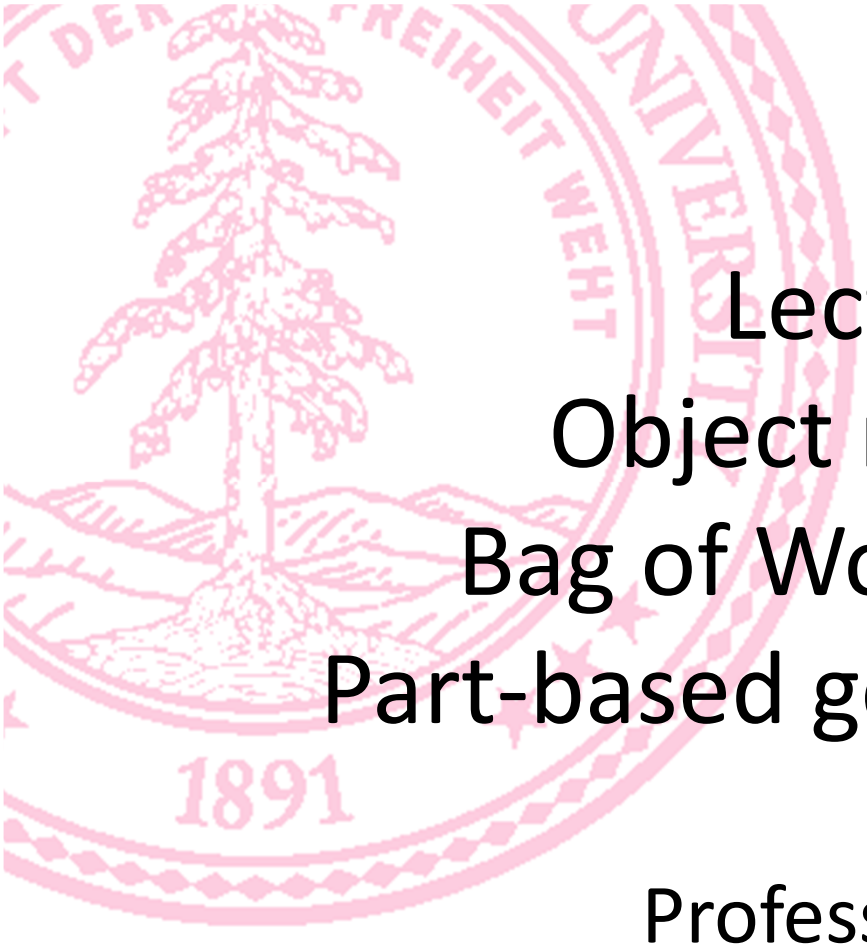


Lecture 15: Object recognition: Bag of Words models & Part-based generative models

Professor Fei-Fei Li

Stanford Vision Lab

Basic issues

- Representation
  - How to represent an object category; which classification scheme?
- Learning
  - How to learn the classifier, given training data
- Recognition
  - How the classifier is to be used on novel data

What we will learn today?

- Bag of Words model (Problem Set 4 (Q2))
  - Basic representation
  - Different learning and recognition algorithms
- Constellation model
  - Weakly supervised training
  - One-shot learning (supplementary materials)
- (Problem Set 4 (Q1))

What we will learn today?

- Bag of Words model (Problem Set 4 (Q2))
  - Basic representation
  - Different learning and recognition algorithms
- Constellation model
  - Weakly supervised training
  - One-shot learning (supplementary materials)
- (Problem Set 4 (Q1))

Part 1: Bag-of-words models

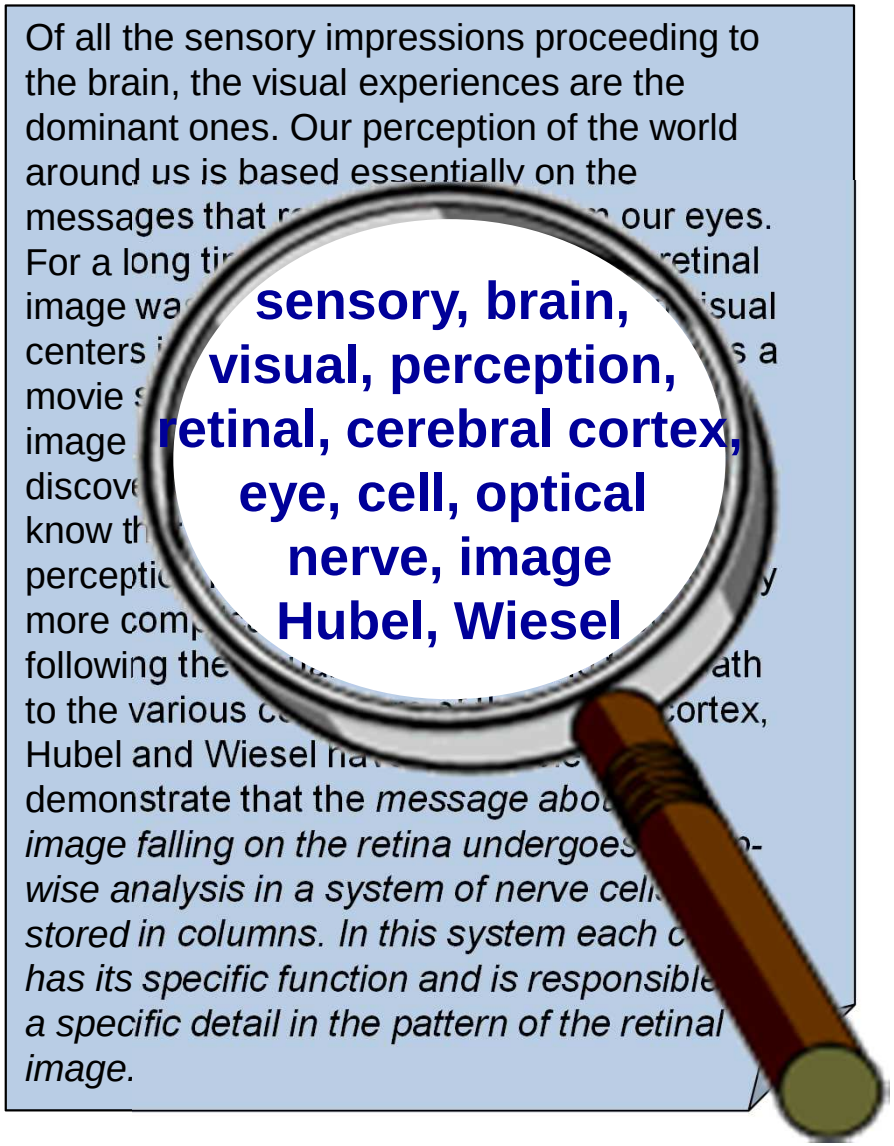
This segment is based on the tutorial *"Recognizing and Learning Object Categories: Year 2007"*, by Prof L. Fei-Fei, A. Torralba, and R. Fergus

Related works

- Early "bag of words" models: mostly texture recognition
  - Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003;
- Hierarchical Bayesian models for documents (pLSA, LDA, etc.)
  - Hoffman 1999; Blei, Ng & Jordan, 2004; Teh, Jordan, Beal & Blei, 2004
- Object categorization
  - Csurka, Bray, Dance & Fan, 2004; Sivic, Russell, Efros, Freeman & Zisserman, 2005; Sudderth, Torralba, Freeman & Willsky, 2005;
- Natural scene categorization
  - Vogel & Schiele, 2004; Fei-Fei & Perona, 2005; Bosch, Zisserman & Munoz, 2006

