Deformable part models

Ross Girshick
UC Berkeley

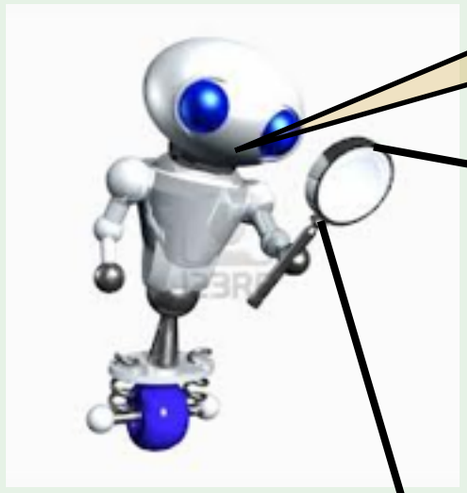
CS231B Stanford University
Guest Lecture April 16, 2013

Image understanding

Snack time in the lab

photo by “thomas pix” http://www.flickr.com/photos/thomaspix/2591427106

What objects are where?

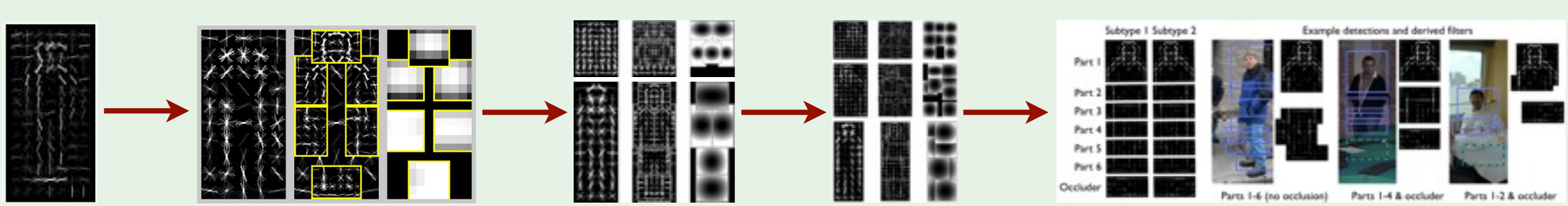


robot: “I see a table with twinkies, pretzels, fruit, and some mysterious chocolate things...”

DPM lecture overview

Part 1: modeling

Part 2: learning



AP 12% 27% 36% 45% 49%

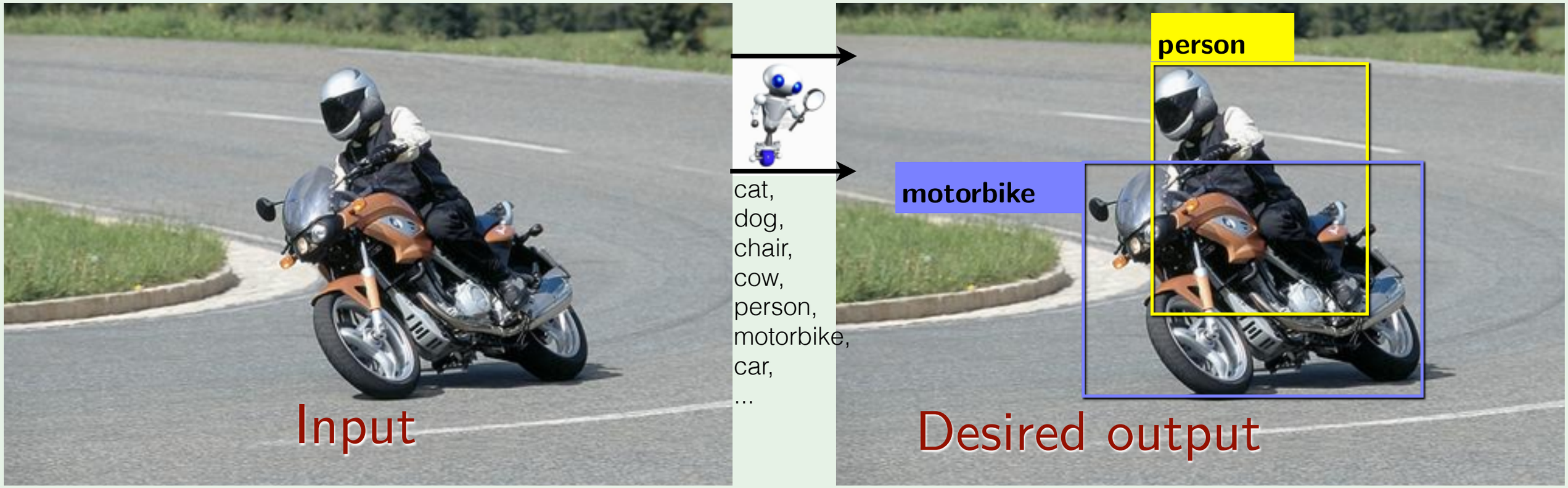
2005 2008 2009 2010 2011

Formalizing the object detection task

Many possible ways

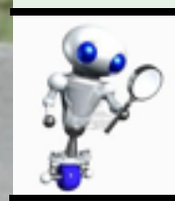
Formalizing the object detection task

Many possible ways, this one is popular:

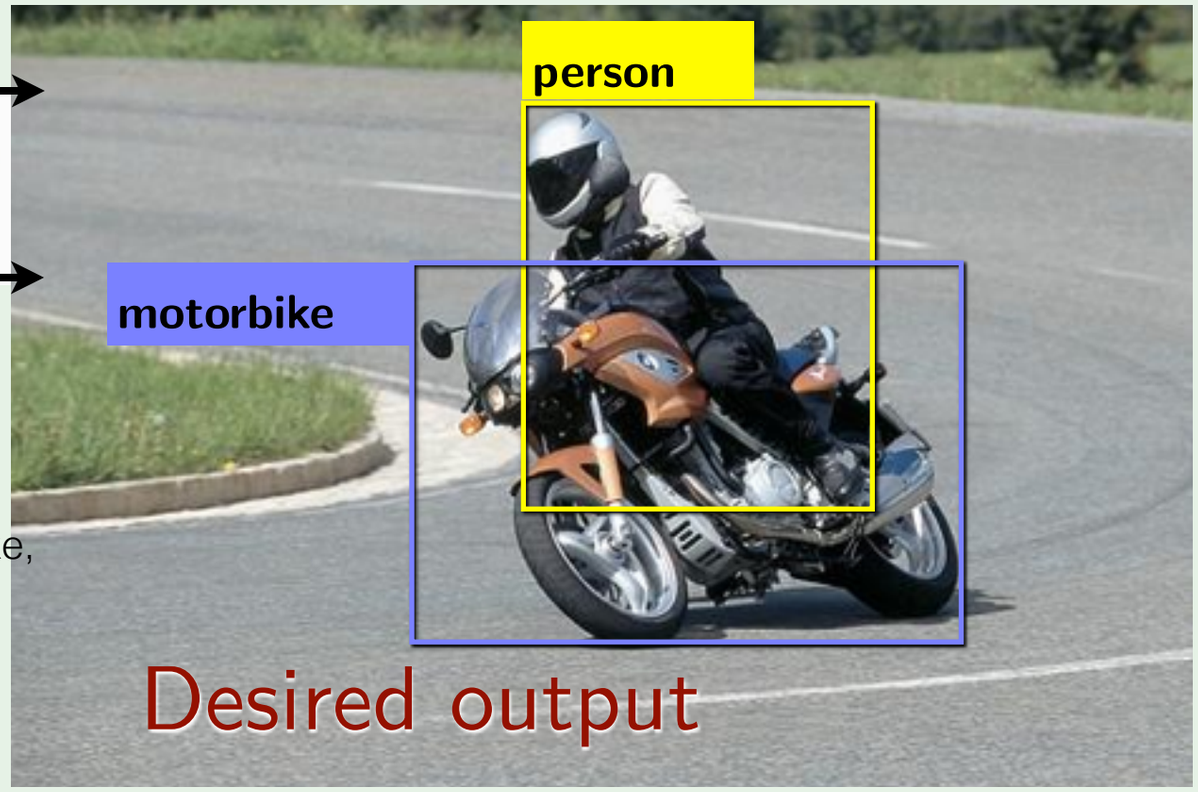


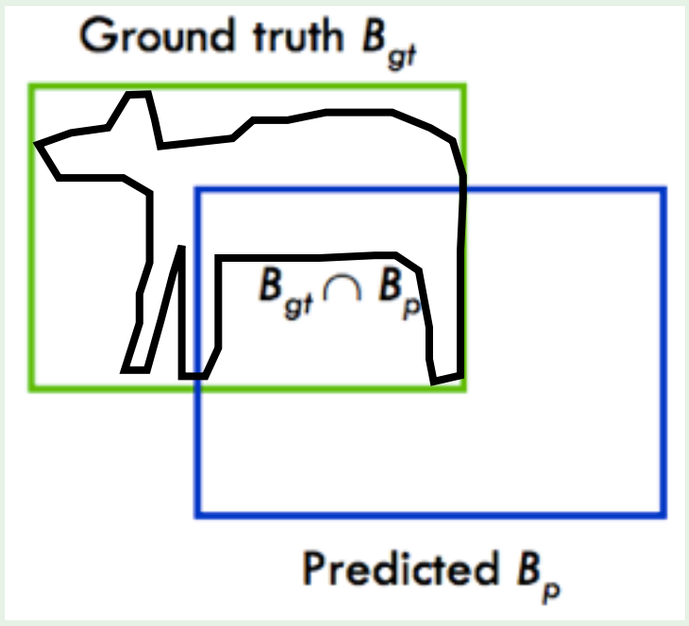
Formalizing the object detection task

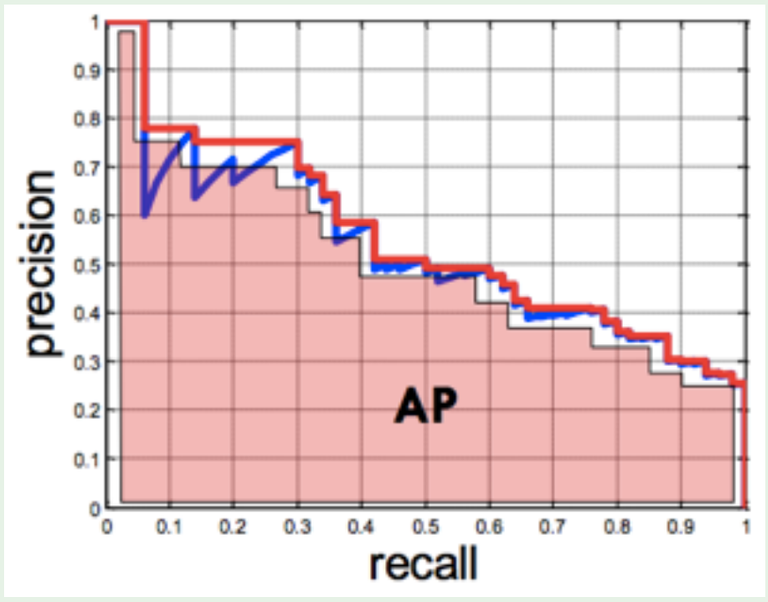
Many possible ways, this one is popular:



cat,
dog,
chair,
cow,
person,
motorbike,
car,
...







Performance summary:

Average Precision (AP)
0 is worst 1 is perfect

Benchmark datasets

PASCAL VOC 2005 – 2012
- 54k objects in 22k images
- 20 object classes
- annual competition

Benchmark datasets

PASCAL VOC 2005 – 2012
- 54k objects in 22k images
- 20 object classes
- annual competition







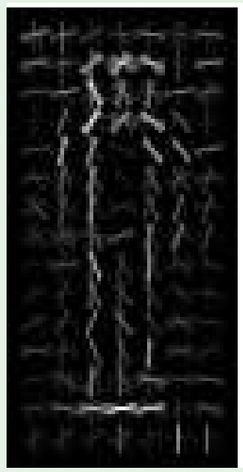

Reduction to binary classification

pos = { ...  ... }

neg = { ... background patches ... }

HOG

SVM



“Sliding window” detector

Dalal & Triggs (CVPR’05)

Sliding window detection

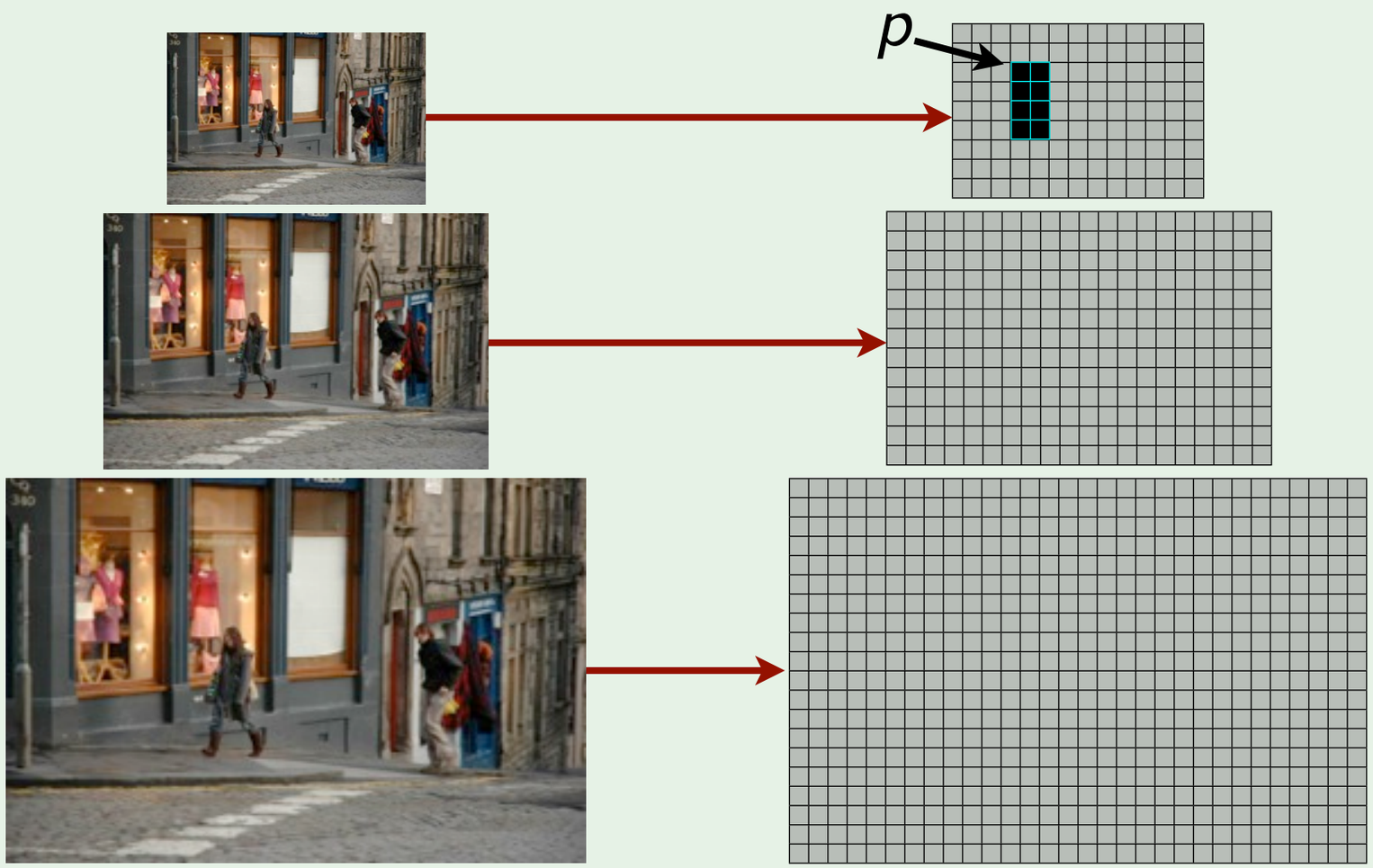
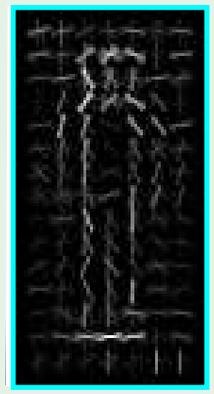


Image pyramid

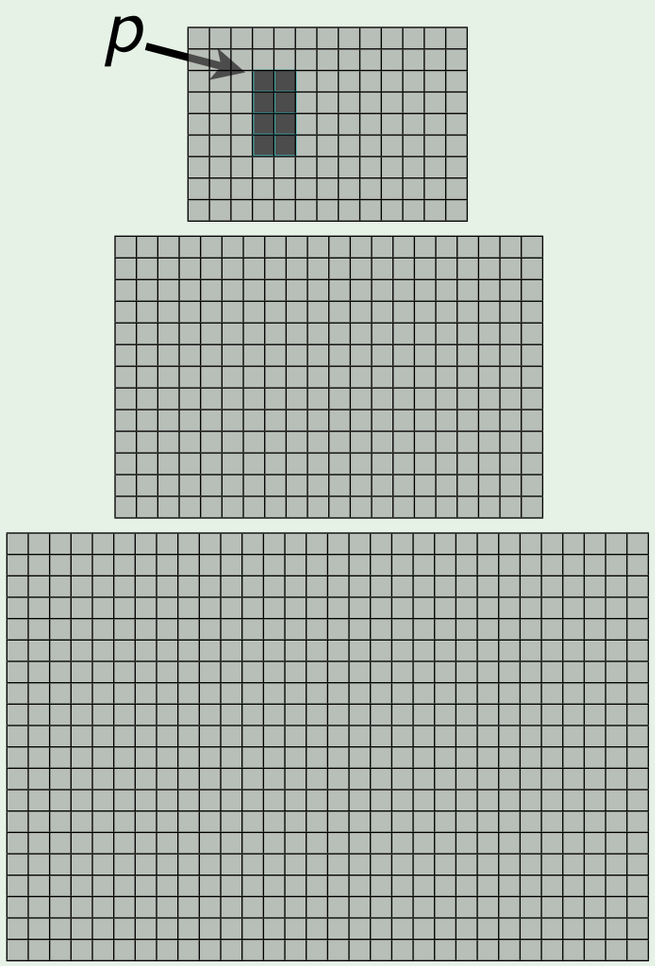
HOG feature pyramid

$$score(I, p) = \mathbf{w} \cdot \phi(I, p)$$



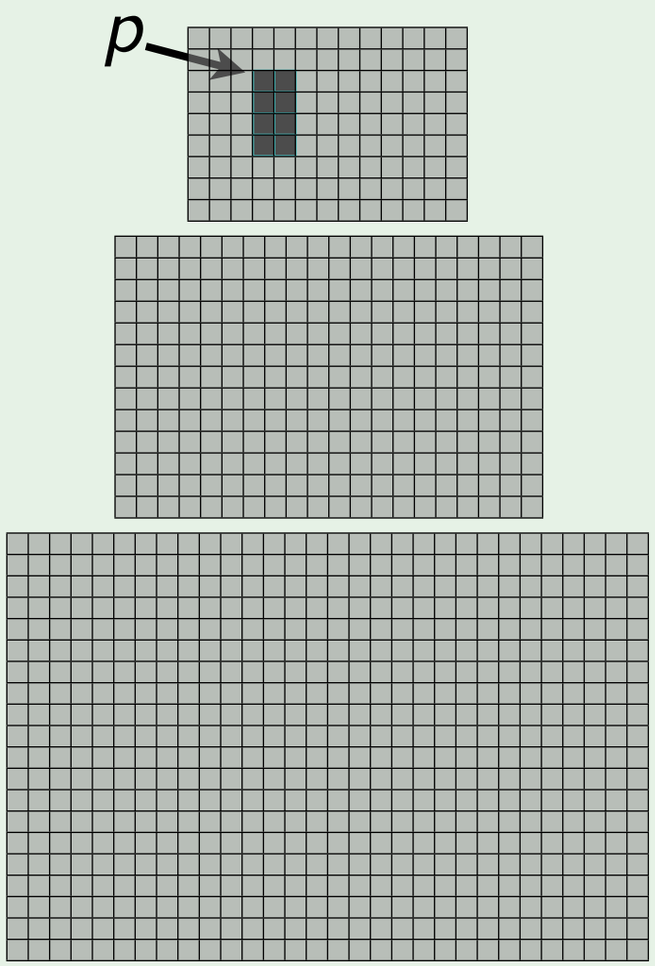
- Compute HOG of the whole image at multiple resolutions
- Score every subwindow of the feature pyramid
- Apply non-maxima suppression

