Category-level Localization

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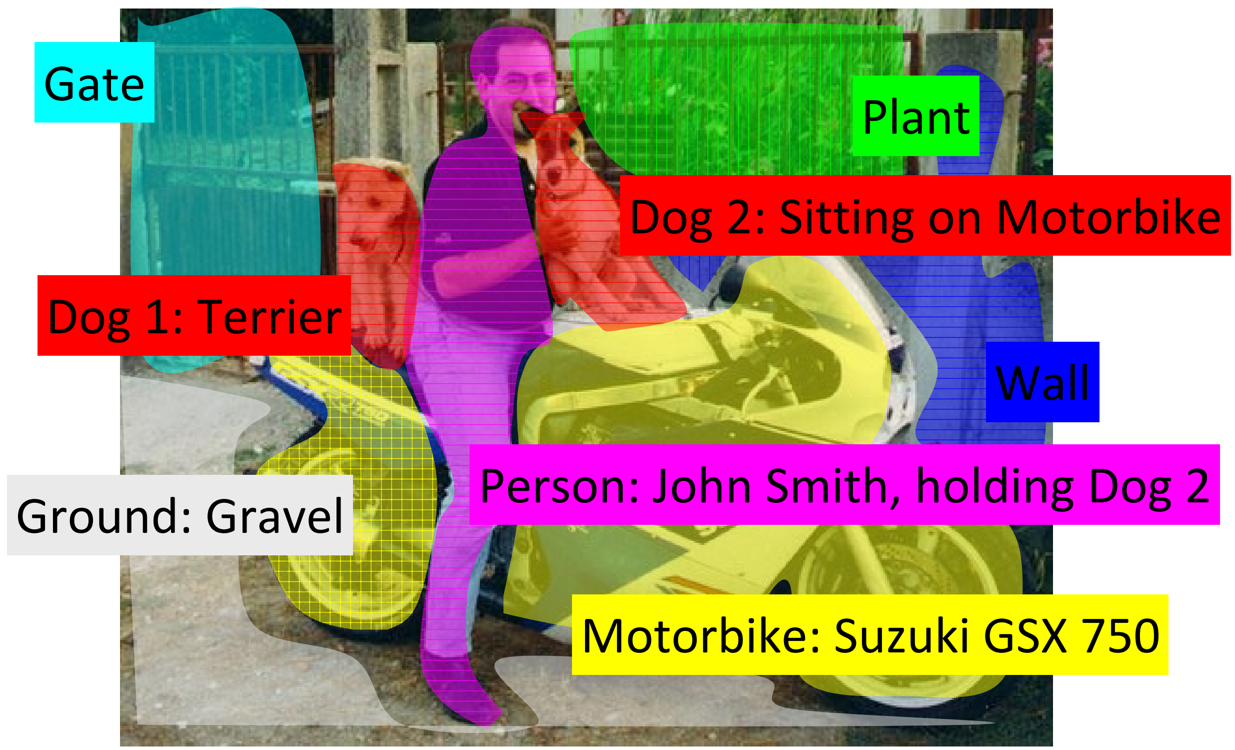
What we would like to be able to do…

- Visual scene understanding
- **<u>What</u>** is in the image and **<u>where</u>**



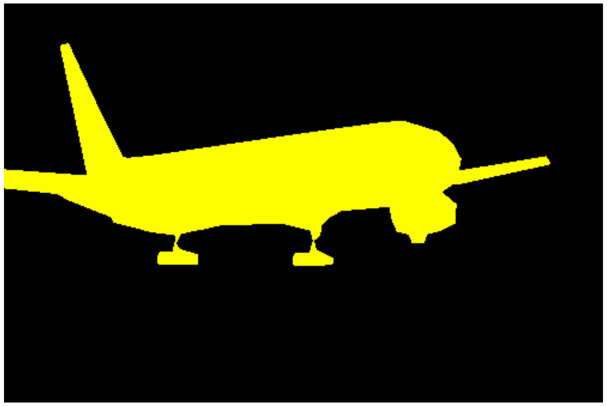
- Object categories, identities, properties, activities, relations, …

Recognition Tasks

- **Image Classification**
  - Does the image contain an aeroplane?

- **Object Class Detection/Localization**
  - Where are the aeroplanes (if any)?

- **Object Class Segmentation**
  - Which pixels are part of an aeroplane (if any)?



Things vs. Stuff

Ted Adelson, Forsyth et al. 1996.

Thing (n): An object with a specific size and shape.

Stuff (n): Material defined by a homogeneous or repetitive pattern of fine-scale properties, but has no specific or distinctive spatial extent or shape.

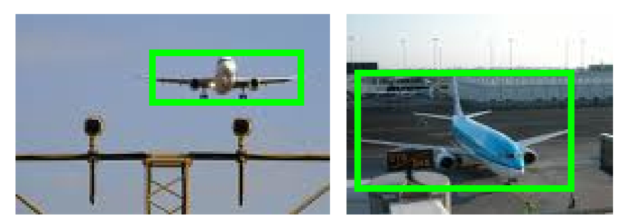
Slide: Geremy Heitz

Recognition Task

- **Object Class Detection/Localization**
  - Where are the aeroplanes (if any)?

- **Challenges**
  - Imaging factors e.g. lighting, pose, occlusion, clutter
  - Intra-class variation

- **Compared to Classification**
  - Detailed prediction e.g. bounding box
  - Location usually provided for training



Challenges: Background Clutter

Challenges: Occlusion and truncation

Challenges: Intra-class variation

Object Category Recognition by Learning

- Difficult to define model of a category. Instead, **<u>learn</u>** from **<u>example images</u>**

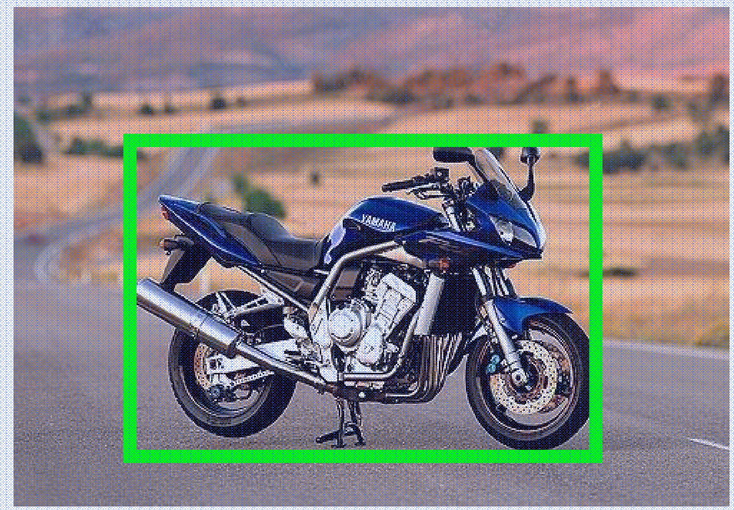
    

Level of Supervision for Learning

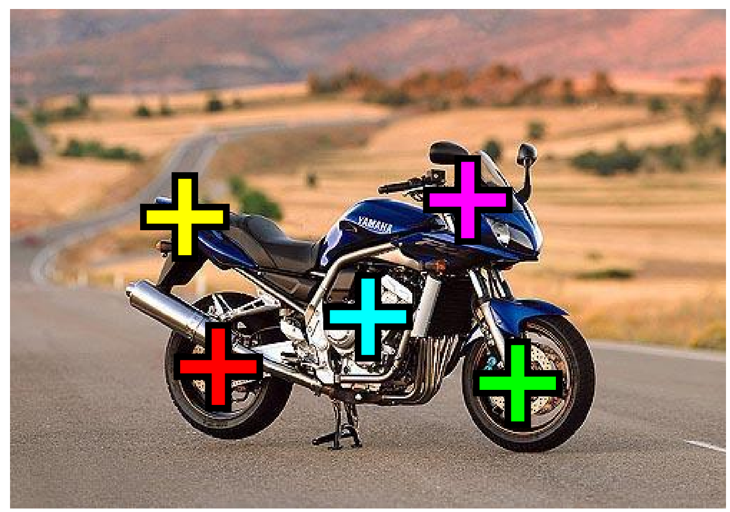
Image-level label

Bounding box



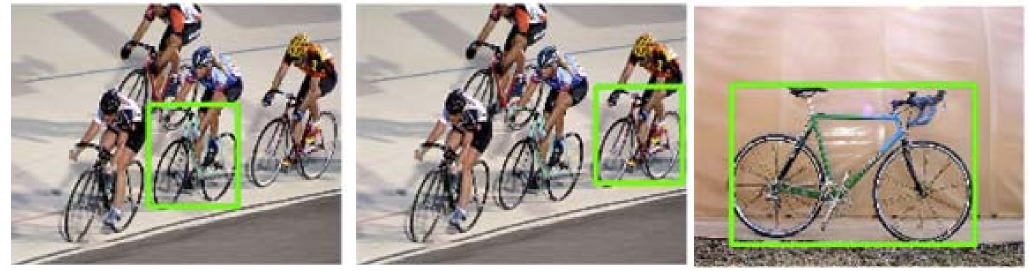
Pixel-level segmentation

“Parts”



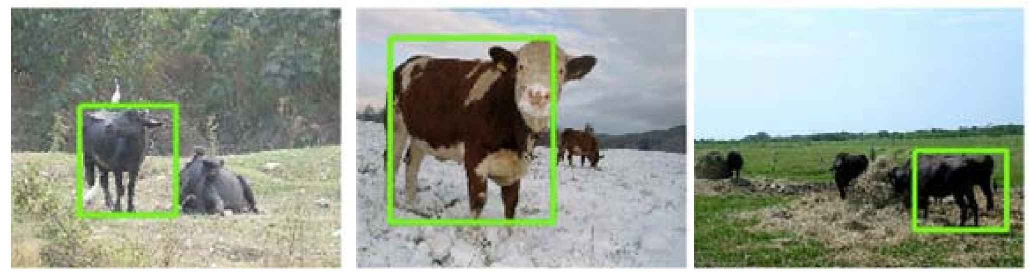
Preview of typical results

aeroplane



bicycle

car



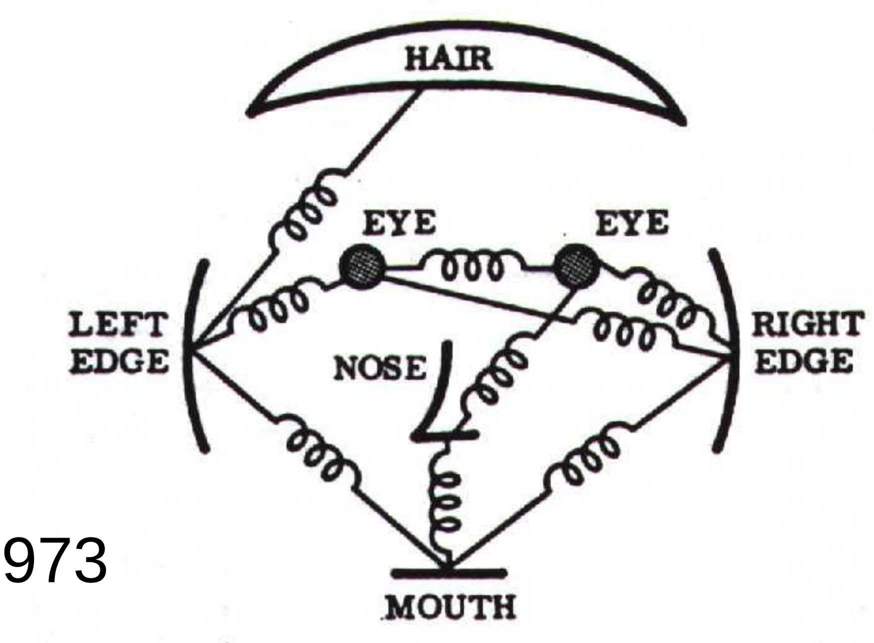
cow

horse

motorbike

Class of model: Pictorial Structure

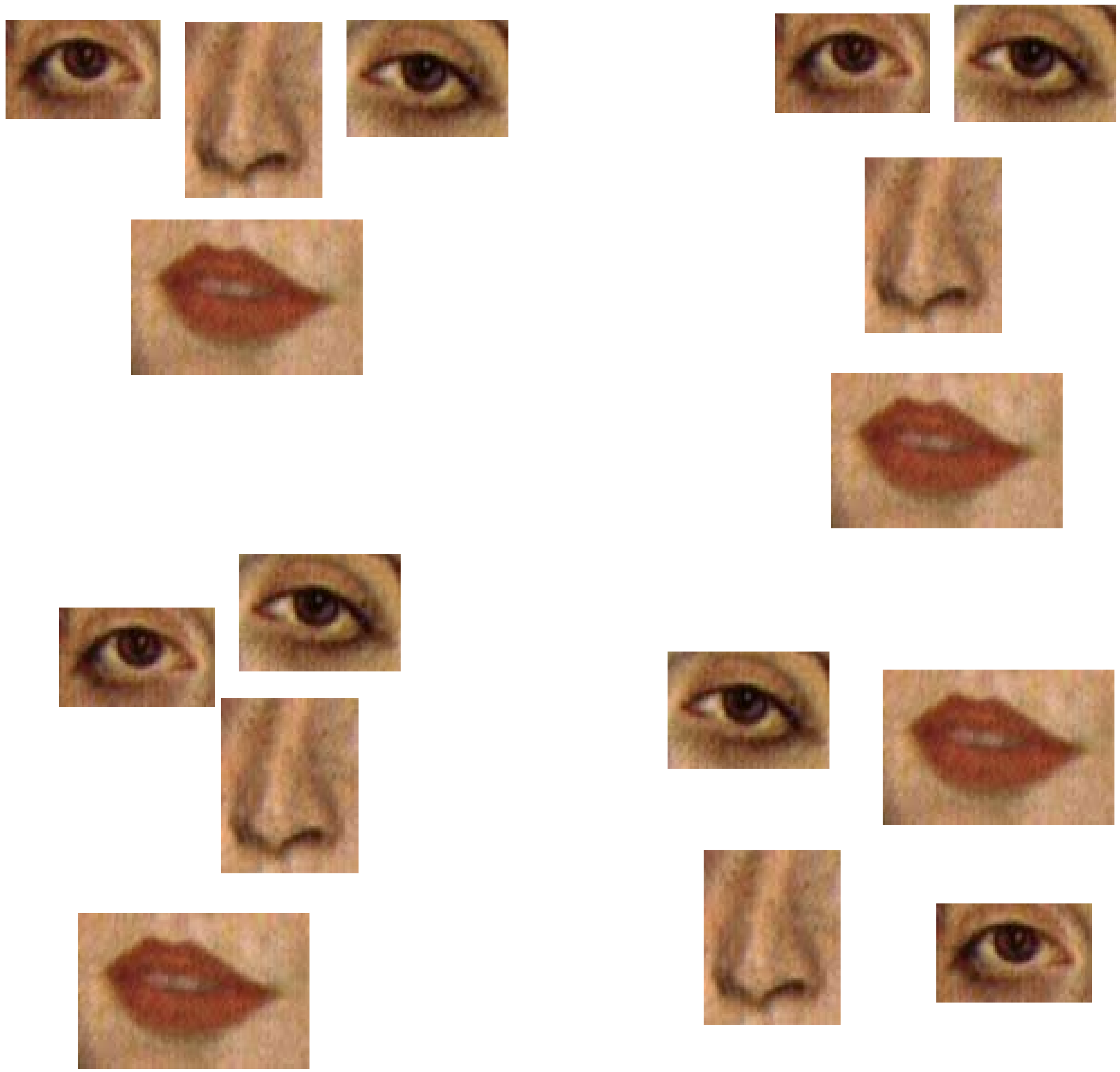
- Intuitive model of an object
- Model has two components
  1. parts (2D image fragments)
  2. structure (configuration of parts)
- Dates back to Fischler & Elschlager 1973



Is this complexity of representation necessary ?

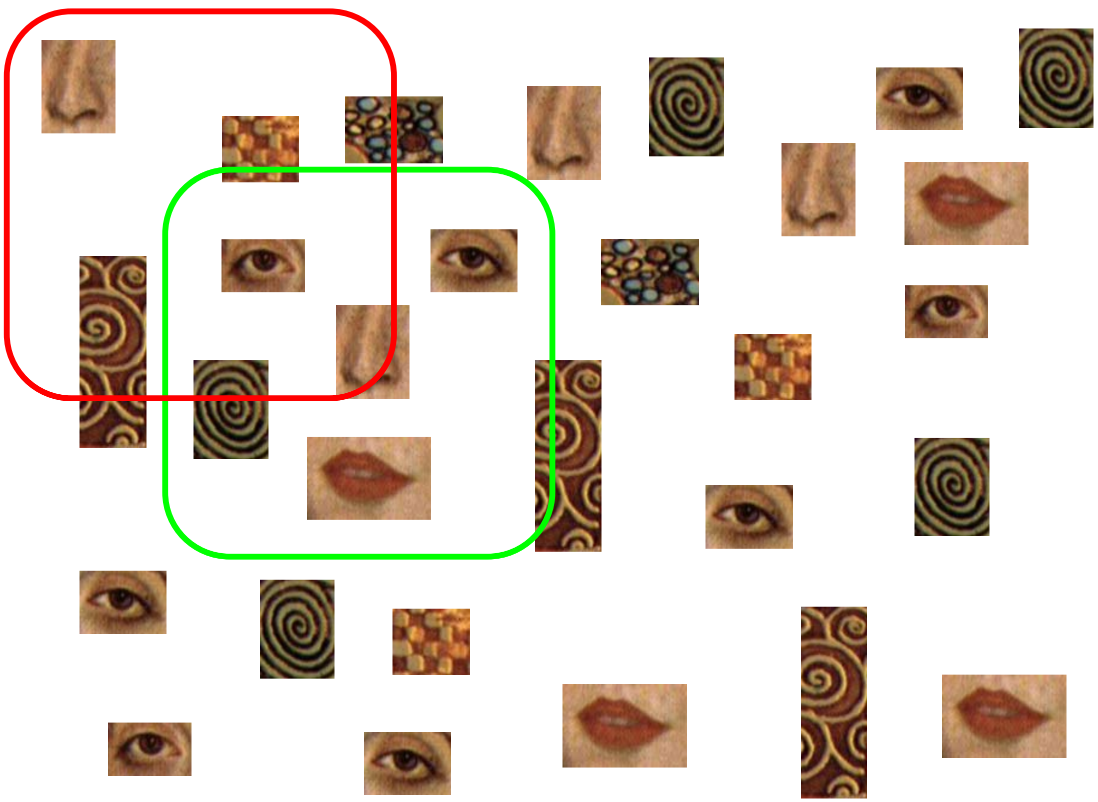
Which features?

Restrict spatial deformations



Problem of background clutter

- Use a sub-window
  - At correct position, no clutter is present
  - Slide window to detect object
  - Change size of window to search over scale



Outline

1. Sliding window detectors

2. Features and adding spatial information

3. Histogram of Oriented Gradients (HOG)

4. PASCAL VOC and a state of the art detection algorithm

5. The future and challenges

Outline

1. Sliding window detectors
   - Start: feature/classifier agnostic
   - Method
   - Problems/limitations
2. Features and adding spatial information
3. Histogram of Oriented Gradients (HOG)
4. PASCAL VOC and a state of the art detection algorithm
5. The future and challenges

Detection by Classification

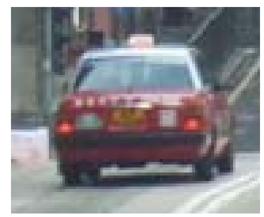
- Basic component: binary classifier

Car/non-car
Classifier

No,
not a car

Detection by Classification

- Detect objects in clutter by **search**

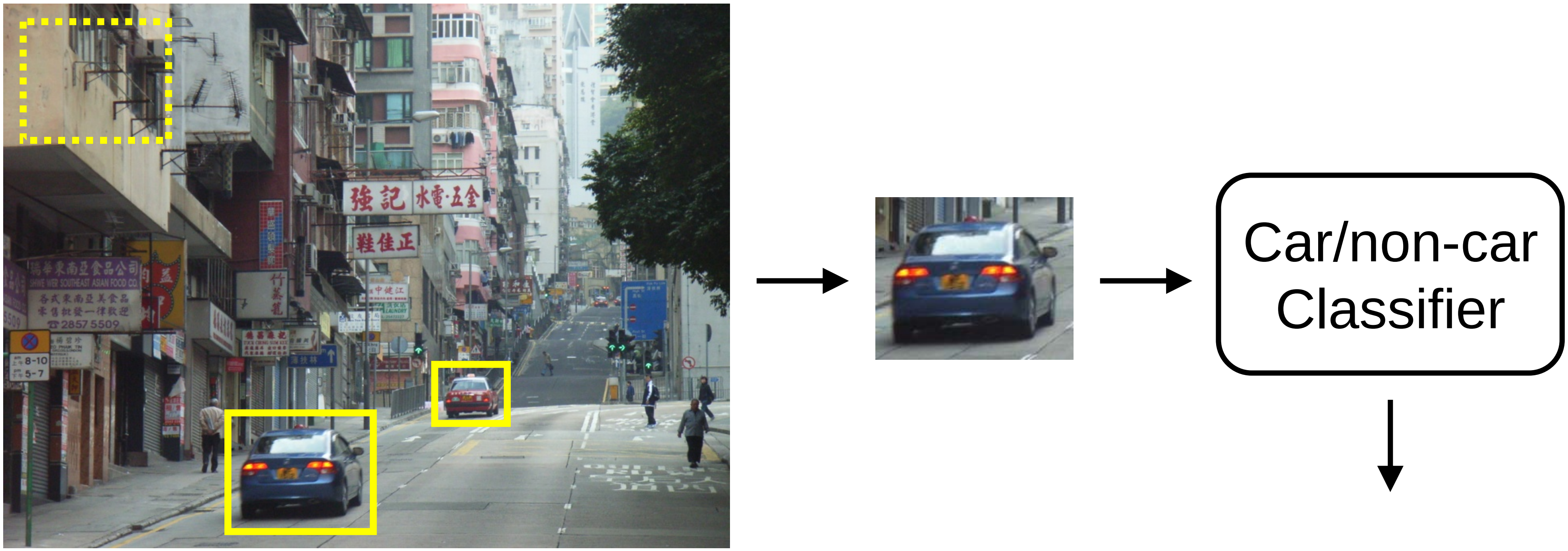


Car/non-car Classifier

- **Sliding window**: exhaustive search over position and scale

Detection by Classification

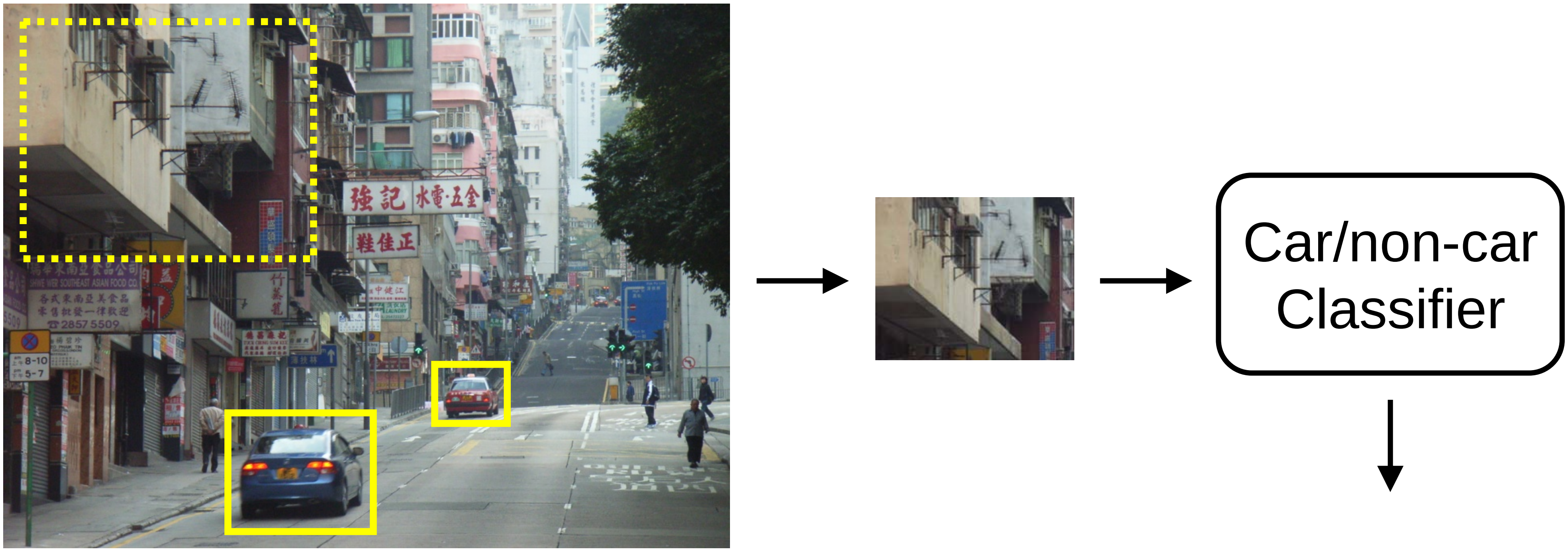
• Detect objects in clutter by **<u>search</u>**



• **Sliding window**: exhaustive search over position and scale

Detection by Classification

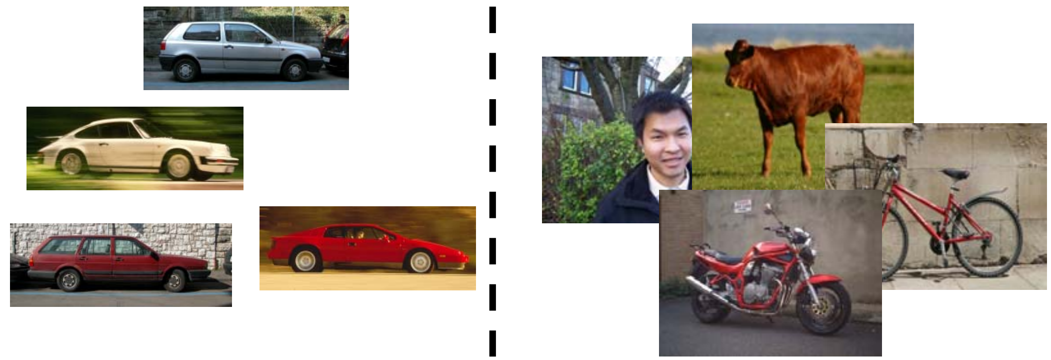
• Detect objects in clutter by **search**



• **Sliding window**: exhaustive search over position and scale (can use same size window over a spatial pyramid of images)

Window (Image) Classification

Training Data



→ Feature Extraction → $\mathbf{x}$ → Classifier $F(x)$

↓

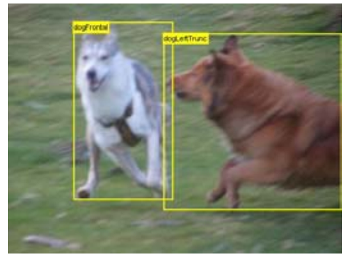
Car/Non-car

$$P(c|\mathbf{x}) \propto F(\mathbf{x})$$

- Features usually engineered
- Classifier learnt from data

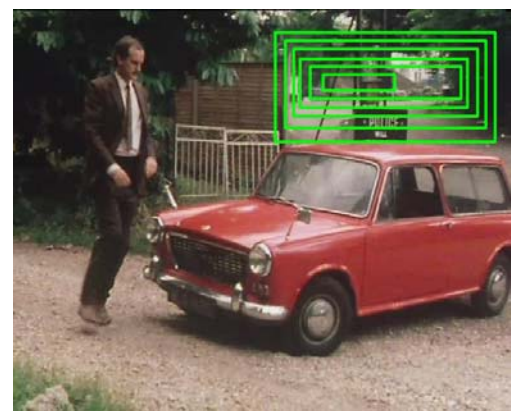
Problems with sliding windows …

- aspect ratio
- granuality (finite grid)
- partial occlusion
- multiple responses



See work by

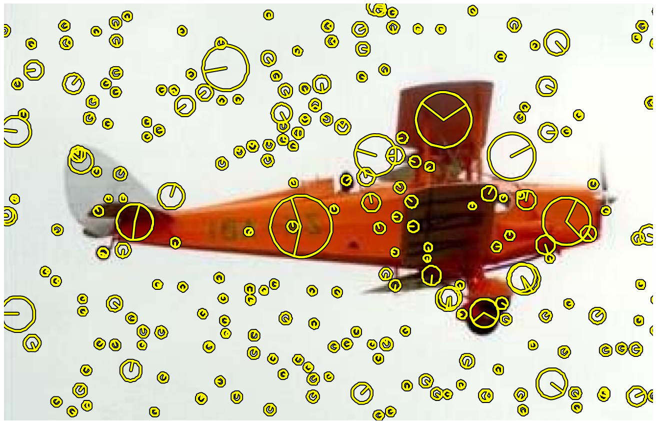
- Christoph Lampert et al CVPR 08, ECCV 08



Outline

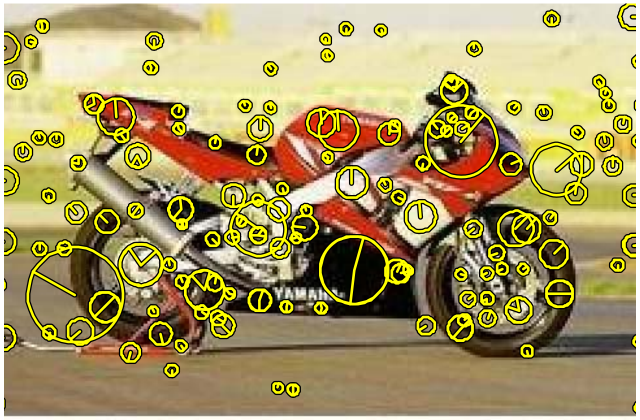
1. Sliding window detectors
2. Features and adding spatial information
   - Bag of visual word (BoW) models
   - Beyond BoW I: Implicit Shape Model (ISM) models
   - Beyond BoW II: Grids and spatial pyramids
3. Histogram of Oriented Gradients (HOG)
4. PASCAL VOC and a state of the art detection algorithm
5. The future and challenges

Recap: Bag of (visual) Words representation



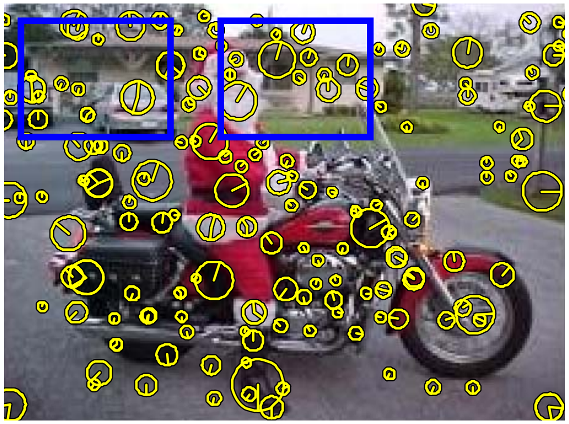
- Detect affine invariant local features (e.g. affine-Harris)

- Represent by high-dimensional descriptors, e.g. 128-D for SIFT



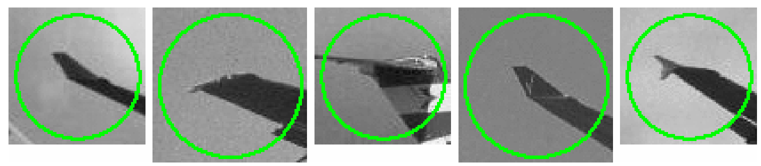
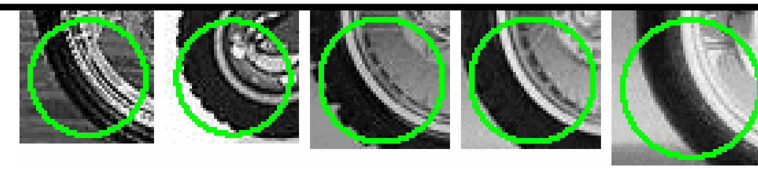
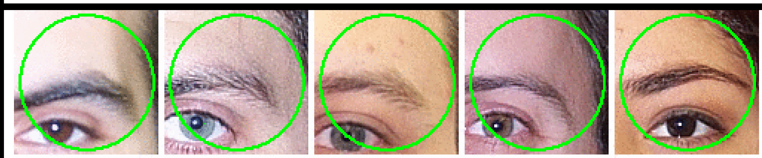
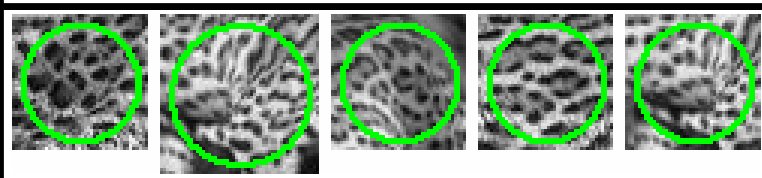
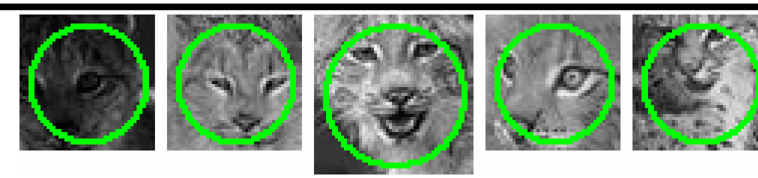
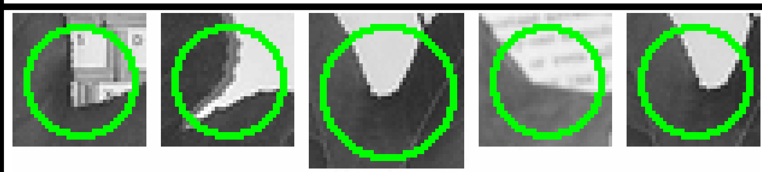
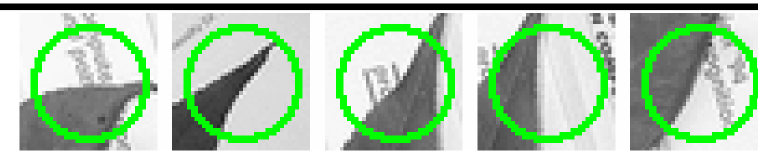
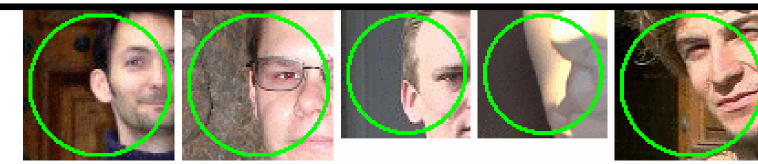
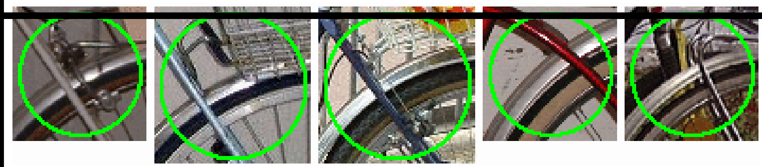
- Map descriptors onto a common vocabulary of **visual words**

