Object detection, deep learning, and R-CNNs

Partly from Ross Girshick

Microsoft Research

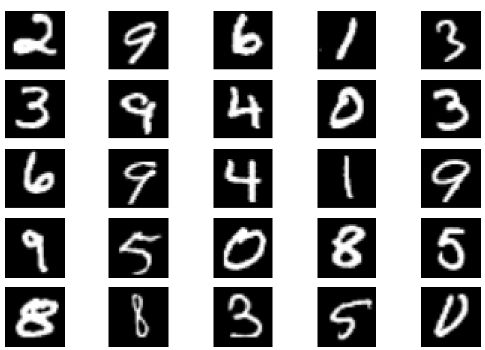
Now at Facebook

Outline

- Object detection
  - the task, evaluation, datasets
- Convolutional Neural Networks (CNNs)
  - overview and history
- Region-based Convolutional Networks (R-CNNs)

Image classification

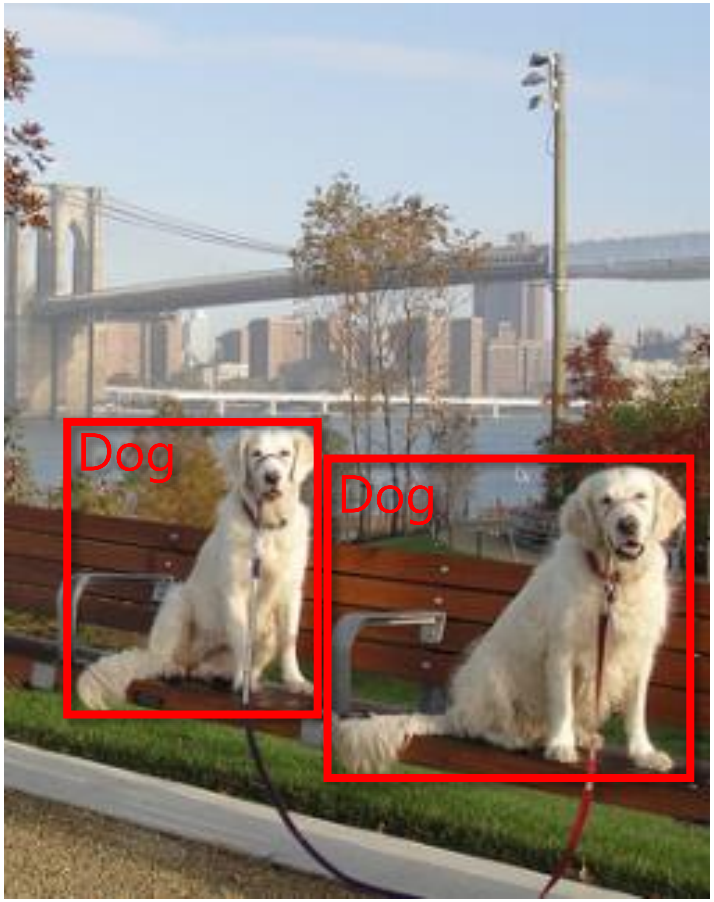
- K classes
- Task: assign correct class label to the whole image



Digit classification (MNIST)

Object recognition (Caltech-101)

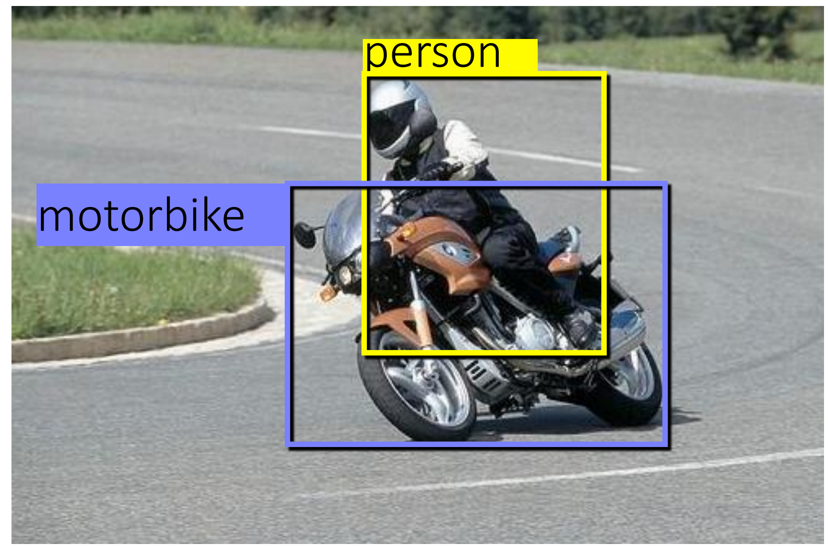
Classification vs. Detection



Problem formulation

{ airplane, bird, motorbike, person, sofa }

Input



Desired output

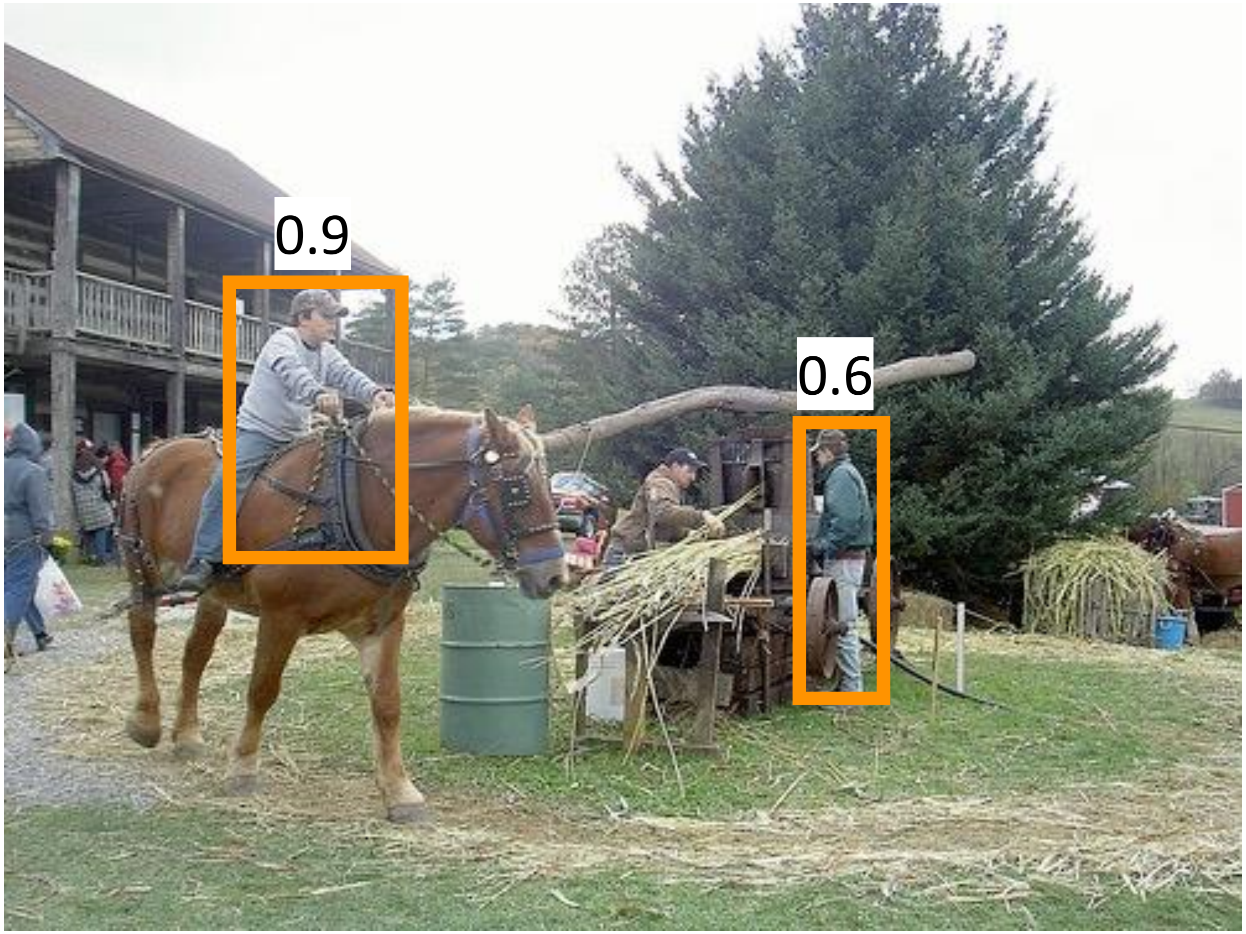
Evaluating a detector

Test image (previously unseen)

First detection ...

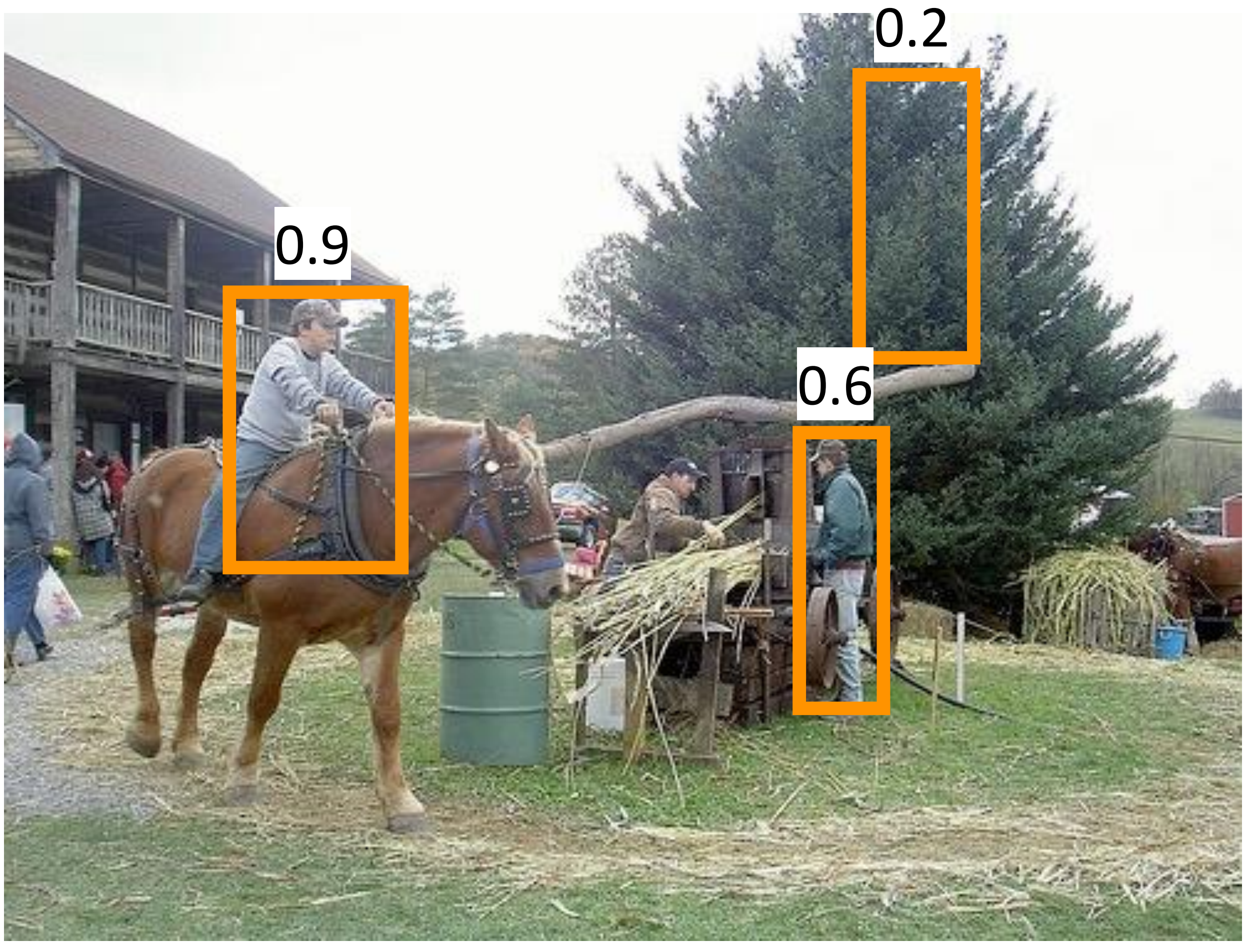
‘person’ detector predictions

Second detection ...



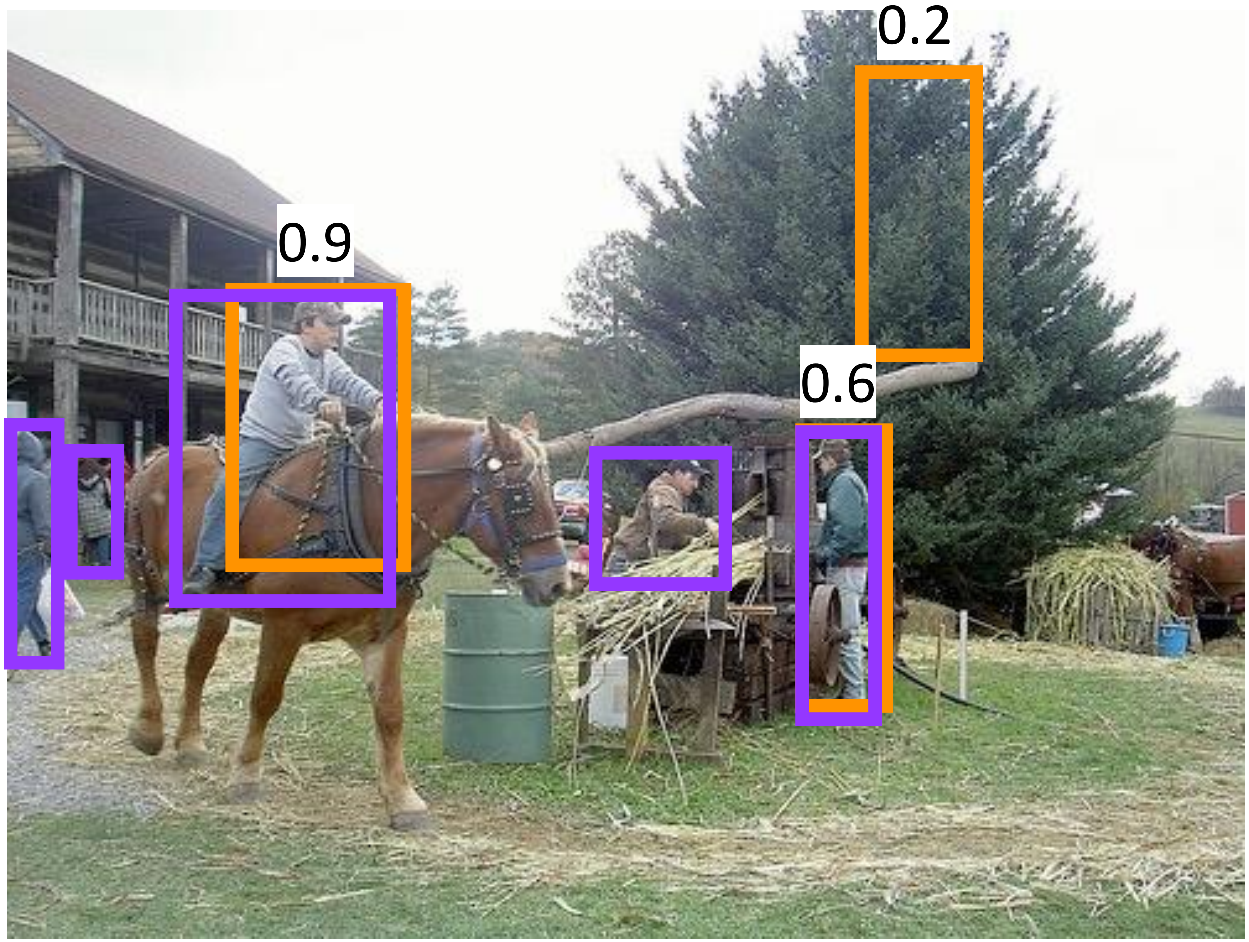
'person' detector predictions

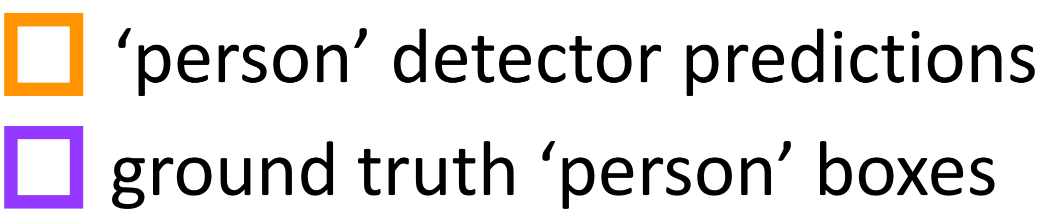
Third detection …



‘person’ detector predictions

Compare to ground truth





Sort by confidence

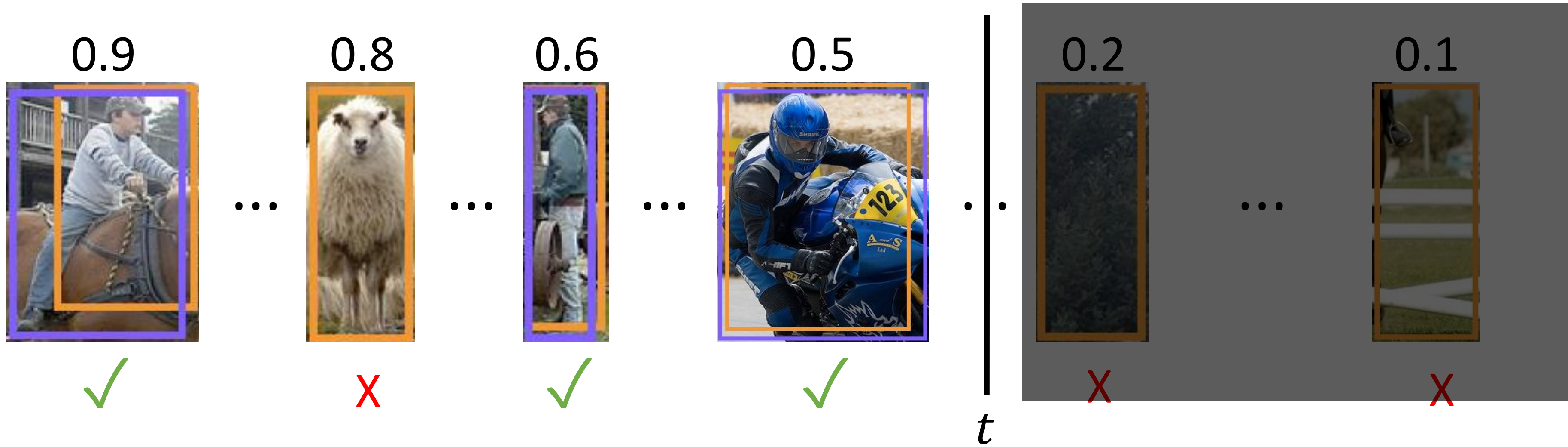
0.9 0.8 0.6 0.5 0.2 0.1

✓ x ✓ ✓ x x

true
positive
(high overlap)

false
positive
(no overlap,
low overlap, or
duplicate)

