Lecture 17: object detection

Professor Fei-Fei Li

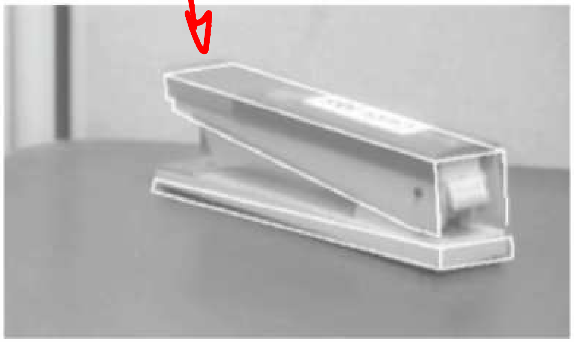
Stanford Vision Lab

segmentation

Object detection

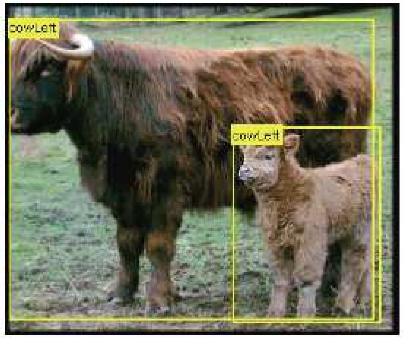
bounding box

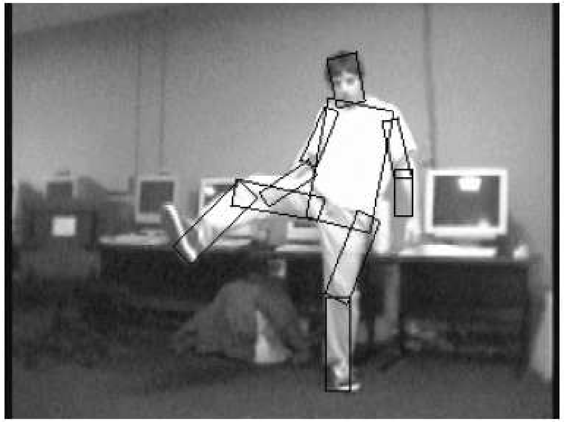
Detecting rigid objects



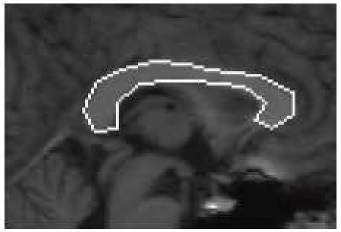
det

PASCAL challenge

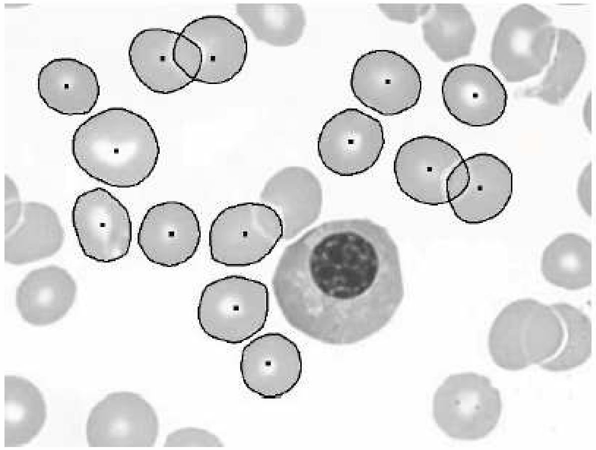




Detecting non-rigid objects



Medical image analysis



Segmenting cells

What we will learn today?

- Implicit Shape Model
  - Representation
  - Recognition
  - Experiments and results
- Deformable Models
  - The PASCAL challenge
  - Latent SVM Model

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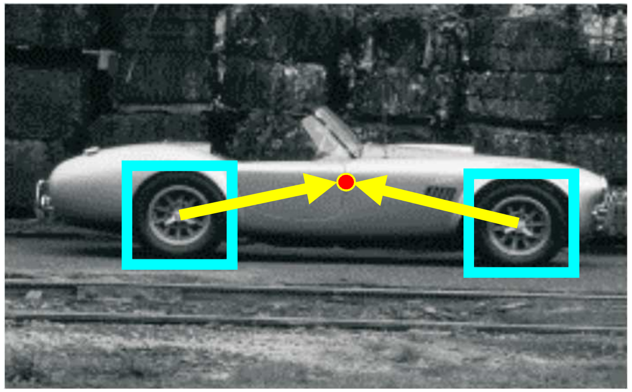
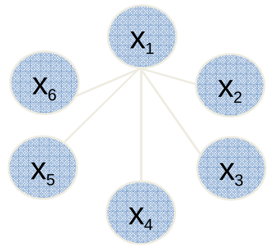


Implicit Shape Model (ISM)

- Basic ideas
  - Learn an appearance codebook
  - Learn a star-topology structural model
    - Features are considered independent given obj. center

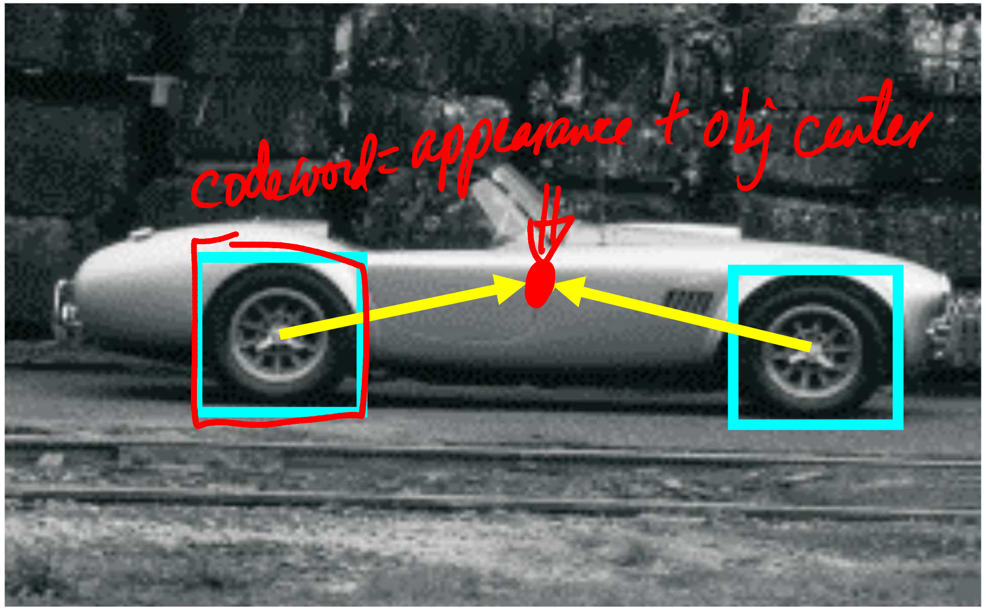


- Algorithm: probabilistic Gen. Hough Transform
  - Exact correspondences → Prob. match to object part
  - NN matching → Soft matching
  - Feature location on obj. → Part location distribution
  - Uniform votes → Probabilistic vote weighting
  - Quantized Hough array → Continuous Hough space

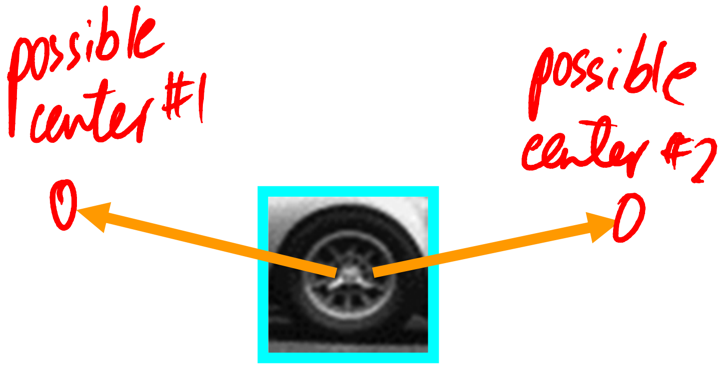
Source: Bastian Leibe

Implicit Shape Model: Basic Idea

- Visual vocabulary is used to index votes for object position [a visual word = “part”].



Training image



Visual codeword with displacement vectors

B. Leibe, A. Leonardis, and B. Schiele, [Robust Object Detection with Interleaved Categorization and Segmentation](), International Journal of Computer Vision, Vol. 77(1-3), 2008.

Source: Bastian Leibe

Implicit Shape Model: Basic Idea

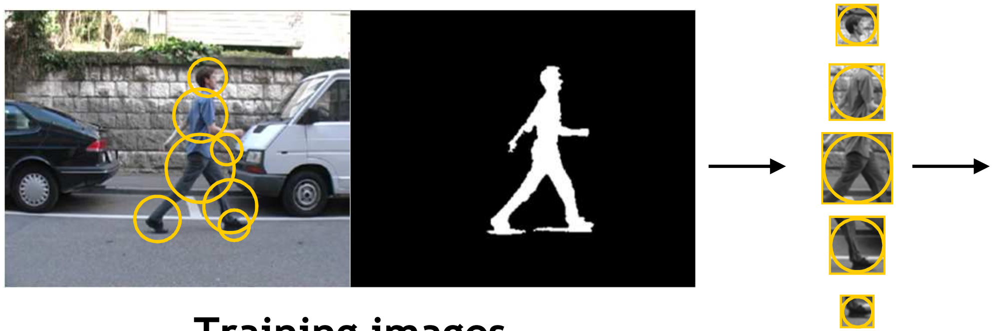
- Objects are detected as consistent configurations of the observed parts (visual words).

Test image

B. Leibe, A. Leonardis, and B. Schiele, [Robust Object Detection with Interleaved Categorization and Segmentation](), International Journal of Computer Vision, Vol. 77(1-3), 2008.

Source: Bastian Leibe

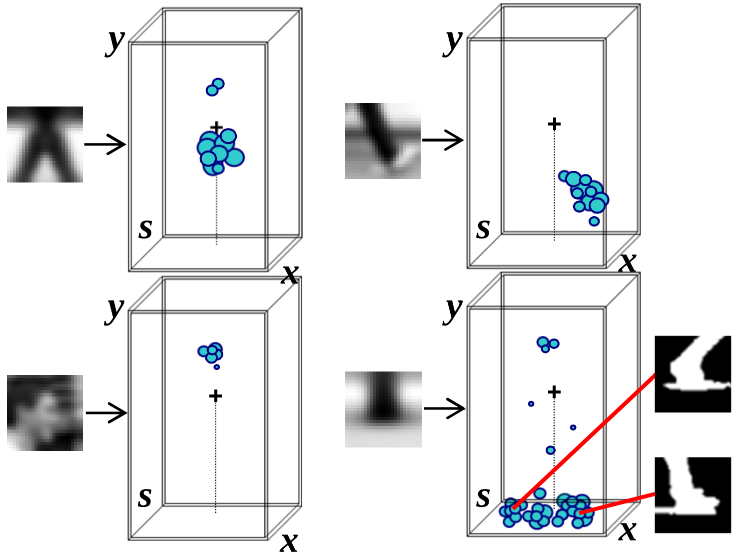
Implicit Shape Model - Representation



Training images
(+reference segmentation)

Appearance codebook

- Learn appearance codebook
  - Extract local features at interest points
  - Agglomerative clustering ⇒ codebook
- Learn spatial distributions
  - Match codebook to training images
  - Record matching positions on object

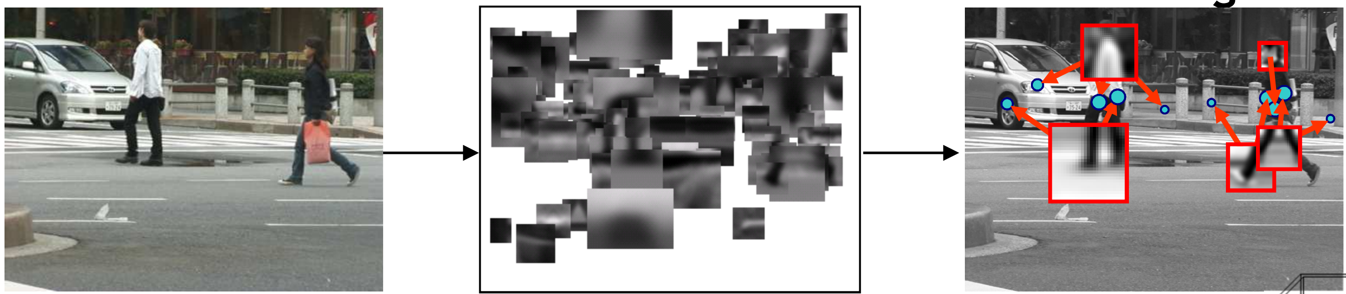


Spatial occurrence distributions
+ local figure-ground labels

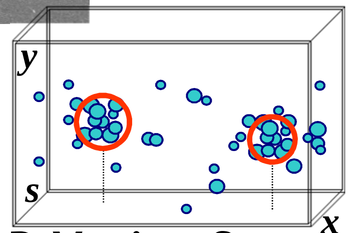
Source: Bastian Leibe

Implicit Shape Model - Recognition

Interest Points | **Matched Codebook Entries** | **Probabilistic Voting**

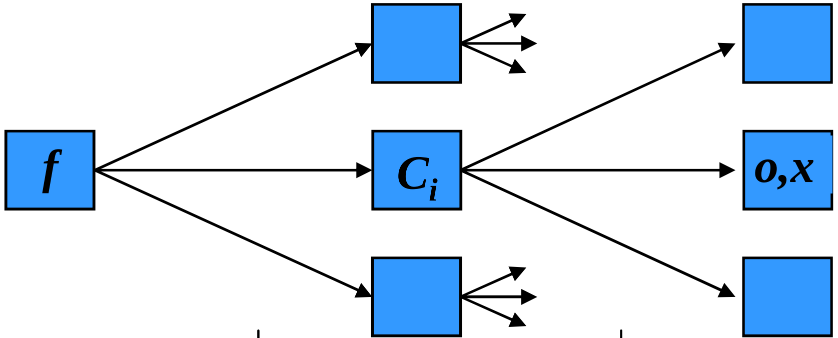


position scale (x, y, s)



3D Voting Space (continuous)