Represent **sliding window** as a histogram over visual words – a **bag of words**

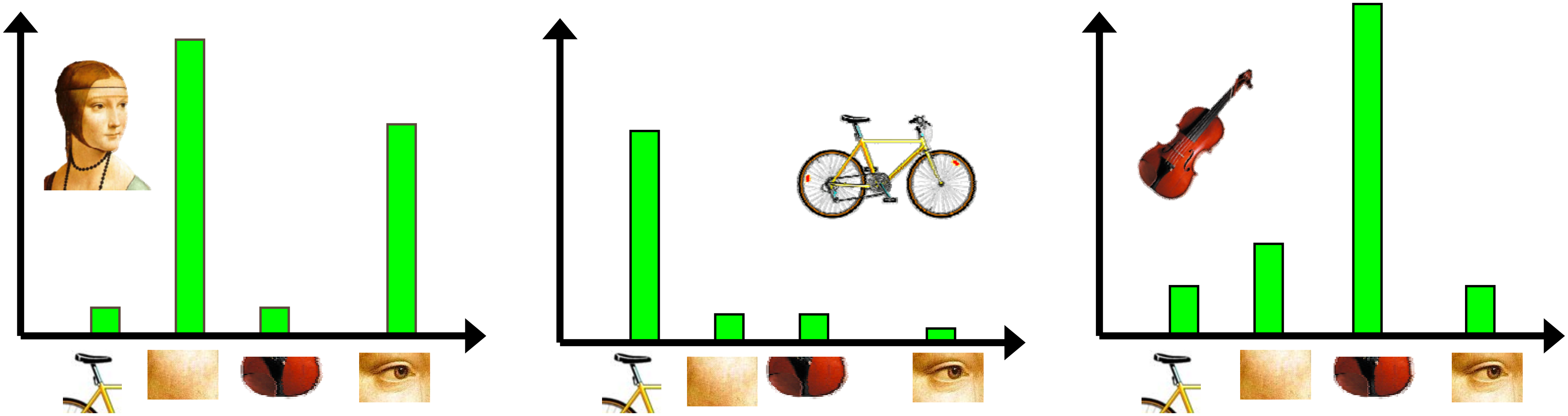


- Summarizes sliding window content in a fixed-length vector suitable for classification

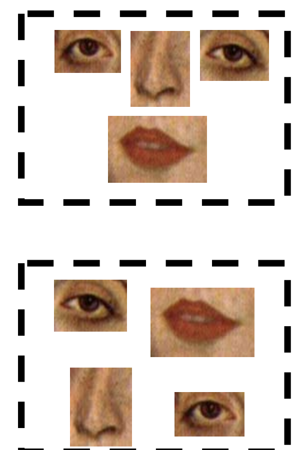
Examples for visual words

Airplanes		
Motorbikes		
Faces		
Wild Cats		
Leaves		
People		
Bikes		

Intuition

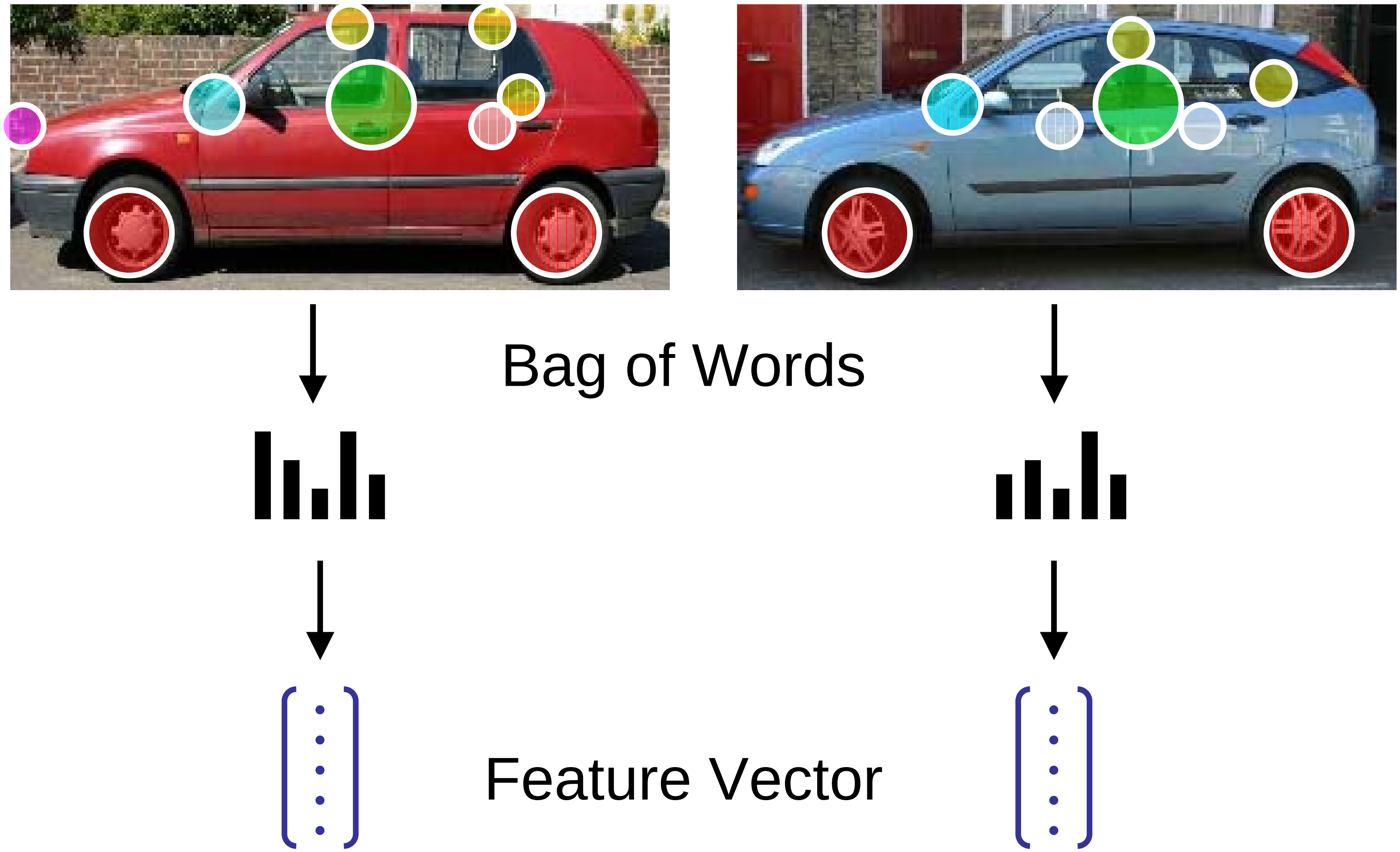


Visual Vocabulary



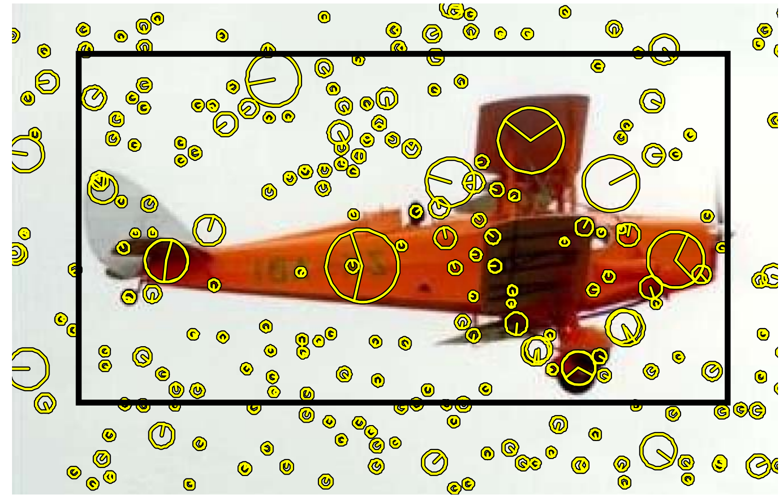
- Visual words represent “iconic” image fragments
- Feature detectors and SIFT give invariance to local rotation and scale
- Discarding spatial information gives configuration invariance

Learning from positive ROI examples

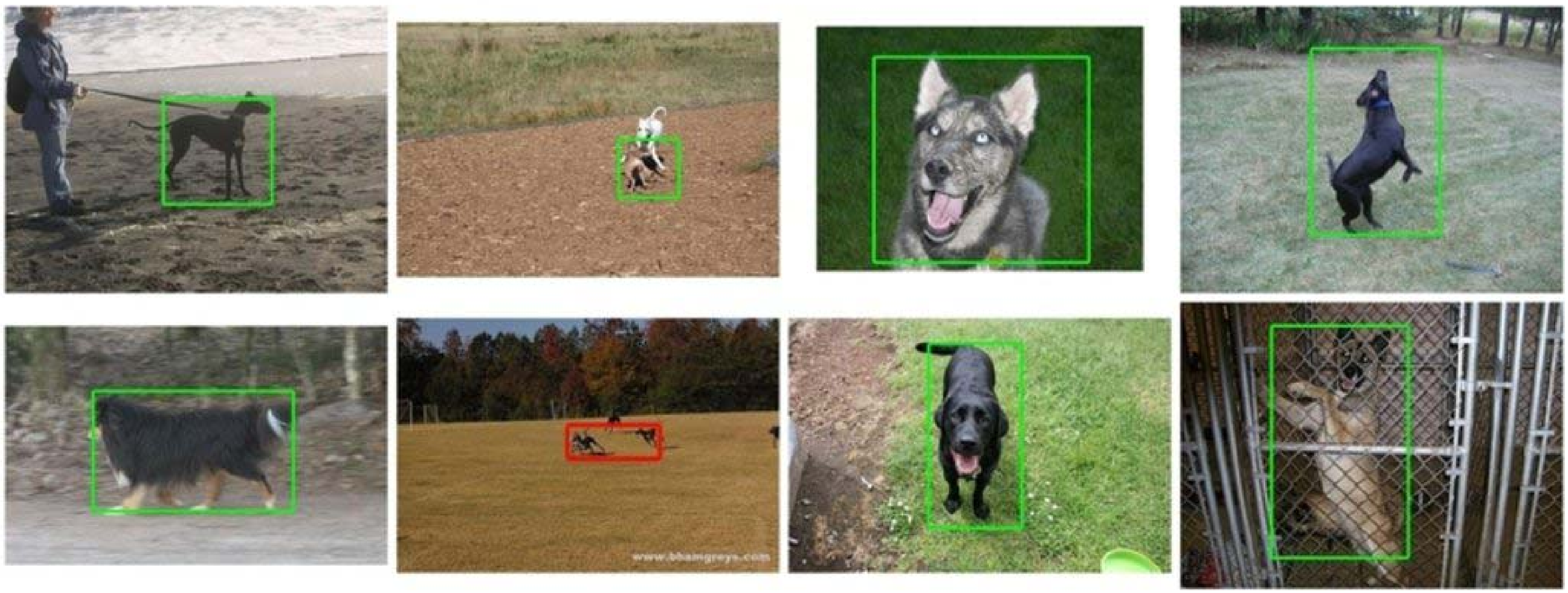


Sliding window detector

- Classifier: SVM with linear kernel
- BOW representation for ROI



Example detections for dog



Lampert et al CVPR 08: Efficient branch and bound search over all windows

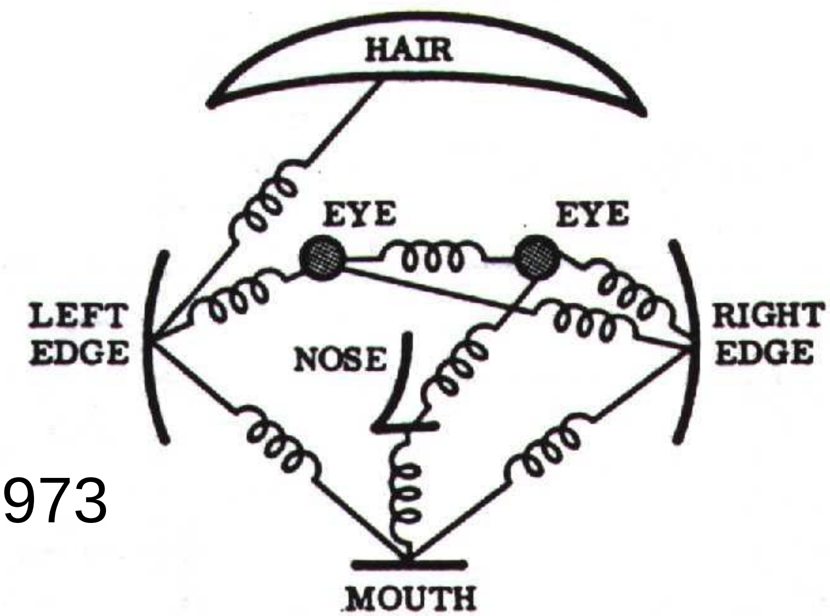
Discussion: ROI as a Bag of Visual Words

- Advantages
  - No explicit modelling of spatial information $\Rightarrow$ high level of invariance to position and orientation in image
  - Fixed length vector $\Rightarrow$ standard machine learning methods applicable

- Disadvantages
  - No explicit modelling of spatial information $\Rightarrow$ less discriminative power
  - Inferior to state of the art performance

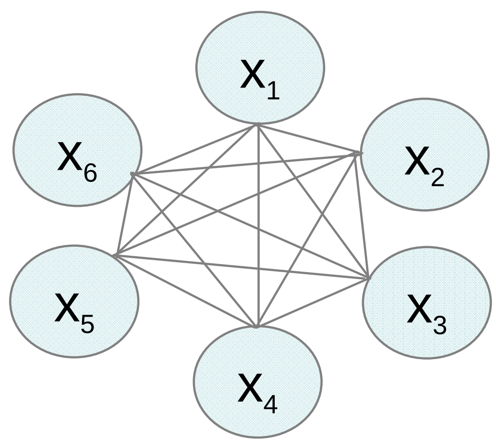
Beyond BOW I: Pictorial Structure

- Intuitive model of an object
- Model has two components
  1. parts (2D image fragments)
  2. structure (configuration of parts)
- Dates back to Fischler & Elschlager 1973

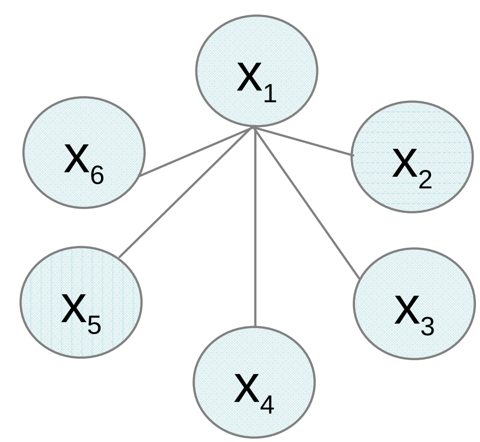


Example spatial structures:

Fully connected shape model



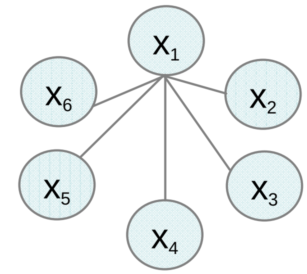
"Star" shape model



Implicit Shape Model (ISM)

Leibe, Leonardis, Schiele, 03/04

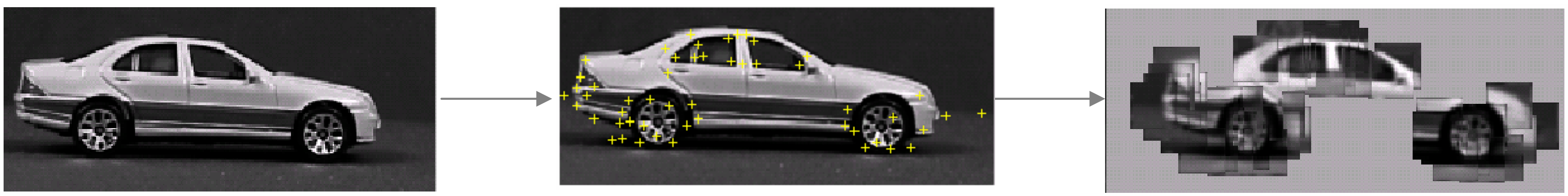
- Basic ideas
  - Learn an appearance codebook
  - Learn a star-topology structural model
    - Features are considered independent given object centre



- Algorithm: probabilistic Generalized Hough Transform

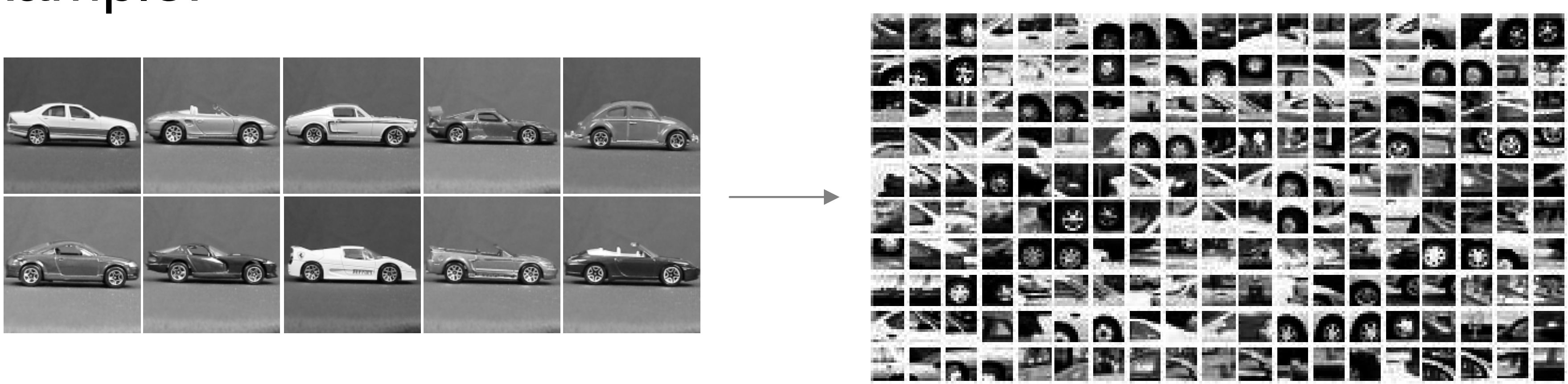
Codebook Representation

- Extraction of local object features
  - Interest Points (e.g. Harris detector)
  - Sparse representation of the object appearance



- Collect features from whole training set

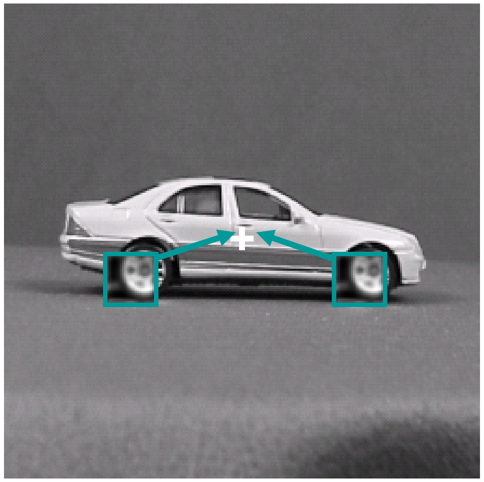
- Example:

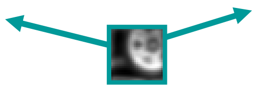


Class specific vocabulary

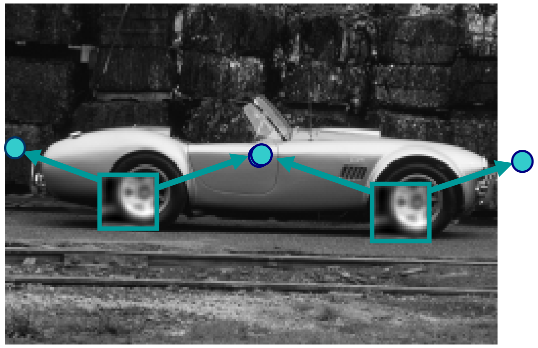
Leibe & Schiele 03/04: Generalized Hough Transform

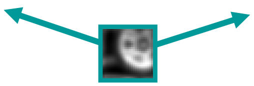
- Learning: for every cluster, store possible “occurrences”



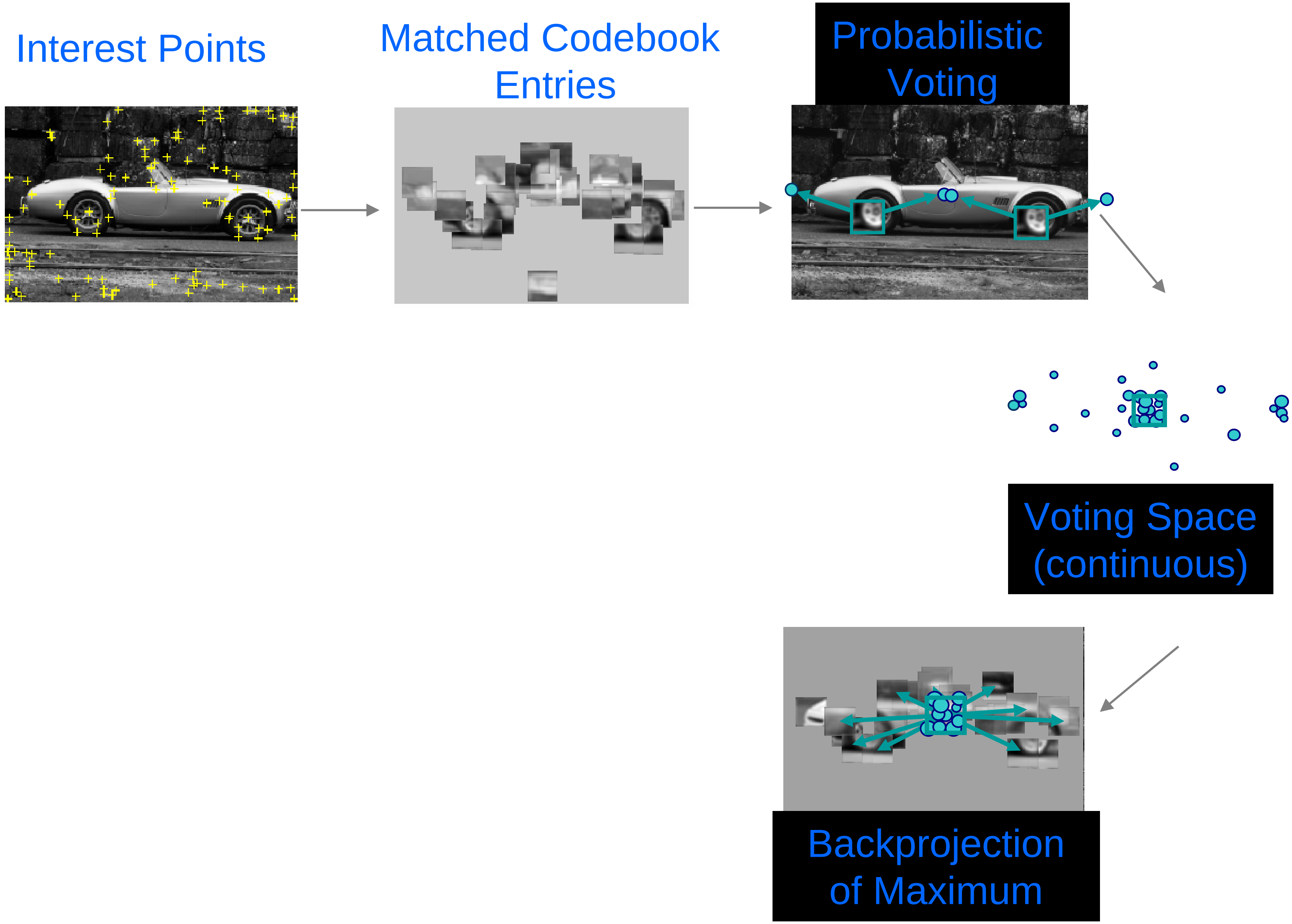


- Recognition: for new image, let the matched patches vote for possible object positions

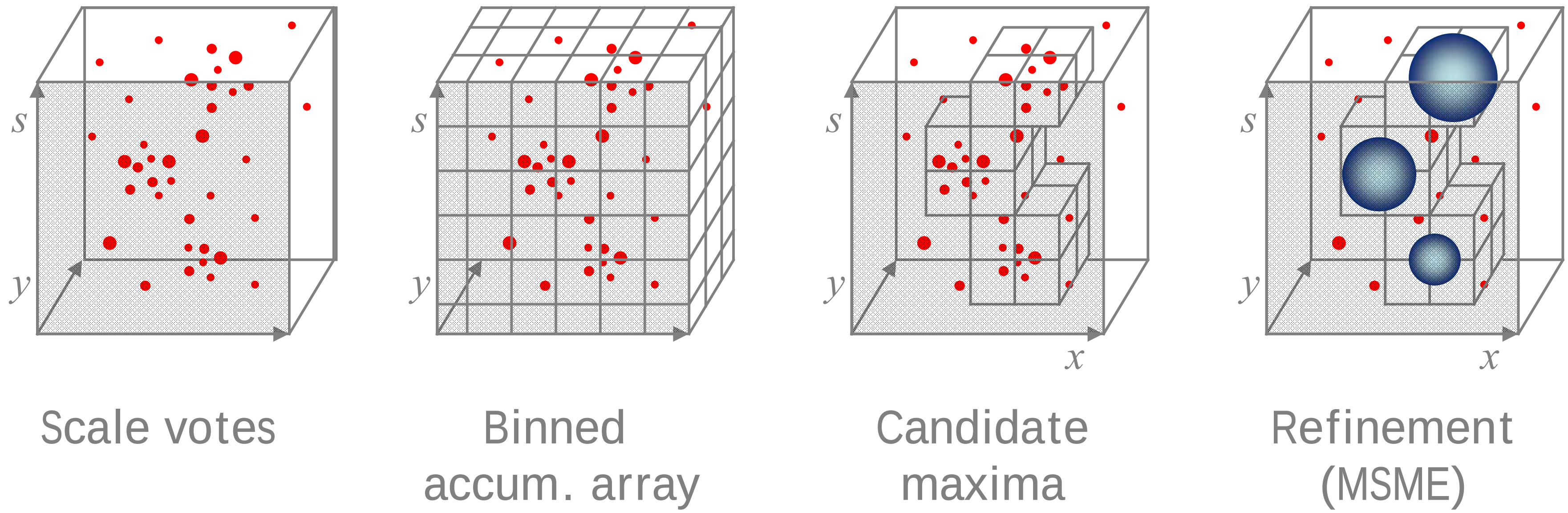




Leibe & Schiele 03/04: Generalized Hough Transform



Scale Voting: Efficient Computation



- Mean-Shift formulation for refinement
  - Scale-adaptive *balloon density estimator*

$$\hat{p}(o_n, x) = \frac{1}{V_b} \sum_k \sum_j p(o_n, x_j | f_k, \ell_k) K\left(\frac{x - x_j}{b}\right)$$

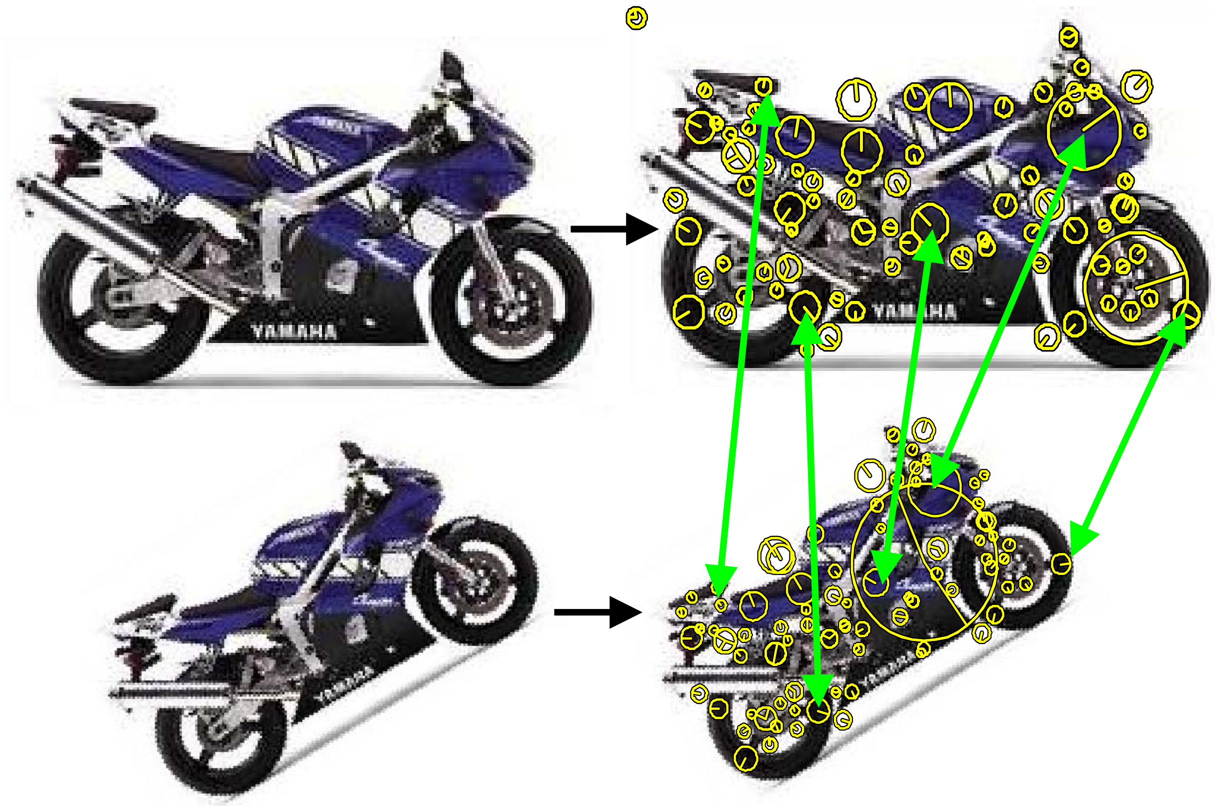
Detection Results

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

Discussion: ISM and related models

Advantages

- Scale and rotation invariance can be built into the representation from the start
- Relatively cheap to learn and test (inference)
- Works well for many different object categories
- Max-margin extensions possible, Maji & Malik, CVPR09



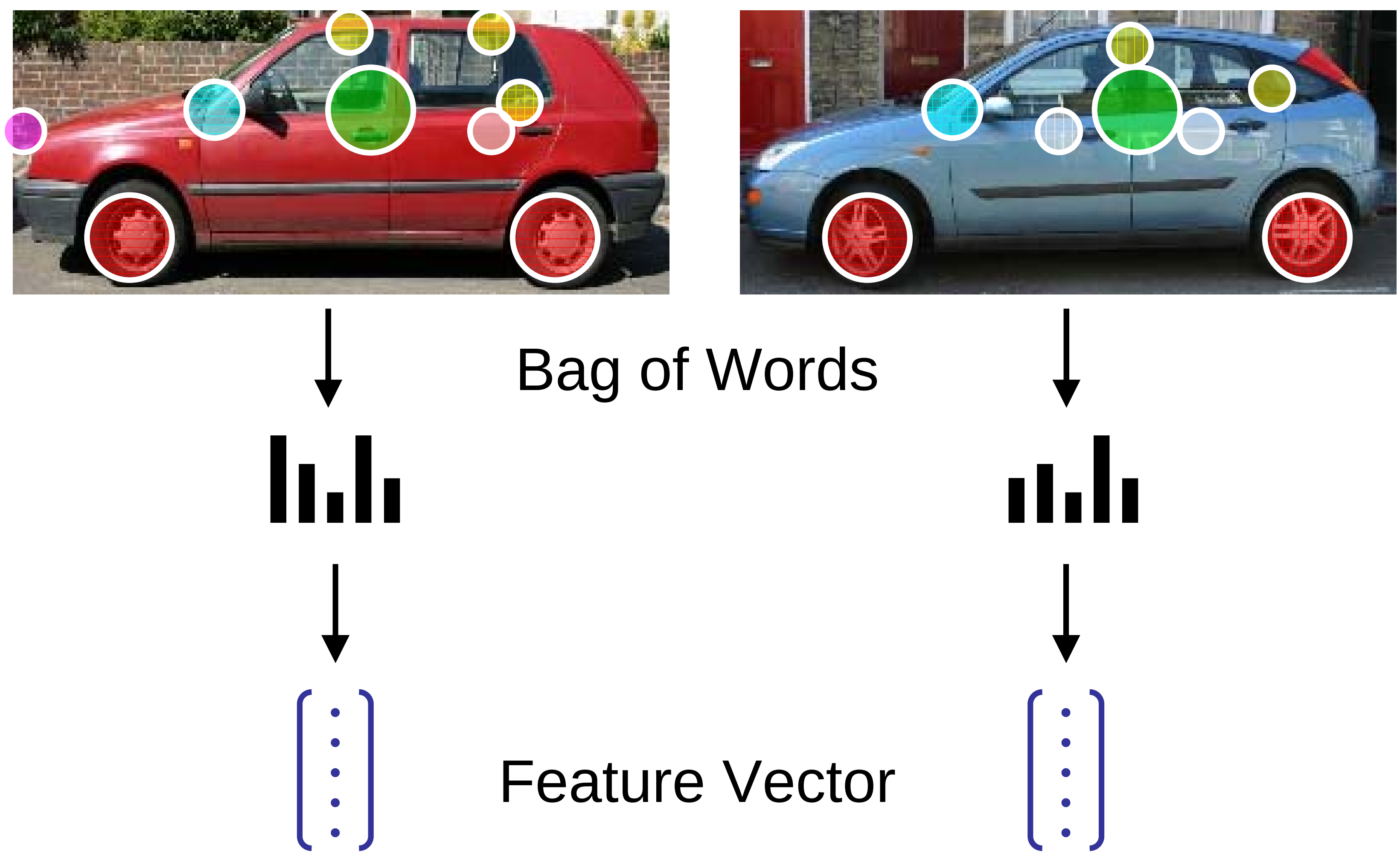
Disadvantages

- Requires searching for modes in the Hough space
- Similar to sliding window in this respect
- Is such a degree of invariance required? (many objects are horizontal)

