Category-level localization

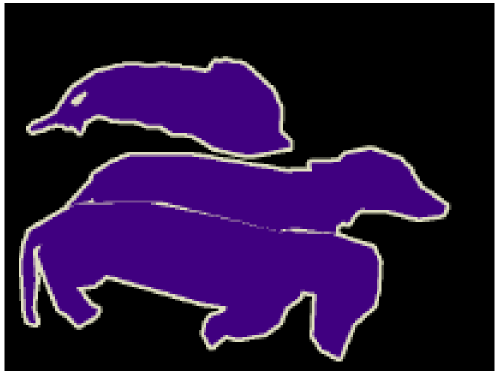
Cordelia Schmid

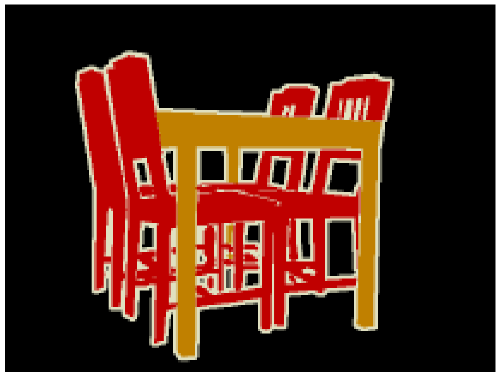
Recognition

- 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

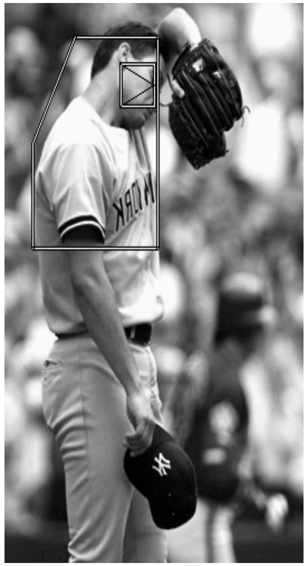
Pixel-level object classification

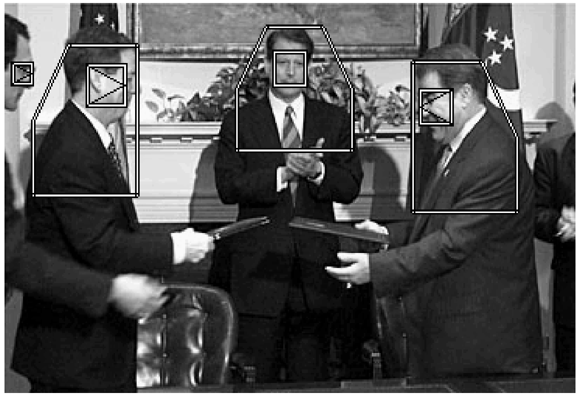



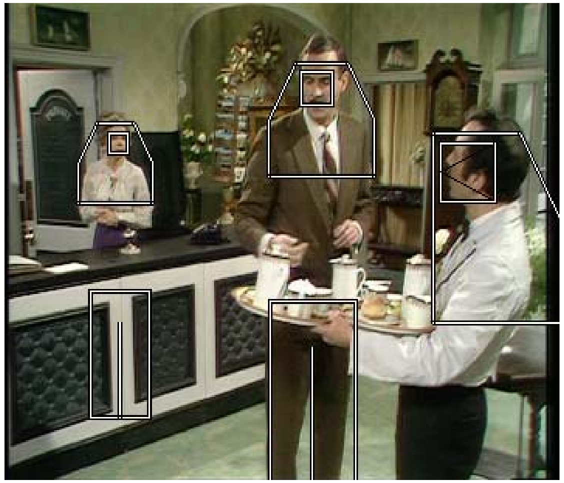


Difficulties

- 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

- Multiple aspects of categories

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

  => high capacity classifiers, i.e. Fisher vector, CNNs

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

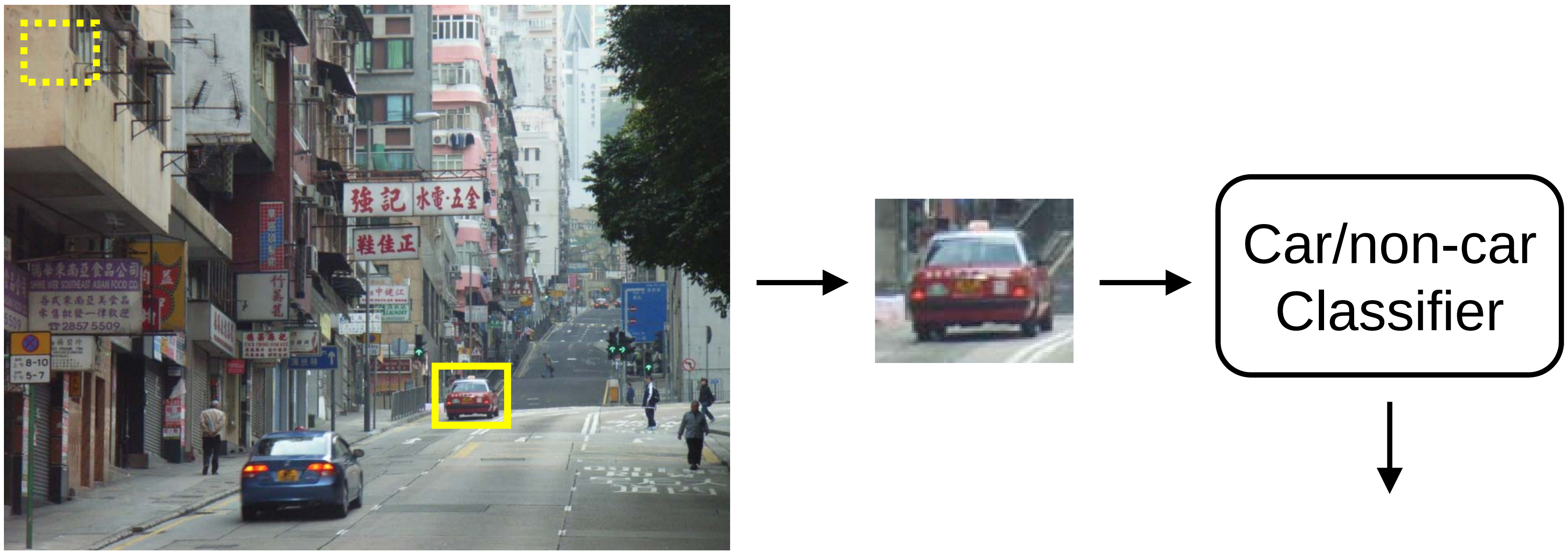
- Basic component: binary classifier

Car/non-car Classifier

No,
not a car

Sliding window detector

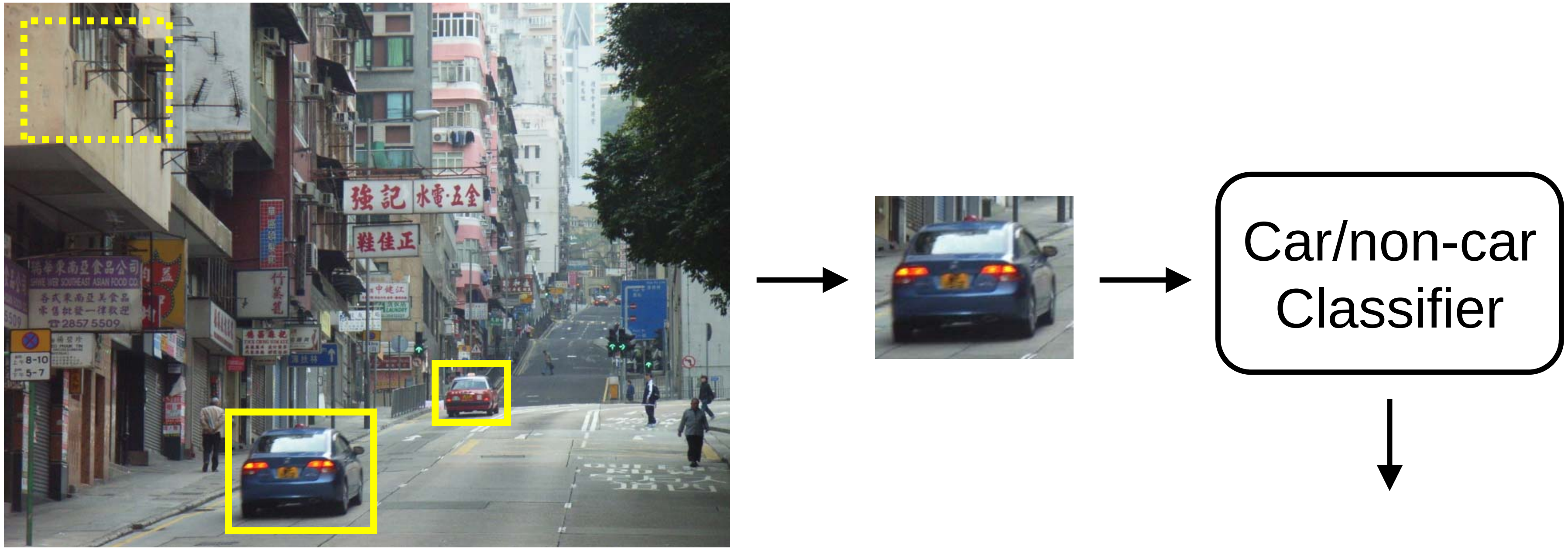
- Detect objects in clutter by **search**



