Computer Vision 2
WS 2018/19

Part 6 – Tracking by Detection
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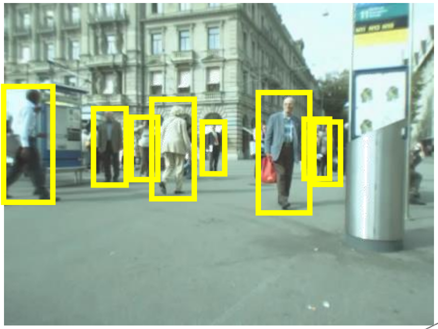
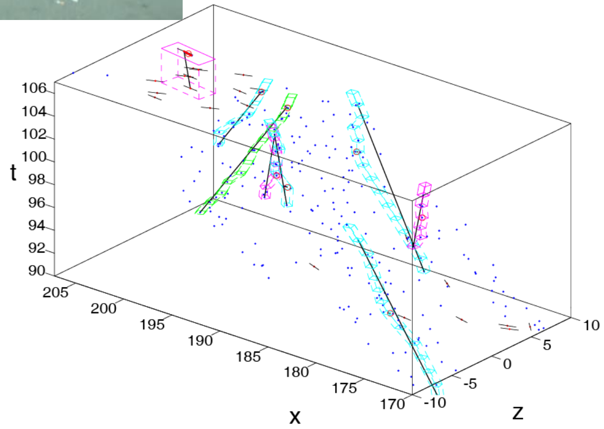
Course Outline

- Single-Object Tracking
  - Background modeling
  - Template based tracking
  - Tracking by online classification
  - Tracking-by-detection

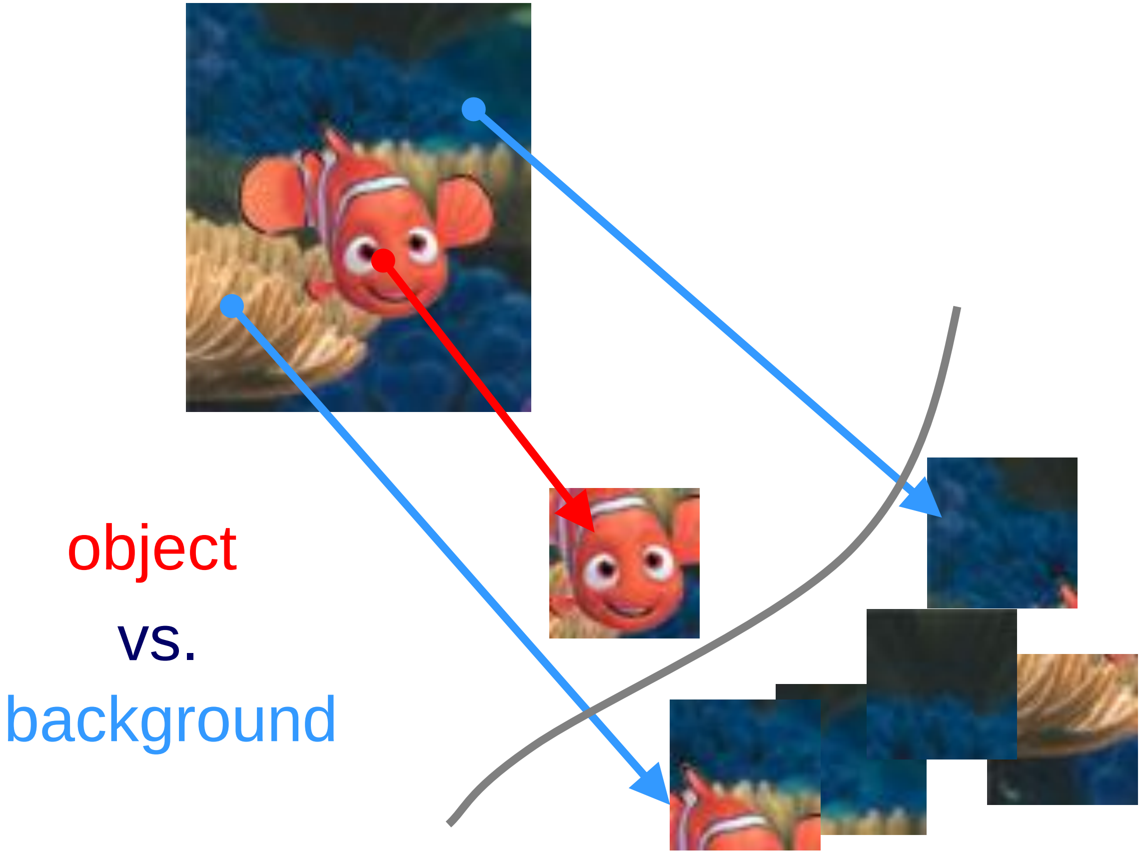




- Bayesian Filtering
- Multi-Object Tracking
- Visual Odometry
- Visual SLAM & 3D Reconstruction
- Deep Learning for Video Analysis

Recap: Tracking as Online Classification

- Tracking as binary classification problem

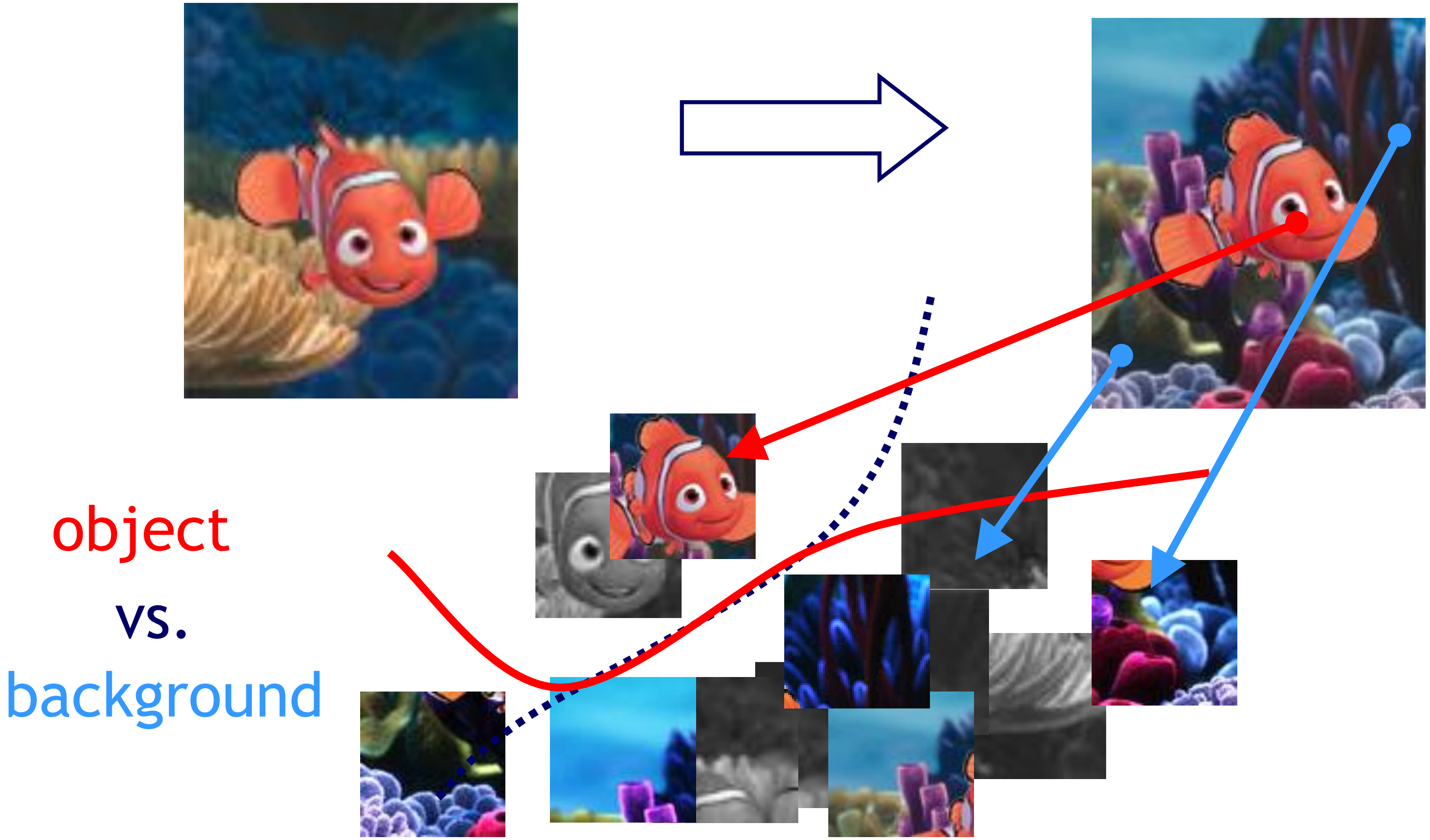


Slide credit: Helmut Grabner

Image source: Disney/Pixar

Recap: Tracking as Online Classification

- Tracking as binary classification problem



  – Handle object <u>and</u> background changes by online updating

Slide credit: Helmut Grabner

Image source: Disney/Pixar

Recap: AdaBoost – "Adaptive Boosting"

- Main idea [Freund & Schapire, 1996]
  - Iteratively select an ensemble of classifiers
  - Reweight misclassified training examples after each iteration to focus training on difficult cases.

- Components
  - $h_m(\mathbf{x})$: "weak" or base classifier
    - Condition: <50% training error over any distribution
  - $H(\mathbf{x})$: "strong" or final classifier

- AdaBoost:
  - Construct a strong classifier as a thresholded linear combination of the weighted weak classifiers:

$$H(\mathbf{x}) = sign\left(\sum_{m=1}^{M} \alpha_m h_m(\mathbf{x})\right)$$

Recap: AdaBoost – Algorithm

1. Initialization: Set $w_n^{(1)} = \frac{1}{N}$ for $n = 1,\ldots,N$.
2. For $m = 1,\ldots,M$ iterations
   a) Train a new weak classifier $h_m(\mathbf{x})$ using the current weighting coefficients $\mathbf{W}^{(m)}$ by minimizing the weighted error function

   $$J_m = \sum_{n=1}^{N} w_n^{(m)} I(h_m(\mathbf{x}) \neq t_n)$$

   $$I(A) = \begin{cases} 1, & \text{if } A \text{ is true} \\ 0, & \text{else} \end{cases}$$

   b) Estimate the weighted error of this classifier on $\mathbf{X}$:

   $$\epsilon_m = \frac{\sum_{n=1}^{N} w_n^{(m)} I(h_m(\mathbf{x}) \neq t_n)}{\sum_{n=1}^{N} w_n^{(m)}}$$

   c) Calculate a weighting coefficient for $h_m(\mathbf{x})$:

   $$\alpha_m = \ln\left\{\frac{1-\epsilon_m}{\epsilon_m}\right\}$$

   d) Update the weighting coefficients:

   $$w_n^{(m+1)} = w_n^{(m)} \exp\{\alpha_m I(h_m(\mathbf{x}_n) \neq t_n)\}$$

From Offline to Online Boosting

- Main issue
  - Computing the weight distribution for the samples.
  - We do not know a priori the difficulty of a sample! (Could already have seen the same sample before...)
- Idea of Online Boosting
  - Estimate the importance of a sample by propagating it through a set of weak classifiers.
  - This can be thought of as modeling the information gain w.r.t. the first n classifiers and code it by the importance weight λ for the $n+1$ classifier.
  - Proven [Oza]: Given the same training set, Online Boosting converges to the same weak classifiers as Offline Boosting in the limit of $N \to \infty$ iterations.

N. Oza and S. Russell. Online Bagging and Boosting. Artificial Intelligence and Statistics, 2001.

Recap: From Offline to Online Boosting

off-line

Given:

- set of labeled training samples $\mathcal{X} = \{\langle \mathbf{x_1}, y_1 \rangle, ..., \langle \mathbf{x_L}, y_L \rangle \mid y_i \pm 1\}$
- weight distribution over them $D_0 = 1/L$

for n = 1 to N

- train a weak classifier using samples and weight dist.

$$h_n^{weak}(\mathbf{x}) = \mathcal{L}(\mathcal{X}, D_{n-1})$$

- calculate error e_n
- calculate weight $\alpha_n = f(e_n)$
- update weight dist. D_n

next

$$h^{strong}(\mathbf{x}) = \text{sign}\left(\sum_{n=1}^{N} \alpha_n \cdot h_n^{weak}(\mathbf{x}) \right)$$

on-line

Given:

- ONE labeled training sample $\langle \mathbf{x}, y \rangle \mid y \pm 1$
- strong classifier to update

- initial importance $\lambda = 1$

for n = 1 to N

- update the weak classifier using samples and importance

$$h_n^{weak}(\mathbf{x}) = \mathcal{L}(h_n^{weak}, \langle x, y \rangle, \lambda)$$

- update error estimation $\widehat{e_n}$
- update weight $\alpha_n = f(\widehat{e_n})$
- update importance weight λ

next

$$h^{strong}(\mathbf{x}) = \text{sign}\left(\sum_{n=1}^{N} \alpha_n \cdot h_n^{weak}(\mathbf{x}) \right)$$

Slide credit: Helmut Grabner

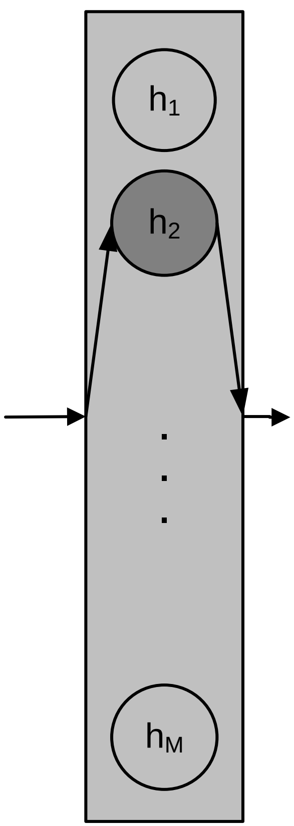
Recap: Online Boosting for Feature Selection

- Introducing “Selector”
  - Selects one feature from its local feature pool

$$\mathcal{H}^{weak} = \{h_1^{weak}, ..., h_M^{weak}\}$$
$$\mathcal{F} = \{f_1, ..., f_M\}$$

$$h^{sel}(\mathbf{x}) = h_m^{weak}(\mathbf{x})$$
$$m = \arg\min_i e_i$$

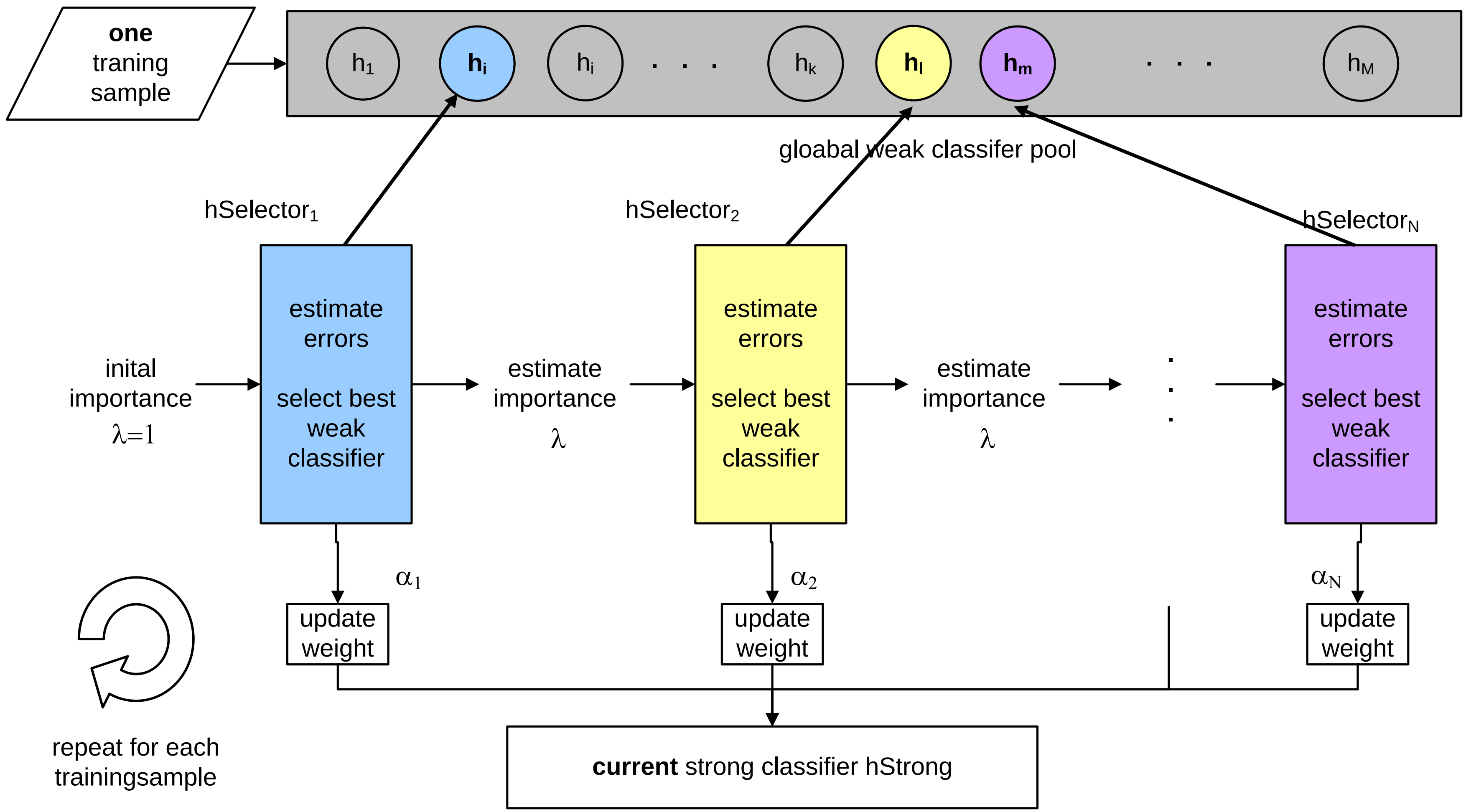
On-line boosting is performed on the Selectors and not on the weak classifiers directly.



H. Grabner and H. Bischof. On-line boosting and vision. CVPR, 2006.

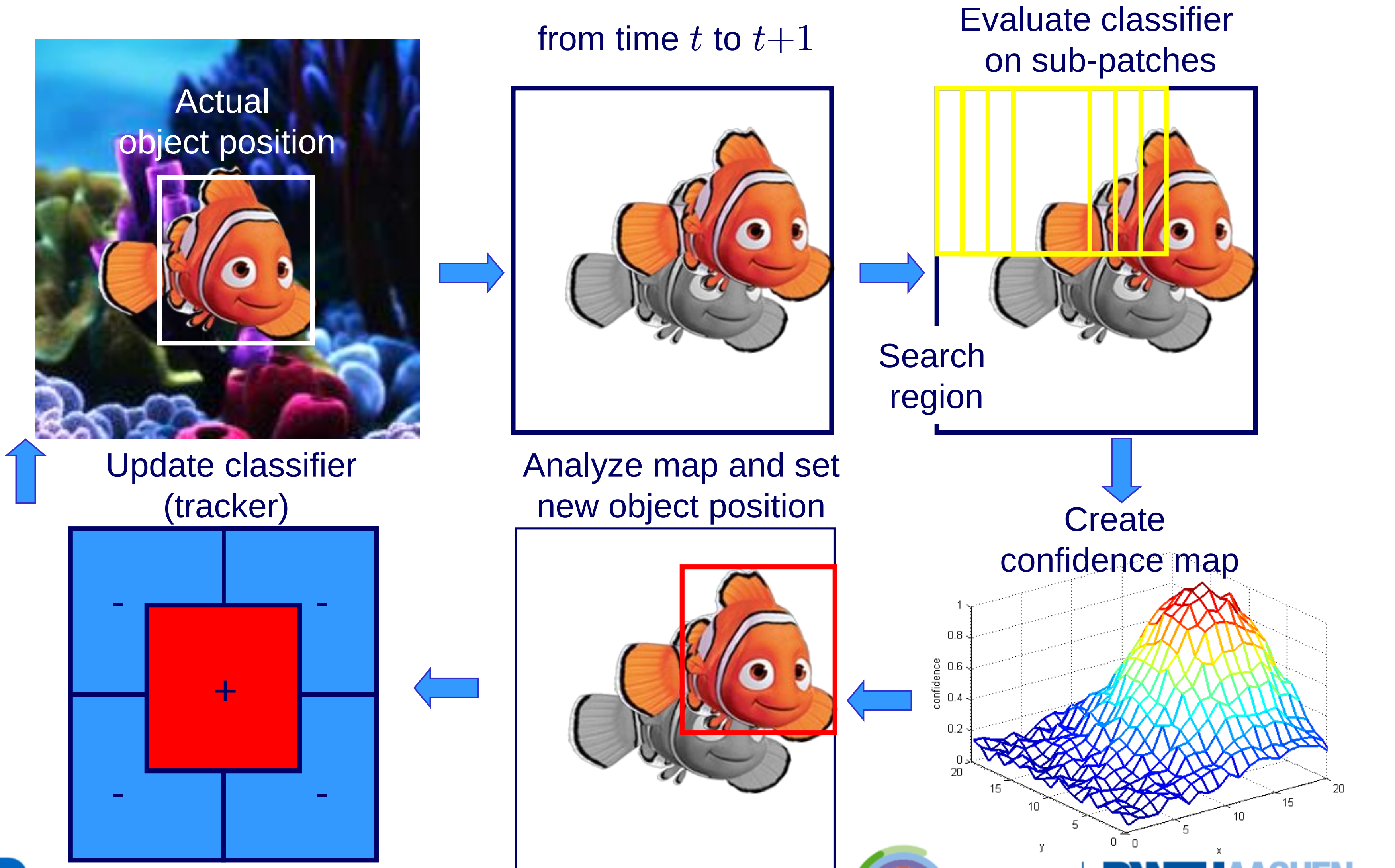
Slide credit: Helmut Grabner

Recap: Direct Feature Selection



Slide credit: Helmut Grabner

Recap: Tracking by Online Classification

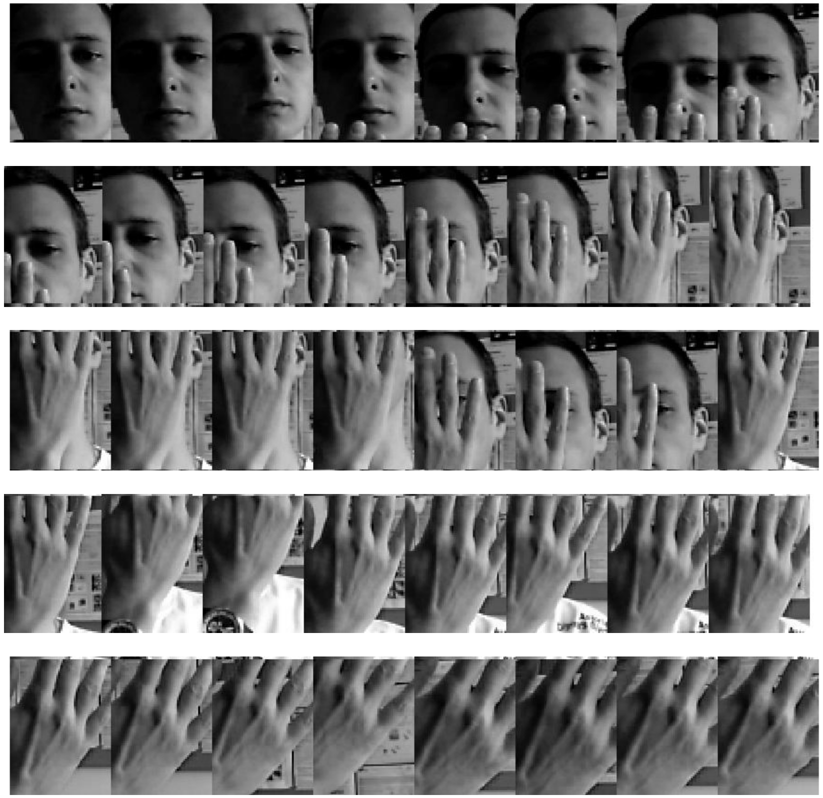


Slide credit: Helmut Grabner

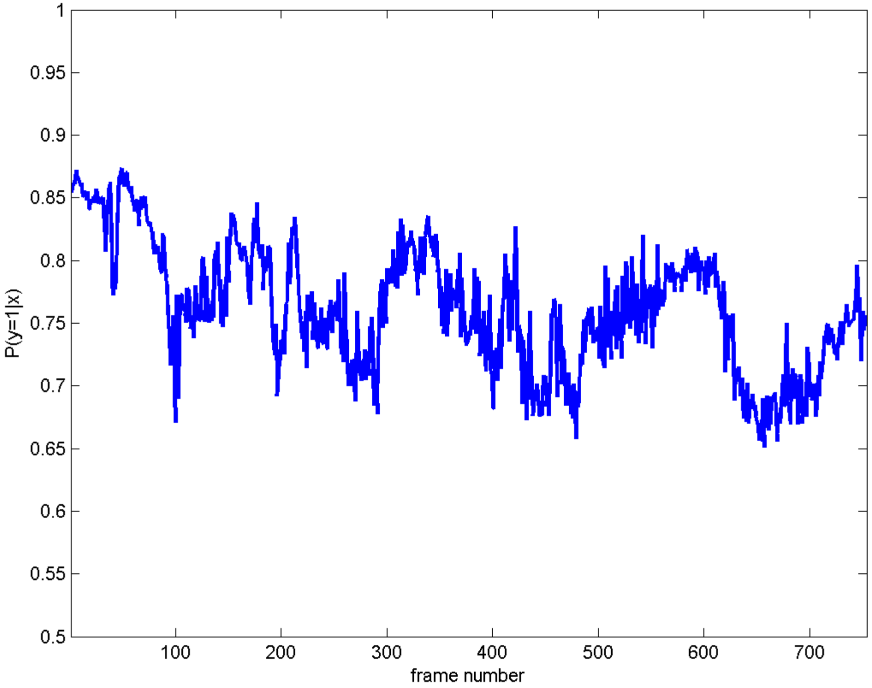
Image source: Disney/Pixar

Recap: Drifting Due to Self-Learning Policy

Tracked Patches



Confidence

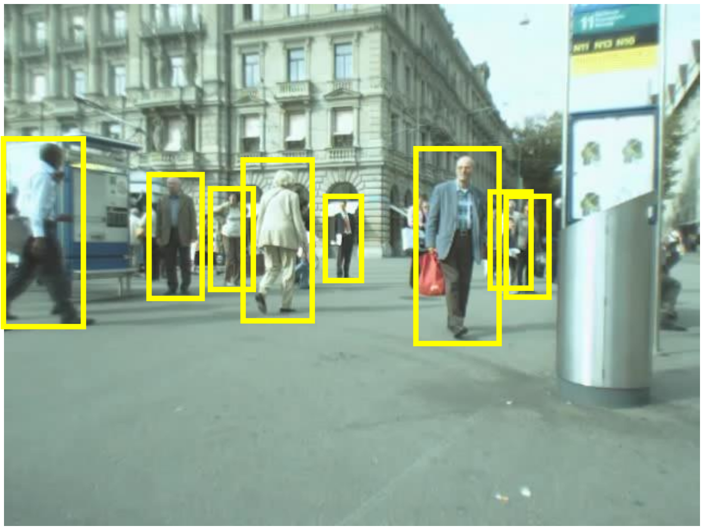


⇒ Not only does it drift, it also remains confident about it!

