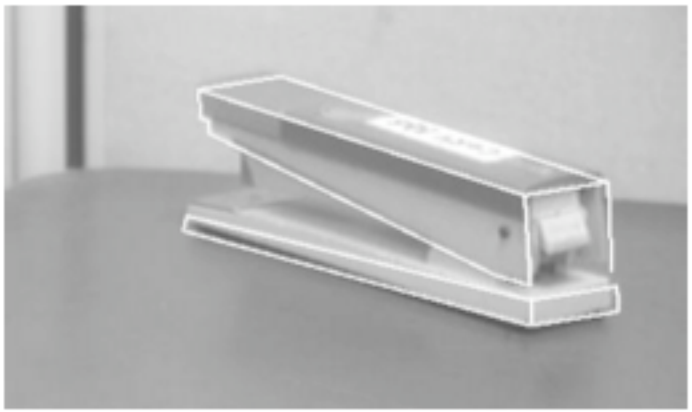
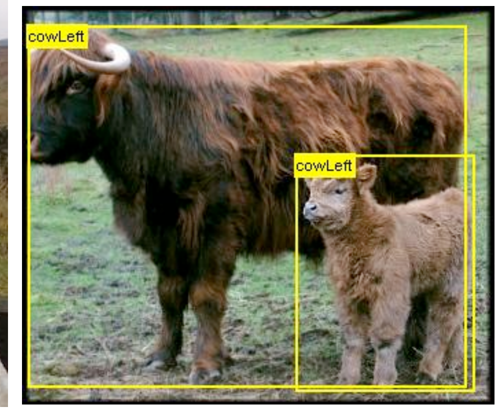
Object detection and recognition

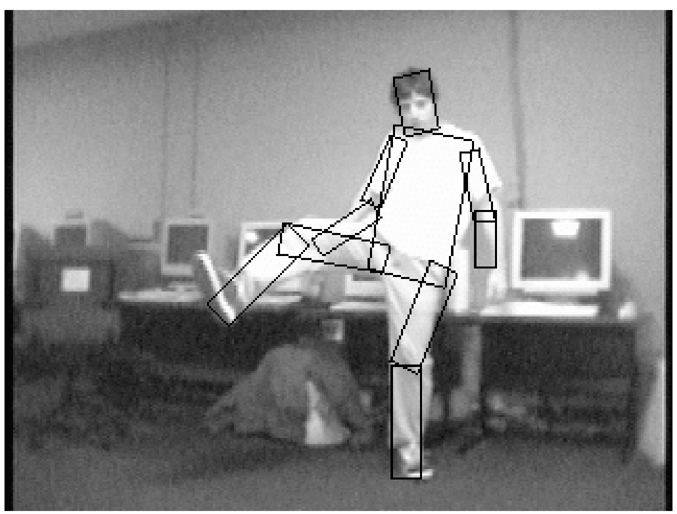
Example problems

Detecting rigid objects

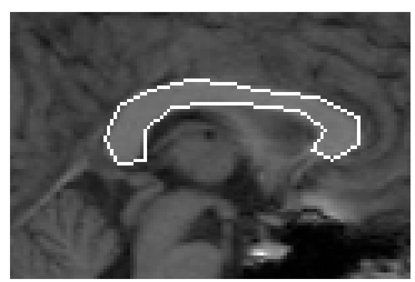


PASCAL challenge

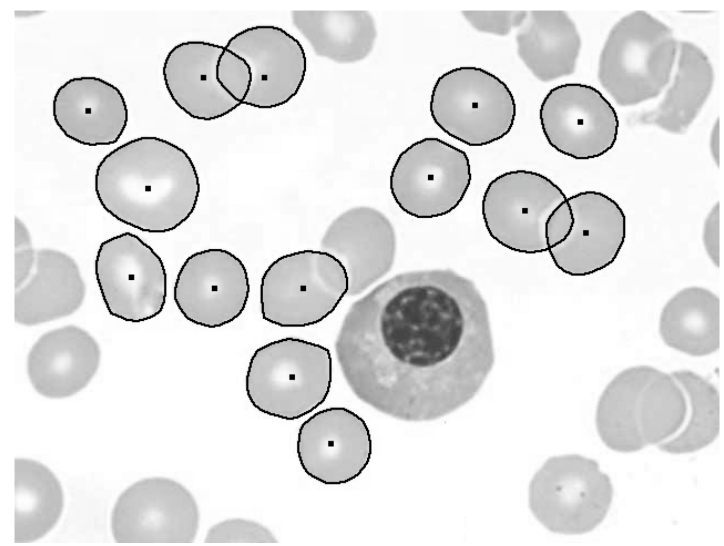




Detecting non-rigid objects



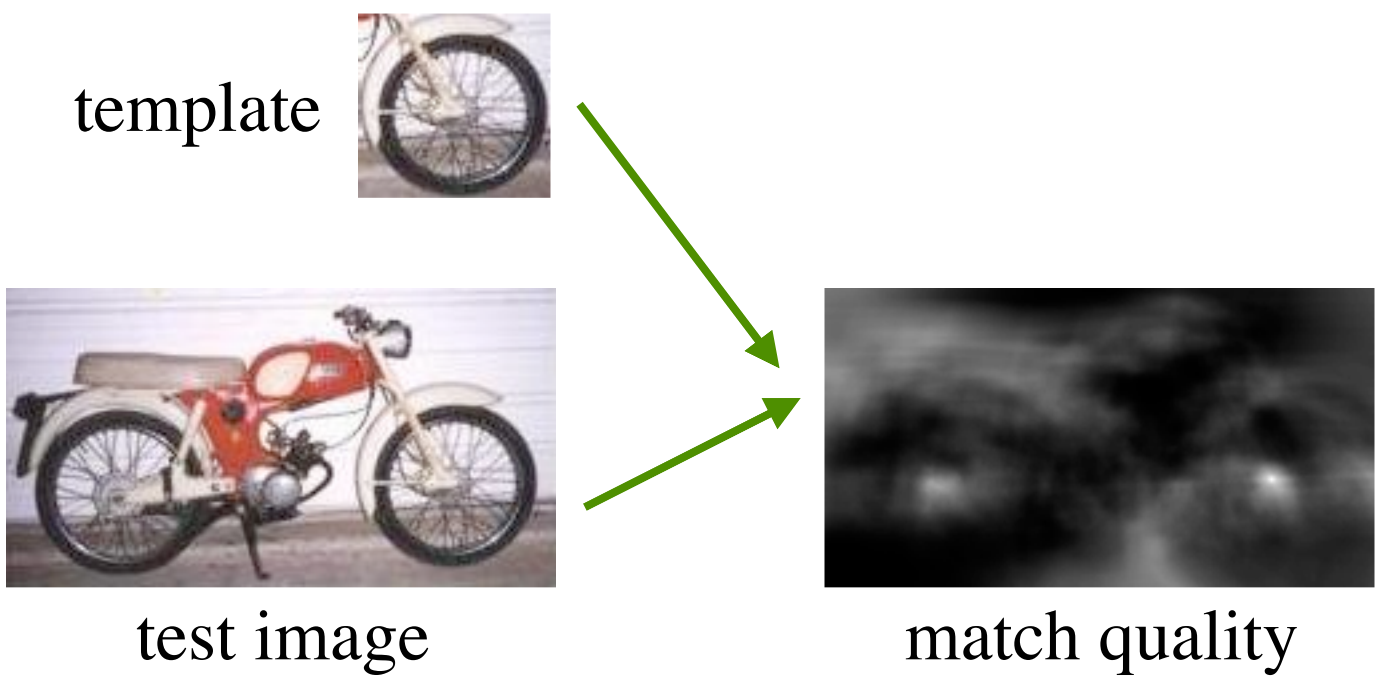
Medical image analysis



Segmenting cells

Template matching

- "Appearance based method".
- Object of interest defined by a template.
- Compare template to image data under each possible shift.
  - Scale template or image to find objects of different sizes