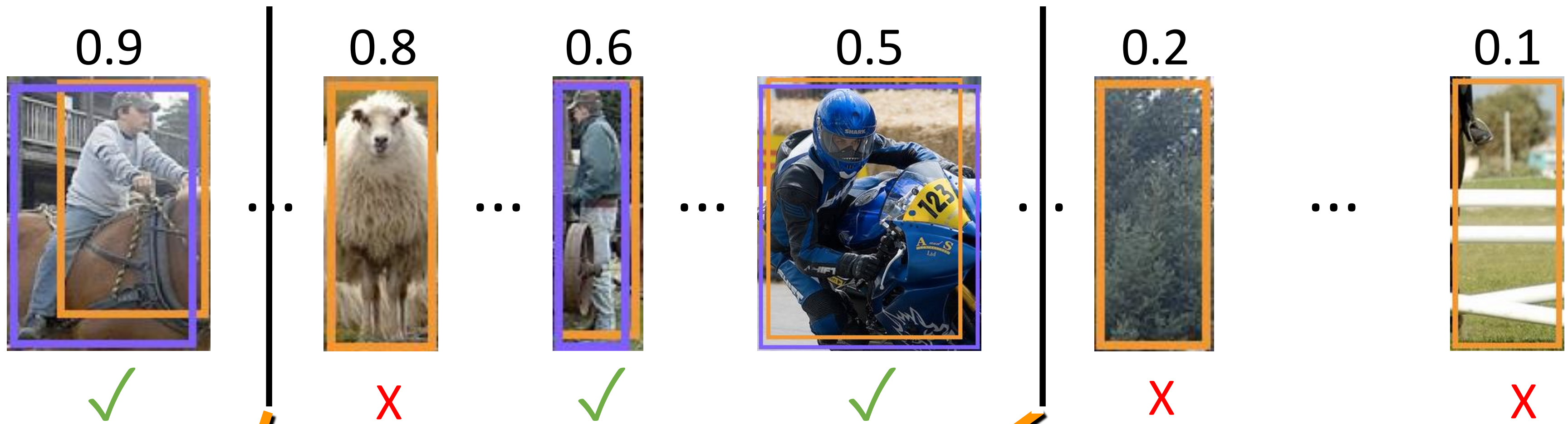
Evaluation metric

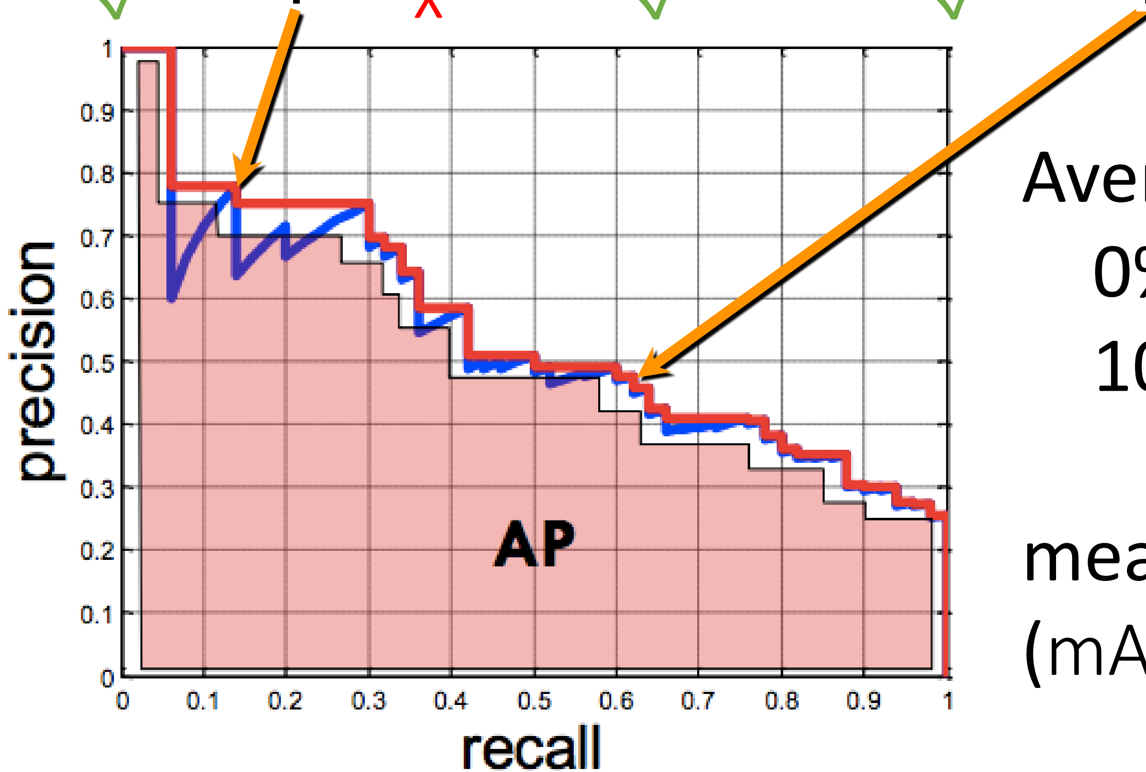


$$precision@t = \frac{\#true\ positives@t}{\#true\ positives@t + \#false\ positives@t} \qquad \frac{\checkmark}{\checkmark + X}$$

$$recall@t = \frac{\#true\ positives@t}{\#ground\ truth\ objects}$$

Evaluation metric





Average Precision (AP)

0% is worst

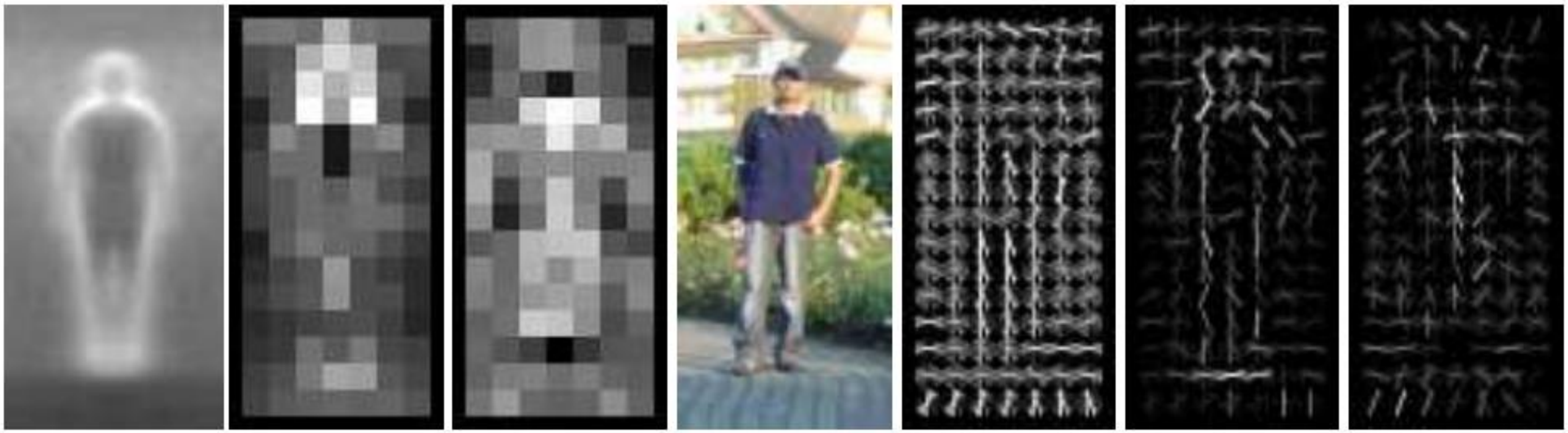
100% is best

mean AP over classes (mAP)

Pedestrians

Histograms of Oriented Gradients for Human Detection,
Dalal and Triggs, CVPR 2005

AP ~77%
More sophisticated methods: AP ~90%



(a) (b) (c) (d) (e) (f) (g)

(a) average gradient image over training examples
(b) each "pixel" shows max positive SVM weight in the block centered on that pixel
(c) same as (b) for negative SVM weights
(d) test image
(e) its R-HOG descriptor
(f) R-HOG descriptor weighted by positive SVM weights
(g) R-HOG descriptor weighted by negative SVM weights

Overview of HOG Method

1. Compute gradients in the region to be described
2. Put them in bins according to orientation
3. Group the cells into large blocks
4. Normalize each block
5. Train classifiers to decide if these are parts of a human

Details

- Gradients

  [-1 0 1] and $[-1\ 0\ 1]^T$ were good enough filters.

- Cell Histograms

  Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation. (9 channels worked)

- Blocks

  Group the cells together into larger blocks, either R-HOG blocks (rectangular) or C-HOG blocks (circular).

More Details

- Block Normalization

They tried 4 different kinds of normalization.
Let υ be the block to be normalized and e be a small constant.

L2-norm: $$f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}}$$

L2-hys: L2-norm followed by clipping (limiting the maximum values of v to 0.2) and renormalizing,

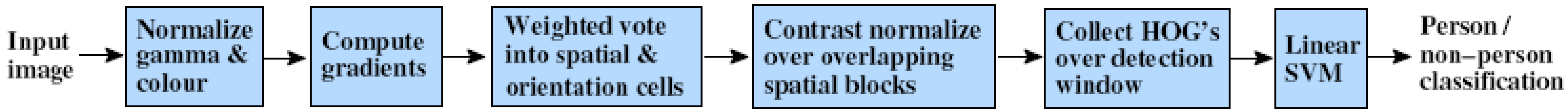
L1-norm: $$f = \frac{v}{(\|v\|_1 + e)}$$

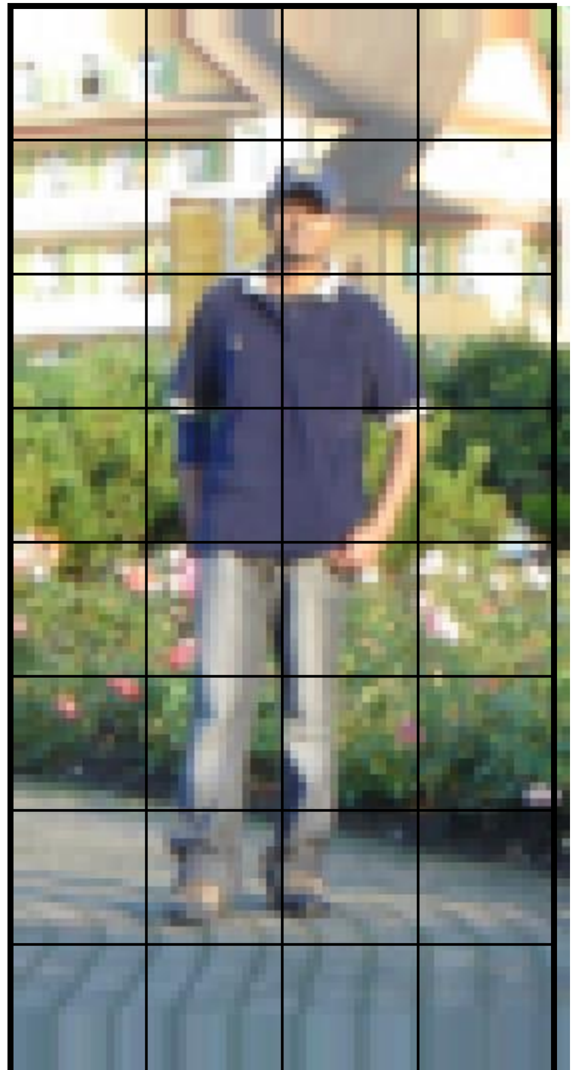
L1-sqrt: $$f = \sqrt{\frac{v}{(\|v\|_1 + e)}}$$

Example: Dalal-Triggs pedestrian

1. Extract fixed-sized (64x128 pixel) window at each position and scale
2. Compute HOG (histogram of gradient) features within each window
3. Score the window with a linear SVM classifier
4. Perform non-maxima suppression to remove overlapping detections with lower scores

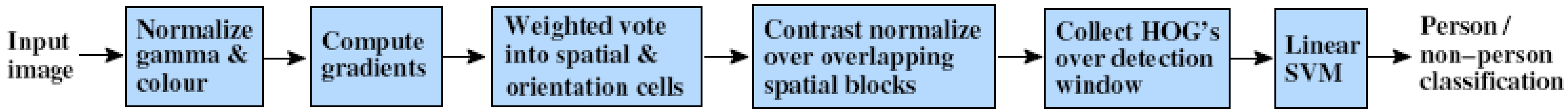
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05





Slides by Pete Barnum

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05



Outperforms

-1	0	1

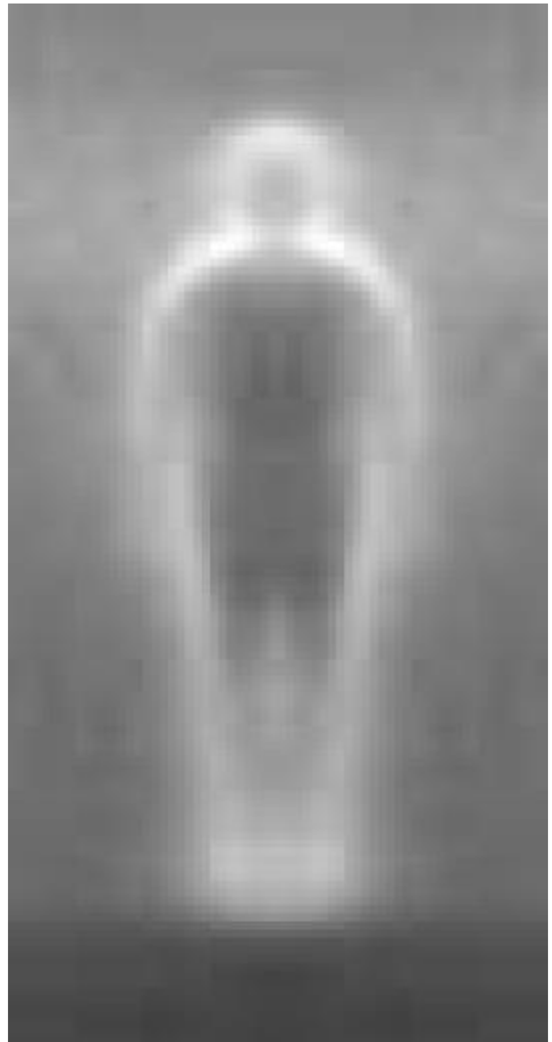
centered

-1	1

uncentered

1	-8	0	8	-1

cubic-corrected



0	1
-1	0

diagonal

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

Sobel

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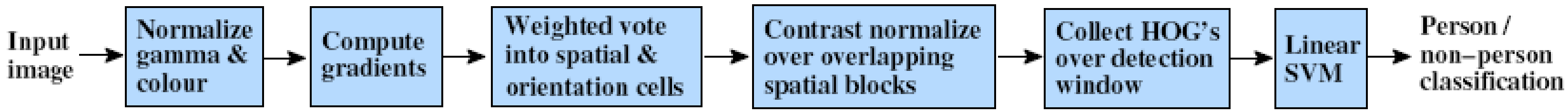
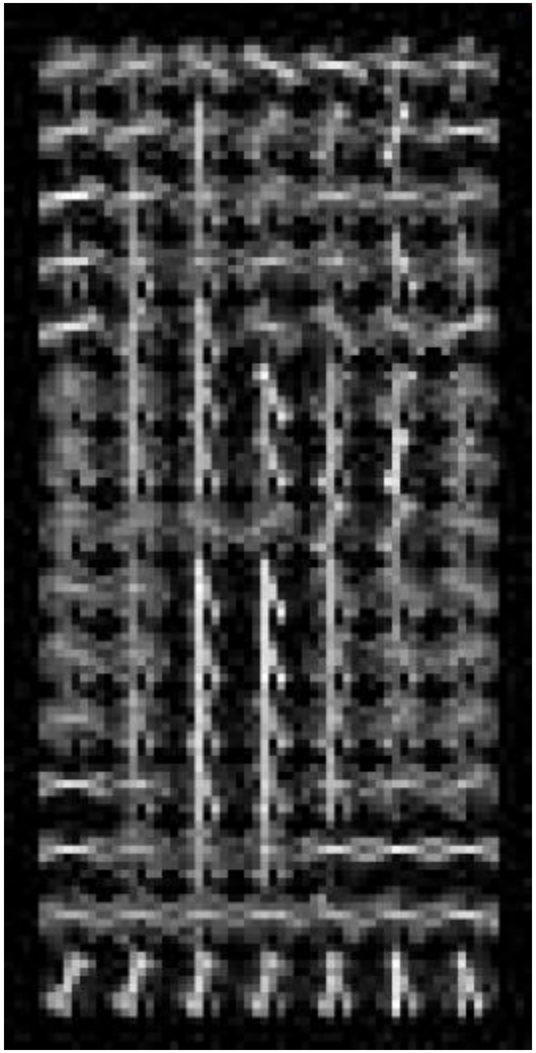
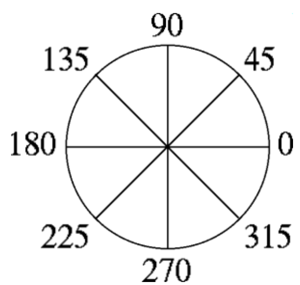
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05



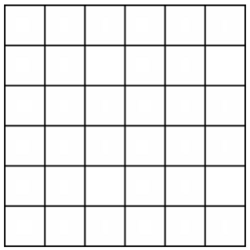
- Histogram of gradient orientations



Orientation: 9 bins (for unsigned angles)



Histograms in 8x8 pixel cells



- Votes weighted by magnitude
- Bilinear interpolation between cells

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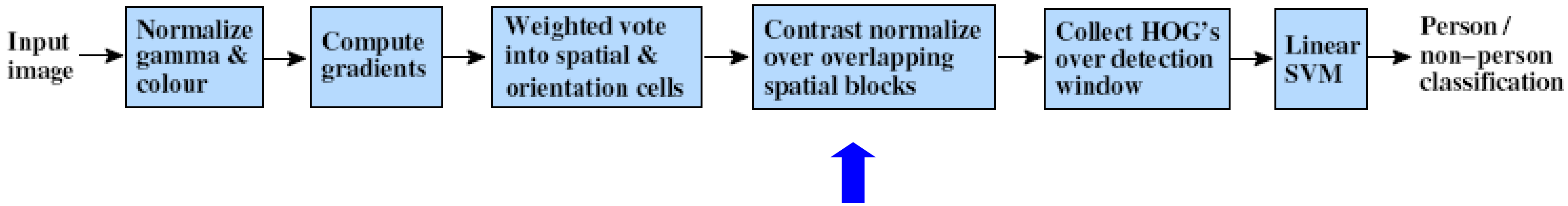
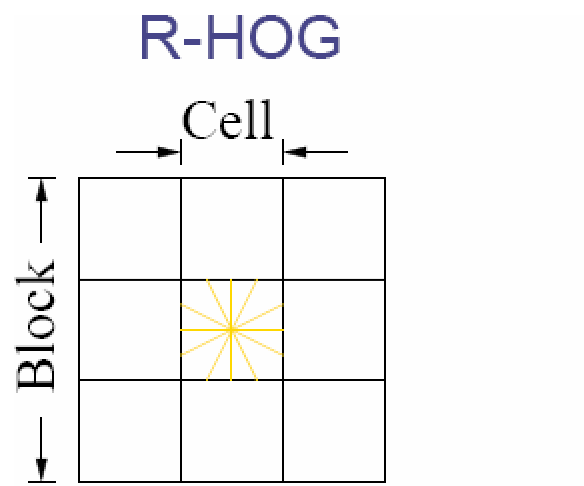


Normalize with respect to surrounding cells



$$L2-norm : v \longrightarrow v / \sqrt{||v||_2^2 + \epsilon^2}$$

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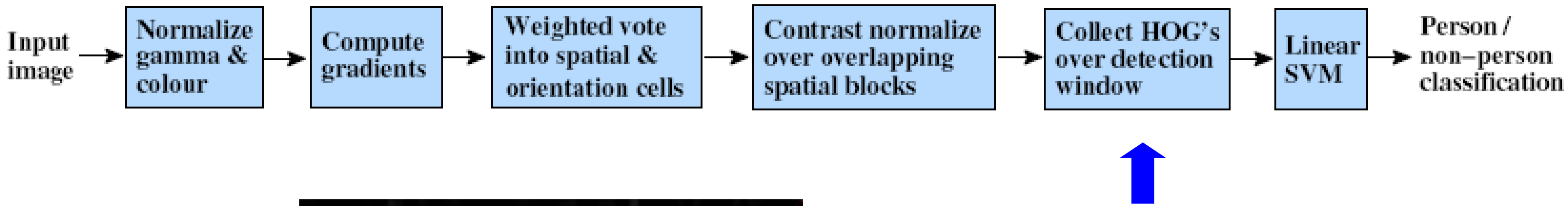
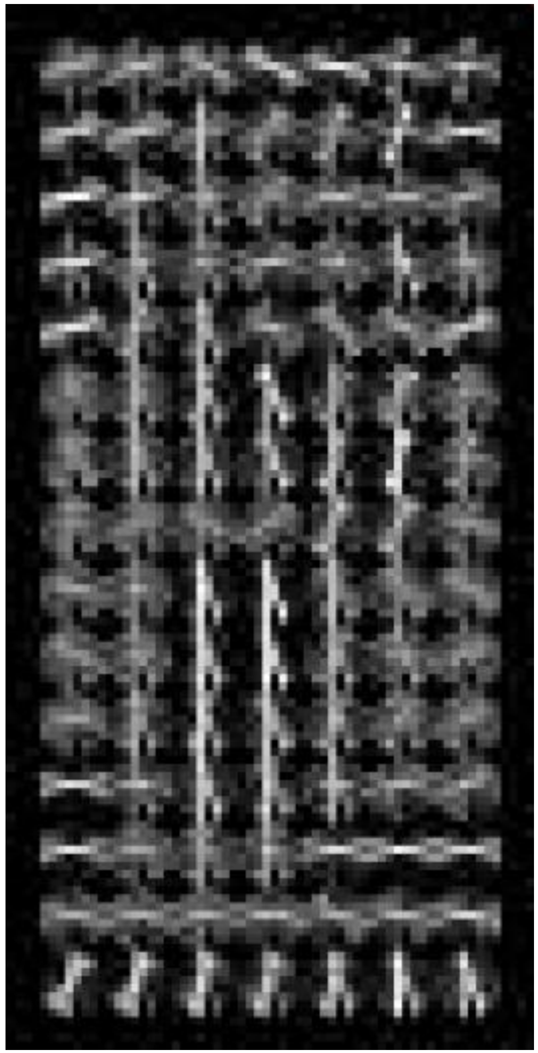
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05