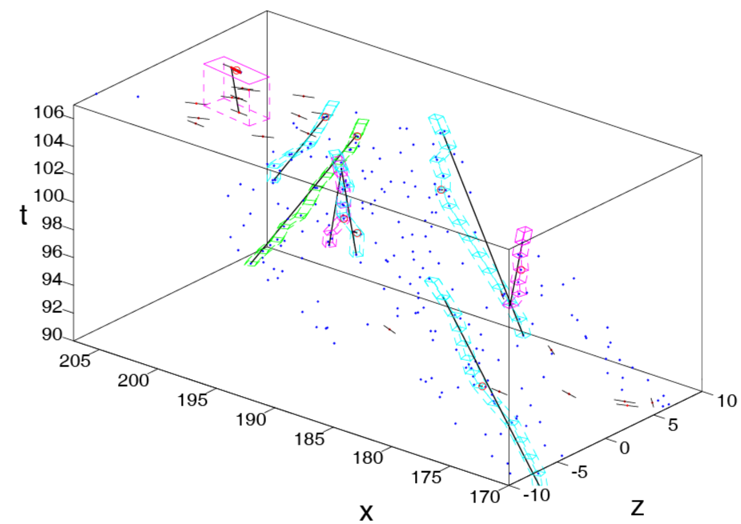
Slide credit: Helmut Grabner

Image source: Grabner et al., ECCV'08

Today: Tracking by Detection



Object detections



Spacetime trajectories

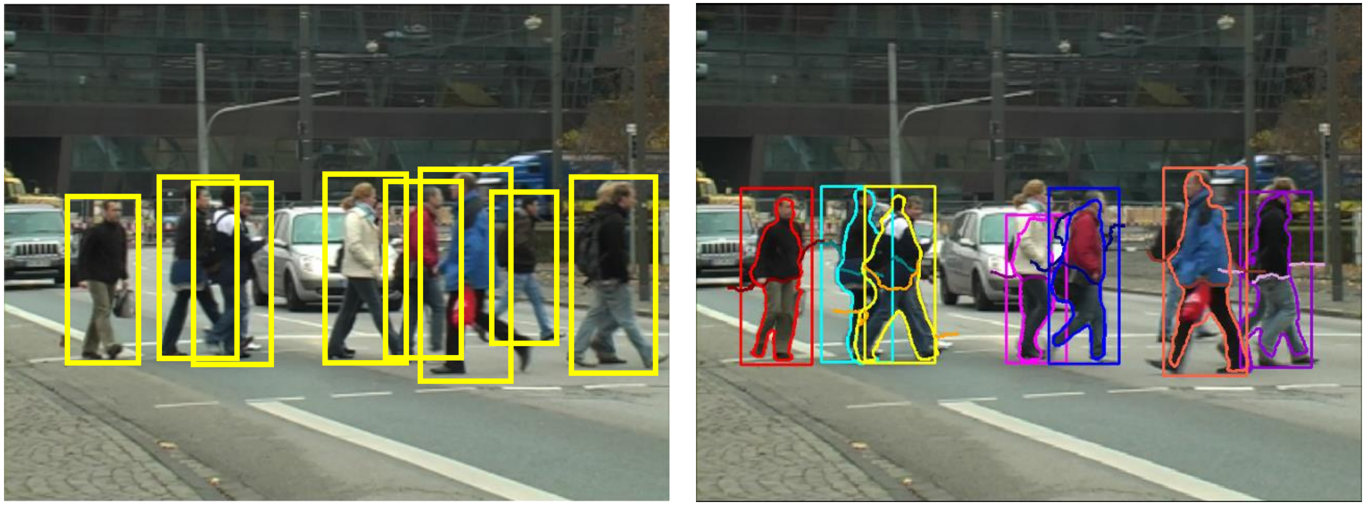
Can we use generic object detection to track people?

Image source: B. Leibe

Topics of This Lecture

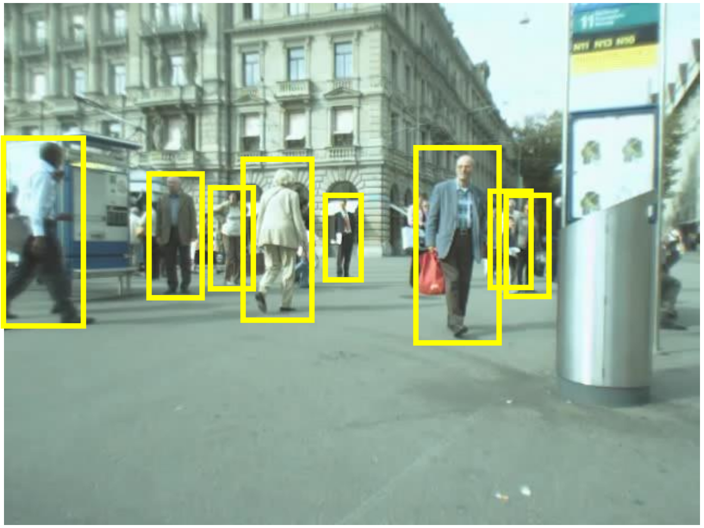
- Tracking by Detection
  - Motivation
  - Recap: Object detection
- SVM based Detectors
  - Recap: HOG
  - DPM
- AdaBoost based Detectors
  - Recap: Viola-Jones
  - Integral Channel features
  - VeryFast/Roerei
- CNN-based Detectors
  - Recap: CNNs
  - R-CNN, Faster R-CNN
  - YOLO, SSD

Detection-Based Tracking

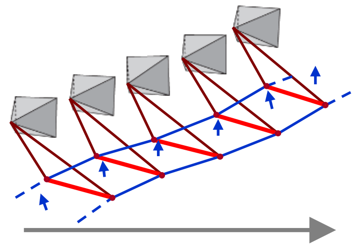


- Main ideas
  - Apply a generic object detector to find objects of a certain class
  - Based on the detections, extract object appearance models
    - Even possible to derive figure-ground segmentations from detection results
  - Link detections into trajectories

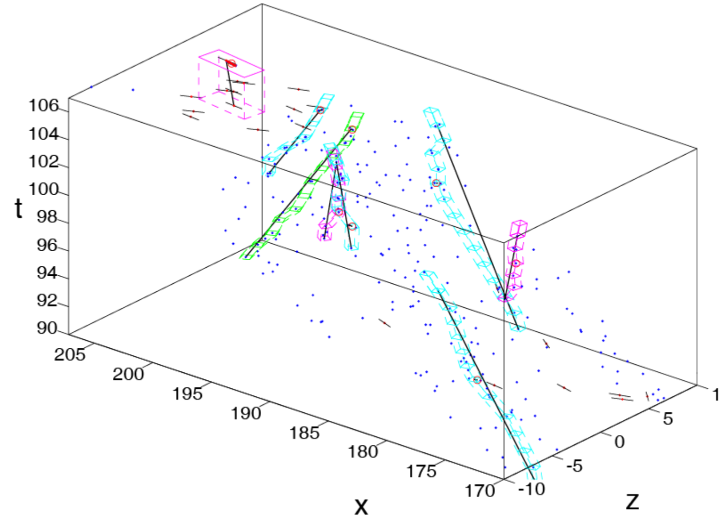
Tracking-by-Detection in 3D



Object detections



3D Camera path estimation



Spacetime trajectories

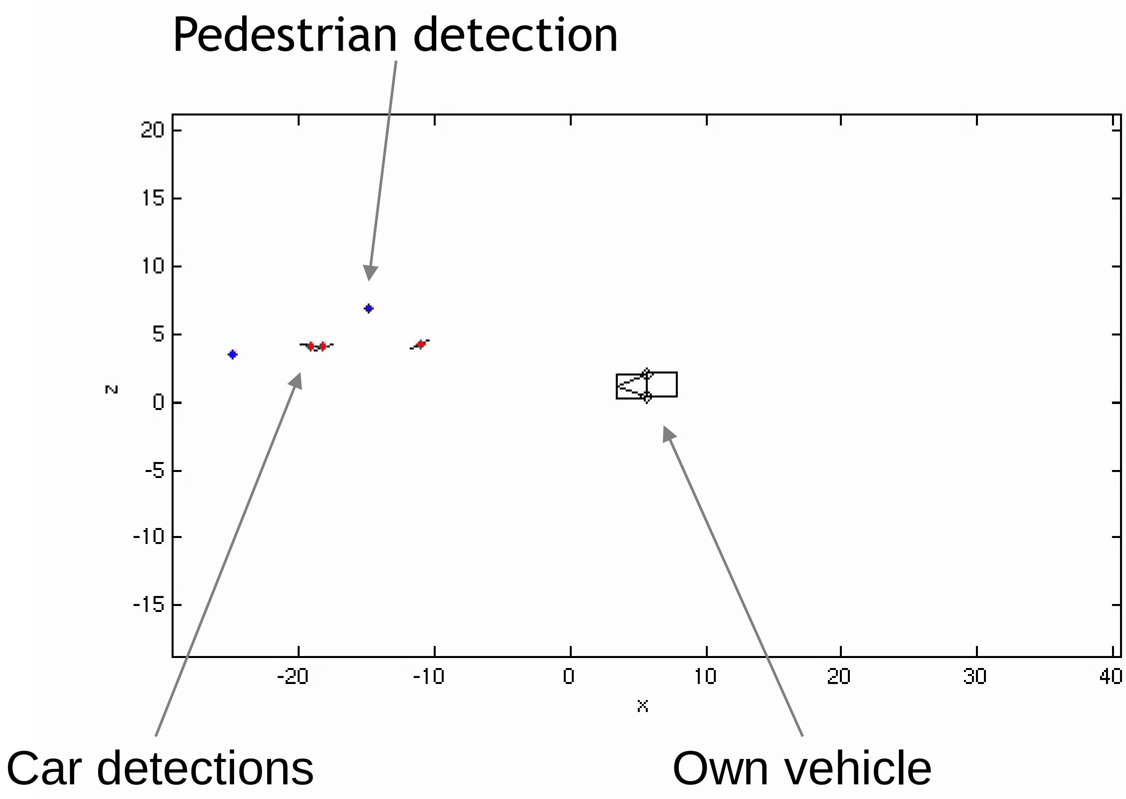
Simple f/g model:
E.g., elliptical region in detection box

Main Issue:
Data Association

(We'll come to that later…)

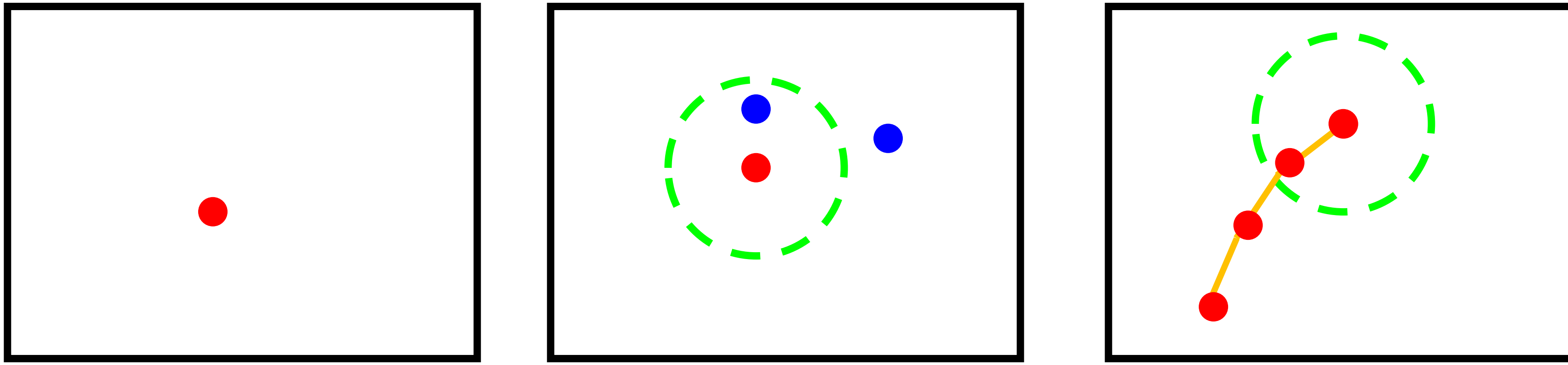
[Leibe, Cornelis, Schindler, Van Gool, PAMI'08]

Spacetime Trajectory Analysis



[Leibe, Cornelis, Schindler, Van Gool, CVPR'07]

Elements of Tracking



Detection | Data association | Prediction

- Detection
  - *Where are candidate objects?*

Today's topic

- Data association
  - *Which detection corresponds to which object?*
- Prediction
  - *Where will the tracked object be in the next time step?*

Recap: Sliding-Window Object Detection

- Basic component: a binary classifier

Car/non-car Classifier

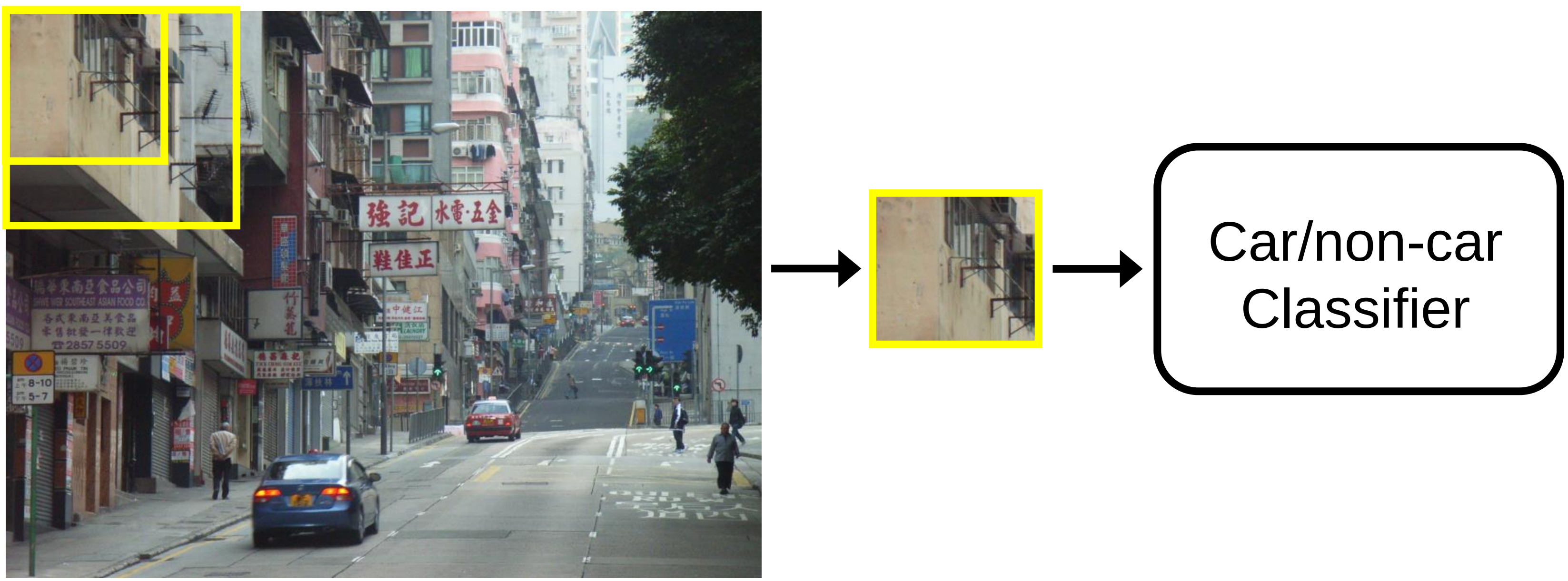
No, not a car.

Yes, car.

Slide credit: Kristen Grauman

Recap: Sliding-Window Object Detection

- If object may be in a cluttered scene, slide a window around looking for it.



- Essentially, this is a brute-force approach with many local decisions.

Slide credit: Kristen Grauman

What *is* a Sliding Window Approach?

- Search over space and scale

- Detection as subwindow classification problem
- *"In the absence of a more intelligent strategy, any global image classification approach can be converted into a localization approach by using a sliding-window search."*

Recap: Non-Maximum Suppression

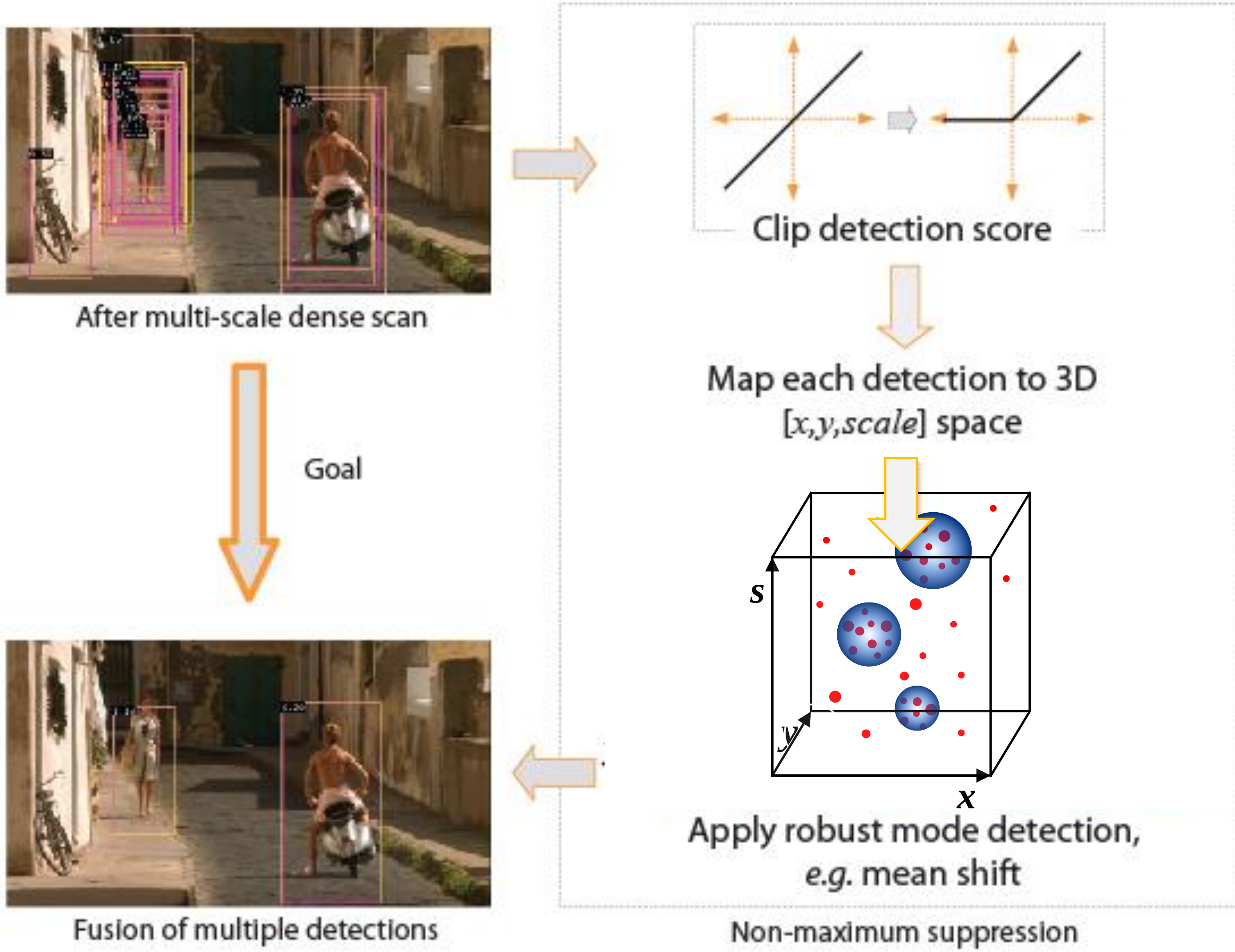
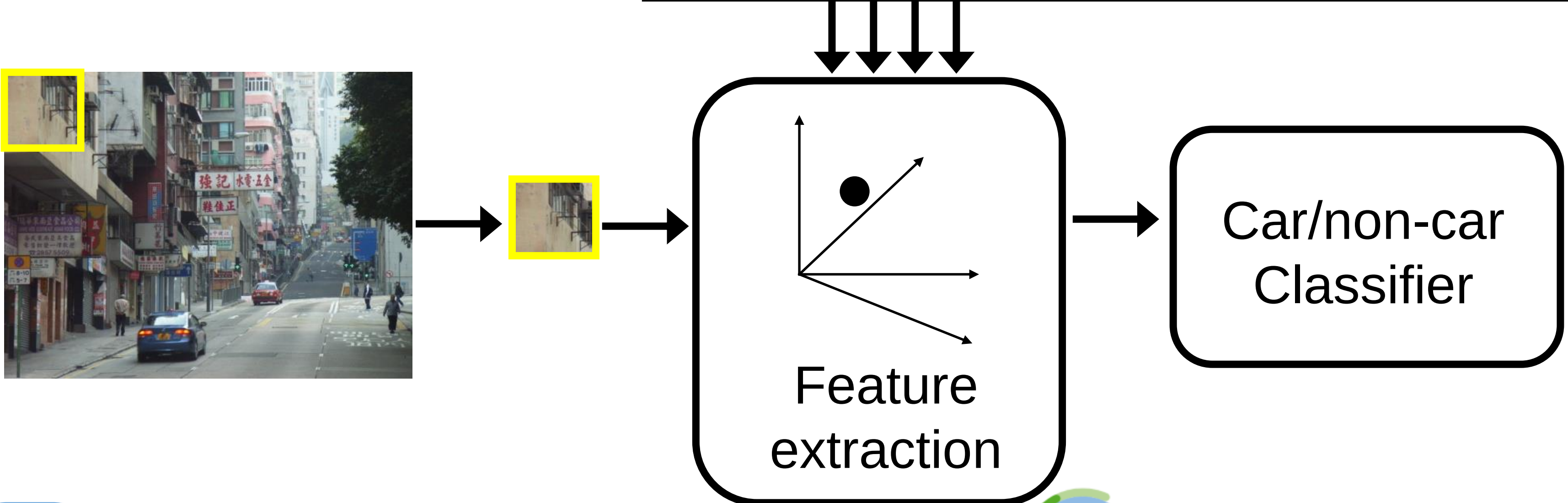


Image source: Navneet Dalal, PhD Thesis

Recap: Sliding-Window Object Detection

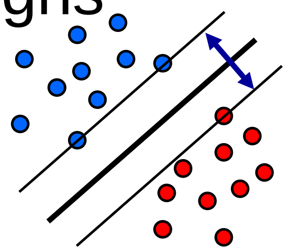
- Fleshing out this pipeline a bit more, we need to:
  1. Obtain training data
  2. Define features
  3. Define classifier



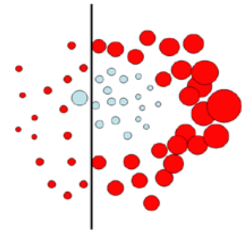
Slide credit: Kristen Grauman

Object Detector Design

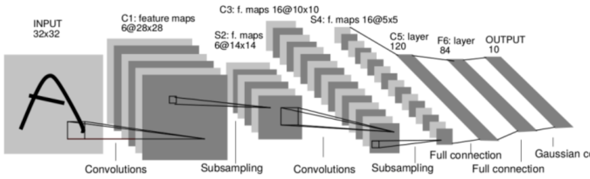
- In practice, the classifier often determines the design.
  - Types of features
  - Speedup strategies
- Today, we'll look at 3 state-of-the-art detector designs
  - Based on SVMs



