Category-level localization

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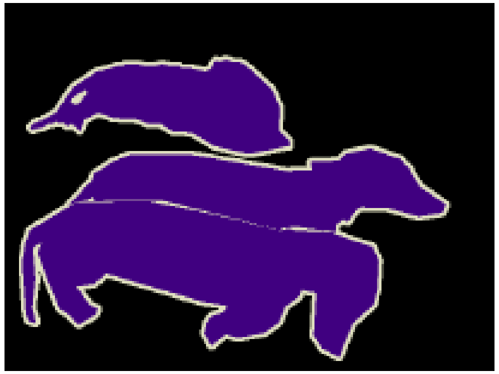
Recognition

- Classification
  - Object present/absent in an image
  - Often presence of a significant amount of background clutter

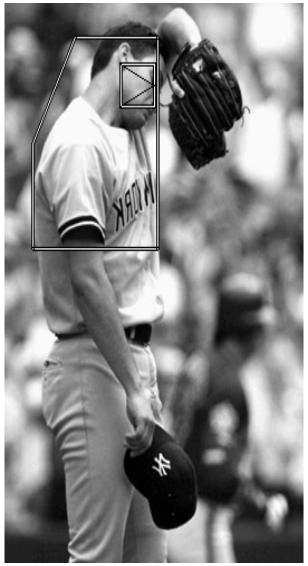
- Localization / Detection
  - Localize object within the frame
  - Bounding box or pixel-level segmentation

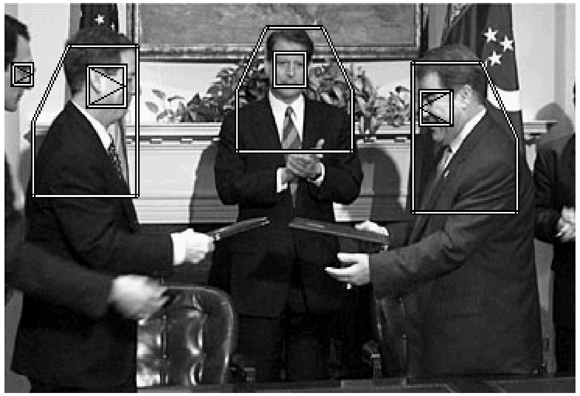
Pixel-level object classification

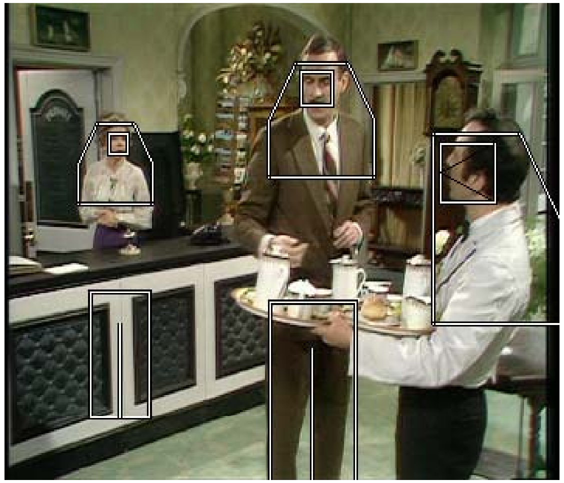




Difficulties

- Intra-class variations







- Scale and viewpoint change
- Multiple aspects of categories

Approaches

- Intra-class variation

  => Modeling of the variations, mainly by learning from a large dataset, for example by SVMs

- Scale + limited viewpoints changes

  => multi-scale approach or invariant local features

- Multiple aspects of categories

  => separate detectors for each aspect, front/profile face, build an approximate 3D “category” model

Outline

1. *Sliding window detectors*
2. Features and adding spatial information
3. Histogram of Oriented Gradients (HOG)
4. State of the art algorithms and PASCAL VOC

Sliding window detector

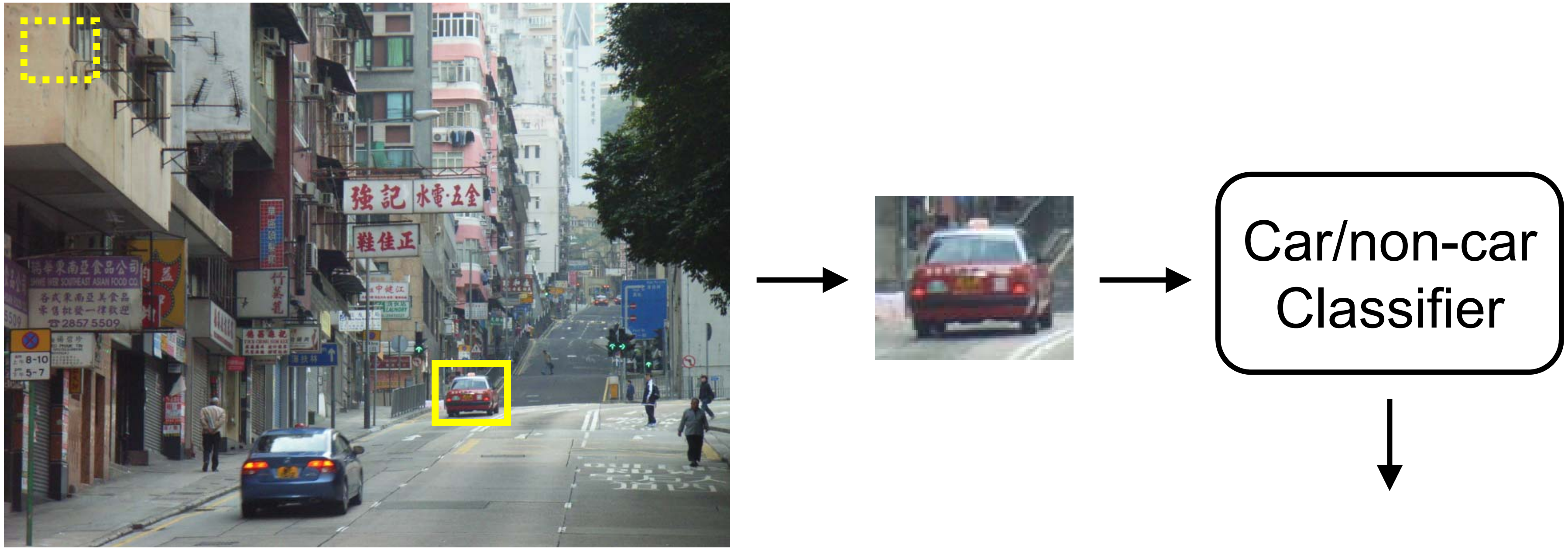
- Basic component: binary classifier

Car/non-car
Classifier

No,
not a car

Sliding window detector

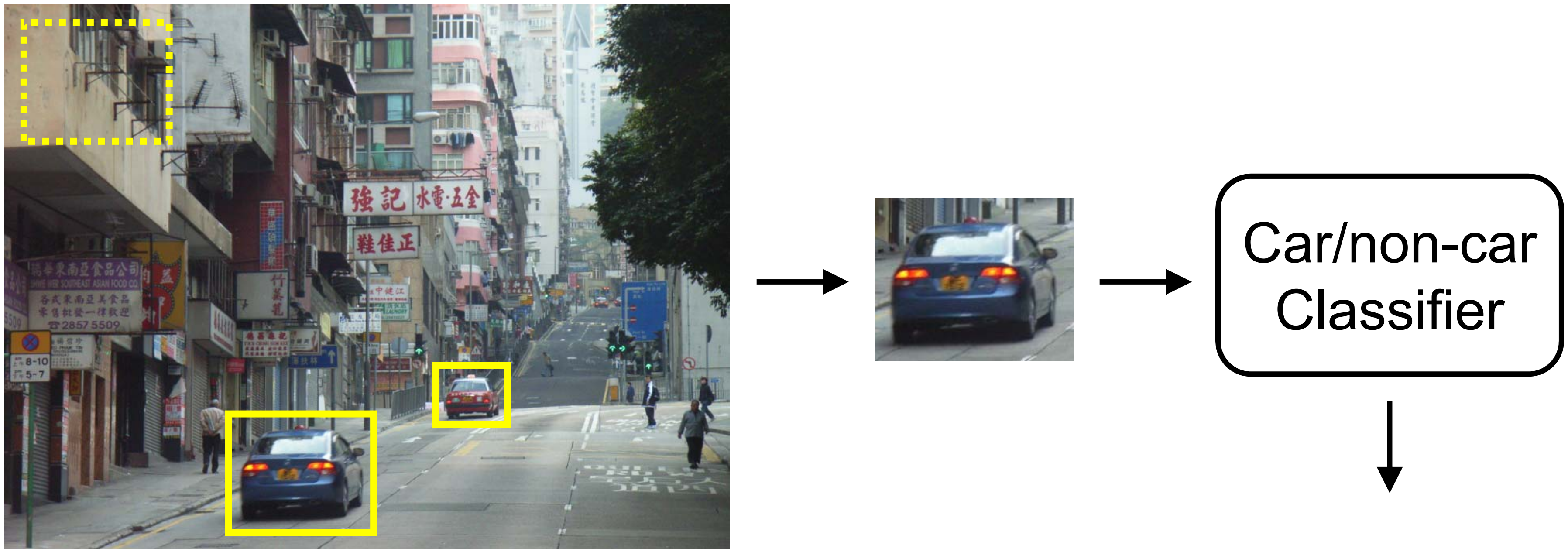
- Detect objects in clutter by <u>**search**</u>



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

Sliding window detector

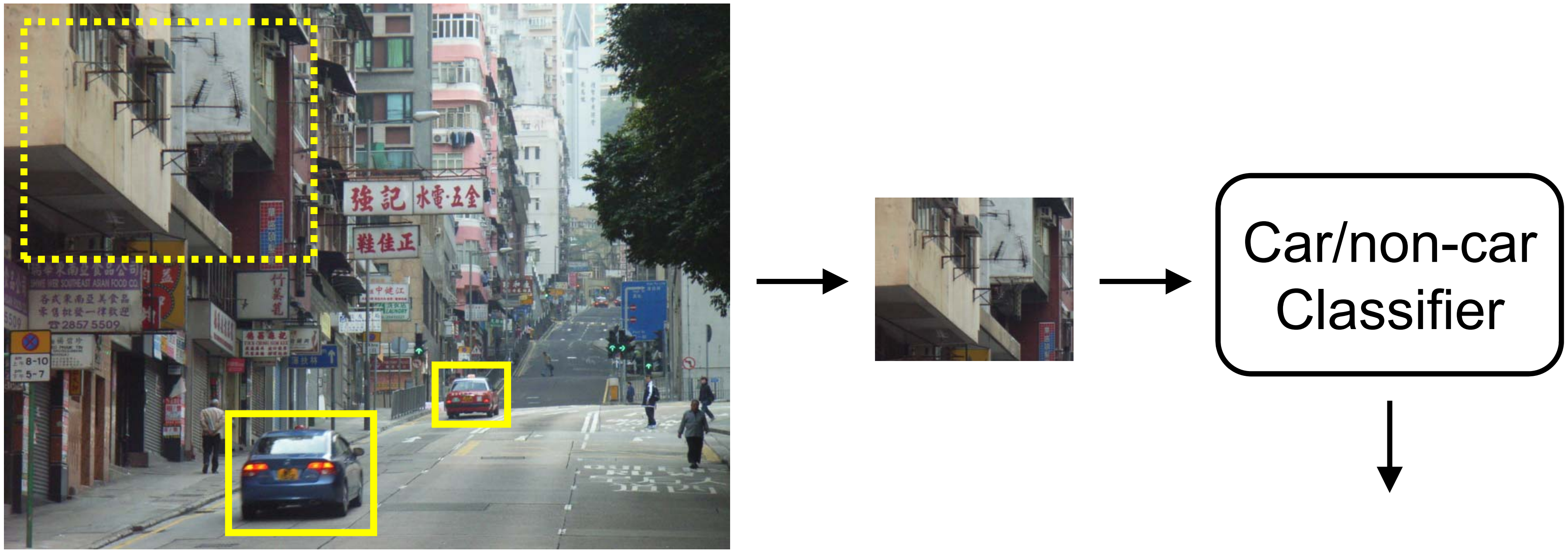
- Detect objects in clutter by <u>**search**</u>



- **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

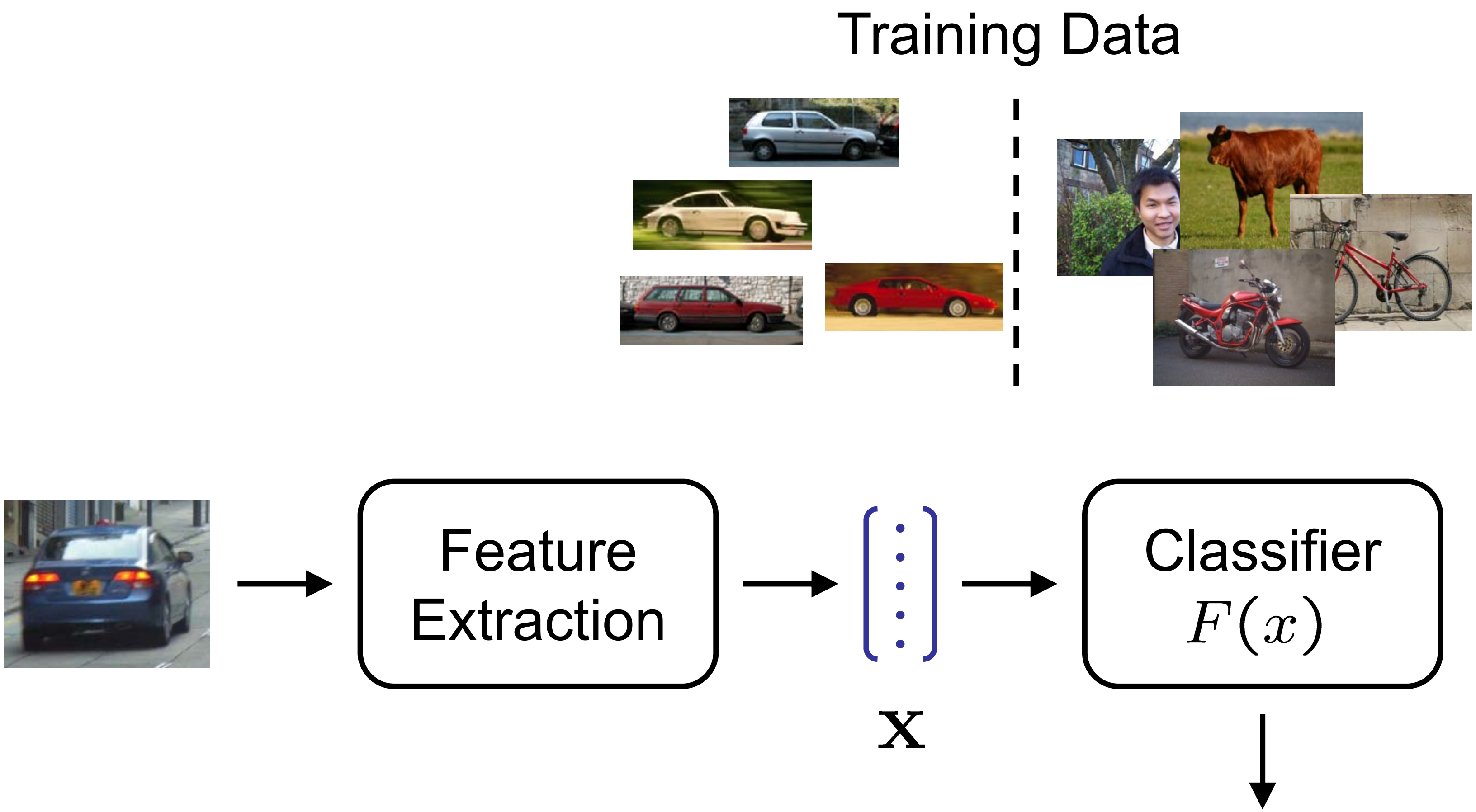
(can use same size window over a spatial pyramid of images)

Feature Extraction

Classification	Detection
	
Does the image contain a car?	Does the image contain a car?