Object → Bag of ‘words’

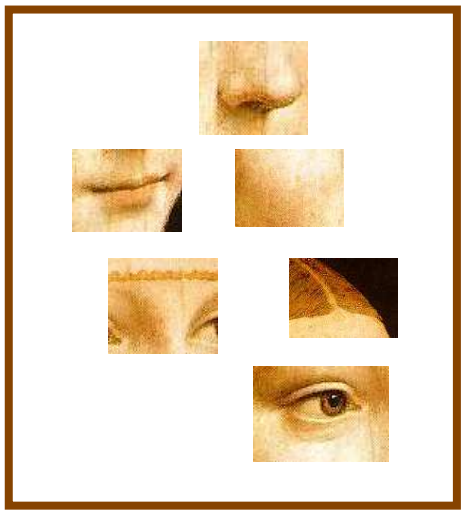
Analogy to documents



definition of “BoW”

– Independent features

face



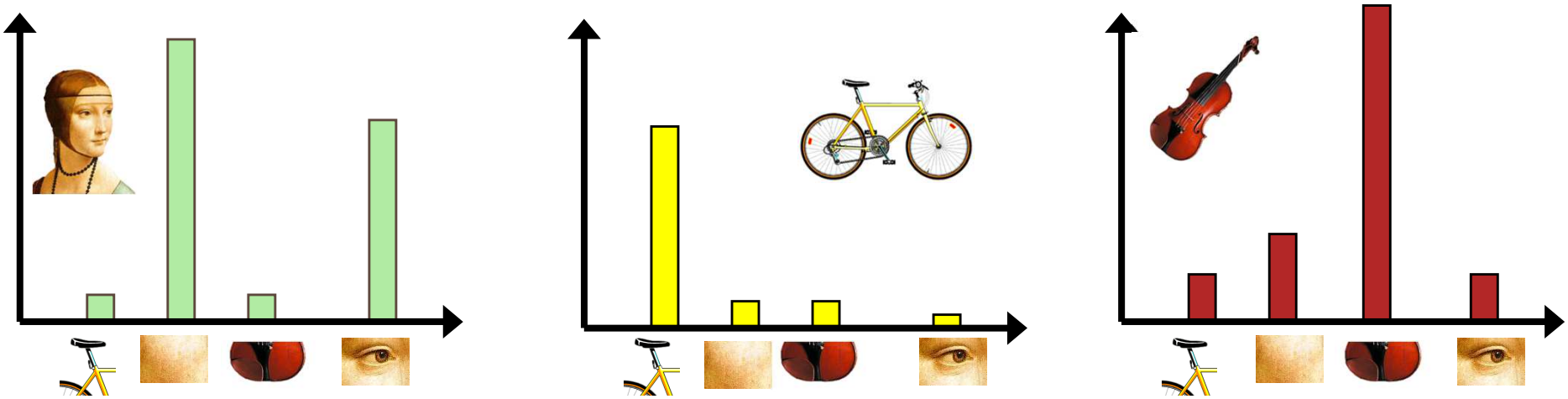
bike

violin

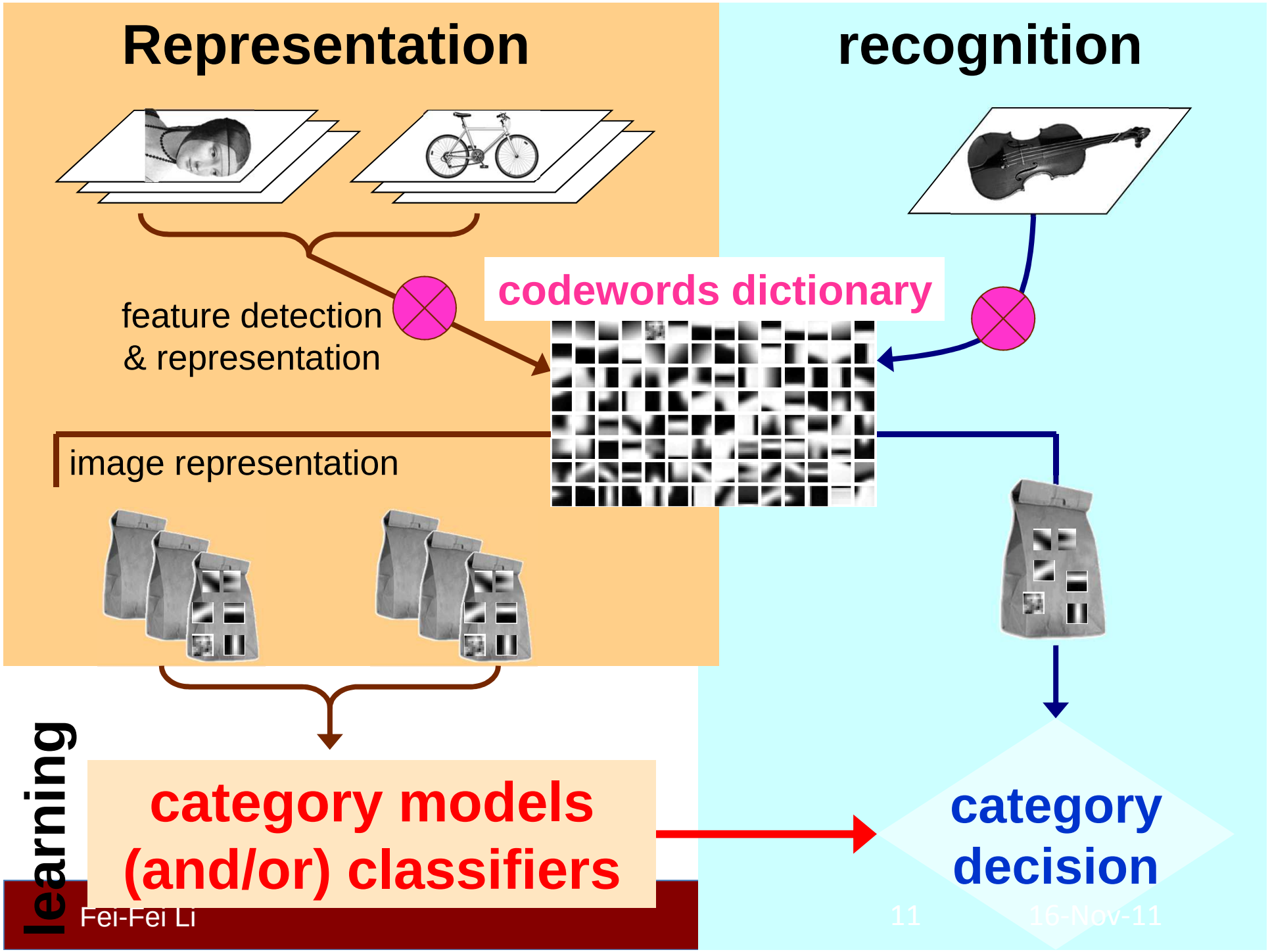
definition of “BoW”