X=



orientations

features = $\underbrace{15 \times 7}_{\#\text{ cells}} \times 9 \times 4 = 3780$

cells

normalizations by neighboring cells

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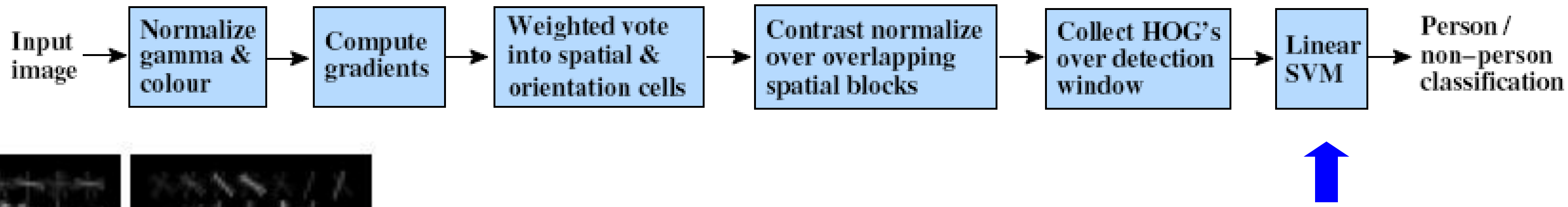
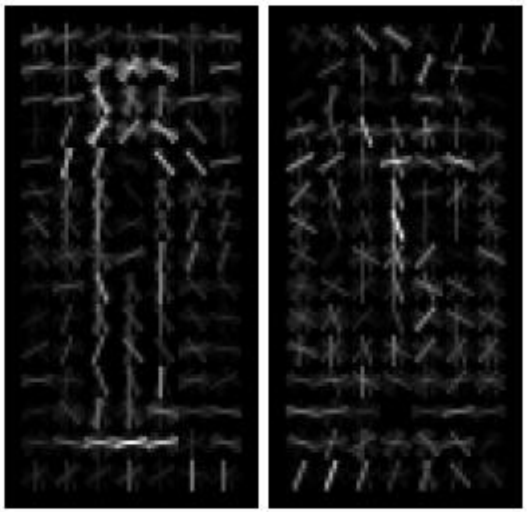
Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

Training set

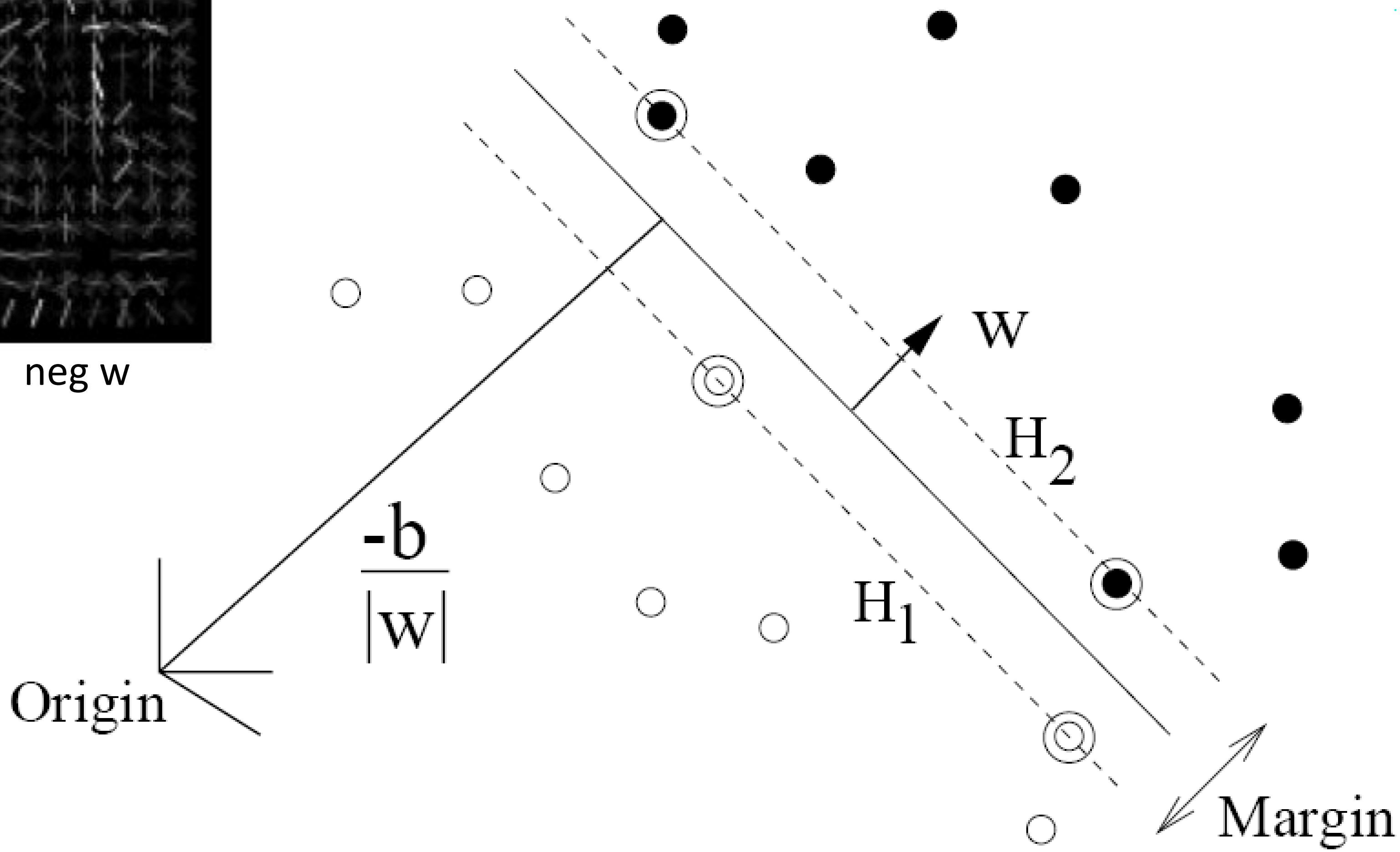
+

−





pos w neg w



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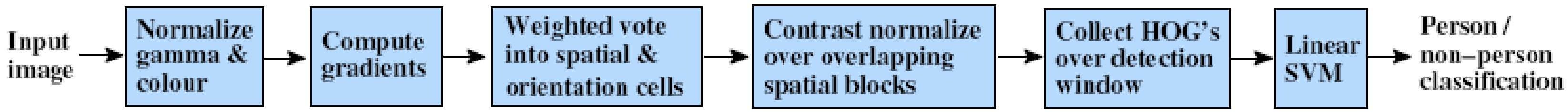


$$0.16 = w^T x - b$$

$$sign(0.16) = 1$$

$=>$ pedestrian

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

Detection examples

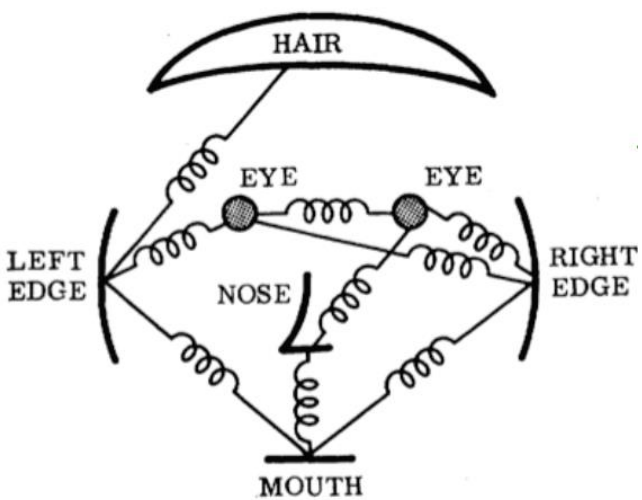
Deformable Parts Model

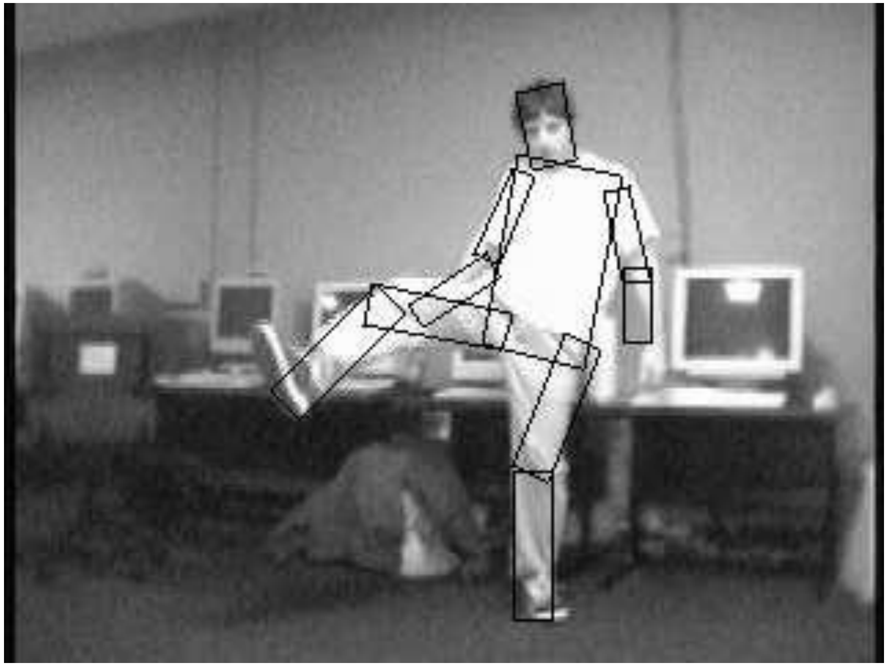
- Takes the idea a little further
- Instead of one rigid HOG model, we have multiple HOG models in a spatial arrangement
- One root part to find first and multiple other parts in a tree structure.

The Idea

Articulated parts model

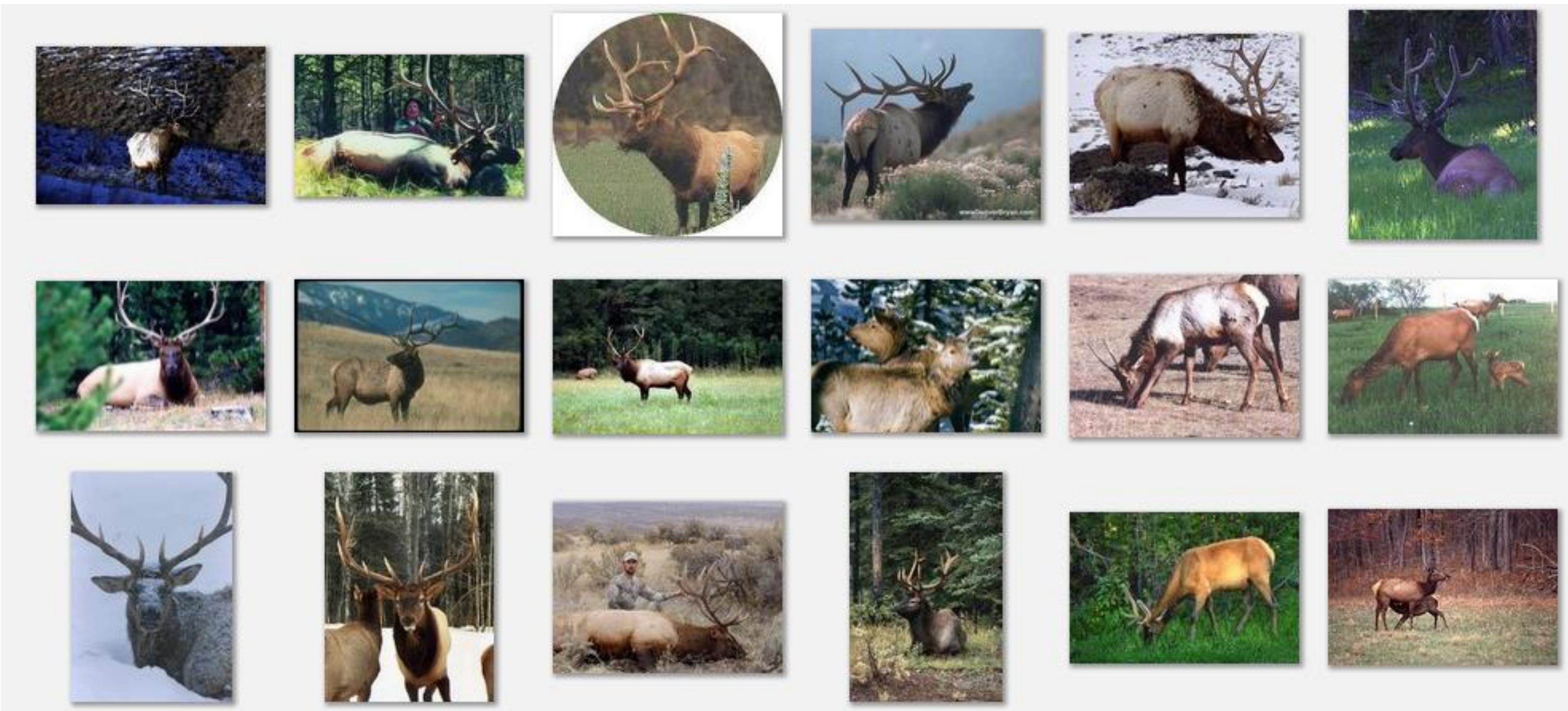
- Object is configuration of parts
- Each part is detectable





