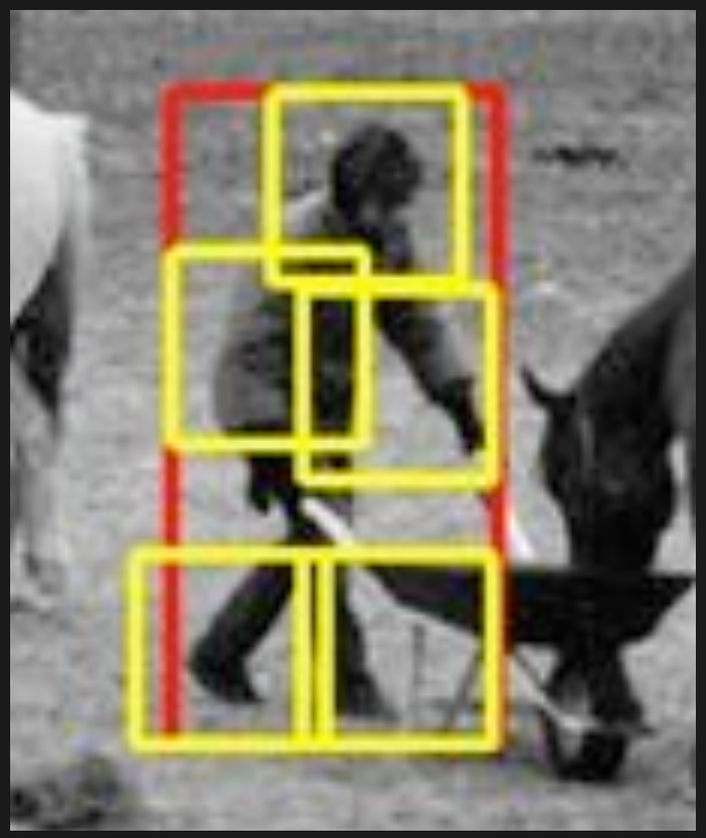
A Discriminatively Trained, Multiscale, Deformable Part Model

Pedro Felzenszwalb[1] & David McAllester[2] & Deva Ramanan[23]

University of Chicago[1]
Toyota Technological Institute at Chicago[2]
UC Irvine[3]

Model overview



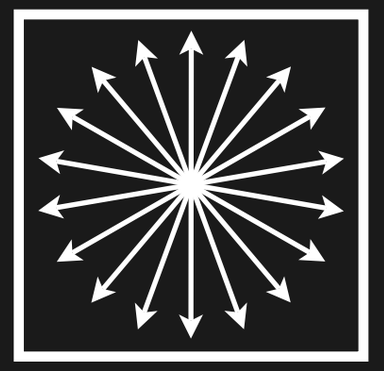
Model consists of root filter plus
deformable parts

We have built & tested
models for all 20 classes
(no class tuning)

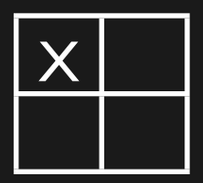
Image features - histograms of gradients

- Our implementation of DalalTriggs HOG features

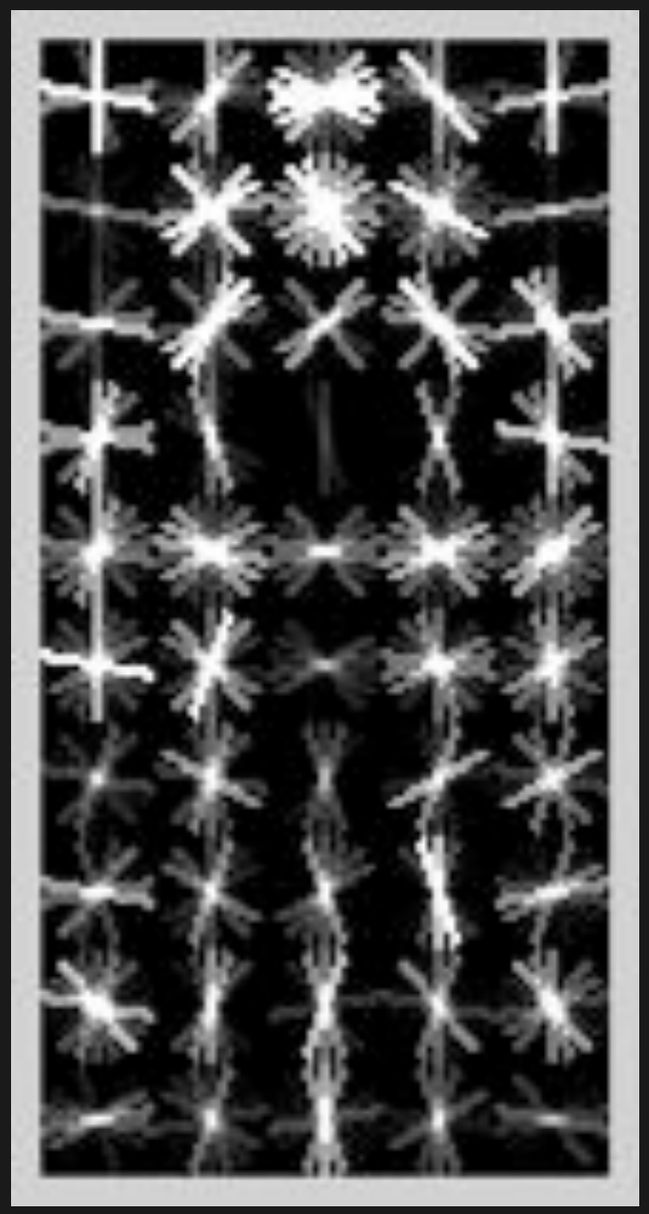
- Bin fine-scale gradients into 8x8 spatial neighborhoods and 9 orientation channels