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

Sliding window detector

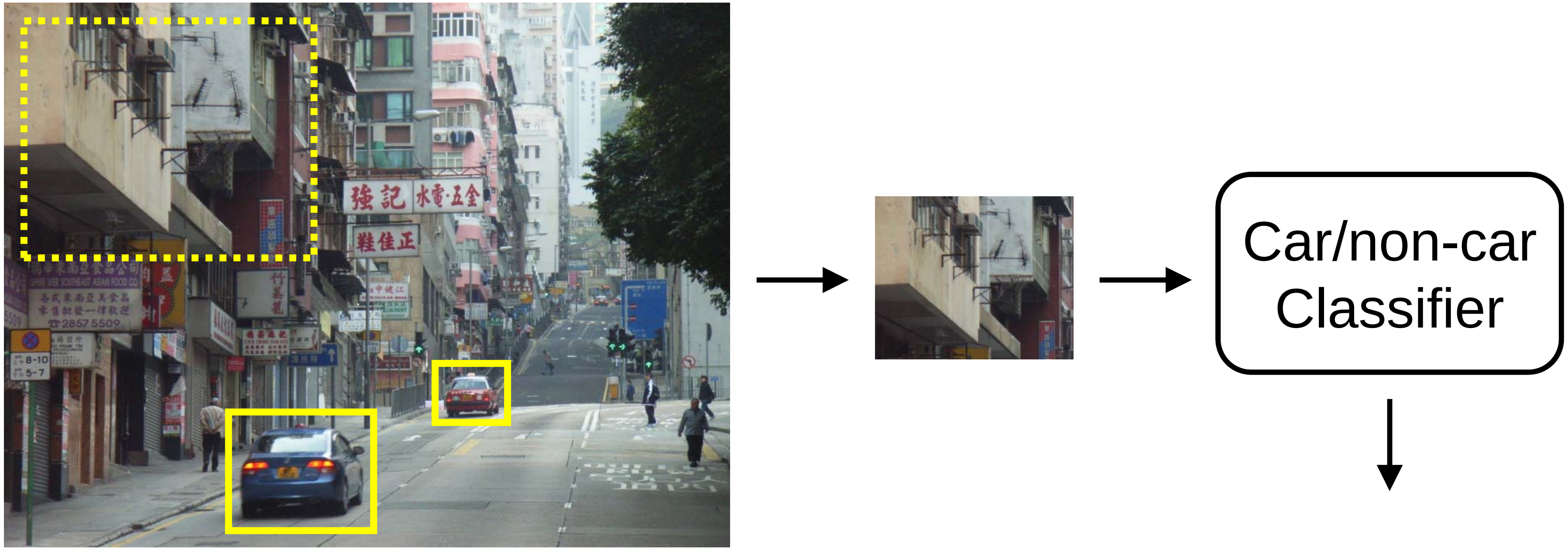
• Detect objects in clutter by **search**



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

Detection by Classification

- Detect objects in clutter by **search**

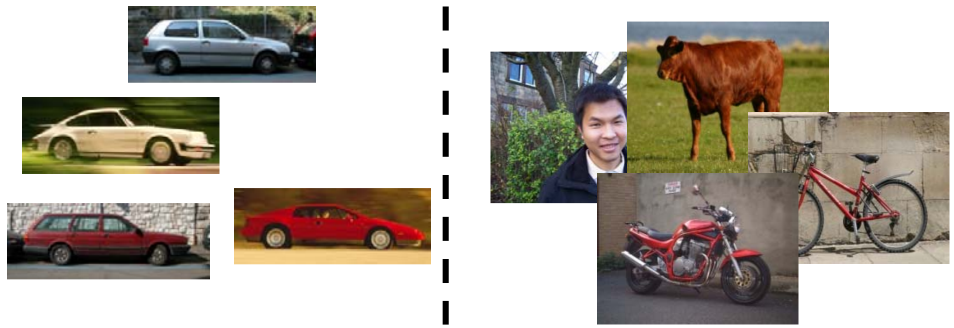


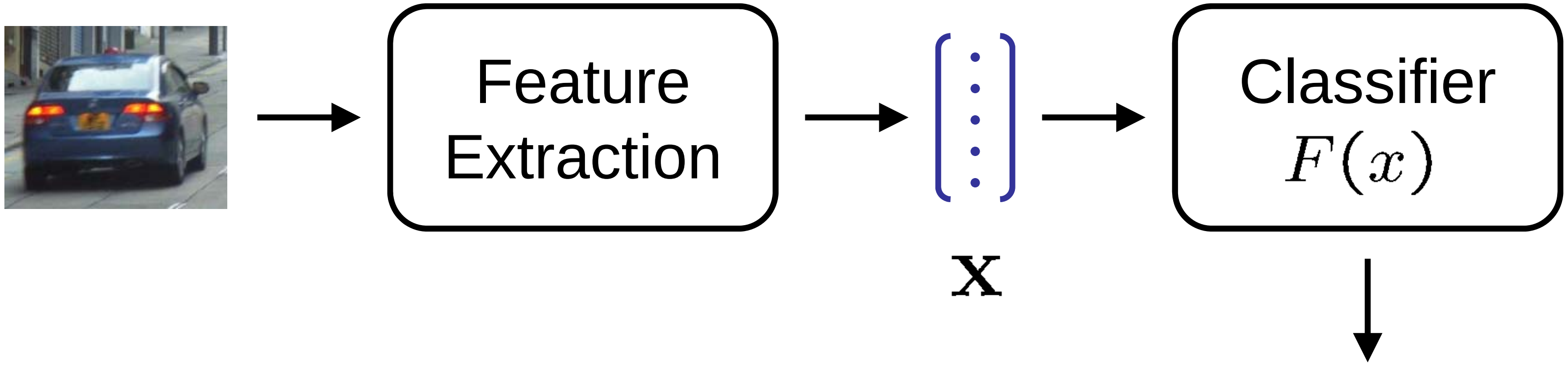
- **Sliding window**: exhaustive search over position and scale

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

Window (Image) Classification

Training Data





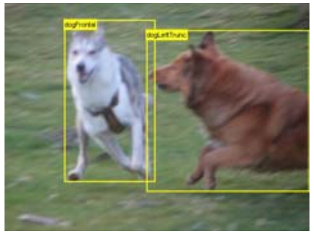
Car/Non-car

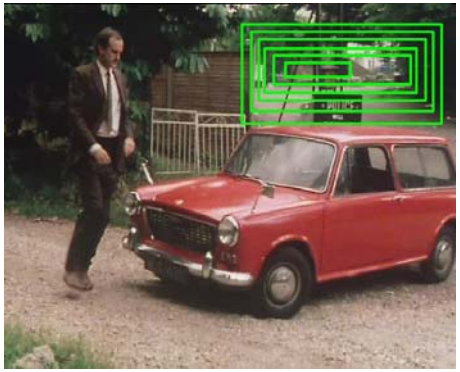
$$P(c|\mathbf{x}) \propto F(\mathbf{x})$$