Image Feature | **Interpretation (Codebook match)** | **Object Position**

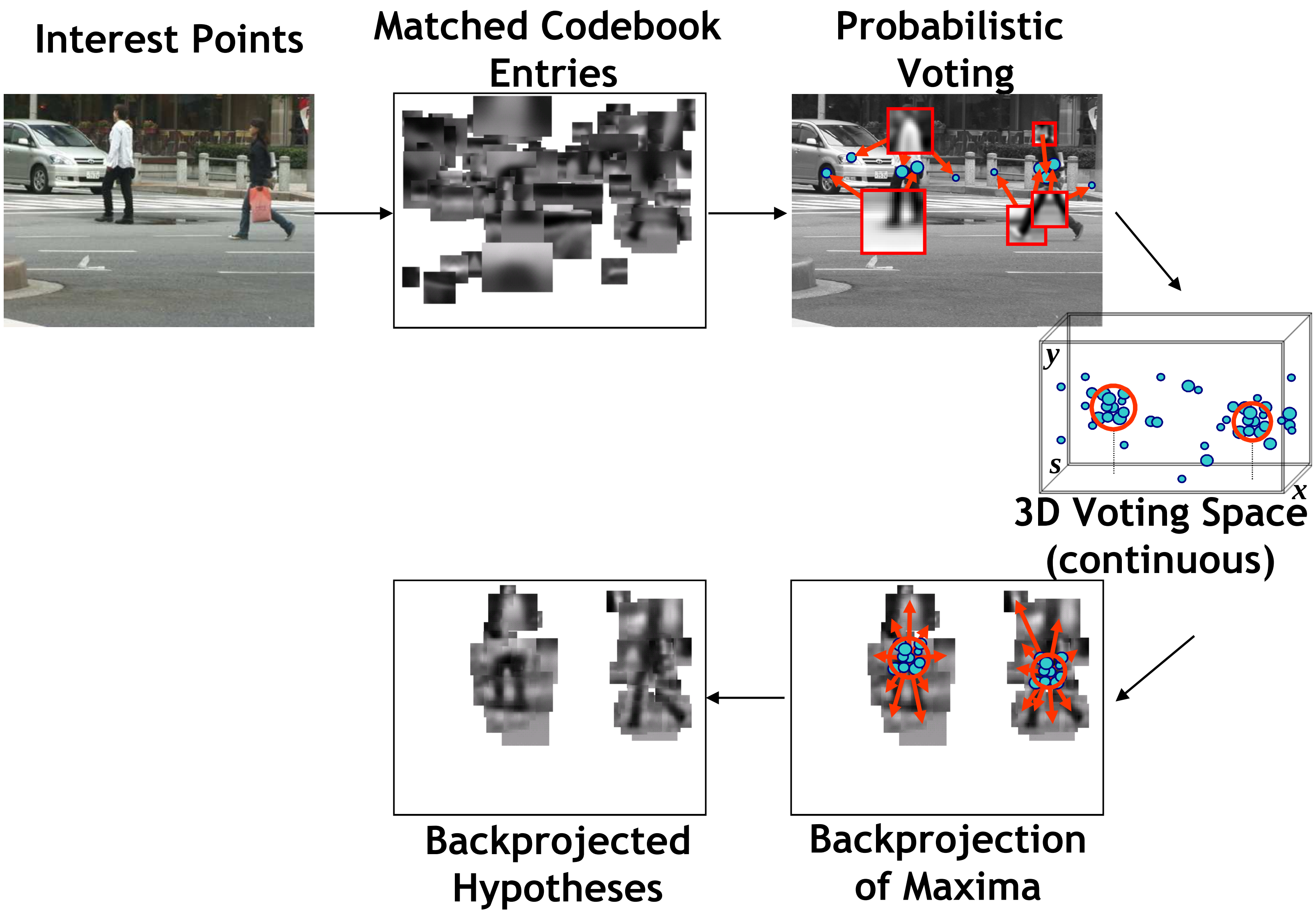


$p(C_i | f)$ $\quad$ $p(o_n, x | C_i, \ell)$

Probabilistic vote weighting
(will be explained later in detail)

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Implicit Shape Model - Recognition



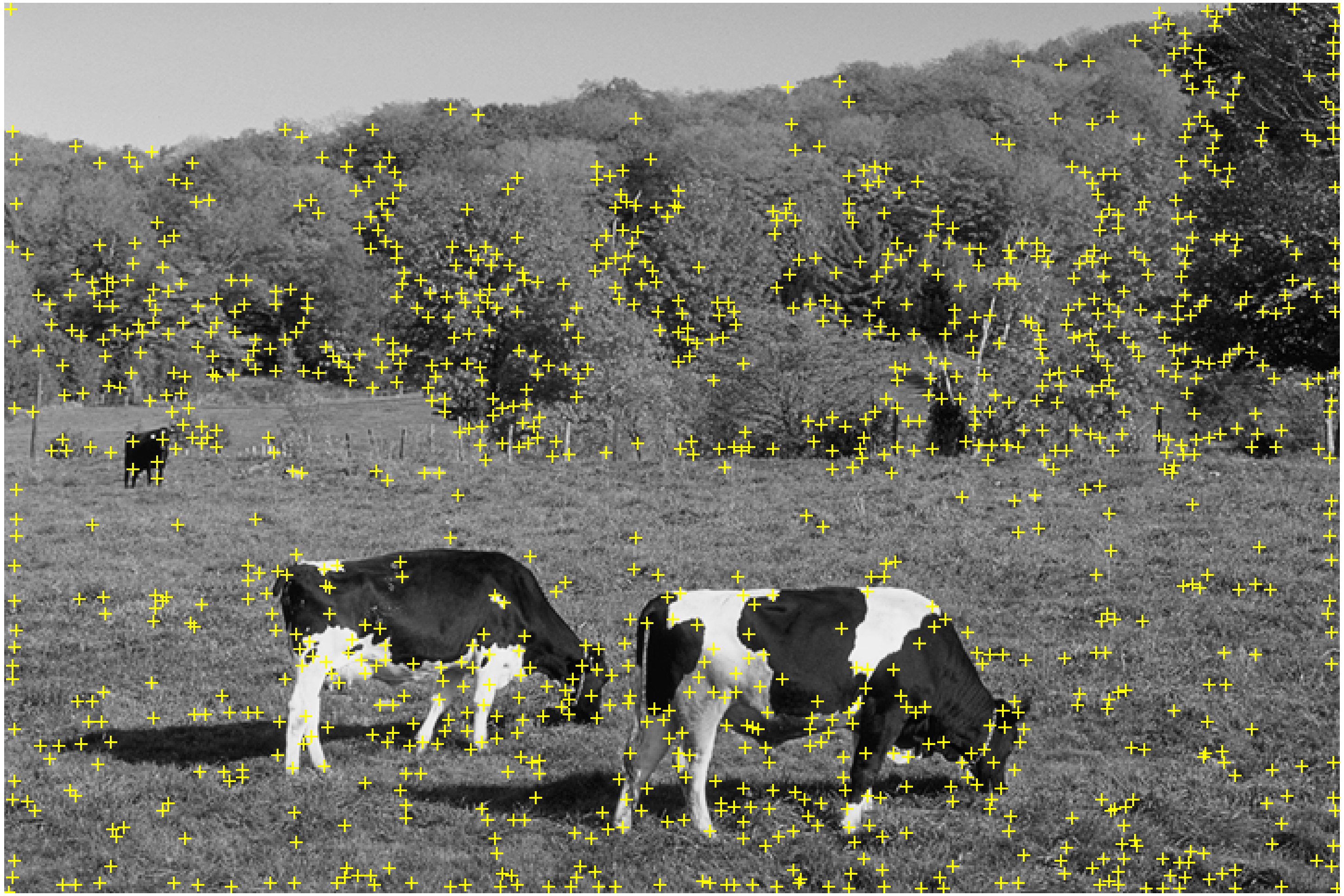
[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Example: Results on Cows

Original image

Source: Bastian Leibe

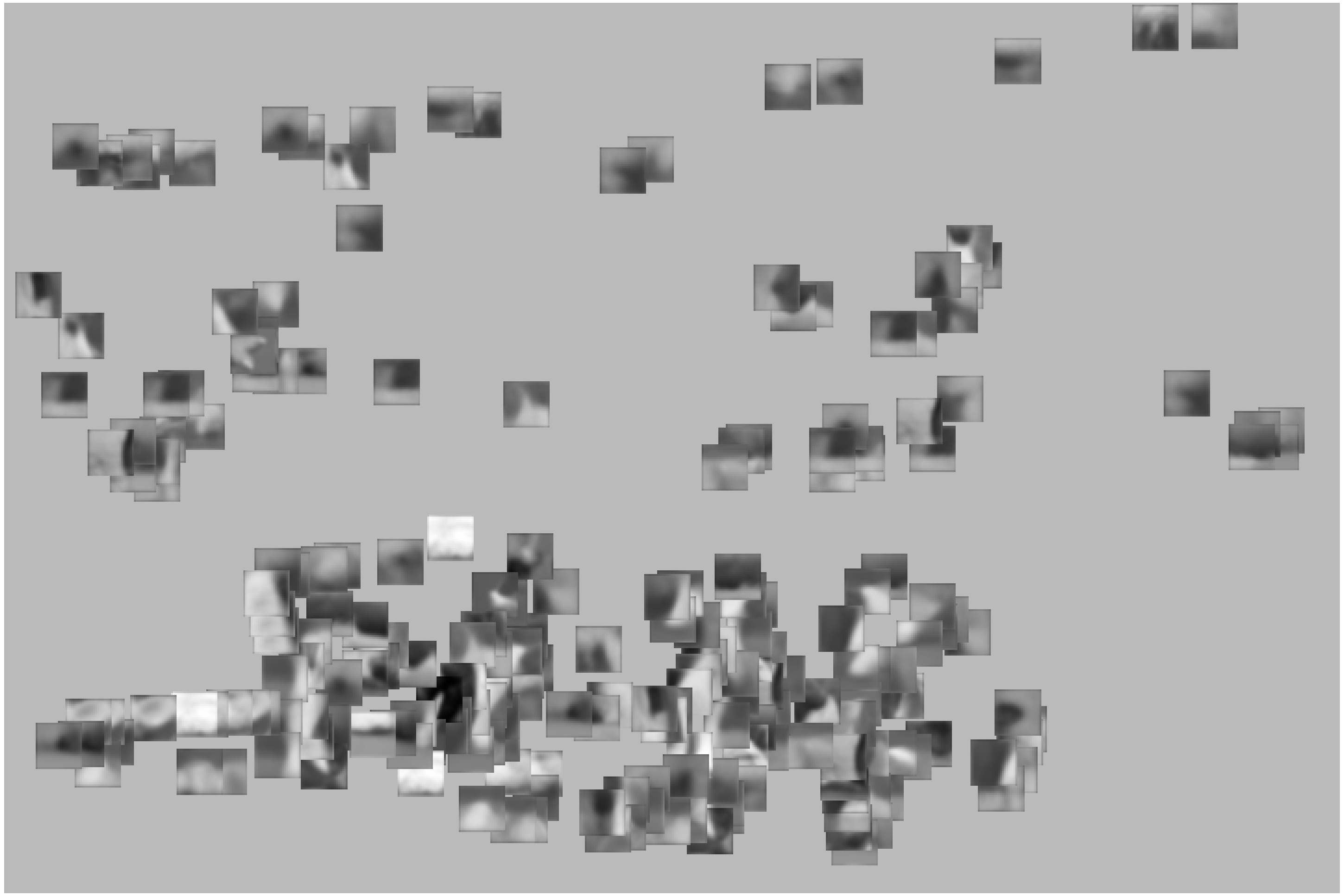
Example: Results on Cows



Interest points

Source: Bastian Leibe

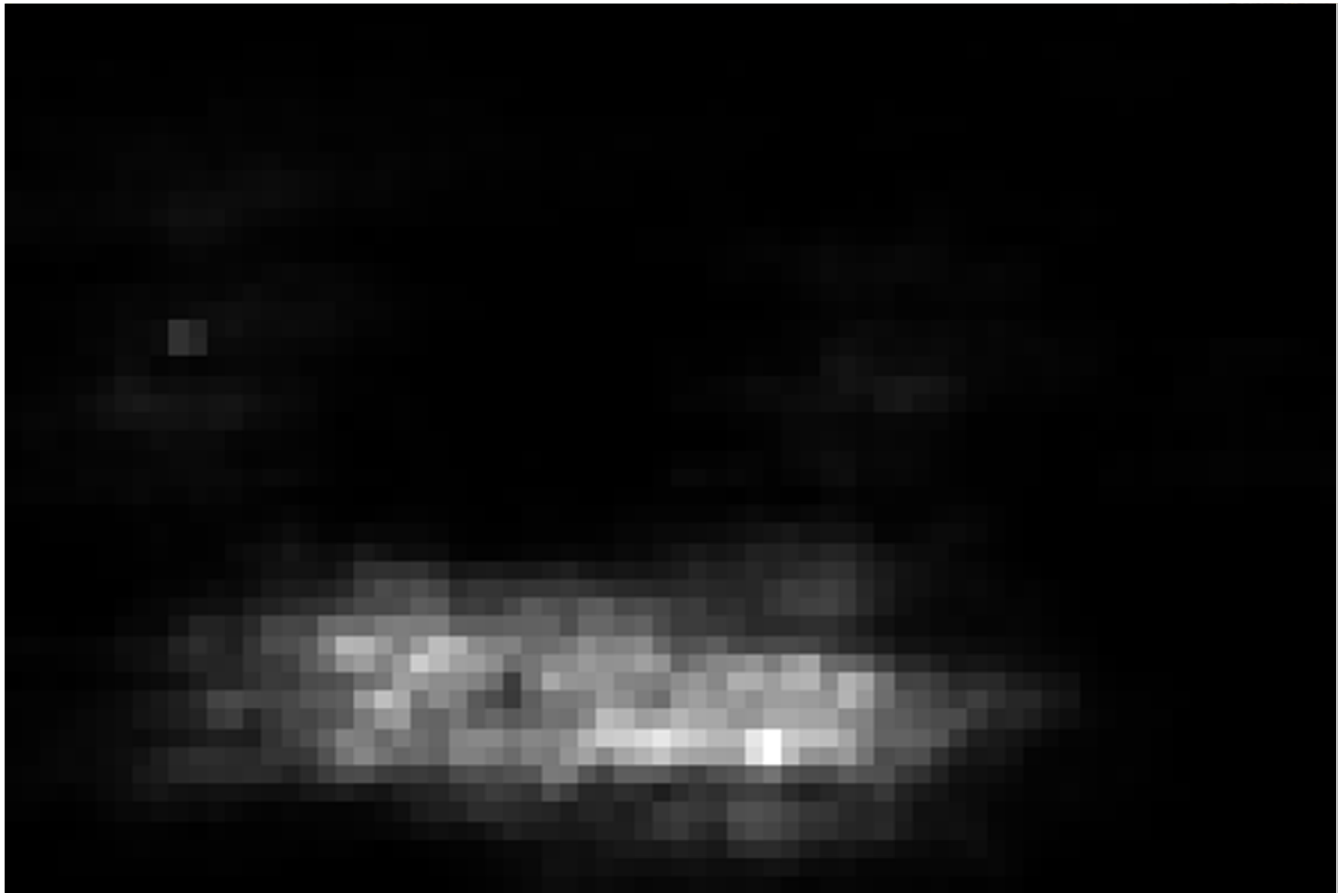
Example: Results on Cows



Matched patches

Source: Bastian Leibe

Example: Results on Cows



Prob. Votes

Source: Bastian Leibe

Example: Results on Cows

1st hypothesis

Source: K. Grauman & B. Leibe

Example: Results on Cows

2nd hypothesis

Source: Bastian Leibe

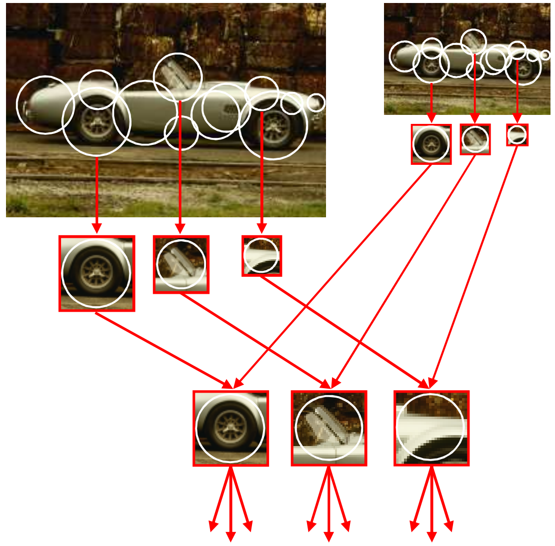
Example: Results on Cows

3rd hypothesis

Source: Bastian Leibe

Scale Invariant Voting

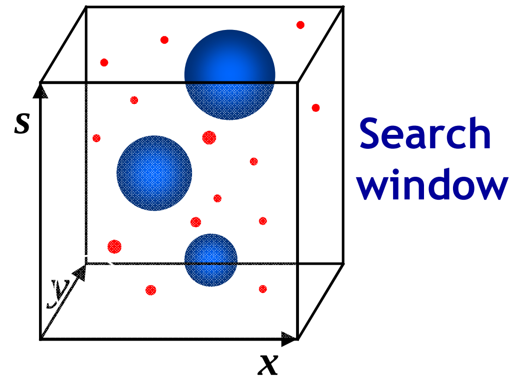
- Scale-invariant feature selection
  - Scale-invariant interest points
  - Rescale extracted patches
  - Match to constant-size codebook