- Normalize with respect to multiple local 16x16 regions

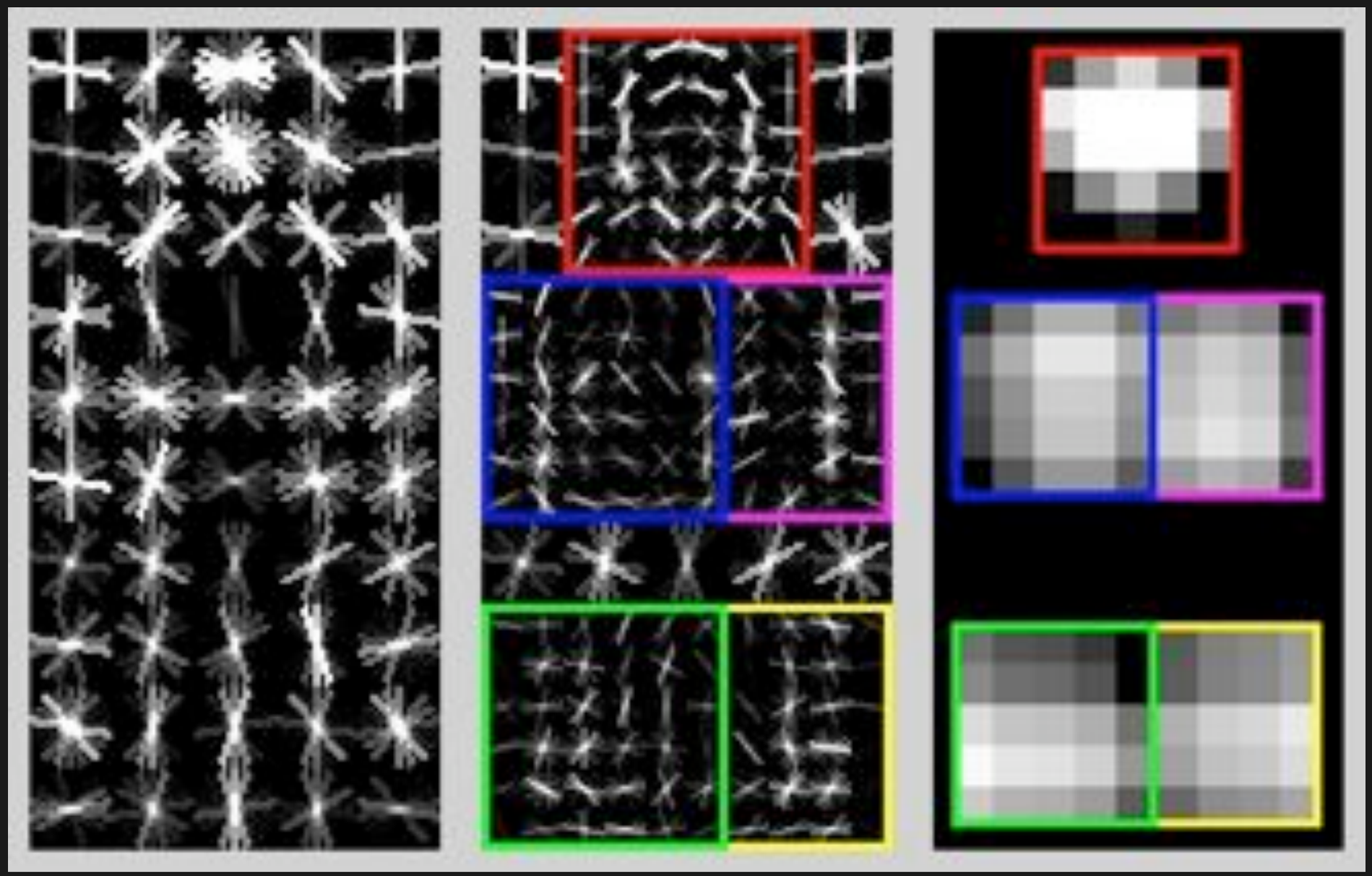


Multi-scale star model



root filter
8x8
resolution

Multi-scale star model



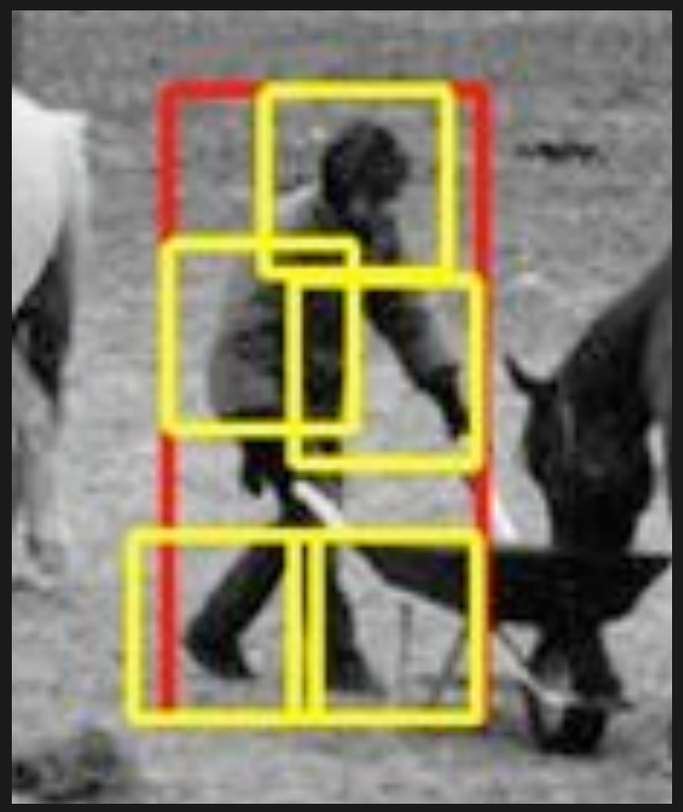
root filter
8x8
resolution

part filters
4x4
resolution

discrete
spatial model

Formal model