- Features usually engineered
- Classifier learnt from data

Problems with sliding windows …

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





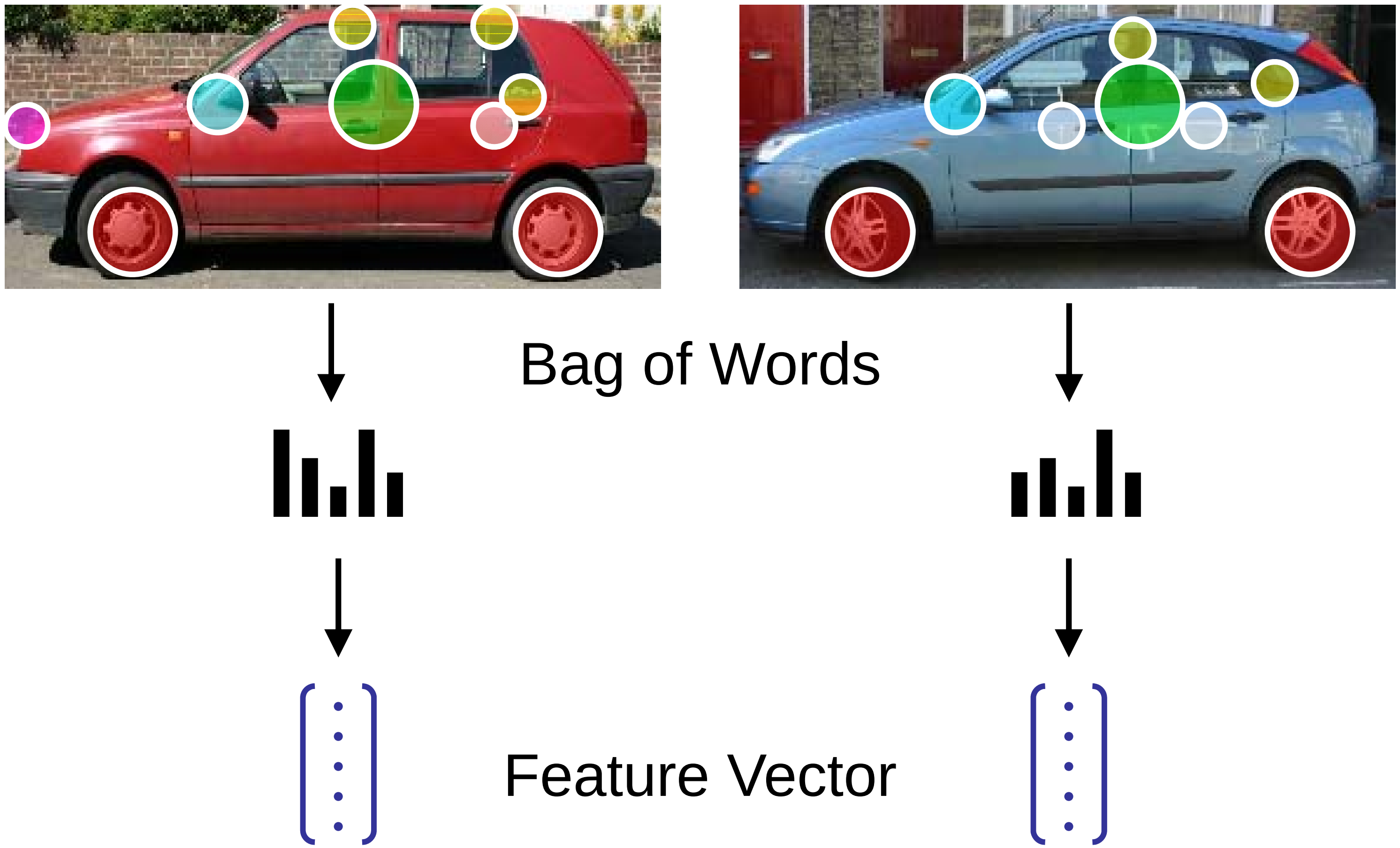
Outline

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

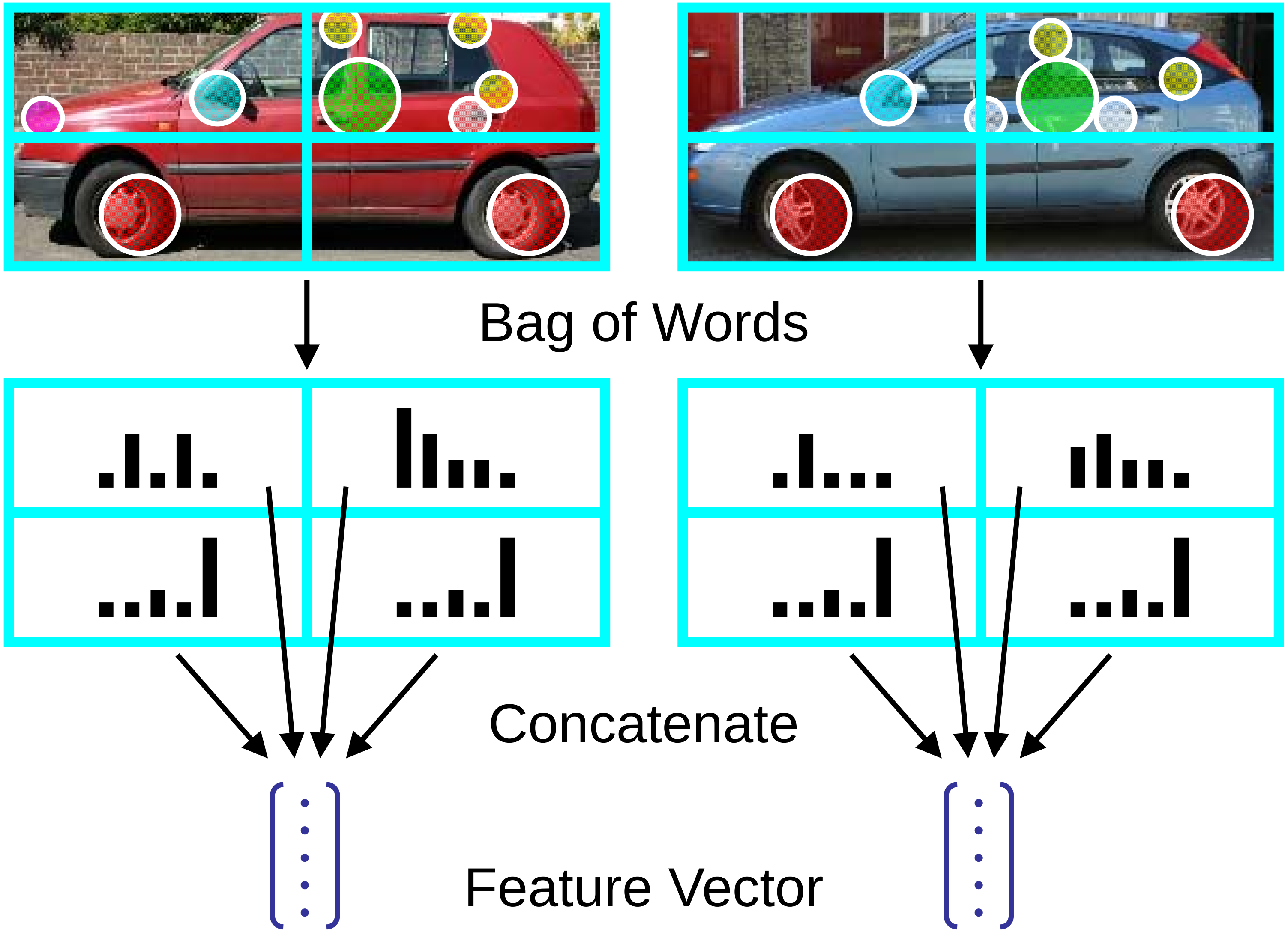
BOW + Spatial pyramids

Start from BoW for region of interest (ROI)

- no spatial information recorded
- sliding window detector

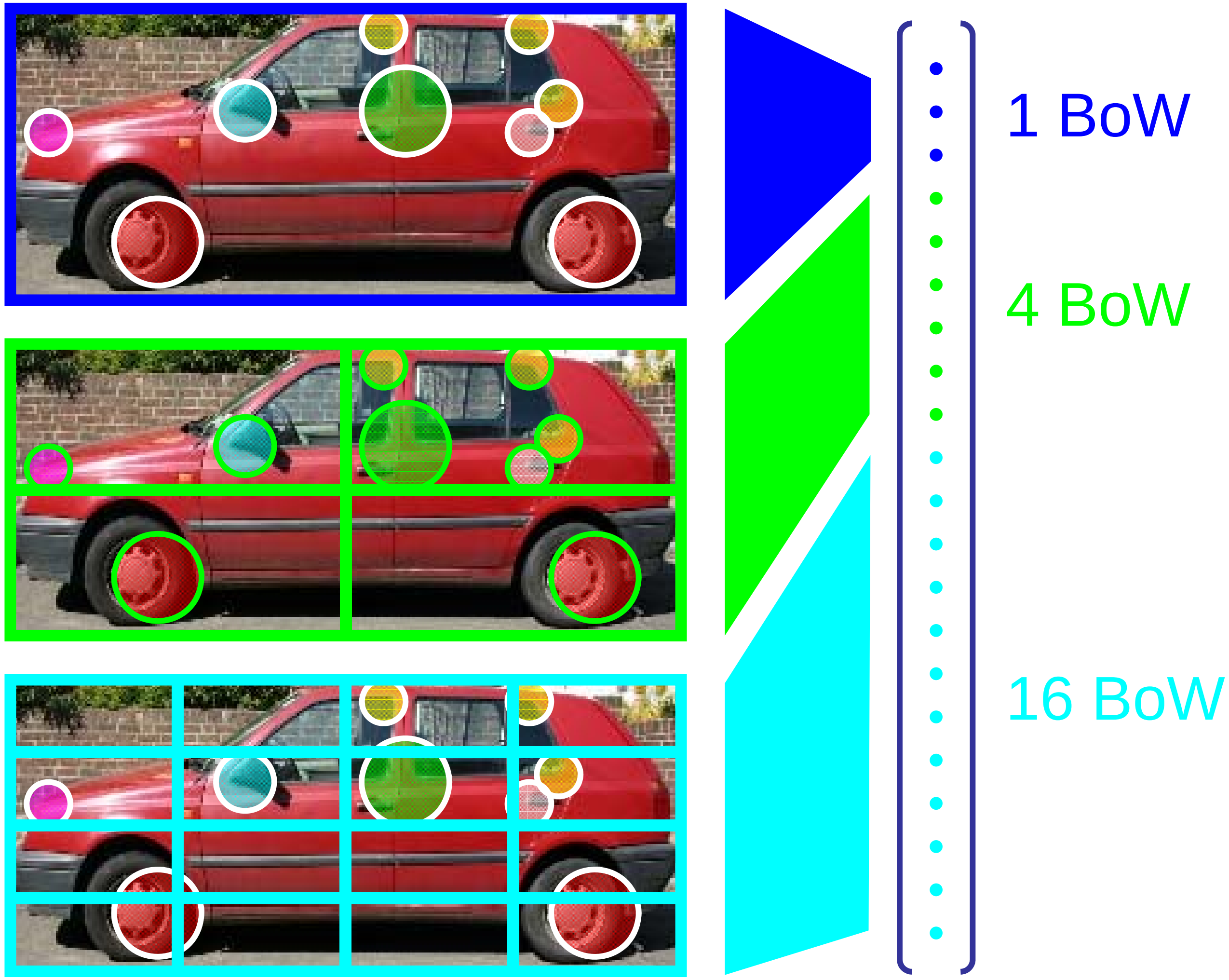


Adding Spatial Information to Bag of Words



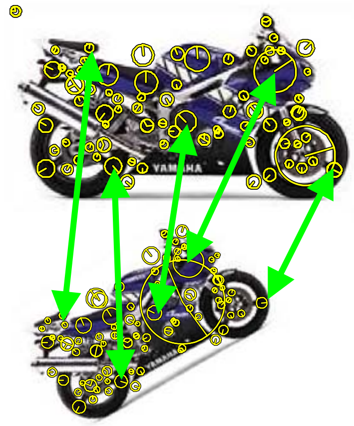
Keeps fixed length feature vector for a window

Spatial Pyramid – represent correspondence



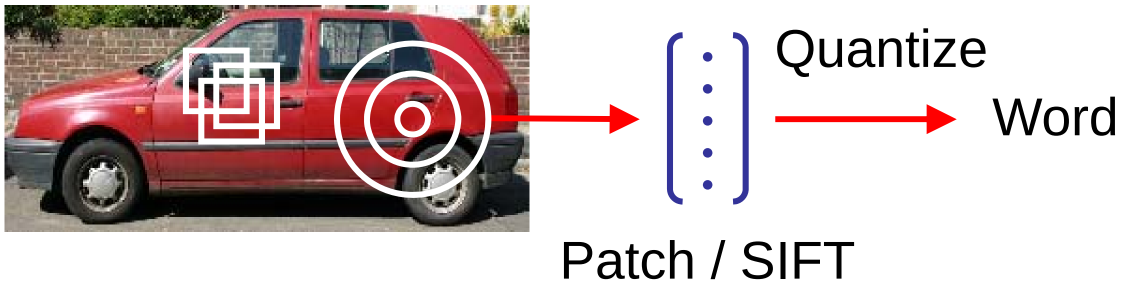
Dense Visual Words

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



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

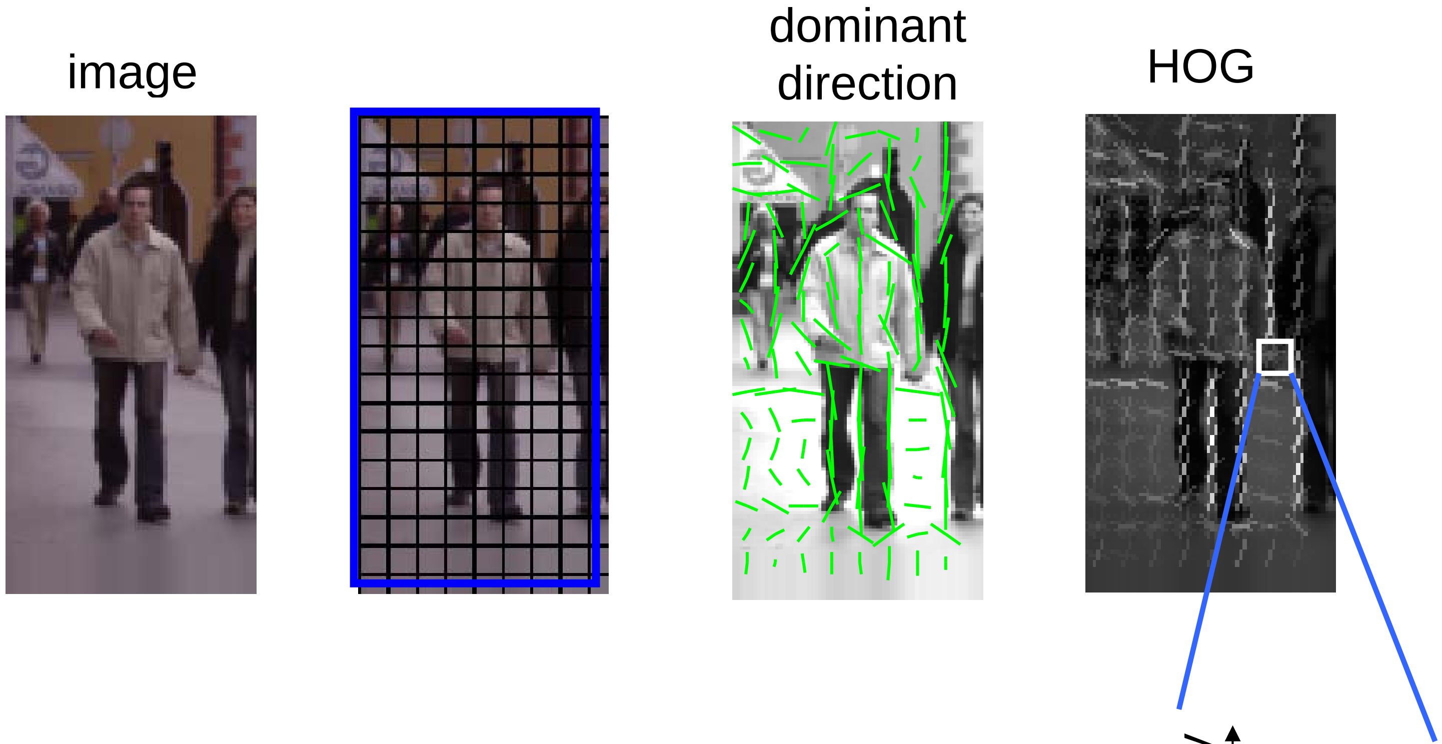
- Extract **dense** visual words on an overlapping grid