- Generate scale votes
  - Scale as 3rd dimension in voting space

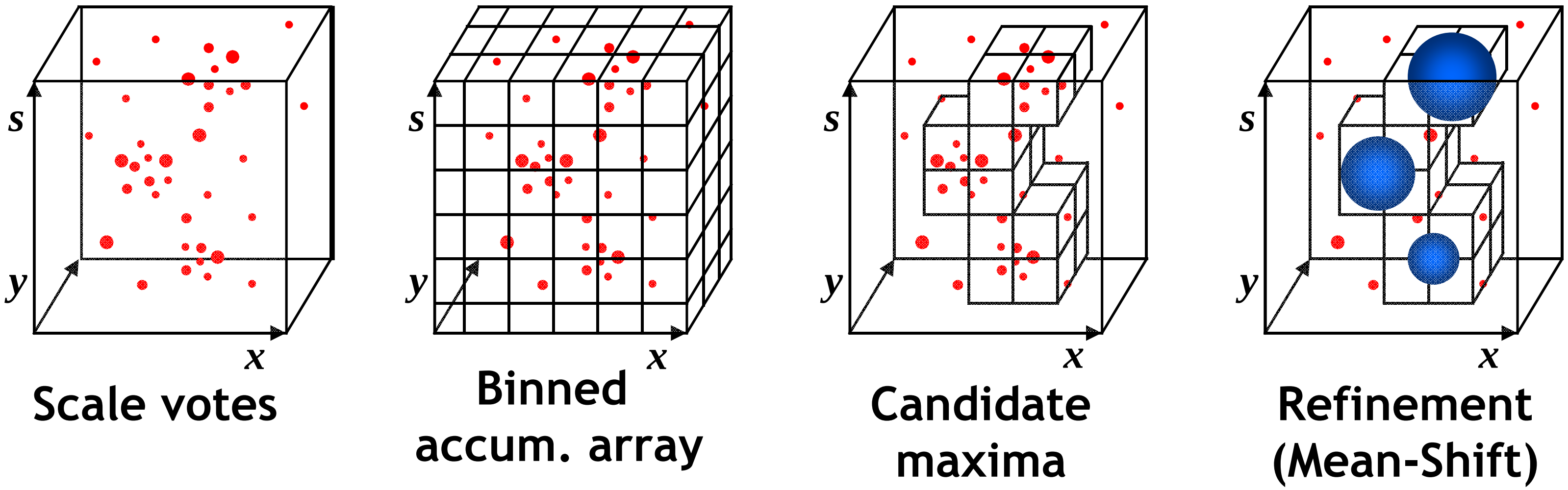
$$\begin{aligned} x_{vote} &= x_{img} - x_{occ}(s_{img}/s_{occ}) \\ y_{vote} &= y_{img} - y_{occ}(s_{img}/s_{occ}) \\ s_{vote} &= (s_{img}/s_{occ}). \end{aligned}$$

  - Search for maxima in 3D voting space



Source: Bastian Leibe

Scale Voting: Efficient Computation



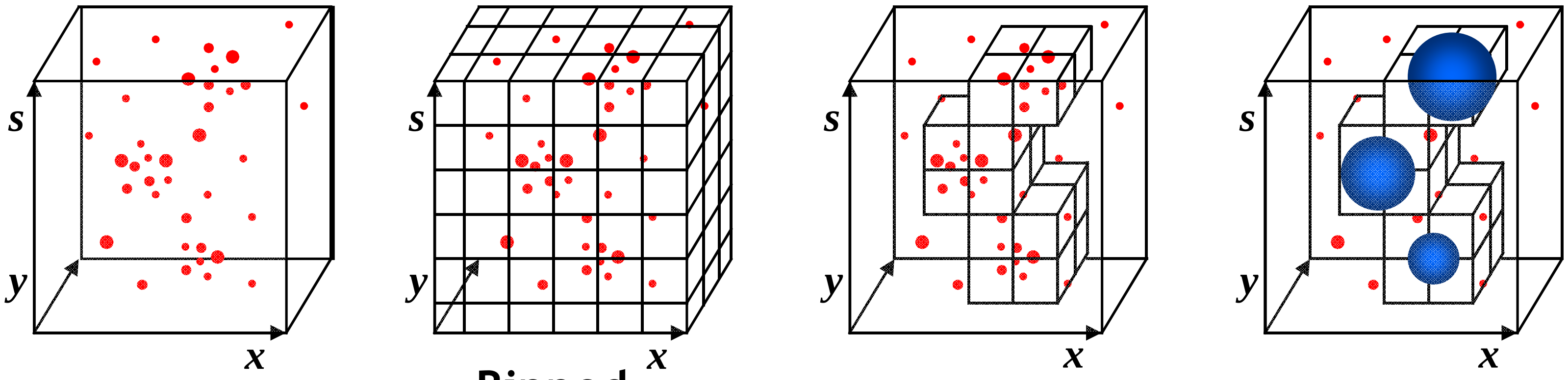
- Continuous Generalized Hough Transform
  - Binned accumulator array similar to standard Gen. Hough Transf.
  - Quickly identify candidate maxima locations
  - Refine locations by Mean-Shift search only around those points

  $\Rightarrow$ Avoid quantization effects by keeping exact vote locations.

  $\Rightarrow$ Mean-shift interpretation as kernel prob. density estimation.

Source: Bastian Leibe

Scale Voting: Efficient Computation



Scale votes | Binned accum. array | Candidate maxima | Refinement (Mean-Shift)

- Scale-adaptive Mean-Shift search for refinement
  - Increase search window size with hypothesis scale
  - Scale-adaptive *balloon density estimator*

Source: Bastian Leibe

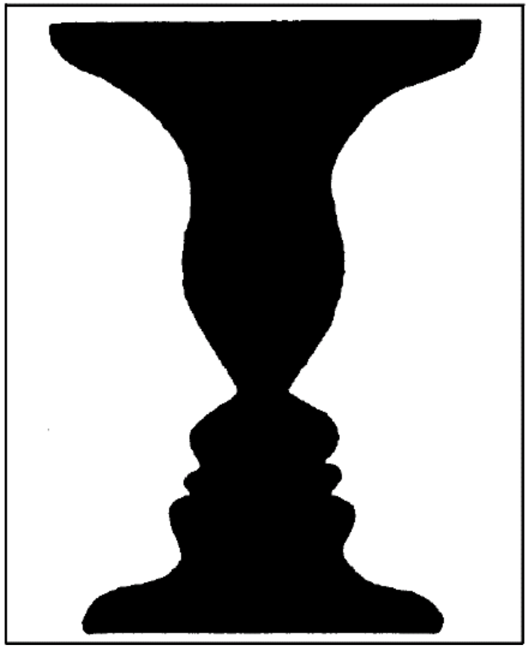
Detection Results

- Qualitative Performance
  - Recognizes different kinds of objects
  - Robust to clutter, occlusion, noise, low contrast

Source: Bastian Leibe

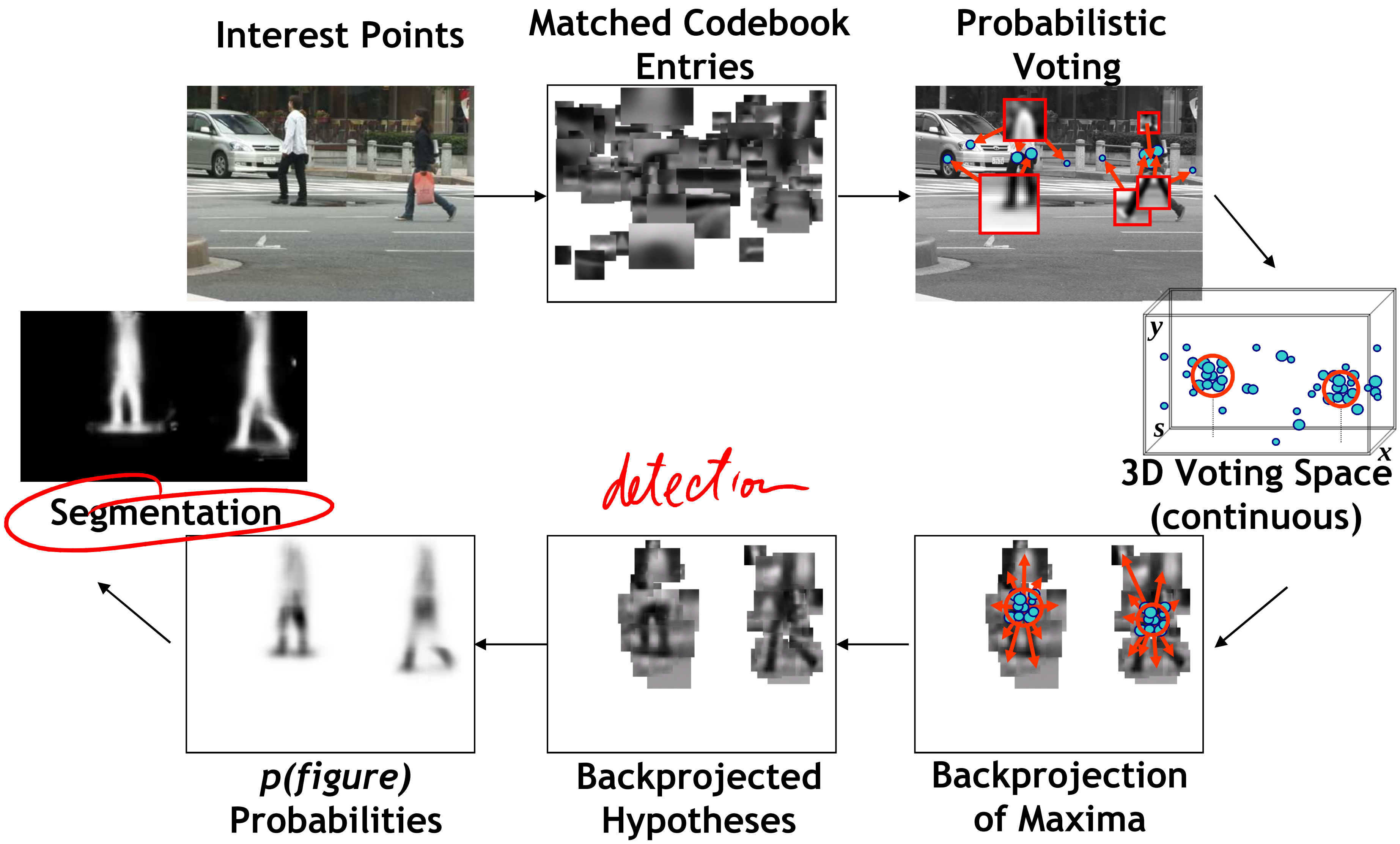
Figure-Ground Segregation

- What happens first – segmentation or recognition?
- Problem extensively studied in Psychophysics
- Experiments with ambiguous figure-ground stimuli
- Results:
  - Evidence that object recognition can and does operate before figure-ground organization
  - Interpreted as Gestalt cue *familiarity*.



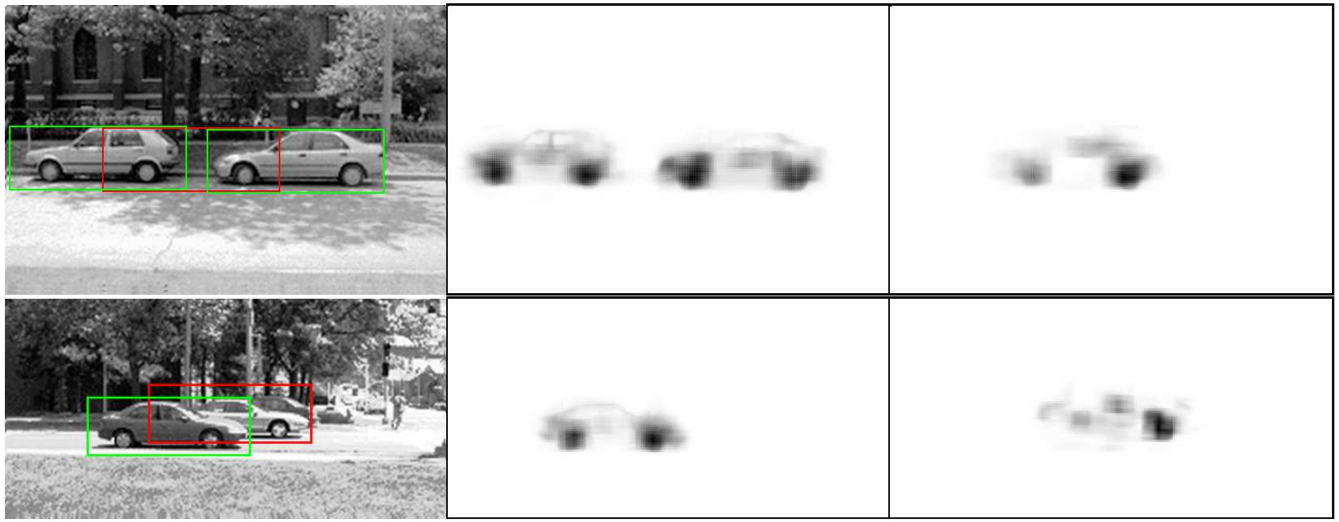
M.A. Peterson, "Object Recognition Processes Can and Do Operate Before Figure-Ground Organization", *Cur. Dir. in Psych. Sc.*, 3:105-111, 1994.

ISM – Top-Down Segmentation



[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Top-Down Segmentation: Motivation



- Secondary hypotheses ("mixtures of cars/cows/etc.")
  - Desired property of algorithm! ⇒ robustness to occlusion
  - Standard solution: reject based on bounding box overlap
    ⇒ Problematic - may lead to missing detections!

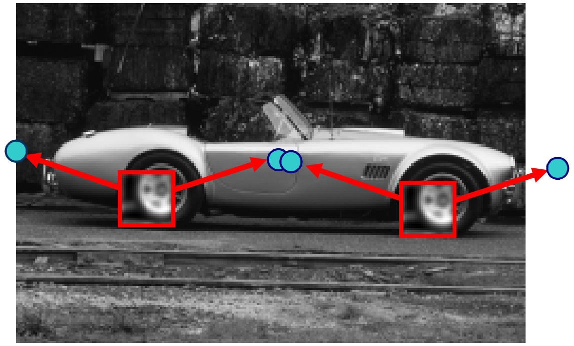
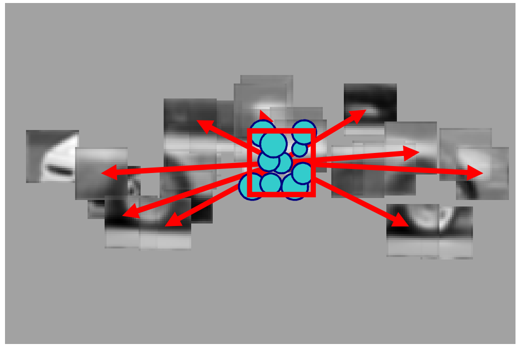
Source: Bastian Leibe

Top-Down Segmentation: Motivation

- Secondary hypotheses (“mixtures of cars/cows/etc.”)
  - Desired property of algorithm! $\Rightarrow$ robustness to occlusion
  - Standard solution: reject based on bounding box overlap
    $\Rightarrow$ Problematic - may lead to missing detections!
    $\Rightarrow$ Use segmentations to resolve ambiguities instead.
  - Basic idea: each observed pixel can only be explained by (at most) one detection.