  - Based on Boosting



  - Based on CNNs



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  - Motivation
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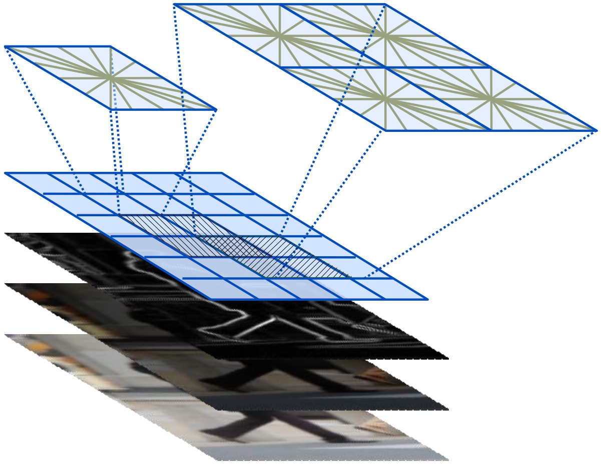
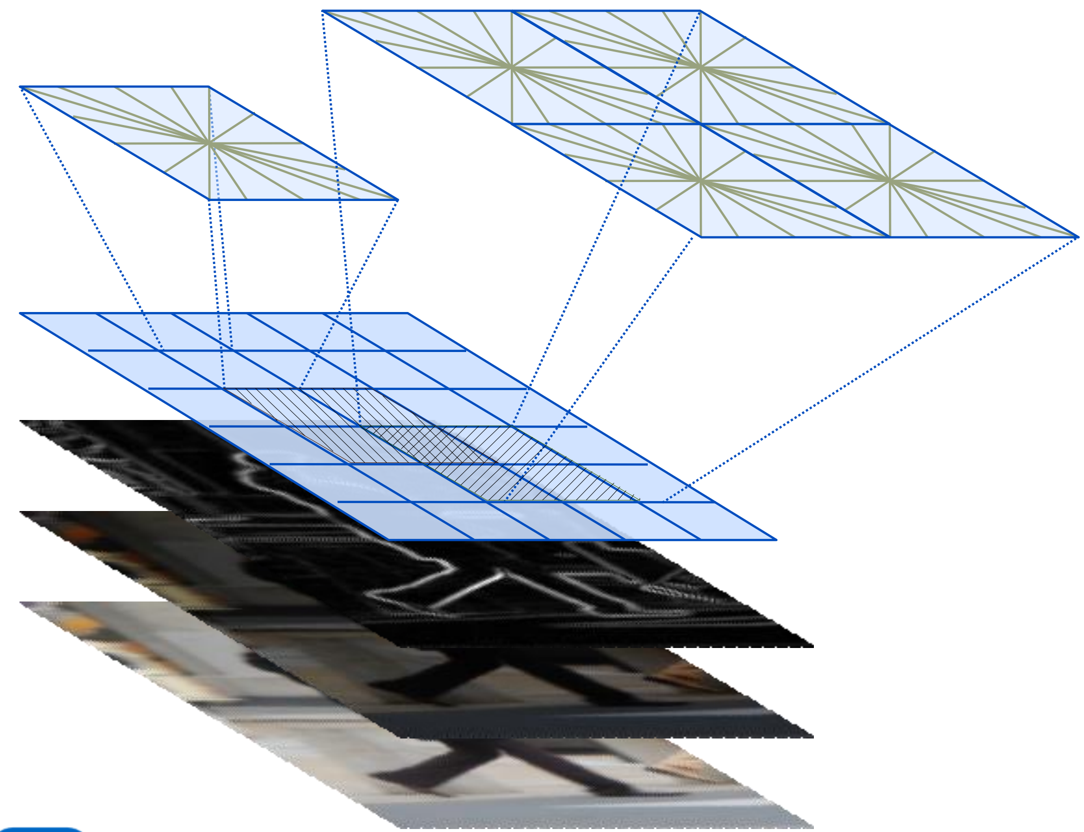
  - Recap: HOG
  - DPM
- AdaBoost based Detectors
  - Recap: Viola-Jones
  - Integral Channel features
  - VeryFast/Roerei
- CNN-based Detectors
  - Recap: CNNs
  - R-CNN



Recap: Histograms of Oriented Gradients (HOG)

- Holistic object representation
  – Localized gradient orientations



Object/Non-object

↑

Linear SVM

↑

Collect HOGs over detection window

↑

Contrast normalize over overlapping spatial cells

↑

Weighted vote in spatial & orientation cells

↑

Compute gradients

↑

Gamma compression

↑

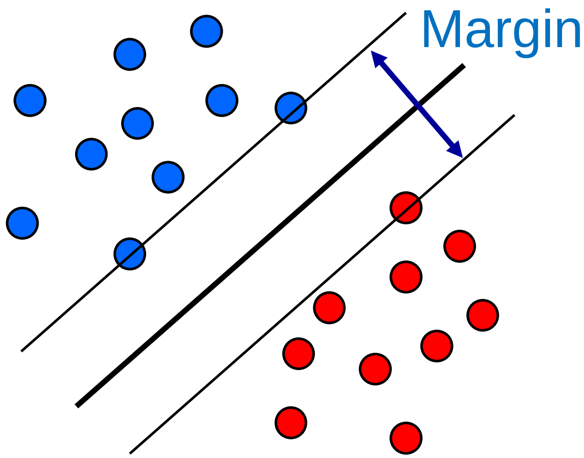
Image Window

Slide adapted from Navneet Dalal

Recap: Support Vector Machine (SVM)

- Basic idea
  - The SVM tries to find a classifier which maximizes the margin between pos. and neg. data points.
  - Up to now: consider linear classifiers

$$\mathbf{w}^{\mathrm{T}}\mathbf{x} + b = 0$$



- Formulation as a convex optimization problem
  - Find the hyperplane satisfying

$$\arg\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2$$

under the constraints

$$t_n(\mathbf{w}^{\mathrm{T}}\mathbf{x}_n + b) \geq 1 \quad \forall n$$

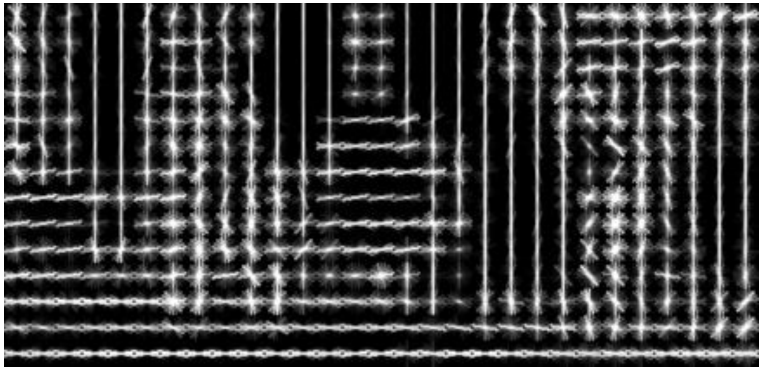
based on training data points $\mathbf{x}_n$ and target values $t_n \in \{-1, 1\}$

Recap: Pedestrian Detection with HOG

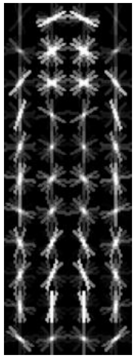
- Train a pedestrian template using a linear SVM
- At test time, convolve feature map with template

$$y(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\mathbf{x} + b$$

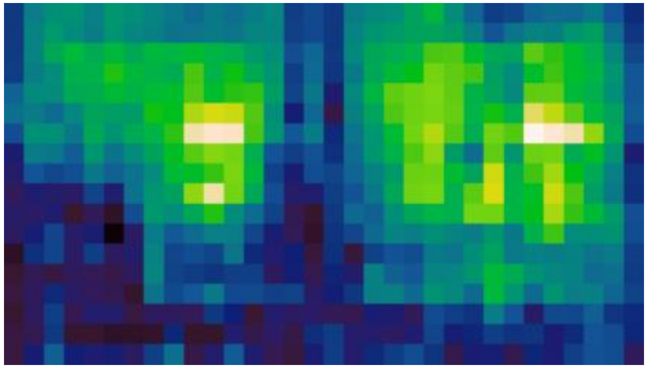
HOG feature map



Template



Detector response map



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

Slide credit: Svetlana Lazebnik

Pedestrian detection with HoGs & SVMs

N. Dalal and B. Triggs, [Histograms of Oriented Gradients for Human Detection](), CVPR 2005

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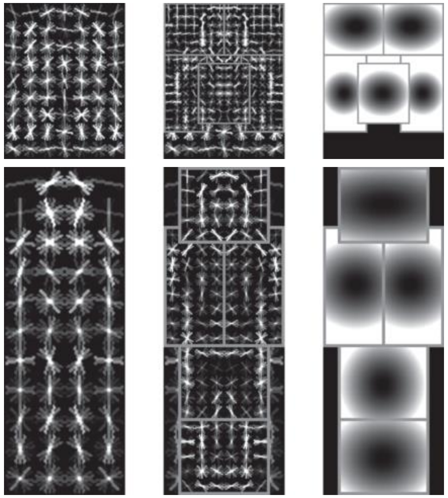
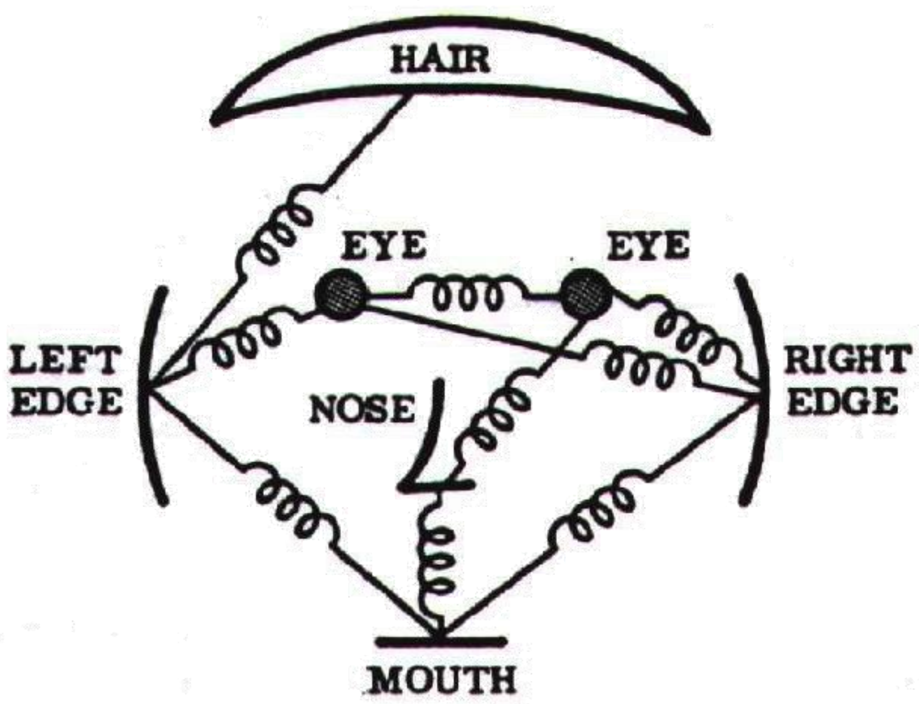


Recap: Part-Based Models

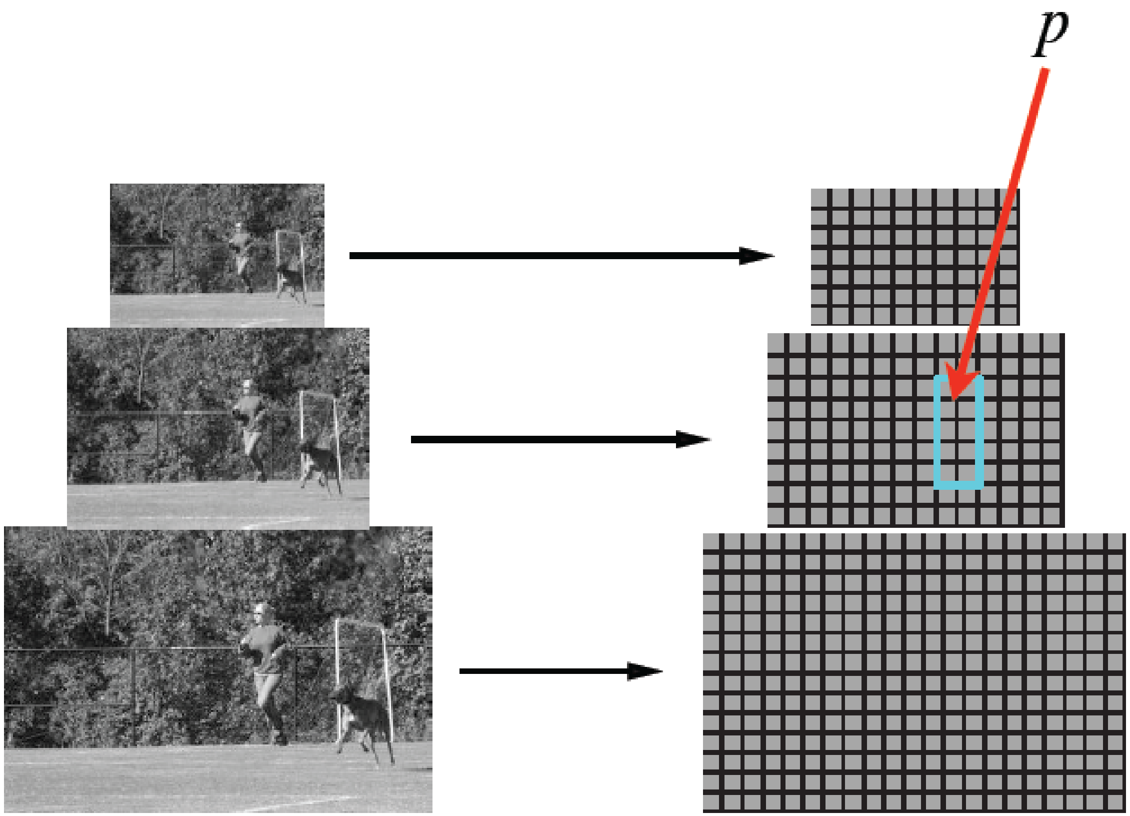
- Pictorial Structures model
  – [Fischler & Elschlager 1973]
- Model has two components
  – Parts
    (2D image fragments)
  – Structure
    (configuration of parts)



- Use in Deformable Part-based Model (DPM)
  – Parts ≡ 5-7 semantically meaningful parts
  – Probabilistic model enabling efficient inference

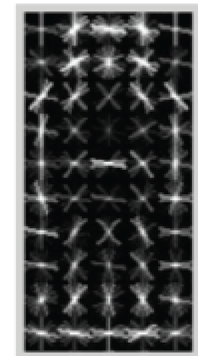
Slide adapted from Kristen Grauman

Starting Point: HOG Sliding-Window Detector



HOG pyramid H

Filter F



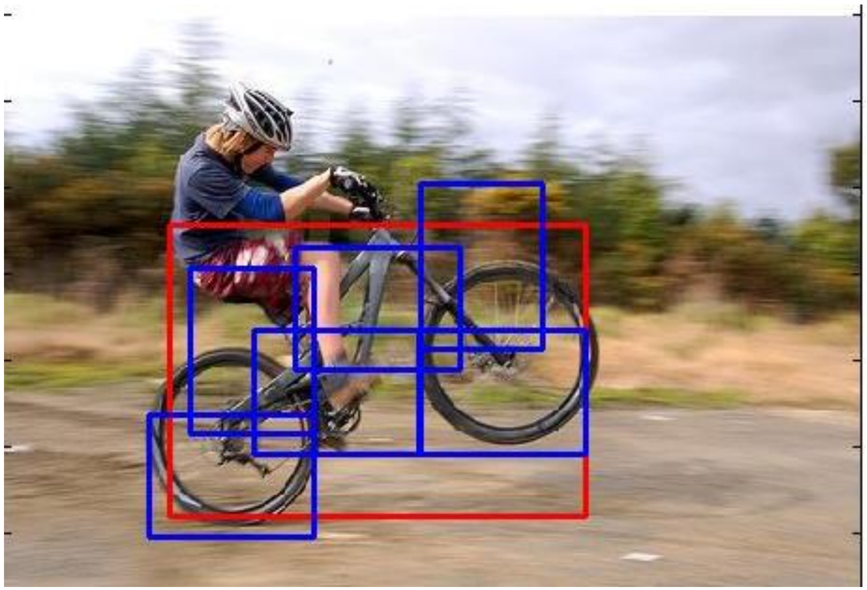
Score of F
at position p is
$F \cdot \phi(p, H)$

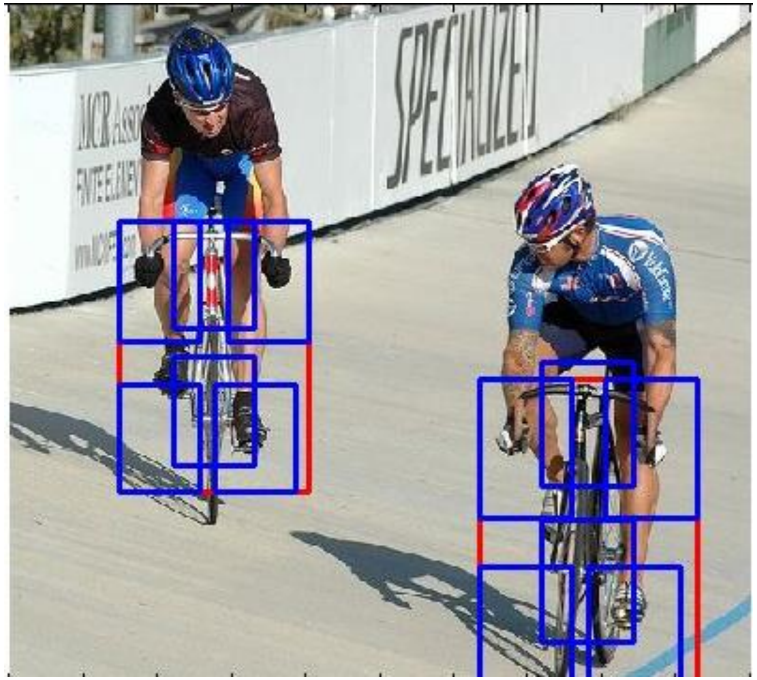
$\phi(p, H)$ = concatenation of HOG features from window specified by p.

- Array of weights for features in window of HOG pyramid
- Score is dot product of filter and vector

Slide adapted from Pedro Felzenszwalb, Deva Ramanan

Deformable Part-based Models



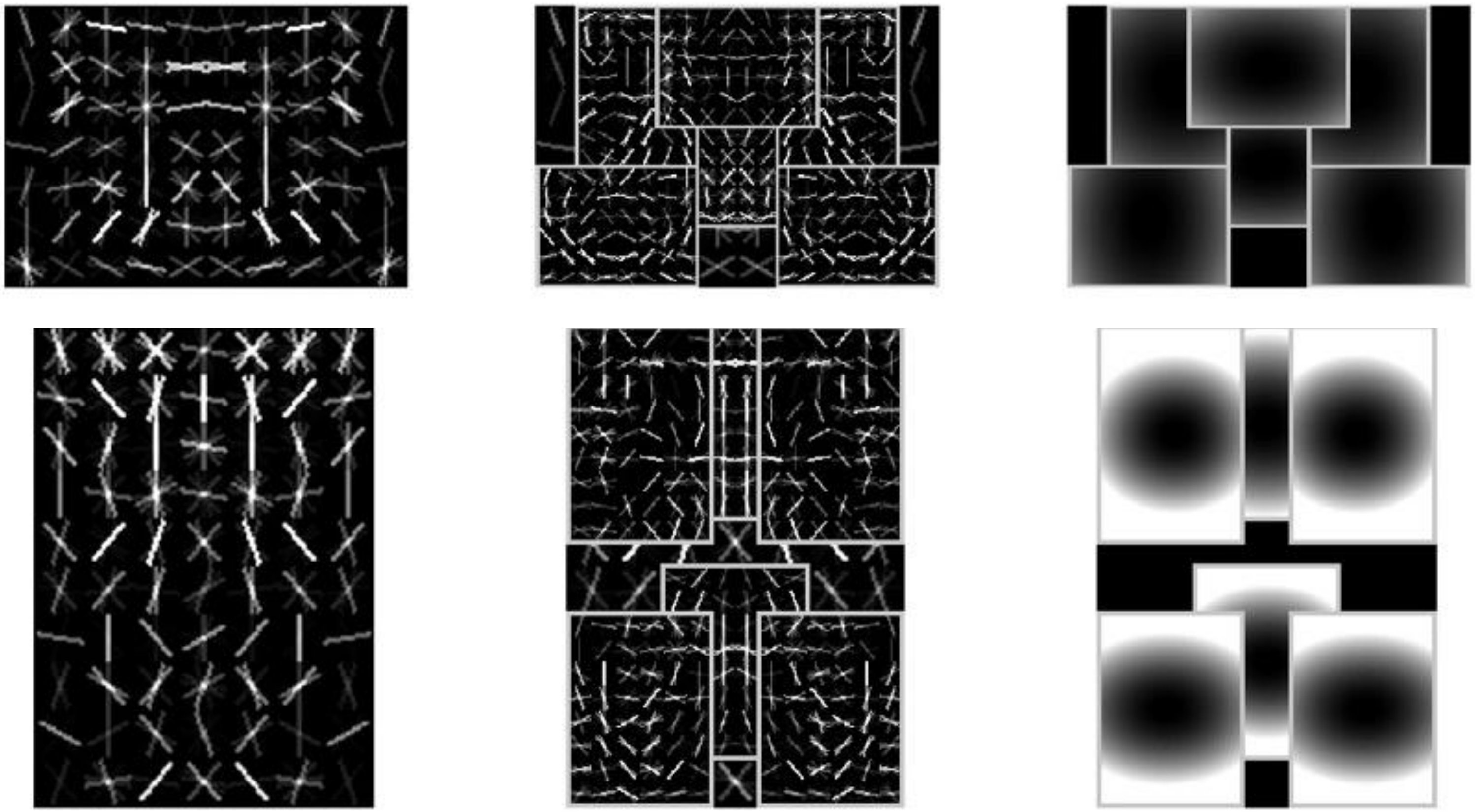


- Mixture of deformable part models (Pictorial Structures)
- Each component has global template + deformable parts
- Fully trained from bounding boxes alone

Slide credit: Pedro Felzenszwalb

[Felzenszwalb, McAllister, Ramanan, CVPR'08]

2-Component Bicycle Model



Root filters
coarse resolution

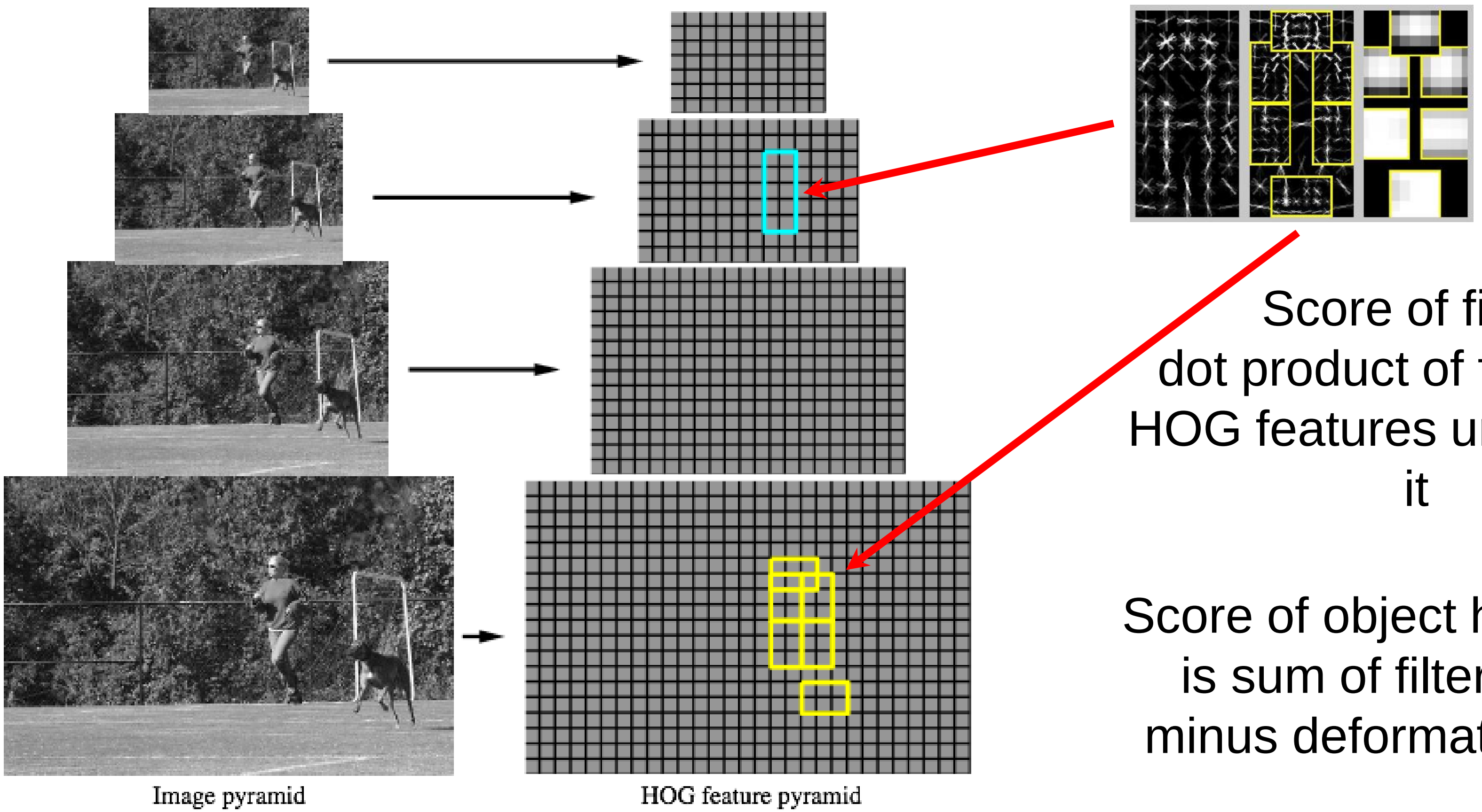
Part filters
finer resolution

Deformation
models

Slide credit: Pedro Felzenszwalb

[Felzenszwalb, McAllister, Ramanan, CVPR'08]