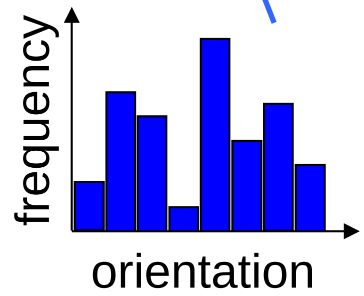


Outline

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

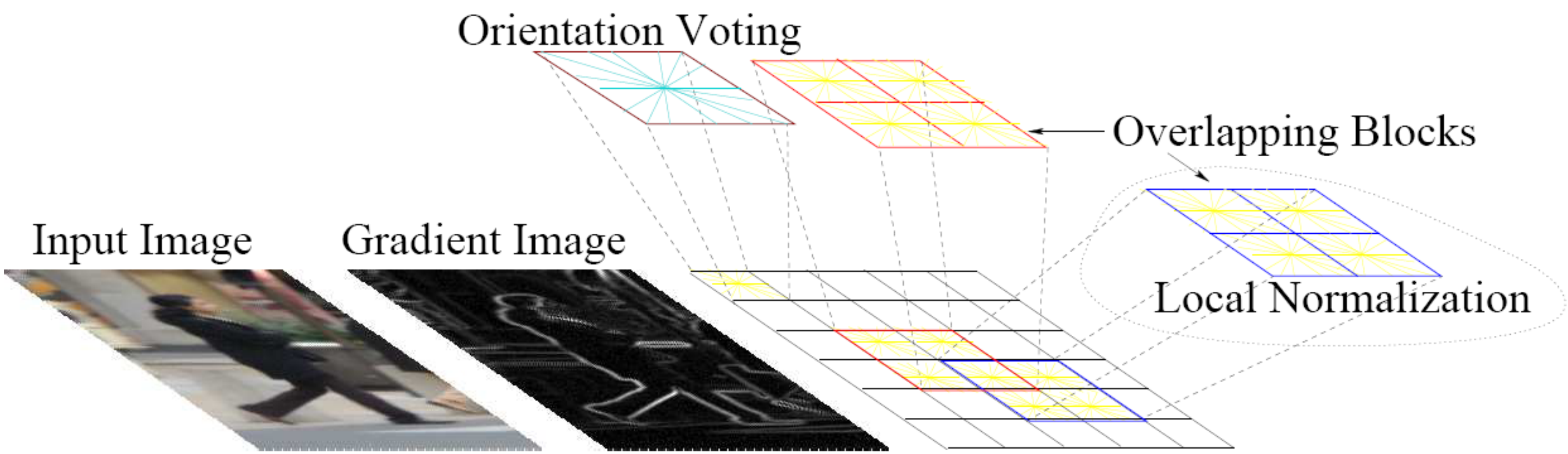
Feature: Histogram of Oriented Gradients (HOG)





- 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)

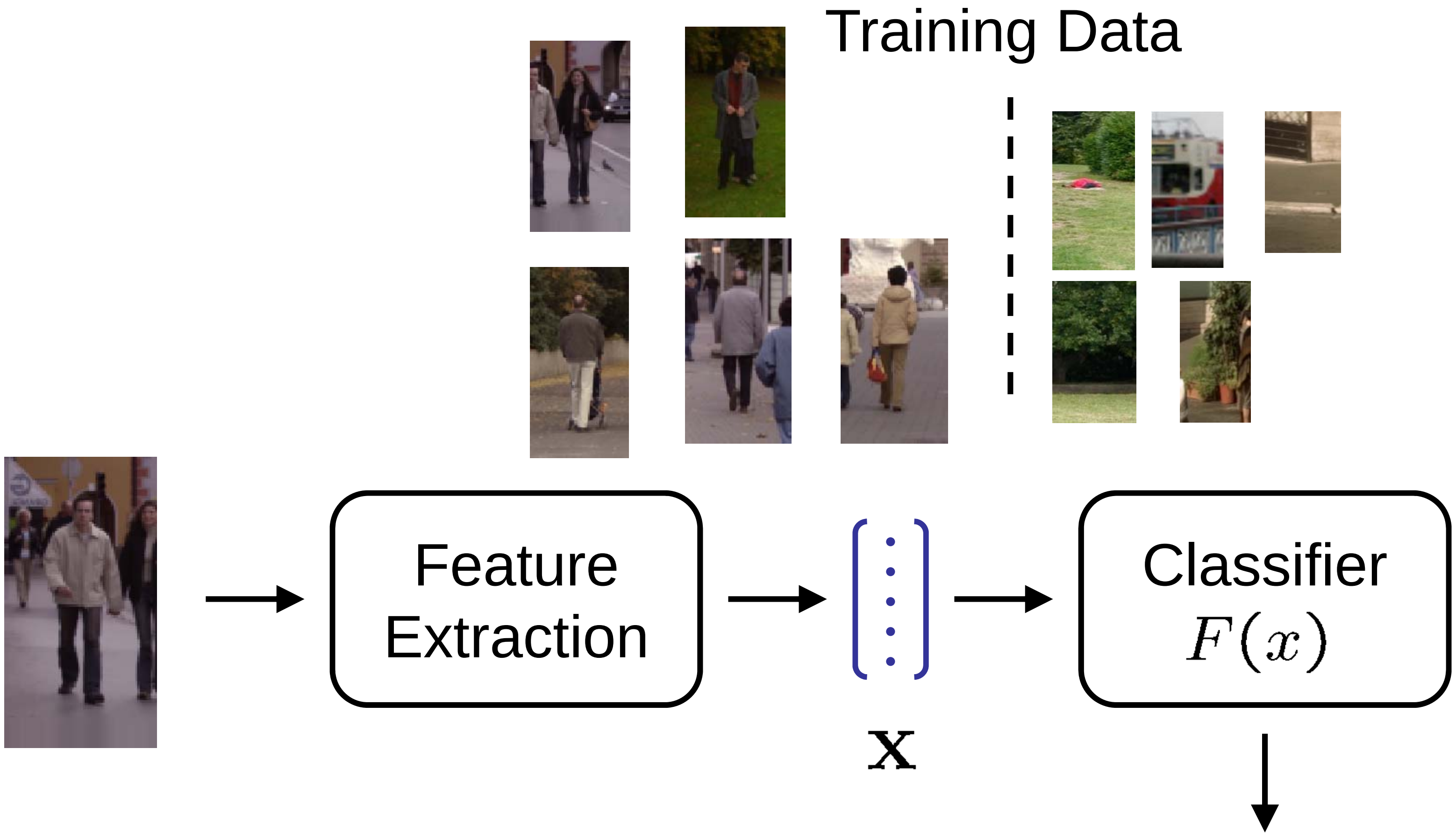
Histogram of Oriented Gradients (HOG) continued



