Image Processing and Computer Graphics

Image Processing

Class 10

Object recognition and deep learning

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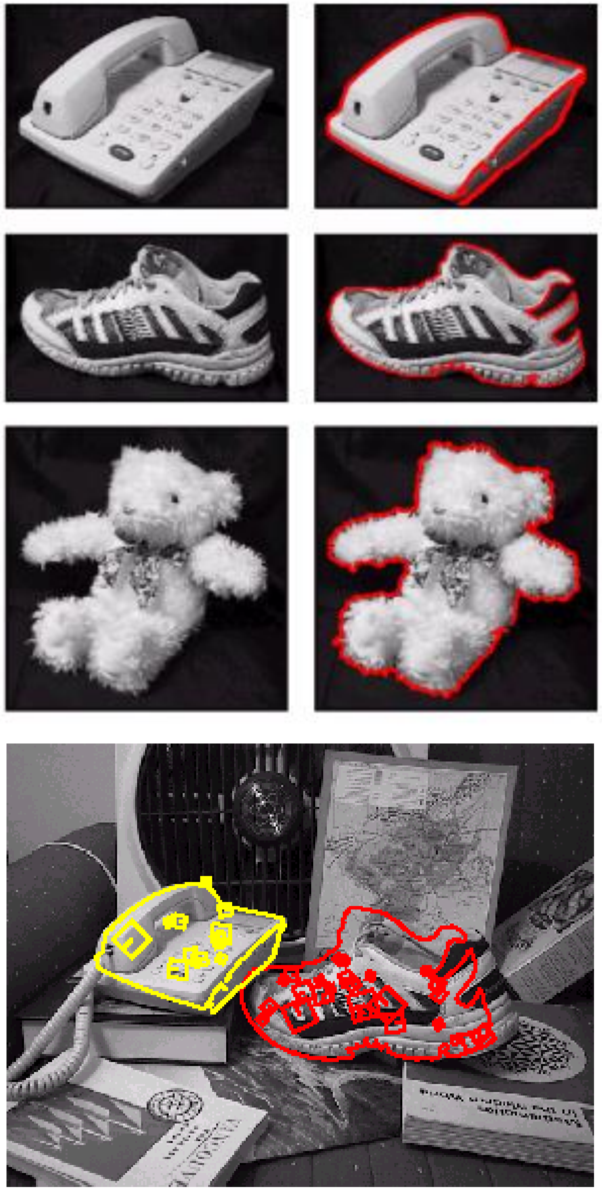
What is object recognition?

- **Instance recognition** seeks to detect the presence of a known object in a new image.
- Often the object should also be localized in the image (detection).
- Major problem: the object can look quite different in the new image due to different viewpoint, lighting, occlusions.
- Important difference to **object class recognition** or object class localization: the same instance of an object class is seen in the two images.
- There can be large differences between two instances of an object class (e.g. two dogs).



Author: David Lowe

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A classification problem

- Object recognition consists of two main parts:
  1. A set of **features** that describe the object
  2. A **classifier** that separates objects/object classes

- Classical approach:
  Use a handcrafted feature representation and learn the classifier

- Deep learning:
  Learn the feature representation and the classifier

- Typical classifiers (see also Statistical Pattern Recognition):
  - **Support vector machine** (two-class)
  - **Logistic regression** (multi-class, used in deep networks)
  - Nearest neighbor classifier (multi-class)

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Support vector machine

- Basic idea: learn a decision function with maximum margin (distance to most critical training points).

- Decision function modeled as a linear combination of features:

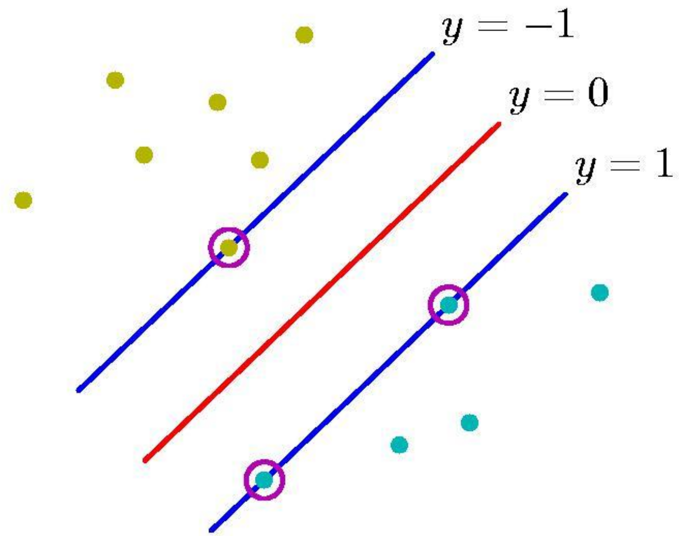
$$y(\mathbf{x}) = \mathbf{w}^\top \phi(\mathbf{x}) + b$$

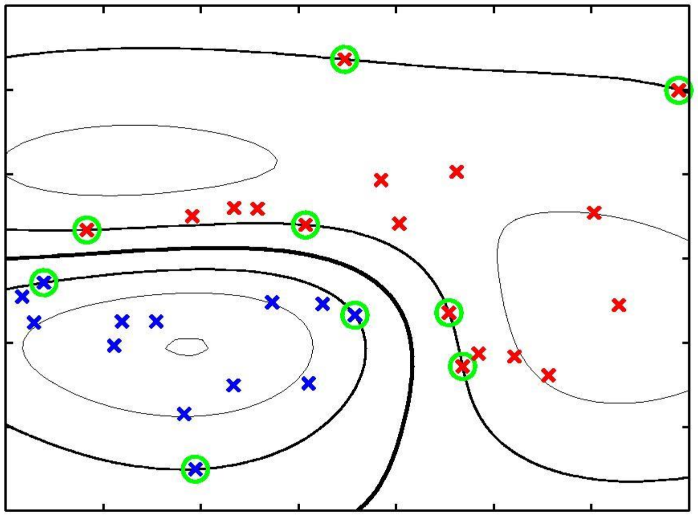
- Large margin concept leads to a convex optimization problem:

$$\mathrm{argmin}_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2$$

subject to $t_n(\mathbf{w}^\top \phi(\mathbf{x}_n) + b) \geq 1$

- Efficient code is publicly available (e.g. libSVM, liblinear)





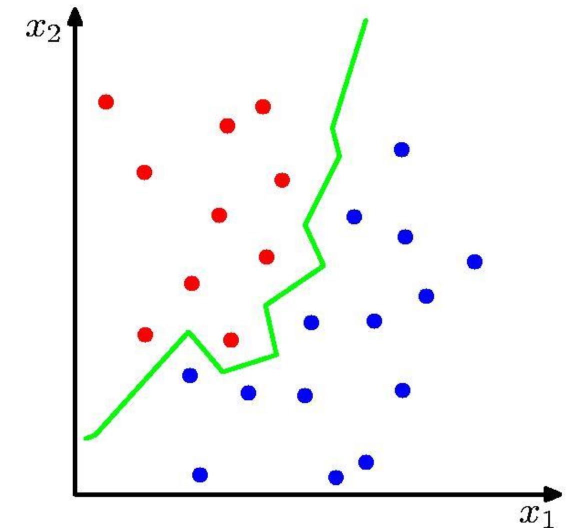
Author: Christopher Bishop

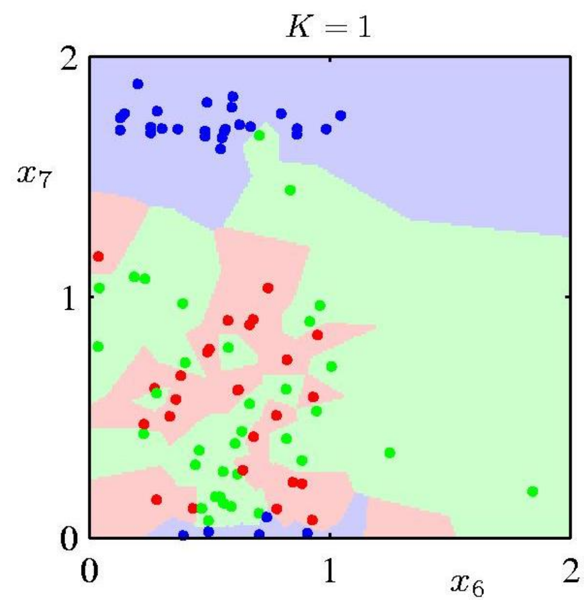
Nearest neighbor classifier

- Simple idea: assign the class label of the most similar training point.

