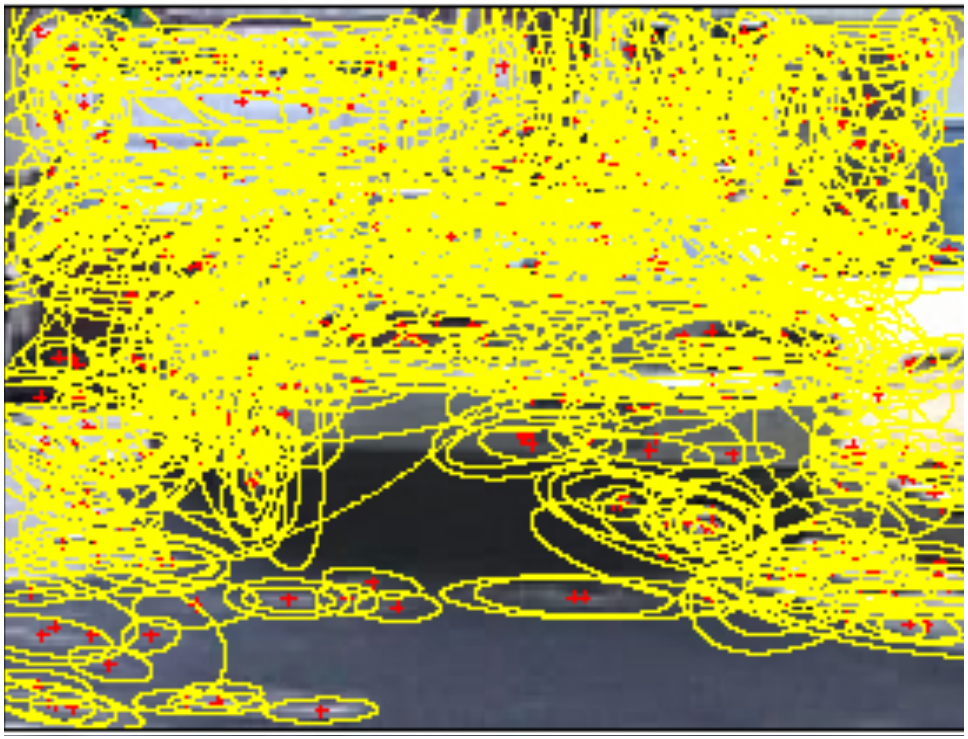
Lecture 12
Visual recognition

- Object Classification – BoW models (part 2)
- 2D Object Detection
  - Template based approaches
  - Part-based approaches

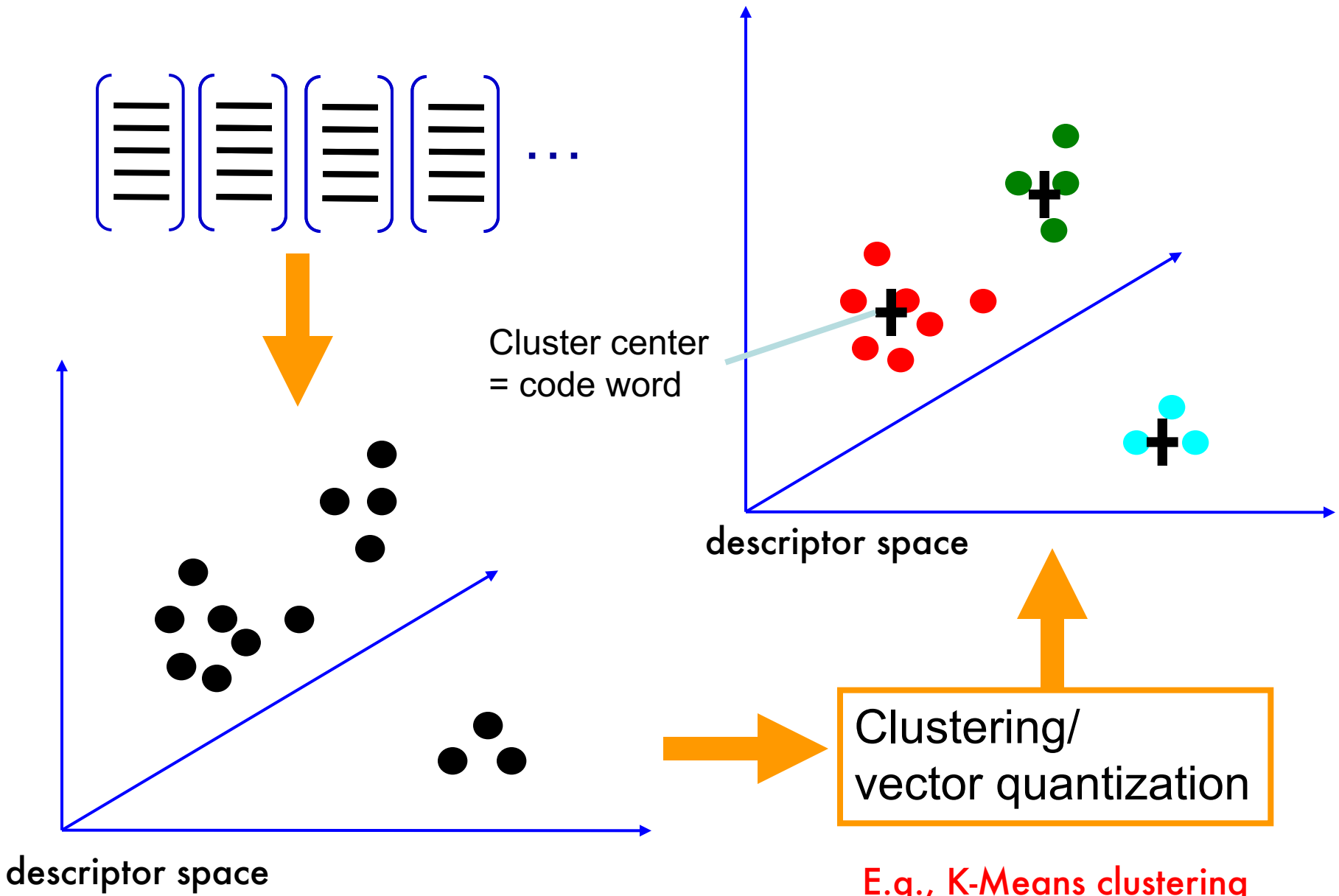
Object → Bag of ‘words’

1.Feature detection and description

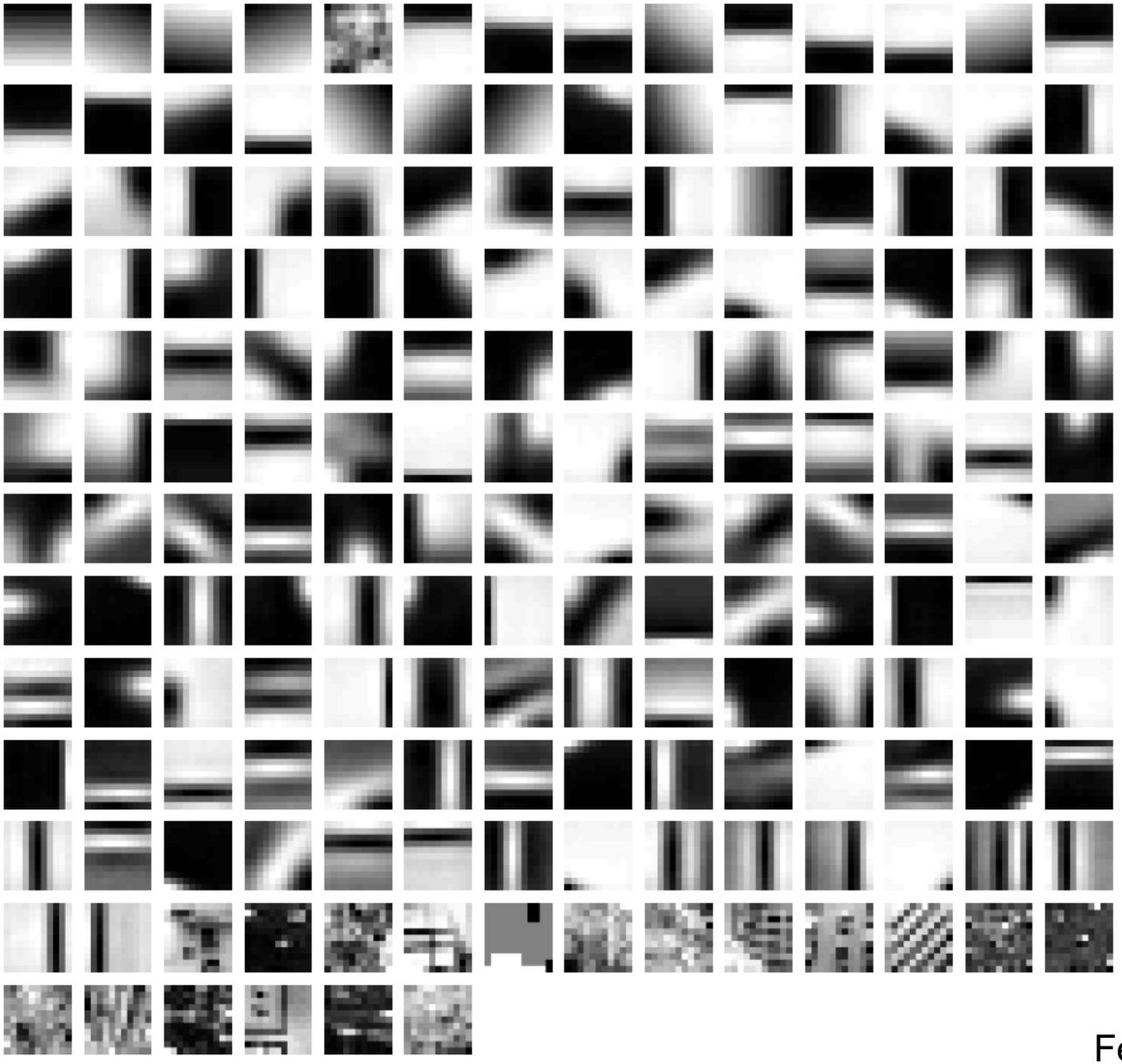
- Regular grid
  - Vogel & Schiele, 2003
  - Fei-Fei & Perona, 2005
- Interest point detector
  - Csurka, et al. 2004
  - Fei-Fei & Perona, 2005
  - Sivic, et al. 2005



2. Codewords dictionary formation

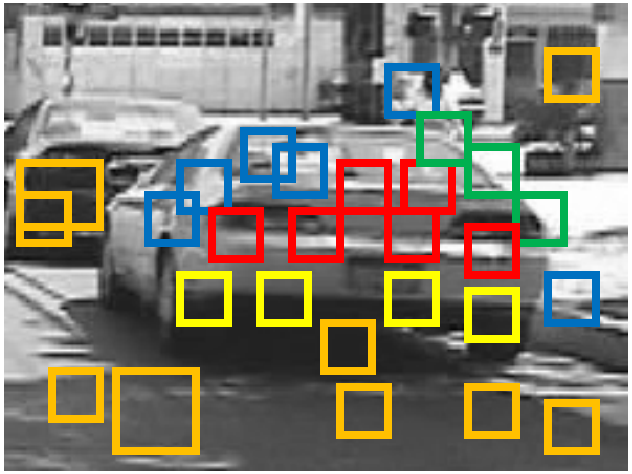


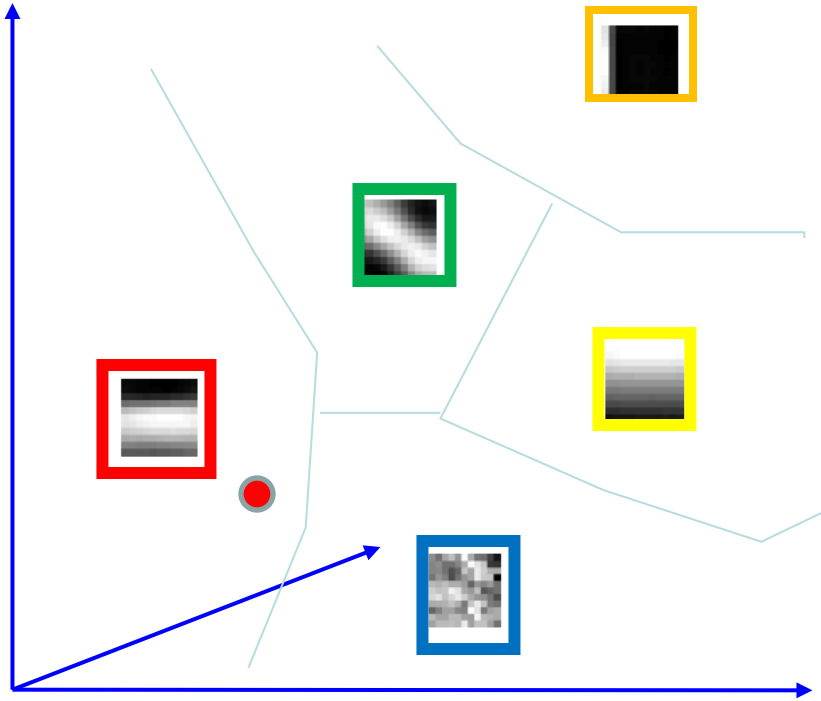
2. Codewords dictionary formation

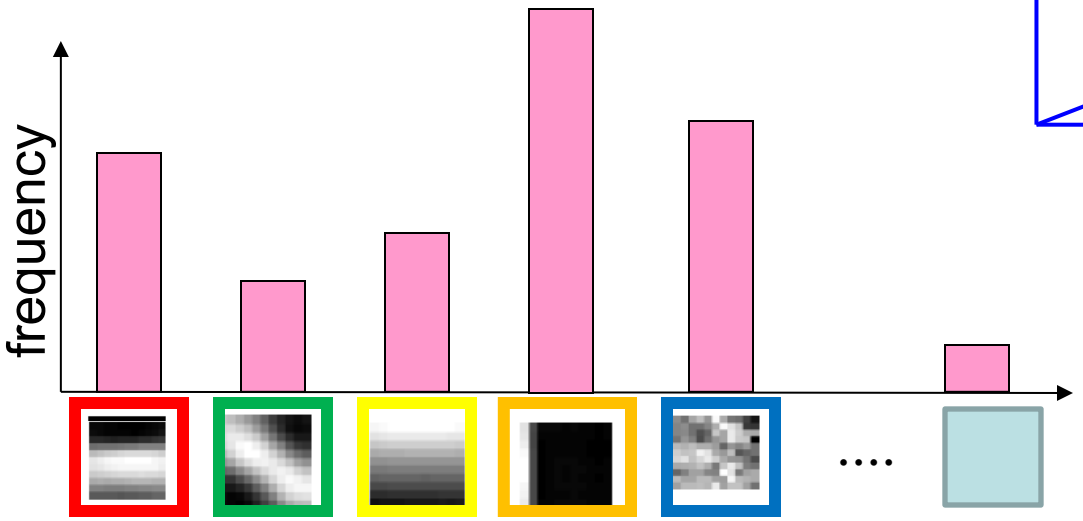


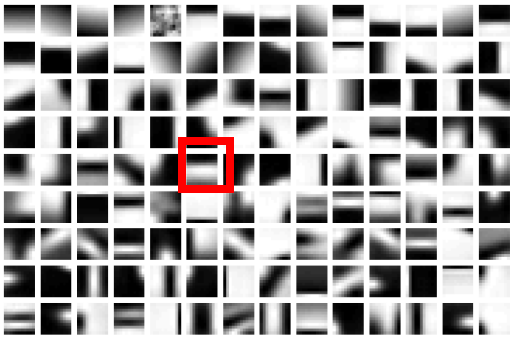
Fei-Fei et al. 2005

3. Bag of word representation









Codewords dictionary

Invariance issues

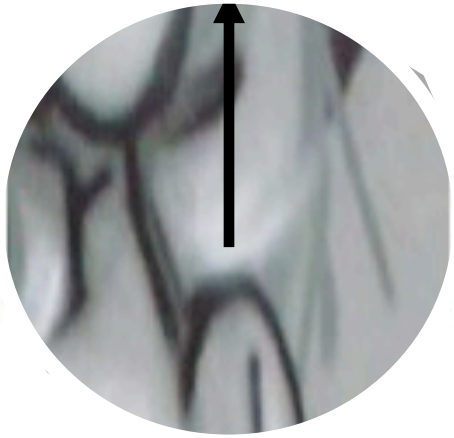
- Scale? Rotation? View point? Occlusions?
  - Implicit
  - Depends on detectors and descriptors

Kadir and Brady. 2003

View invariant descriptors

View 1

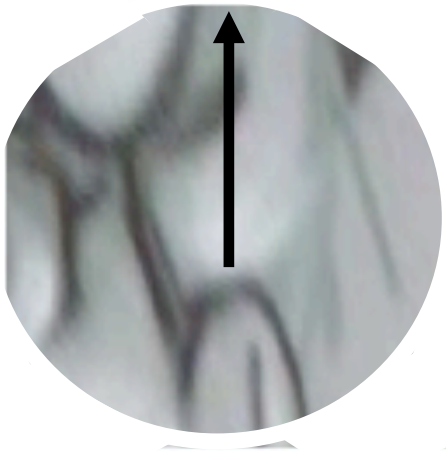
Rectification



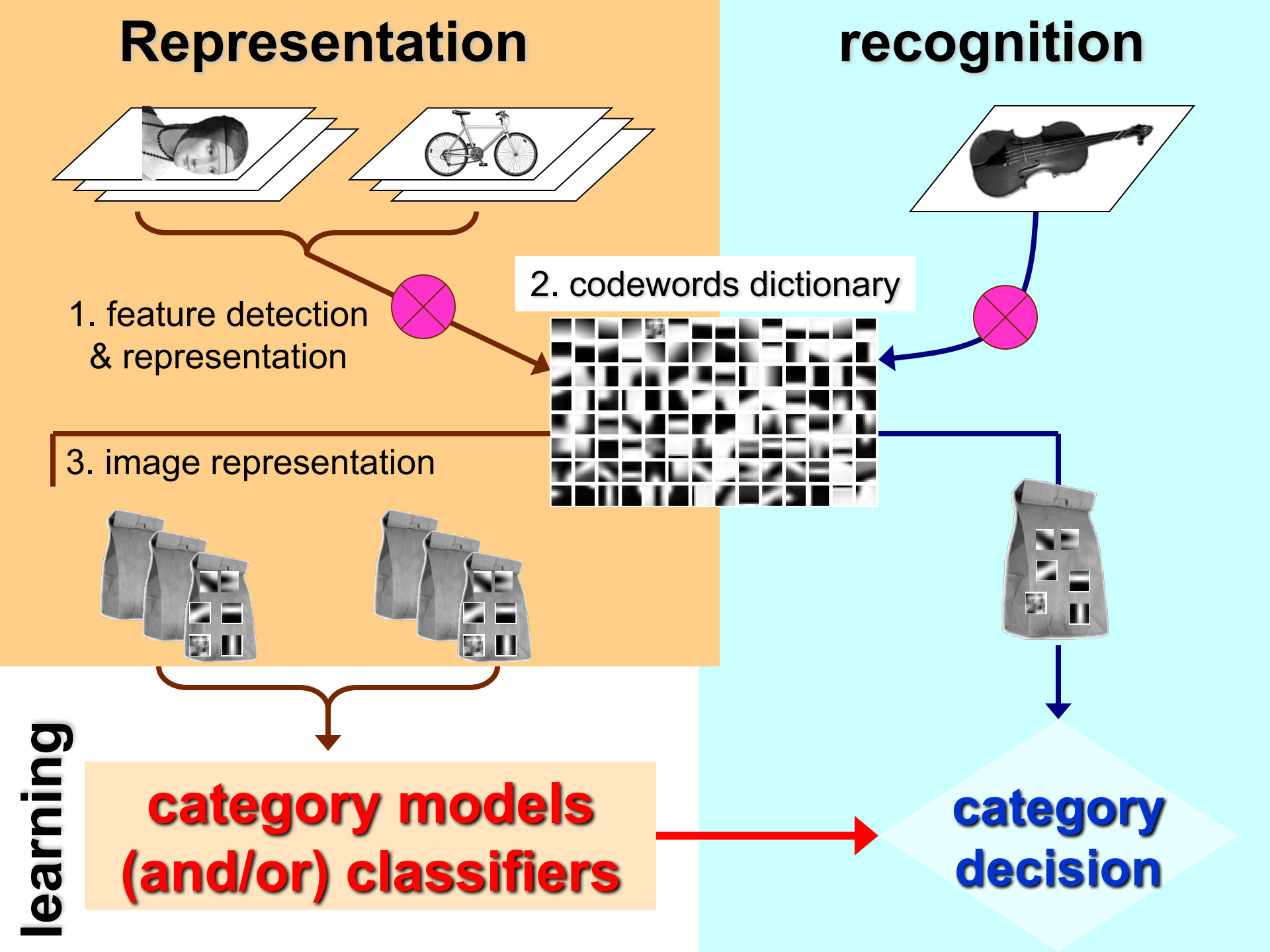
SIFT

View 2

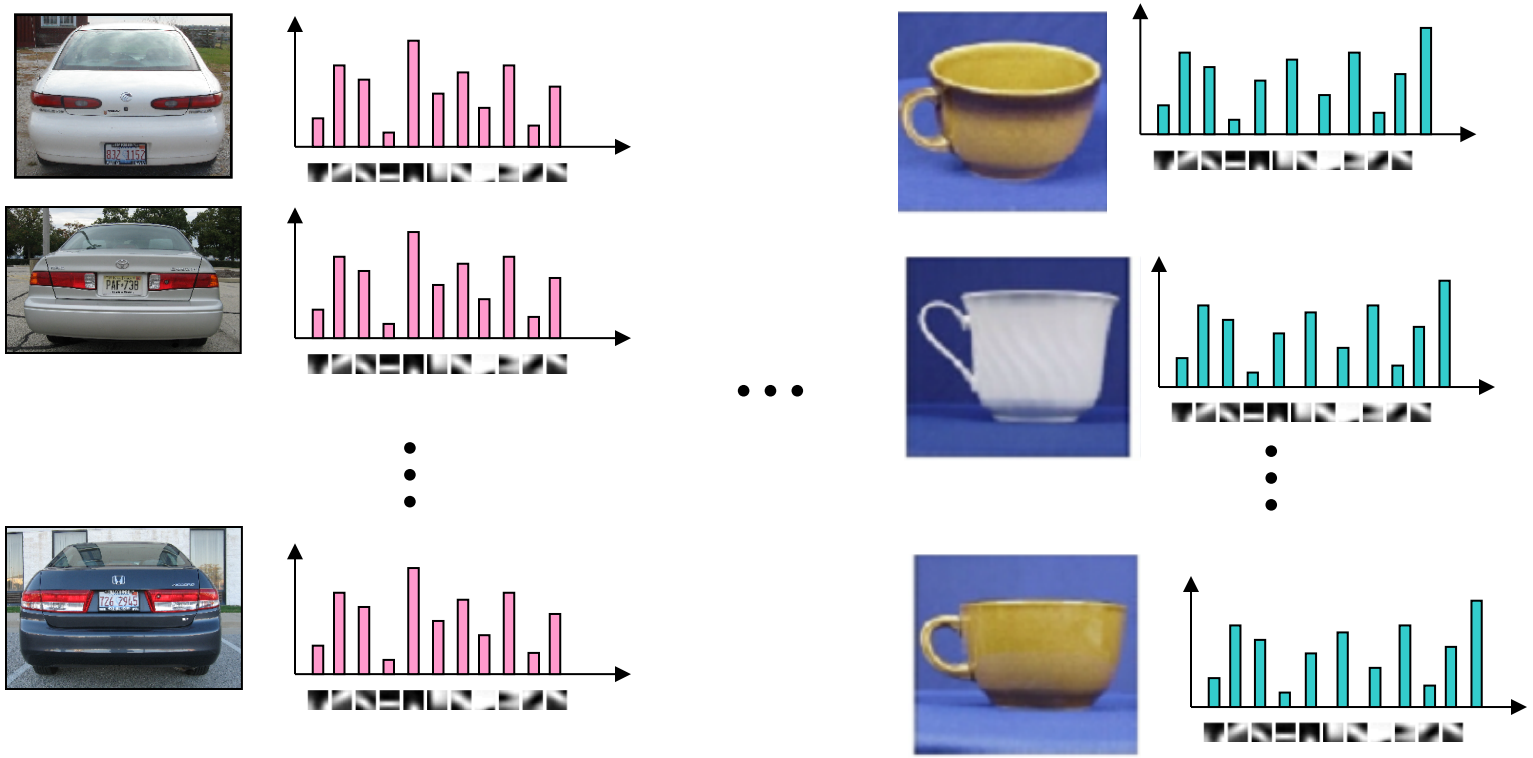
Rectification



SIFT


Representation
recognition
1. feature detection & representation
2. codewords dictionary
3. image representation
learning
category models (and/or) classifiers
category decision