- Classification: Unknown location + clutter) lots of invariance
- Detection: Uncluttered, normalized image) more “detail”

Window (Image) Classification



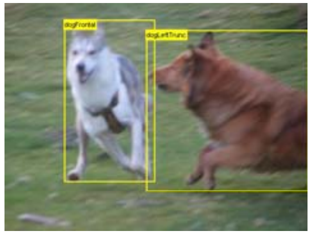
Car/Non-car

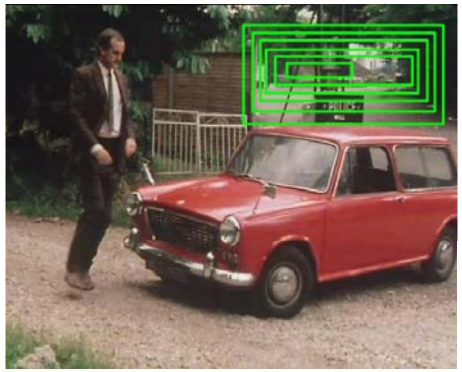
$$P(c|\mathbf{x}) \propto F(\mathbf{x})$$

- Features usually engineered
- Classifier learnt from data

Problems with sliding windows …

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





Outline

1. Sliding window detectors
2. *Features and adding spatial information*
3. Histogram of Oriented Gradients (HOG)
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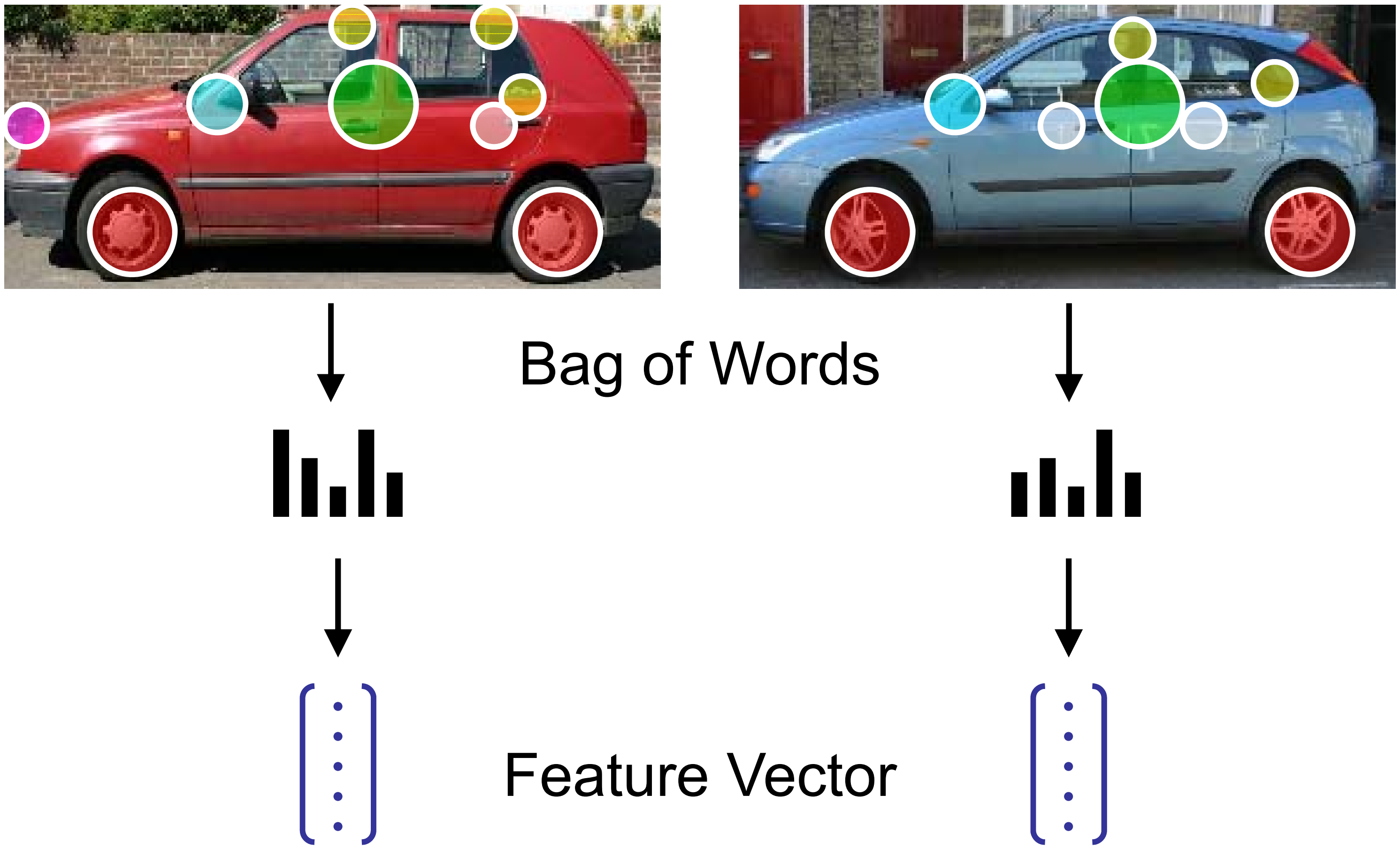
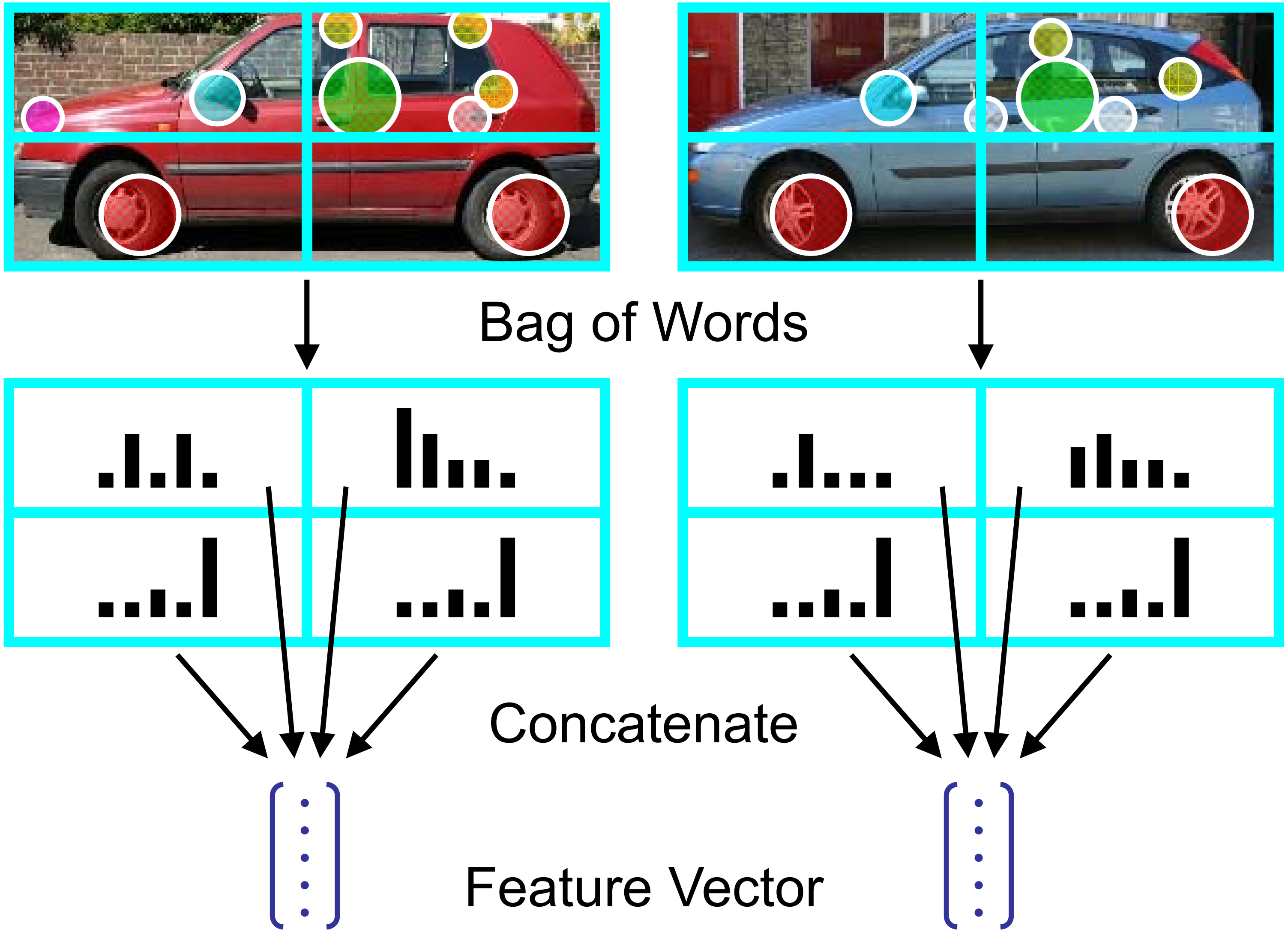
BOW + Spatial pyramids

Start from BoW for region of interest (ROI)

- no spatial information recorded
- sliding window detector

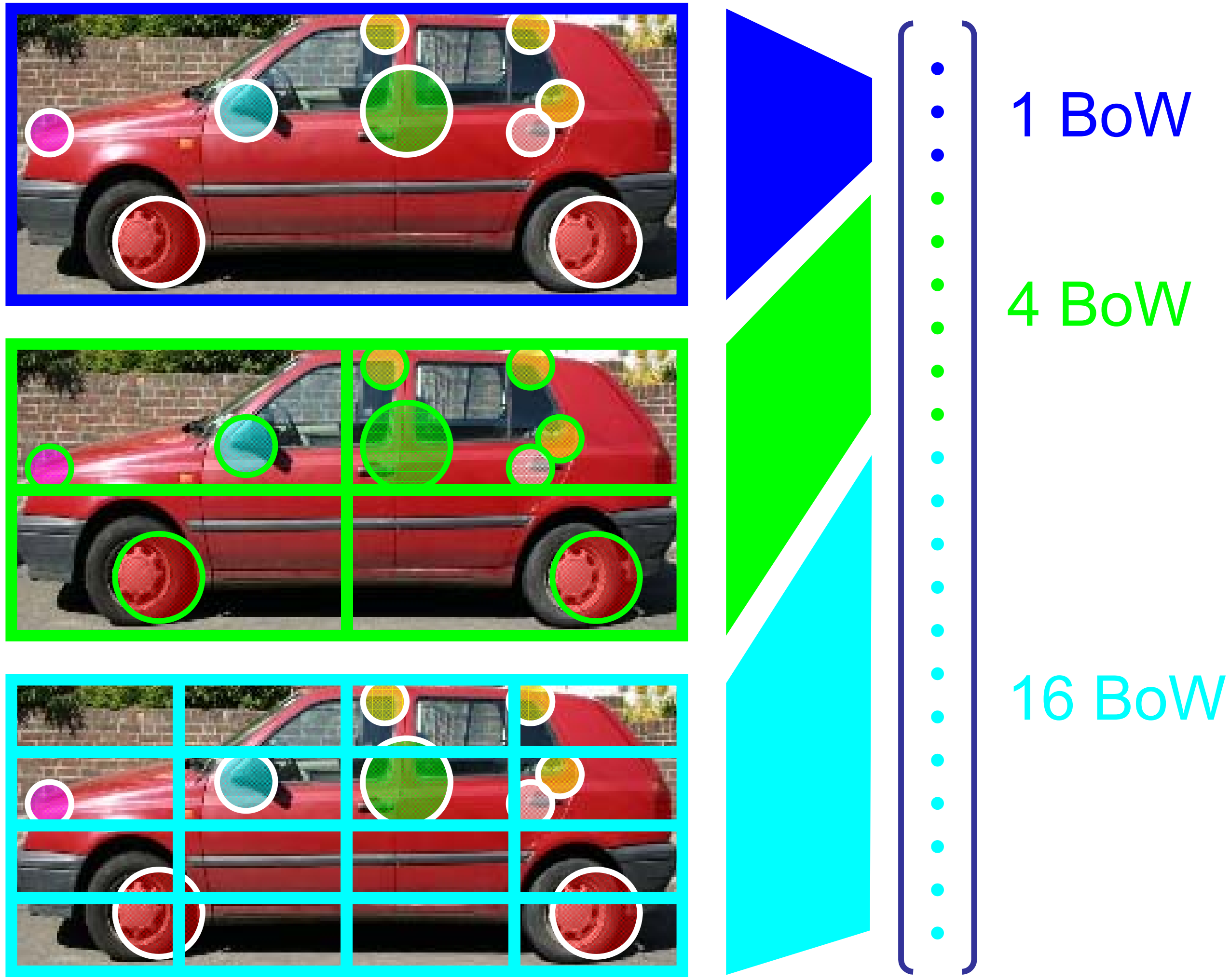


Adding Spatial Information to Bag of Words



Keeps fixed length feature vector for a window

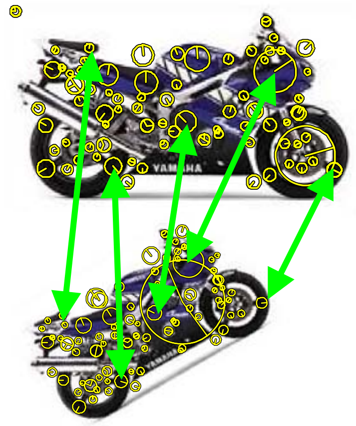
Spatial Pyramid – represent correspondence



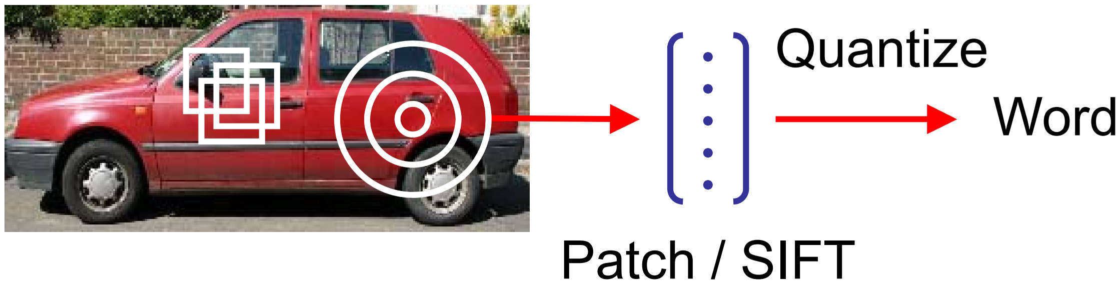
Dense Visual Words

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

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



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

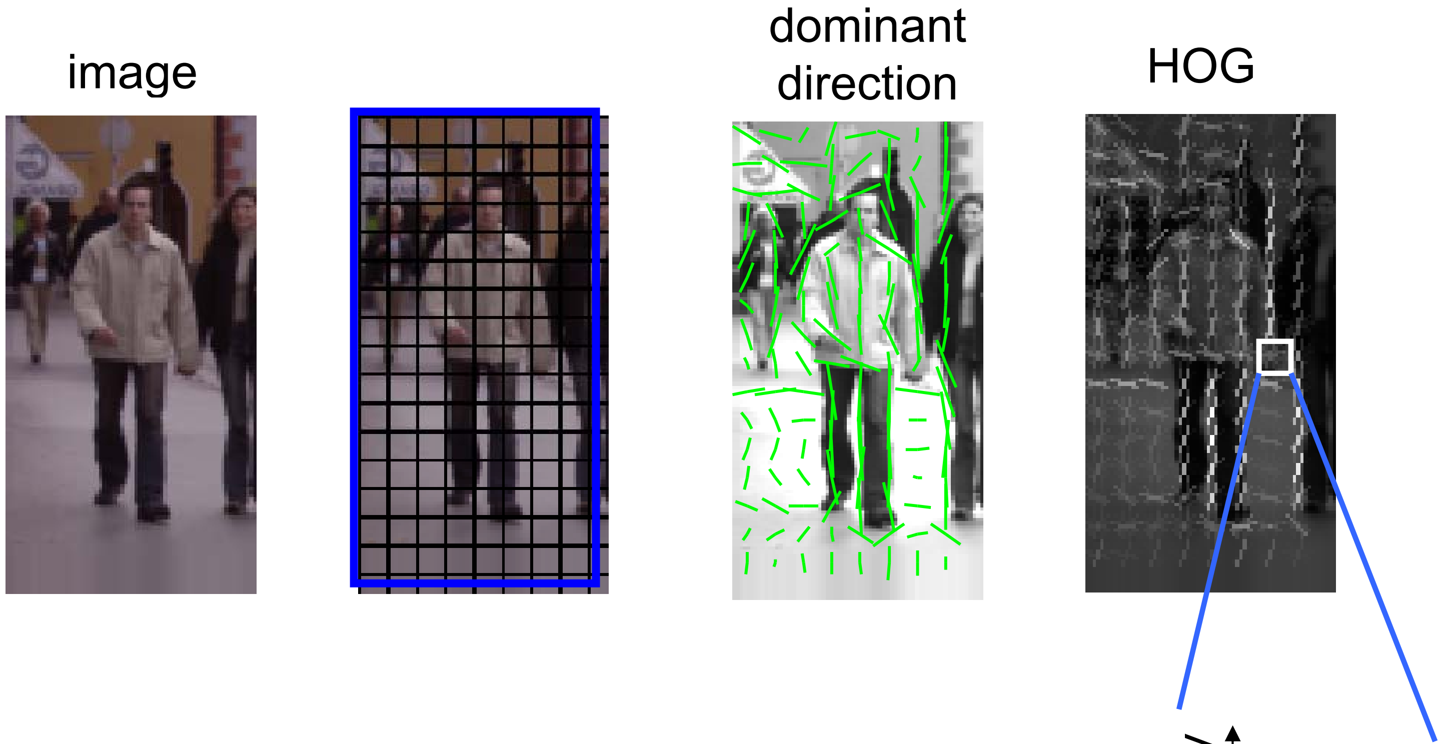


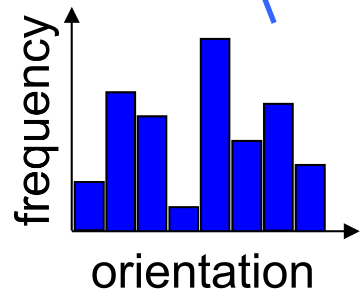
- More “detail” at the expense of invariance

Outline

1. Sliding window detectors
2. Features and adding spatial information
3. *Histogram of Oriented Gradients + linear SVM classifier*
4. State of the art algorithms and PASCAL VOC