- 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

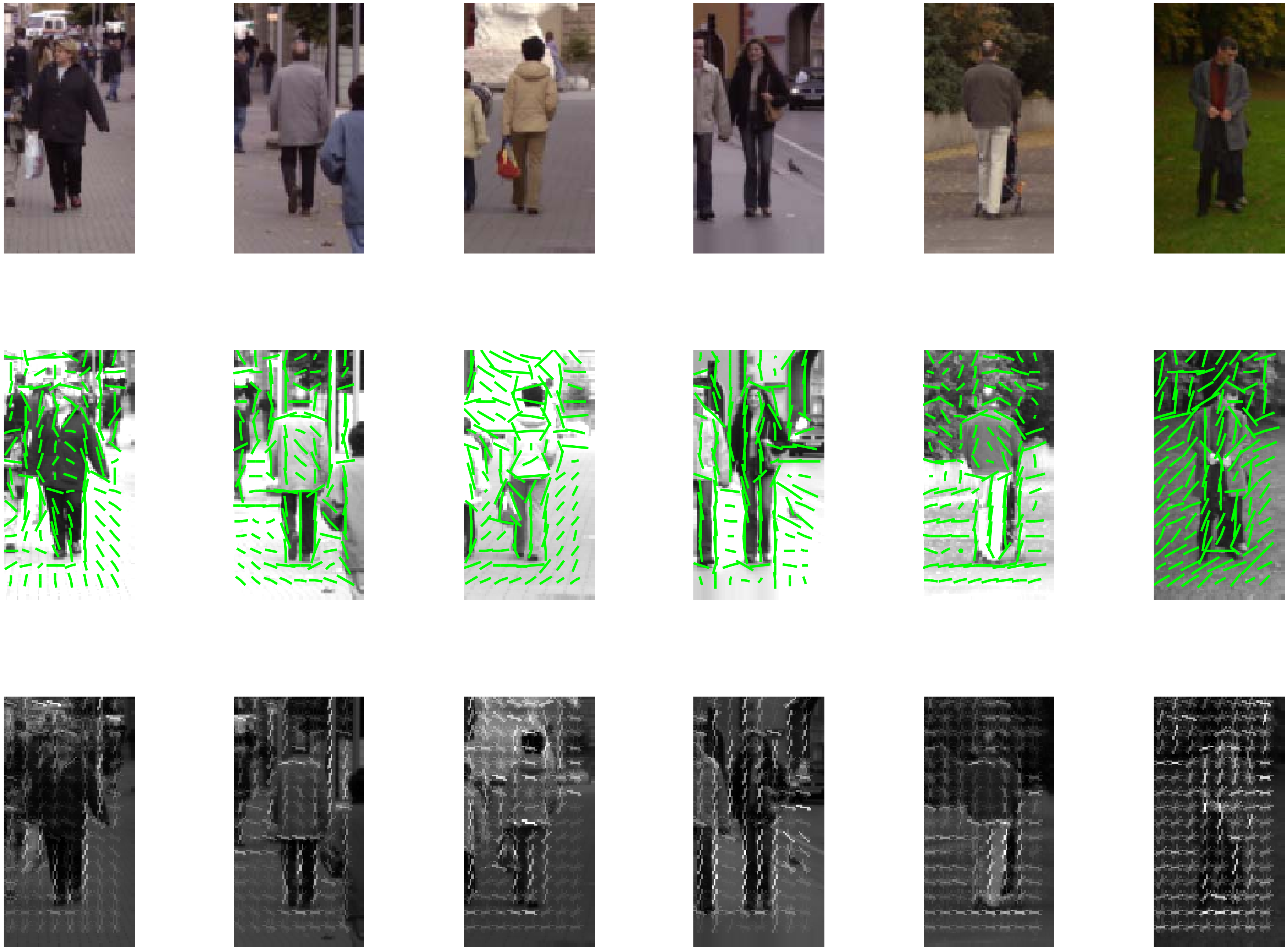
Window (Image) Classification



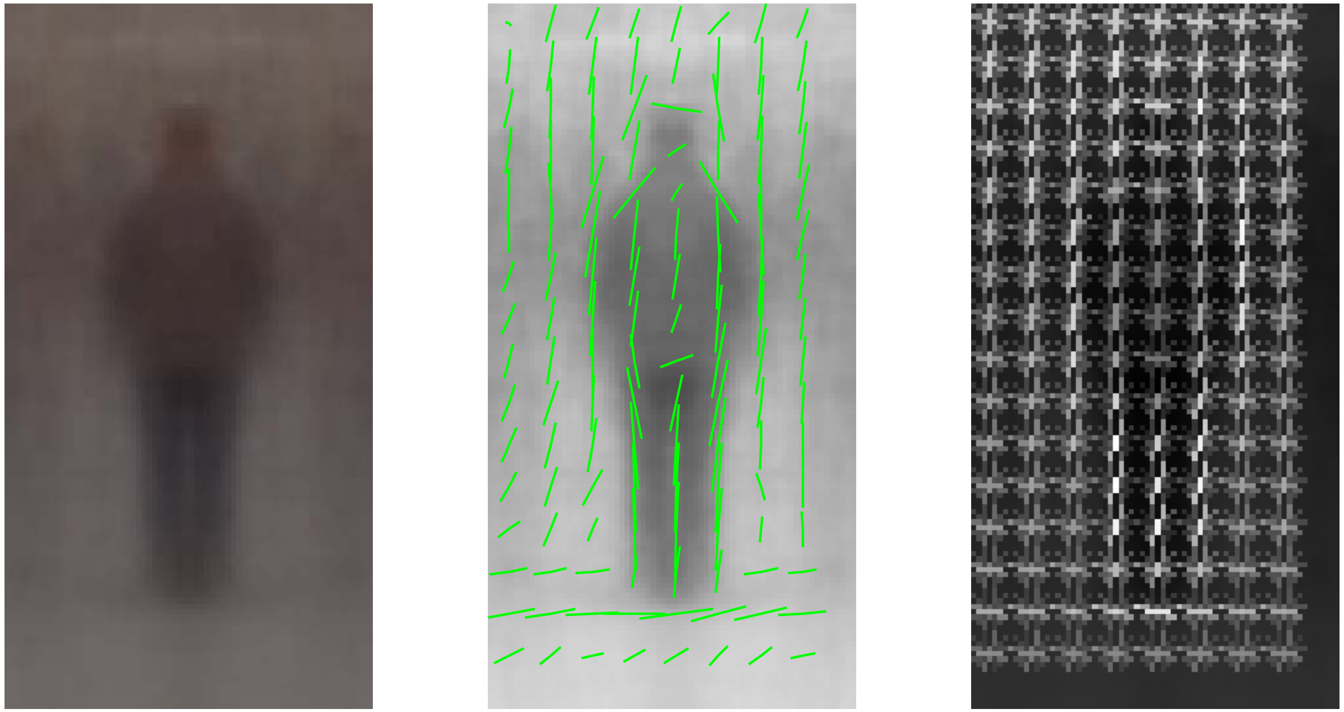
pedestrian/Non-pedestrian

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

- HOG Features
- Linear SVM classifier



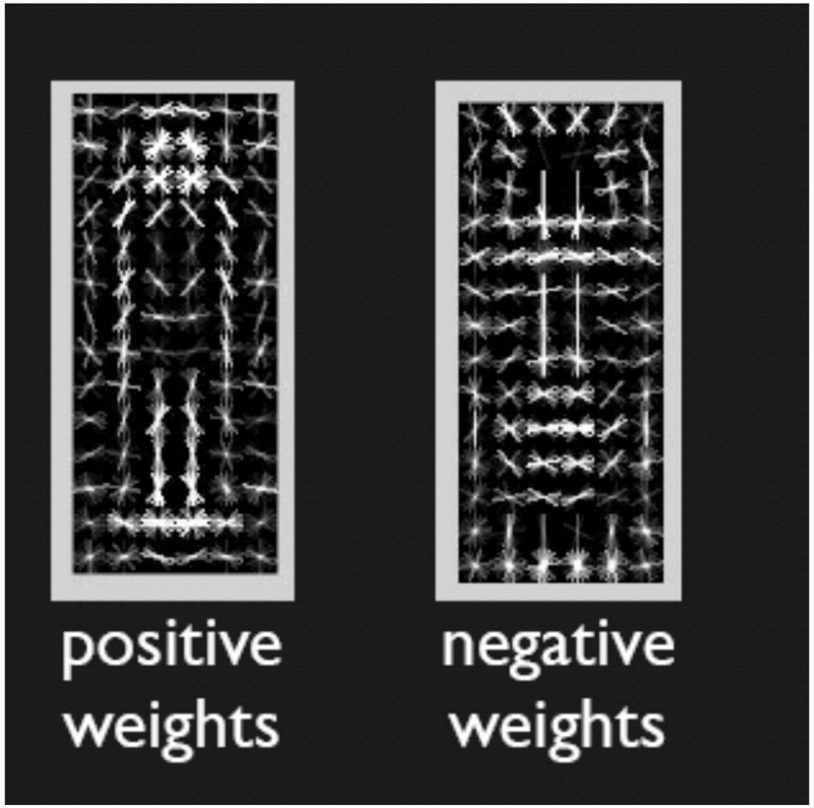
Averaged examples

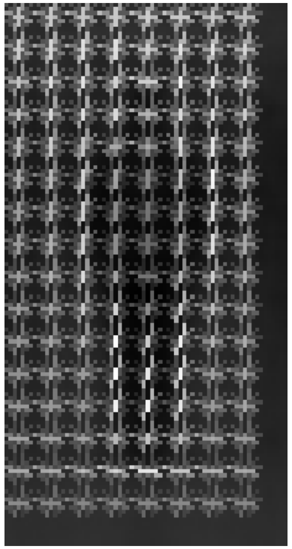


Dalal and Triggs, CVPR 2005

Learned model

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





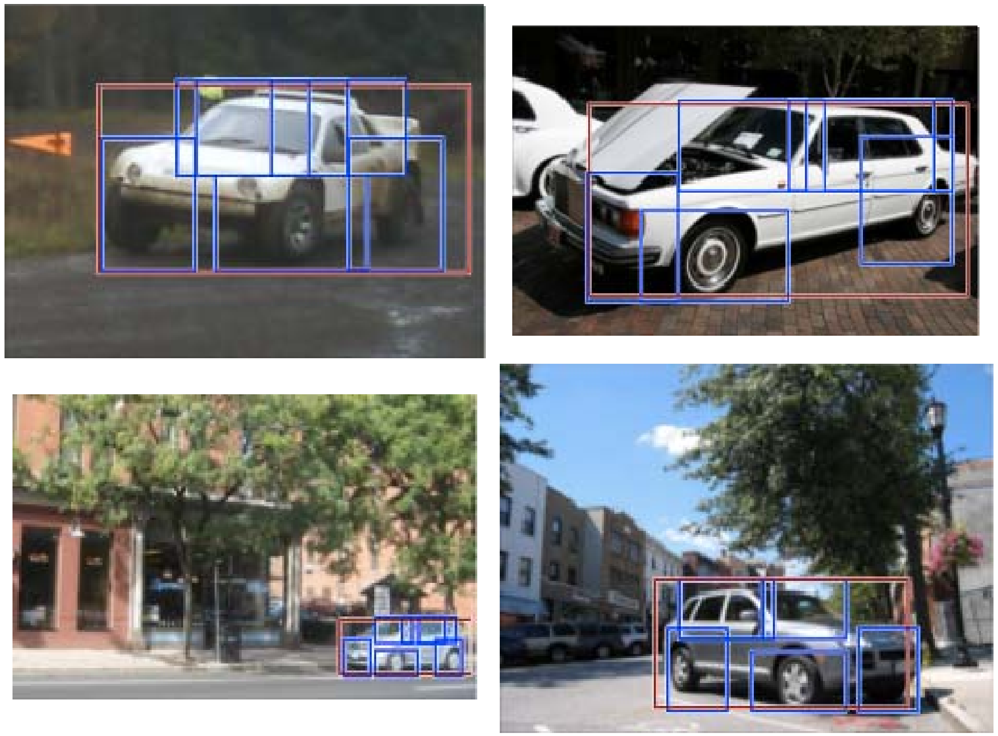
average over
positive training data

Training a sliding window detector

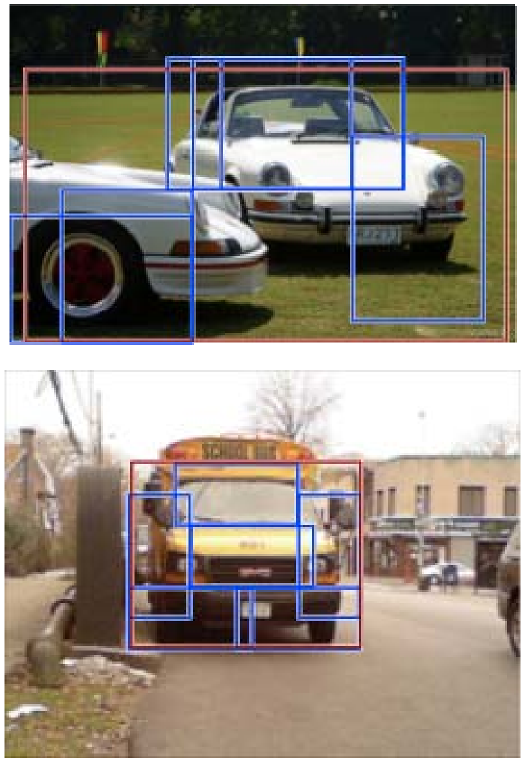
- Unlike training an image classifier, there are a (virtually) infinite number of possible negative windows
- Training (learning) generally proceeds in three distinct stages:
  1. Bootstrapping: learn an initial window classifier from positives and random negatives
  2. Hard negatives: use the initial 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

