Object Detection with Discriminatively Trained Part Based Models

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Roadmap

1. **Introduction**
2. Related Work
3. Model Overview
4. Latent SVM
5. Features & Post Processing
6. Experiments

Introduction

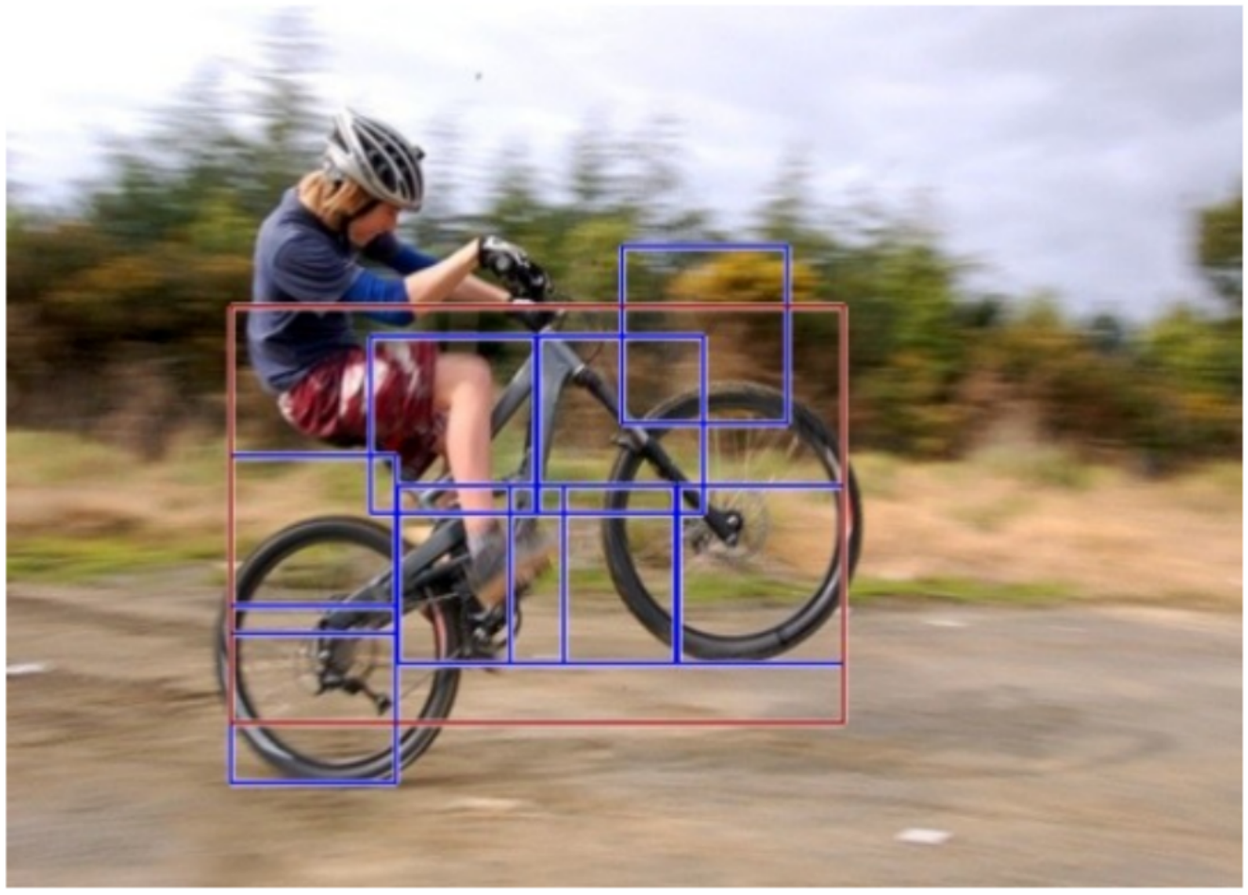
- **Problem**: Detecting and localizing generic objects from various categories, such as cars, people, etc.

- **Challenges:** Illumination, viewpoint, deformations, intraclass variability

How they solve it

Mixtures of multi-scale deformable part model

- Trained with a discriminative procedure
- Data is partially labeled (bounding boxes, not parts)

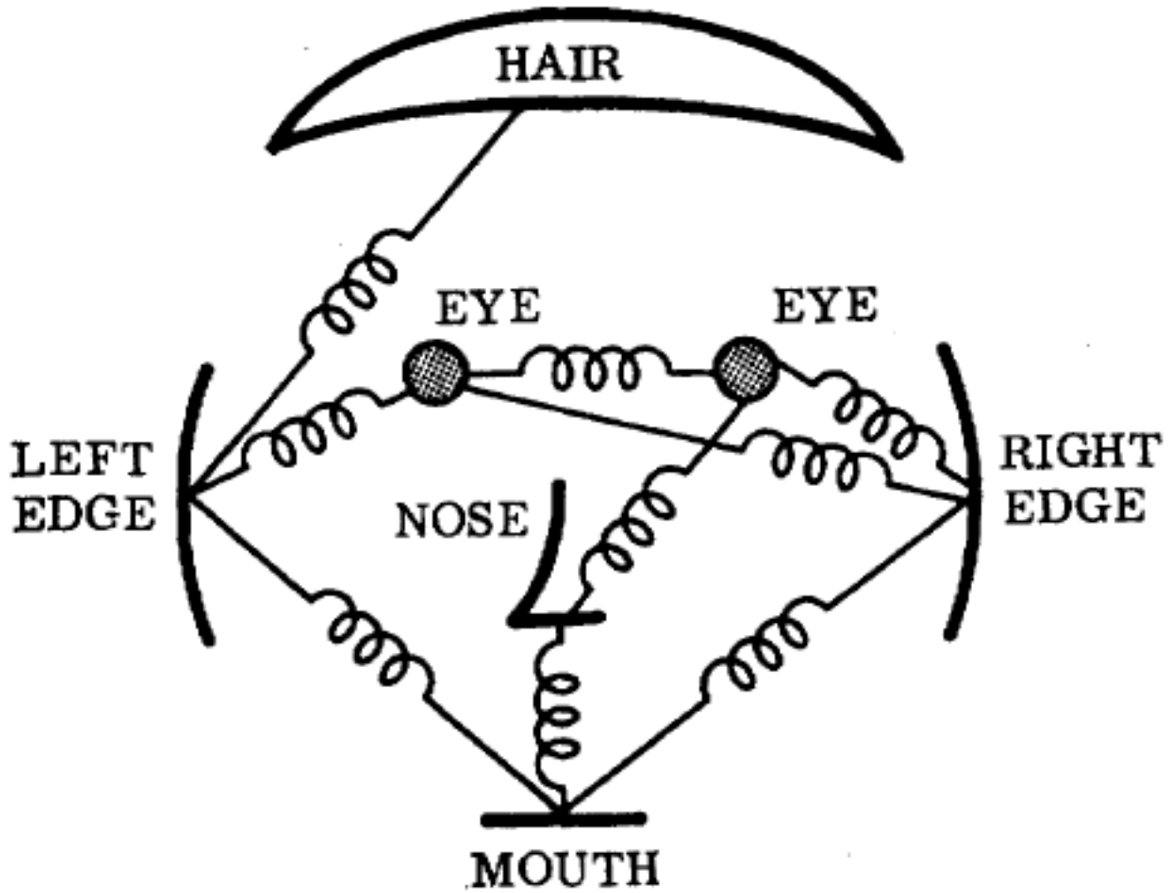


Deformable parts model

- Represents an object as a collection of parts arranged in a deformable configuration

- Each part represents local appearances

- Spring-like connections between certain pairs of parts

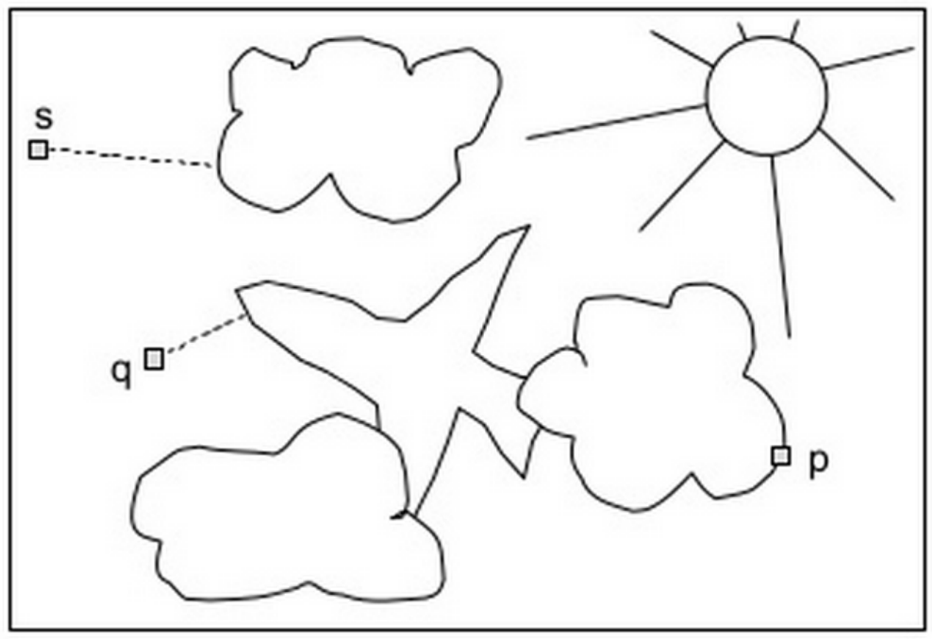


One motivation of this paper

To address the performance gap between simpler models:

Bag of 'words'

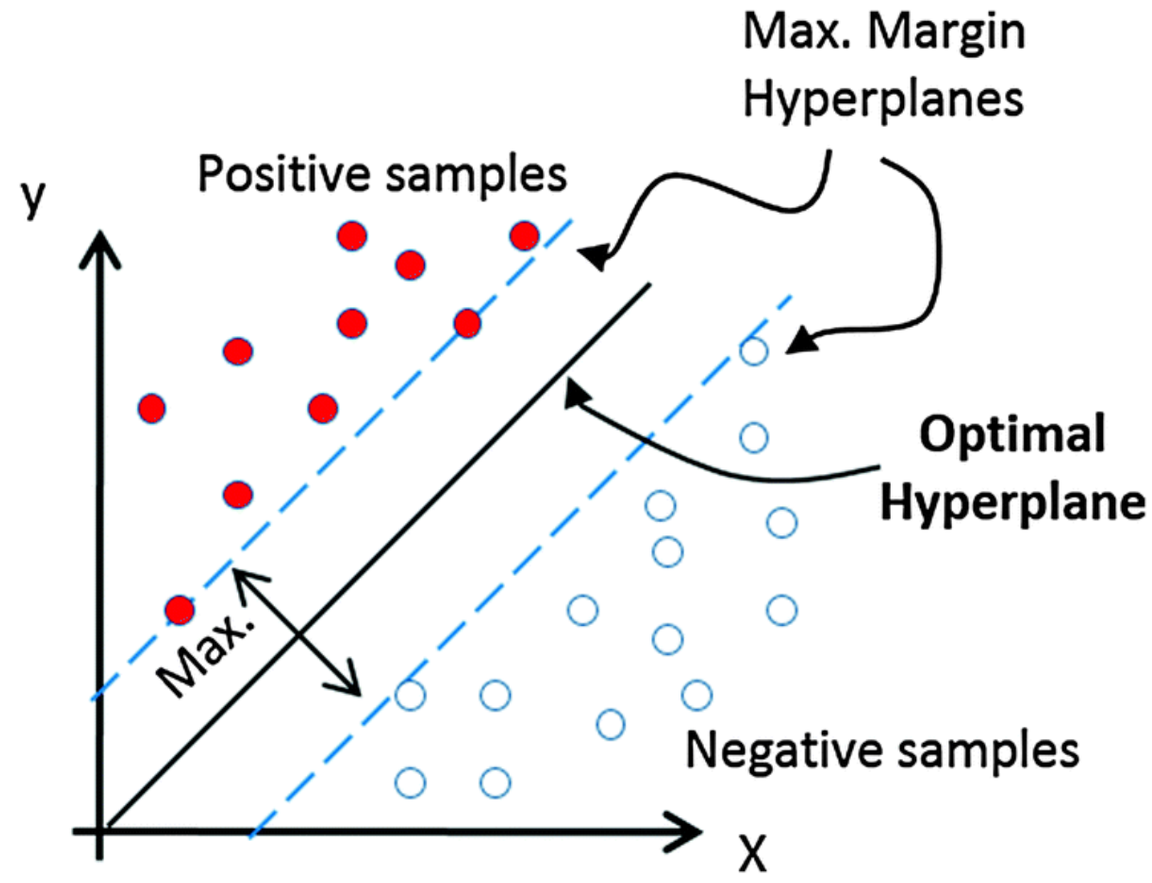
Rigid templates



… and sophisticated models like **deformable parts**

Why do simpler models perform better?

- Simple models are easily trained using **discriminative methods** such as SVMs



- Richer models use **latent information** (location of parts)

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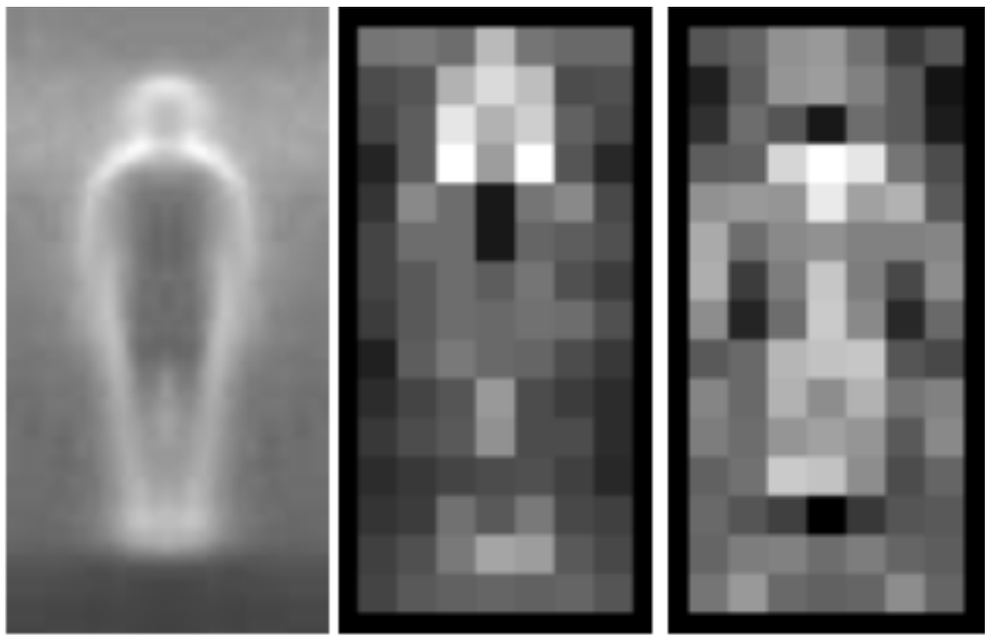
Related Work: Detection

- **Bag-of-Features**
- **Rigid Templates**
  - Dalal-Triggs
- **Deformable Models**
  - Deformable Templates (e.g. Active Appearance Models)
  - Part-Based Models — Constellation, Pictorial Structure

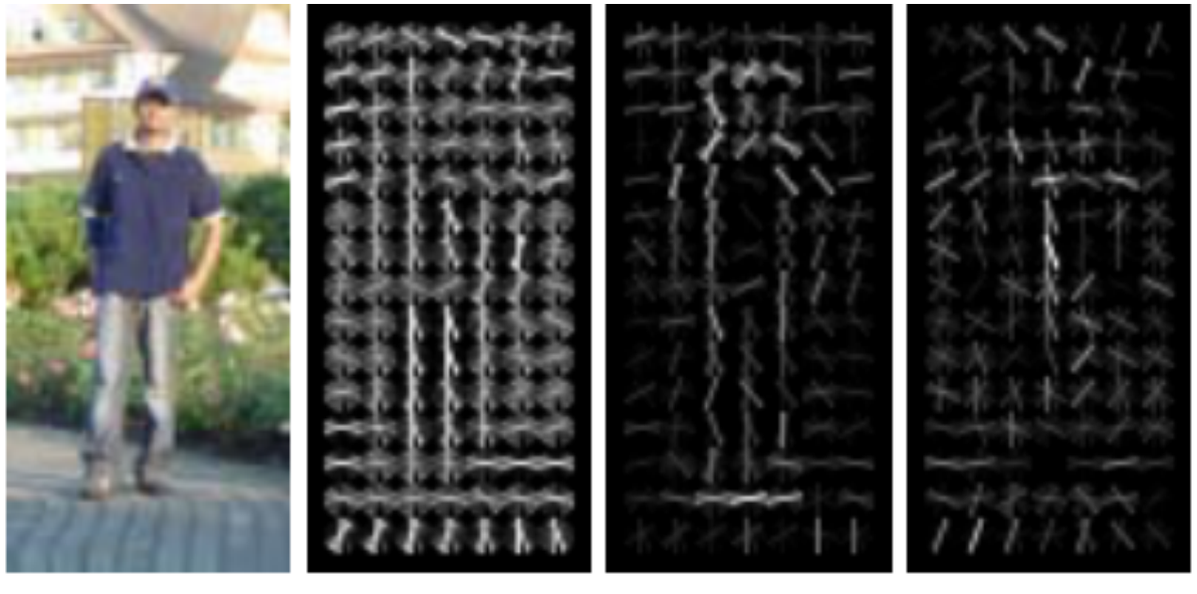
Dalal-Triggs Method

- ***Histogram of Oriented Gradients for Human Detection*** - Dalal and Triggs, 2005



- Sliding Window, HOG feature extraction + Linear SVM

- One of the most influential papers in CV!