Object Hypothesis



Score of filter:
dot product of filter with HOG features underneath it

Score of object hypothesis is sum of filter scores minus deformation costs

- Multiscale model captures features at two resolutions

Slide credit: Pedro Felzenszwalb

[Felzenszwalb, McAllister, Ramanan, CVPR'08]

Score of a Hypothesis

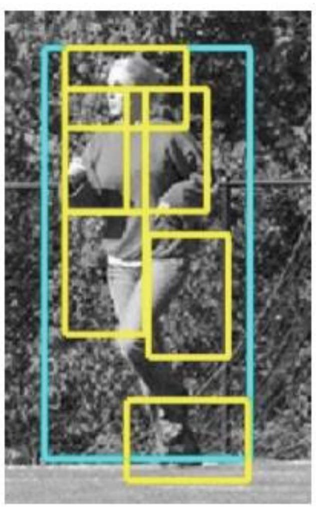
"data term" "spatial prior"

$$\text{score}(p_0, \ldots, p_n) = \sum_{i=0}^{n} F_i \cdot \phi(H, p_i) - \sum_{i=1}^{n} d_i \cdot (dx_i^2, dy_i^2)$$

filters

displacements

deformation parameters



$$\text{score}(z) = \beta \cdot \Psi(H, z)$$

concatenation filters and deformation parameters

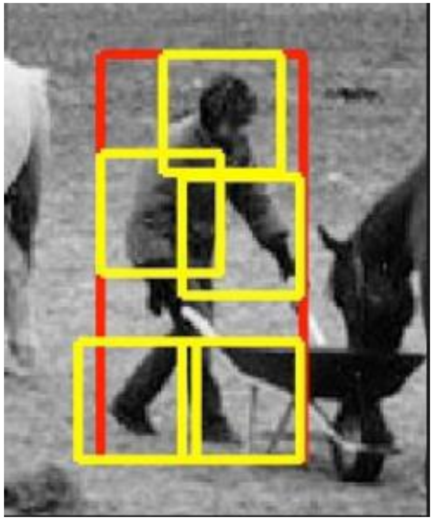
concatenation of HOG features and part displacement features

Slide credit: Pedro Felzenszwalb

[Felzenszwalb, McAllister, Ramanan, CVPR'08]

Recognition Model

$$f_w(x) = w \cdot \Phi(x)$$

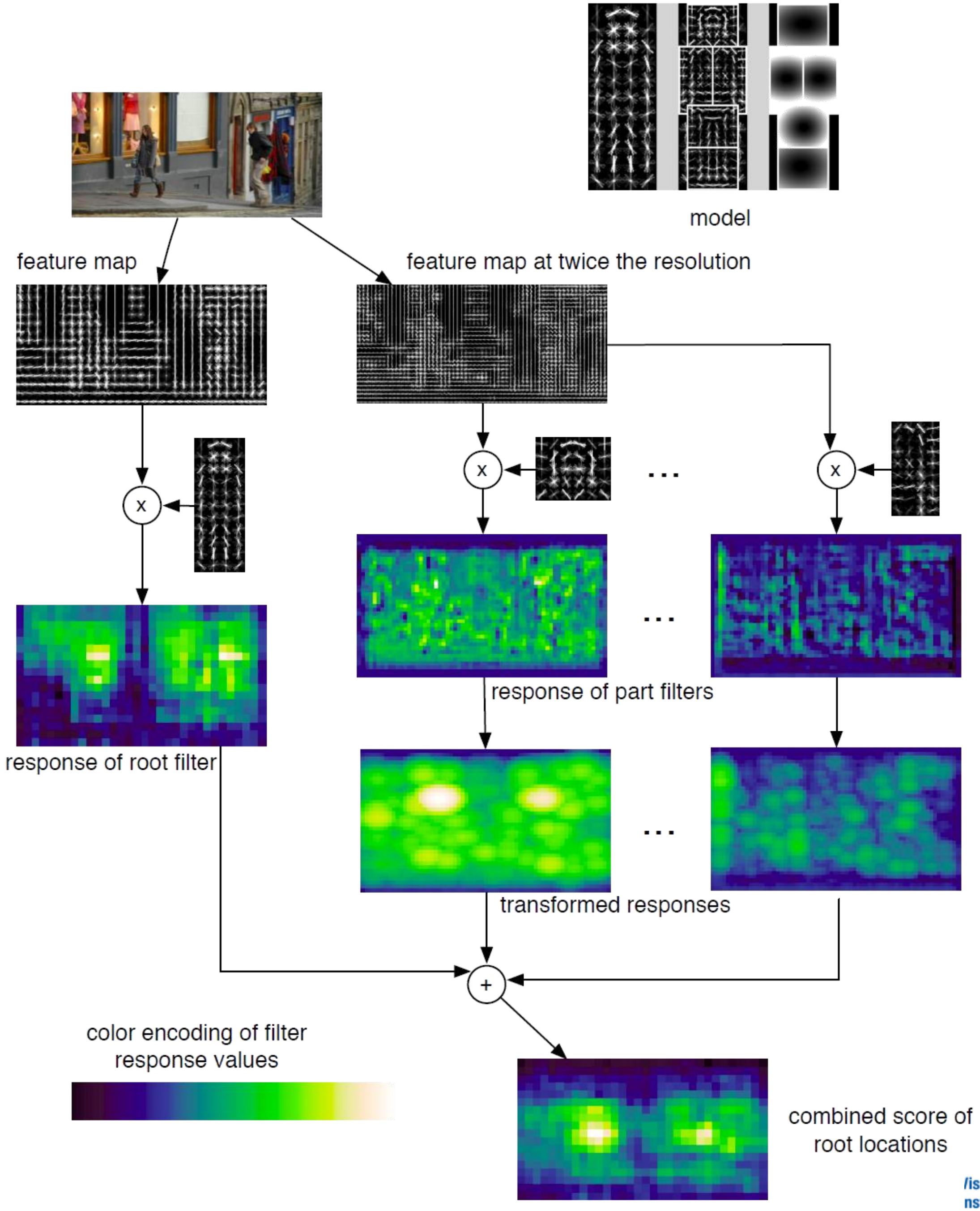


$$f_w(x) = \max_z w \cdot \Phi(x, z)$$

- Difference to standard HOG model
  - Hidden variable z: vector of part offsets
  - $\Phi(x,z)$: vector of HOG features (from root filter & appropriate part sub-windows) and part offsets

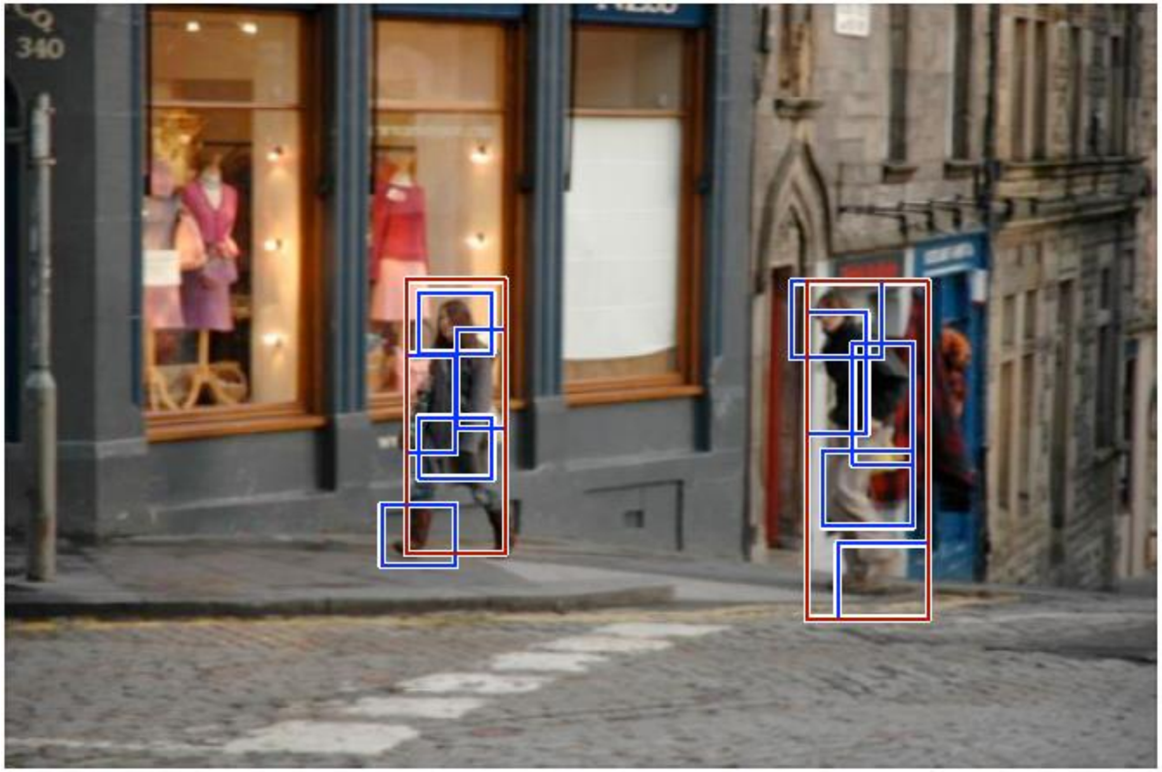
  $\Rightarrow$ Need to optimize over all possible part positions

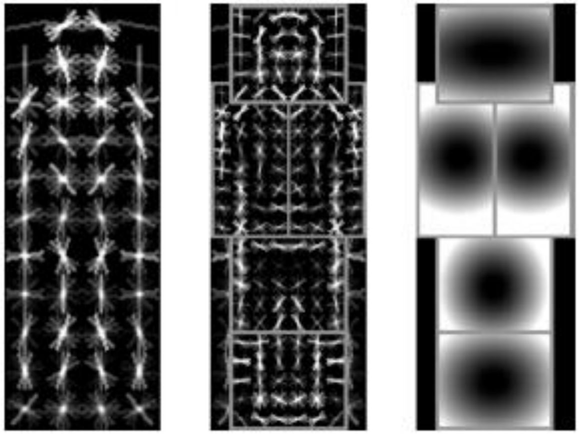
Slide credit: Pedro Felzenszwalb



Slide credit: Pedro Felzenszwalb

Results: Persons

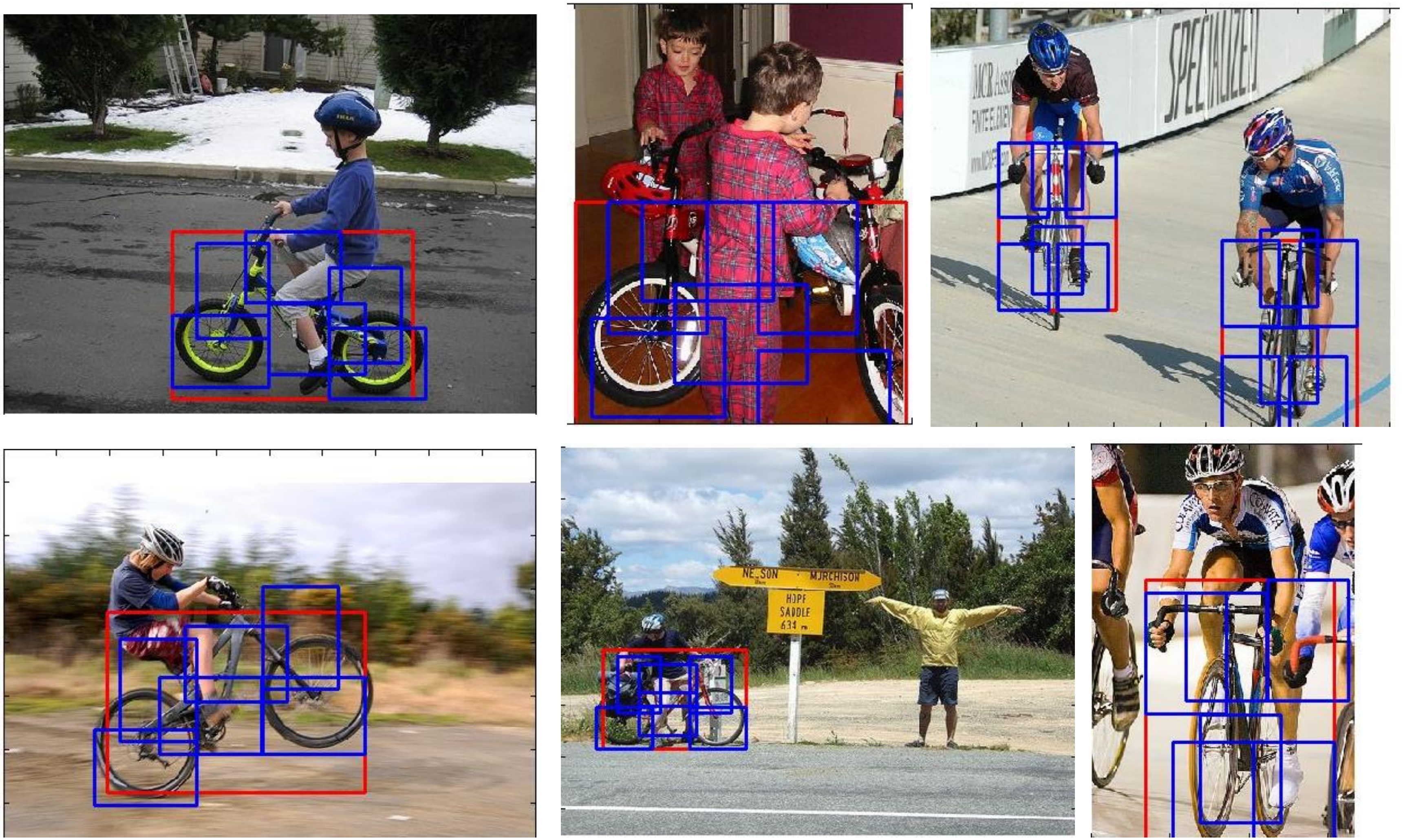




- Results (after non-maximum suppression)
  - ~1s to search all scales

Slide credit: Pedro Felzenszwalb

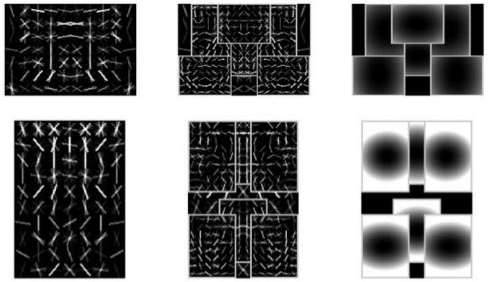
Results: Bicycles



Slide adapted from Trevor Darrell

Extensions and Detailed Improvements

- More efficient features
  - Very simplified version of HOG
- Latent part (re-)learning
  - Perform several rounds of training, adapting the annotation bboxes
- Multi-aspect detection
  - Mixture model of different aspects to capture different viewpoints of objects
- Bounding box prediction
  - Infer final detection bounding box from detected part locations
- Multi-resolution models
- Cascaded evaluation



[Felzenszwalb, McAllister, Ramanan, PAMI'10]

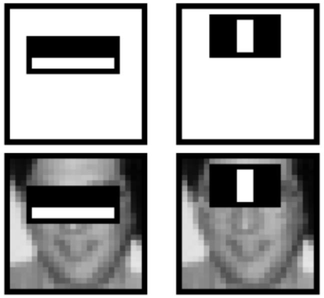
You Can Try It At Home…

- Deformable part-based models have been very successful in several evaluations.
  $\Rightarrow$ Approach was state-of-the-art until few years ago

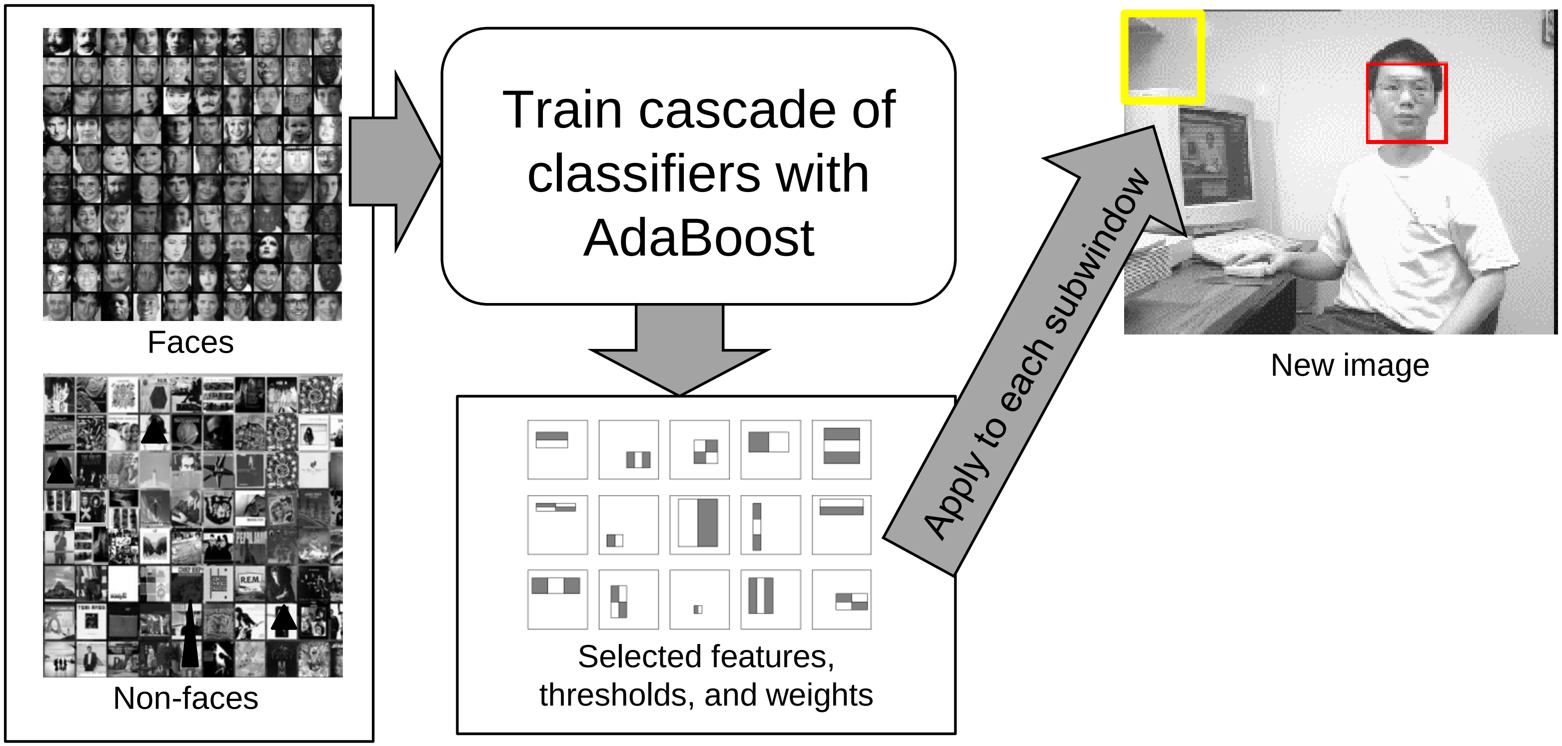
- Source code and models trained on PASCAL 2006, 2007, and 2008 data are available here:
  http://www.cs.uchicago.edu/~pff/latent

Topics of This Lecture

- Tracking by Detection
  - Motivation
  - Recap: Object detection
- SVM based Detectors
  - Recap: HOG
  - DPM
- AdaBoost based Detectors
  - Recap: Viola-Jones
  - Integral Channel features
  - VeryFast/Roerei
- CNN-based Detectors
  - Recap: CNNs
  - R-CNN



Recap: Viola-Jones Face Detector

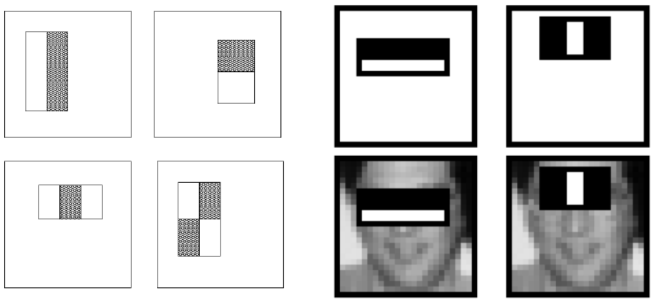


- Train with 5K positives, 350M negatives
- Real-time detector using 38 layer cascade (6061 features in final layer)
- [Implementation available in OpenCV: http://sourceforge.net/projects/opencvlibrary/]

Slide credit: Kristen Grauman

Recap: Haar Wavelets

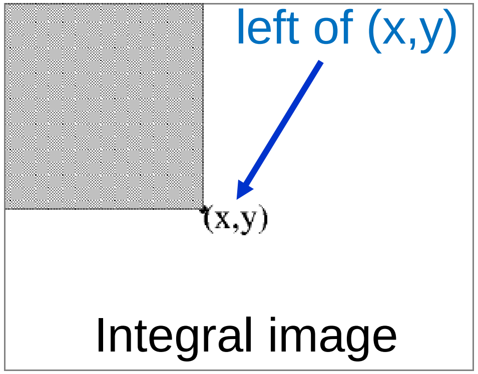
"Rectangular" filters

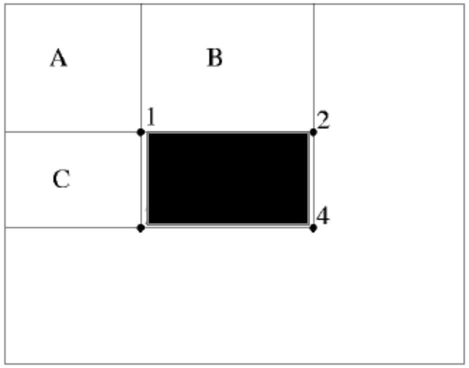


Feature output is difference between adjacent regions

Value at (x,y) is sum of pixels above and to the left of (x,y)

Efficiently computable with integral image: any sum can be computed in constant time





Avoid scaling images
$\Rightarrow$ Scale features directly for same cost

$$
\begin{aligned}
D &= 1 + 4 - (2 + 3) \\
&= A + (A + B + C + D) - (A + C + A + B) \\
&= D
\end{aligned}
$$

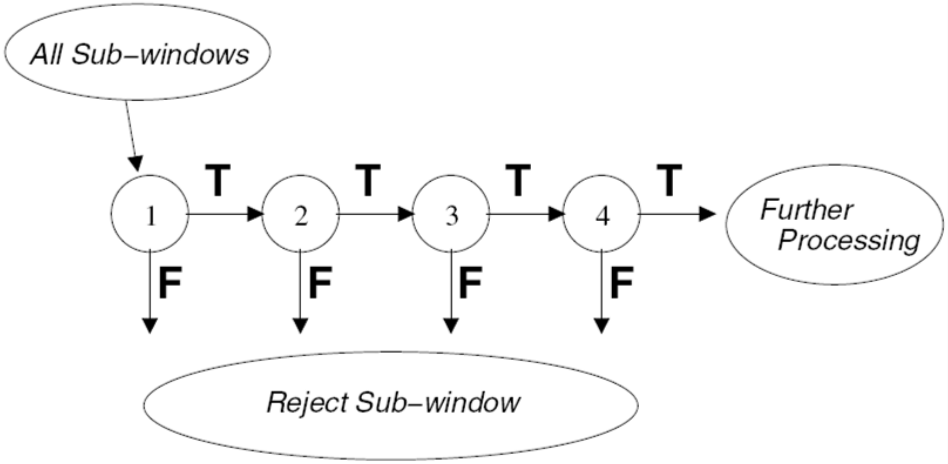
Slide credit: Kristen Grauman

Visual Computing Institute
RWTH AACHEN UNIVERSITY

[Viola & Jones, CVPR 2001]

Recap: Cascading Classifiers for Detection

- Even if the filters are fast to compute, each new image has a lot of possible windows to search...