Source: Bastian Leibe

Segmentation: Probabilistic Formulation

- Influence of patch on object hypothesis (vote weight)

$$\boxed{p(f,\ell|o_n,x)} = \frac{\sum_i p(o_n,x|C_i)p(C_i|f)p(f,\ell)}{p(o_n,x)}$$

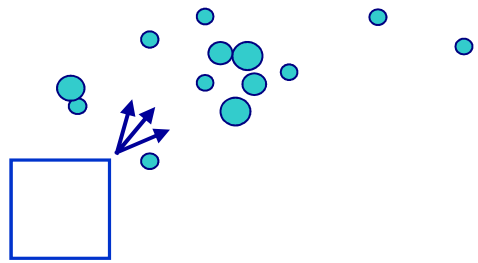
Backprojection to features *f* and pixels p:

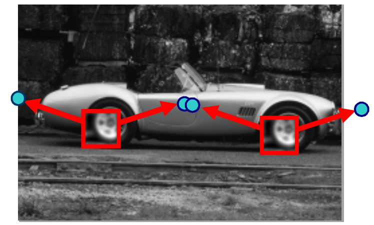
$$p(\mathbf{p} = figure\,|\,o_n,x) = \sum_{\mathbf{p}\in(f,\ell)} \underbrace{p(\mathbf{p} = figure\,|\,f,\ell,o_n,x)}_{\text{Segmentation information}} \underbrace{\boxed{p(f,\ell\,|\,o_n,x)}}_{\text{Influence on object hypothesis}}$$

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

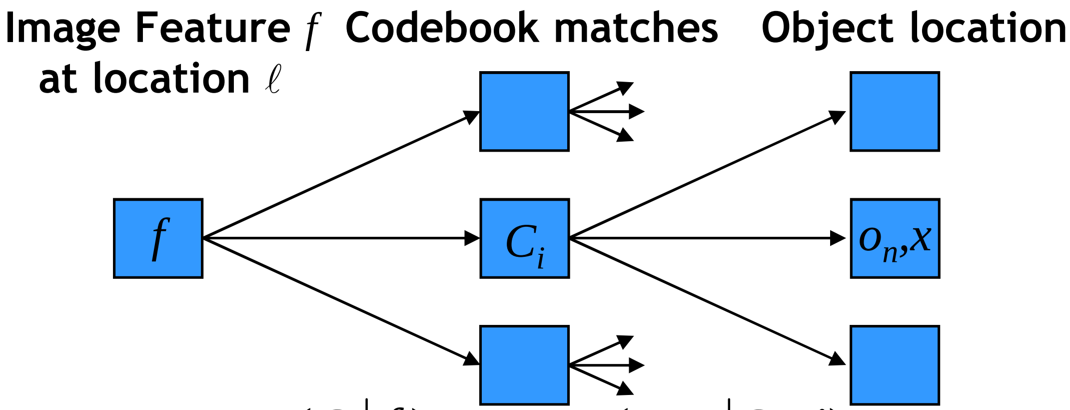
Derivation: ISM Recognition

- Algorithm stages
  1. Voting
  2. Mean-shift search
  3. Backprojection





- Vote weights: contribution of a single feature f



$p(C_i | f)$ $\qquad$ $p(o_n, x | C_i, \ell)$

Matching probability $\qquad$ **Occurrence distribution**

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

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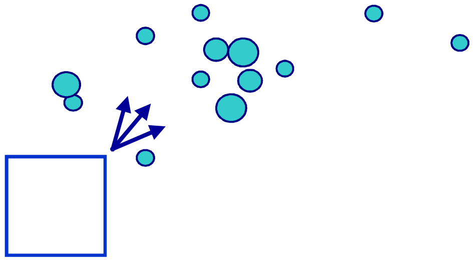

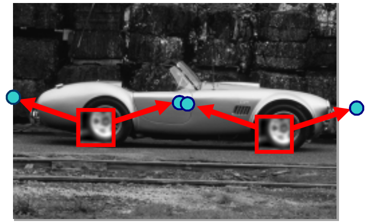

- Vote weights: contribution of a single feature f
  - Probability that object o_n occurs at location x given (f,ℓ)

$$p(o_n, x | f, \ell) = \sum_i p(C_i | f) \quad p(o_n, x | C_i, \ell)$$

Matching probability **Occurrence distribution**

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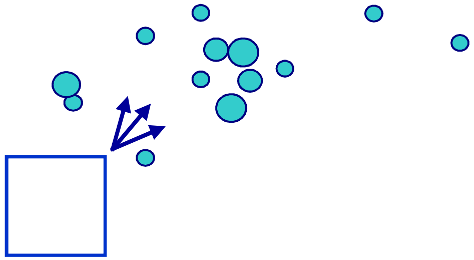

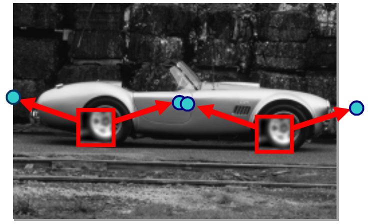

- Vote weights: contribution of a single feature f
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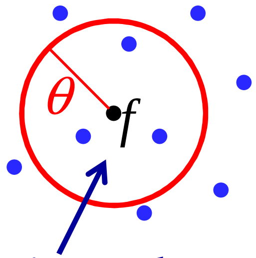
$$p(o_n, x \mid f, \ell) = \sum_i p(C_i \mid f) \quad p(o_n, x \mid C_i, \ell)$$

  - How to measure those probabilities?

$$p(C_i \mid f) = \frac{1}{|C|}, \quad \text{where} \quad C = \{C_i \mid d(C_i, f) \leq \theta\}$$

$$p(o_n, x \mid C_i, \ell) = \frac{1}{\#occurrences(C_i)}$$



[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

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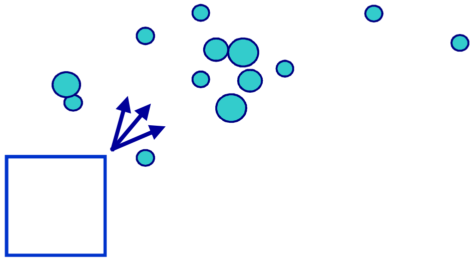

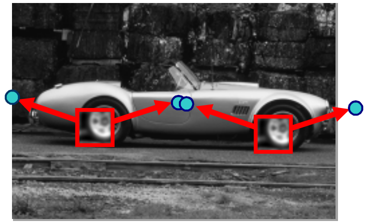

- Vote weights: contribution of a single feature f
  - Probability that object o_n occurs at location x given (f,ℓ)

$$p(o_n, x \mid f, \ell) = \sum_i p(C_i \mid f) \quad p(o_n, x \mid C_i, \ell)$$

  - Likelihood of the observed features given the object hypothesis

$$p(f,\ell \mid o_n, x) = \frac{p(o_n, x \mid f,\ell)\, p(f,\ell)}{p(o_n, x)} = \frac{\sum_i p(o_n, x \mid C_i, \ell)\, p(C_i \mid f)\, p(f,\ell)}{p(o_n, x)}$$

$p(f,\ell)$: **Indicator variable for sampled features**

$p(o_n, x)$: **Prior for the object location**

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Derivation: ISM Recognition

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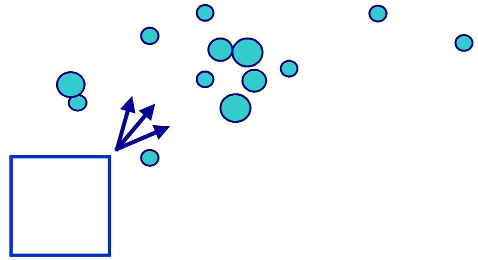

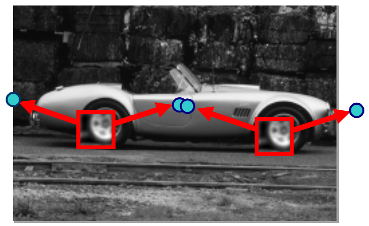

- Vote weights: contribution of a single feature *f*

$$p(f,\ell \mid o_n, x) = \frac{p(o_n, x \mid f,\ell)\, p(f,\ell)}{p(o_n, x)} = \frac{\sum_i p(o_n, x \mid C_i, \ell)\, p(C_i \mid f)\, p(f,\ell)}{p(o_n, x)}$$

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

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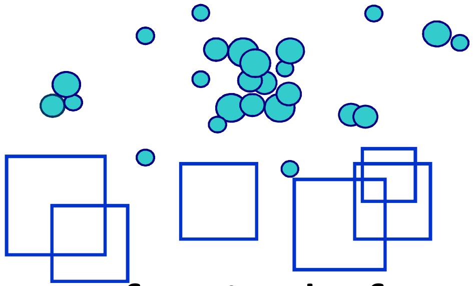

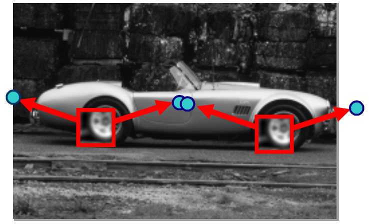

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[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

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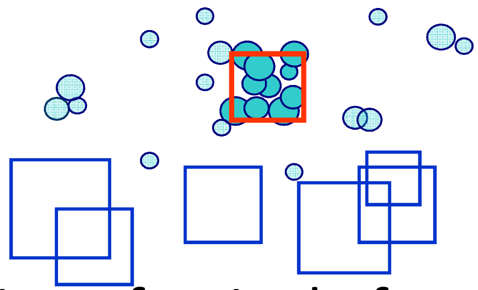

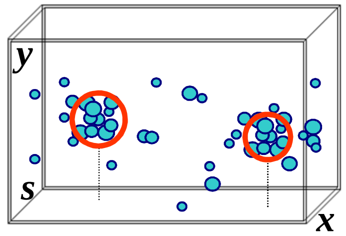

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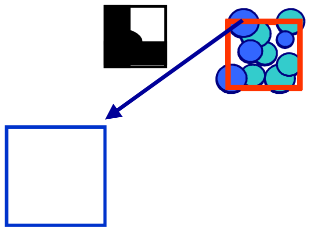
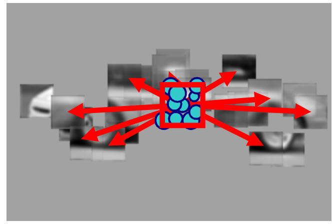
[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Derivation: ISM Top-Down Segmentation

- Algorithm stages
  1. Voting
  2. Mean-shift search
  3. Backprojection





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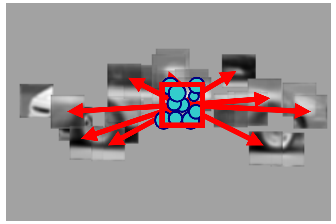
- Figure-ground backprojection

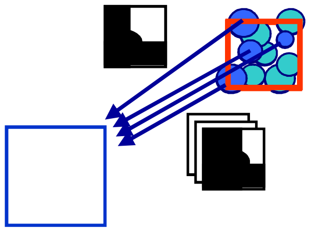
$$p(\mathbf{p} = \mathit{figure} \mid o_n, x, f, C_i, \ell) = \underbrace{p(\mathbf{p} = \mathit{fig.} \mid o_n, x, C_i, \ell)}_{\textbf{Fig./Gnd. label for each occurrence}} \underbrace{\boxed{\frac{p(o_n, x \mid C_i, \ell)\, p(C_i \mid f)\, p(f,\ell)}{p(o_n, x)}}}_{\textbf{Influence on object hypothesis}}$$

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Derivation: ISM Top-Down Segmentation



- Algorithm stages
  1. Voting
  2. Mean-shift search
  3. Backprojection



- Vote weights: contribution of a single feature f

$$p(f,\ell \mid o_n, x) = \frac{p(o_n, x \mid f,\ell)\, p(f,\ell)}{p(o_n, x)} = \sum_i \boxed{\frac{p(o_n, x \mid C_i,\ell)\, p(C_i \mid f)\, p(f,\ell)}{p(o_n, x)}}$$

- Figure-ground backprojection

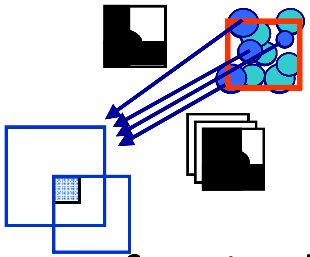
$$p(\mathbf{p} = figure \mid o_n, x, f, \ell) = \boxed{\sum_i} \underbrace{p(\mathbf{p} = fig. \mid o_n, x, C_i, \ell)}_{\text{Fig./Gnd. label for each occurrence}} \underbrace{\boxed{\frac{p(o_n, x \mid C_i,\ell)\, p(C_i \mid f)\, p(f,\ell)}{p(o_n, x)}}}_{\text{Influence on object hypothesis}}$$

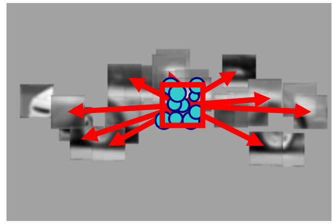
Marginalize over all codebook entries matched to f

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Derivation: ISM Top-Down Segmentation

- Algorithm stages
  1. Voting
  2. Mean-shift search
  3. Backprojection





- Vote weights: contribution of a single feature f

$$p(f,\ell \mid o_n, x) = \frac{p(o_n, x \mid f,\ell)\, p(f,\ell)}{p(o_n, x)} = \sum_i \boxed{\frac{p(o_n, x \mid C_i, \ell)\, p(C_i \mid f)\, p(f,\ell)}{p(o_n, x)}}$$

- Figure-ground backprojection

$$p(\mathbf{p} = \mathit{figure} \mid o_n, x) = \boxed{\sum_{\mathbf{p} \in (f,\ell)}} \sum_i \underbrace{p(\mathbf{p} = \mathit{fig.} \mid o_n, x, C_i, \ell)}_{\text{Fig./Gnd. label for each occurrence}} \underbrace{\boxed{\frac{p(o_n, x \mid C_i, \ell)\, p(C_i \mid f)\, p(f,\ell)}{p(o_n, x)}}}_{\text{Influence on object hypothesis}}$$

Marginalize over all features containing pixel $\mathbf{p}$

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Top-Down Segmentation Algorithm

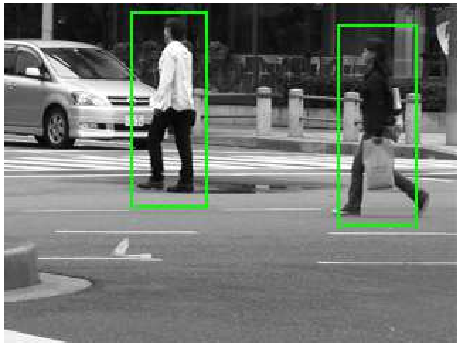
Algorithm 5 The top-segmentation algorithm.