Active Appearance Model

- ***Active Appearance Models*** - Cootes, Edwards, and Taylor, 1998

- Attempts to match statistical model to new image using iterative scheme

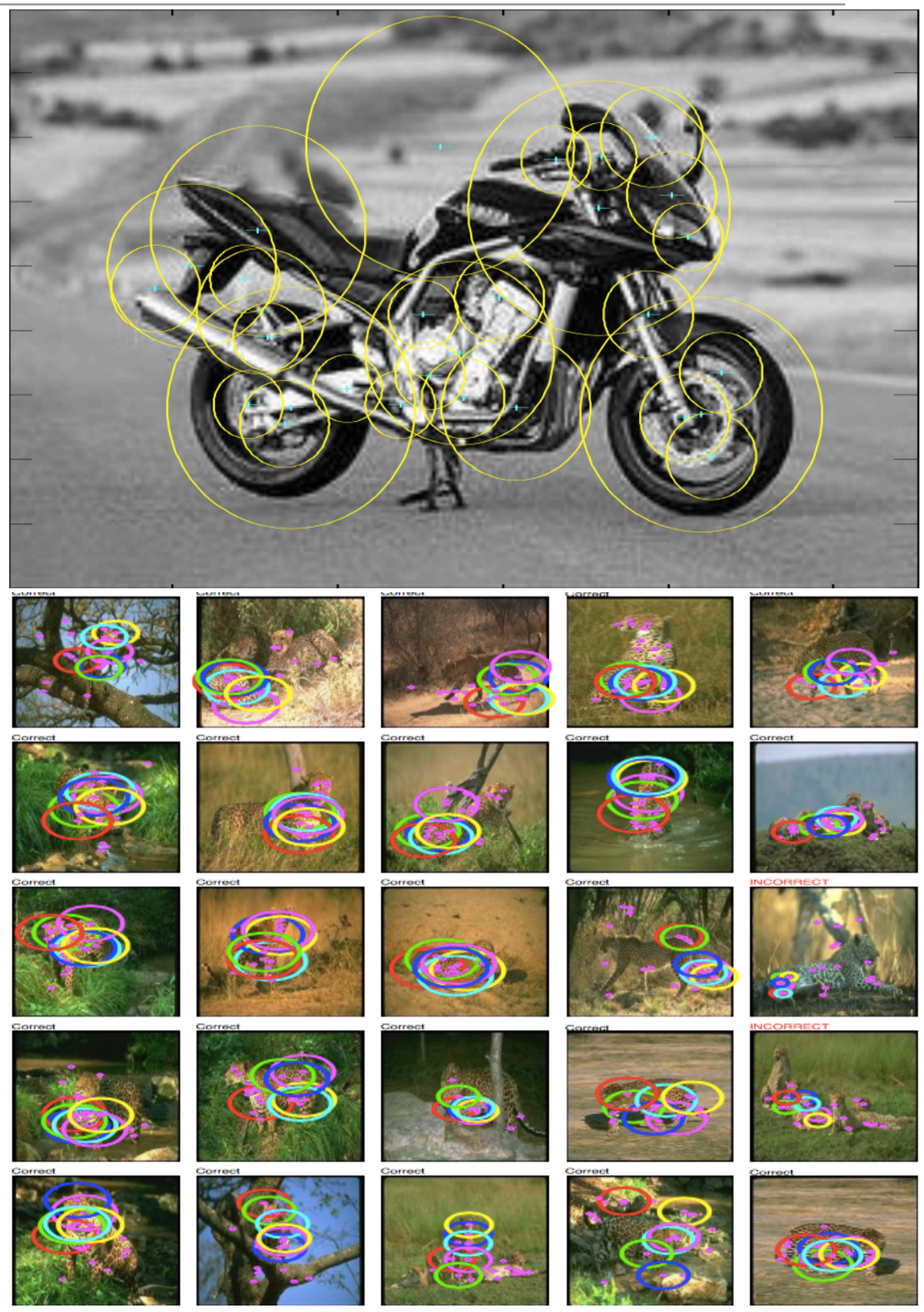
Deformable Models — Constellation

- ***Object class recognition by unsupervised scale-invariant learning*** - Fergus et al., 2003

- Utilizes Expectation Maximization to determine parameters of scale-invariant model

- Entropy-based feature detector.

- Appearance learnt simultaneously with shape.



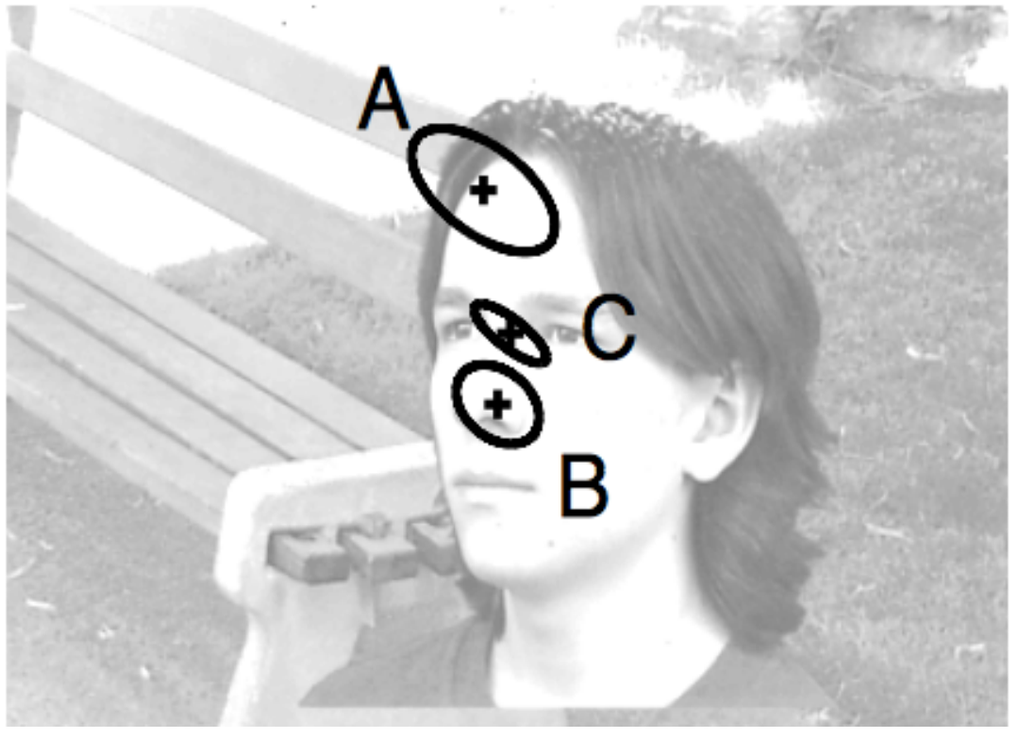
Constellation Models

- ***Towards Automatic Discovery of Object Categories*** - Weber et al., 2000

- Derives Mixture Models and a probabilistic framework for modeling classes with large variability

- Constrained to testing on faces, leaves, and cars.

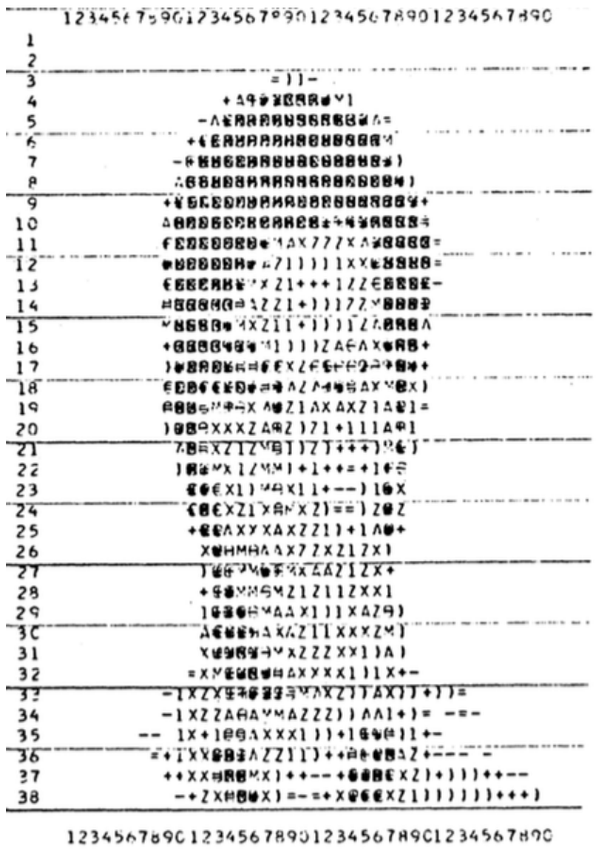
- Automatically selects distinctive features of object class

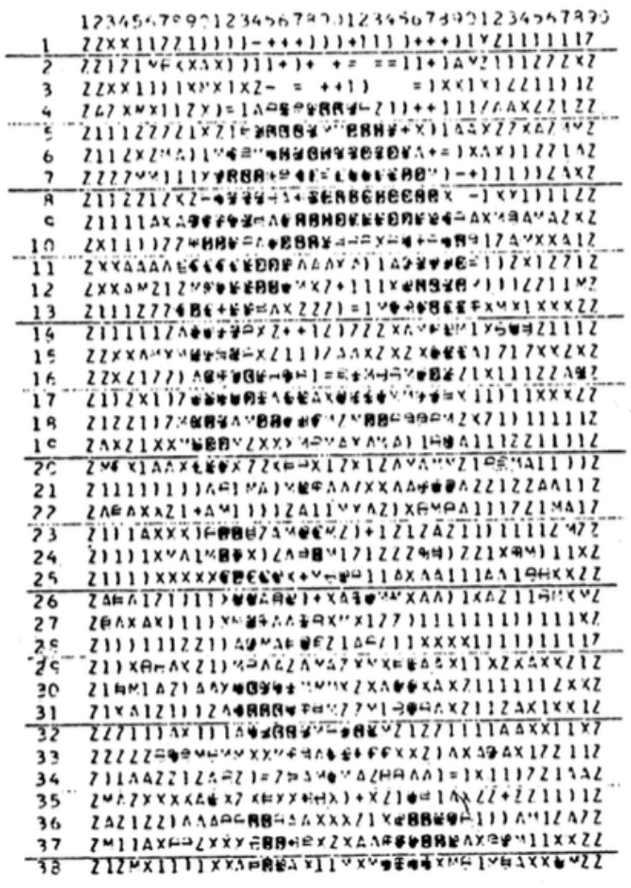


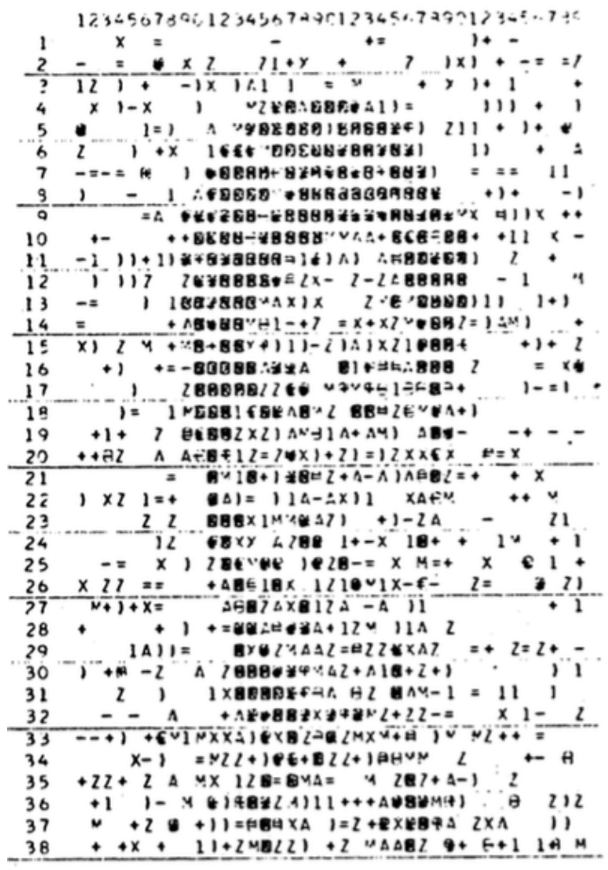
Pictorial Structure Models

- **The Representation and Matching of Pictorial Structures** - Fischler & Elschlager, 1973

- Formalizes a dynamic programming approach ("Linear Embedding Algorithm") to find optimal configuration of part-based model.