Category models

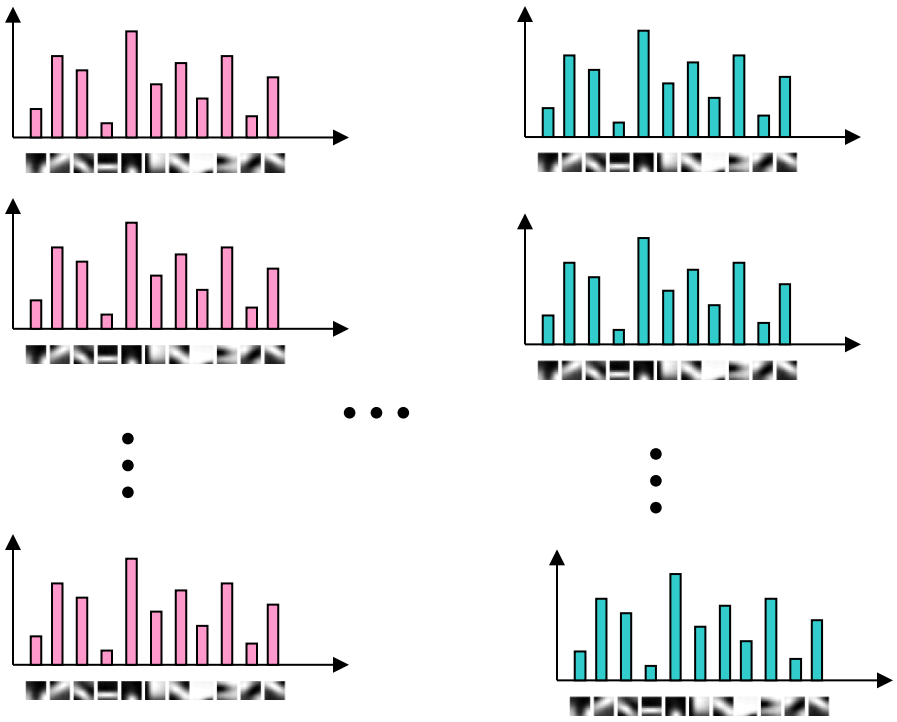


Class 1

Class N

Discriminative classifiers

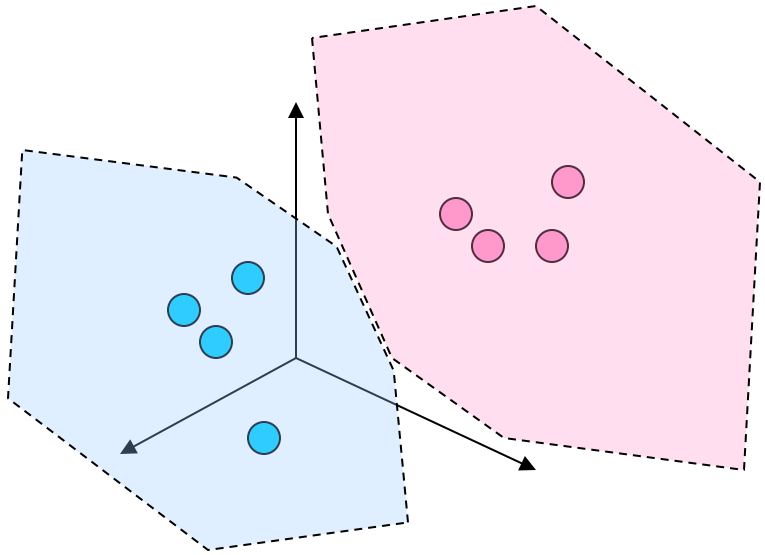
category models



Class 1

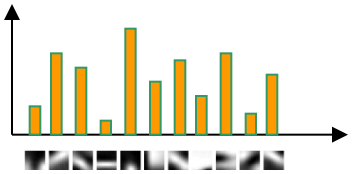
Class N

model space



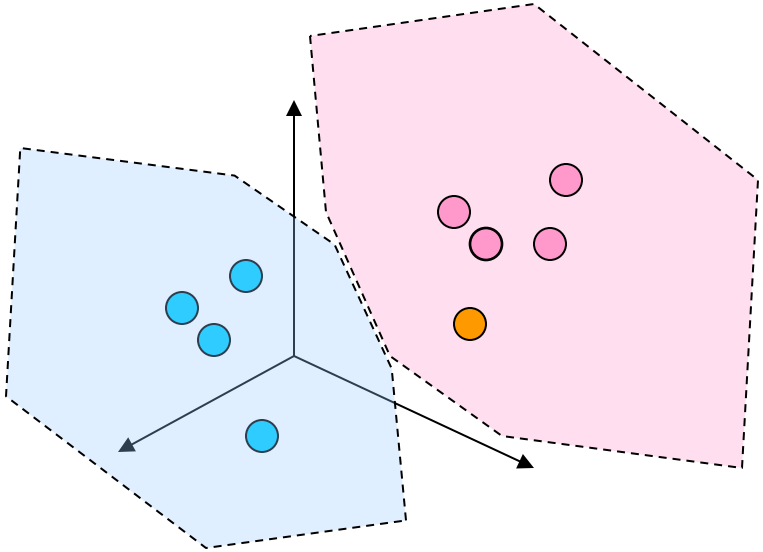
Discriminative classifiers

Query image



Winning class: pink

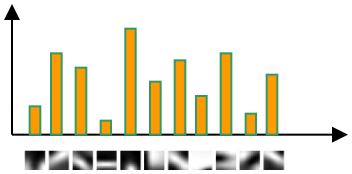
model space



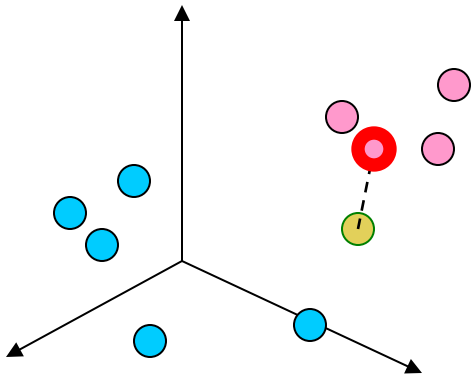
- Nearest neighbors
- Linear classifier
- SVM

Nearest neighbors classifiers

Query image



model space

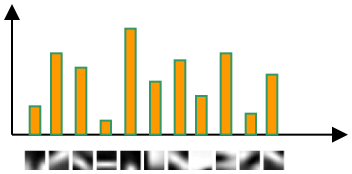


Winning class: pink

- Assign label of nearest training data point to each test data point

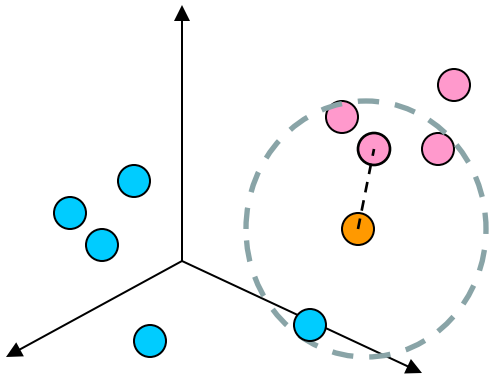
K-nearest neighbors classifiers

Query image



Winning class: pink

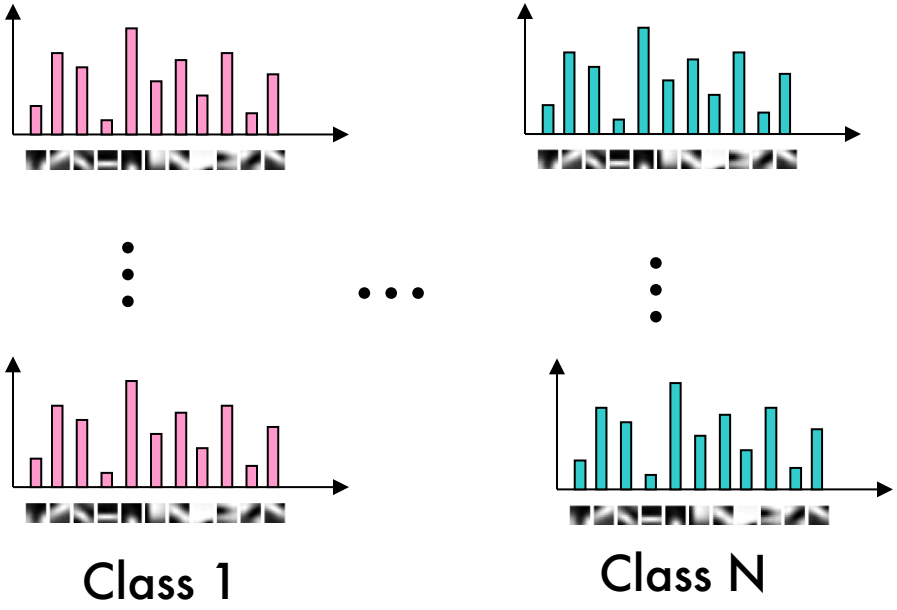
model space



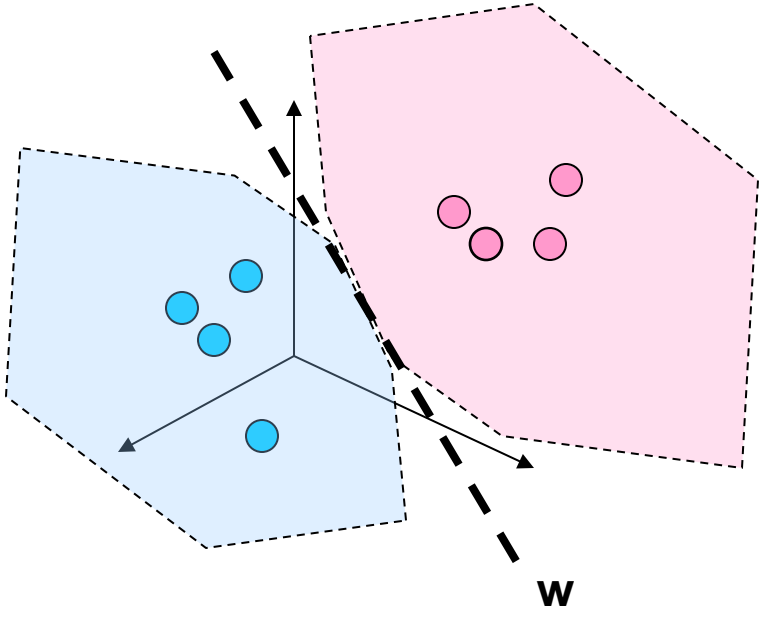
- For a new query histogram, find the k closest points from training data
- Query histogram is classified by a majority vote of its K nearest neighbors
- Works well provided there is lots of data

Linear classifiers

category models

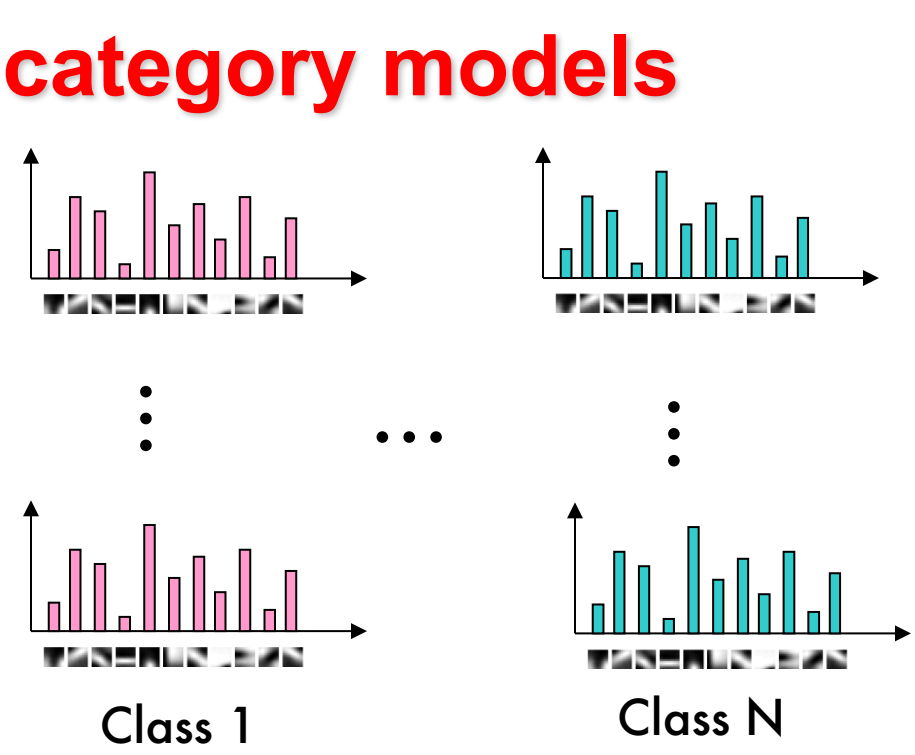


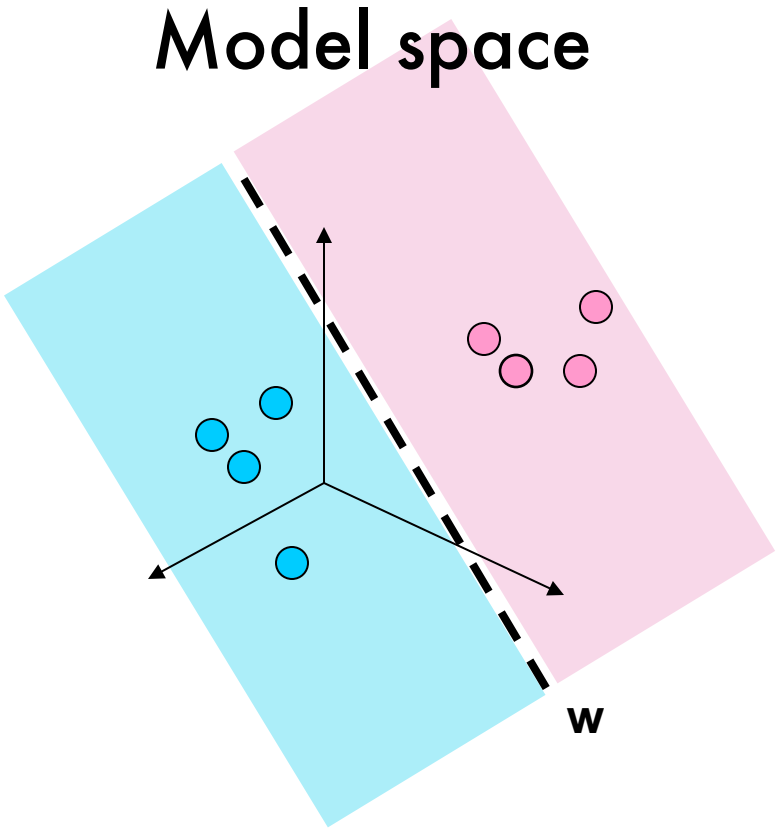
Model space



- Instead of modeling decision regions, it estimates a hyperplane **w** that separates training points that belong to different classes

Linear classifiers

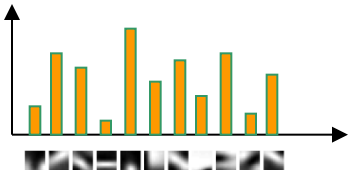




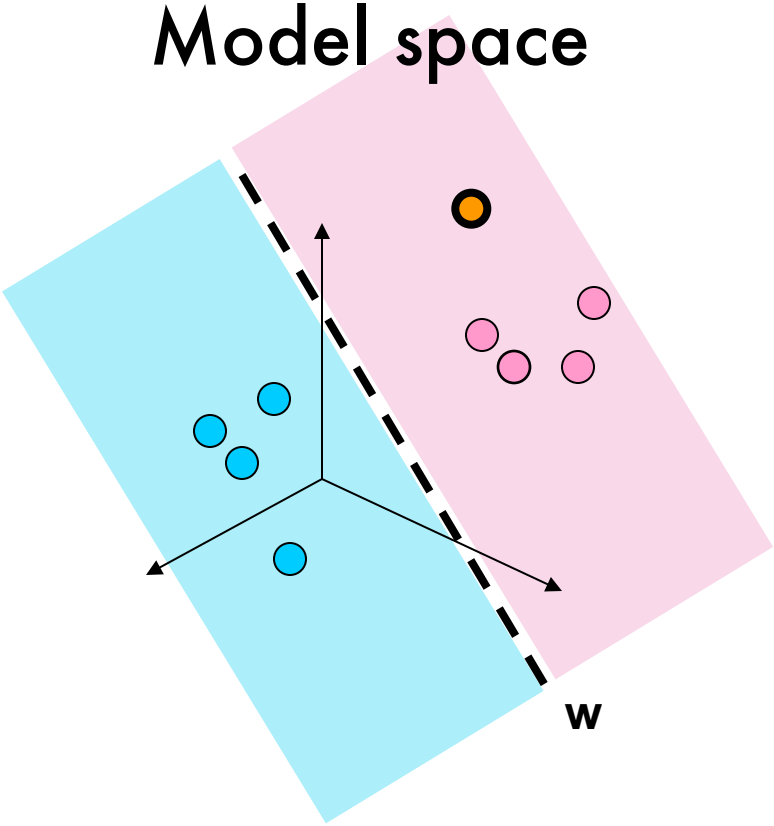
- Instead of modeling decision regions, it estimates a hyperplane **w** that separates **training points** that belong to **different classes**
- The training data is used to learn parameters of **w** and then discarded

Linear classifiers

Query image



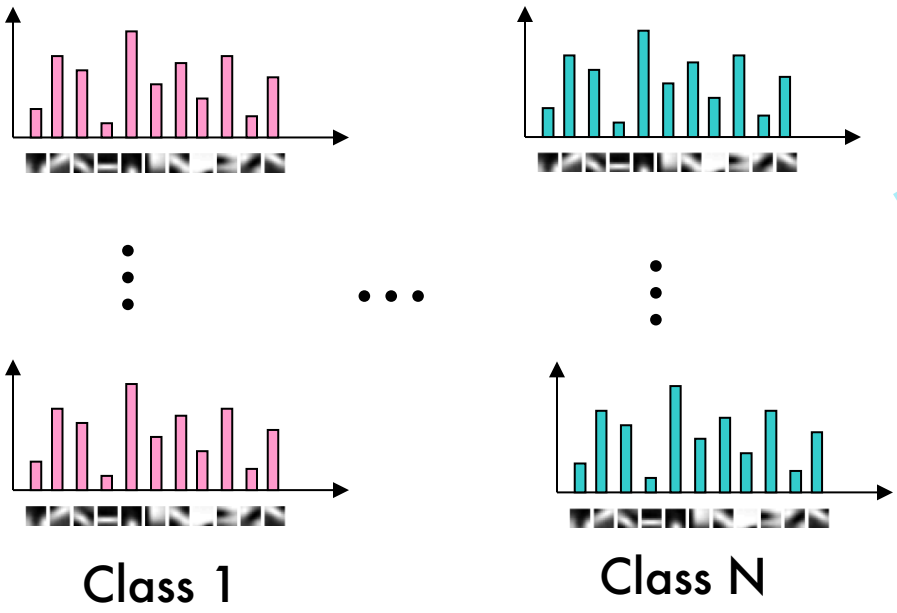
Winning class: pink

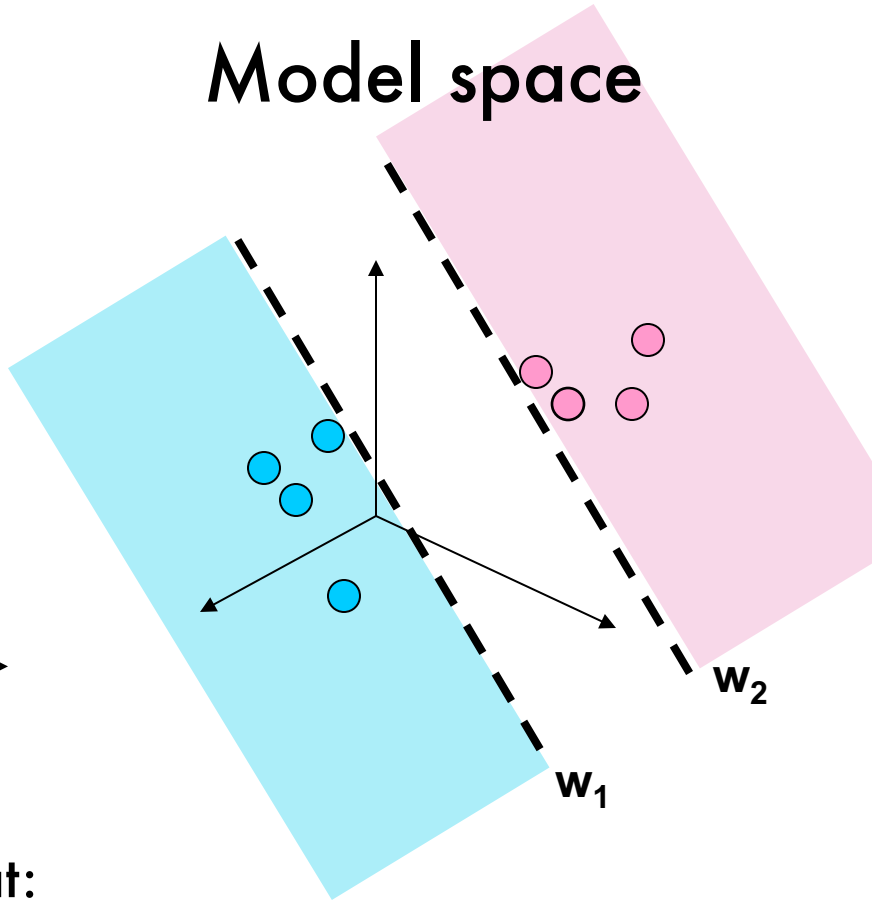


- In training, we only need **w** for classifying new data!

SVM classifiers

category models



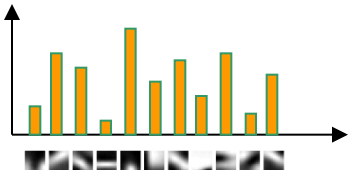


Select two hyperplanes such that:

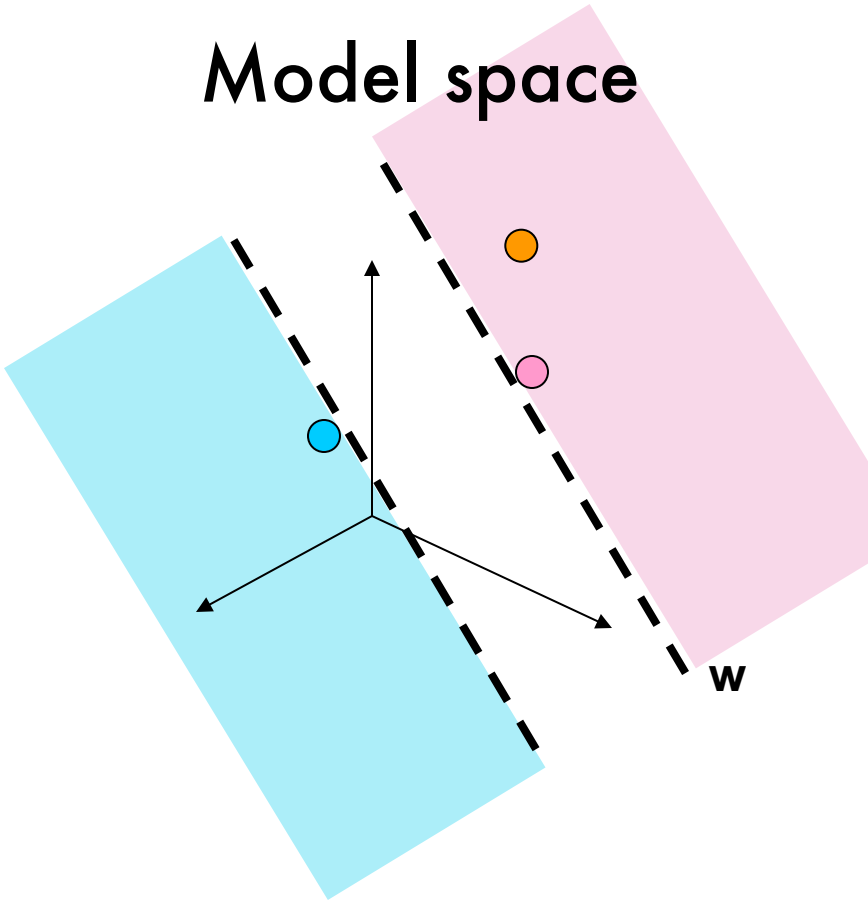
1. They separate the training points
2. There are no points between them
3. Their distance is maximized

SVM classifiers

Query image



Winning class: pink



SVMs: Pros and cons

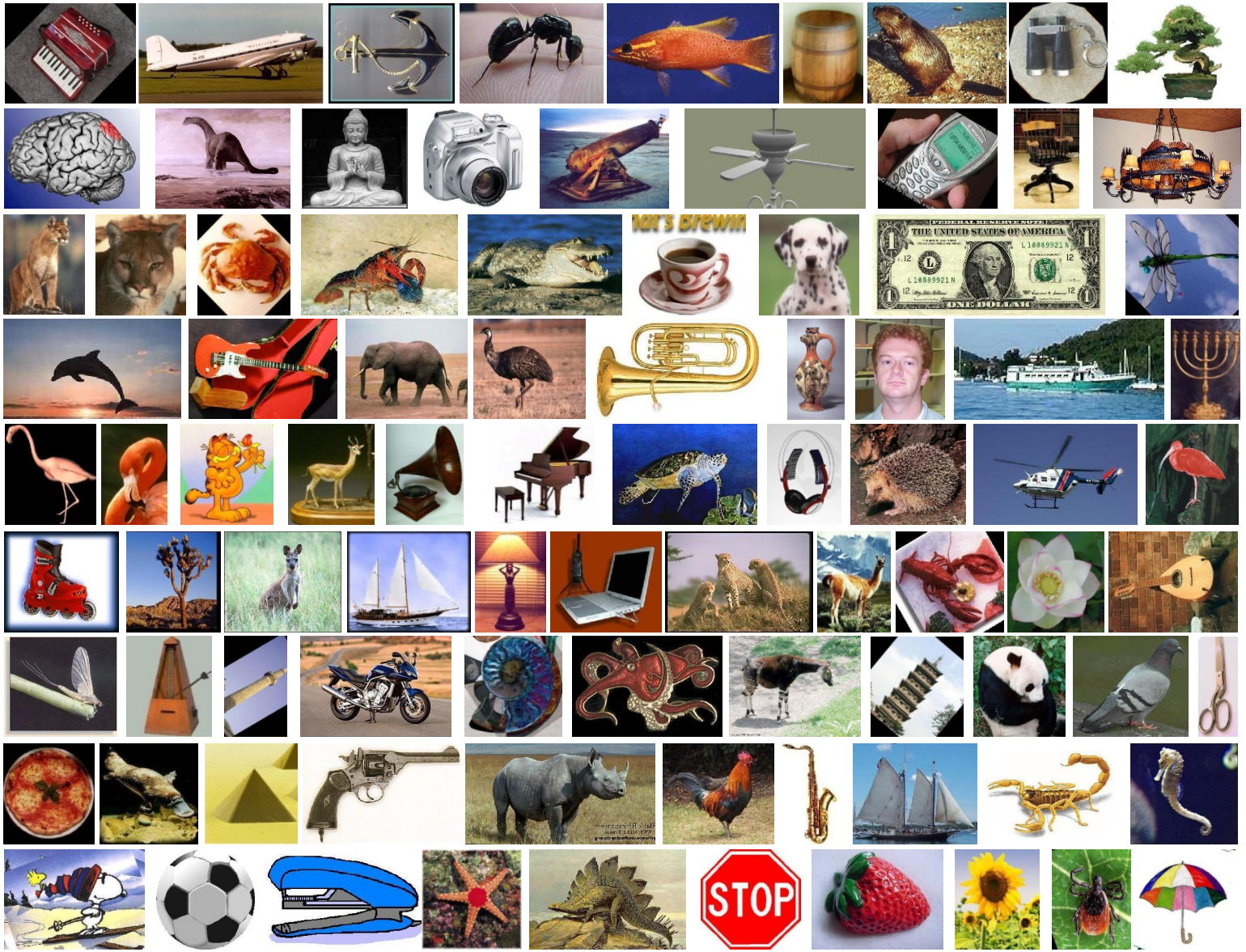
- Pros
  - Many publicly available SVM packages: http://www.kernel-machines.org/software
  - Kernel-based framework is very powerful, flexible
  - SVMs work very well in practice, even with very small training sample sizes (unlike neural networks or CNNs)
- Cons
  - Computation, memory
  - Learning can take a very long time for large-scale problems
  - No "direct" multi-class SVM, must combine two-class SVMs

How to design multi-class SVMs?

