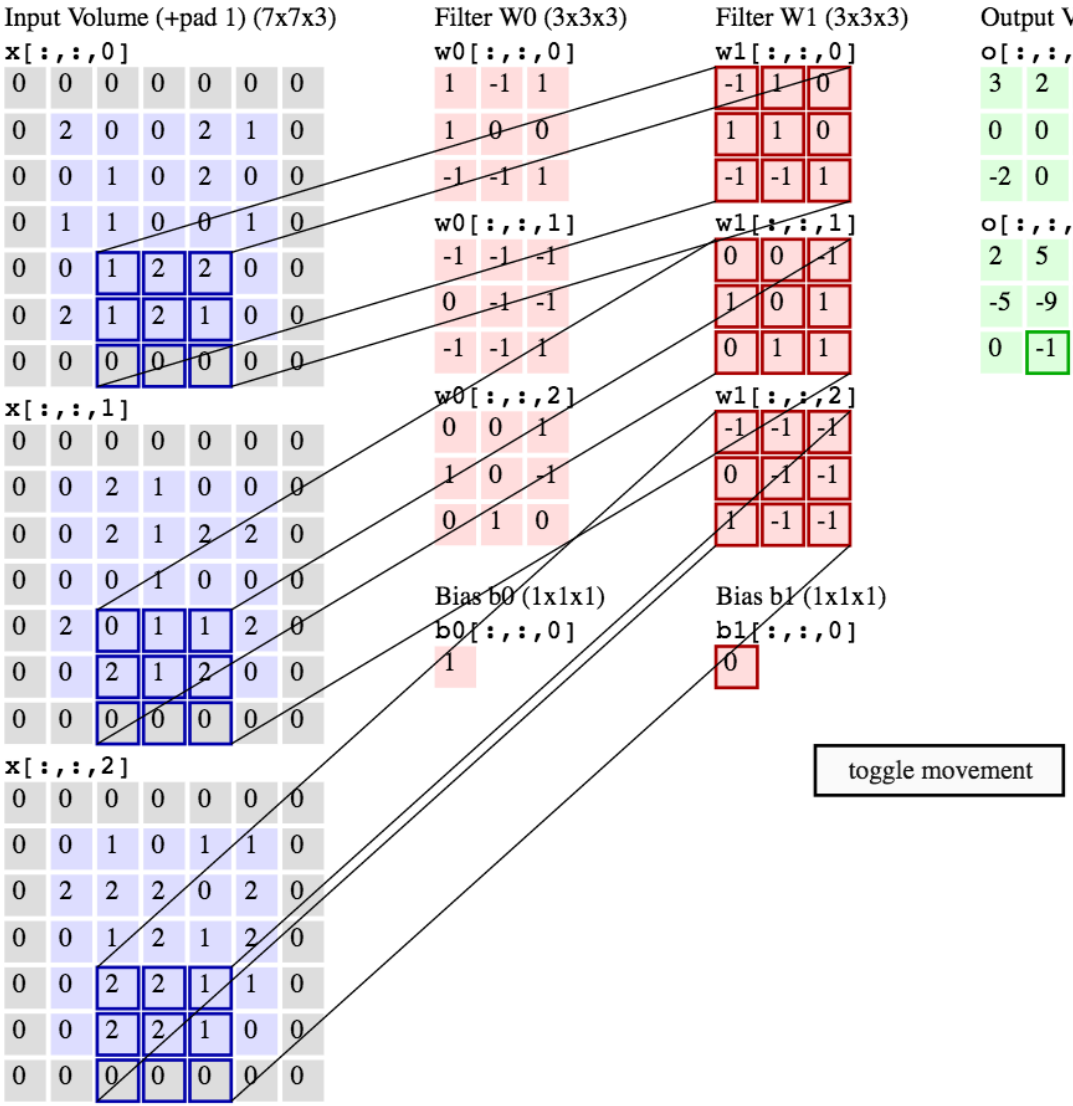
-1	0	1
-2	0	2
-1	0	1

Horizontal

-1	-2	-1
0	0	0
-1	-2	-1

Vertical

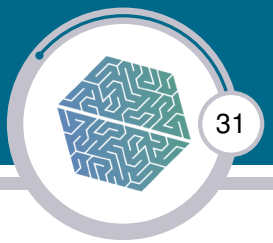
Convolutional Layers: Animation



source:

cs231n.github.io/assets/conv-demo/index.html

Convolutional Layers: Mathematics



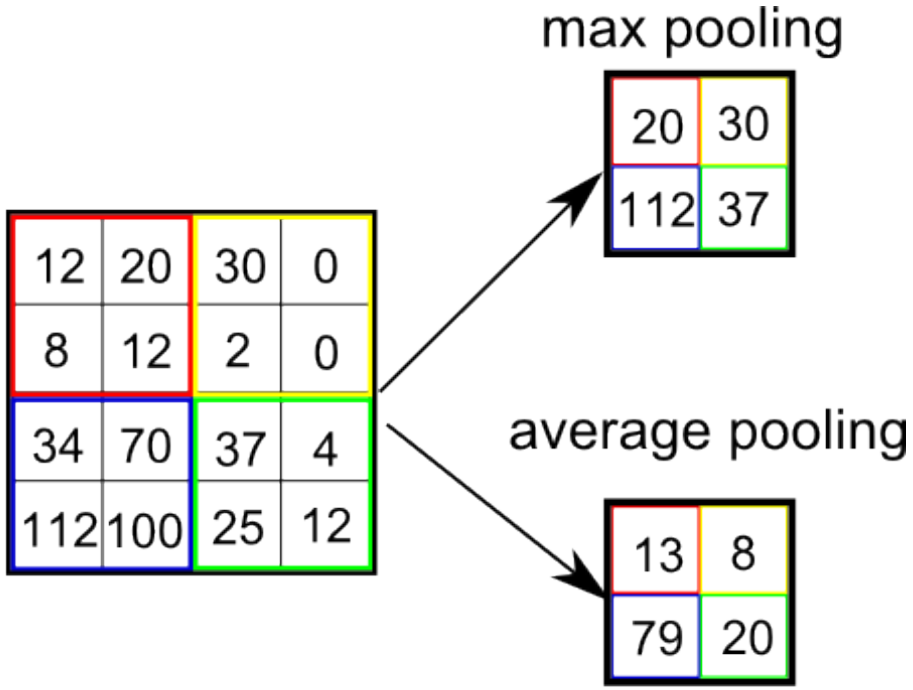
- Convolution in 2D (5x5)

$$F_{n,m}(\boldsymbol{x}; \boldsymbol{w}) = \sigma\left(b + \sum_{k=-2}^{2}\sum_{l=-2}^{2} w_{k,l} \cdot x_{n+k,m+l}\right)$$