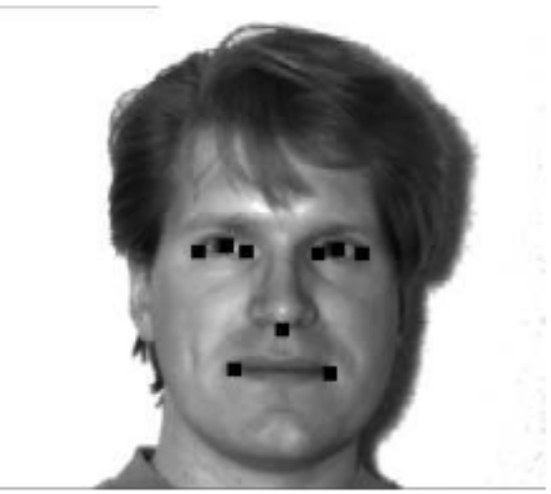


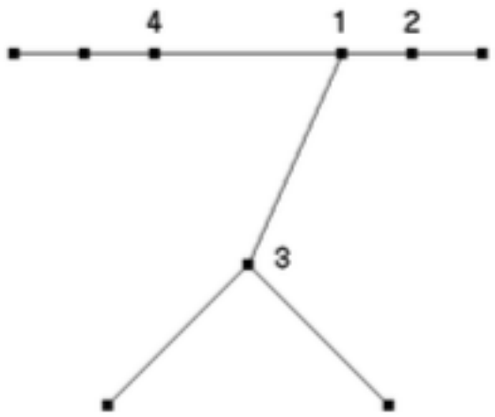
Pictorial Structure Models

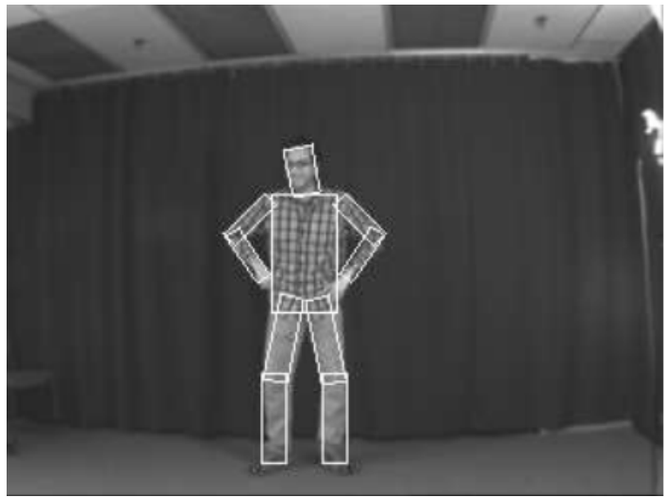
- ***Pictorial Structures for Object Recognition -*** Felzenszwalb et al., 2005

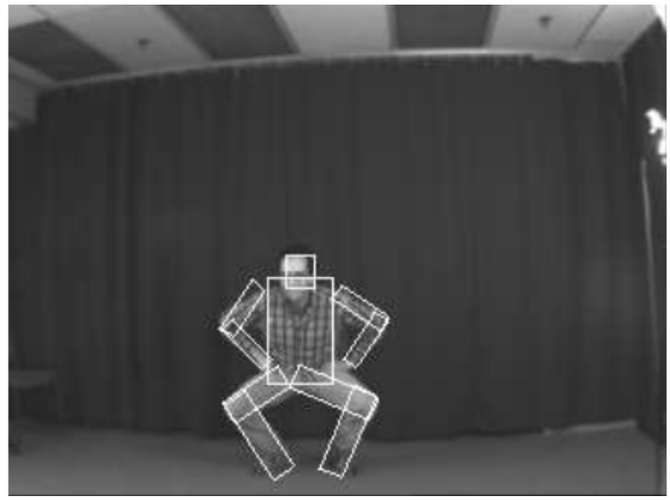
- Finds multiple optimal hypotheses; presents framework as a energy minimization problem over graph

- Poses novel, efficient minimization techniques to achieve reasonable results on face/body image data.









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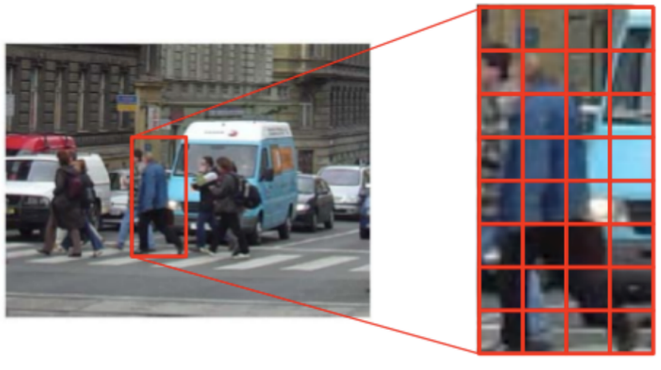
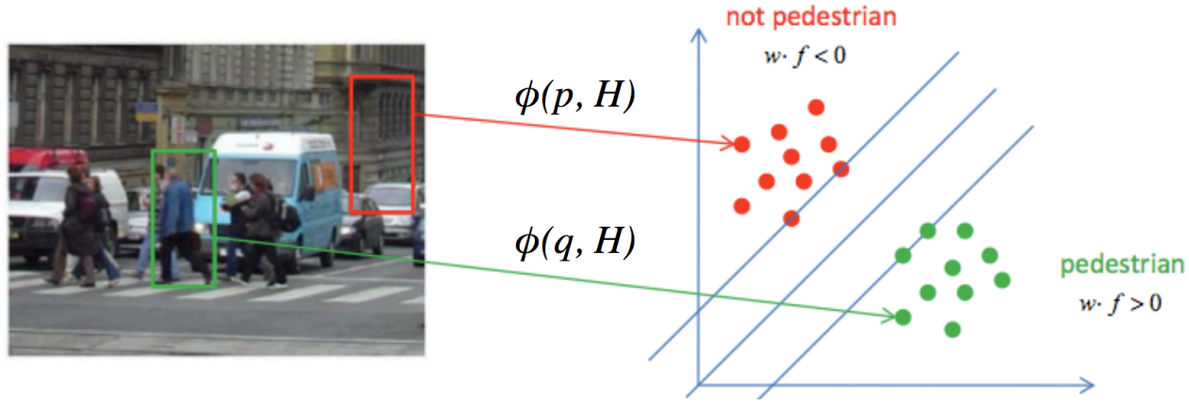
Starting point: sliding window classifiers



Feature vector

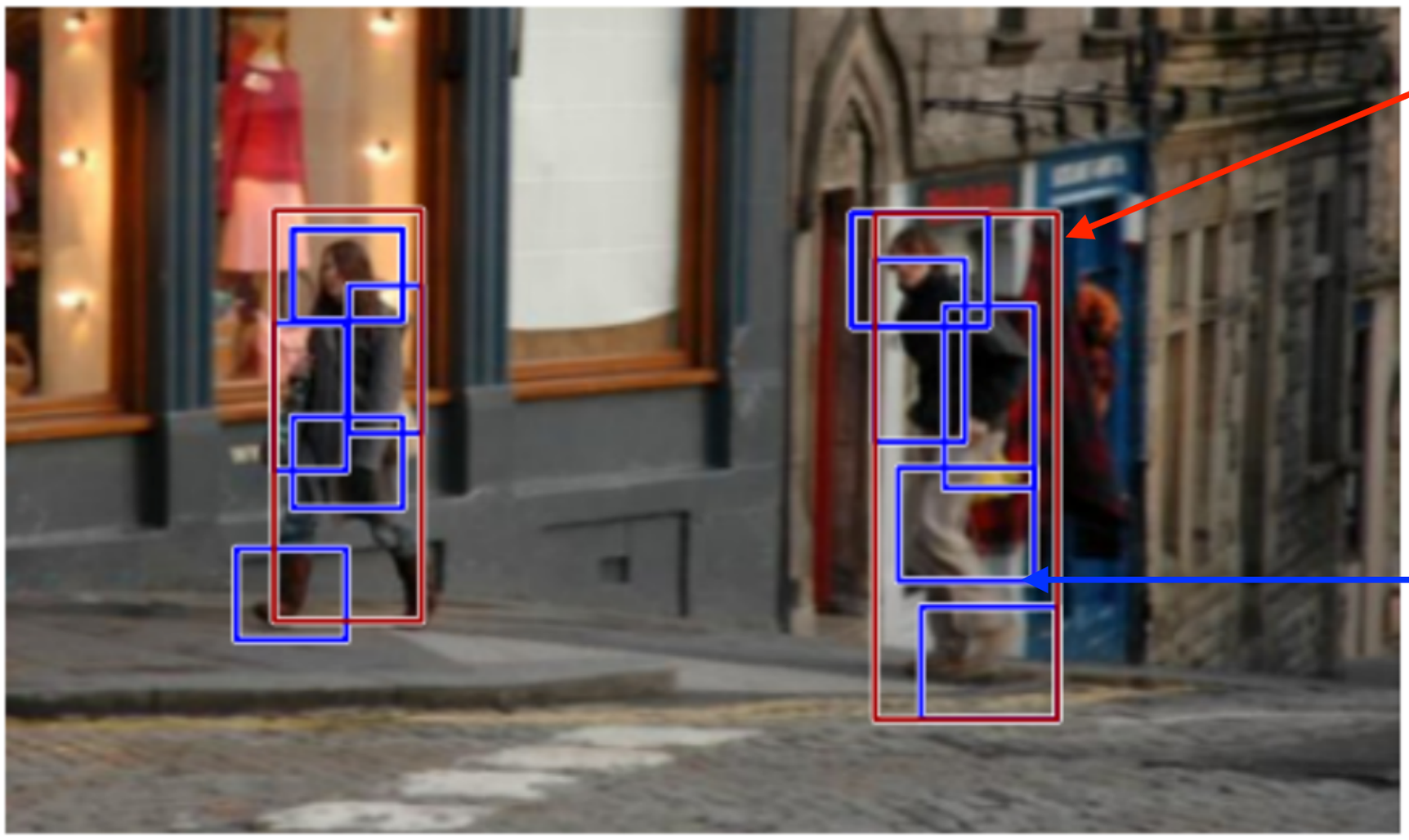
$x = [\dots, \dots, \dots, \dots]$



- Detect objects by testing each sub-window
  - Reduces object detection to binary classification
  - Dalal & Triggs: HOG features + linear SVM classifier
  - Previous state of the art for detecting people

Innovations on Dalal-Triggs

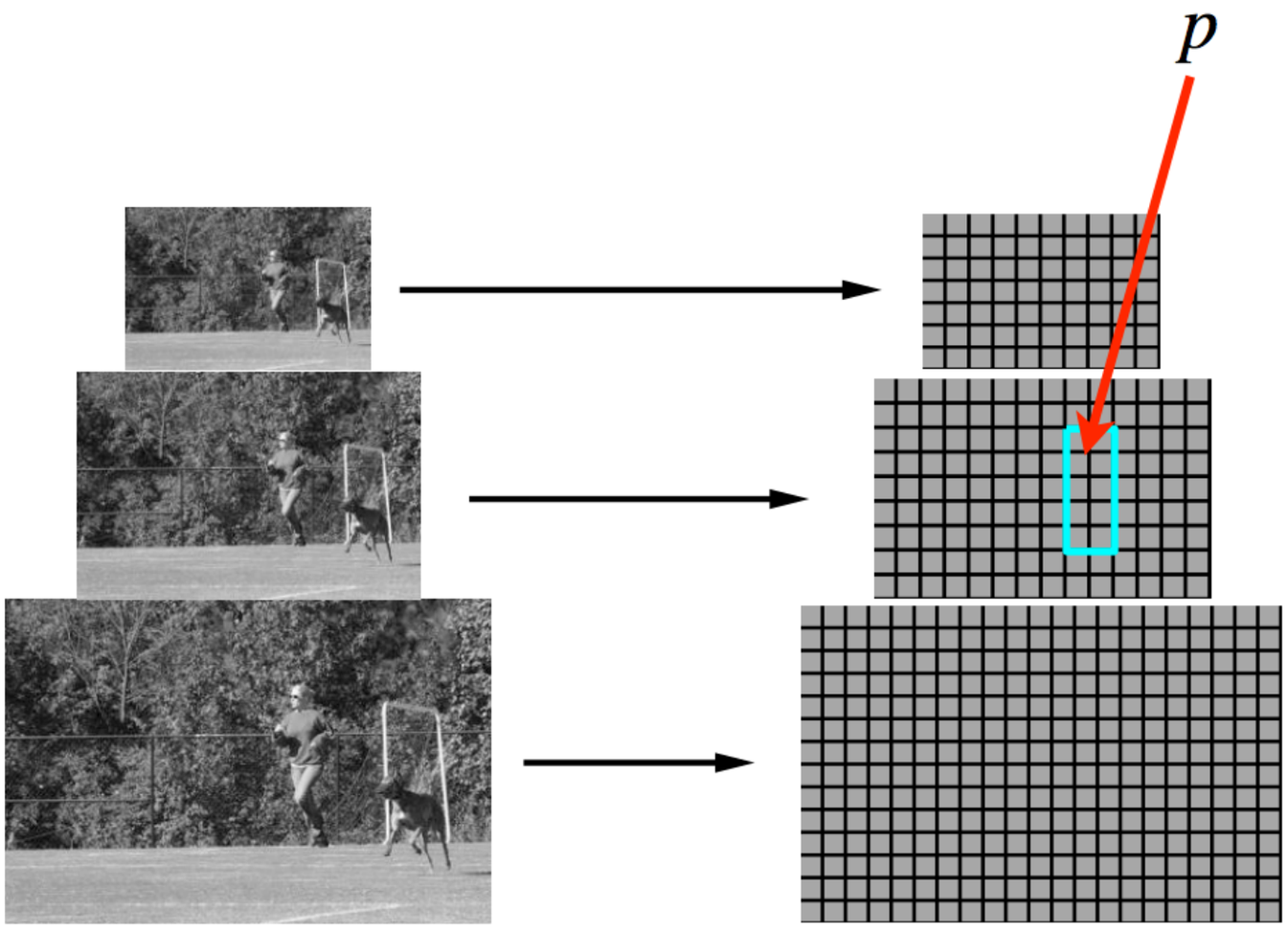
- Star model = root filter + set of part filters and associated deformation models



HOG Filters

- Models use linear filters applied to dense feature maps
- **Feature map** = array of feature vectors, where each feature vector describes a local image patch
- **Filter** = rectangular template = array of weight vectors
- **Score** = dot product of the filter and a sub-window of the feature map

Feature Pyramid



HOG pyramid H

Filter F

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

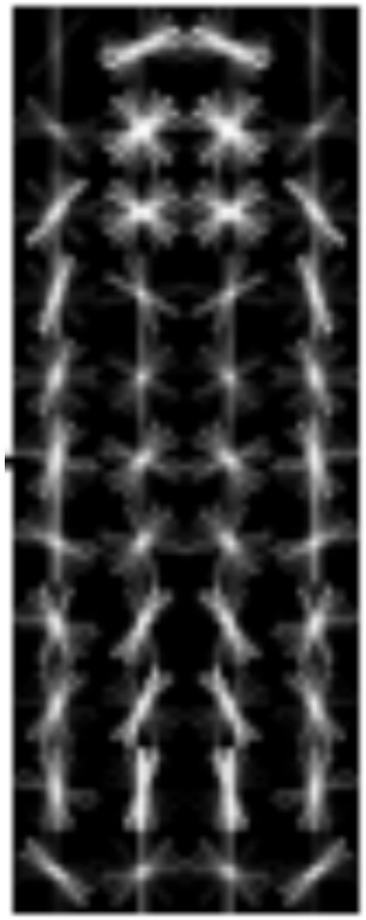
$\phi(p, H)$ = concatenation of HOG features from subwindow specified by p

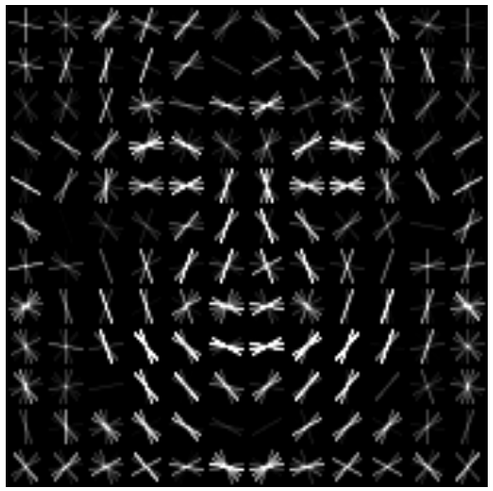
Model Overview

- Mixture of deformable part models
- Each component has global component + deformable parts
- Fully trained from bounding boxes alone

Deformable Part Models

- Star model: coarse root filter + higher resolution part filters





- Higher resolution features for part filters is essential for high recognition performance