- Advantages:
  - Simple concept
  - Works for multiple classes

- Drawbacks:
  - All training samples must be stored.
  - Search for most similar training sample may consume too much time
  - Does not generalize well





Author: Christopher Bishop

Feature representation

- Color
  - Discriminative capabilities very restricted (tomato = red car)

- Local descriptors (e.g. SIFT)
  - Discriminative properties good (if sufficiently textured)
  - Easy to extract from input images
  - Describe the object **locally**
    → robust to occlusions, local variation
  - Fixed level of abstraction
    → problems with complex variations

- Deep representations
  - Multiple levels of abstraction
  - Learned from training data

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Invariance requirements in object recognition

- Aim: the object should be recognized even if its appearance has changed due to some typical transformations.

- Then the descriptors and classifiers are called **invariant** with respect to this transformation.

- There is a tradeoff between invariance and discriminative power of a descriptor

- Instance recognition: invariance needed with respect to
  - Viewpoint (includes translation, scaling, rotation, perspective distortion)
  - Background
  - Lighting
  - Partial occlusion

- Class recognition: needs complex invariant features learned from training examples

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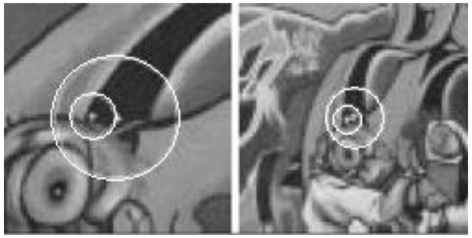
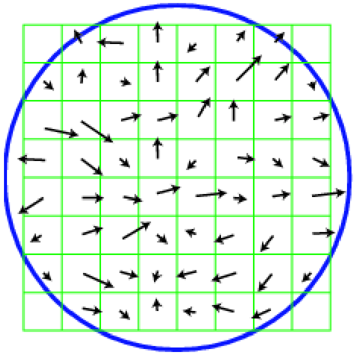
Some popular local descriptors

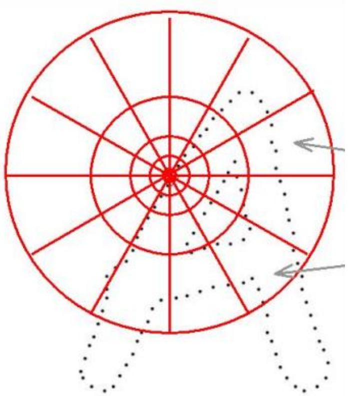
- Distortion corrected patches
  - distortion correction provides affine invariance



- SIFT/HOG (Lowe 2004, Dalal-Triggs 2005)
  - based on gradient orientation histograms
  - can be made invariant to scaling, rotation, and brightness/contrast change



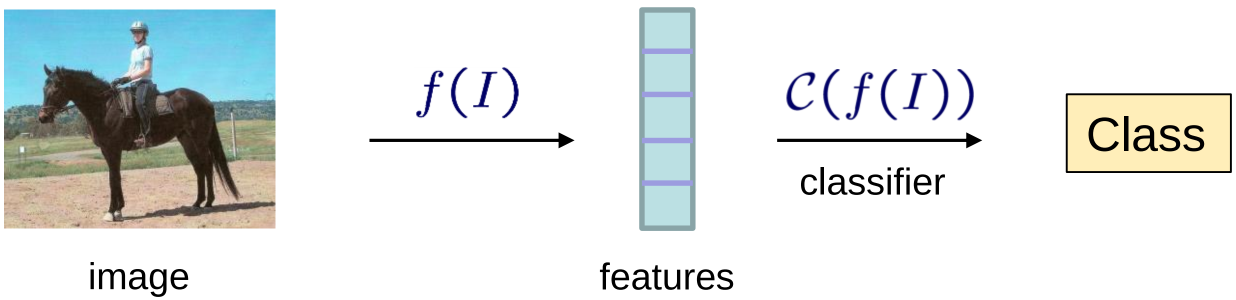
- Shape context (Belongie-Malik 2002)
  - based on object contours or edges
  - histogram of relative position of other contour points in the local neighborhood



Feature learning

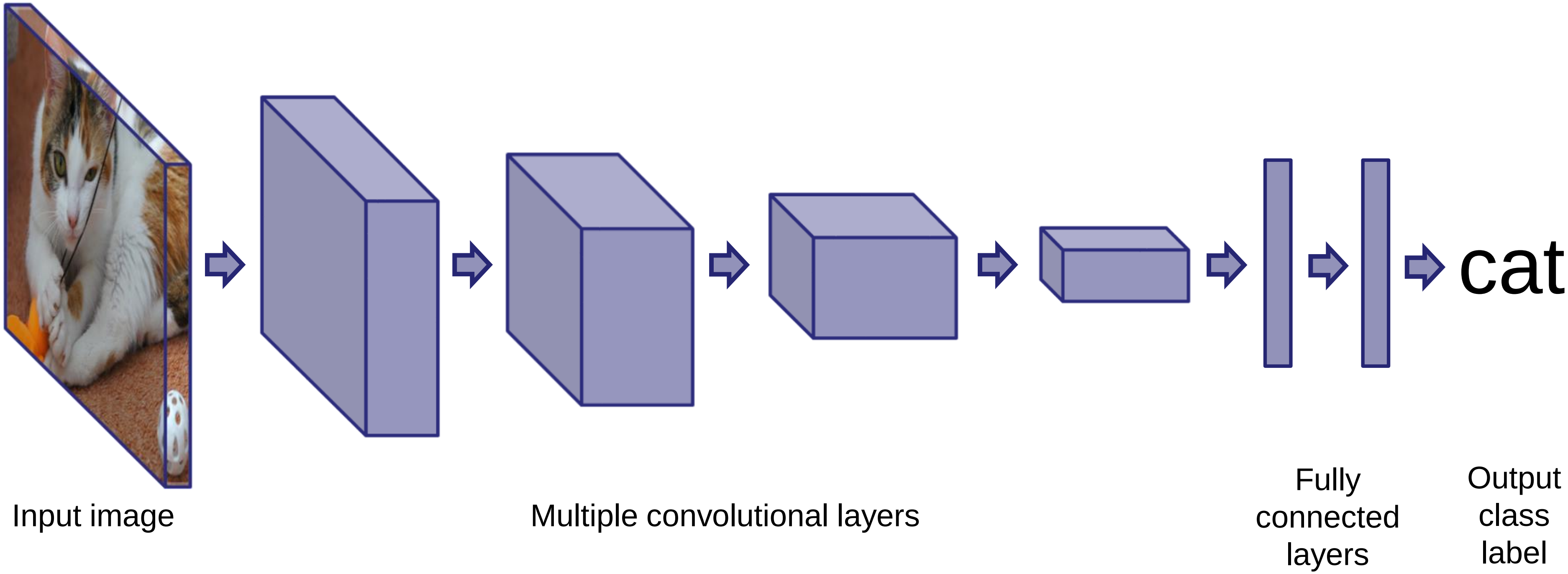
- Instead of manual descriptor design, let the computer find the optimal descriptor for a task defined by a training set