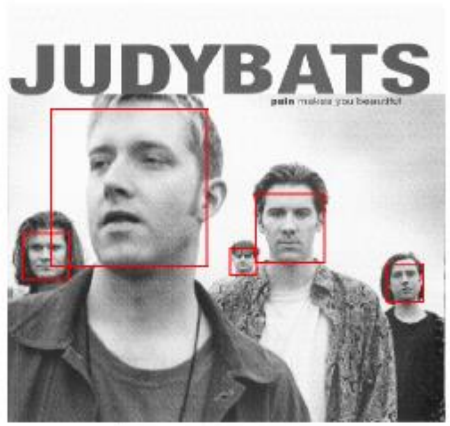
- Idea: Classifier cascade
  - Observation: most image windows are negative and look very different from the searched object class.
  - Filter for promising regions with an initial inexpensive classifier
  - Build a chain of classifiers, choosing cheap ones with low false negative rates early in the chain

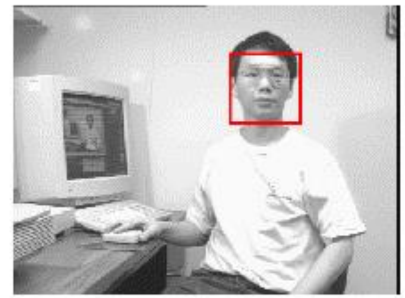
[Fleuret & Geman, IJCV'01; Rowley et al., PAMI'98; Viola & Jones, CVPR'01]

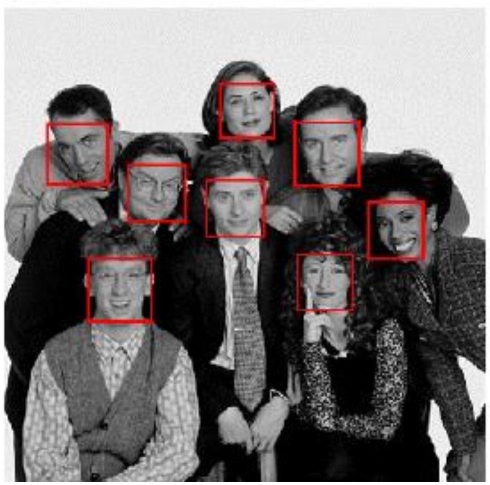
Slide credit: Kristen Grauman

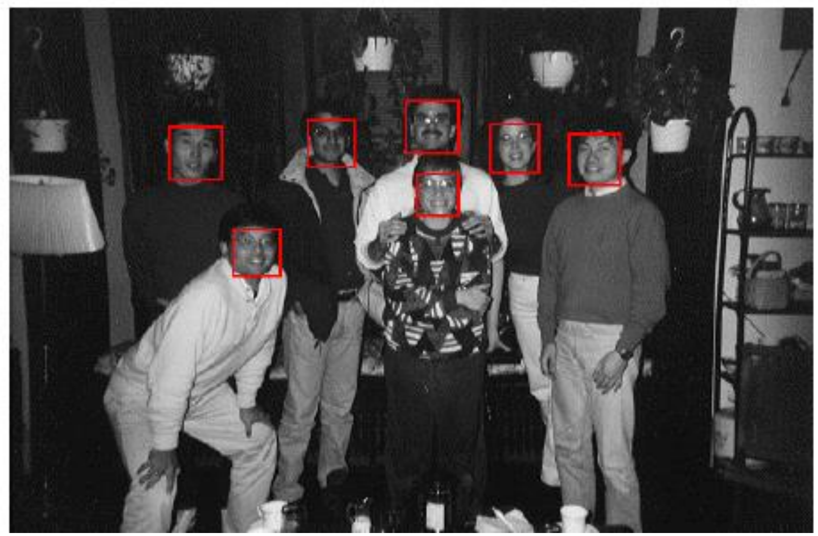
Figure from [Viola & Jones, CVPR 2001]

Viola-Jones Face Detector: Results









Slide credit: Kristen Grauman

You Can Try It At Home…

- The Viola & Jones detector was a huge success
  - First real-time face detector available
  - Many derivative works and improvements

- C++ implementation available in OpenCV [Lienhart, 2002]
  - http://sourceforge.net/projects/opencvlibrary/
- Matlab wrappers for OpenCV code available, e.g. here
  - http://www.mathworks.com/matlabcentral/fileexchange/19912

P. Viola, M. Jones, Robust Real-Time Face Detection, IJCV, Vol. 57(2), 2004

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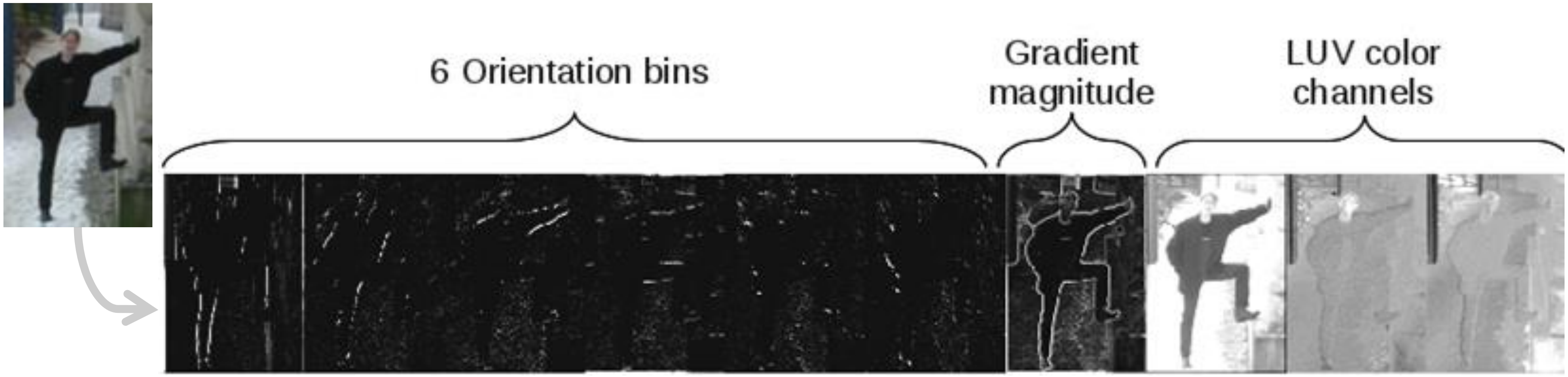
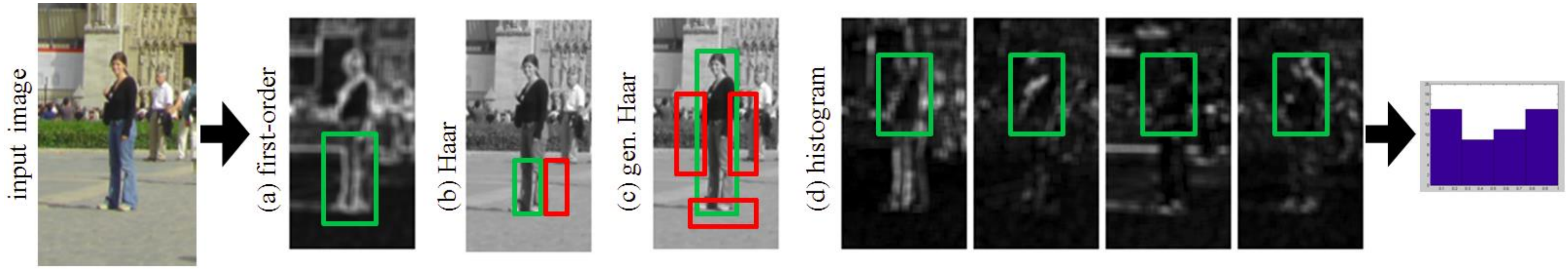
Integral Channel Features



- Generalization of Haar Wavelet idea from Viola-Jones
  - Instead of only considering intensities, also take into account other feature channels (gradient orientations, color, texture).
  - Still efficiently represented as integral images.

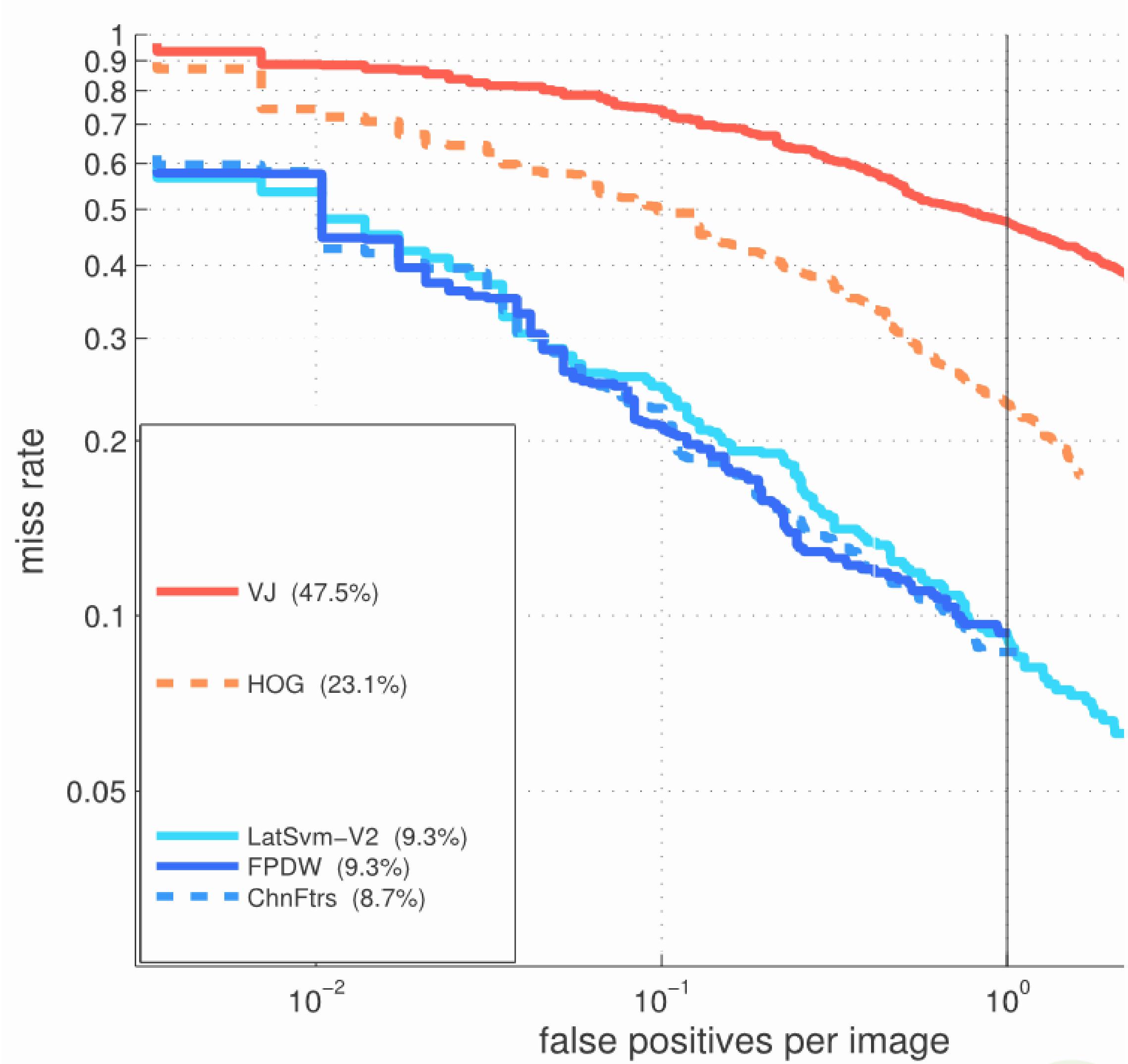
P. Dollar, Z. Tu, P. Perona, S. Belongie. [Integral Channel Features](), BMVC'09.

Integral Channel Features



- Generalize also block computation
  - 1^{st} order features:
    - Sum of pixels in rectangular region.
  - 2^{nd}-order features:
    - Haar-like difference of sum-over-blocks
  - Generalized Haar:
    - More complex combinations of weighted rectangles
  - Histograms
    - Computed by evaluating local sums on quantized images.

Results: Integral Channel Features



[Viola&Jones 2004]

fastHOG
~10 Hz on GPU
[Prisacariu 2009]

DPM
[Felzenszwalb 2008]

ChnFtrs/FPDW
~5 Hz on CPU
[Dollar 2009+2010]

Slide credit: Rodrigo Benenson

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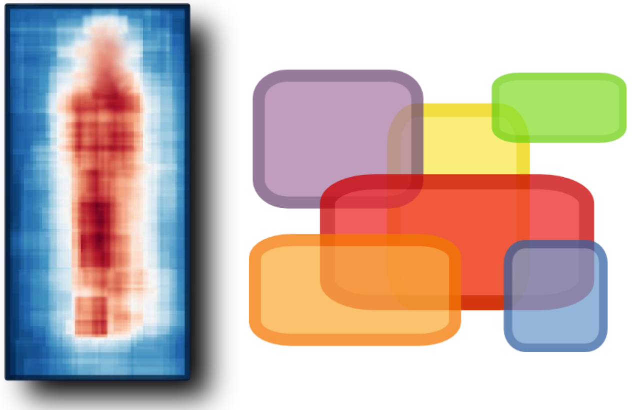
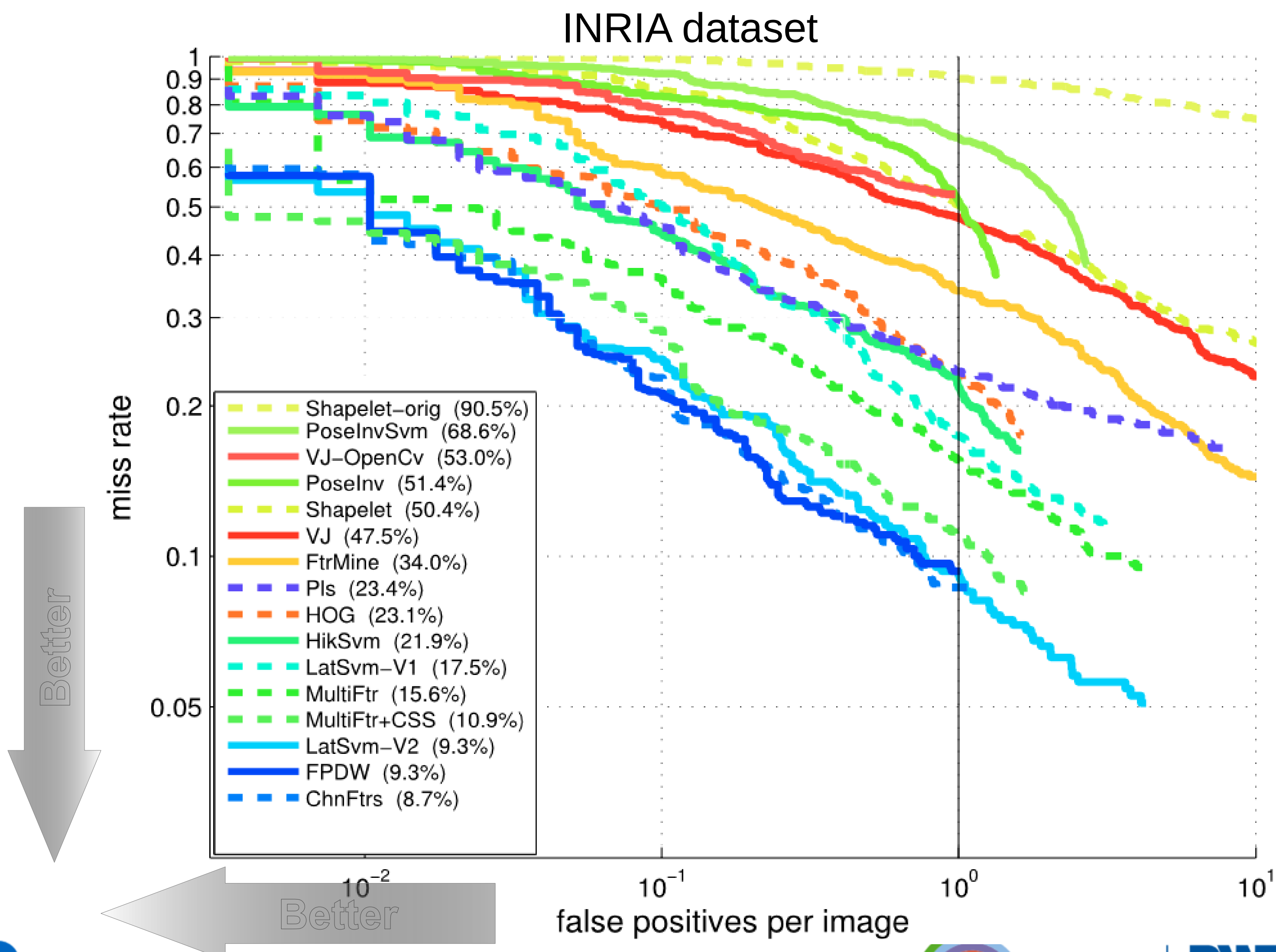
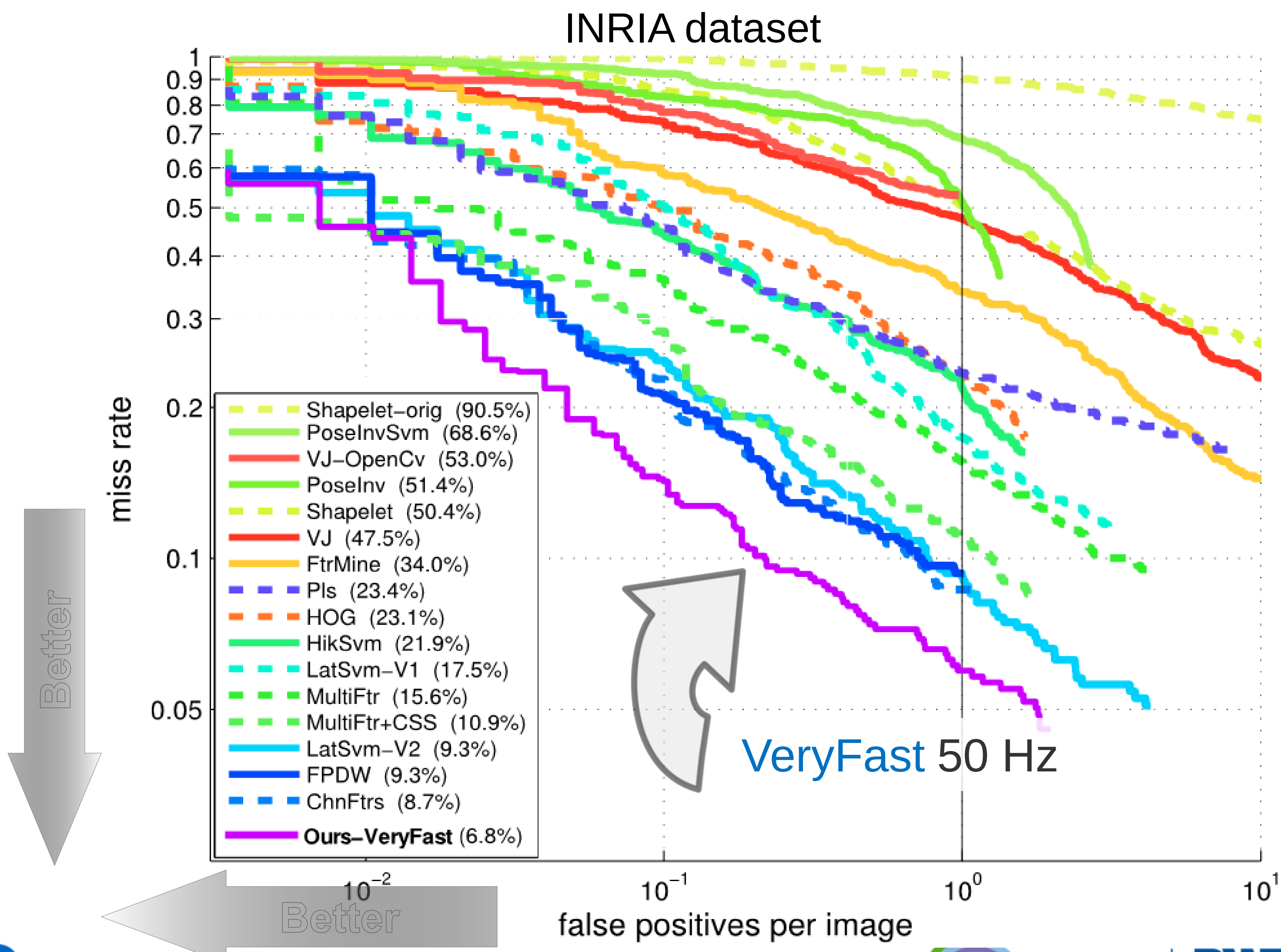


Performance Comparison of Detectors



Slide credit: Rodrigo Benenson

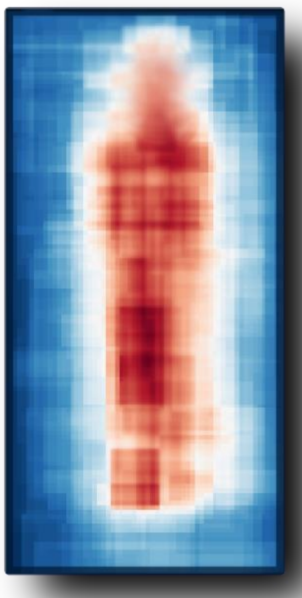
Performance Comparison of Detectors

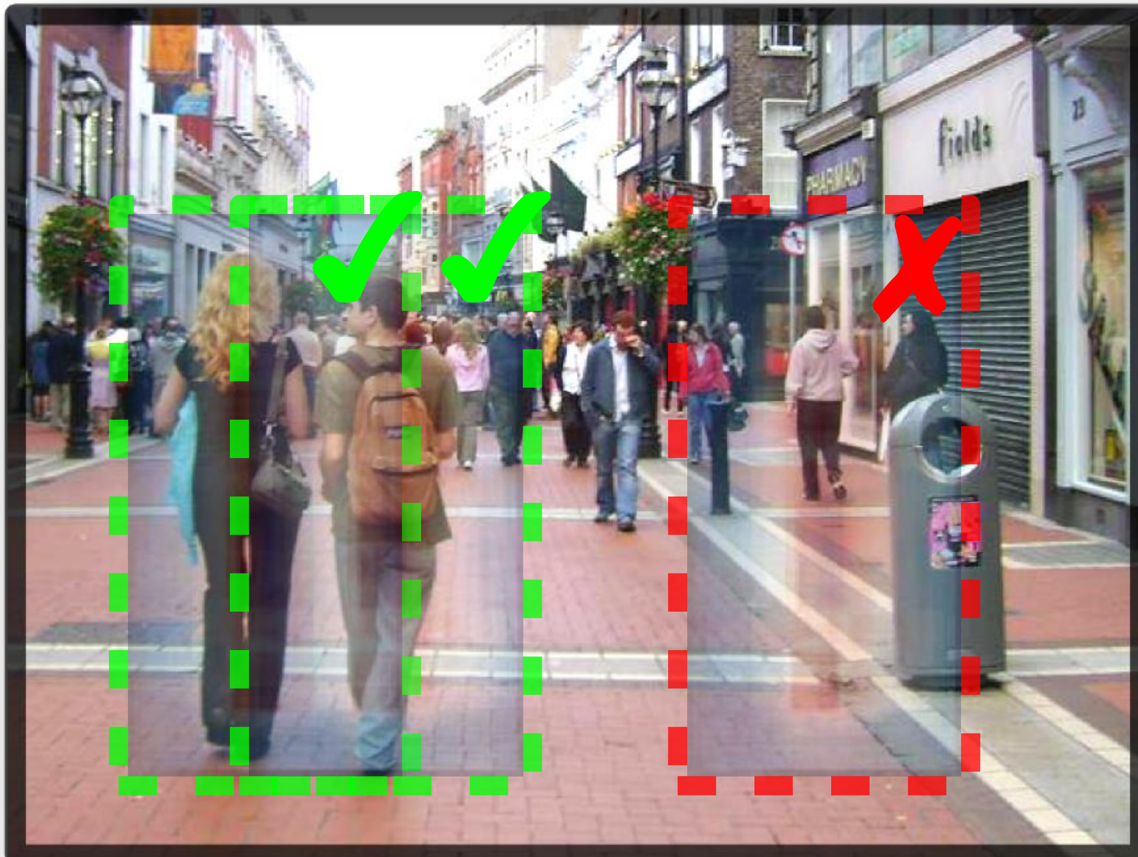


Slide credit: Rodrigo Benenson

Issues for Efficient Detection

- One template cannot detect at multiple scales...