  - (n, m): center of receptive field
  - $\boldsymbol{x}$: image (2D pixel field)
  - $\boldsymbol{w}$: weights = arranged as a 2D mask
  - related to convolution in mathematics

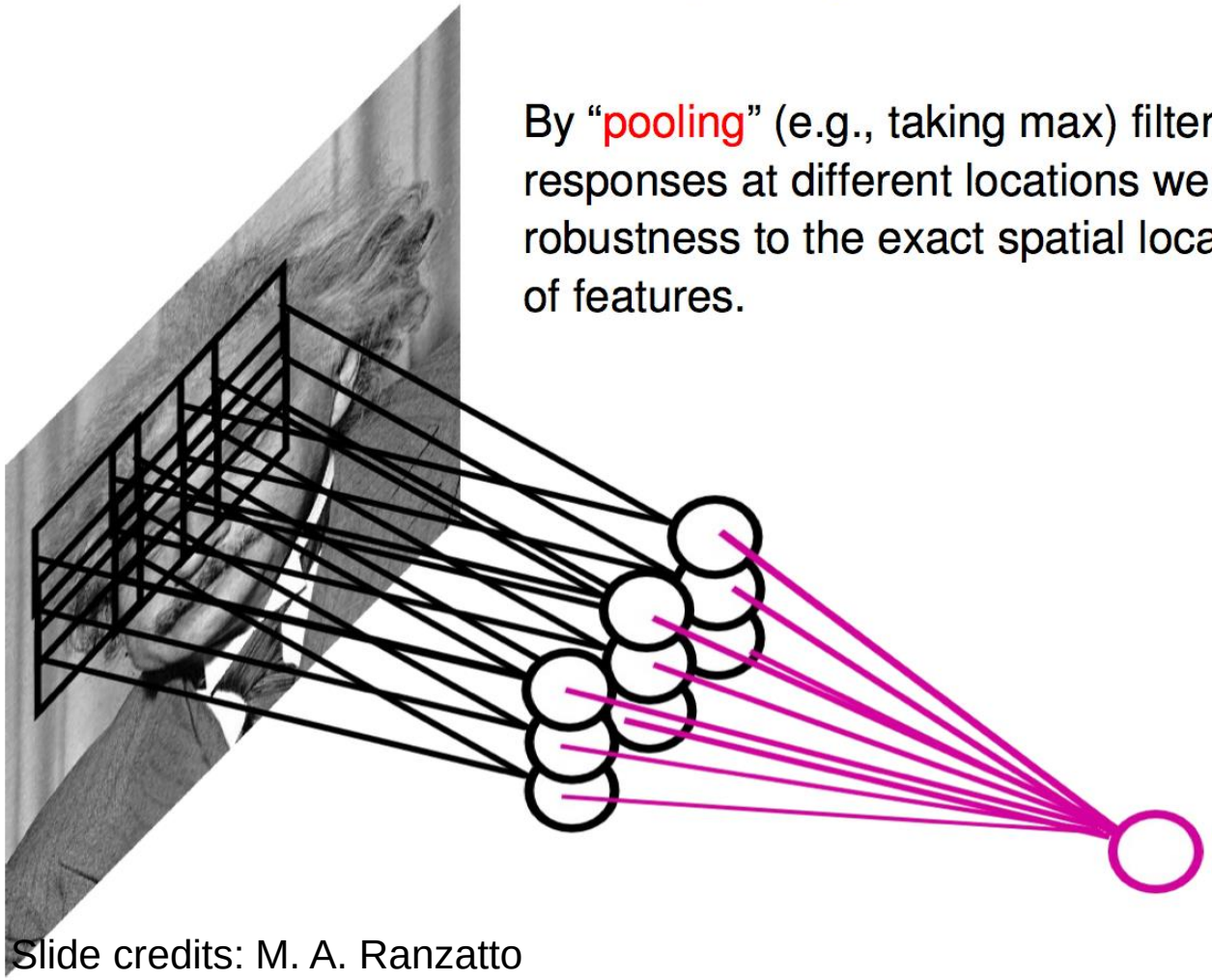
Pooling

- Reduce size of convolutional layers by down-sampling
- Take average over window (e.g. 2x2)
- Common practice: max pooling = take maximum in window



Pooling

Pooling Layer



By "pooling" (e.g., taking max) filter responses at different locations we gain robustness to the exact spatial location of features.

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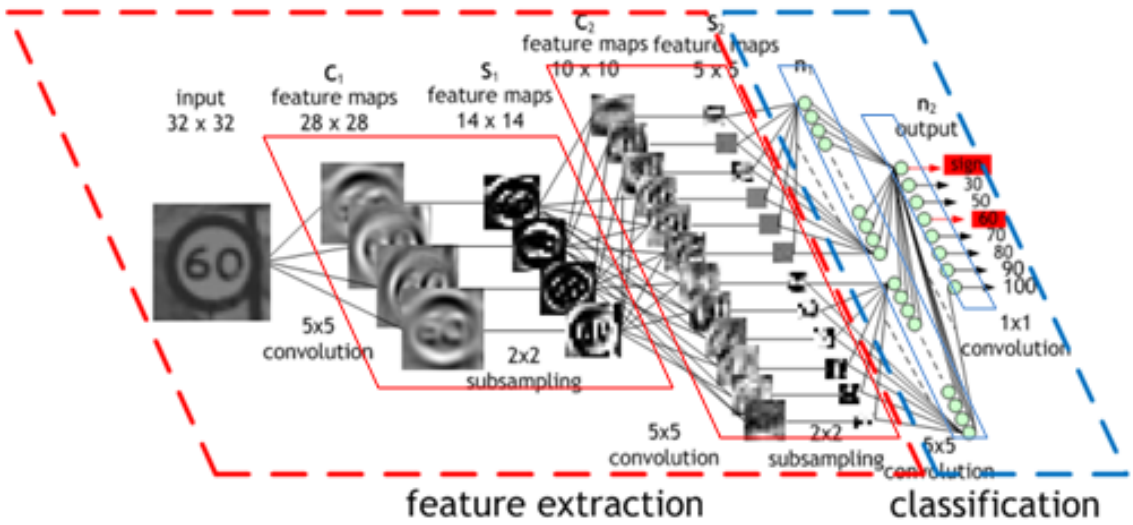
Ranzato