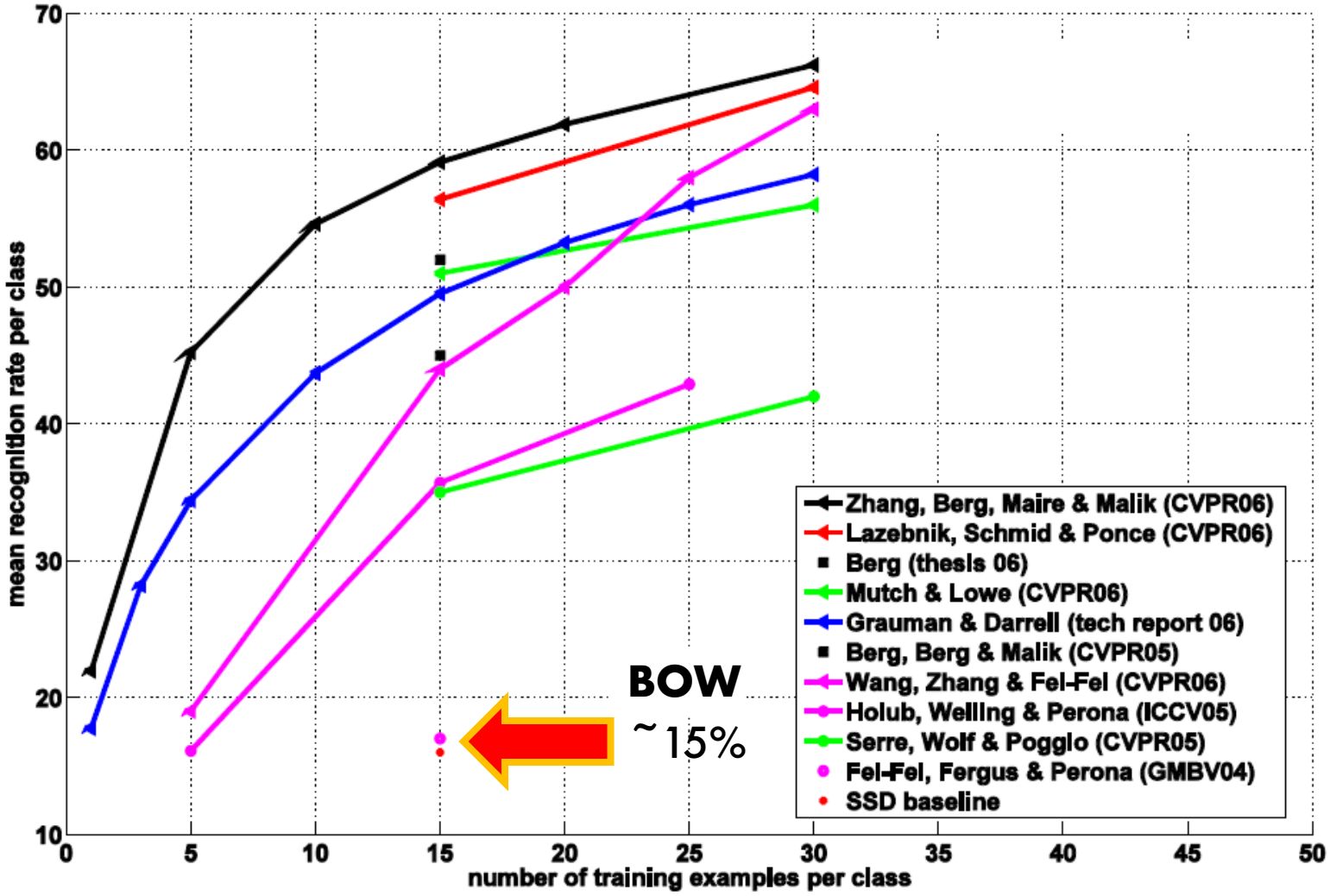
- A multi-class SVM can be obtained by combining multiple two-class SVMs
- One vs. others
  - Traning: learn an SVM for each class vs. the others
  - Testing: apply each SVM to test example and assign to it the class of the SVM that returns the highest decision value
- One vs. one
  - Training: learn an SVM for each pair of classes
  - Testing: each learned SVM "votes" for a class to assign to the test example

Credit slide: S. Lazebnik

Caltech 101 images



Caltech 101



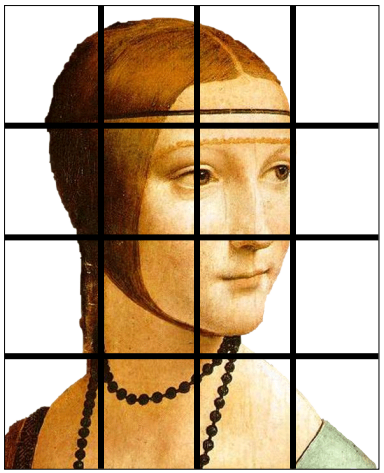
Random classification: 0.01%

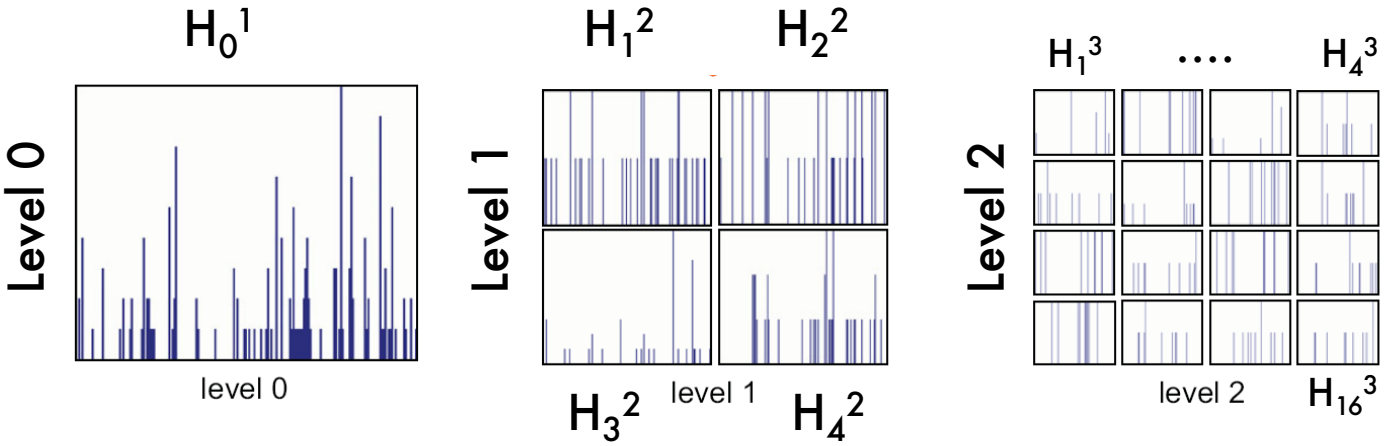
Major drawback of BOW models

Don’t capture spatial information!

Spatial Pyramid Matching

Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories. S. Lazebnik, C. Schmid, and J. Ponce.. 2006

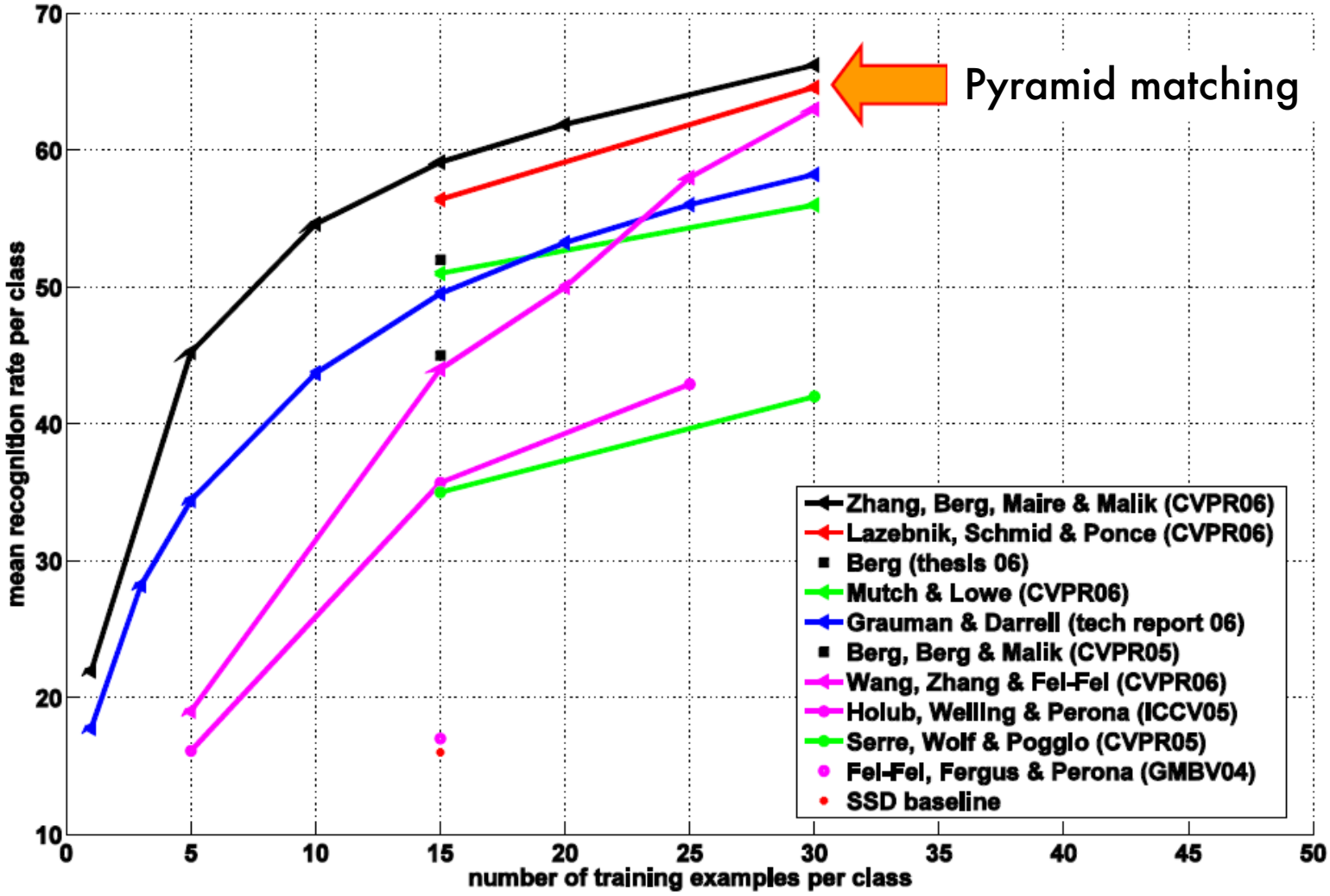




$H = [H_0^1\ H_1^2 \ldots H_4^2\ H_1^3\ \ldots H_{16}^3]$

or, H = combination of H_i^j with appropriate weights

Caltech 101


Pyramid matching
mean recognition rate per class
number of training examples per class
70
60
50
40
30
20
10
0
5
10
15
20
25
30
35
40
45
50
Zhang, Berg, Maire & Malik (CVPR06)
Lazebnik, Schmid & Ponce (CVPR06)
Berg (thesis 06)
Mutch & Lowe (CVPR06)
Grauman & Darrell (tech report 06)
Berg, Berg & Malik (CVPR05)
Wang, Zhang & Fei-Fei (CVPR06)
Holub, Welling & Perona (ICCV05)
Serre, Wolf & Poggio (CVPR05)
Fei-Fei, Fergus & Perona (GMBV04)
SSD baseline

Conclusions

- Pros:
  - Very simple and effective
  - Still used today for image retrieval problems

- Cons:
  - Not ideal for solving detection problems
  - Outperformed by CNNs but require way less training data

Discriminative models

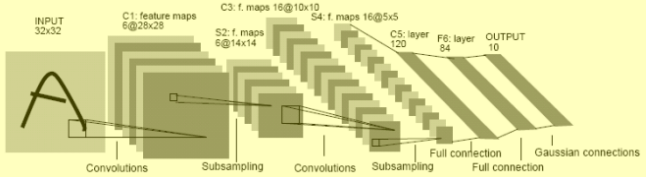
See lecture 15!

Nearest neighbor

10^6 examples

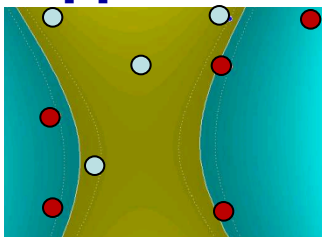
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005...

Neural networks



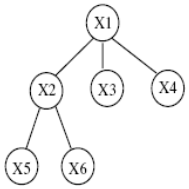
LeCun, Bottou, Bengio, Haffner 1998
Krizhevsky, Sutskever, Hinton, 2012

Support Vector Machines



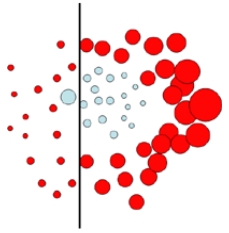
Guyon, Vapnik,
Heisele, Serre, Poggio...

Latent SVM
Structural SVM



Felzenszwalb 2000
Ramanan 2003,2008...

Boosting



Viola, Jones 2001,
Torralba et al. 2004,
Opelt et al. 2006,...

Courtesy of Vittorio Ferrari
Slide credit: Kristen Grauman

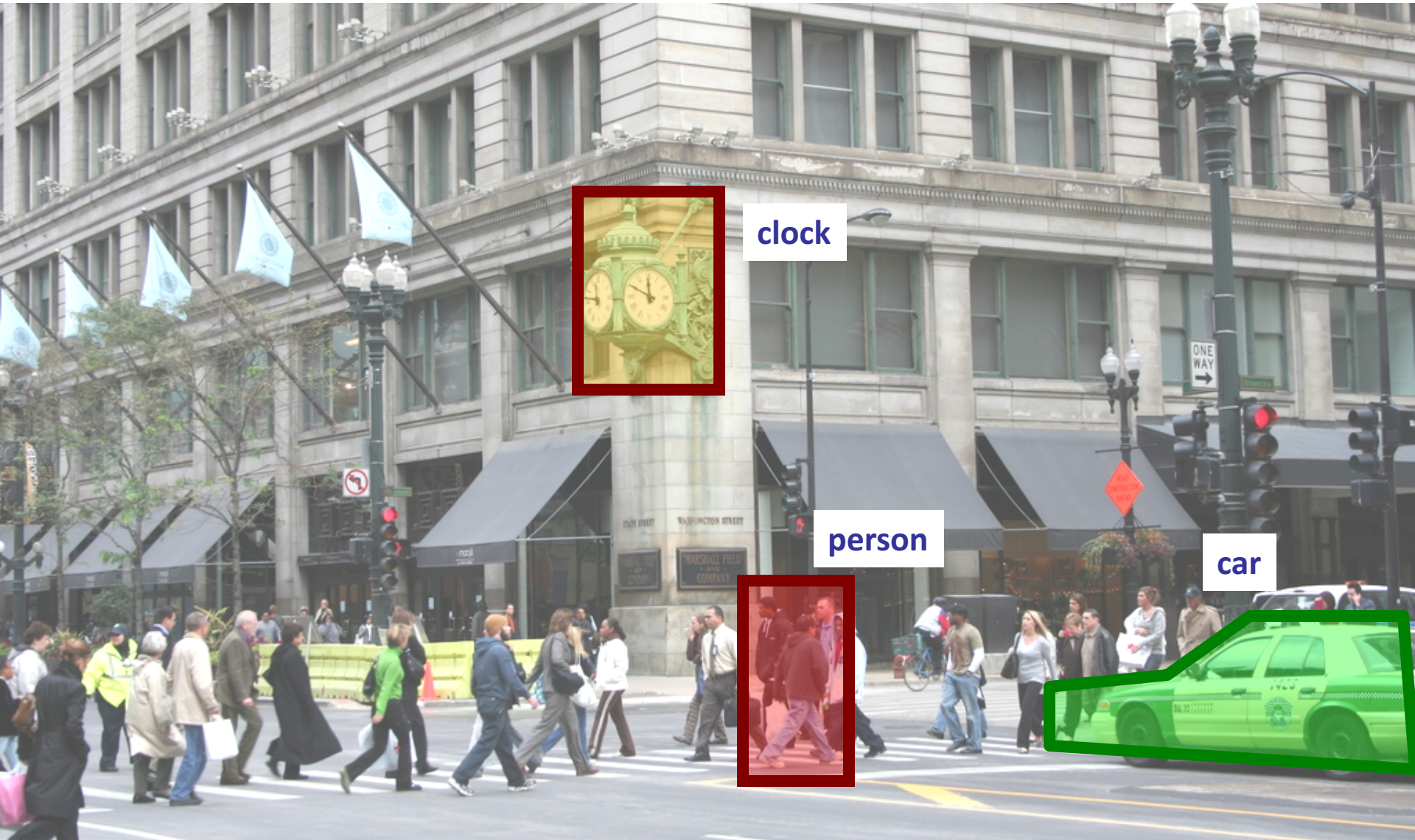
Slide adapted from Antonio Torralba

Lecture 14
Visual recognition

- Object Classification – BoW models (part 2)
- 2D Object Detection
  - Template based approaches
  - Part-based approaches

Detection

Which object does this image contain? [where?]

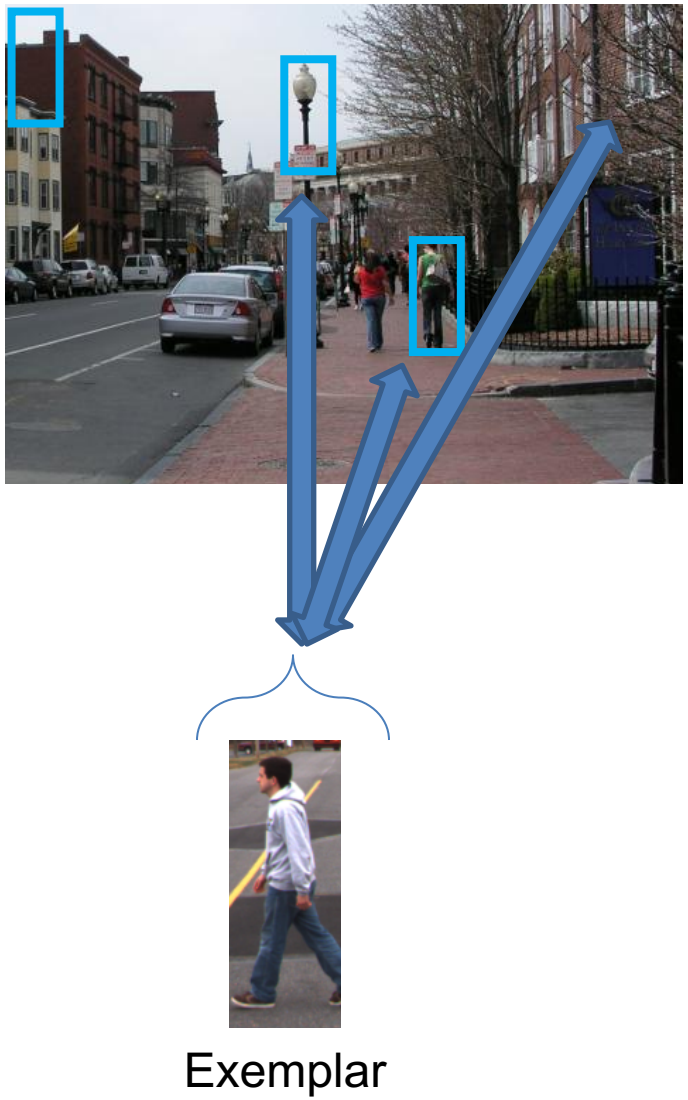


Template-based detection

1. Slide a window in image
   - E.g., choose position, scale orientation

2. Compare it with a template
   - Compute similarity to an example object or to a summary representation

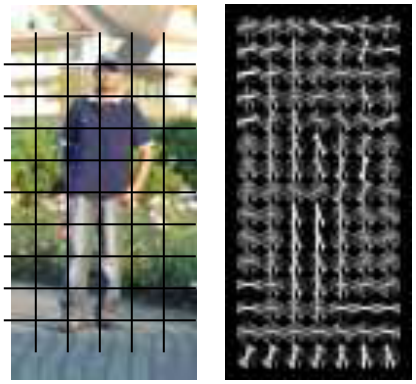
3. Compute a score for each comparison and compute non-max suppression to remove weak scores



Dalal-Triggs pedestrian detector

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

Section 17.1 [FP]



Represent an object as a collection of HoG templates

1. Extract fixed-sized window at each position and scale
2. Compute HOG (histogram of gradient) features within each window
3. Score the window with a linear SVM classifier
4. Perform non-maxima suppression to remove overlapping detections with lower scores

Classic template-based Detectors

- Sung-Poggio (1994, 1998) : ~2000 citations
  - Basic idea of statistical template detection, bootstrapping to get "face-like" negative examples, multiple whole-face prototypes (in 1994)
- Rowley-Baluja-Kanade (1996-1998) : ~3600
  - "Parts" at fixed position, non-maxima suppression, simple cascade, rotation, pretty good accuracy, fast
- Schneiderman-Kanade (1998-2000,2004) : ~1700
  - Careful feature engineering, excellent results, cascade
- **Viola-Jones (2001, 2004) : ~11,000**
  - Haar-like features, Adaboost as feature selection, hyper-cascade, very fast, easy to implement
- Dalal-Triggs (2005) : ~6500
  - Careful feature engineering, excellent results, HOG feature, online code

Courtesy of J Hayes

Limitations of template based approaches

They work

- *very well* for faces
- *fairly well* for cars and pedestrians
- *badly* for cats and dogs

- Why are some classes easier than others?

Courtesy of J Hayes

Limitations of template based approaches

Strengths

- Works very well for non-deformable objects with canonical orientations: faces, cars, pedestrians
- Fast detection

Weaknesses

- Not so well for highly deformable objects or “stuff”
- Not robust to occlusion
- Requires more training data if view points need to be encoded

Courtesy of J Hayes

Lecture 14
Visual recognition

- Object Classification – BoW models (part 2)
- 2D Object Detection
  - Template based approaches
  - Part-based approaches

Part Based Representation

- Object as set of parts
- Model:
  - Relative locations between parts
  - Appearance of each part

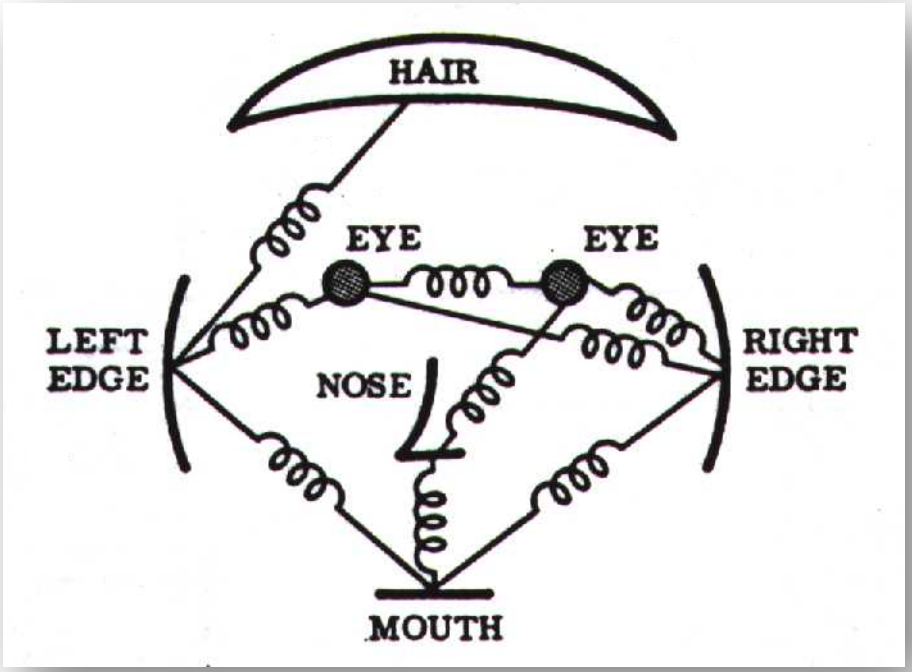
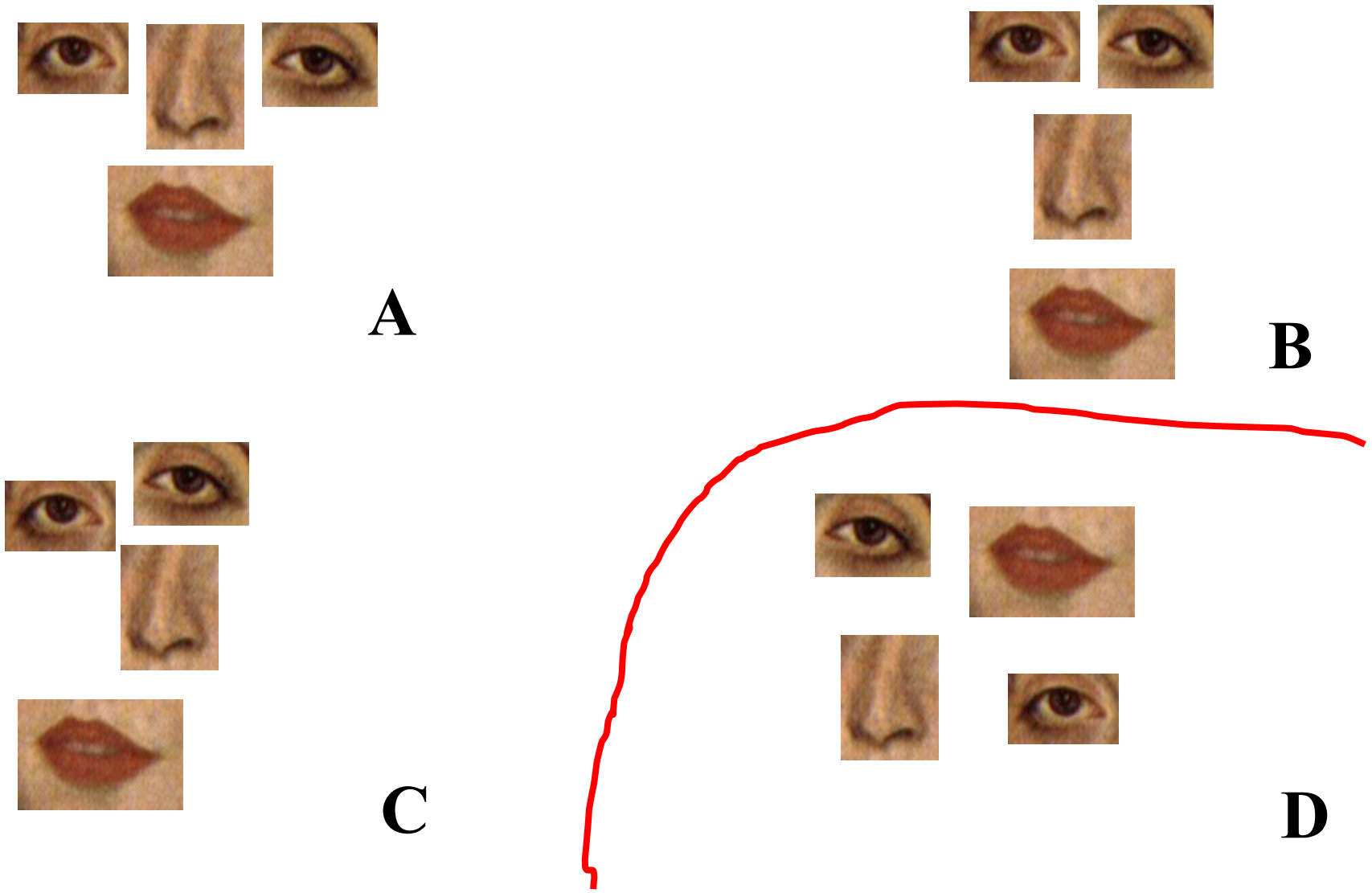
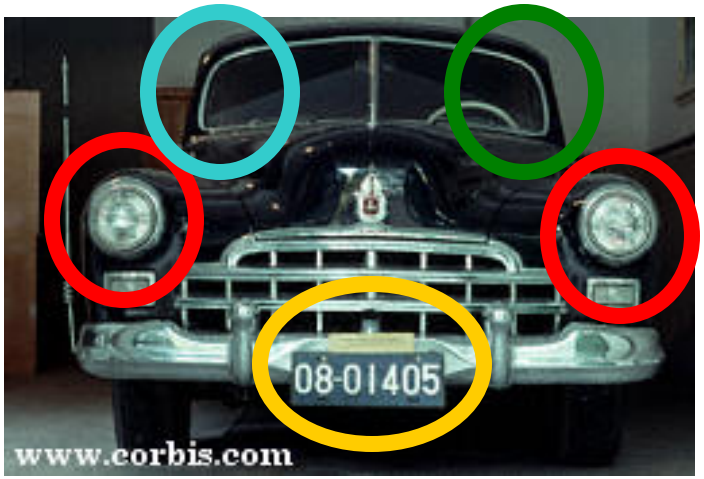