Detection



number of locations p ~ 250,000 per image

Detection

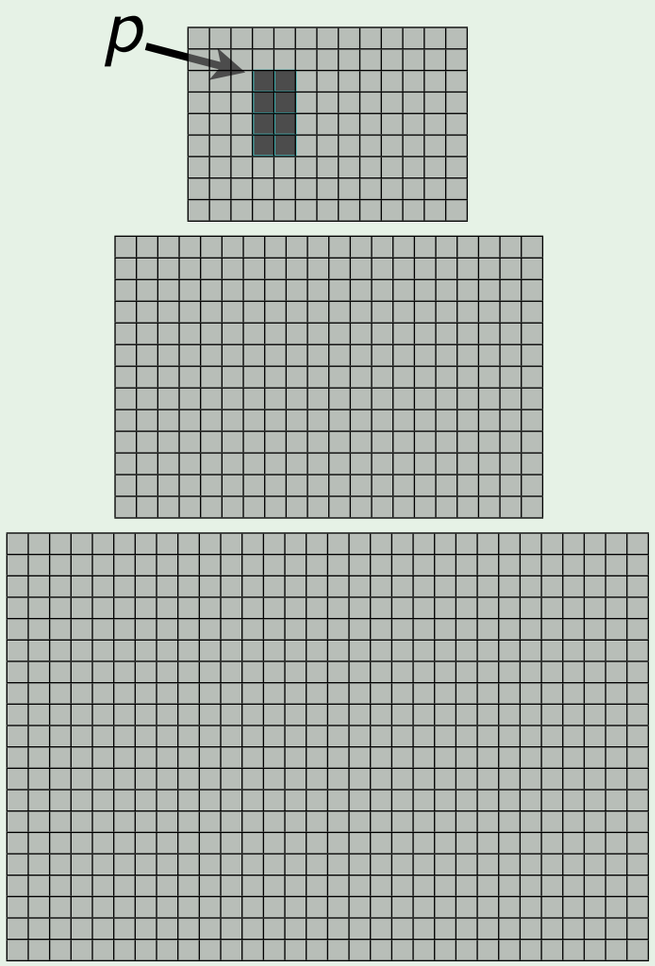


number of locations p ~ 250,000 per image

test set has ~ 5000 images

>> 1.3×10^9 windows to classify

Detection



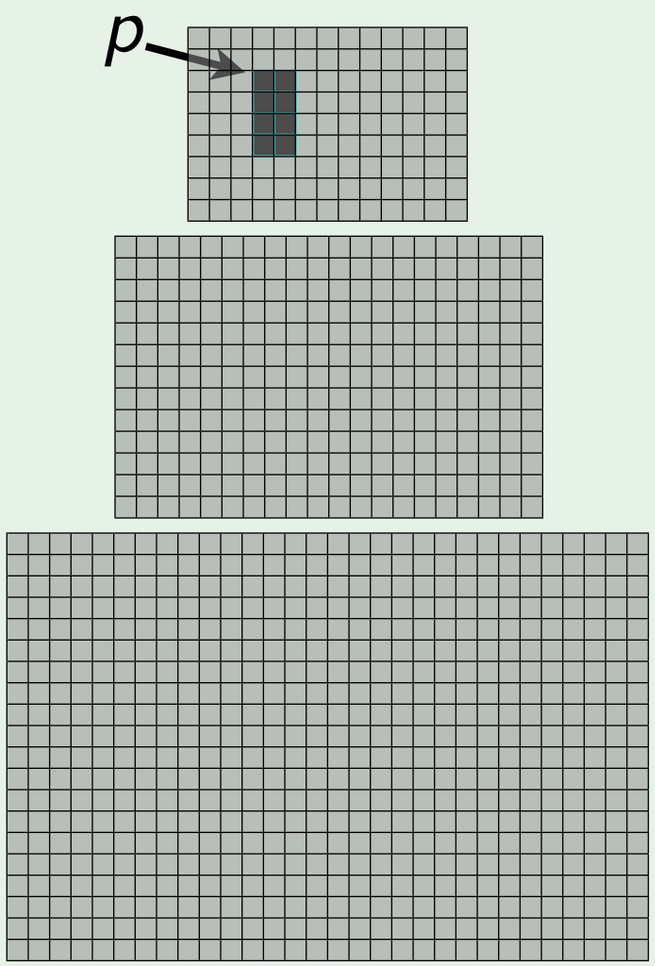
number of locations p ~ 250,000 per image

test set has ~ 5000 images

>> 1.3×10^9 windows to classify

typically only ~ 1,000 true positive locations

Detection



number of locations *p* ~ 250,000 per image

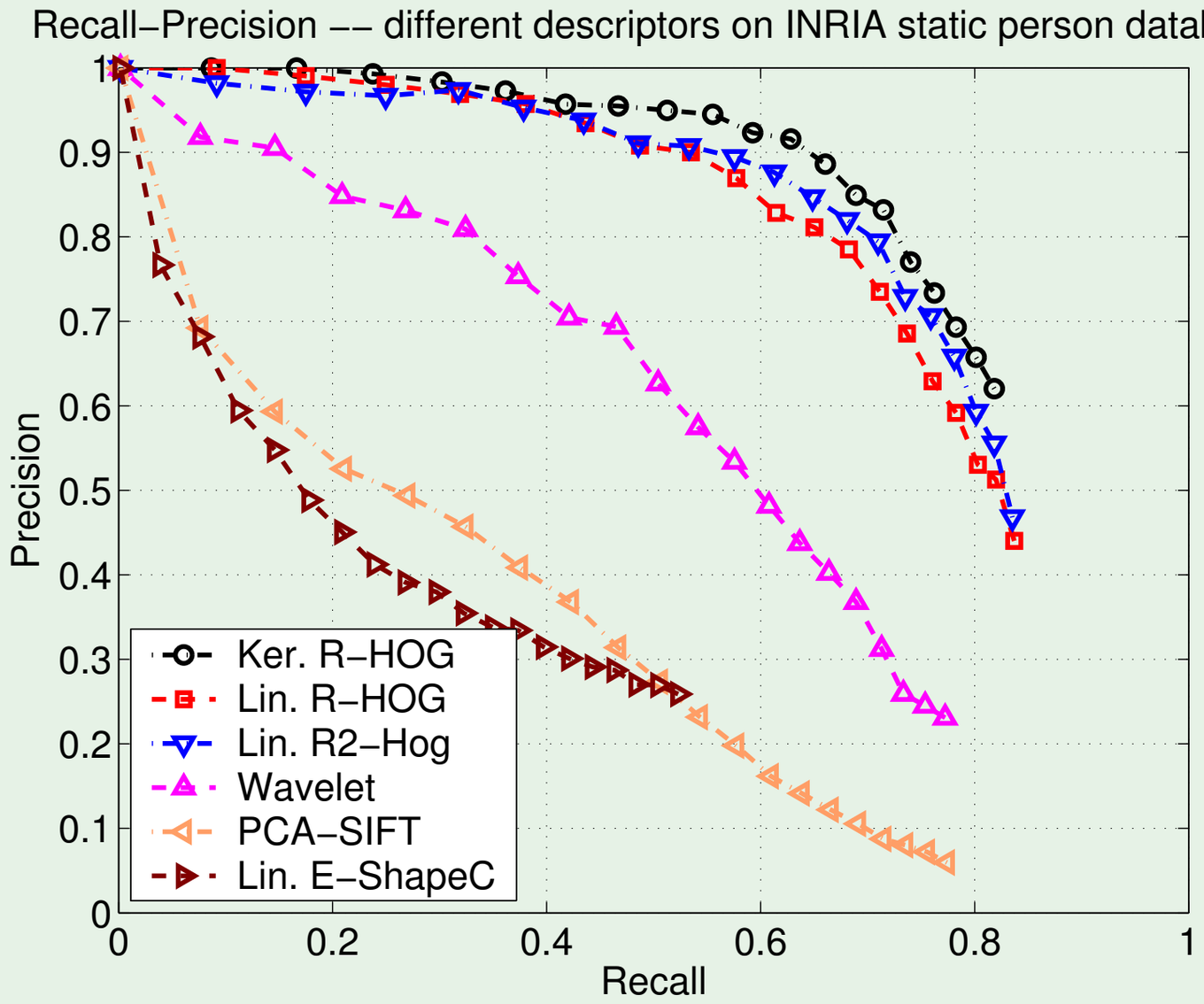
test set has ~ 5000 images

>> 1.3x10^9 windows to classify

typically only ~ 1,000 true positive locations

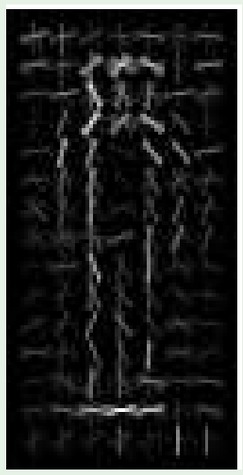
Extremely unbalanced binary classification

Dalal & Triggs detector on INRIA



- AP = 75%
  - (79% in my implementation)
- Very good
  - Declare victory and go home?

Dalal & Triggs on PASCAL VOC 2007



AP = 12%

(using my implementation)

How can we do better?

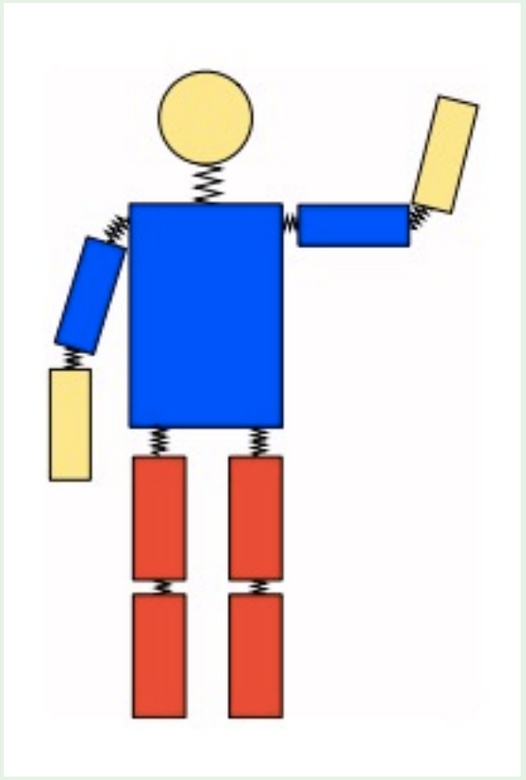
Revisit an old idea: part-based models (“pictorial structures”)

- Fischler & Elschlager ‘73, Felzenszwalb & Huttenlocher ’00

Combine with modern features and machine learning

Part-based models

- Parts — local appearance templates
- “Springs” — spatial connections between parts (geom. prior)



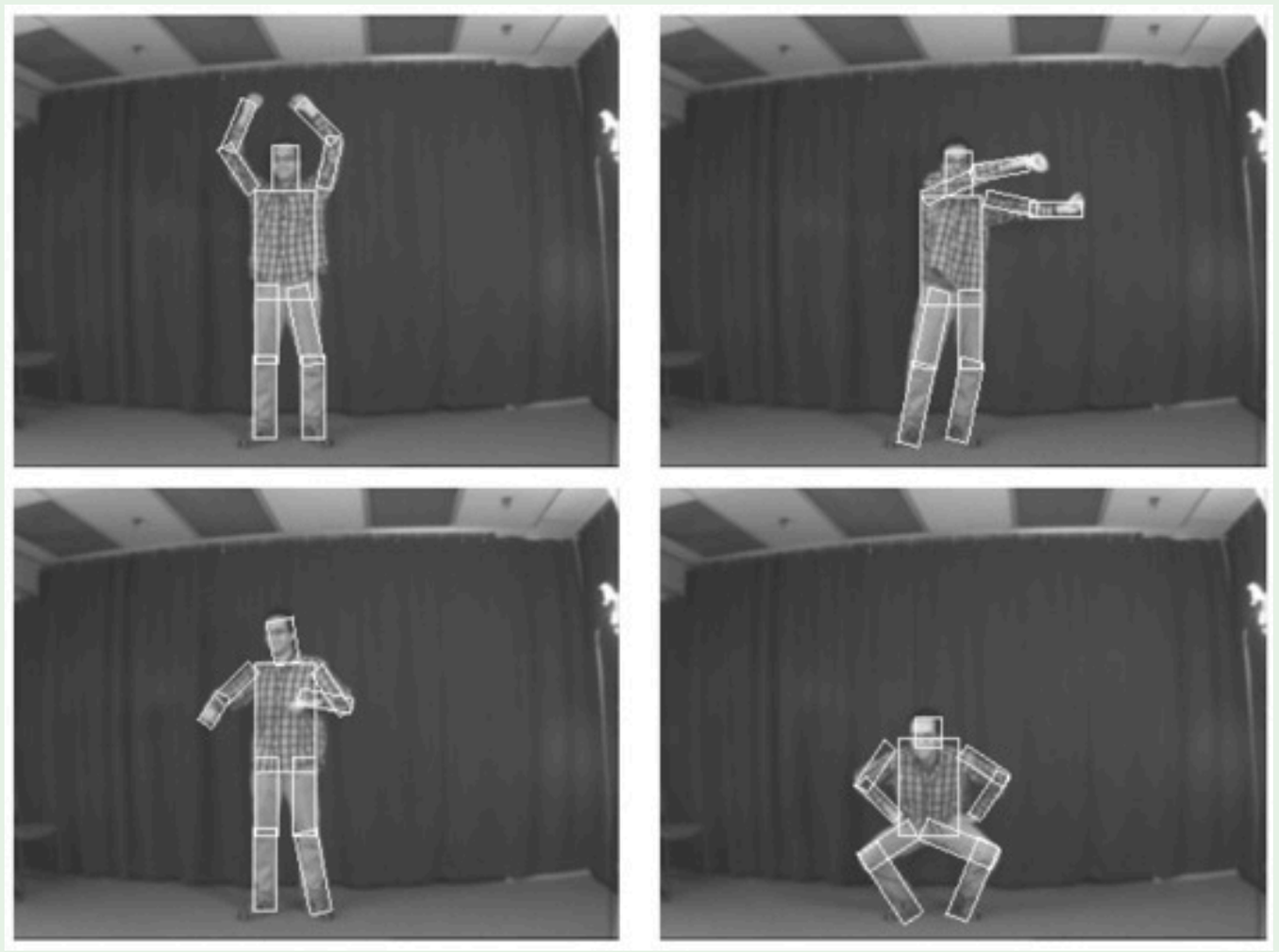
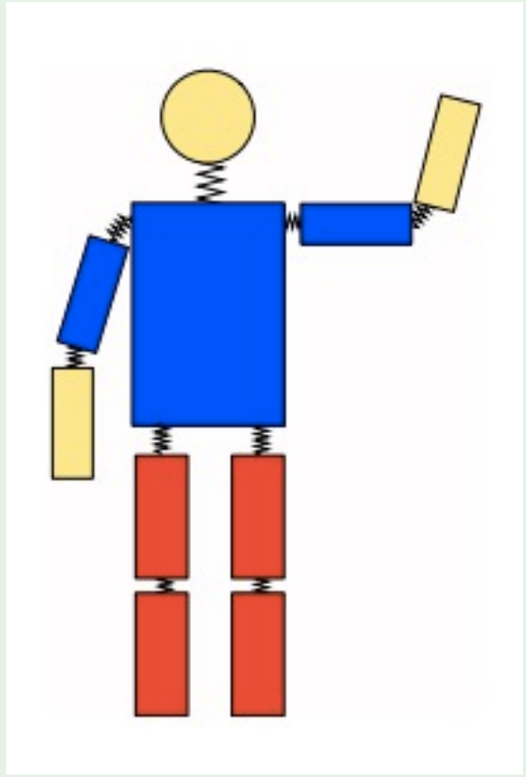


Image: [Felzenszwalb and Huttenlocher 05]

Part-based models

- Local appearance is easier to model than the global appearance
  - Training data shared across deformations
  - “part” can be local or global depending on resolution
- Generalizes to previously unseen configurations

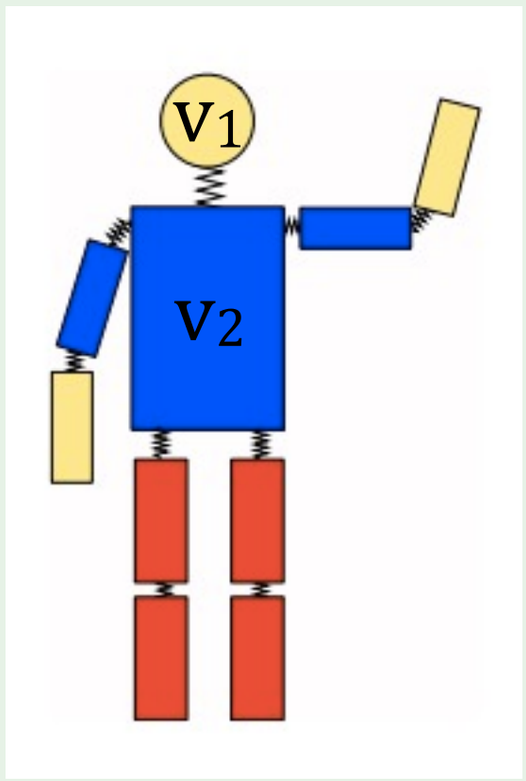


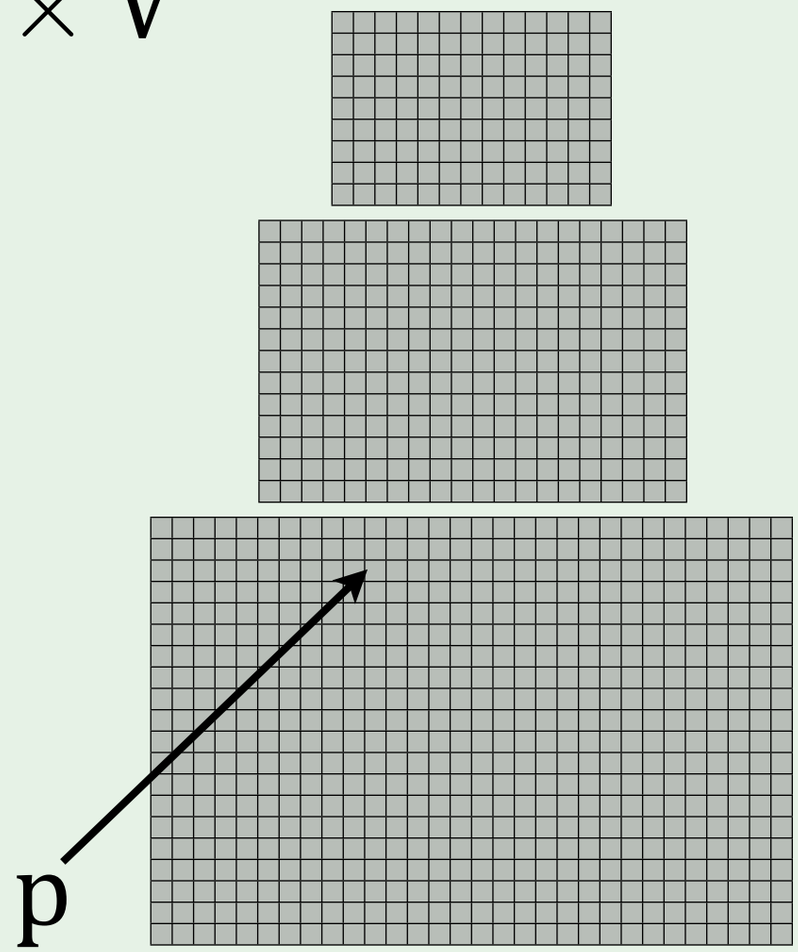
General formulation

$$G = (V, E)$$

$$V = (v_1, \ldots, v_n) \quad E \subseteq V \times V$$

$$(p_1, \ldots, p_n) \in P^n$$





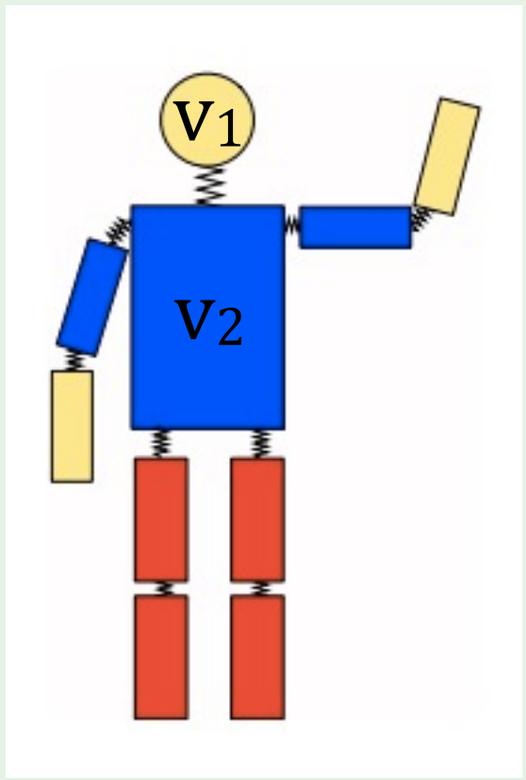
part locations in the image
(or feature pyramid)