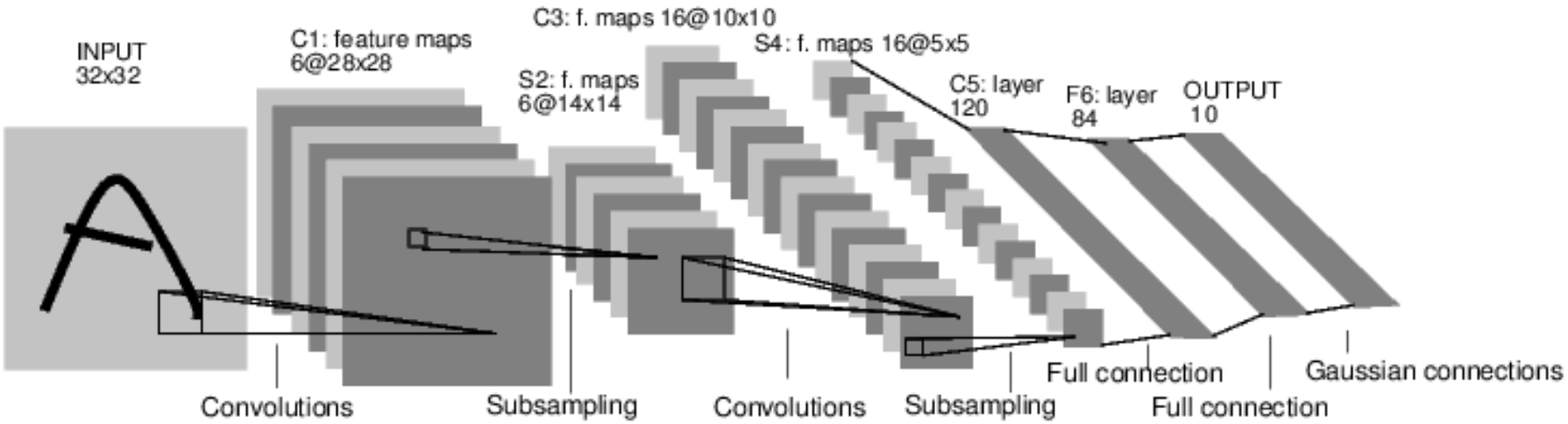
Slide credits: M. A. Ranzatto

Fully-connected layer

- High-level reasoning
- Connects all neurons in the previous layer to every single neuron it has

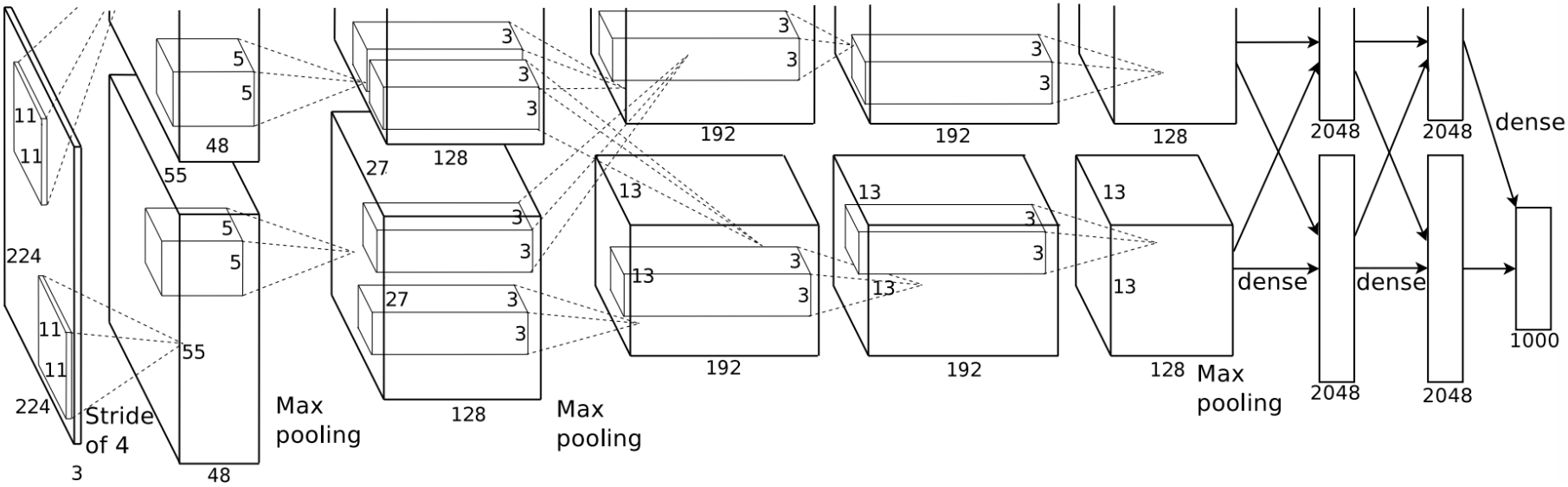


LeNet5



- Architecture LeNet5
  - layers C1/S2: 6 channels, cutting at border, 2x subsampling (4704 neurons)
  - layers C3/S4: 16 channels, cutting at border, 2x subsampling (1600 neurons)
  - layers F5/F6: fully-connected
  - output: Gaussian noise model (squared loss)