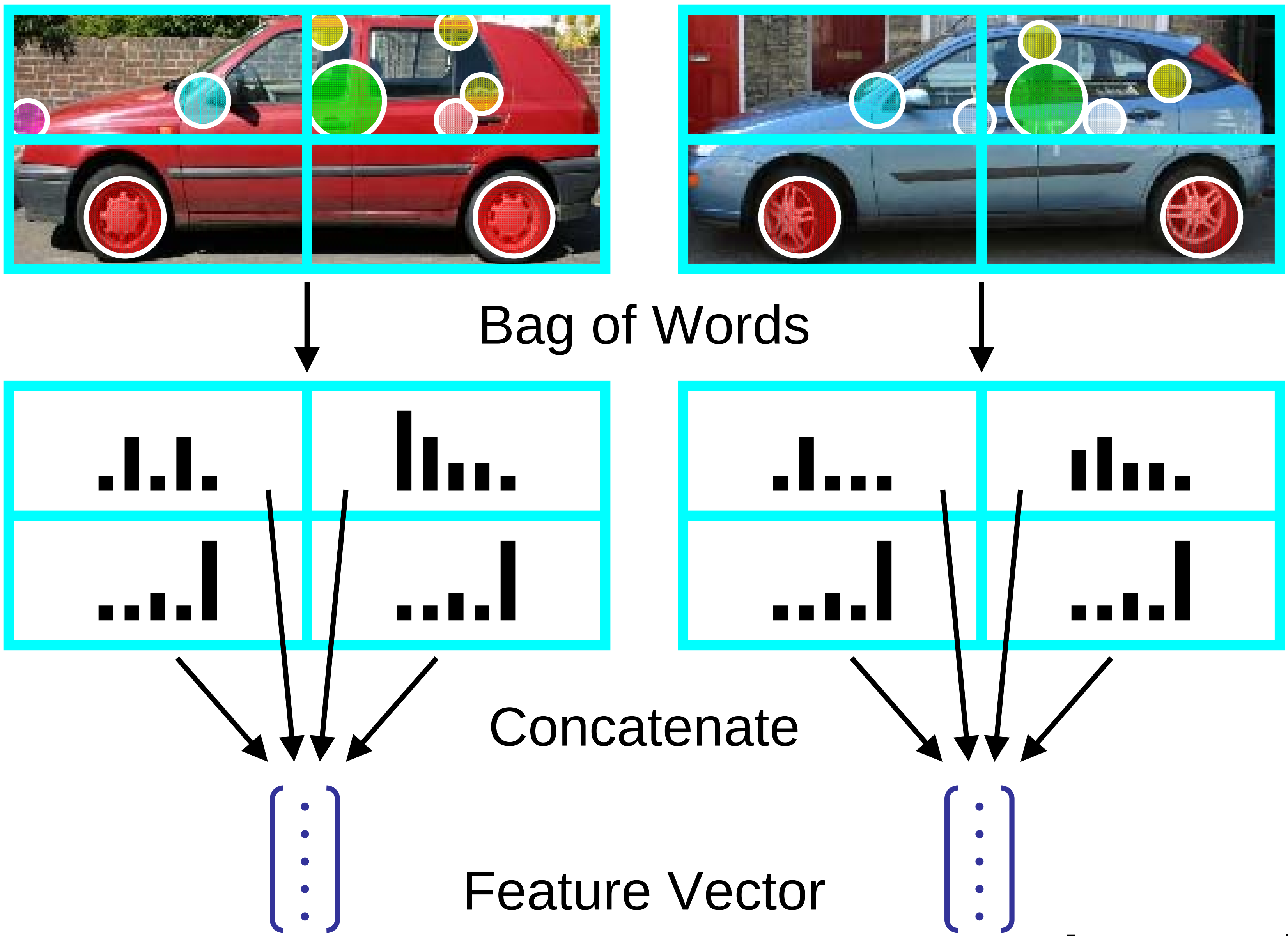
Beyond BOW II: Grids and spatial pyramids

Start from BoW for ROI

- no spatial information recorded
- sliding window detector



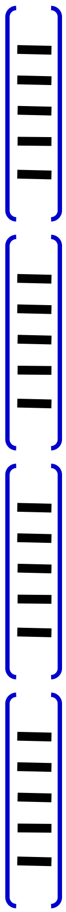
Adding Spatial Information to Bag of Words



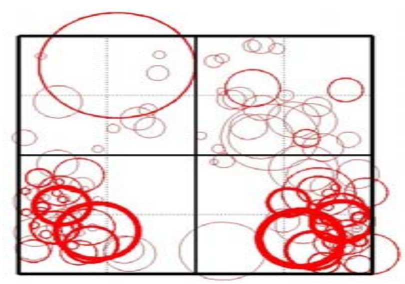
[Fergus et al, 2005]

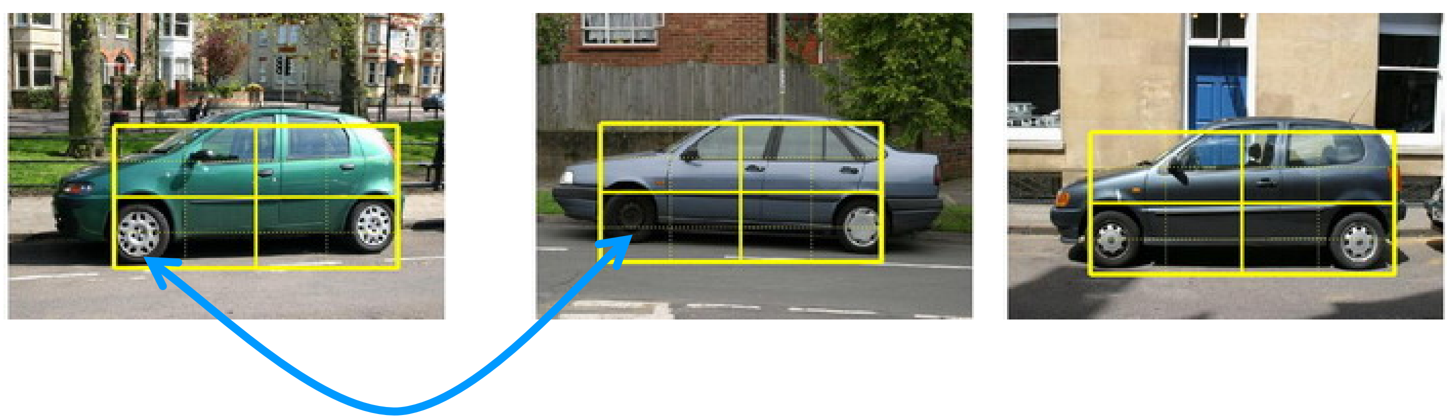
Keeps fixed length feature vector for a window

Tiling defines (records) the spatial correspondence of the words



- parameter: number of tiles

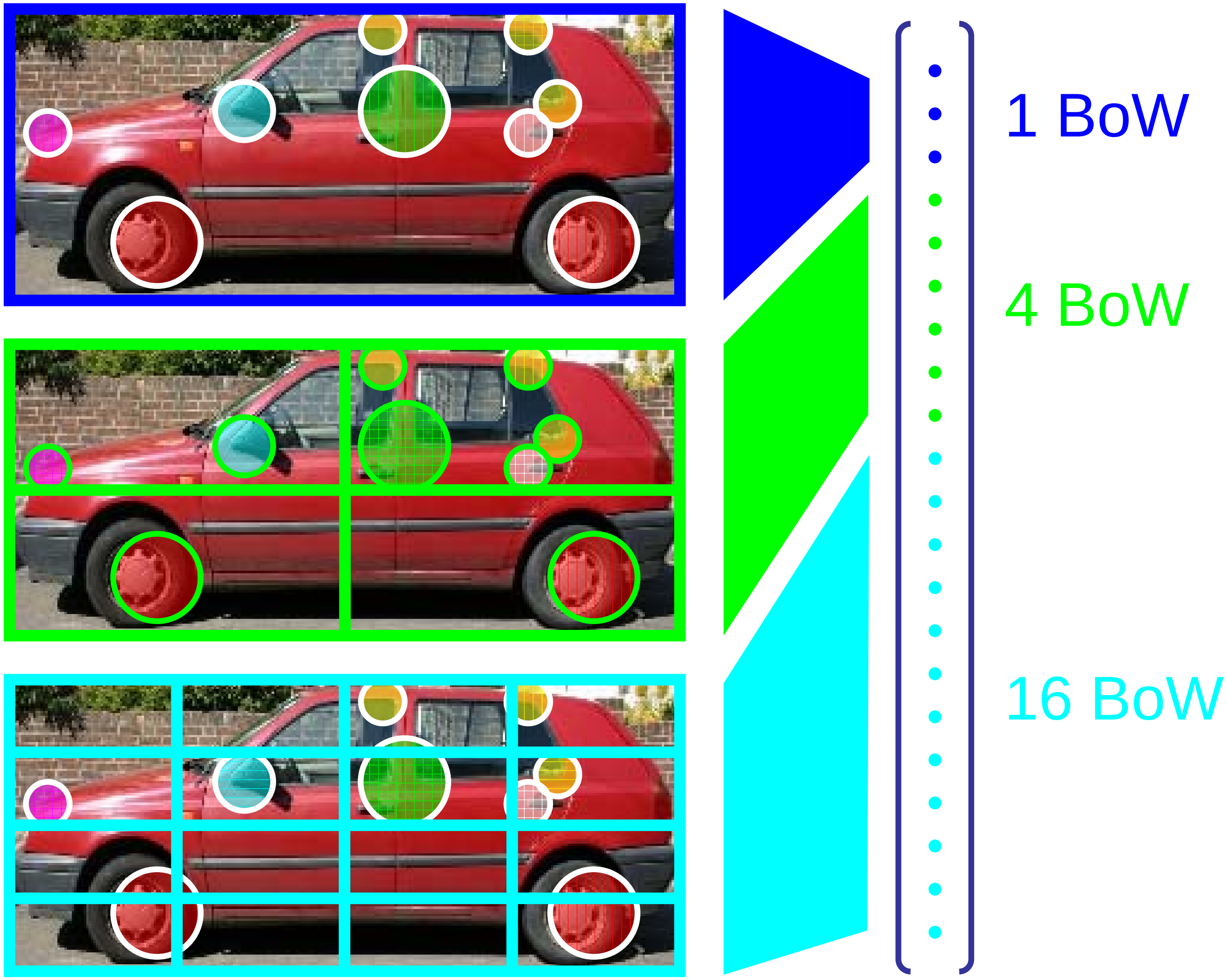




If codebook has V visual words, then representation has dimension 4V

Fergus et al ICCV 05

Spatial Pyramid – represent correspondence

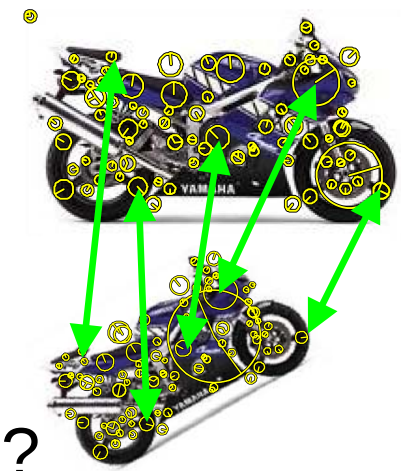


• As in scene/image classification can use pyramid kernel

[Grauman & Darrell, 2005] [Lazebnik et al, 2006]

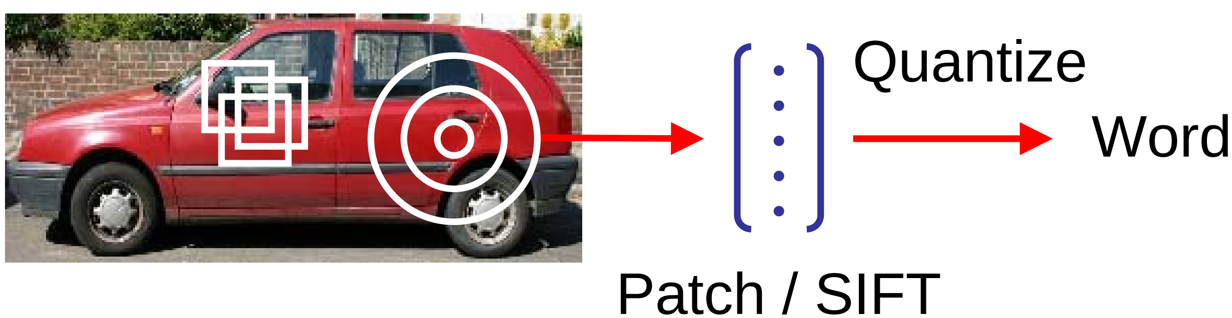
Dense Visual Words

- Why extract only **sparse** image fragments?



- Good where lots of invariance and matches are needed, but not relevant to sliding window detection?

- Extract **dense** visual words on an overlapping grid



[Luong & Malik, 1999]
[Varma & Zisserman, 2003]
[Vogel & Schiele, 2004]
[Jurie & Triggs, 2005]
[Fei-Fei & Perona, 2005]
[Bosch et al, 2006]

- More “detail” at the expense of invariance
- Pyramid histogram of visual words (PHOW)

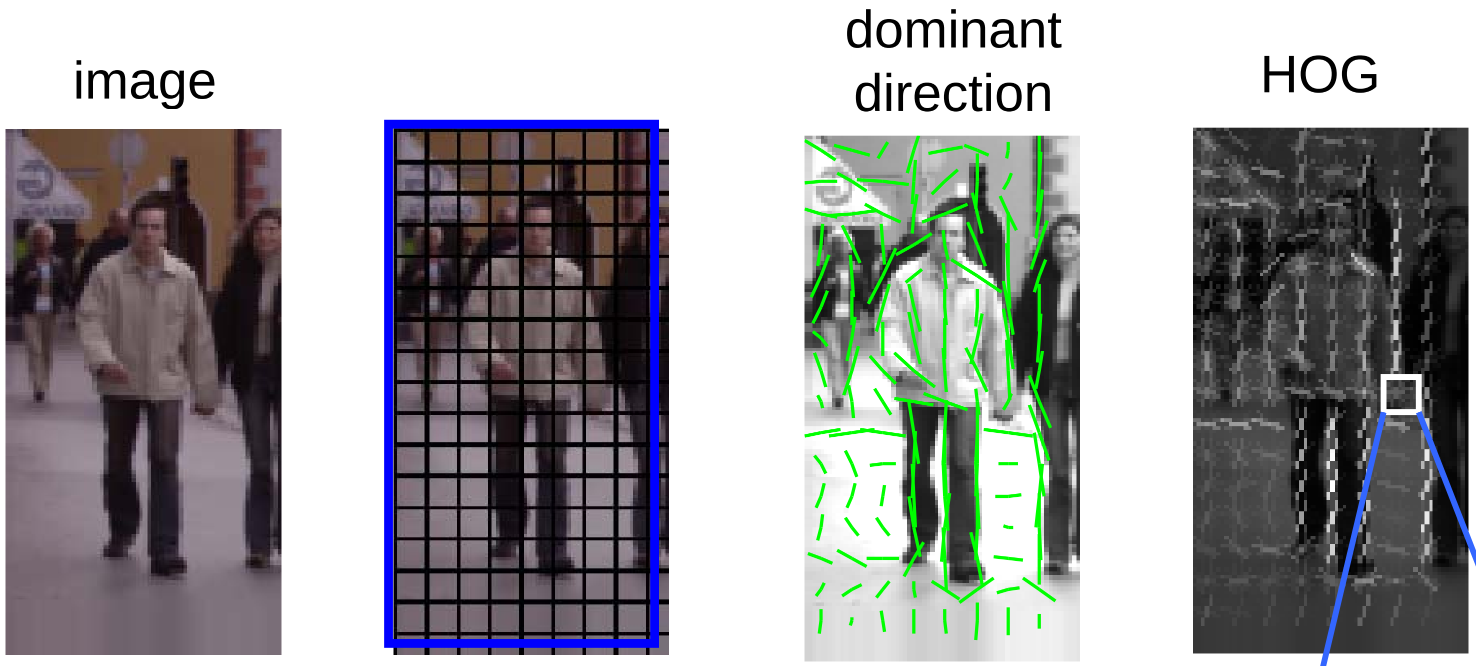
Outline

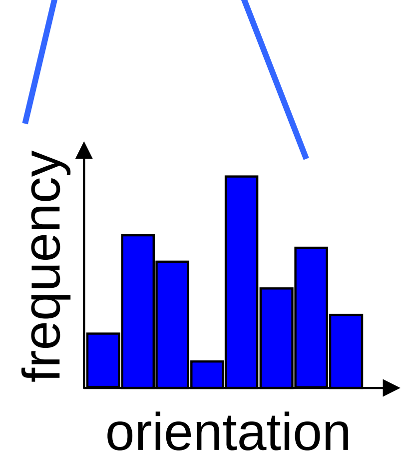
1. Sliding window detectors
2. Features and adding spatial information
3. Histogram of Oriented Gradients + linear SVM classifier
    - Dalal & Triggs pedestrian detector
    - HOG and history
    - Training an object detector
4. PASCAL VOC and a state of the art detection algorithm
5. The future and challenges

Dalal & Triggs CVPR 2005
Pedestrian detection

- Objective: detect (localize) standing humans in an image
- Sliding window classifier
- Train a binary classifier on whether a window contains a standing person or not
- Histogram of Oriented Gradients (HOG) feature
- Although HOG + SVM originally introduced for pedestrians has been used very successfully for many object categories

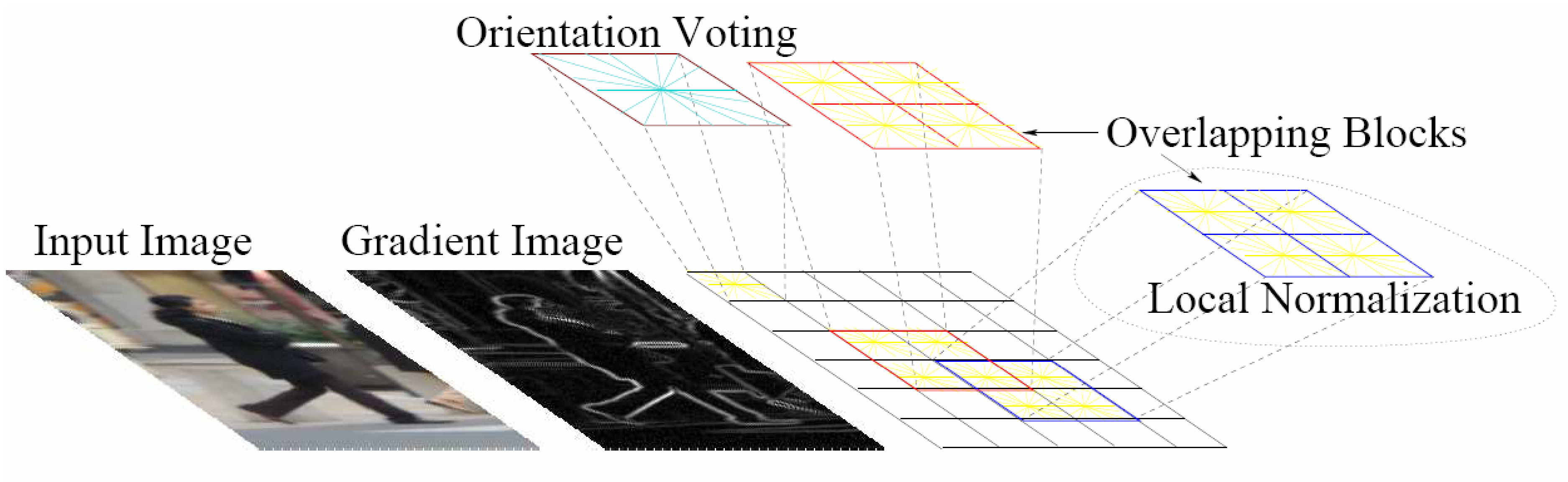
Feature: Histogram of Oriented Gradients (HOG)





- tile 64 x 128 pixel window into 8 x 8 pixel cells
- each cell represented by histogram over 8 orientation bins (i.e. angles in range 0-180 degrees)

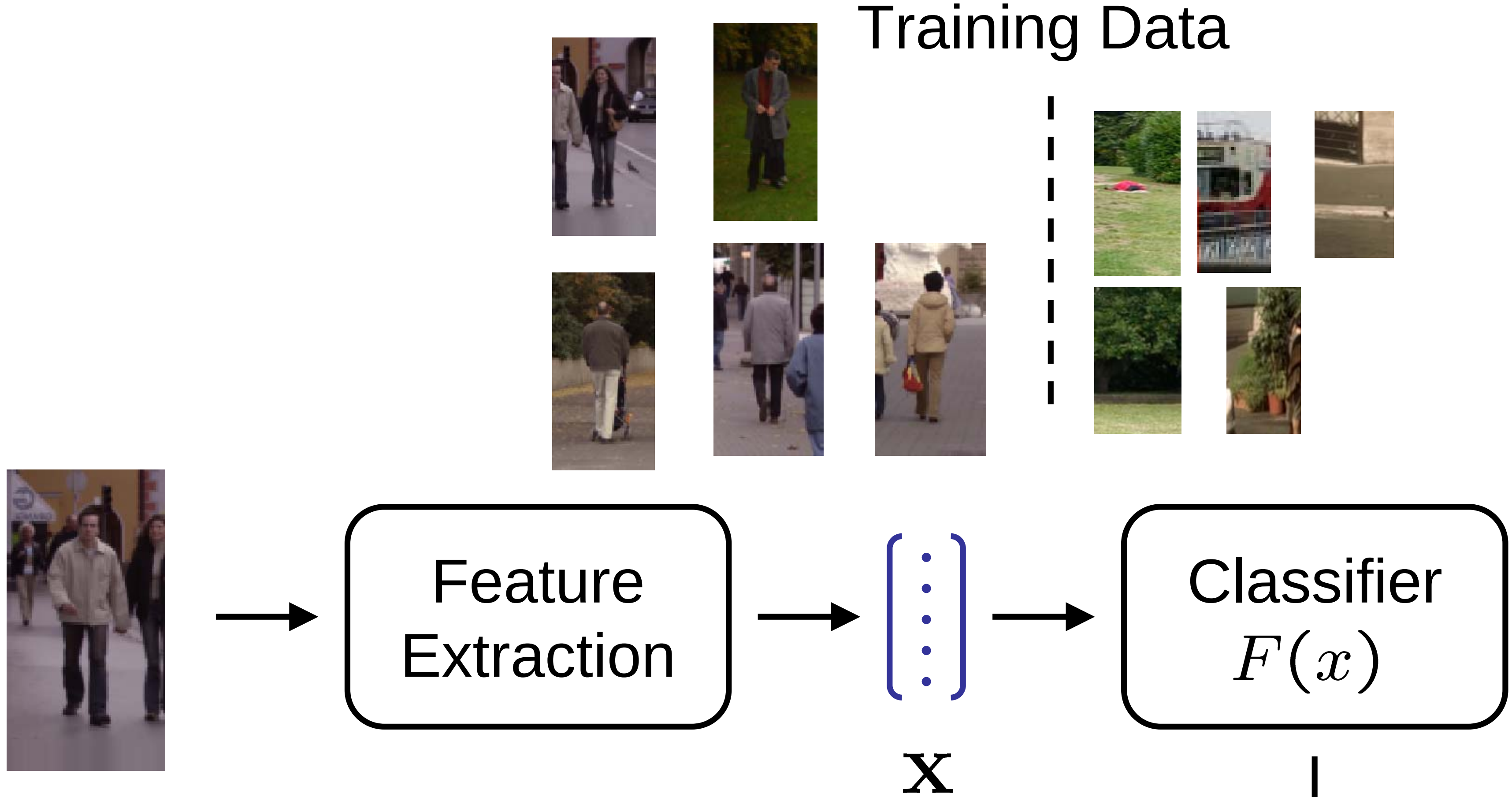
Histogram of Oriented Gradients (HOG) continued



- Adds a second level of overlapping spatial bins re-normalizing orientation histograms over a larger spatial area

- Feature vector dimension (approx) = 16 x 8 (for tiling) x 8 (orientations) x 4 (for blocks) = 4096

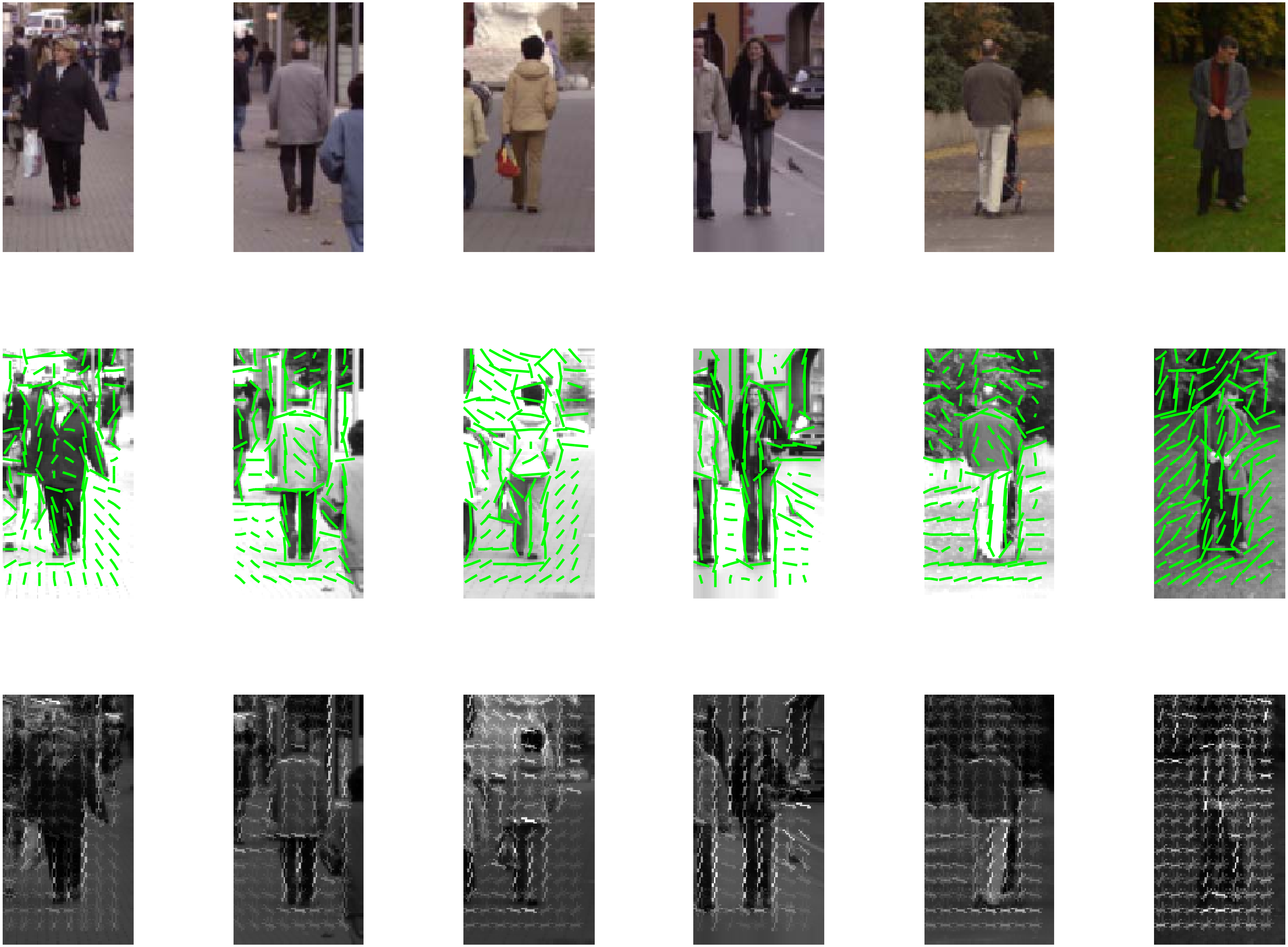
Window (Image) Classification



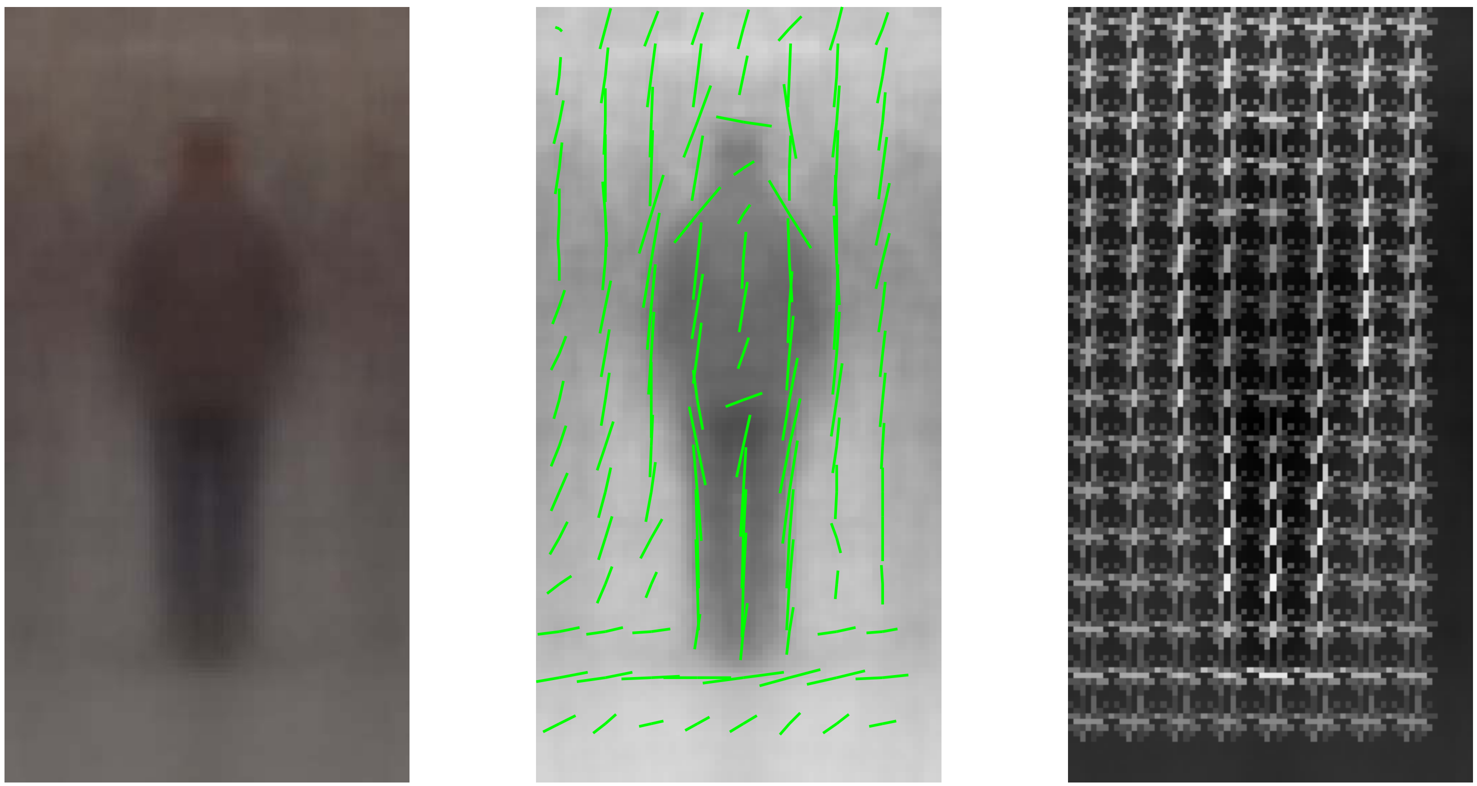
pedestrian/Non-pedestrian

$$P(c|\mathbf{x}) \propto F(\mathbf{x})$$

- HOG Features
- Linear SVM classifier



Averaged examples



Classifier: linear SVM

Advantages of linear SVM: $f(x) = \mathbf{w}^\top \mathbf{x} + b$

- Training (Learning)
  - Very efficient packages for the linear case, e.g. LIBLINEAR for batch training and Pegasos for on-line training.
  - Complexity O(N) for N training points (cf O(N^3) for general SVM)
- Testing (Detection)

Non-linear $$f(\mathbf{x}) = \sum_i^S \alpha_i k(\mathbf{x}_i, \mathbf{x}) + b$$

S = # of support vectors

= (worst case) N

size of training data

Linear $$\begin{aligned} f(\mathbf{x}) &= \sum_i^S \alpha_i \mathbf{x}_i{}^\top \mathbf{x} + b \\ &= \mathbf{w}^\top \mathbf{x} + b \end{aligned}$$

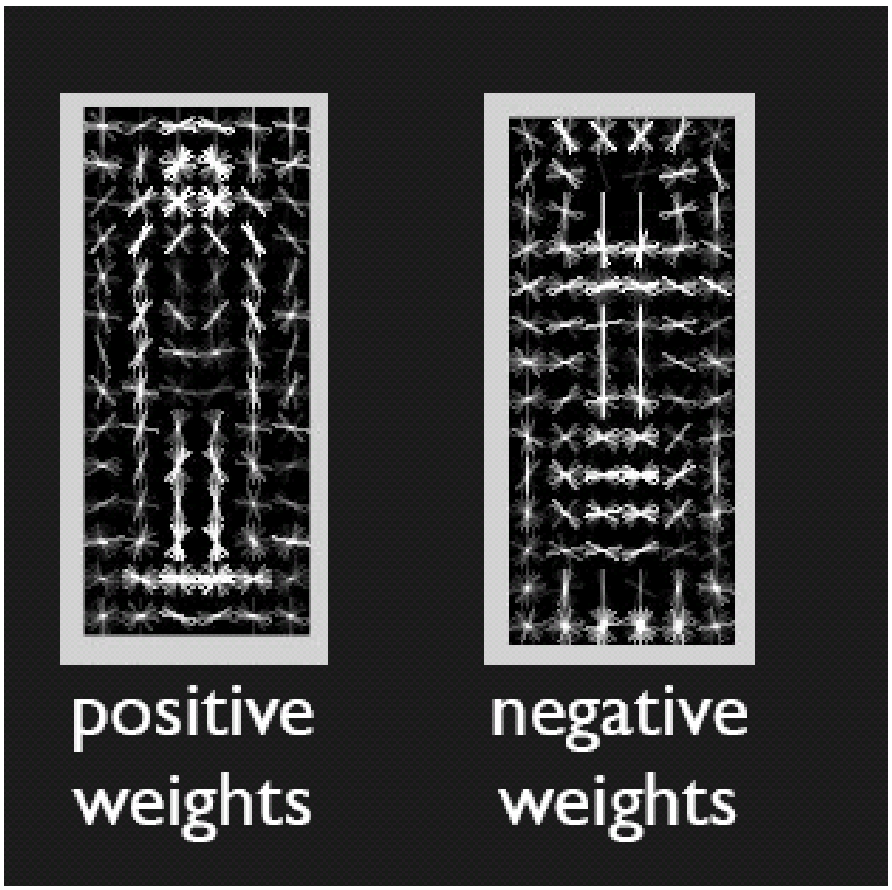
Independent of size of training data

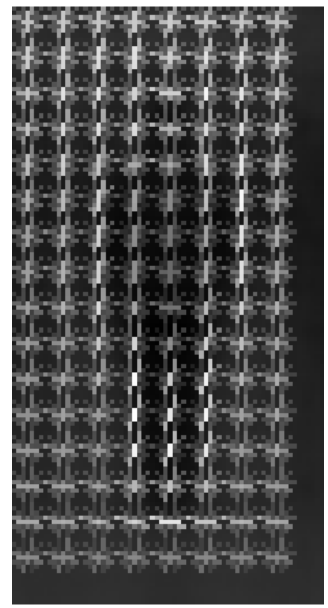
More on linear/non-linear in the image classification practical