- Task: object classification
→ training set consists of images and their class labels



- Shallow modeling of the function $f(I)$ is not efficient to cover all the variation that appears in an object class
→ hierarchy of functions, "deep" representation

Typical deep network for image classification



- Each layer produces a more abstract representation of the input
- Layers are similar in structure
- Weights of connections between layers (filters) learned from training data

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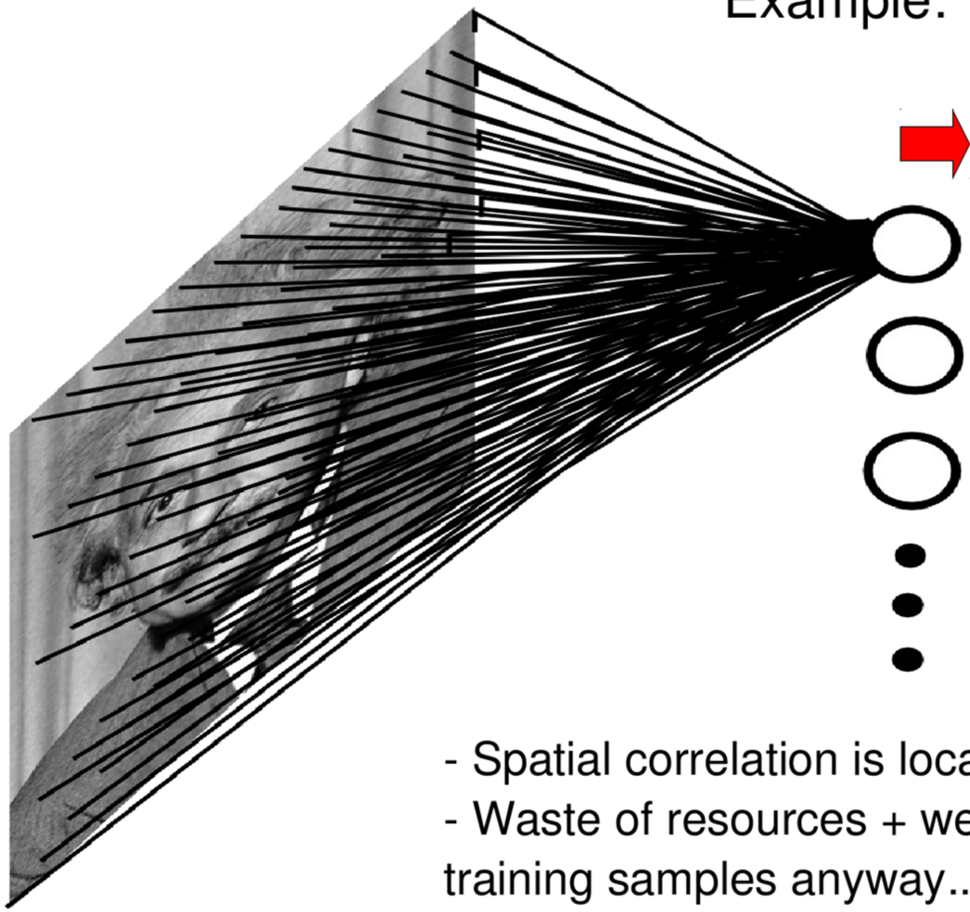
Convolutional network vs. fully connected network

Fully Connected Layer



Example: 200x200 image
40K hidden units
~2B parameters!!!

- Spatial correlation is local
- Waste of resources + we have not enough training samples anyway..

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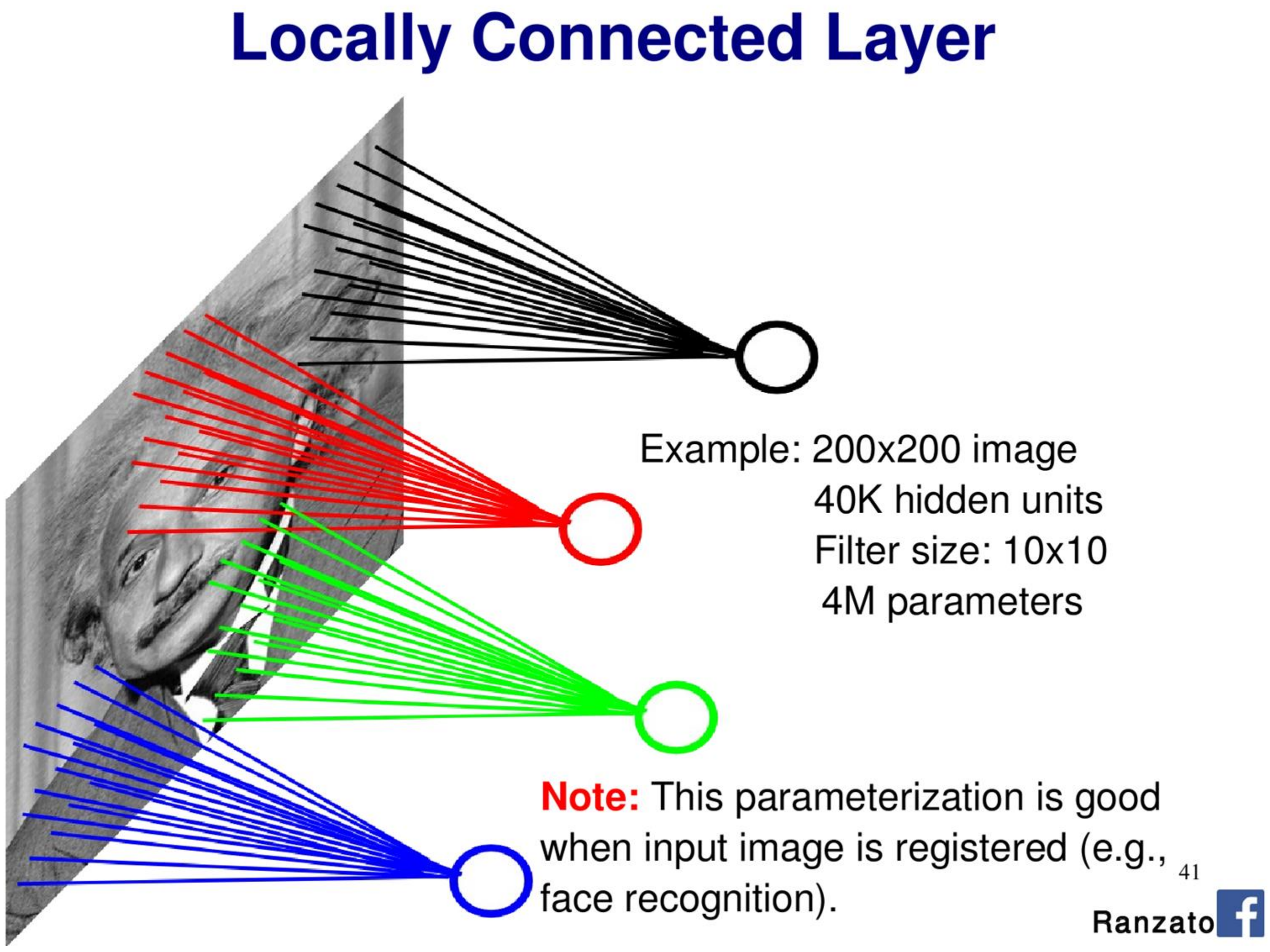
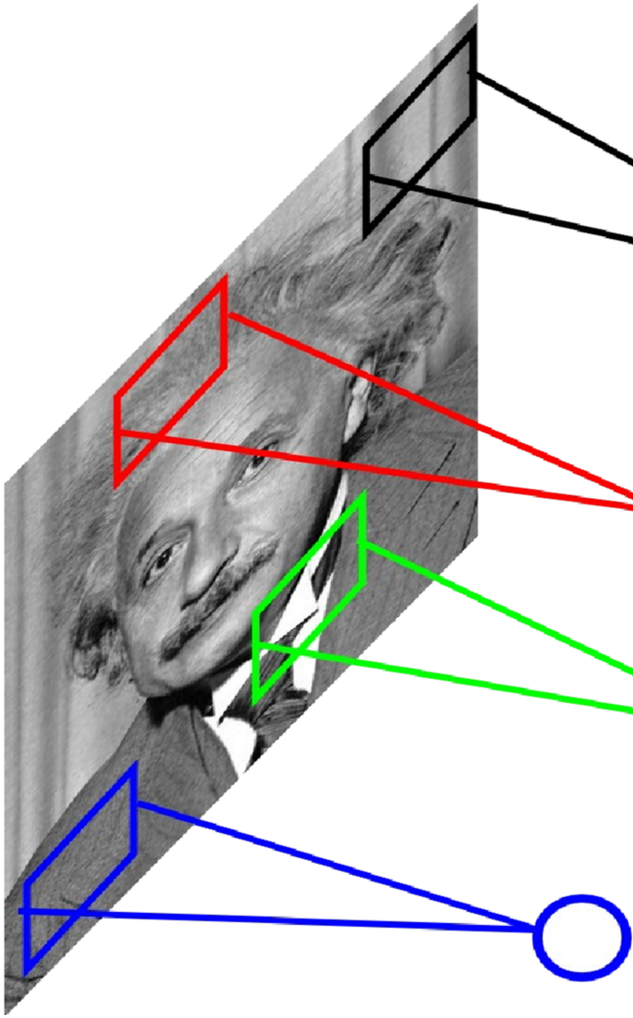
Convolutional network vs. fully connected network