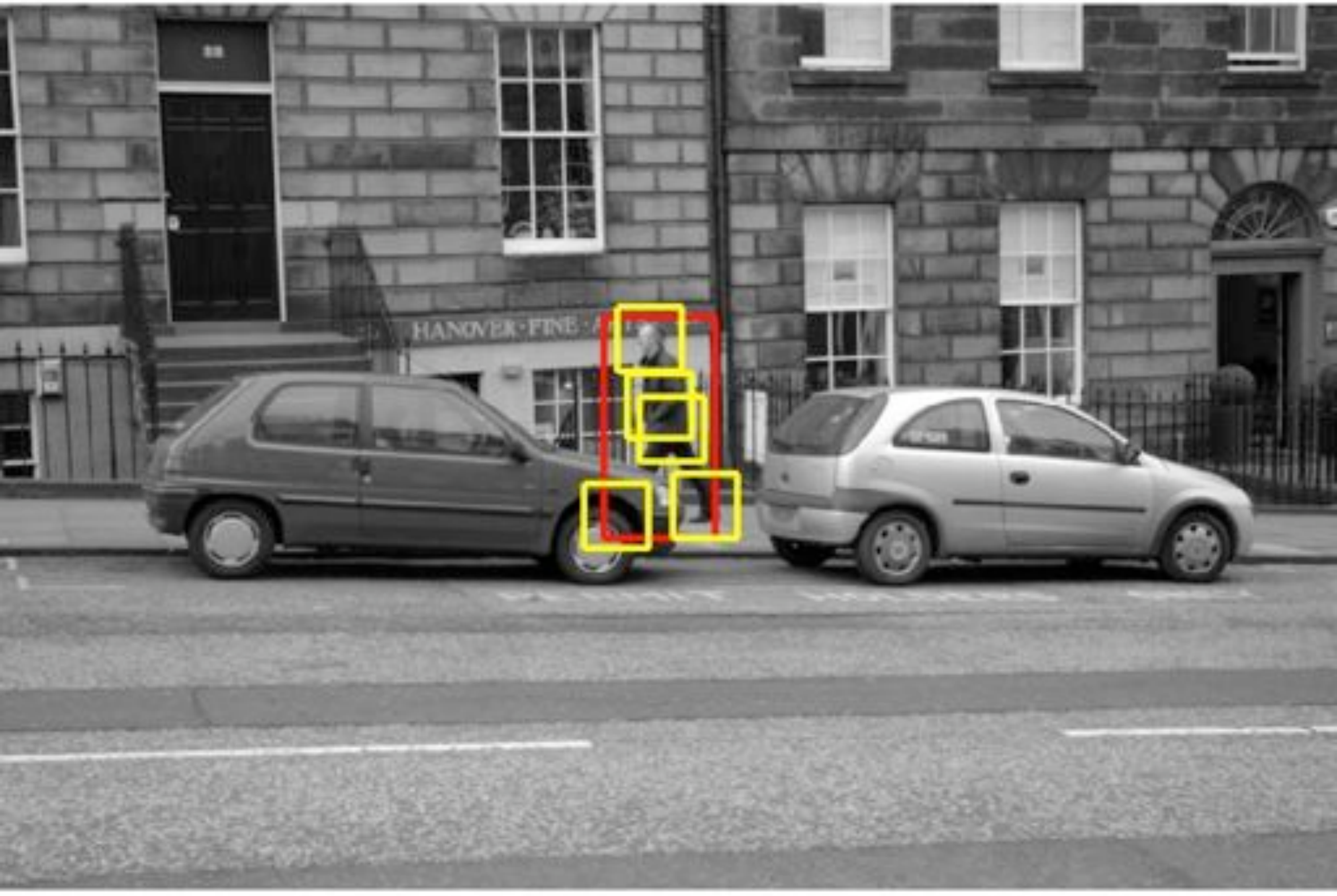
$$f_w(x) = w \cdot \Phi(x)$$



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

Z = vector of part offsets

$\Phi(x, z)$= vector of HOG features (from root filter & appropriate part sub-windows) and part offsets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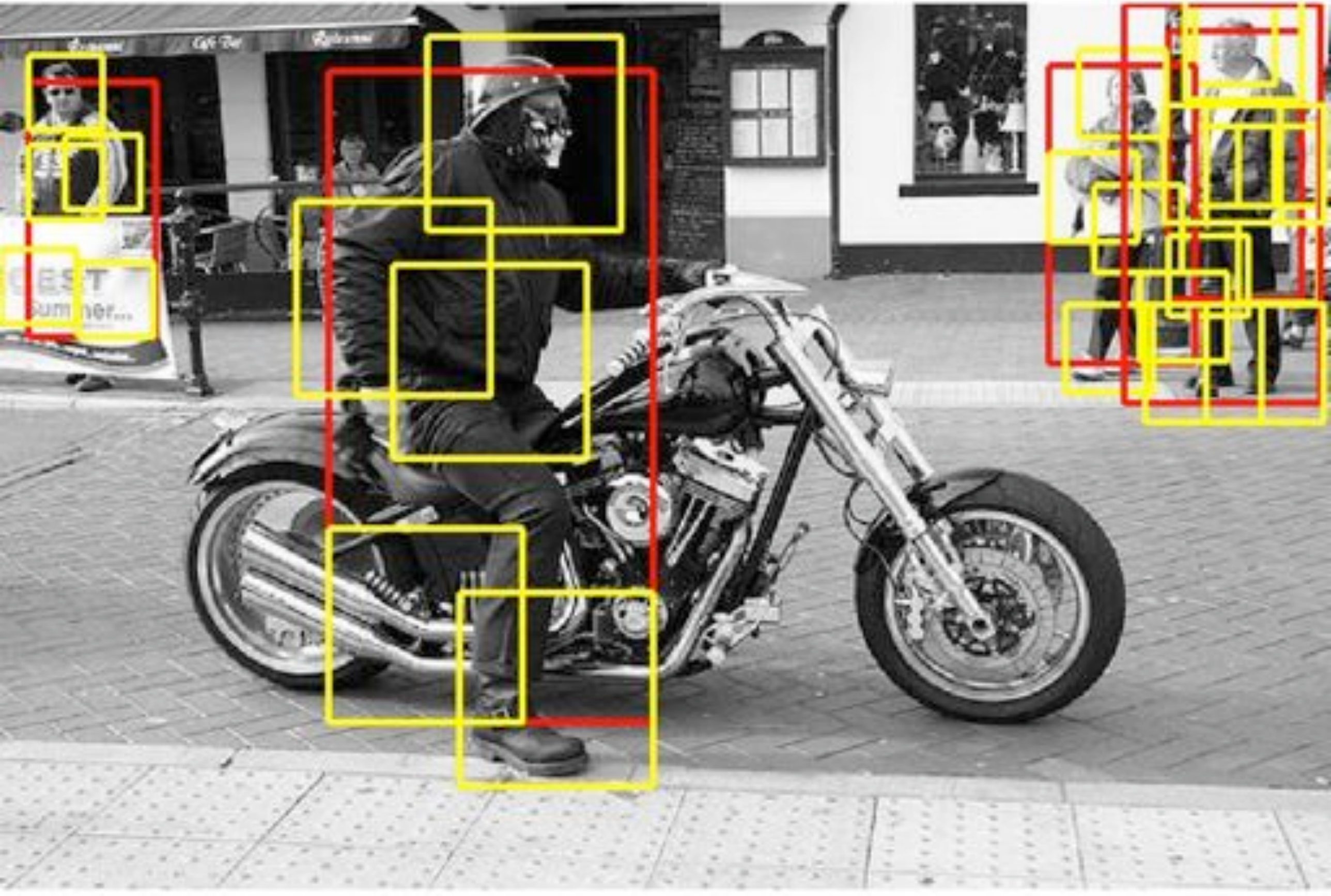