Images from Felzenszwalb

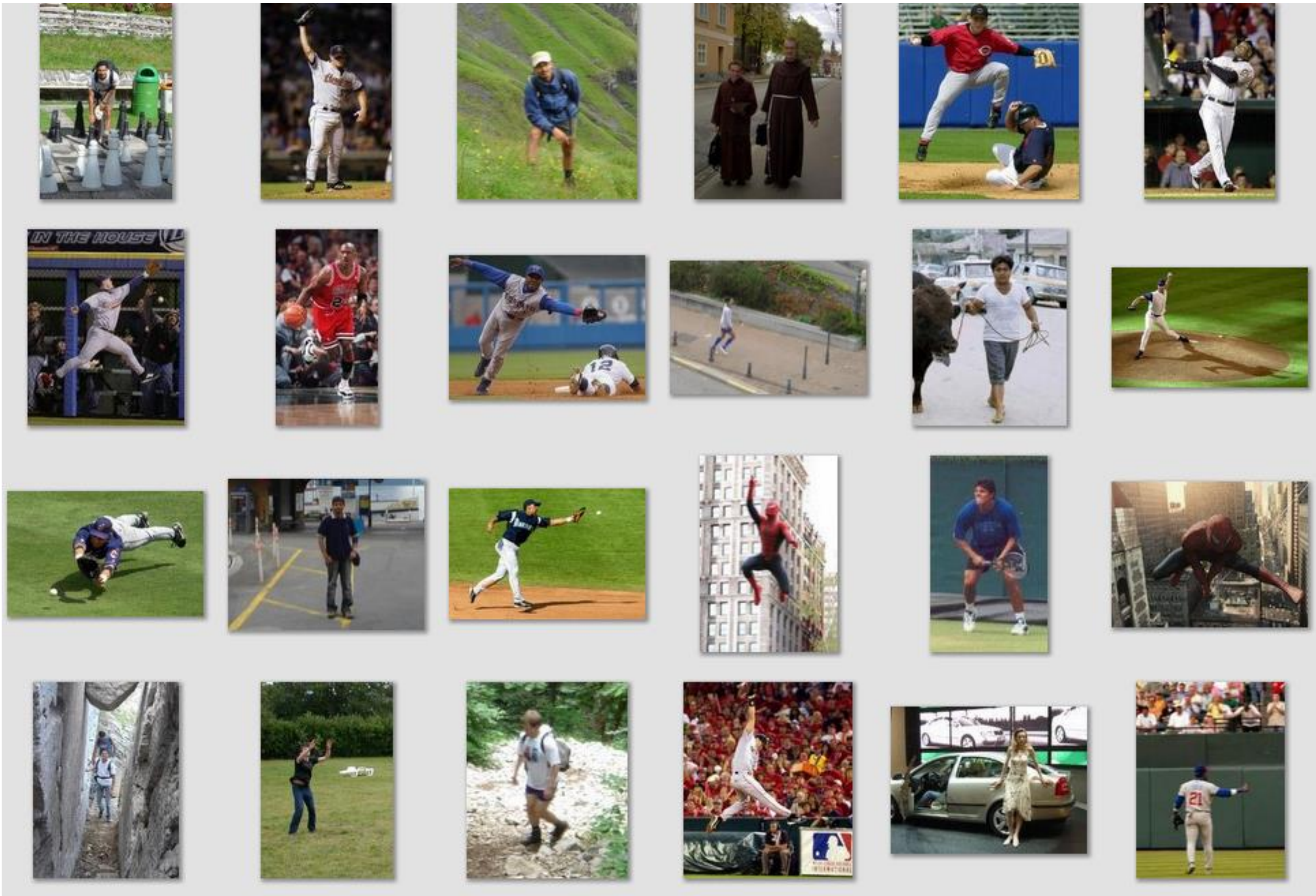
Deformable objects



Images from Caltech-256

Slide Credit: Duan Tran

Deformable objects

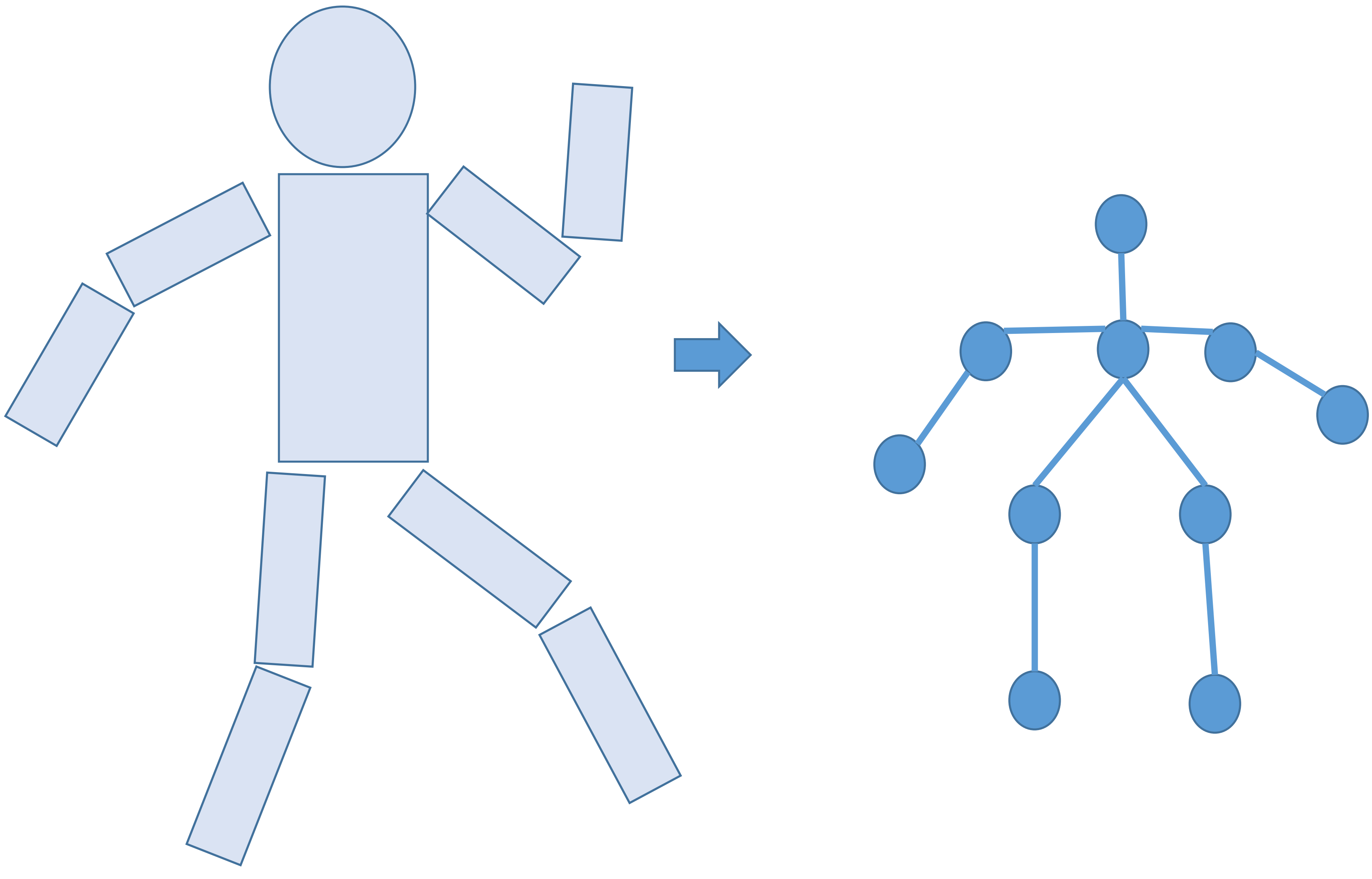


Images from D. Ramanan's dataset

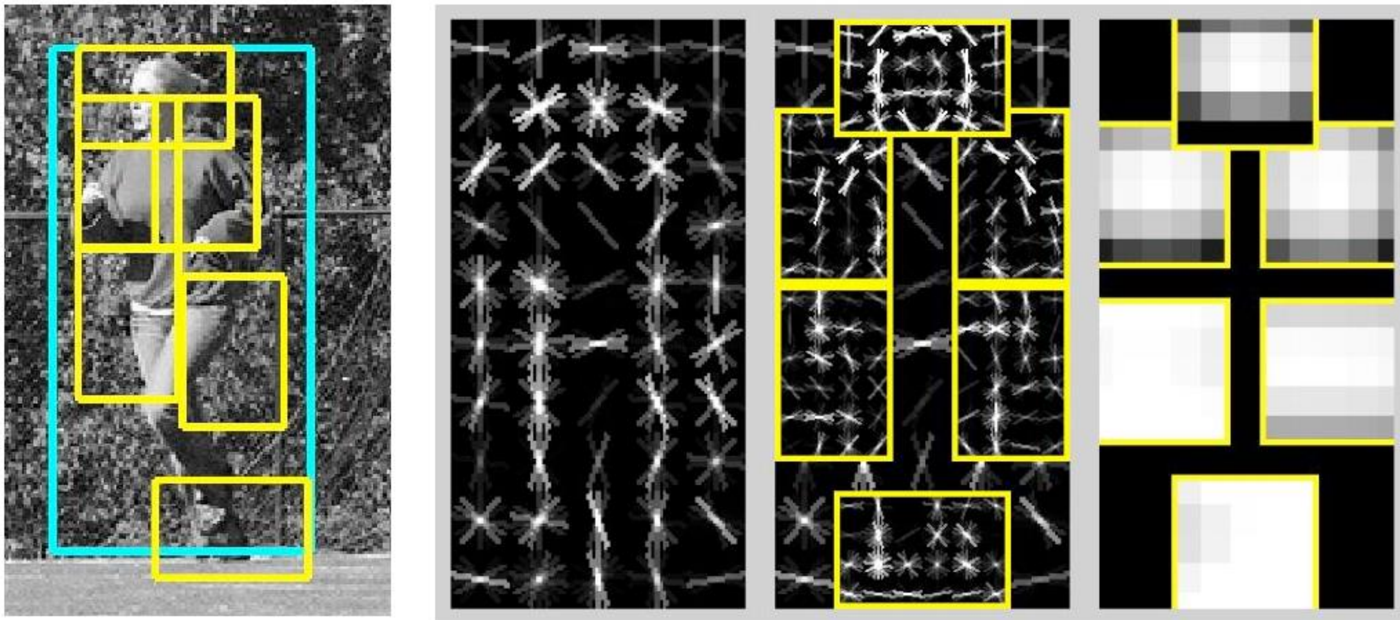
Slide Credit: Duan Tran

How to model spatial relations?

- Tree-shaped model



Model Overview

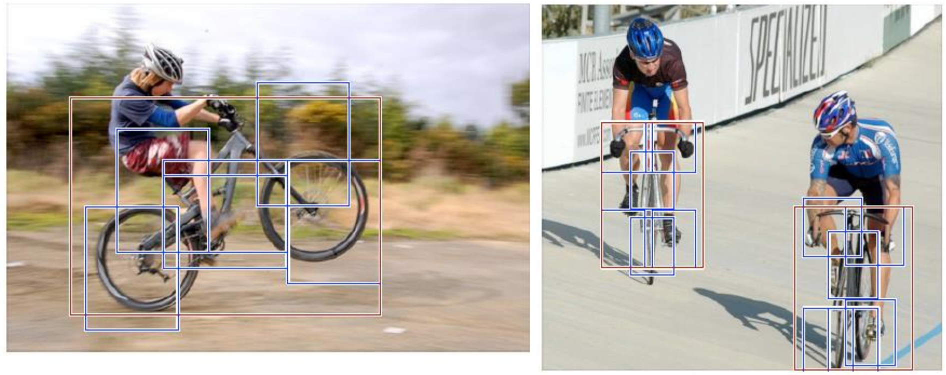


detection root filter part filters deformation models

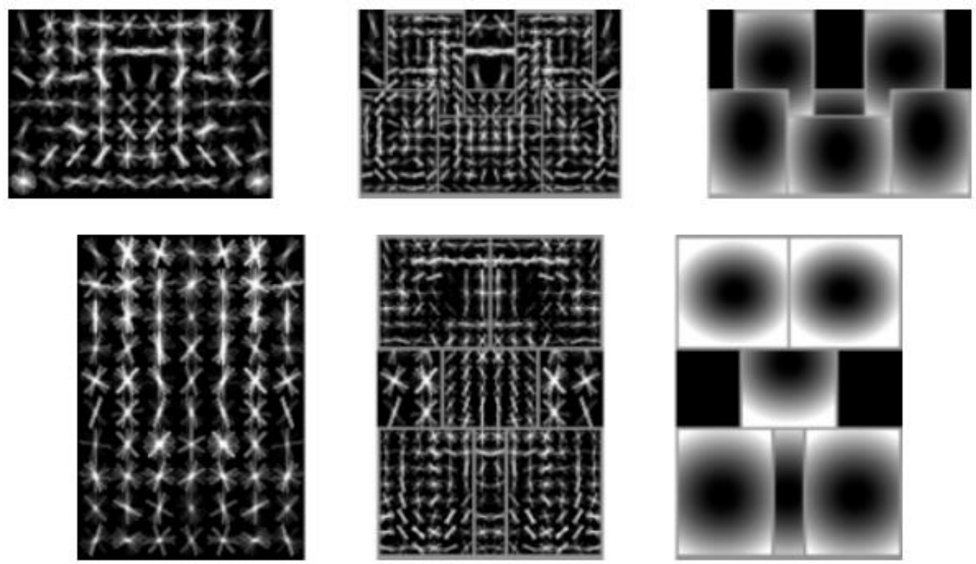
Model has a root filter plus deformable parts

Hybrid template/parts model

Detections



Template Visualization



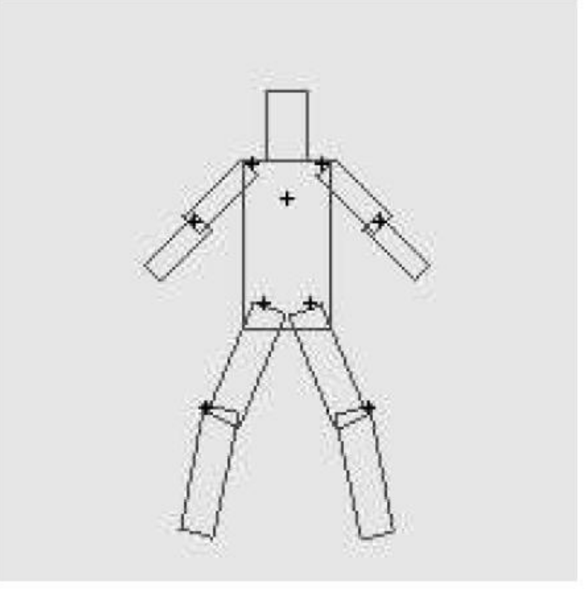
root filters
coarse resolution

part filters
finer resolution

deformation
models

Felzenszwalb et al. 2008

Pictorial Structures Model

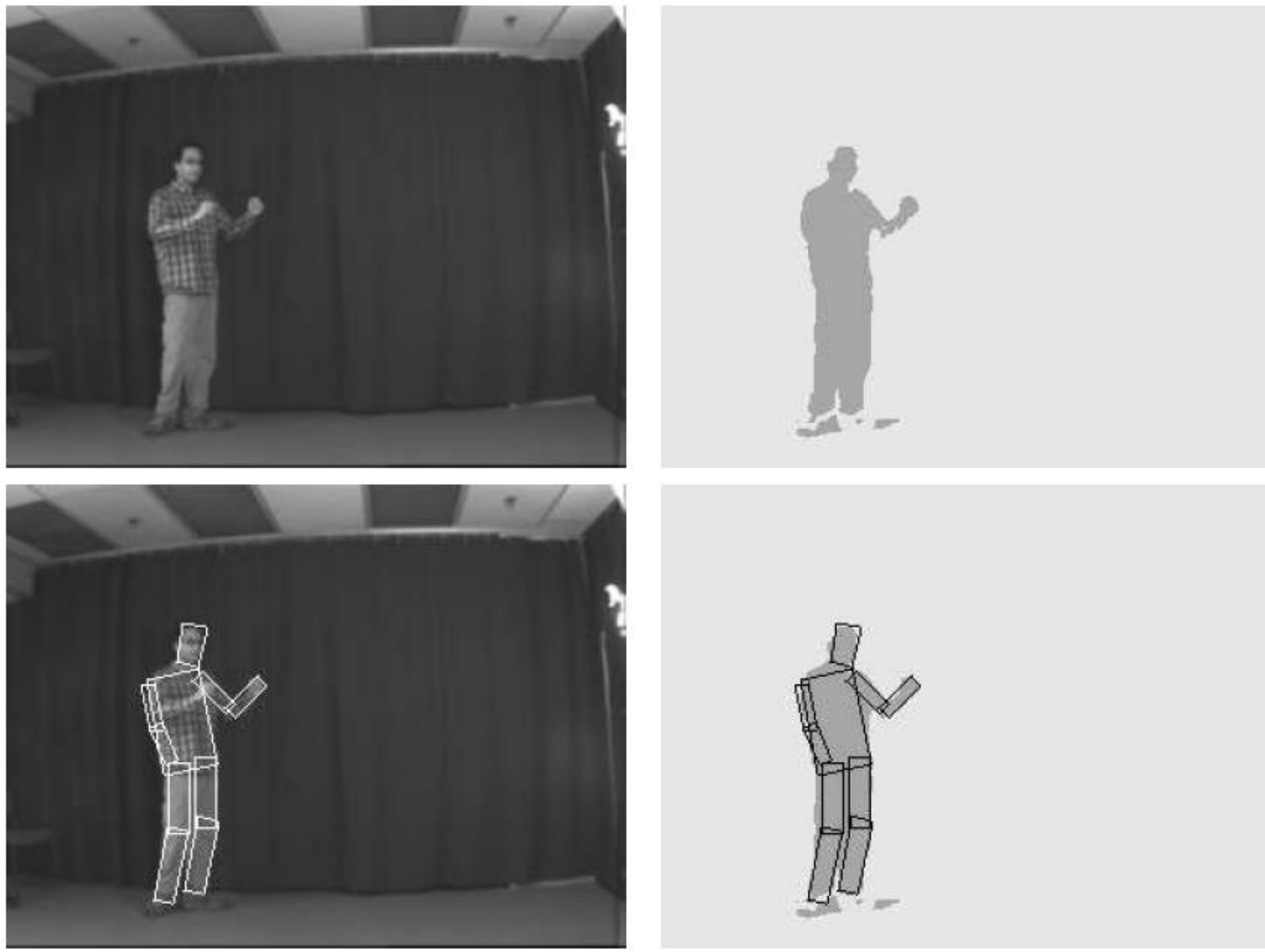


$$P(L|I,\theta) \propto \left(\prod_{i=1}^{n} p(I|l_i, u_i) \prod_{(v_i,v_j)\in E} p(l_i, l_j|c_{ij}) \right)$$

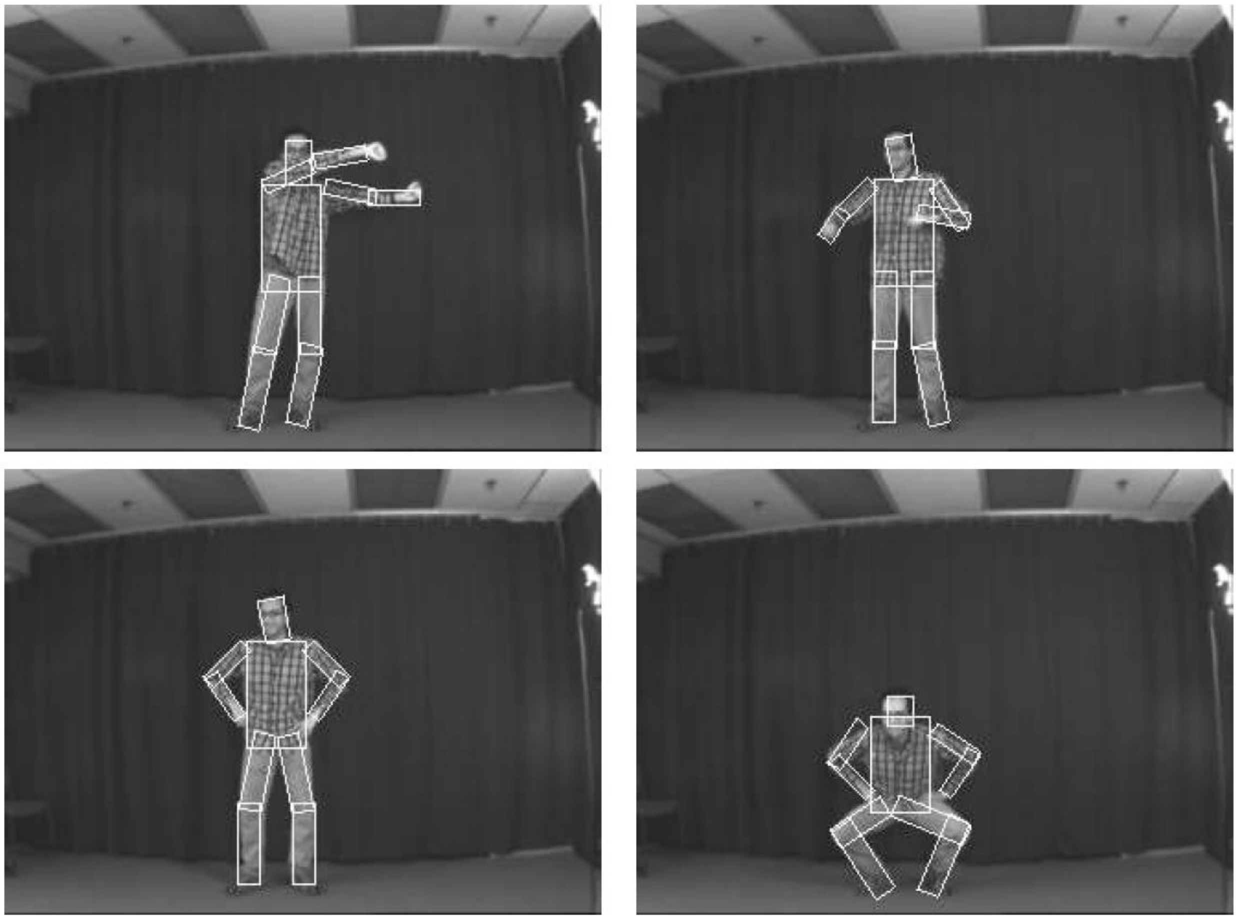
Appearance likelihood

Geometry likelihood

Results for person matching

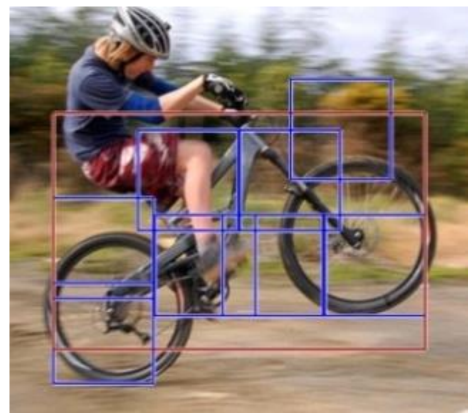


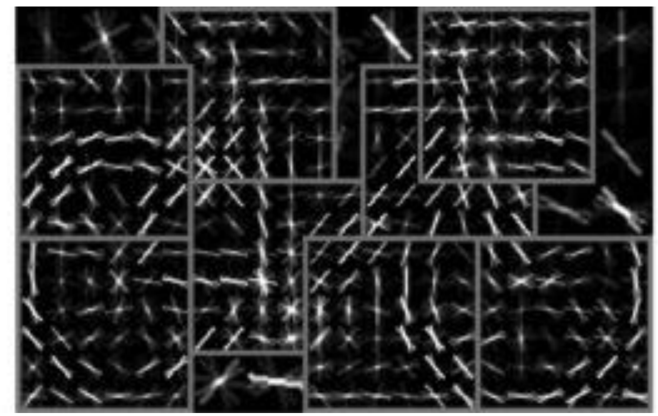
Results for person matching




1
2
3
4
5
6
a
b
c
d

2012 State-of-the-art Detector: Deformable Parts Model (DPM)





1. Strong low-level features based on HOG
2. Efficient matching algorithms for deformable part-based models (pictorial structures)
3. Discriminative learning with latent variables (latent SVM)

Felzenszwalb et al., 2008, 2010, 2011, 2012

Why did gradient-based models work?