// Given: hypothesis h and supporting votes $\mathcal{V}_h$.
for all supporting votes $(x, w, occ, \ell) \in \mathcal{V}_h$ **do**
  Let img_{mask} be the segmentation mask corresponding to occ.
  Let sz be the size at which the interest region ℓ was sampled.
  Rescale img_{mask} to sz.
  $u_0 \leftarrow (\ell_x - \frac{1}{2}\mathrm{sz})$
  $v_0 \leftarrow (\ell_y - \frac{1}{2}\mathrm{sz})$
  for all $u \in [0, \mathrm{sz} - 1]$ **do**
    for all $v \in [0, \mathrm{sz} - 1]$ **do**
      $img_{pfig}(u - u_0, v - v_0) {+}{=} w \cdot img_{mask}(u, v)$
      $img_{pgnd}(u - u_0, v - v_0) {+}{=} w \cdot (1 - img_{mask}(u, v))$
    end for
  end for
end for

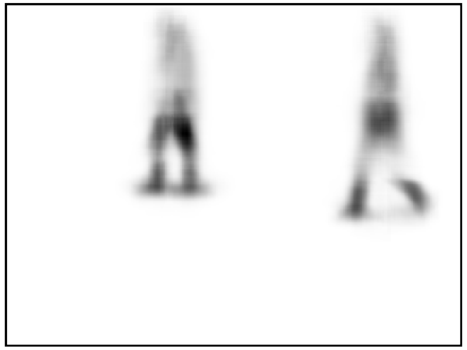
- This may sound quite complicated, but it boils down to a very simple algorithm…

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

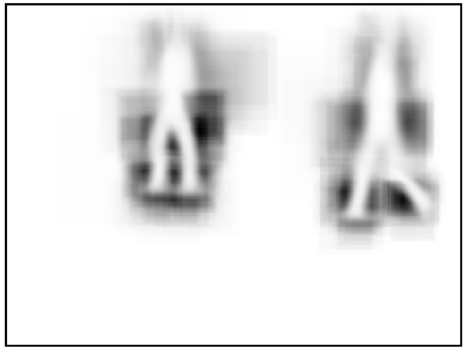
Segmentation



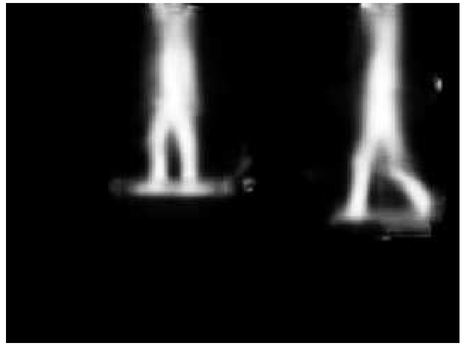
Original image



p(figure)



p(ground)



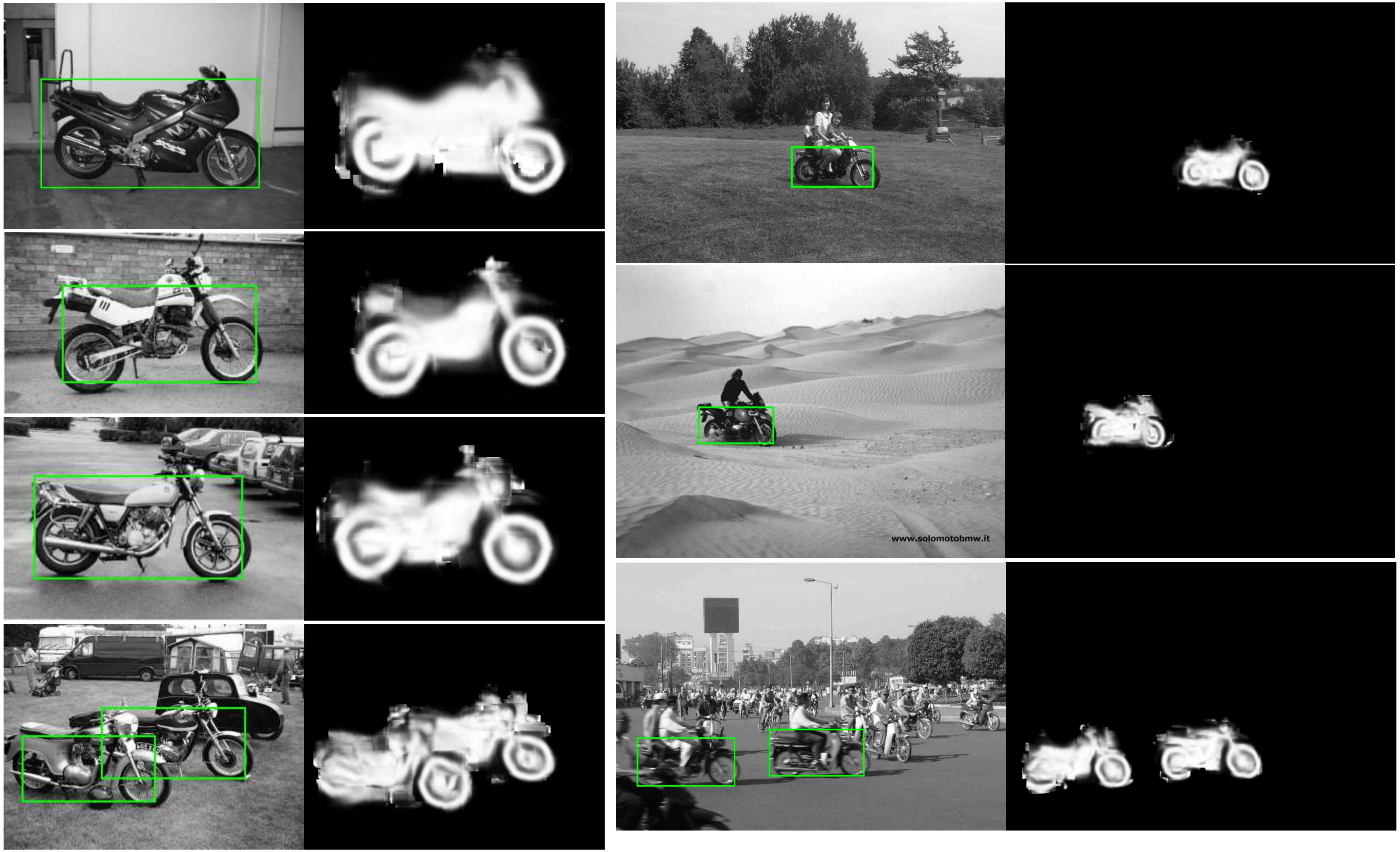
Segmentation

$$\frac{p(figure)}{p(ground)}$$

- Interpretation of *p(figure)* map
  - per-pixel confidence in object hypothesis
  - Use for hypothesis verification

[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

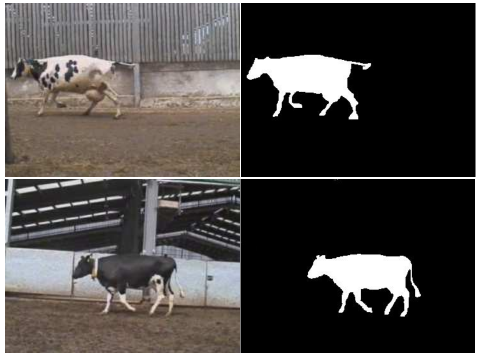
Example Results: Motorbikes



[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Example Results: Cows

- Training
  - 112 hand-segmented images

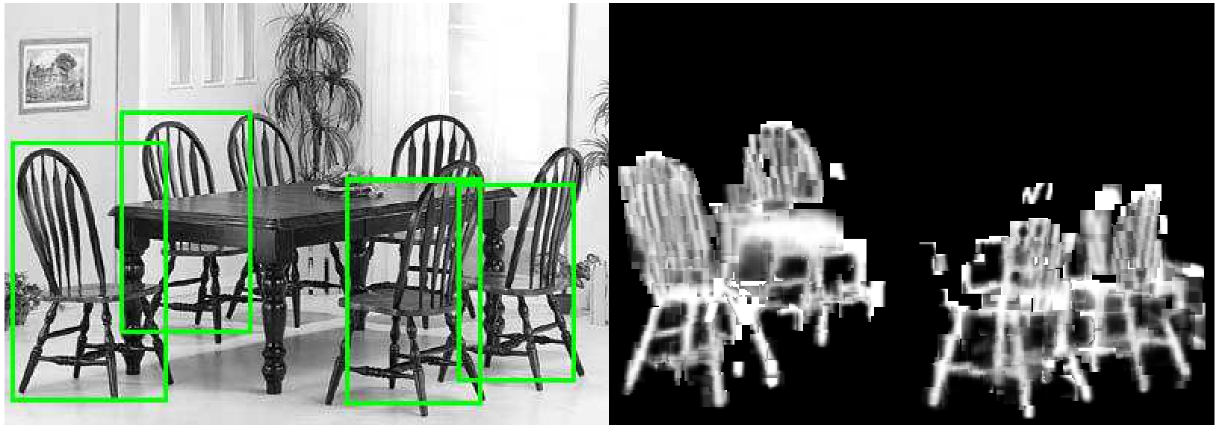


- Results on novel sequences:

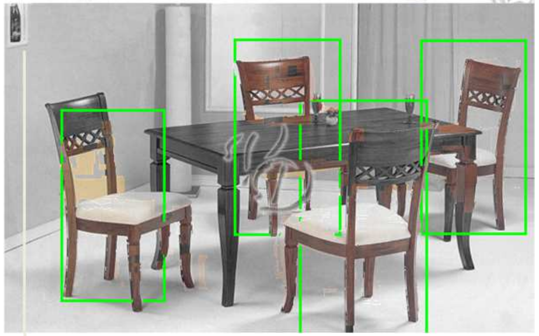
Single-frame recognition - No temporal continuity used!

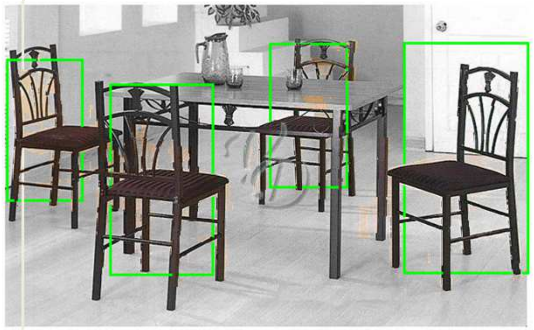
[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

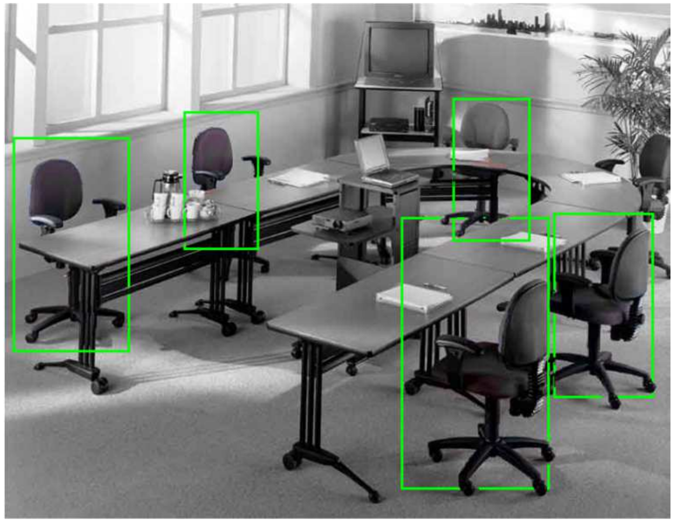
Example Results: Chairs

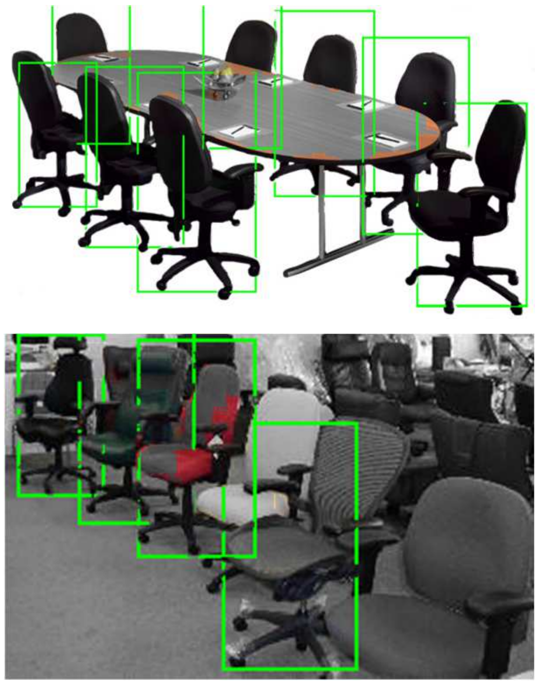


Dining room chairs





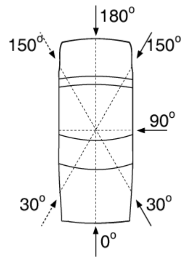




Office chairs

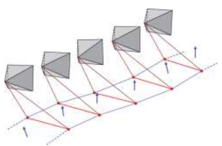
Source: Bastian Leibe

Detections Using Ground Plane Constraints



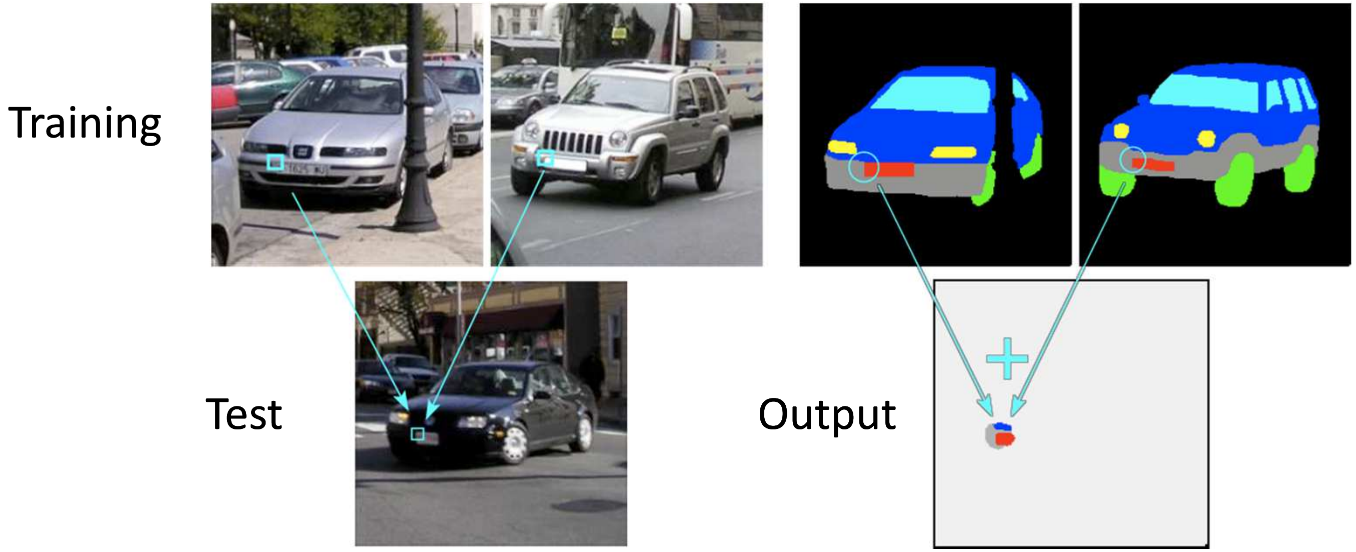
Battery of 5 ISM detectors for different car views