Some stats

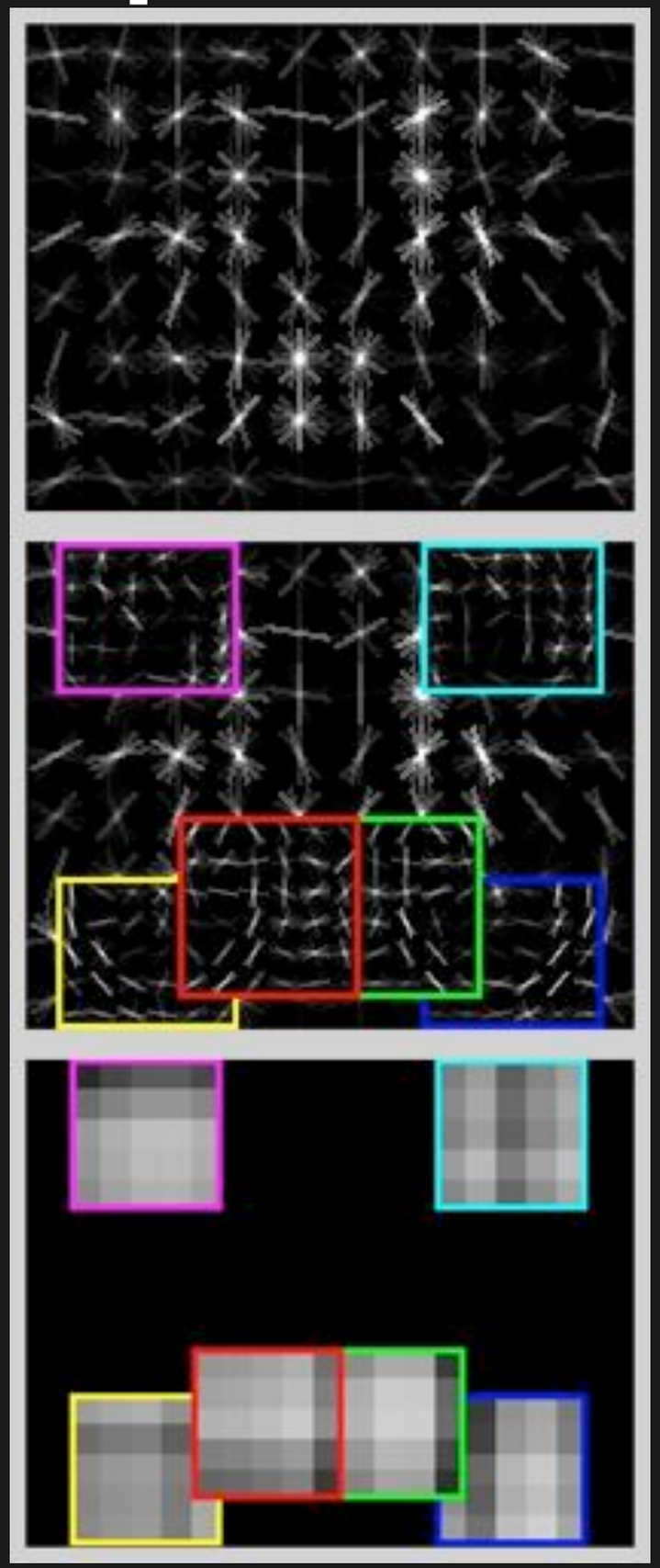
- We search over scales with an image pyramid (1.05 scaling)

- We search over 8-pixel strides for root filter, 4-pixel strides for part filter