Average gradient image

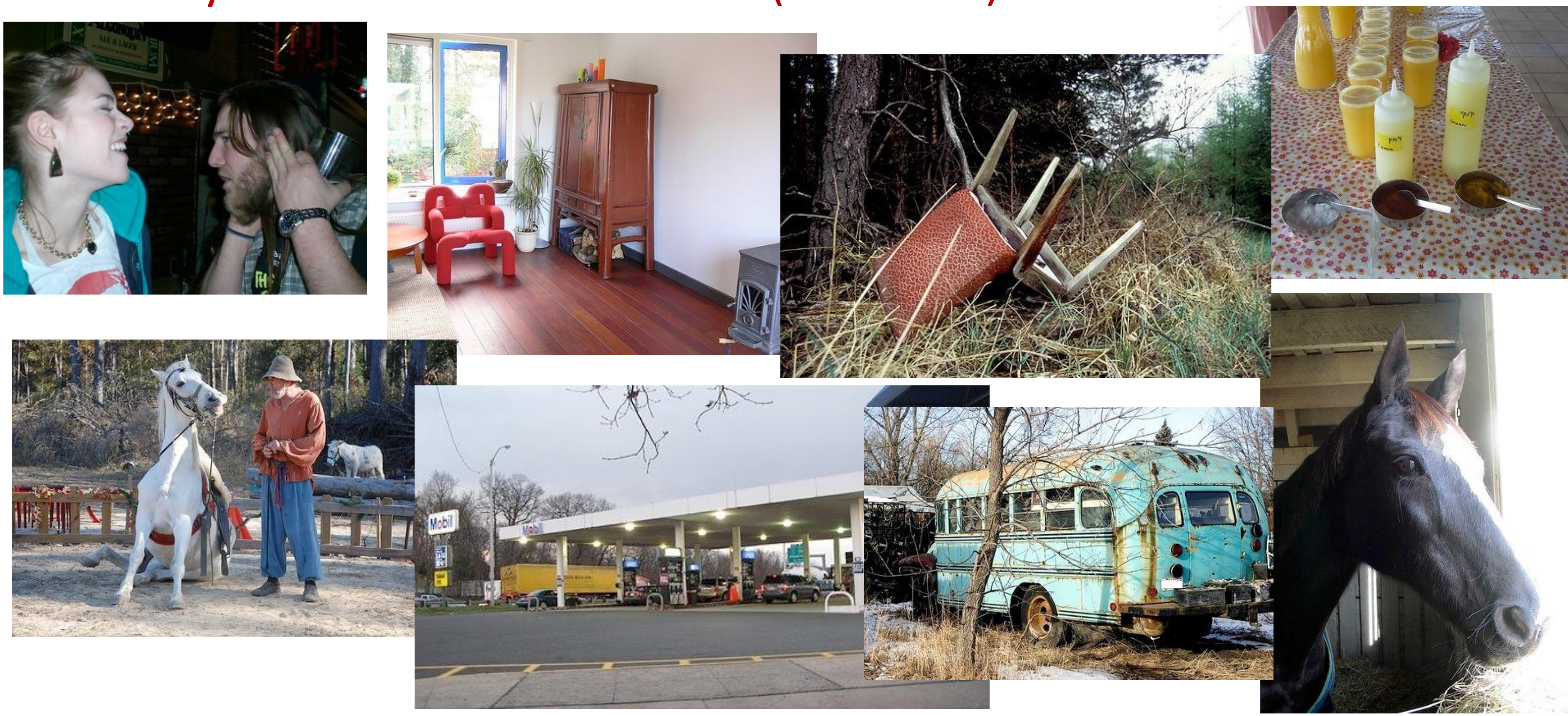
Generic categories

Can we detect people, chairs, horses, cars, dogs, buses, bottles, sheep …?

PASCAL Visual Object Categories (VOC) dataset

Generic categories

Why doesn't this work (as well)?



Can we detect people, chairs, horses, cars, dogs, buses, bottles, sheep …?

PASCAL Visual Object Categories (VOC) dataset

Quiz time
(Back to Girshick)

Warm up

This is an average image of which object class?

Warm up

pedestrian

A little harder

?

A little harder

?

Hint: airplane, bicycle, bus, car, cat, chair, cow, dog, dining table

A little harder

bicycle (PASCAL)

A little harder, yet

?

A little harder, yet

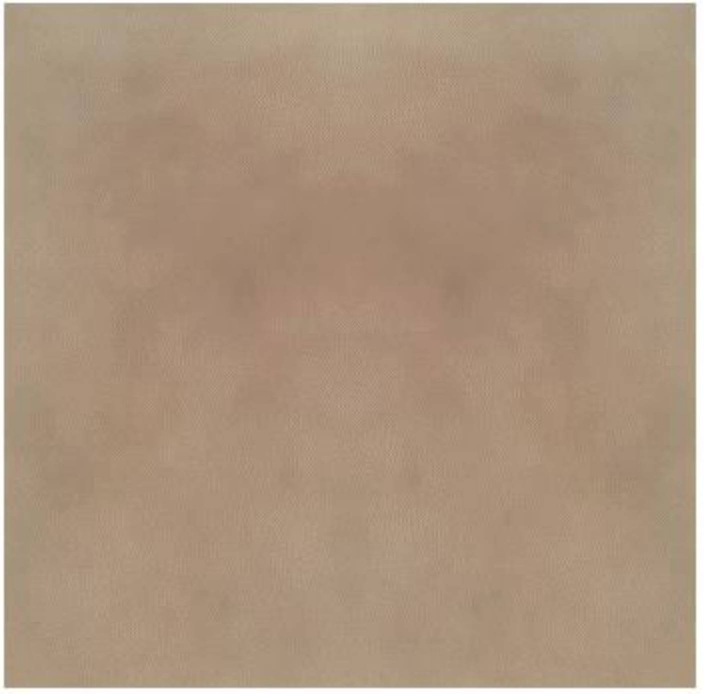
?

Hint: white blob on a green background

A little harder, yet

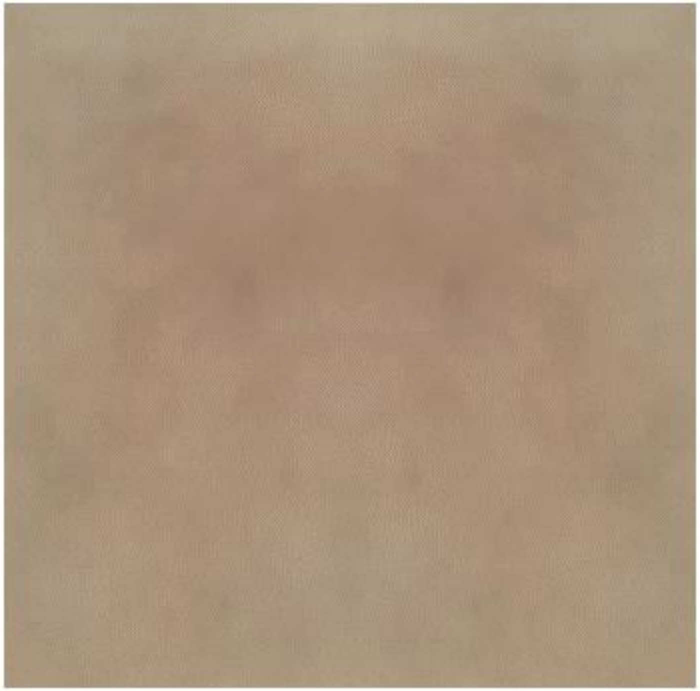
sheep (PASCAL)

Impossible?



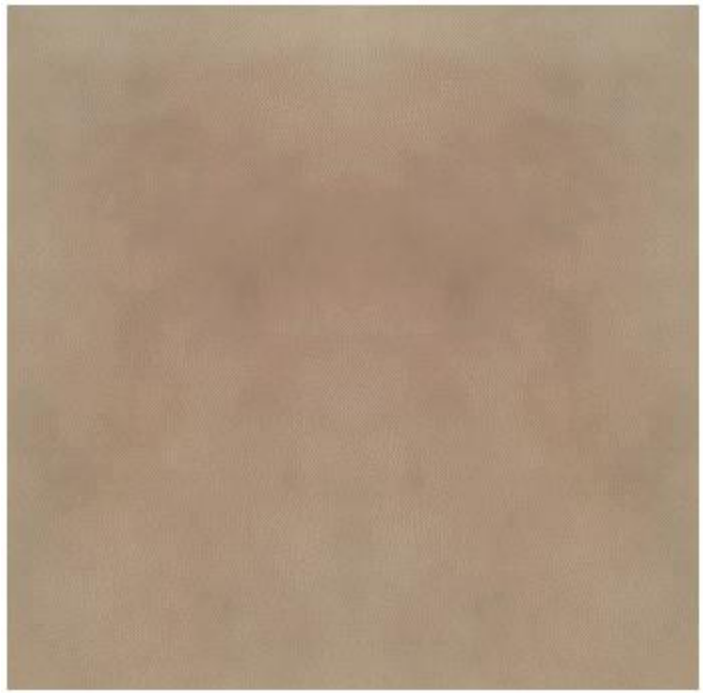
?

Impossible?



dog (PASCAL)

Impossible?



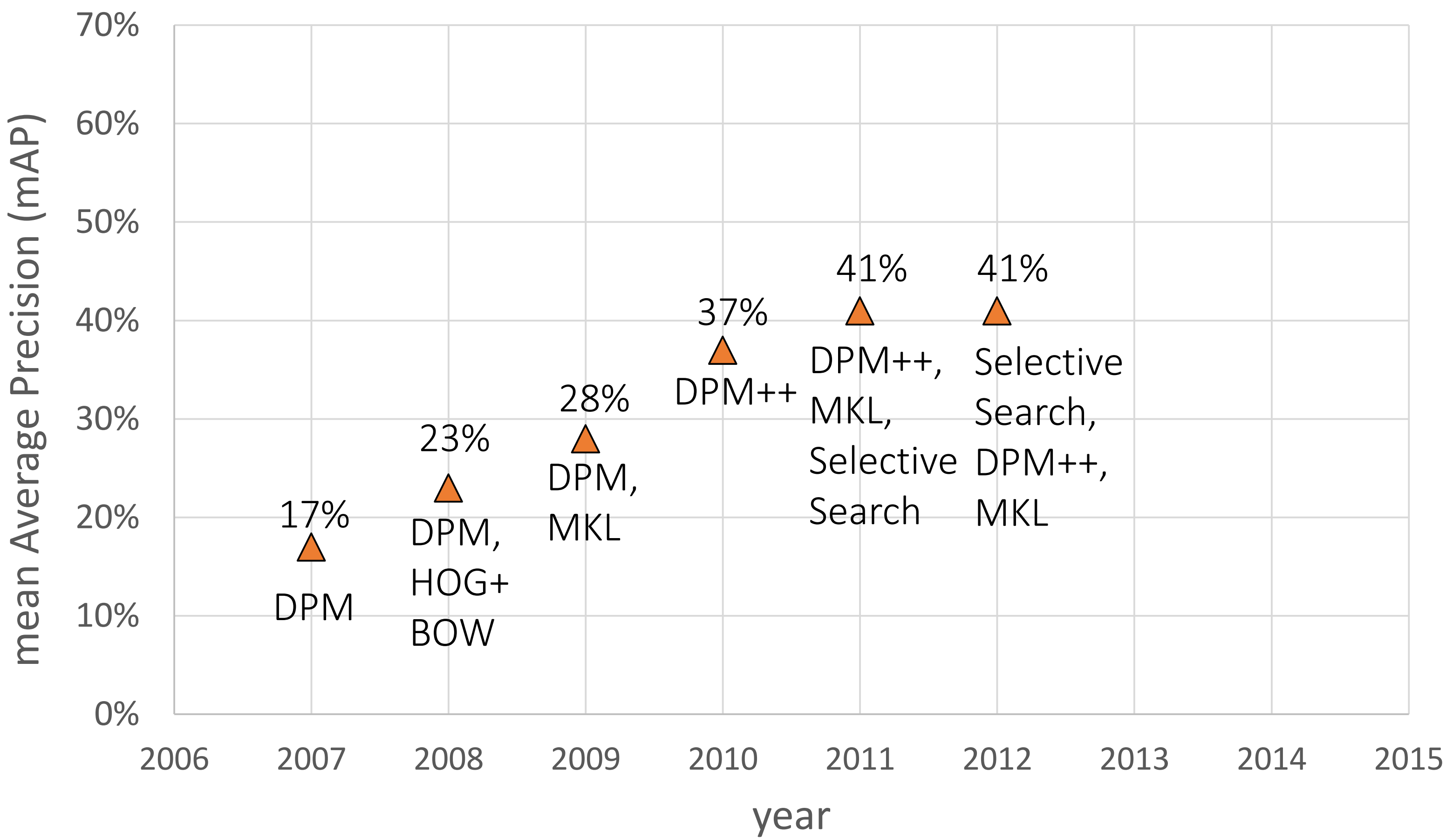
dog (PASCAL)

Why does the mean look like this?

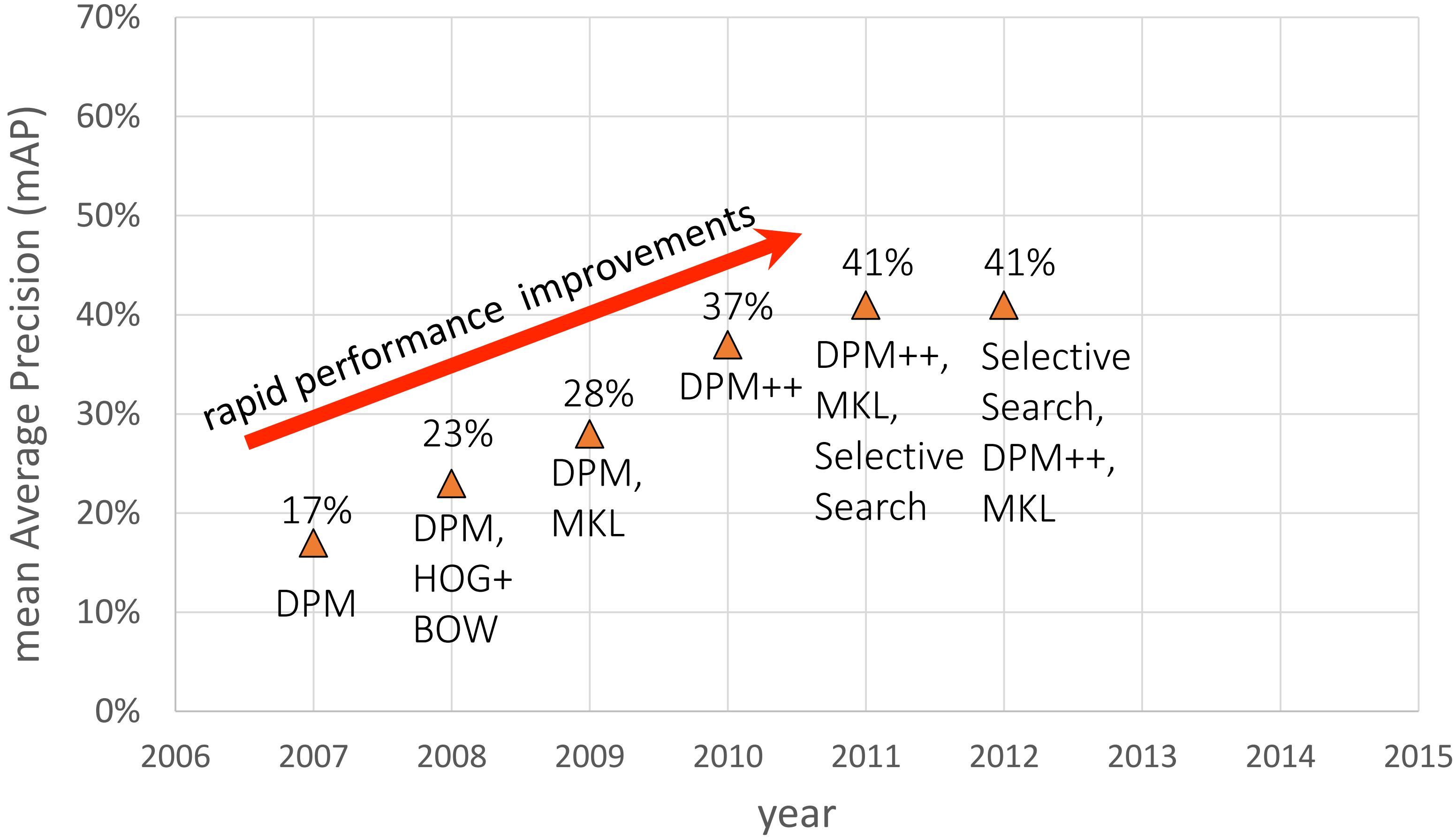
There's no alignment between the examples!

How do we combat this?