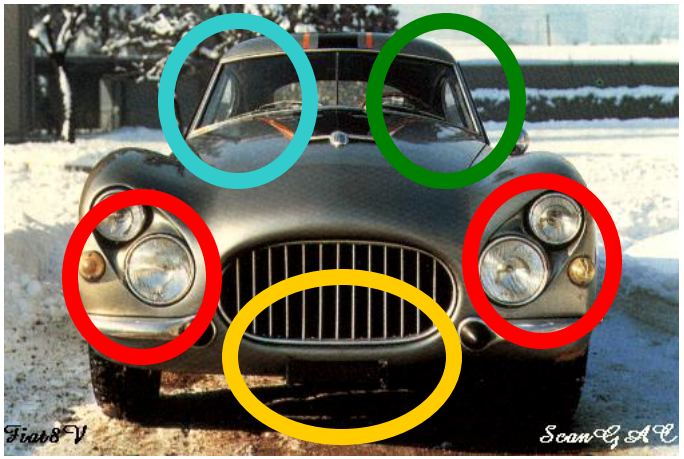
Figure from [Fischler & Elschlager 73]

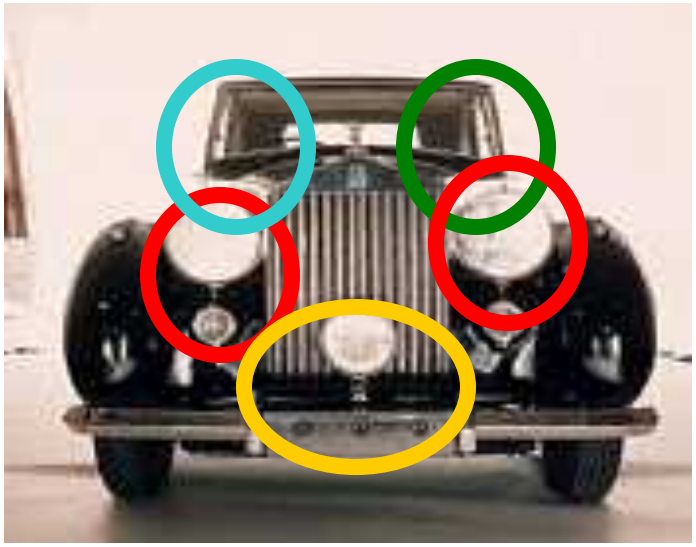
Deformations



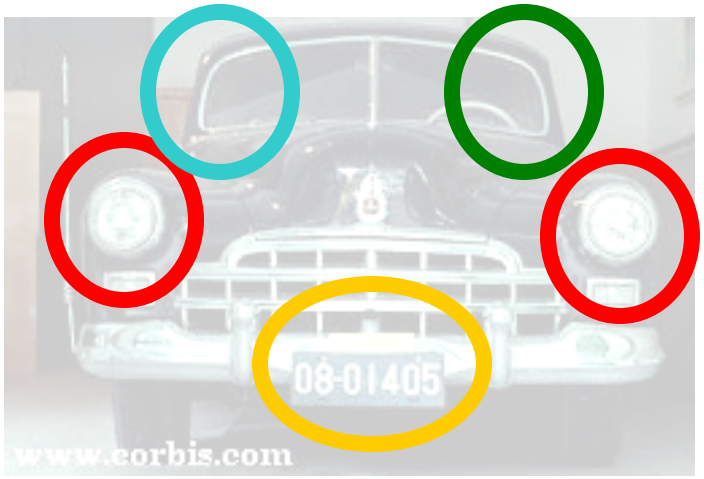
Intraclass variation

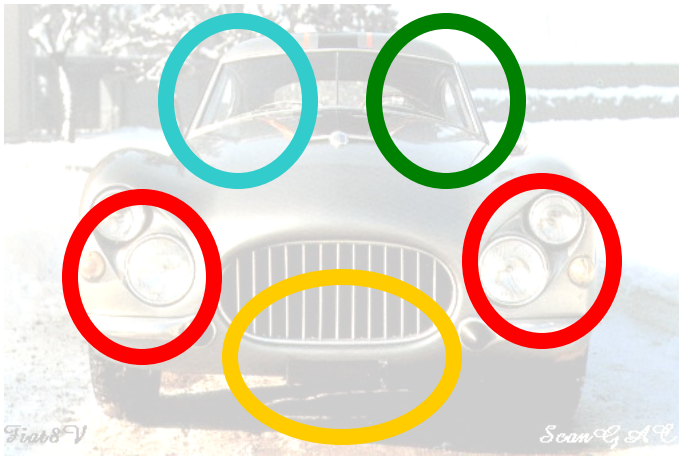


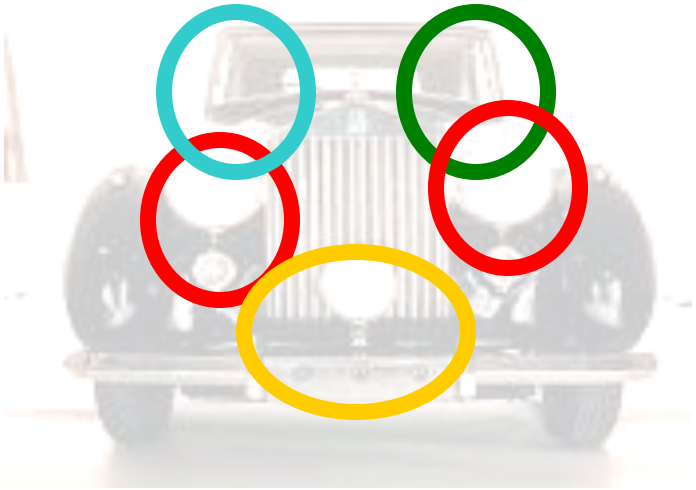




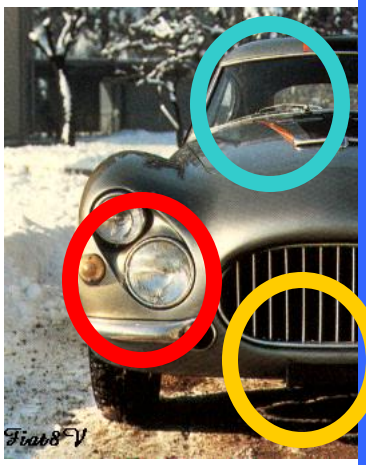
Intraclass variation







Presence / Absence of Features



occlusion

Sparse representation

Computationally tractable (10^5 pixels → 10^1 – 10^2 parts)

… but throw away potentially useful image information

Larger discrimination power

Parts can help fine-grained discrimination

History of parts-based approaches

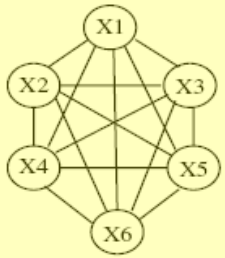
- Fischler & Elschlager 1973

- Yuille ‘91
- Brunelli & Poggio ‘93
- Lades, v.d. Malsburg et al. ‘93
- Cootes, Lanitis, Taylor et al. ‘95
- Amit & Geman ‘95, ‘99
- Perona et al. ‘95, ‘96, ’98, ’00, ’03, ‘04, ’05
- Ullman et al. 02
- Felzenszwalb & Huttenlocher ’00, ’04
- Crandall & Huttenlocher ’05, ’06
- Leibe & Schiele ’03, ’04

- Many papers since 2000

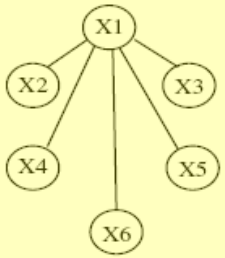
Different connectivity structures

Fergus et al. ’03
Fei-Fei et al. ‘03



a) Constellation [13]

Crandall et al. ‘05
Leibe 05; Felzenszwalb 09



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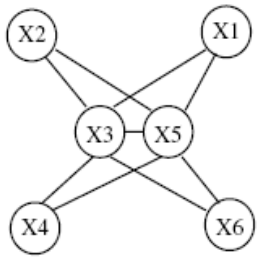
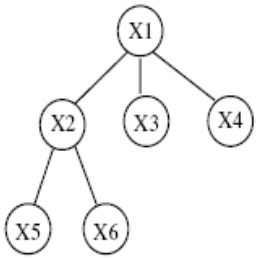
Crandall et al. ‘05

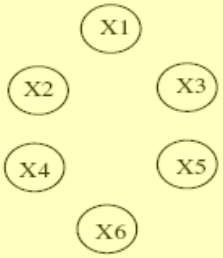


c) k-fan ($k = 2$) [9]

Felzenszwalb &
Huttenlocher ‘00



d) Tree [12]



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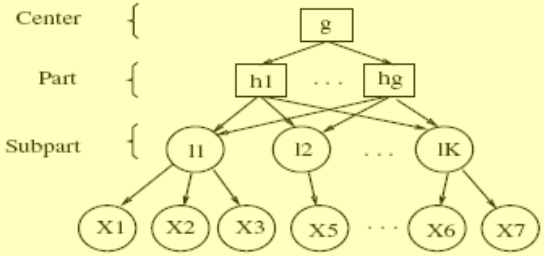
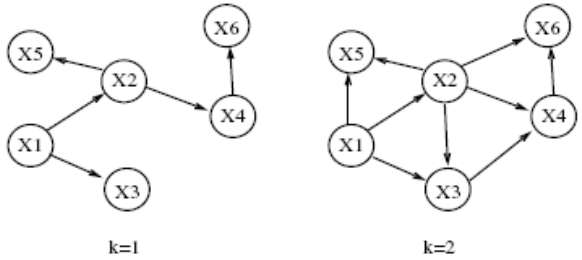
Csurka ’04
Vasconcelos ‘00



f) Hierarchy [4]
Bouchard & Triggs ‘05



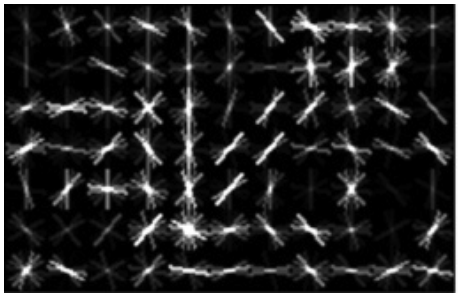
g) Sparse flexible model
Carneiro & Lowe ‘06

from Sparse Flexible Models of Local Features
Gustavo Carneiro and David Lowe, ECCV 2006

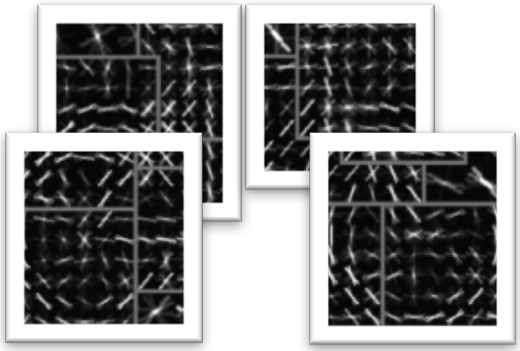
Deformable Part Models (DPM)

Felzenszwalb, et al., **Discriminatively Trained Deformable Part Models,** http://people.cs.uchicago.edu/~pff/latent/

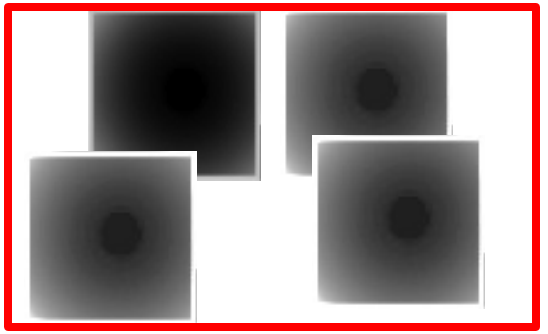
Score is computed by:
- comparing HOG features for each filter
- computing a "deformation" cost.



root filters (coarse)



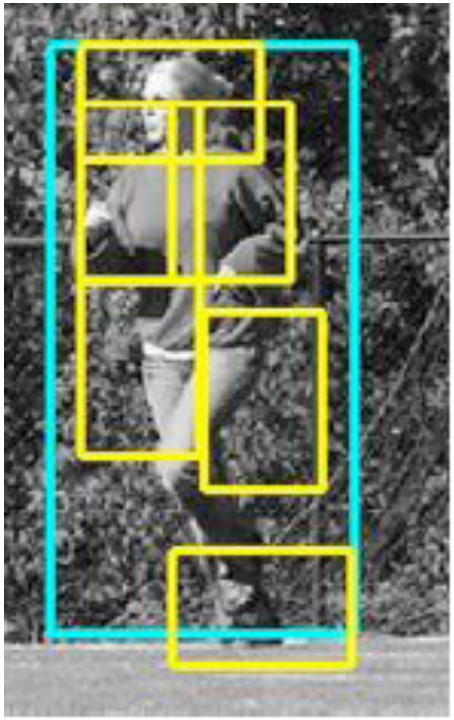
part filters (fine)

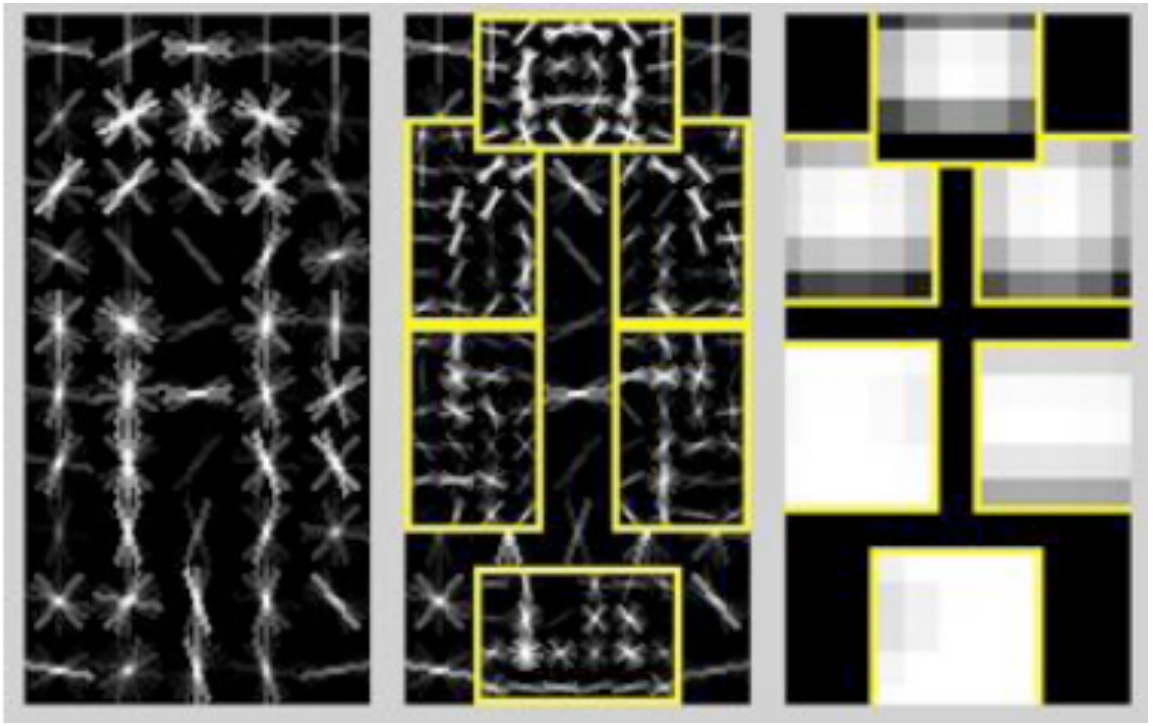


deformation models

Deformable Part Models (DPM)

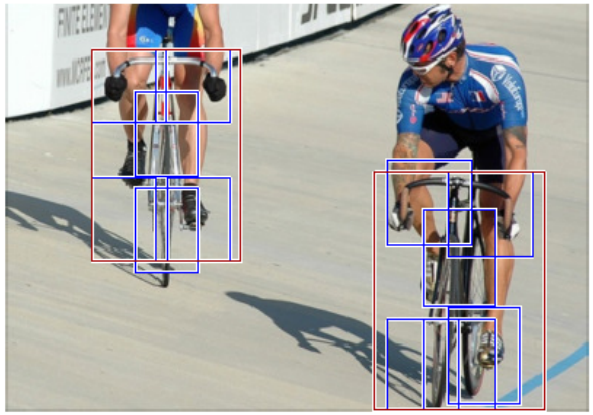
Felzenszwalb, et al., **Discriminatively Trained Deformable Part Models**, http://people.cs.uchicago.edu/~pff/latent/

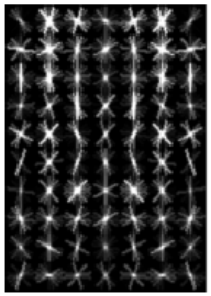


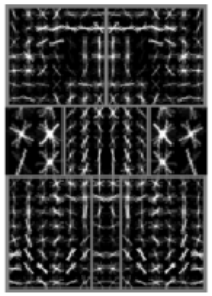


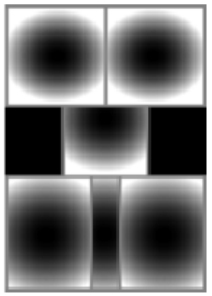
Mixture of components

"frontal" component

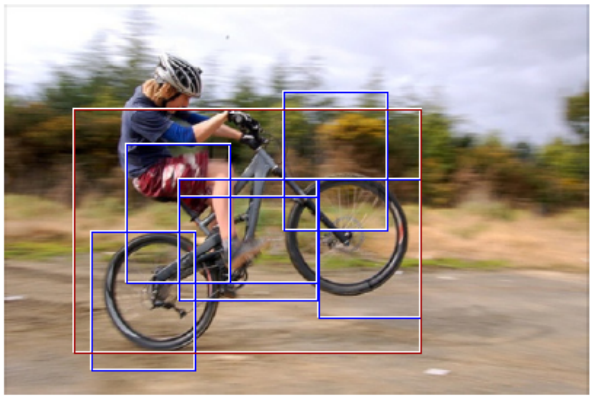


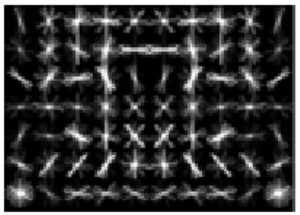


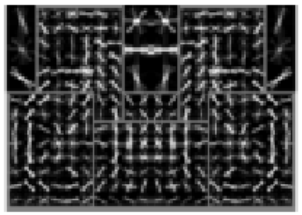


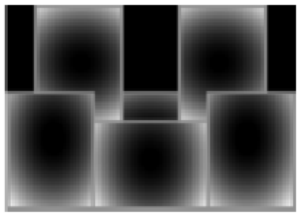


"side" component









SVM with mixtures of components

http://www.cs.berkeley.edu/~rbg/latent/index.html

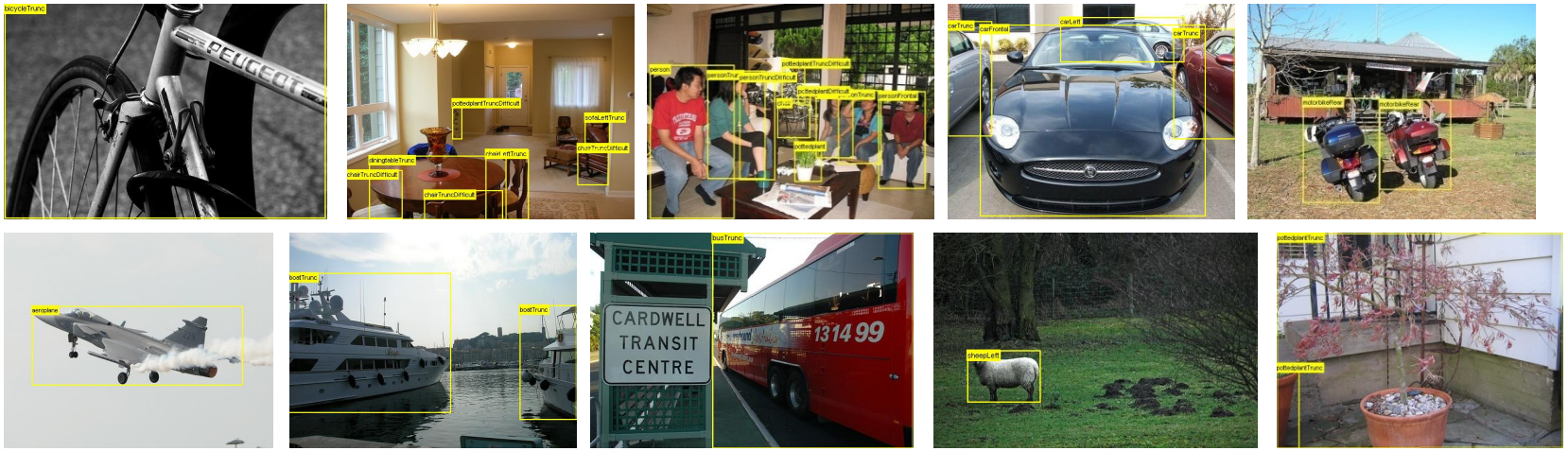
Source code available!

Pascal Dataset

http://host.robots.ox.ac.uk/pascal/VOC/voc2012/index.html

- 20 classes: aeroplane, bicycle, boat, bottle, bus, car, cat, chair, cow, dining table, dog, horse, motorbike, person, potted plant, sheep, train, TV

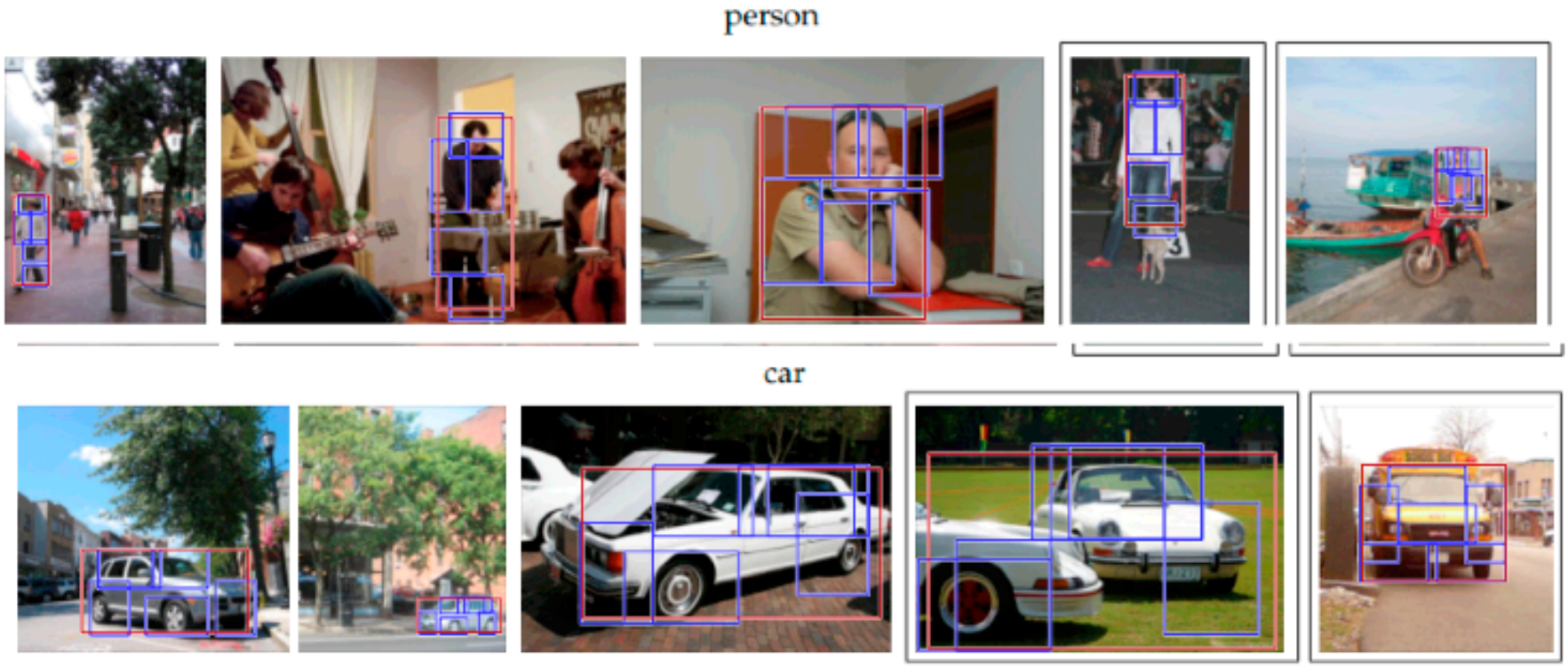
- Real images downloaded from flickr, not filtered for "quality"



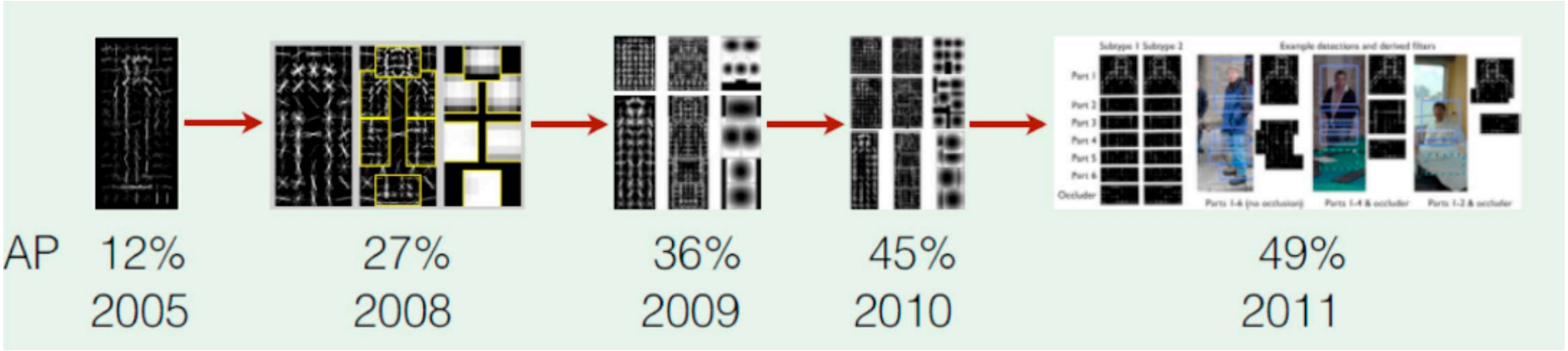
- Complex scenes, scale, pose, lighting, occlusion, ...