Deformable Part Models

- A model for an object with n parts is a $(n+2)$ tuple:

$$(F_0, P_1, \cdots, P_n, b)$$

Root filter — Model for 1st part — Bias term

- Each part-based model defined as:

$$(F_i, v_i, d_i)$$

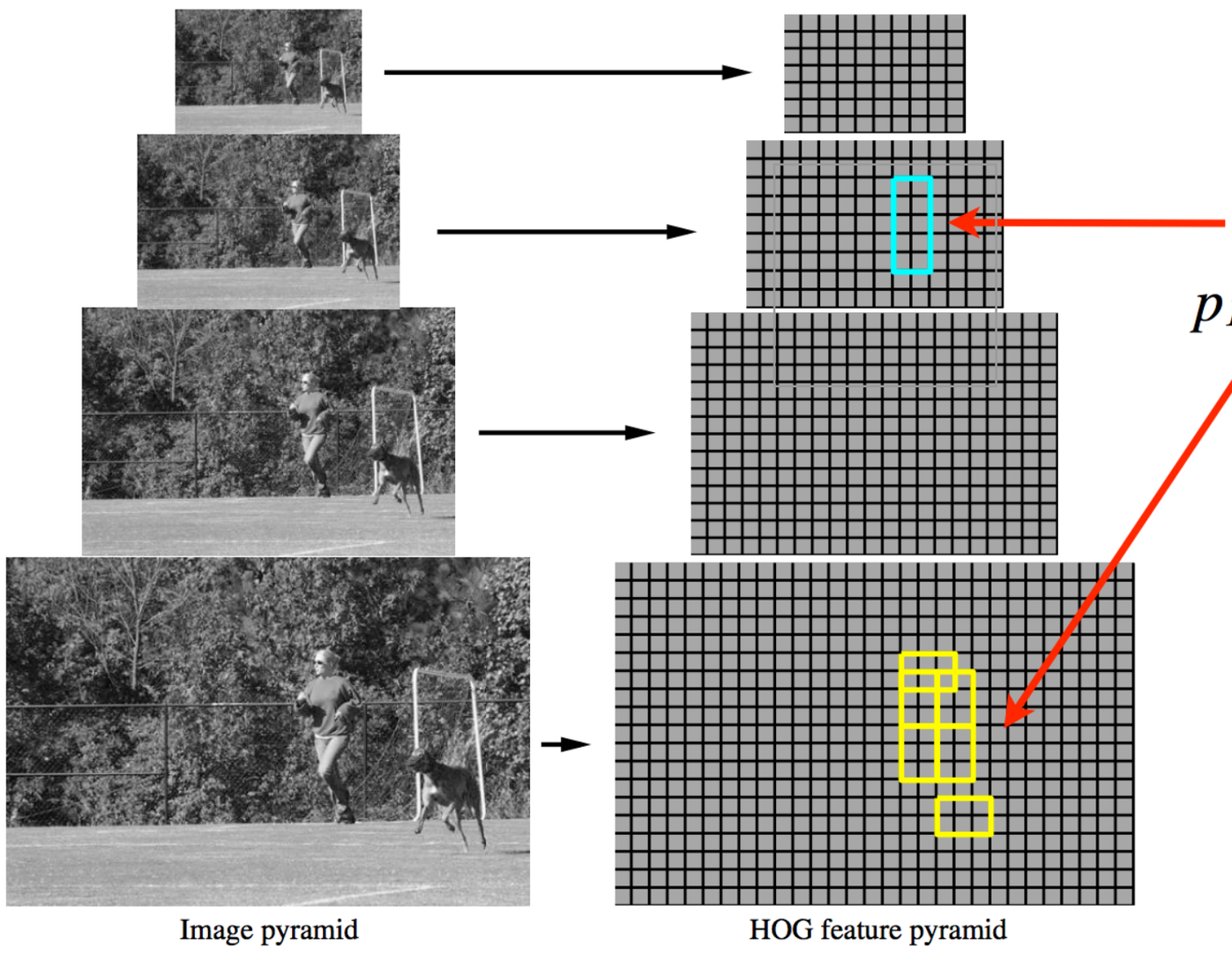
F_i filter for the *i*-th part

v_i "anchor" position for part *i* relative to the root position

d_i defines a deformation cost for each possible placement of the part relative to the anchor position

Object Hypothesis

$p_i = (x_i, y_i, l_i)$ specifies the level and position of the *i*-th filter



Multiscale model captures features at two-resolutions

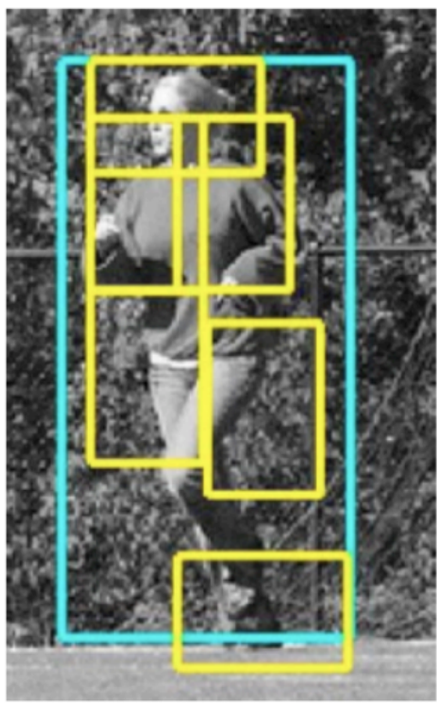
Score of Object Hypothesis

$$\text{score}(p_0, \ldots, p_n) = \underbrace{\sum_{i=0}^{n} F_i \cdot \phi(H, p_i)}_{\text{“data term”}} - \underbrace{\sum_{i=1}^{n} d_i \cdot (dx_i^2, dy_i^2)}_{\text{“spatial prior”}} + b$$

filters

displacements

deformation parameters



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

concatenation filters and deformation parameters

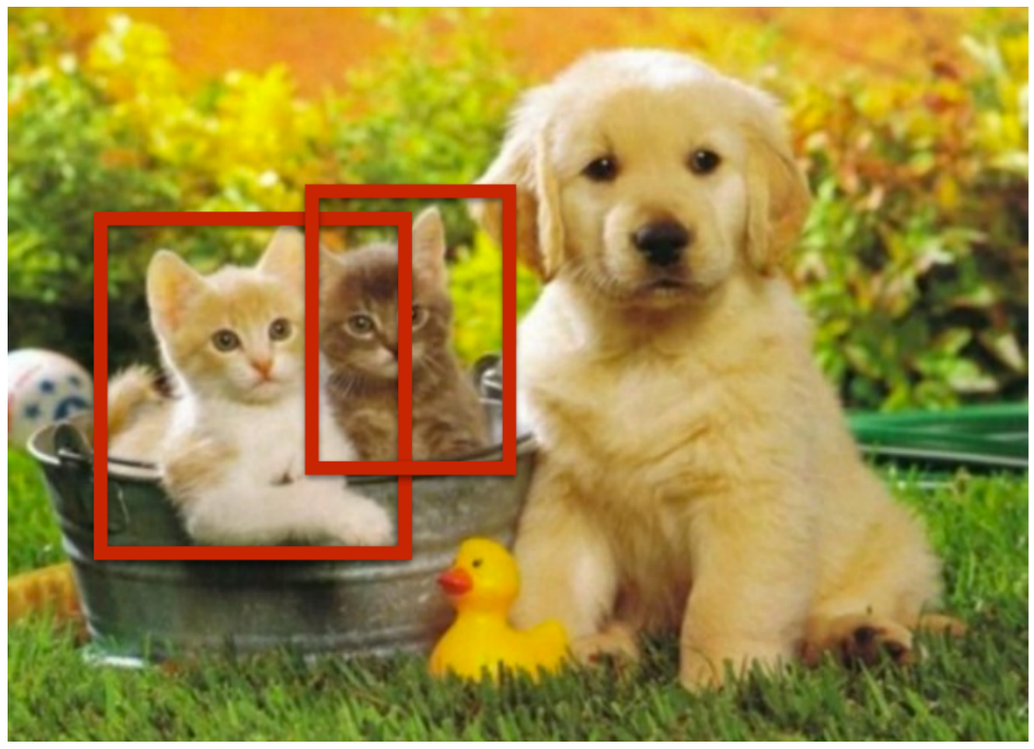
concatenation of HOG features and part displacement features

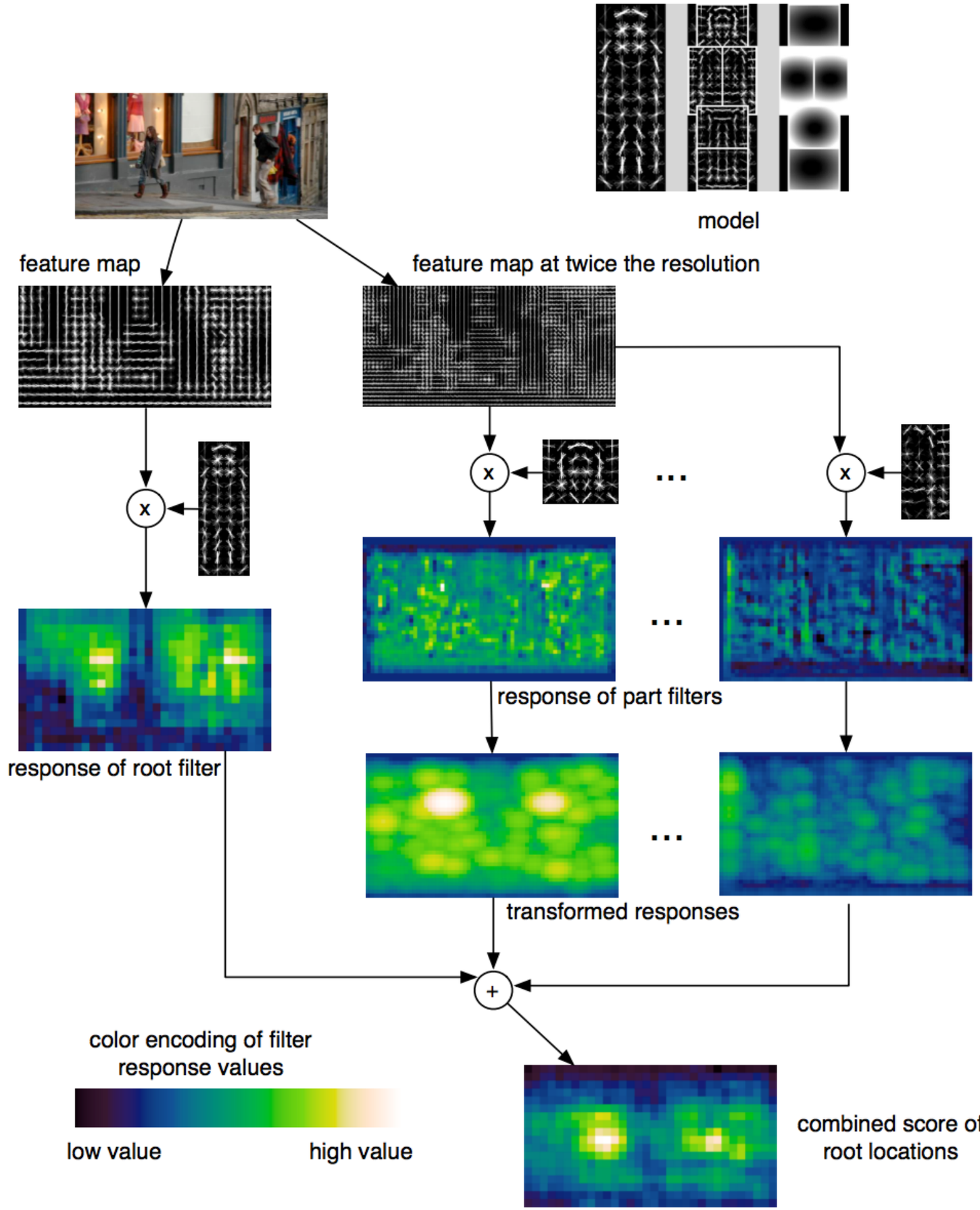
Matching

- Define an overall score for each root location according to the best placement of parts:

$$\text{score}(p_0) = \max_{p_1,\ldots,p_n} \text{score}(p_0,\ldots,p_n)$$

- High scoring root locations define detections (“sliding window approach”)

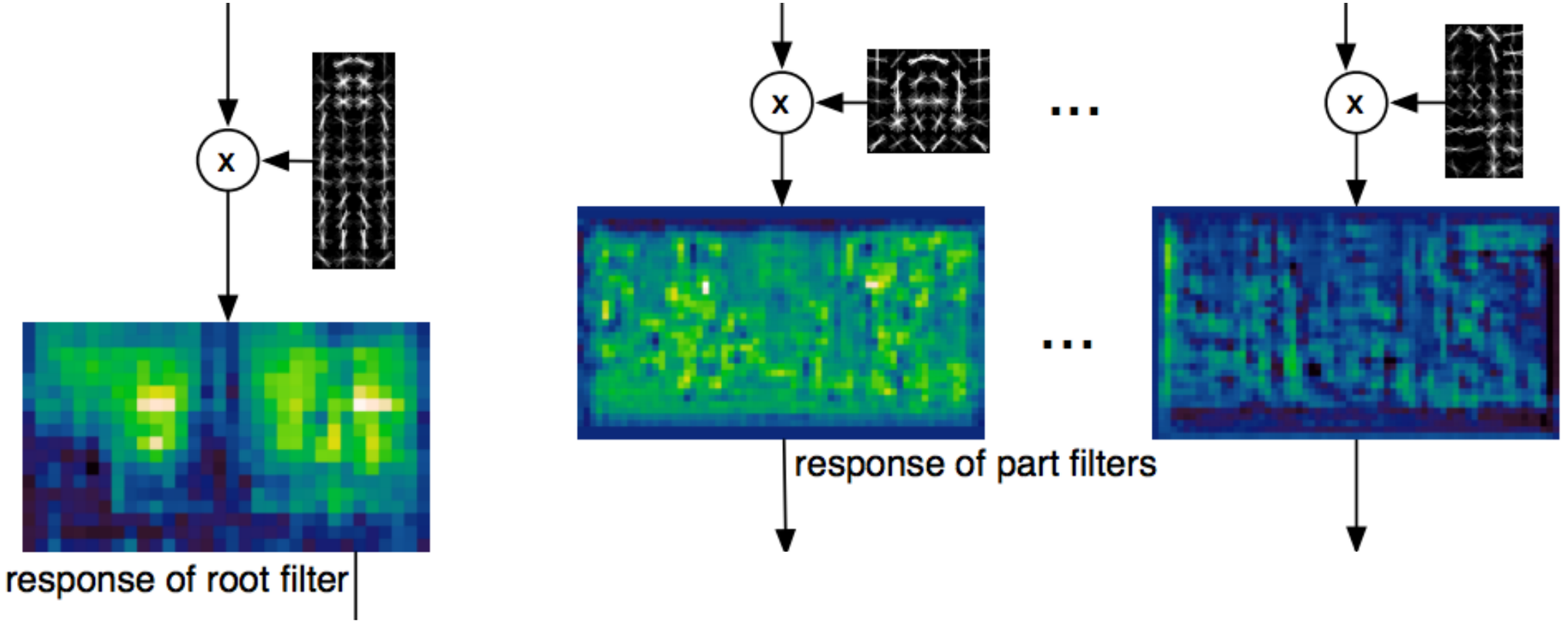



model
feature map
feature map at twice the resolution
x
x
x
response of root filter
response of part filters
transformed responses
+
color encoding of filter
response values
low value
high value
combined score of
root locations

Matching Step 1: Compute filter responses

- Compute arrays storing the response of the *i*-th model filter in the *l*-th level of the feature pyramid (**cross correlation**):