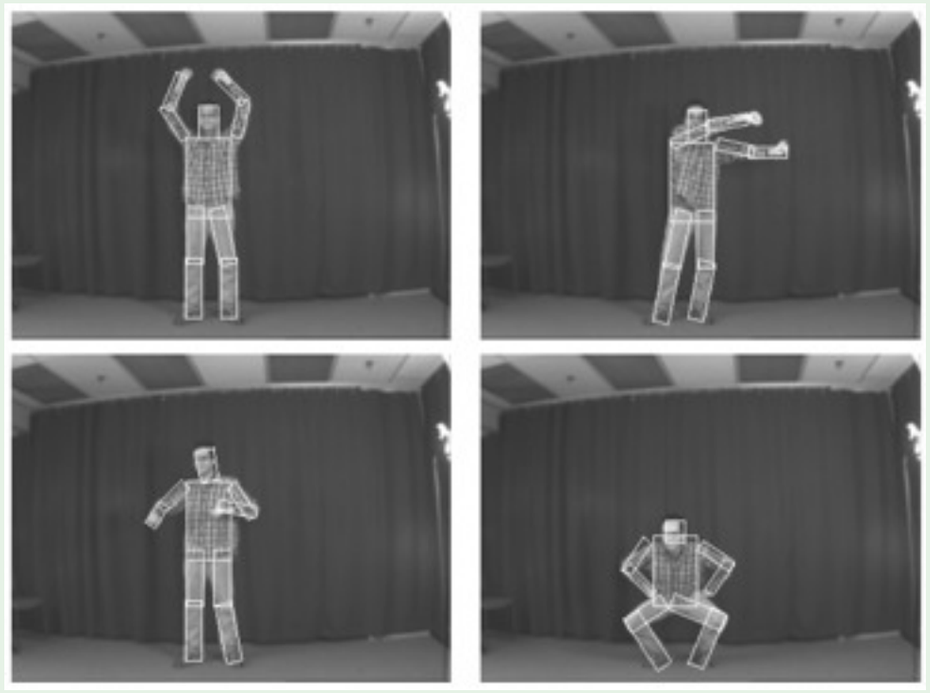
Part configuration score function

$$\text{score}(p_1, \ldots, p_n) = \sum_{i=1}^{n} m_i(p_i) - \sum_{(i,j)\in E} d_{ij}(p_i, p_j)$$

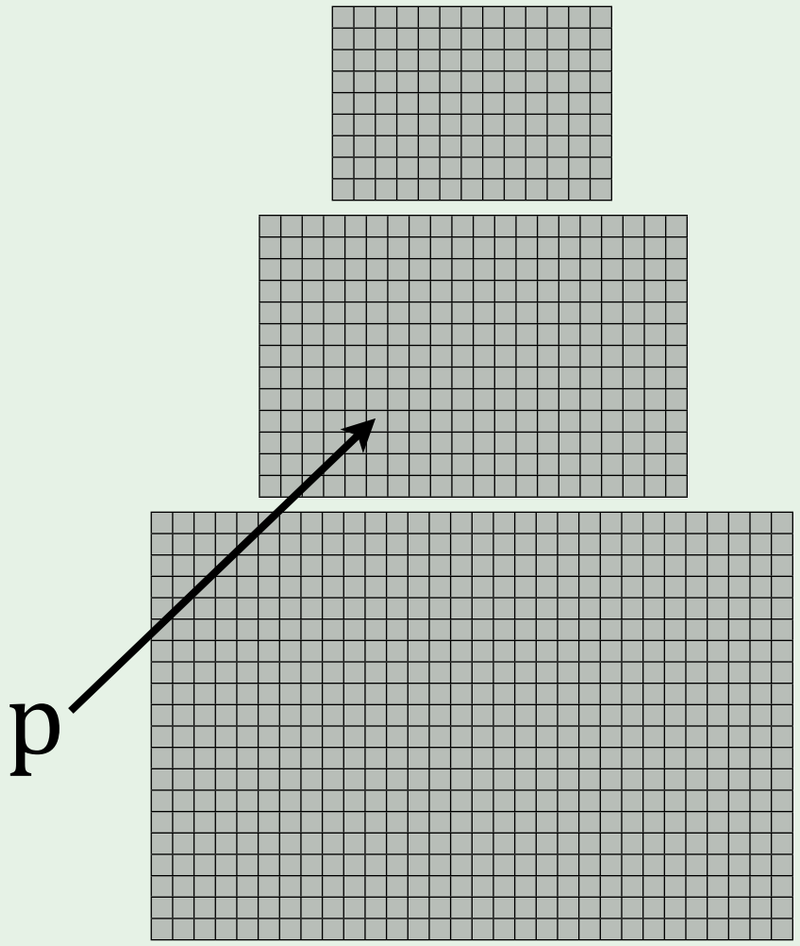
spring costs

Part match scores





Highest scoring configurations



Part configuration score function

$$\text{score}(p_1, \ldots, p_n) = \sum_{i=1}^{n} m_i(p_i) - \sum_{(i,j) \in E} d_{ij}(p_i, p_j)$$

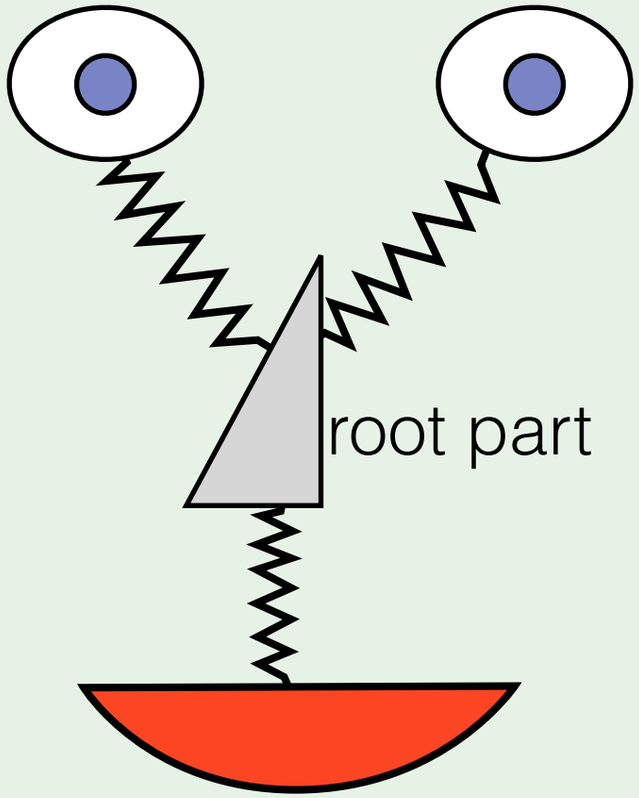
Part match scores

spring costs

- Objective: maximize score over $p_1,\ldots,p_n$
- h^n configurations! ($h = |P|$, about 250,000)
- Dynamic programming
  - If $G = (V,E)$ is a tree, $O(nh^2)$ general algorithm
    - $O(nh)$ with some restrictions on d_{ij}

Star-structured deformable part models

test image



“star” model

detection

Recall the Dalal & Triggs detector

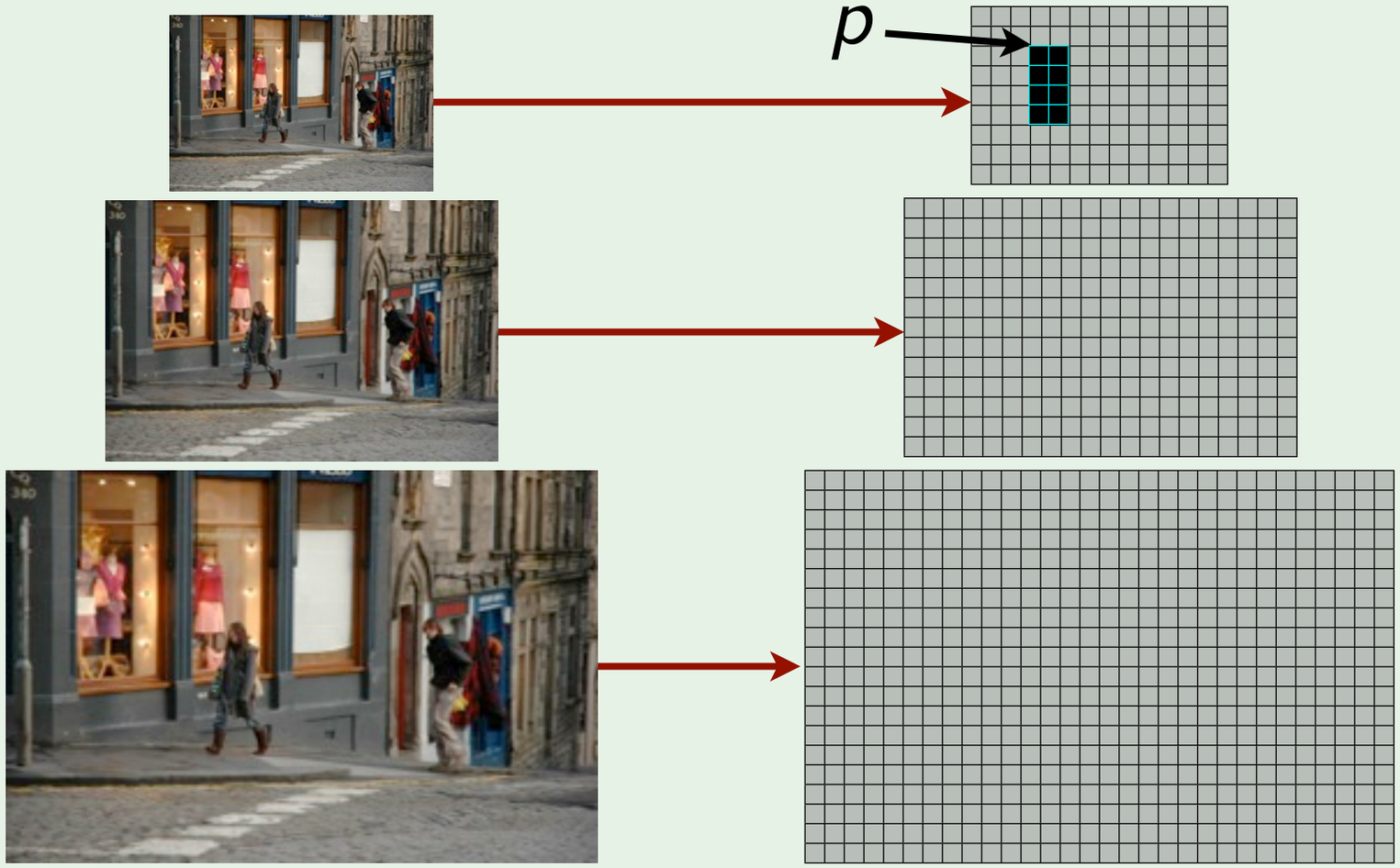
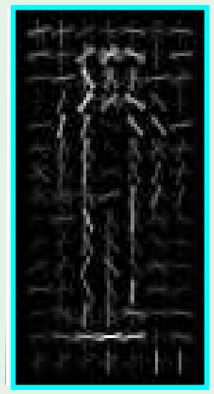


Image pyramid HOG feature pyramid

$$score(I, p) = \mathbf{w} \cdot \phi(I, p)$$



- HOG feature pyramid
- Linear filter / sliding-window detector
- SVM training to learn parameters w

D&T + parts

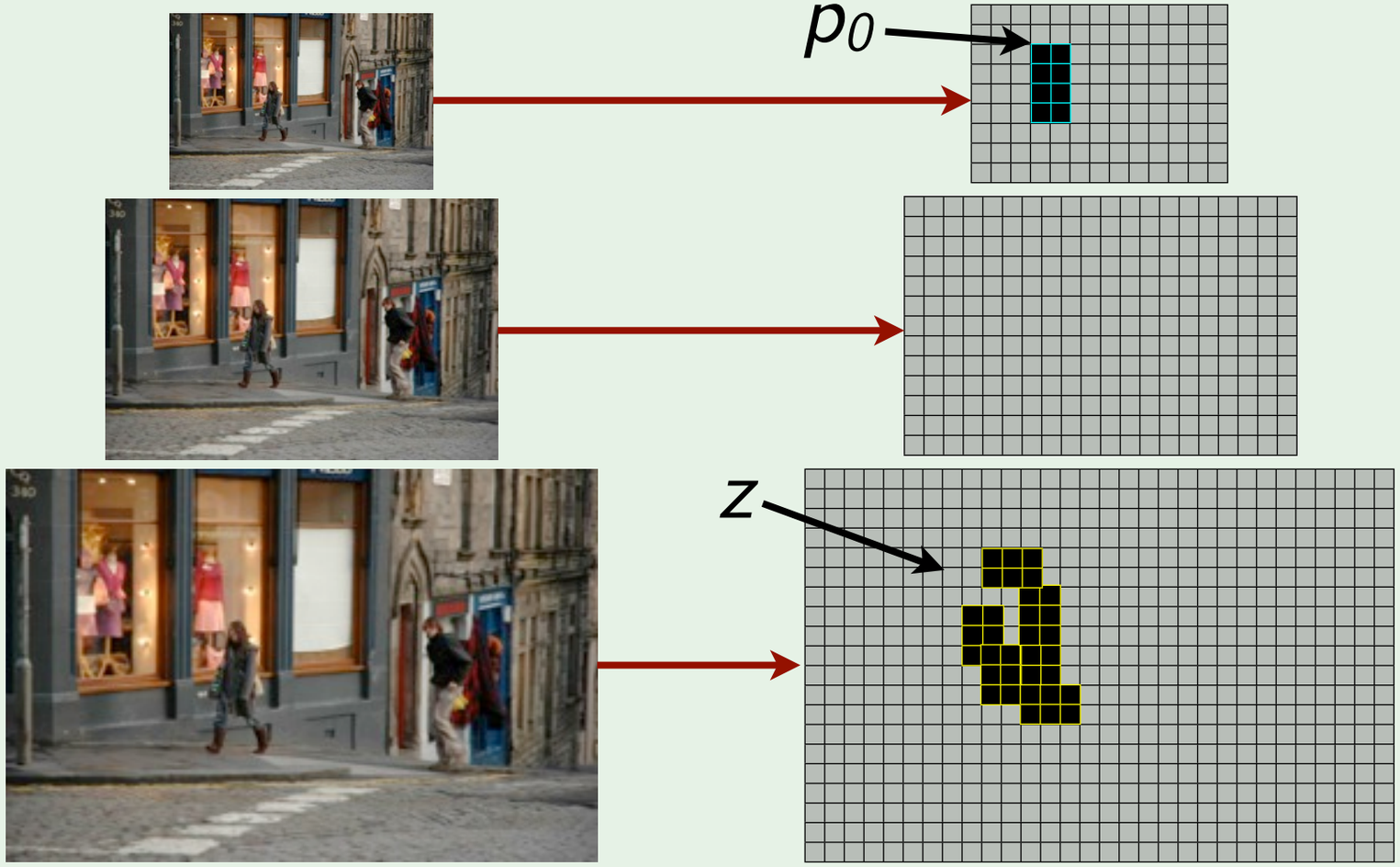
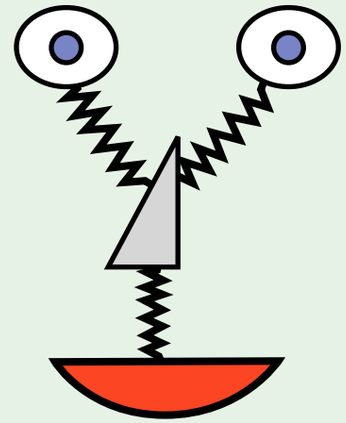
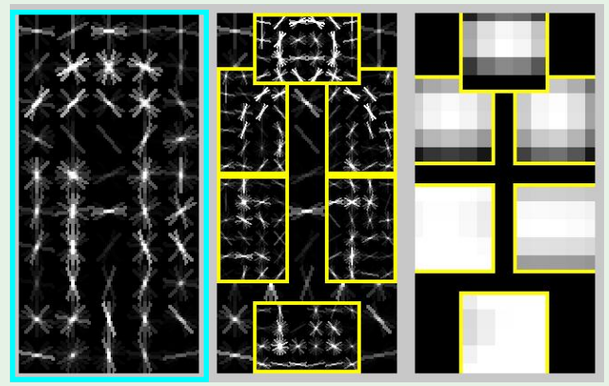


Image pyramid

HOG feature pyramid



root

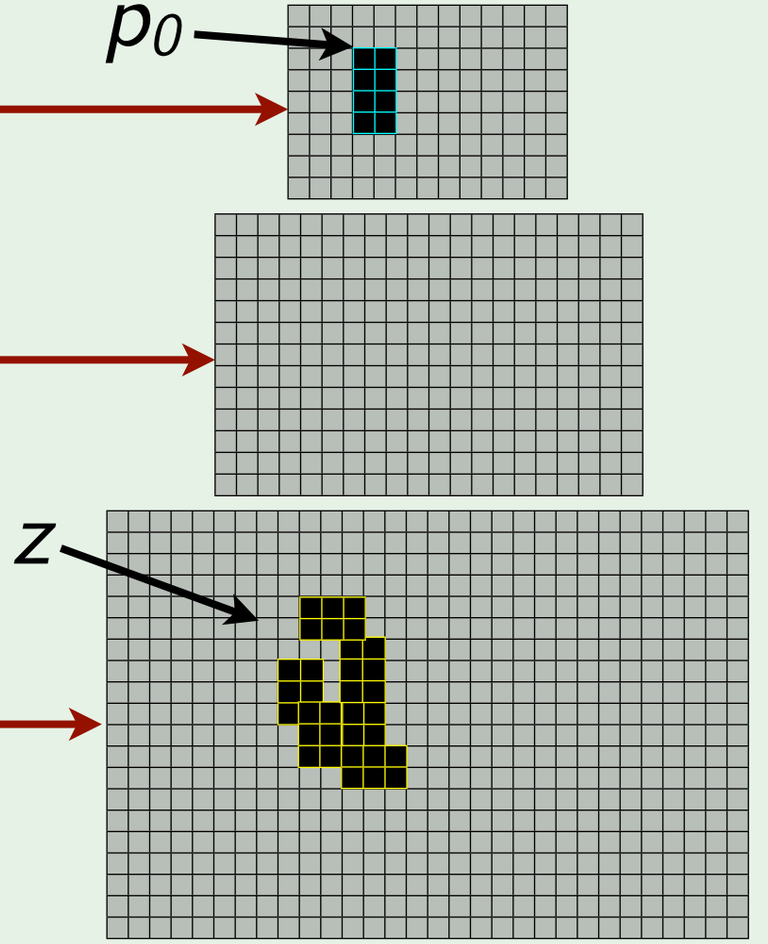


[FMR CVPR'08]
[FGMR PAMI'10]