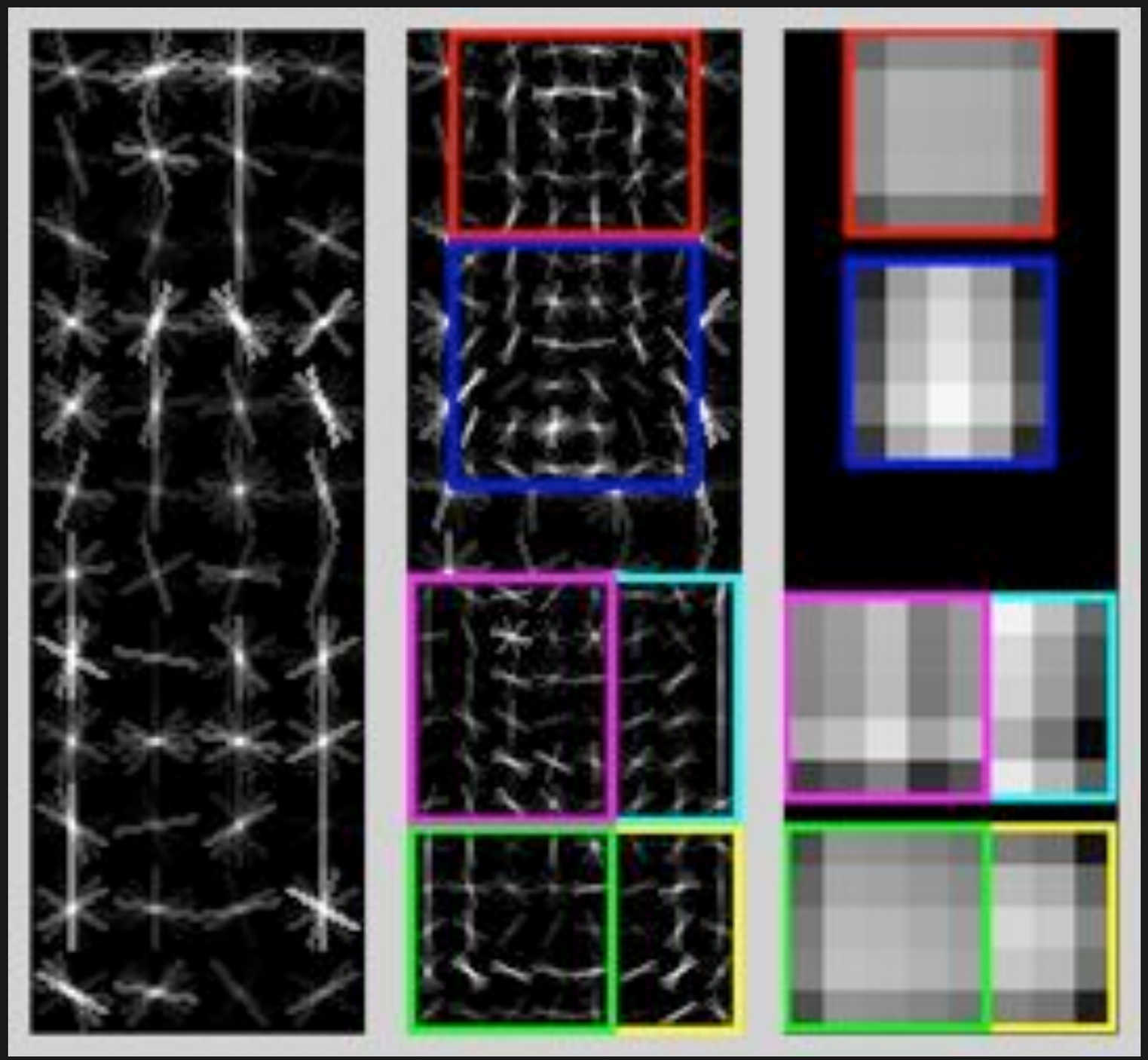
- Training time: 3-4 hours per class using 1 cpu, including learning part models automatically

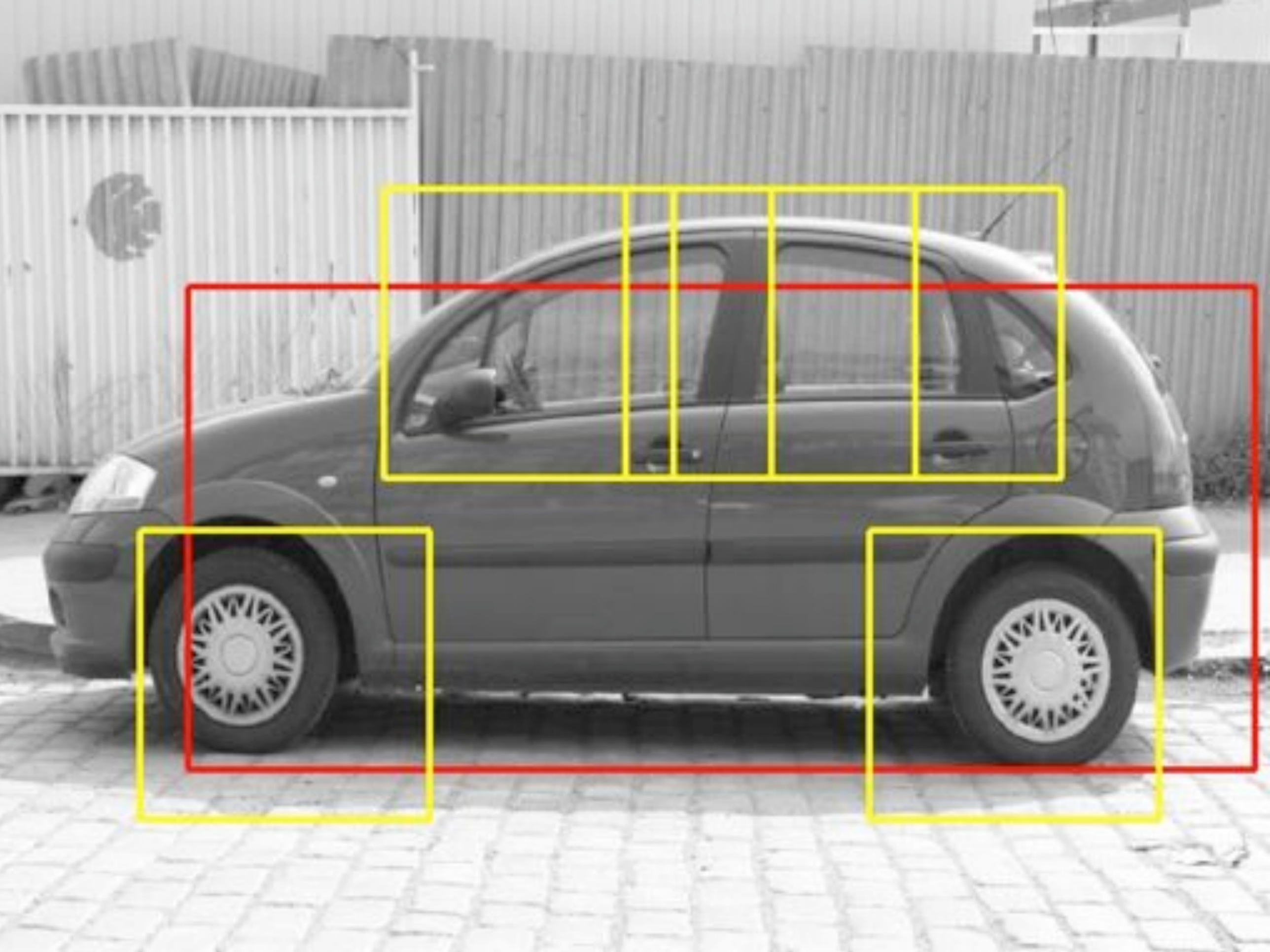
- Testing time: 2 seconds per image per model