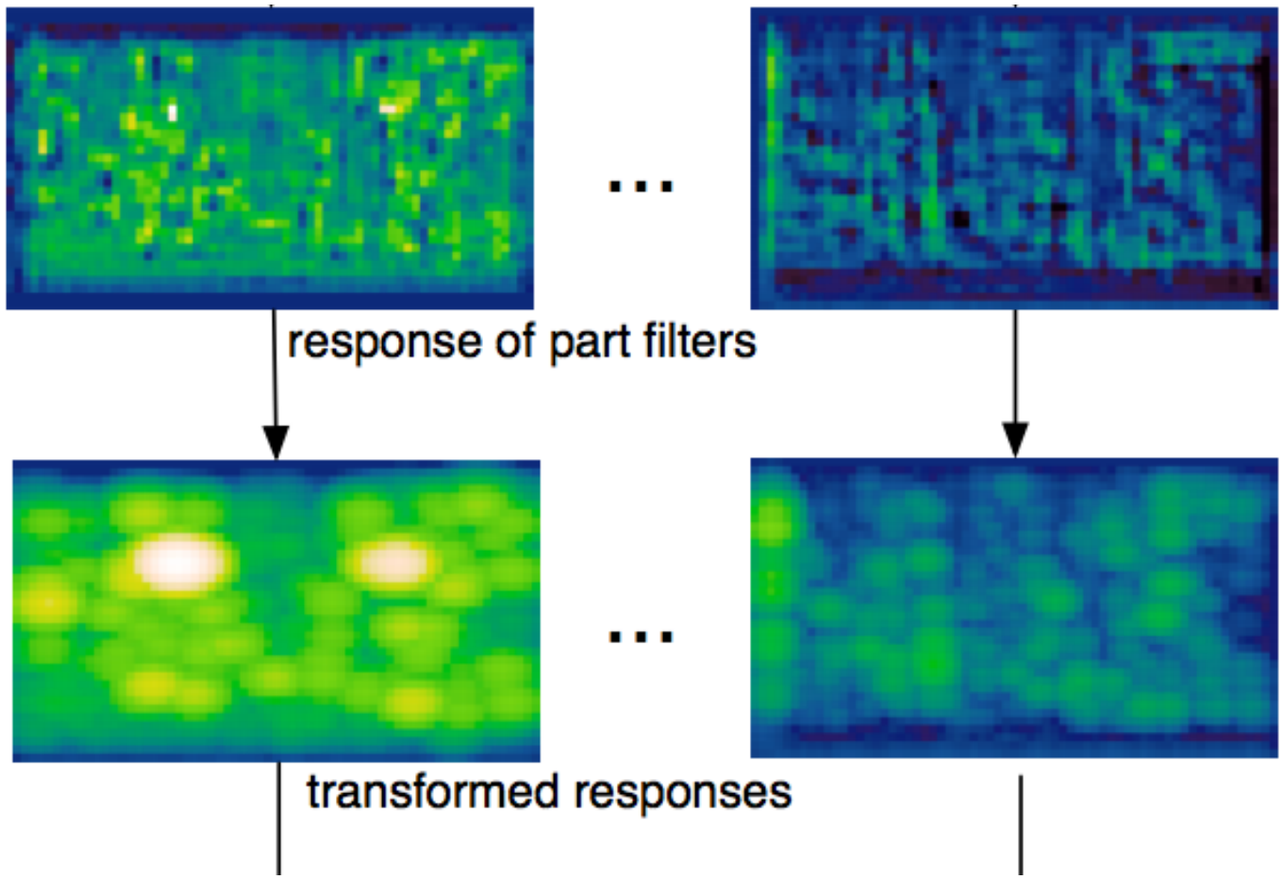
$$R_{i,l}(x,y) = F_i' \cdot \phi(H,(x,y,l))$$



Matching Step 2: Spatial Uncertainty

- Transform the responses of the **part filters** to allow for spatial uncertainty:

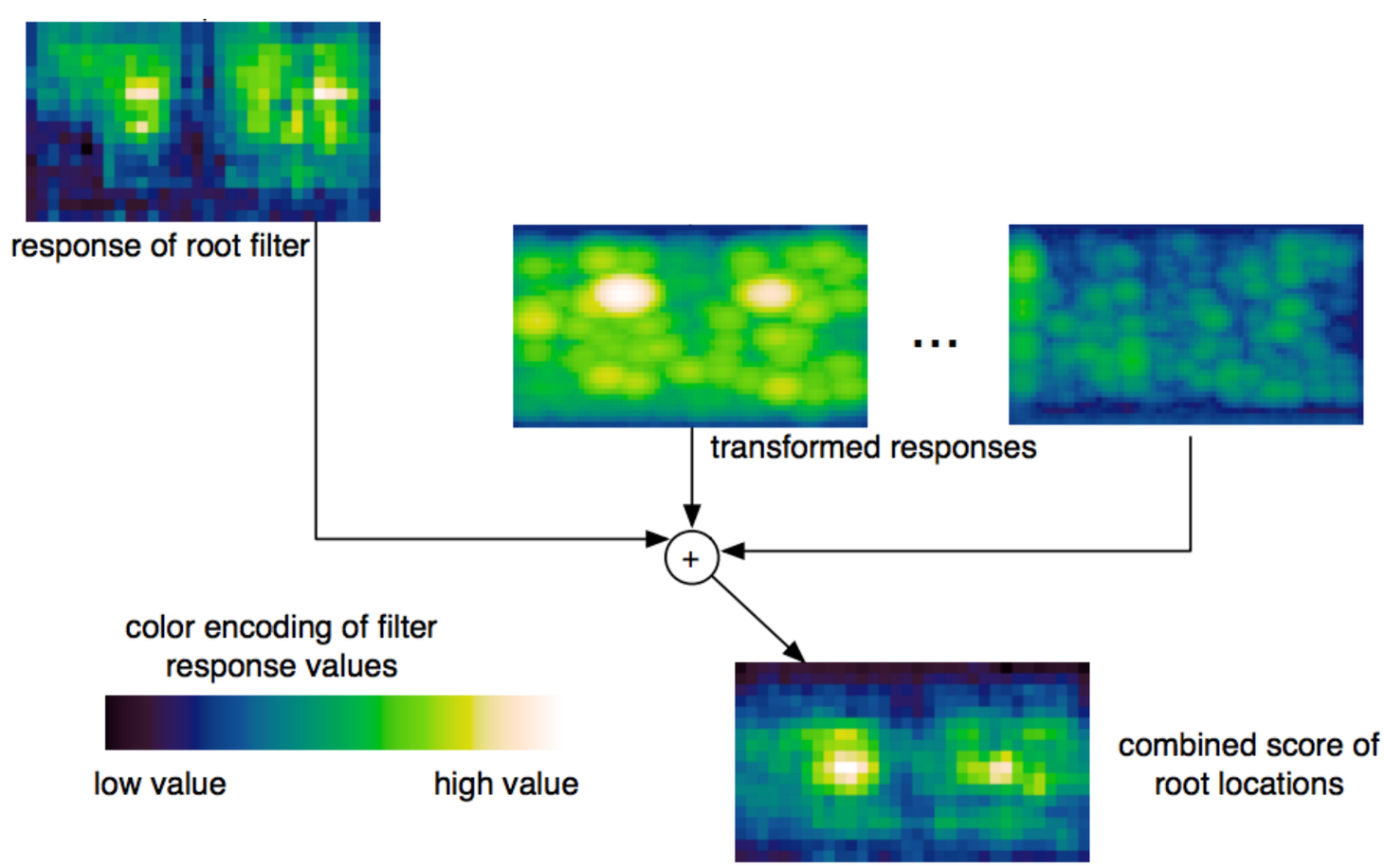
$$D_{i,l}(x, y) = \max_{dx,dy}(R_{i,l}(x + dx, y + dy) - d_i \cdot \phi_d(dx, dy))$$



Matching Step 3: Compute overall root scores

- Compute overall root score at each level by summing the root filter response at that level, plus the contributions from each part:

$$\text{score}(x_0, y_0, l_0) = R_{0,l_0}(x_0, y_0) + \sum_{i=1}^{n} D_{i,l_0-\lambda}(2(x_0, y_0) + v_i) + b$$



Matching Step 4: Compute optimal part displacements

$$P_{i,l}(x,y) = \arg\max_{dx,dy}(R_{i,l}(x+dx, y+dy) - d_i \cdot \phi_d(dx,dy))$$

- After finding a root location (x_0, y_0, l_0) with a high score, we can find the corresponding part locations by looking up the optimal displacements in $P_{i,l_0-\lambda}(2(x_0,y_0)+v_i)$

Mixture Models

A mixture model with m components is $M = (M_1, \ldots, M_m)$ where M_c is the model for the c-th component

An object hypothesis for a mixture model consists of:

- A mixture component, $1 \leq c \leq m$
- A location for each filter of M_c, $z = (c, p_0, \ldots, p_{n_c})$

Score of hypothesis: $\beta \cdot \phi(H, z) = \beta_c \cdot \phi(H, z')$

To detect objects using a mixture model we use the matching algorithm to find root locations that yield high scoring hypotheses independently for each component

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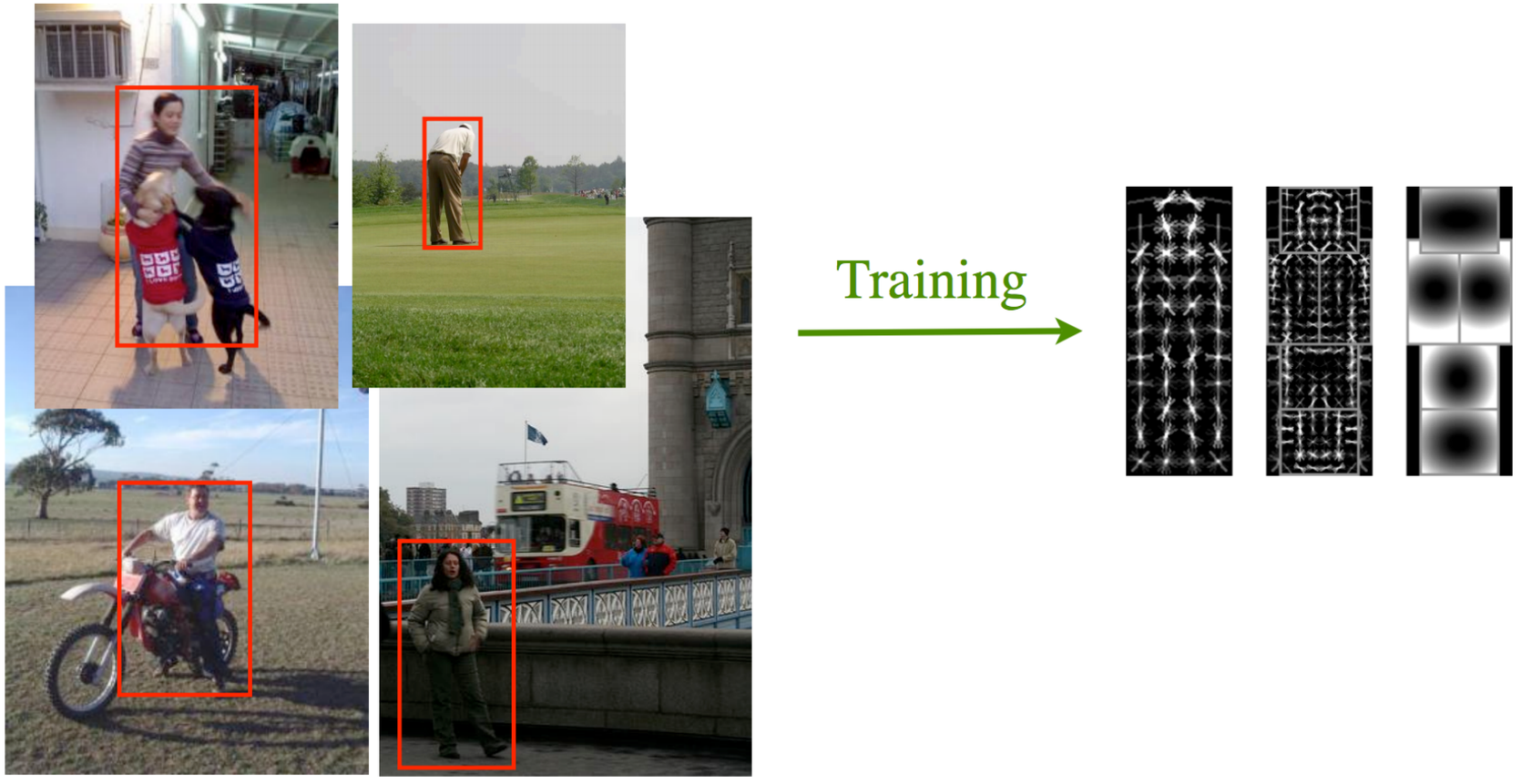
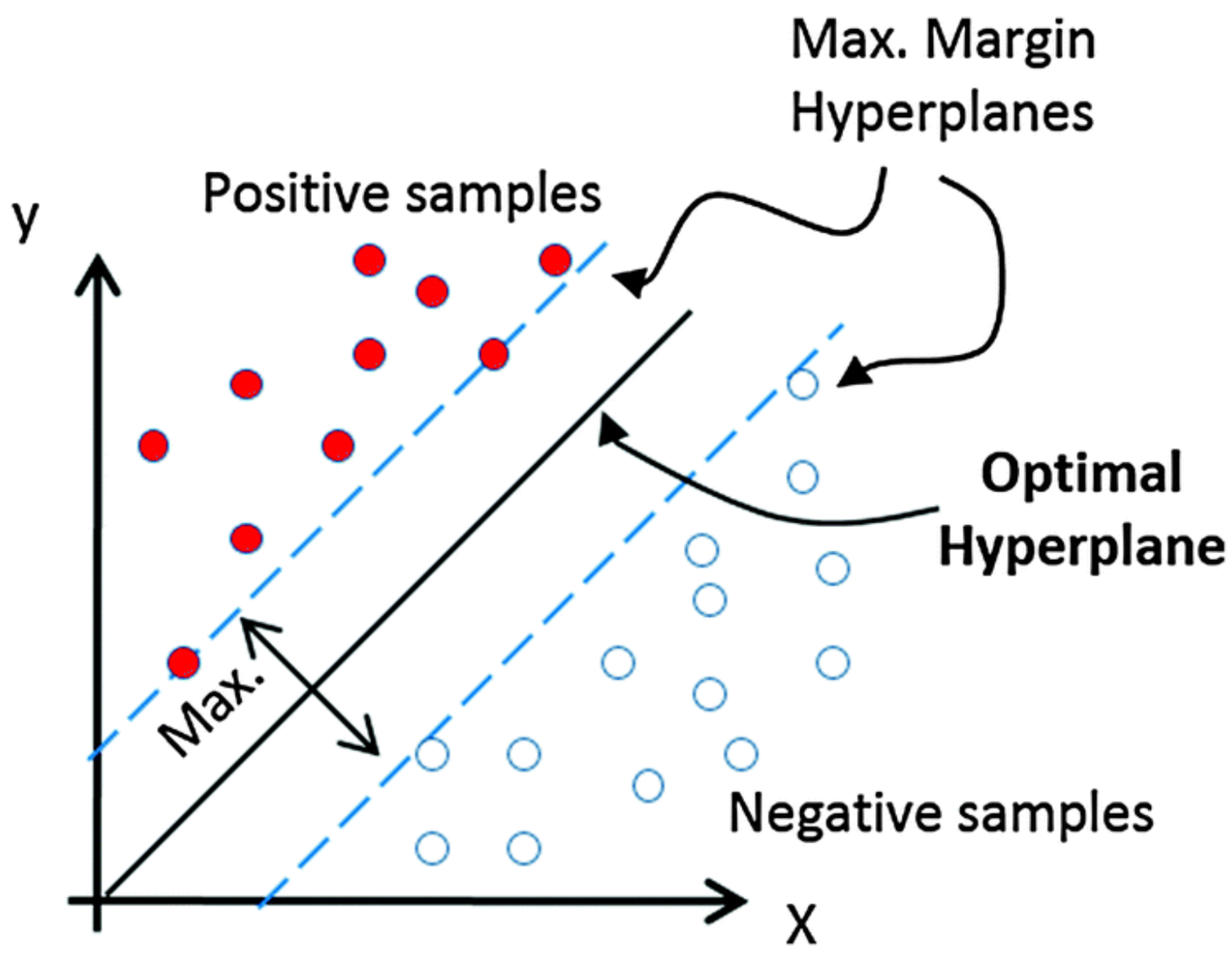
Training