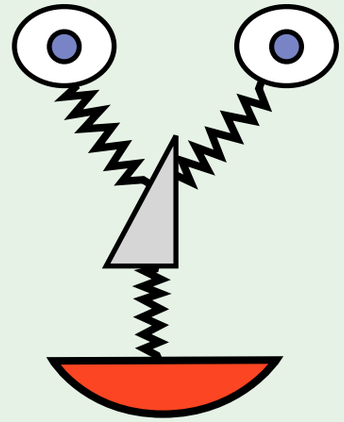
- Add parts to the Dalal & Triggs detector
  - HOG features
  - Linear filters / sliding-window detector
  - Discriminative training

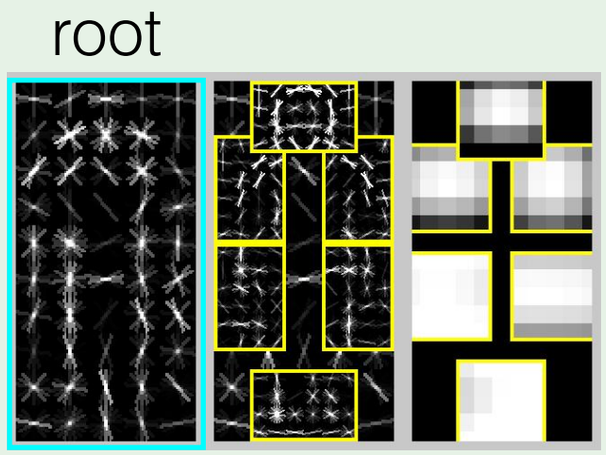
Sliding window DPM score function

Image pyramid



HOG feature pyramid



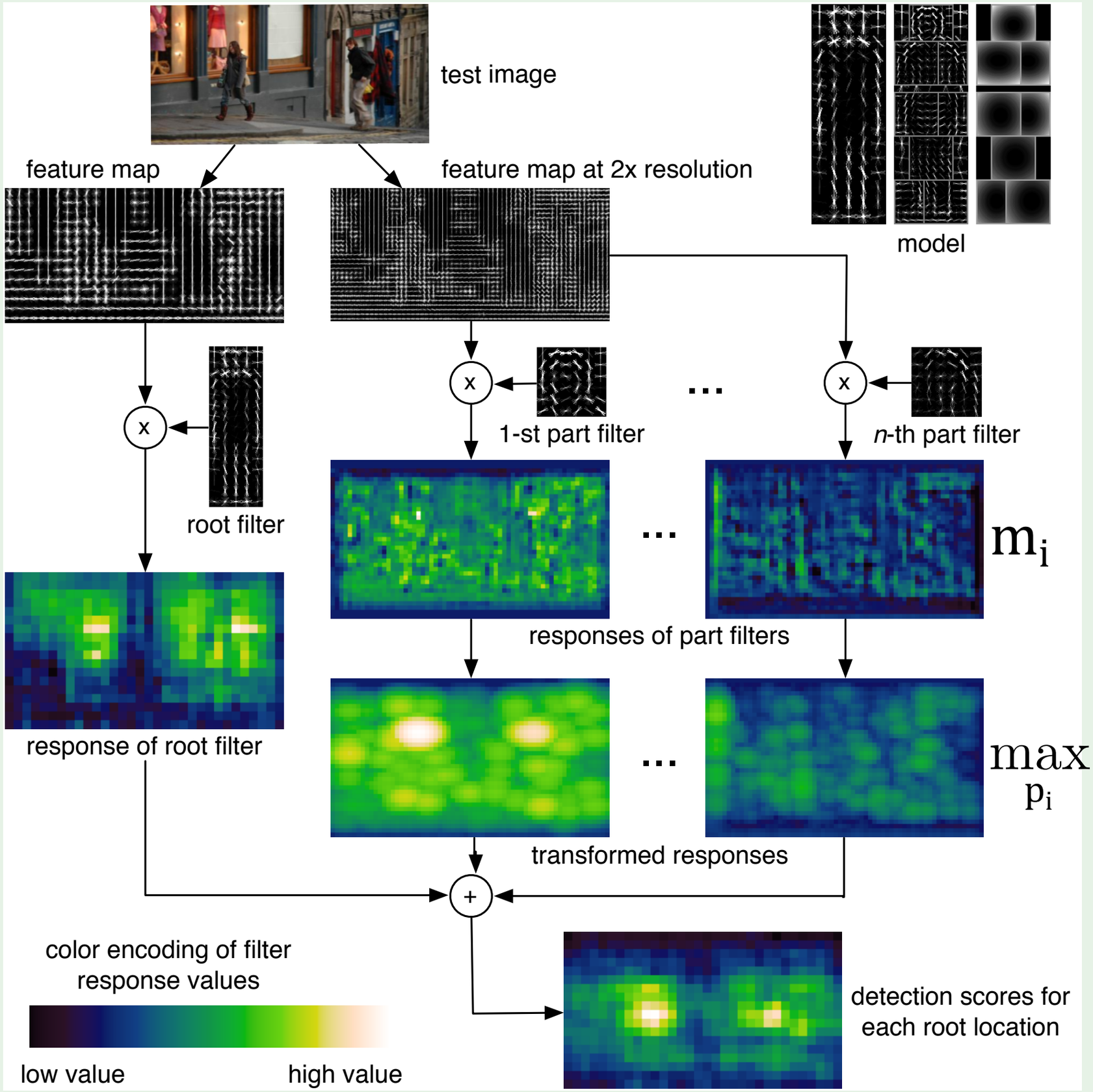


$$z = (p_1, \ldots, p_n)$$

$$\text{score}(I, p_0) = \max_{p_1,\ldots,p_n} \sum_{i=0}^{n} m_i(I, p_i) - \sum_{i=1}^{n} d_i(p_0, p_i)$$

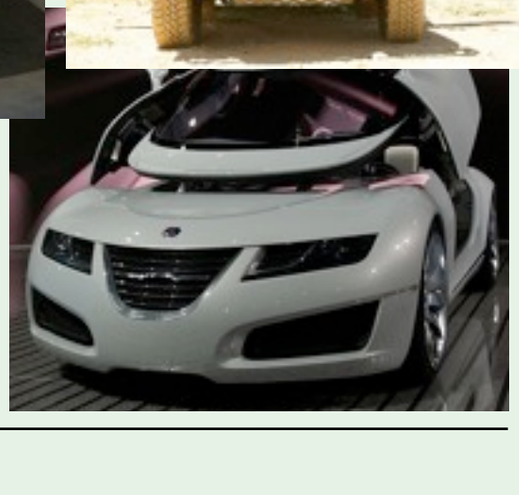
Filter scores Spring costs

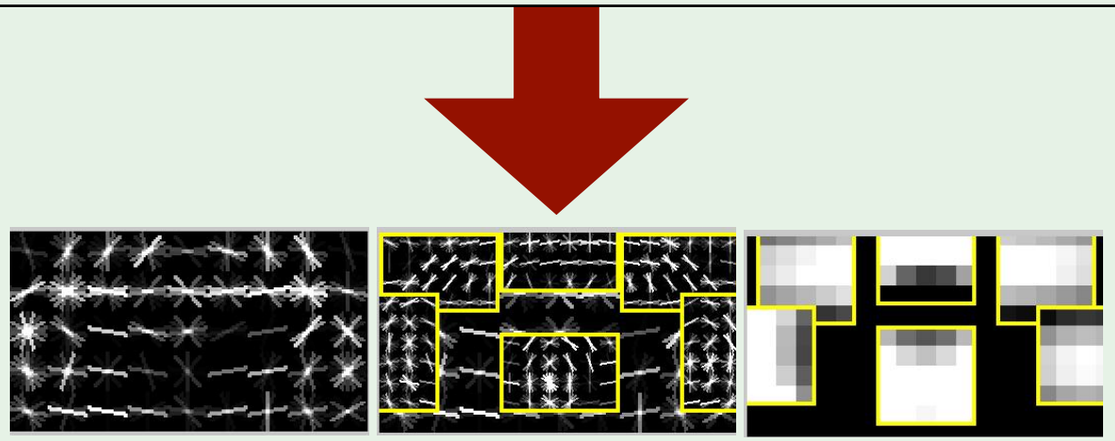
Detection in a slide



What are the parts?

Aspect soup

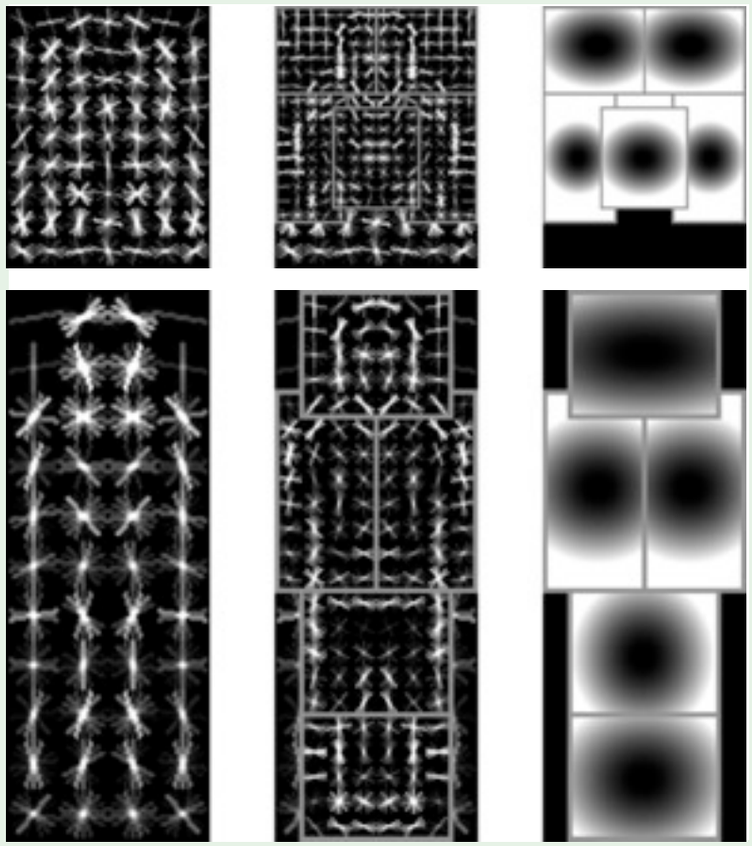


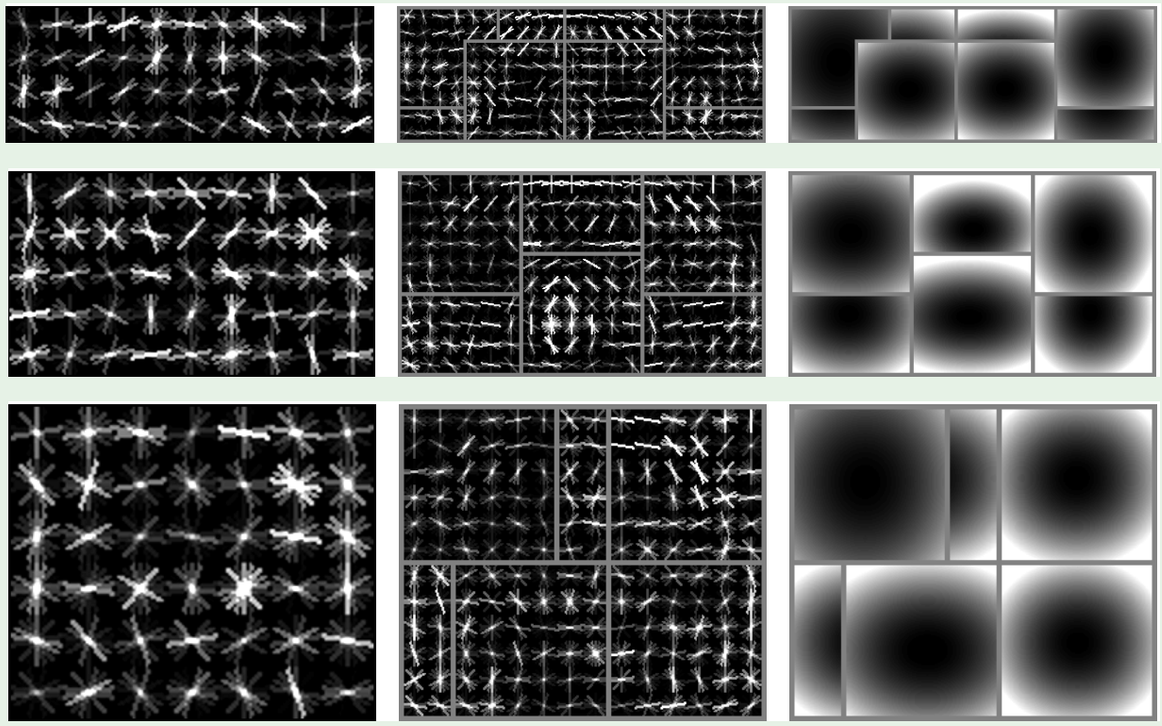


General philosophy: enrich models to better represent the data

Mixture models

Data driven: aspect, occlusion modes, subclasses



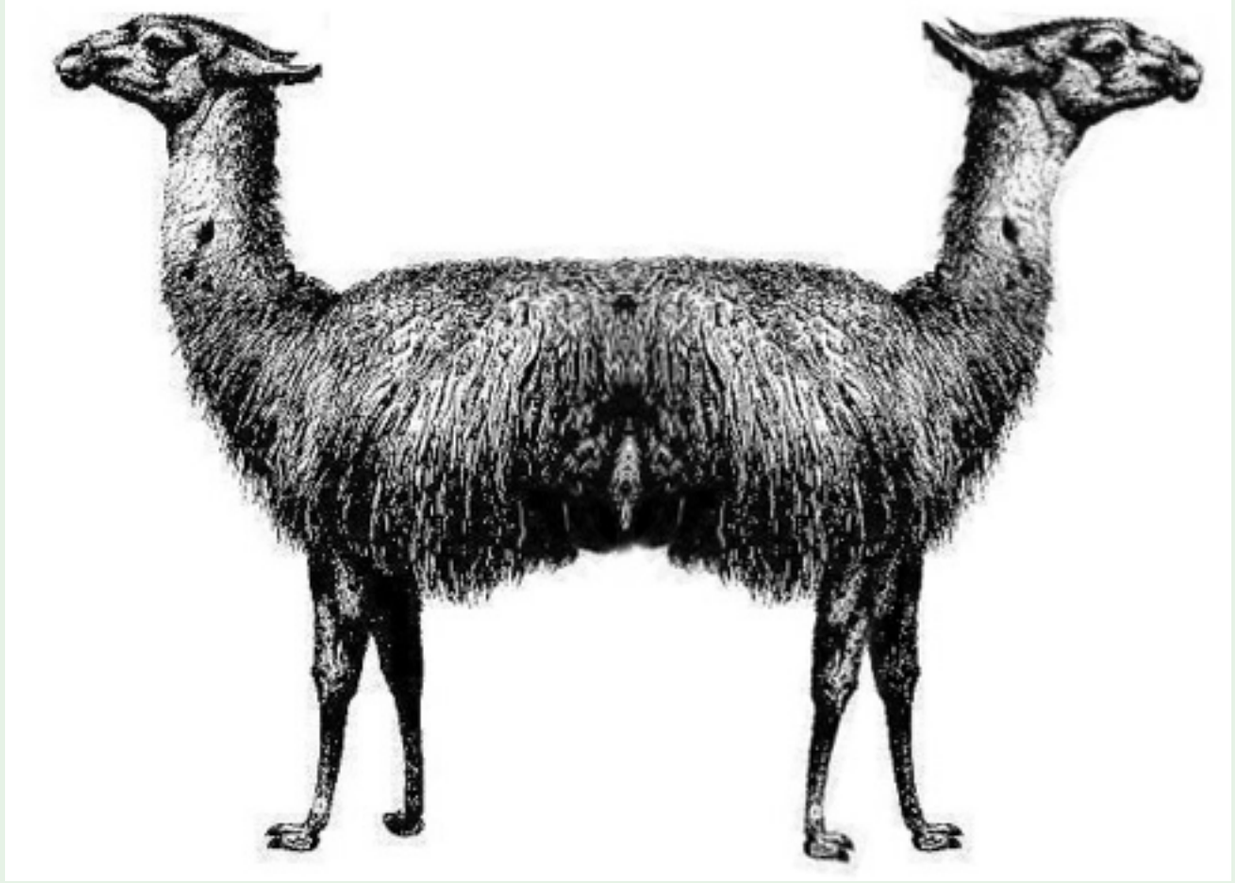


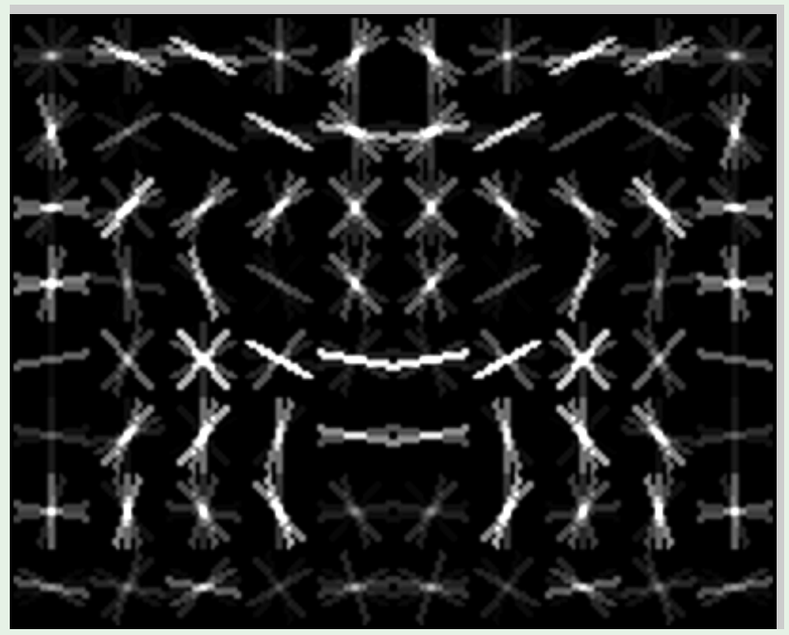
FMR CVPR ’08: AP = 0.27 (person)

FGMR PAMI ’10: AP = 0.36 (person)

Pushmi–pullyu?