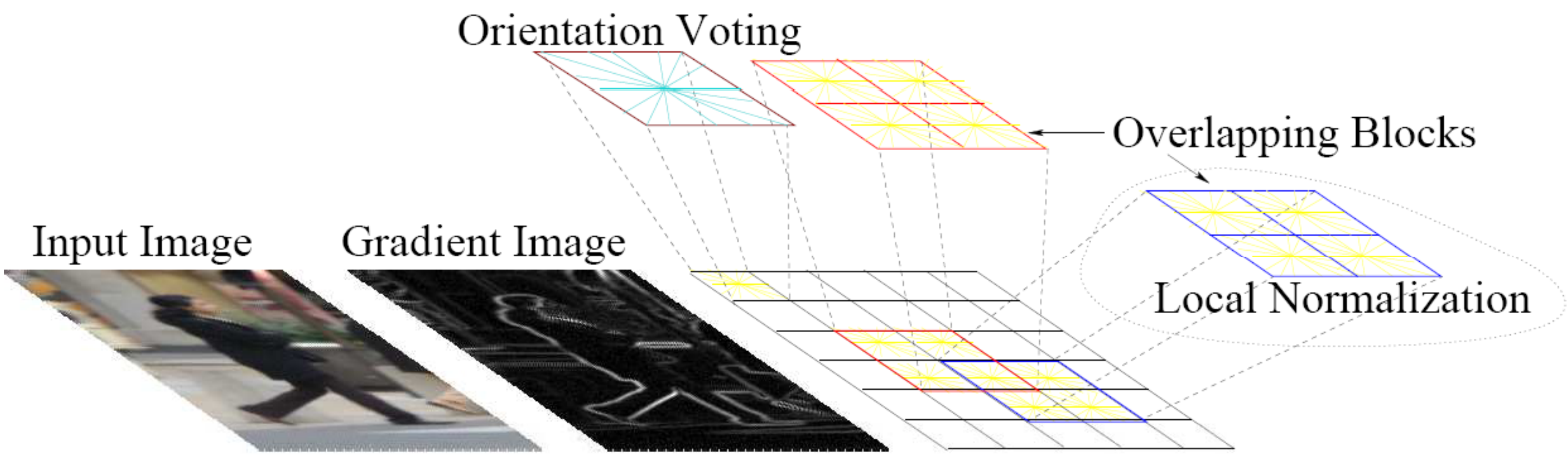
Feature: Histogram of Oriented Gradients (HOG)





- 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)

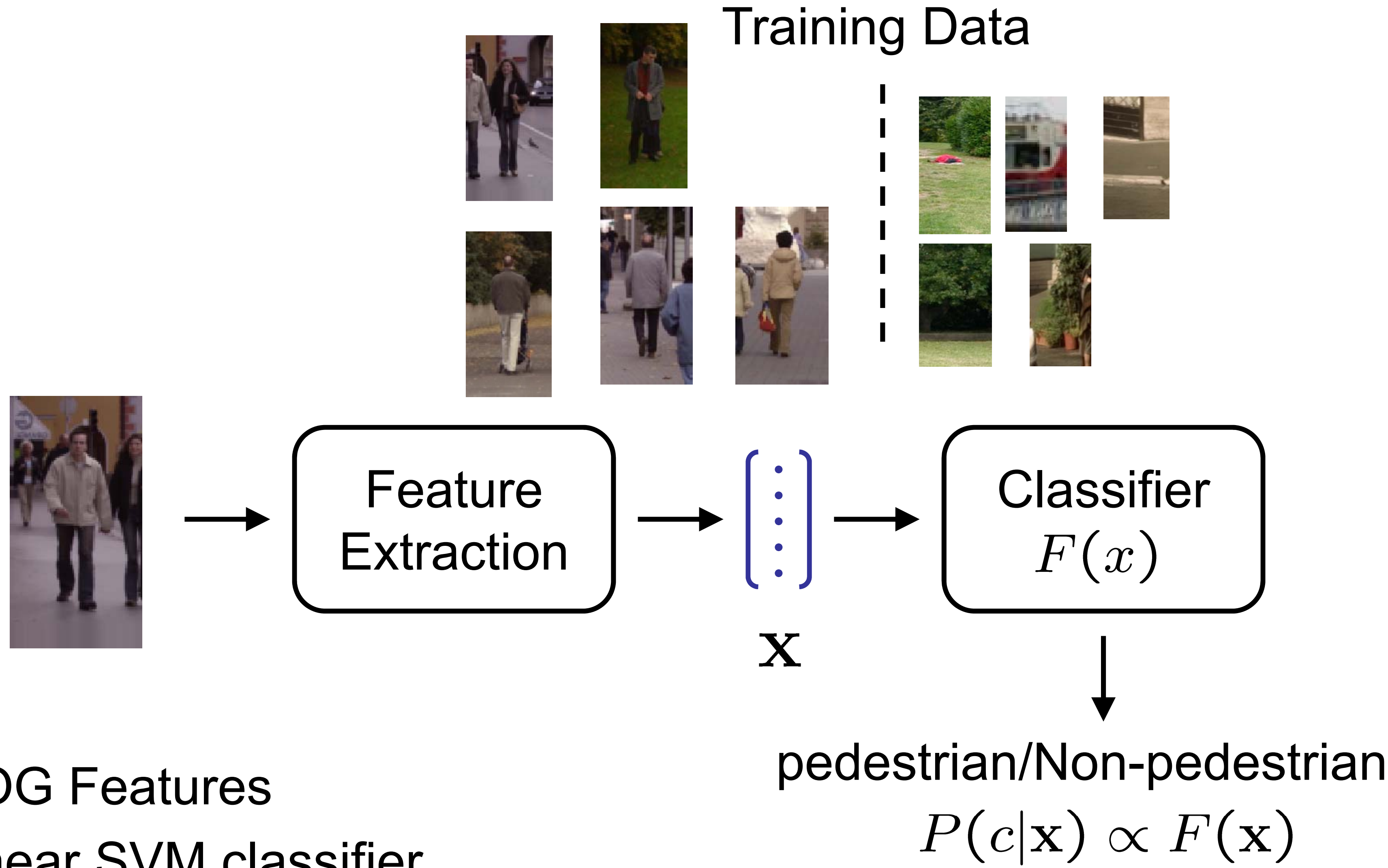
Histogram of Oriented Gradients (HOG) continued



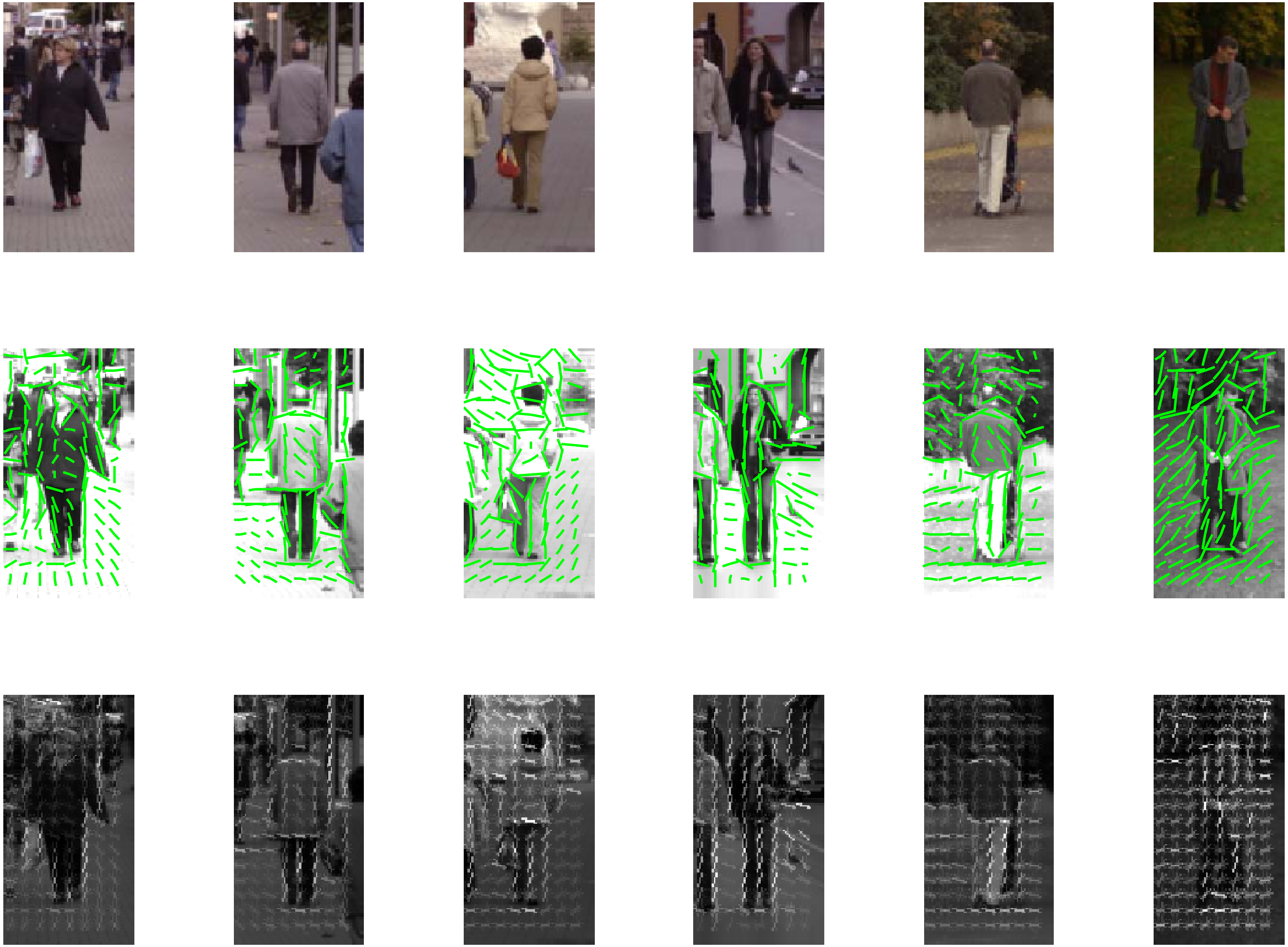
- Adds a second level of overlapping spatial bins re-normalizing orientation histograms over a larger spatial area

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

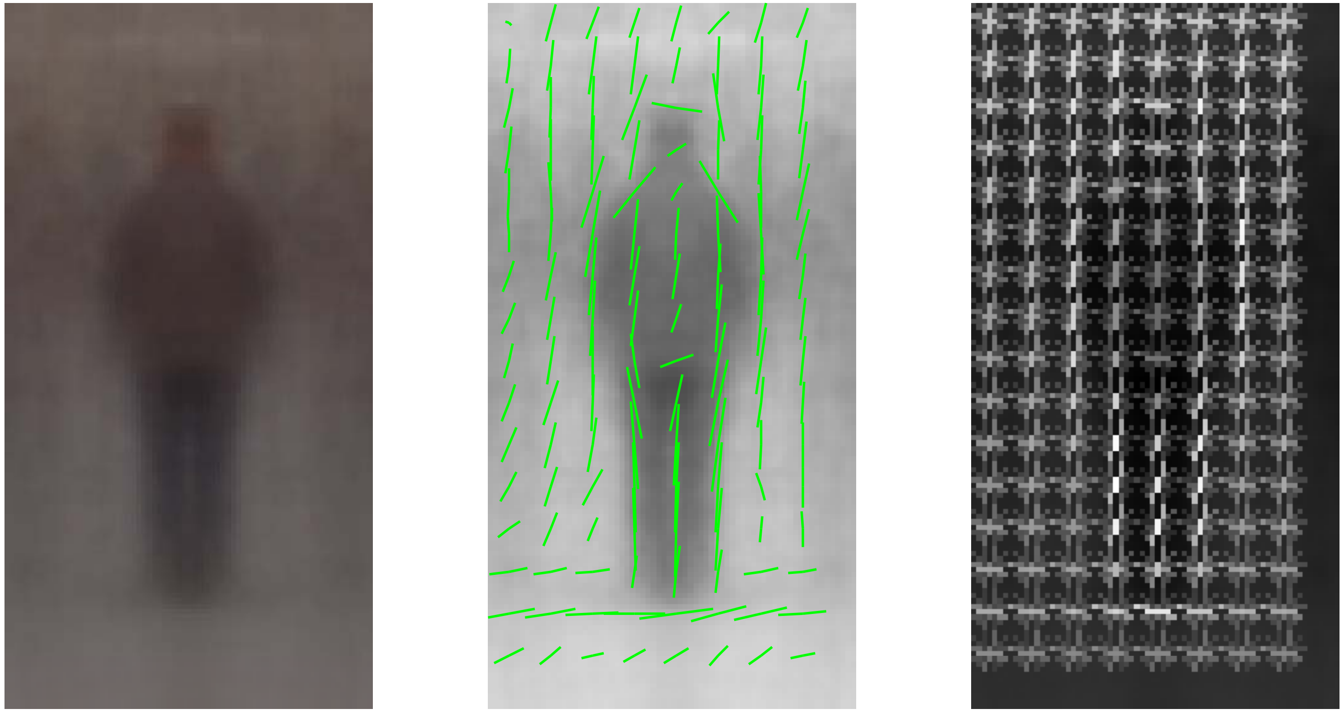
Window (Image) Classification



- HOG Features
- Linear SVM classifier



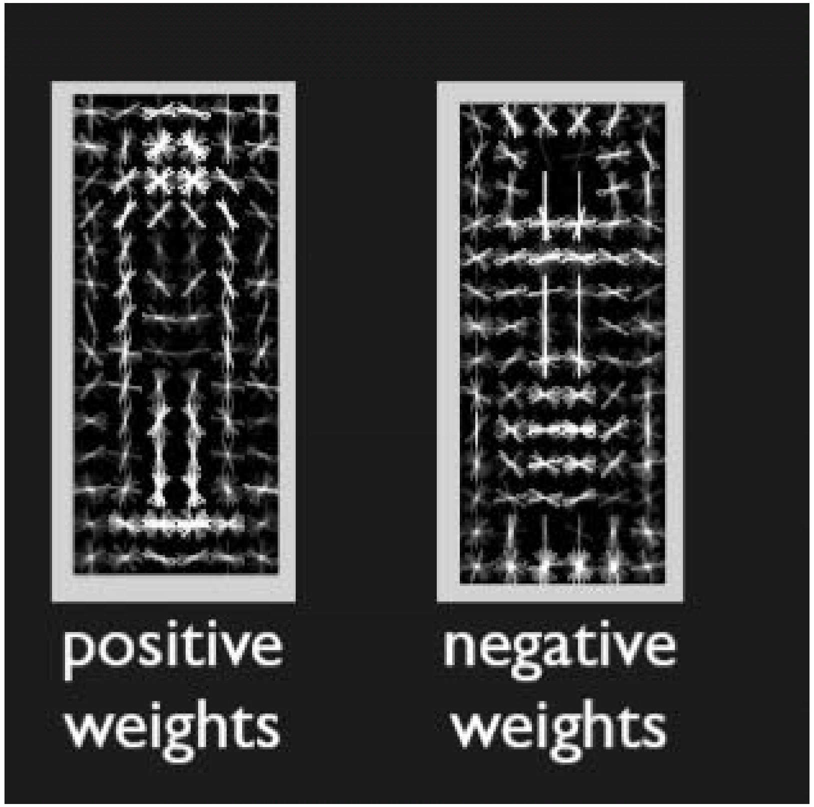
Averaged examples

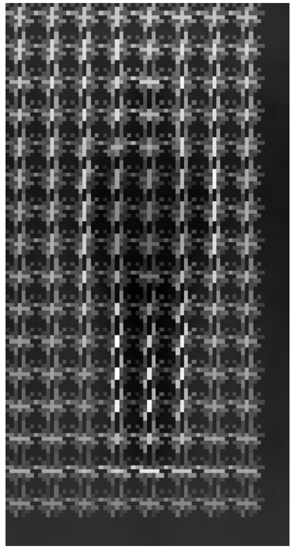


Dalal and Triggs, CVPR 2005

Learned model

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





average over positive training data

Training a sliding window detector

- Unlike training an image classifier, there are a (virtually) infinite number of possible negative windows
- Training (learning) generally proceeds in three distinct stages:

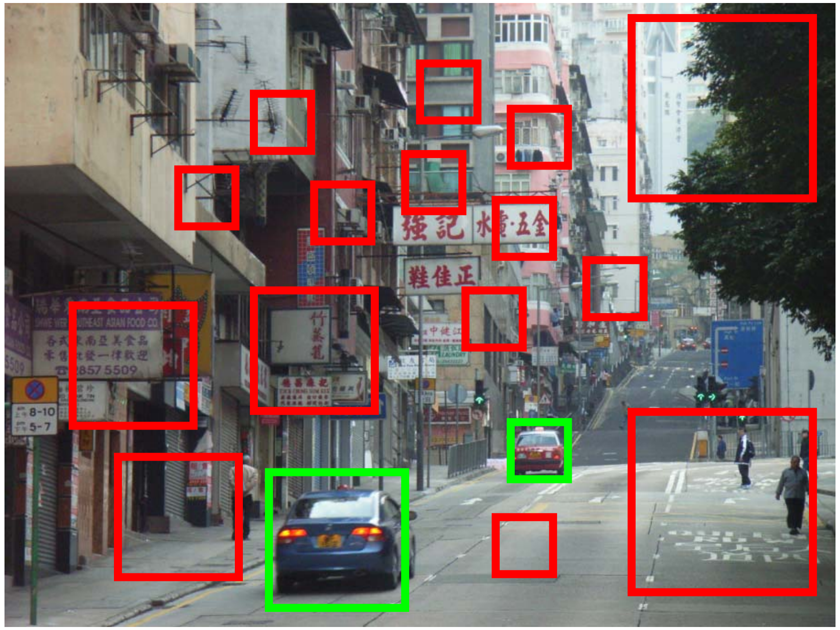
  1. Bootstrapping: learn an initial window classifier from positives and random negatives

  2. Hard negatives: use the initial window classifier for detection on the training images (inference) and identify false positives with a high score