- Training data consists of images with labeled bounding boxes
  - **Weakly labeled setting** since the bounding boxes don't specify component labels or part locations
- Need to learn the model structure, filters and deformation costs



SVM Review

- Separable by a hyperplane in high-dimensional space
- Choose the hyperplane with the max margin



Latent SVM

- Classifiers that score an example x using

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

Vector of HOG features and part offsets

  - β are model parameters, z are latent values

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

- Learning: find β such that $y_i f_\beta(x_i) > 0$

- Minimize:

Regularization

Hinge loss

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

Semi-convexity

- Maximum of convex functions is convex

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

$\max(0, 1 - y_i f_\beta(x_i))$ is convex for negative examples

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

- Convex if latent values for positive examples are fixed

- Important because it makes optimizing β a convex optimization problem, even though the latent values for the negative examples are not fixed

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 via gradient descent with data-mining

Training Models

- Reduce to Latent SVM training problem
- Positive example specifies some z should have high score
- Bounding box defines range of root locations
  - Parts can be anywhere
  - This defines $Z(x)$ (vector of part offsets)

Training Algorithm

Data:
Positive examples $P = \{(I_1, B_1), \ldots, (I_n, B_n)\}$
Negative images $N = \{J_1, \ldots, J_m\}$
Initial model β

Result: New model β

$F_n := \emptyset$
for *relabel* $:= 1$ **to** *num-relabel* **do**
  $F_p := \emptyset$
  for $i := 1$ **to** n **do**
    Add `detect-best` (β, I_i, B_i) to F_p
  end
  for *datamine* $:= 1$ **to** *num-datamine* **do**
    for $j := 1$ **to** m **do**
      if $|F_n| \geq$ *memory-limit* **then** break
      Add `detect-all` $(\beta, J_j, -(1+\delta))$ to F_n
    end
    $\beta :=$`gradient-descent` $(F_p \cup F_n)$
    Remove (i, v) with $\beta \cdot v < -(1+\delta)$ from F_n
  end
end

Procedure `Train`

Training Algorithm

Data:
Positive examples $P = \{(I_1, B_1), \ldots, (I_n, B_n)\}$
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Initial model β

Result: New model β

```
1  F_n := ∅
2  for relabel := 1 to num-relabel do
3  |   F_p := ∅
4  |   for i := 1 to n do
5  |   |   Add detect-best(β,I_i,B_i) to F_p
6  |   end
7  |   for datamine := 1 to num-datamine do
8  |   |   for j := 1 to m do
9  |   |   |   if |F_n| ≥ memory-limit then break
10 |   |   |   Add detect-all(β,J_j,−(1+δ)) to F_n
11 |   |   end
12 |   |   β := gradient-descent(F_p ∪ F_n)
13 |   |   Remove (i,v) with β·v < −(1+δ) from F_n
14 |   end
15 end
```

Procedure `Train`

Finds the highest scoring object hypothesis with a root filter that significantly overlaps *B* in *I*. Implemented with matching procedure

Training Algorithm

Data:
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    Remove (i, v) with $\beta \cdot v < -(1+\delta)$ from F_n
  end
end

Procedure `Train`

Computes the best object hypothesis for each root location and selects the ones that score above a threshold. Implemented with matching procedure

Training Algorithm

Data:
Positive examples $P = \{(I_1, B_1), \ldots, (I_n, B_n)\}$
Negative images $N = \{J_1, \ldots, J_m\}$
Initial model β

Result: New model β

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    end
    $\beta :=$`gradient-descent` $(F_p \cup F_n)$
    Remove (i, v) with $\beta \cdot v < -(1+\delta)$ from F_n
  end
end

Procedure `Train`

Trains β using cached feature vectors

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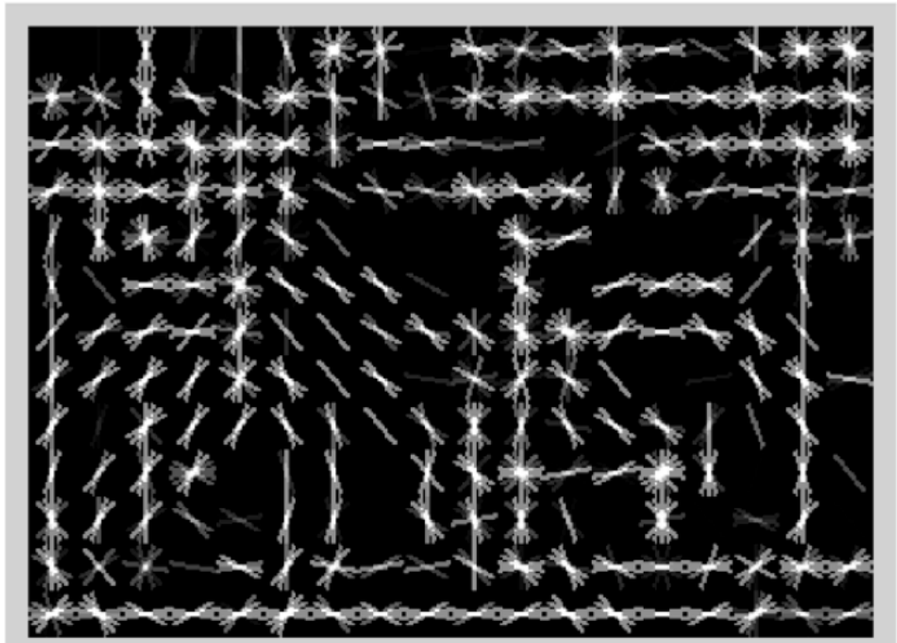
Histogram of Gradient features



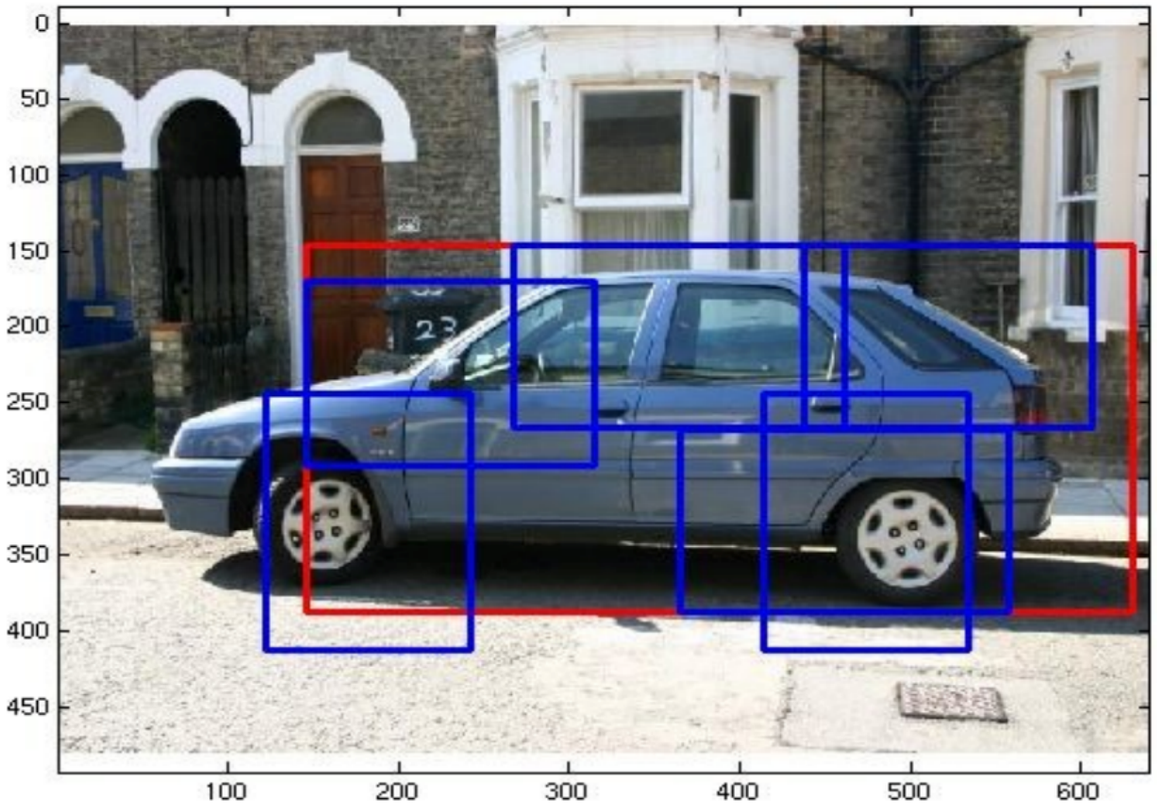
- Image is partitioned into 8x8 pixel blocks
- In each block we compute a histogram of gradient orientations
  - Invariant to changes in lighting, small deformations
- Compute features at different resolutions (pyramid)
  - They use $\lambda = 5 \text{ in training}, \lambda = 10 \text{ in testing}$

= number of levels we need to go down in the pyramid to get to a feature map computed at twice the resolution of another one

Background

- Negative example specifies no z should have high score
- One negative example per root location in a background image
- Huge number of negative examples
- Consistent with requiring low false-positive rate

Post Processing: Bounding Box Prediction



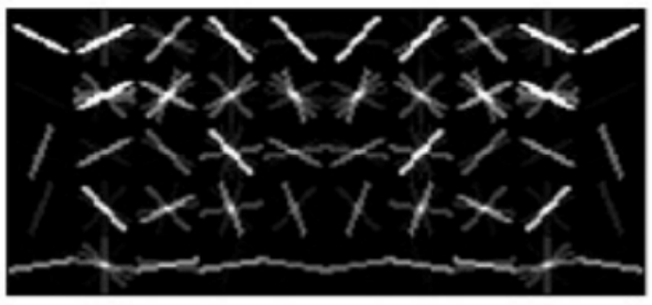
- Predict (x_1, y_1) and (x_2, y_2) from part locations

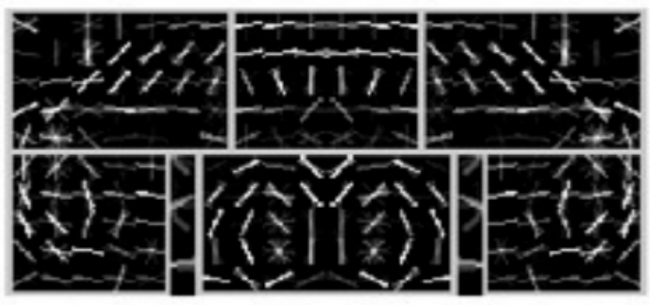
- Learn four linear functions for predicting x_1, x_2, y_1, y_2
  Done via linear least-squares regression, independently for each component of a mixture model.

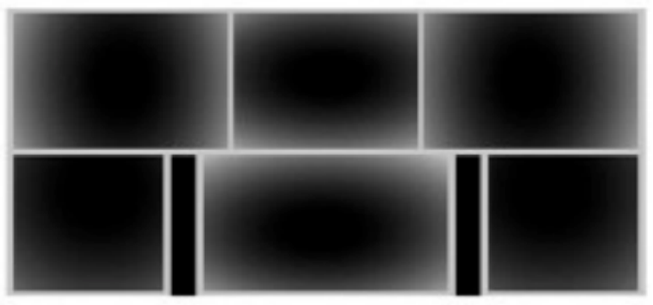
Roadmap

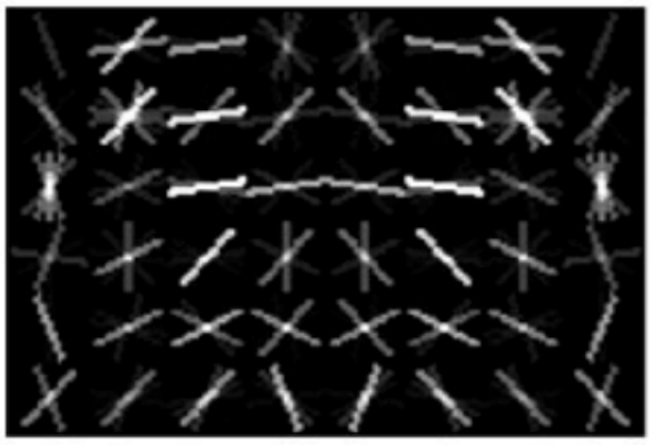
1. Introduction
2. Related Work
3. Model Overview
4. Latent SVM
5. Features & Post Processing
6. **Experiments**