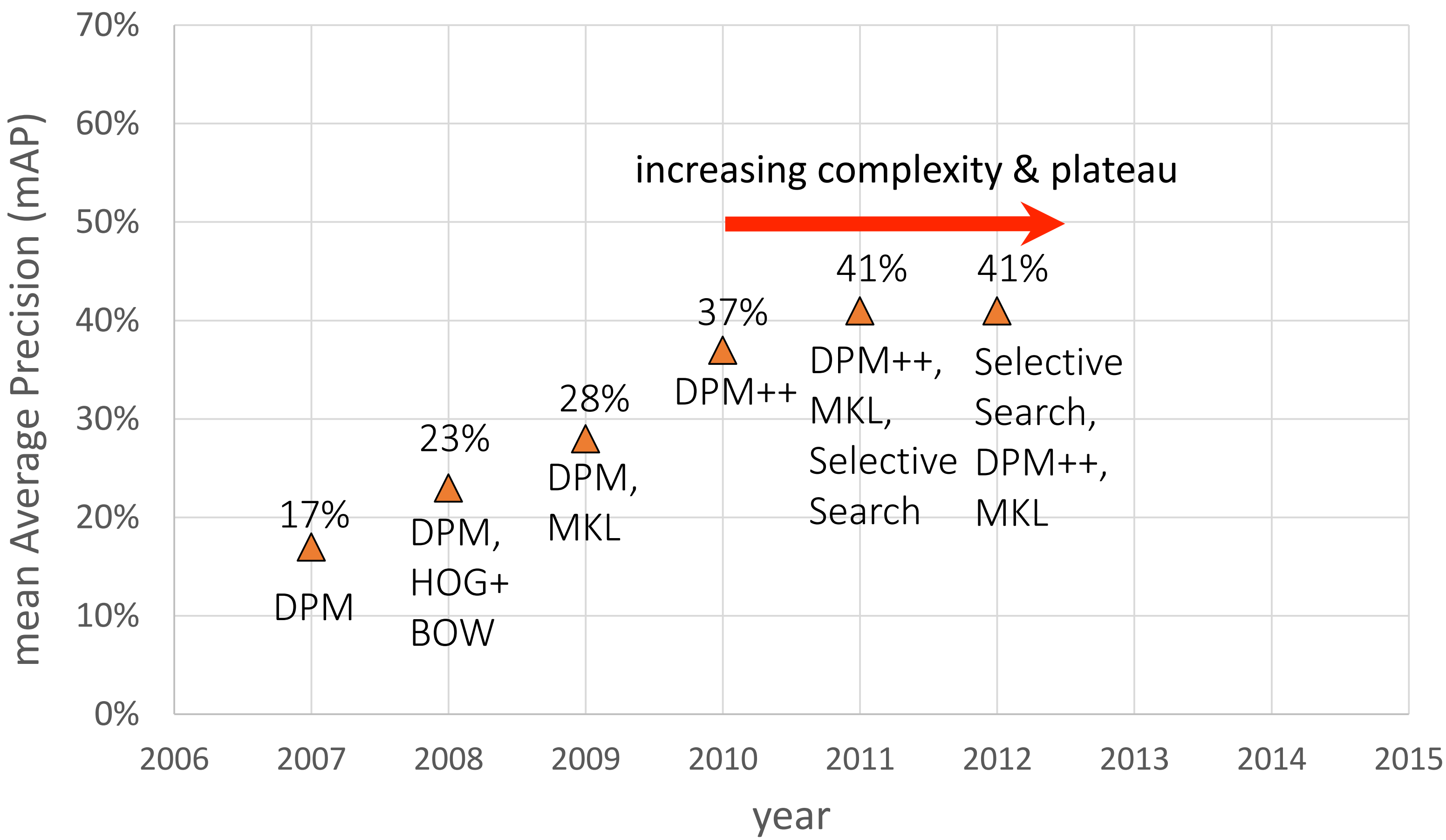
PASCAL VOC detection history



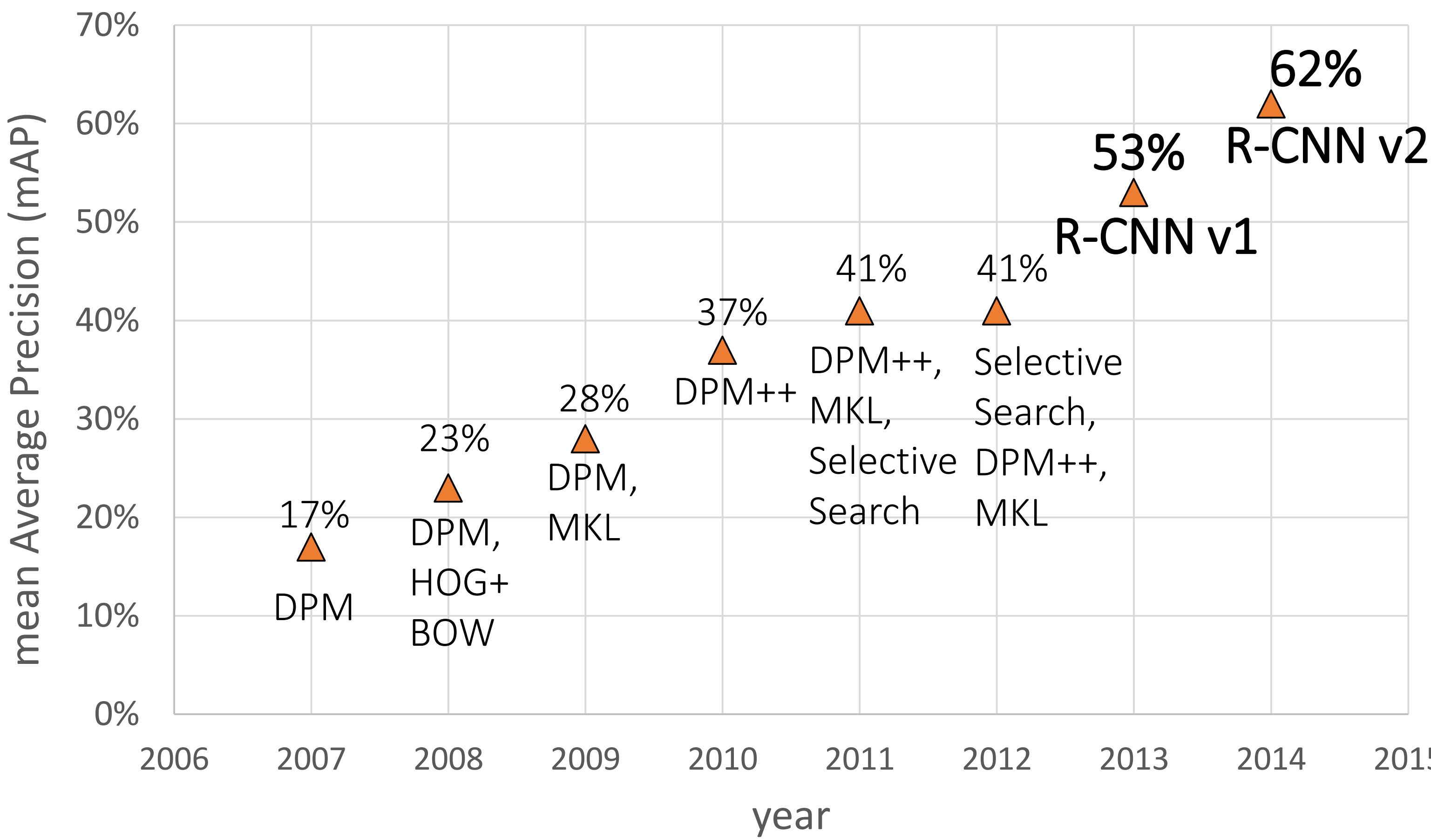
Part-based models & multiple features (MKL)



Kitchen-sink approaches

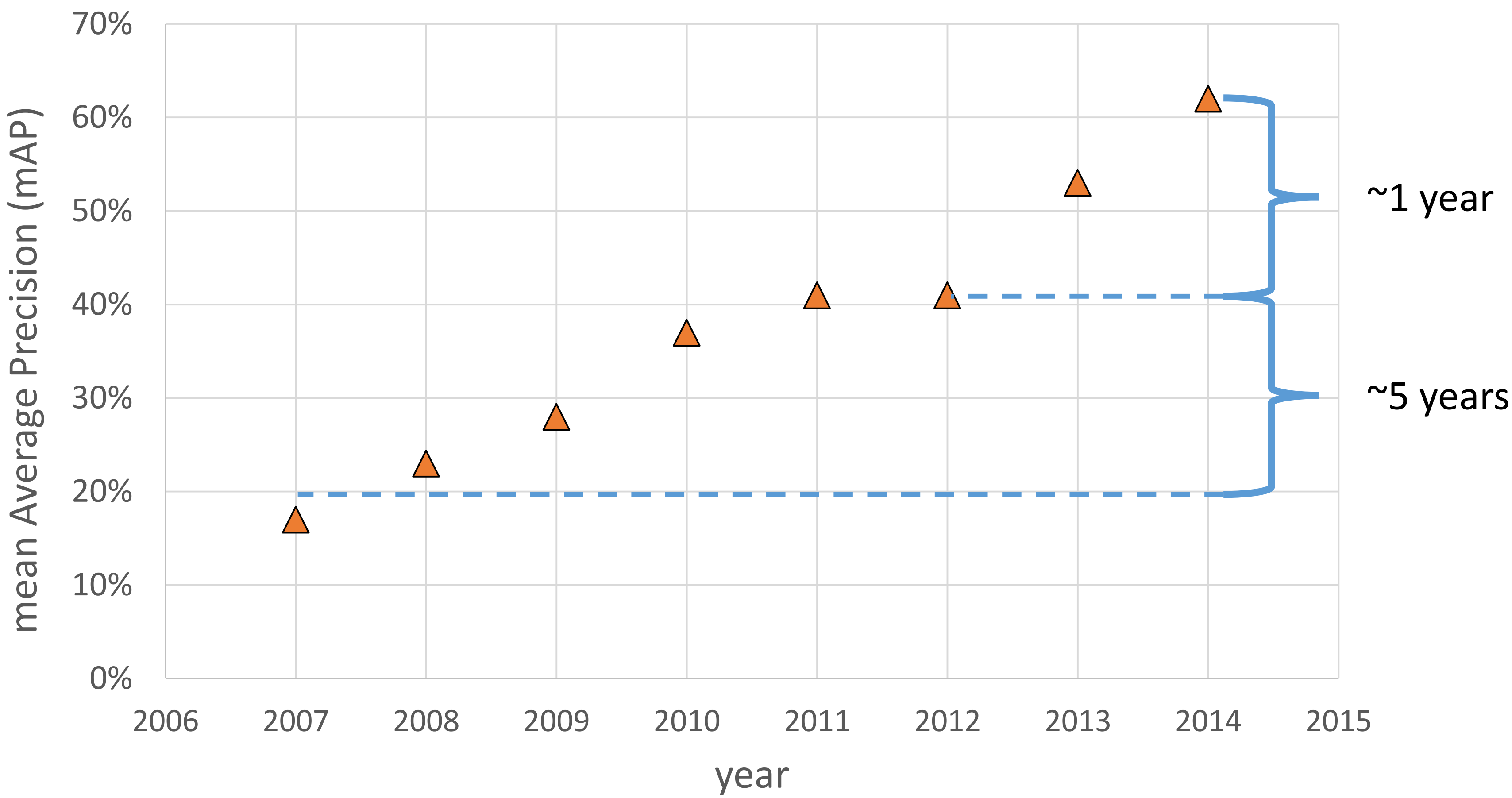


Region-based Convolutional Networks (R-CNNs)



[R-CNN. Girshick et al. CVPR 2014]

Region-based Convolutional Networks (R-CNNs)

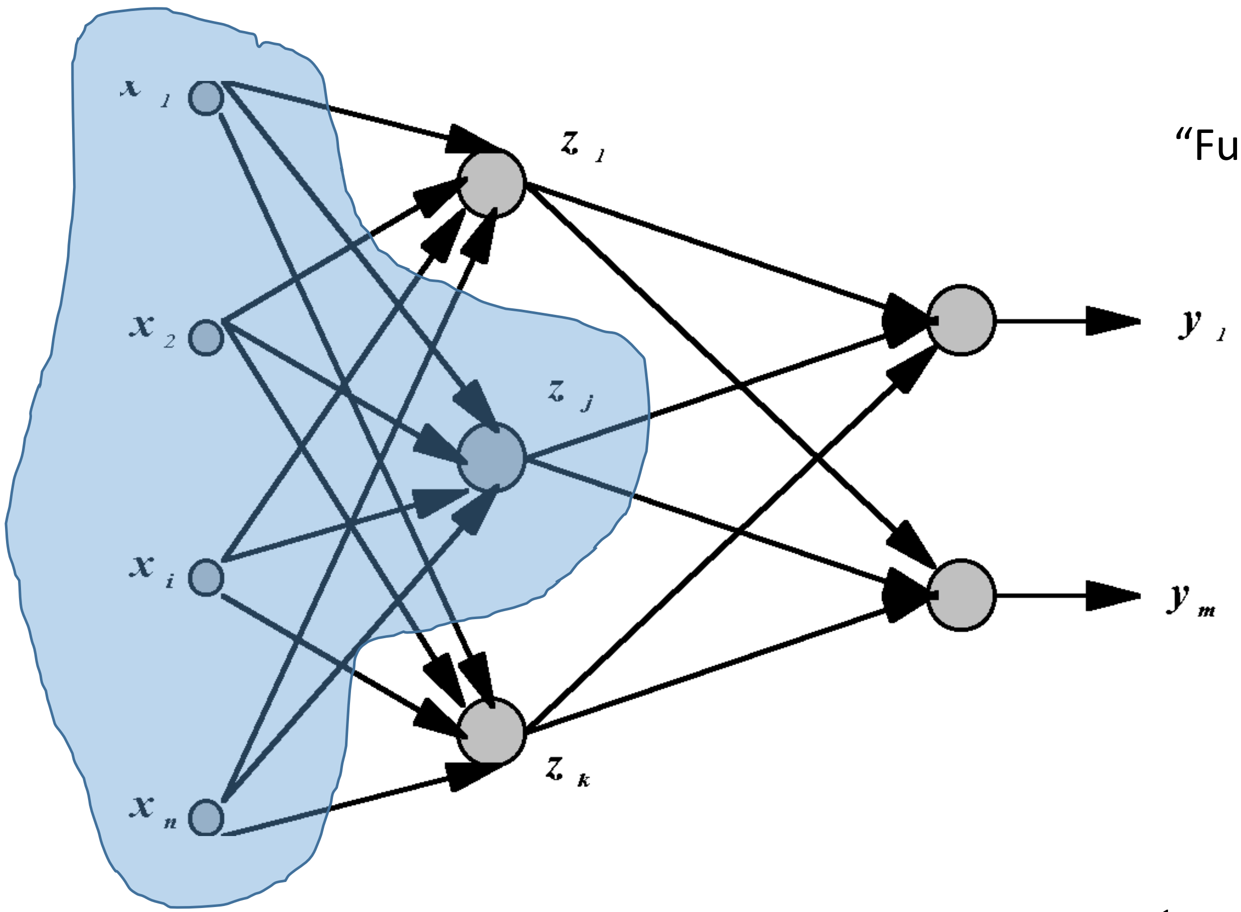


[R-CNN. Girshick et al. CVPR 2014]

Convolutional Neural Networks

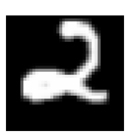
- Overview

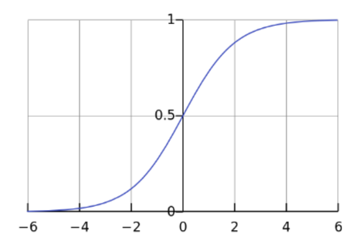
Standard Neural Networks



"Fully connected"

$$\boldsymbol{x} = (x_1, \ldots, x_{784})^T \qquad z_j = g(\boldsymbol{w}_j^T \boldsymbol{x}) \qquad g(t) = \frac{1}{1+e^{-t}}$$

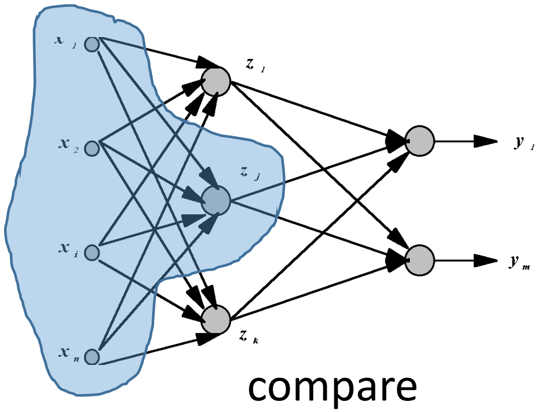




From NNs to Convolutional NNs

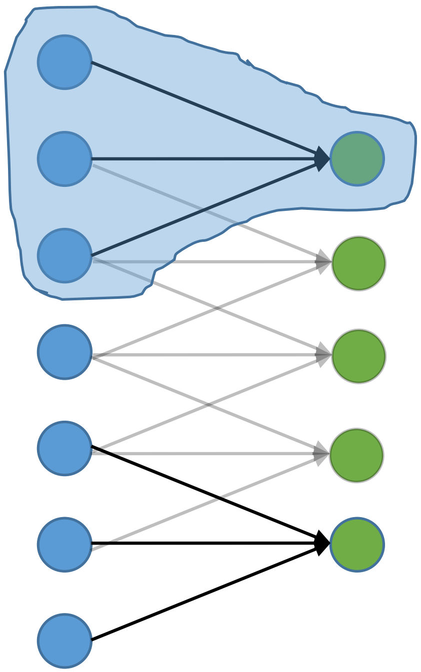
- Local connectivity
- Shared (“tied”) weights
- Multiple feature maps
- Pooling

Convolutional NNs



compare

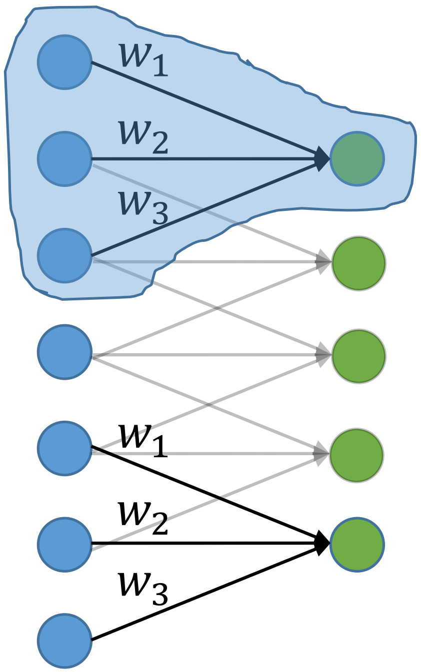
- Local connectivity



- Each green unit is only connected to (3) **neighboring** blue units

Convolutional NNs

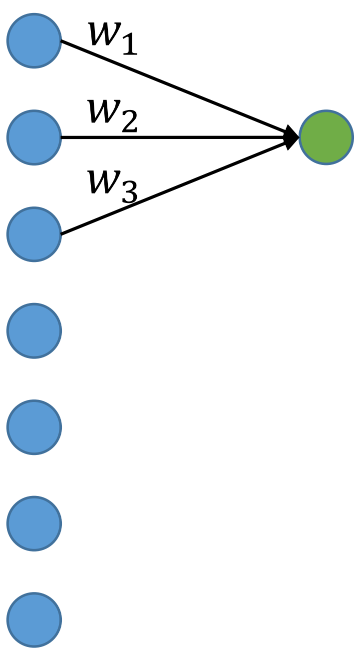
- Shared ("tied") weights



- All green units **share** the same parameters $\boldsymbol{w}$
- Each green unit computes the **same function,** but with a **different input window**

Convolutional NNs

- Convolution with 1-D filter: $[w_3, w_2, w_1]$



- All green units **share** the same parameters $\boldsymbol{w}$
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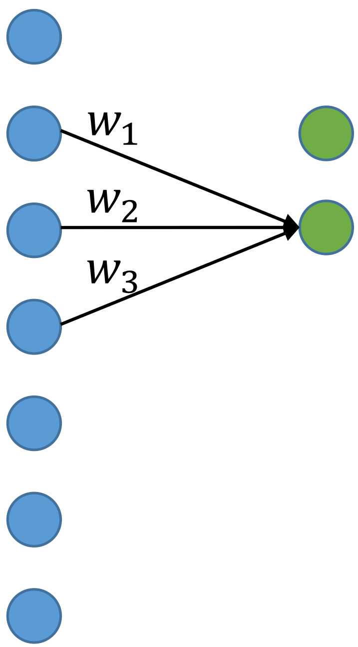
Convolutional NNs

- Convolution with 1-D filter: $[w_3, w_2, w_1]$



- All green units **share** the same parameters $\boldsymbol{w}$
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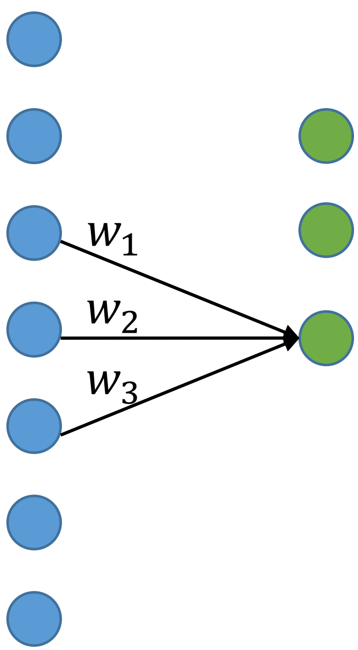
Convolutional NNs

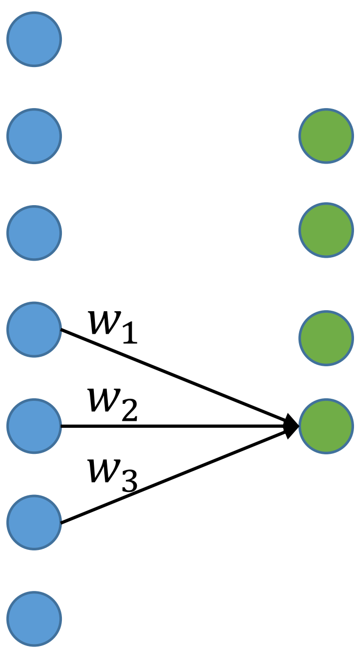
- Convolution with 1-D filter: $[w_3, w_2, w_1]$



- All green units **share** the same parameters $\boldsymbol{w}$
- Each green unit computes the **same function,** but with a **different input window**

Convolutional NNs

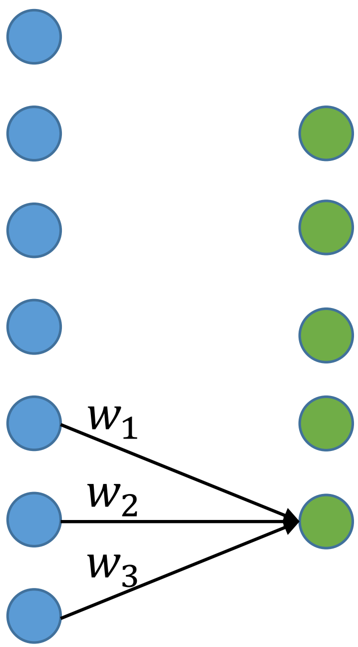
- Convolution with 1-D filter: $[w_3, w_2, w_1]$



- All green units **share** the same parameters $\boldsymbol{w}$
- Each green unit computes the **same function,** but with a **different input window**

Convolutional NNs

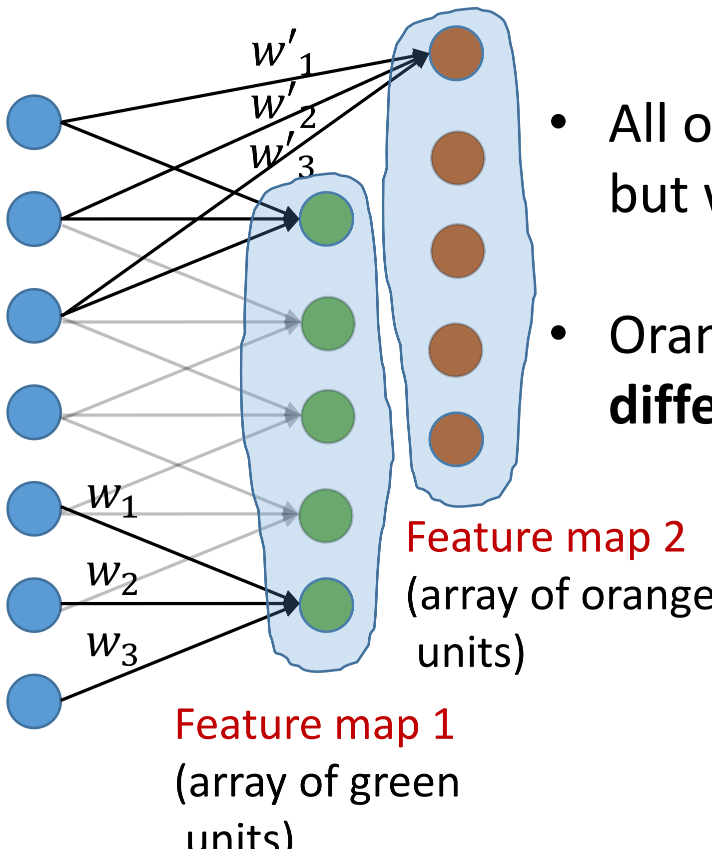
- Convolution with 1-D filter: $[w_3, w_2, w_1]$