Dalal and Triggs, CVPR 2005

Learned model

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





average over
positive training data

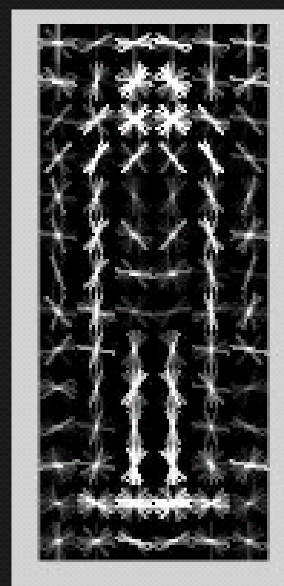
What do negative weights mean?

$$wx > 0$$

$$(w_+ - w_-)x > 0$$

$$w_+ > w_- x$$

pedestrian model



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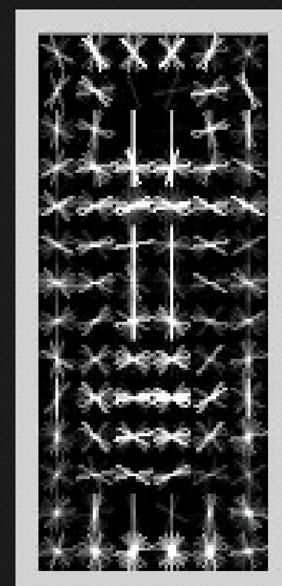


pedestrian background model

Complete system should compete pedestrian/pillar/doorway models

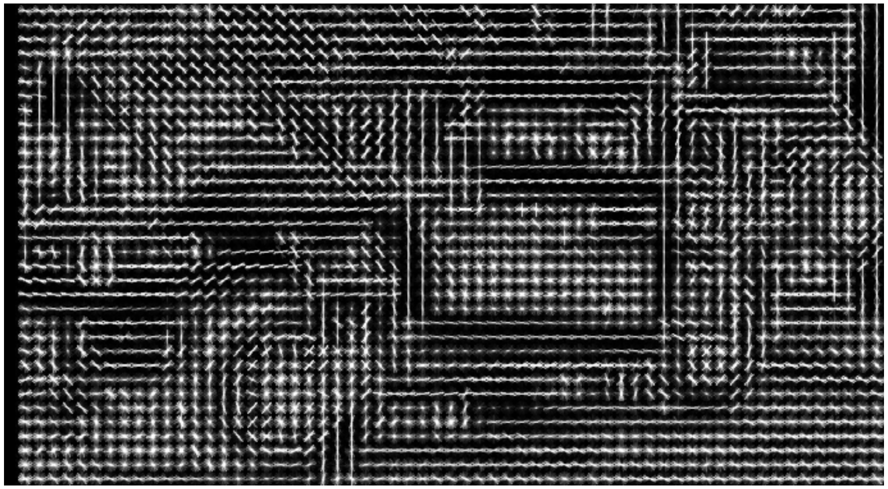
Discriminative models come equipped with own bg

(avoid firing on doorways by penalizing vertical edges)

Slide from Deva Ramanan

What is represented by HOG

HOG



Inverse

Original

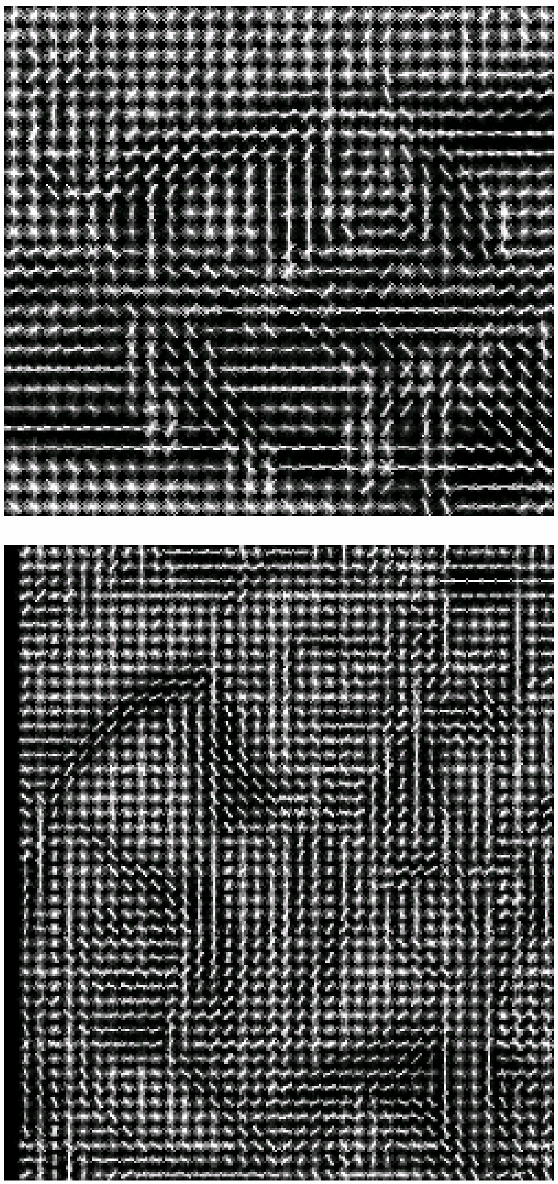
Inverting and Visualizing Features for Object Detection

Carl Vondrick Aditya Khosla Tomasz Malisiewicz Antonio Torralba

http://web.mit.edu/vondrick/ihog/index.html

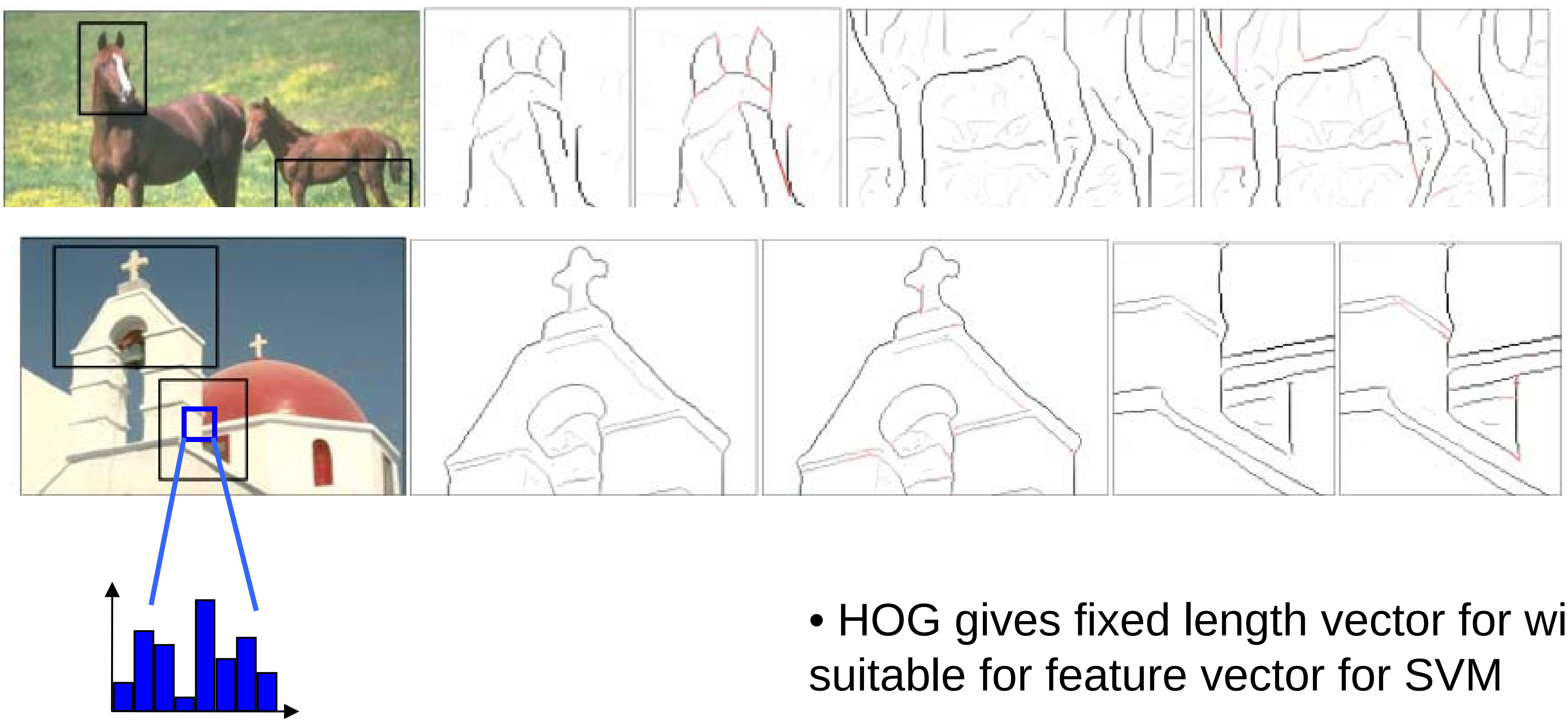
What is represented by HOG

HOG



Why does HOG + SVM work so well?

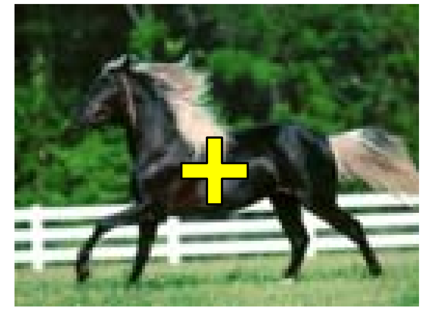
- Similar to SIFT, records spatial arrangement of histogram orientations
- Compare to learning only edges:
  - Complex junctions can be represented
  - Avoids problem of early thresholding
  - Represents also soft internal gradients
- Older methods based on edges have become largely obsolete



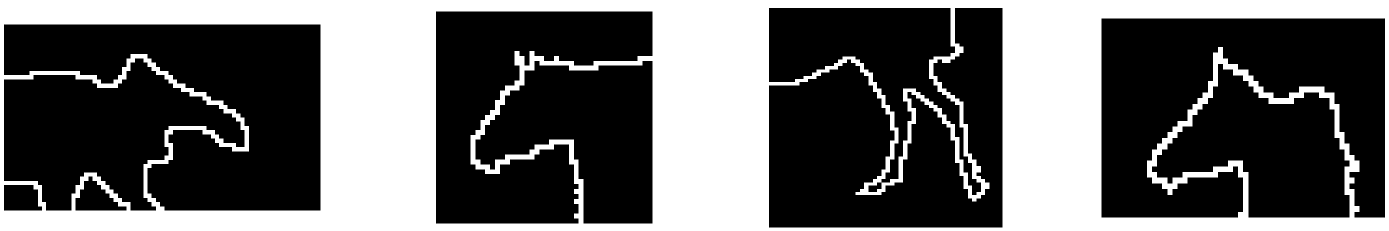
- HOG gives fixed length vector for window, suitable for feature vector for SVM

Contour-fragment models

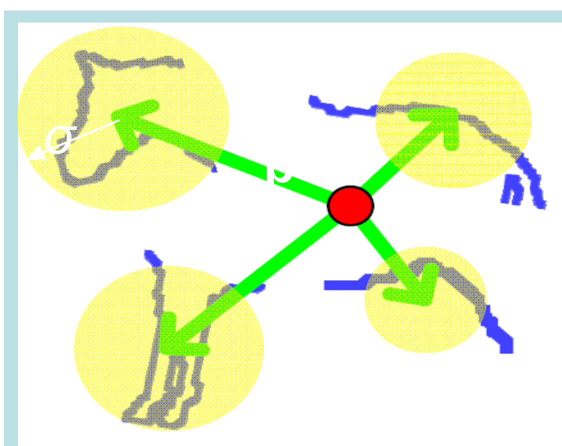
Shotton et al ICCV 05, Opelt et al ECCV 06

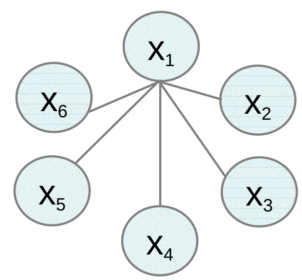


- Generalized Hough like representation using contour fragments
- Contour fragments learnt from edges of training images



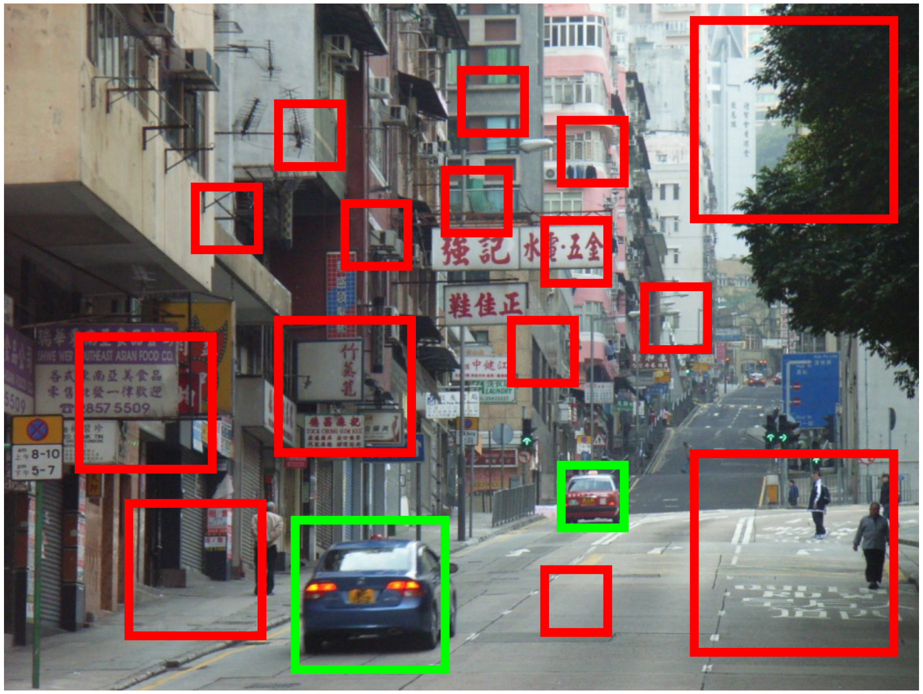
- Hough like voting for detection





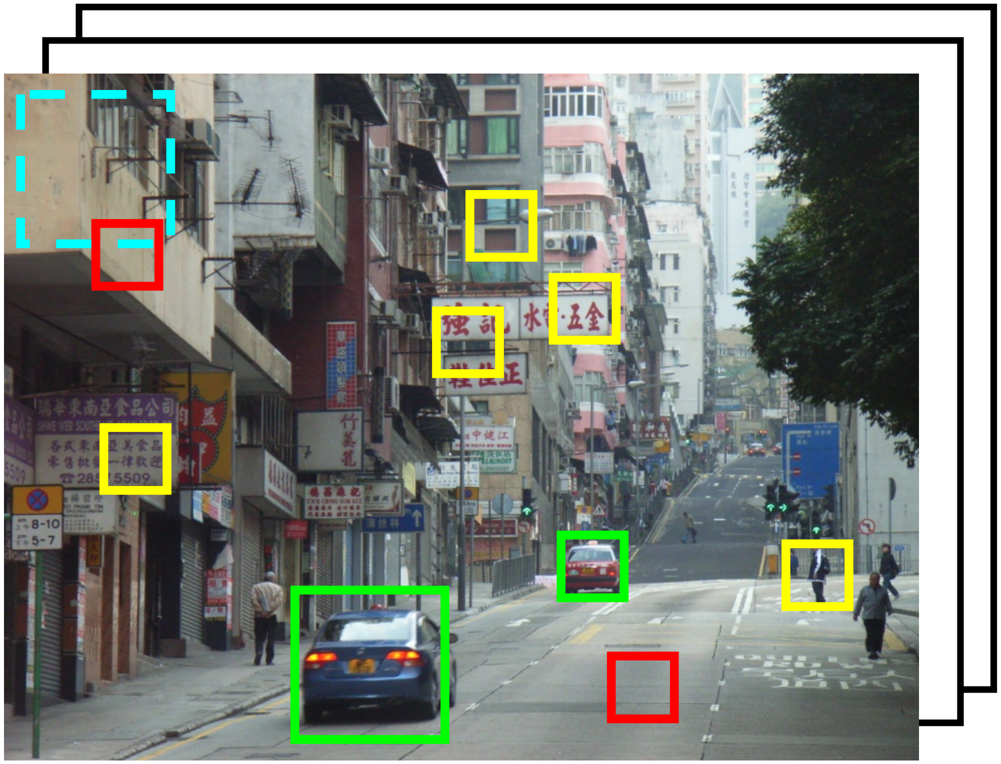
Training a sliding window detector

- Object **detection** is inherently asymmetric: much more “non-object” than “object” data



- Classifier needs to have very low false positive rate
- Non-object category is very complex – need lots of data

Bootstrapping



1. Pick negative training set at random
2. Train classifier
3. Run on training data
4. Add false positives to training set
5. Repeat from 2

- Collect a finite but diverse set of non-object windows
- Force classifier to concentrate on **hard negative** examples

- For some classifiers can ensure equivalence to training on entire data set

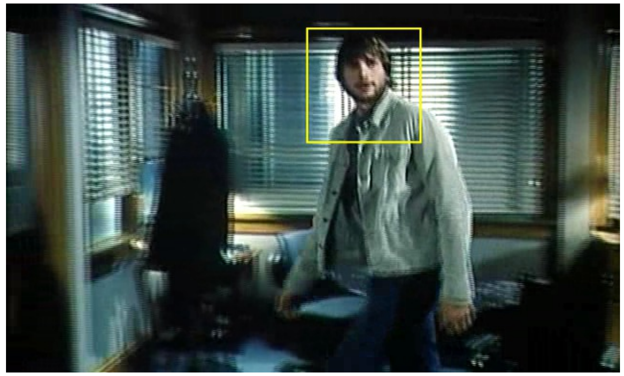
Example: train an upper body detector

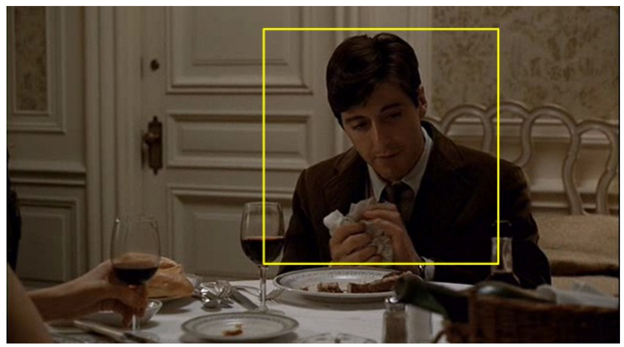
- Training data – used for training and validation sets
  - 33 Hollywood2 training movies
  - 1122 frames with upper bodies marked

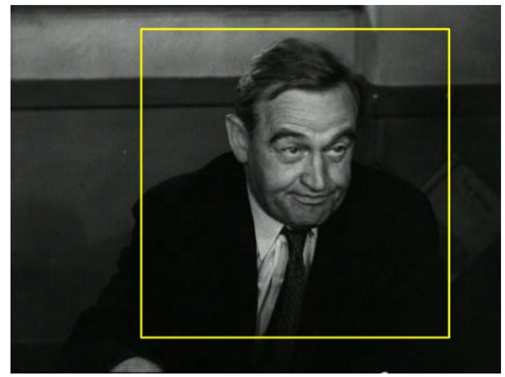
- First stage training (bootstrapping)
  - 1607 upper body annotations jittered to 32k positive samples
  - 55k negatives sampled from the same set of frames

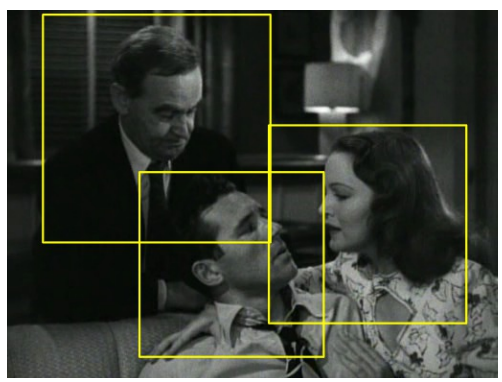
- Second stage training (retraining)
  - 150k hard negatives found in the training data

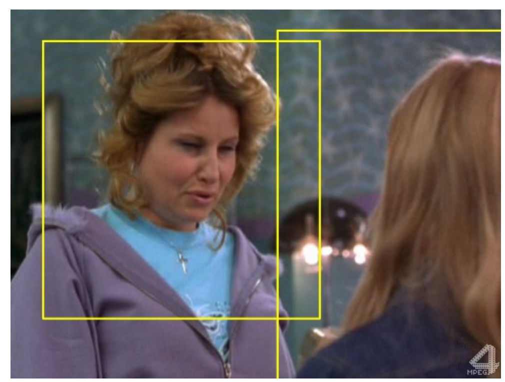
Training data – positive annotations









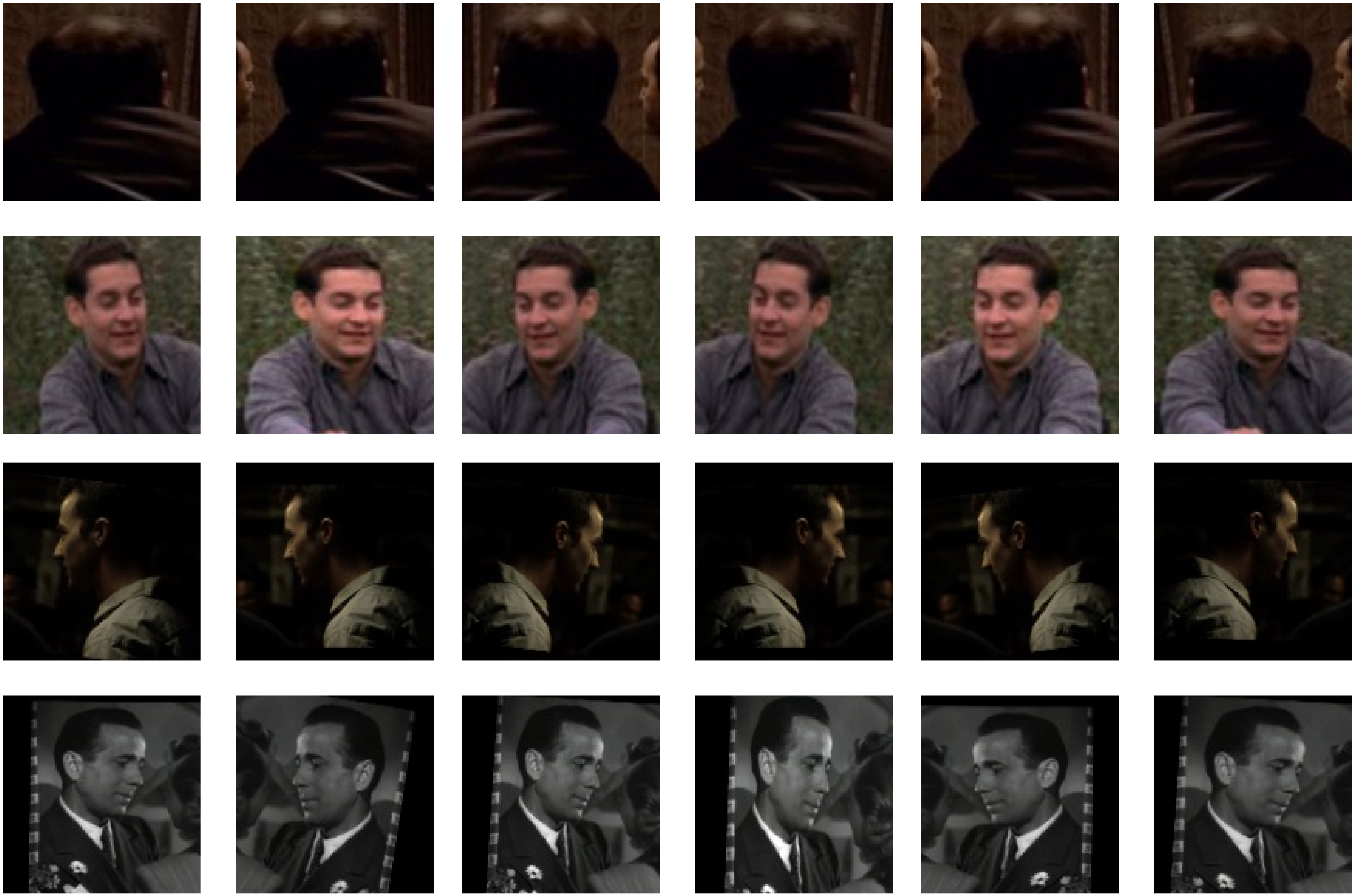


Positive windows

Note: common size and alignment

Jittered positives

Jittered positives



Random negatives

Random negatives

Window (Image) first stage classification

Jittered positives
random negatives

HOG Feature Extraction

$\mathbf{x}$

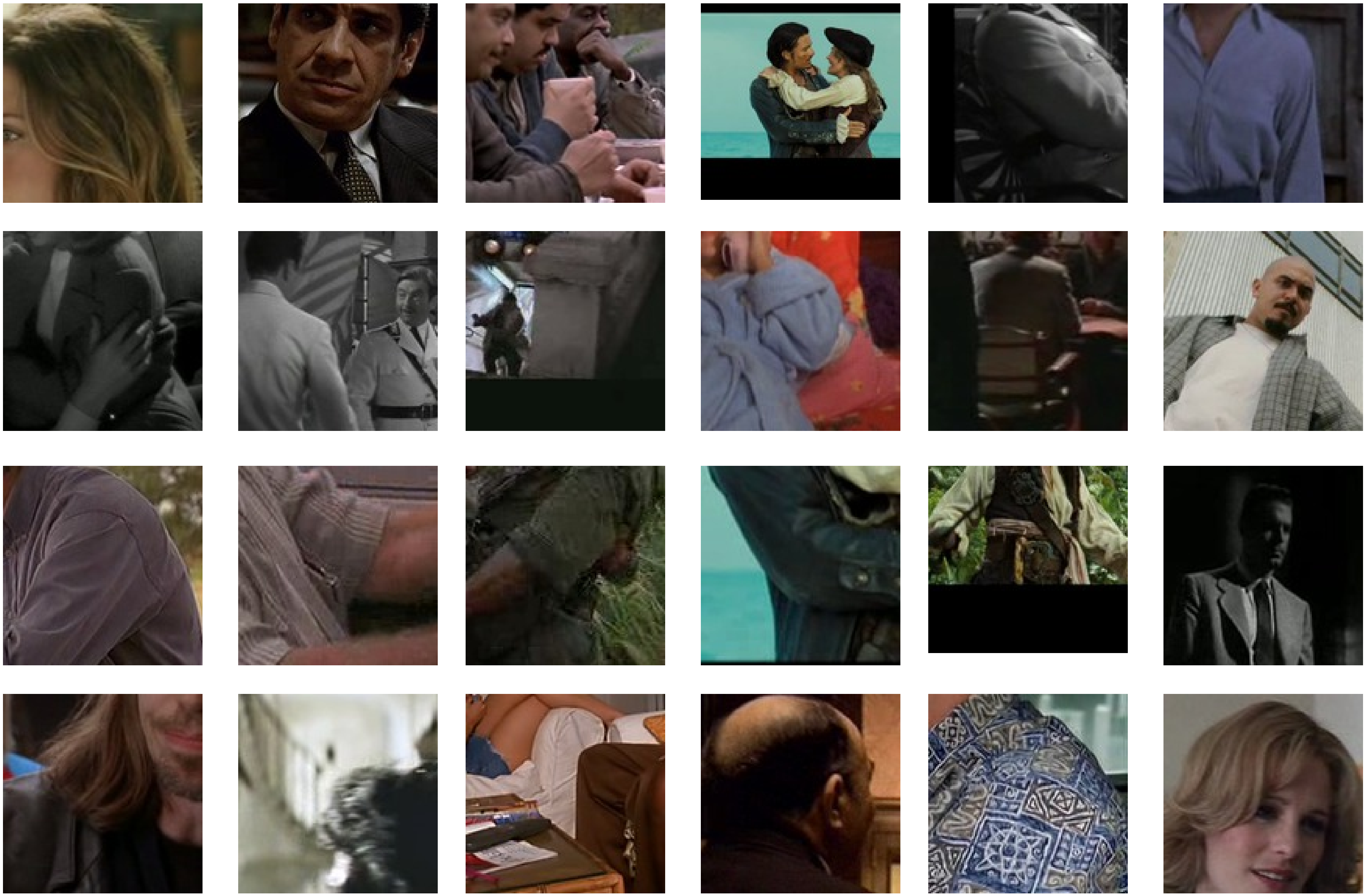
Linear SVM Classifier
$f(x) = \mathbf{w}^\top \mathbf{x} + b$

• find high scoring false positives detections

• these are the hard negatives for the next round of training

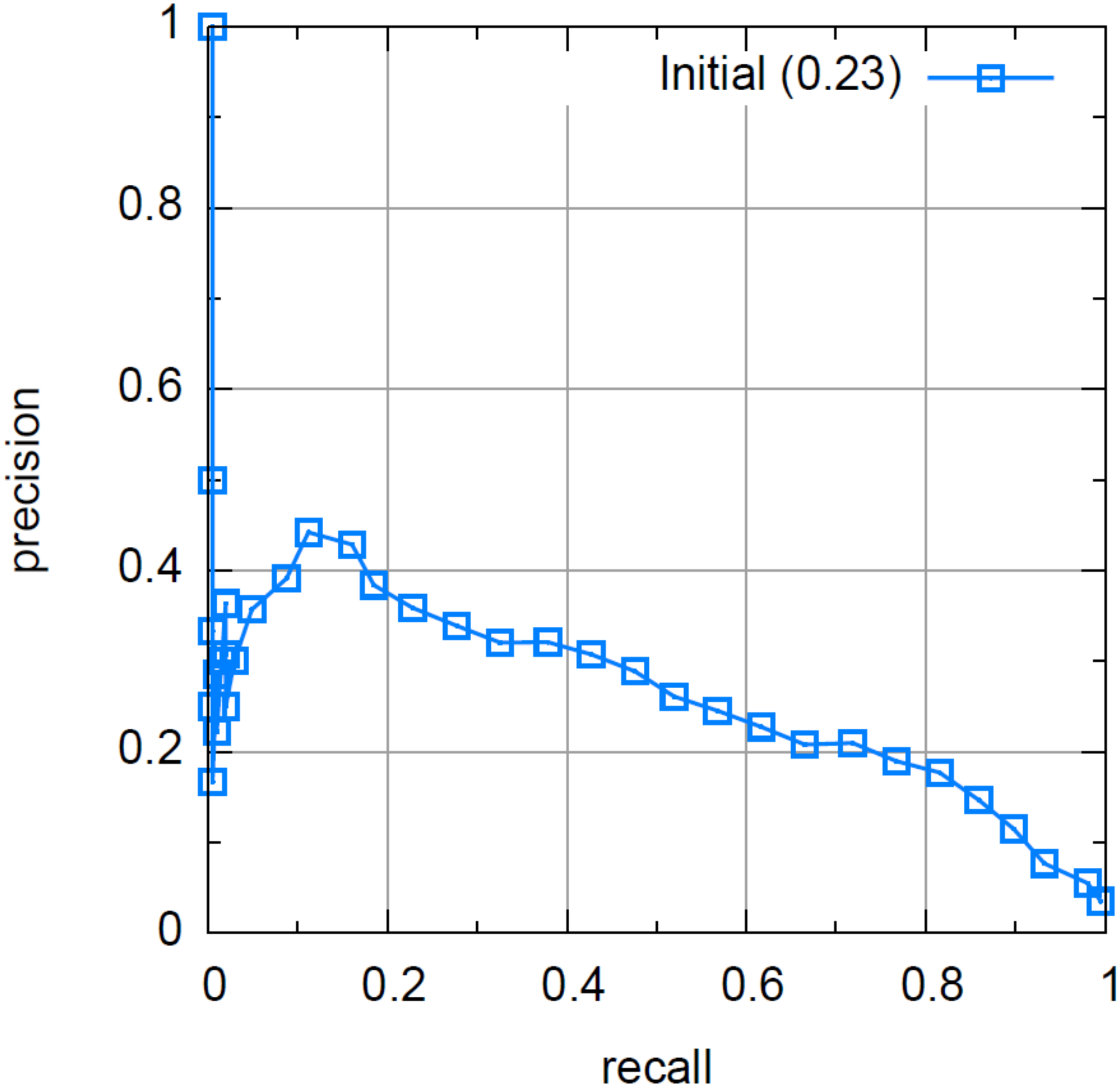
• cost = # training images x inference on each image

Hard negatives

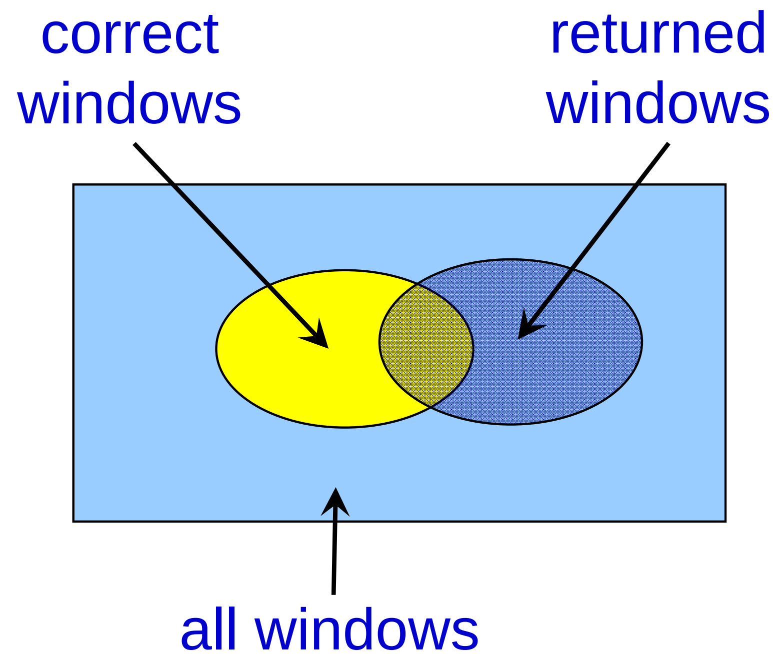


Hard negatives

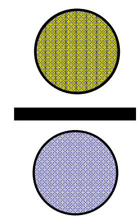
First stage performance on validation set