left camera
1175 frames



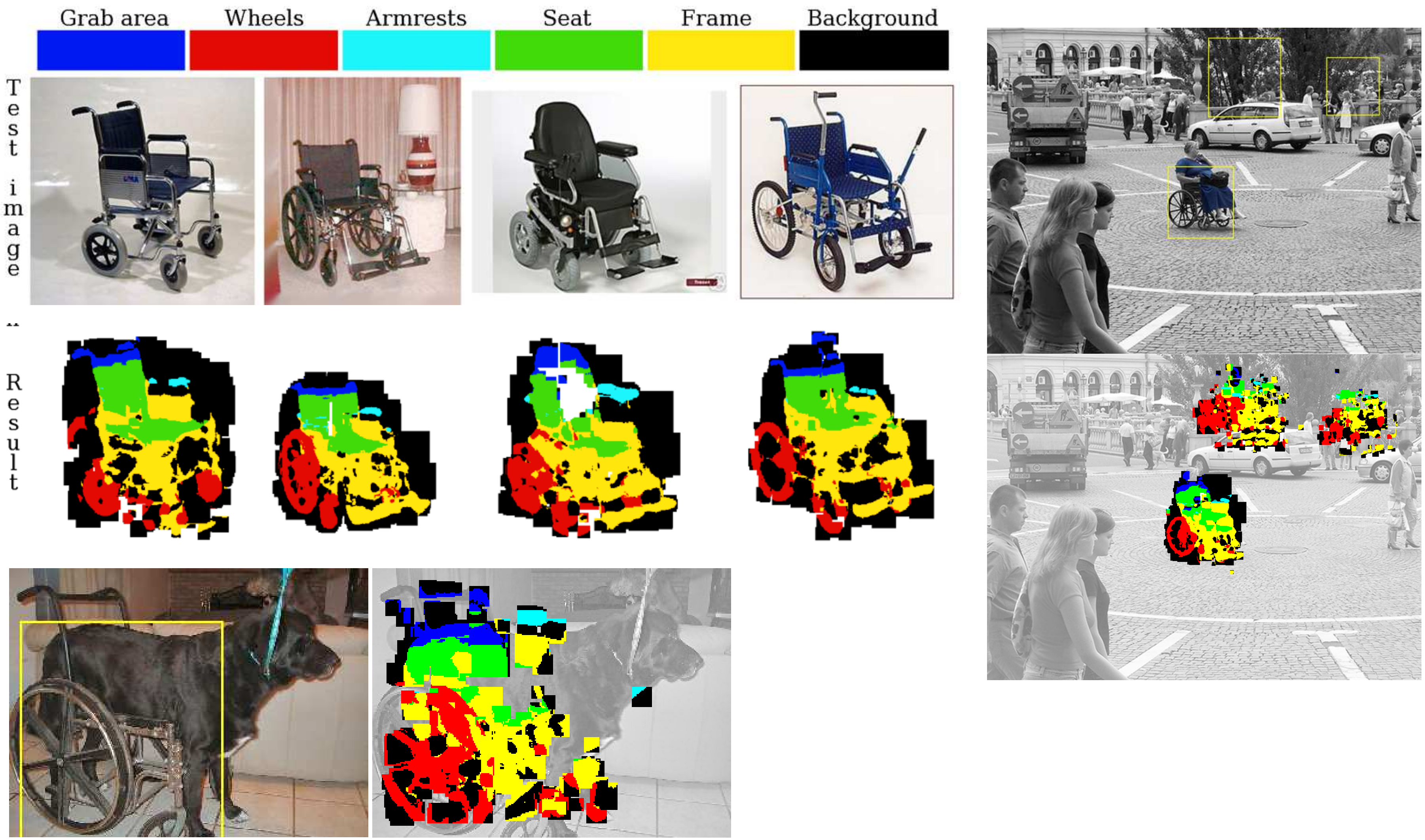
[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Inferring Other Information: Part Labels (1)



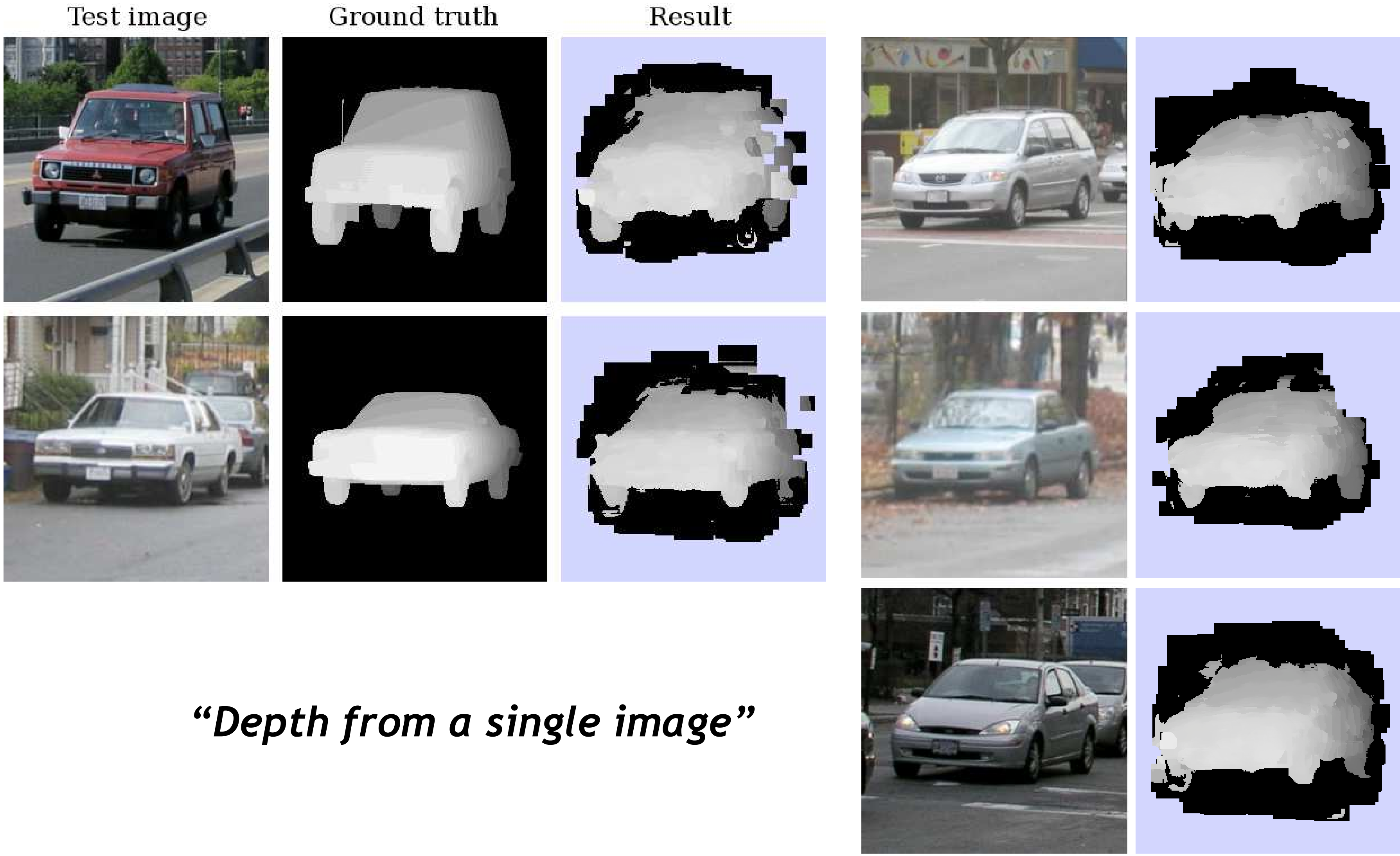
[Thomas, Ferrari, Tuytelaars, Leibe, Van Gool, 3DRR'07; RSS'08]

Inferring Other Information: Part Labels (2)



[Thomas, Ferrari, Tuytelaars, Leibe, Van Gool, 3DRR'07; RSS'08]

Inferring Other Information: Depth Maps

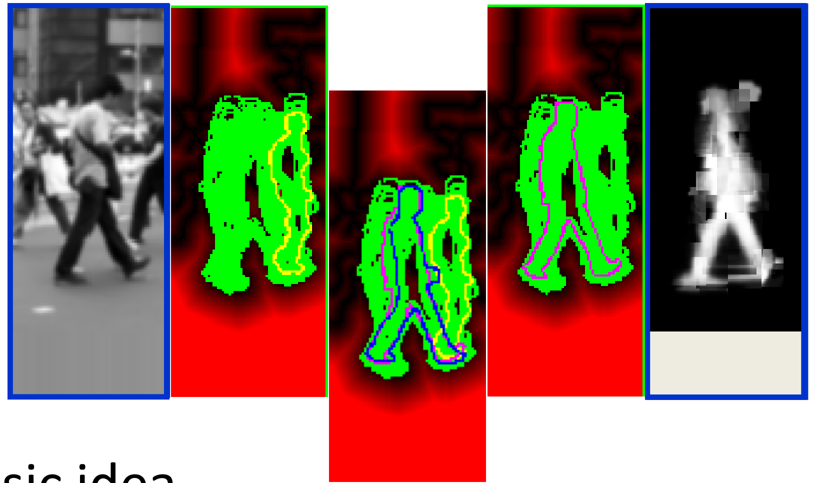


"Depth from a single image"

[Thomas, Ferrari, Tuytelaars, Leibe, Van Gool, 3DRR'07; RSS'08]

Extension: Estimating Articulation

- Try to fit silhouette to detected person

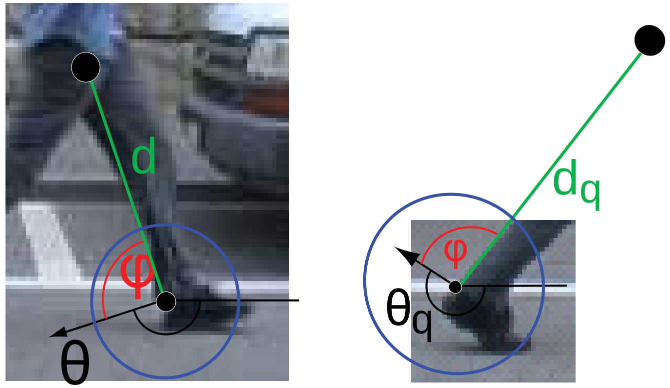


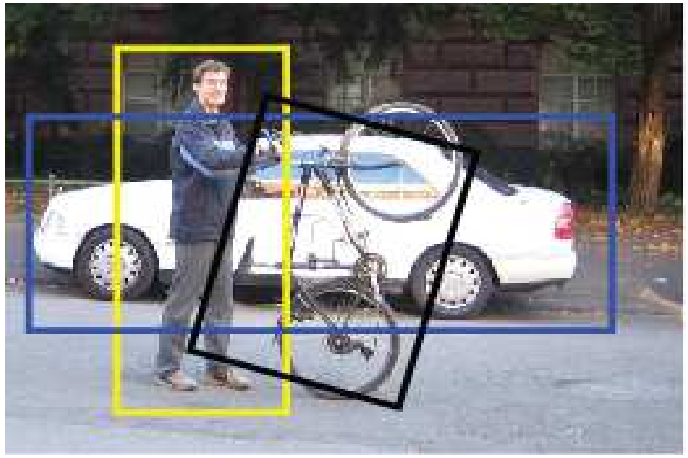
- Basic idea
  - Search for the silhouette that simultaneously optimizes the
    - Chamfer match to the distance-transformed edge image
    - Overlap with the top-down segmentation
  - Enforces global consistency
  - Caveat: introduces again reliance on global model

[Leibe, Seemann, Schiele, CVPR’05]

Extension: Rotation-Invariant Detection

- Polar instead of Cartesian voting scheme





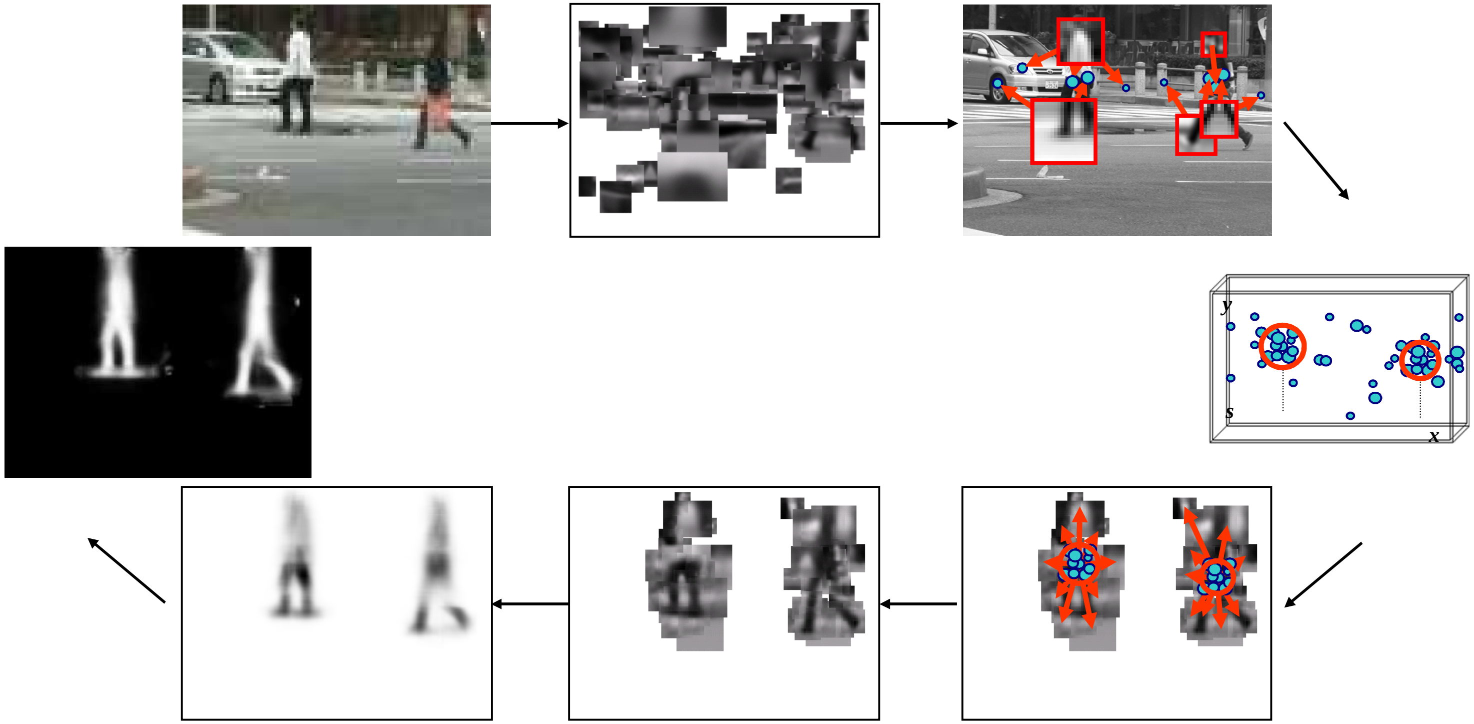
- Benefits:
  - Recognize objects under image-plane rotations
  - Possibility to share parts between articulations.
- Caveats:
  - Rotation invariance should only be used when it's really needed. (Also increases false positive detections)

[Mikolajczyk, Leibe, Schiele, CVPR'06]

Sometimes, Rotation Invariance Is Needed…

[Mikolajczyk et al., CVPR'06]