Convolutional network vs. fully connected network

Locally Connected Layer



STATIONARITY? Statistics is similar at different locations

Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

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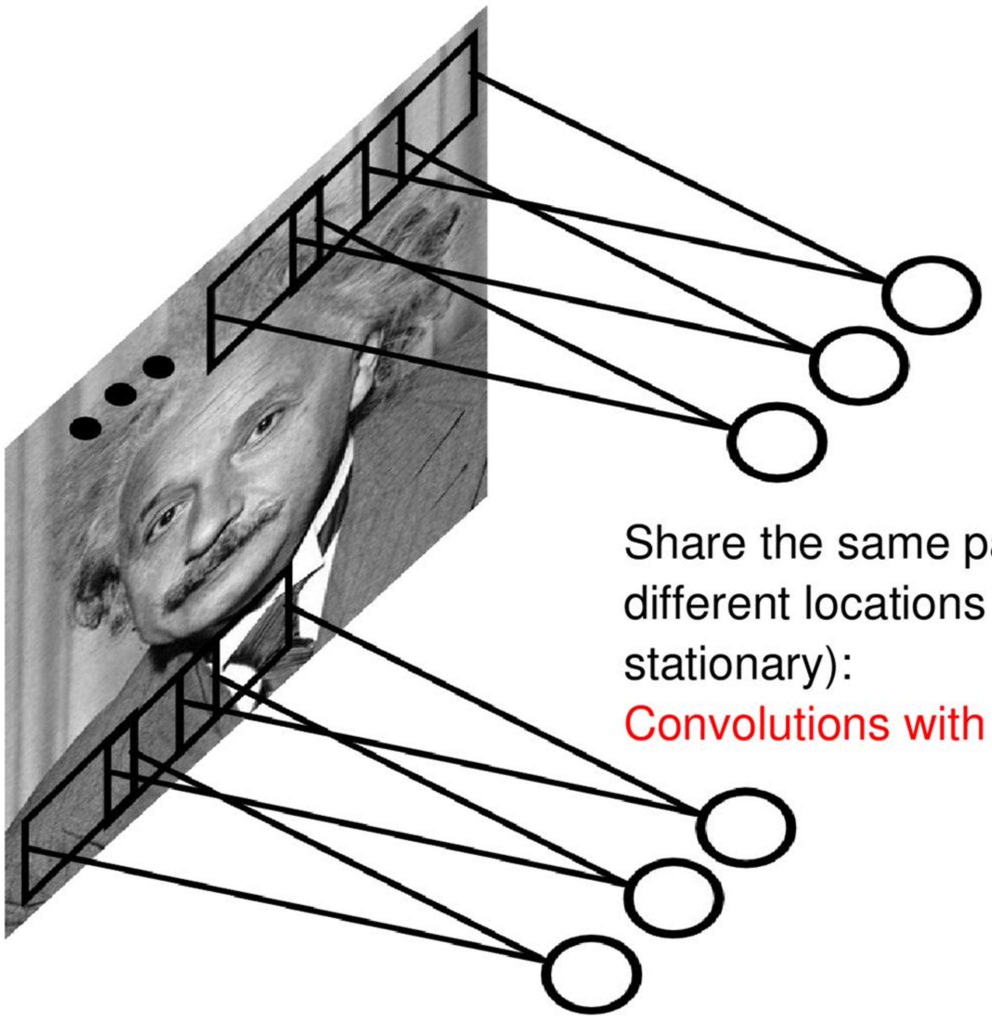
Convolutional network vs. fully connected network

Convolutional Layer



Share the same parameters across different locations (assuming input is stationary):
Convolutions with learned kernels

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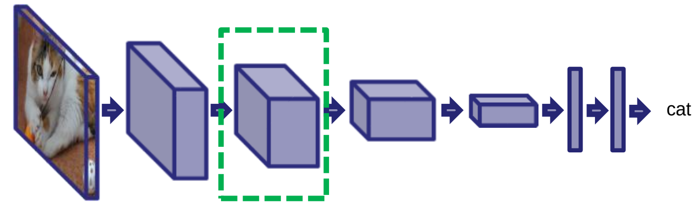
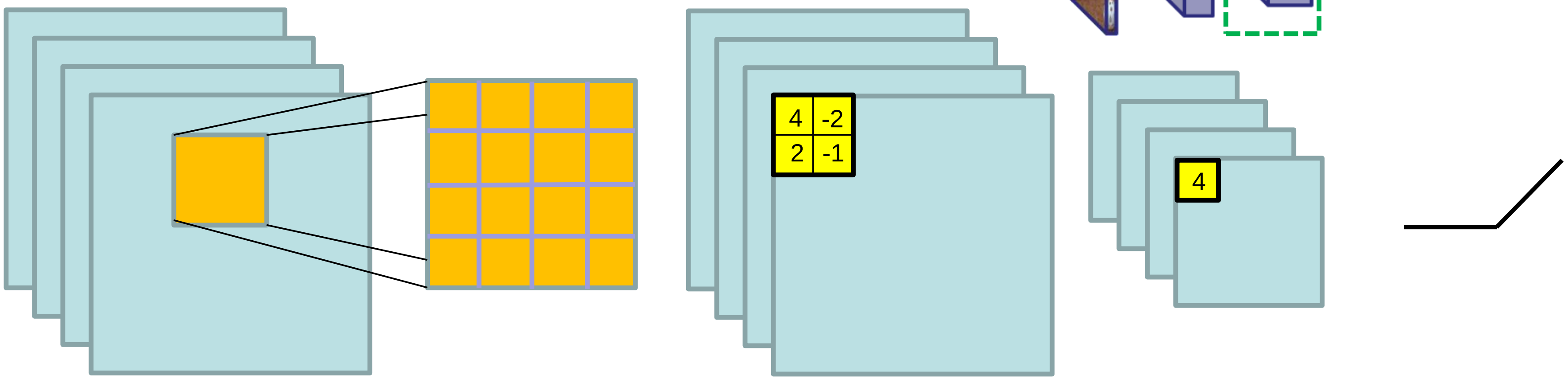
Single layer module of a convolutional network