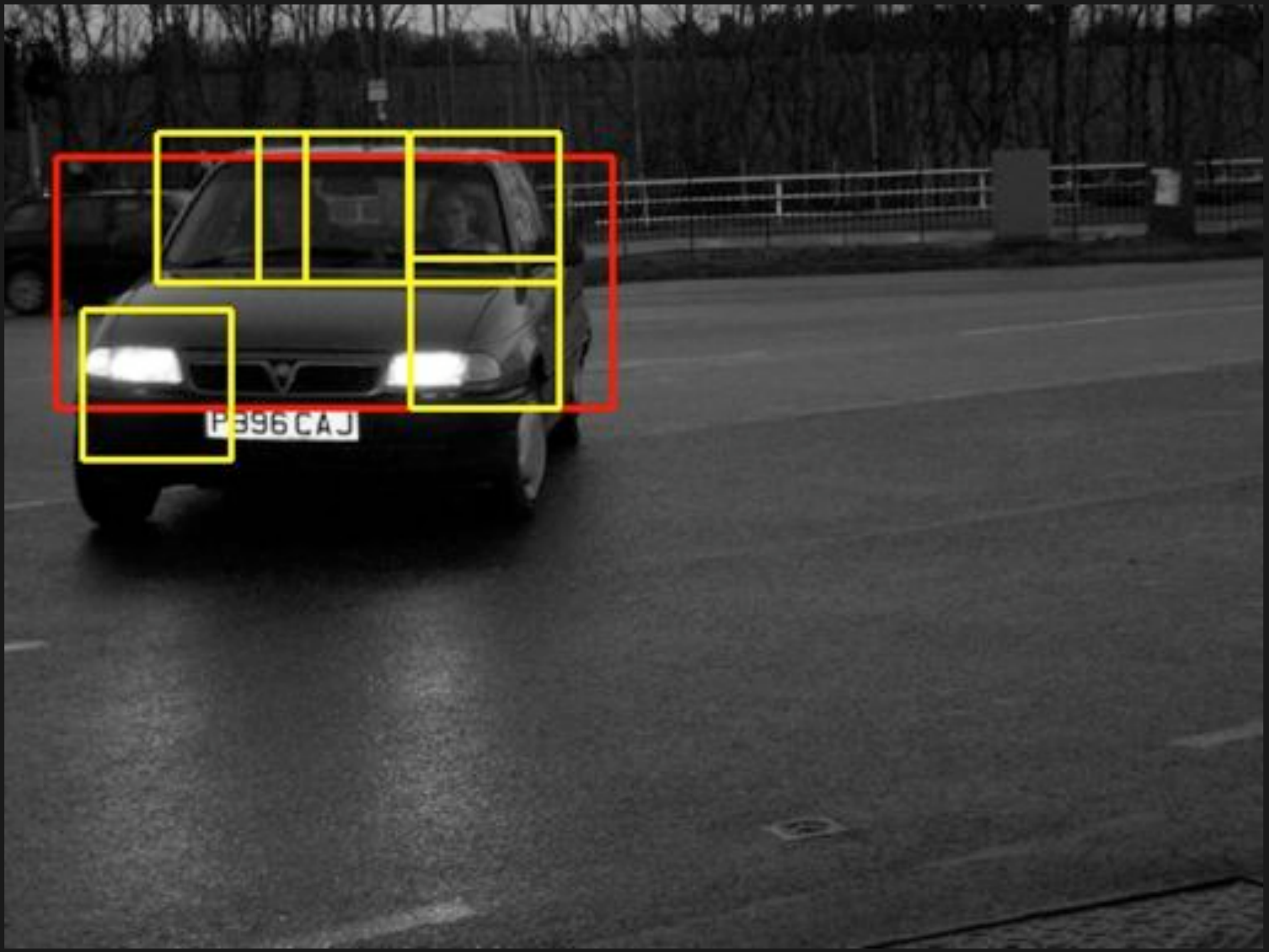
Example models



Example models



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Latent SVMs

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

Assume we are given positive and negative training windows $\{x_i\}$

$$w^* = \arg\min_w \lambda||w||^2 + \ ...$$

$$\sum_{i \in pos} \max(0, 1 - f_w(x_i)) + \sum_{i \in neg} \max(0, 1 + f_w(x_i))$$

If f() is linear classifier, this is a standard SVM (convex)

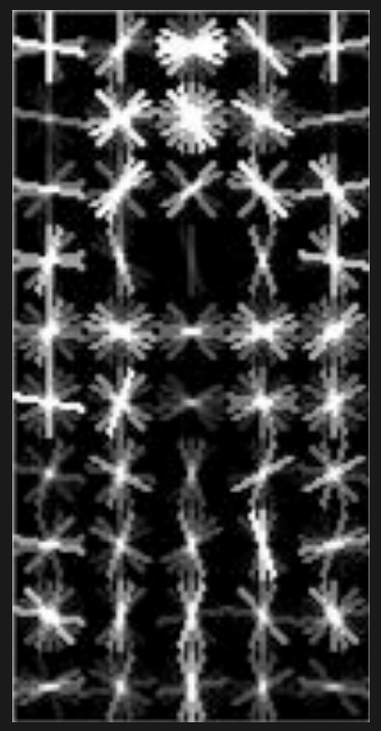
If f() is an arbitrary classifier, this (in general) is not convex

If f() is convex in w, the training objective is 'semi-convex'

(Instance of LeCun's Energy Based Model)