Results on the PASCAL dataset

One of the most advanced version of DPM achieves an average precision of 41%



Results on detecting deformable objects (humans)



HOG templates
Dalal & Triggs 2005

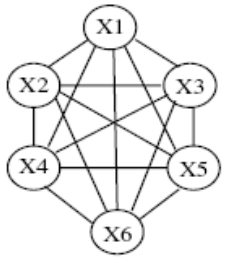
DPM
Felzenszwalb et al 2010

DPM by flexible Mixtures-of-Parts
Yang & Ramanan,2012

Courtesy of Girshick

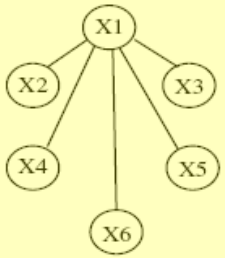
Different connectivity structures

Fergus et al. ’03
Fei-Fei et al. ‘03



a) Constellation [13]

Crandall et al. ‘05
Leibe 05; Felzenszwalb 09



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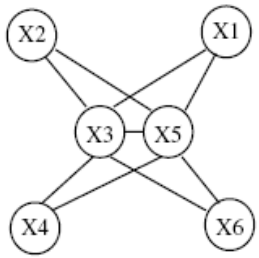

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Felzenszwalb &
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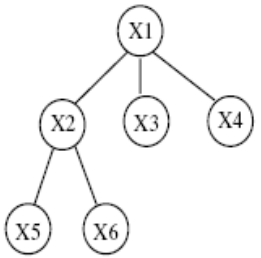

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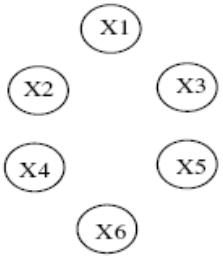

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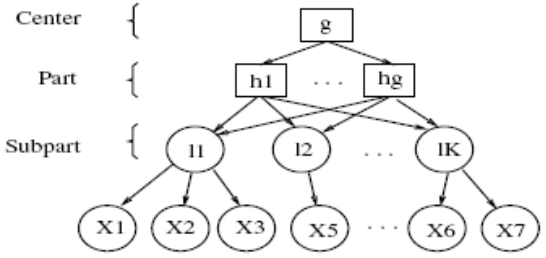

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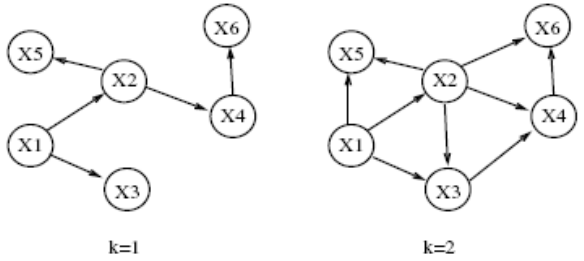


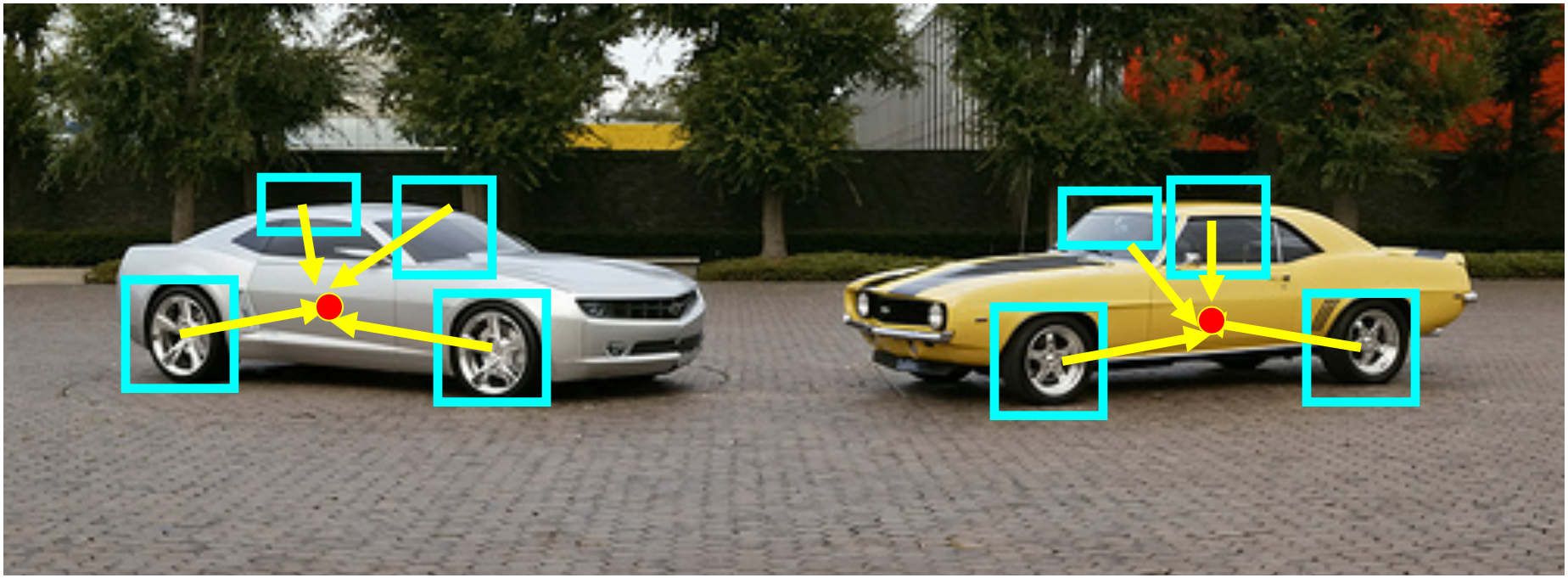
g) Sparse flexible model
Carneiro & Lowe ‘06

from Sparse Flexible Models of Local Features
Gustavo Carneiro and David Lowe, ECCV 2006

Implicit shape models by generalized Hough voting

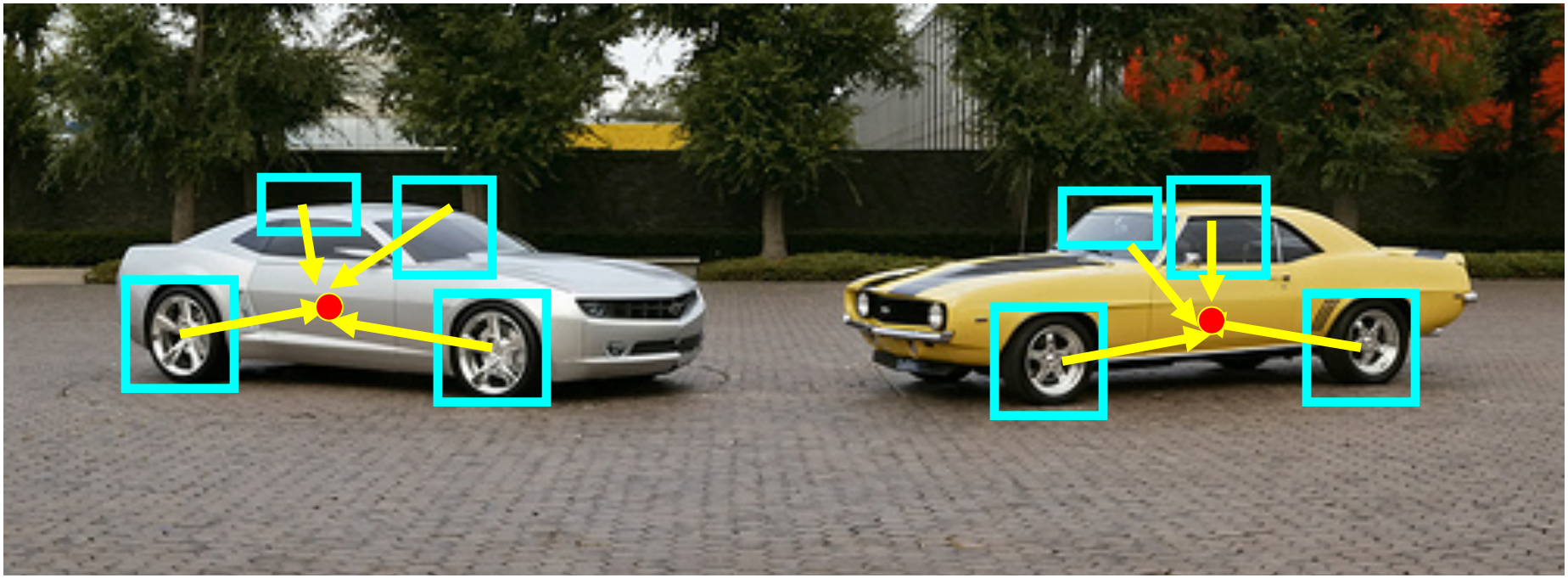
B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV Workshop on Statistical Learning in Computer Vision 2004

Object representation:
Constellation of parts w.r.t object centroid



B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV Workshop on Statistical Learning in Computer Vision 2004

Object representation:
How to capture constellation of parts?
Using Hough Voting



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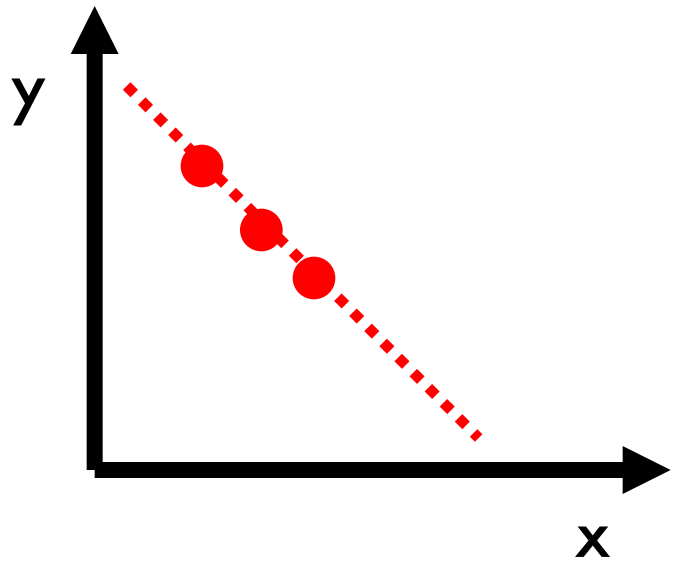
Hough transform

P.V.C. Hough, *Machine Analysis of Bubble Chamber Pictures,* Proc. Int. Conf. High Energy Accelerators and Instrumentation, 1959

Given a set of points, find the curve or line that explains the data points best



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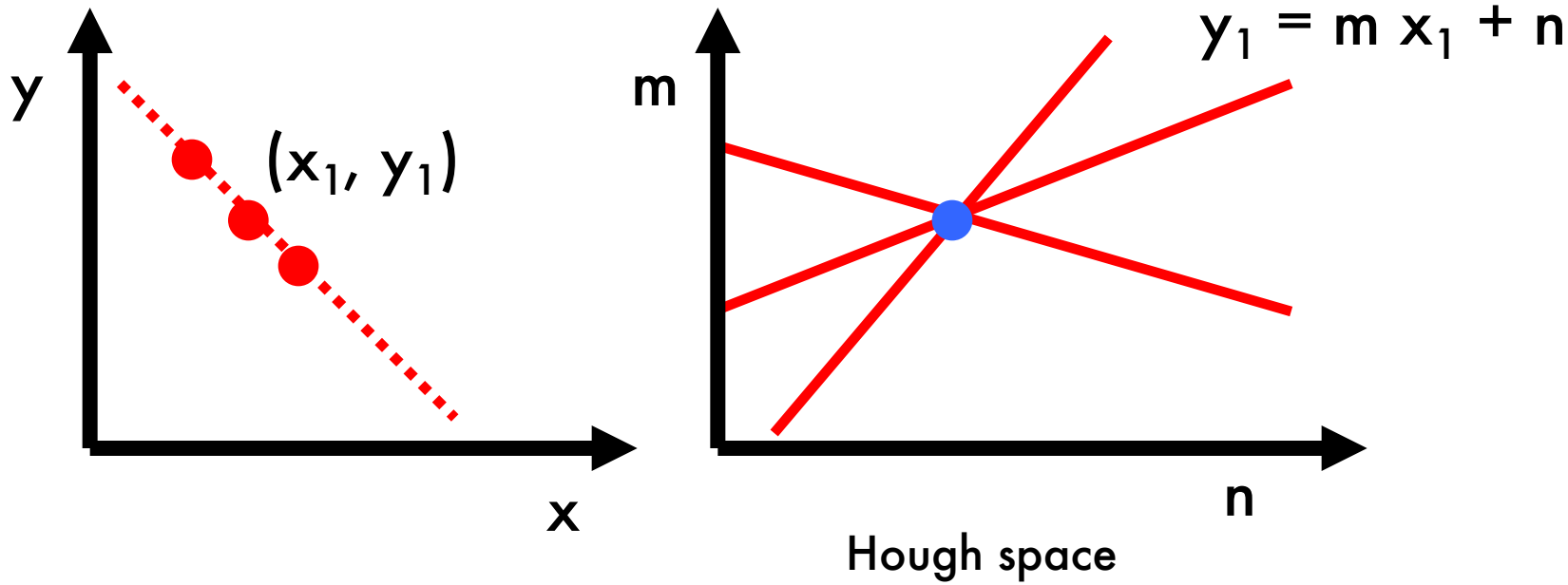
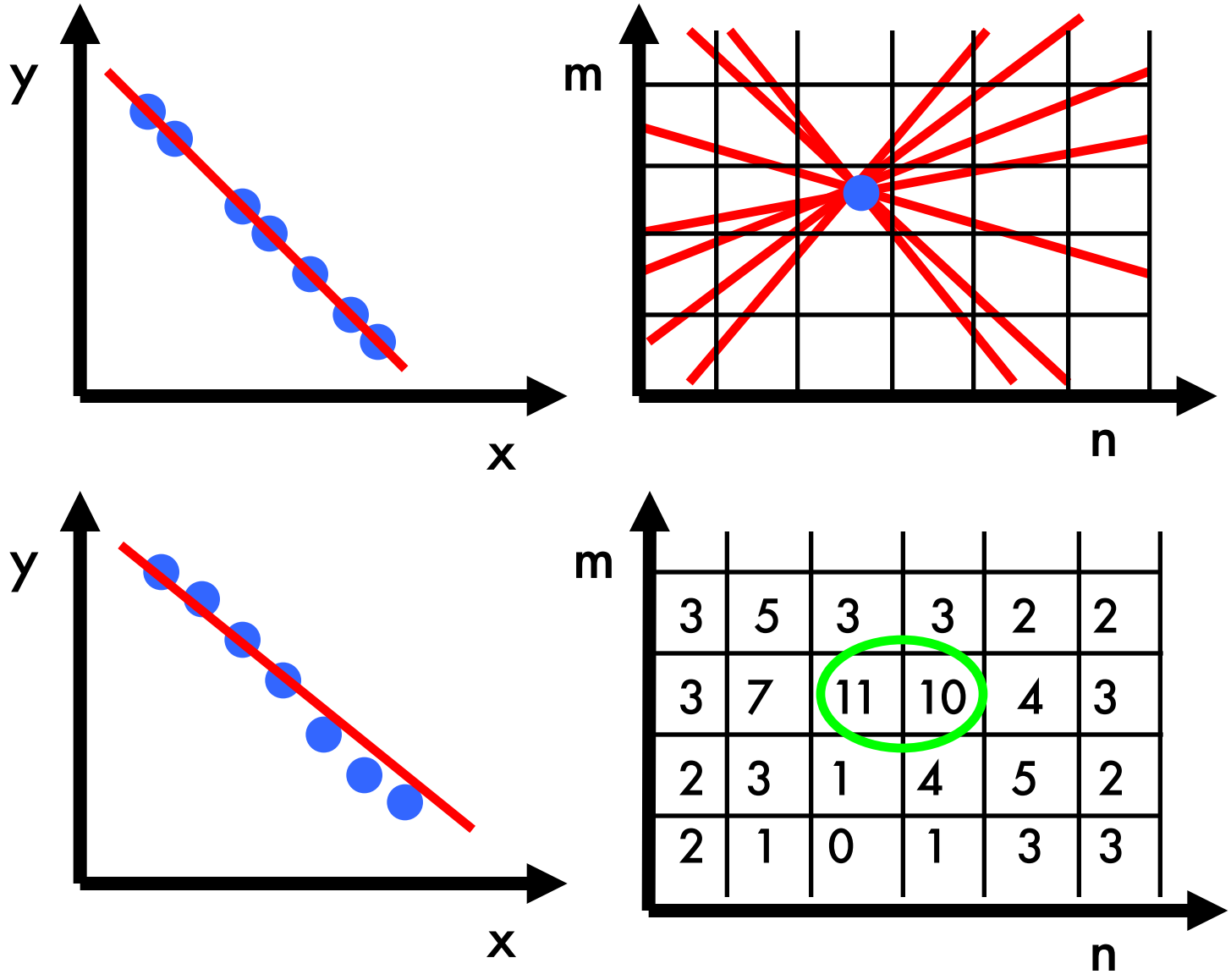


$$y = m\,x + n$$

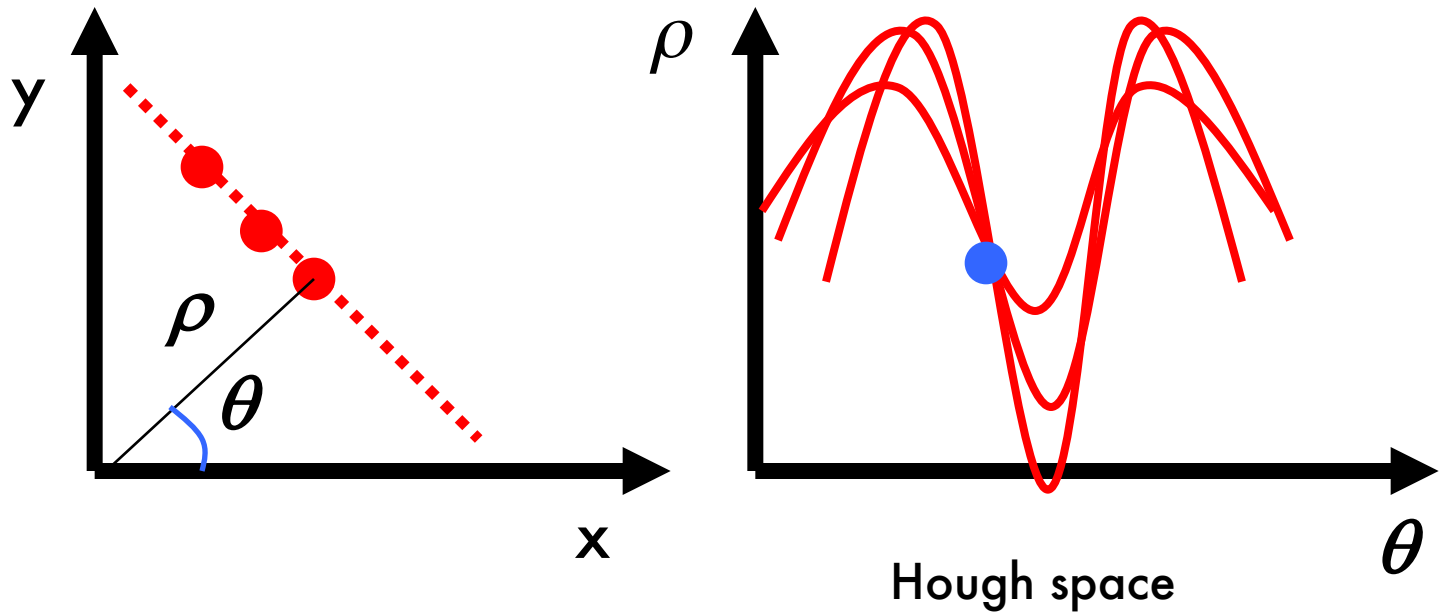
Hough transform



Hough transform

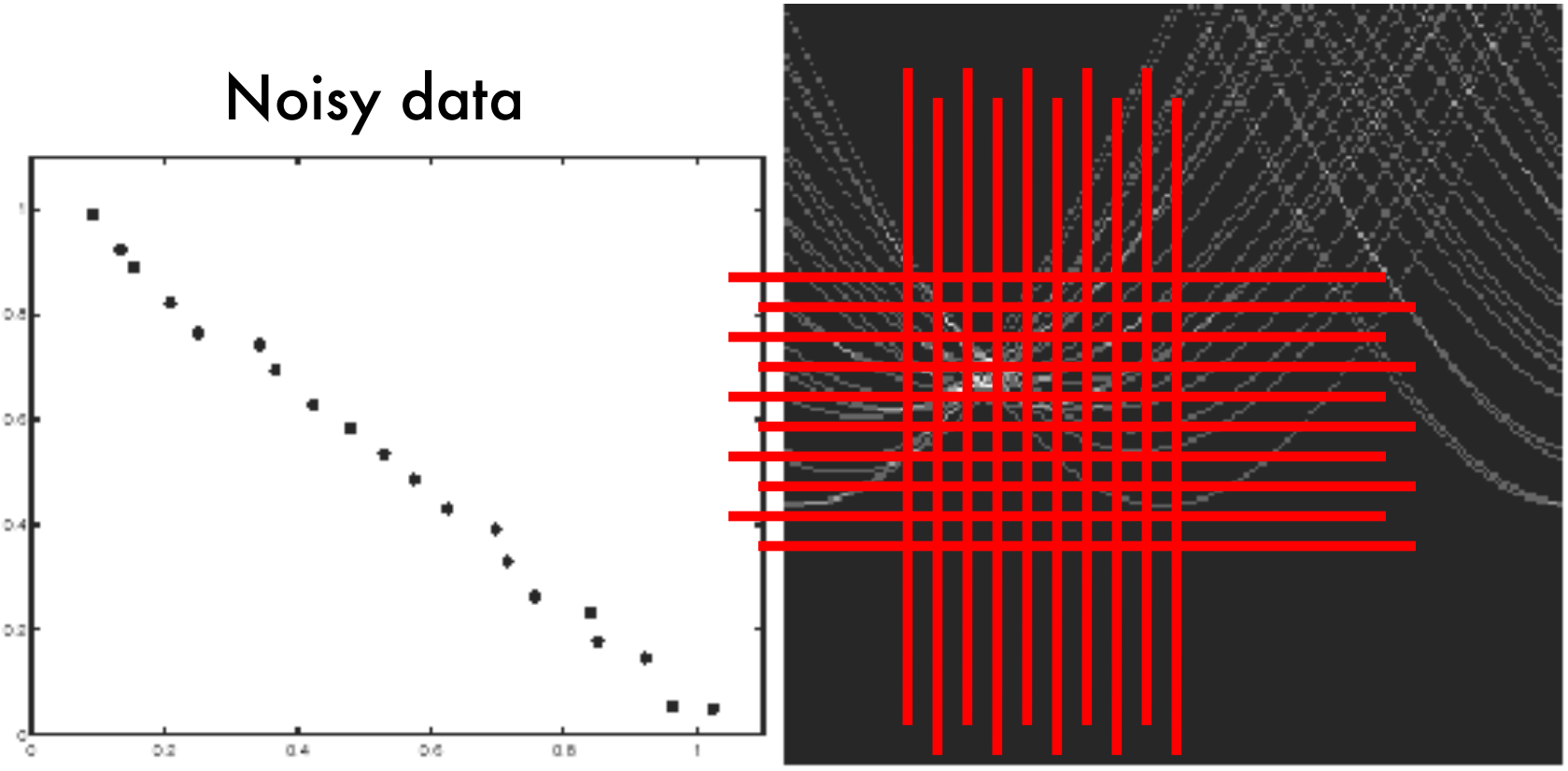
P.V.C. Hough, *Machine Analysis of Bubble Chamber Pictures,* Proc. Int. Conf. High Energy Accelerators and Instrumentation, 1959

Use a polar representation for the parameter space



$$x\cos\theta + y\sin\theta = \rho \quad \text{[Eq. 1]}$$

Hough transform - experiments

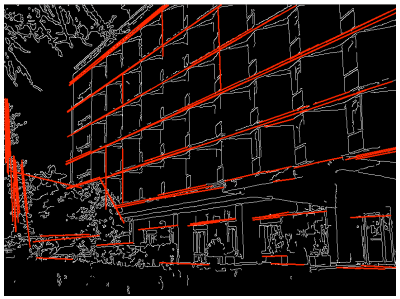
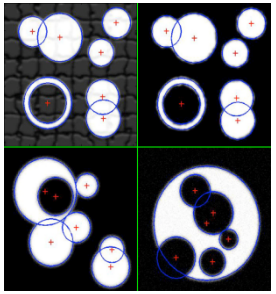
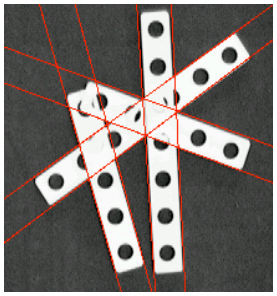


IDEA: introduce a grid to count intersection points in each cell

Issue: Grid size needs to be adjusted…

Generalized Hough Transform

- Parts in query image vote for a learnt model
- Significant aggregations of votes correspond to models
- Popular for detecting parameterized shapes
  - Hough'59, Duda&Hart'72, Ballard'81,…

Slide Modified from *S. Maji*

Generalized Hough Transform

- GOAL: detect arbitrary shapes defined by boundary points and a reference point

Learning a model:

For a given shape S, at each boundary point $\mathbf{p}_i$ of S, compute displacement vector $\mathbf{r}_i = \mathbf{a} - \mathbf{p}_i$ [Eq. 2]

Store these vector $\mathbf{r}_i$ in a table indexed by the gradient orientation θ_i computed at $\mathbf{p}_i$

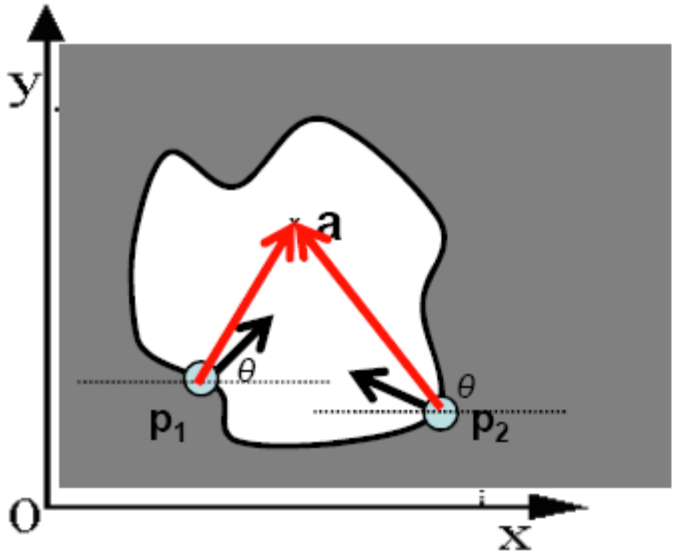
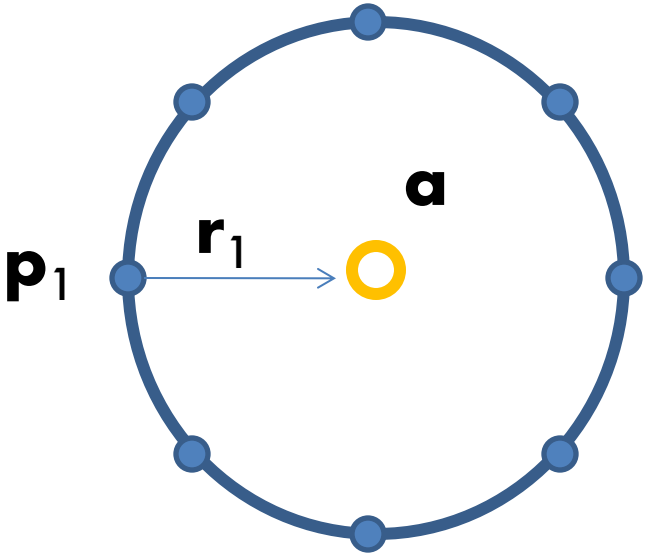


Image space

[Dana H. Ballard, Generalizing the Hough Transform to Detect Arbitrary Shapes, 1980]

Credit slide: C. *Grauman*

Example: a circle



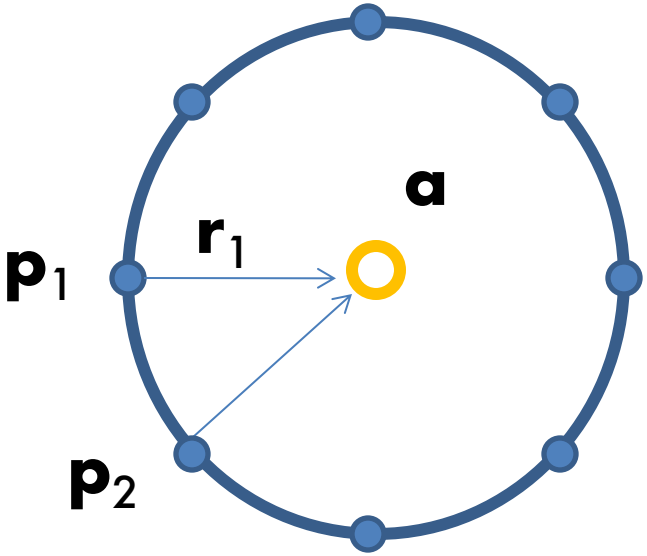
p	θ	r_x	r_y
1	0	1	0

Learning a model:

For a given shape S, at each boundary point $\mathbf{p}_i$ of S, compute displacement vector $\mathbf{r}_i = \mathbf{a} - \mathbf{p}_i$ [Eq. 2]

Store these vector $\mathbf{r}_i$ in a table indexed by the gradient orientation θ_i computed at $\mathbf{p}_i$

Example: a circle



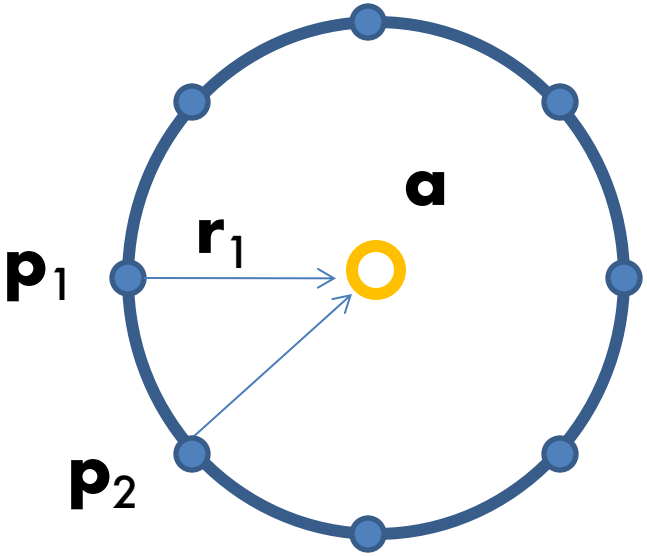
p	θ	r_x	r_y
1	0	1	0
2	?	?	?