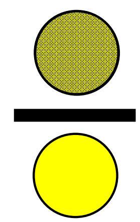
Precision – Recall curve

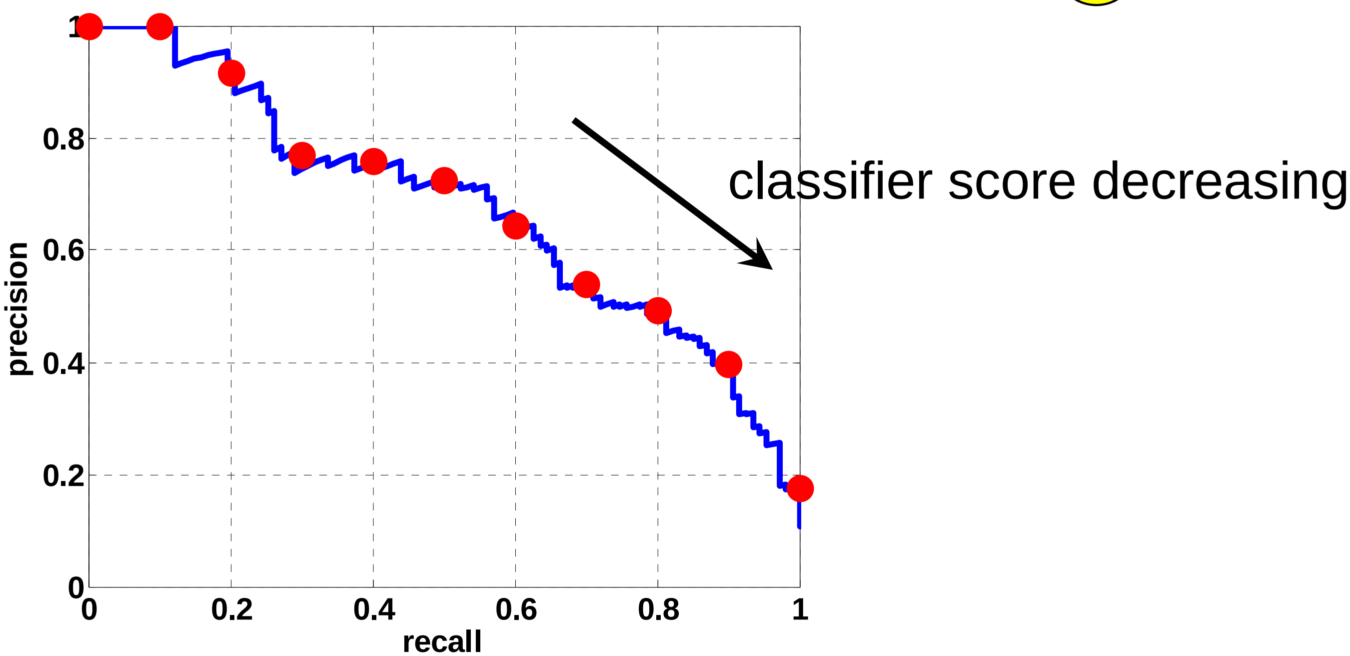


• Precision: % of returned windows that are correct

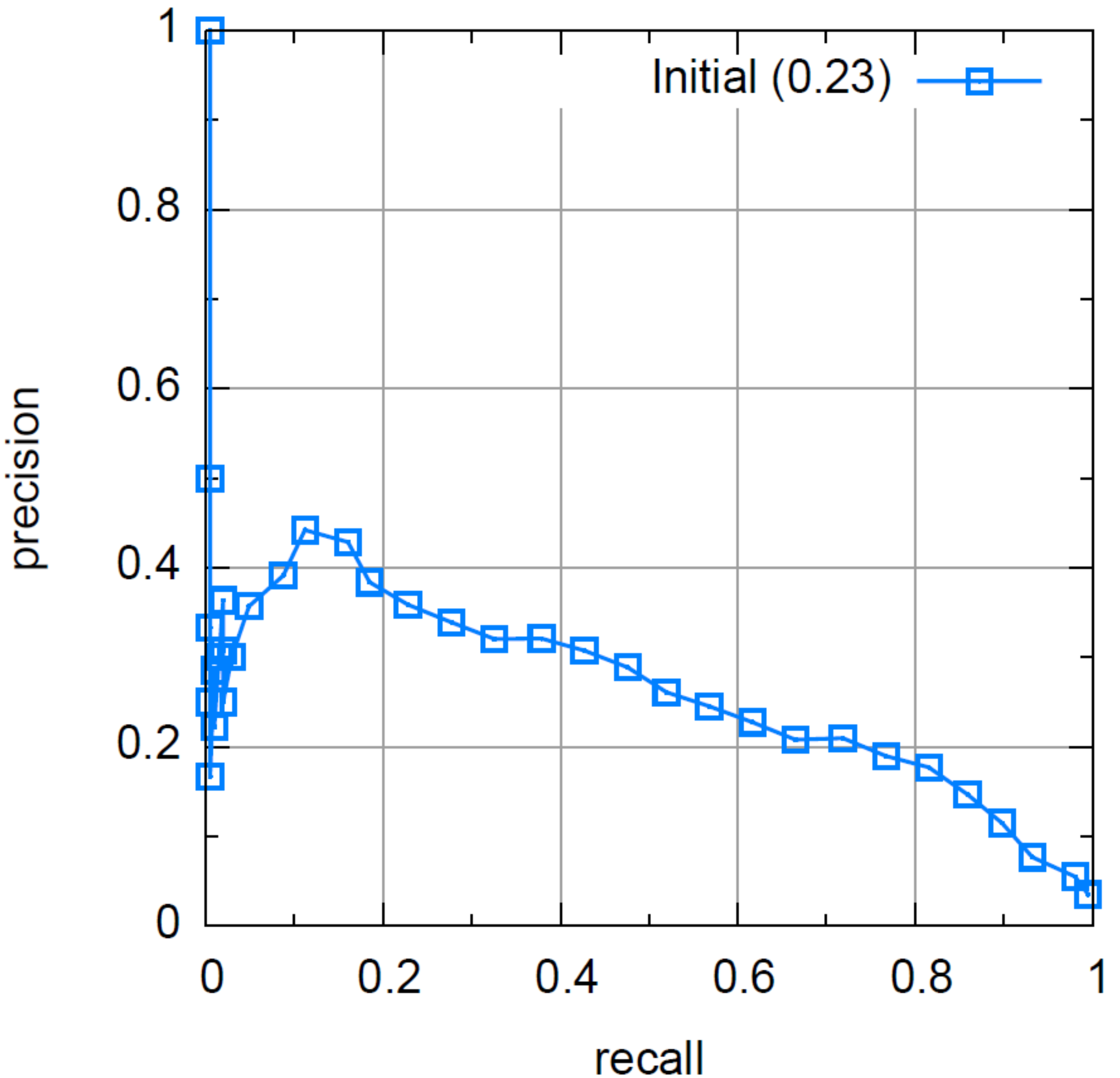


• Recall: % of correct windows that are returned

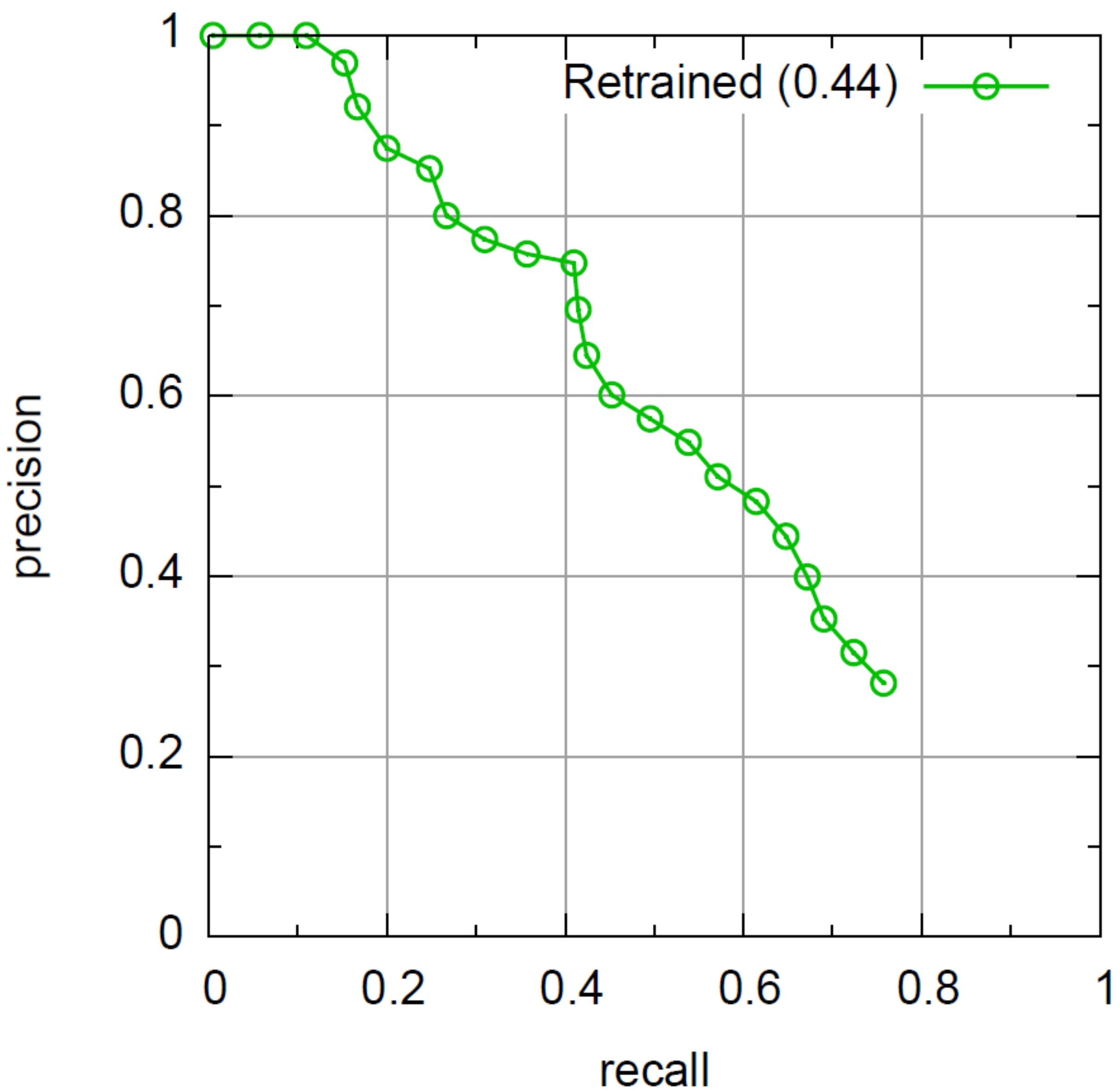




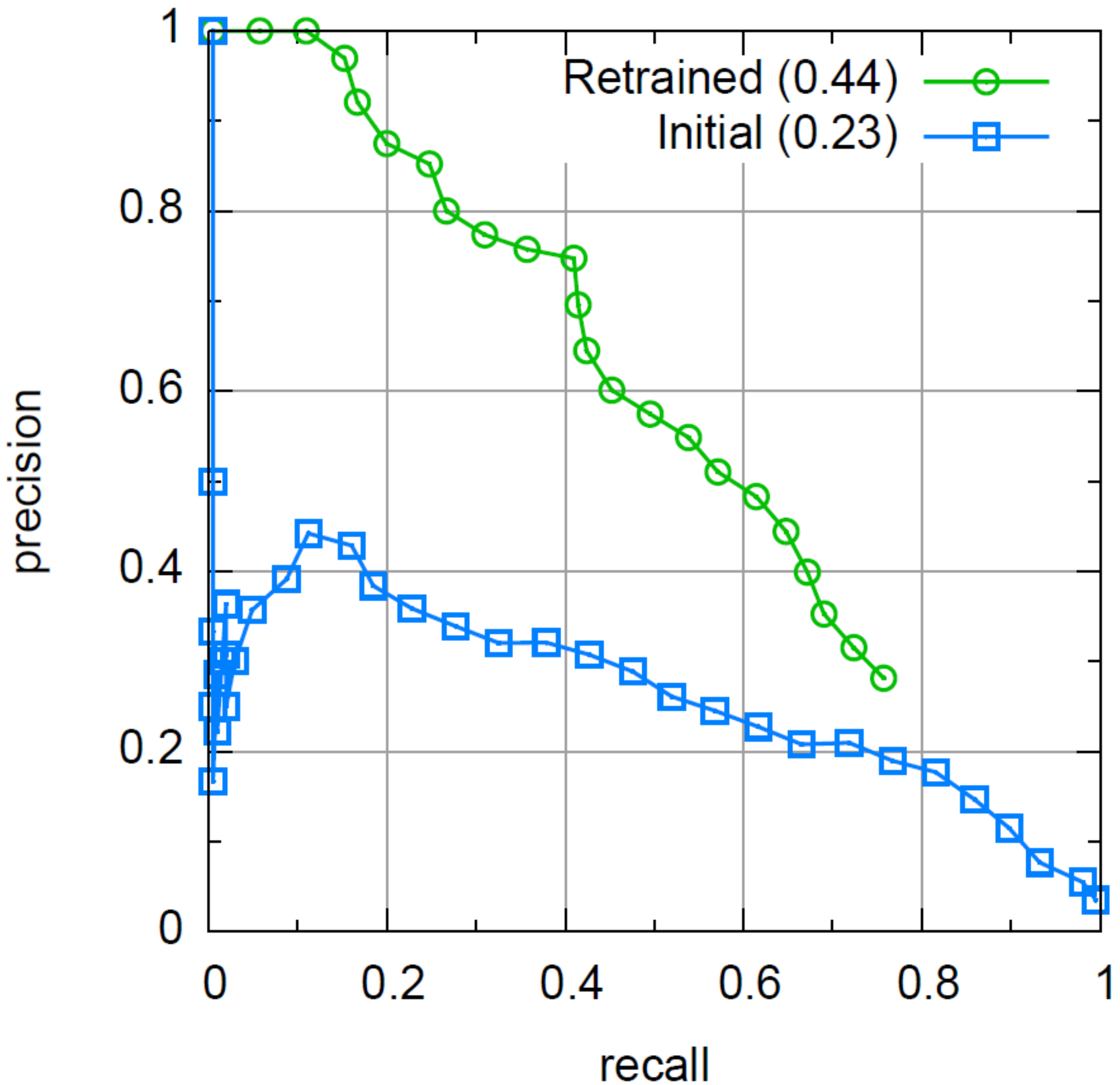
First stage performance on validation set



Performance after retraining

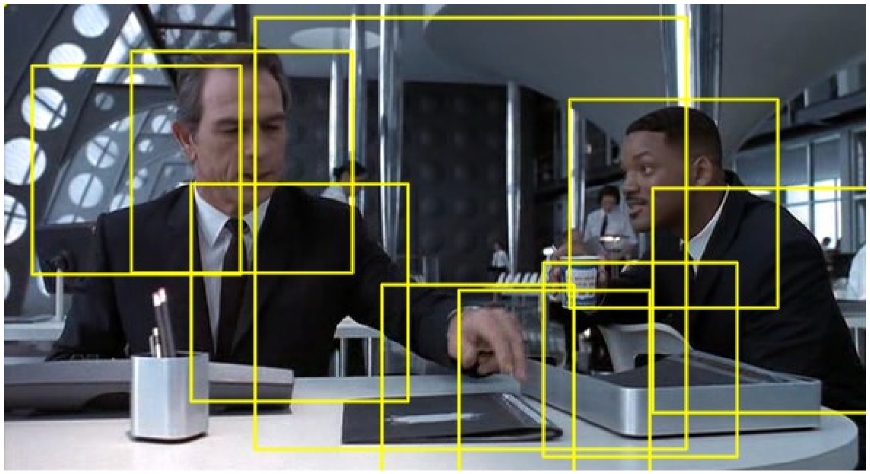


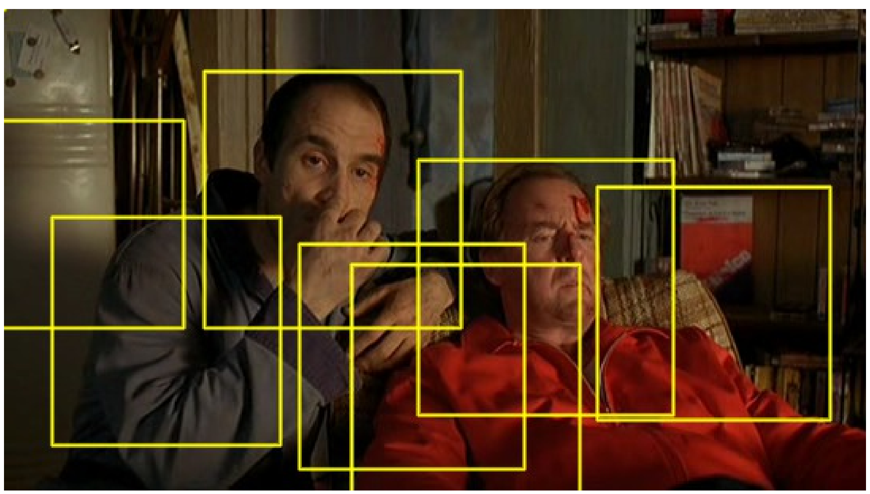
Effects of retraining



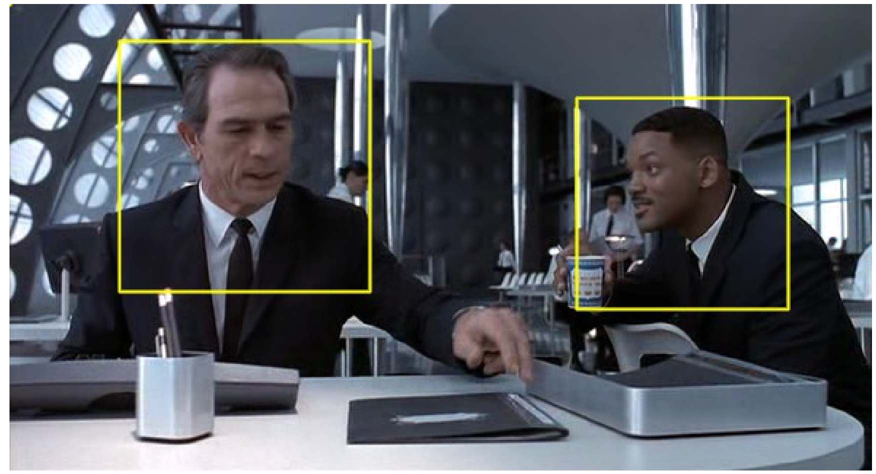
Side by side

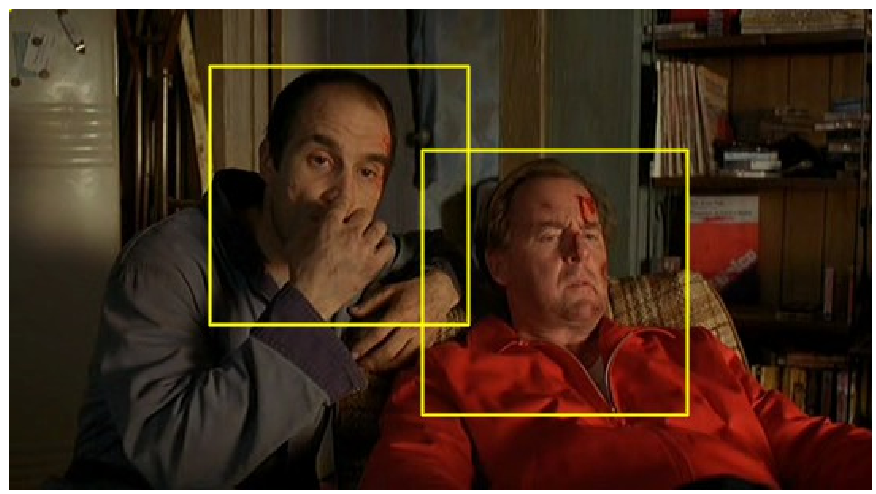
before retraining





after retraining

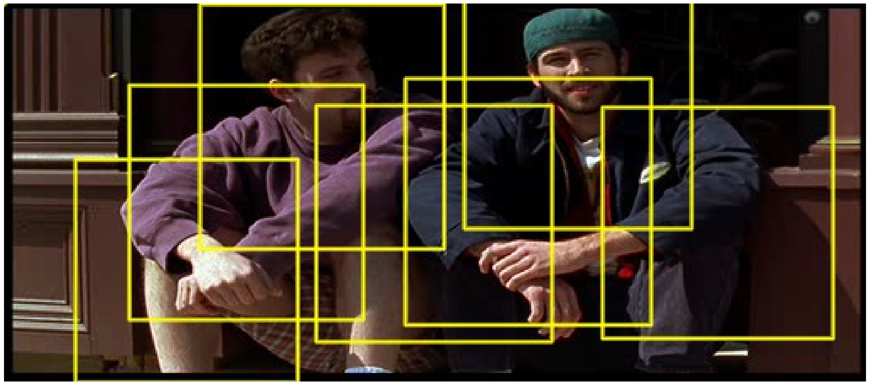


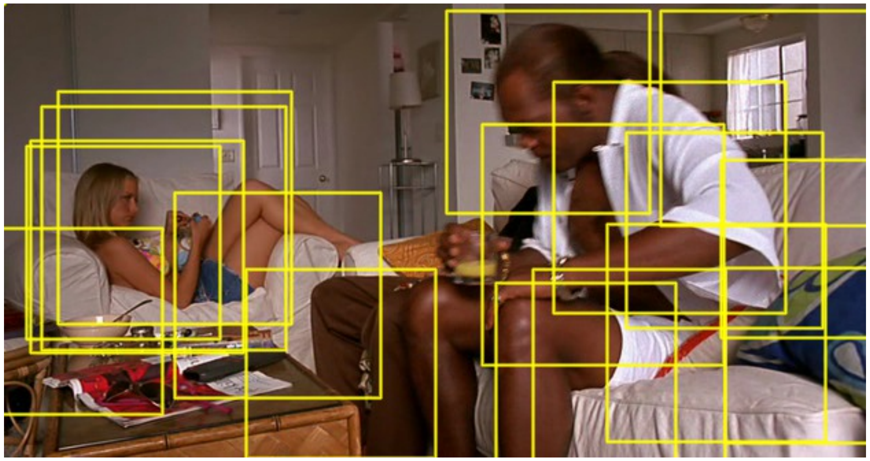


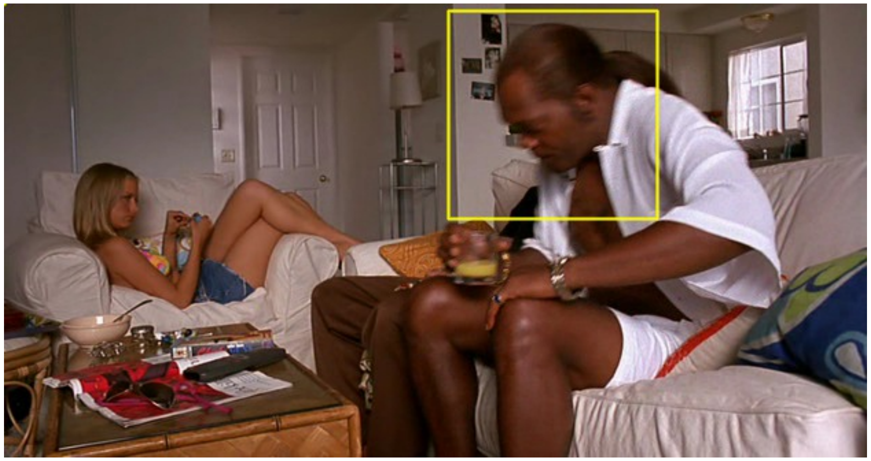
Side by side

before retraining

after retraining

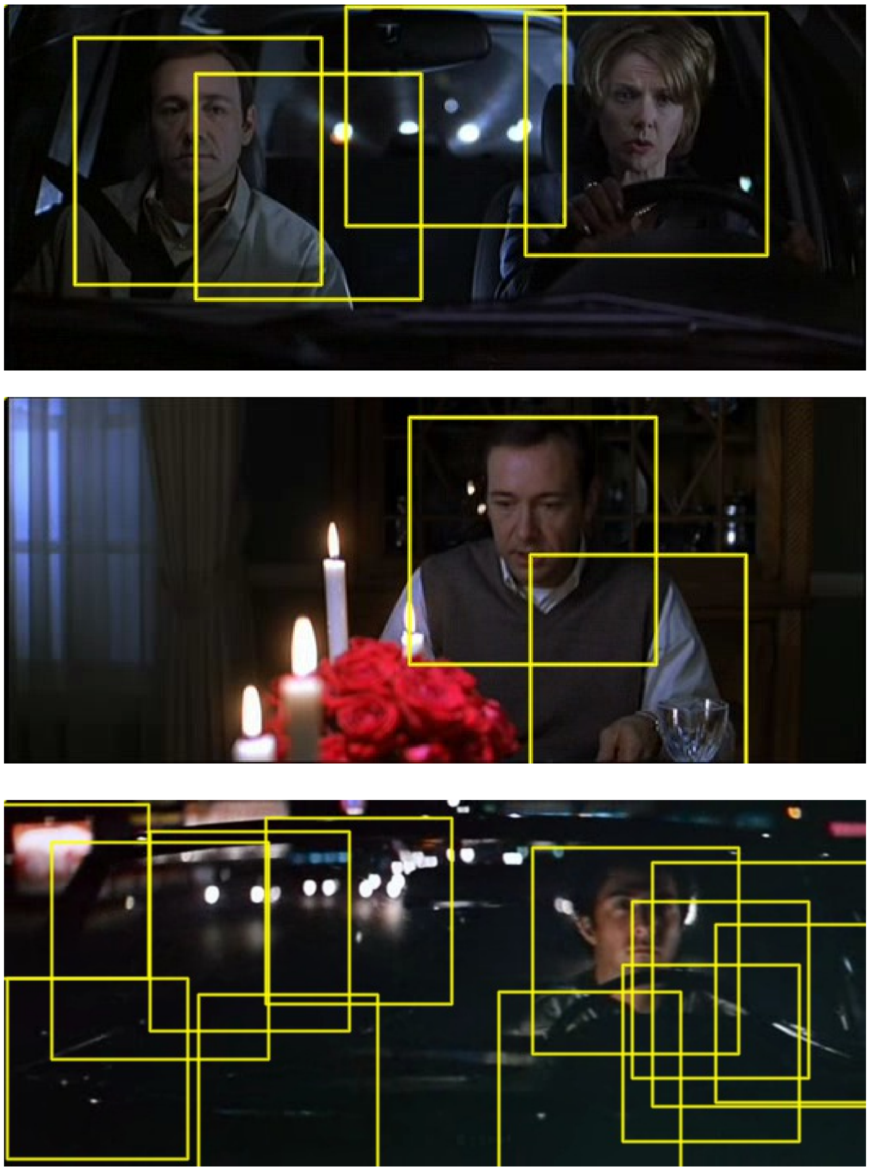






Side by side

before retraining



after retraining

Tracked upper body detections

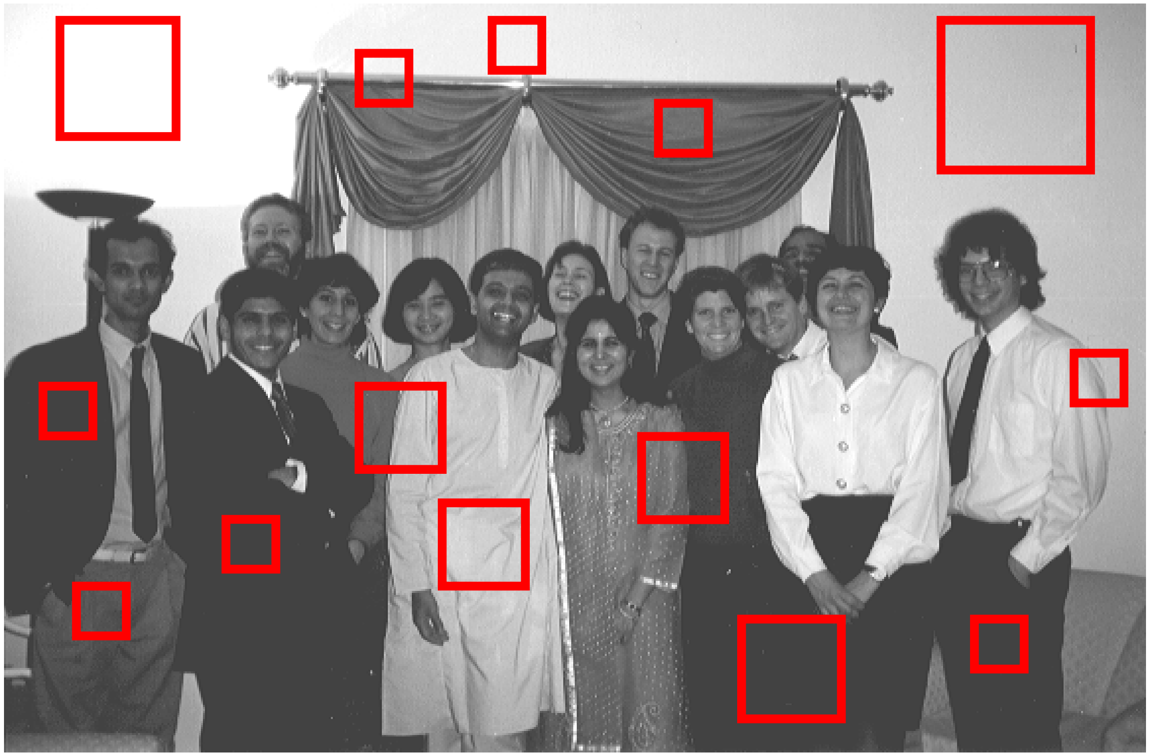
Notes

- Training (bootstrapping, retraining) can be done in a more principled way using Structured Output learning with the cutting plane algorithm
  - See Christoph Lampert's lecture on Wednesday

- An object category detector can be learnt from a **single** positive example
  - See Exemplar SVM by Malisiewicz, Gupta, Efros, ICCV 2011

Accelerating Sliding Window Search

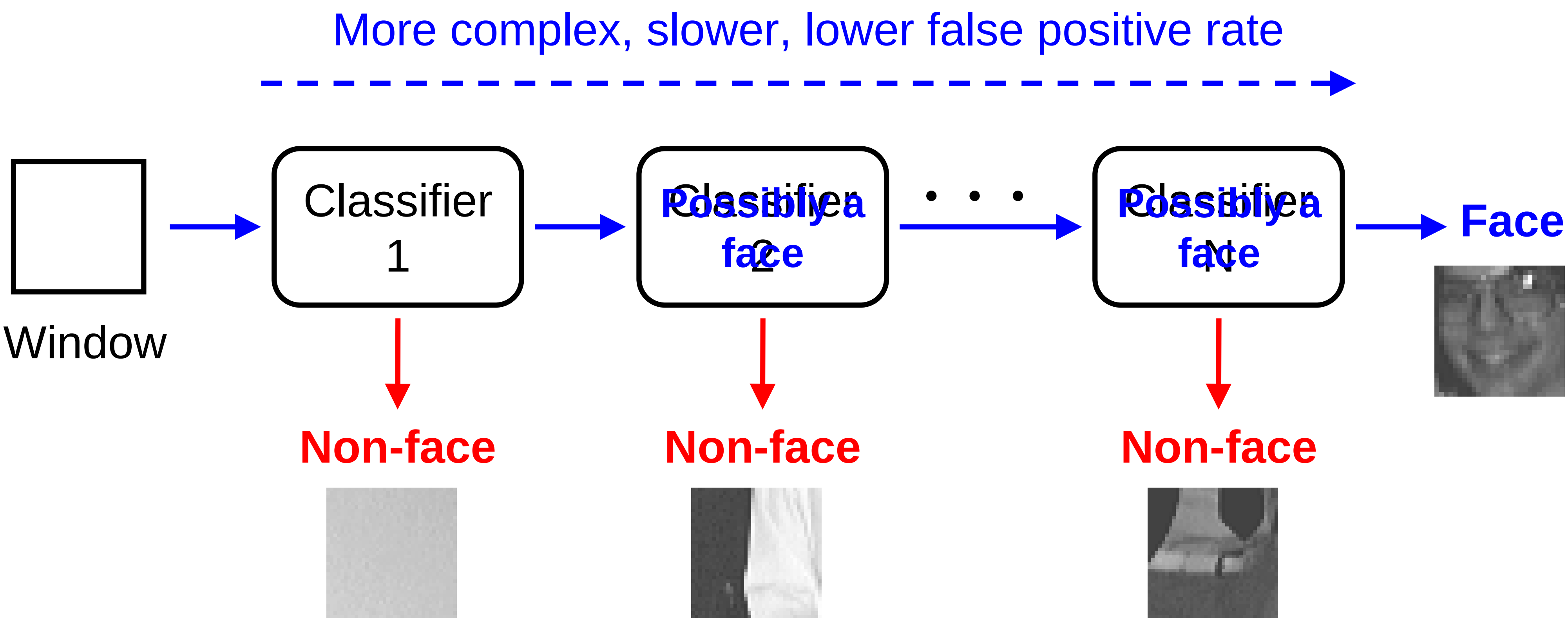
- Sliding window search is slow because so many windows are needed e.g. $x \times y \times$ scale $\approx$ 100,000 for a 320×240 image



- Most windows are clearly not the object class of interest
- Can we speed up the search?