Root filter initialization

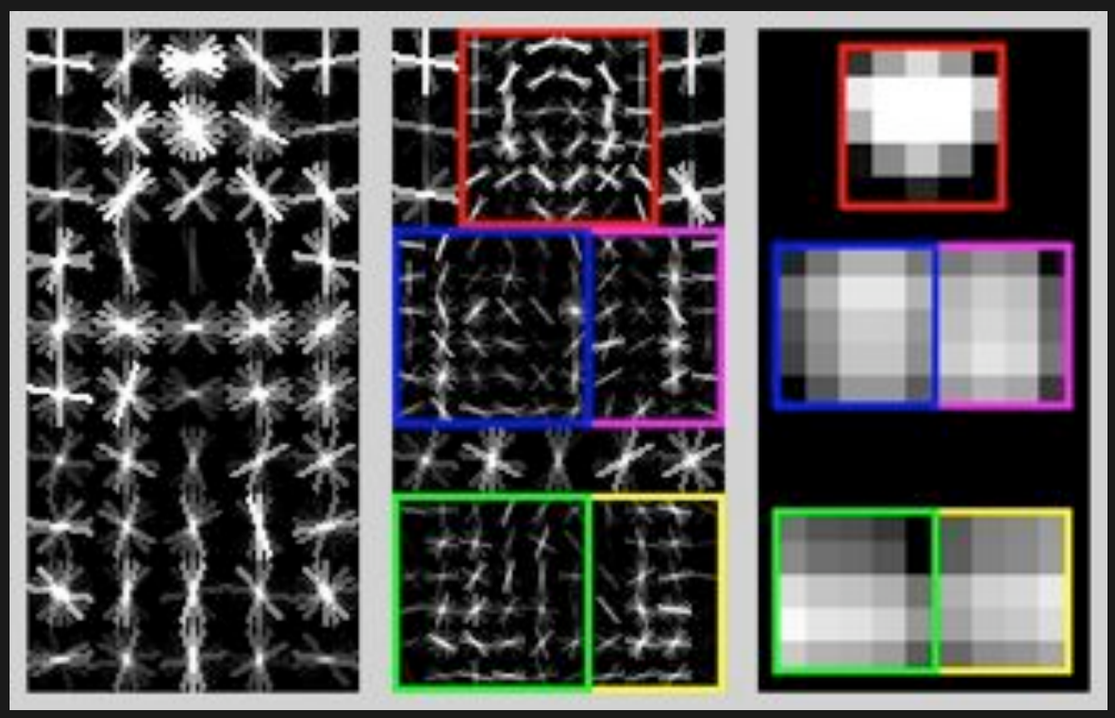
- We select the aspect and size by a heuristic tuned on 2006 data (use most common aspect and smallest area > 80% of training bounding boxes)
- Train a root filter with SVM-light: use non-truncated positives (warped to fixed aspect & size) and random negatives



Part filter initialization

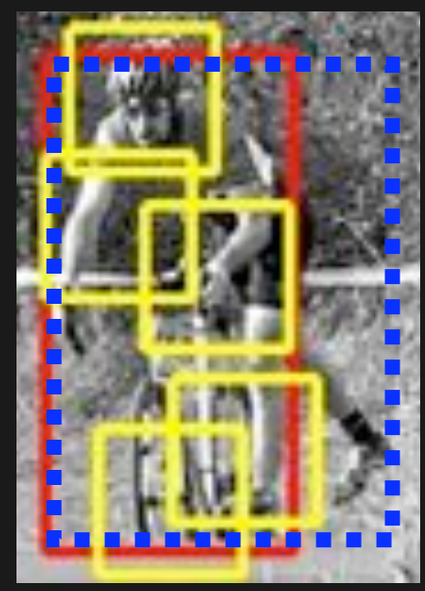
- Look for regions in root filter with lots of positive energy - part filter initialized to subwindow doubled in resolution

- Spatial model allows for a bounded offset from original anchor point - discrete deformation cost initialized to 0 everywhere

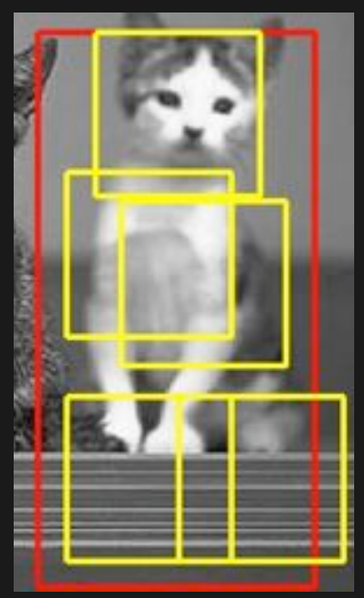


Model update

- Update positives
  - -Apply current detector over all positions & scales
  - -Find best-scoring $\Phi(x_i, z_i)$ that overlaps > 50% with ground truth positive bounding box
  - -Allows for automatic adjustment of b. box



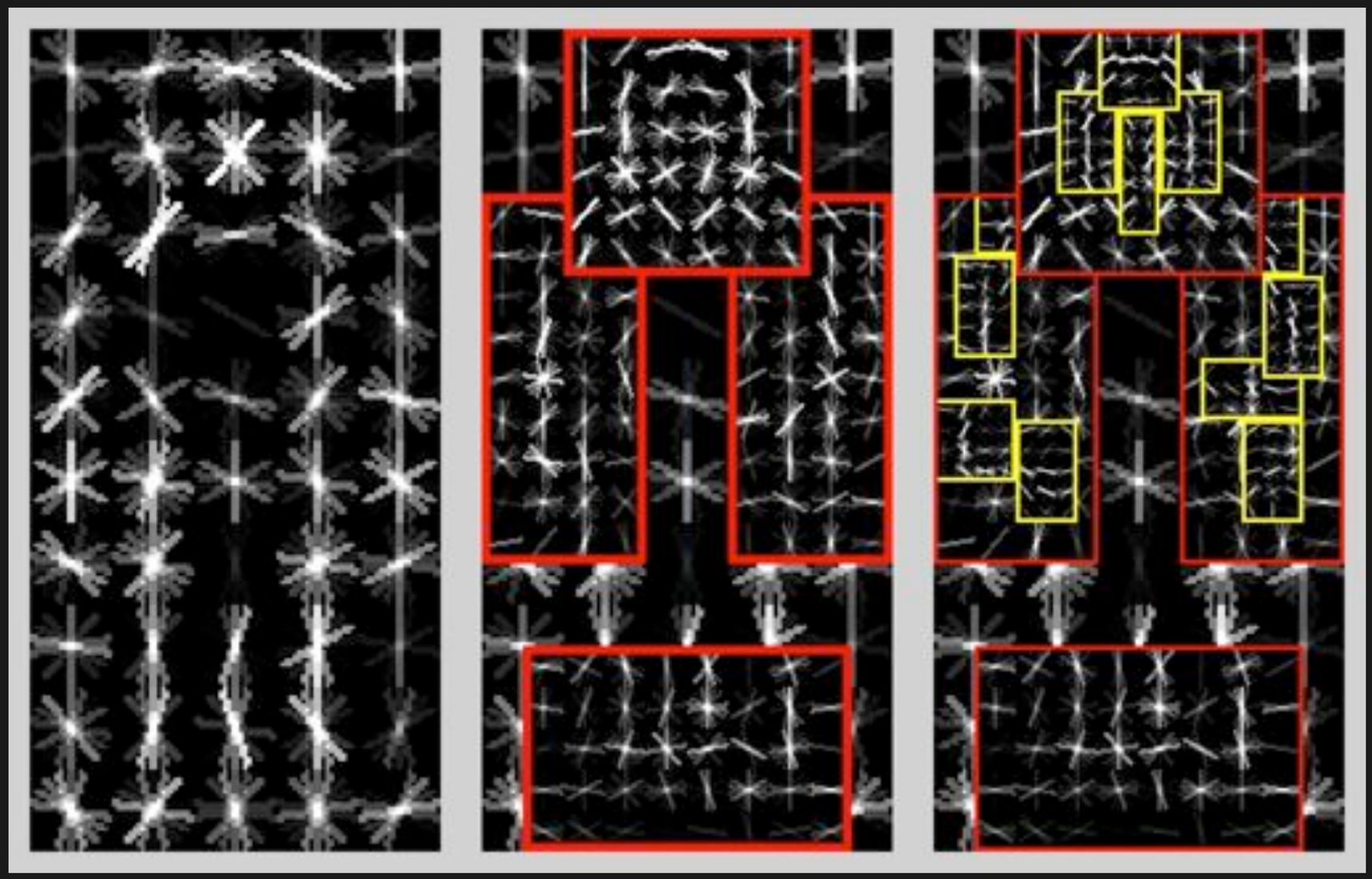
- Collect negative $\Phi(x_i, z_i)$`s by finding high-scoring detections, cycling through negative training images