Input (image or feature map from previous layer) | m filter masks (learned) | Feature map (m filter outputs) | Max-pooling | Nonlinearity ReLU

- **Max-pooling** replaces a small local area of the feature map by the maximum value in that area (= downsampling)
  → data reduction, loss of localization accuracy
  → allows for larger receptive fields in the next layer

- **ReLU nonlinearity** sets negative values to 0 (no activation)

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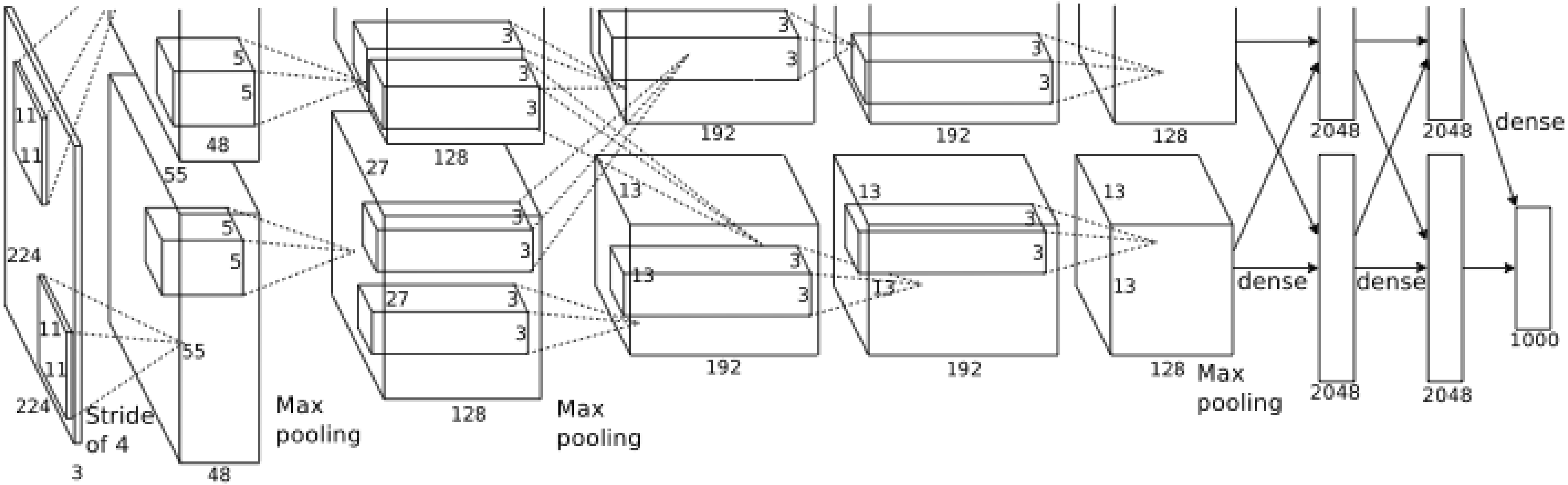
Large ConvNet

Author: Alex Krizhevsky



- Modern networks have 30 layers or more

- Cost function for training the weights: cross entropy on training set (in principle the classification error, but better)

$$\mathbf{w}^* = \mathrm{argmin}_{\mathbf{w}} - \sum_i \sum_c y_i^c \log(f_{\mathbf{w}}^c(x_i))$$

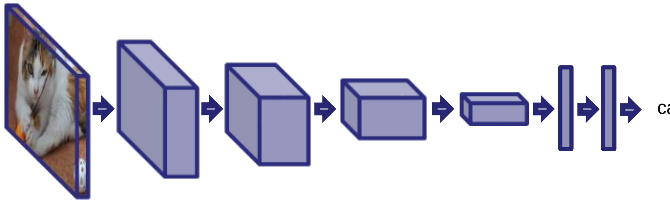
- Optimization by gradient descent (**back-propagation**)

Back-propagation

Optimization problem:

$$L(\mathbf{w}) = -\sum_i y_i^\top \log(f_{\mathbf{w}}(x_i)) \qquad \mathbf{w}^* = \text{argmin}_{\mathbf{w}} L(\mathbf{w})$$

1. Initialize the weights (starting point for gradient descent)
2. Compute $f_{\mathbf{w}}(x_i)$ by forward-propagating a sample through the network
3. Gradient with regard to a weight in a certain layer: use **chain rule**



$$\frac{dL}{df} = \sum_i (f_{\mathbf{w}}(x_i) - y_i)$$

Error

$$\frac{dL}{dw_{l_{\max}}} = \boxed{\frac{dL}{df}} \frac{df}{dw_{l_{\max}}}$$

Error propagated to the last layer

$$\frac{dL}{dw_{l_{\max-1}}} = \boxed{\frac{dL}{df}\frac{df}{dh_{l_{\max-1}}}} \frac{dh_{l_{\max-1}}}{dw_{l_{\max-1}}}$$

Error propagated to the second last layer

and so on

4. Update the weights

$$\mathbf{w}^{k+1} = \mathbf{w}^k - \tau \nabla L$$

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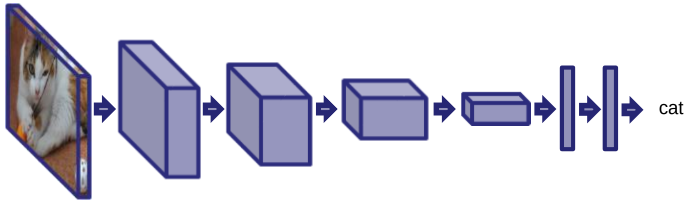
Nice properties of CNNs

- Filters of different layers capture different scales due to max-pooling
  - Filters at low layers are well localized and consider only a small image area (small **receptive field**).
  - Filters at high layers are badly localized and capture the context of a large image area (large receptive field).
- Feature sharing: the same features obtained at low layers can be useful for assembling various complex features at higher layers



- Successive abstraction

  Features close to the image input resemble simple edge filters

  Features close to the class output are invariant to the typical appearance variations

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Localization tasks

- Image classification only provides a class label per image

- **Object localization**: provide a bounding box of the object

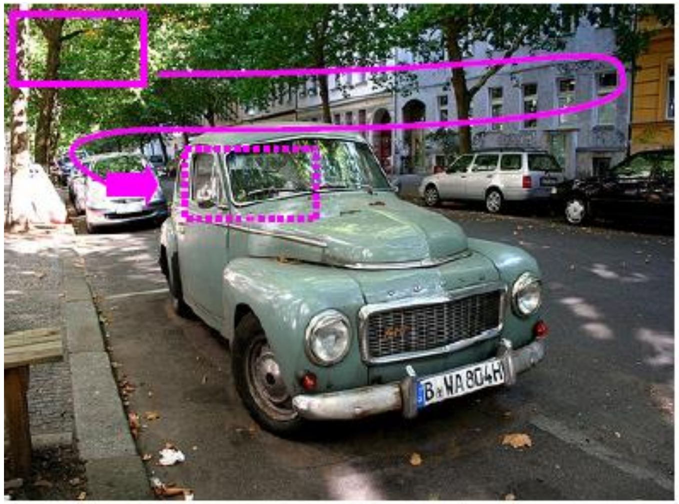
- **Object detection**: bounding boxes for potentially many object instances in the image

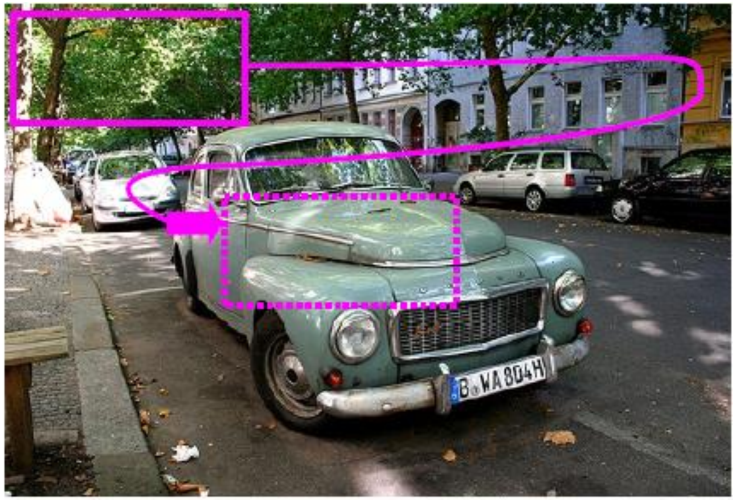
- **Semantic segmentation**: say for each pixel to which object class it belongs