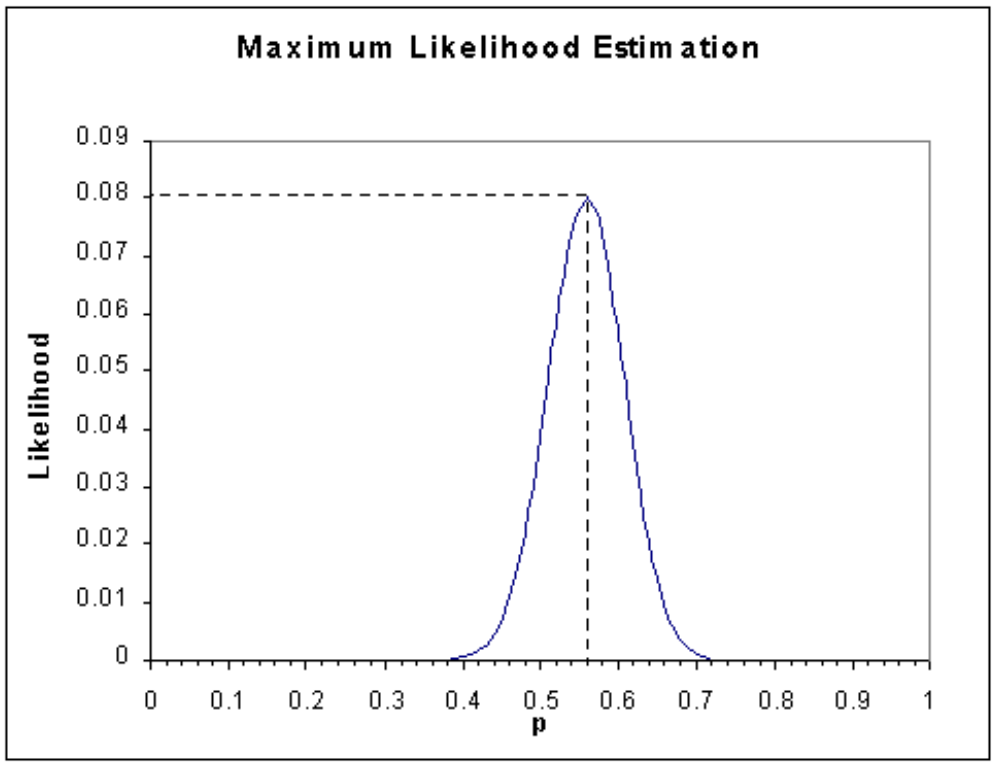
AlexNet



- AlexNet
  - Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, 2012 ImageNet Classification with Deep Convolutional NN
  - 60 million parameters and 500,000 neurons
  - 5 convolutional layers, some followed by max-pooling
  - 2 globally connected layers with a final 1000-way softmax

Optimization

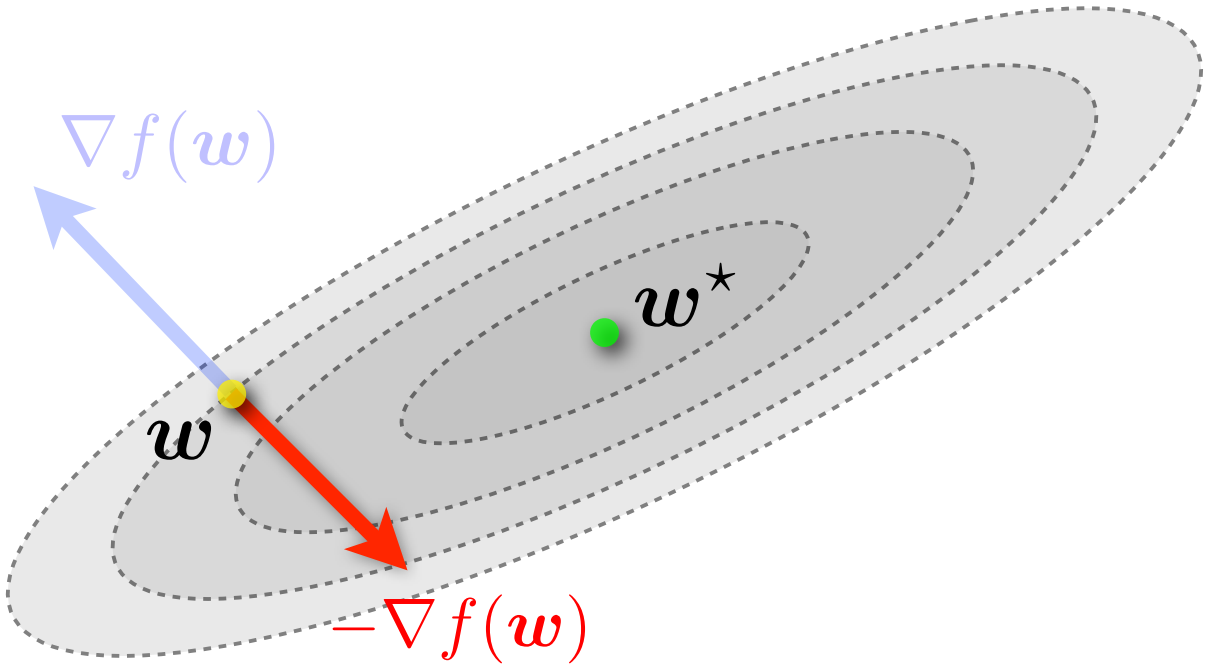
- The typical loss function $L(\boldsymbol{x}; \boldsymbol{w})$ used to train CNNs is **maximum likelihood**
  - Find the parameters $\boldsymbol{w}$ that are most likely to have generated the data $\boldsymbol{x}$