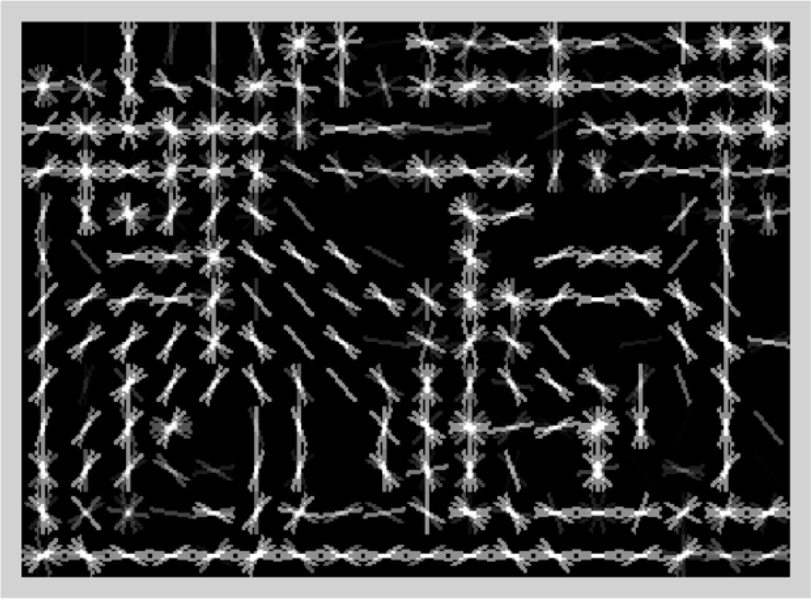


Issues

- How to compare template to image?
  - Sum of squared differences, dot product, etc.
- What should we use as the template?
  - Cropped picture of the object.
  - Average of multiple pictures.
- How do we handle variation in appearance?
  - Variations due to pose, lighting, non-rigid objects, etc.
  - Don't compare image intensities directly.
  - Works well for certain classes of objects (face detection).

Image intensities

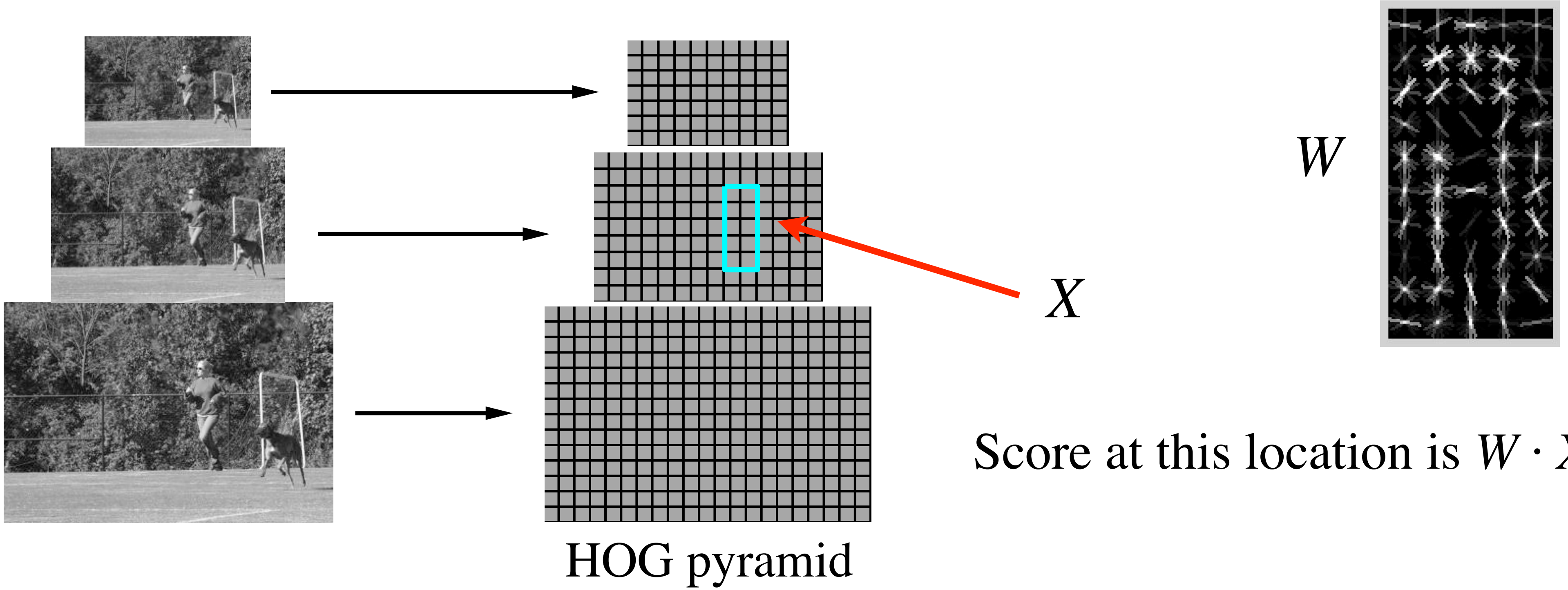
Histogram of Gradient (HOG) features



- Discretize gradient orientation at each pixel into 9 possible values.
- Image is partitioned into 8x8 pixel blocks.
- In each block we compute a histogram of gradient orientations.
  - 9 dimensional feature vector.
  - Invariant to changes in lighting, small deformations, etc.

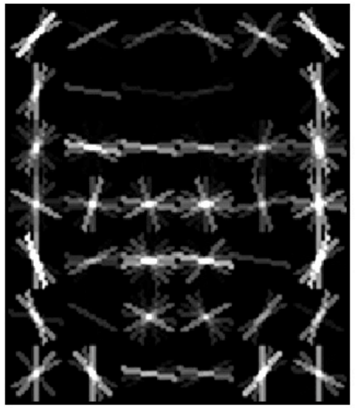
Template matching with HOG features

- Templates define weights for features in rectangular window.
  - *N*x*M*x*9* weights for a window of size *N*x*M*.
- Take dot product of template and subwindow of HOG pyramid.