– Independent features

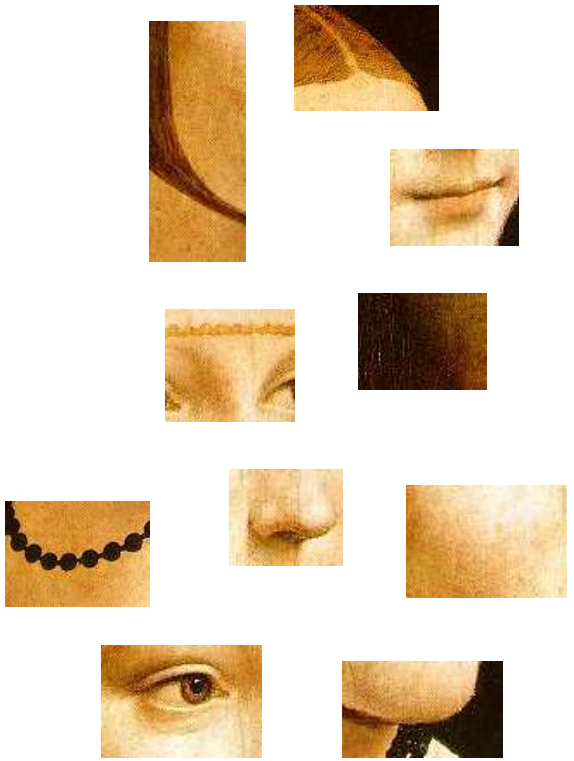
– histogram representation



codewords dictionary

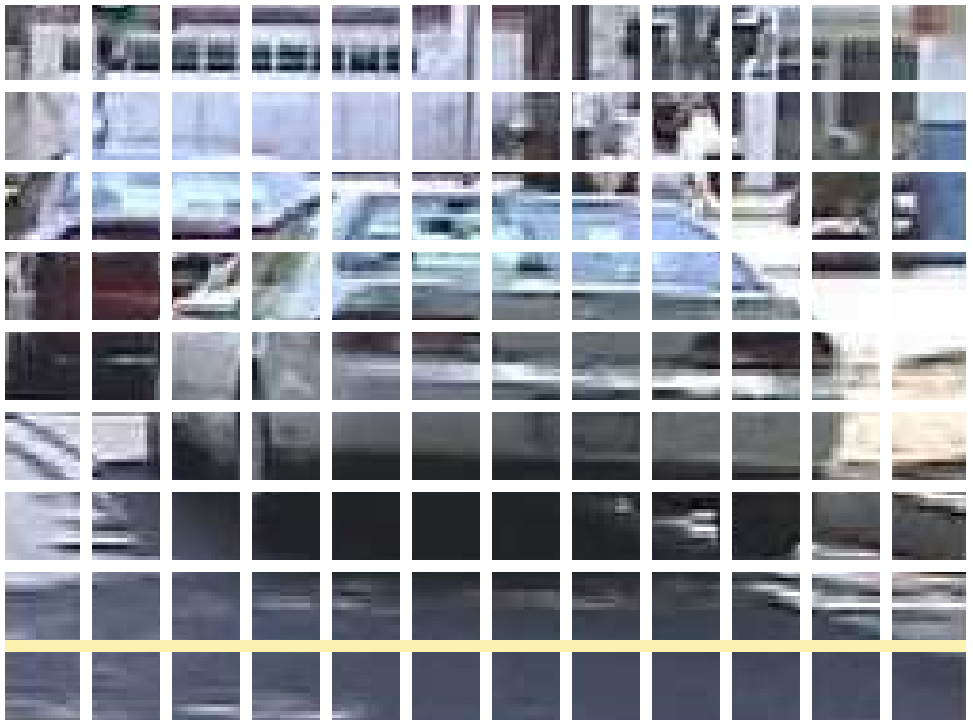

Representation
recognition
codewords dictionary
feature detection
& representation
image representation
learning
category models
(and/or) classifiers
category
decision