Good generalization properties on Doctor Dolittle's farm

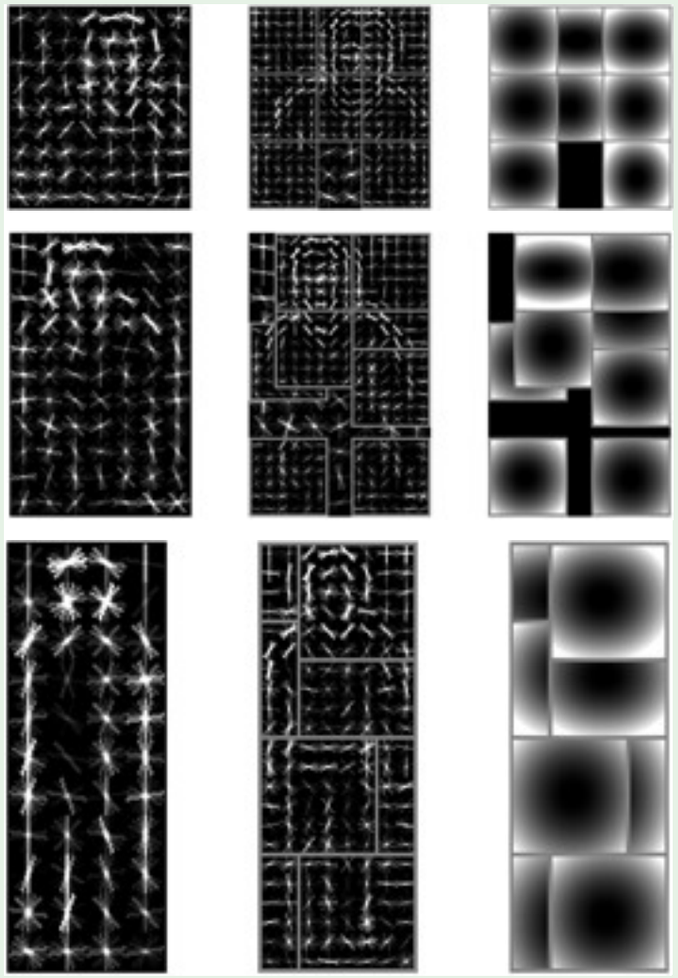


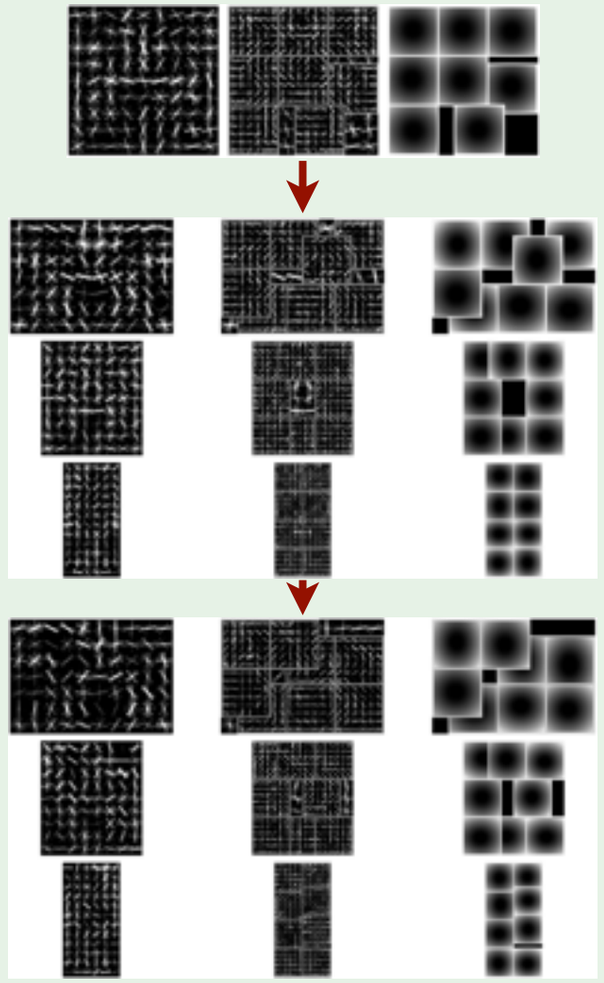


This was supposed to detect horses

Latent orientation

Unsupervised left/right orientation discovery





horse AP

0.42

0.47

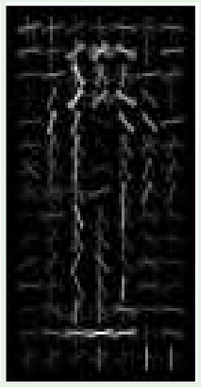
0.57

FGMR PAMI ’10: AP = 0.36 (person)

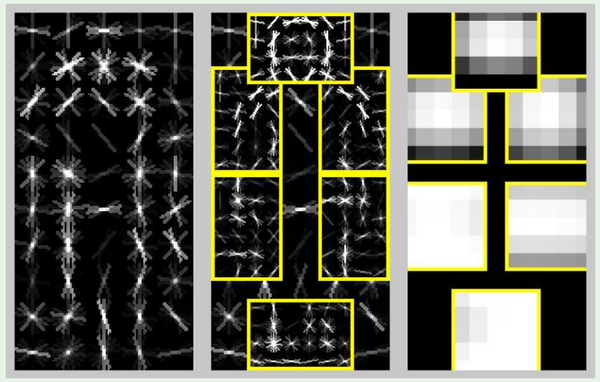
voc-release5: AP = 0.45 (person)

Publicly available code for the whole system: current voc-release5

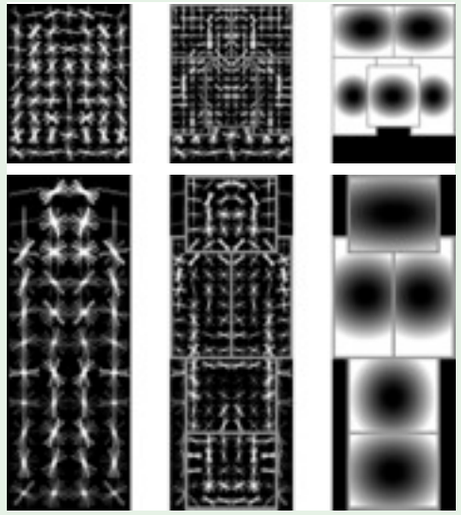
Summary of results



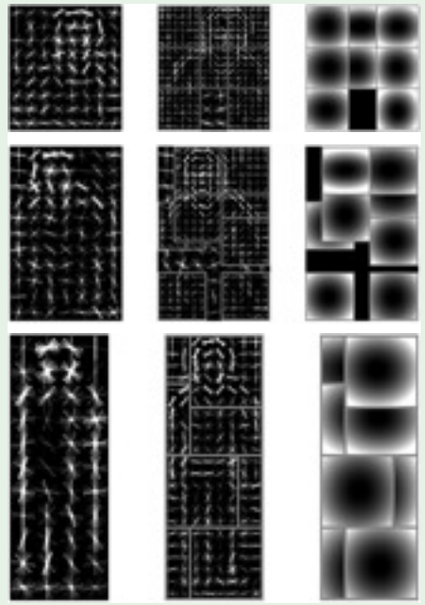
[DT'05]
AP 0.12



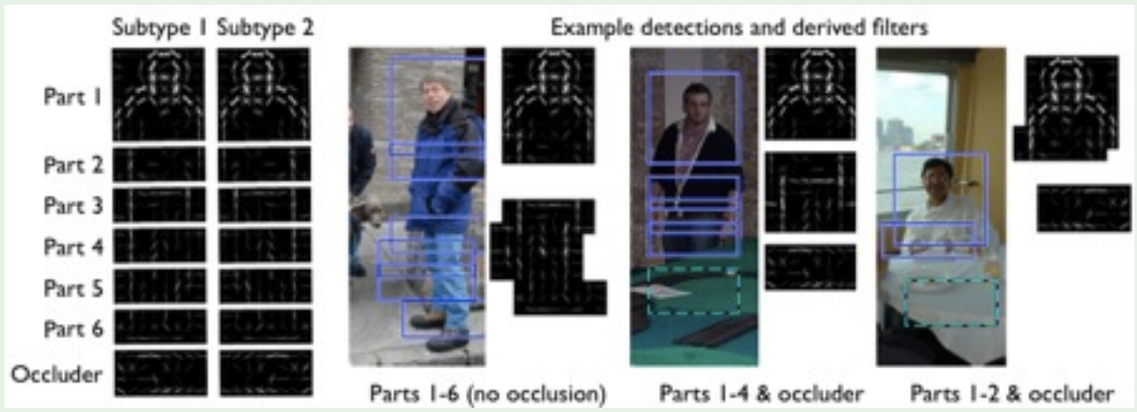
[FMR'08]
AP 0.27



[FGMR'10]
AP 0.36



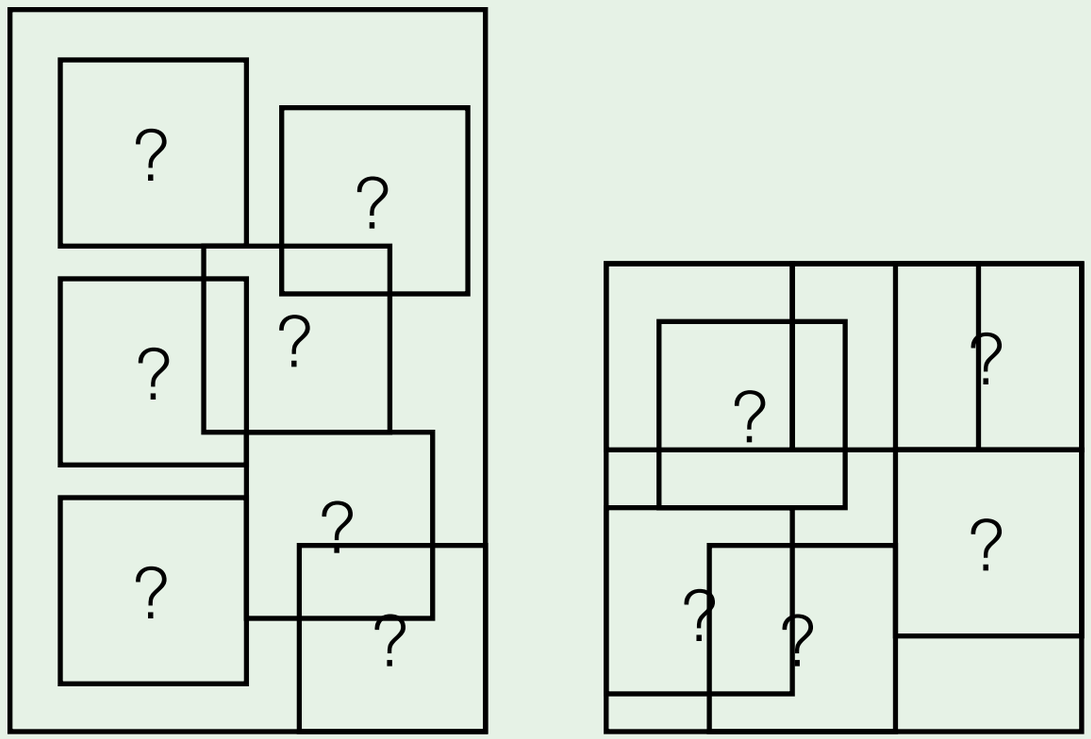
[GFM voc-release5]
AP 0.45



[GFM'11]
AP 0.49

Part 2: DPM parameter learning

fixed model *structure*

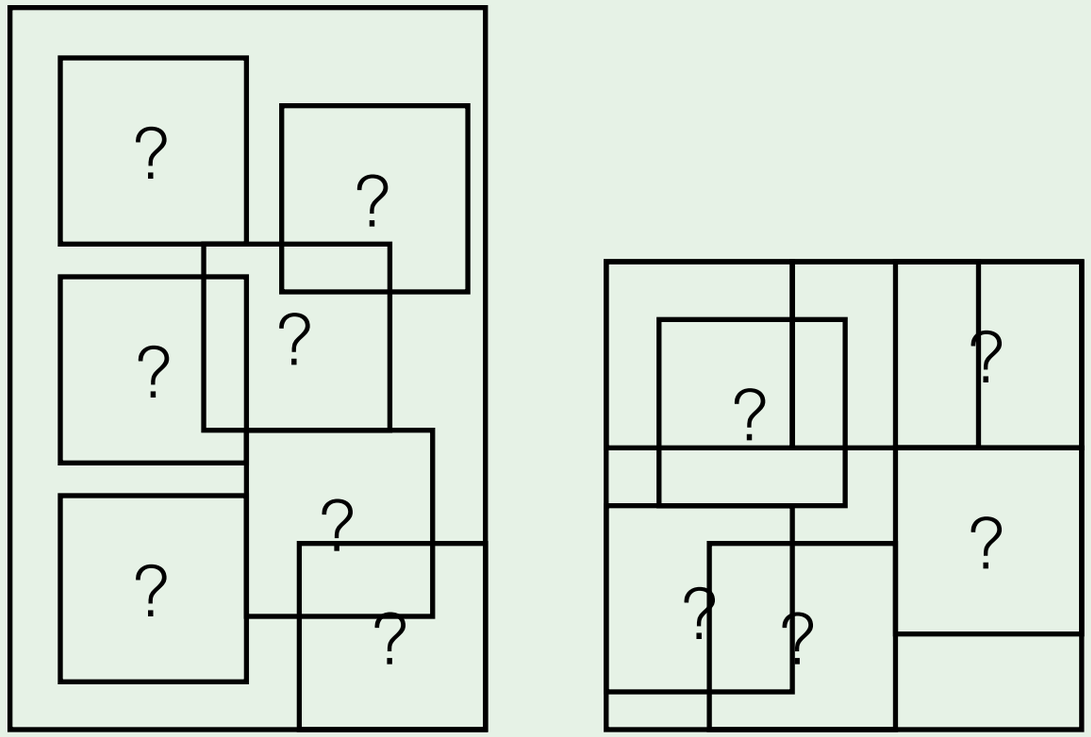


component 1

component 2

Part 2: DPM parameter learning

fixed model *structure*



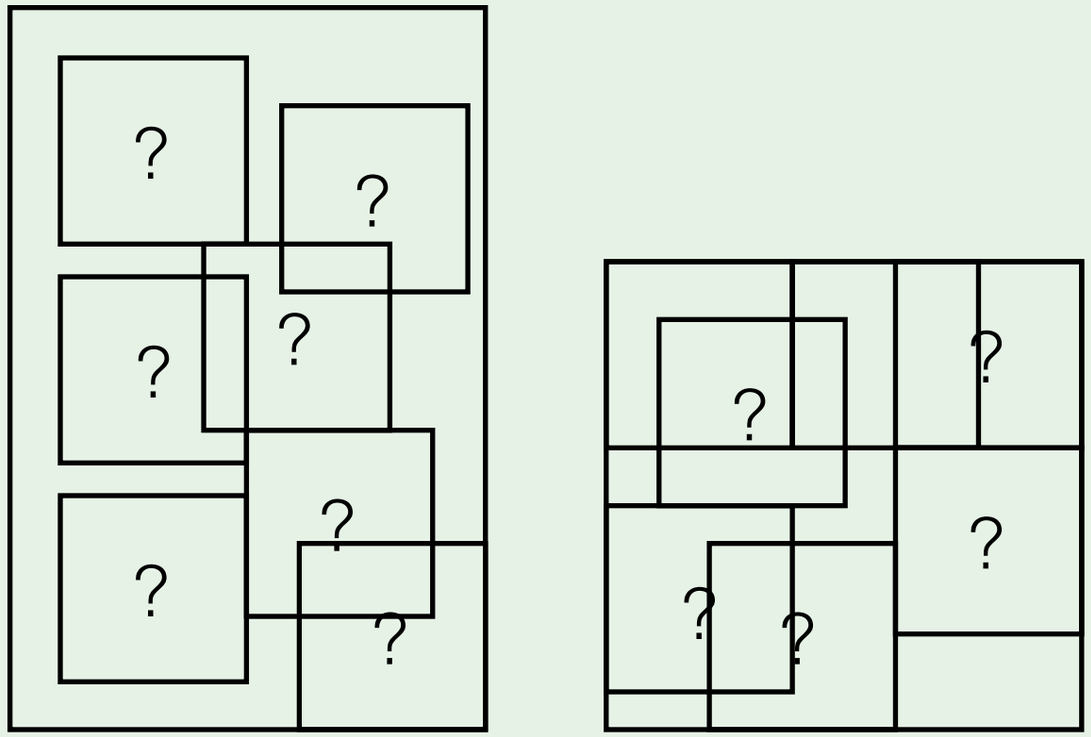
component 1 component 2

training images *y*

+1

Part 2: DPM parameter learning

fixed model *structure*



component 1 component 2

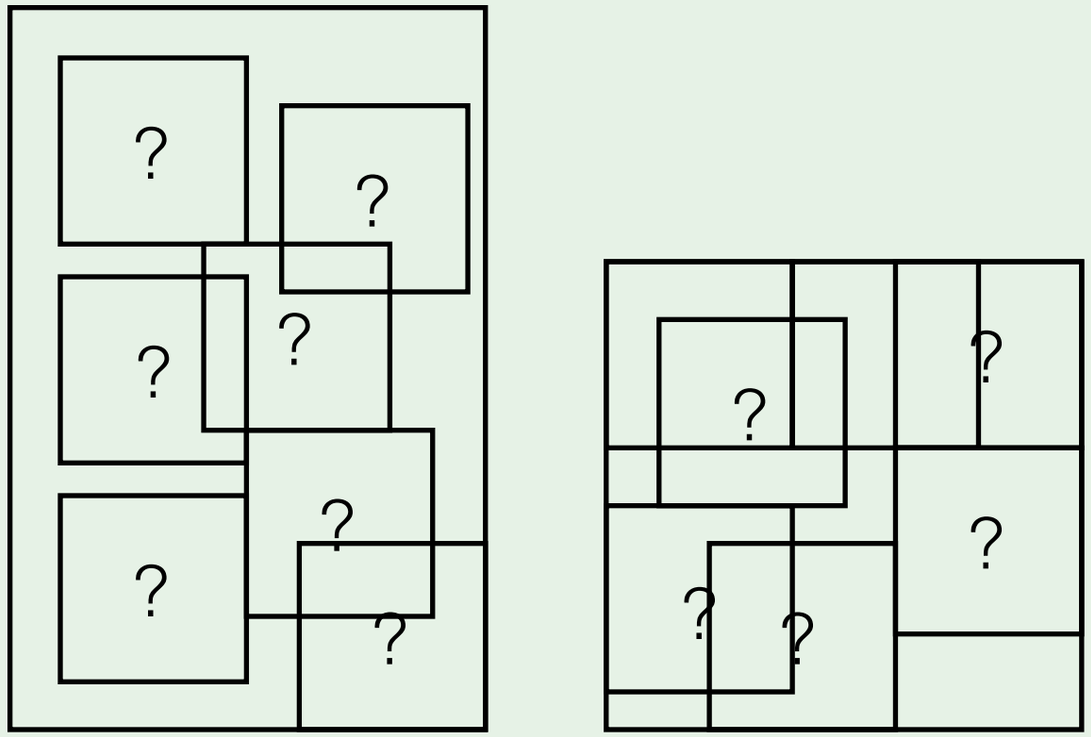
training images *y*

+1

-1

Part 2: DPM parameter learning

fixed model *structure*



component 1 component 2

training images *y*

+1

-1

Parameters to learn:
- biases (per component)
- deformation costs (per part)
- filter weights

Linear parameterization

$$z = (p_1, \ldots, p_n)$$

$$\text{score}(I, p_0) = \max_{p_1,\ldots,p_n} \sum_{i=0}^{n} m_i(I, p_i) - \sum_{i=1}^{n} d_i(p_0, p_i)$$

Filter scores Spring costs

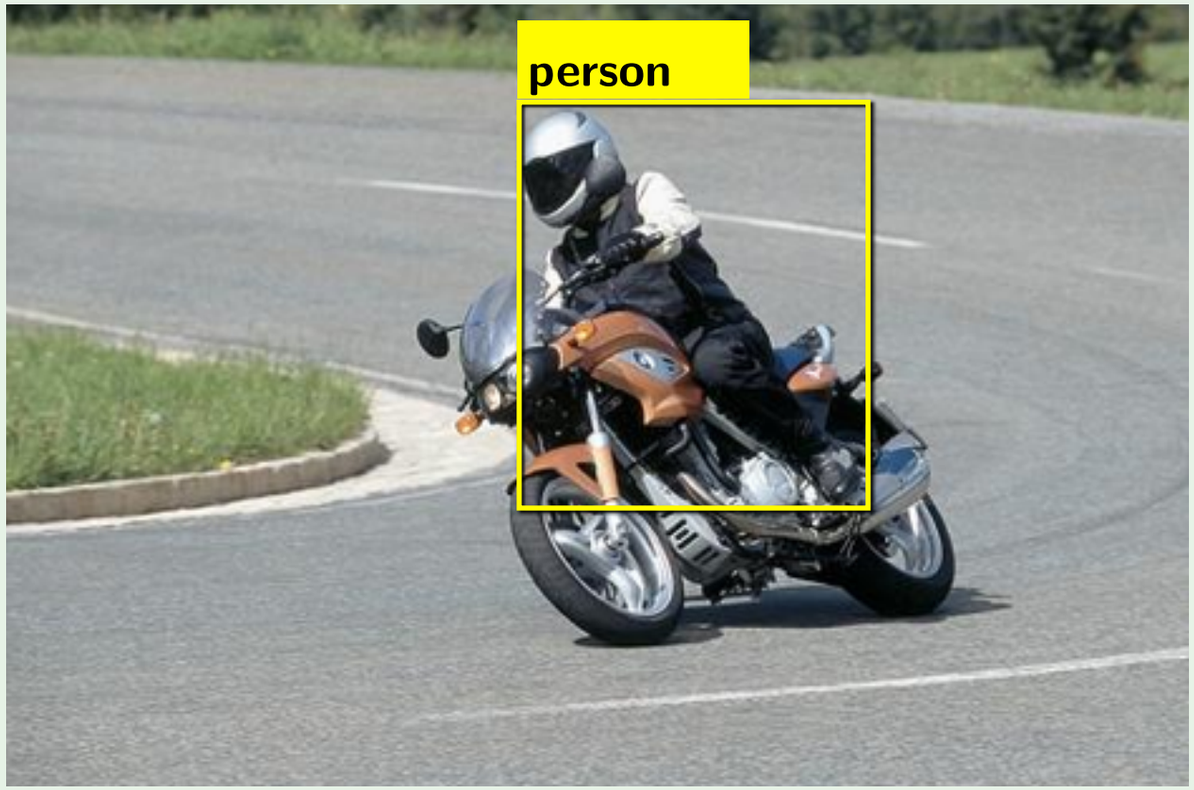
Filter scores $$m_i(I, p_i) = \mathbf{w}_i \cdot \phi(I, p_i)$$