You Can Try It At Home…

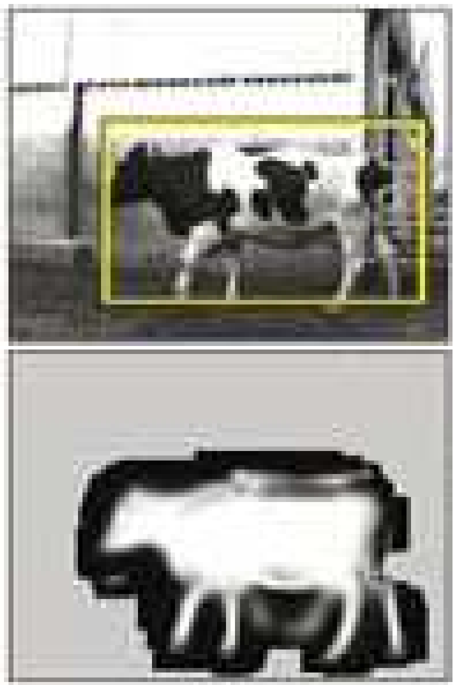


- Linux binaries available
  - Including datasets & several pre-trained detectors
  - http://www.vision.ee.ethz.ch/bleibe/code

Source: Bastian Leibe

Discussion: Implicit Shape Model

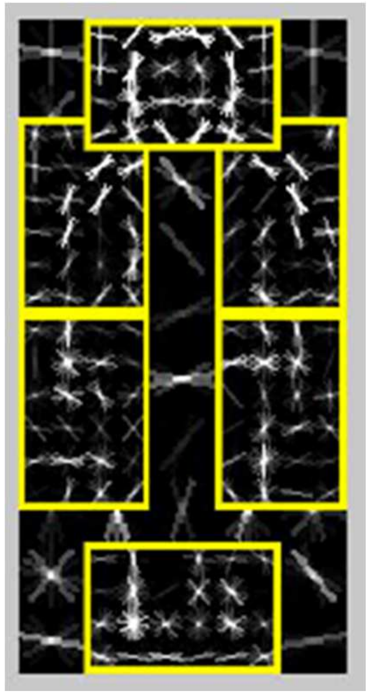
- Pros:
  - Works well for many different object categories
    - Both rigid and articulated objects
  - Flexible geometric model
    - Can recombine parts seen on different training examples
  - Learning from relatively few (50-100) training examples
  - Optimized for detection, good localization properties
- Cons:
  - Needs supervised training data
    - Object bounding boxes for detection
    - Reference segmentations for top-down segm.
  - Only weak geometric constraints
    - Result segmentations may contain superfluous body parts.
  - Purely representative model
    - No discriminative learning



Source: Bastian Leibe

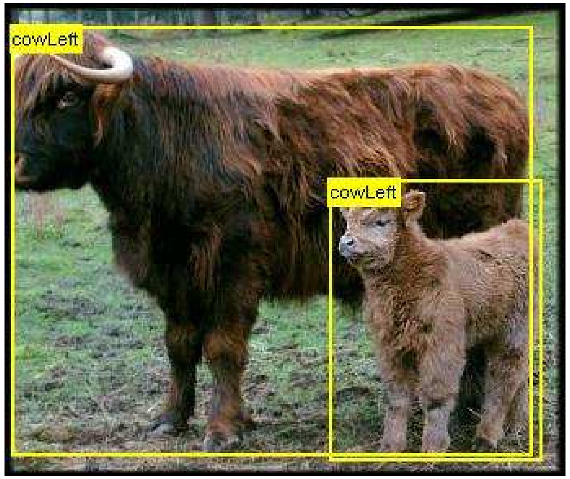
What we will learn today?

- Implicit Shape Model
  - Representation
  - Recognition
  - Experiments and results
- Deformable Models
  - The PASCAL challenge
  - Latent SVM Model



Object Detection
– the PASCAL Challenge

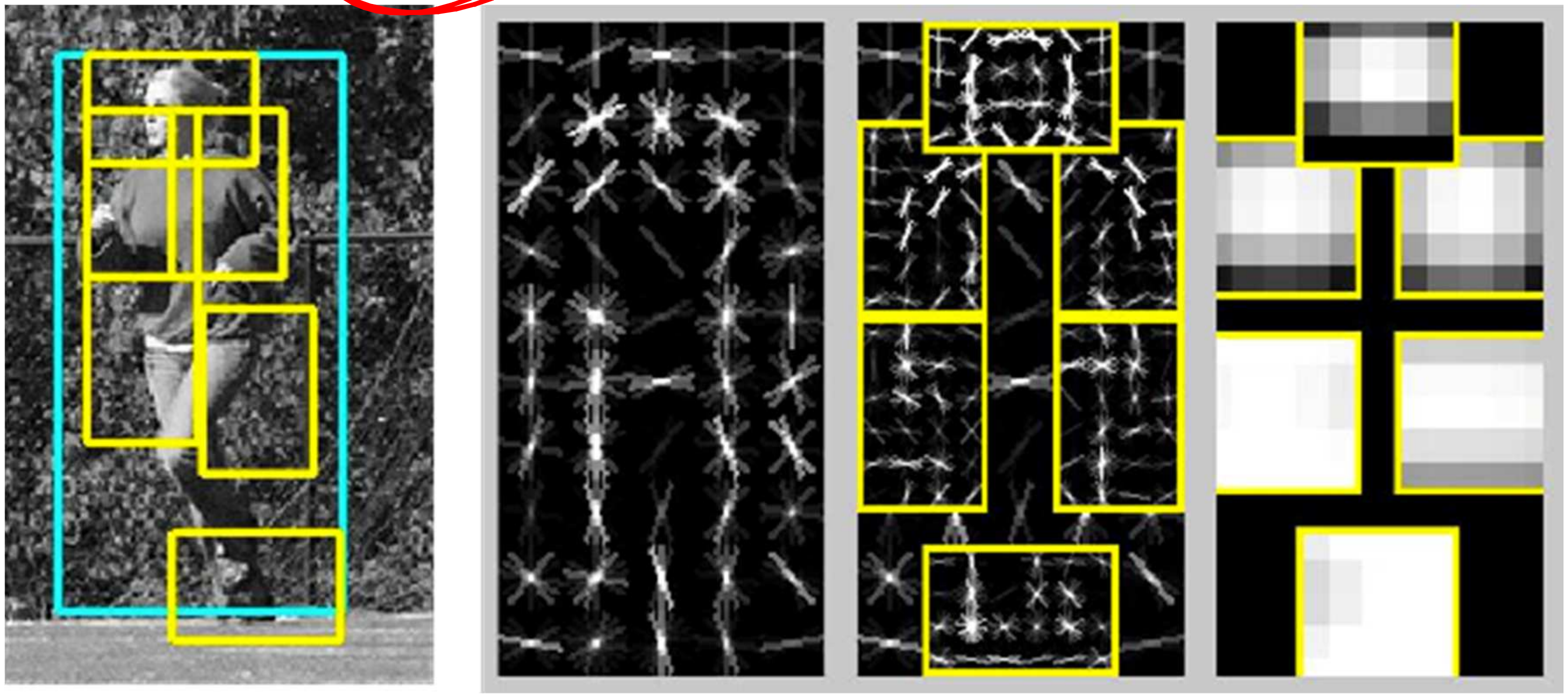
- ~10,000 images, with ~25,000 target objects.
  - Objects from 20 categories (person, car, bicycle, cow, table...).
  - Objects are annotated with labeled bounding boxes.



Source: Pedro Felzenswalb


aeroplane
Bicycle Assembly Area
personLeftTrunc
bicycleRight
bus
carLeftTrunc
car
boatTrunc
boat
personTruncDifficult
personTrunc
car
horseRightTrunc
Morgan
chair
chairLeft
diningtable
chairRight
chair
motorbikeRear
motorbikeRear
dogFrontal
dogLeftTrunc

Latent SVM Model: an Overview



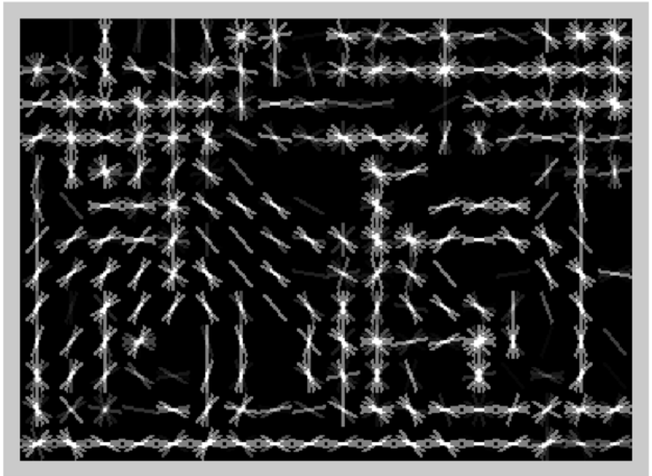
detection root filter part filters deformation models

- very similar to the constellation model

Source: Pedro Felzenswalb

Histogram of Oriented Gradient (HOG) Features

≈ SIFT

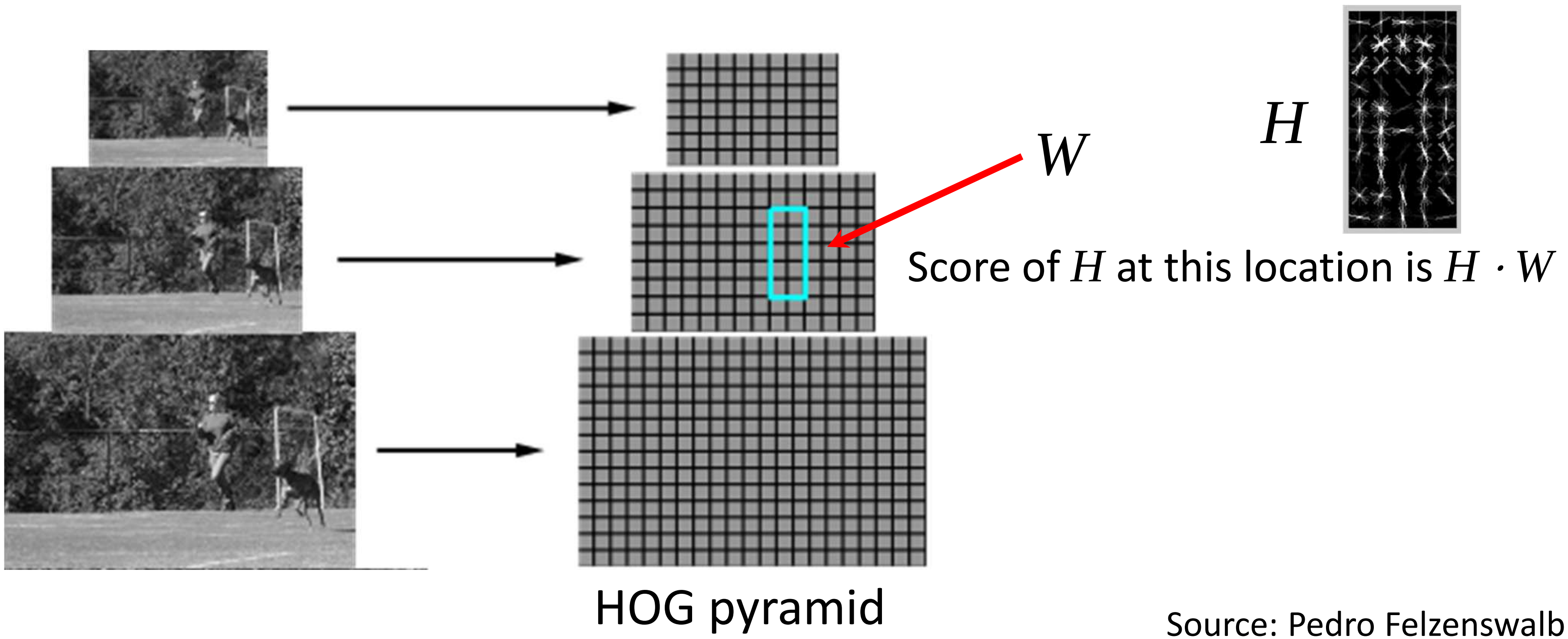


- Image is partitioned into 8x8 pixel blocks.
- In each block we compute a histogram of gradient orientations.
  - **Invariant** to changes in lighting, small deformations, etc.
- We compute features at different resolutions (pyramid).

Source: Pedro Felzenswalb

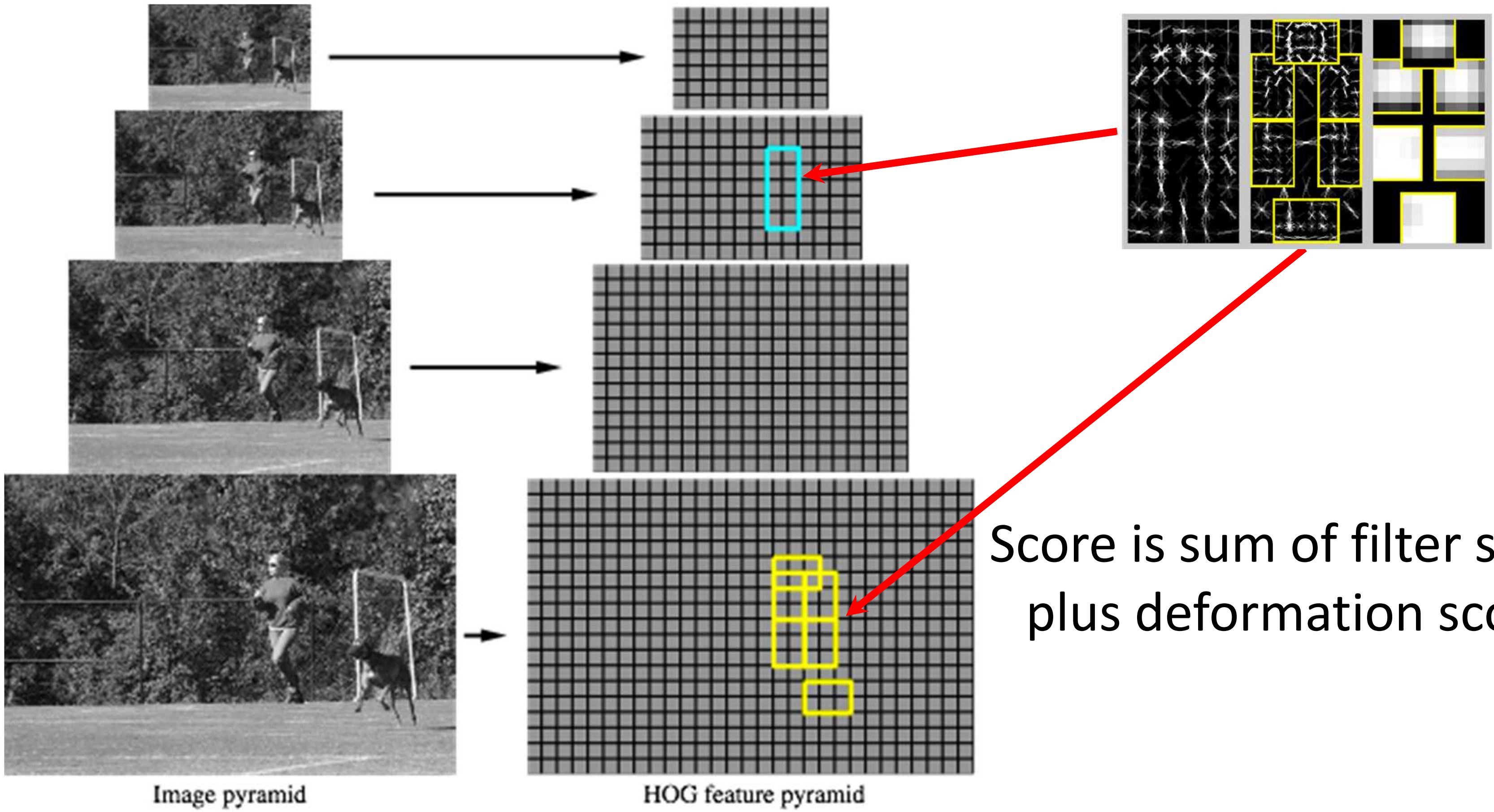
Filters

- Filters are rectangular templates defining weights for features.
- Score is dot product of filter and subwindow of HOG pyramid.