Car Detections

high scoring true positives

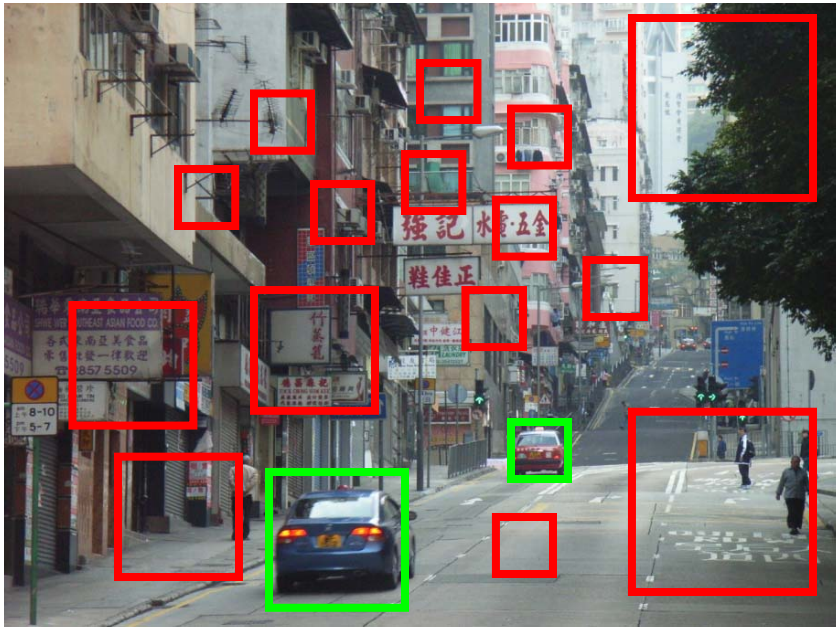


high scoring false positives



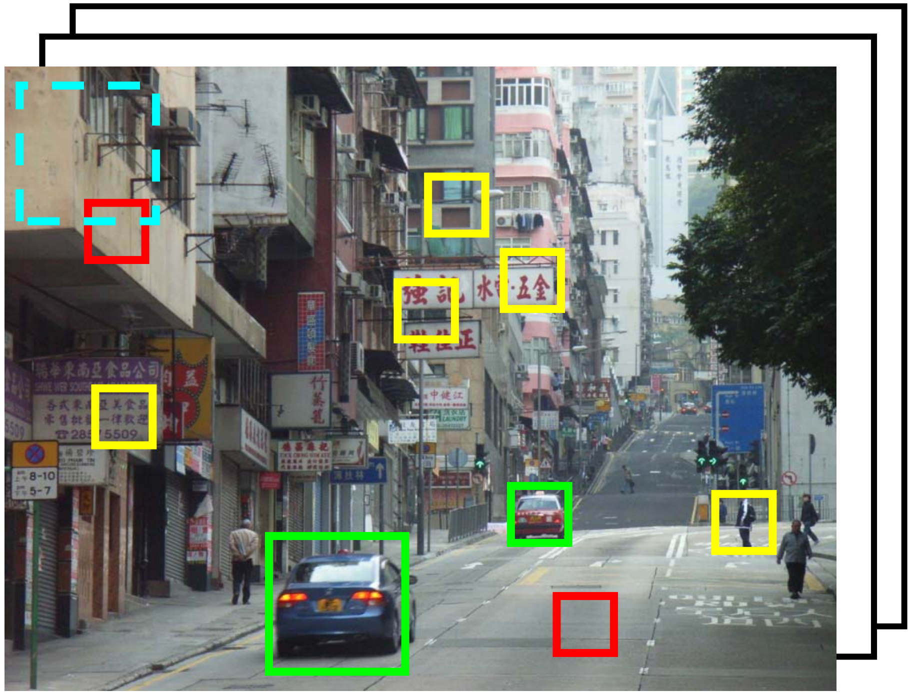
Training a sliding window detector

- 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



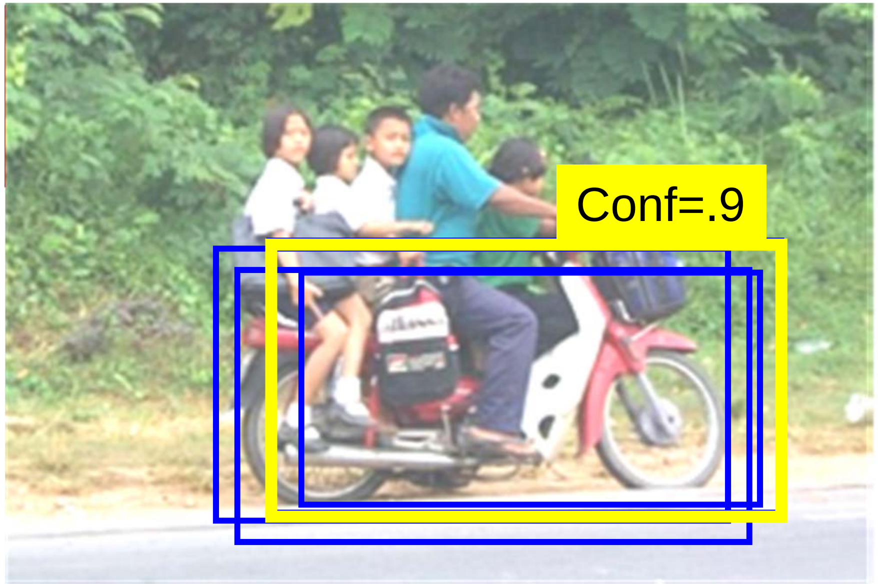
1. Pick negative training set at random
2. Train classifier
3. Run on training data
4. Add false positives to training set
5. Repeat from 2

- 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

Test: Non-maximum suppression (NMS)

- Scanning-window detectors typically result in multiple responses for the same object



- To remove multiple responses, a simple greedy procedure called "Non-maximum suppression" is applied:

NMS:
1. Sort all detections by detector confidence
2. Choose most confident detection d_i; remove all d_j s.t. $overlap(d_i,d_j)>T$
3. Repeat Step 2. until convergence

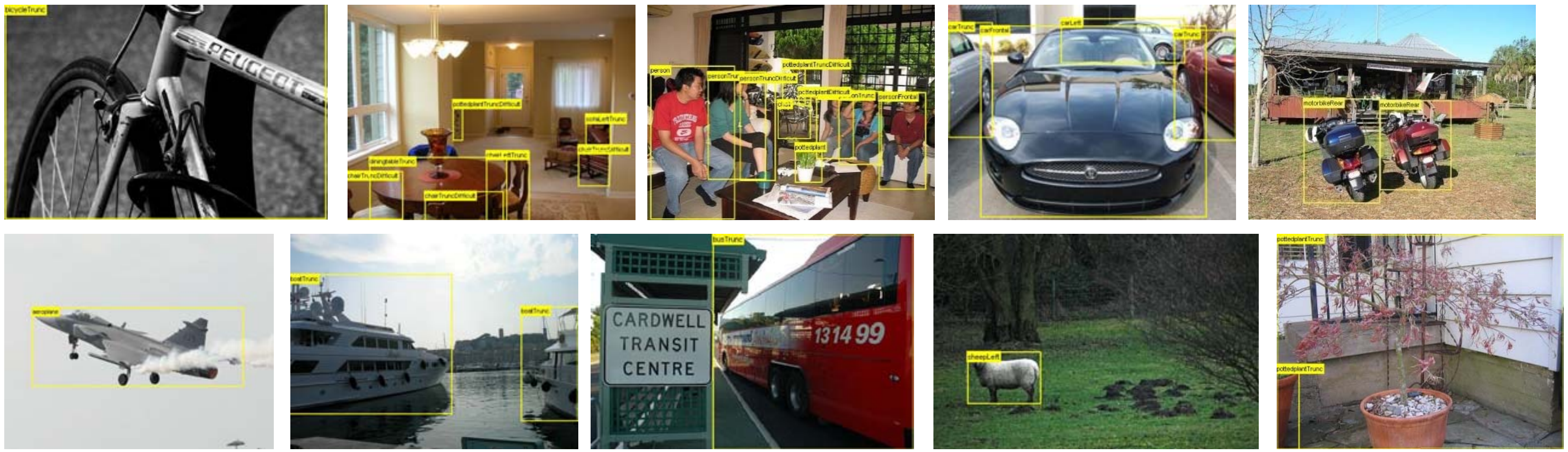
Outline

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

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”



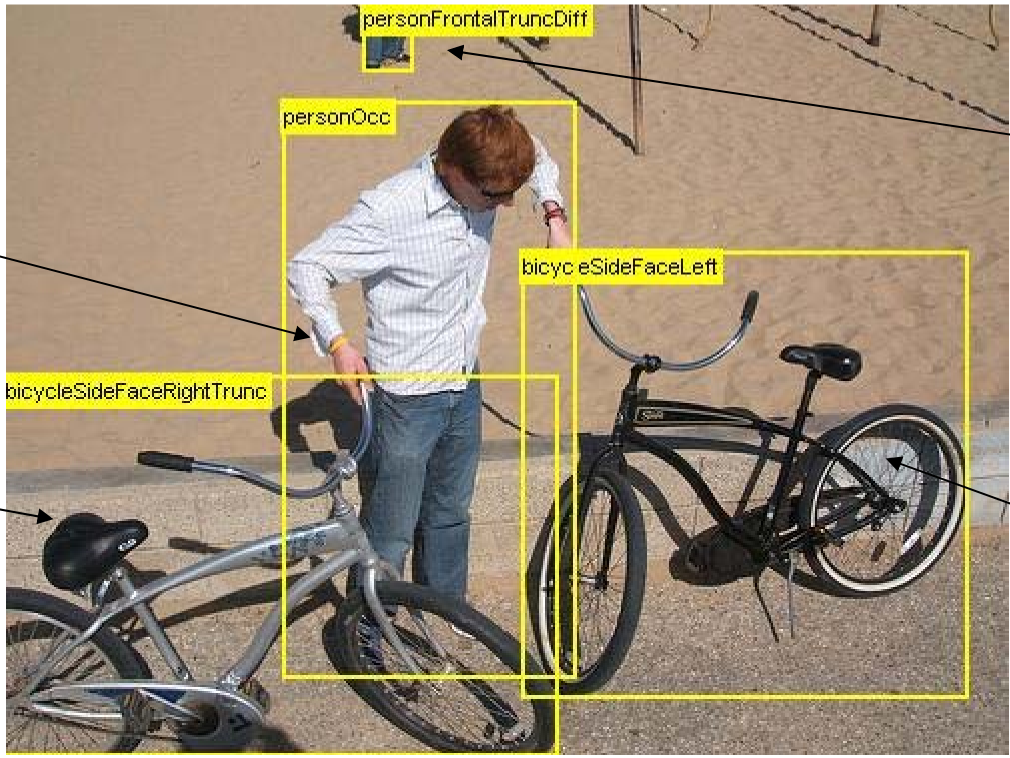
- Complex scenes, scale, pose, lighting, occlusion, ...