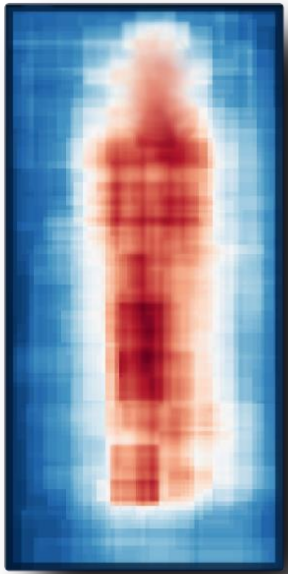


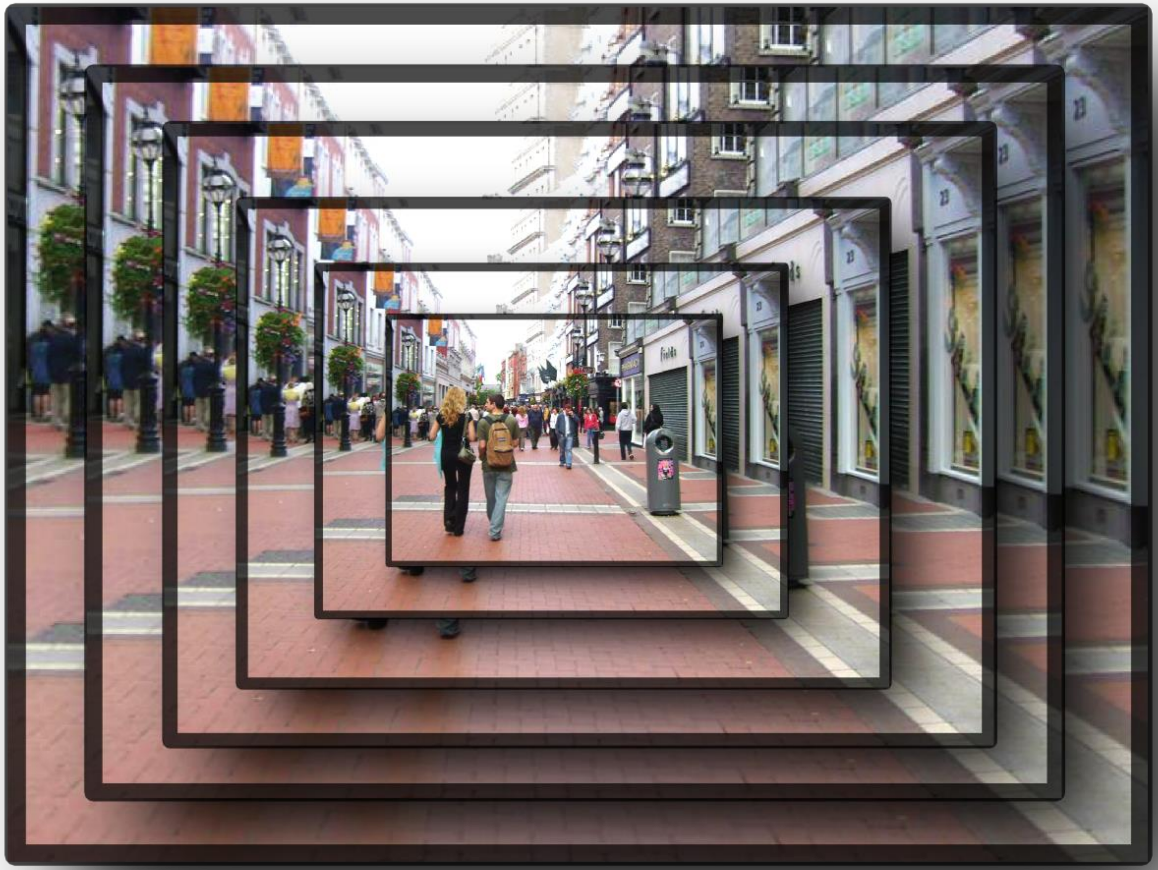
Slide credit: Rodrigo Benenson

Issues for Efficient Detection

- Typically, features are computed many times

~50 scales



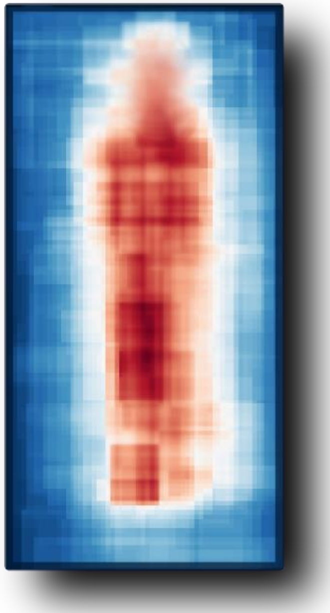


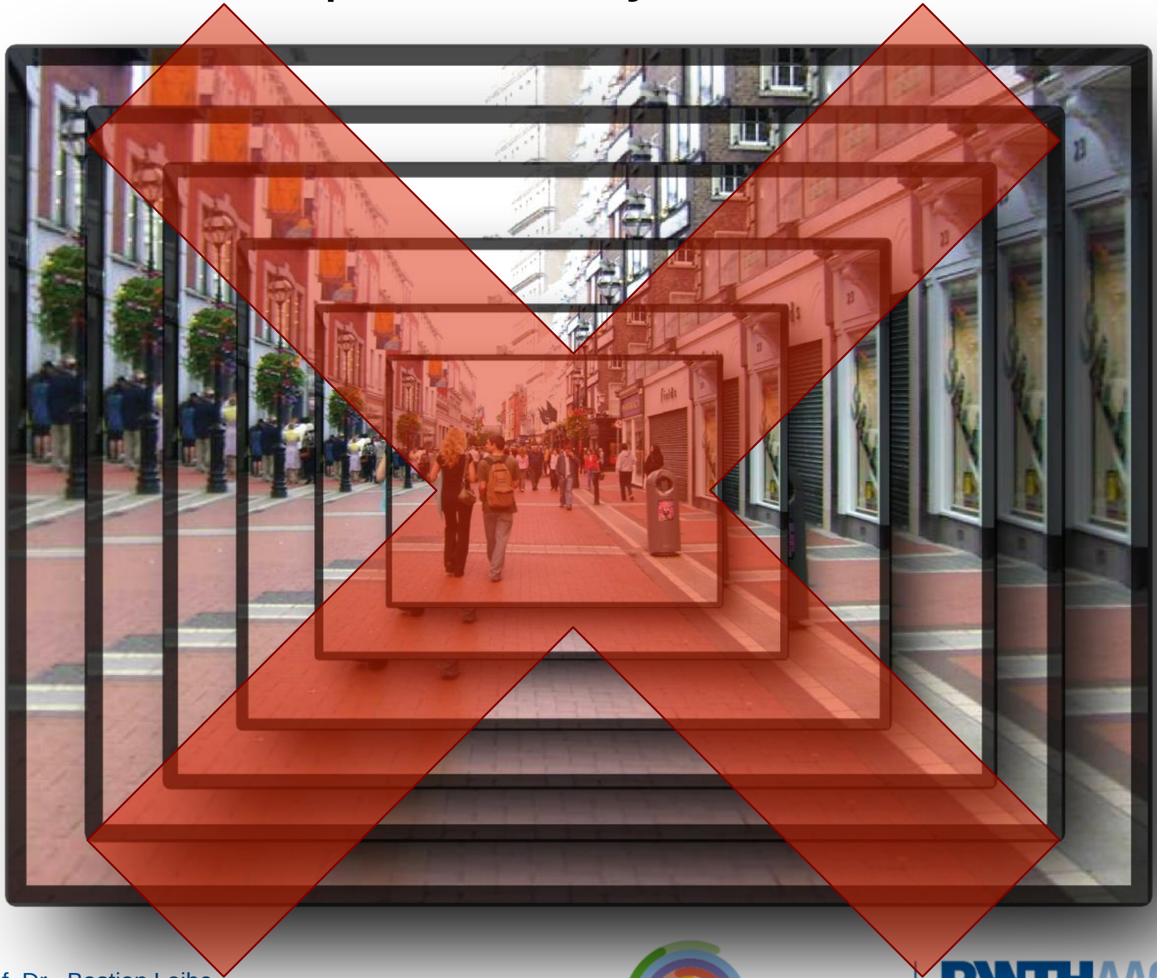
Slide credit: Rodrigo Benenson

Issues for Efficient Detection

- Typically, features are computed many times

~50 scales

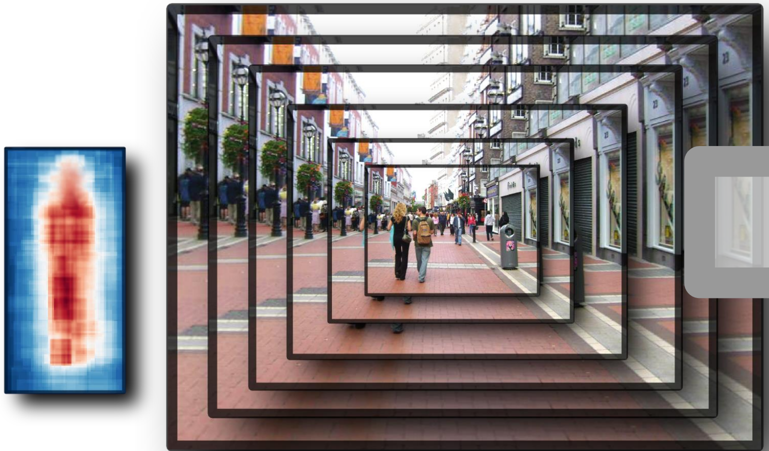




Slide credit: Rodrigo Benenson

VeryFast Detector

- Idea 1: Invert the relation



1 model,
50 image scales

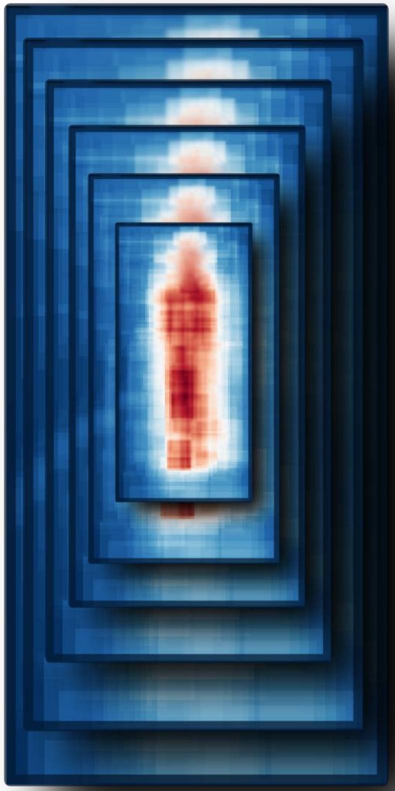
50 models,
1 image scale

R. Benenson, M. Mathias, R. Timofte, L. Van Gool. Pedestrian Detection at 100 Frames per Second, CVPR'12.

Slide credit: Rodrigo Benenson

Practical Considerations

- Training and running 1 model/scale is too expensive




Slide credit: Rodrigo Benenson

VeryFast Detector

- Idea 2: Reduce training time by feature interpolation

5 models,
1 image scale

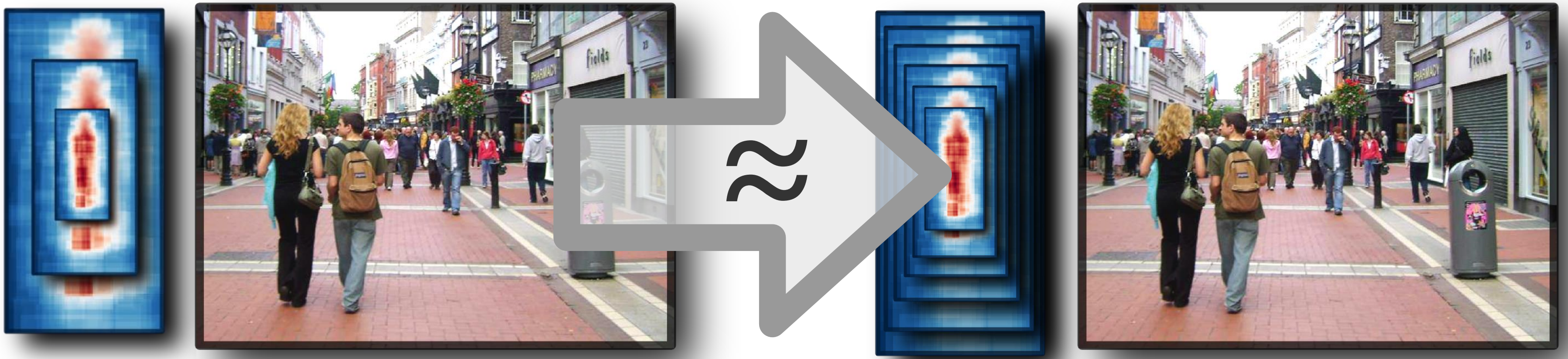
50 models,
1 image scale

- Shown to be possible for Integral Channel features
  - P. Dollár, S. Belongie, Perona. The Fastest Pedestrian Detector in the West, BMVC 2010.

Slide credit: Rodrigo Benenson

VeryFast Detector

- Effect: Transfer test time computation to training time



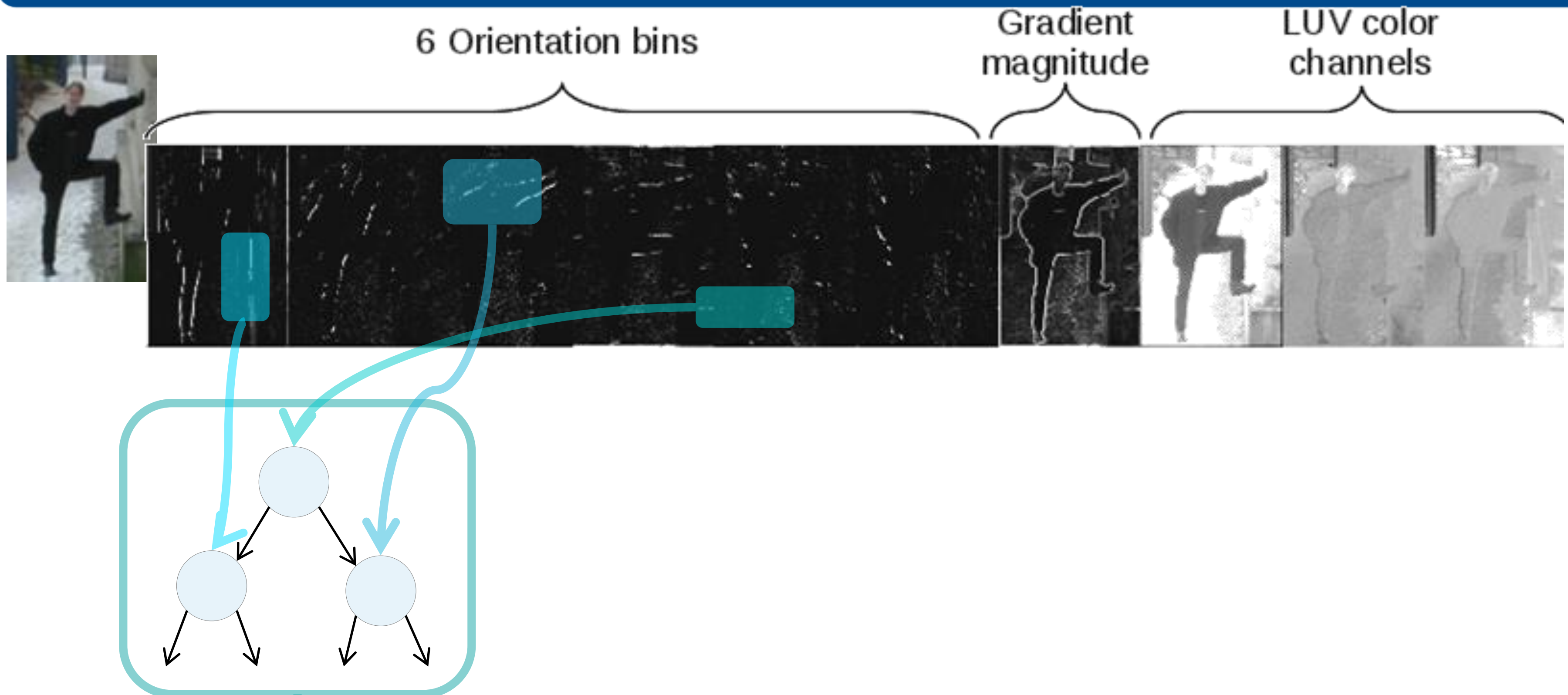
5 models,
1 image scale

50 models,
1 image scale

⇒ *Result: 3x reduction in feature computation*

Slide credit: Rodrigo Benenson

VeryFast: Classifier Construction

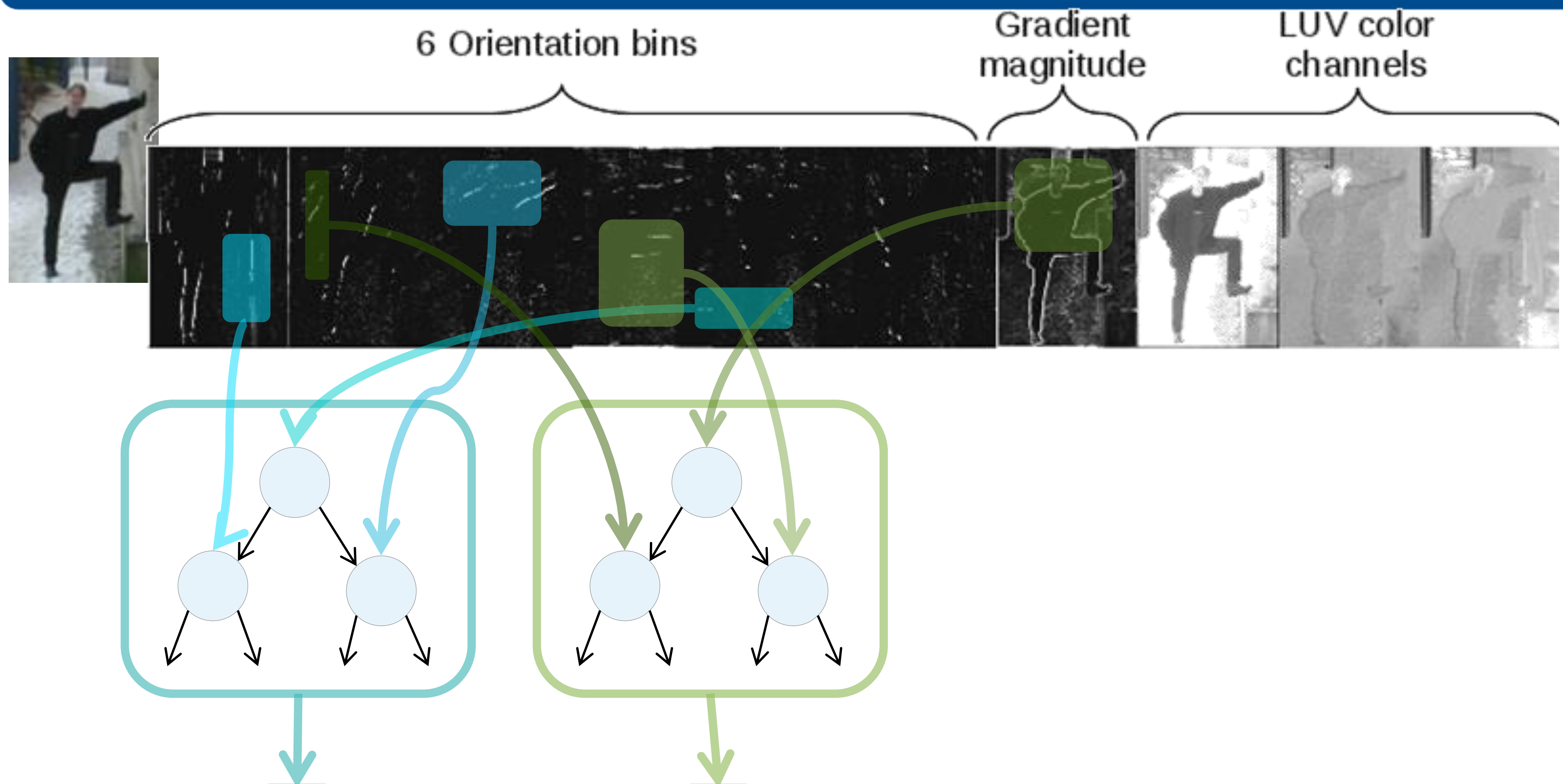


$$score = \; w_1 \cdot \boxed{h_1} +$$

- Ensemble of short trees, learned by AdaBoost

Slide credit: Rodrigo Benenson

VeryFast: Classifier Construction

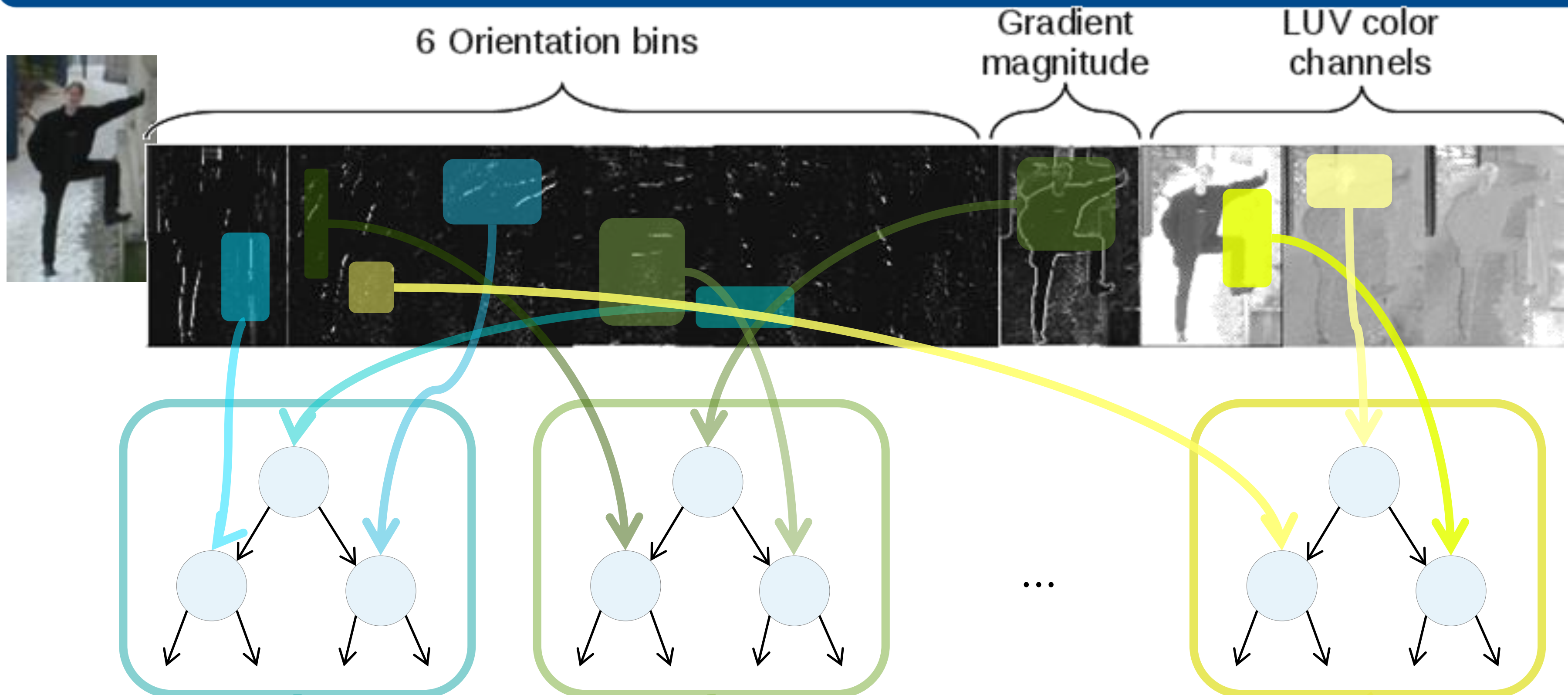


$$score = w_1 \cdot \boxed{h_1} + \quad w_2 \cdot \boxed{h_2} +$$

- Ensemble of short trees, learned by AdaBoost

Slide credit: Rodrigo Benenson

VeryFast: Classifier Construction

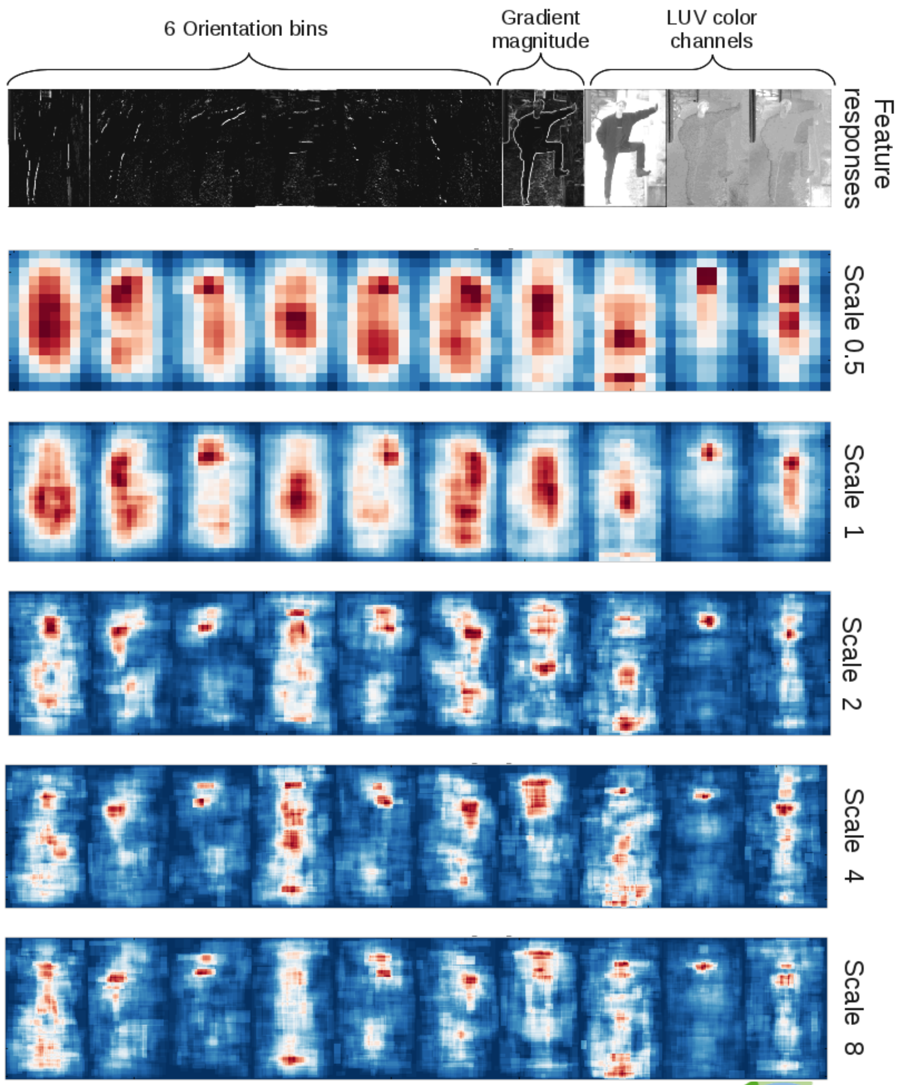


$$score = w_1 \cdot \boxed{h_1} + \quad w_2 \cdot \boxed{h_2} + \quad \dots \quad + w_N \cdot \boxed{h_N}$$