Spring costs $$d_i(p_0, p_i) = \mathbf{d}_i \cdot (dx^2, dy^2, dx, dy)$$

$$score(I, p_0) = \max_z \mathbf{w} \cdot \Phi(I, (p_0, z))$$

Positive examples ($y = +1$)

x specifies an image and bounding box



We want

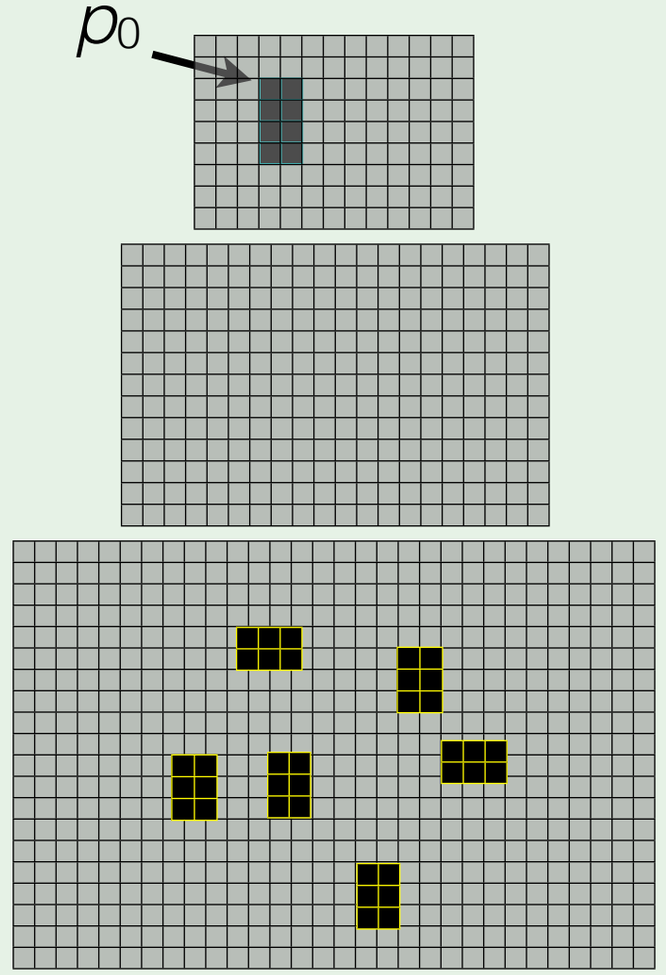
$$f_{\mathbf{w}}(x) = \max_{z \in Z(x)} \mathbf{w} \cdot \Phi(x, z)$$

to score >= +1

$Z(x)$ includes all z with more than 70% overlap with ground truth

Negative examples (y = -1)

x specifies an image and a HOG pyramid location p_0



We want

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

to score <= -1

$Z(x)$ restricts the root to p_0 and allows *any* placement of the other filters

Typical dataset

300 – 8,000 positive examples

500 million to 1 billion negative examples
(not including latent configurations!)

Large-scale*

*unless someone from google is here

How we learn parameters: latent SVM

$$E(\mathbf{w}) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_i \max\{0, 1 - y_i f_{\mathbf{w}}(x_i)\}$$

How we learn parameters: latent SVM

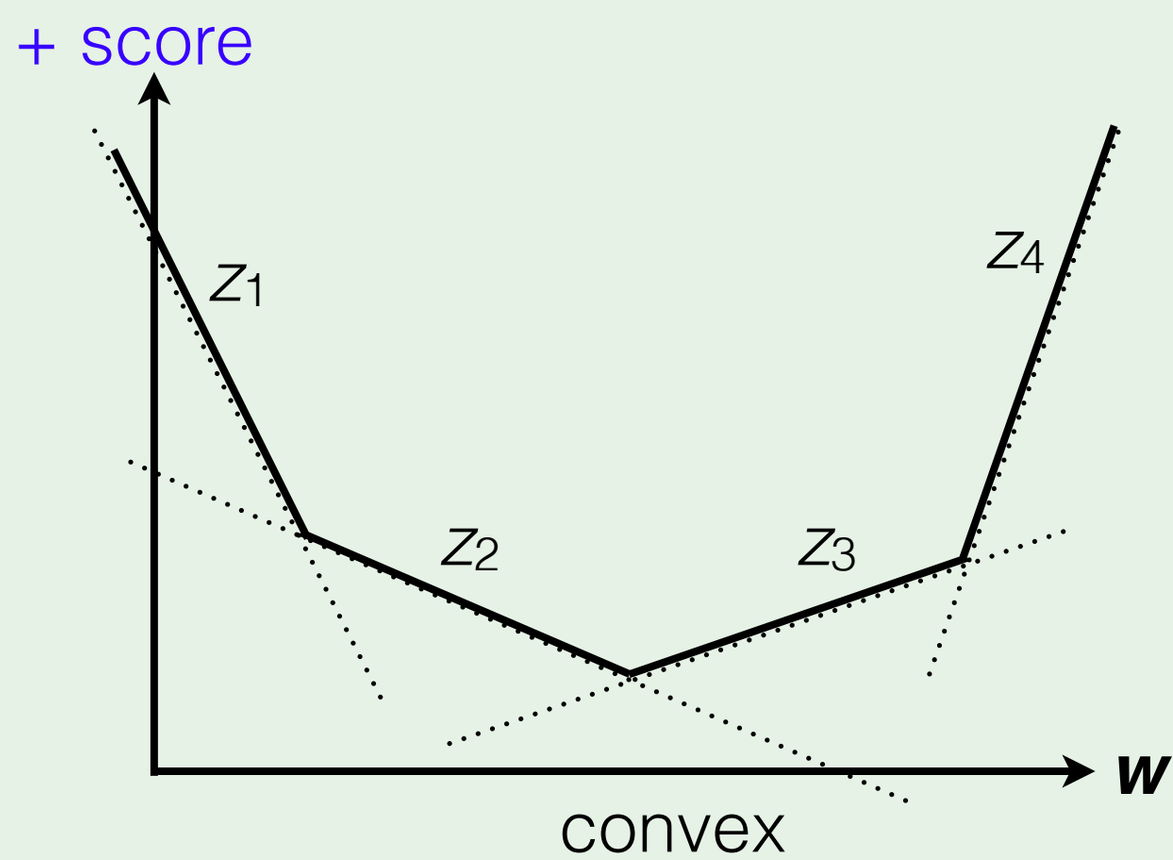
$$E(\mathbf{w}) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_i \max\{0, 1 - y_i f_{\mathbf{w}}(x_i)\}$$

$$E(\mathbf{w}) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i\in P} \max\{0, 1 - \max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$
$$+ C\sum_{i\in N} \max\{0, 1 + \max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$

How we learn parameters: latent SVM

$$E(\mathbf{w}) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_i \max\{0, 1 - y_i f_{\mathbf{w}}(x_i)\}$$

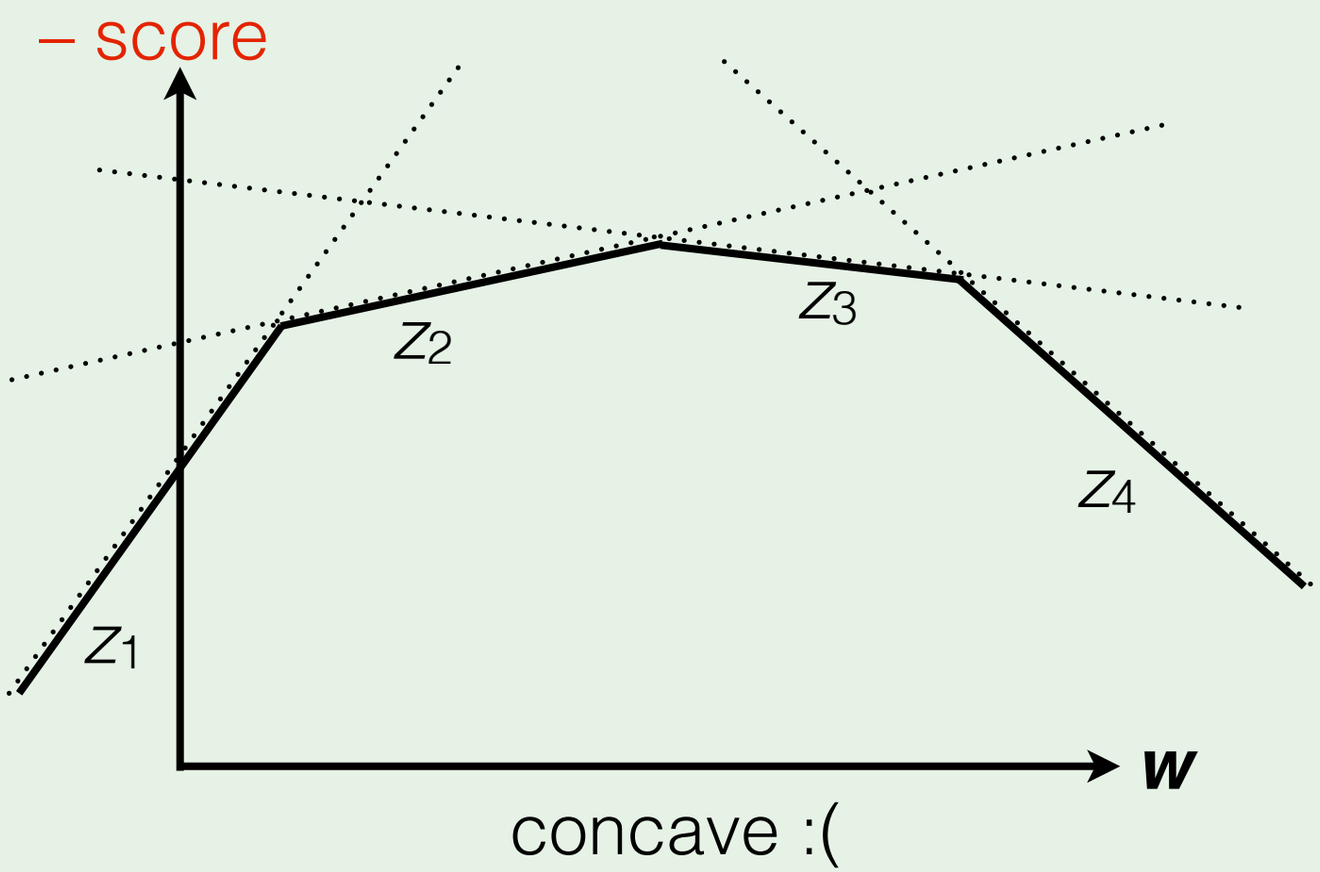
$$E(\mathbf{w}) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i\in P} \max\{0, 1 - \max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$
$$+ C\sum_{i\in N} \max\{0, 1 + \max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$



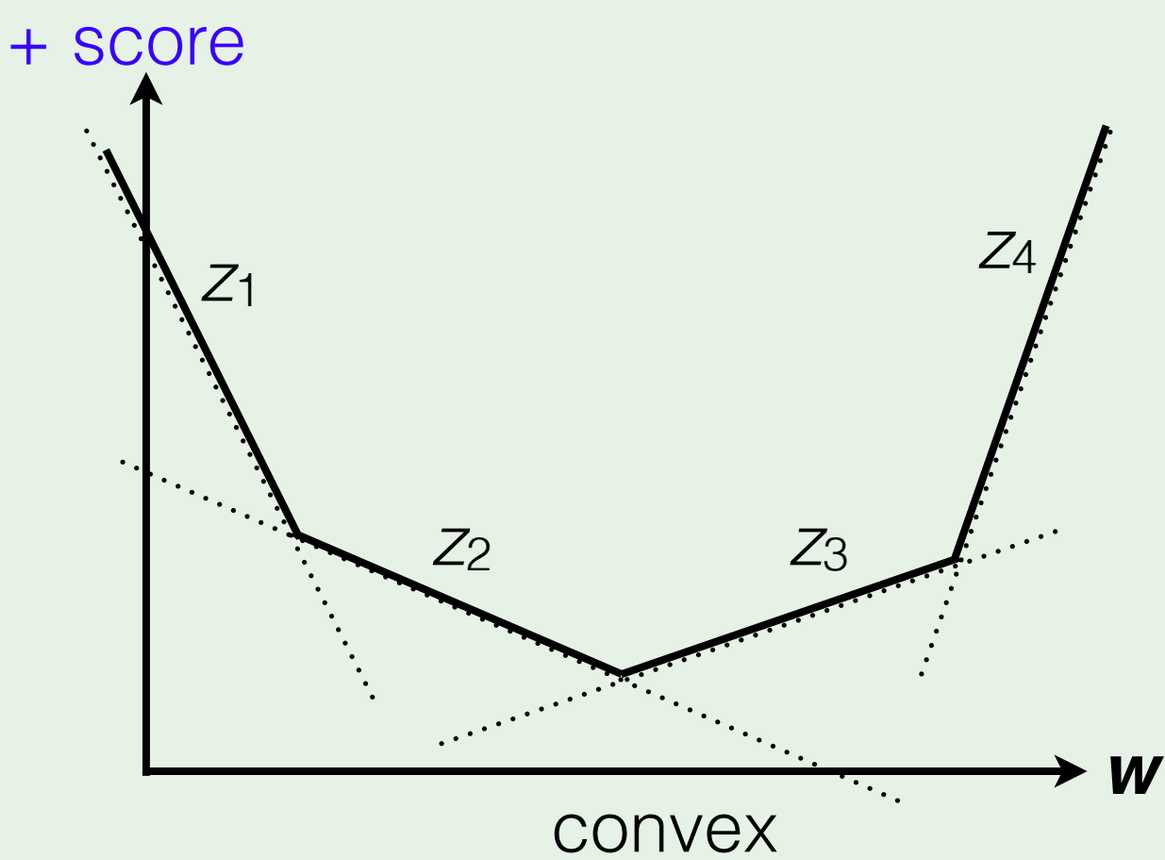
How we learn parameters: latent SVM

$$E(\mathbf{w}) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_i \max\{0, 1 - y_i f_{\mathbf{w}}(x_i)\}$$

$$E(\mathbf{w}) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i\in P} \max\{0, 1 - \max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$
$$+ C\sum_{i\in N} \max\{0, 1 + \max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$