Optimization

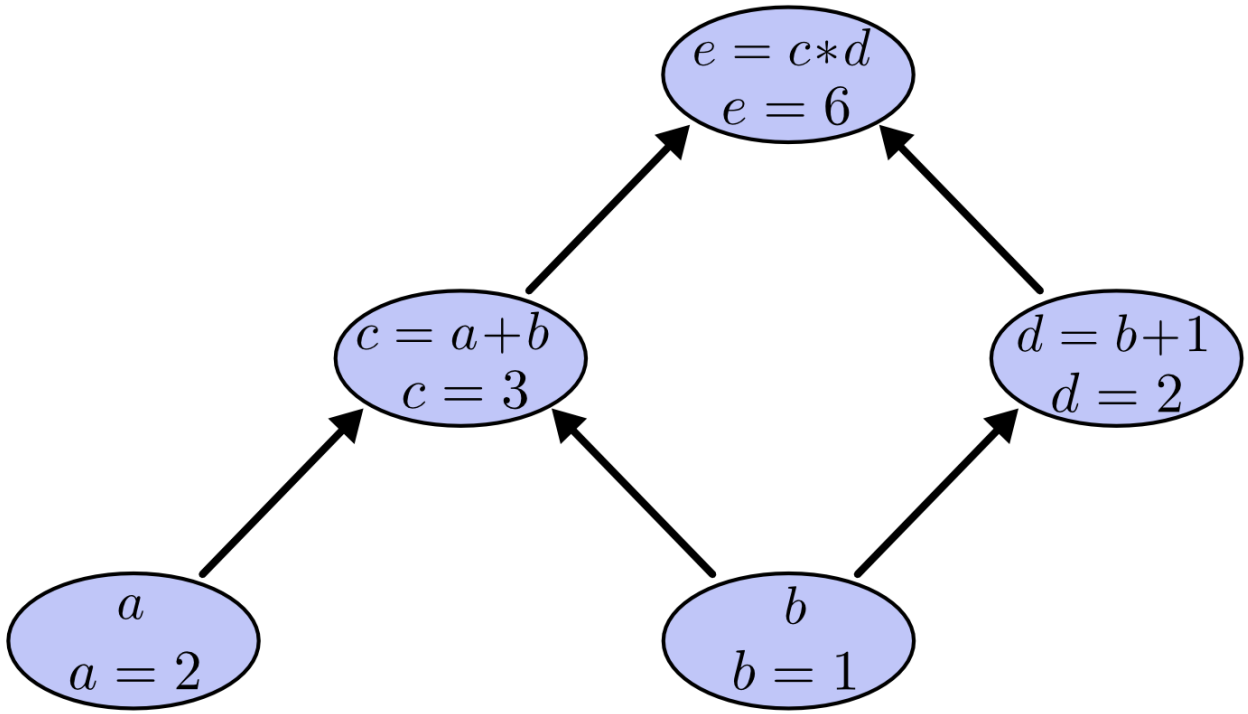
- Minimize $L(\boldsymbol{x}; \boldsymbol{w})$ using stochastic gradient descent, i.e.

$$\boldsymbol{w} \leftarrow \boldsymbol{w} - \eta \nabla_{\boldsymbol{w}} L(\boldsymbol{x}_i; \boldsymbol{w})$$



Computational graph

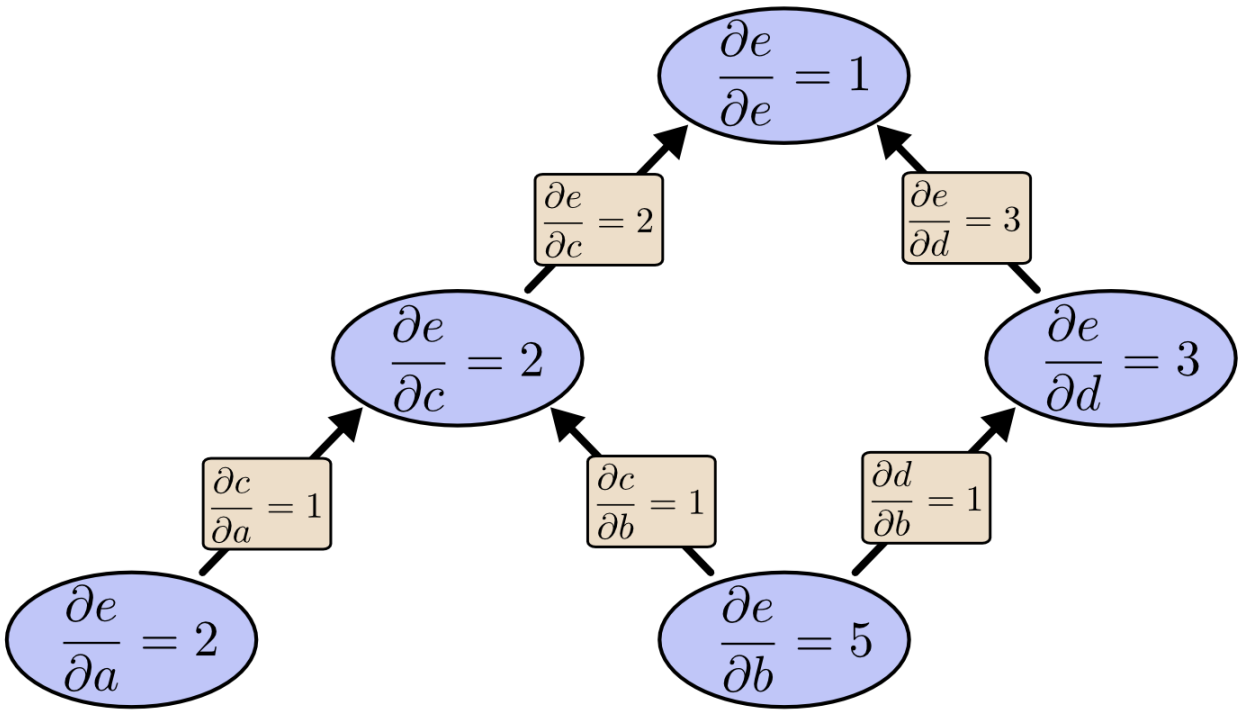
- Consider the function $f(a, b) = \underbrace{(a + b)}_{=c} \times \underbrace{(b + 1)}_{=d}$



source: `http://colah.github.io/posts/2015-08-Backprop/`

Computational graph

- Compute $\frac{\partial e}{\partial a}$?
- Chain rule: $\frac{\partial e}{\partial a} = \frac{\partial e}{\partial c} \cdot \frac{\partial c}{\partial a} = (b+1) \cdot 1$