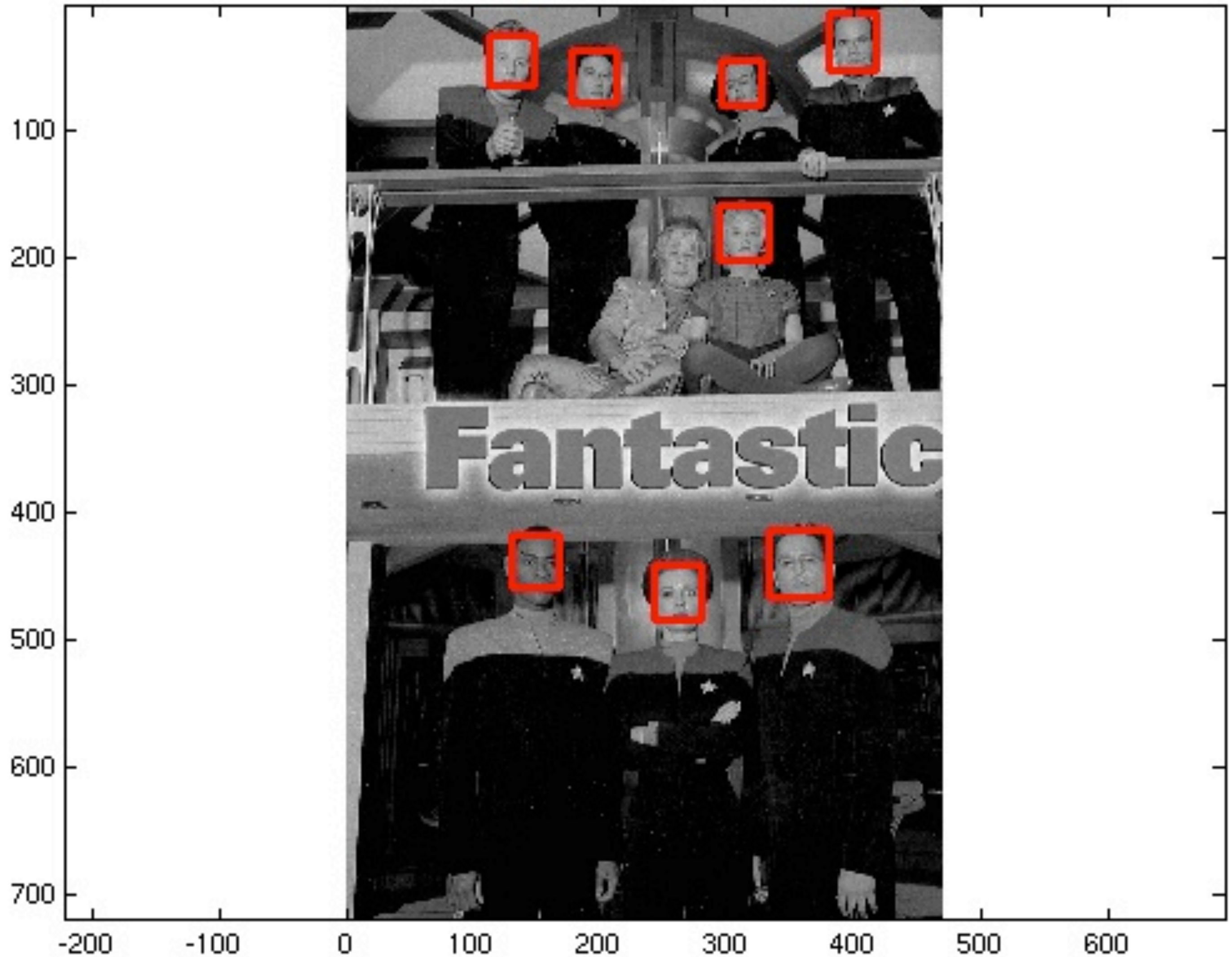


Score at this location is $W \cdot X$

Face detection



template



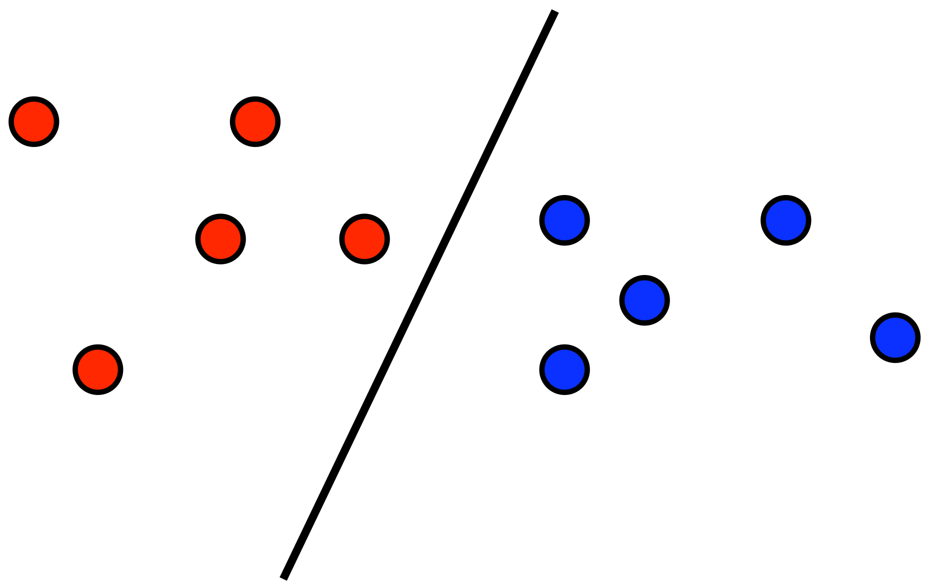
example result

Learning the template

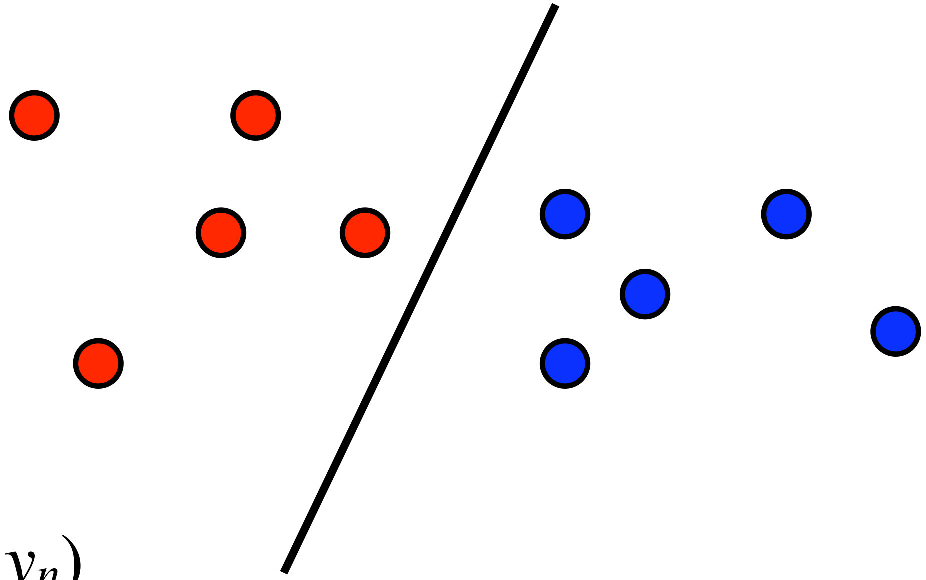
- Suppose we have positive and negative examples:
  - $(x_1, y_1),\ldots, (x_n, y_n)$
  - x_i is a subwindow of a HOG pyramid.
  - $y_i = 1$ if subwindow contains a face
  - $y_i = -1$ otherwise
- Look for template W such that every positive example scores higher than every negative example.
  - $(W \cdot x_i) > b$ if $y_i = 1$
  - $(W \cdot x_i) < b$ if $y_i = -1$

Linear classifiers

- Linear classifier:
  - Defined by a weight vector W and bias b.
  - $(W \cdot x_i) > b$ if $y_i = 1$
  - $(W \cdot x_i) < b$ if $y_i = -1$
- W and b define a hyperplane separating the positive and negative examples. W is the orientation, b is the distance from the origin.



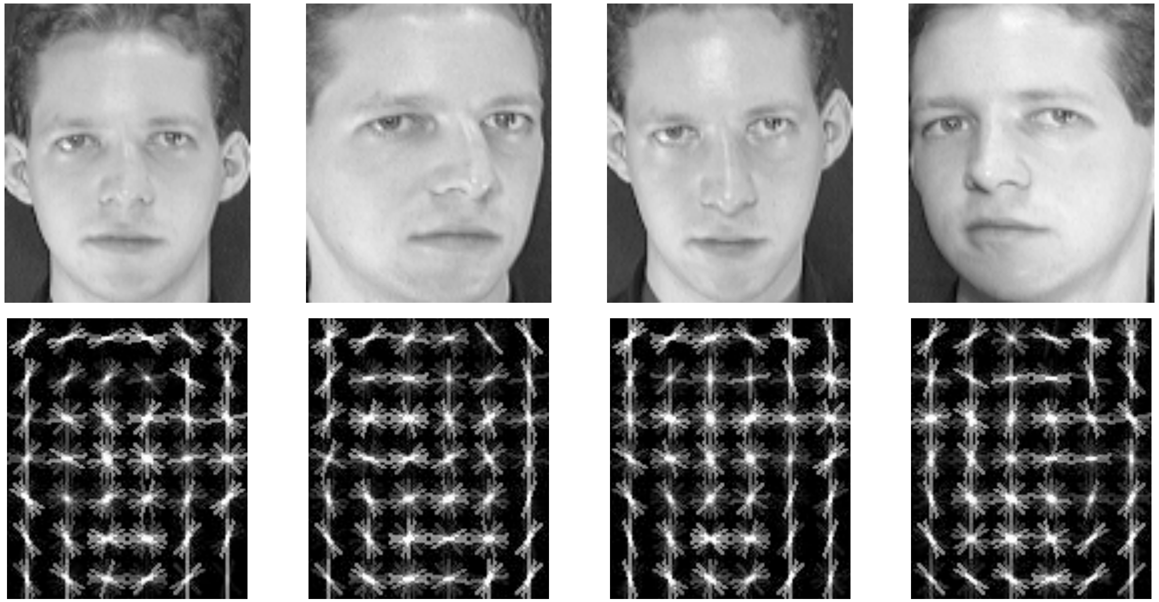
Learning linear classifiers



- Given $(x_1, y_1),\ldots, (x_n, y_n)$
- Find hyperplane separating positive and negative examples
- Classical problem in pattern recognition/machine learning
  - Linear programming
  - Perceptron algorithm
  - Support vector machines

Training a face model

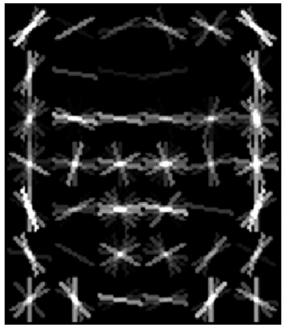
- Positive examples:



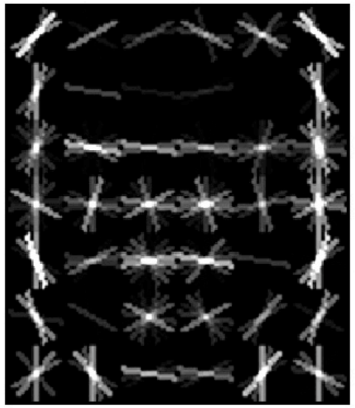
. . .