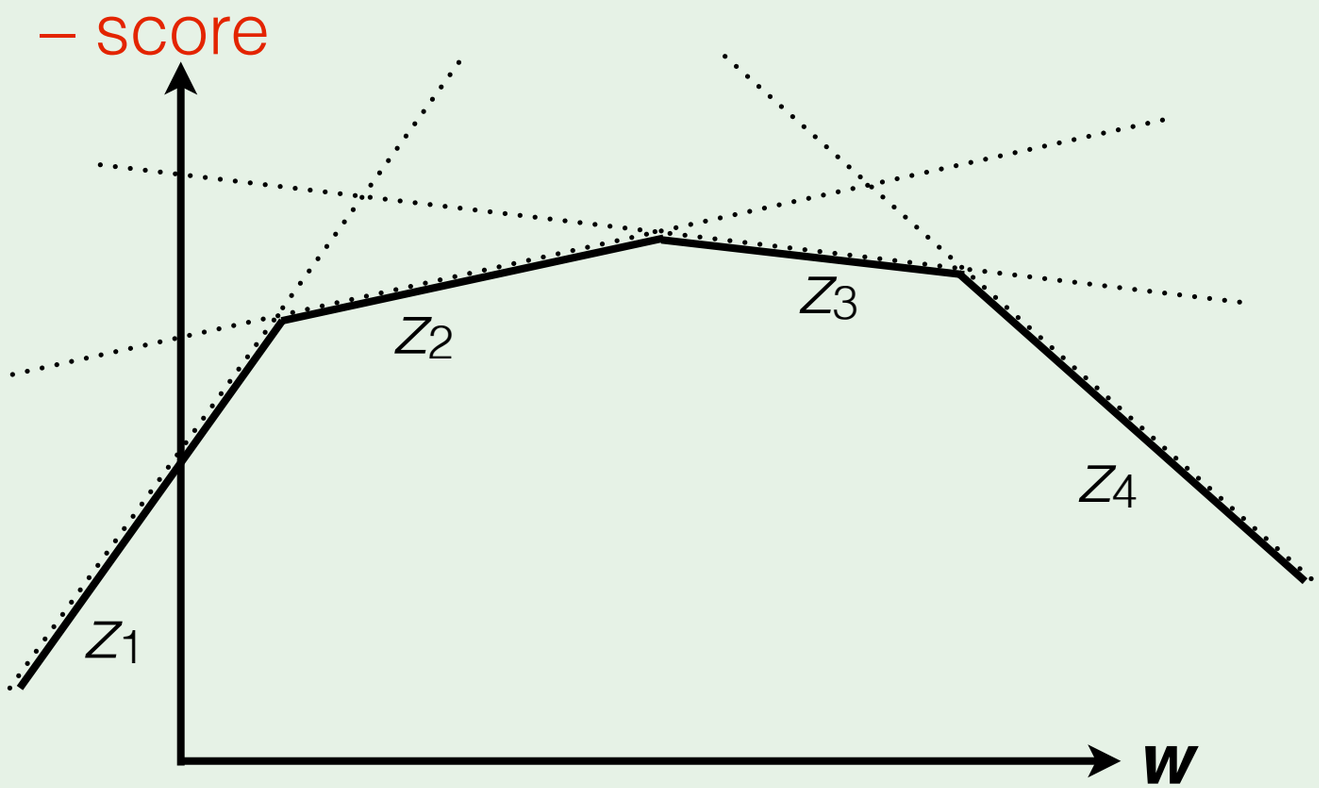


concave :(

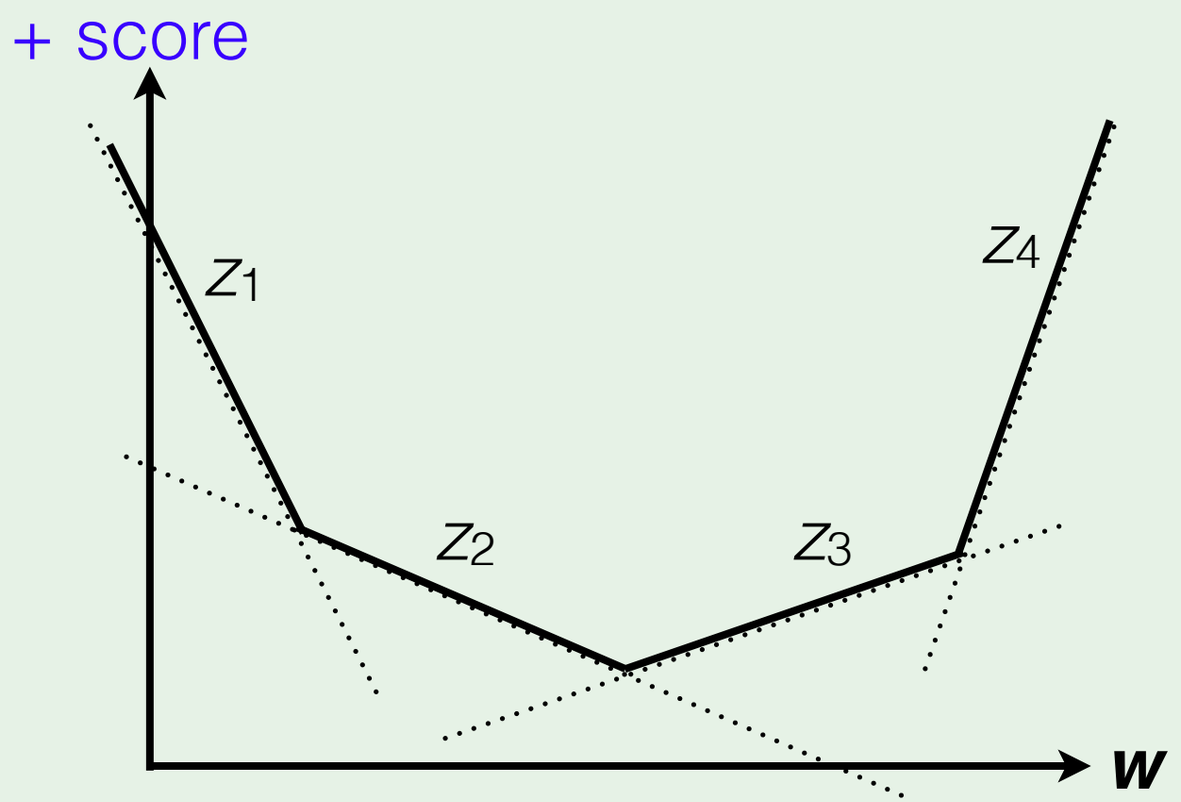


convex

Observations



concave :(



convex

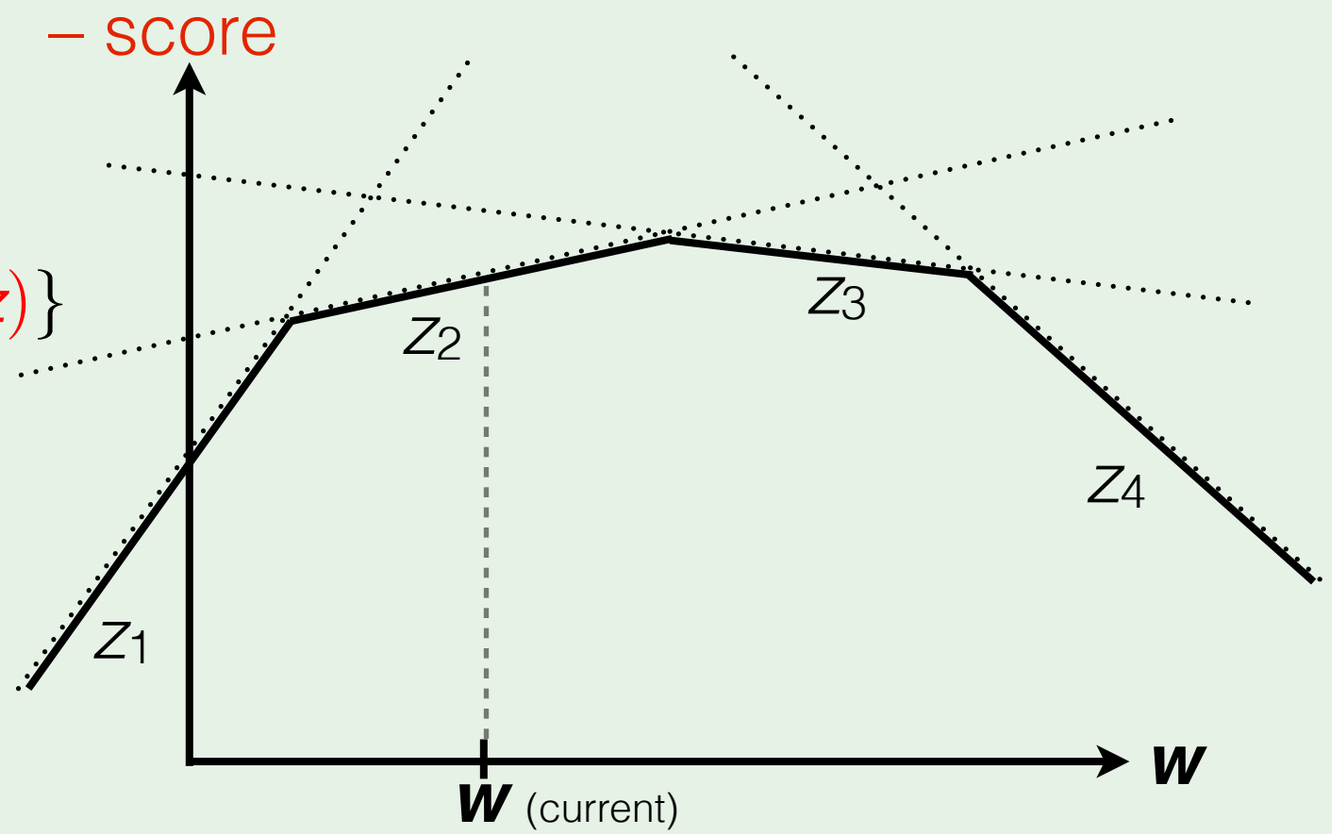
Latent SVM objective is convex in the negatives

but not in the positives

>> “semi-convex”

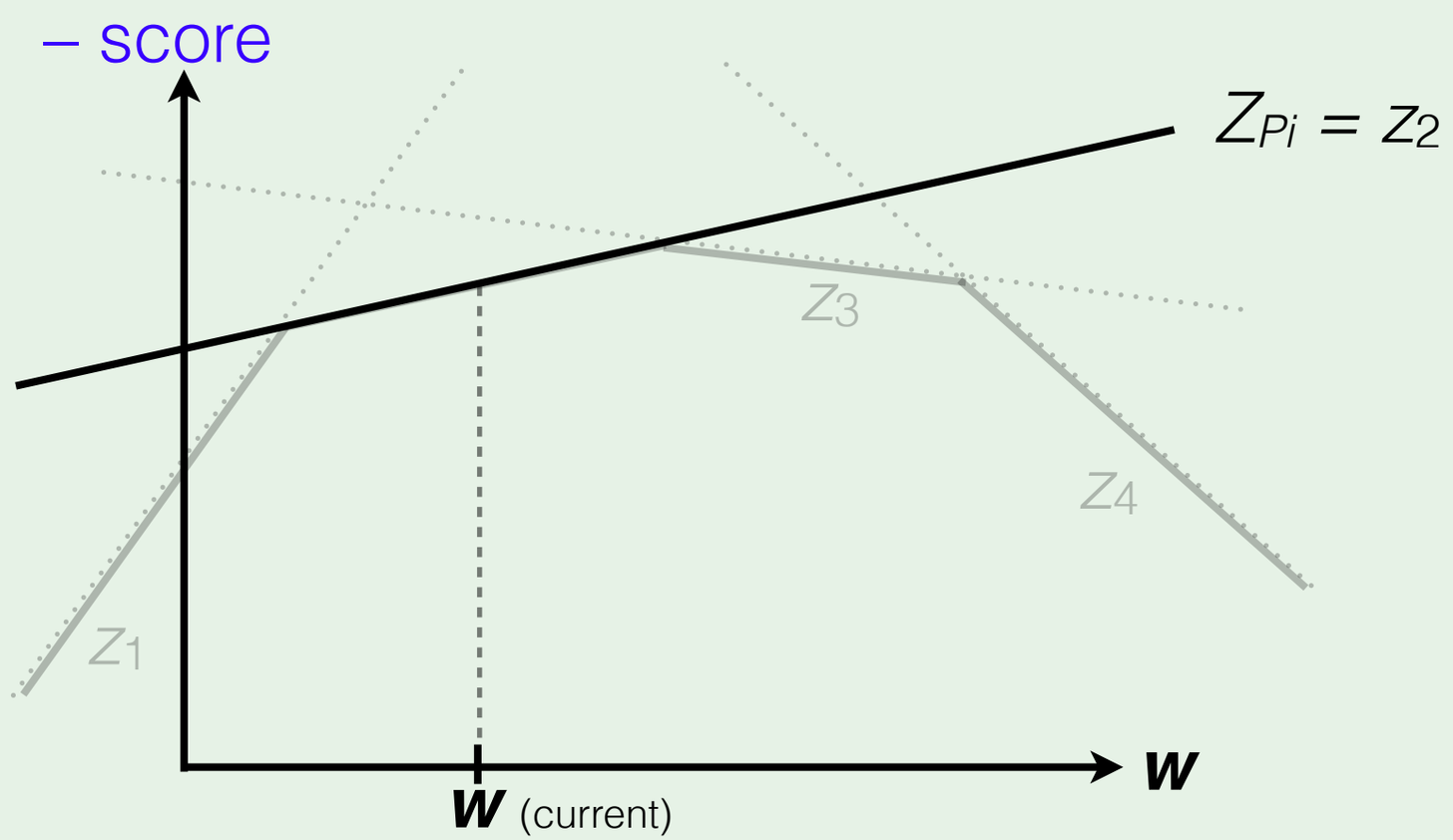
Convex upper bound on loss

$$\max\{0, 1 - \max_{z \in Z(x)} \mathbf{w} \cdot \Phi(x_i, z)\}$$



$$\max\{0, 1 - \mathbf{w} \cdot \Phi(x_i, Z_{Pi})\}$$

convex



Auxiliary objective

Let $Z_P = \{Z_{P1}, Z_{P2}, \dots\}$

$$E(\mathbf{w}, Z_P) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i \in P} \max\{0, 1 - \mathbf{w} \cdot \Phi(x_i, Z_{Pi})\}$$
$$+ C\sum_{i \in N} \max\{0, 1 + \max_{z \in Z(x)} \mathbf{w} \cdot \Phi(x_i, z)\}$$

Auxiliary objective

Let $Z_P = \{Z_{P1}, Z_{P2}, \dots\}$

$$E(\mathbf{w}, Z_P) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i\in P} \max\{0, 1 - \mathbf{w}\cdot\Phi(x_i, Z_{Pi})\} + C\sum_{i\in N} \max\{0, 1 + \max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$

Note that $E(\mathbf{w}, Z_p) \geq \min_{Z_P} E(\mathbf{w}, Z_P) = E(\mathbf{w})$

Auxiliary objective

Let $Z_P = \{Z_{P1}, Z_{P2}, \ldots\}$

$$E(\mathbf{w}, Z_P) = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i \in P} \max\{0, 1 - \mathbf{w} \cdot \Phi(x_i, Z_{Pi})\}$$
$$+ C\sum_{i \in N} \max\{0, 1 + \max_{z \in Z(x)} \mathbf{w} \cdot \Phi(x_i, z)\}$$

Note that $E(\mathbf{w}, Z_p) \geq \min_{Z_P} E(\mathbf{w}, Z_P) = E(\mathbf{w})$

and $\mathbf{w}^* = \min_{\mathbf{w}, Z_P} E(\mathbf{w}, Z_P) = \min_{\mathbf{w}} E(\mathbf{w})$

Auxiliary objective

$$\mathbf{w}^* = \min_{\mathbf{w}, Z_P} E(\mathbf{w}, Z_P) = \min_{\mathbf{w}} E(\mathbf{w})$$

This isn't any easier to optimize

Auxiliary objective

$$\mathbf{w}^* = \min_{\mathbf{w}, Z_P} E(\mathbf{w}, Z_P) = \min_{\mathbf{w}} E(\mathbf{w})$$

This isn't any easier to optimize

Find stationary point by coordinate descent on $E(\mathbf{w}, Z_P)$

Auxiliary objective

$$\mathbf{w}^* = \min_{\mathbf{w}, Z_P} E(\mathbf{w}, Z_P) = \min_{\mathbf{w}} E(\mathbf{w})$$

This isn't any easier to optimize

Find stationary point by coordinate descent on $E(\mathbf{w}, Z_P)$

Initialization: either by picking a $\boldsymbol{w}_{(0)}$ (or Z_P)

Auxiliary objective

$$\mathbf{w}^* = \min_{\mathbf{w}, Z_P} E(\mathbf{w}, Z_P) = \min_{\mathbf{w}} E(\mathbf{w})$$

This isn't any easier to optimize

Find stationary point by coordinate descent on $E(\mathbf{w}, Z_P)$

Initialization: either by picking a $\boldsymbol{w}_{(0)}$ (or Z_P)

Step 1:

$$Z_{Pi} = \operatorname*{argmax}_{z \in Z(x_i)} \mathbf{w}_{(t)} \cdot \Phi(x_i, z) \quad \forall i \in P$$

Auxiliary objective

$$\mathbf{w}^* = \min_{\mathbf{w}, Z_P} E(\mathbf{w}, Z_P) = \min_{\mathbf{w}} E(\mathbf{w})$$

This isn't any easier to optimize

Find stationary point by coordinate descent on $E(\mathbf{w}, Z_P)$

Initialization: either by picking a $\boldsymbol{w}_{(0)}$ (or Z_P)

Step 1:

$$Z_{Pi} = \operatorname*{argmax}_{z \in Z(x_i)} \mathbf{w}_{(t)} \cdot \Phi(x_i, z) \quad \forall i \in P$$

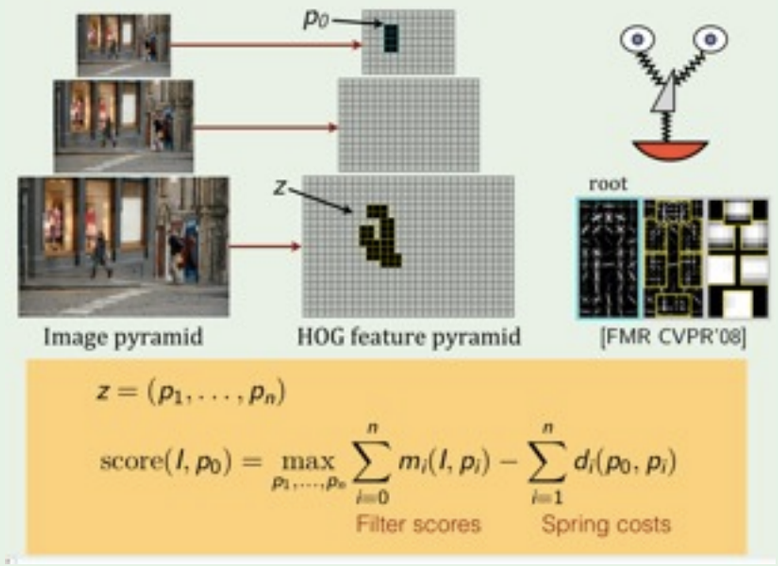
Step 2:

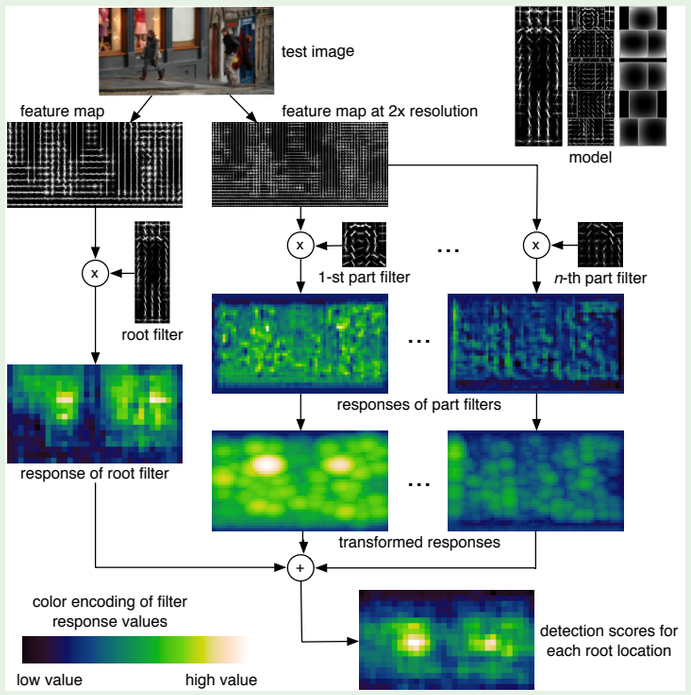
$$\mathbf{w}_{(t+1)} = \operatorname*{argmin}_{\mathbf{w}} E(\mathbf{w}, Z_P)$$

Step 1

$$Z_{Pi} = \underset{z \in Z(x_i)}{\operatorname{argmax}} \mathbf{w}_{(t)} \cdot \Phi(x_i, z) \quad \forall i \in P$$

This is just detection:





Step 2

$$\min_{\mathbf{w}} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i\in P} \max\{0, 1 - \mathbf{w}\cdot\Phi(x_i, z_{Pi})\}$$
$$+ C\sum_{i\in N} \max\{0, 1 + \max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$

Convex

Step 2

$$\min_{\mathbf{w}} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i\in P} \max\{0, 1-\mathbf{w}\cdot\Phi(x_i, Z_{Pi})\}$$
$$+ C\sum_{i\in N} \max\{0, 1+\max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$

Convex

Similar to a structural SVM

Step 2

$$\min_{\mathbf{w}} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i \in P} \max\{0, 1 - \mathbf{w} \cdot \Phi(x_i, Z_{Pi})\}$$
$$+ C\sum_{i \in N} \max\{0, 1 + \max_{z \in Z(x)} \mathbf{w} \cdot \Phi(x_i, z)\}$$

Convex

Similar to a structural SVM

But, recall 500 million to 1 billion negative examples!

Step 2

$$\min_{\mathbf{w}} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i\in P} \max\{0, 1-\mathbf{w}\cdot\Phi(x_i, Z_{Pi})\}$$
$$+ C\sum_{i\in N} \max\{0, 1+\max_{z\in Z(x)} \mathbf{w}\cdot\Phi(x_i, z)\}$$

Convex

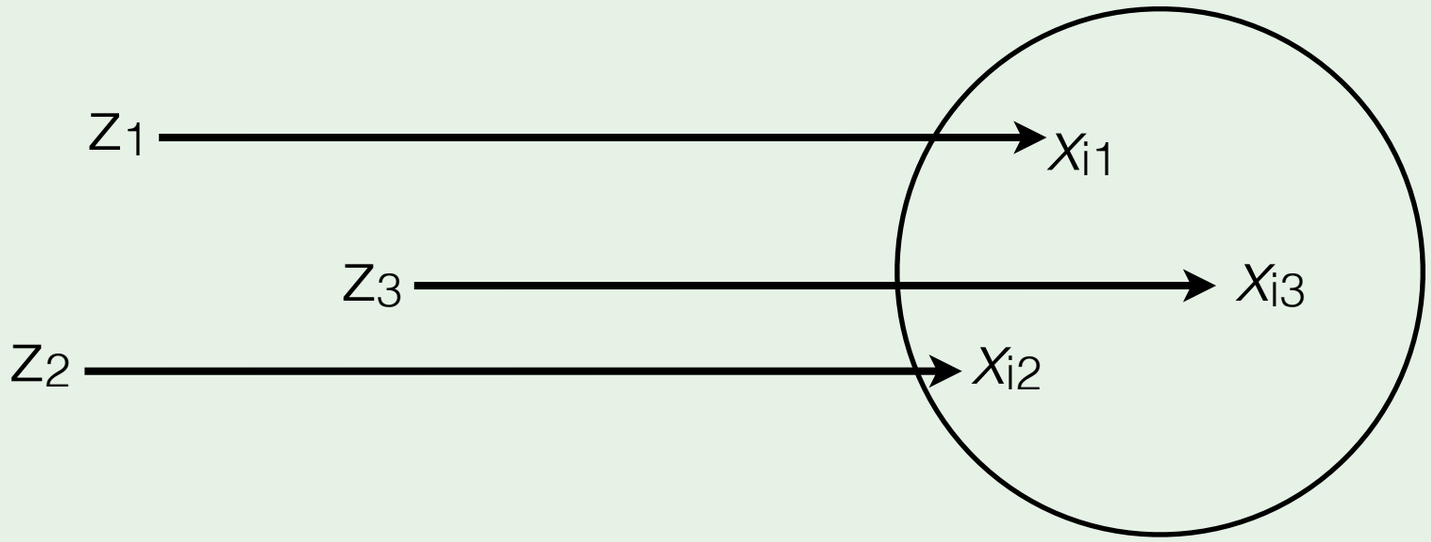
Similar to a structural SVM

But, recall 500 million to 1 billion negative examples!