1.Feature detection and representation



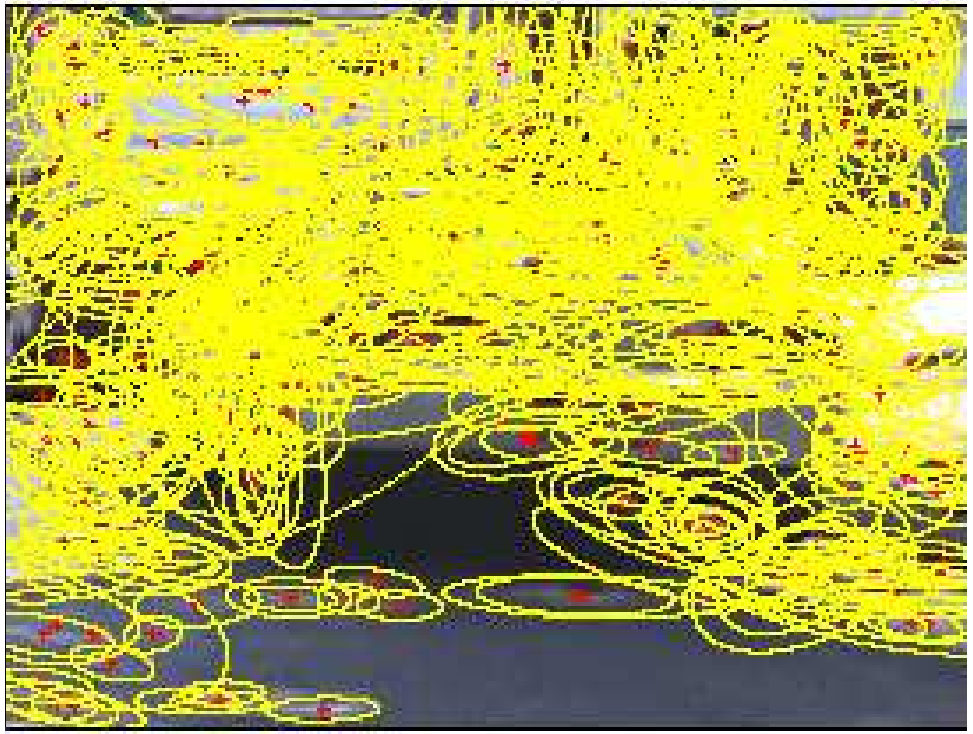
1.Feature detection and representation

- Regular grid
  - Vogel & Schiele, 2003
  - Fei-Fei & Perona, 2005



1.Feature detection and representation

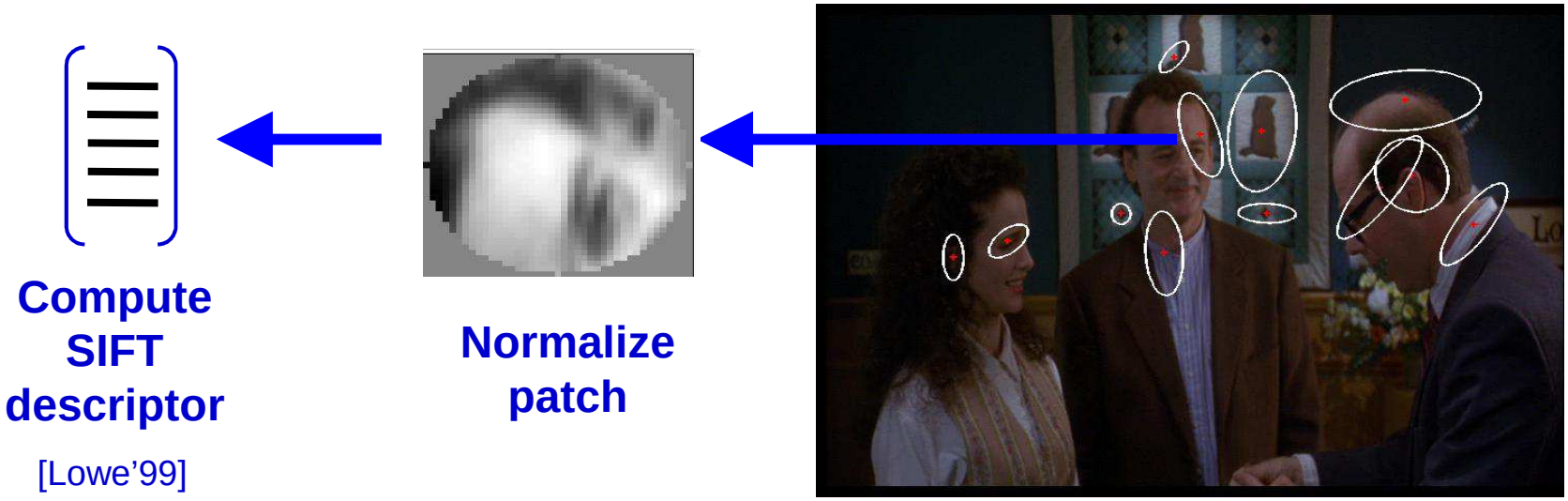
- Regular grid
  - Vogel & Schiele, 2003
  - Fei-Fei & Perona, 2005
- Interest point detector
  - Csurka, et al. 2004
  - Fei-Fei & Perona, 2005
  - Sivic, et al. 2005



1.Feature detection and representation

- Regular grid
  - Vogel & Schiele, 2003
  - Fei-Fei & Perona, 2005
- Interest point detector
  - Csurka, Bray, Dance & Fan, 2004
  - Fei-Fei & Perona, 2005
  - Sivic, Russell, Efros, Freeman & Zisserman, 2005
- Other methods
  - Random sampling (Vidal-Naquet & Ullman, 2002)
  - Segmentation based patches (Barnard, Duygulu, Forsyth, de Freitas, Blei, Jordan, 2003)

1.Feature detection and representation



Compute SIFT descriptor

[Lowe'99]

Normalize patch

Detect patches

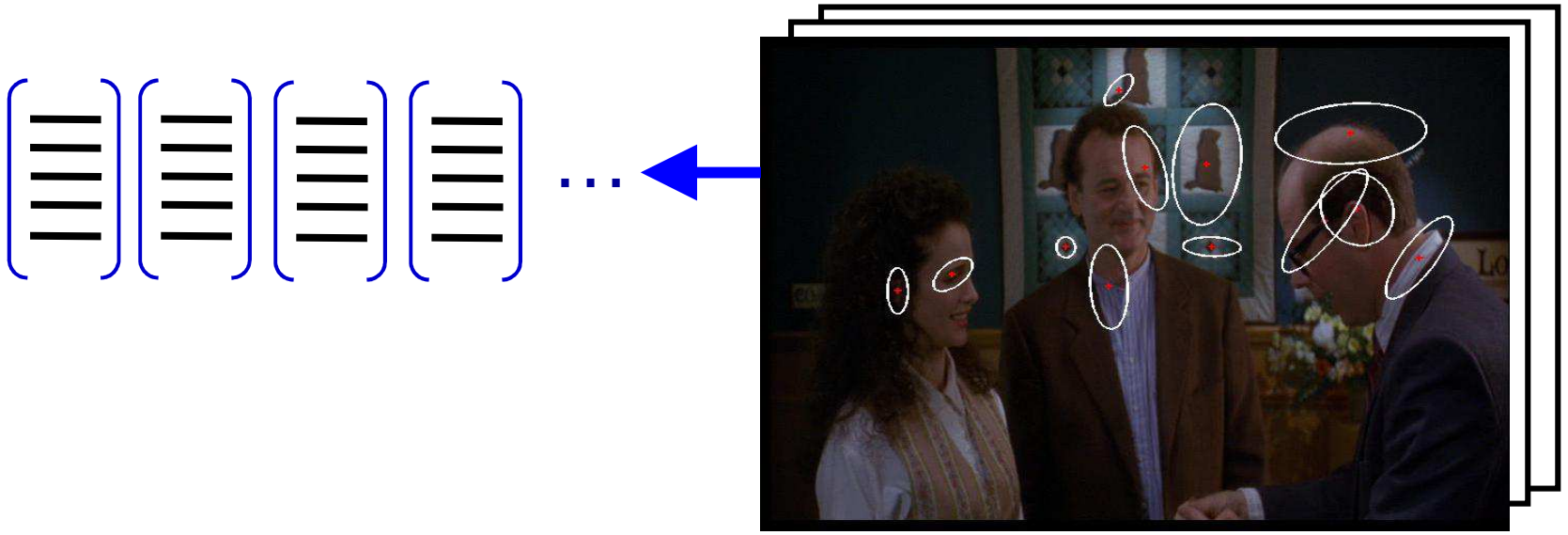
[Mikojaczyk and Schmid '02]

[Mata, Chum, Urban & Pajdla, '02]

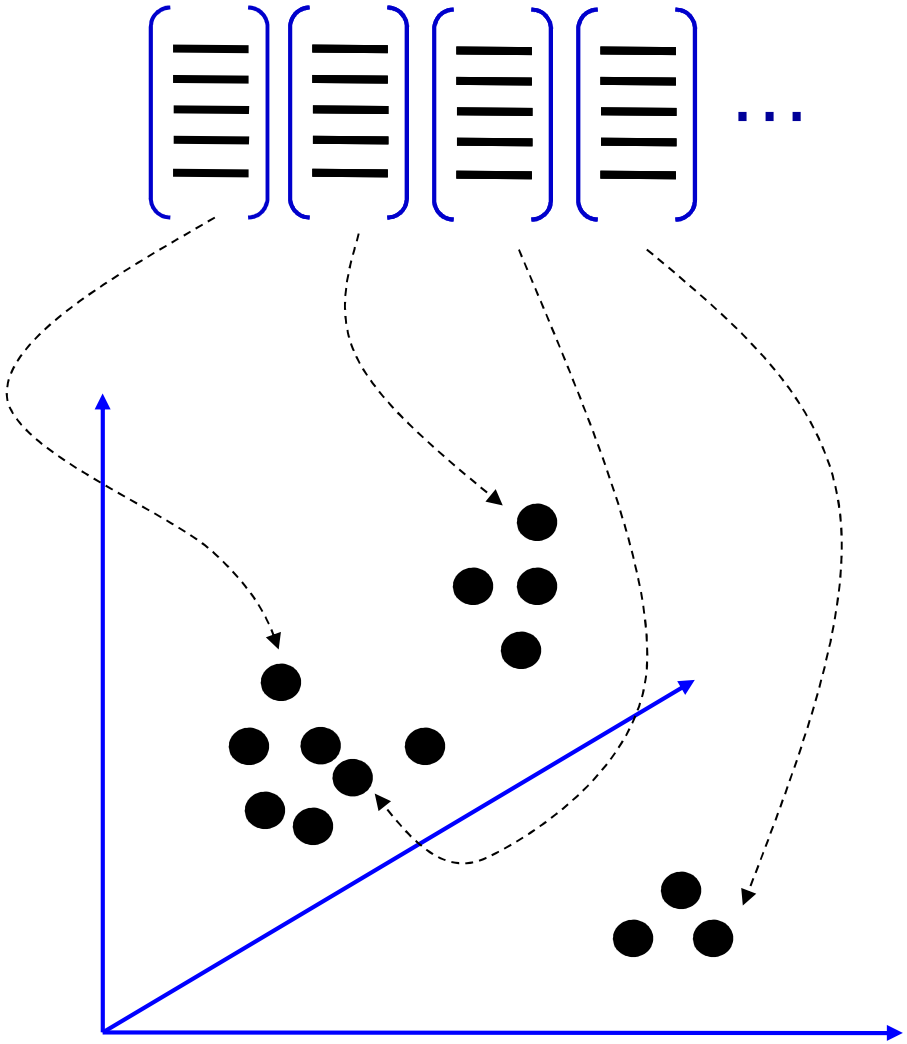
[Sivic & Zisserman, '03]