- Negative examples: random patches from images without faces

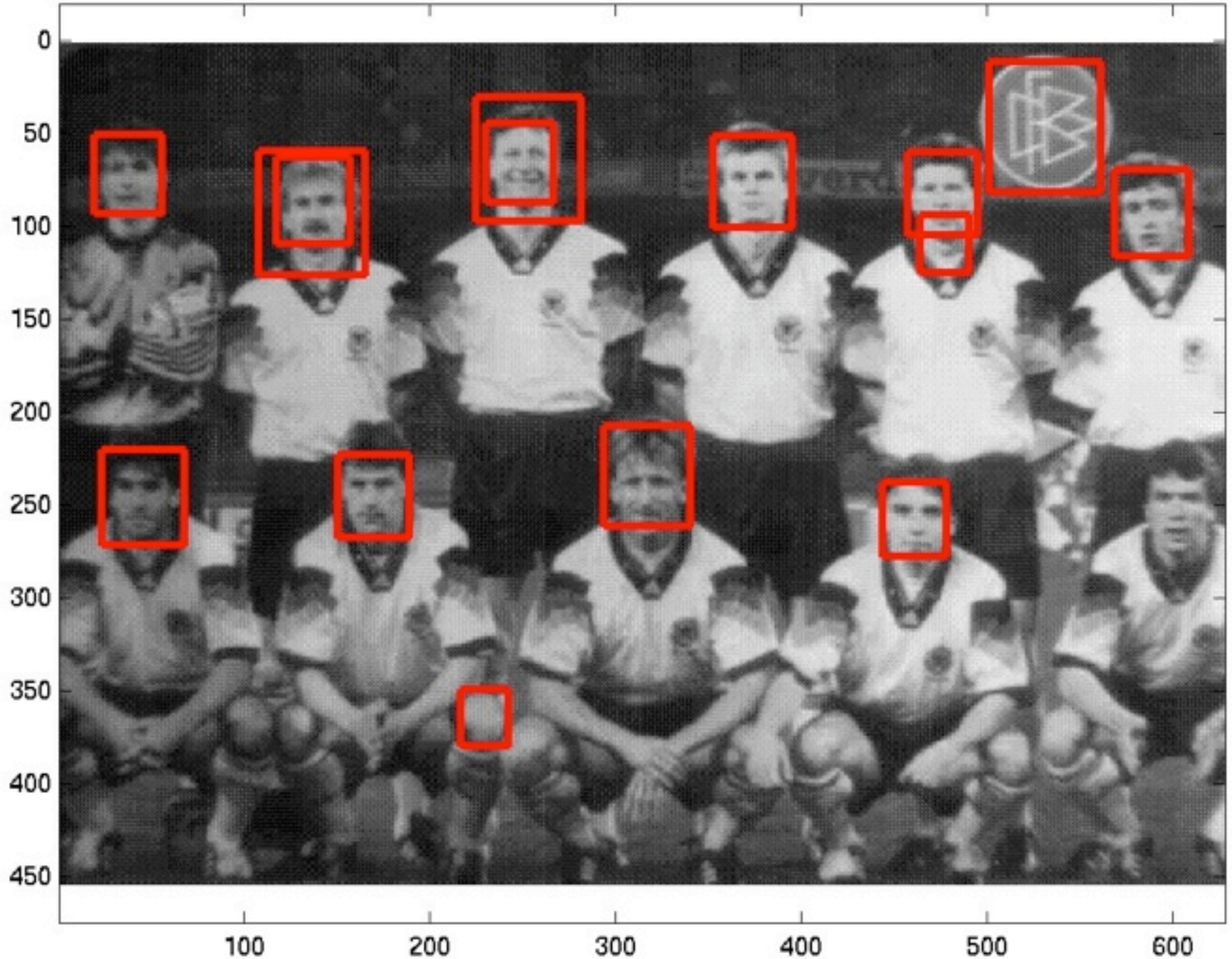
- Model learned with SVM:



Face detection

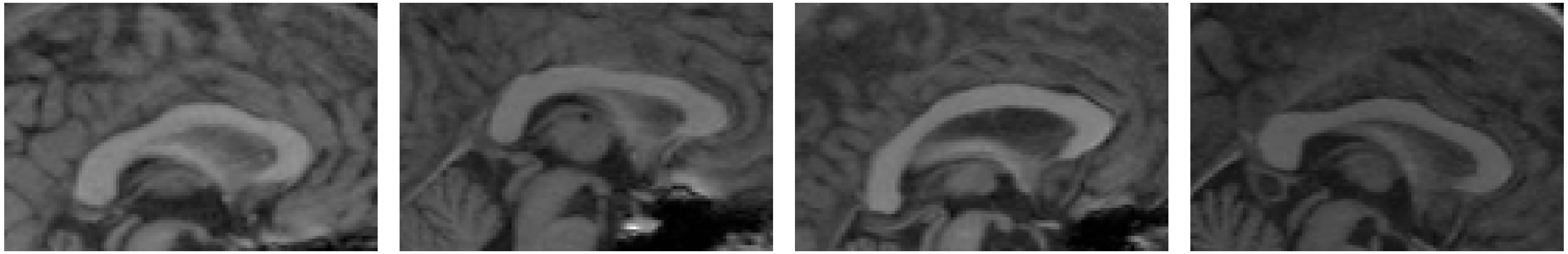


template



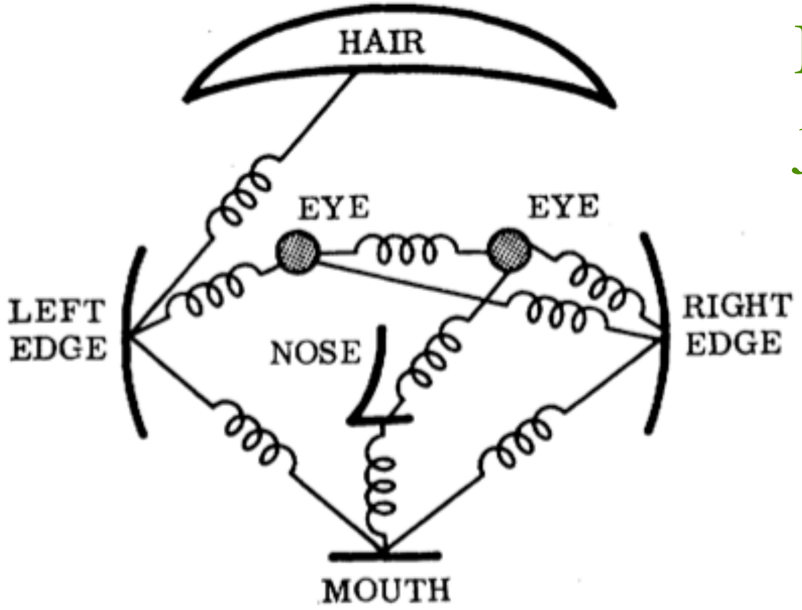
Deformable Models

- Template matching works well for faces but...
- How do we handle other types of objects
  - People, cars, etc.
  - Non-rigid objects, object categories, etc.
- Deformable models approach:
  - Consider each object as a deformed version of a template.