Cascaded Classification

• Build a sequence of classifiers with increasing complexity



• Reject easy non-objects using simpler and faster classifiers

Cascaded Classification

- Slow expensive classifiers only applied to a few windows $\Rightarrow$ significant speed-up

- Controlling classifier complexity/speed:
  - Number of support vectors [Romdhani et al, 2001]
  - Number of features [Viola & Jones, 2001]
  - Type of SVM kernel [Vedaldi et al, 2009]
  - Number of parts [Felzenszwalb et al, 2011]

"Accelerating" Training

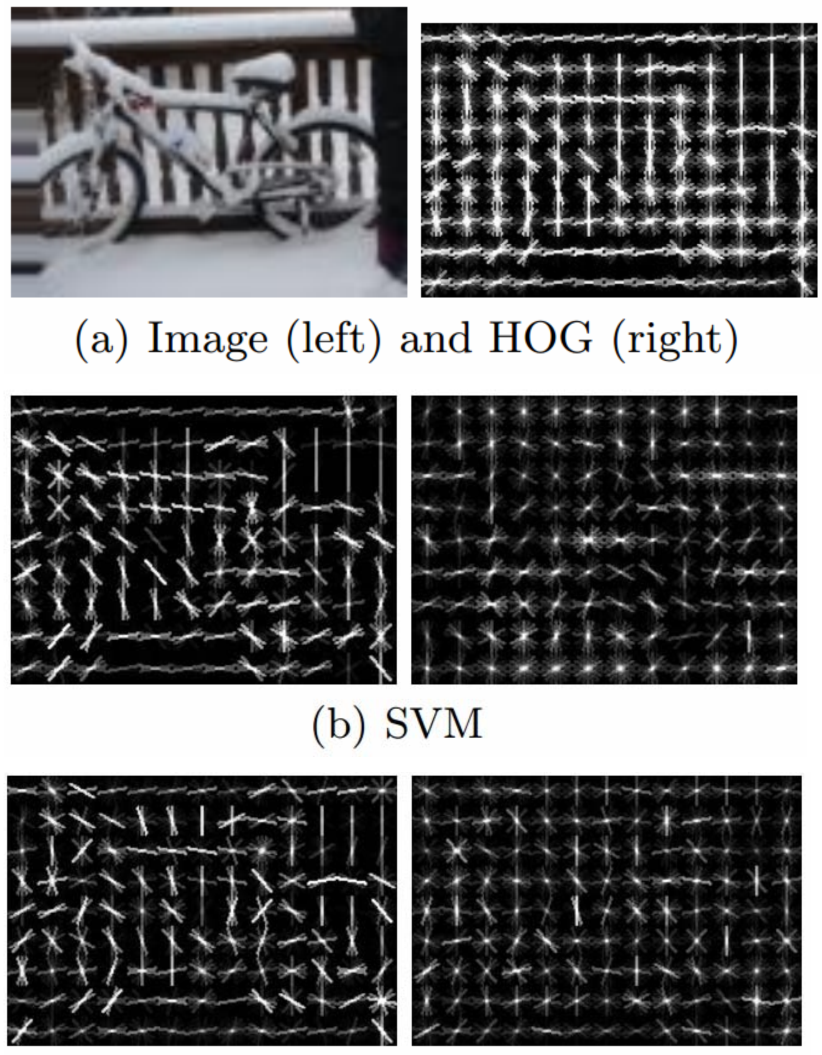
Discriminative Decorrelation for Clustering and Classification
Bharath Hariharan, Jitendra Malik and Deva Ramanan, ECCV 2012

Problem: **SVM training is expensive**

- Mining for hard negatives, bootstrapping

Solution: LDA (Linear Discriminant Analysis)

- ***Extremely fast training, very similar performance***



(a) Image (left) and HOG (right)

(b) SVM

(d) LDA

Linear Discriminant Analysis (LDA)

Assumptions

$$P(x|y) = N(x; \mu_y, \Sigma)$$

μ_y are class-dependent

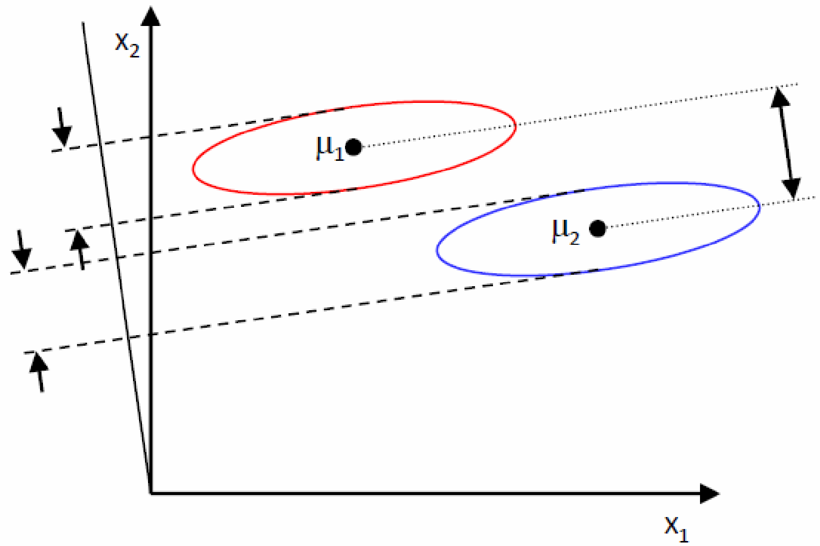
covariance matrix Σ is class-independent

Learning - Classification

x is classified as a positive

if $P(y=1|x) > P(y=0|x)$

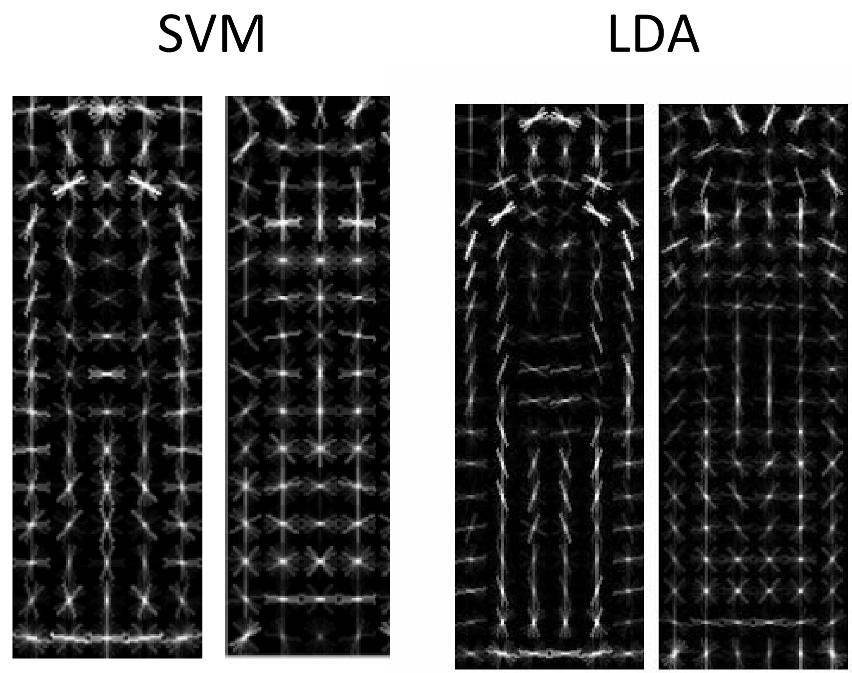
$$w = \Sigma^{-1}\underbrace{(\mu_1 - \mu_0)}_{\text{difference in class means}}$$



Pedestrian Detection
Linear Discriminant Models

$$w = \Sigma^{-1}(\mu_1 - \mu_0)$$

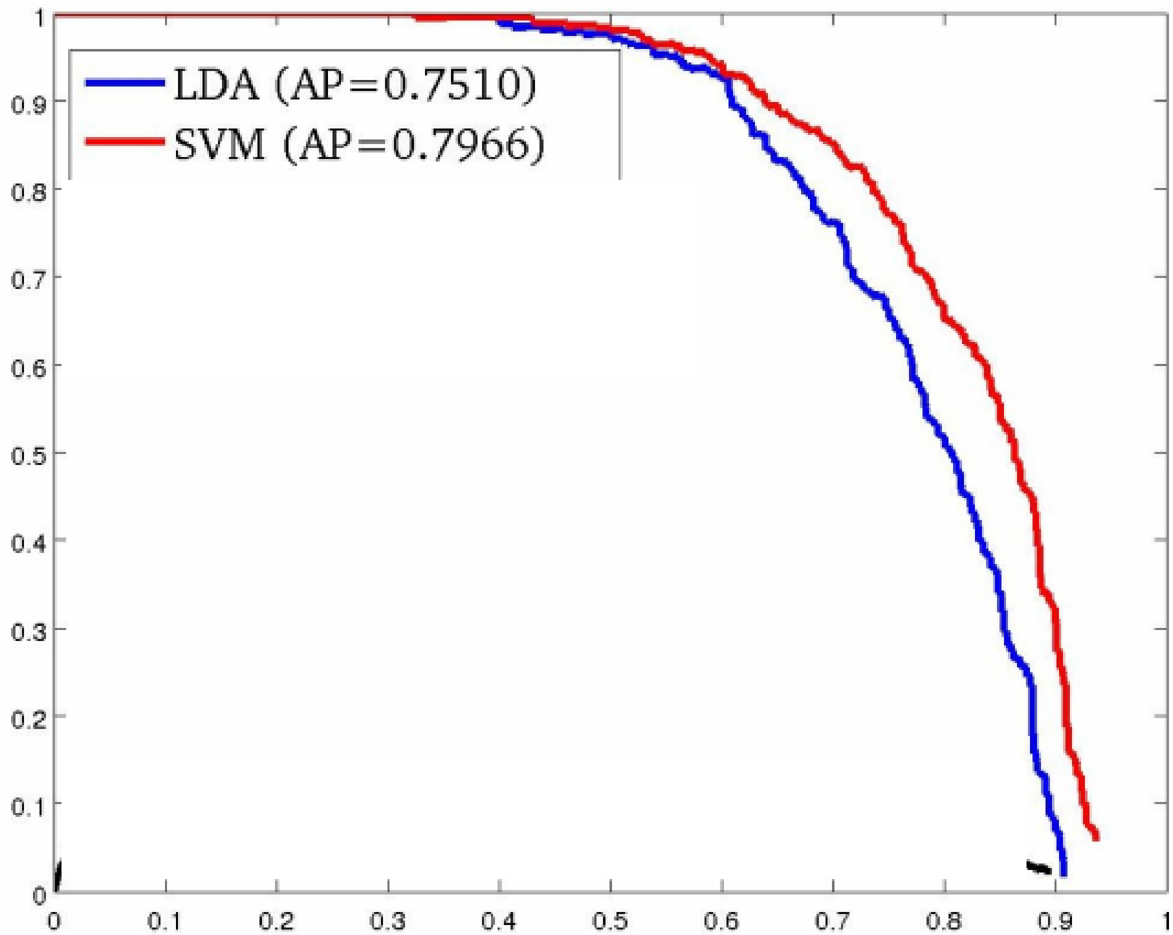
covariance　　mean positives　　mean negatives



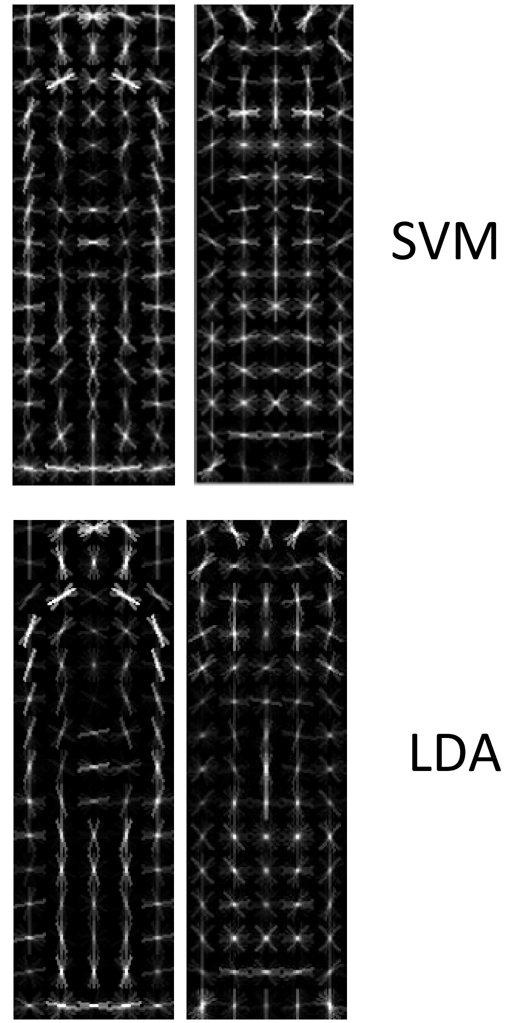
- μ_1 – quick to compute
- μ_0, Σ – compute once, use for any class

- no need for costly bootstrapping and hard negatives
- very fast for learning multiple classes
- Intuition: covariance learns correlation on HOGs in advance, so learning the classifier can concentrate on discriminative gradients
- whitened HOG also better for clustering

Pedestrian Detection
Linear Discriminant Models



Precision-Recall graph on INRIA dataset

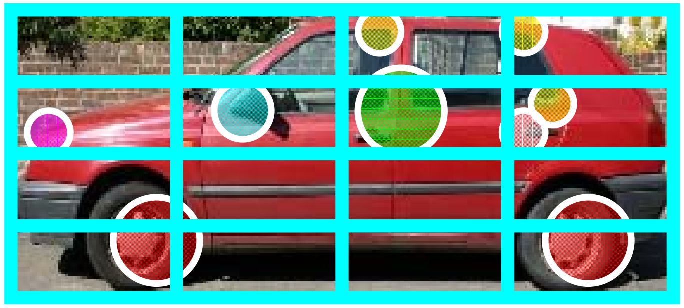


Summary: Sliding Window Detection

- Can convert any image classifier into an object detector by sliding window. Efficient search methods available.

- Requirements for invariance are reduced by searching over e.g. translation and scale

- Spatial correspondence can be "engineered in" by spatial tiling



Outline

1. Sliding window detectors
2. Features and adding spatial information
3. HOG + linear SVM classifier
4. PASCAL VOC and a state of the art detection algorithm
   - VOC challenge
   - Felzenswalb *et al.* – multiple parts, latent SVM
5. The future and challenges

The PASCAL Visual Object Classes (VOC) Dataset and Challenge

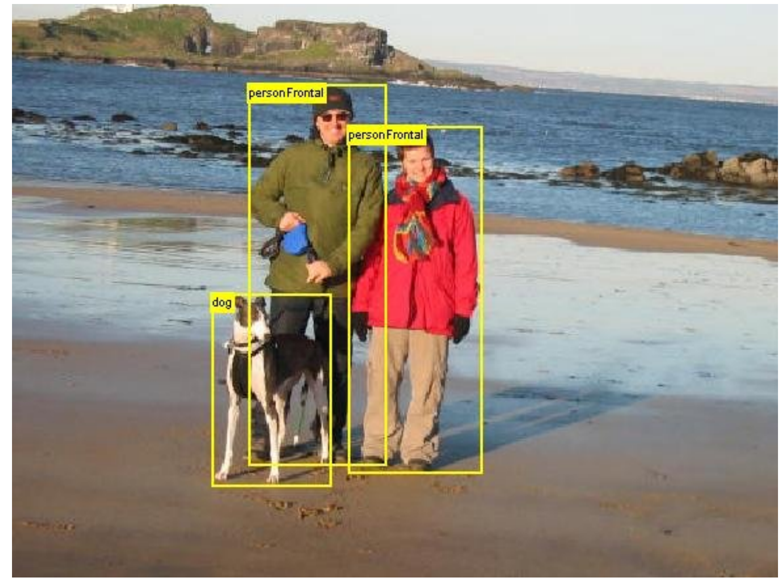
Mark Everingham
Luc Van Gool
Chris Williams
John Winn
Andrew Zisserman

PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

The PASCAL VOC Challenge

- Challenge in visual object recognition funded by PASCAL network of excellence

- Publicly available dataset of annotated images



- Main competitions are classification (is there an X in this image), detection (where are the X's), and segmentation (which pixels belong to X)

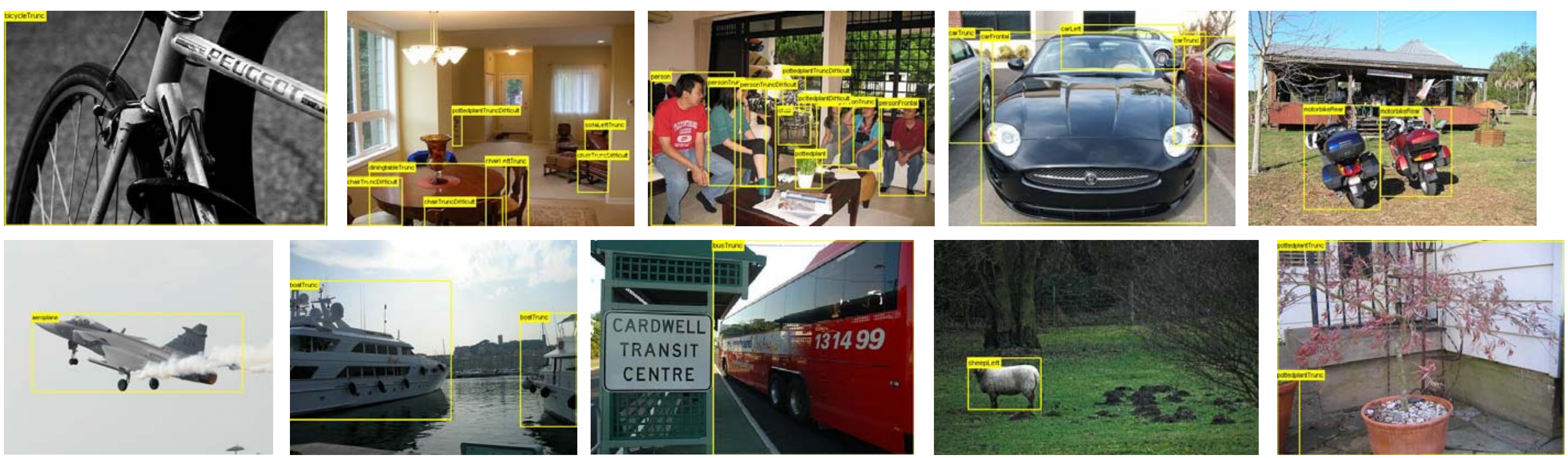
- "Taster competitions" in 2-D human "pose estimation" (2007-12) and static action classes (2010-12)

- Standard evaluation protocol (software supplied)

Dataset Content

- 20 classes: aeroplane, bicycle, boat, bottle, bus, car, cat, chair, cow, dining table, dog, horse, motorbike, person, potted plant, sheep, train, TV

- Real images downloaded from flickr, not filtered for “quality”



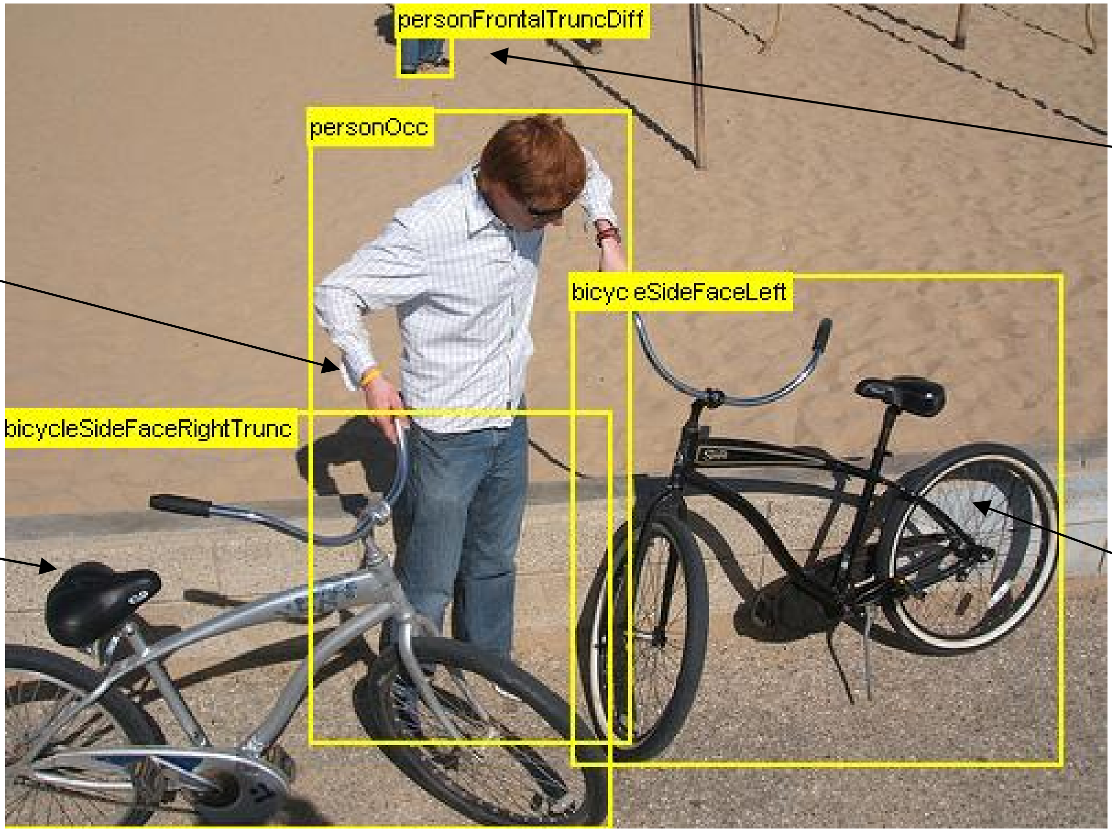
- Complex scenes, scale, pose, lighting, occlusion, ...

Annotation

- Complete annotation of all objects
- Annotated in one session with written guidelines

Occluded
Object is significantly occluded within BB

Truncated
Object extends beyond BB



Difficult
Not scored in evaluation

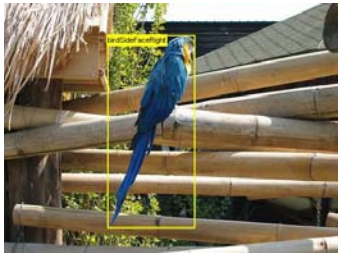
Pose
Facing left

Examples

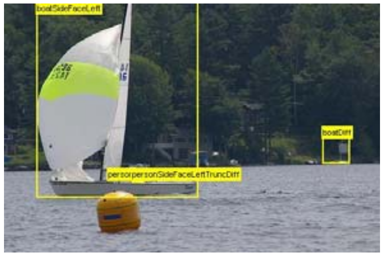
Aeroplane

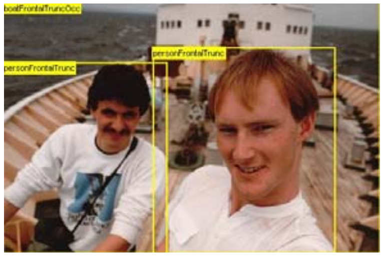
Bicycle

Bird



Boat





Bottle

Bus

Car

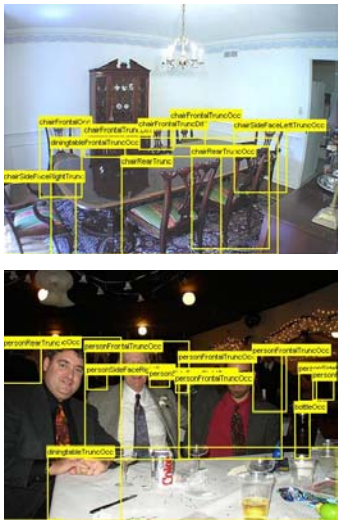
Cat

Chair

Cow

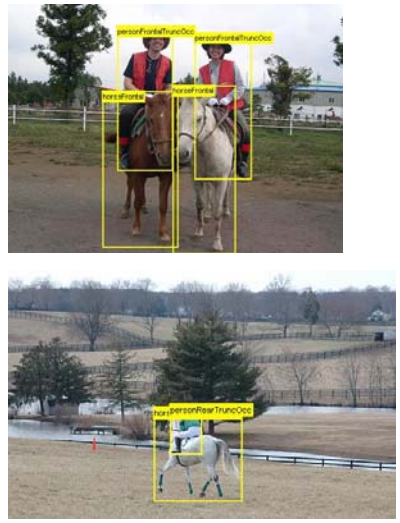
Examples

Dining Table



Dog

Horse

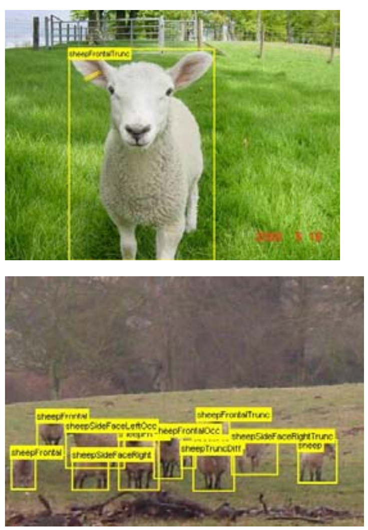


Motorbike

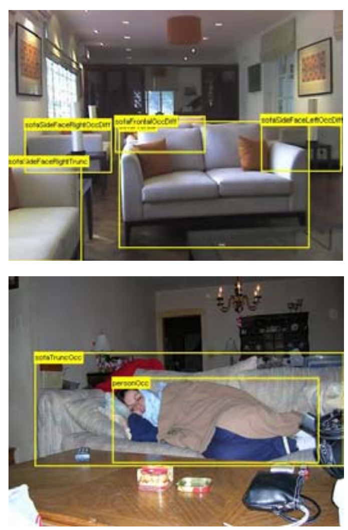
Person

Potted Plant

Sheep

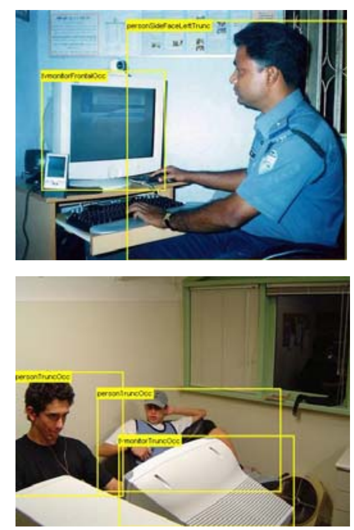


Sofa



Train

TV/Monitor



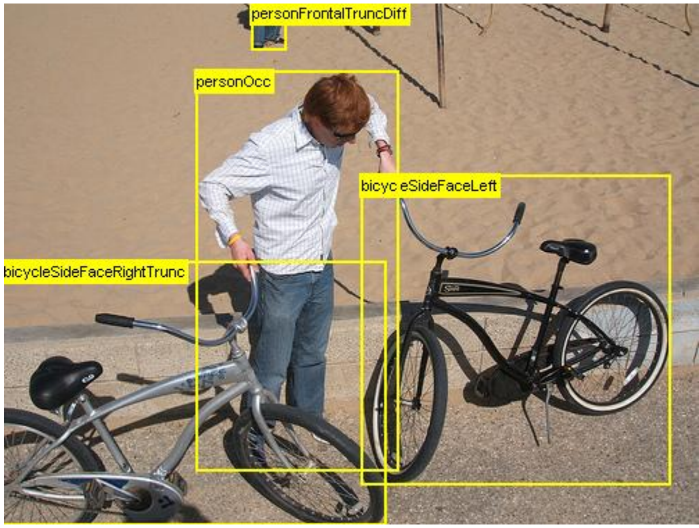
Challenges

20 object classes

1. Classification Challenge: Name Objects
   - Predict whether at least one object of a given class is present in an image

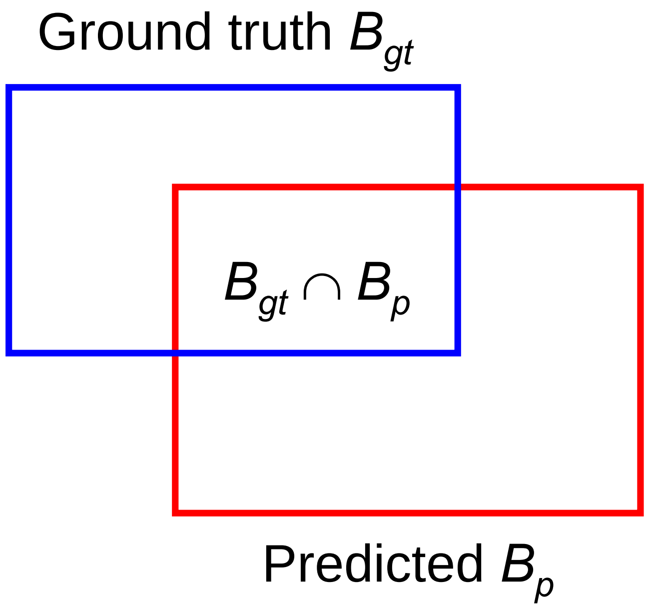
2. Detection Challenge: Localize objects
   - Predict the bounding boxes of all objects of a given class in an image (if any)