Learning a model:

For a given shape S, at each boundary point $\mathbf{p}_i$ of S, compute displacement vector $\mathbf{r}_i = \mathbf{a} - \mathbf{p}_i$ [Eq. 2]

Store these vector $\mathbf{r}_i$ in a table indexed by the gradient orientation θ_i computed at $\mathbf{p}_i$

Example: a circle



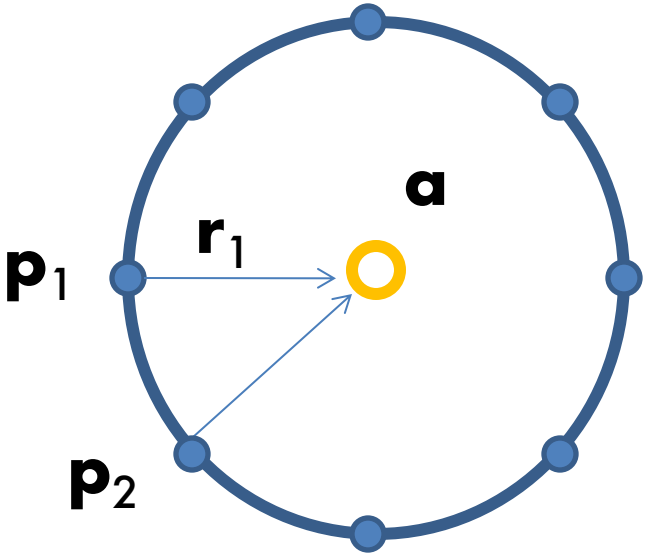
p	θ	r_x	r_y
1	0	1	0
2	45	0.7	0.7

Learning a model:

For a given shape S, at each boundary point $\mathbf{p}_i$ of S, compute displacement vector $\mathbf{r}_i = \mathbf{a} - \mathbf{p}_i$ [Eq. 2]

Store these vector $\mathbf{r}_i$ in a table indexed by the gradient orientation θ_i computed at $\mathbf{p}_i$

Example: a circle



p	θ	r_x	r_y
1	0	1	0
2	45	0.7	0.7
3	90	0	1
4	135	-0.7	0.7
	…		
8	270	0.7	-0.7

Learning a model:

For a given shape S, at each boundary point $\mathbf{p}_i$ of S, compute displacement vector $\mathbf{r}_i = \mathbf{a} - \mathbf{p}_i$ [Eq. 2]

Store these vector $\mathbf{r}_i$ in a table indexed by the gradient orientation θ_i computed at $\mathbf{p}_i$

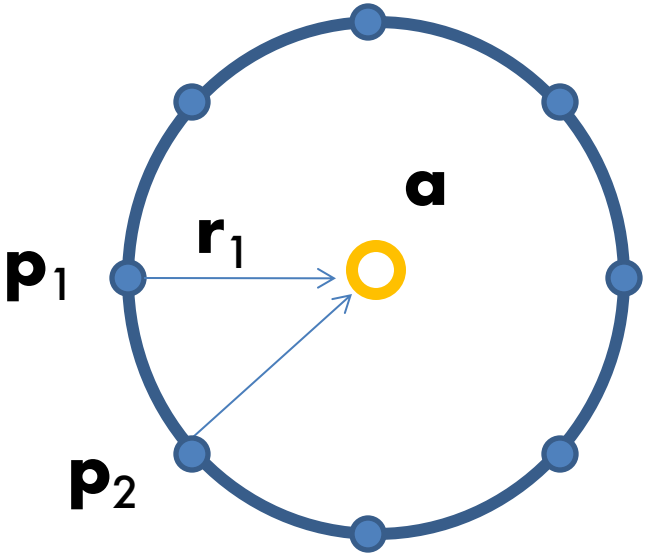
Generalized Hough Transform

Detecting the *model shape in a new image:*

- For each edge point
  – Index into table with its gradient orientation θ
  – Use retrieved r vectors to vote for position of reference point
- Peak in this Hough space is reference point with most supporting edges

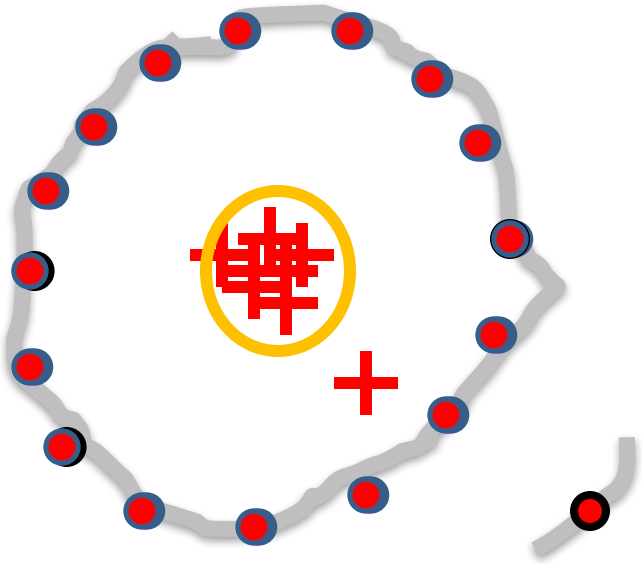
Assuming translation is the only transformation here, i.e., orientation and scale are fixed.

Example: a circle



p	θ	r_x	r_y
1	0	1	0
2	45	0.7	0.7
3	90	0	1
4	135	-0.7	0.7
	…		
8	270	0.7	-0.7

Query



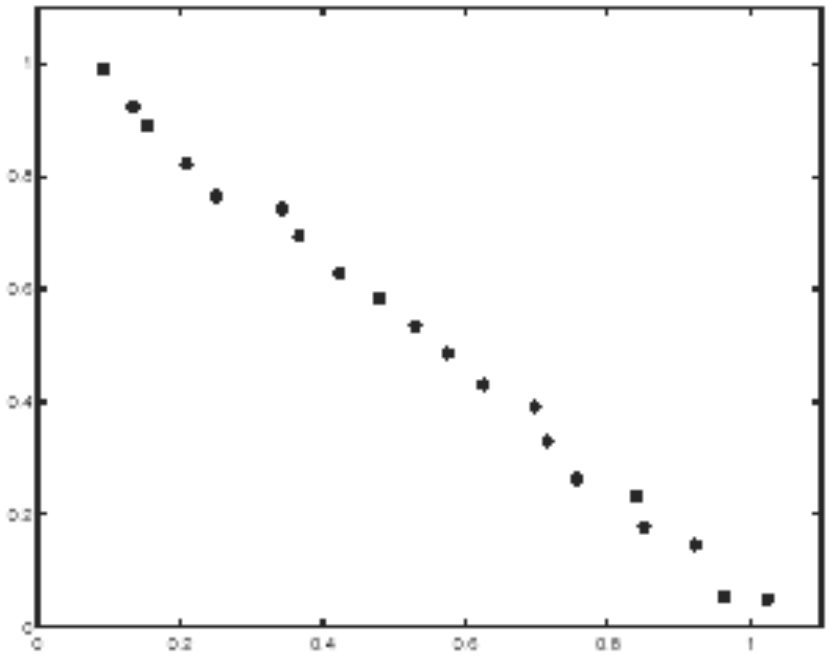
$Q_1 \rightarrow \theta = 0 \rightarrow R = [r_x, r_y] = [1,0] \rightarrow C_1 = Q_1 + R$

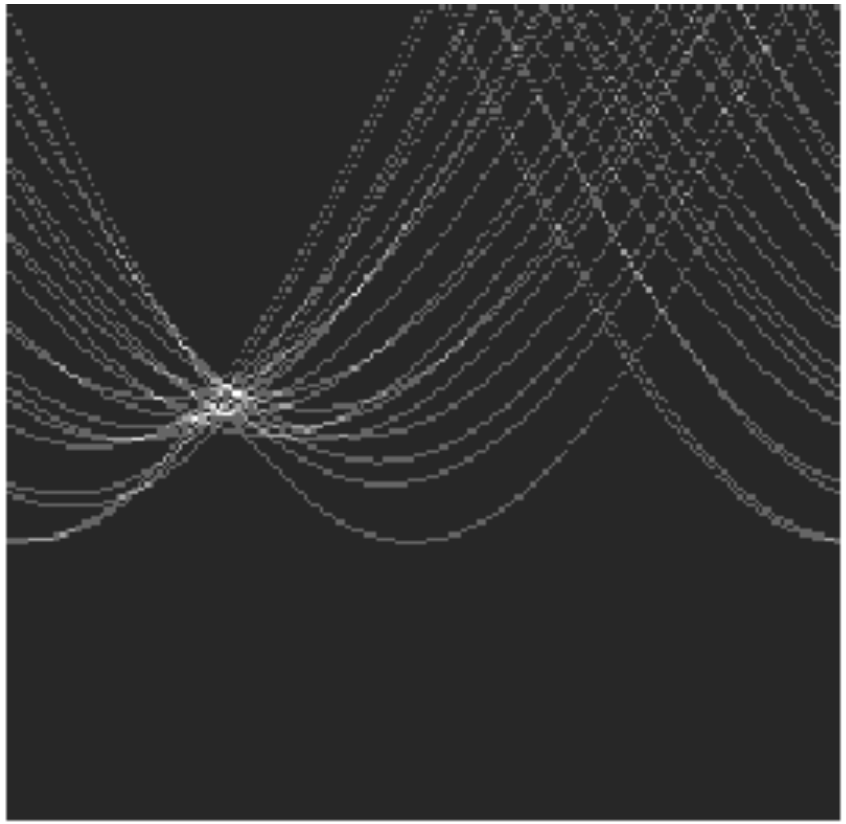
$Q_2 \rightarrow \theta = 45 \rightarrow R = [r_x, r_y] = [.7,.7] \rightarrow C_2 = Q_2 + R$

$Q_k \rightarrow \theta = -180 \rightarrow R = [r_x, r_y] = [-1, 0] \rightarrow C_k = Q_k + R$

⋮

Conceptually similar to

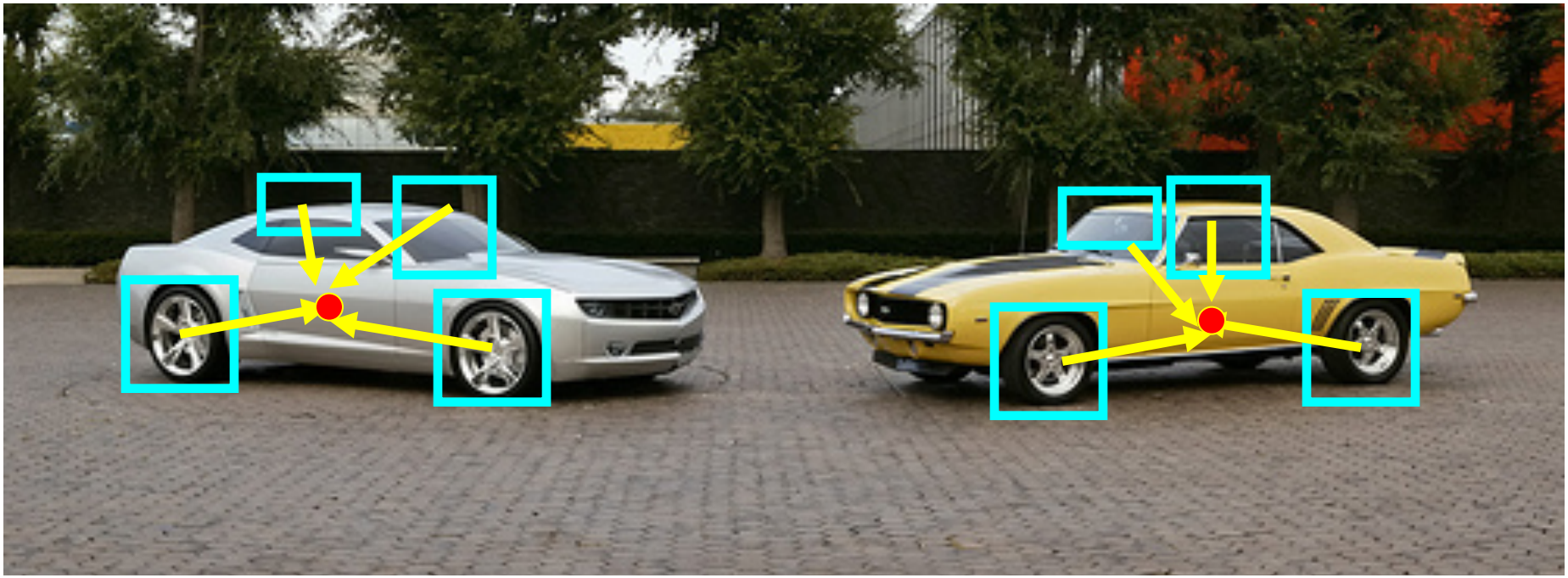




Implicit Shape Model

Captures constellation of parts using Hough Voting

- Instead of indexing displacements by gradient orientations, index by "visual codeword"

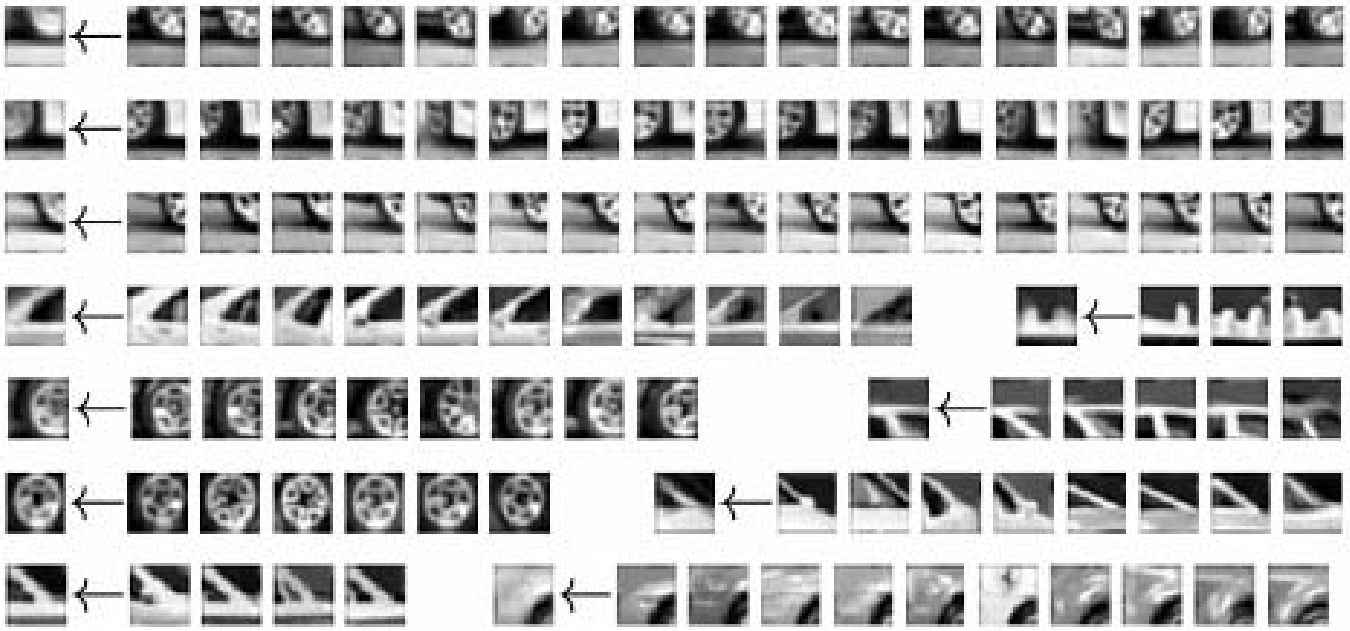


- Enable detection without sliding windows!

B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV Workshop on Statistical Learning in Computer Vision 2004

Implicit shape models: Training

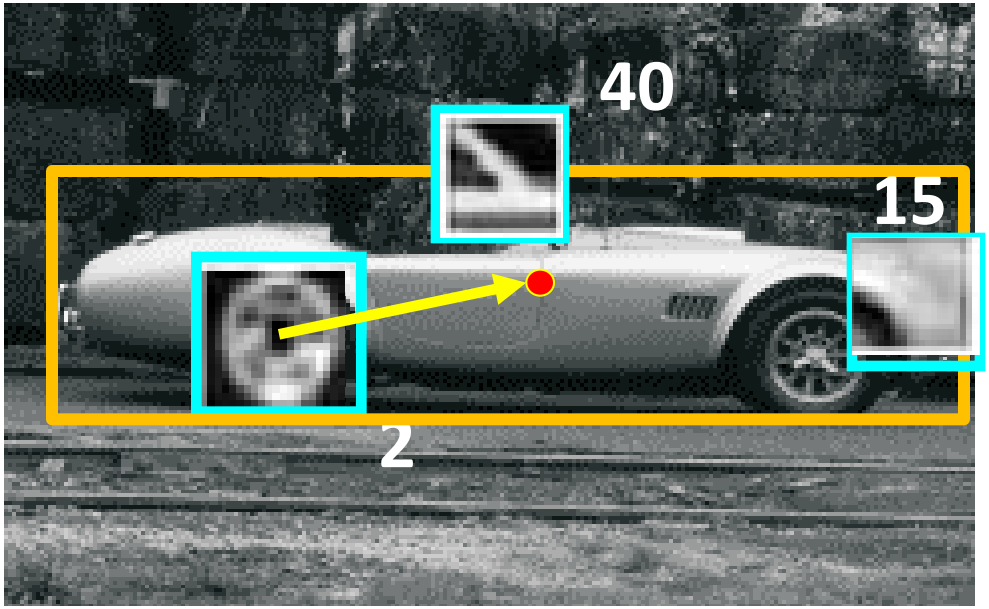
1. Build codebook of patches around extracted interest points using clustering (same as for BOW models)



Credit slide: S. Lazebnik

Implicit shape models: Training

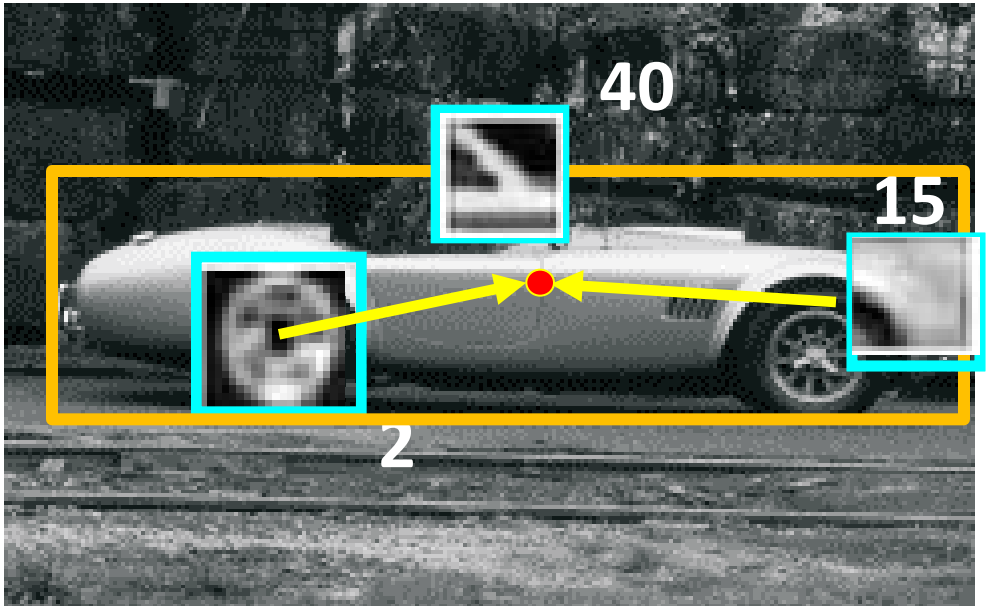
1. Build codebook of patches around extracted interest points using clustering
2. Map the patch around each interest point to closest codebook entry
3. For each codebook entry, store all positions relative to object center [center is given] and scale [bounding box is given]



CW	rx	ry
2	0.9	0.1

Implicit shape models: Training

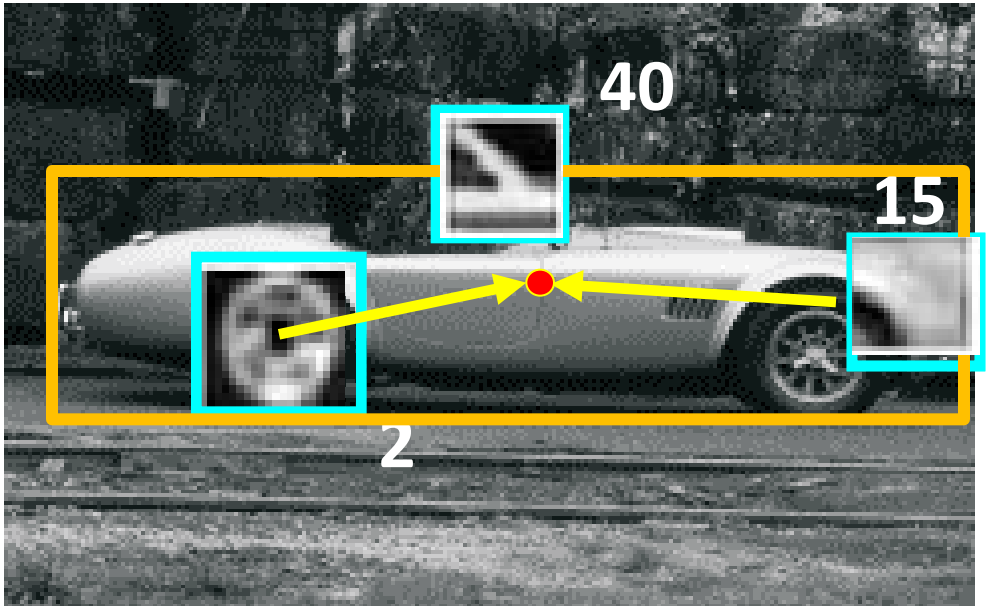
1. Build codebook of patches around extracted interest points using clustering
2. Map the patch around each interest point to closest codebook entry
3. For each codebook entry, store all positions relative to object center [center is given] and scale [bounding box is given]



CW	rx	ry
2	0.9	.1
15	?	?