Pictorial Structures

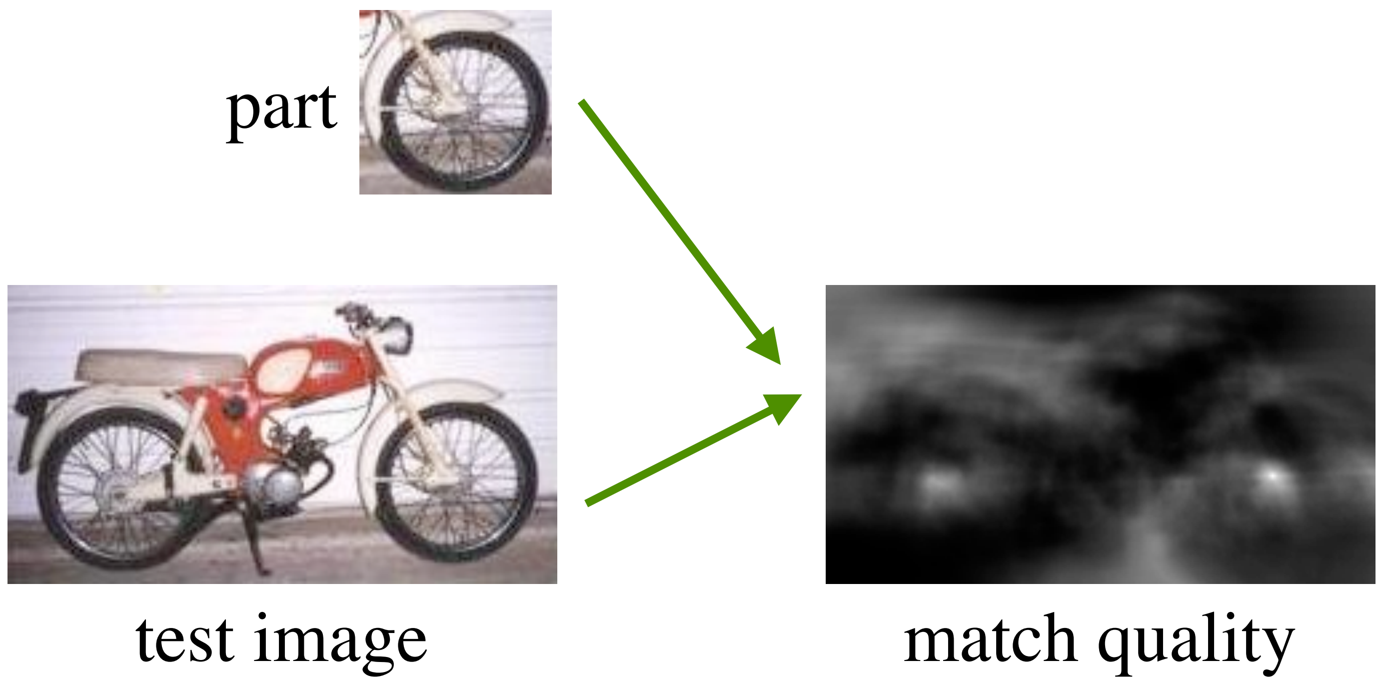
- Introduced by Fischler and Elschlager in 1973.
- Part-based models:
  - Each part represents local visual properties.
  - "Springs" capture spatial relationships.



Matching model to image involves joint optimization of part locations "stretch and fit"

Local evidence + global decision

- Parts have a match quality at each image location.
- Local evidence is noisy.
  - Parts are detected in the context of the whole model.



Matching problem

- Model is represented by a graph $G = (V, E)$.
  - $V = \{v_1,\ldots,v_n\}$ are the parts.
  - $(v_i,v_j) \in E$ indicates a connection between parts.
- $m_i(l_i)$ is a cost for placing part i at location l_i.
- $d_{ij}(l_i,l_j)$ is a deformation cost.
- Optimal configuration for the object is $L = (l_1,\ldots,l_n)$ minimizing

$$E(L) = \sum_{i=1}^{n} m_i(l_i) + \sum_{(v_i,v_j) \in E} d_{ij}(l_i,l_j)$$

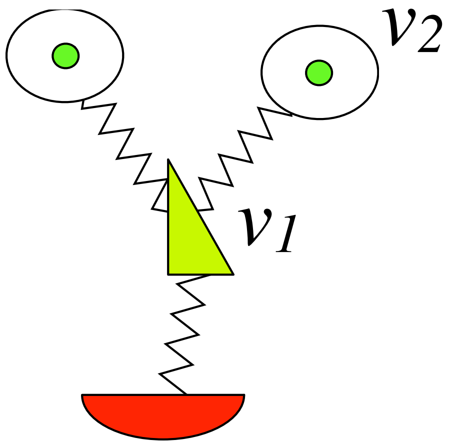
Matching problem

$$E(L) = \sum_{i=1}^{n} m_i(l_i) + \sum_{(v_i,v_j) \in E} d_{ij}(l_i,l_j)$$

- Assume n parts, k possible locations for each part.
  - There are k^n configurations L.
- If graph is a tree we can use dynamic programming.
  - $O(nk^2)$ algorithm.
- If $d_{ij}(l_i,l_j) = g(l_i-l_j)$ we can use min-convolutions.
  - $O(nk)$ algorithm.
  - As fast as matching each part separately!

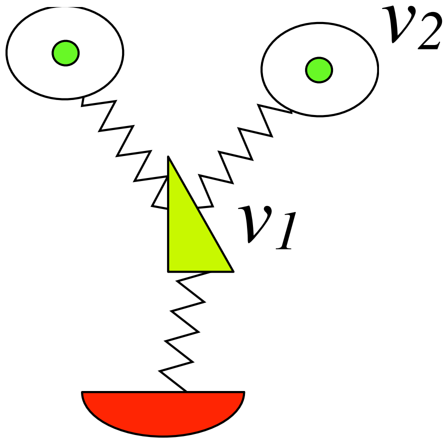
Dynamic Programming on Trees

$$E(L) = \sum_{i=1}^{n} m_i(l_i) + \sum_{(v_i,v_j) \in E} d_{ij}(l_i,l_j)$$



- For each l_1 find best l_2:
  - $\text{Best}_2(l_1) = \min \left[m_2(l_2) + d_{12}(l_1,l_2) \right]$
- "Delete" v_2 and solve problem with smaller model.
  - Let $m_1(l_1) = m_1(l_1) + \text{Best}_2(l_1)$
- Keep removing leafs until there is a single part left.

Min-convolution speedup



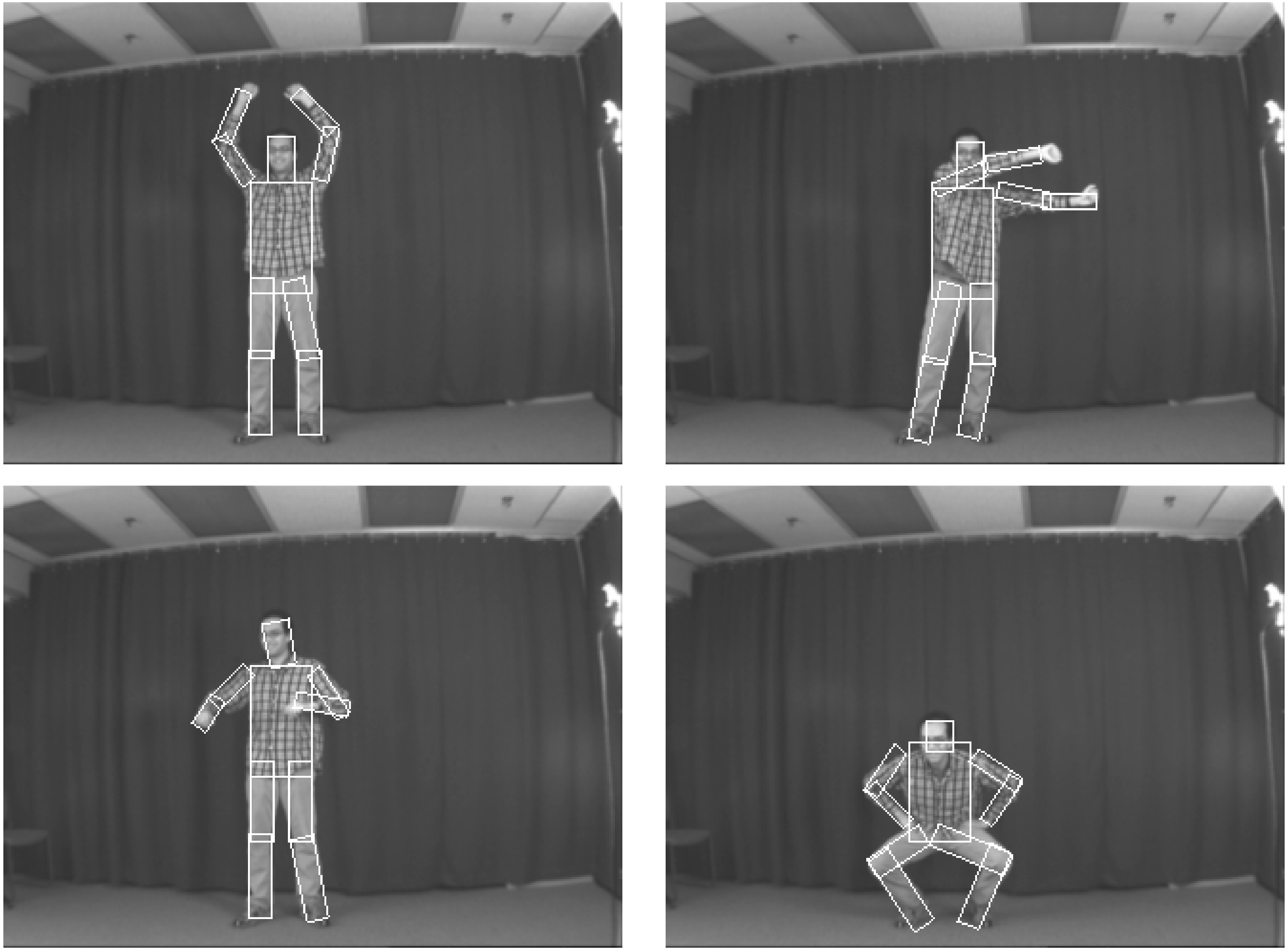
$$\text{Best}_2(l_1) = \min \left[m_2(l_2) + d_{12}(l_1,l_2) \right]$$

- Brute force: $O(k^2)$ --- k is number of locations.
- Suppose $d_{12}(l_1,l_2) = g(l_1-l_2)$:
  - $\text{Best}_2(l_1) = \min \left[m_2(l_2) + g(l_1-l_2) \right]$
- Min-convolution: $O(k)$ if g is convex.