Can be solved by a working set method
- "bootstrapping"
- "data mining"
- "constraint generation"
- requires a bit of engineering to make this fast

Comments

Latent SVM is mathematically equivalent to MI-SVM (Andrews et al. NIPS 2003)



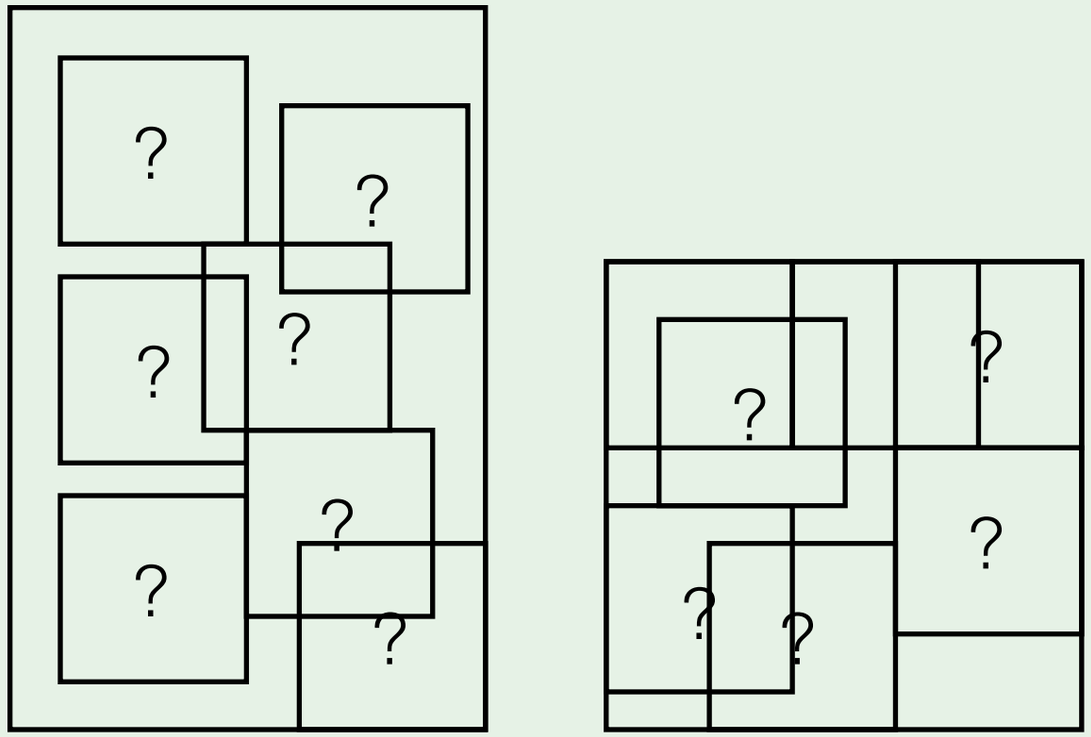
latent labels for x_i bag of instances for x_i

Latent SVM can be written as a latent structural SVM (Yu and Joachims ICML 2009)

- natural optimization algorithm is concave-convex procedure
- similar to, but not exactly the same as, coordinate descent

What about the model structure?

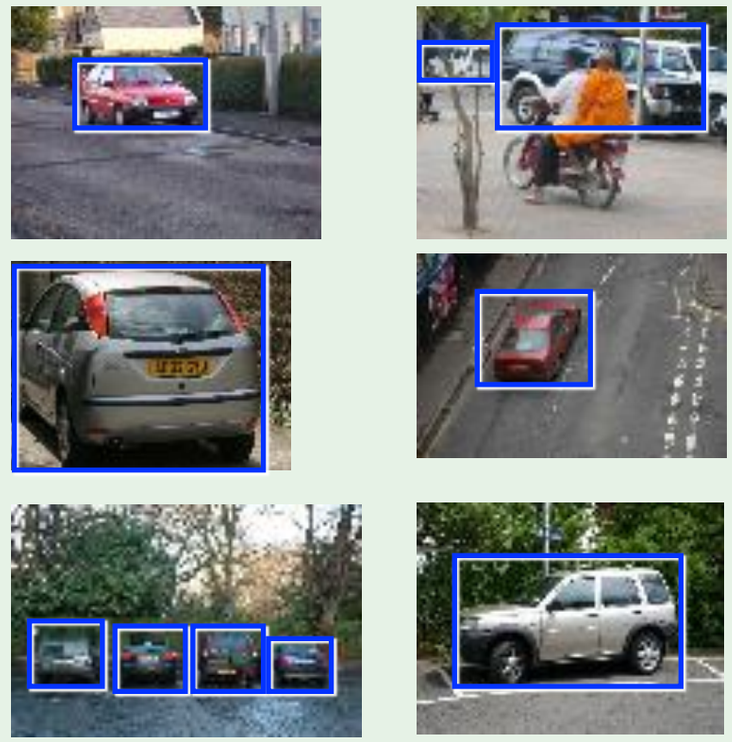
fixed model *structure*



component 1 component 2

Model structure
- # components
- # parts per component
- root and part filter shapes
- part anchor locations

training images *y*

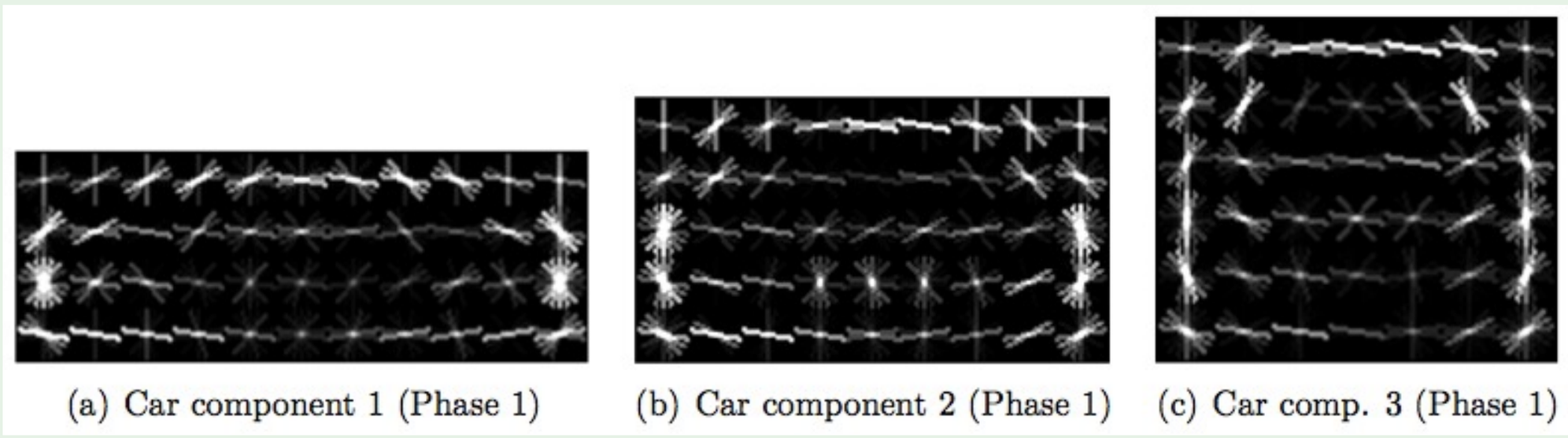


+1

-1

Learning model structure

Split positives by aspect ratio

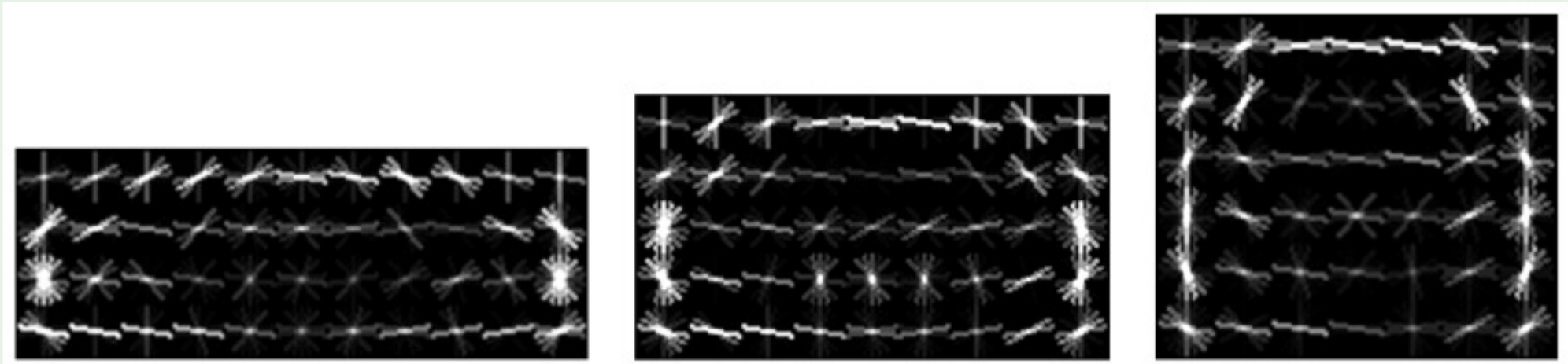


(a) Car component 1 (Phase 1) (b) Car component 2 (Phase 1) (c) Car comp. 3 (Phase 1)

Warp to common size

Train Dalal & Triggs model for each aspect ratio on its own

Learning model structure

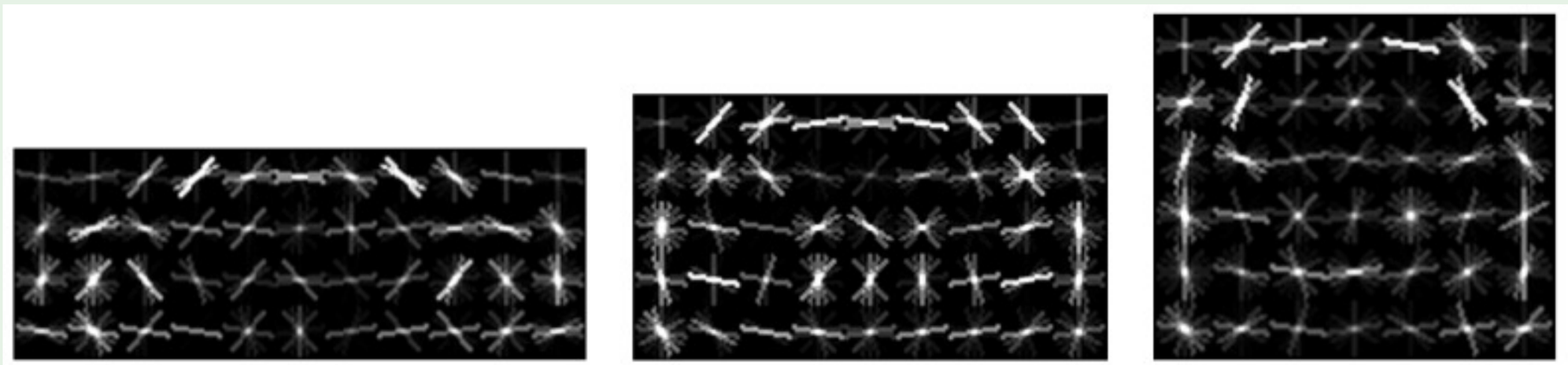


(a) Car component 1 (Phase 1) (b) Car component 2 (Phase 1) (c) Car comp. 3 (Phase 1)

Use D&T filters as initial **w** for LSVM training

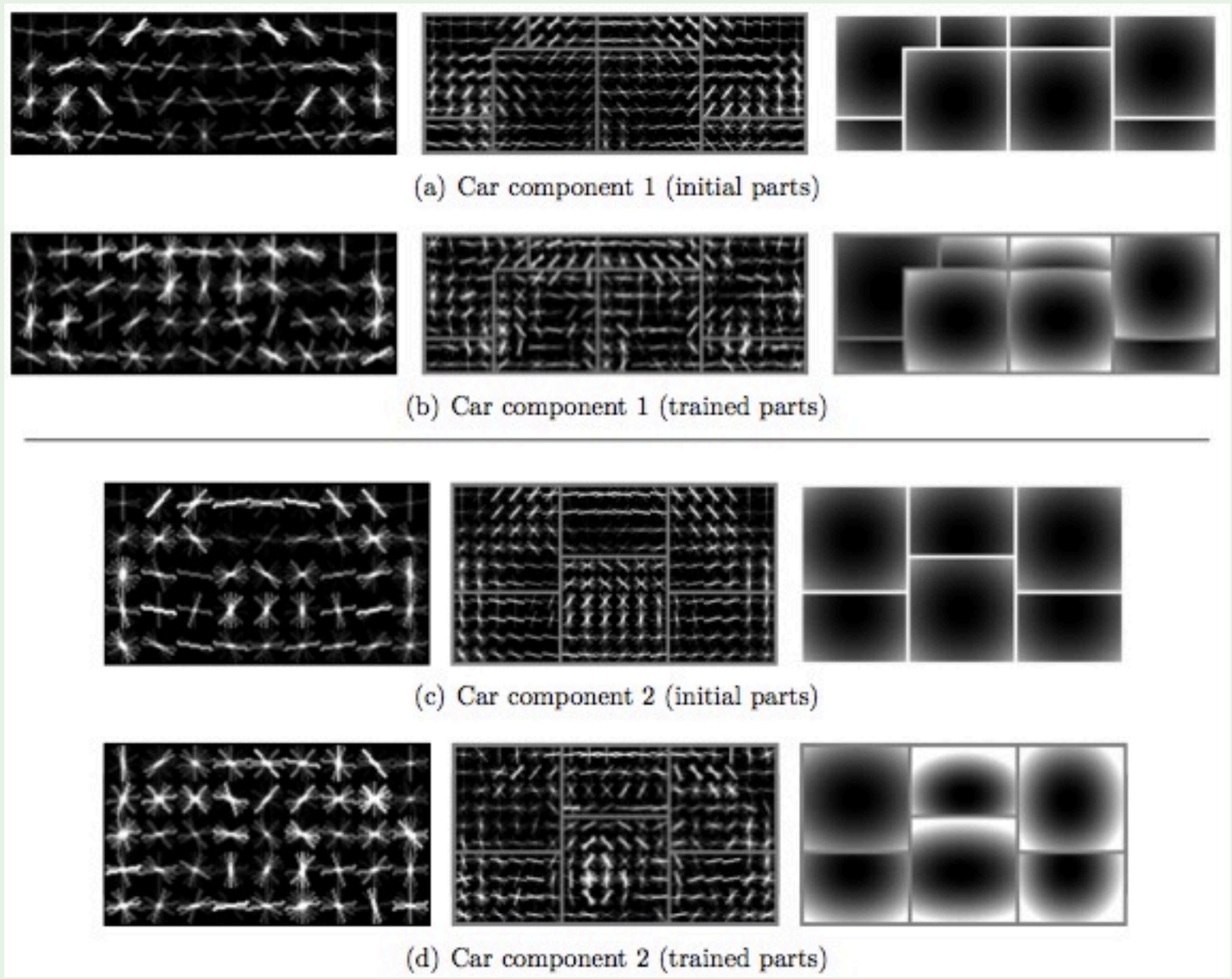
Merge components

Root filter placement and component choice are latent



(d) Car component 1 (Phase 2) (e) Car component 2 (Phase 2) (f) Car comp. 3 (Phase 2)

Learning model structure



(a) Car component 1 (initial parts)

(b) Car component 1 (trained parts)

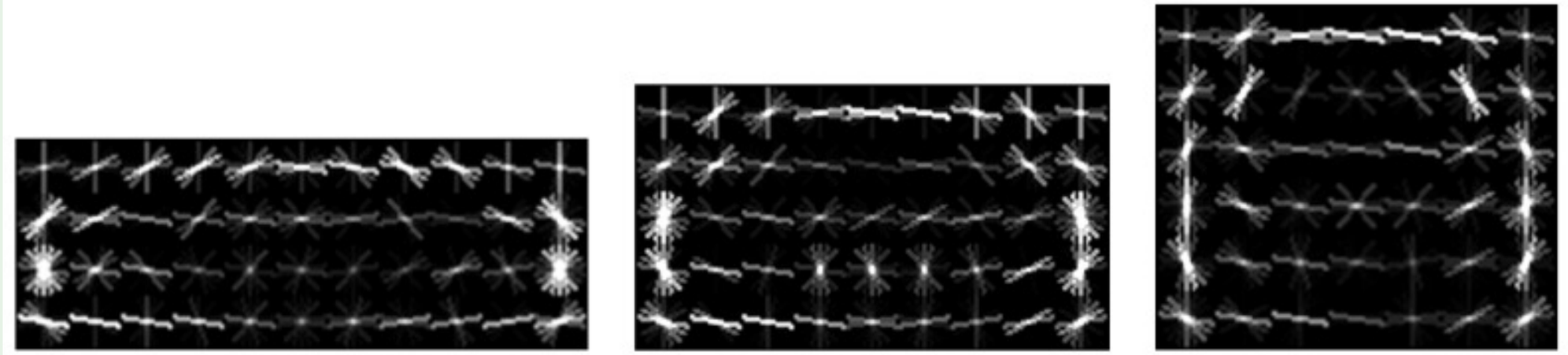
(c) Car component 2 (initial parts)

(d) Car component 2 (trained parts)

Add parts to cover high-energy areas of root filters

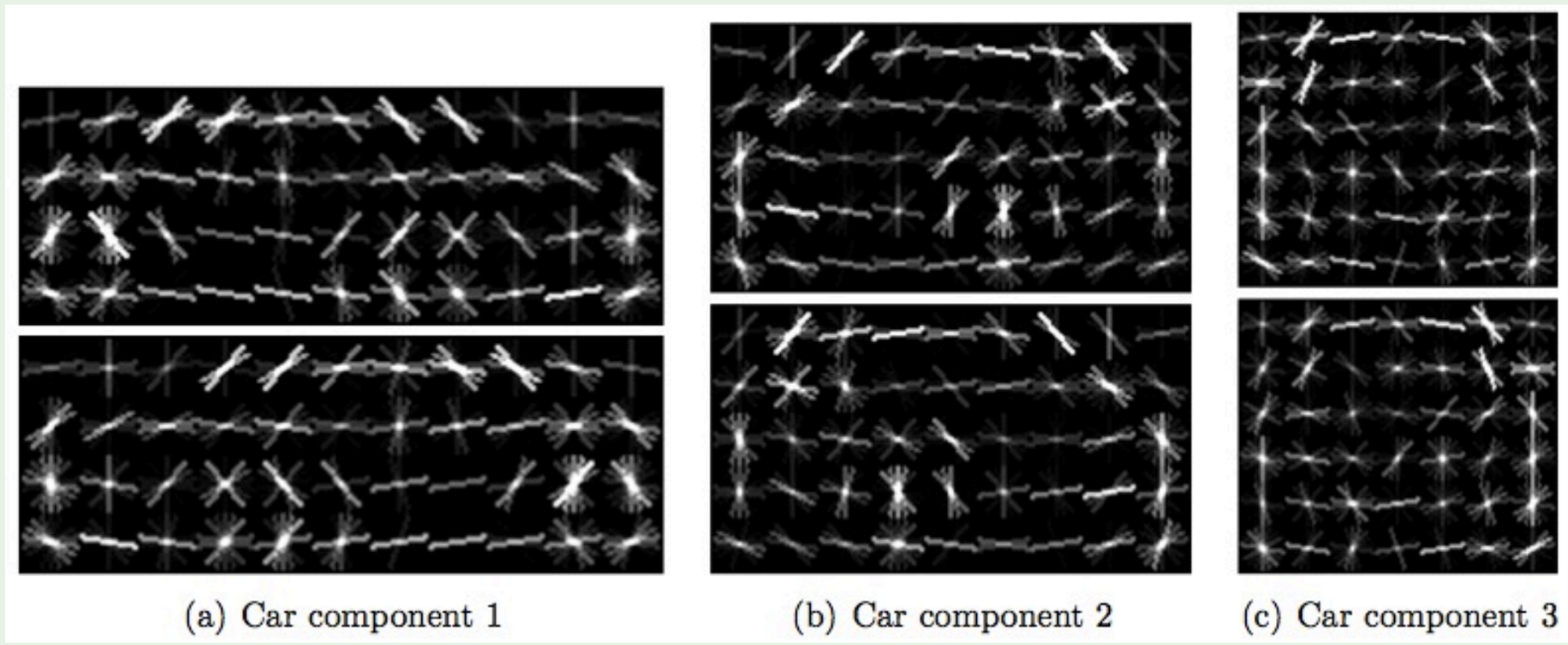
Continue training model with LSVM

Learning model structure



(a) Car component 1 (Phase 1) (b) Car component 2 (Phase 1) (c) Car comp. 3 (Phase 1)

without orientation clustering



(a) Car component 1 (b) Car component 2 (c) Car component 3

with orientation clustering

Learning model structure

In summary

– repeated application of LSVM training to models of increasing complexity

– structure learning involves many heuristics (and vision insight!)