- Use $\Phi(x_i, z_i)$`s to train a new detector (w) with SVM-light (Joachims)

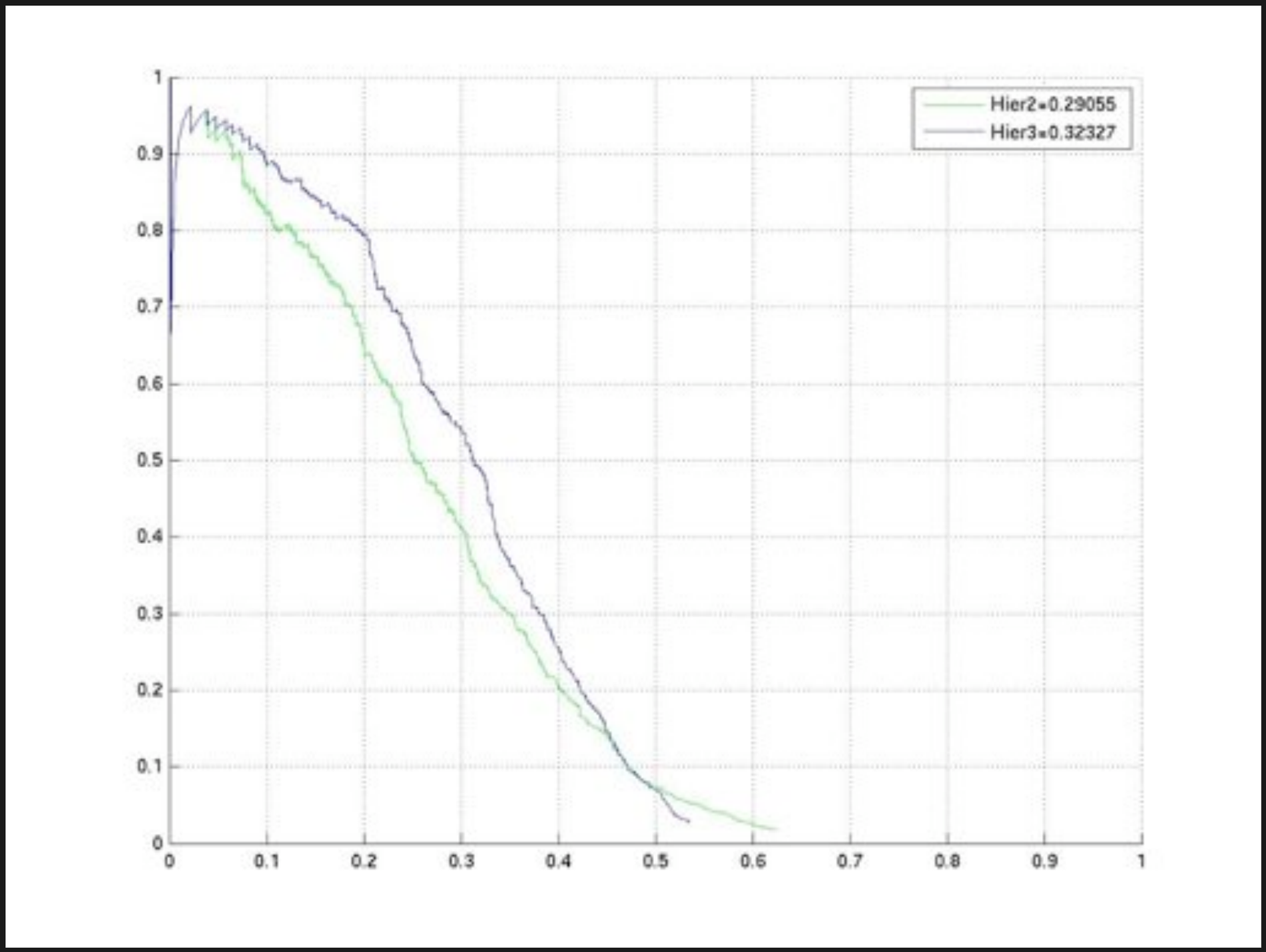
- Repeat update 10 times

Ongoing work



Hierarchically learn parts

Ongoing work



Improves performance by 10% (AP of .29 vs .32)

Training & testing on Person2006

Conclusions

Deformable part model
Histograms-of-gradient features
Multi-scale / hierarchical
Discriminatively-trained