  3. Retraining: use the hard negatives as additional training data

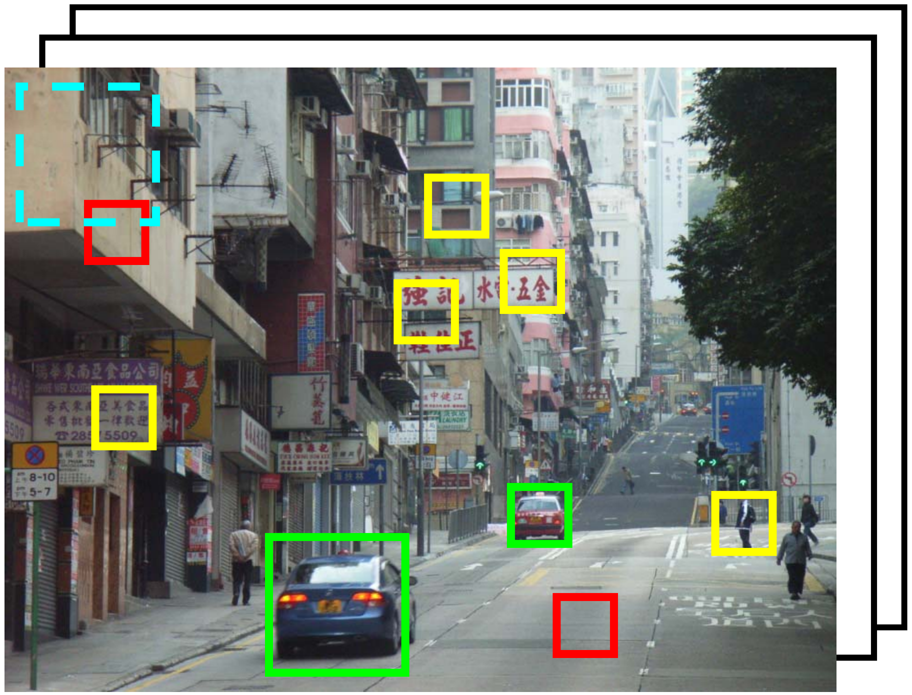
Training a sliding window detector

- 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

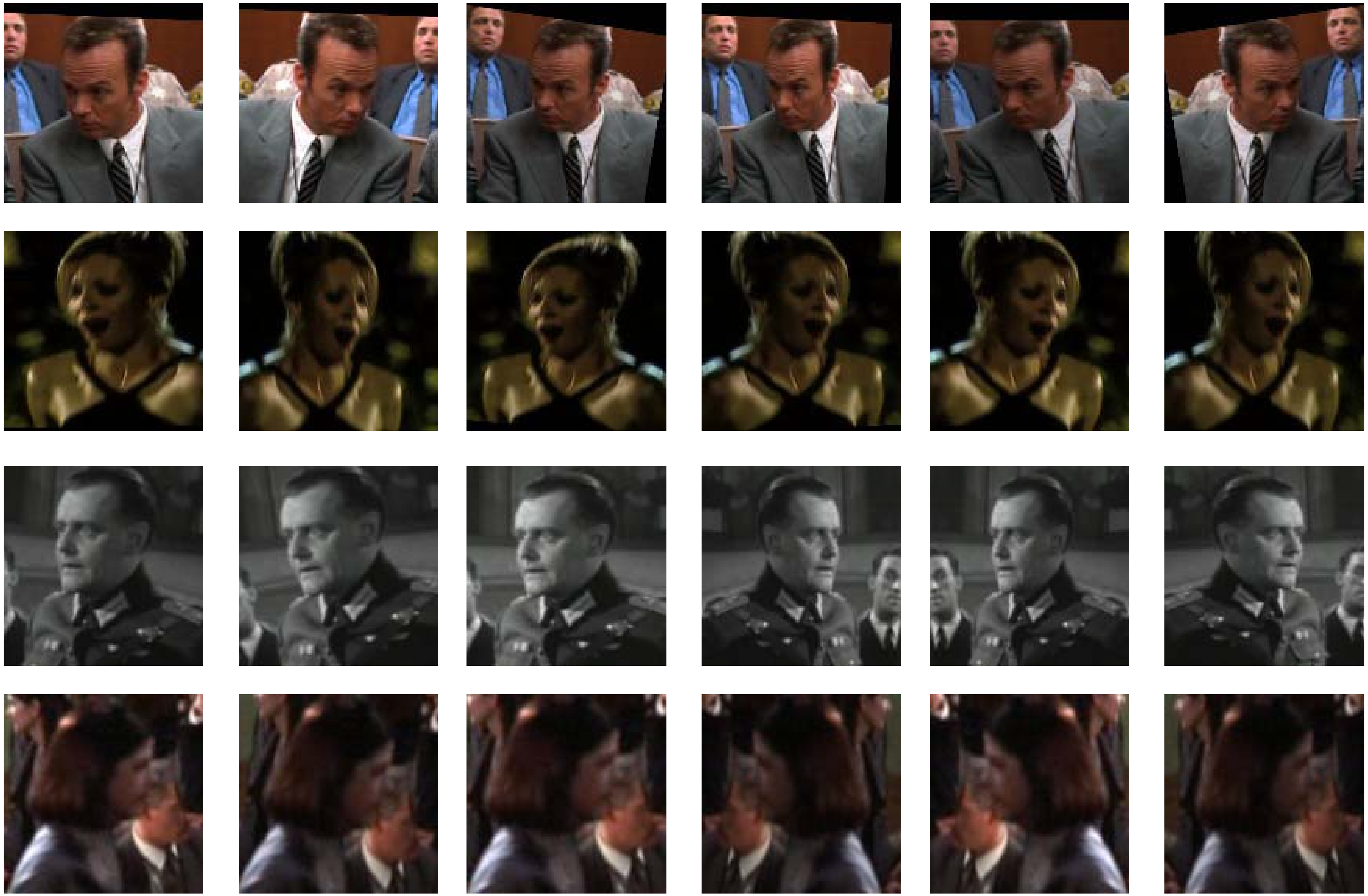
- Second stage training (retraining)
  - 150k hard negatives found in the training data

Training data – positive annotations

Positive windows

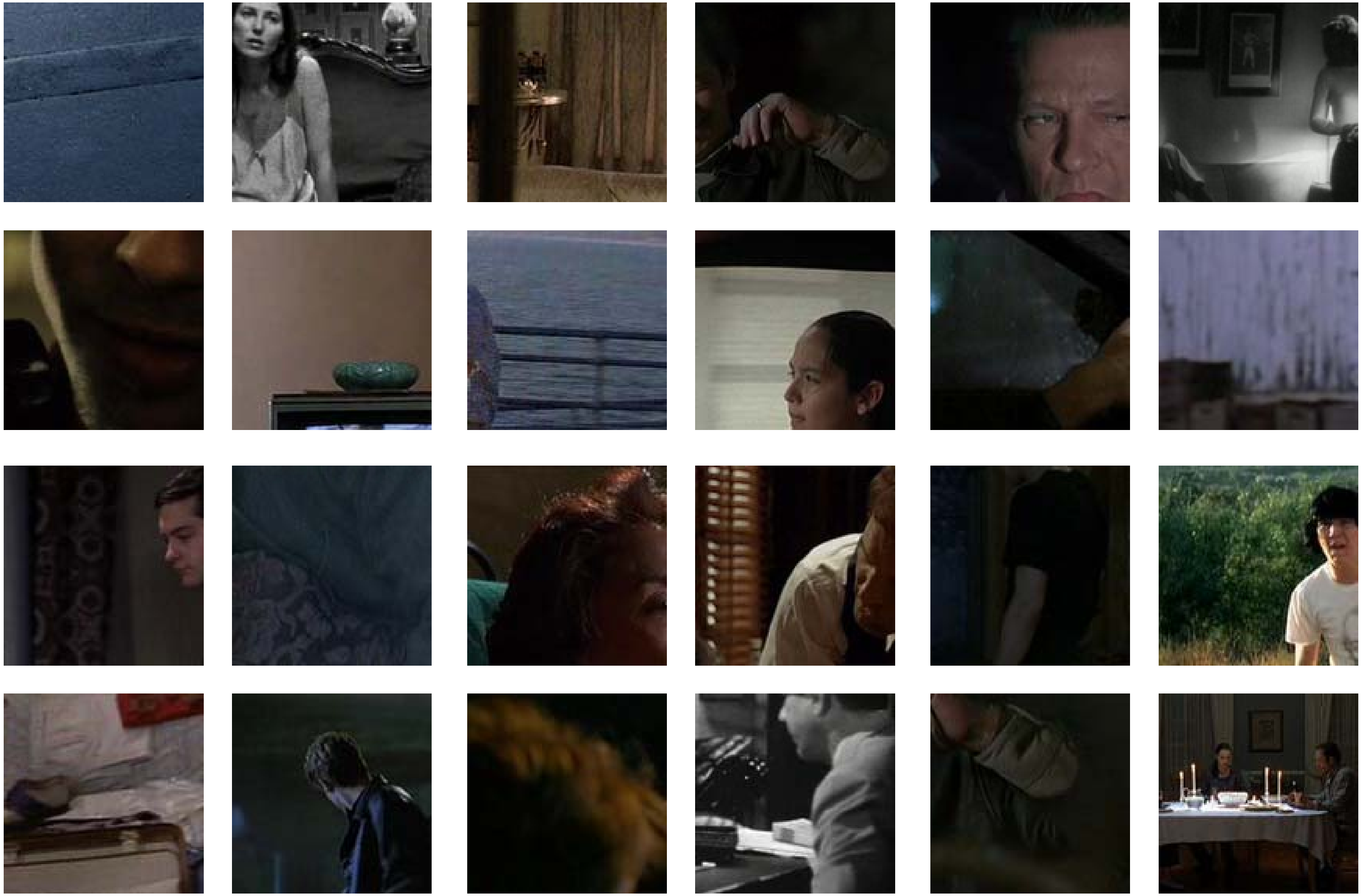
Note: common size and alignment

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

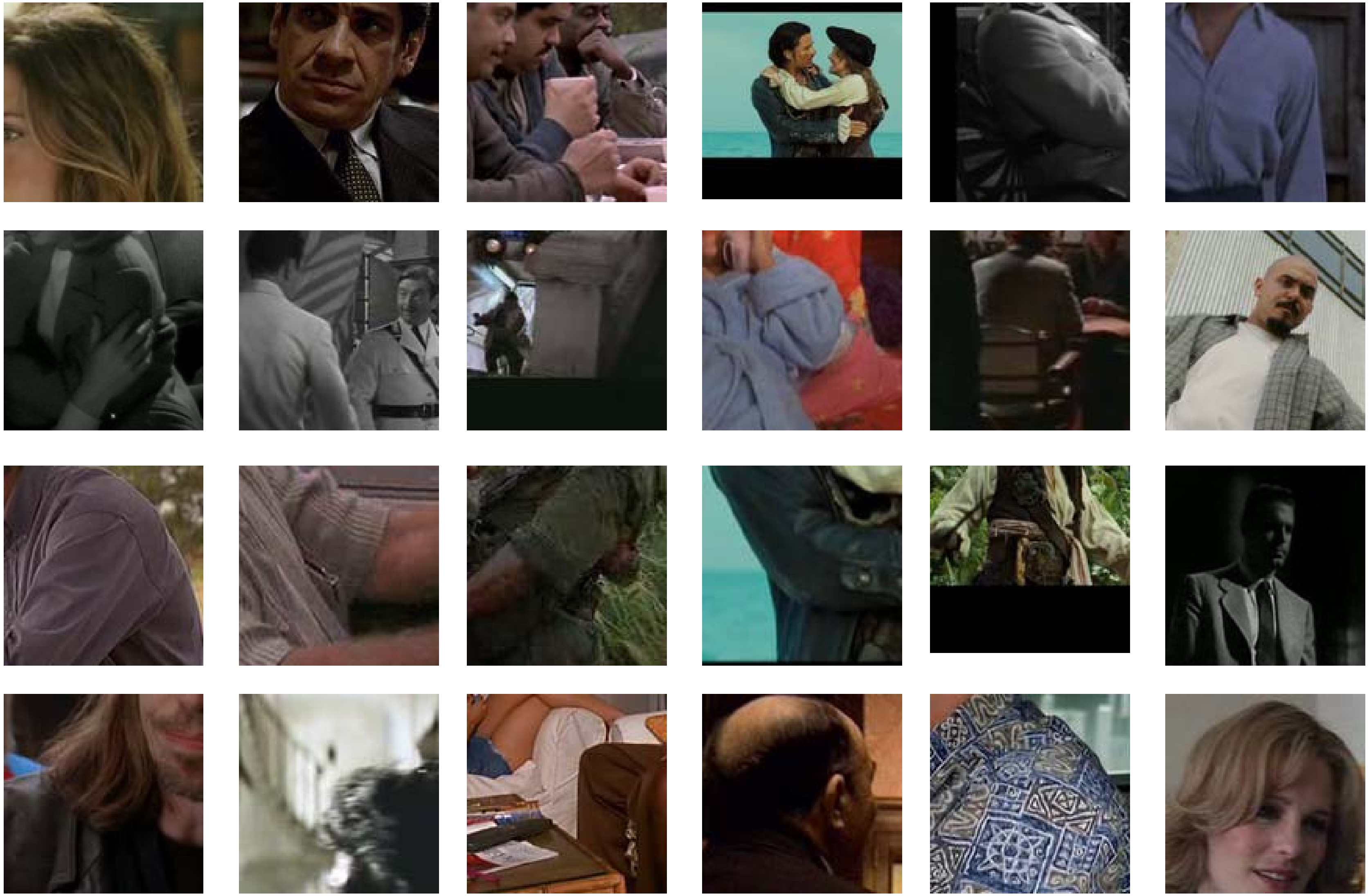
$f(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b$

- find high scoring false positives detections

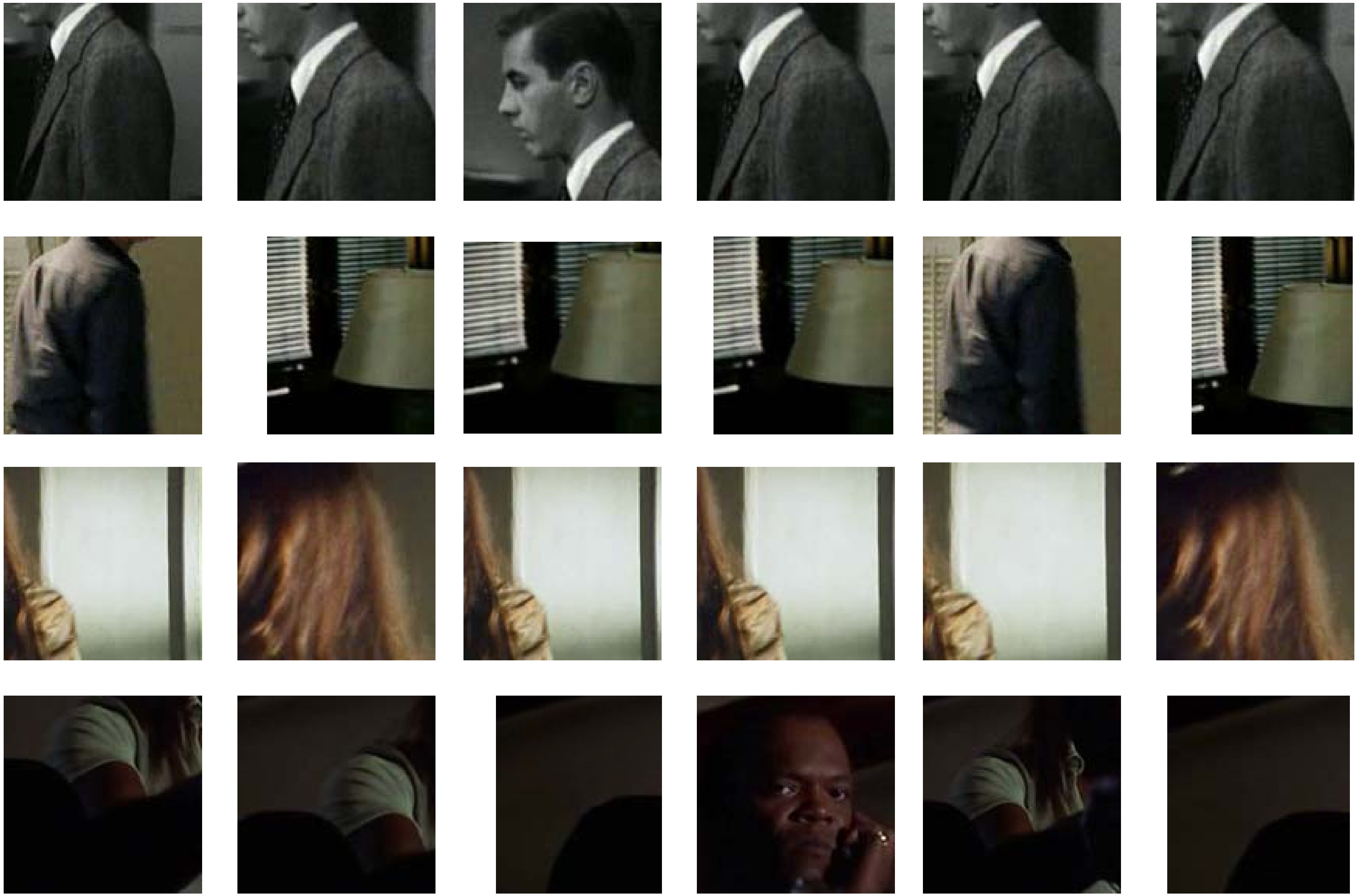
- these are the hard negatives for the next round of training