Implicit shape models: Training

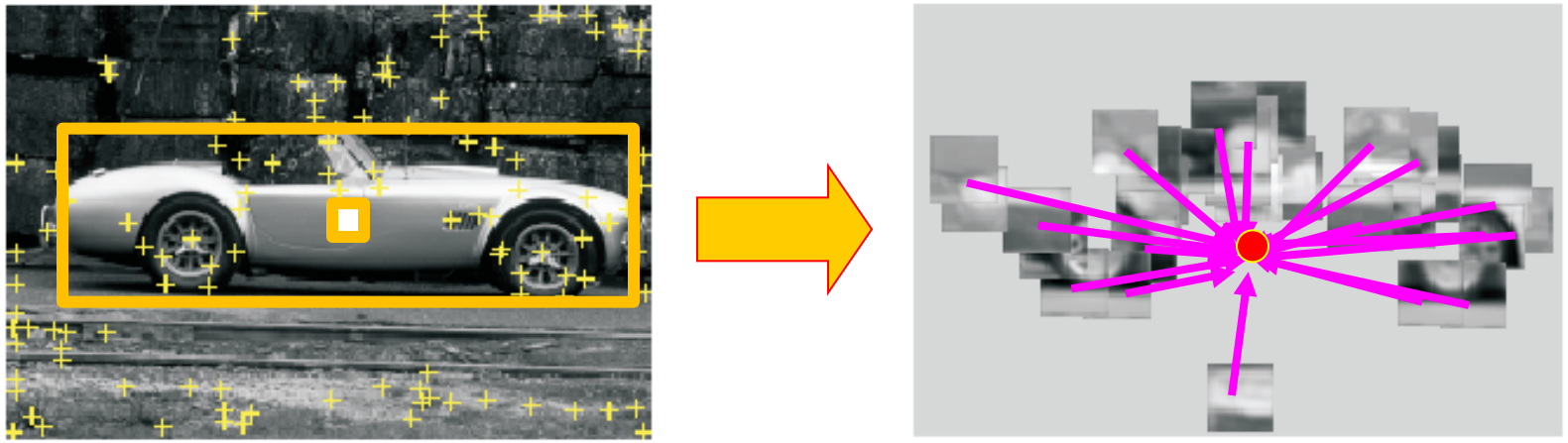
1. Build codebook of patches around extracted interest points using clustering
2. Map the patch around each interest point to closest codebook entry
3. For each codebook entry, store all positions relative to object center [center is given] and scale [bounding box is given]



CW	rx	ry
2	0.9	.1
15	-1	0
…	…	…
N	0.7	-0.7

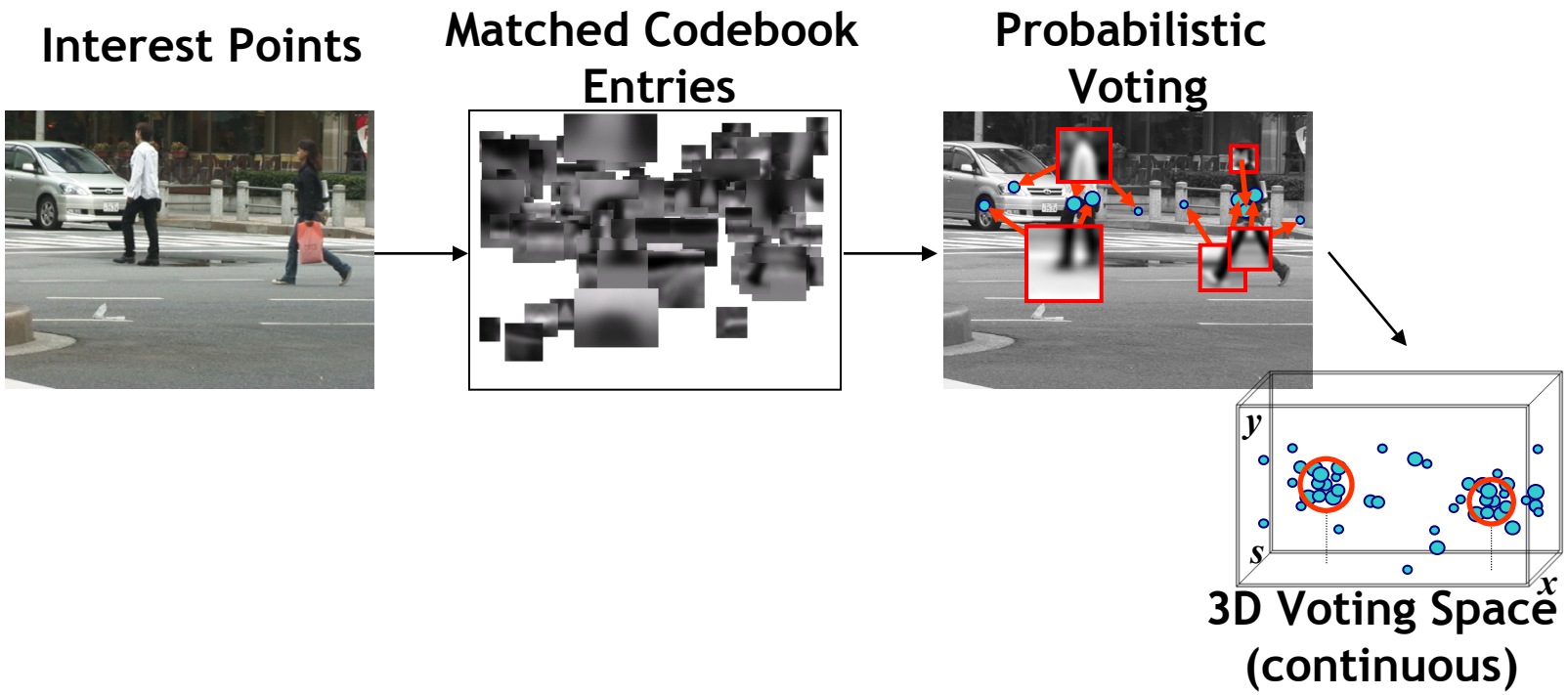
Implicit shape models: Training

1. Build codebook of patches around extracted interest points using clustering
2. Map the patch around each interest point to closest codebook entry
3. For each codebook entry, store all positions relative to object center [center is given] and scale [bounding box is given]



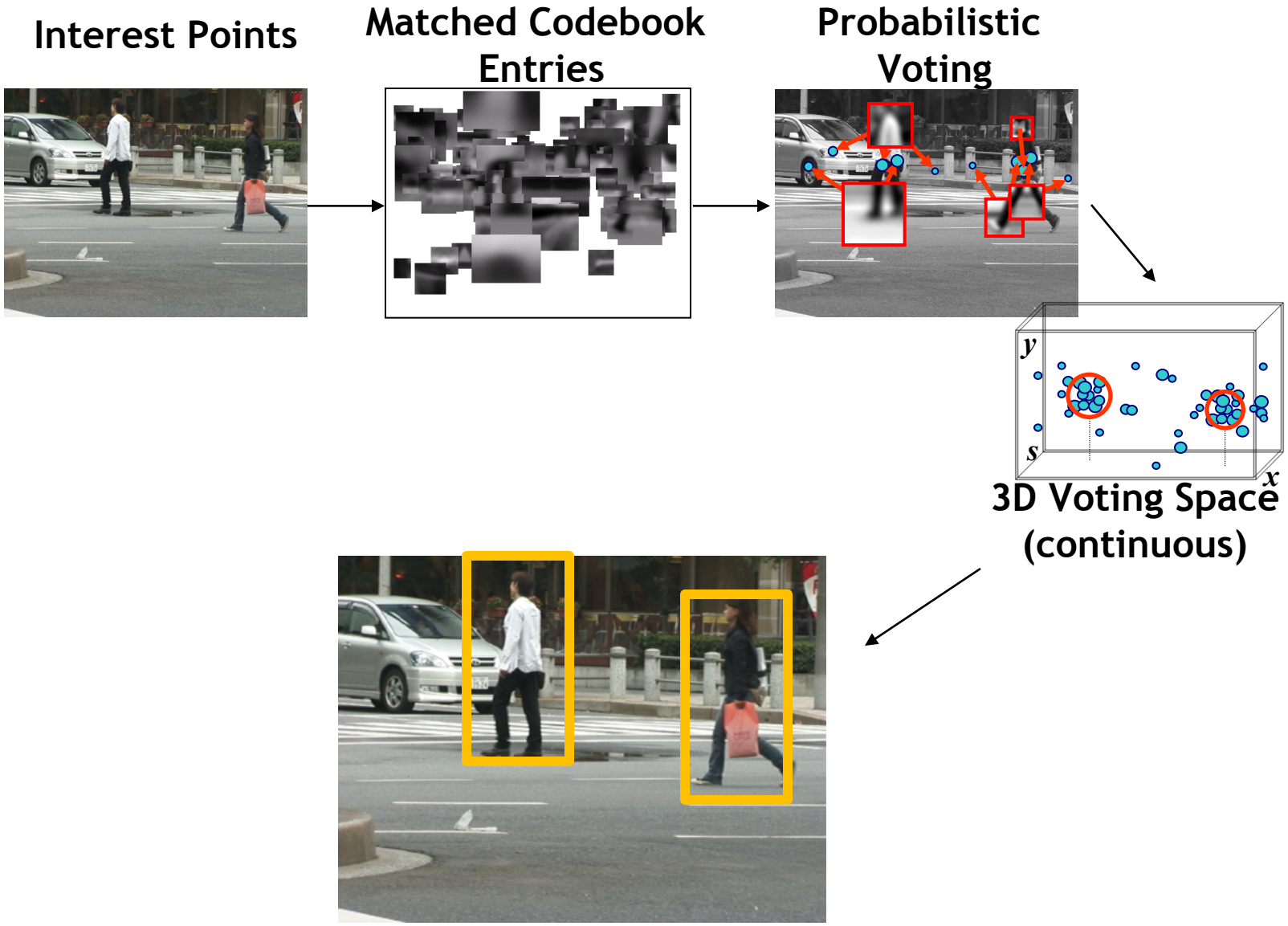
Credit slide: S. Lazebnik

Implicit Shape Model - Recognition



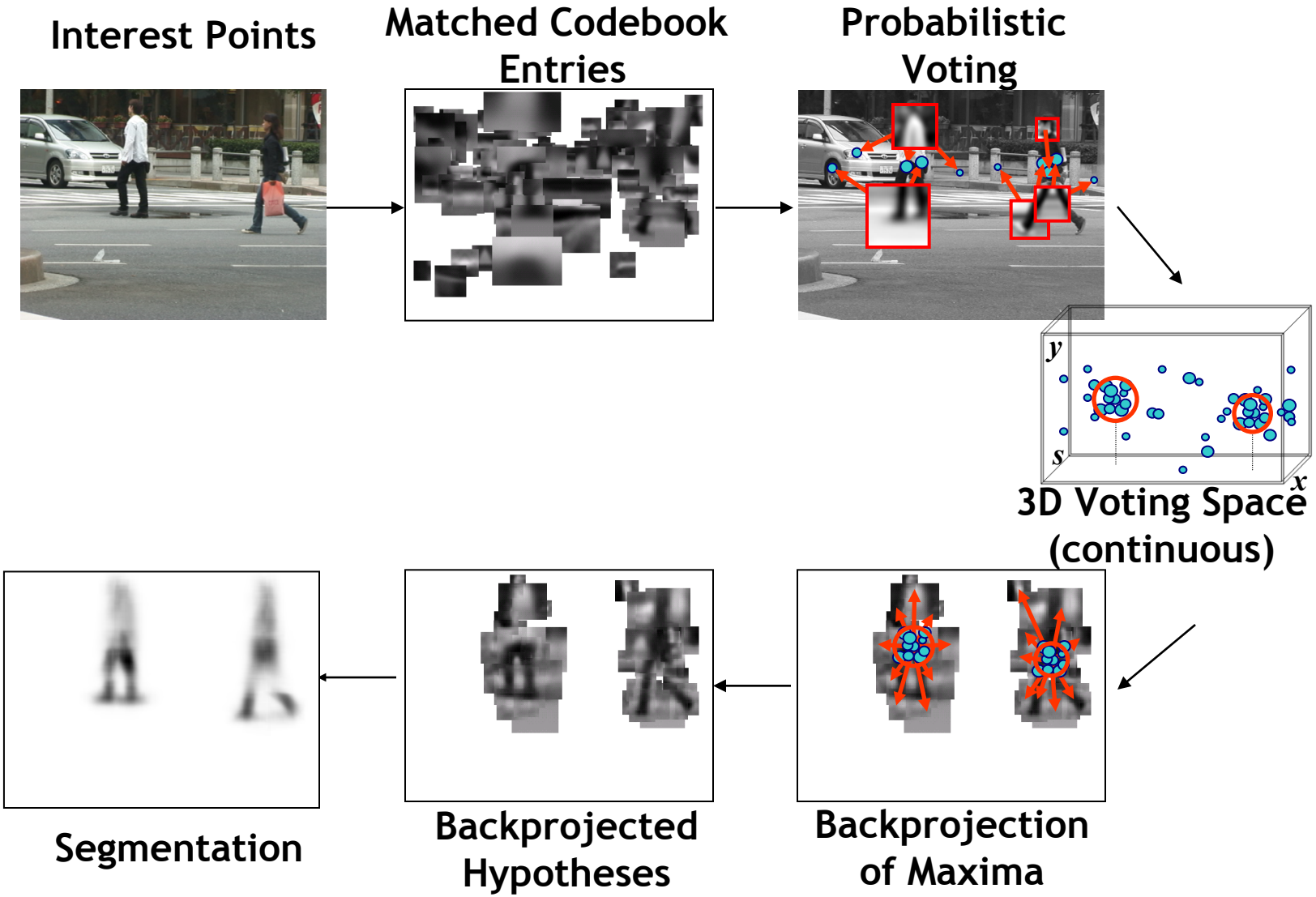
[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Implicit Shape Model - Recognition



[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

Implicit Shape Model - Segmentation



[Leibe, Leonardis, Schiele, SLCV'04; IJCV'08]

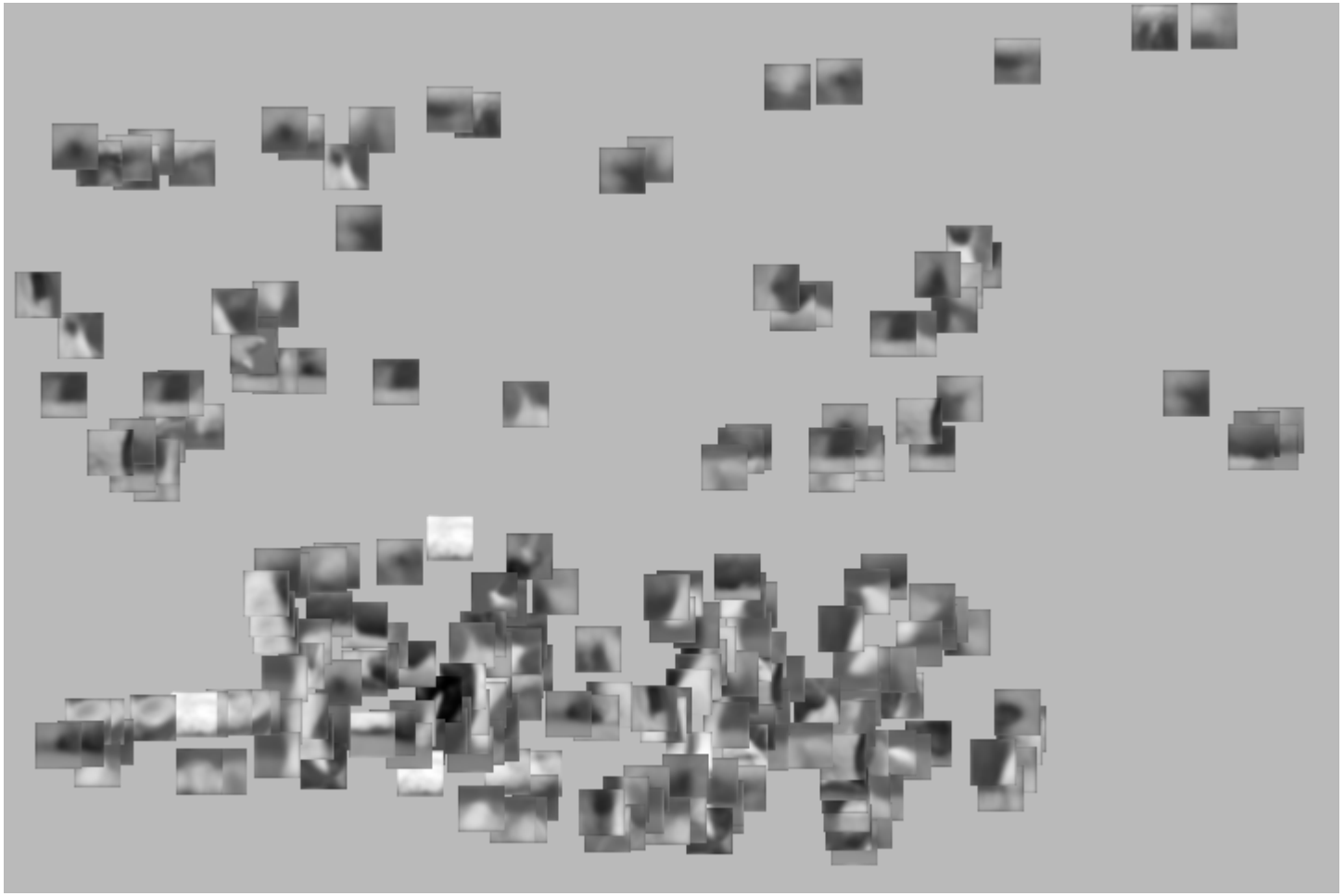
Example: Results on Cows

Original image

Example: Results on Cows

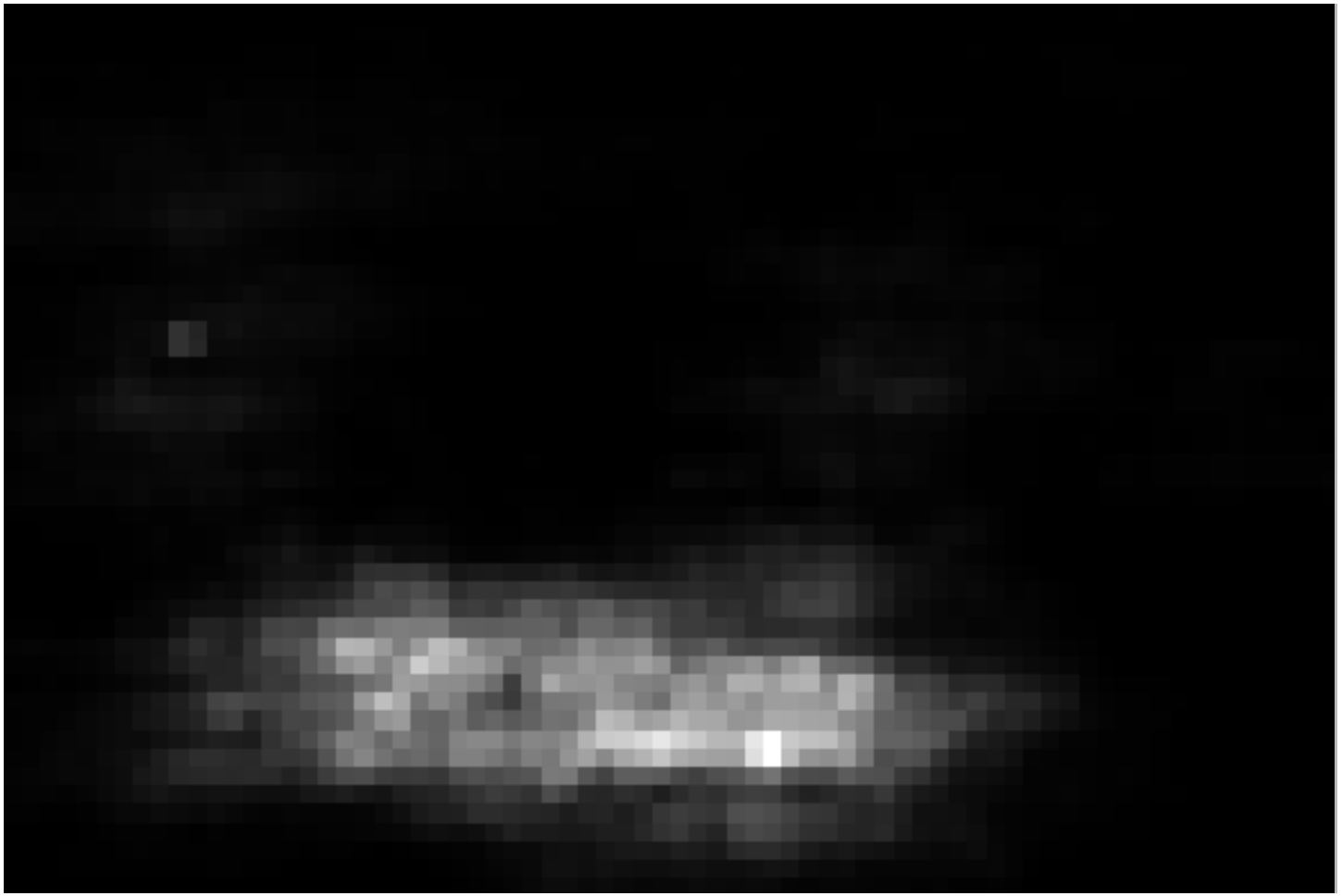
Interest points

Example: Results on Cows



Matched patches

Example: Results on Cows



Prob. Votes

Example: Results on Cows

1st hypothesis

Example: Results on Cows

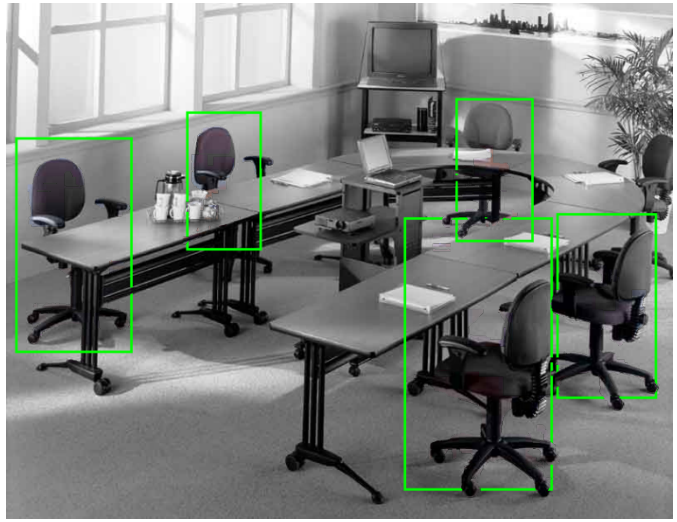
2nd hypothesis

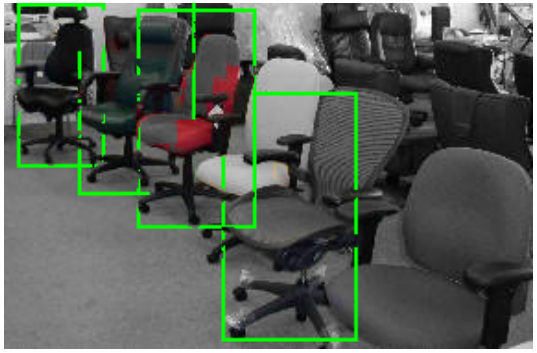
Example: Results on Cows

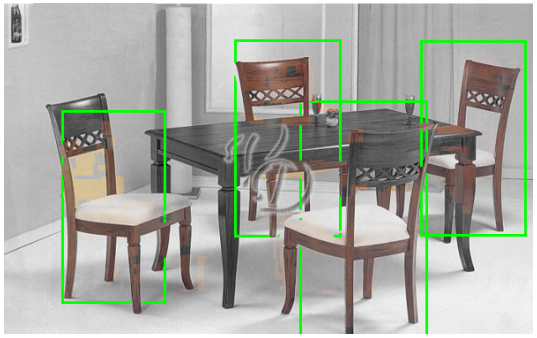
3rd hypothesis

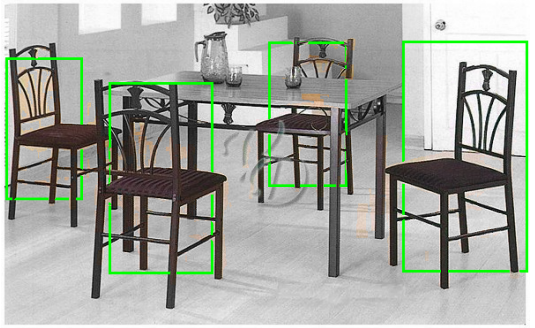
Example Results: Chairs

Dining room chairs









Office chairs

You Can Try It At Home…

- Linux binaries available
  - Including datasets & several pre-trained detectors
  - http://www.vision.ee.ethz.ch/bleibe/code

Many follow up projects:

- Subhransu Maji and Jitendra Malik, Object Detection Using a Max-Margin Hough Transform, CVPR 2009

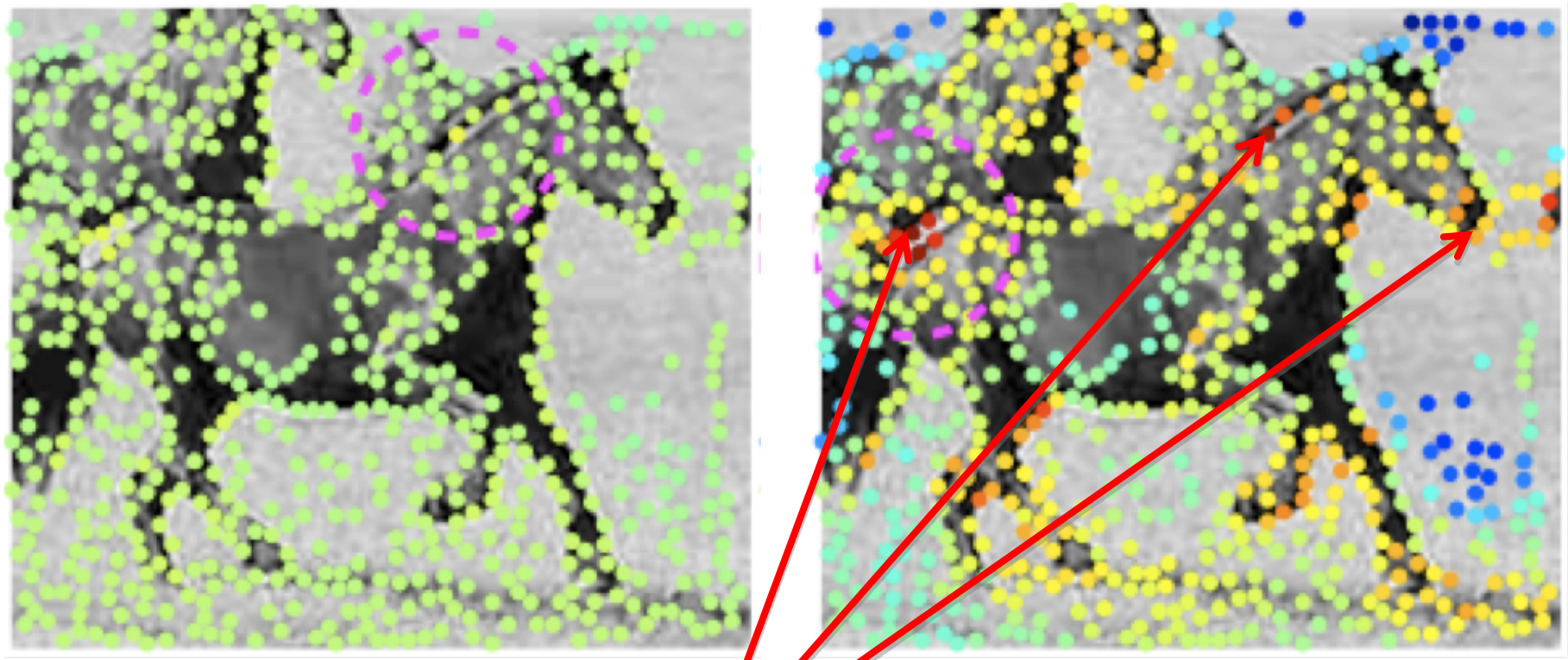
…

- Hough-based tracking of non-rigid objects, M Godec, PM Roth, H Bischof, 2013

Extension: Learning Feature Weights

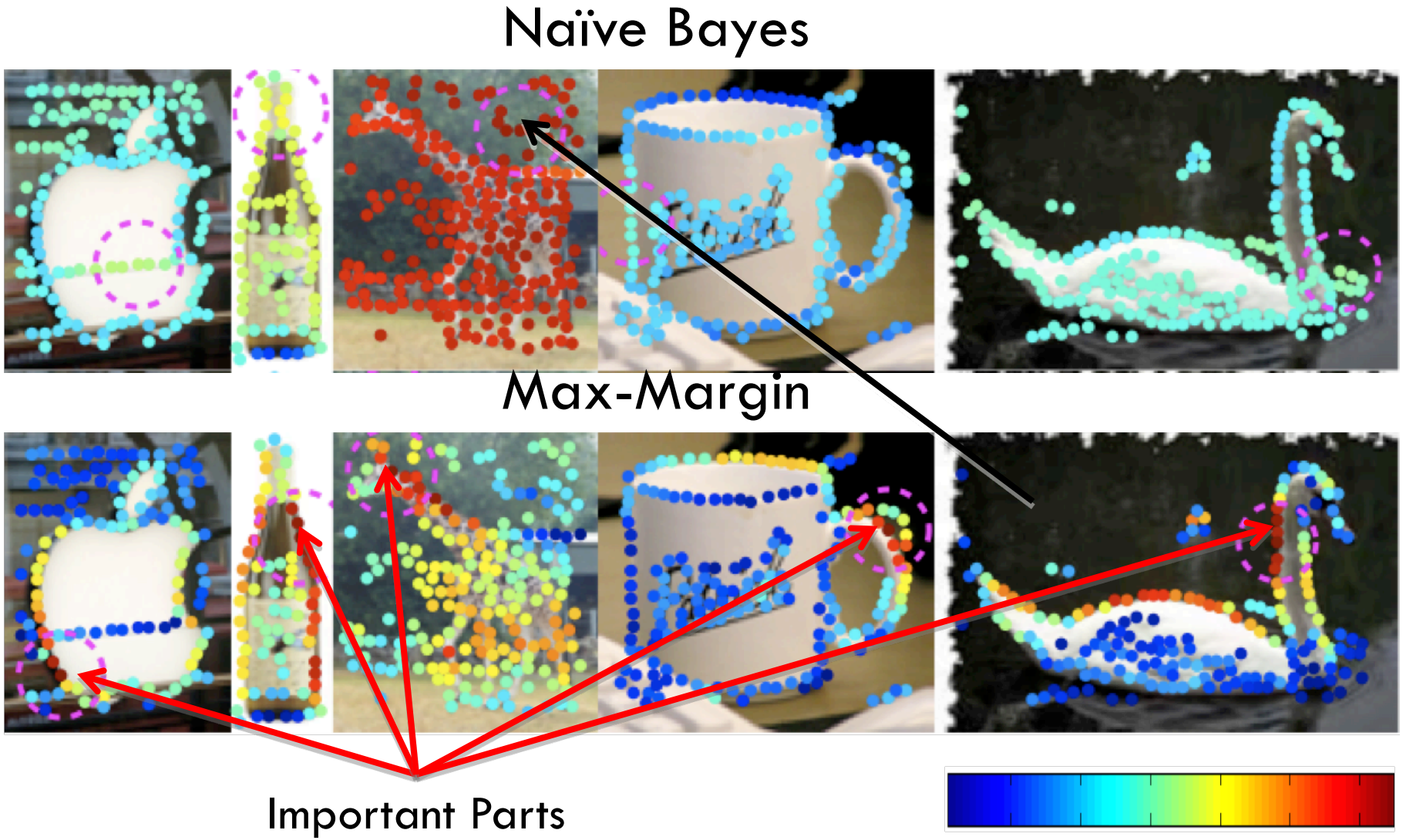
Subhransu Maji and Jitendra Malik, Object Detection Using a Max-Margin Hough Transform, CVPR 2009

Weights can be learned optimally using a max-margin framework.