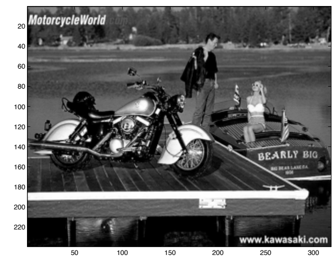
Finding motorbikes

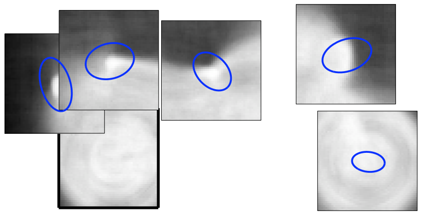
Model with 6 parts:
2 wheels
2 headlights
front & back of seat

Human pose estimation

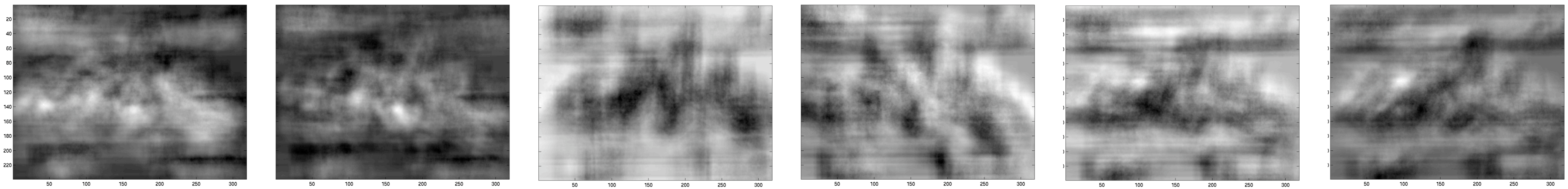


Processing steps

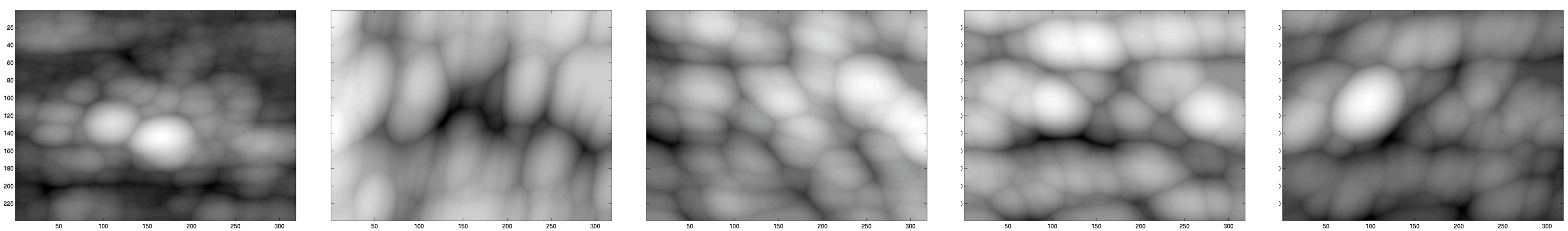




Match costs for each part

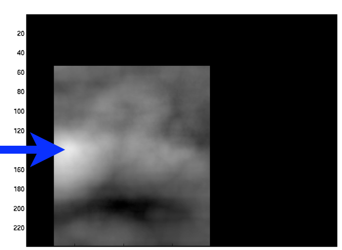


DT of non-reference match costs - min-convolution with parabola

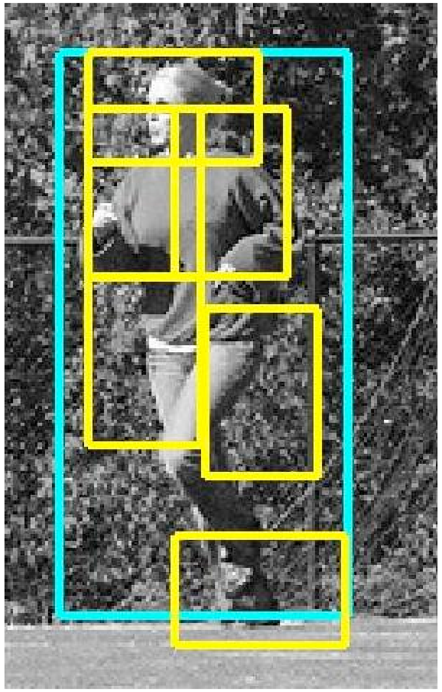


Sum shifted DTs and reference match cost

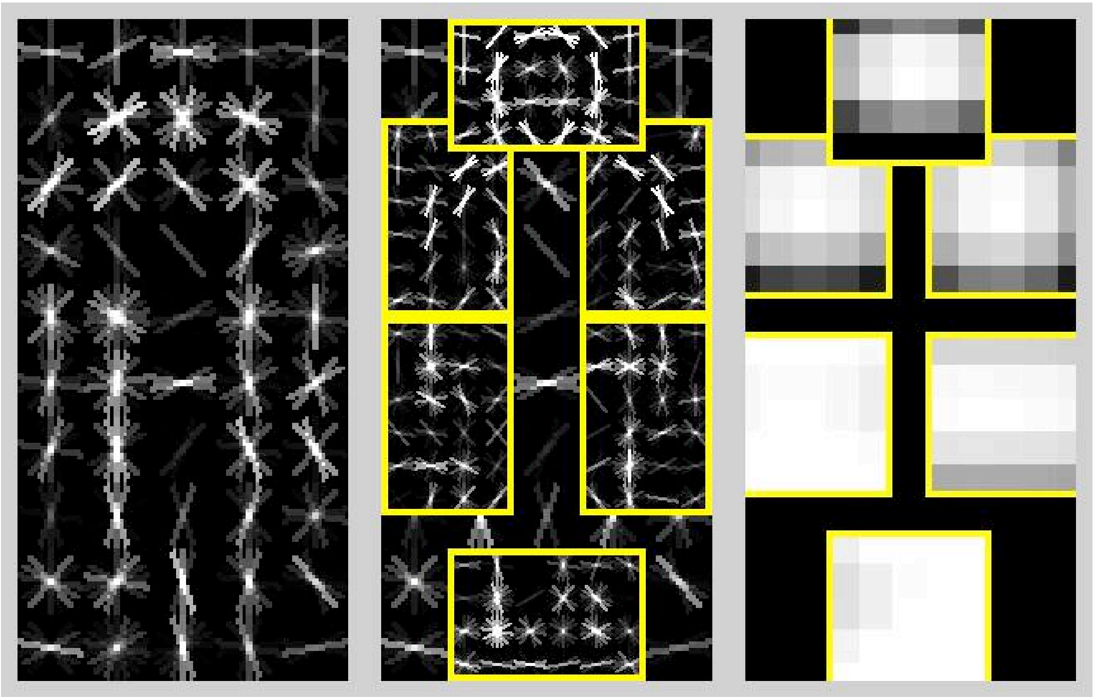
Find best location for reference



Multiscale models with HOG features



detection



root filter part filters deformation models

Model has a root filter plus deformable parts

Object configuration

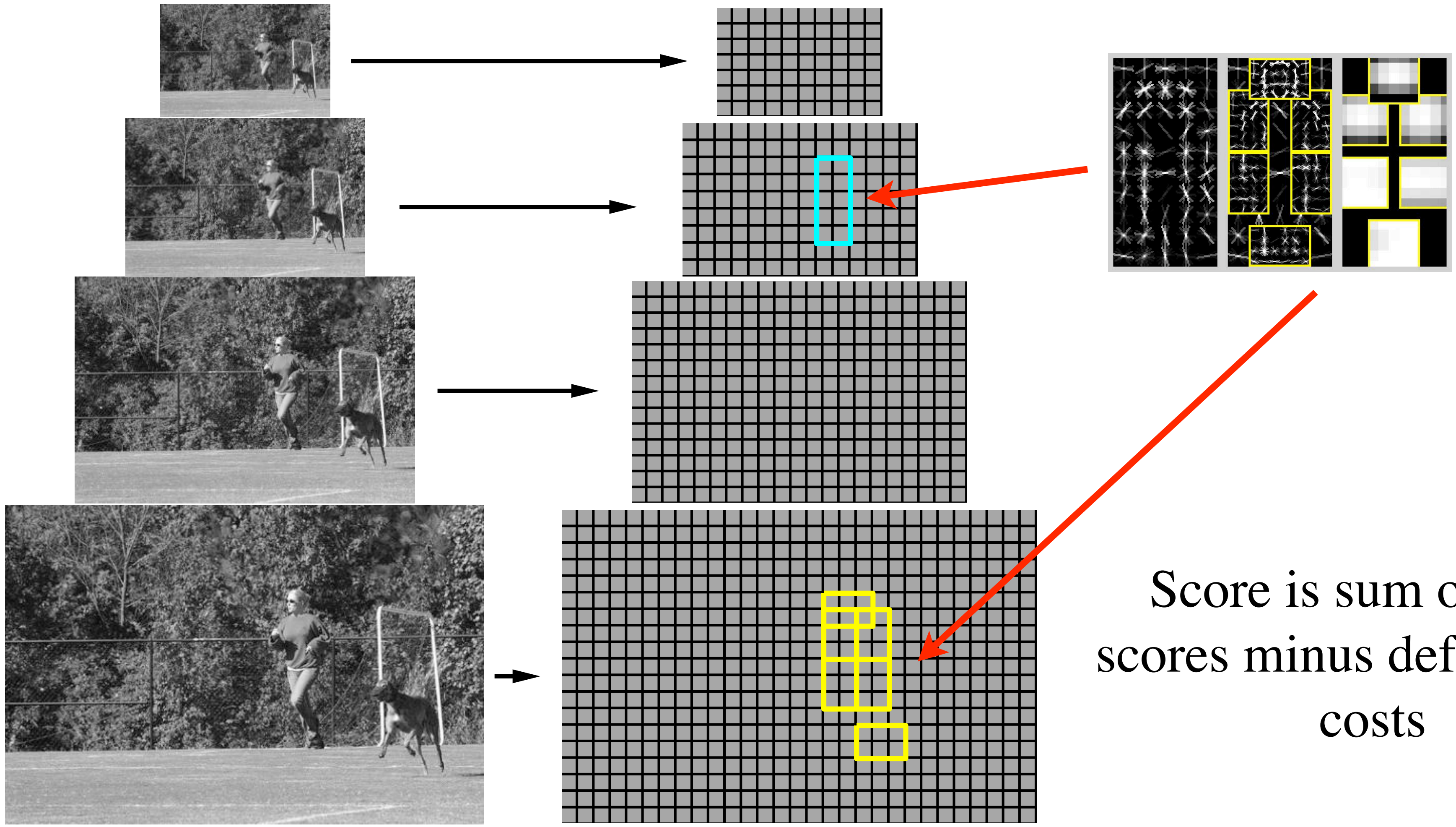


Image pyramid HOG feature pyramid