- Ensemble of short trees, learned by AdaBoost

Slide credit: Rodrigo Benenson

Learned Models



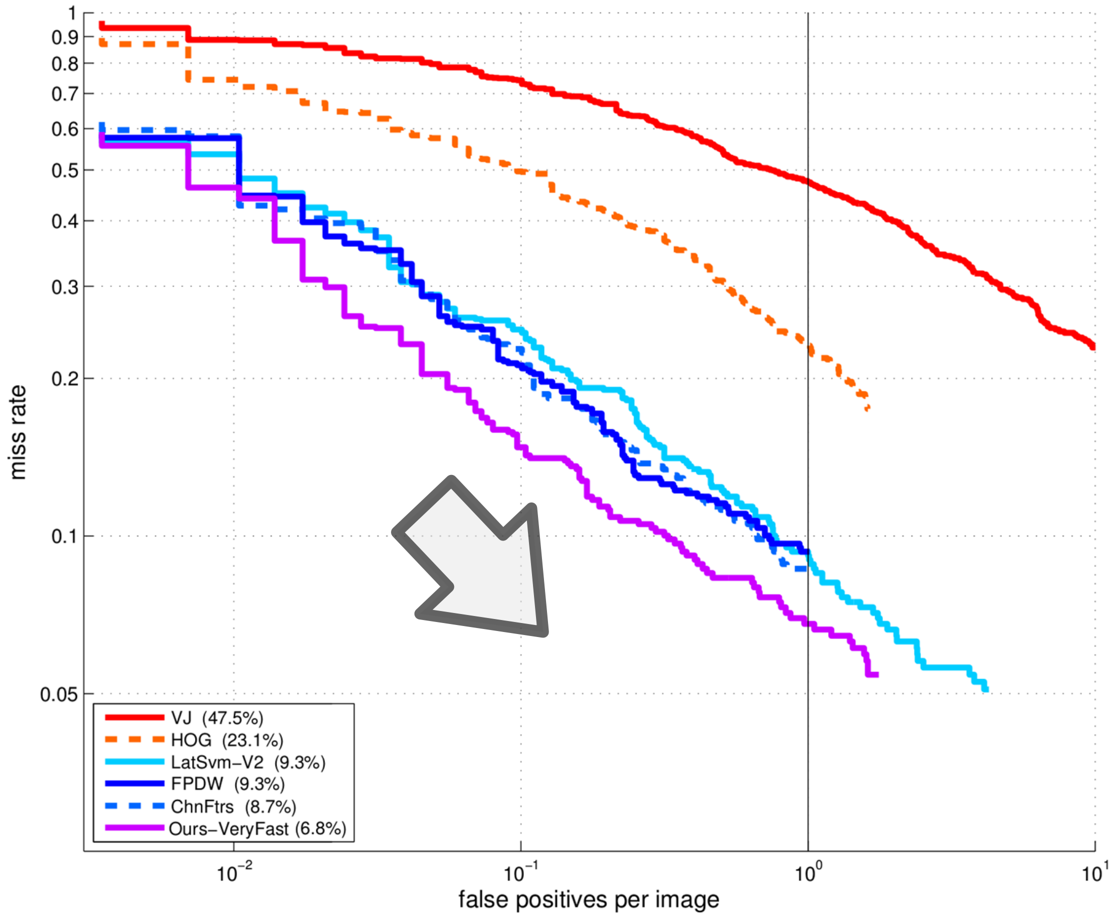
Integral Channel features

Models

⋮

Slide credit: Rodrigo Benenson

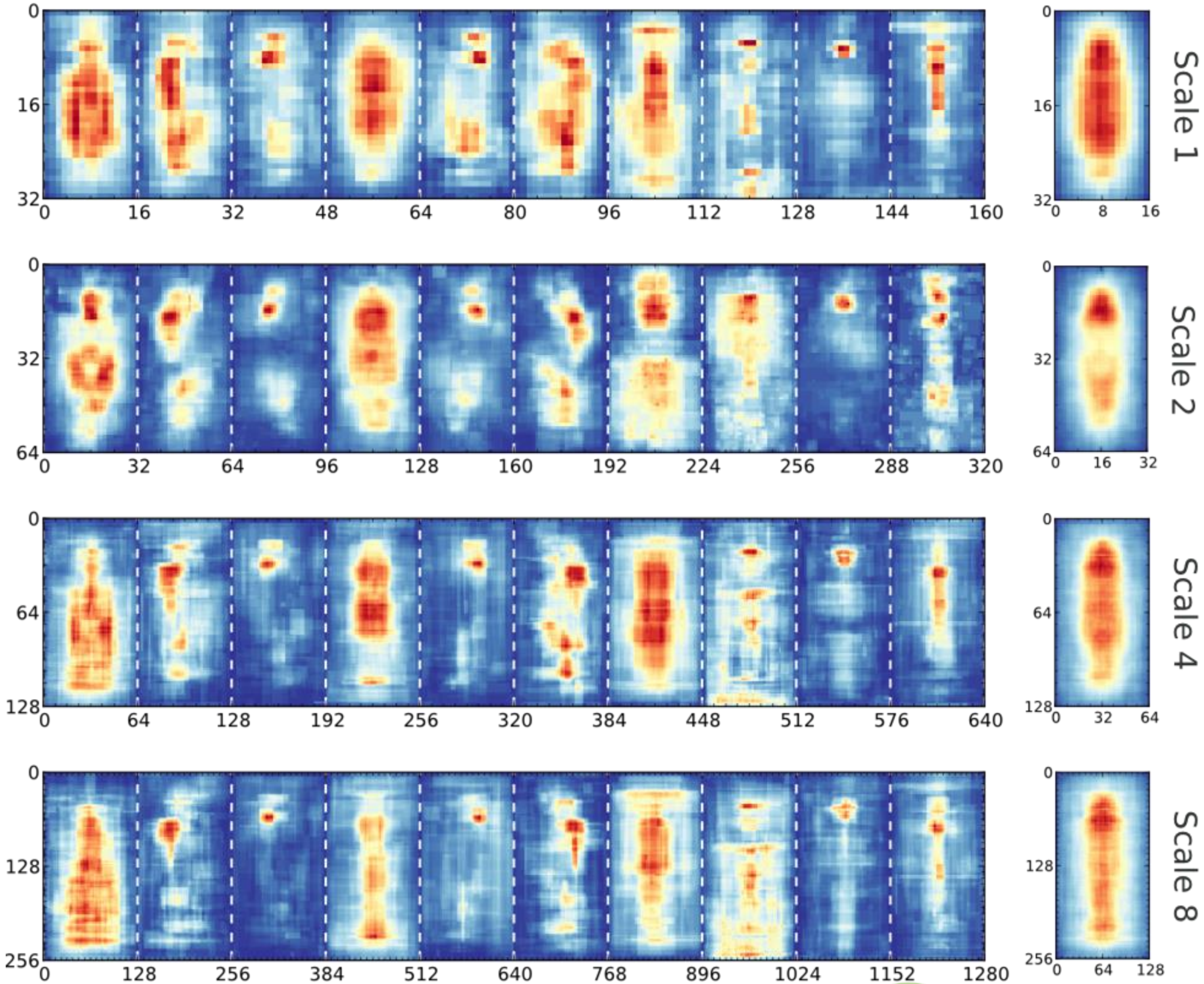
Results



- Detection without resizing improves quality of results

Slide credit: Rodrigo Benenson

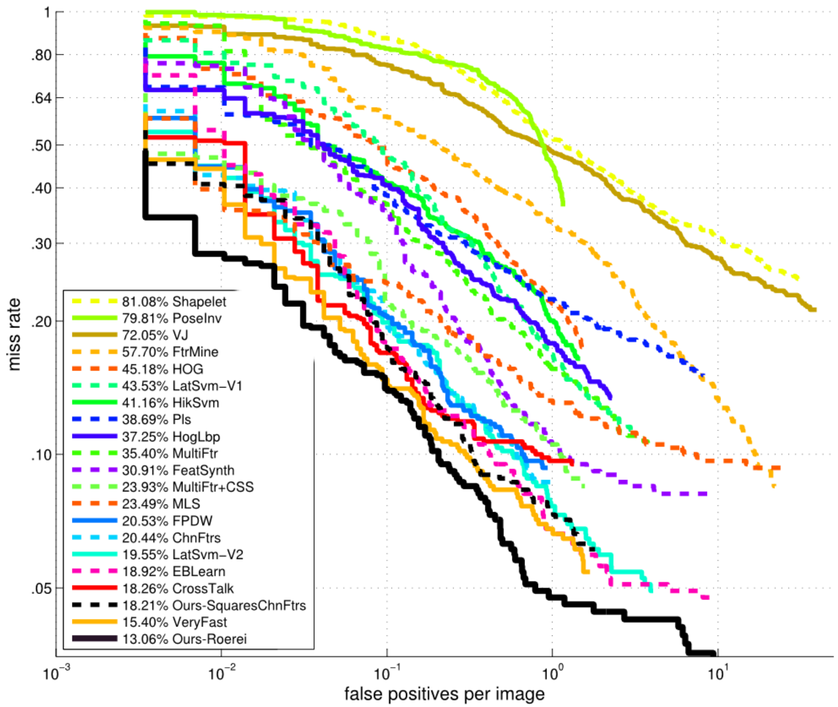
Multi-Scale Models > Single-Scale Model



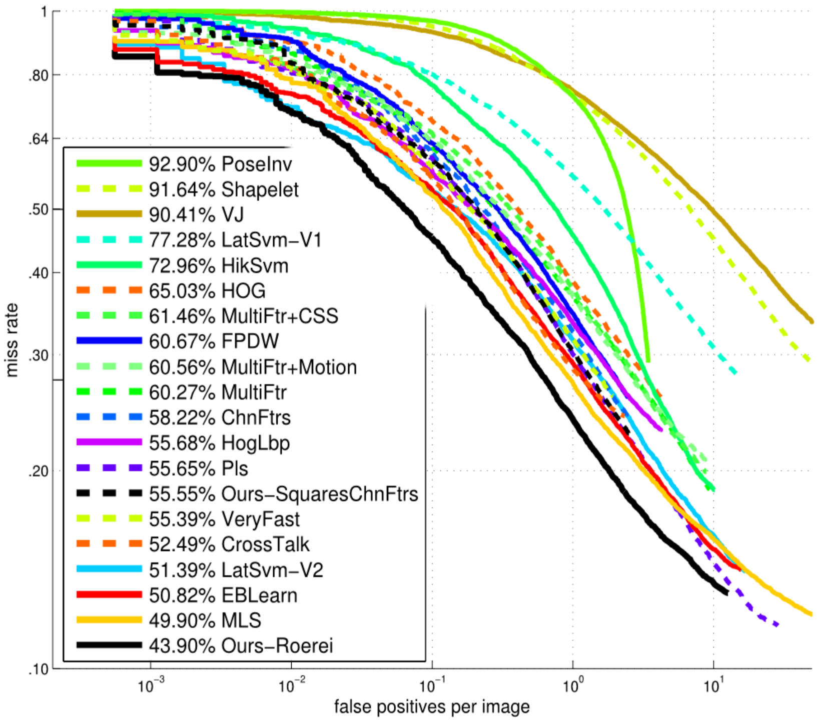
Slide adapted from Rodrigo Benenson

Comparison to State-of-the-Art

INRIA dataset



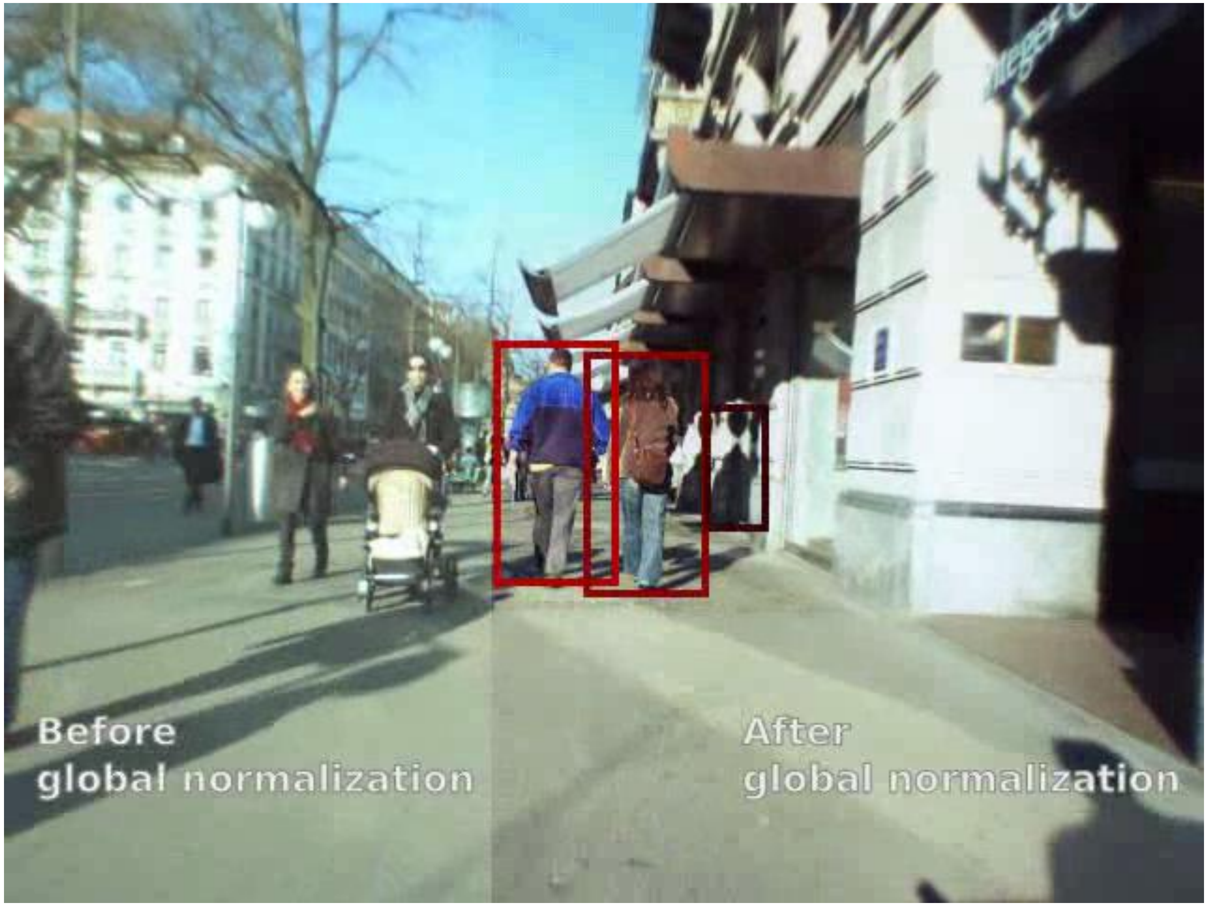
ETH dataset



- Extension: Roerei detector
  - Detailed evaluation of design space
  - Non-regular pooling regions found to work best.

Slide adapted from Rodrigo Benenson

Roerei Results



R. Benenson, M. Mathias, R. Timofte, L. Van Gool. [Seeking the Strongest Rigid Detector](). CVPR'13.

Applications: Mobile Robot Navigation

link to the video

SEVENTH FRAMEWORK PROGRAMME

EUROPA

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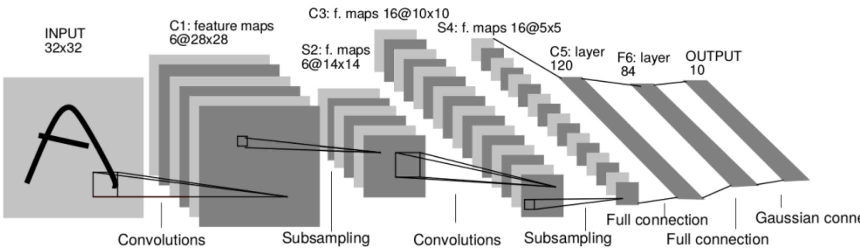
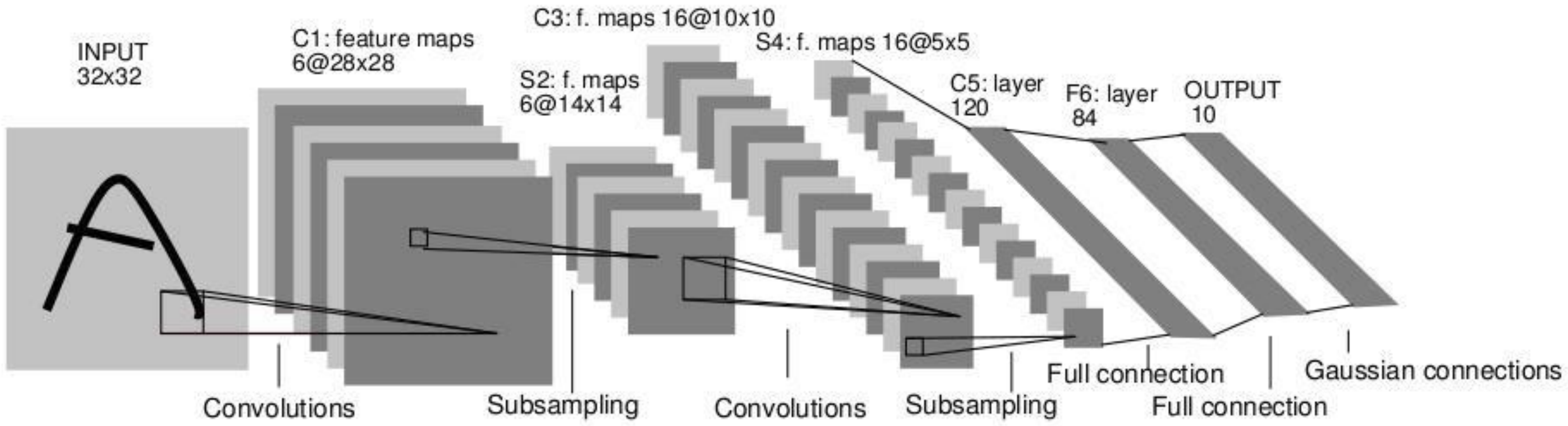


Recap: Convolutional Neural Networks

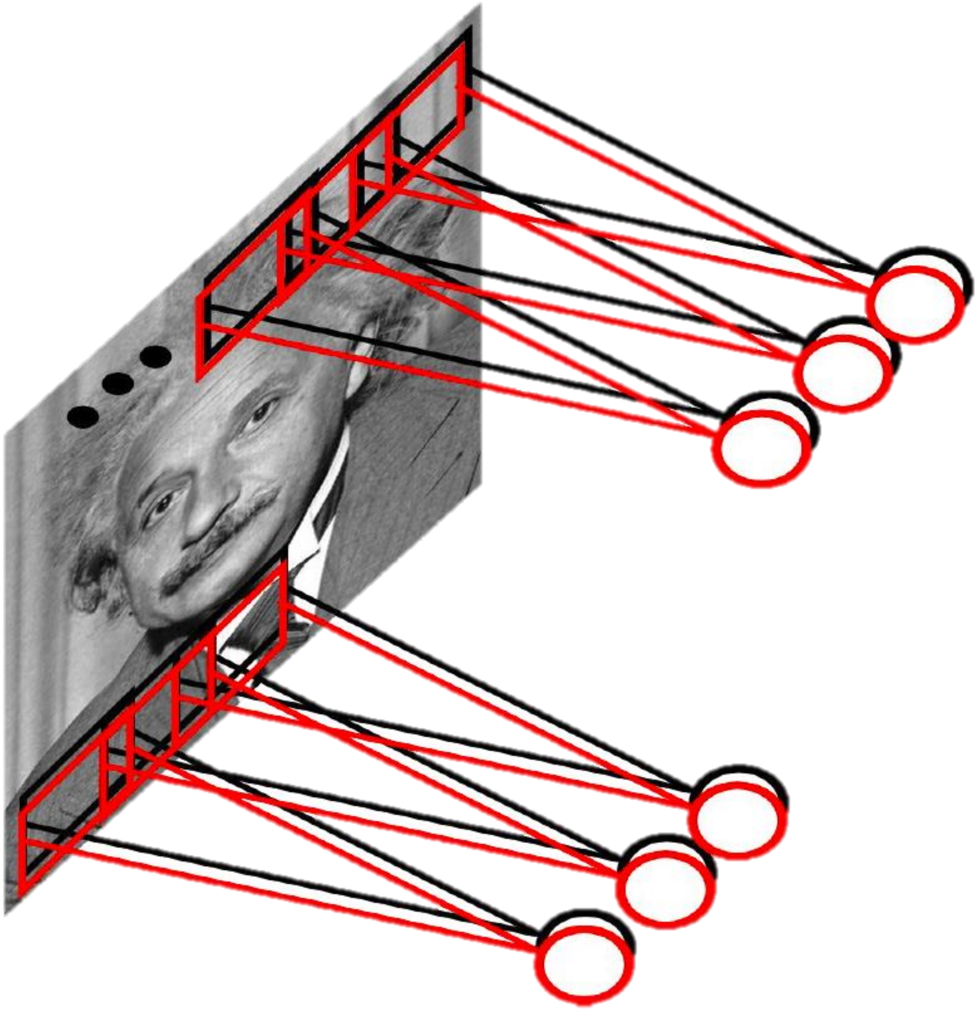


- Neural network with specialized connectivity structure
  - Stack multiple stages of feature extractors
  - Higher stages compute more global, more invariant features
  - Classification layer at the end

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Slide credit: Svetlana Lazebnik

Recap: Intuition of CNNs

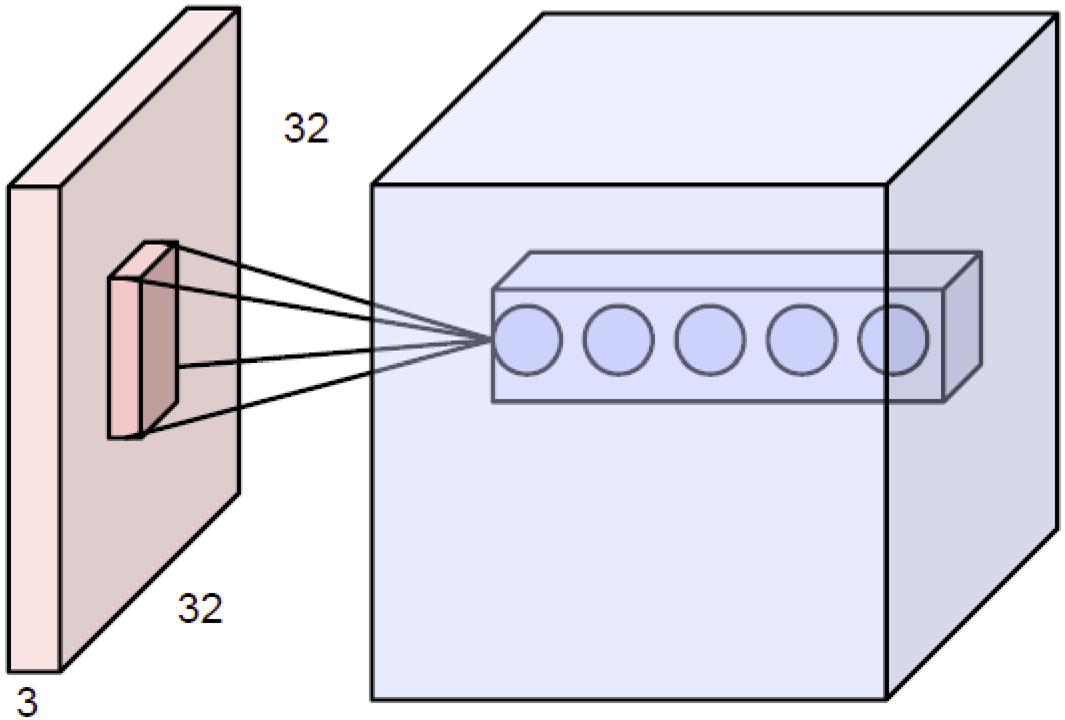


- Convolutional net
  - Share the same parameters across different locations
  - Convolutions with learned kernels
- Learn *multiple* filters
  - E.g. 1000×1000 image
    100 filters
    10×10 filter size

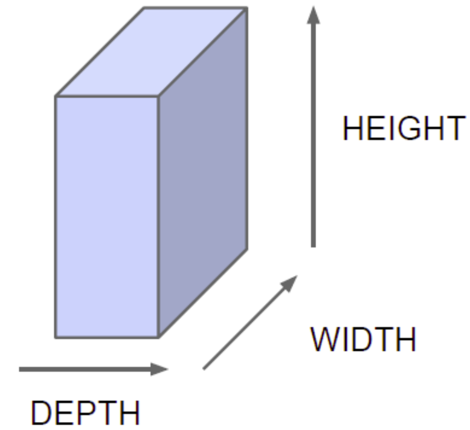
    $\Rightarrow$ only 10k parameters
- Result: Response map
  - size: $1000 \times 1000 \times 100$
  - Only memory, not params!