Annotation

- Complete annotation of all objects

Occluded
Object is significantly occluded within BB

Truncated
Object extends beyond BB



Difficult
Not scored in evaluation

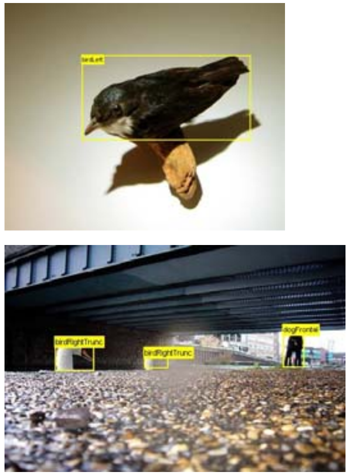
Pose
Facing left

Examples

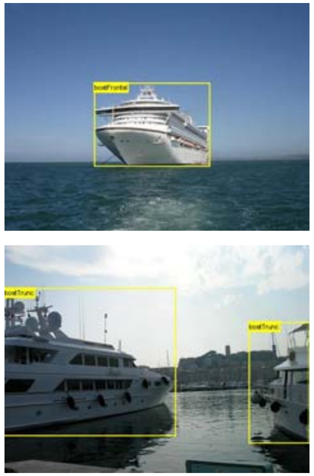
Aeroplane

Bicycle

Bird



Boat

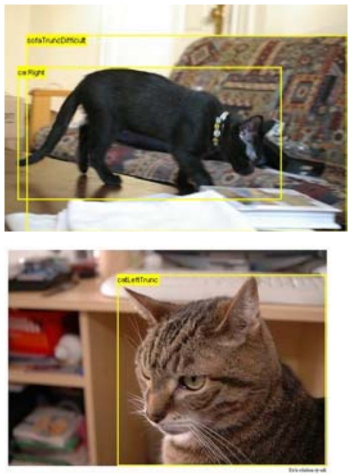


Bottle

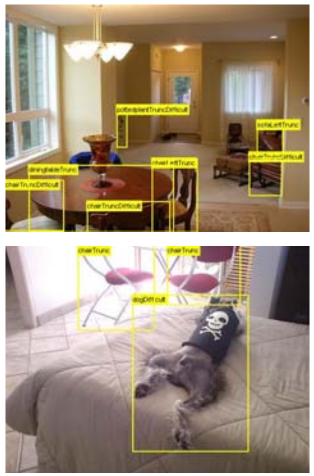
Bus

Car

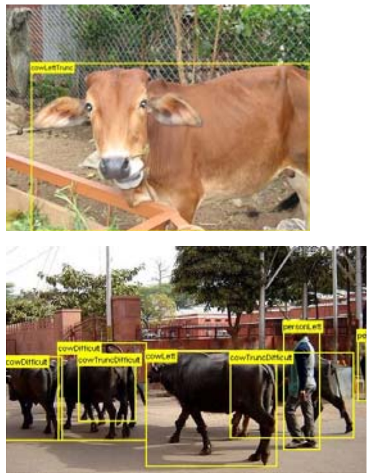
Cat



Chair

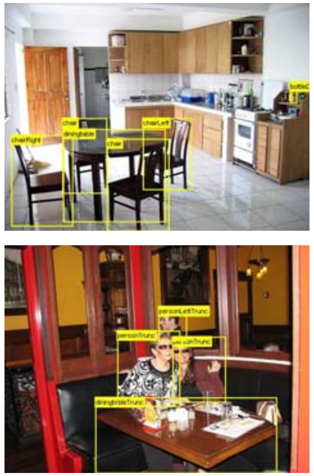


Cow

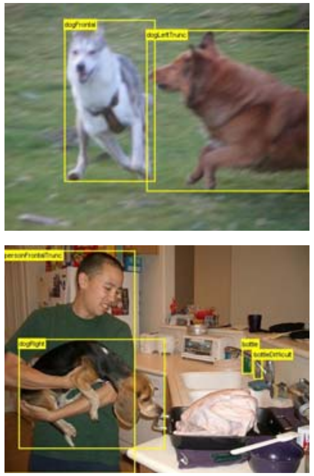


Examples

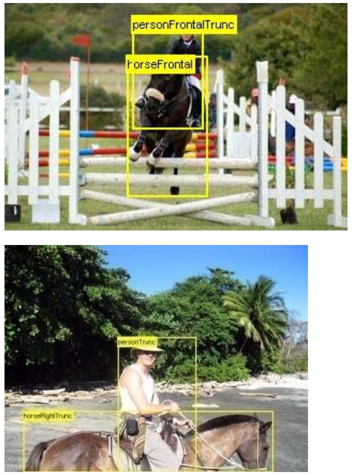
Dining Table



Dog

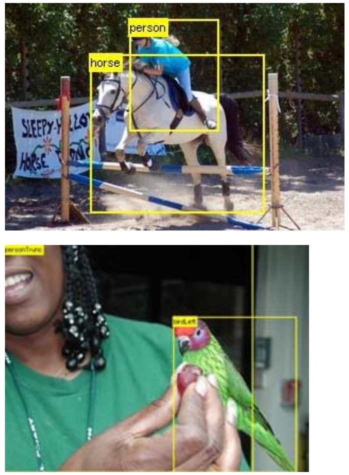


Horse



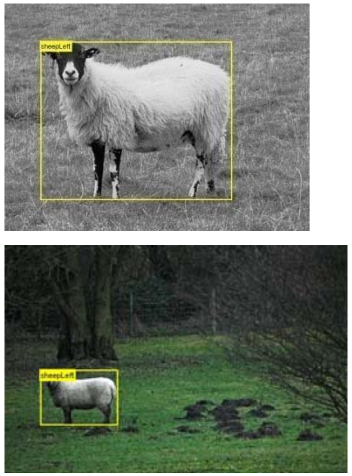
Motorbike

Person

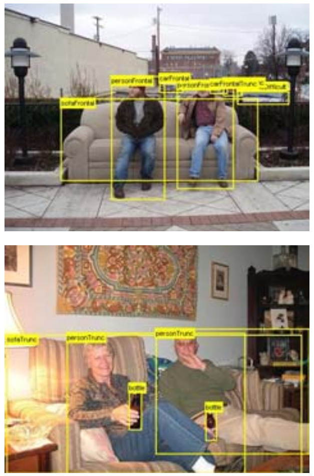


Potted Plant

Sheep

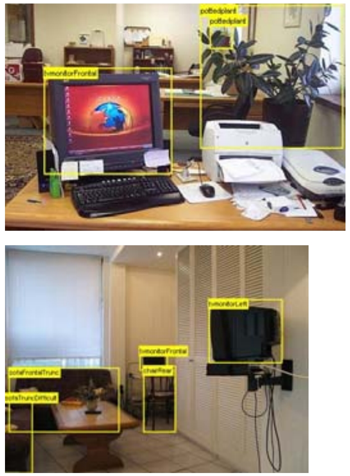


Sofa



Train

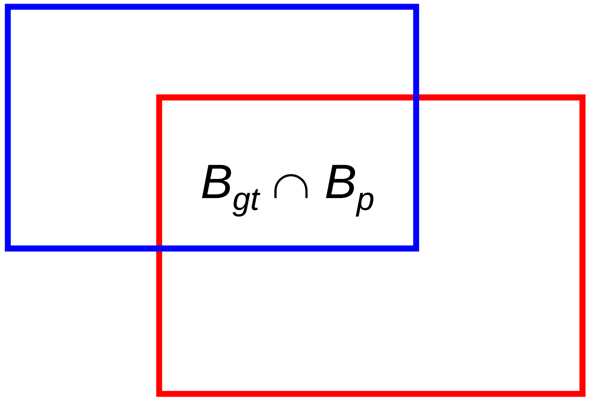
TV/Monitor



Detection: Evaluation of Bounding Boxes

- Area of Overlap (AO) Measure

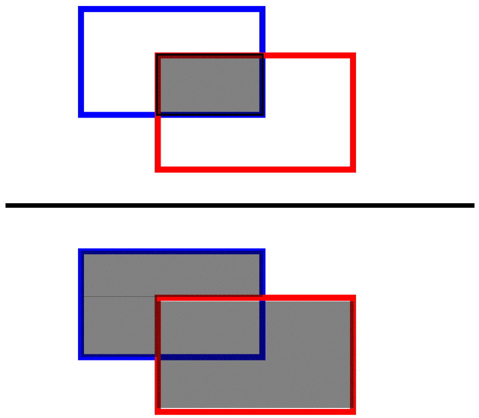
Ground truth B_{gt}



Predicted B_p

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

Detection if

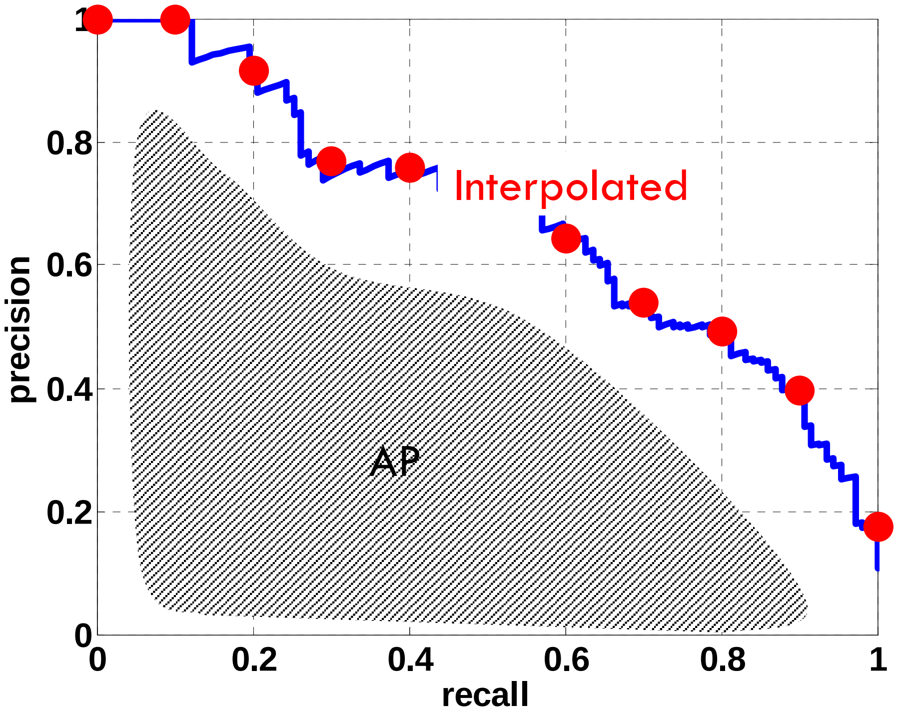


> Threshold

50%

Classification/Detection Evaluation

- Average Precision [TREC] averages precision over the entire range of recall

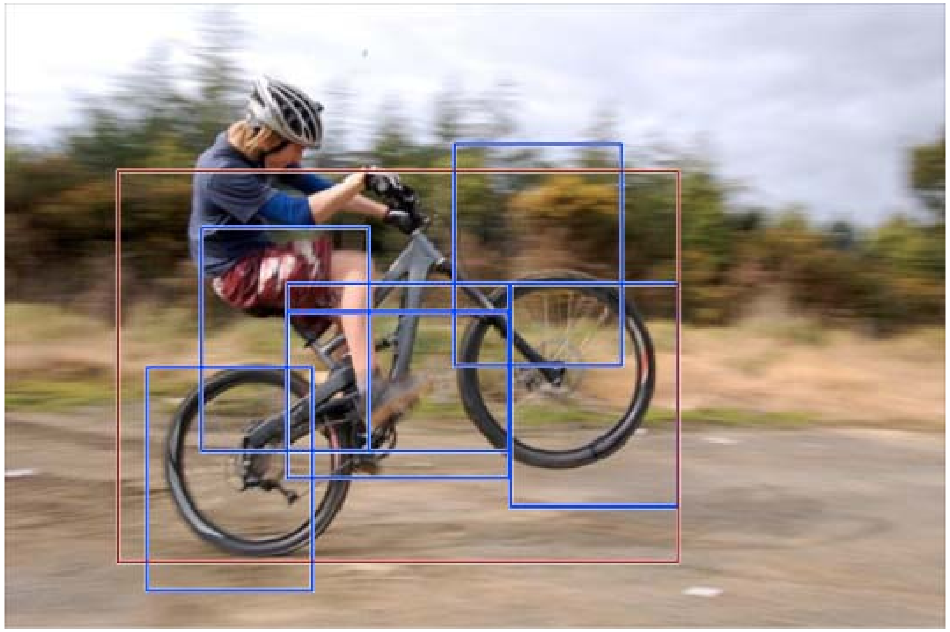


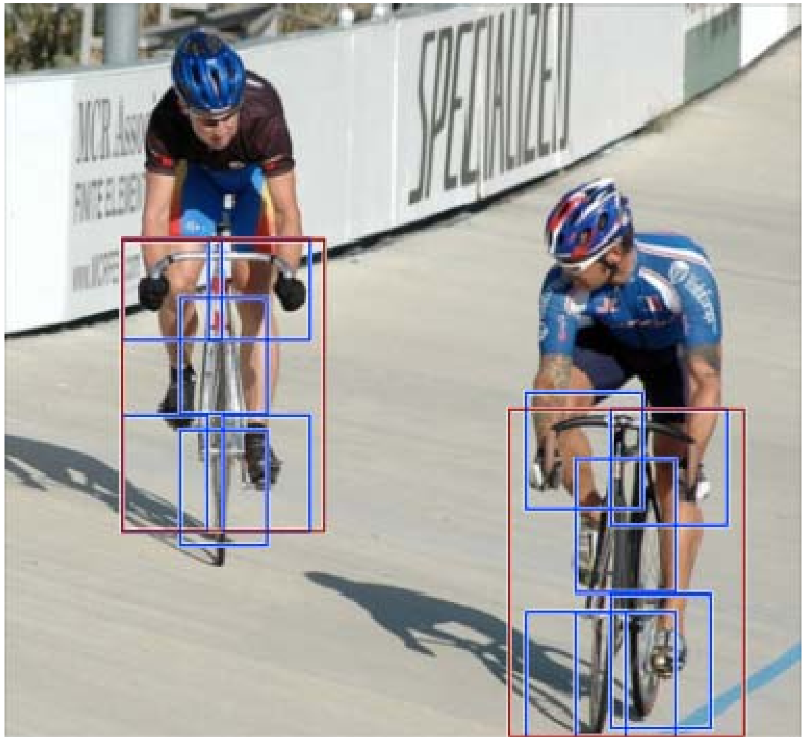
– A good score requires both high recall and high precision