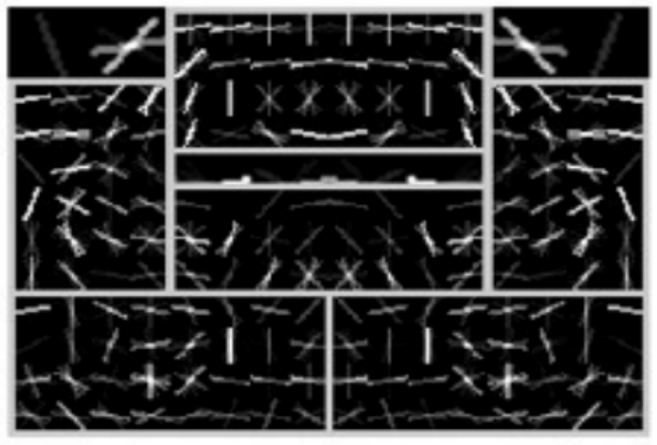
Car Model

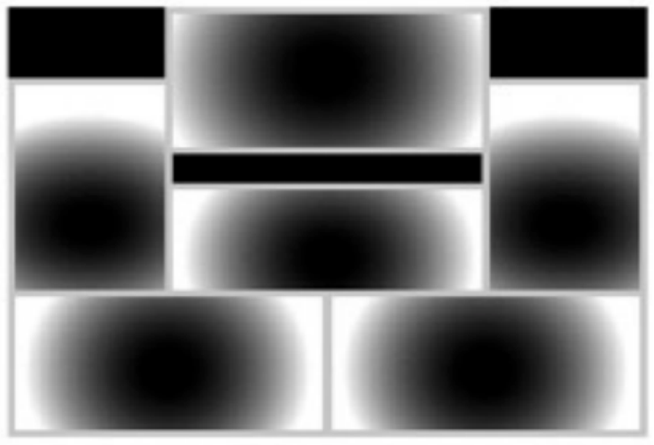












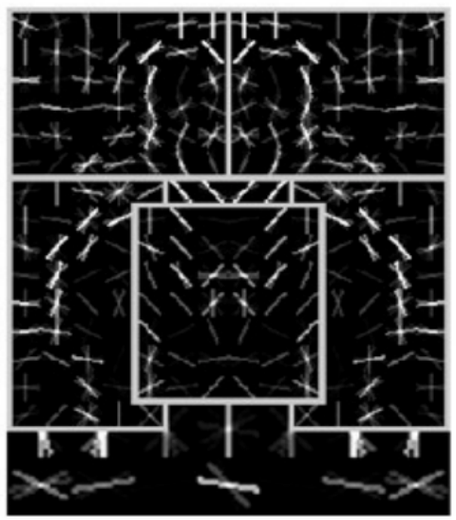
root filters
coarse resolution

part filters
finer resolution

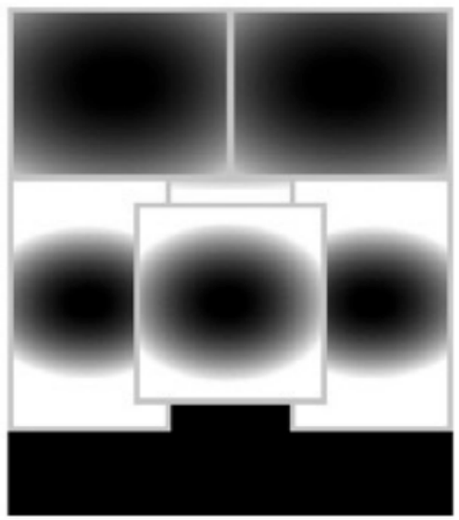
deformation
models

Person Model

root filters
coarse resolution

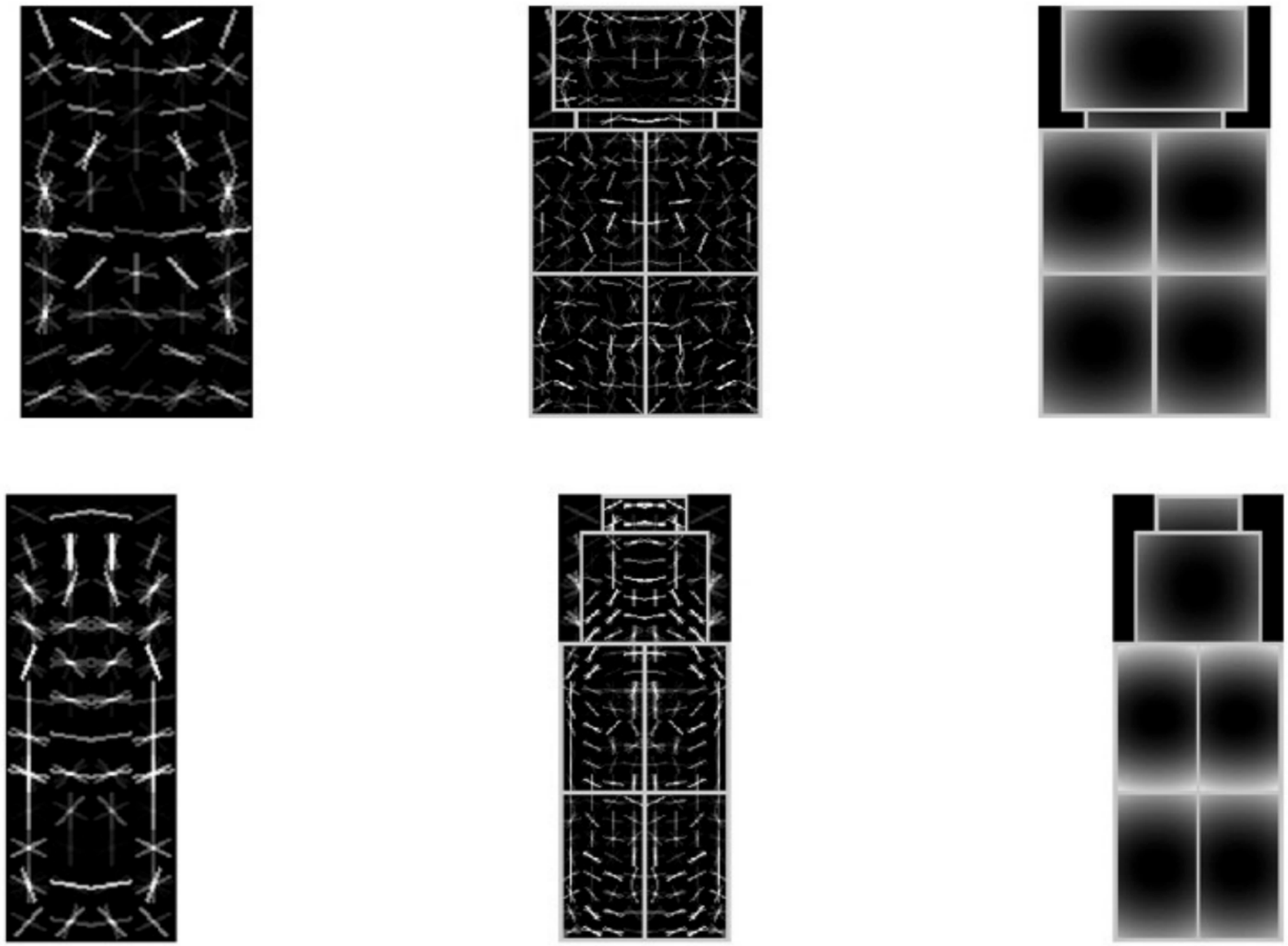


part filters
finer resolution



deformation
models

Bottle Model



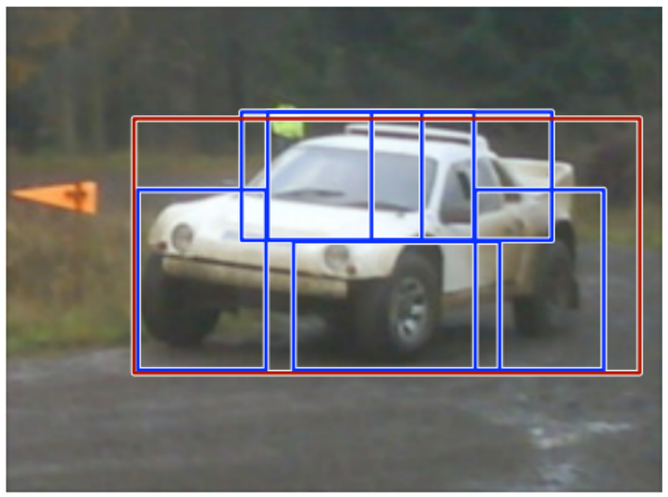
root filters
coarse resolution

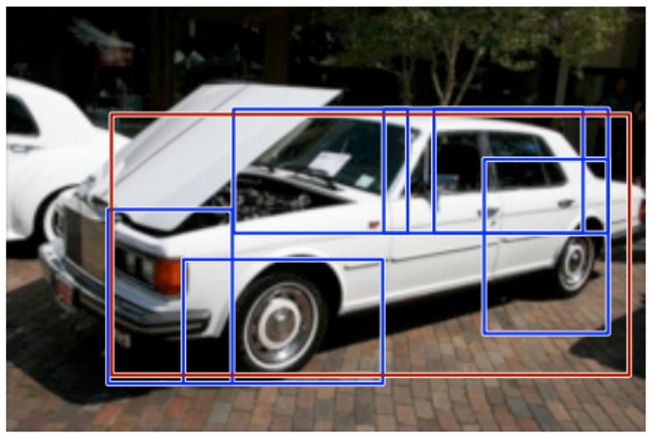
part filters
finer resolution

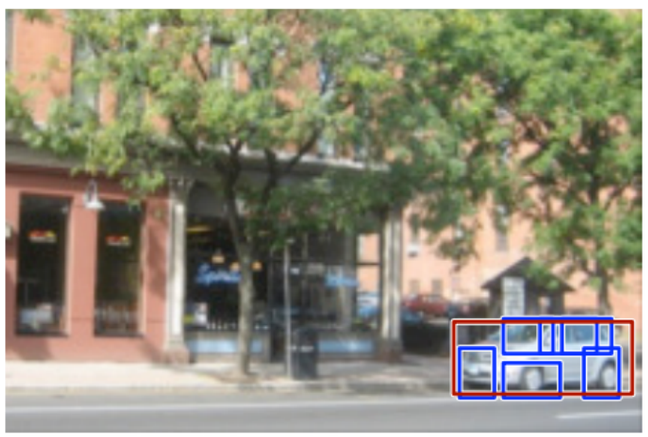
deformation
models

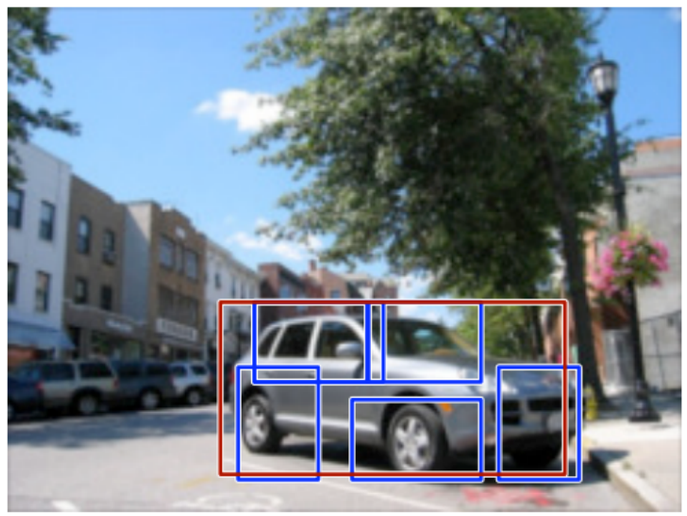
Car Detections

high scoring true positives

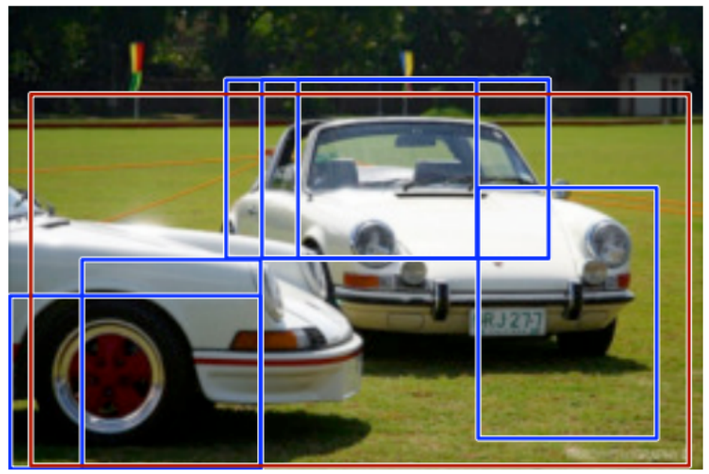


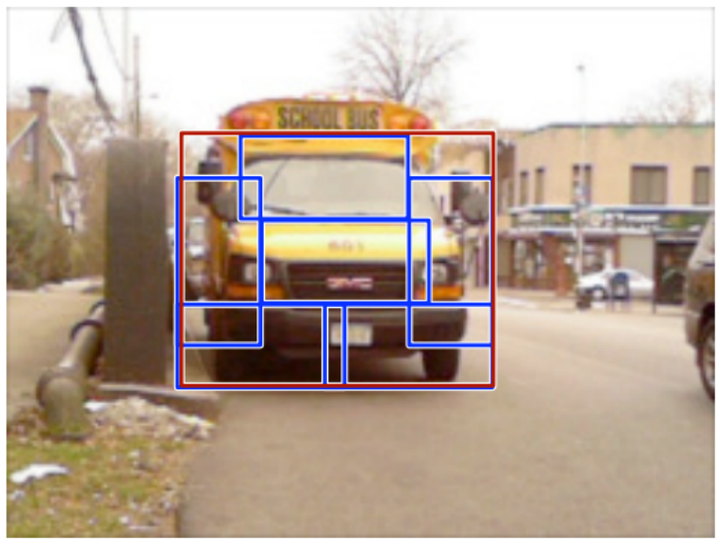






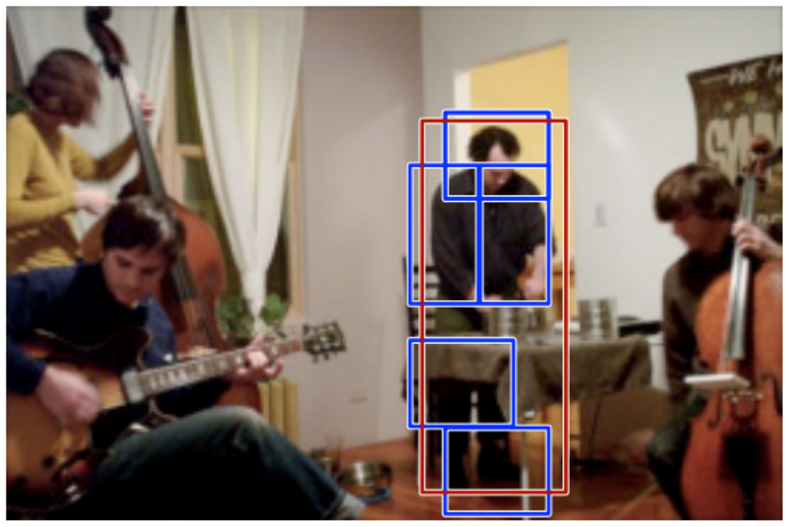
high scoring false positives

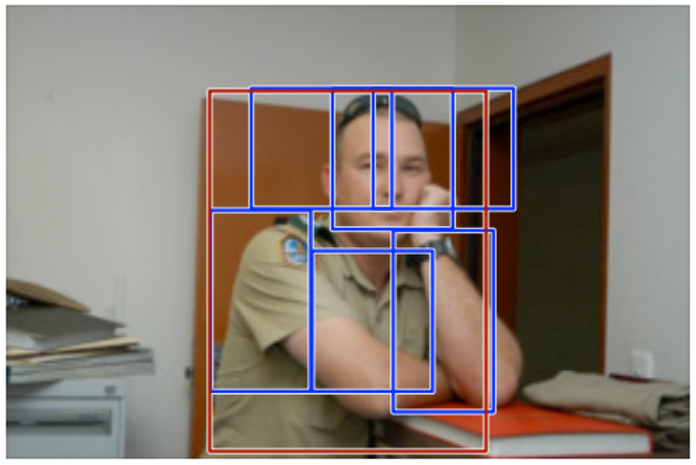


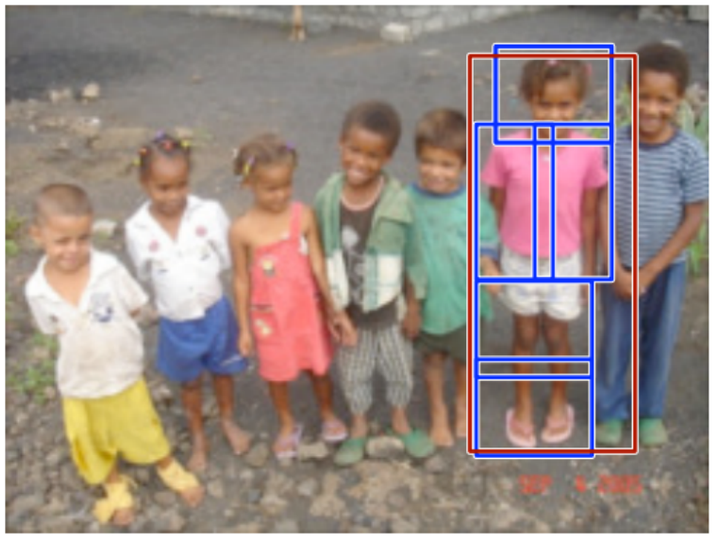


Person Detections

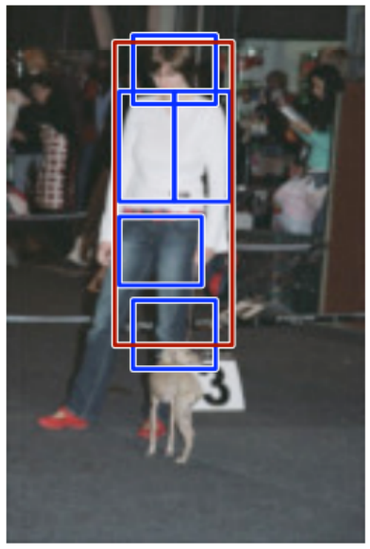
high scoring true positives





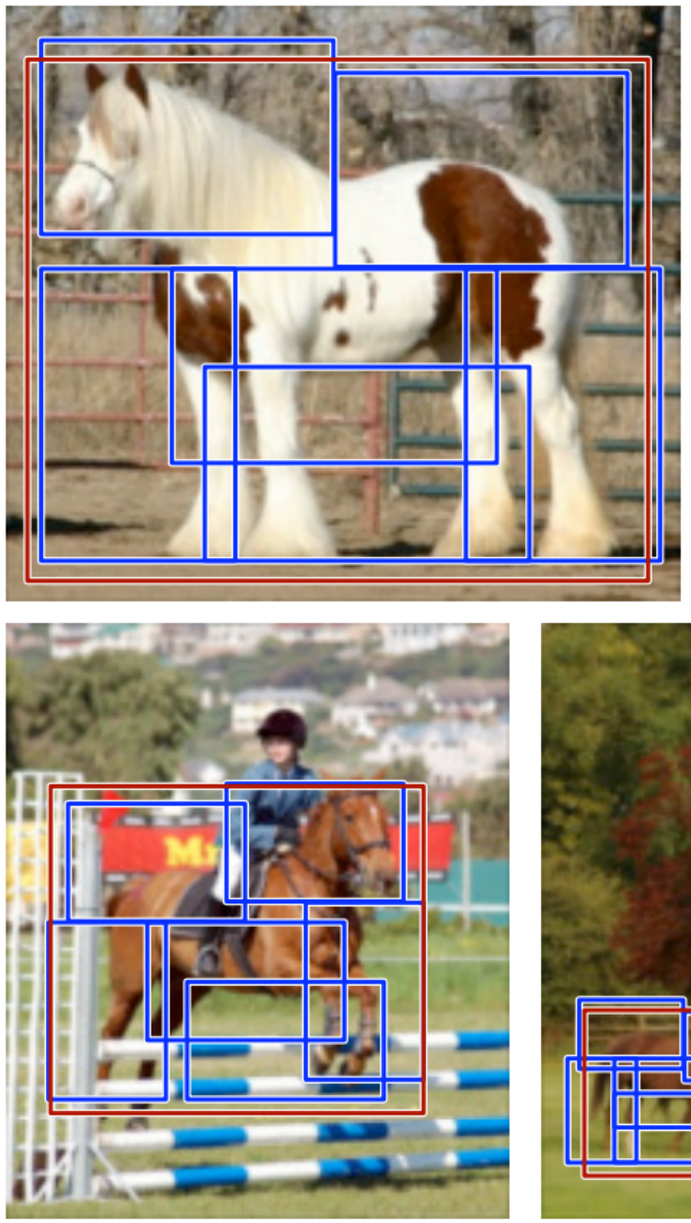


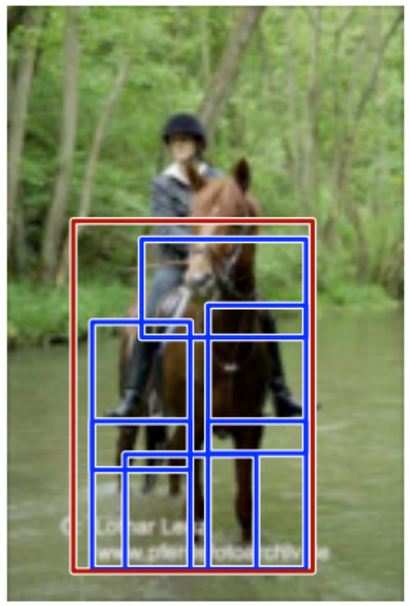
high scoring false positives
(not enough overlap)

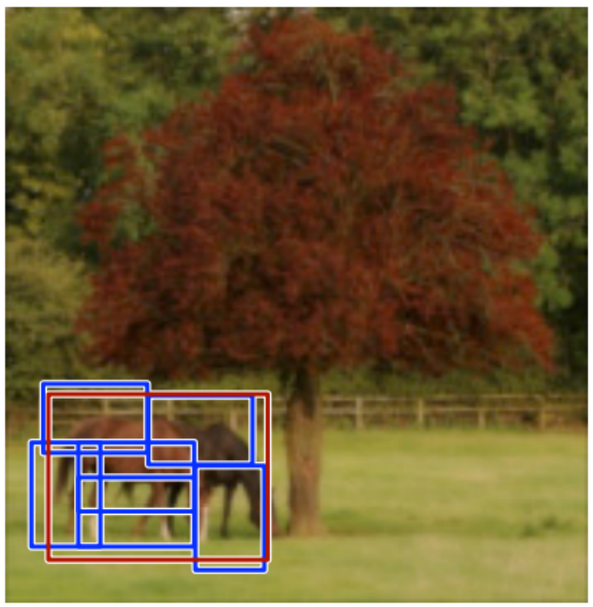


Horse Detections