- **Instance segmentation**: additionally separates different class instances

Sliding window approach (Viola-Jones 2001)

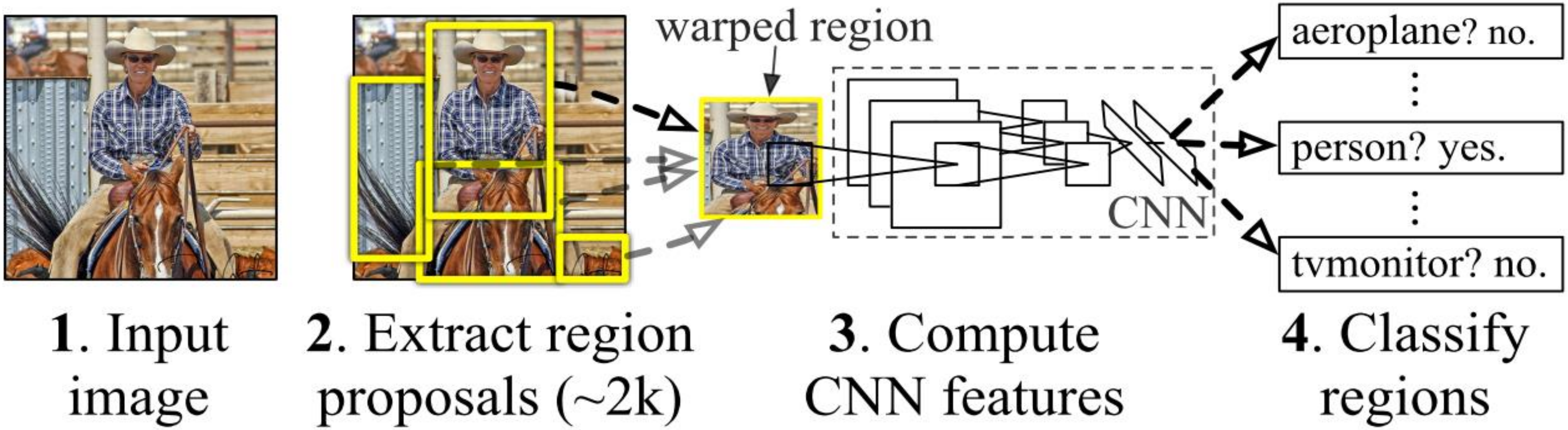
- Define features in a local window
- Consider many (or all) positions and scales and make a binary decision: Is this window a car or not?





- Non-maximum suppression: keep only the local maxima
- Convolutional networks and the sliding window concept are redundant → exploit for larger efficiency (Sermanet et al. 2014)

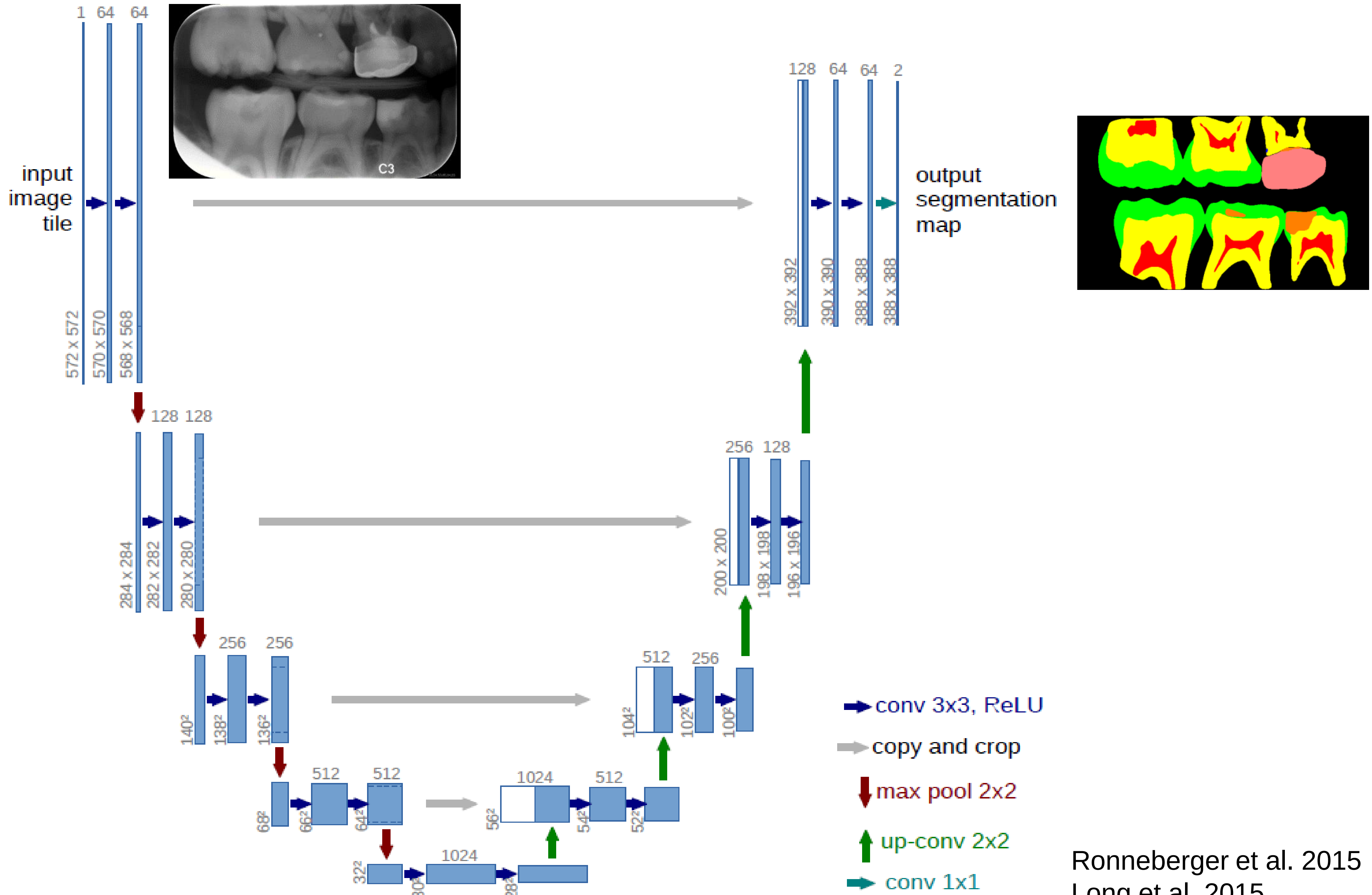
Deep network classification on object window proposals (R-CNN)



Girshick et al. 2014

- Instead of all windows, only ~1000 region proposals are considered
- Faster implementations first compute the ConvNet activations of the whole image and use them to classify the proposal windows

Semantic segmentation with a deep network



Ronneberger et al. 2015
Long et al. 2015

Object recognition benchmarks

- For comparing the performance of different recognition techniques, a common benchmark is needed.
- There are several public benchmarks:
  - ImageNet (localization with 1000 classes, detection): http://www.image-net.org/
  - PASCAL Visual Object Classes (classification, detection, segmentation, …) http://pascallin.ecs.soton.ac.uk/challenges/VOC/
  - Microsoft CoCo (detection, image caption generation) http://mscoco.org/
- Benchmarks come with a **training set** and a **test set** (both annotated)
  - Training set: train classifiers and optimize parameters
  - Test set: run the final method and measure performance
- Detection performance is assessed by precision-recall curves

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Precision-recall curves

- **Precision**: which part of the detected objects is correct?