- cost = # training images x inference on each image

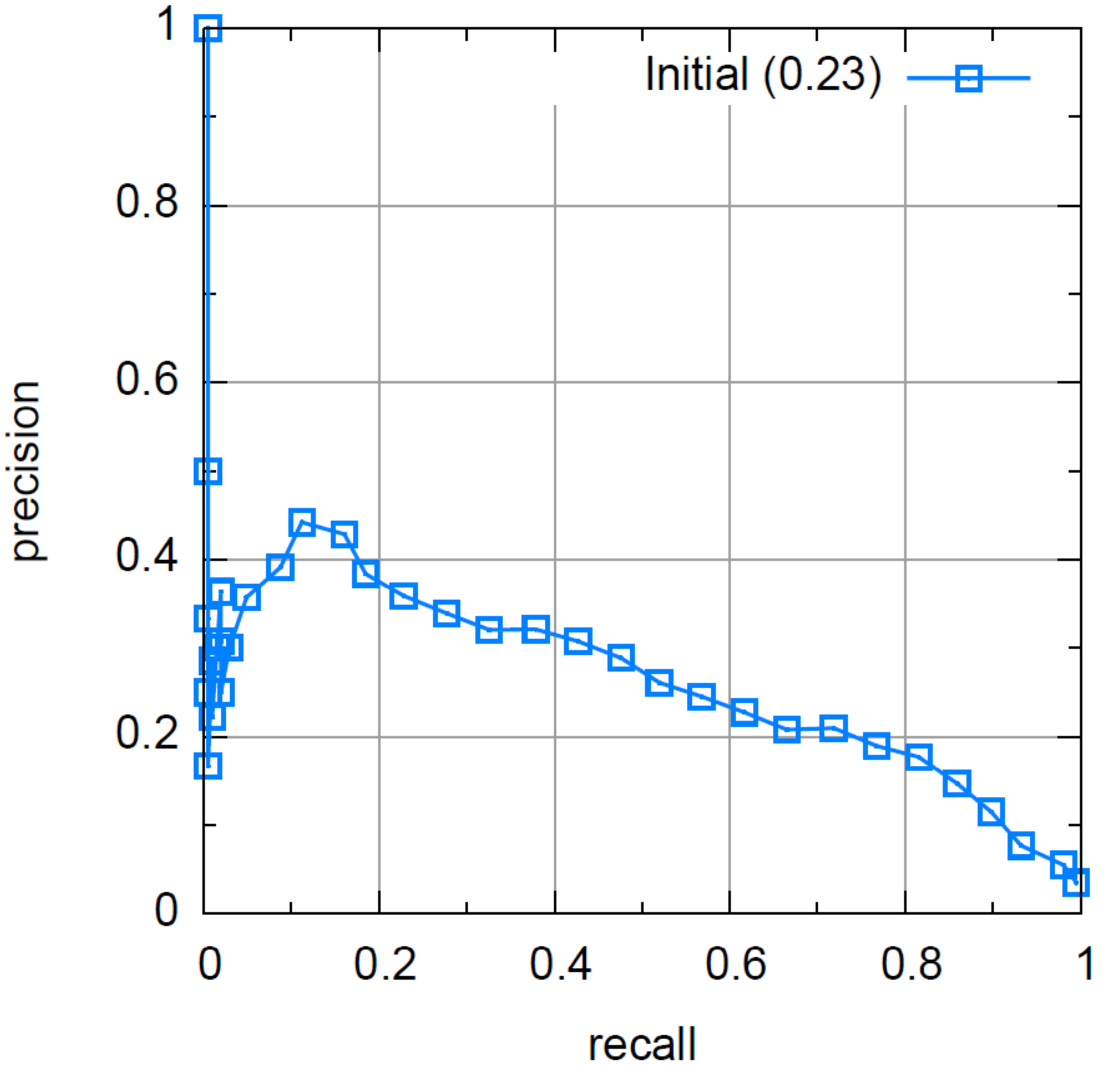
Hard negatives



Hard negatives

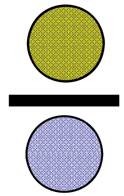


First stage performance on validation set

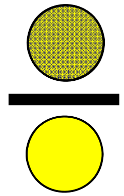


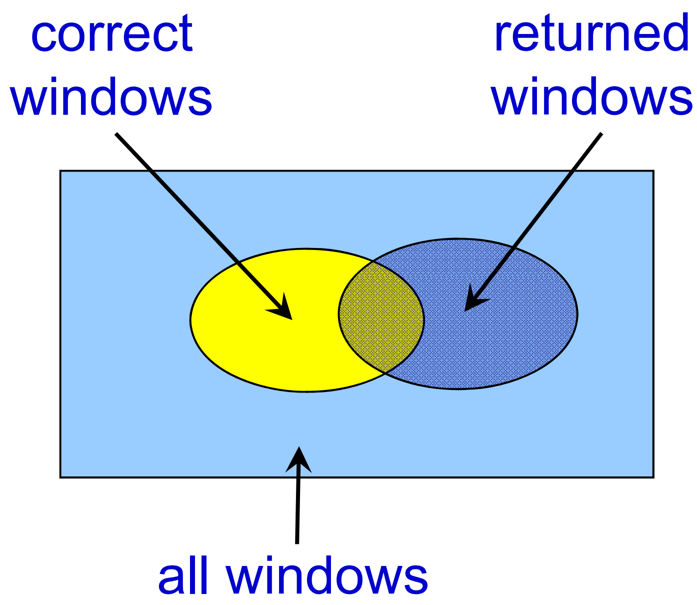
Precision – Recall curve

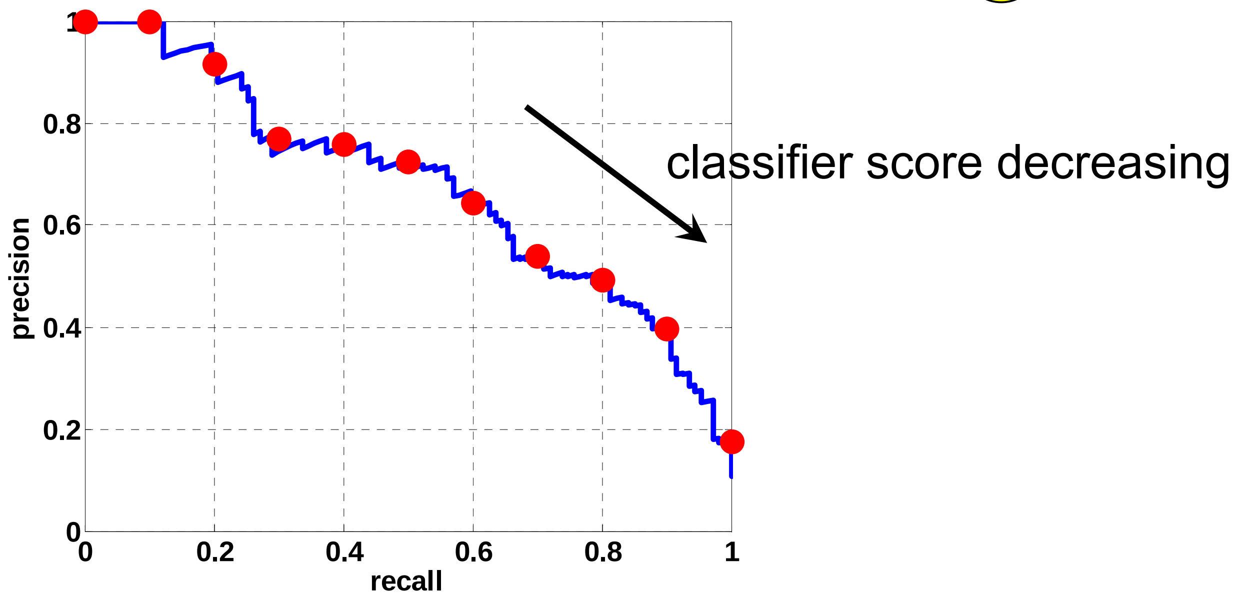
- Precision: % of returned windows that are correct



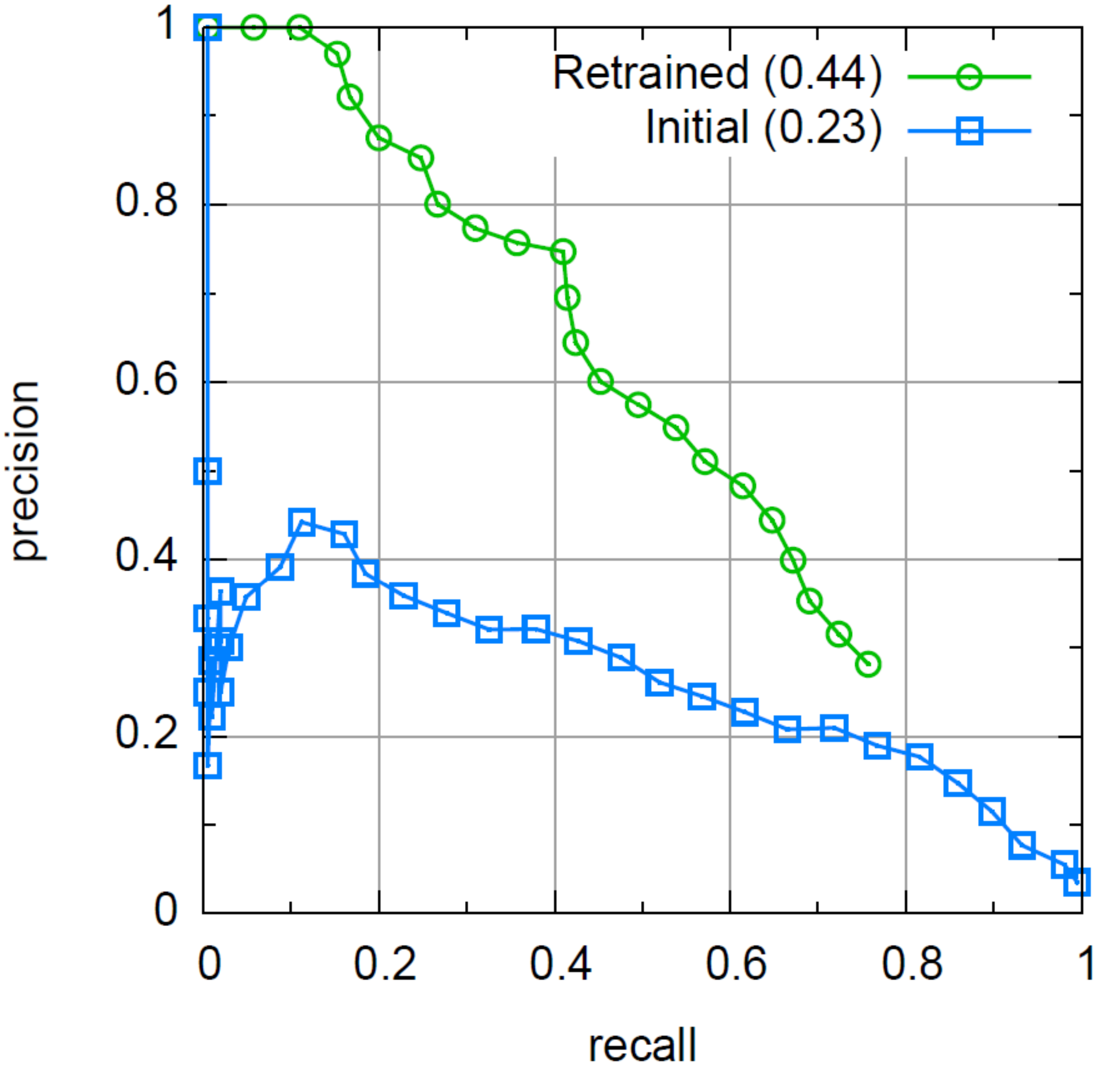
- Recall: % of correct windows that are returned