Source: Pedro Felzenswalb

Object Hypothesis



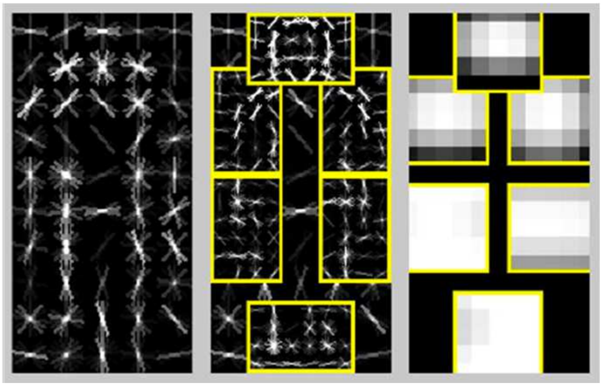
Score is sum of filter scores plus deformation scores

Multiscale model captures features at two-resolutions

Training the Latent SVM Model

- Training data consists of images with labeled bounding boxes.
- Need to learn the model structure, filters and deformation costs.

Training →



Source: Pedro Felzenswalb

Connection with Linear Classifiers

- Score of model is sum of filter scores plus deformation scores
  - Bounding box in training data specifies that the score should be high for some placement in a range

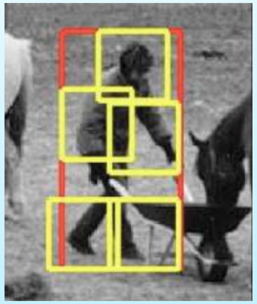
Standard SVM

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

Weight vector

Features

Latent SVM



w is a model
x is a detection window
z are filter placements

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

Concatenation of filters and deformation parameters

Concatenation of features and part displacements

Latent SVM Training

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

Linear in w if z is fixed

Observed variables

Latent variables

- Semi-convex optimization problem
  - $f_w(x) = \max_z w \cdot \Phi(x, z)$ is convex in w
  - convex if we fix z for positive examples
- Iterative optimization procedure:
  - Initialize w
  - Iterate:
    - Pick best z for each positive example
    - Optimize w via gradient descent with data mining

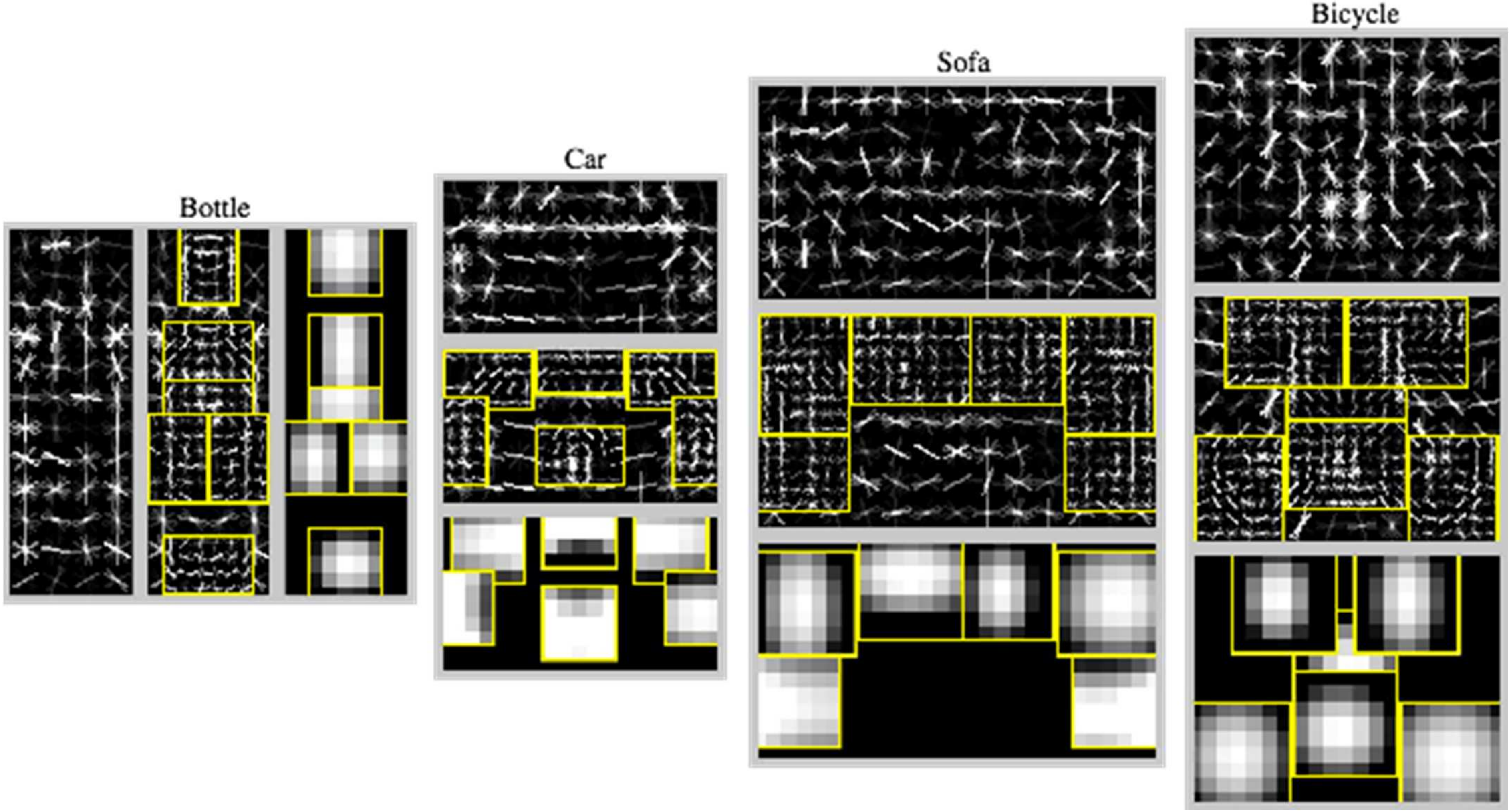
Latent SVM Training: Initializing w

- For k component mixture model:
  - Split examples into k sets based on bounding box aspect ratio

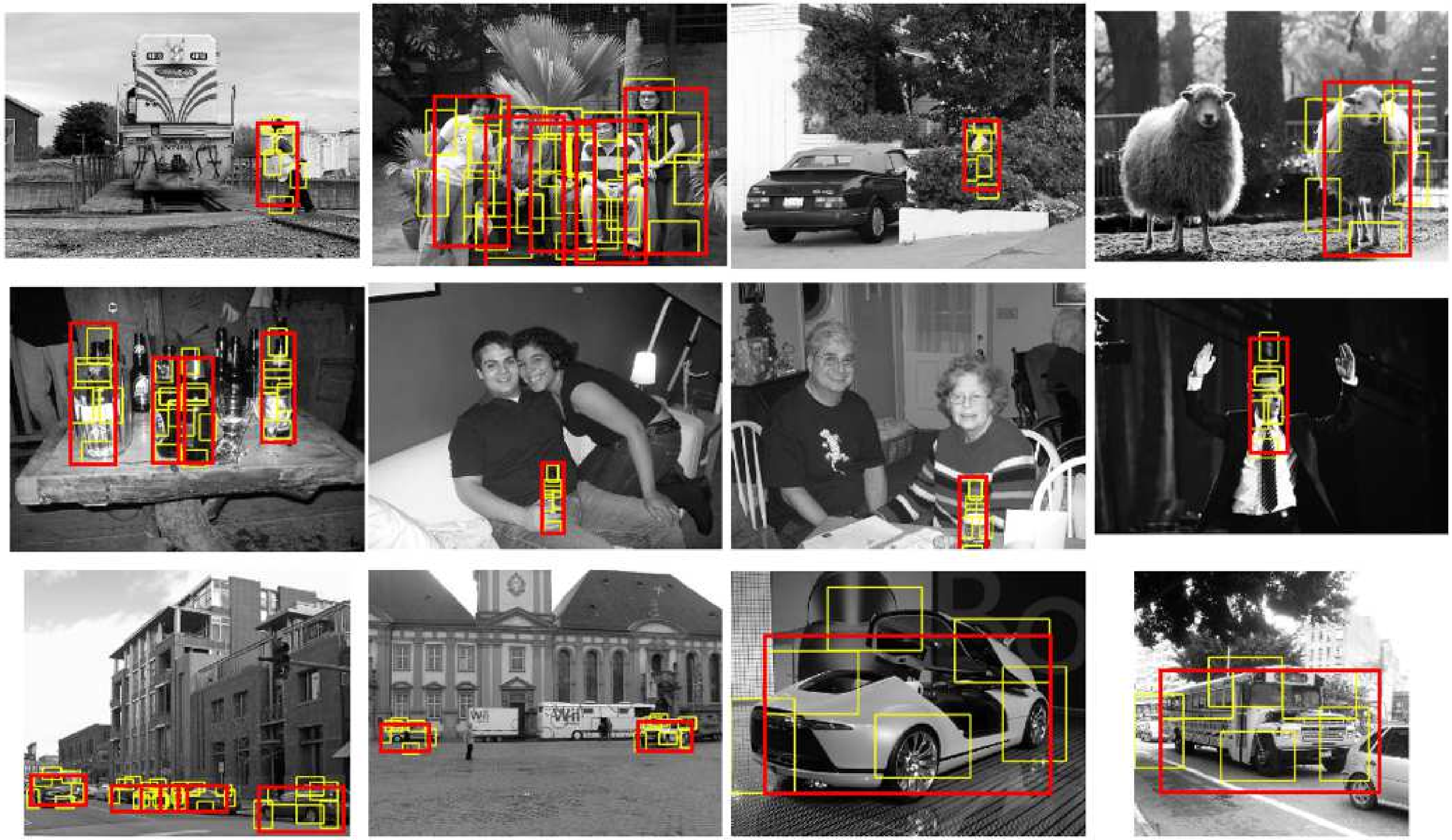
- Learn k root filters using standard SVM
  - Training data: Warped positive examples and random windows from negative images (Dalal & Triggs)

- Initialize parts by selecting patches from root filters:
  - Sub-windows with strong coefficients
  - Interpolate to get higher resolution filters
  - Initialize spatial model using fixed spring constants

Learned Models

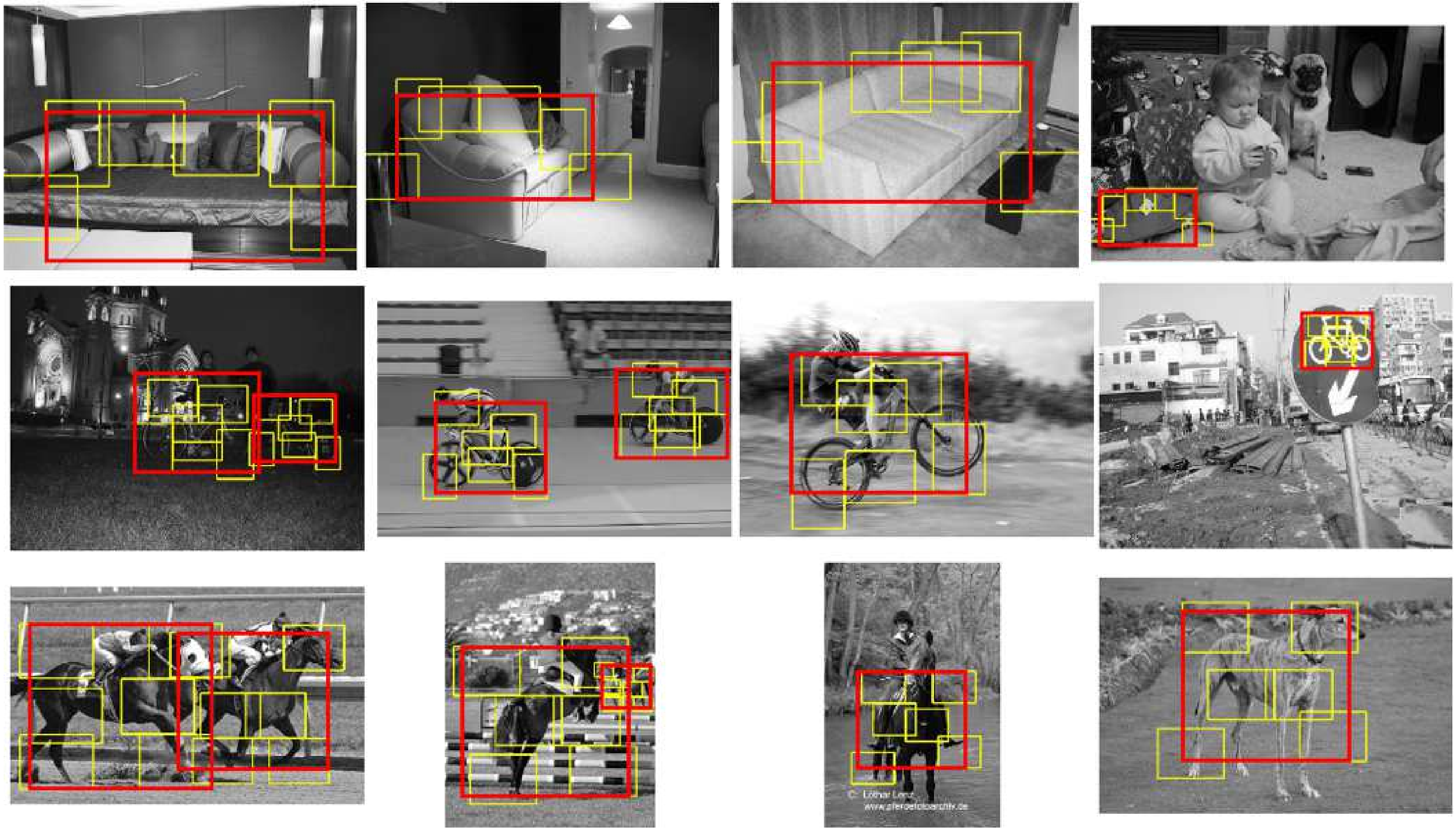


Example Results



Source: Pedro Felzenswalb

More Results



Quantitative Results

- 9 systems competed in the 2007 challenge.
- Out of 20 classes:
  - First place in 10 classes
  - Second place in 6 classes
- Some statistics:
  - It takes ~2 seconds to evaluate a model in one image.
  - It takes ~3 hours to train a model.
  - MUCH faster than most systems.

Source: Pedro Felzenswalb

Code for Latent SVM

Source code for the system and models trained on PASCAL 2006, 2007 and 2008 data are available at:

http://www.cs.uchicago.edu/~pff/latent

Source: Pedro Felzenswalb

Summary

- Deformable models provide an elegant framework for object detection and recognition.
  - Efficient algorithms for matching models to images.
  - Applications: pose estimation, medical image analysis, object recognition, etc.
- We can learn models from partially labeled data.
  - Generalized standard ideas from machine learning.
  - Leads to state-of-the-art results in PASCAL challenge.
- Future work: hierarchical models, grammars, 3D objects.

Source: Pedro Felzenswalb

What we have learned today

- Implicit Shape Model
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- Deformable Models
  - The PASCAL challenge
  - Latent SVM Model