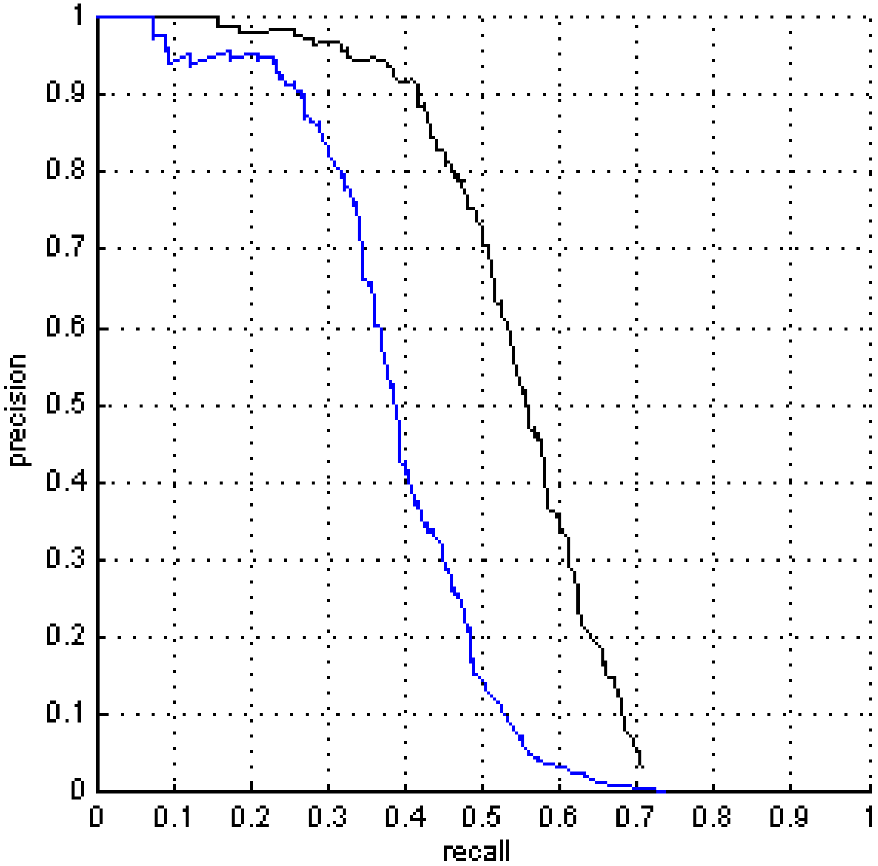
$$\frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

- **Recall**: which percentage of objects is detected?

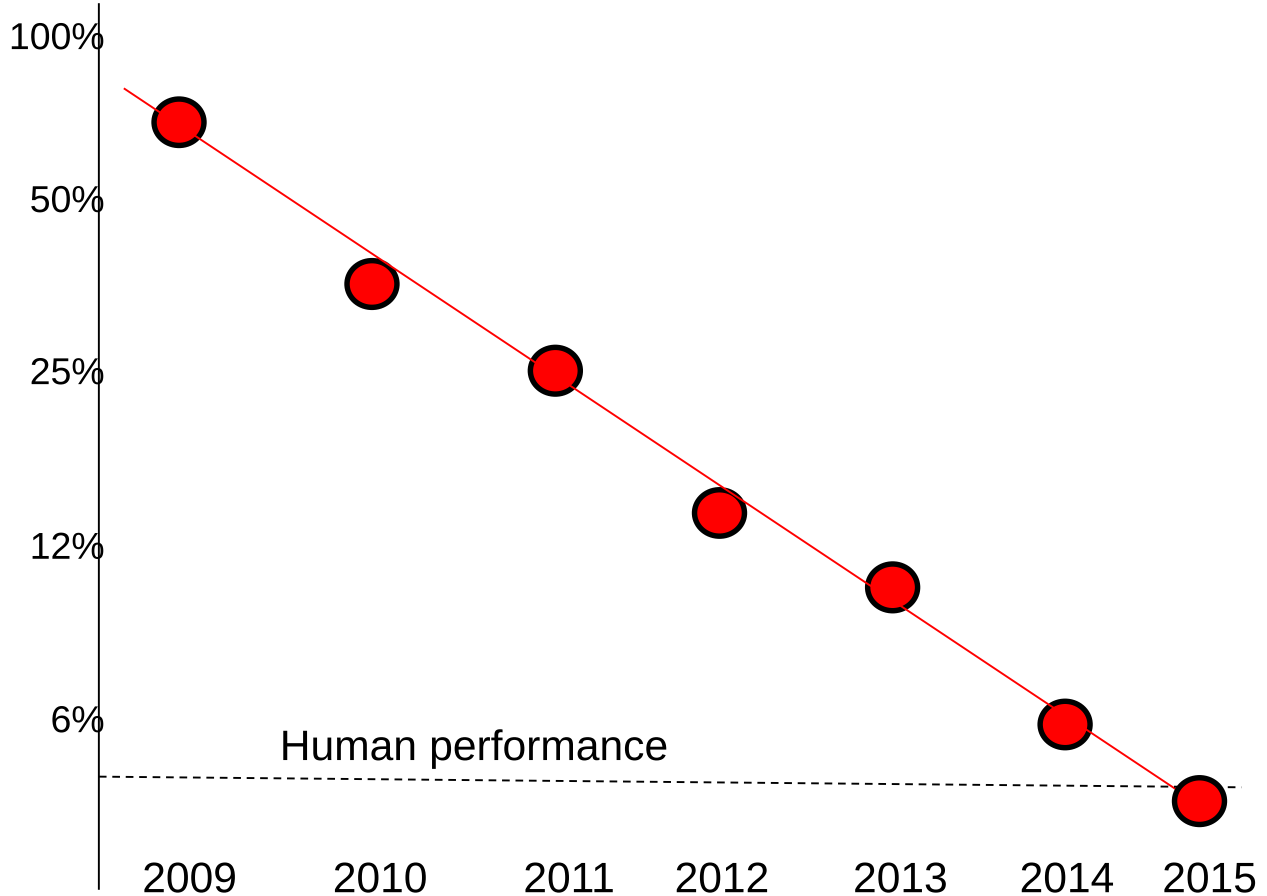
$$\frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

- Precision-recall curves obtained by different thresholds on the classification score

- Single number: **average precision** (area under the curve)



Progress on image classification



Classification error on ImageNet

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Deep learning formulations for other computer vision tasks

- Image enhancement
- Superresolution

- Body part and pose estimation
- Action recognition

- Depth from single image
- Optical flow estimation
- Disparity estimation
- Structure from motion