- All green units **share** the same parameters $\boldsymbol{w}$
- Each green unit computes the **same function,** but with a **different input window**

Convolutional NNs

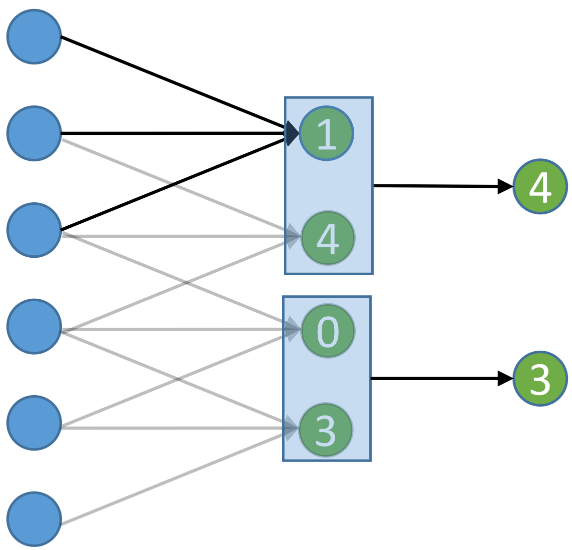
- Multiple feature maps



- All orange units compute the **same function** but with a **different input windows**
- Orange and green units **compute different functions**

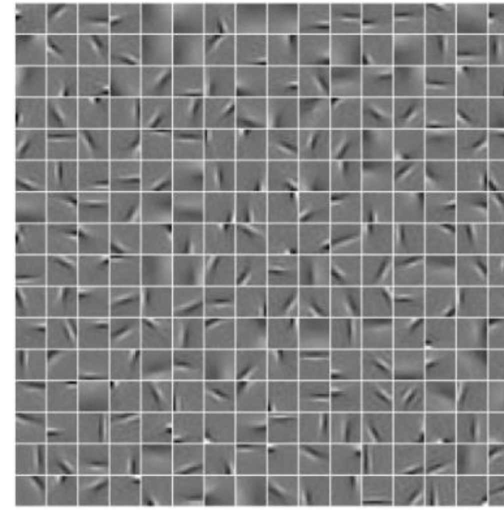
Convolutional NNs

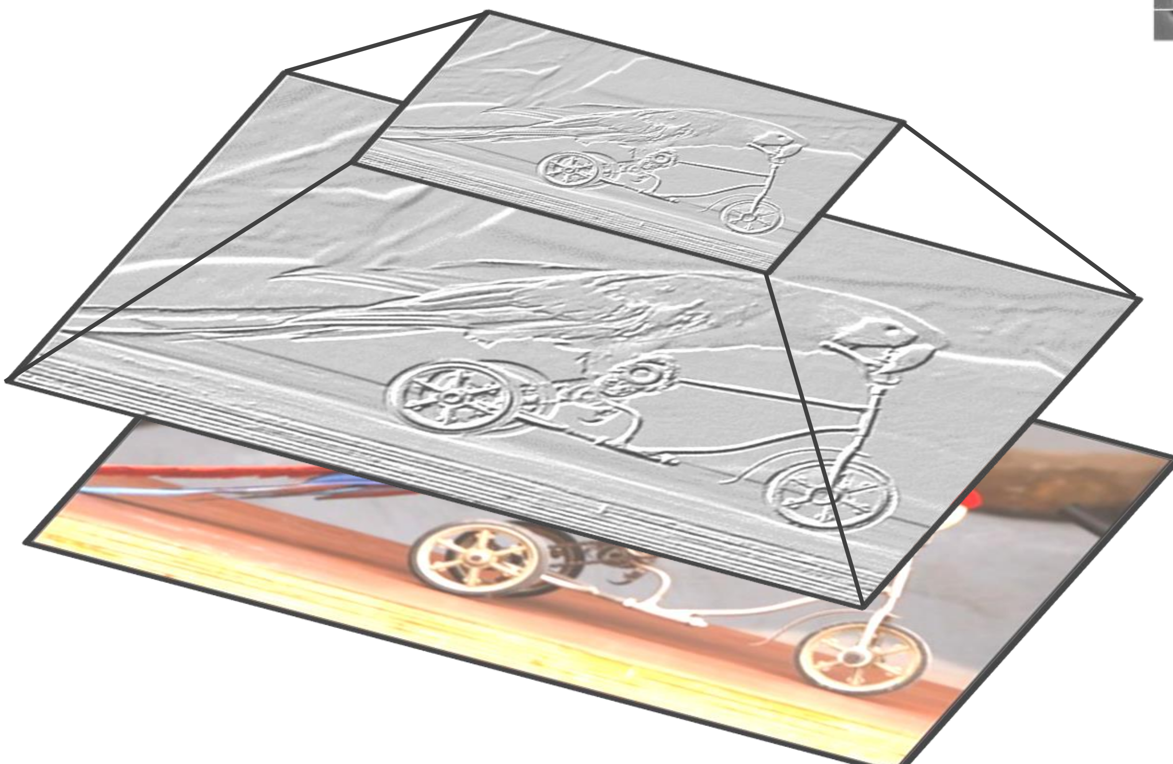
- Pooling (max, average)



- Pooling area: 2 units
- Pooling stride: 2 units
- **Subsamples** feature maps

2D input



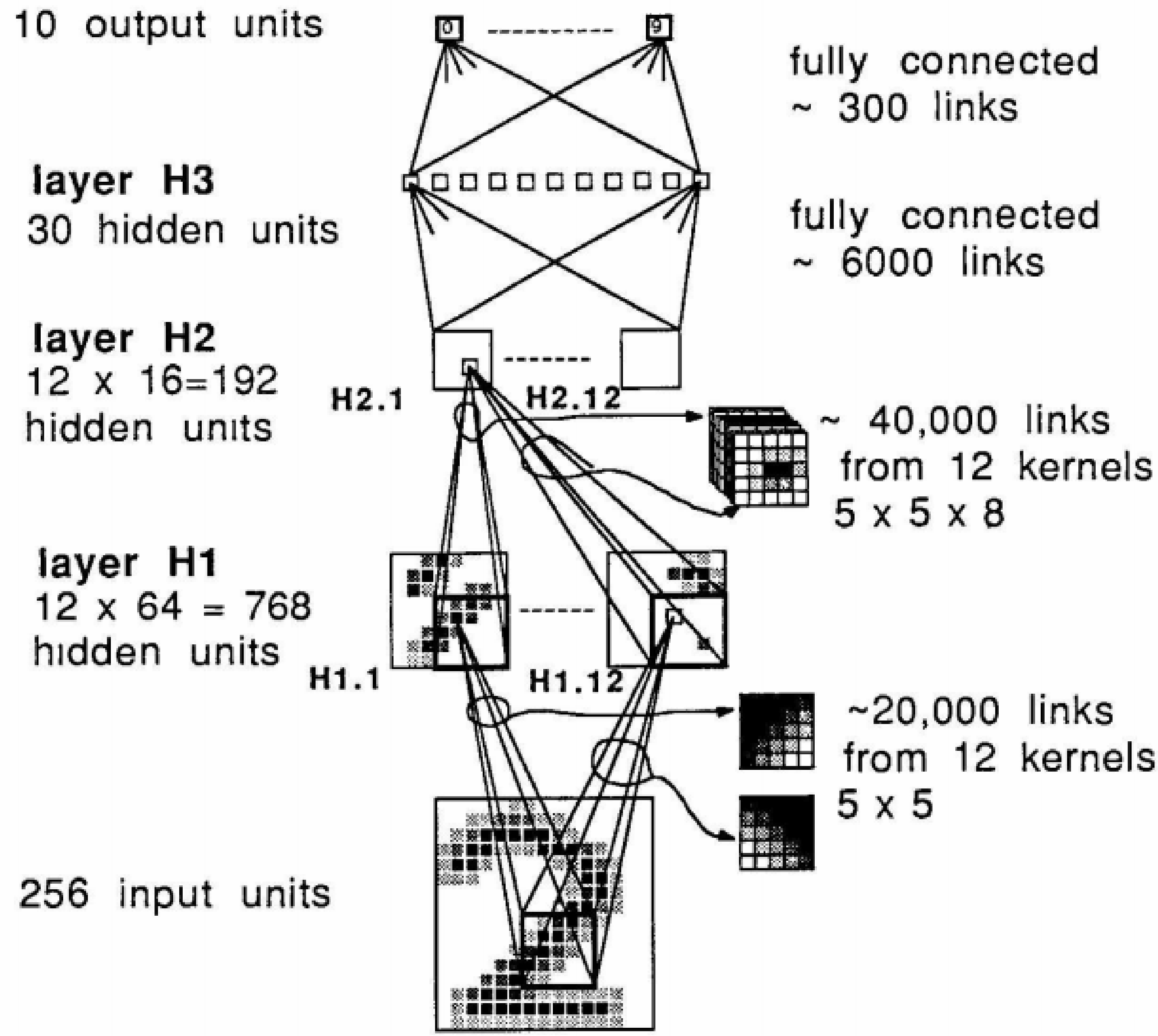


Pooling

Convolution

Image

1989



Backpropagation applied to handwritten zip code recognition,
Lecun et al., 1989

Historical perspective – 1980

Biol. Cybernetics 36, 193–202 (1980)

Biological
Cybernetics

Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

Kunihiko Fukushima

NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan

Historical perspective – 1980

Hubel and Wiesel
1962

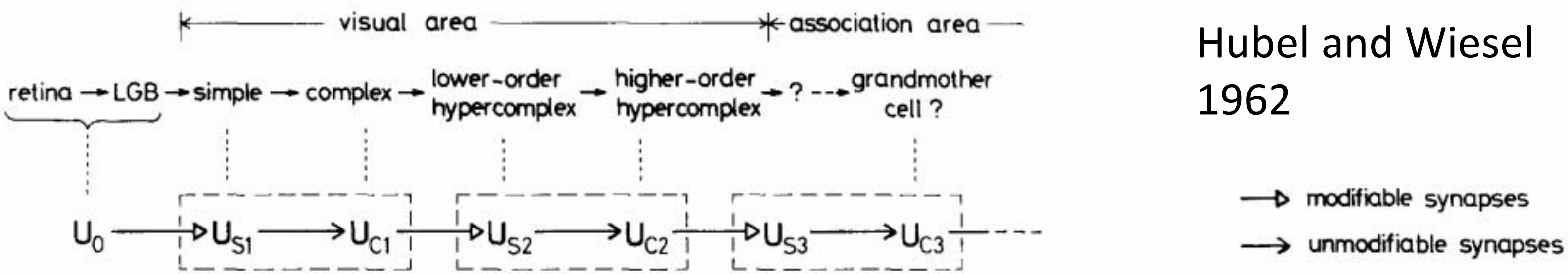


Fig. 1. Correspondence between the hierarchy model by Hubel and Wiesel, and the neural network of the neocognitron

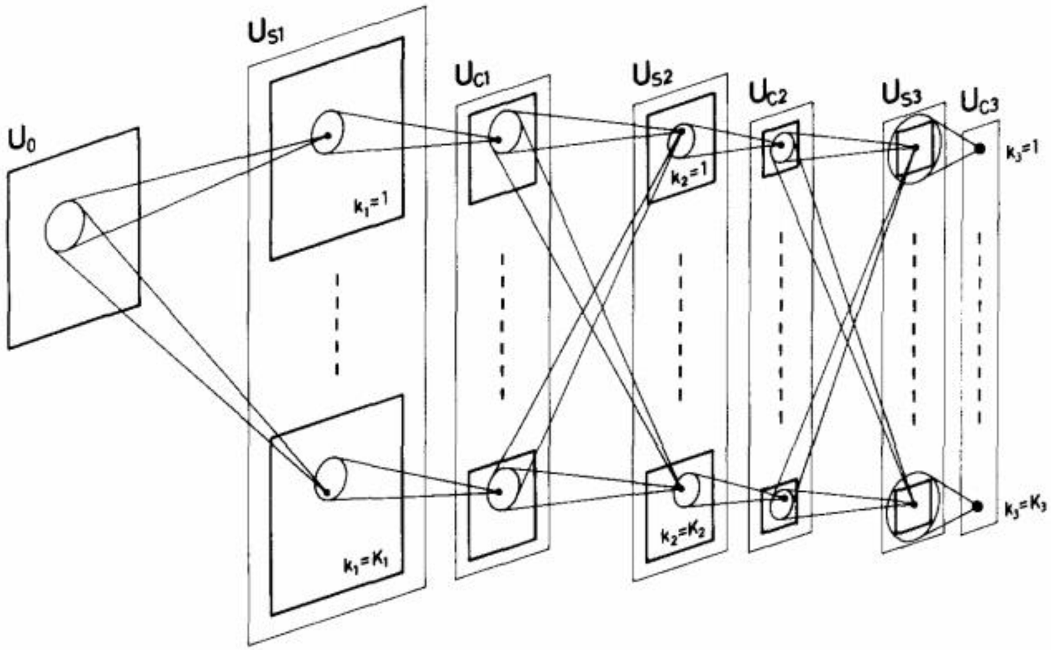


Fig. 2. Schematic diagram illustrating the interconnections between layers in the neocognitron

Included basic ingredients of ConvNets, but no supervised learning algorithm

Supervised learning – 1986

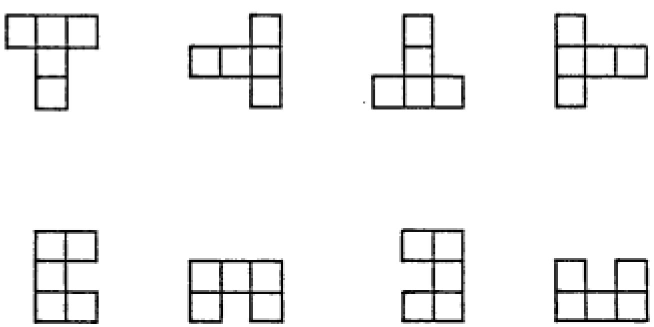
Gradient descent training with error backpropagation

Learning Internal Representations by Error Propagation

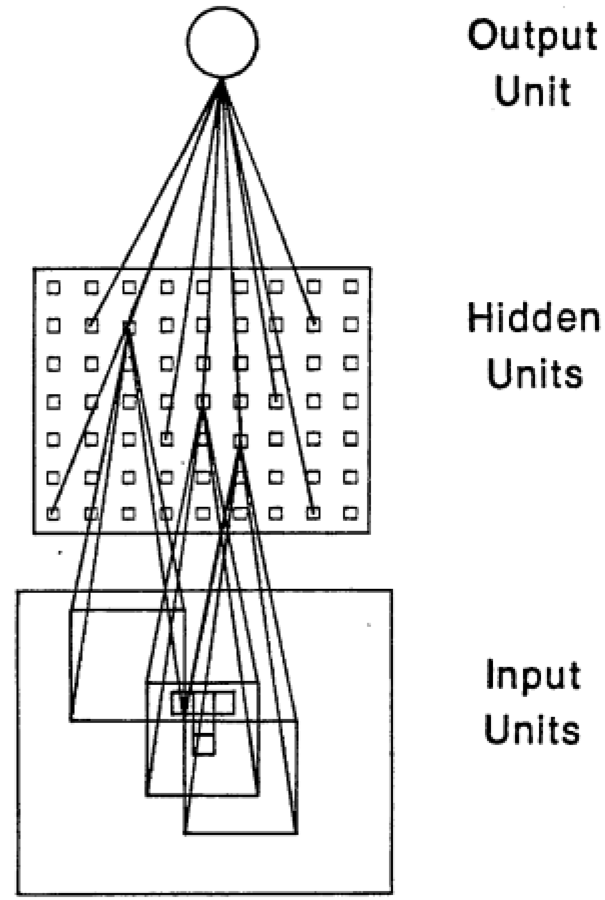
D. E. RUMELHART, G. E. HINTON, and R. J. WILLIAMS

Early demonstration that error backpropagation can be used for supervised training of neural nets (including ConvNets)

Supervised learning – 1986

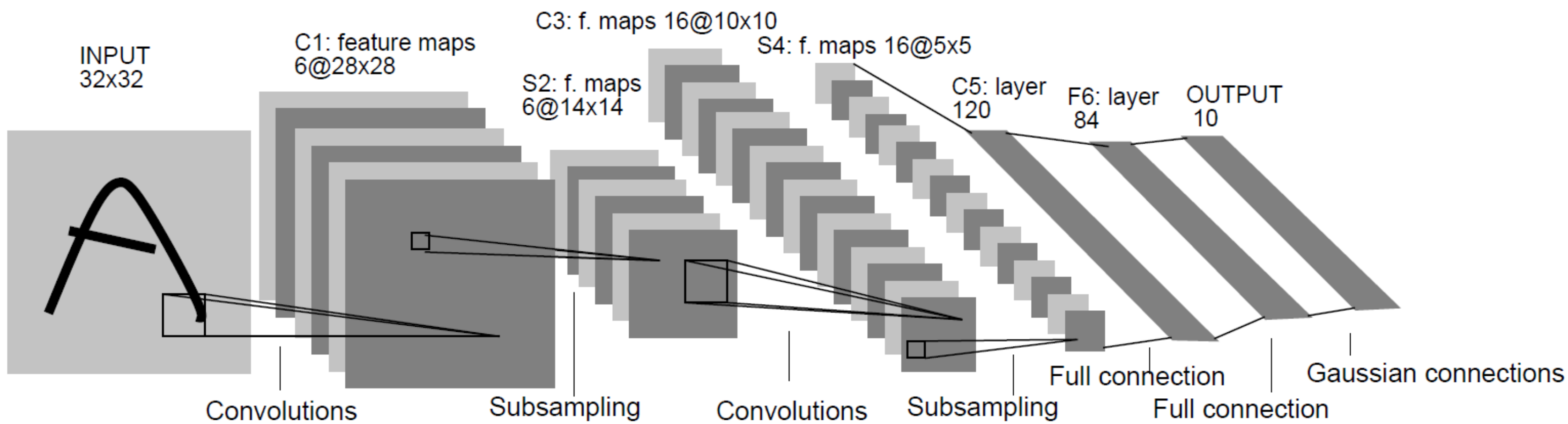


“T” vs. “C” problem



Simple ConvNet

Practical ConvNets



Gradient-Based Learning Applied to Document Recognition,
Lecun et al., 1998

Demo

- http://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html
- ConvNetJS by Andrej Karpathy (Ph.D. student at Stanford)

Software libraries

- Caffe (C++, python, matlab)
- Torch7 (C++, lua)
- Theano (python)

The fall of ConvNets

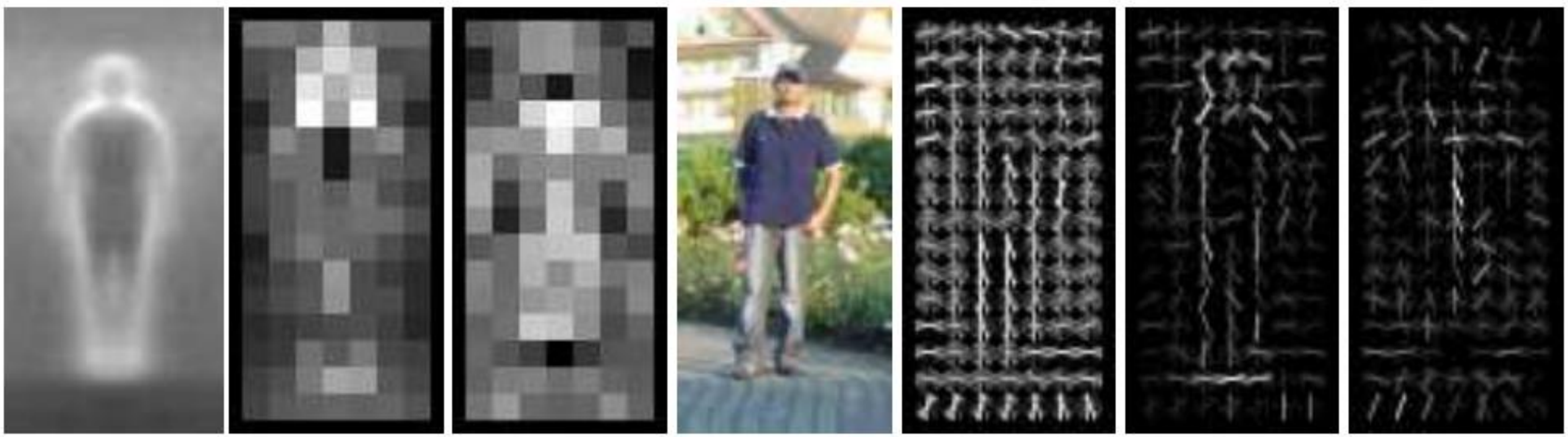
- The rise of Support Vector Machines (SVMs)
- Mathematical advantages (theory, convex optimization)
- Competitive performance on tasks such as digit classification
- Neural nets became unpopular in the mid 1990s

The key to SVMs

- *It's all about the features*

HOG features SVM weights

(+) (-)



(a) (b) (c) (d) (e) (f) (g)

Histograms of Oriented Gradients for Human Detection,
Dalal and Triggs, CVPR 2005

Core idea of “deep learning”

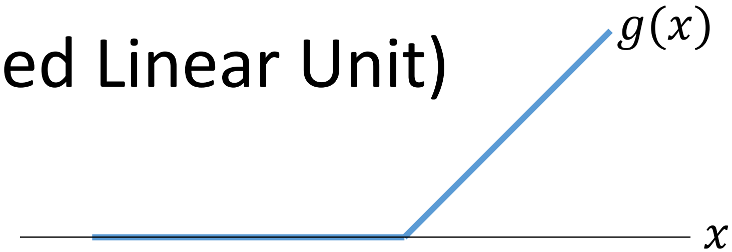
- Input: the “*raw*” signal (image, waveform, …)

- Features: hierarchy of features is *learned* from the raw input

- If SVMs killed neural nets, how did they come back (in computer vision)?