Slide credit: Josef Sivic

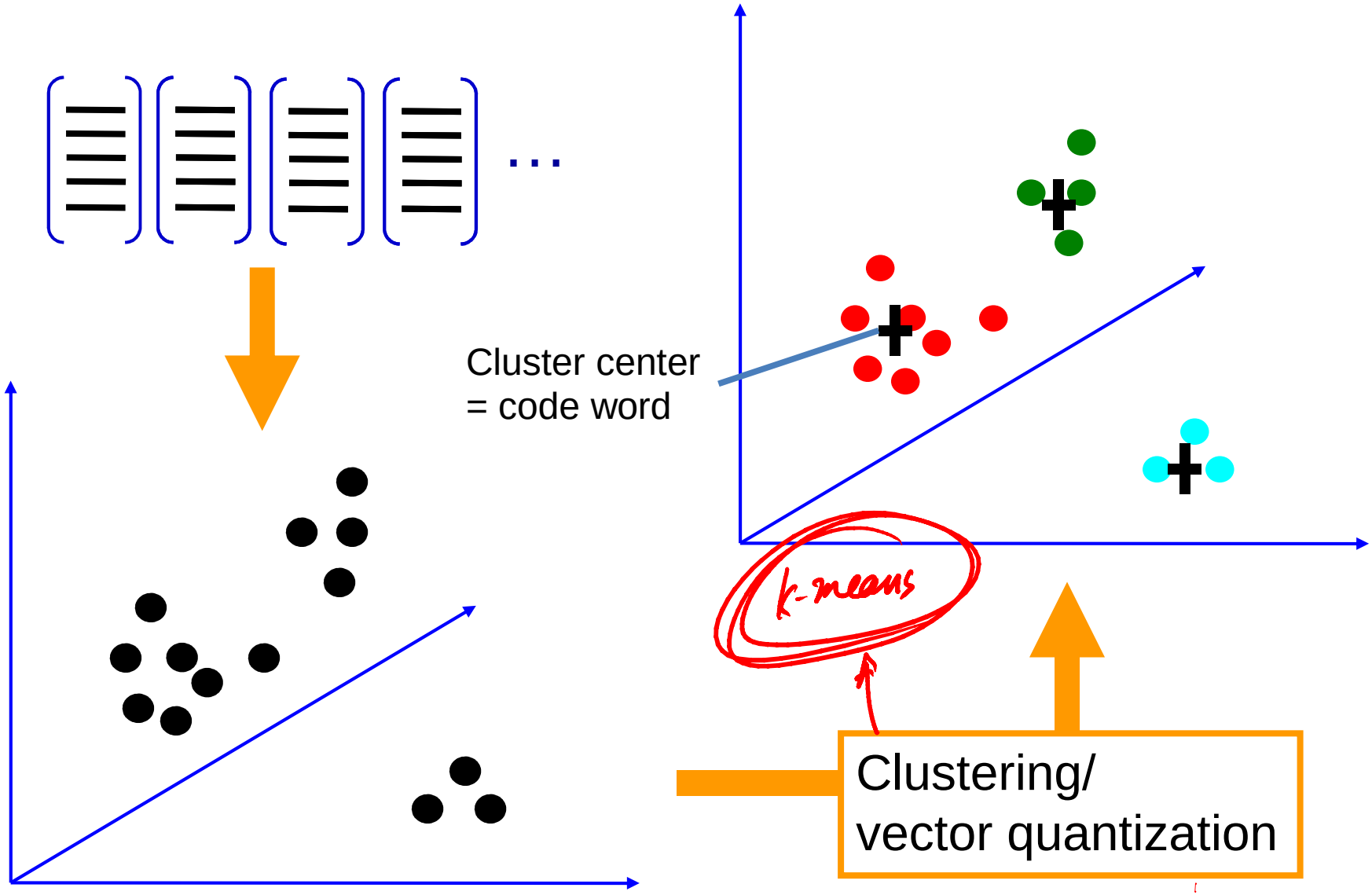
1.Feature detection and representation



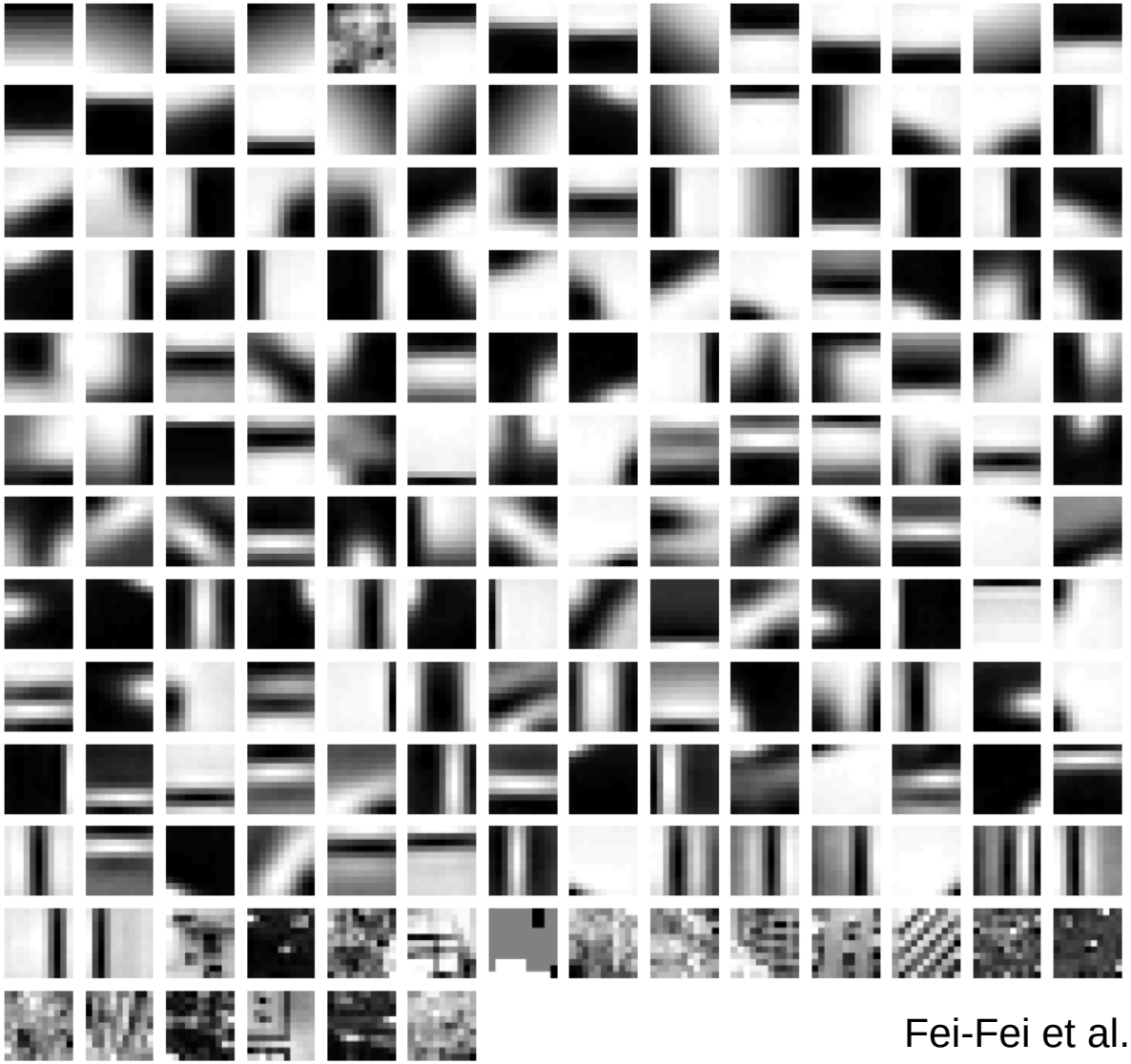
2. Codewords dictionary formation



2. Codewords dictionary formation

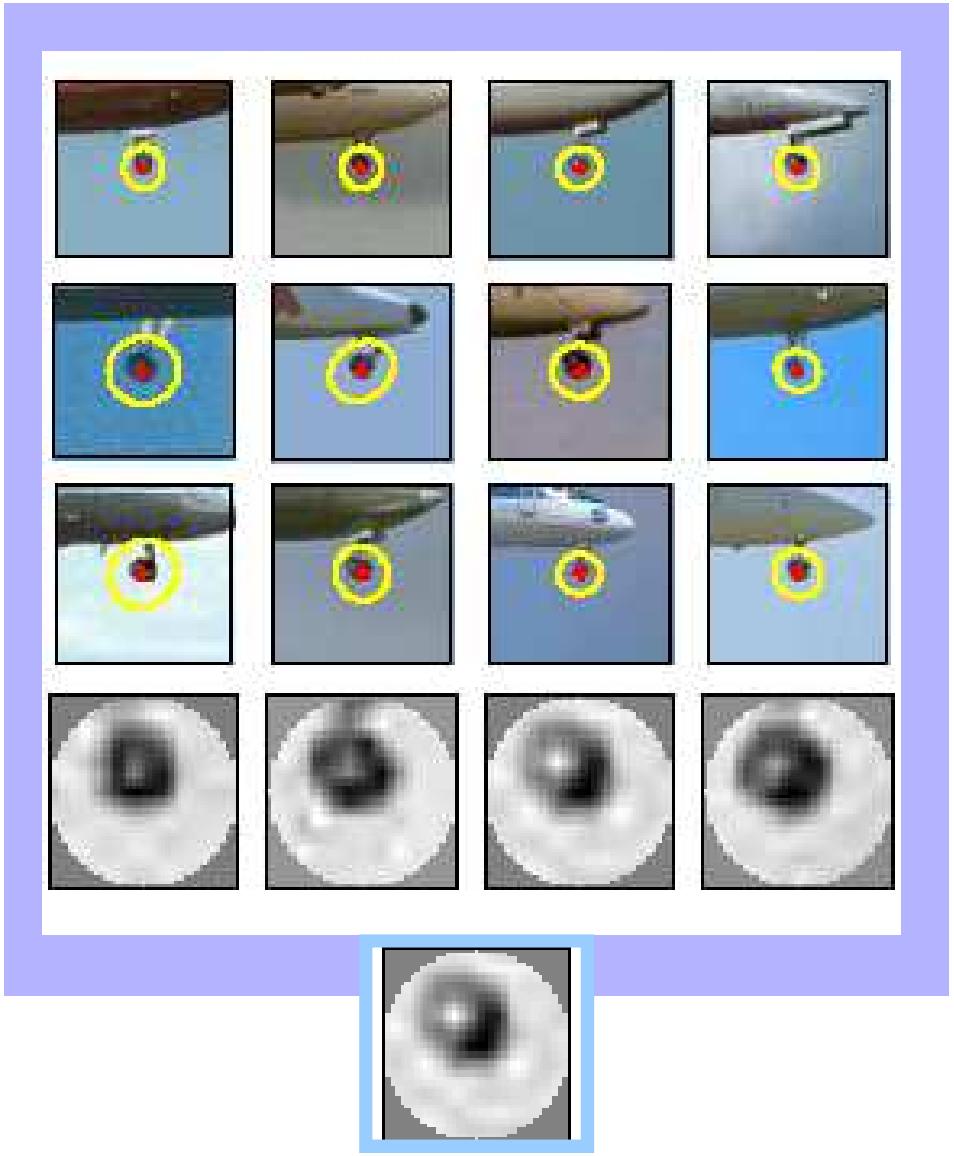


2. Codewords dictionary formation



Fei-Fei et al. 2005