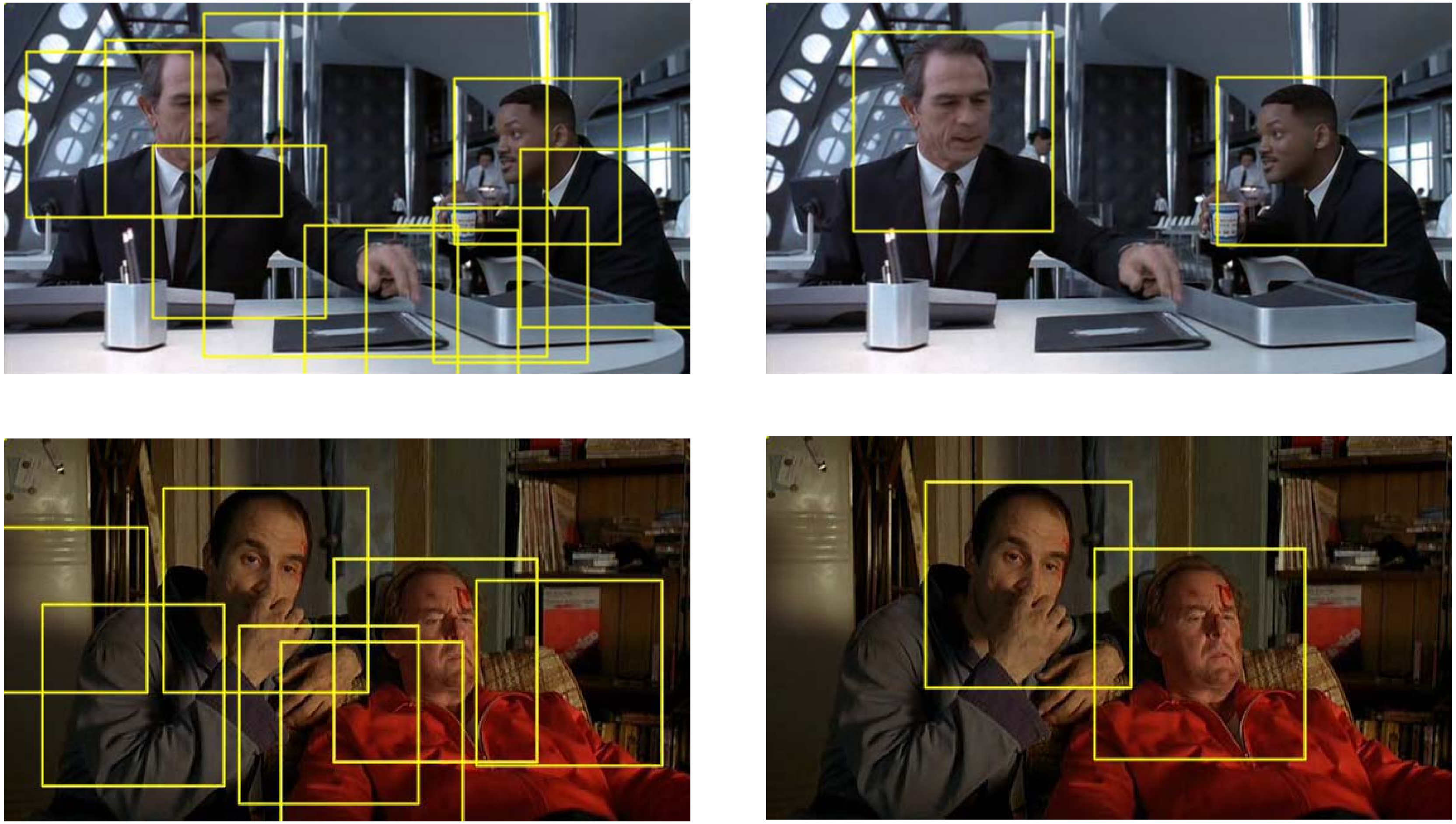
Effects of retraining



Side by side

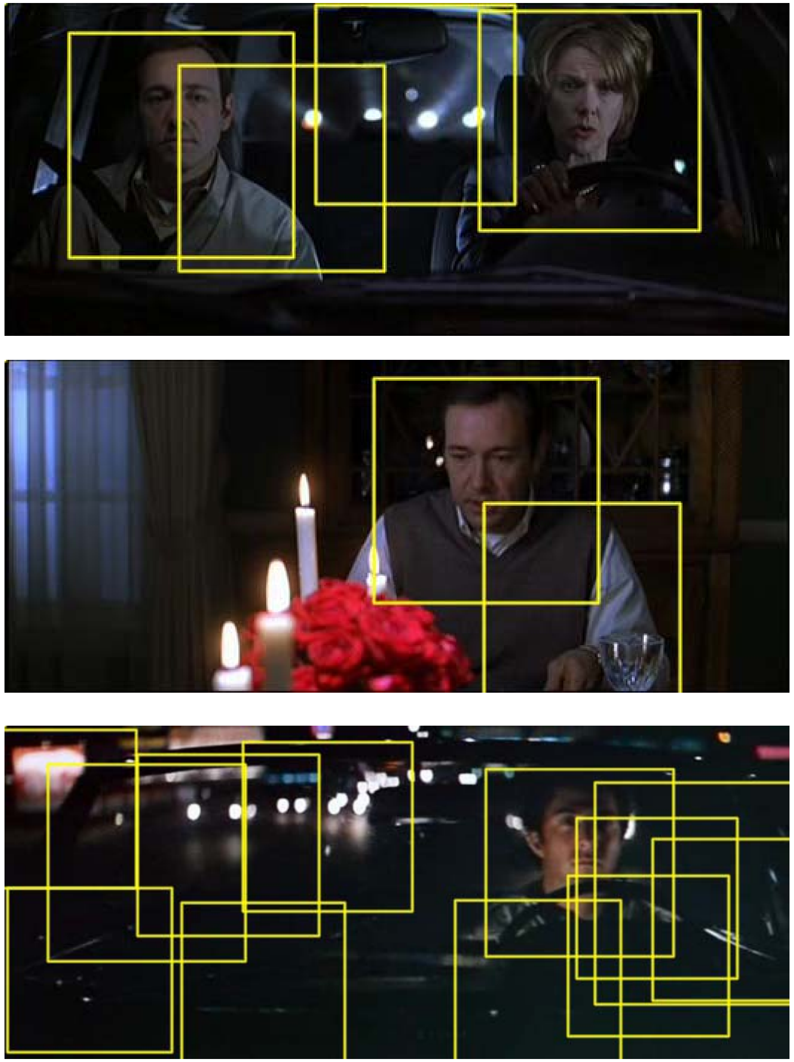
before retraining

after retraining

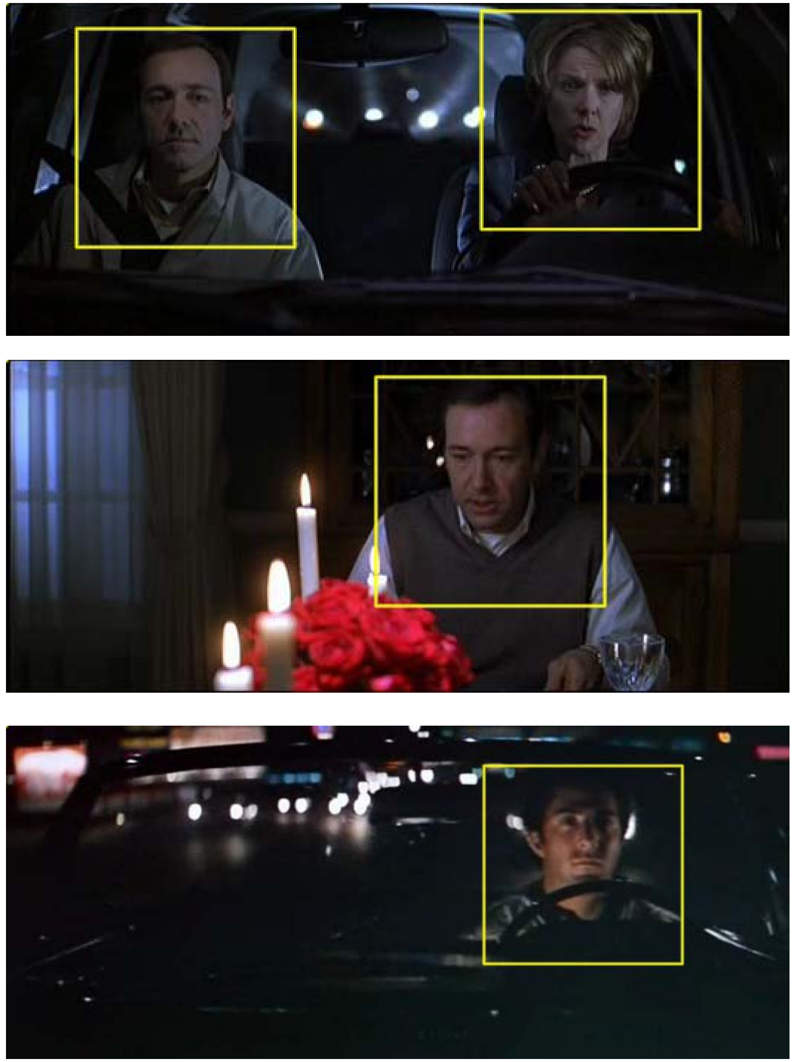


Side by side

before retraining

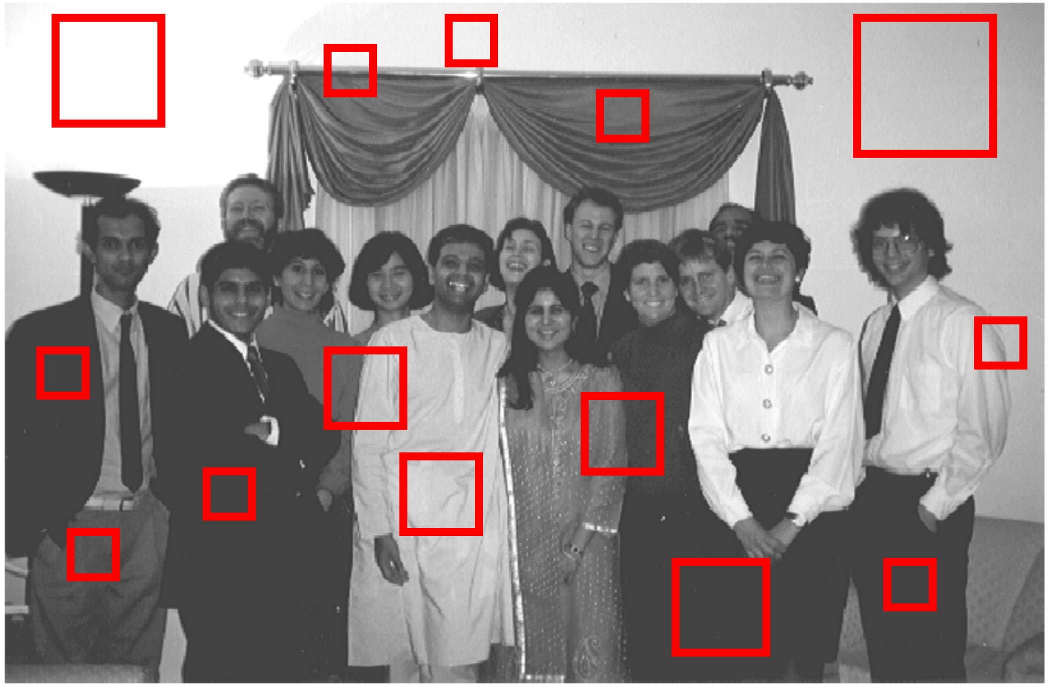


after retraining



Accelerating Sliding Window Search

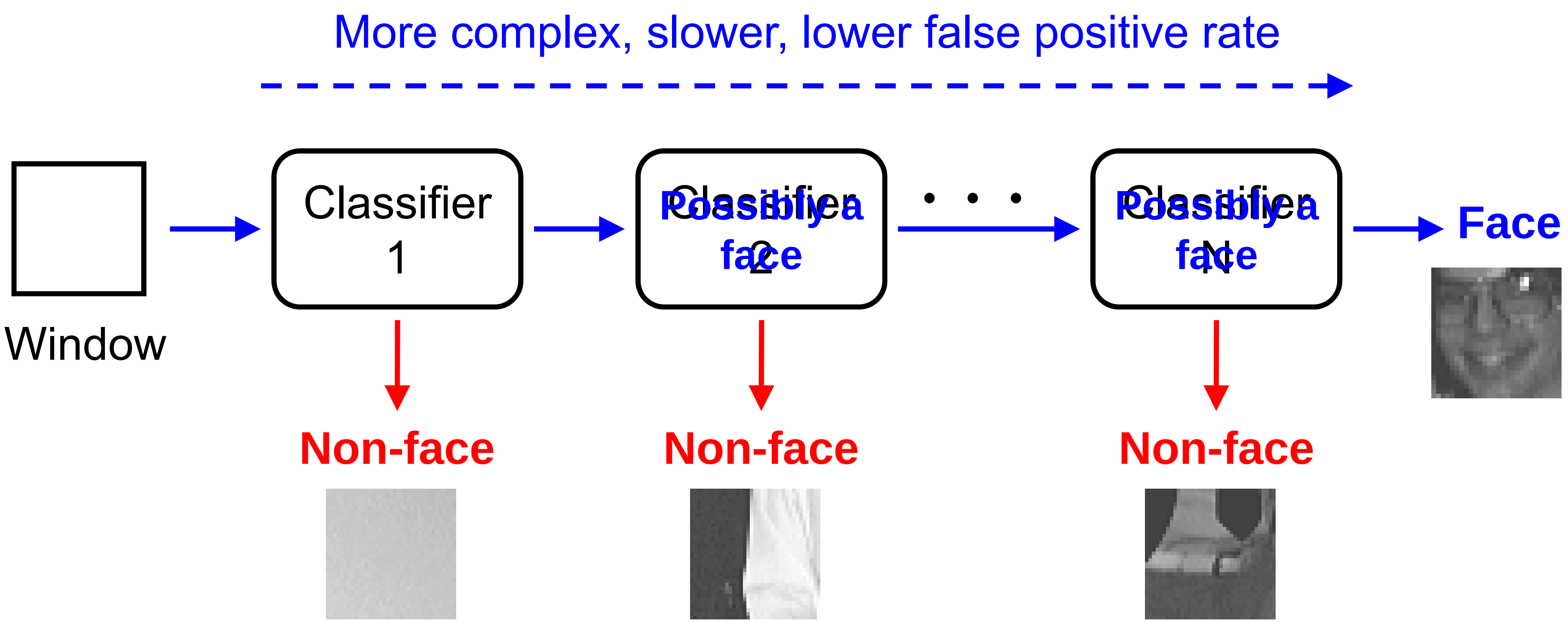
- Sliding window search is slow because so many windows are needed e.g. x × y × scale ≈ 100,000 for a 320×240 image



- 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 ➔ significant speed-up

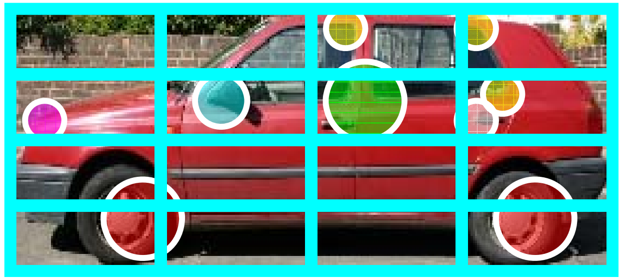
- Controlling classifier complexity/speed:
  - Number of support vectors [Romdhani et al, 2001]
  - Number of features [Viola & Jones, 2001]
  - Two-layer approach [Harzallah et al, 2009]

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



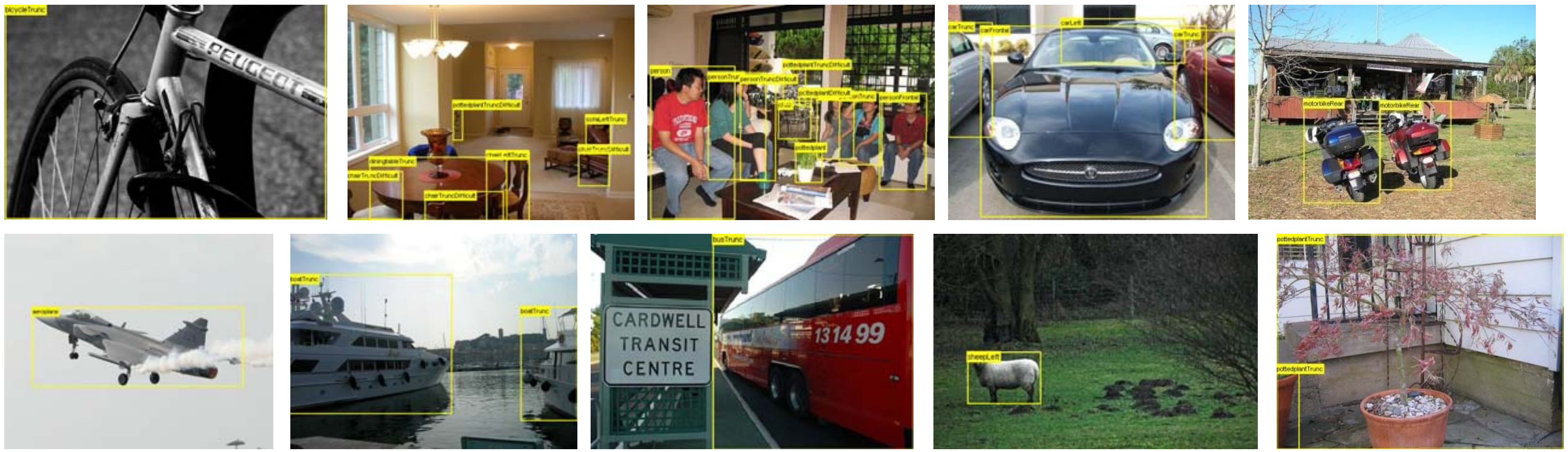
Outline

1. Sliding window detectors
2. Features and adding spatial information
3. HOG + linear SVM classifier
4. *State of the art algorithms and PASCAL VOC*

PASCAL VOC 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”



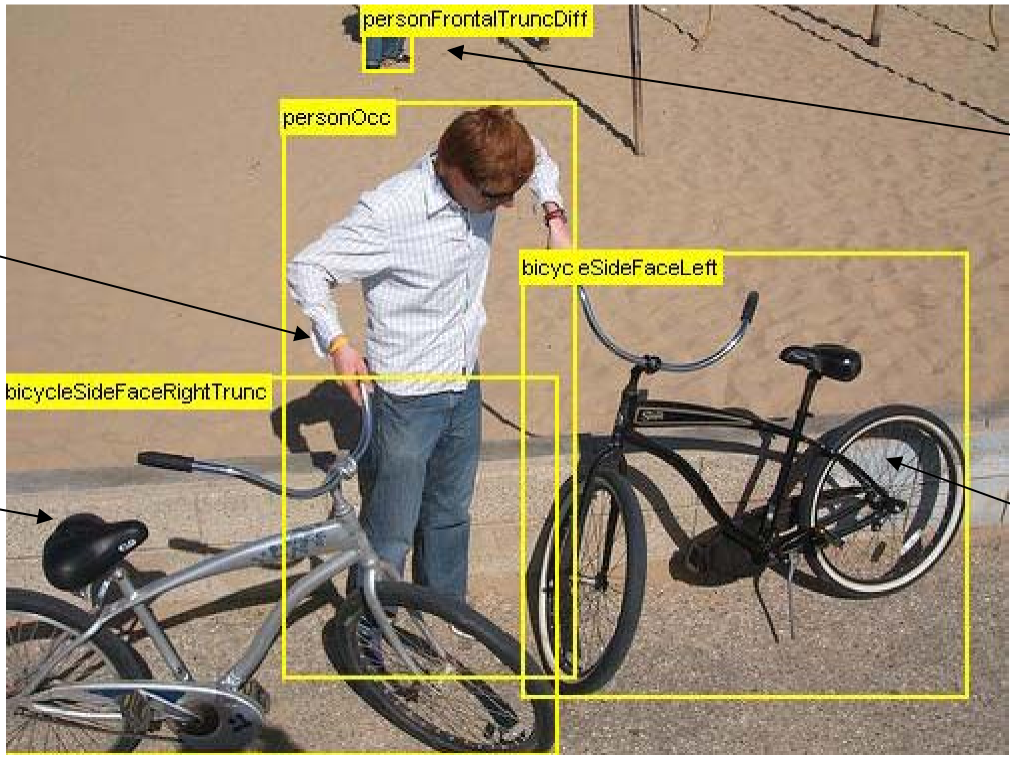
- Complex scenes, scale, pose, lighting, occlusion, ...

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

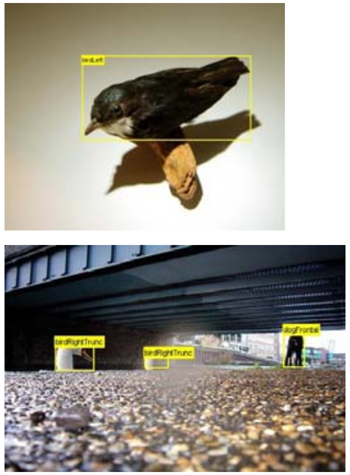
Pose
Facing left

Examples

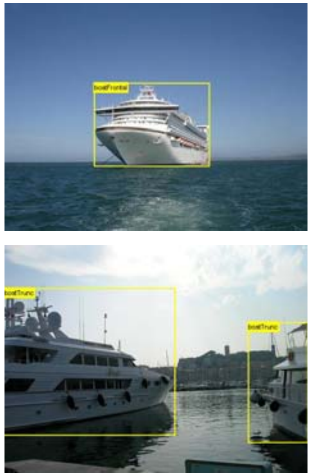
Aeroplane

Bicycle

Bird



Boat

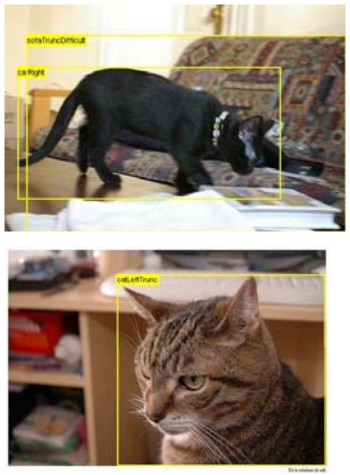


Bottle

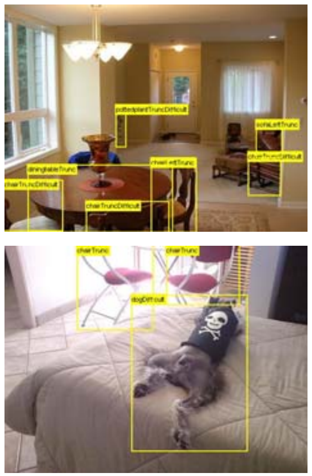
Bus

Car

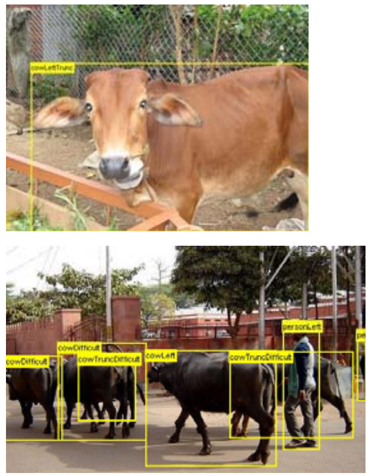
Cat



Chair



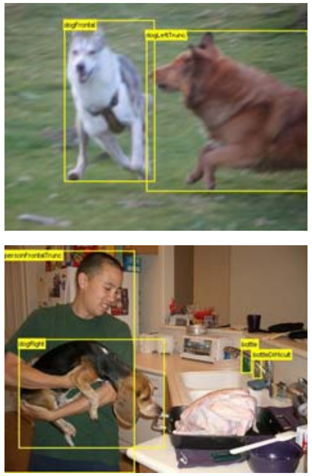
Cow



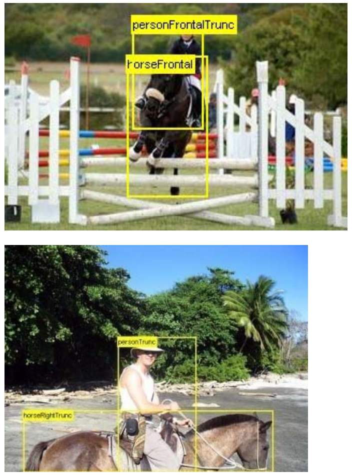
Examples

Dining Table

Dog



Horse

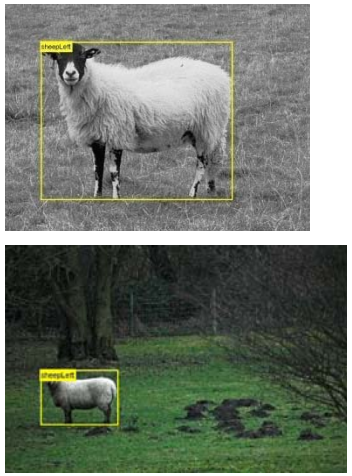


Motorbike

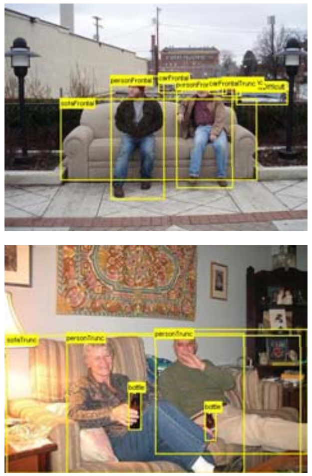
Person

Potted Plant

Sheep



Sofa



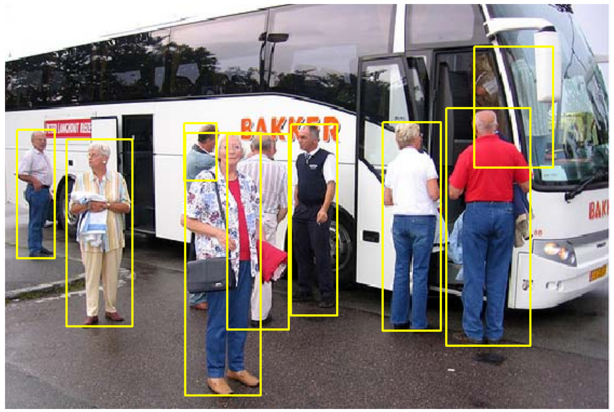
Train

TV/Monitor

Main Challenge Tasks

- **Classification**
  - Is there a dog in this image?
  - Evaluation by precision/recall