Optimization

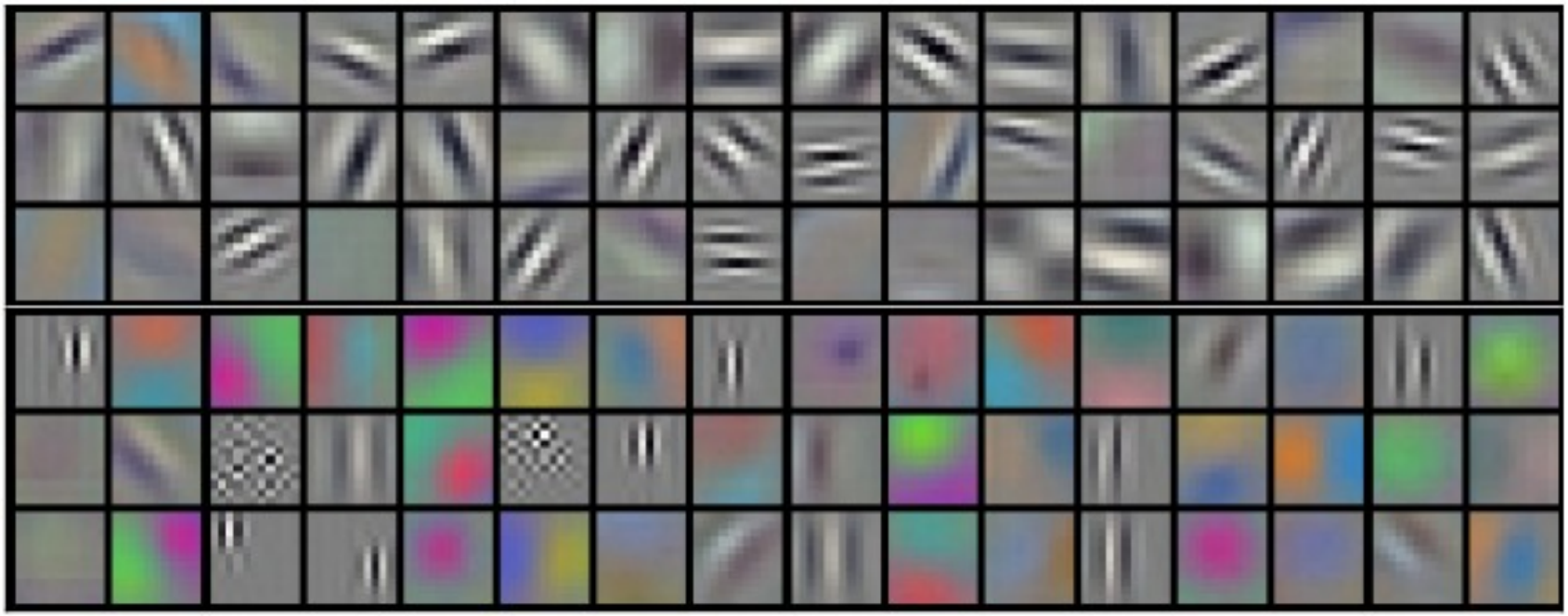
Algorithm 1 SGD to train deep neural networks

1: Given an initial $\boldsymbol{w}_0$
2: **for** $t = 1$ to T **do**
3: Compute $\nabla_{\boldsymbol{w}_t} L(\boldsymbol{x}_i; \boldsymbol{w}_t)$ using back-propagation
4: $\boldsymbol{w}_{t+1} \leftarrow \boldsymbol{w}_t - \eta \nabla_{\boldsymbol{w}_t} L(\boldsymbol{x}_i; \boldsymbol{w}_t)$
5: **end for**

- Practical considerations:
  - Pick initial parameters $\boldsymbol{w}_0$ (see Xavier's initialization)
  - Need to tune the step-size η
  - Fix a maximum number of iterations T (or use another stopping criterion)

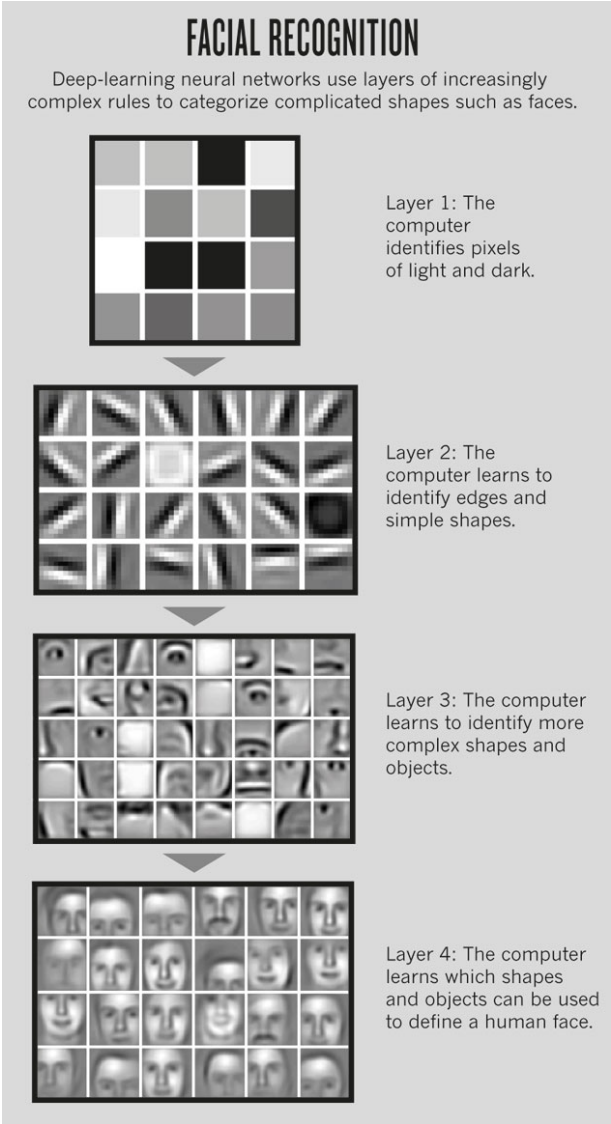
Learning Local Image Features

- Example: filters learned at first layer
- cf. Krizhevsky et al.: 96 filters of size 11x11x3