3. Segmentation Challenge:
   - For each pixel, predict the class of the object containing that pixel or ‘background’.



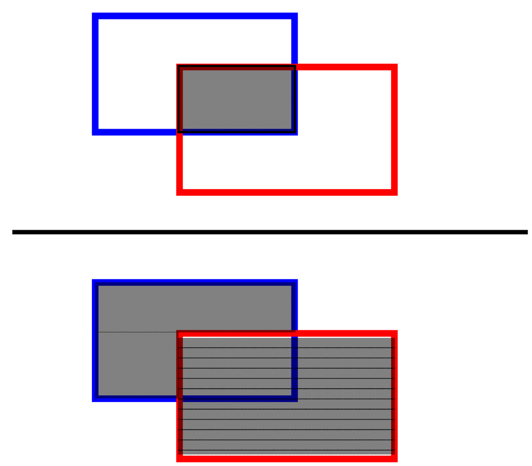
Detection: Evaluation of Bounding Boxes

- Area of Overlap (AO) Measure



$$AO(B_{gt}, B_p) = \frac{|B_{gt} \bigcap B_p|}{|B_{gt} \bigcup B_p|}$$

Detection if

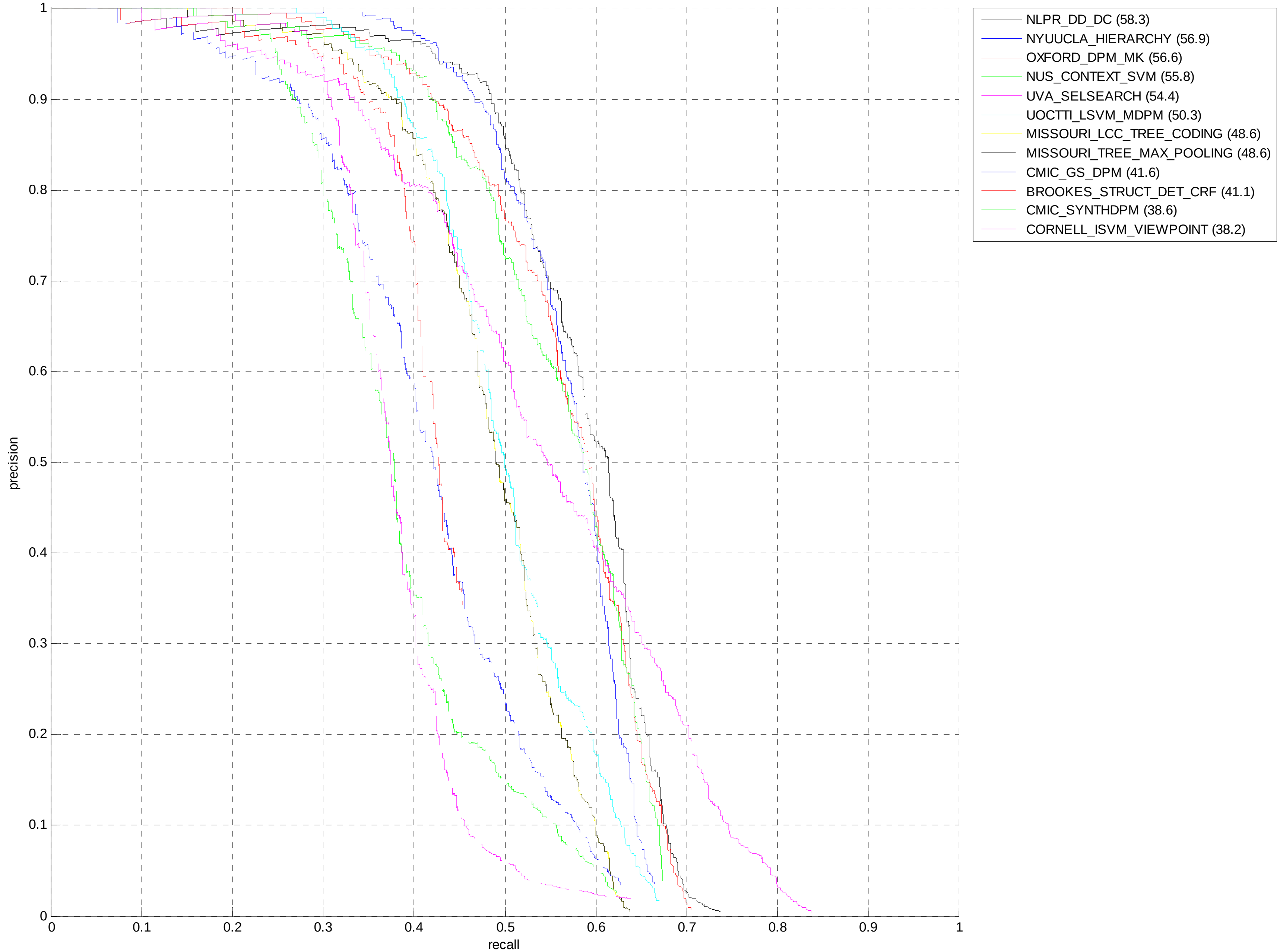


> Threshold

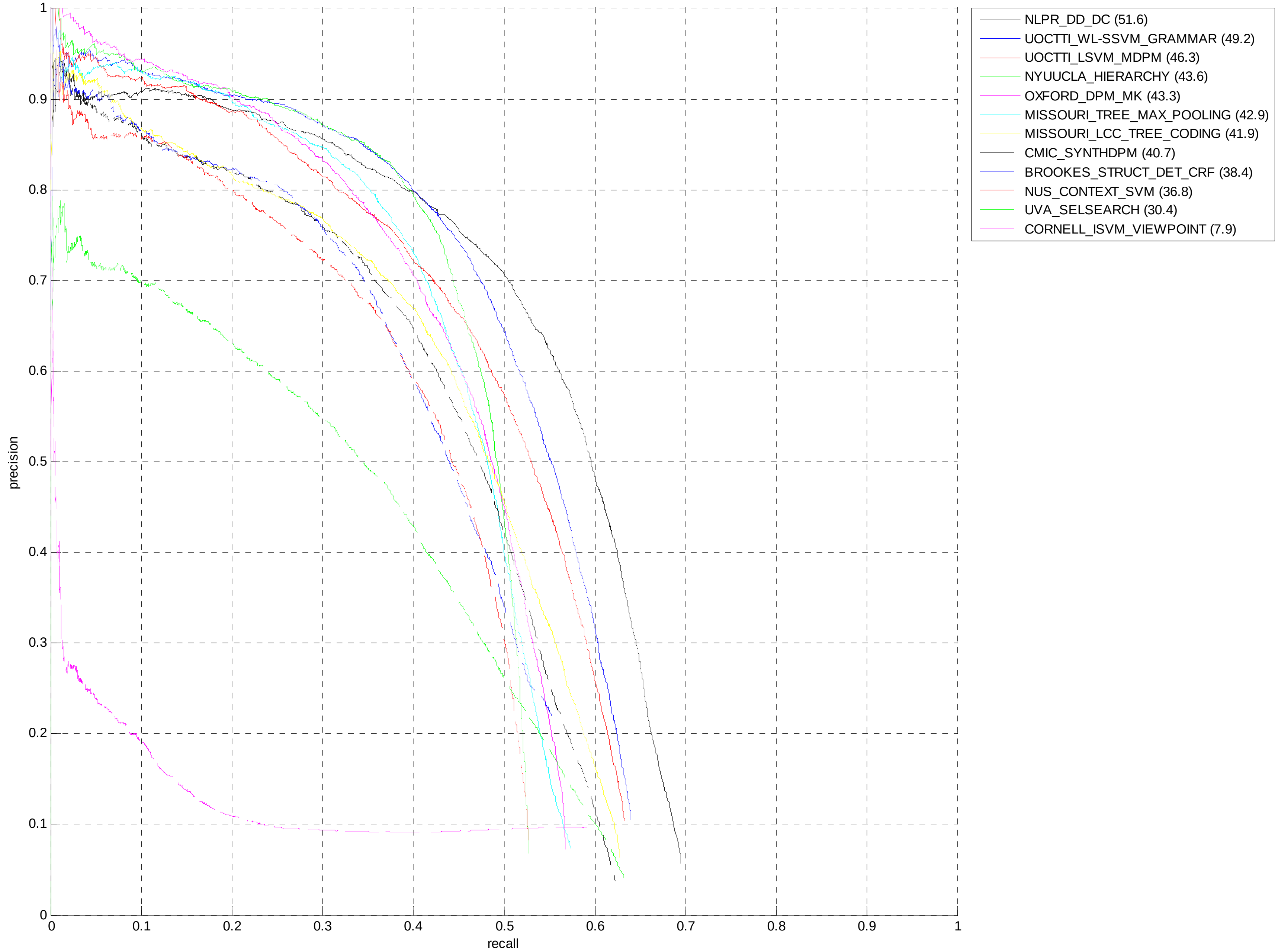
50%

- Evaluation: Average precision per class on predictions

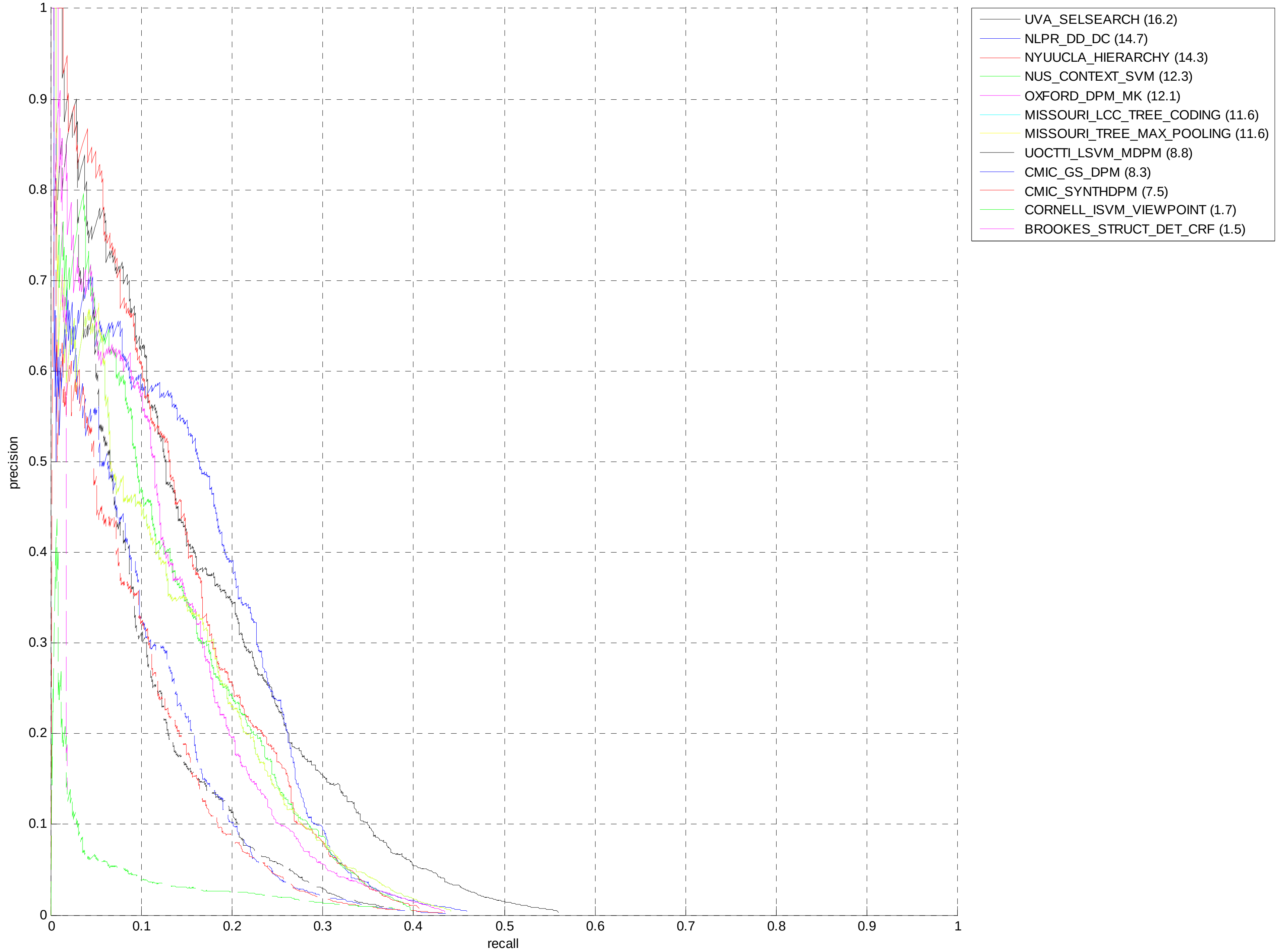
Precision/Recall - Motorbike



Precision/Recall - Person

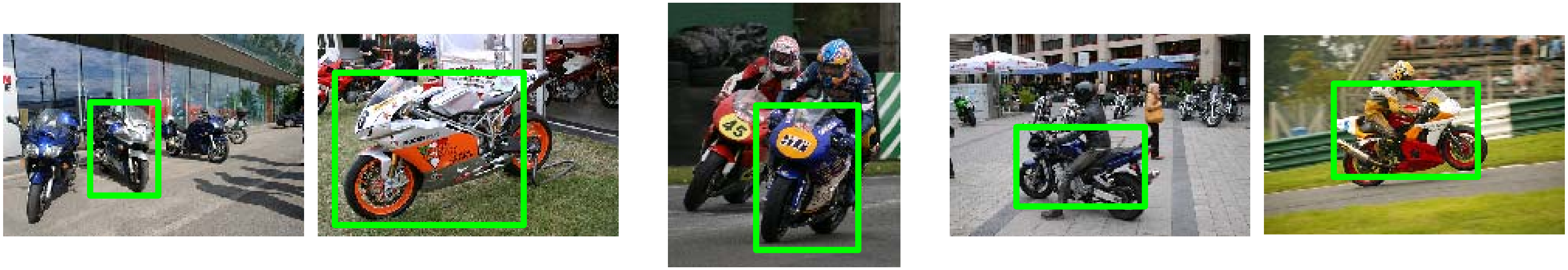


Precision/Recall – Potted plant

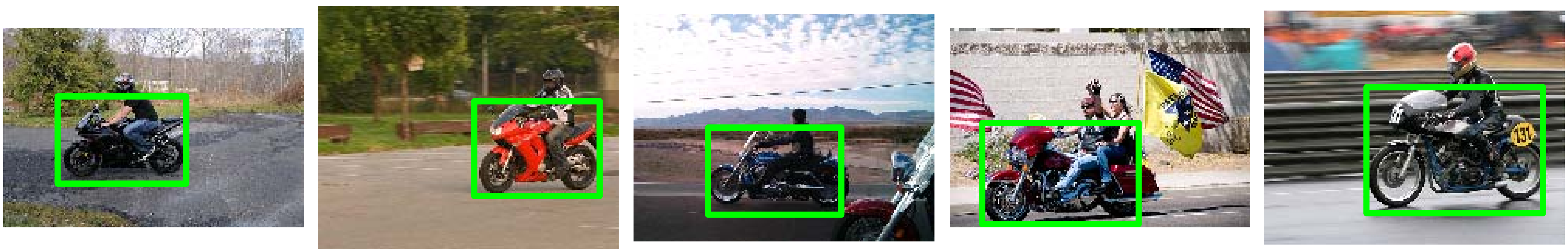


“True Positives” - Motorbike

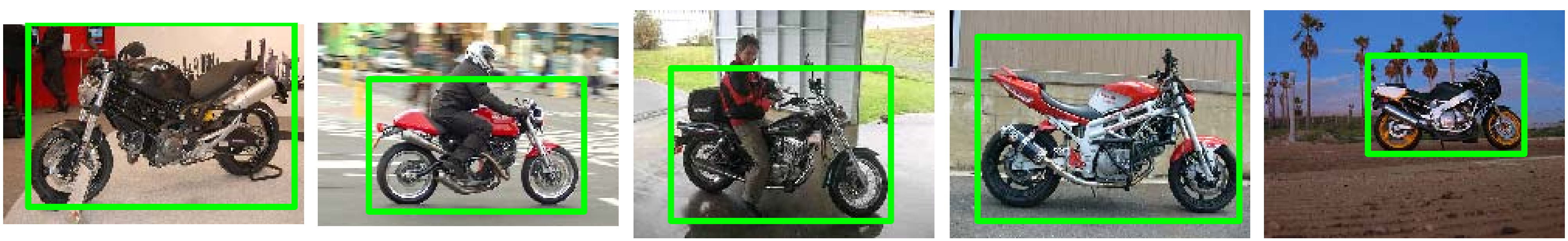
NLPR_DD_DC



NYUUCLA_HIERARCHY



OXFORD_DPM_MK

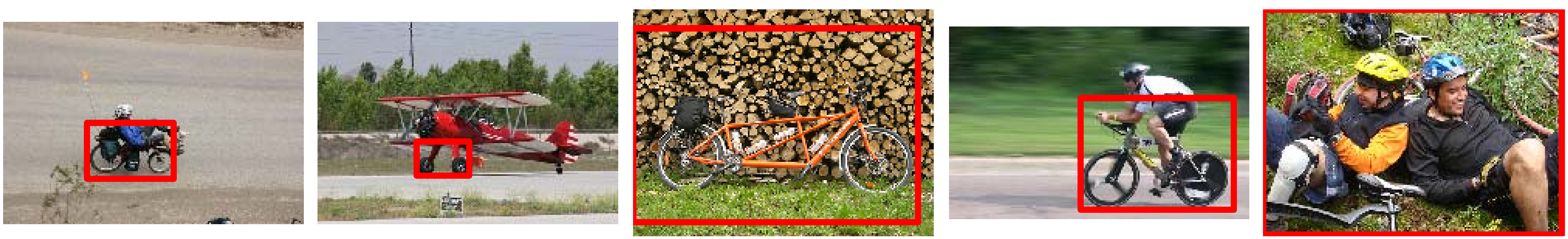


“False Positives” - Motorbike

NLPR_DD_DC

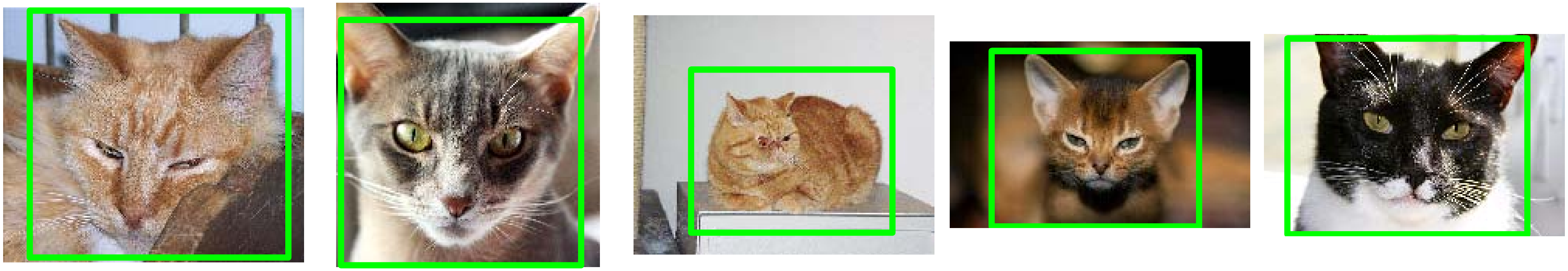
NYUUCLA_HIERARCHY

OXFORD_DPM_MK



“True Positives” - Cat

NYUUCLA_HIERARCHY

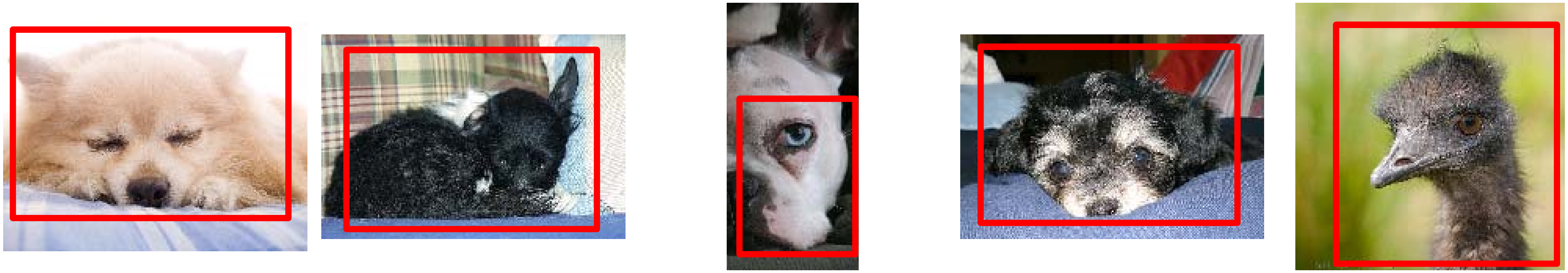


OXFORD_DPM_MK

UVA_SELSEARCH

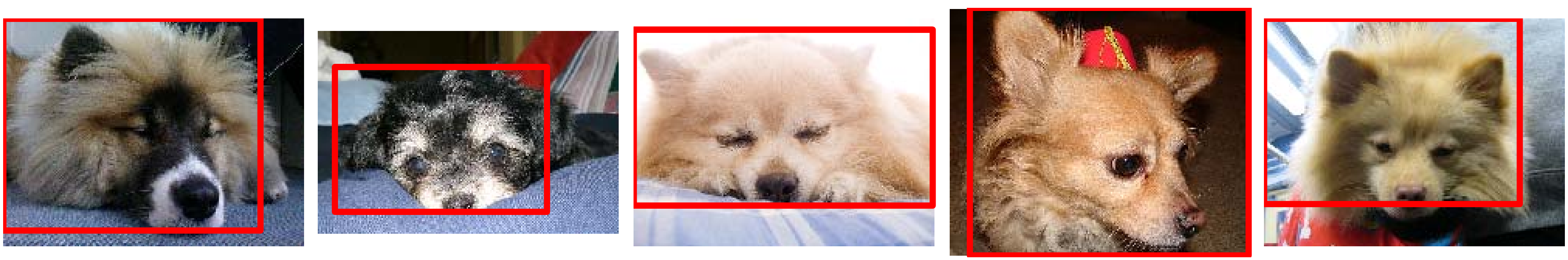
“False Positives” - Cat

NYUUCLA_HIERARCHY

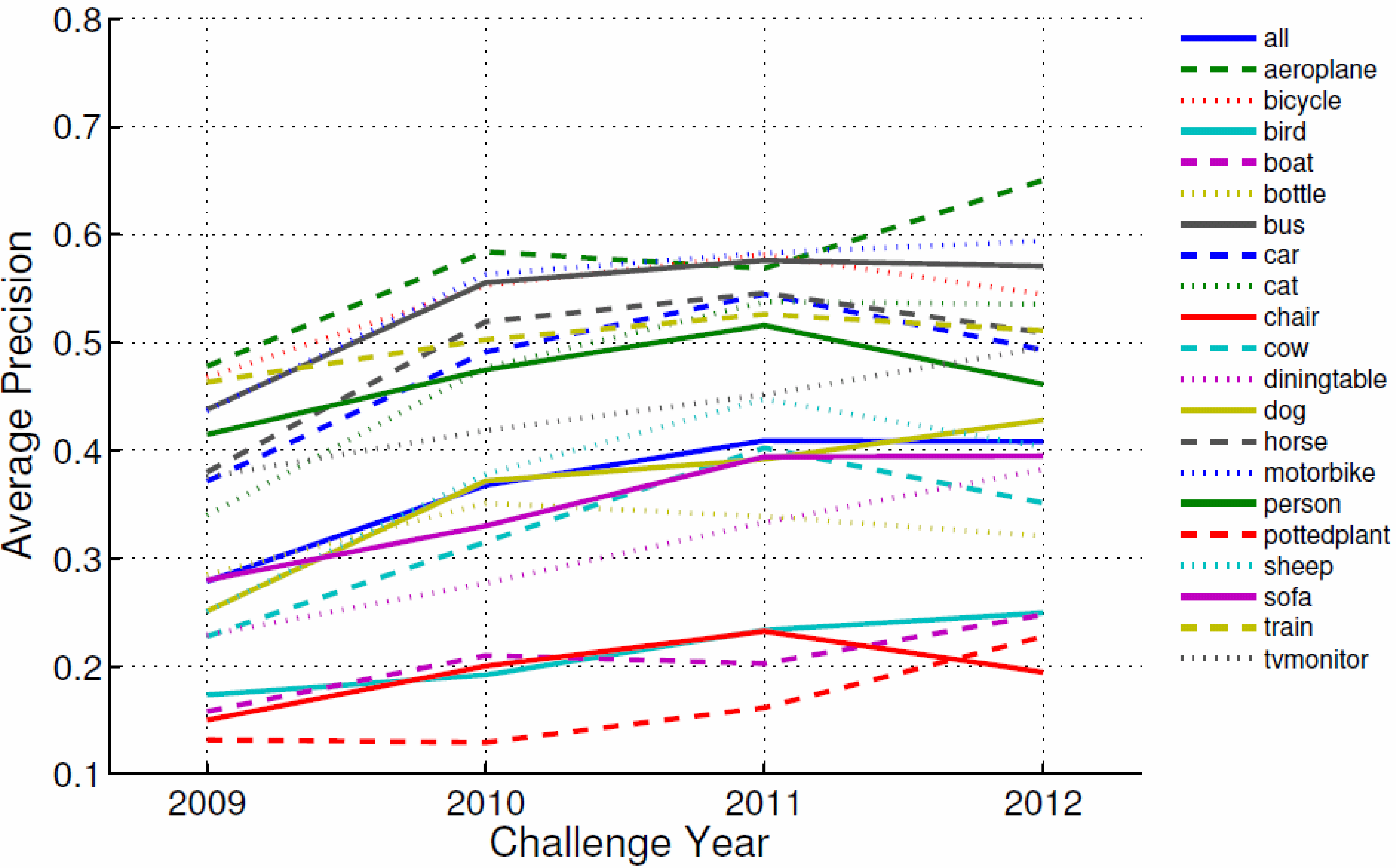


OXFORD_DPM_MK

UVA_SELSEARCH



Progress 2009-2012



ImageNet Challenge 2013

IMAGENET **Large Scale Visual Recognition Challenge 2013 (ILSVRC2013)**

Introduction History Data Tasks Development kit Timetable Organizers Advisors Sponsors Contact

News

- July 15, 2013: Registration page is up! Please register
- March 18, 2013: We are preparing to run the ImageNet Large Scale Visual Recognition Challenge 2013 (ILSVRC2013). Stay tuned!
- March 18, 2013: The new Fine-Grained Challenge 2013 will run concurrently with ILSVRC2013.

Introduction

This challenge evaluates algorithms for object detection and image classification at large scale. This year there will be three competitions:

1. A PASCAL-style detection challenge on fully labeled data for 200 categories of objects, NEW
2. An image classification challenge with 1000 categories, and
3. An image classification plus object localization challenge with 1000 categories.

One high level motivation is to allow researchers to compare progress in detection across a wider variety of objects -- taking advantage of the quite expensive labeling effort. Another motivation is to measure the progress of computer vision for large scale image indexing for retrieval and annotation.

History

- ILSVRC 2012
- ILSVRC 2011

Object Detection with Discriminatively Trained Part Based Models

Pedro F. Felzenszwalb, David Mcallester,
Deva Ramanan, Ross Girshick

PAMI 2010

Single rigid template usually not enough to represent a category

1. Many objects (e.g. humans) are articulated, or have parts that can vary in configuration

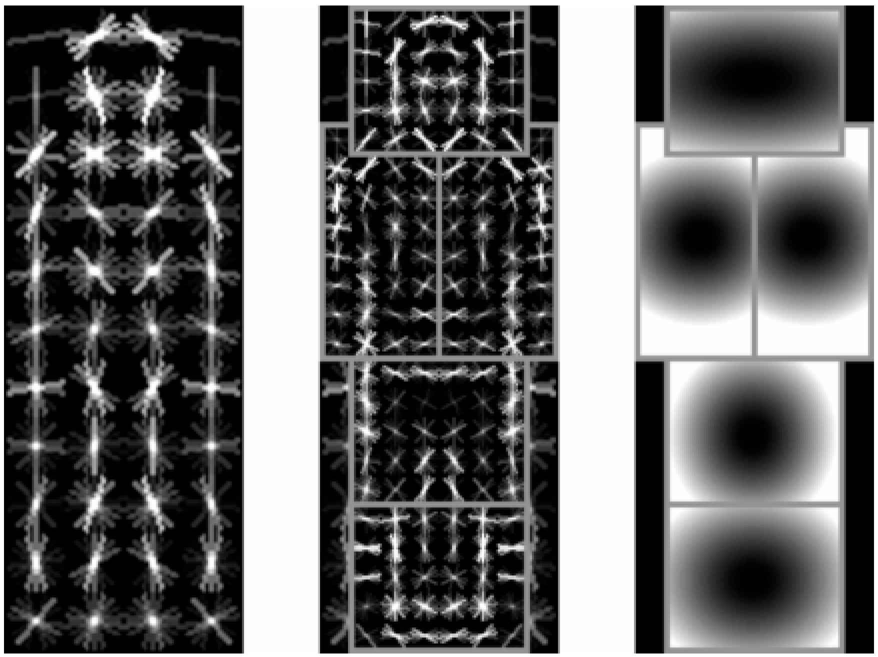
2. Many object categories look very different from different viewpoints, or from instance to instance

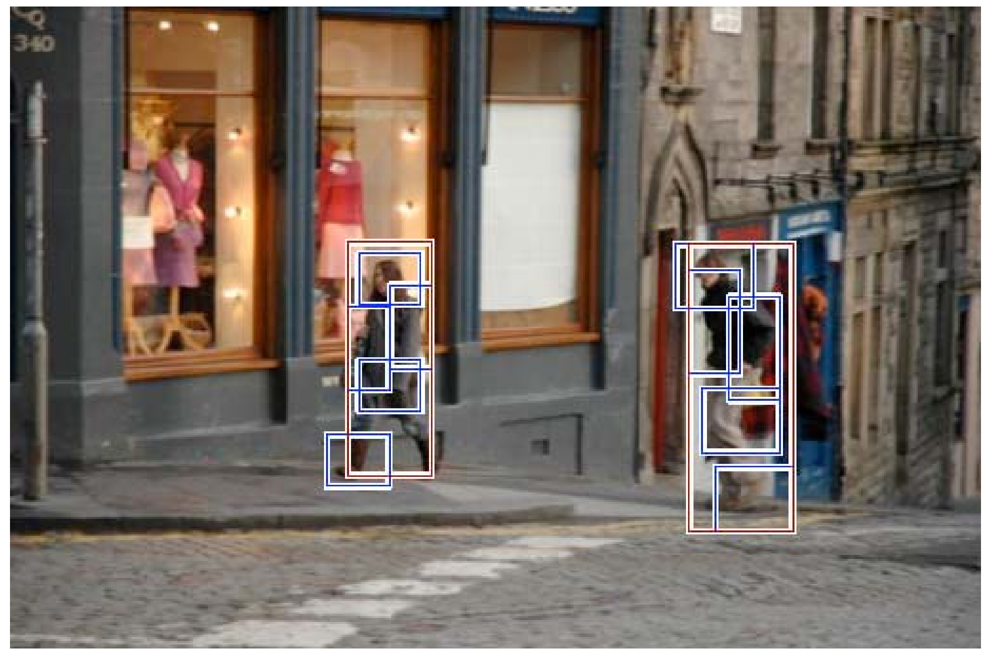
Slide by N. Snavely

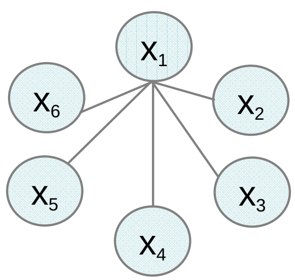
Discriminative part-based models

- One component of person model

Root filter | Part filters | Deformation weights

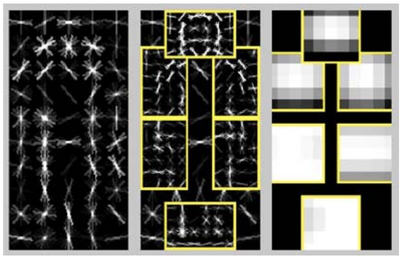






Object Hypothesis

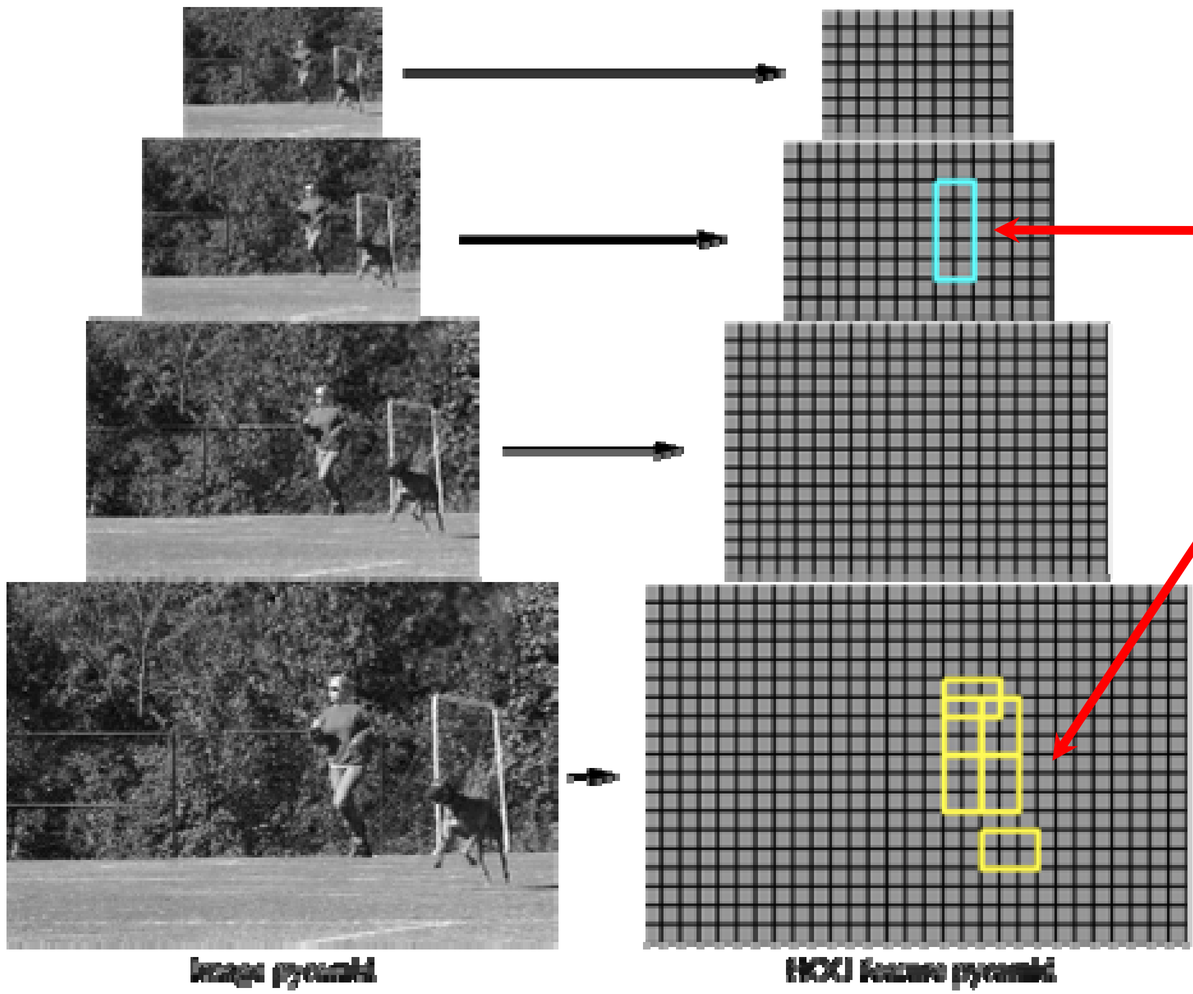
- Position of root + each part
- Each part: HOG filter (at higher resolution)



$z = (p_0, \ldots, p_n)$

p_0 : location of root

$p_1, \ldots, p_n$: location of parts



Score is sum of filter scores minus deformation costs

Score of a Hypothesis

Appearance term — Spatial prior

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

filters

deformation parameters

displacements

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

concatenation of filters and deformation parameters

concatenation of HOG features and part displacement features

- Linear classifier applied to feature subset defined by hypothesis

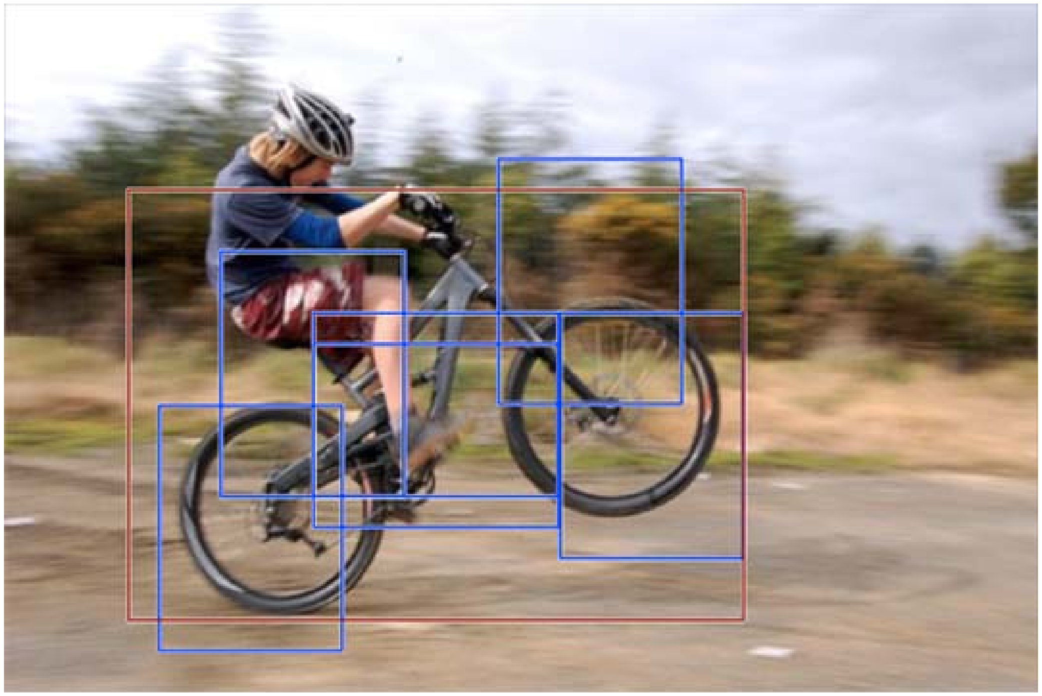
Single rigid template usually not enough to represent a category

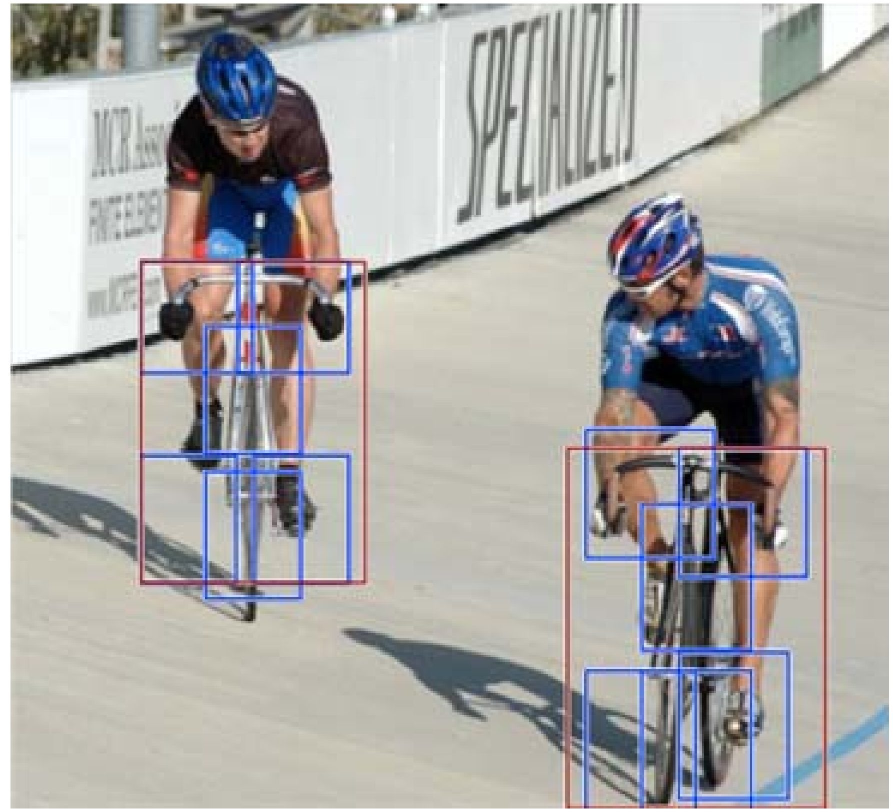
1. Many objects (e.g. humans) are articulated, or have parts that can vary in configuration

2. Many object categories look very different from different viewpoints, or from instance to instance

Slide by N. Snavely

Multiple components

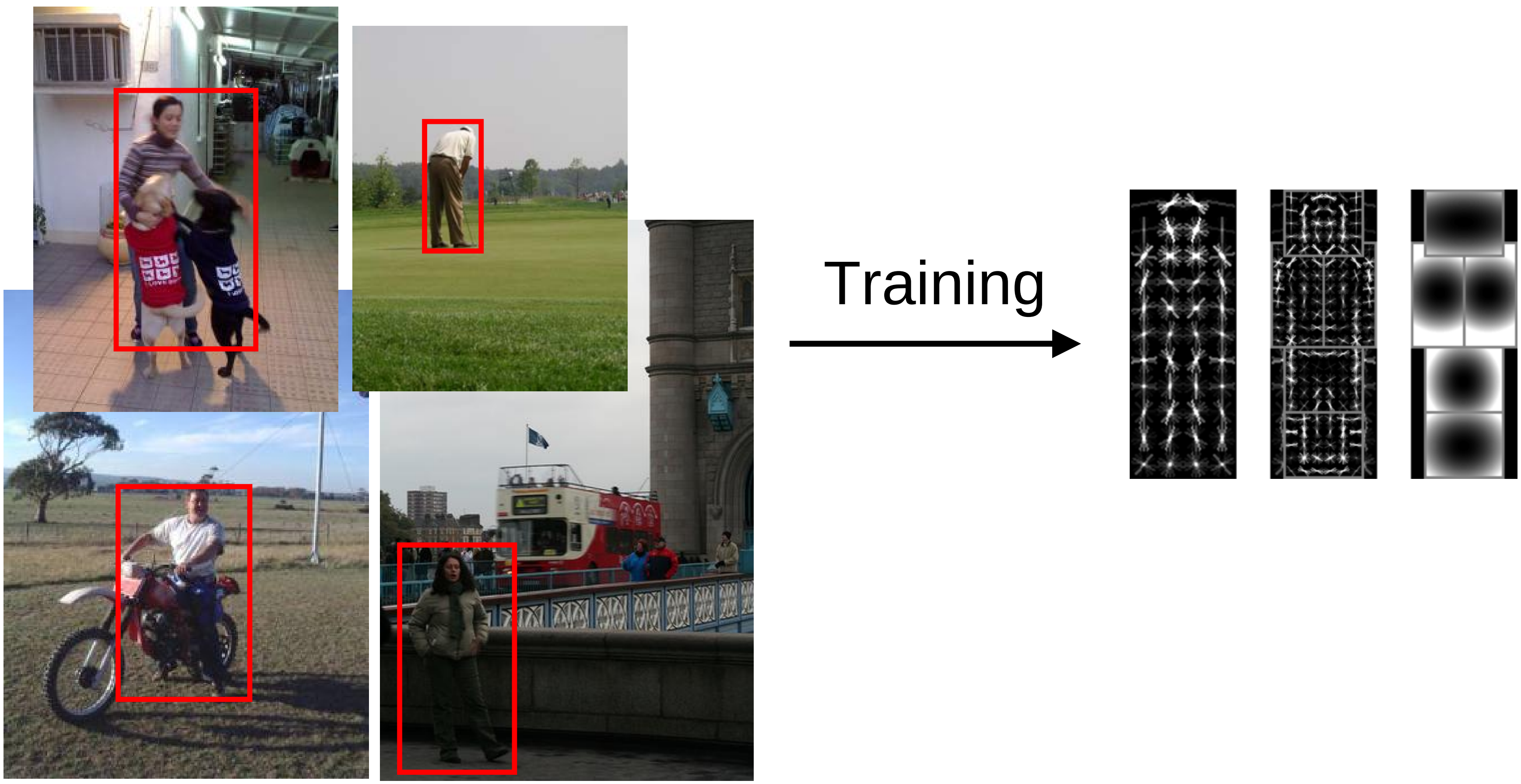




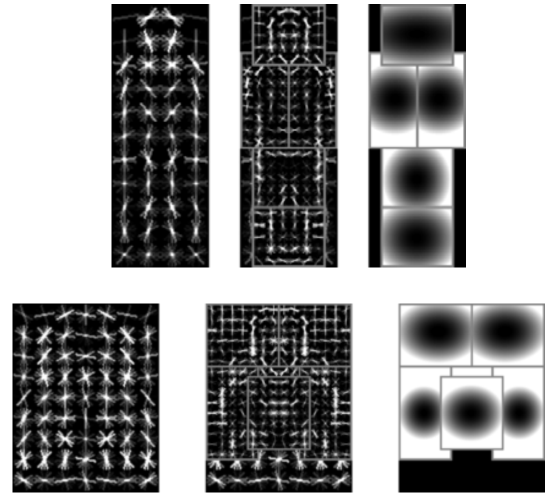
- Mixture of deformable part-based models
  - One component per “aspect” e.g. front/side view
- Each component has global template + deformable parts
- Discriminative training from bounding boxes alone

Training

- Training data = images + bounding boxes
- Need to learn: model structure, filters, deformation costs



Latent SVM (MI-SVM)



Classifiers that score an example x using

$$f_\beta(x) = \max_{z \in Z(x)} \beta \cdot \Phi(x, z)$$

β are model parameters

z are latent values

- Which component?
- Where are the parts?