What’s new since the 1980s?

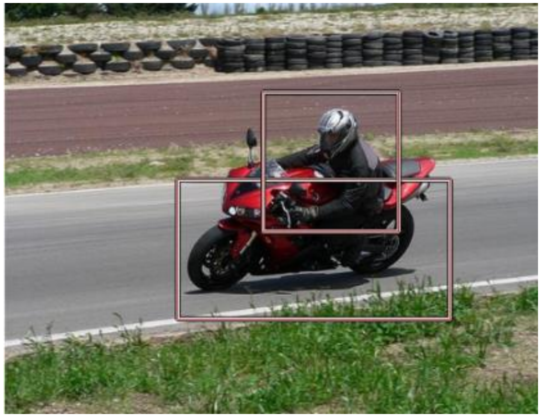
- More layers
  - LeNet-3 and LeNet-5 had 3 and 5 learnable layers
  - Current models have 8 – 20+
- “ReLU” non-linearities (Rectified Linear Unit)
  - $g(x) = \max(0, x)$
  - Gradient doesn’t vanish



- “Dropout” regularization
- Fast GPU implementations
- More data

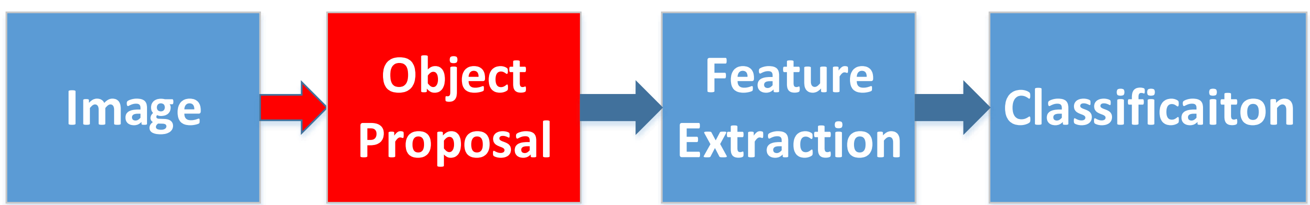
What else? Object Proposals

- Sliding window based object detection

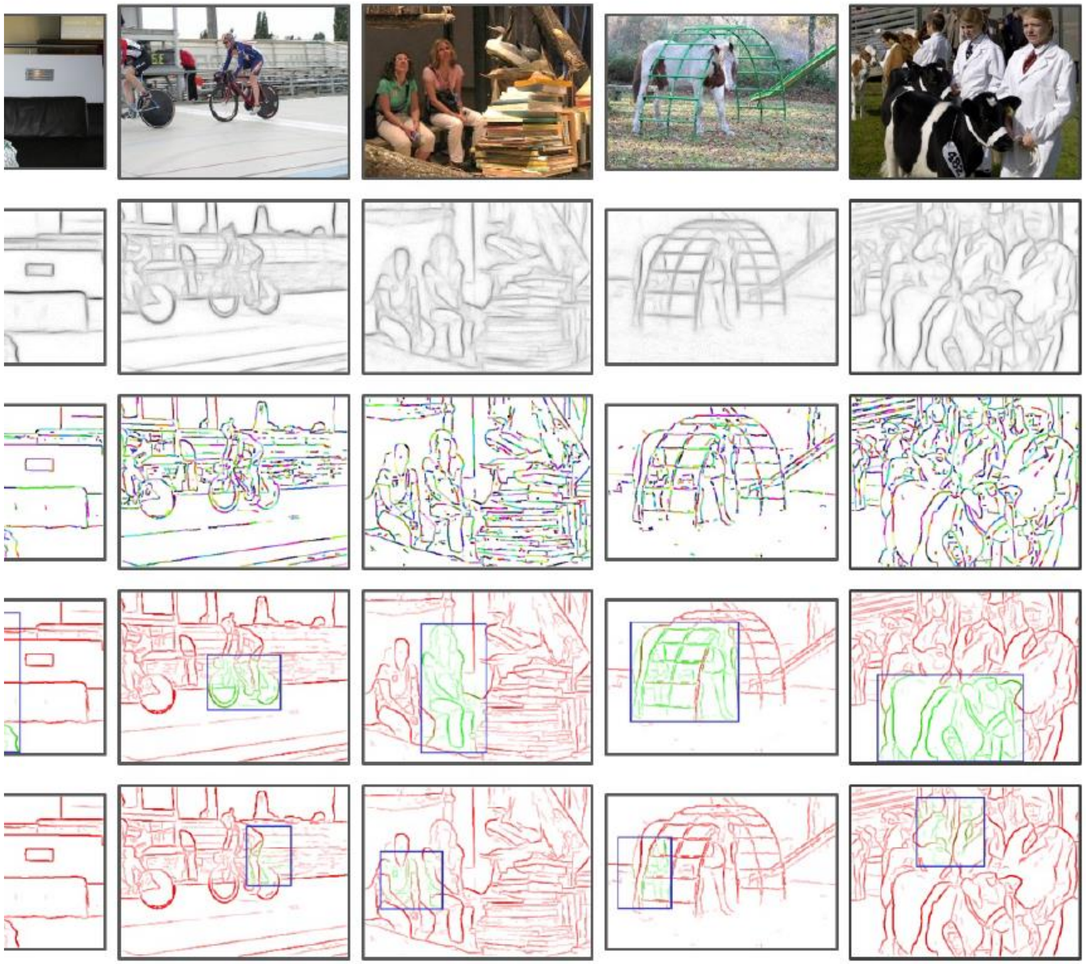


Iterate over window size, aspect ratio, and location

- Object proposals
  - Fast execution
  - High recall with low # of candidate boxes

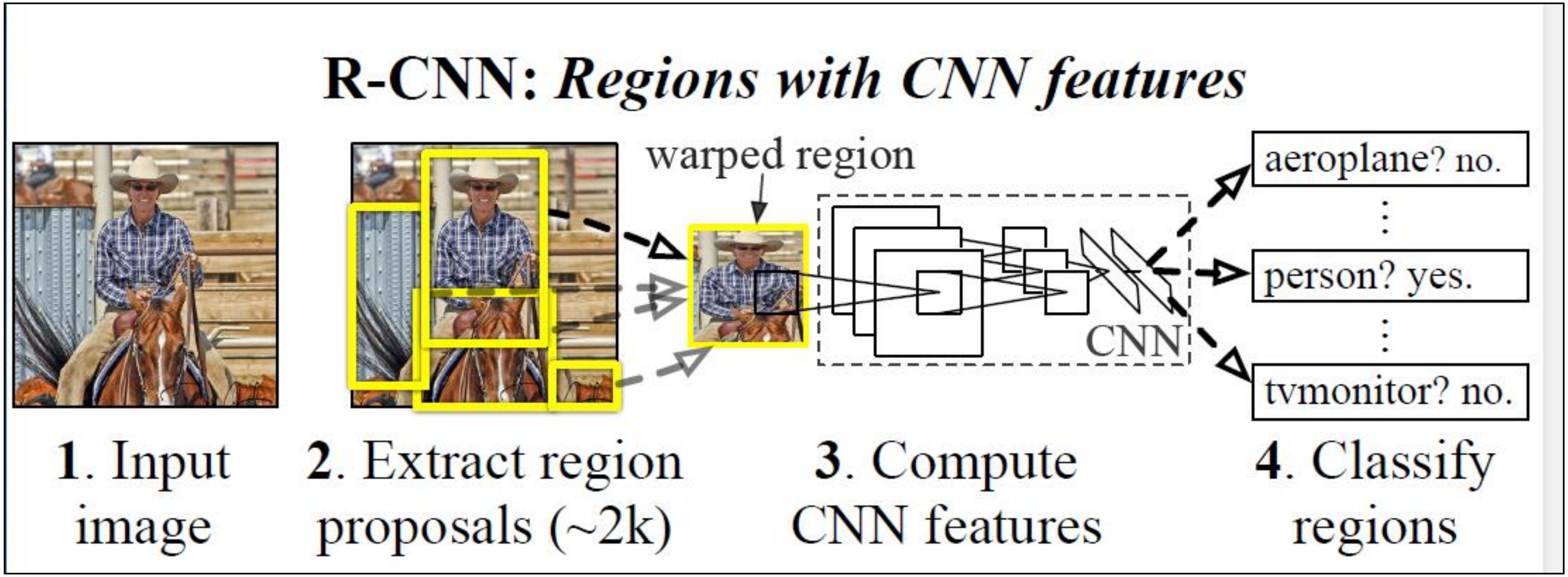


'. Lawrence Zitnick and Piotr Dollár



The number of contours wholly enclosed by a bounding box is indicative of the likelihood of the box containing an object.

Ross's Own System: Region CNNs



Competitive Results

VOC 2010 test	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
DPM v5 [20]†	49.2	53.8	13.1	15.3	35.5	53.4	49.7	27.0	17.2	28.8	14.7	17.8	46.4	51.2	47.7	10.8	34.2	20.7	43.8	38.3	33.4
UVA [39]	56.2	42.4	15.3	12.6	21.8	49.3	36.8	46.1	12.9	32.1	30.0	36.5	43.5	52.9	32.9	15.3	41.1	31.8	47.0	44.8	35.1
Regionlets [41]	65.0	48.9	25.9	24.6	24.5	56.1	54.5	51.2	17.0	28.9	30.2	35.8	40.2	55.7	43.5	14.3	43.9	32.6	54.0	45.9	39.7
SegDPM [18]†	61.4	53.4	25.6	25.2	35.5	51.7	50.6	50.8	19.3	33.8	26.8	40.4	48.3	54.4	47.1	14.8	38.7	35.0	52.8	43.1	40.4
R-CNN	67.1	64.1	46.7	32.0	30.5	56.4	57.2	65.9	27.0	47.3	40.9	66.6	57.8	65.9	53.6	26.7	56.5	38.1	52.8	50.2	50.2
R-CNN BB	**71.8**	**65.8**	**53.0**	**36.8**	**35.9**	**59.7**	**60.0**	**69.9**	**27.9**	**50.6**	**41.4**	**70.0**	**62.0**	**69.0**	**58.1**	**29.5**	**59.4**	**39.3**	**61.2**	**52.4**	**53.7**

Table 1: Detection average precision (%) on VOC 2010 test. R-CNN is most directly comparable to UVA and Regionlets since all methods use selective search region proposals. Bounding-box regression (BB) is described in Section C. At publication time, SegDPM was the top-performer on the PASCAL VOC leaderboard. †DPM and SegDPM use context rescoring not used by the other methods.

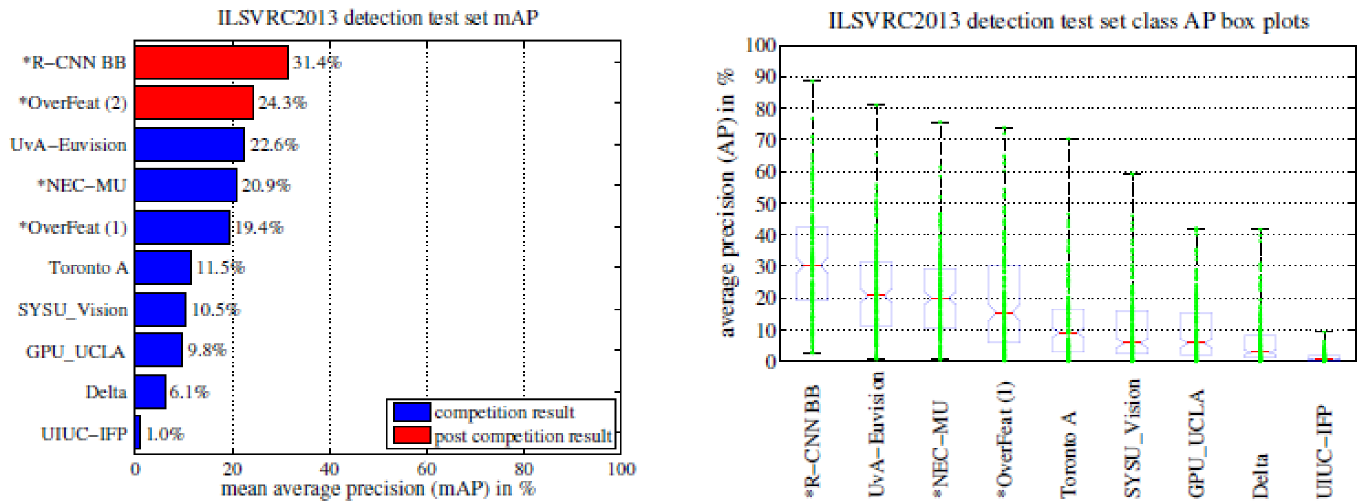


Figure 3: (Left) Mean average precision on the ILSVRC2013 detection test set. Methods preceeded by * use outside training data (images and labels from the ILSVRC classification dataset in all cases). **(Right) Box plots for the 200 average precision values per method.** A box plot for the post-competition OverFeat result is not shown because per-class APs are not yet available (per-class APs for R-CNN are in Table 8 and also included in the tech report source uploaded to arXiv.org; see `R-CNN-ILSVRC2013-APs.txt`). The red line marks the median AP, the box bottom and top are the 25th and 75th percentiles. The whiskers extend to the min and max AP of each method. Each AP is plotted as a green dot over the whiskers (best viewed digitally with zoom).

Top Regions for Six Object Classes

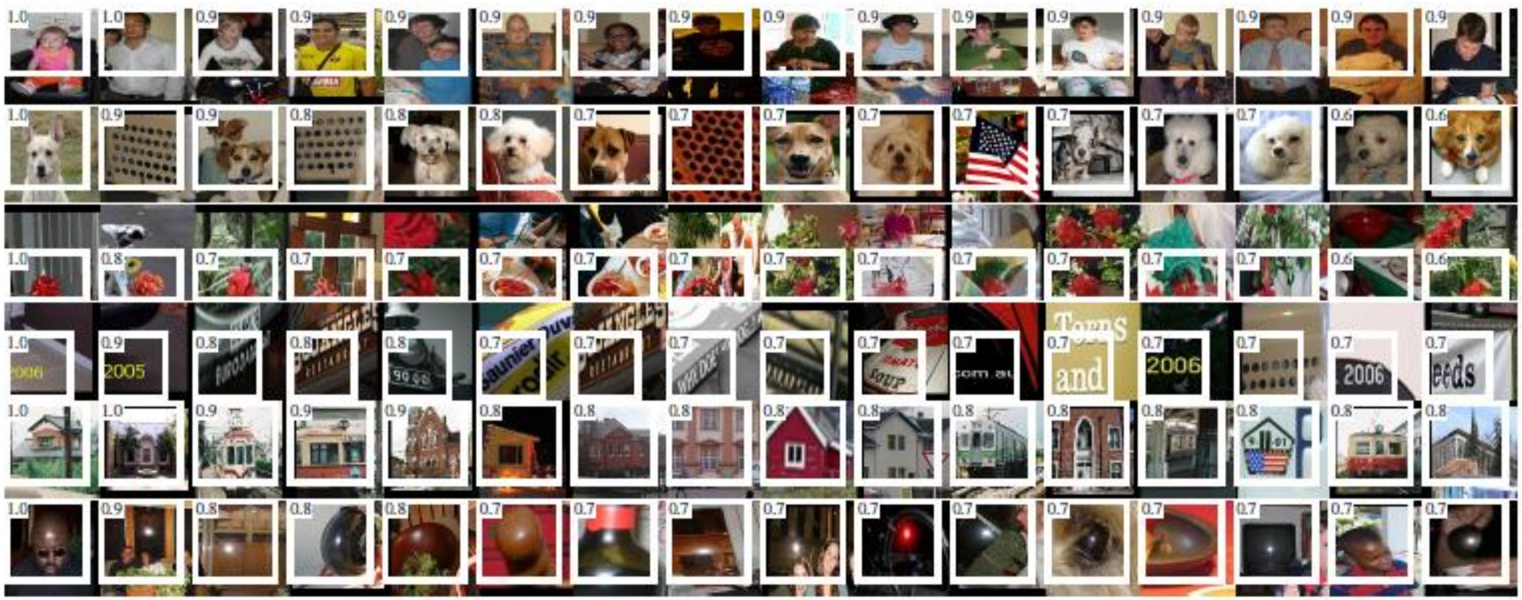
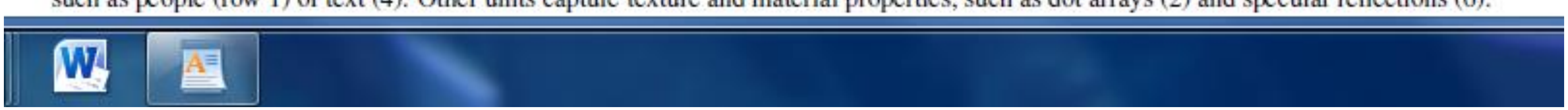


Figure 4: Top regions for six pool$_5$ units. Receptive fields and activation values are drawn in white. Some units are aligned to concepts, such as people (row 1) or text (4). Other units capture texture and material properties, such as dot arrays (2) and specular reflections (6).



What did Girshick do next?

- Fast RCNN trains the very deep VGG16 network 9x faster than R-CNN, is 213x faster at test-time, and achieves a higher mAP on PASCAL VOC 2012.
- Mask RCNN extends Faster R-CNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition.

What did we develop at UW?

- YOLO (and variants): Joseph Redmon, UW CSE

(unified framework for real-time object recognition)

https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Redmon_You_Only_Look_CVPR_2016_paper.pdf

- HATNeT: Sachin Mehta, UW ECE

(transformer-based object recognition, originally for breast biopsies)

https://homes.cs.washington.edu/~shapiro/hatnetfin.pdf