- Image based control
- Image based planning

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FlowNet 2.0

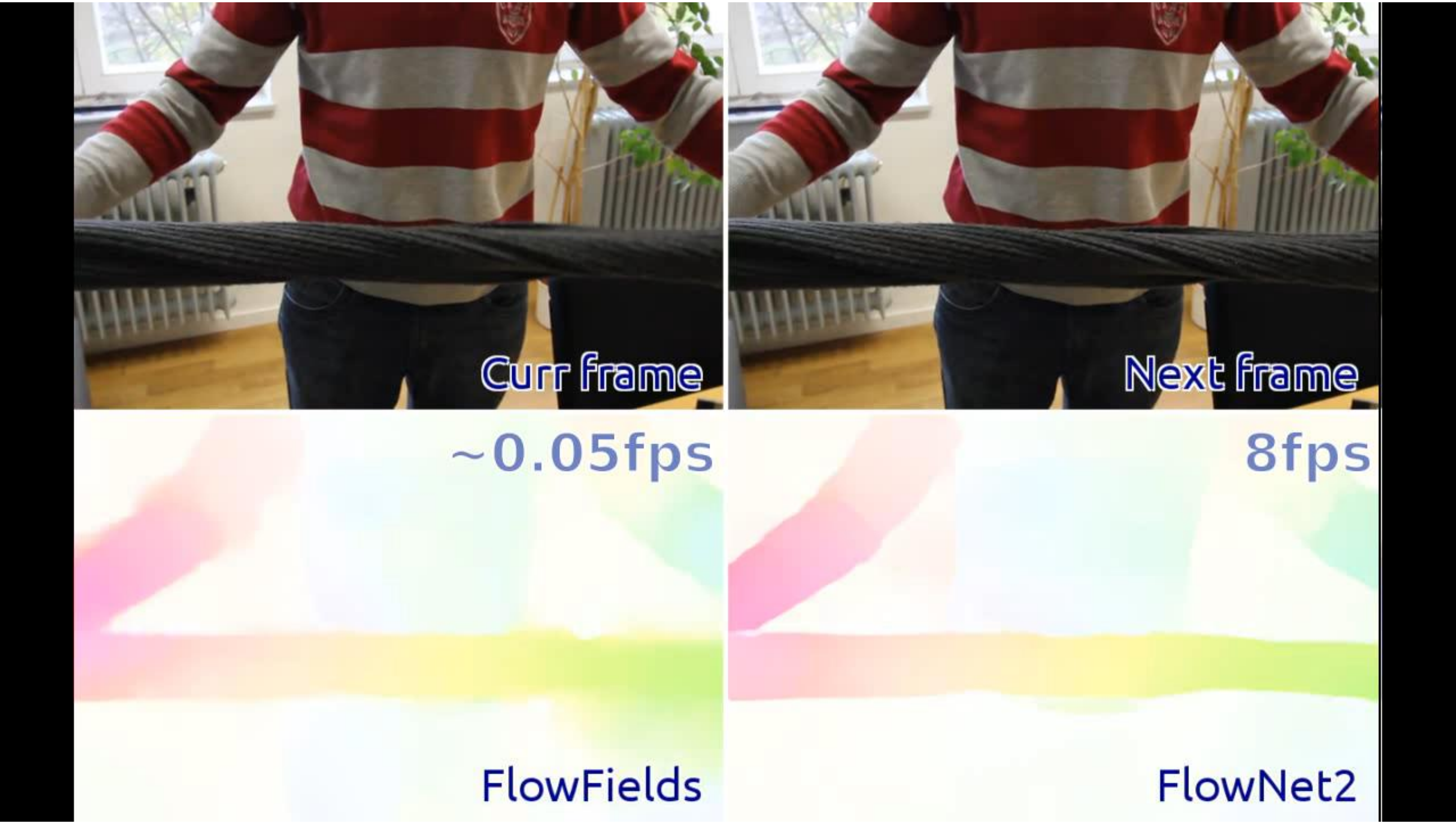

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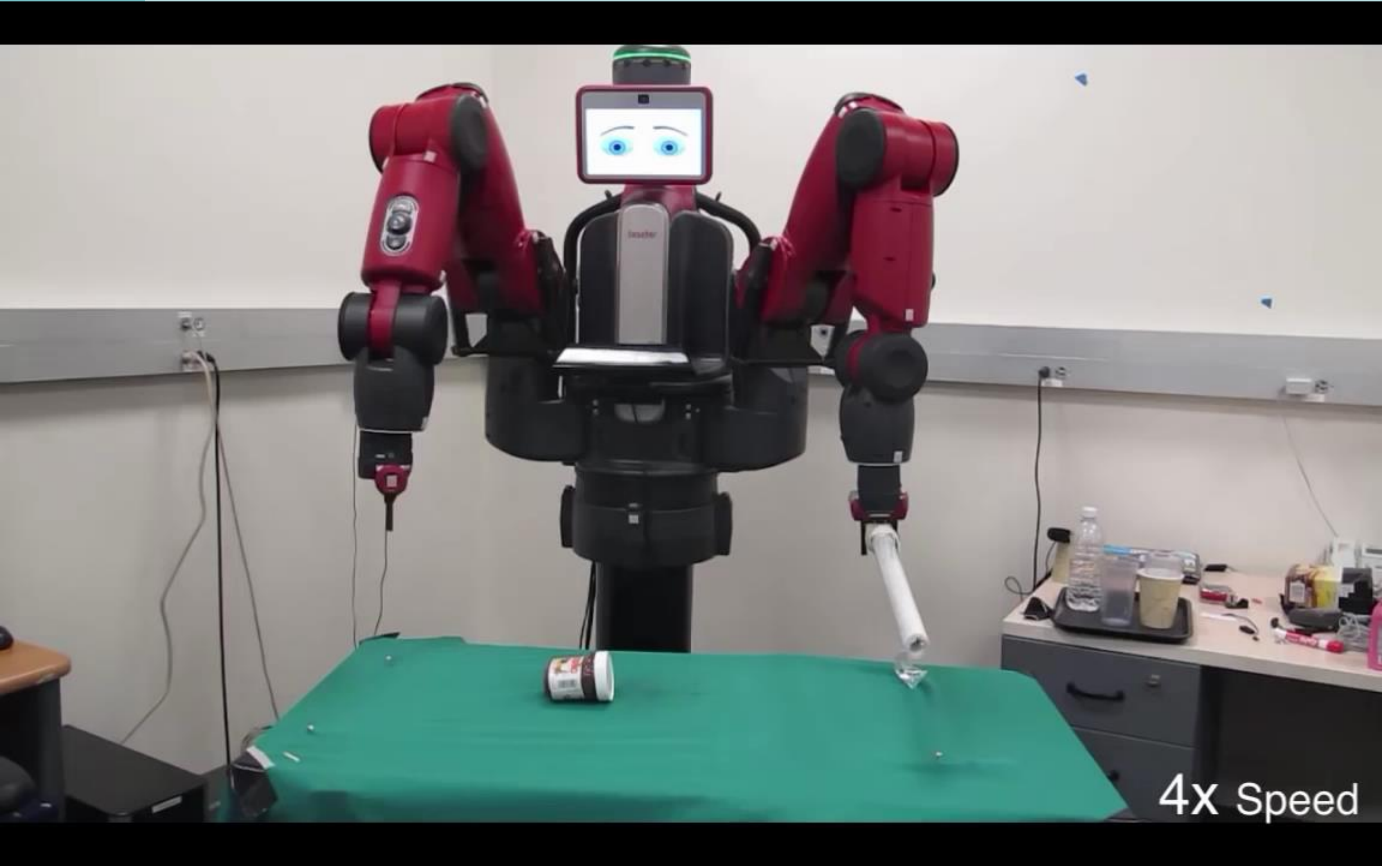
Image based control



Agrawal et al.: Learning to poke by poking

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Summary

- Recognition tasks consist of a feature representation and a classifier
- Deep learning learns a hierarchical feature representation that is usually more powerful than hand-crafted features.
- Deep learning comes down to optimizing a simple (but highly nonlinear and non-convex) loss function with gradient descent
- Convolutional networks use localized filters that are shared across the whole image → vast reduction in the number of parameters
- Object detection and object segmentation require localization of the object (also possible with special convolutional network architectures)
- More or less all tasks can be formulated as learning problems

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Upcoming classes and courses

- Next week: Computer Graphics

- If you liked the field of image processing and computer vision:
  - Statistical Pattern Recognition (summer, 2+2)
  - Computer Vision (winter, 2+2)
  - Seminar (winter and summer)
  - Deep Learning lab course (winter)
  - GPU Programming lab course (summer)
  - Projects, theses

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