Image patch examples of codewords

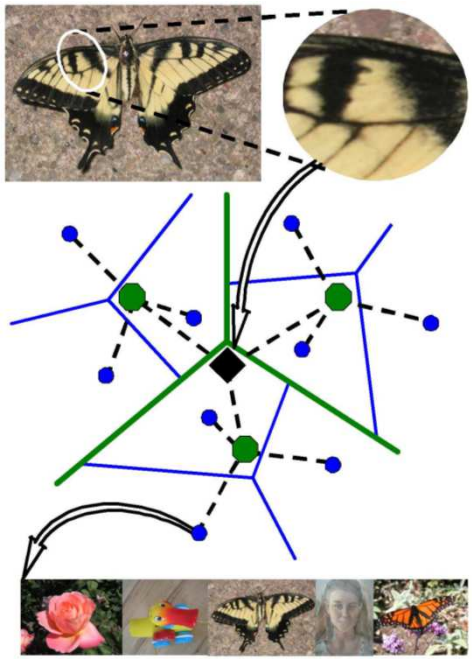


Sivic et al. 2005

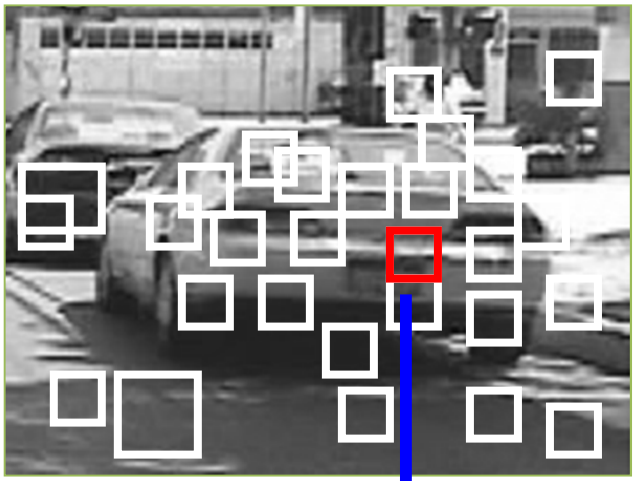
Visual vocabularies: Issues

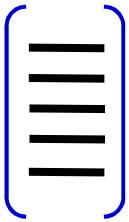
- How to choose vocabulary size?
  - Too small: visual words not representative of all patches
  - Too large: quantization artifacts, overfitting