Score is sum of filter scores minus deformation costs

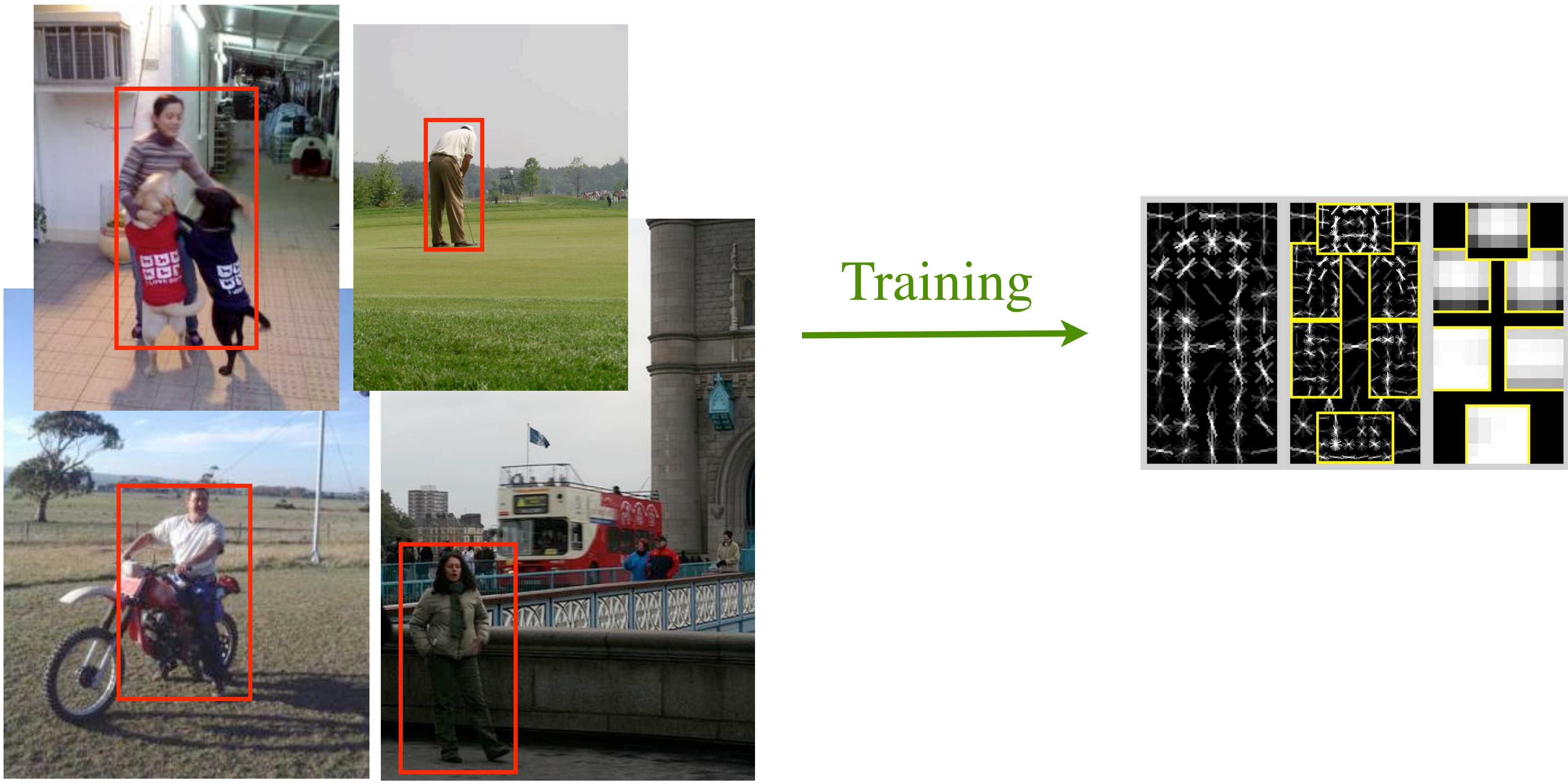
Multiscale model captures features at two-resolutions

Score of hypothesis

- Let z be an object configuration:
  - Specifies location for root and parts in HOG pyramid.
  - Score is sum of filter scores minus deformation costs.
- Optimize using distance transforms:
  - Compute best score for every possible placement of root.
  - Report placements that lead to good score.
- Connection to linear classifier:
  - Score of z on image x is $W \cdot \Phi(x, z)$

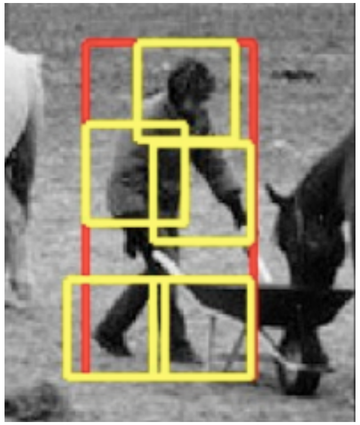
Training

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



Connection to linear classifier

- Positive example specifies that score should be high for some configuration in a range.
- Negative example specifies that score should be low for all configurations in a range.