Training data $D = (\langle x_1, y_1 \rangle, \ldots, \langle x_n, y_n \rangle)$ $\quad y_i \in \{-1, 1\}$

We would like to find β such that: $y_i f_\beta(x_i) > 0$

Minimize

$$L_D(\beta) = \frac{1}{2}||\beta||^2 + C \sum_{i=1}^{n} \max(0, 1 - y_i f_\beta(x_i))$$

SVM objective

Latent SVM Training

$$L_D(\beta) = \frac{1}{2}||\beta||^2 + C\sum_{i=1}^{n} \max(0, 1 - y_i f_\beta(x_i))$$

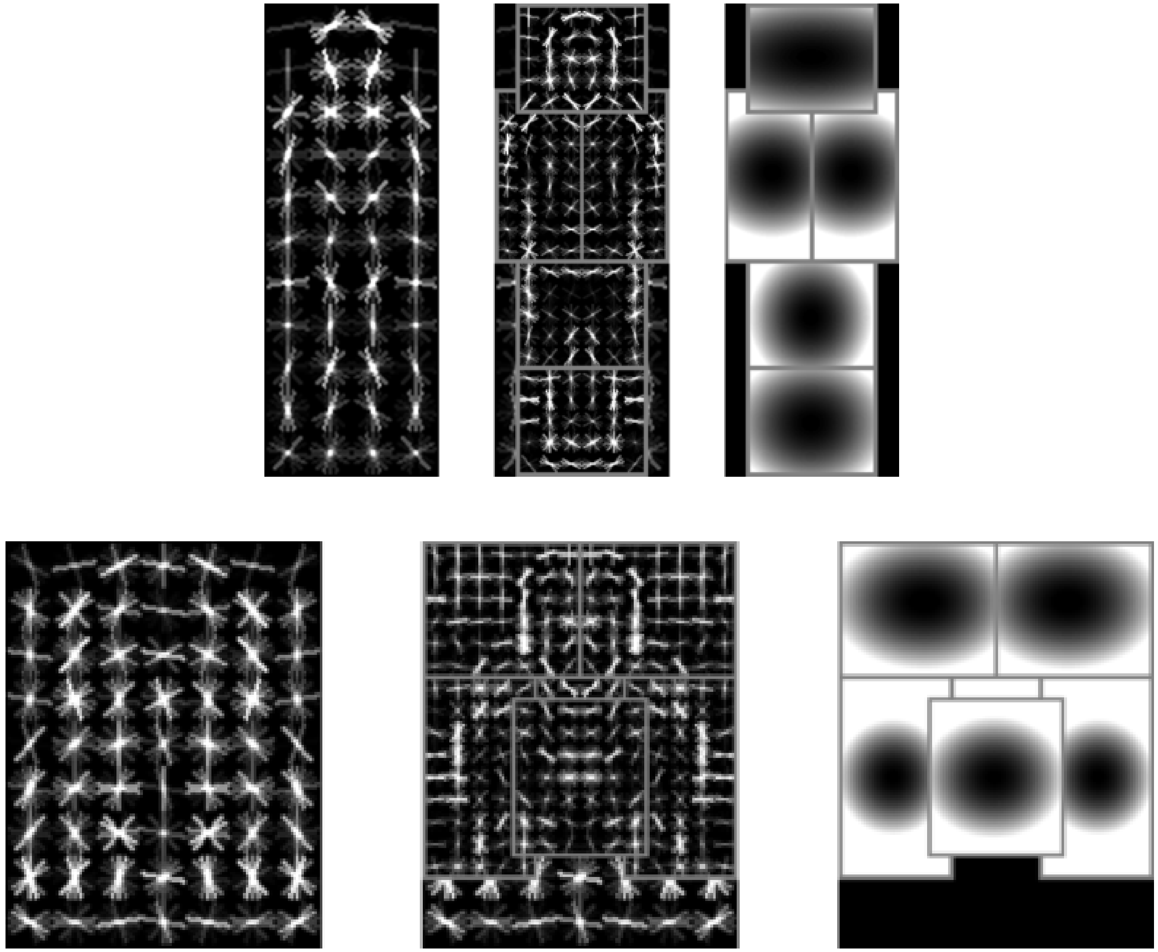
- Convex if we fix z for positive examples

- Optimization:
  - Initialize β and iterate:
    - Pick best z for each positive example
    - Optimize β with z fixed

Alternation strategy

- Local minimum: needs good initialization
  - Parts initialized heuristically from root

Person Model



root filters
coarse resolution

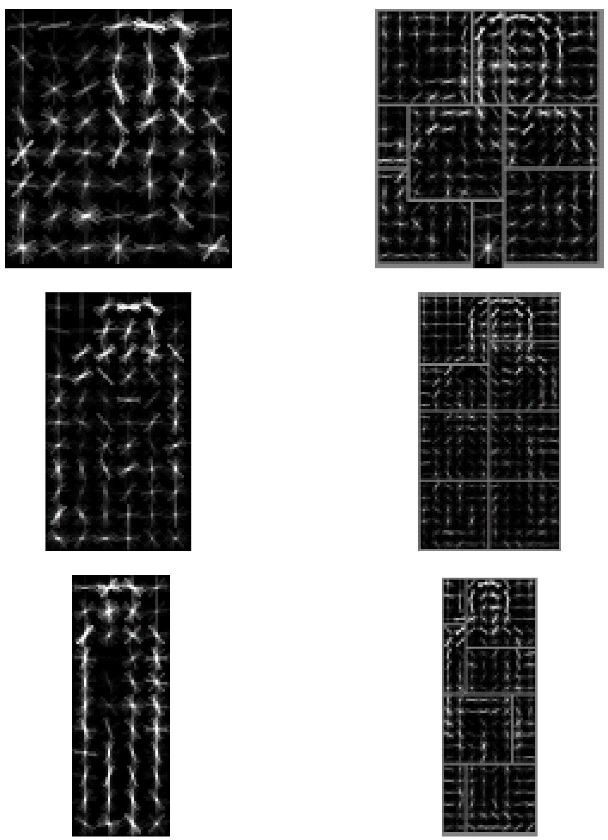
part filters
finer resolution

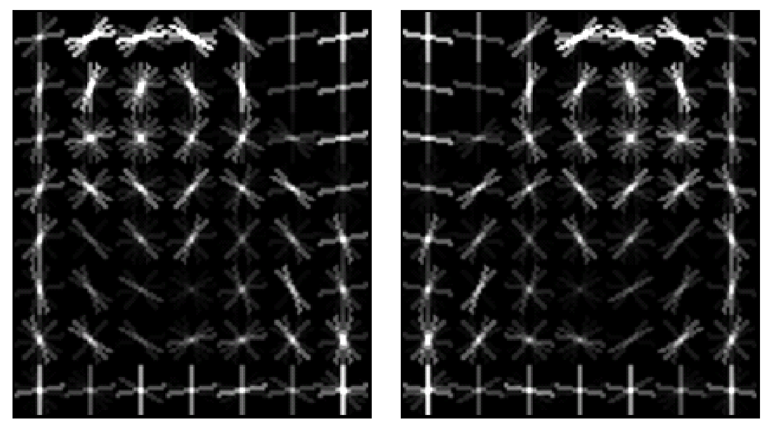
deformation
models

Handles partial occlusion/truncation

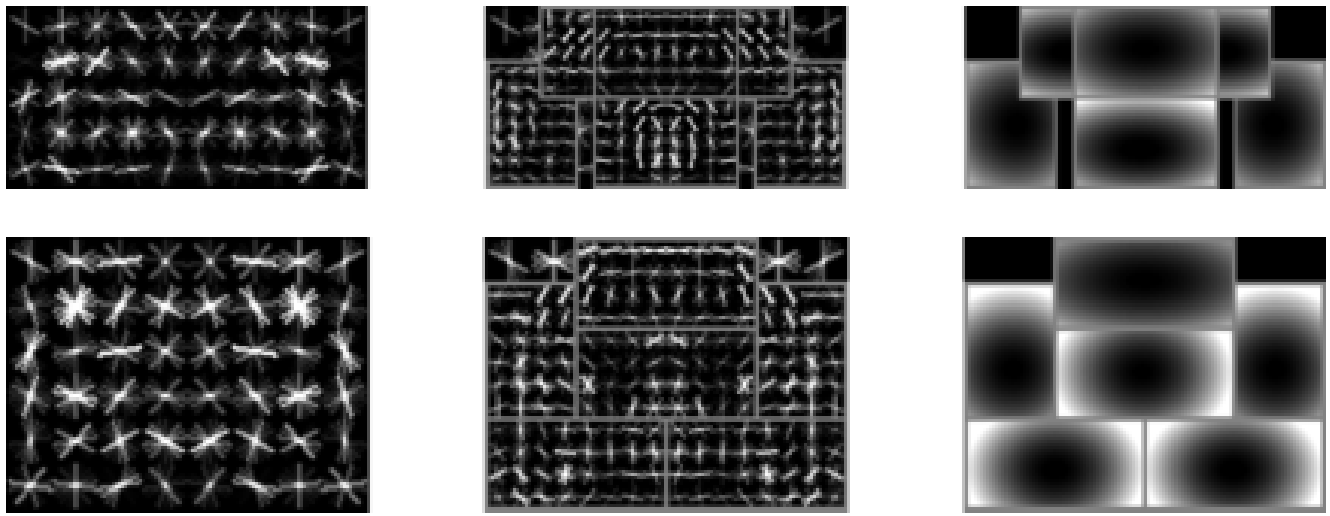
Person model with 3 left-right components

- Mixture model using max over multiple components with left-right pairs





Car Model



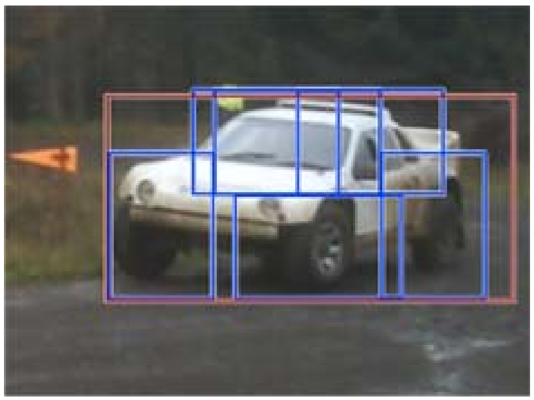
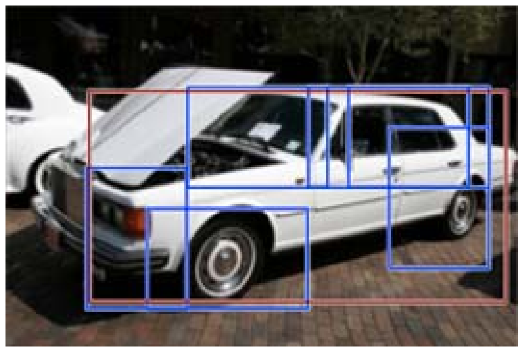
root filters
coarse resolution

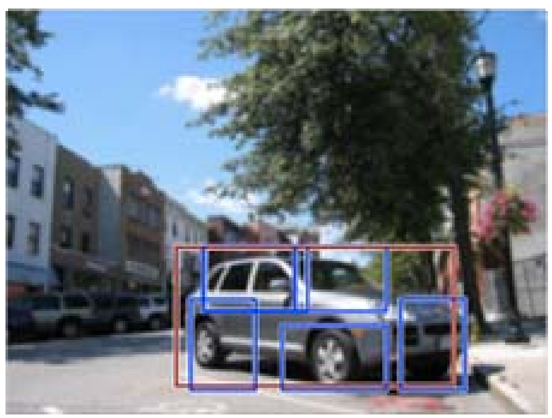
part filters
finer resolution

deformation
models

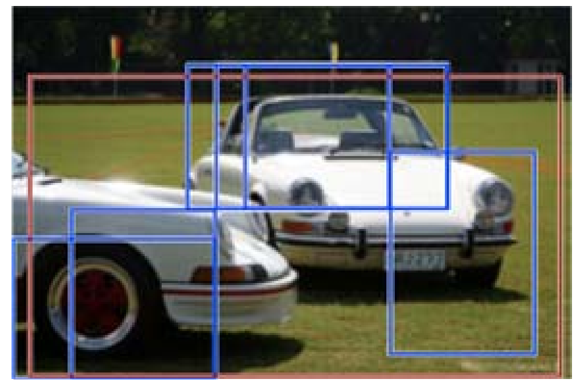
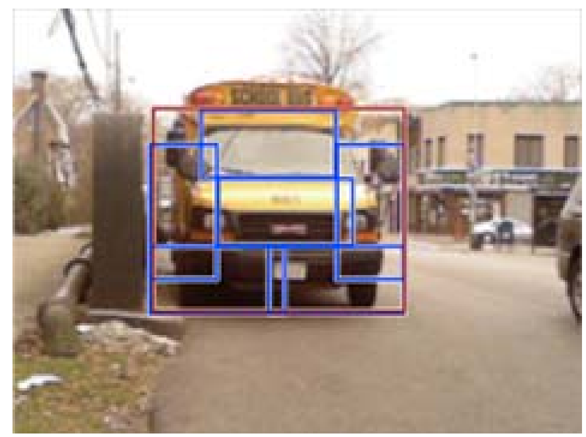
Car Detections

high scoring true positives

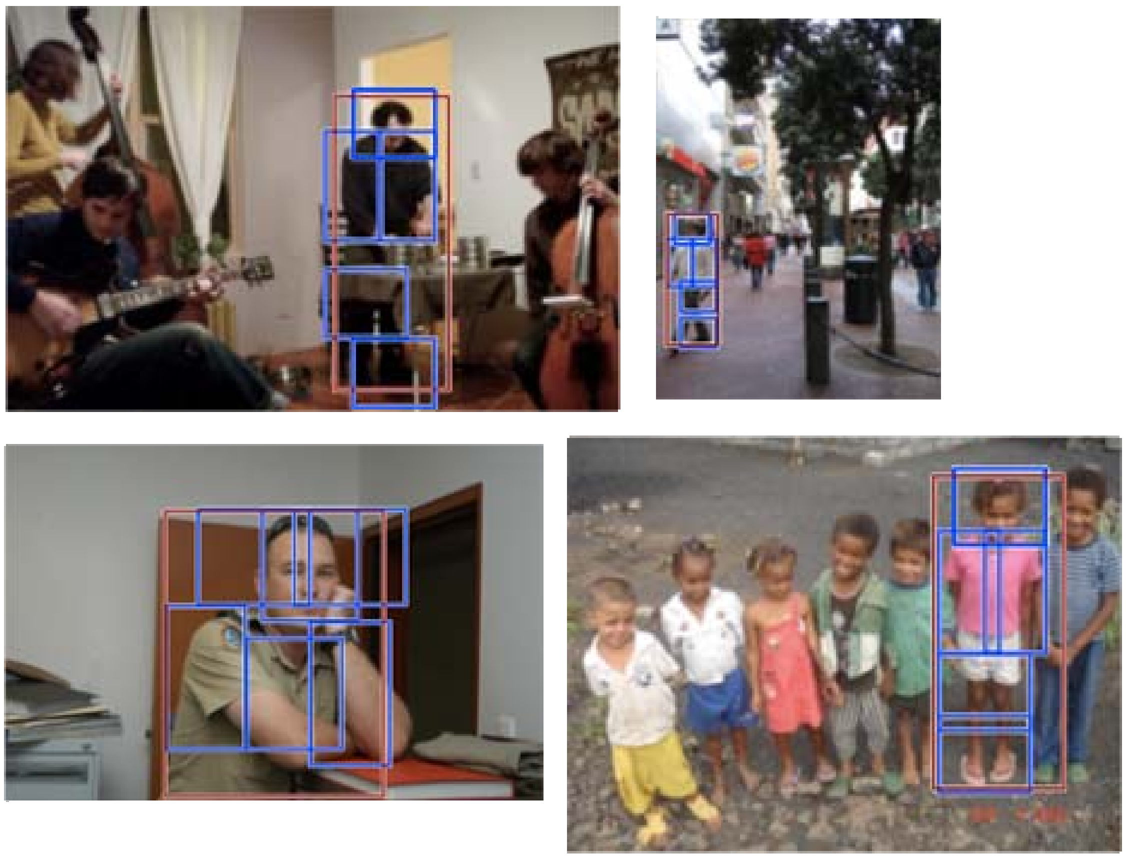


high scoring false positives

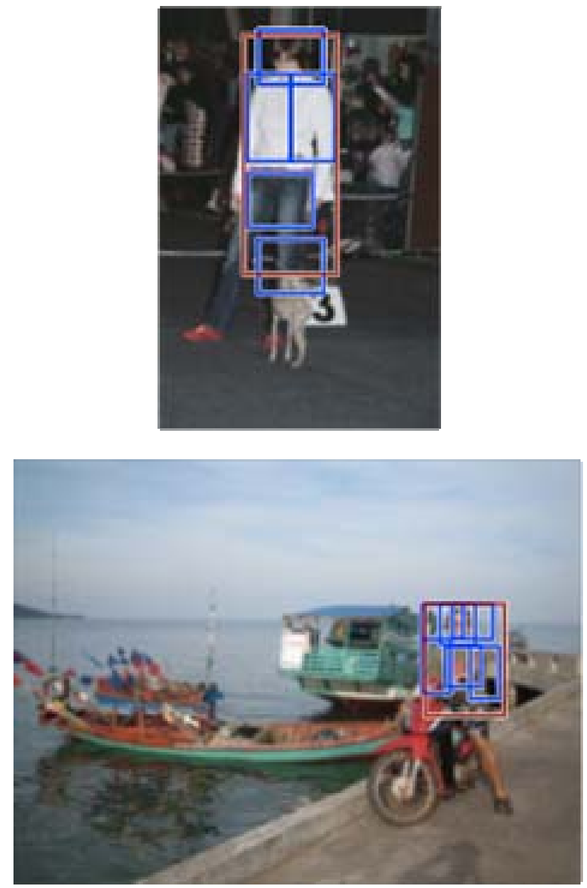



Person Detections

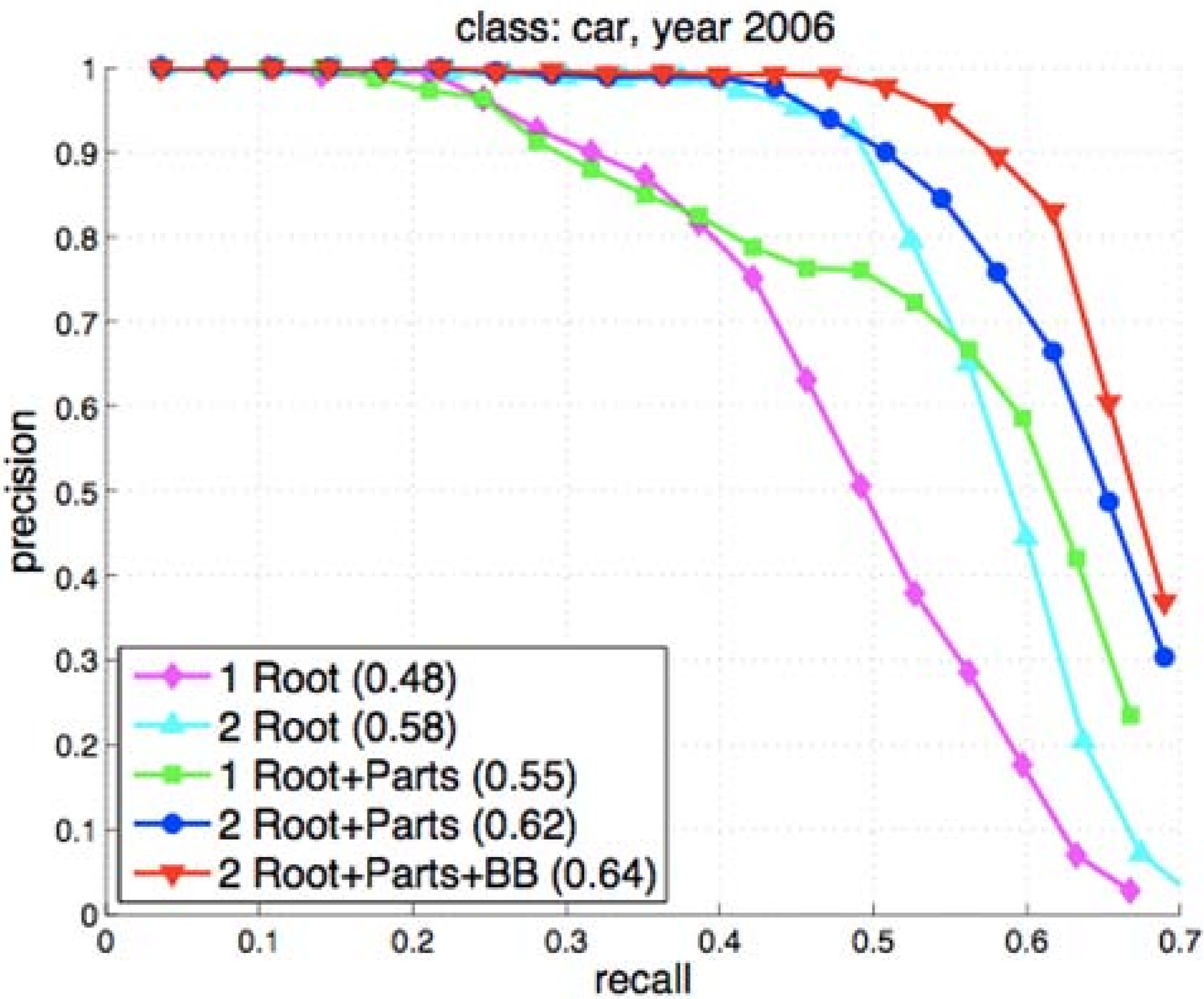
high scoring true positives



high scoring false positives
(not enough overlap)

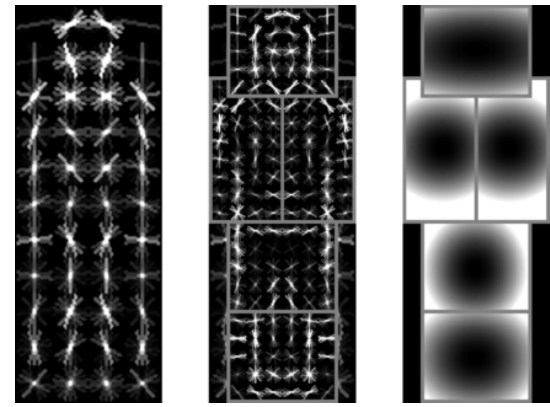


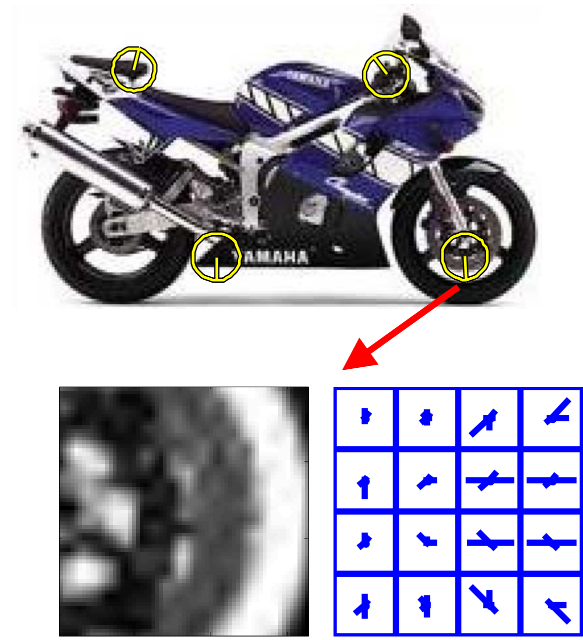
Comparison of Models

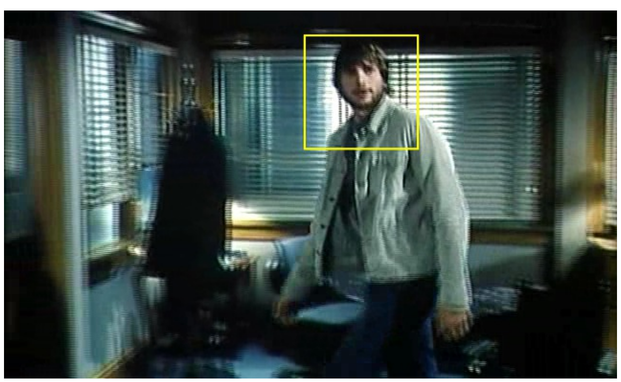


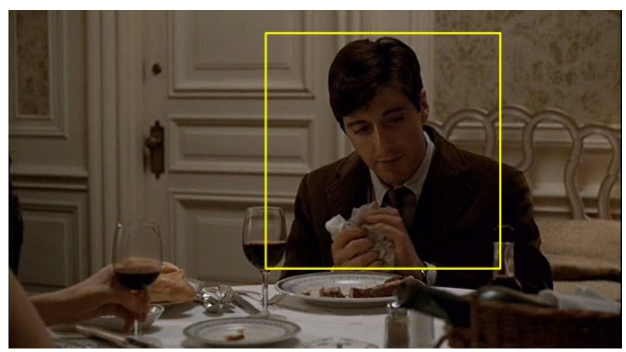
Summary

- Discriminative learning of model with latent variables for single feature (HOG):
  - Latent variables can learn best alignment in the ROI training annotation
  - Parts can be thought of as local SIFT vectors
  - Some similarities to Implicit Shape Model but with discriminative/careful training throughout









NB: Code available for latent model !

Outline

1. Sliding window detectors

2. Features and adding spatial information

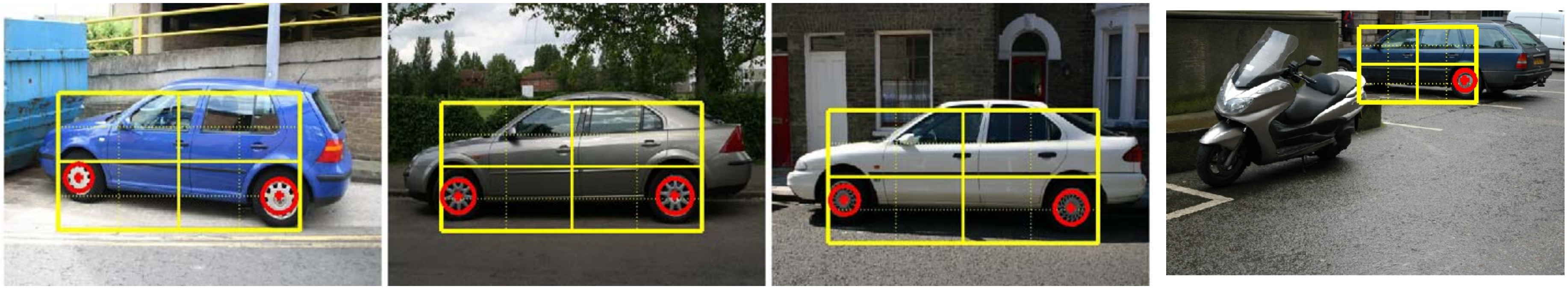
3. HOG + linear SVM classifier

4. PASCAL VOC and a state of the art detection algorithm

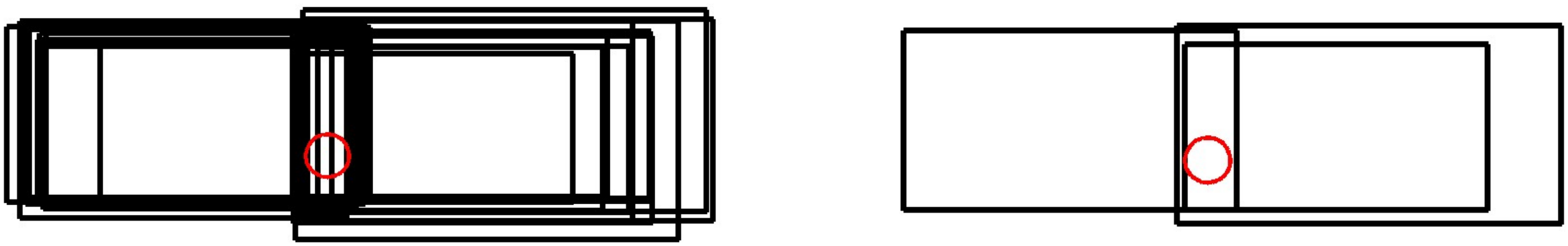
5. The future and challenges

There are alternatives to sliding - jumping window

Training

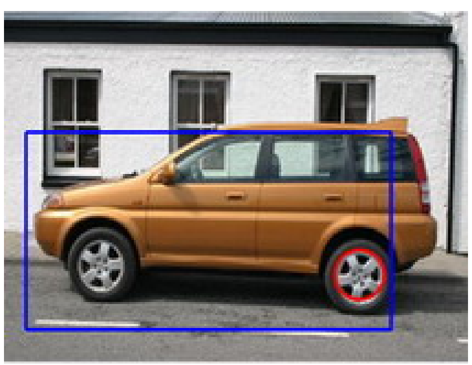


Position of visual word with respect to the object



learn the position/scale/aspect ratio of the ROI with respect to the visual word

Detection



Hypothesis

Handles change of aspect ratio

Current Research Challenges

- Improving precision, e.g. by context
  - from scene properties: GIST, BoW, stuff
  - from other objects, e.g. Felzenszwalb et al, PAMI 10
  - from geometry of scene, e.g. Hoiem et al CVPR 06
- Improving recall, e.g. missed due to occlusion/truncation
  - Winn & Shotton, Layout Consistent Random Field, CVPR 06
  - Vedaldi & Zisserman, NIPS 09
  - Yang et al, Layered Object Detection, CVPR 10
  - Tang et al, Detection and Tracking of Occluded People, BMVC 12
- Weak and noisy supervision, e.g. dot or image level
  - Deselaers et al, IJCV 2012
  - Arteta et al, CVPR 13