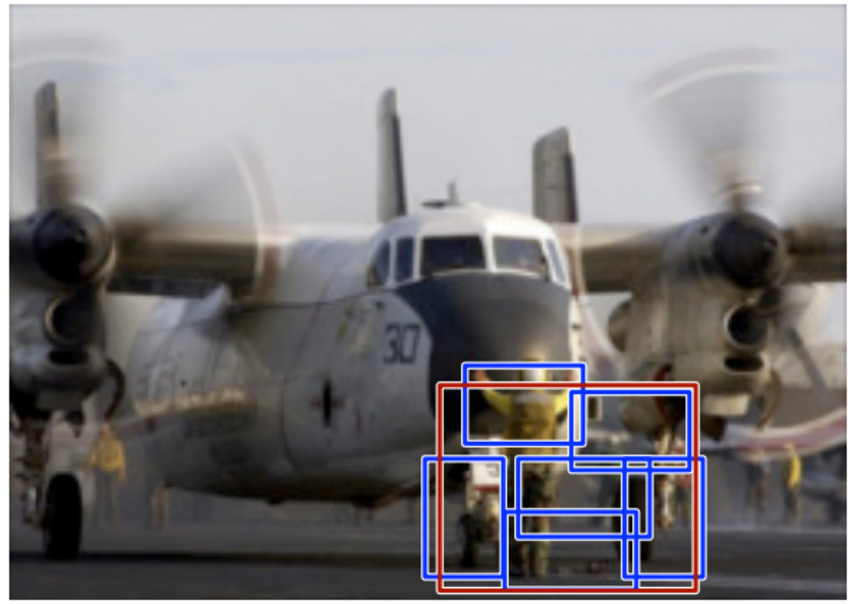
high scoring true positives

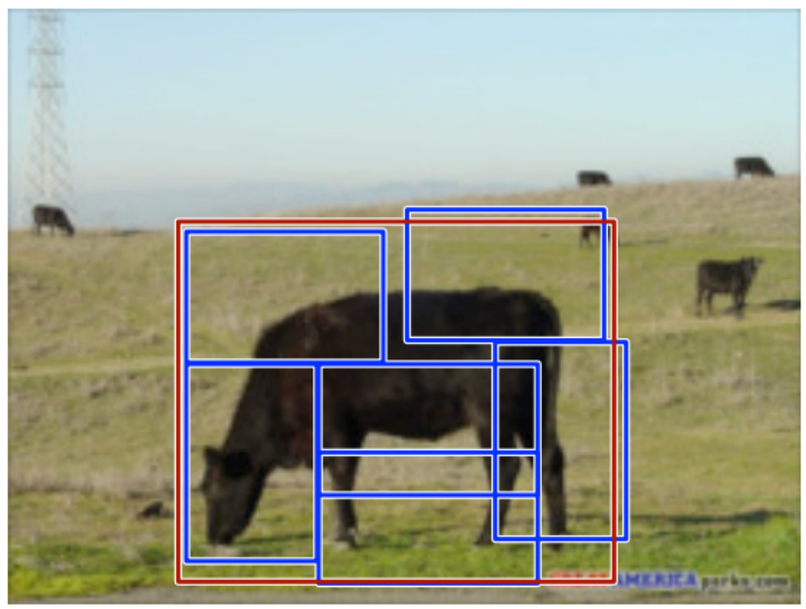






high scoring false positives





Quantitative Results

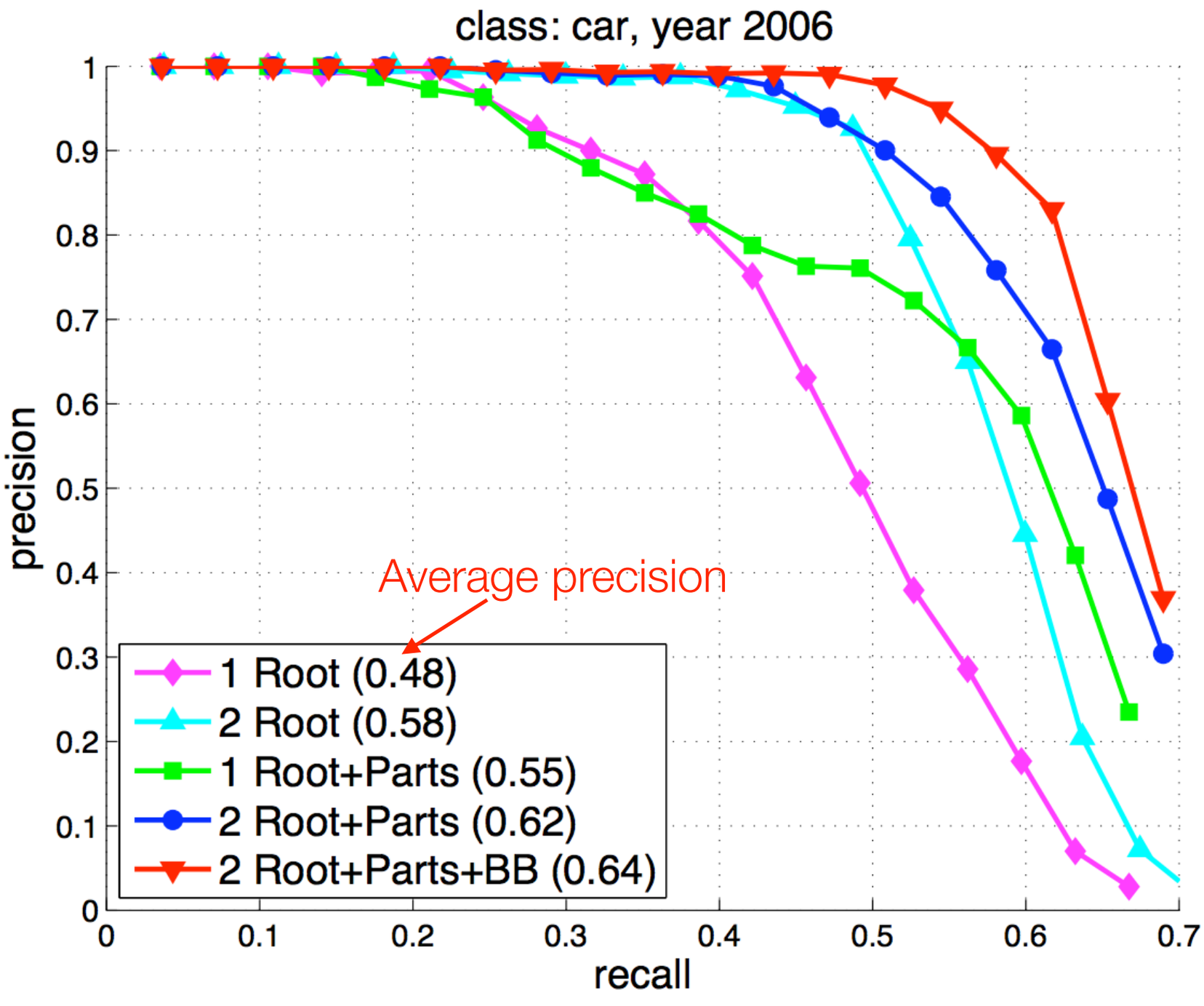
- PASCAL Challenge: ~10,000 images, with ~25,000 target objects
  - Objects from 20 categories (person, car, bicycle, cow, table...)
- Out of 20 classes we got:
  - First place in 7 classes
  - Second place in 8 classes
- Some statistics:
  - Takes ~2 seconds to evaluate a model in one image
  - Takes ~4 hours to train a model
  - MUCH faster than most systems

Comparison of Car Models on 2006 Data

Results for:

1- and 2-component models, with and without parts

2-component model with parts and bounding box prediction

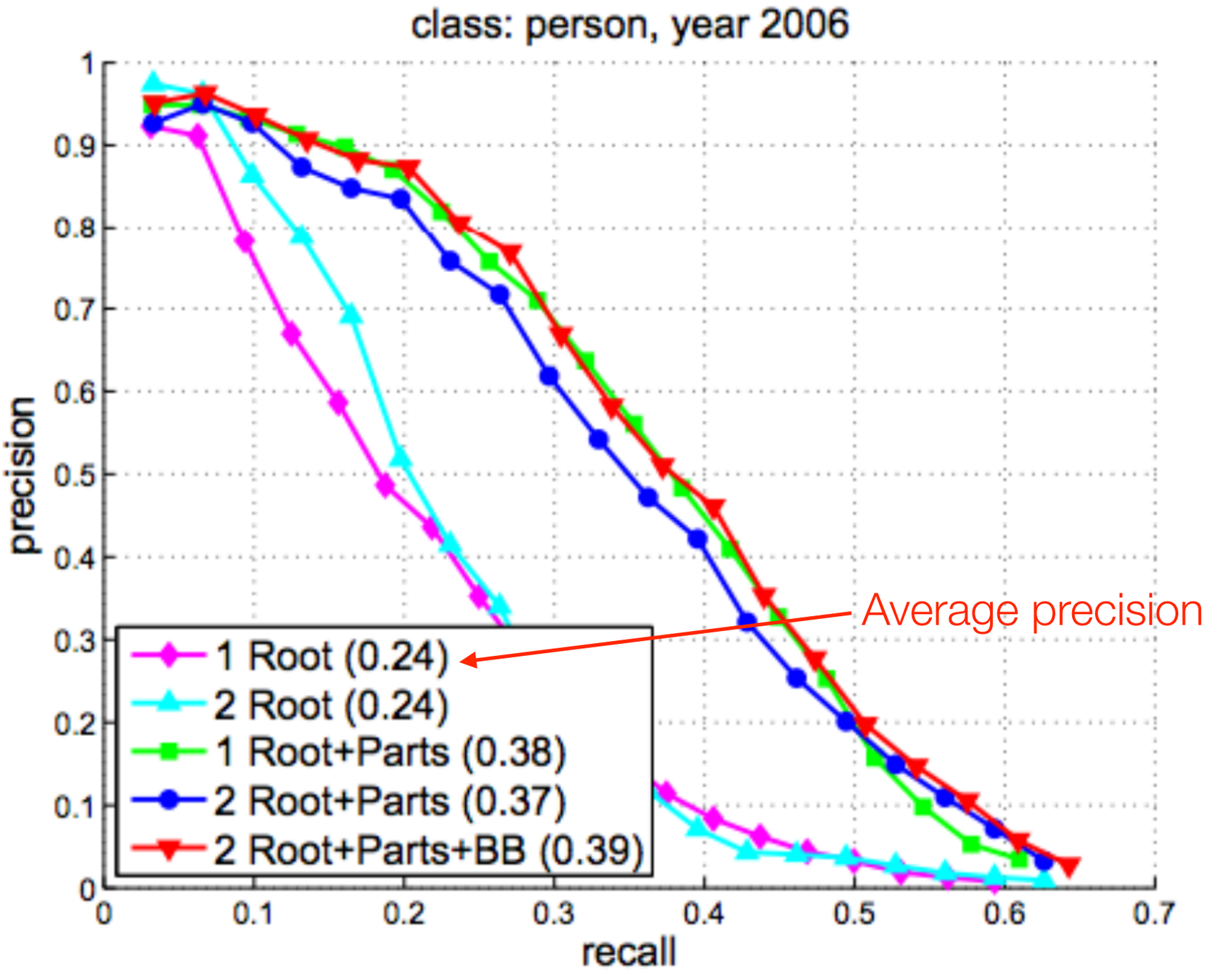


Comparison of Person Models on 2006 Data

Results for:

1- and 2-component models, with and without parts

2-component model with parts and bounding box prediction



Summary

- Object detection based on mixtures of multiscale deformable models
- Discriminative training of classifiers that use latent information
- Fast matching algorithms
- Learning from weakly-labeled data (no component labels or part locations)
- Leads to state-of-the-art results in PASCAL challenge

Questions?