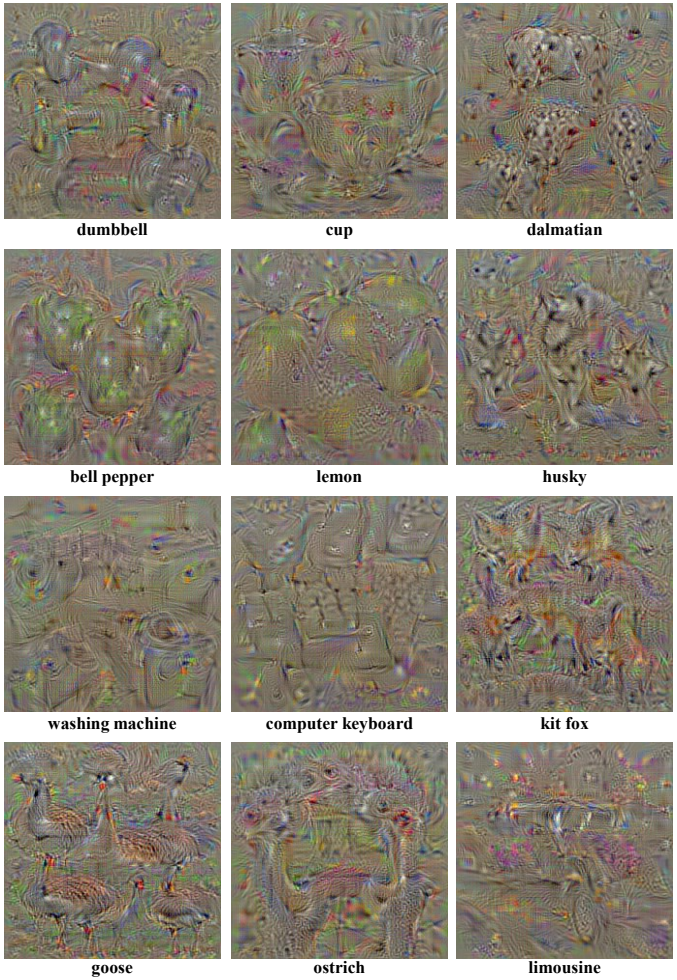


Learning Higher Level Features

- (c) Andrew Ng, trained on face images



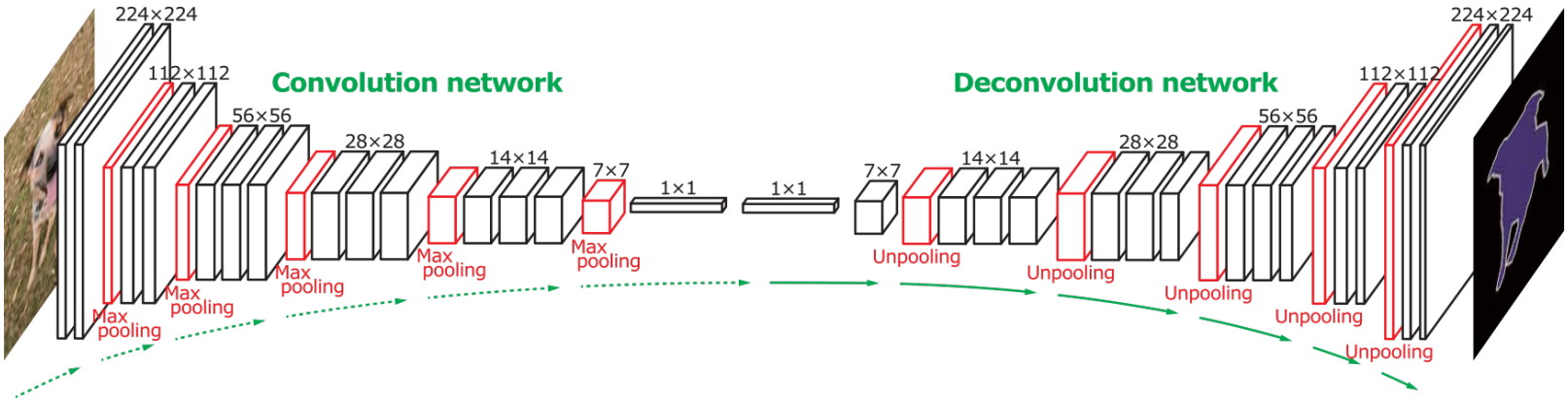
Inside CNNs



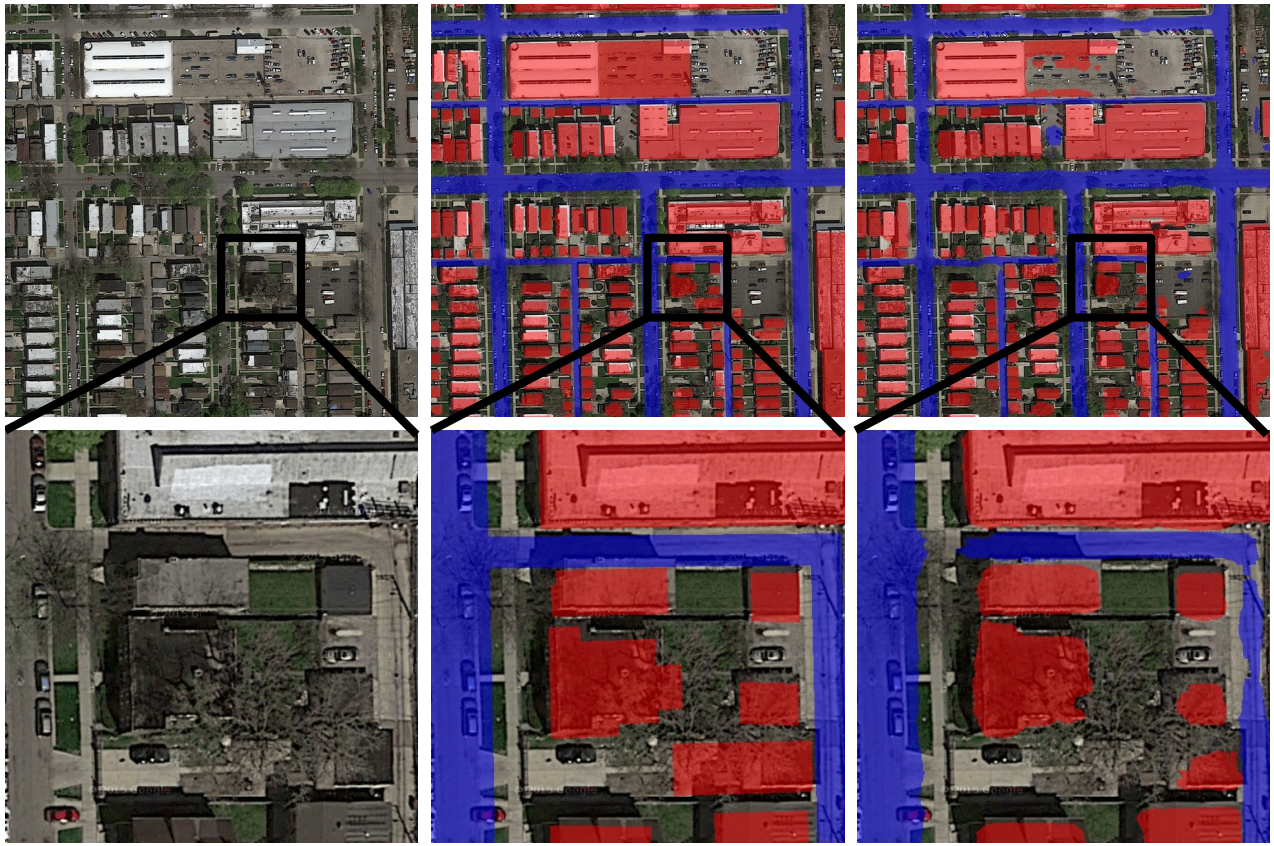
- Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps, Simonyan et al, 2015