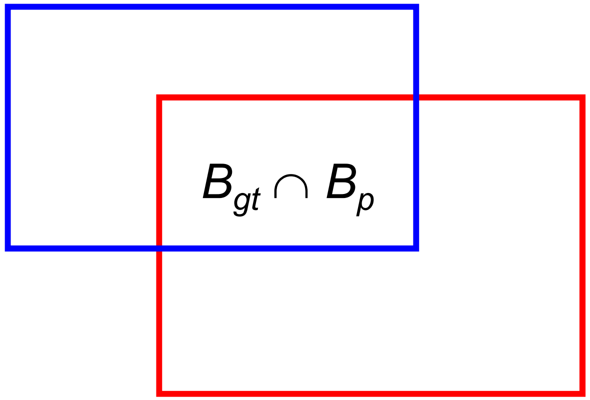
- **Detection**
  - Localize all the people (if any) in this image
  - Evaluation by precision/recall based on bounding box overlap



Detection: Evaluation of Bounding Boxes

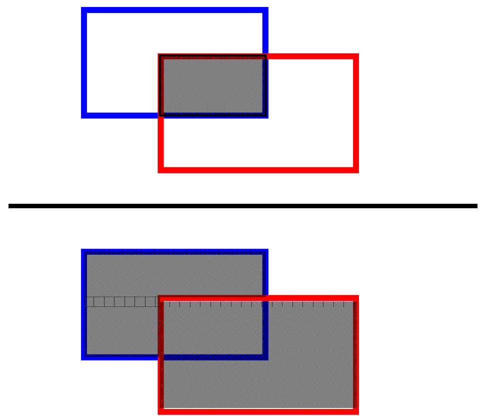
- Area of Overlap (AO) Measure

Ground truth B_{gt}



Predicted B_p

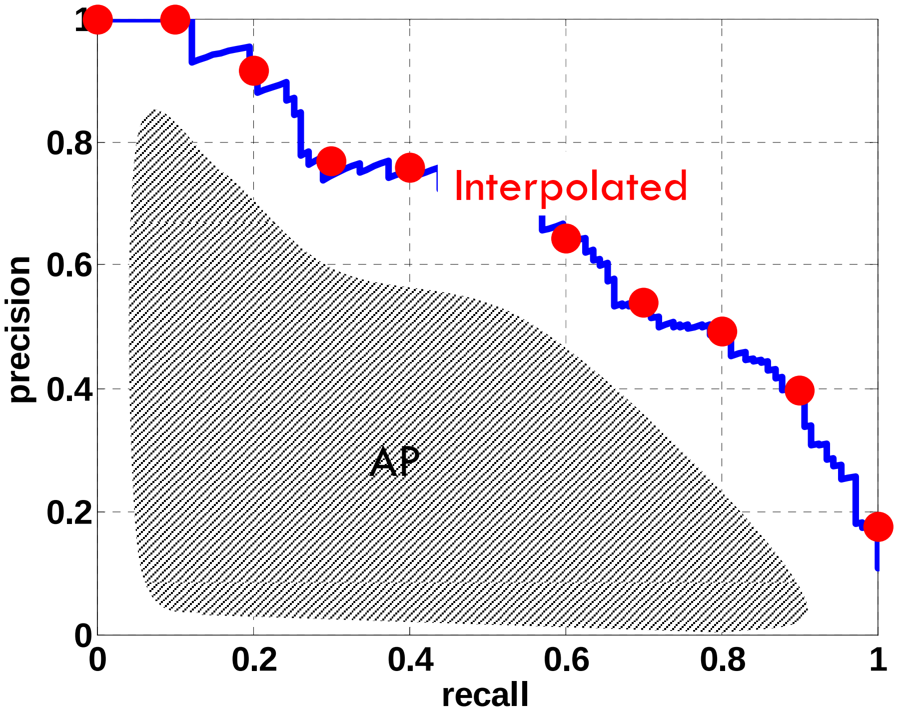
$$AO(B_{gt}, B_p) = \frac{|B_{gt} \bigcap B_p|}{|B_{gt} \bigcup B_p|}$$

Detection if  > Threshold

50%

Classification/Detection Evaluation

- Average Precision [TREC] averages precision over the entire range of recall
  - Curve interpolated to reduce influence of "outliers"



- A good score requires both high recall and high precision
- Application-independent
- Penalizes methods giving high precision but low recall

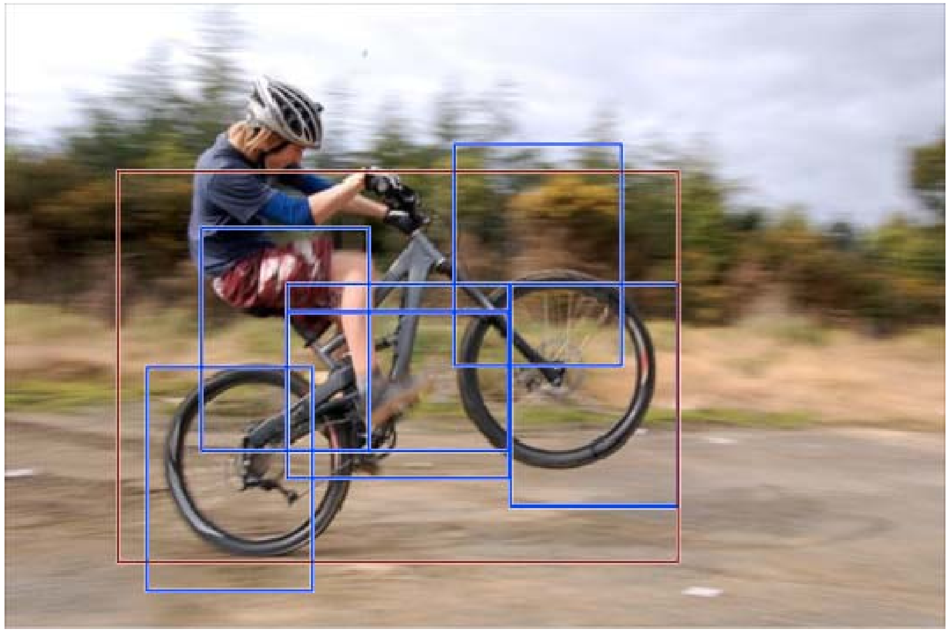
Object Detection with Discriminatively Trained Part Based Models

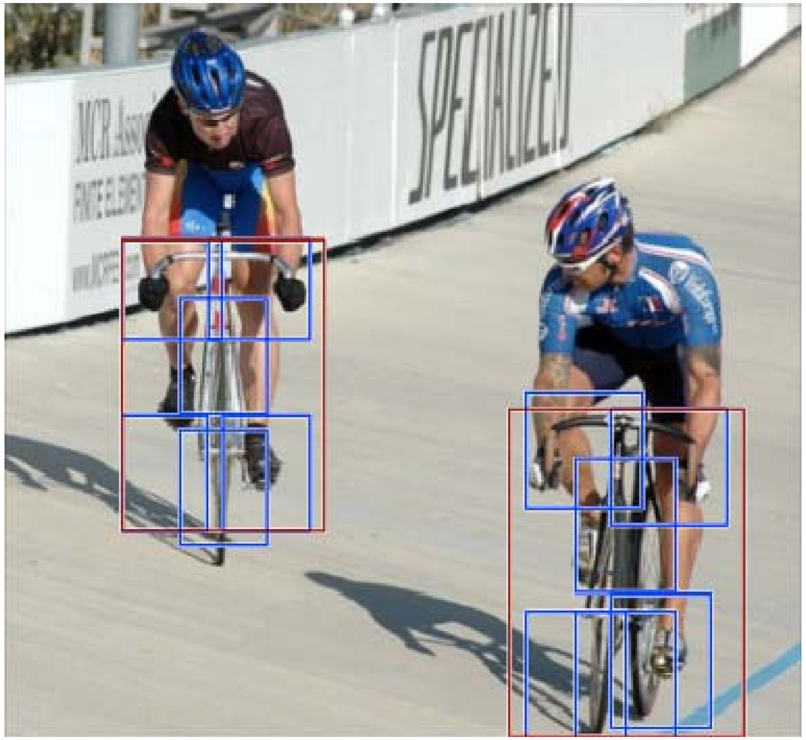
Pedro F. Felzenszwalb, David Mcallester,
Deva Ramanan, Ross Girshick

PAMI 2010

Matlab code available online:
http://www.cs.brown.edu/~pff/latent/

Approach

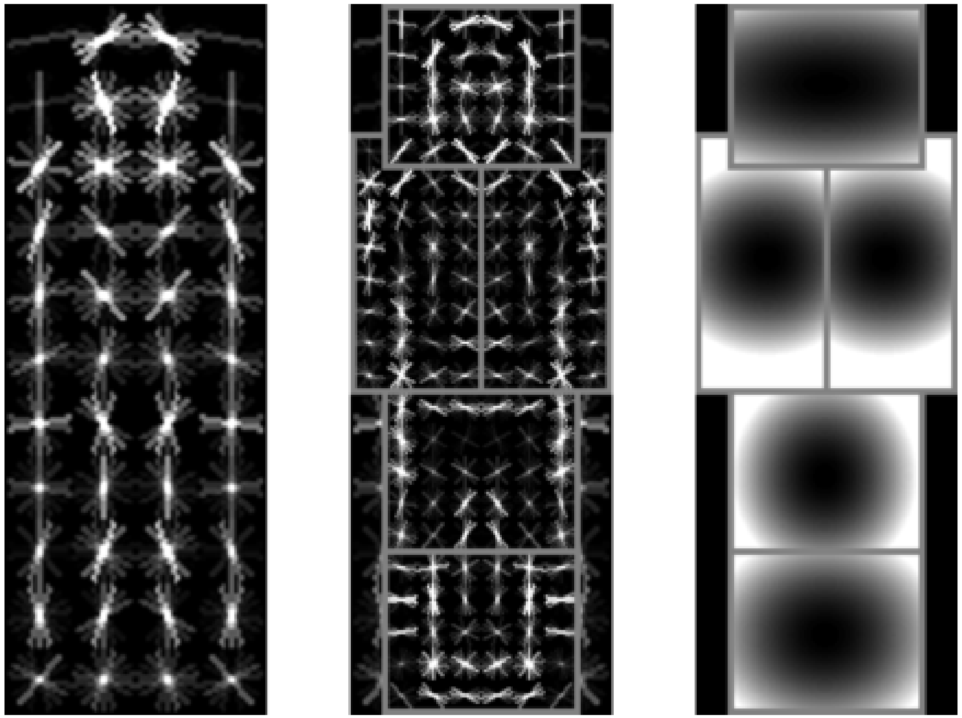




- Mixture of deformable part-based models
  - One component per “aspect” e.g. front/side view
- Each component has global template + deformable parts
- Discriminative training from bounding boxes alone

Example Model

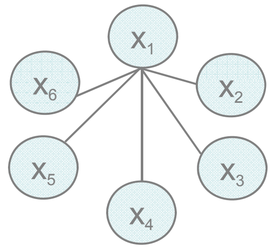
- One component of person model



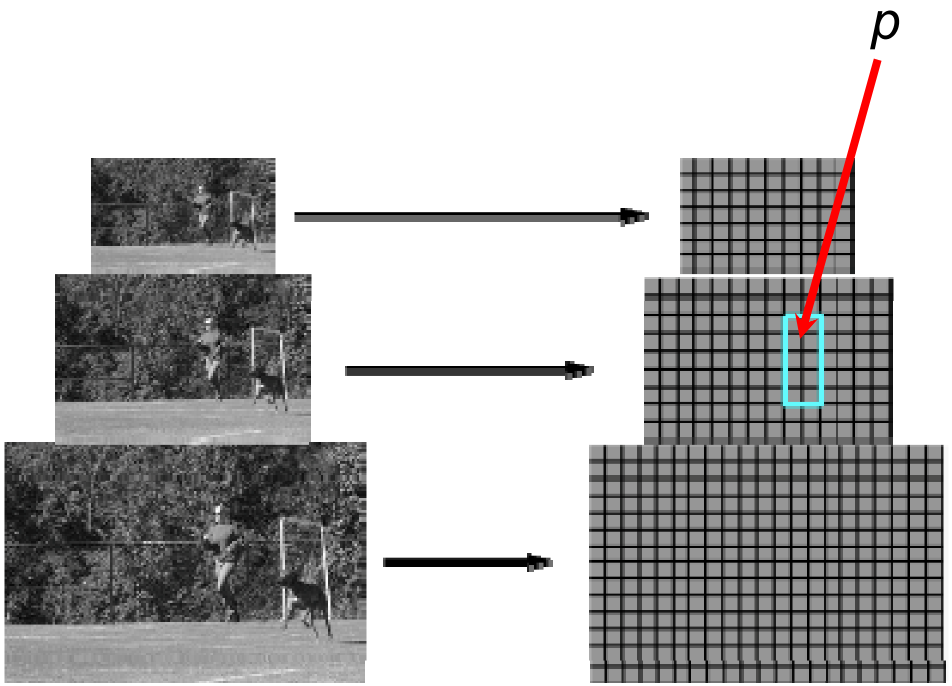
root filters
coarse resolution

part filters
finer resolution

deformation
models

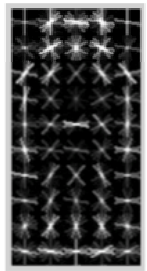


Starting Point: HOG Filter



HOG pyramid H

Filter F



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

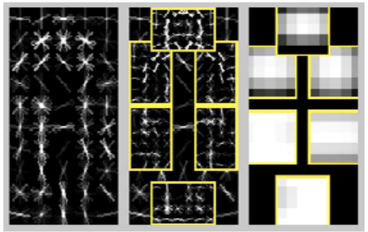
$\varphi(p, H)$ = concatenation of HOG features from subwindow specified by p

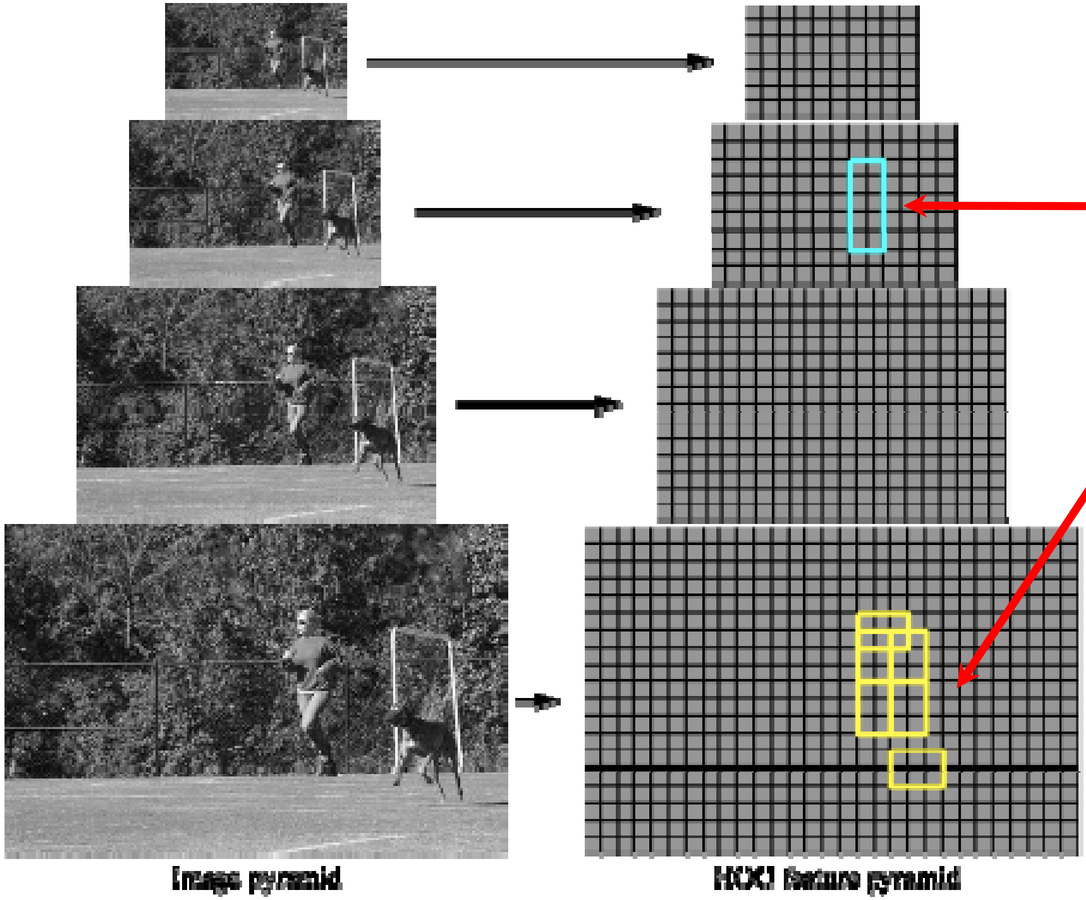
- Search: sliding window over position and scale
- Feature extraction: HOG Descriptor
- Classifier: Linear SVM