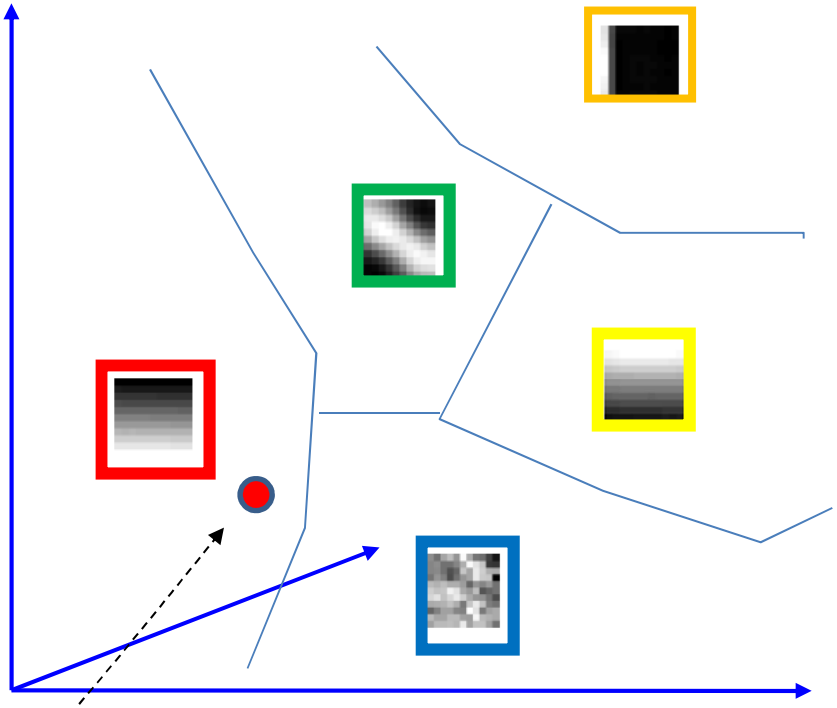
- Computational efficiency
  - Vocabulary trees
    (Nister & Stewenius, 2006)

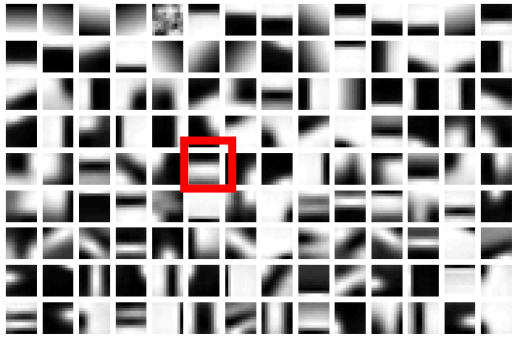


3. Bag of word representation





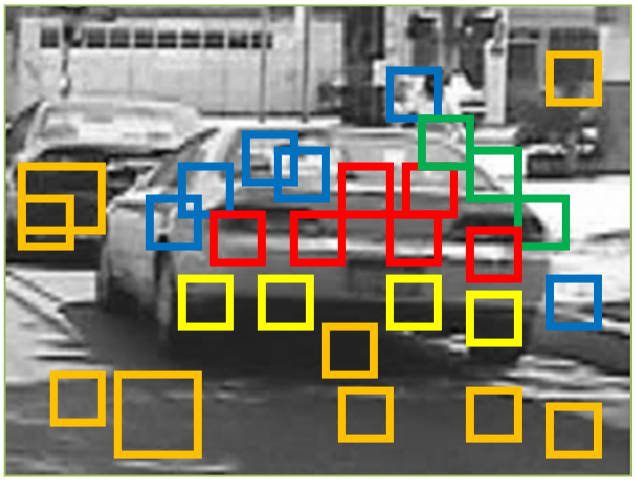


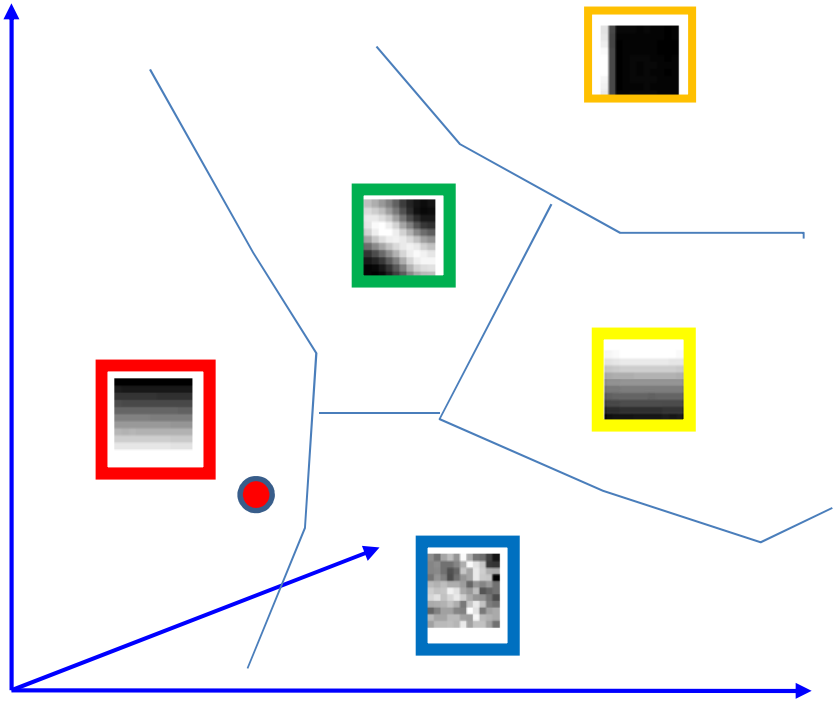


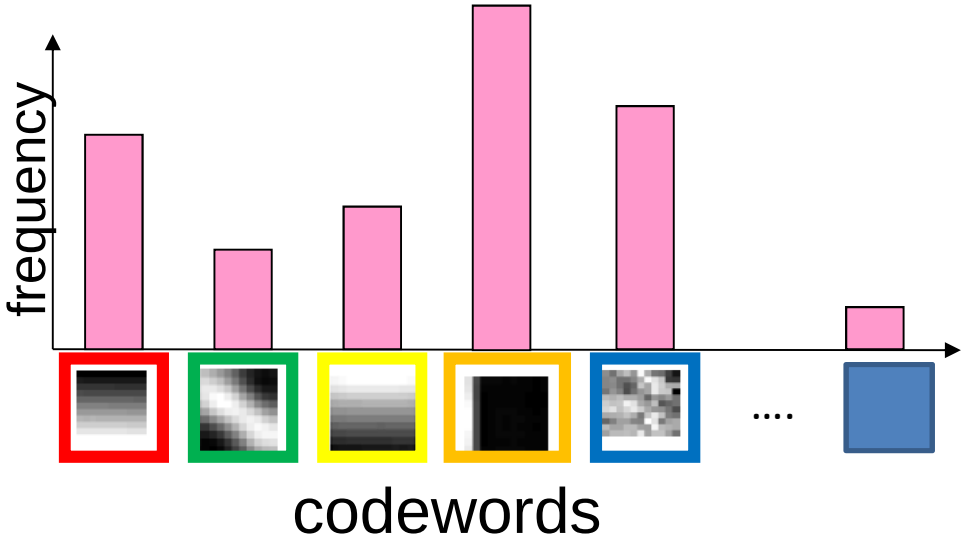
Codewords dictionary

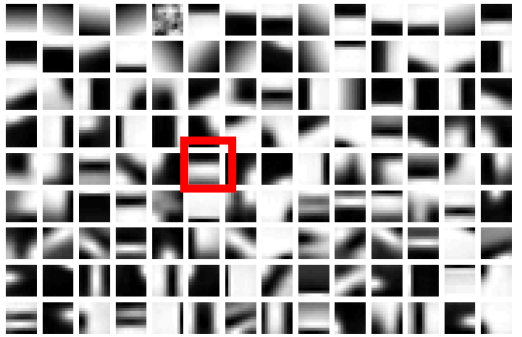
- Nearest neighbors assignment
- K-D tree search strategy