Example - Road segmentation

- Recall that pooling layers shrink the dimension
- For segmentation, we want the final output to be the same size as the input

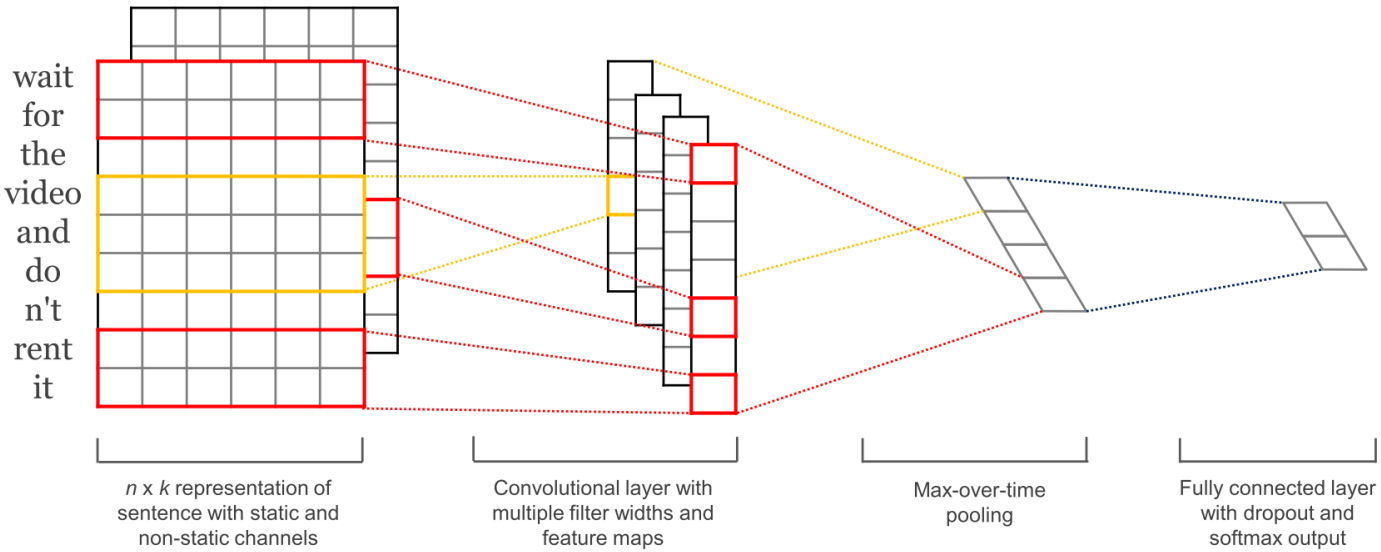


Example - Road segmentation

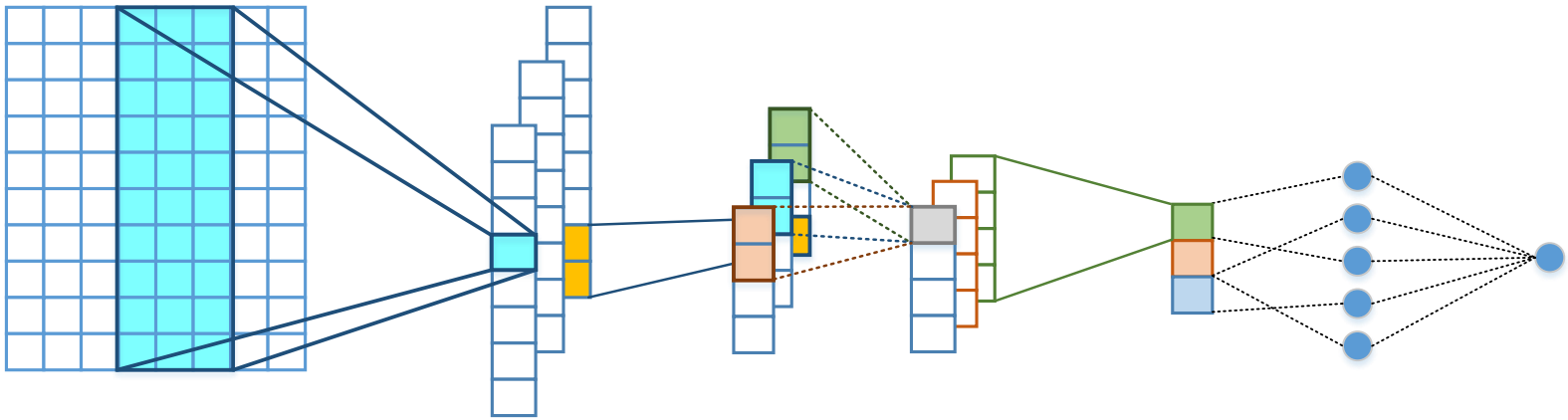


(a) aerial image (b) ground truth labels (c) FCN-8s prediction

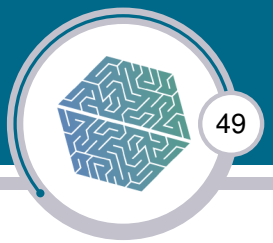
Example - Sentiment classification



Example - Sentiment classification



Available libraries



Language	Library
Python	Theano
Python	Tensorflow
Matlab	MatConvNet

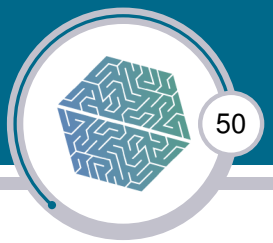
- For more, see `http://deeplearning.net/software_links/`

Thank you!

image credit: Mania Orand

Latex template credit: Lilyana Vankova

Credits



- Some slides, figures, ... were taken from Thomas Hofmann, Martin Jaggi, Yann Lecun, Andrej Karpathy, Hadi Daneshmand
- Additional figures taken from Wikipedia