– Application-independent

– Penalizes methods giving high precision but low recall

Object detection with discriminatively trained part models [Felzenszwalb et al., PAMI'10]



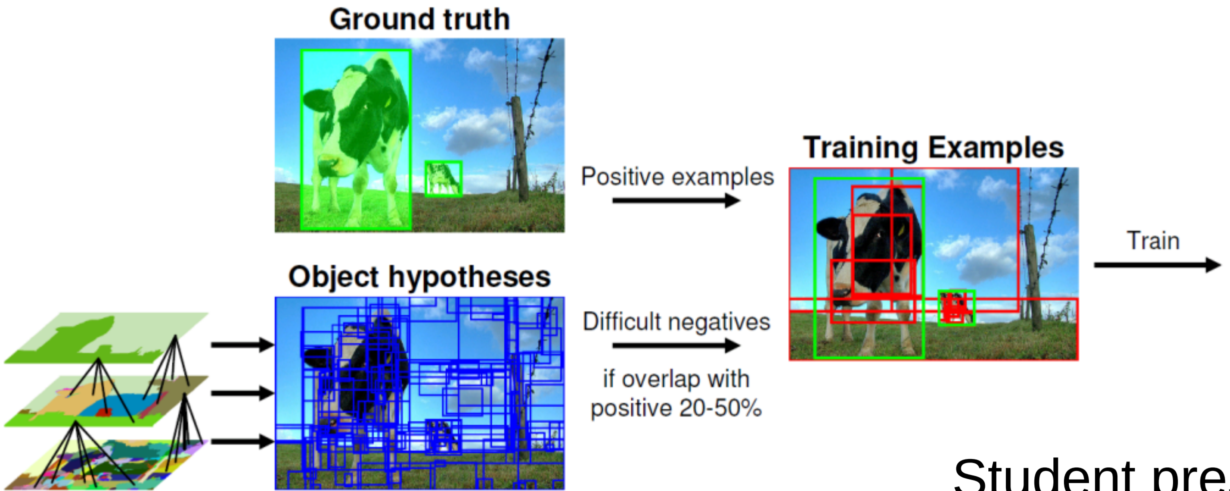


- Mixture of deformable part-based models
  - One component per "aspect" e.g. front/side view
- Each component has global template + deformable parts

Selective search for object location [v.d.Sande et al. 11]

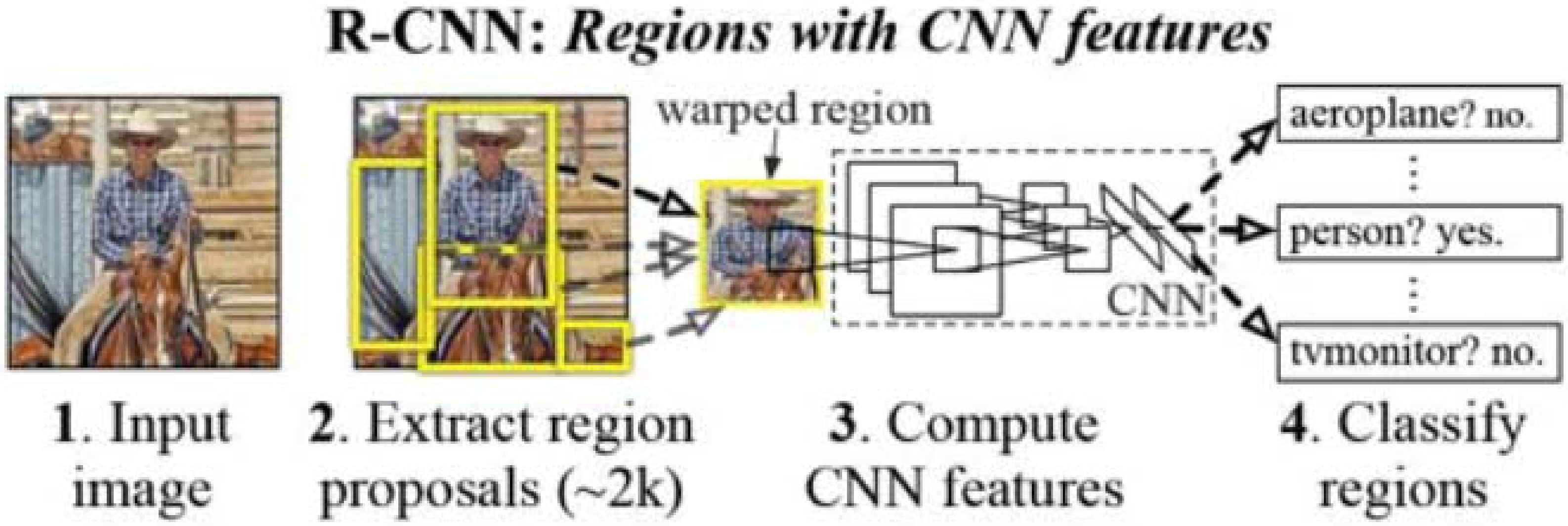
- Pre-select *class-independent* candidate image windows with segmentation

- Local features + bag-of-words
- SVM classifier with histogram intersection kernel + hard negative mining



Student presentation

CNN features for detection



Object detection system overview. Our system (1) takes an input image, (2) extracts around 2000 bottom-up region proposals, (3) computes features for each proposal using a large convolutional neural network (CNN), and then (4) classifies each region using class-specific linear SVMs. **R-CNN achieves a mean average precision (mAP) of 53.7% on PASCAL VOC 2010**. For comparison, Uijlings et al. (2013) report 35.1% mAP using the same region proposals, but with a spatial pyramid and bag-of-visual-words approach. **The popular deformable part models perform at 33.4%.**

R. Girshick, J. Donahue, T. Darrell, and J. Malik,
Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation, CVPR'14

Student presentation