Extension: Learning Feature Weights

Subhransu Maji and Jitendra Malik, Object Detection Using a Max-Margin Hough Transform, CVPR 2009



Detection Results (ETHZ dataset)

Recall @ 1.0 False Positives Per Window

Category	Uniform	Naive Bayes	Max-margin
Applelogos	70.0	70.0	**85.0**
Bottles	62.5	**71.4**	67.0
Giraffes	47.1	47.1	**55.0**
Mugs	35.5	35.5	**55.0**
Swans	47.1	**47.1**	42.5
Average	52.4	54.2	**60.9**

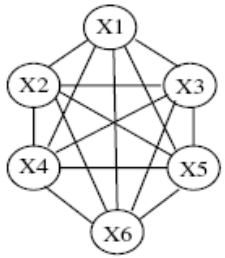
Conclusions

- Pros:
  - Works well for many different object categories
    - Both rigid and articulated objects
  - Doesn't need a sliding window strategy
  - Learns from relatively few (50-100) training examples
  - Enables joint detection and segmentation
  - Still used today for 3D object detection problems

- Cons:
  - Requires supervision
  - Outperformed by CNN-based methods, but require way less training data!

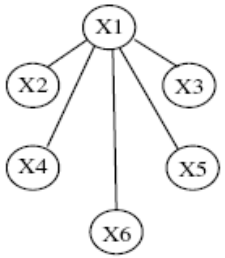
Different connectivity structures

Fergus et al. ’03
Fei-Fei et al. ‘03



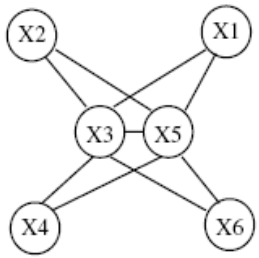
a) Constellation [13]

Crandall et al. ‘05
Leibe 05; Felzenszwalb 09



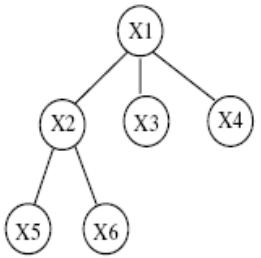
b) Star shape [9, 14]

Crandall et al. ‘05

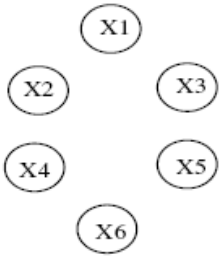


c) k-fan ($k = 2$) [9]

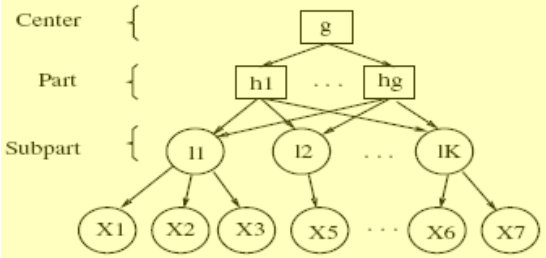
Felzenszwalb &
Huttenlocher ‘00



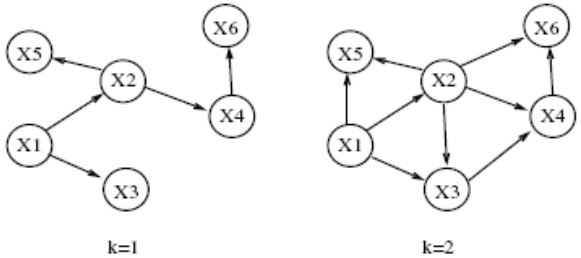
d) Tree [12]



e) Bag of features [10, 21]
Csurka ’04
Vasconcelos ‘00



f) Hierarchy [4]
Bouchard & Triggs ‘05

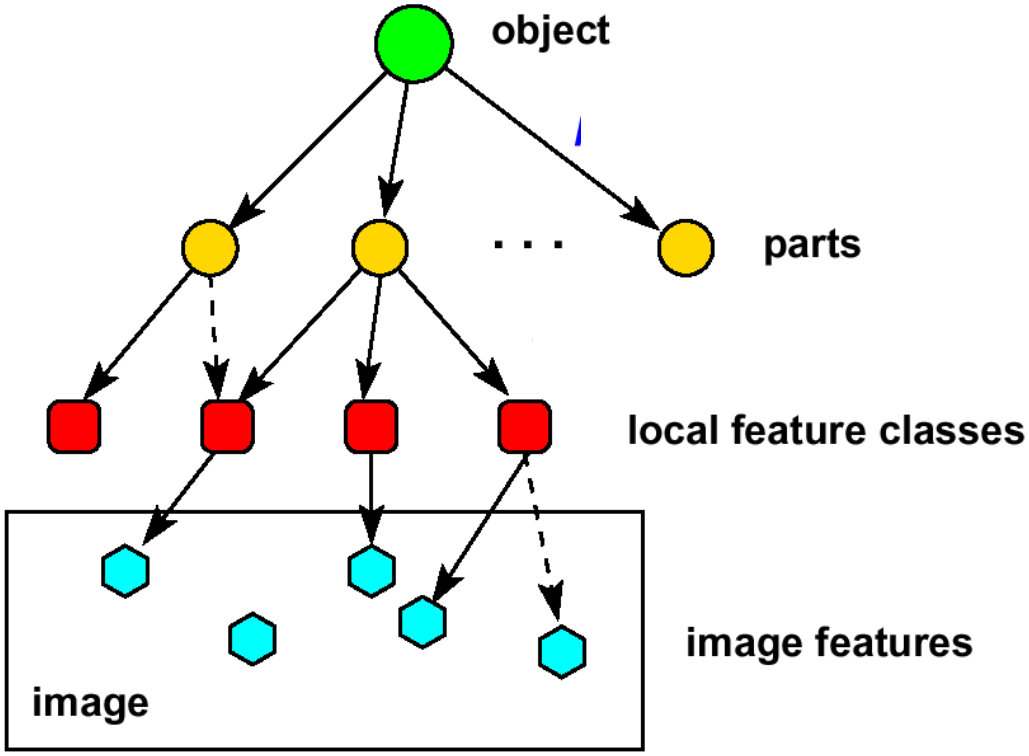


g) Sparse flexible model
Carneiro & Lowe ‘06

from Sparse Flexible Models of Local Features
Gustavo Carneiro and David Lowe, ECCV 2006

Hierarchical representations

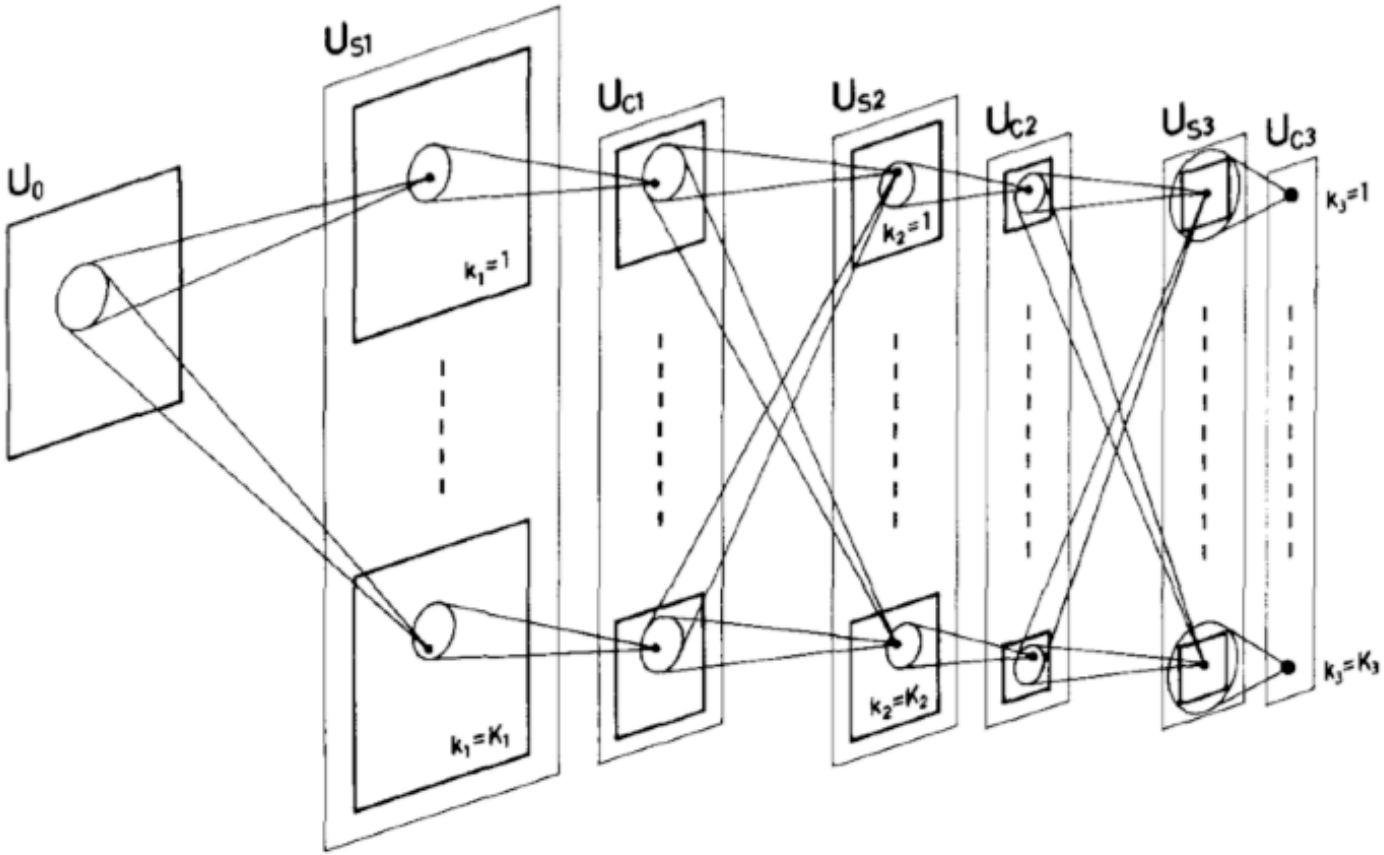
- Pixels → Pixel groupings → Parts → Object



Images from [Amit98,Bouchard05]

Hierarchical representations

- Deep learning architectures and ConvNets

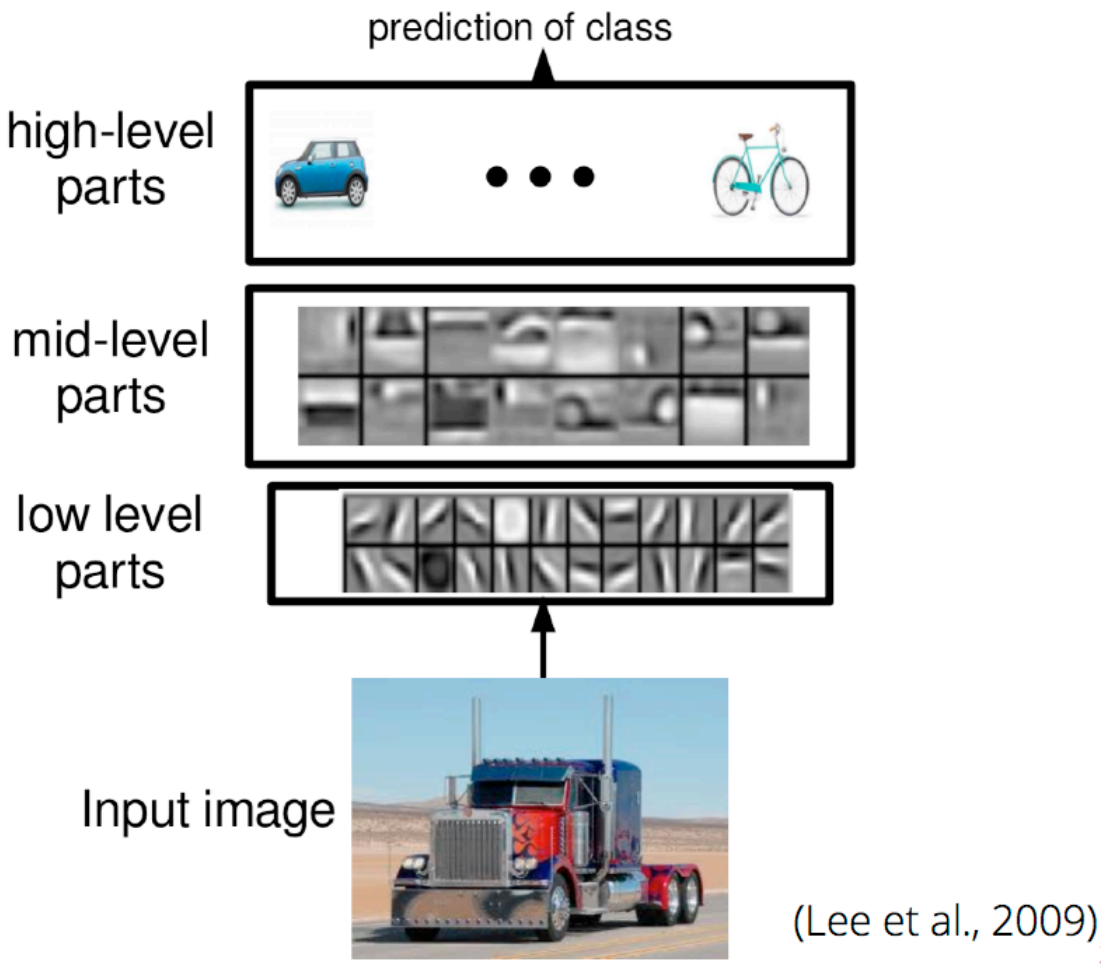


Fukushima,1980
LeCun, 1987

Hierarchical representations

- Deep learning architectures and ConvNets

More on lecture 15!



(Lee et al., 2009)

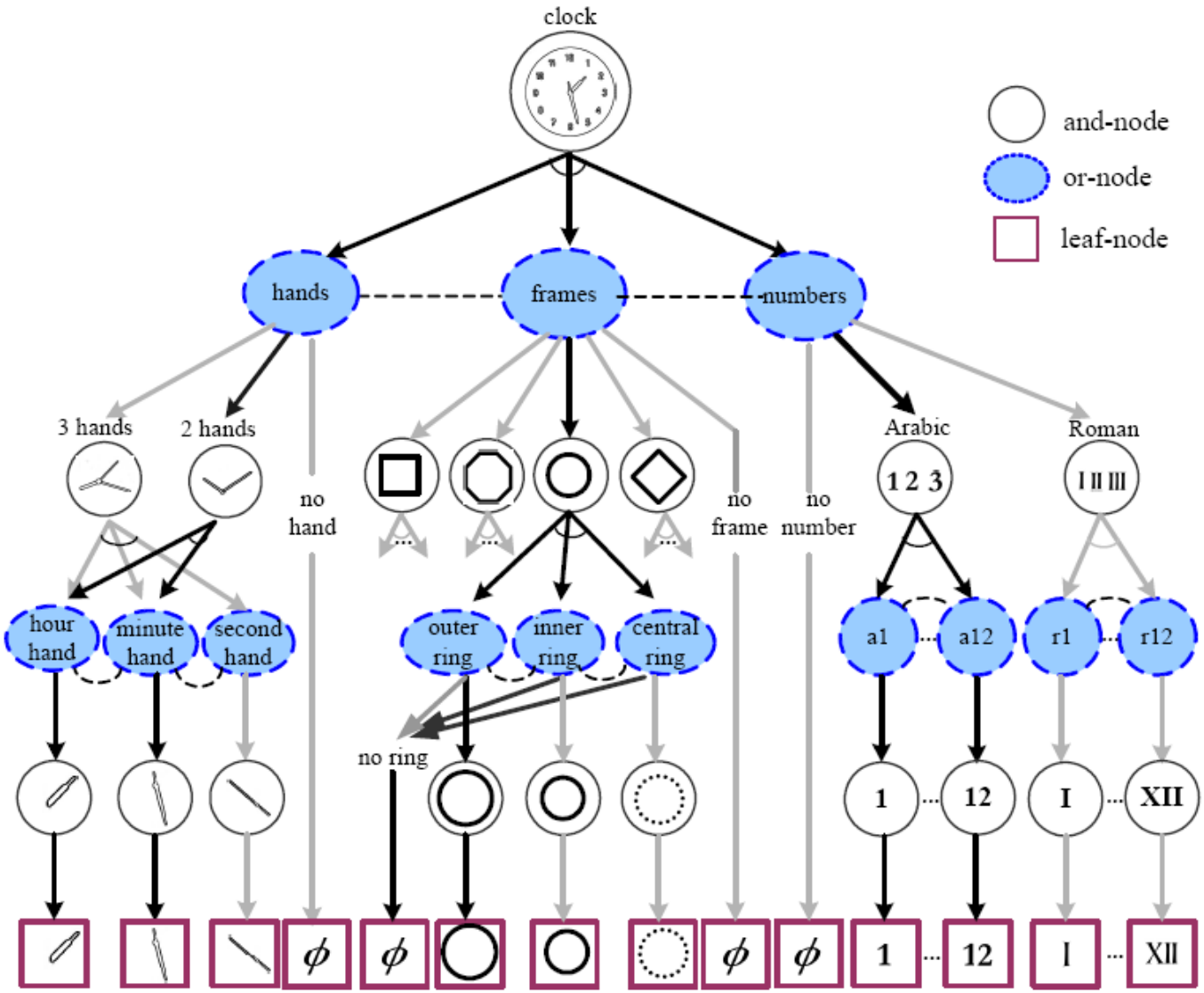
Next lecture

- 2D scene understanding

Appendix

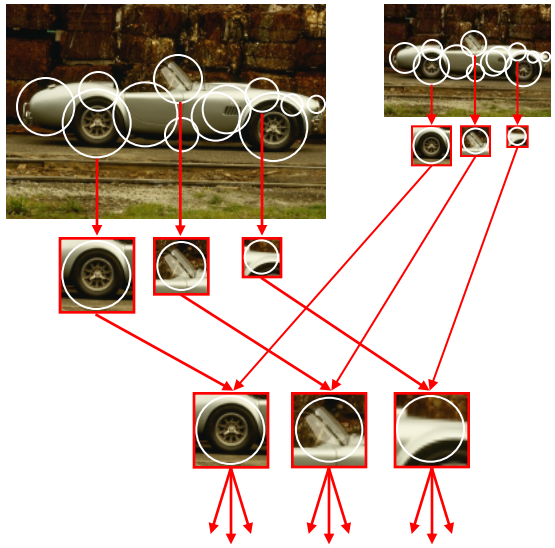
Hierarchical representations

S.C. Zhu et al. and D. Mumford

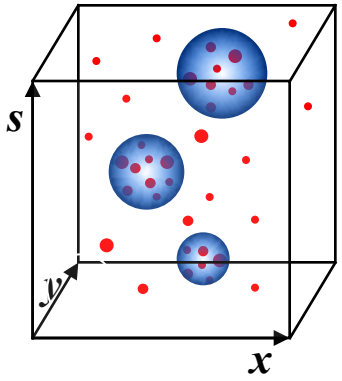


Scale Invariant Voting

- Scale-invariant feature selection
  - Scale-invariant interest points
  - Rescale extracted patches
  - Match to constant-size codebook



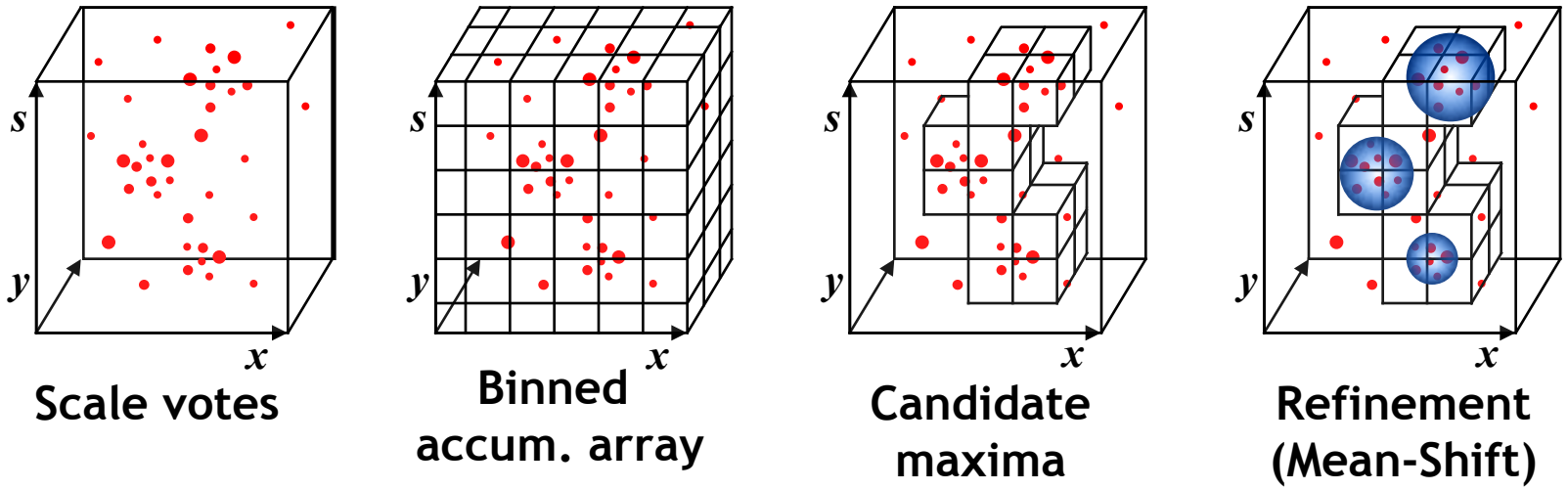
- Generate scale votes
  - Scale as 3rd dimension in voting space
  - Search for maxima in 3D voting space



Search window

Source: Bastian Leibe

Scale Voting: Efficient Computation



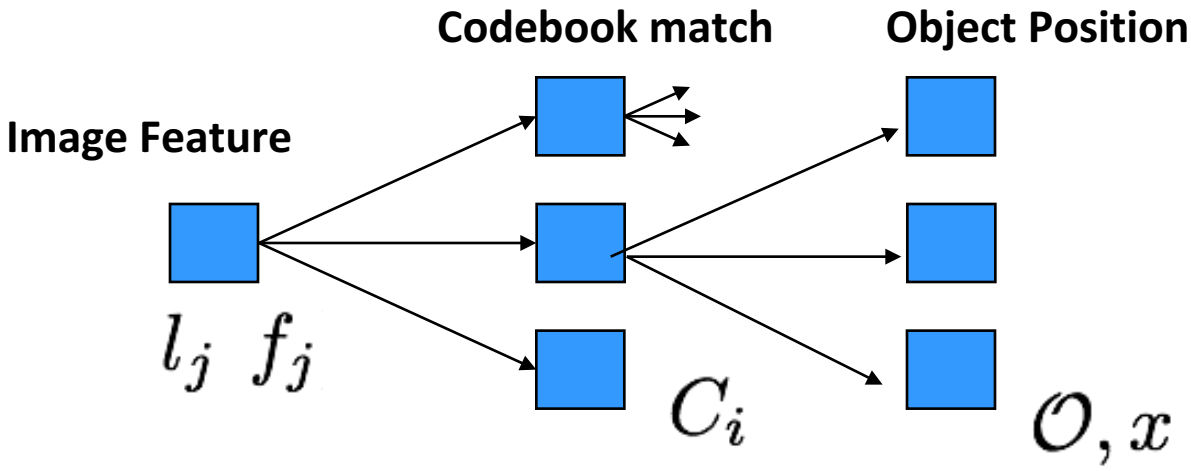
- Continuous Generalized Hough Transform
  - Binned accumulator array similar to standard Gen. Hough Transf.
  - Quickly identify candidate maxima locations
  - Refine locations by Mean-Shift search only around those points

  ⇒ Avoid quantization effects by keeping exact vote locations.

  ⇒ Mean-shift interpretation as kernel prob. density estimation.

Source: Bastian Leibe

Probabilistic Hough Transform



f = features
l = location of the features.
C = codebook entry
O = object class
x = object center

Learnt using a max margin formulation

Maji et al , CVPR 2009

$$S(\mathcal{O}, x) \propto \sum_{i,j} p(x', \mathcal{O}, C_i, l_j', f_j)$$

$$\propto \sum_{i,j} p(x|\mathcal{O}, C_i, l_j) p(C_i|f_j) p(\mathcal{O}|C_i, l_j)$$

Detection Score

Position Posterior distribution of the centroid given the Codeword Ci observed at location lj.

Codeword Match

confidence (or weight) of the codeword Ci.

Influential Works in Detection

- Sung-Poggio (1994, 1998) : ~2000 citations
  - Basic idea of statistical template detection, bootstrapping to get "face-like" negative examples, multiple whole-face prototypes (in 1994)
- Rowley-Baluja-Kanade (1996-1998) : ~3600
  - "Parts" at fixed position, non-maxima suppression, simple cascade, rotation, pretty good accuracy, fast
- Schneiderman-Kanade (1998-2000,2004) : ~1700
  - Careful feature engineering, excellent results, cascade
- Viola-Jones (2001, 2004) : ~11,000
  - Haar-like features, Adaboost as feature selection, hyper-cascade, very fast, easy to implement
- Dalal-Triggs (2005) : ~6500
  - Careful feature engineering, excellent results, HOG feature, online code
- Felzenszwalb-Huttenlocher (2000): ~2100
  - Efficient way to solve part-based detectors
- Weber et al. (2000)
  - Part-based model learnt in a unsupervised fashion; generative
- Felzenszwalb-McAllester-Ramanan (2008): ~1300
  - Excellent template/parts-based blend
- Leibe et al. (2005)
  - Generative approach to detection using hough voting

Courtesy of J Hayes