Dalal & Triggs [2005]

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

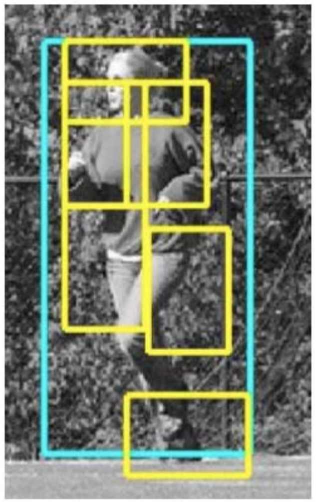
Spatial prior

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

displacements

filters

deformation parameters



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

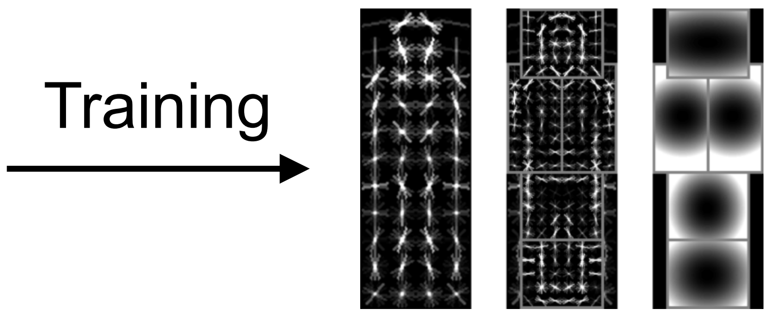
concatenation of filters and deformation parameters

concatenation of HOG features and part displacement features

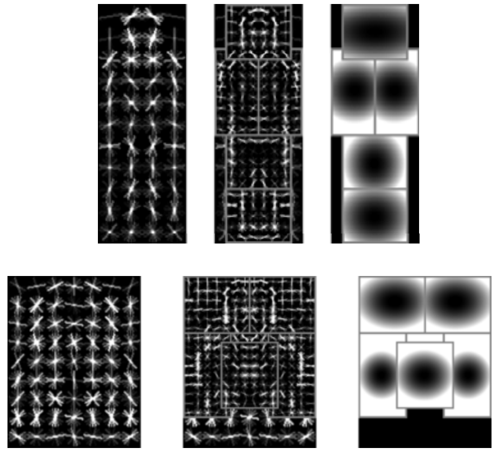
- Linear classifier applied to feature subset defined by hypothesis

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

$$L_D(\beta) = \underbrace{\frac{1}{2}||\beta||^2}_{\text{Regularizer}} + C \sum_{i=1}^{n} \underbrace{\max(0, 1 - y_i f_\beta(x_i))}_{\text{"Hinge loss" on one training example}}$$

SVM objective

Latent SVM Training

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

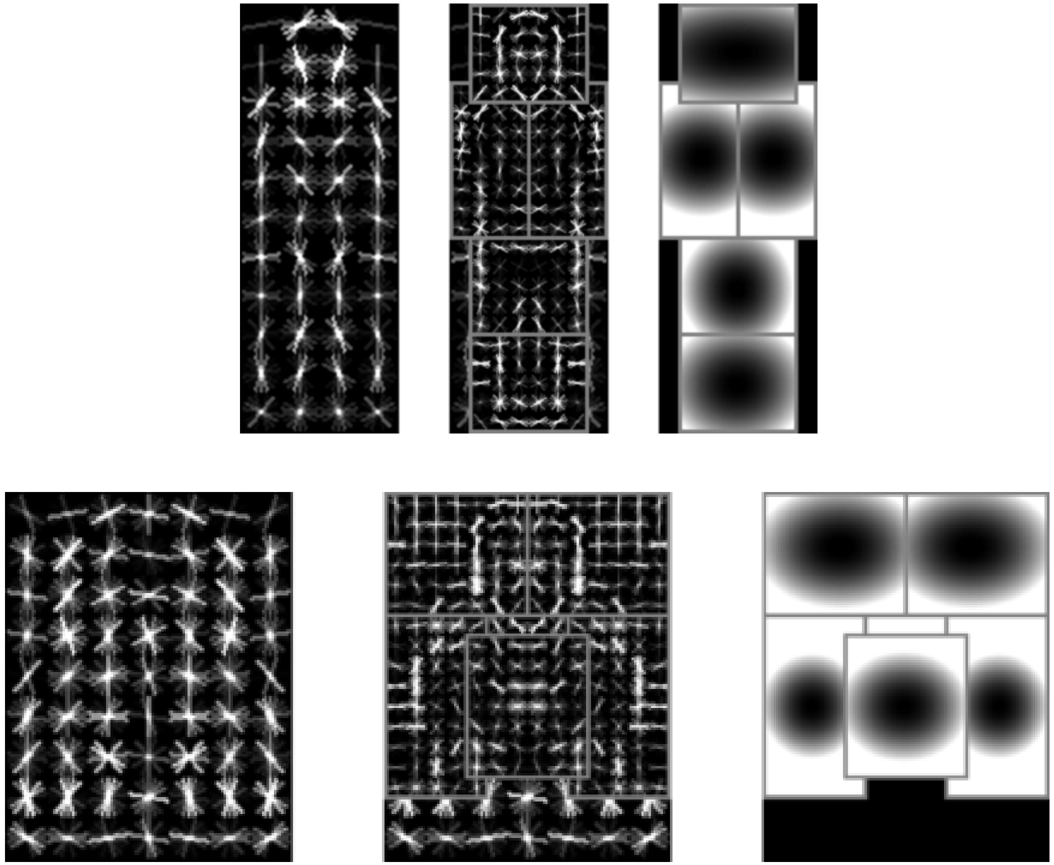
- Convex if we fix z for positive examples

- 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
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finer resolution

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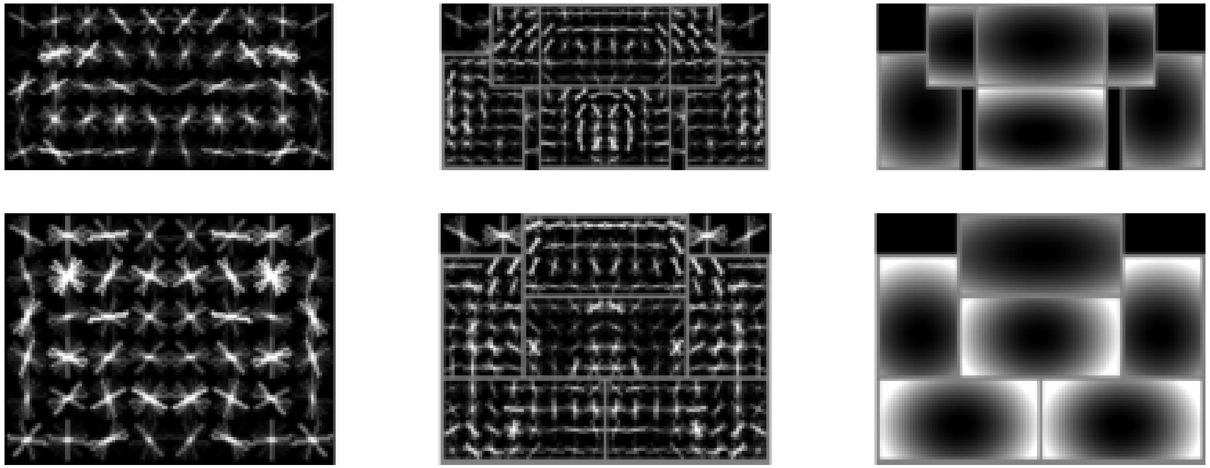
Handles partial occlusion/truncation

Car Model



root filters
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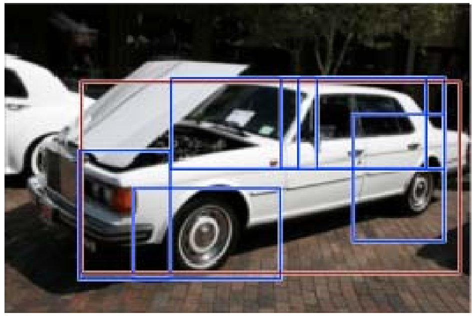
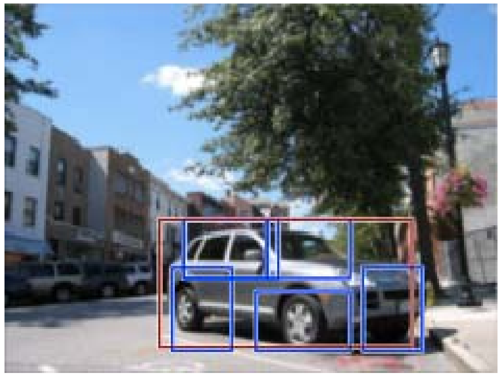
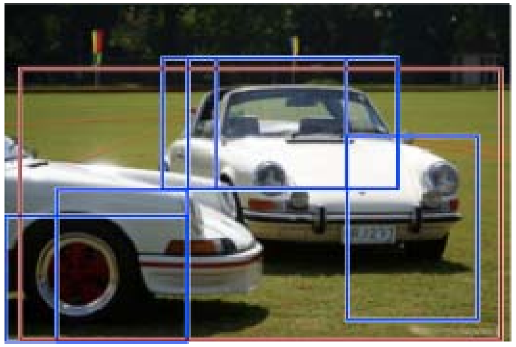
Car Detections

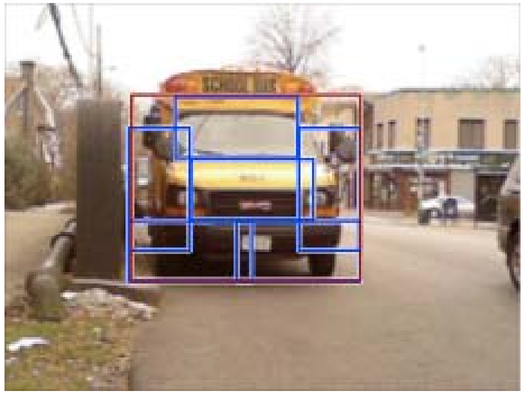
high scoring true positives





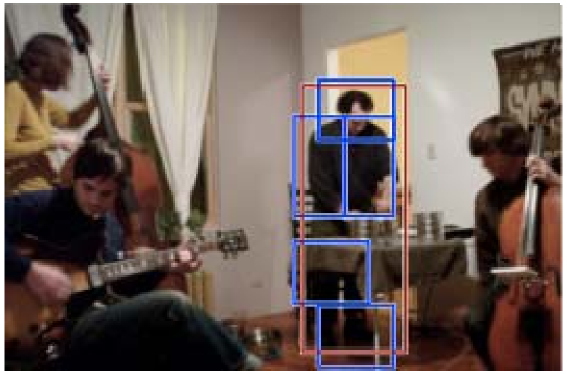
high scoring false positives

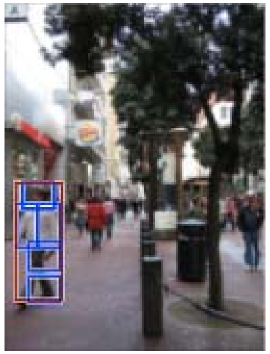


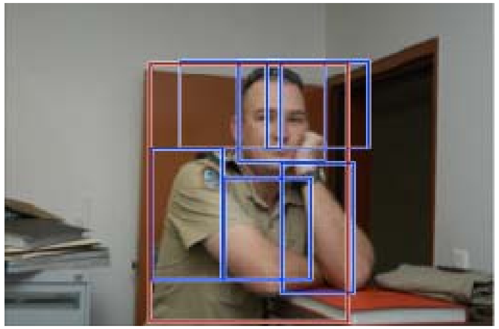


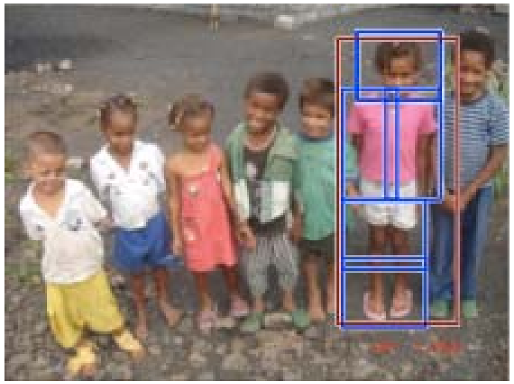
Person Detections

high scoring true positives

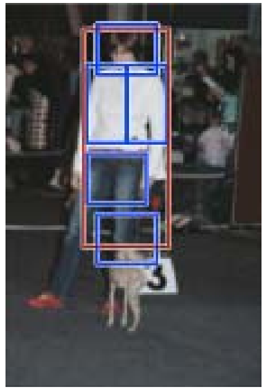








high scoring false positives
(not enough overlap)



Segmentation Driven Object Detection with Fisher Vectors

Ramazan Gokberk Cinbis, Jakob Verbeek,
Cordelia Schmid

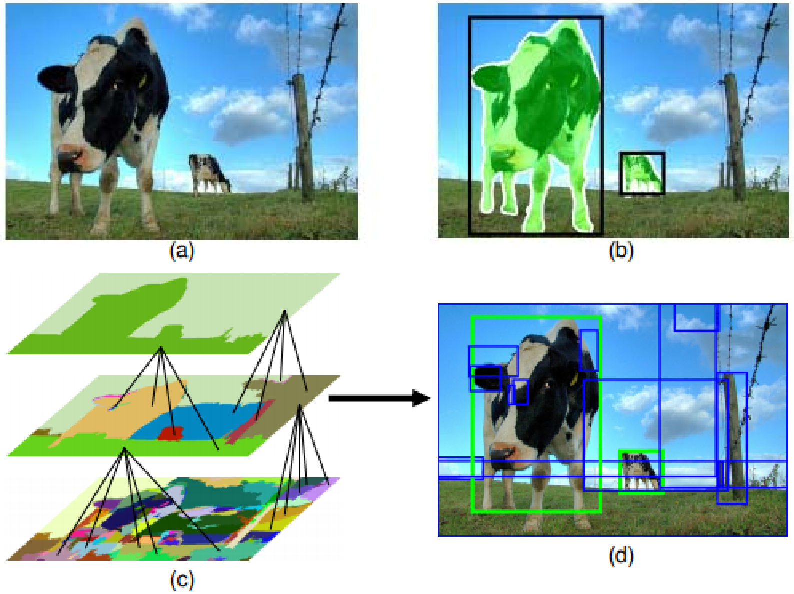
ICCV 2013

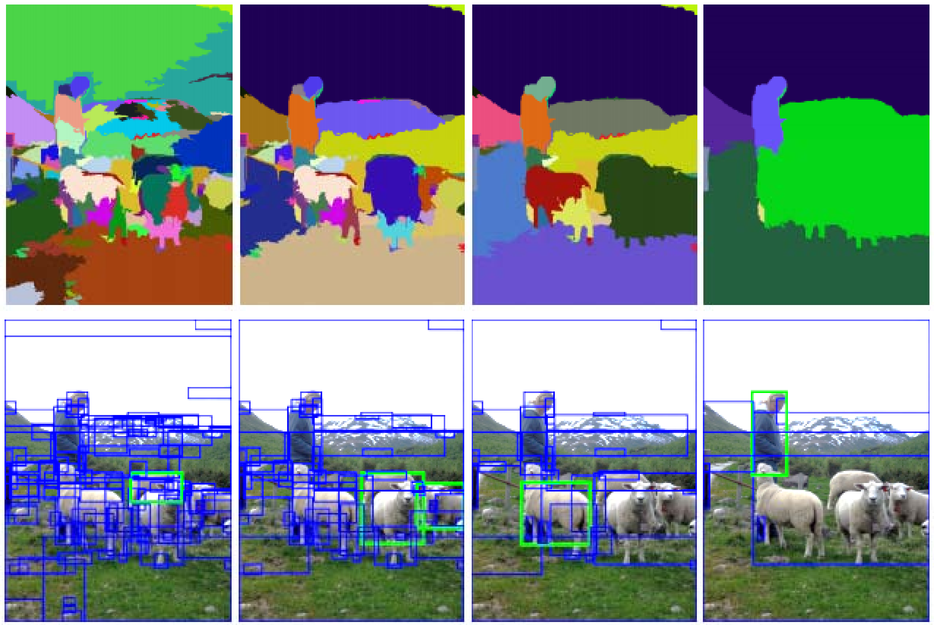
student presentation

Approach

- Pre-select *class-independent* candidate image windows using image segmentation [*van de Sande et al., Segmentation as selective search for object recognition, ICCV'11*]

⇨





Approach

- Local features + feature re-weighting based on object segmentation masks
- Represent windows with Fisher Vector (FV) encoding
- Compressed FV descriptors for efficiency
- Linear SVM classifier with hard negative mining