w is a model
x is a detection window (range)
z are filter placements

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

concatenation of filters and deformation parameters

concatenation of features and part displacements

Latent SVMs

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

Linear in w if z is fixed

Training data: $(x_1, y_1), \ldots, (x_n, y_n)$ with $y_i \in \{-1, 1\}$

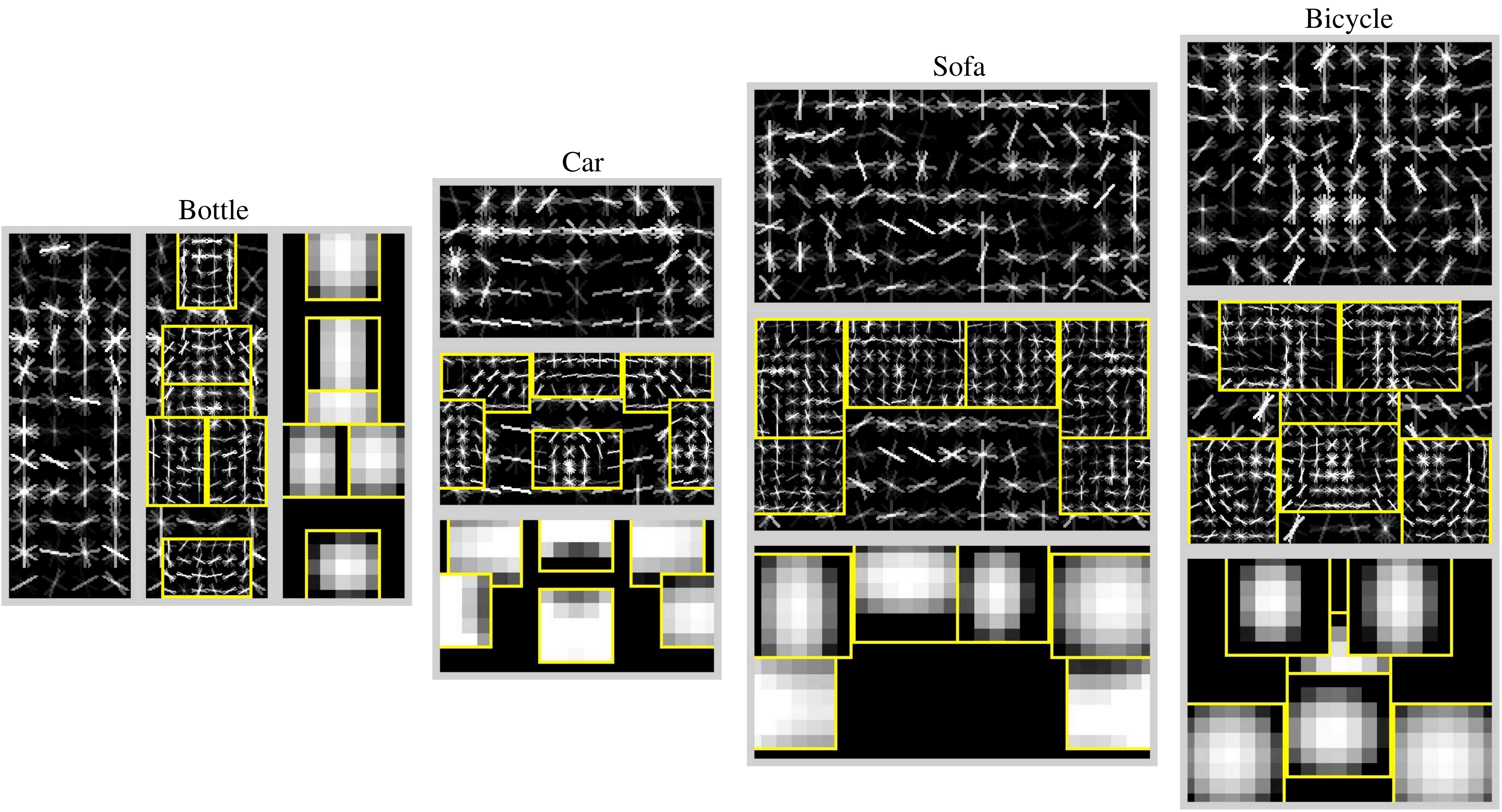
Learning: find w such that $y_i f_w(x_i) > 0$

$$w^* = \underset{w}{\operatorname{argmin}}\, \lambda ||w||^2 + \sum_{i=1}^{n} \max(0, 1 - y_i f_w(x_i))$$

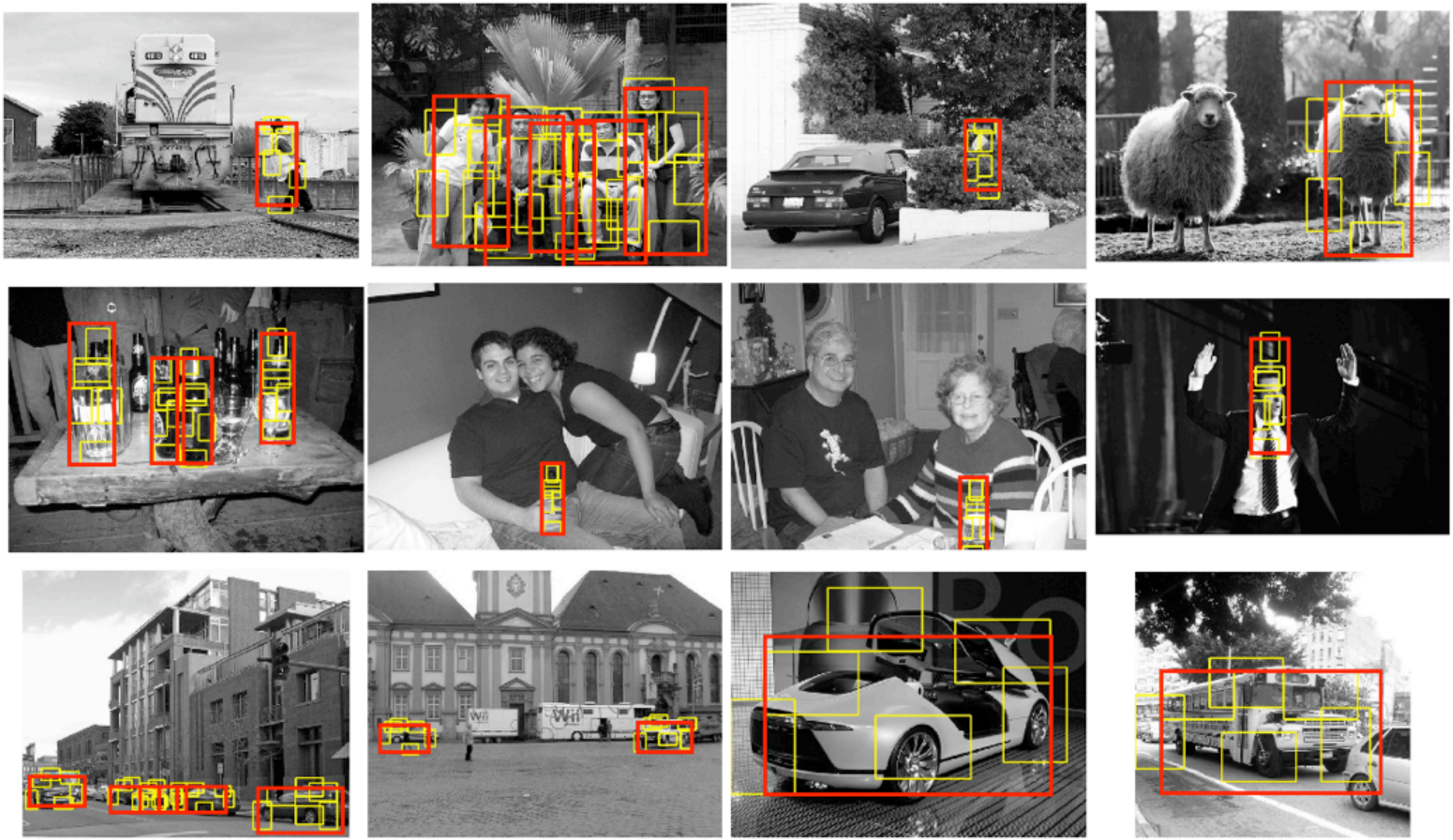
Regularization

Hinge loss

Learned models



Example results



More results