Slide adapted from Marc'Aurelio Ranzato

Recap: Convolution Layers



Naming convention:

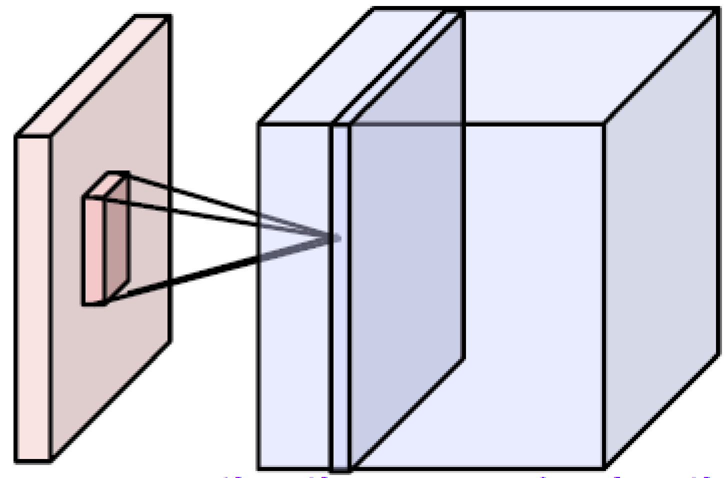


- All Neural Net activations arranged in 3 dimensions
  – Multiple neurons all looking at the same input region, stacked in depth
  – Form a single [$1\times1\times$depth] depth column in output volume.

Slide credit: FeiFei Li, Andrej Karpathy

Recap: Activation Maps

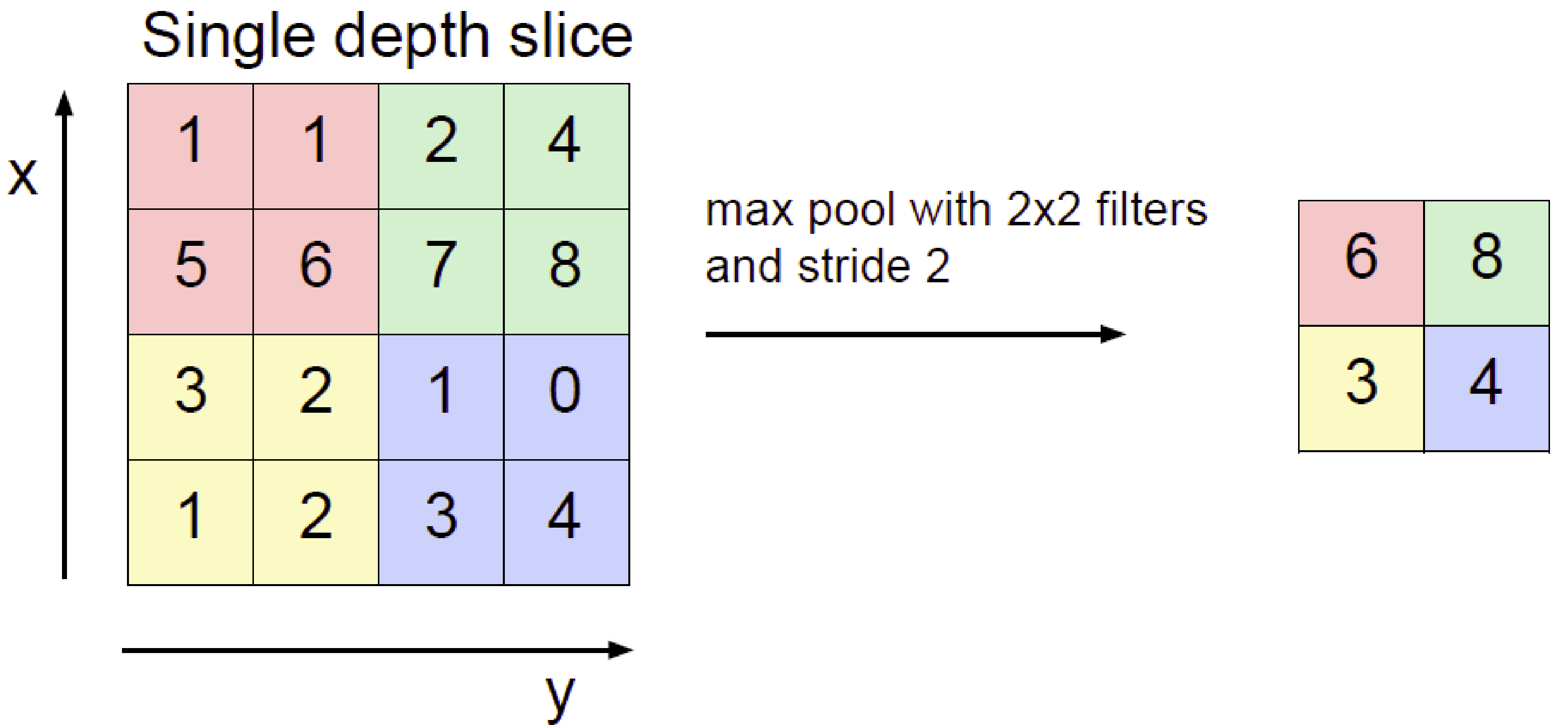
5×5 filters



Activation maps

Slide adapted from FeiFei Li, Andrej Karpathy

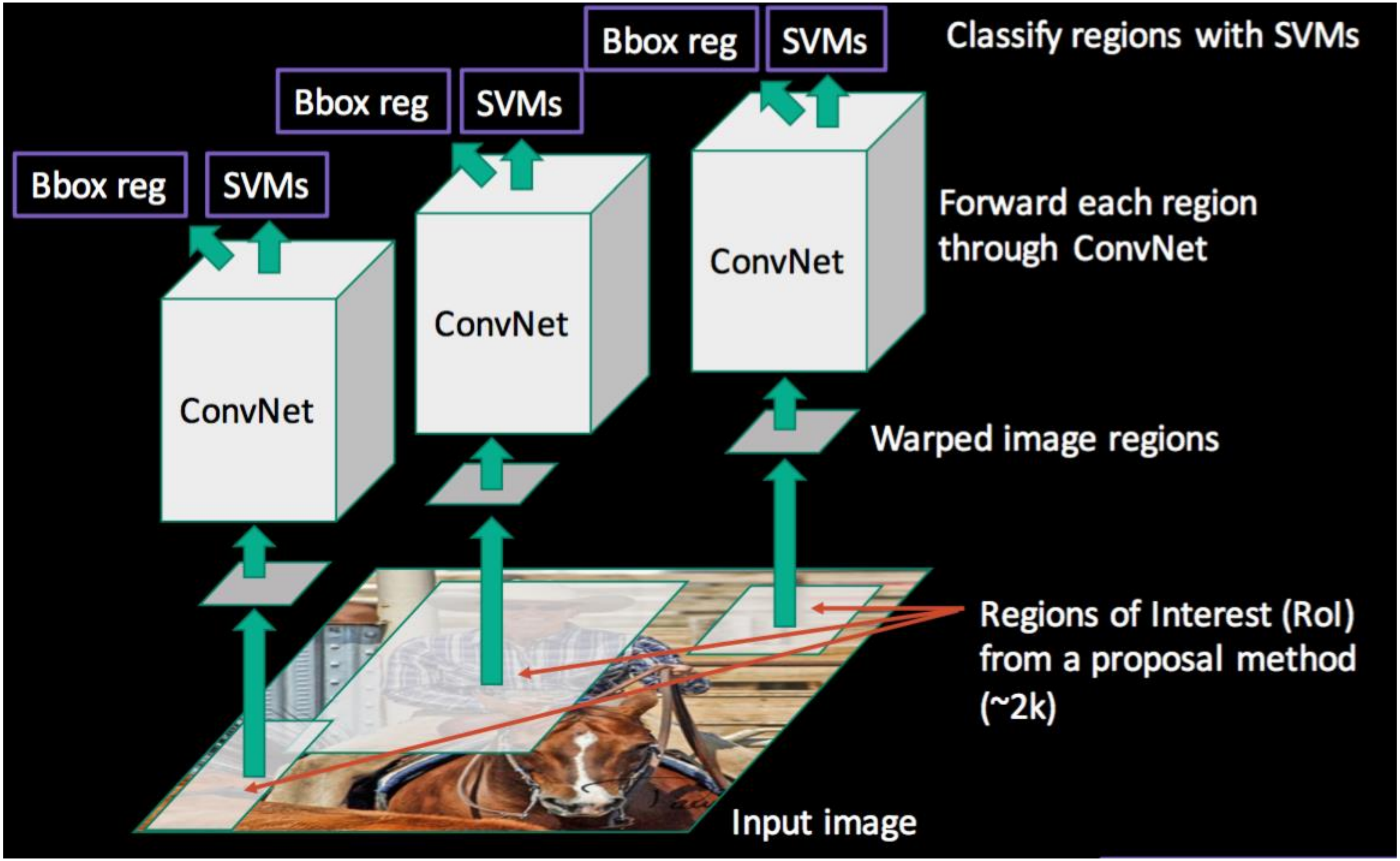
Recap: Pooling Layers



- Effect:
  - Make the representation smaller without losing too much information
  - Achieve robustness to translations

Slide adapted from FeiFei Li, Andrej Karpathy

Recap: R-CNN for Object Detection

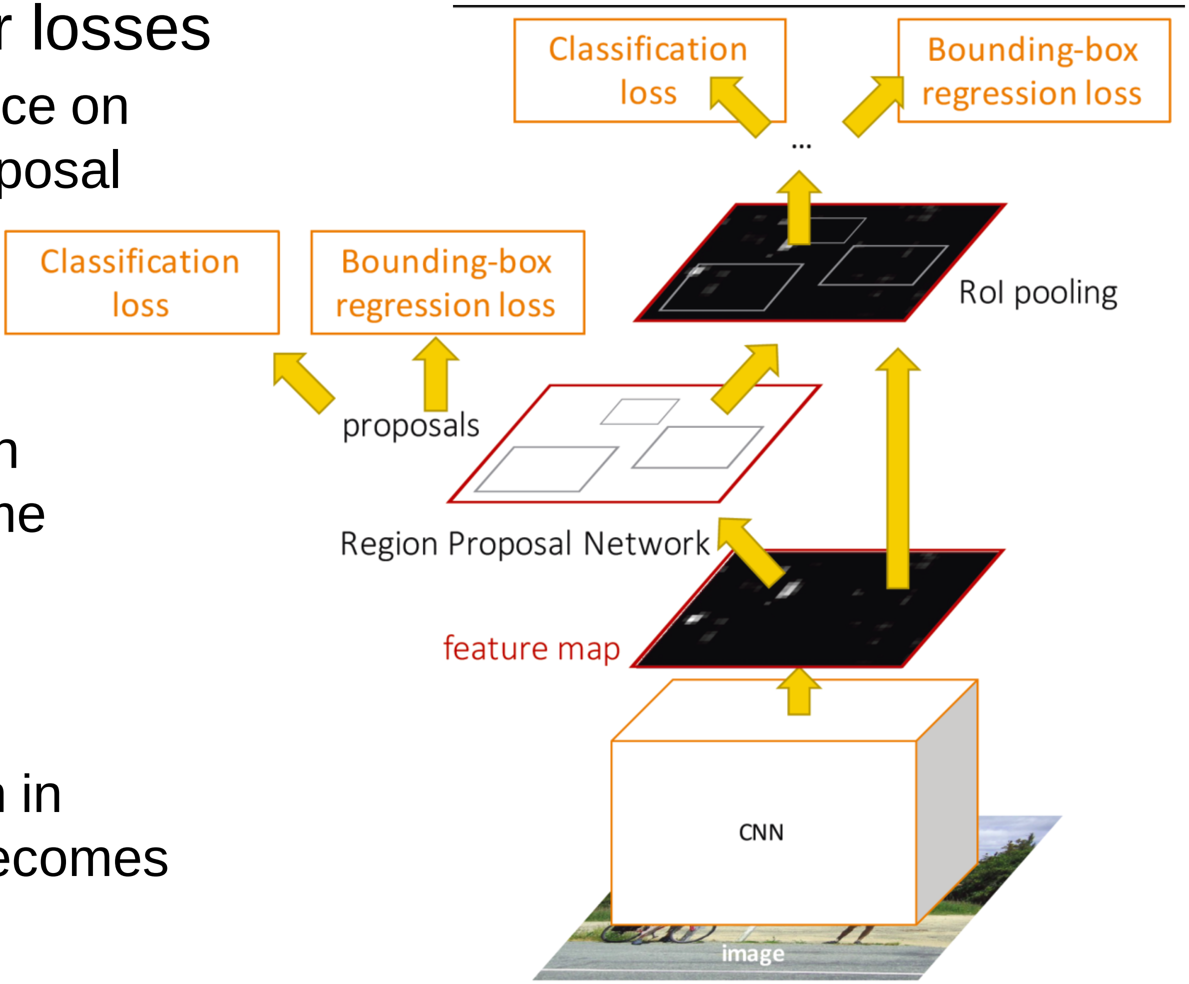


Slide credit: Ross Girshick

Recap: Faster R-CNN

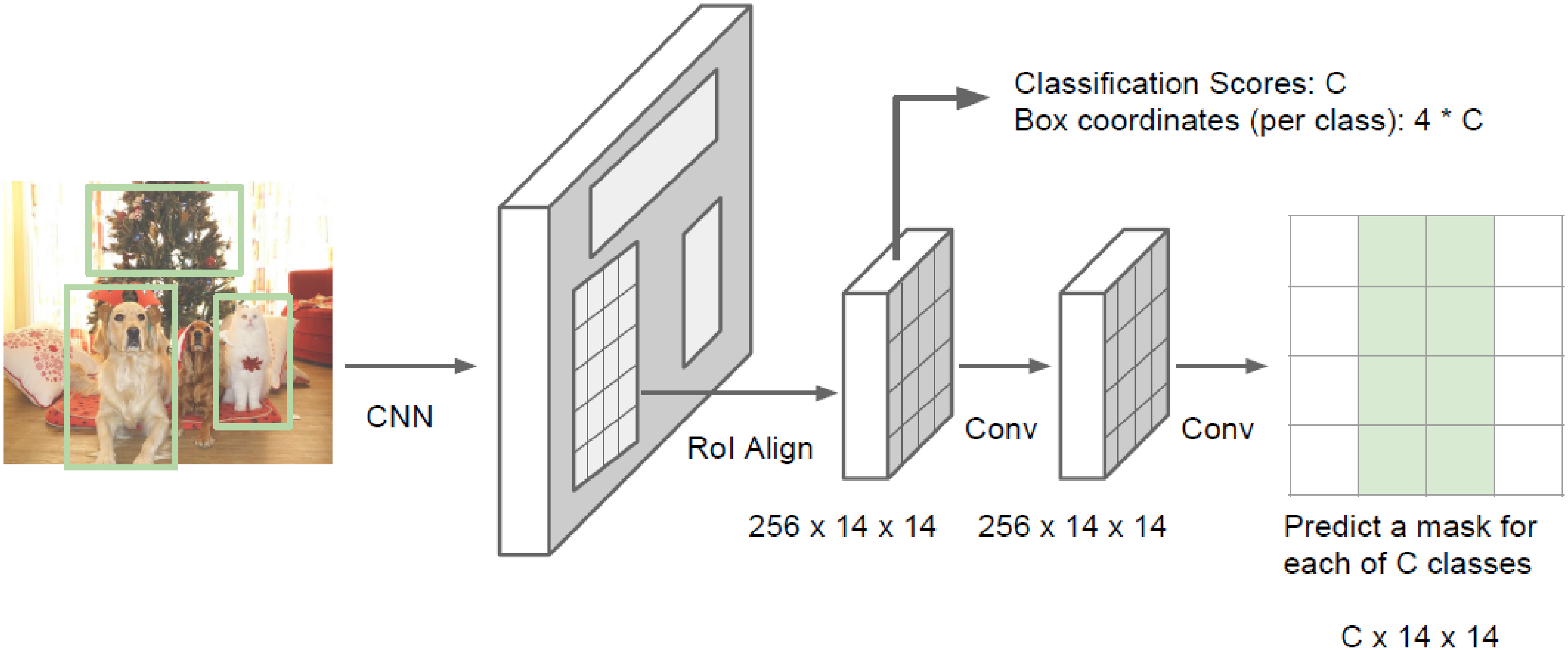
- One network, four losses
  - Remove dependence on external region proposal algorithm.
  - Instead, infer region proposals from same CNN.
  - Feature sharing
  - Joint training

    ⇒ Object detection in a single pass becomes possible.



Slide credit: Ross Girshick

Most Recent Version: Mask R-CNN

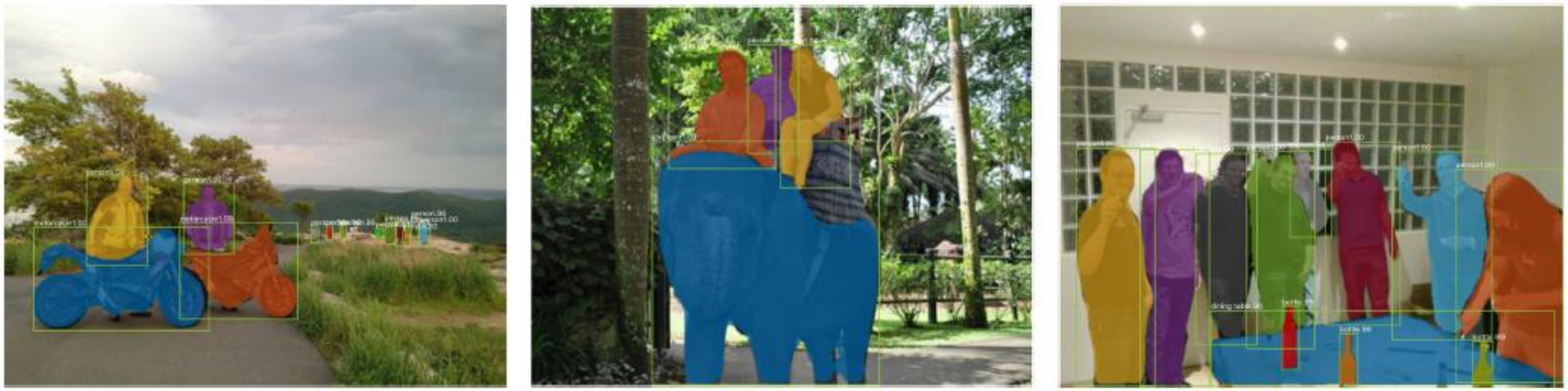


K. He, G. Gkioxari, P. Dollar, R. Girshick, [Mask R-CNN](), arXiv 1703.06870.

Slide credit: FeiFei Li

Mask R-CNN Results

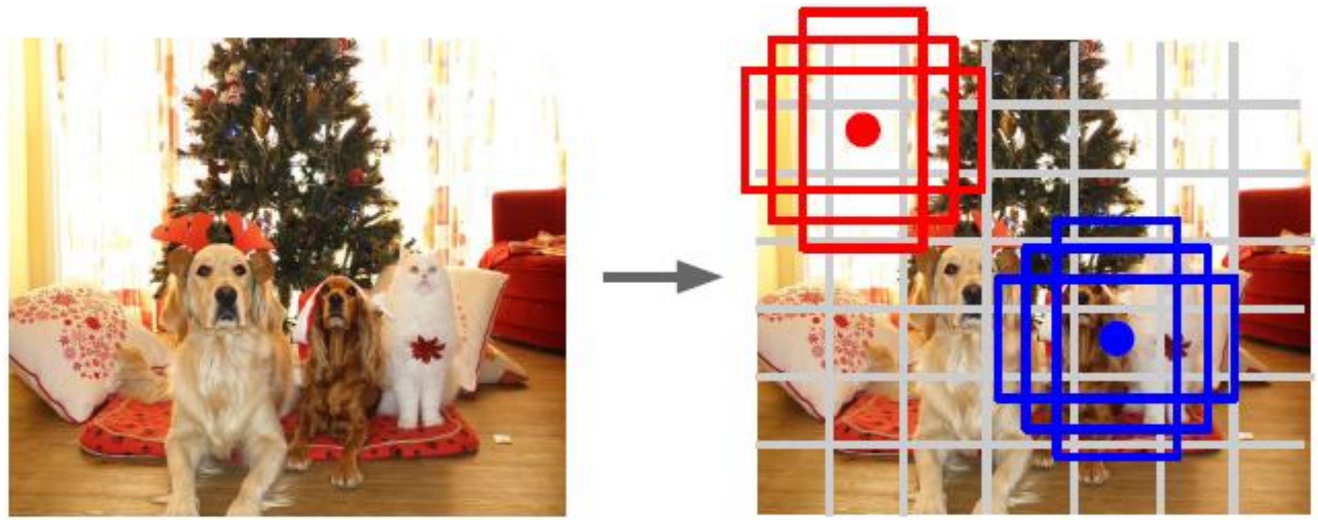
- Detection + Instance segmentation



- Detection + Pose estimation

Figure credit: K. He, G. Gkioxari, P. Dollar, R. Girshick

YOLO / SSD



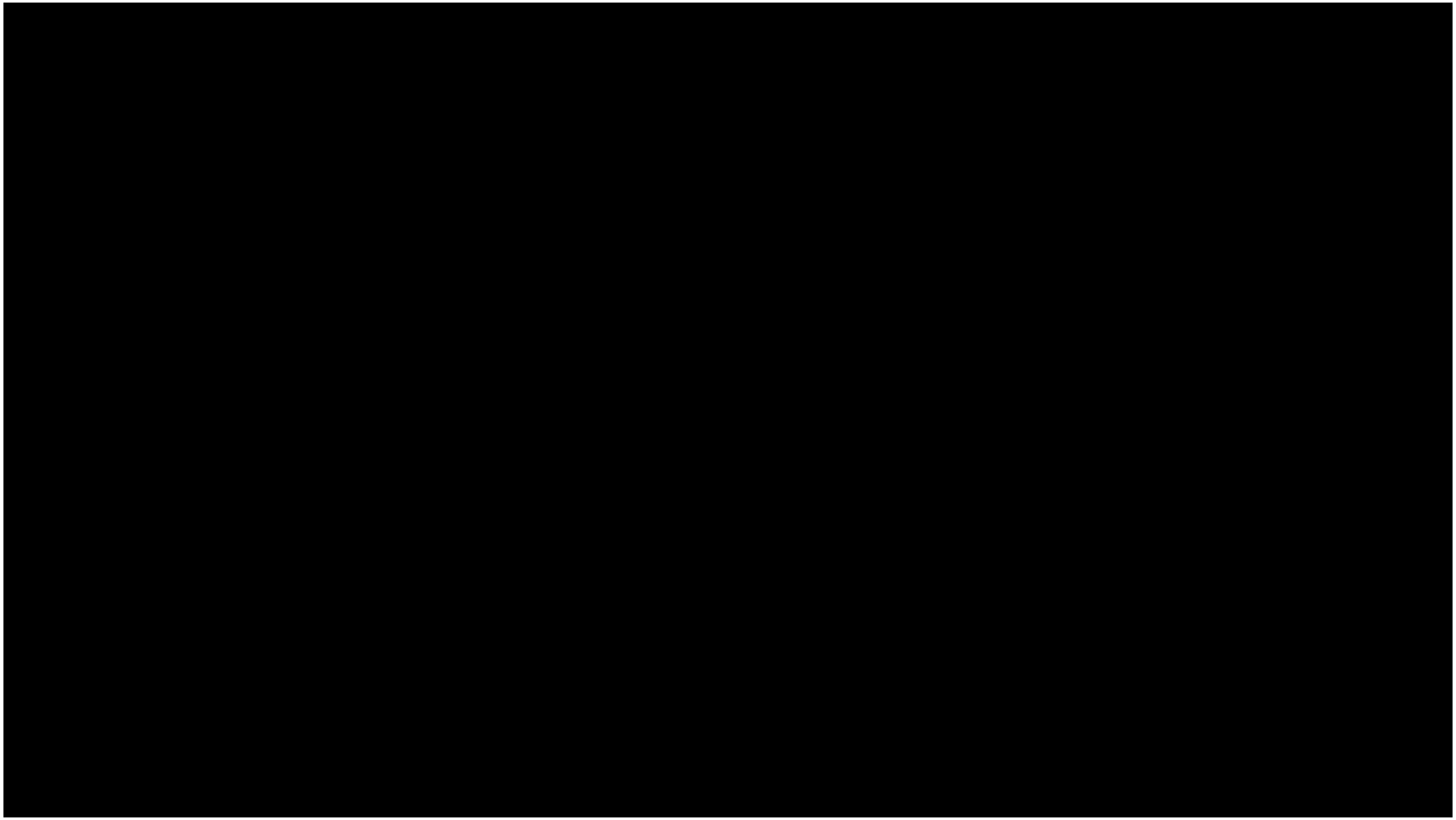
Input image
3 x H x W

Divide image into grid
7 x 7

- Idea: Directly go from image to detection scores
- Within each grid cell
  - Start from a set of anchor boxes
  - Regress from each of the B anchor boxes to a final box
  - Predict scores for each of C classes (including background)

Slide credit: FeiFei Li

YOLO-v2 Results



J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You Only Look Once: Unified, Real-Time Object Detection, CVPR 2016.

You Can Try All of This At Home…

- Detector code is publicly available
  - HOG:
    - Dalal's original implementation:
      http://www.navneetdalal.com/software/
    - Our CUDA-optimized *groundHOG* code (>80 fps on GTX 580)
      http://www.vision.rwth-aachen.de/software/groundhog
  - DPM:
    - Felzenswalb's original implementation:
      http://www.cs.uchicago.edu/~pff/latent
  - VeryFast
    - Benenson's original implementation:
      https://bitbucket.org/rodrigob/doppia/
  - YOLO
    - Joe Redmon's original implementation (YOLO v3):
      https://pjreddie.com/darknet/yolo/