3. Bag of word representation



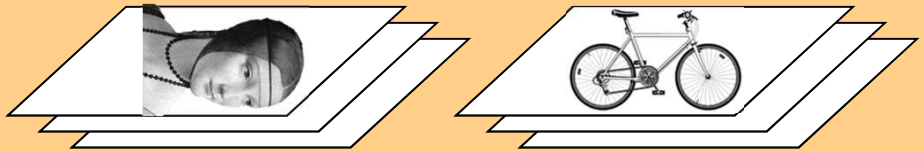






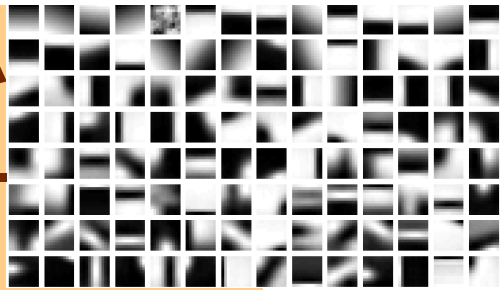
Codewords dictionary

Representation



2.

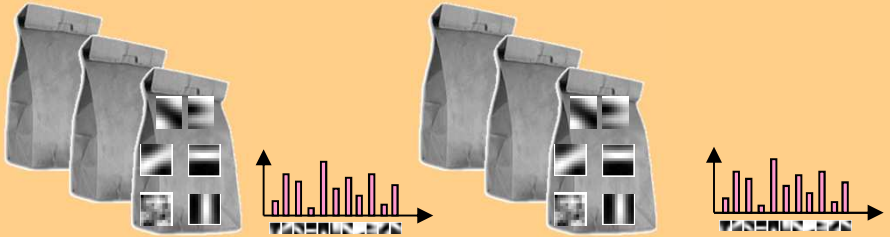
codewords dictionary



1. feature detection & representation

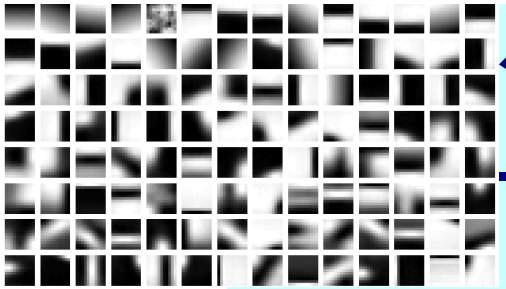
image representation

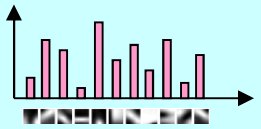
3.

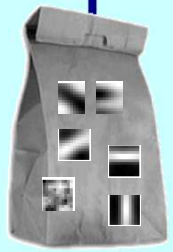


Learning and Recognition

codewords dictionary







category models (and/or) classifiers

category decision

Learning and Recognition

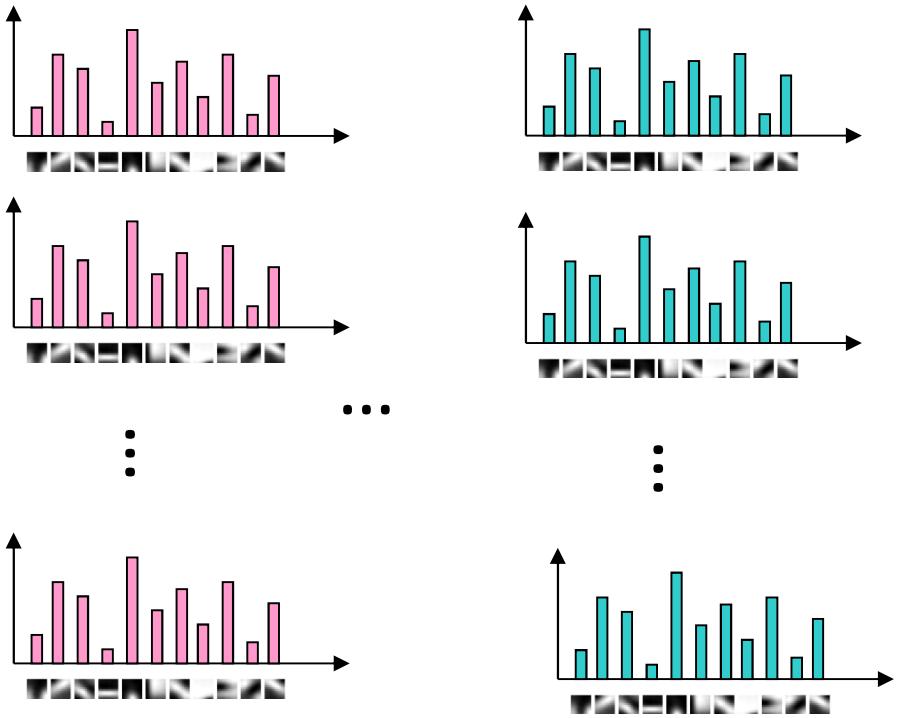
1. Discriminative method:
   - NN
   - SVM

2.Generative method:
   - graphical models

category models (and/or) classifiers

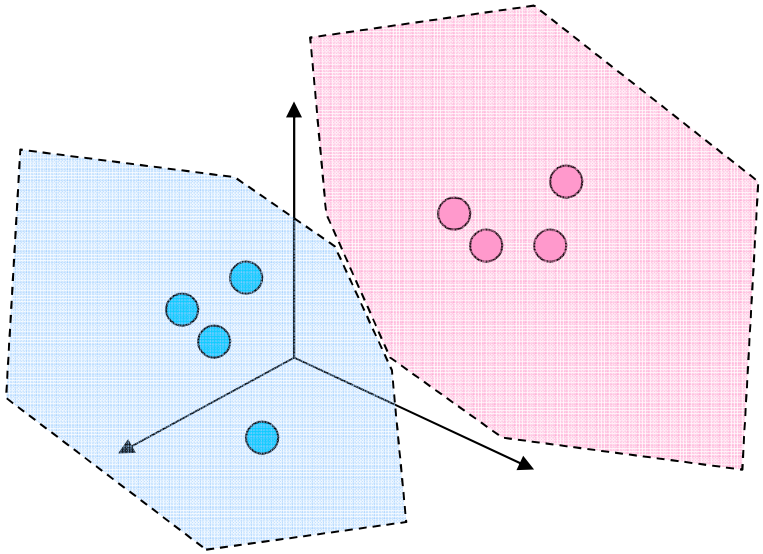
Discriminative classifiers

category models



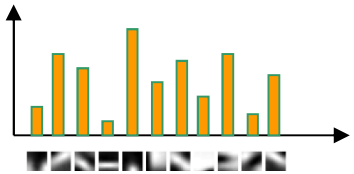
Class 1 Class N

Model space



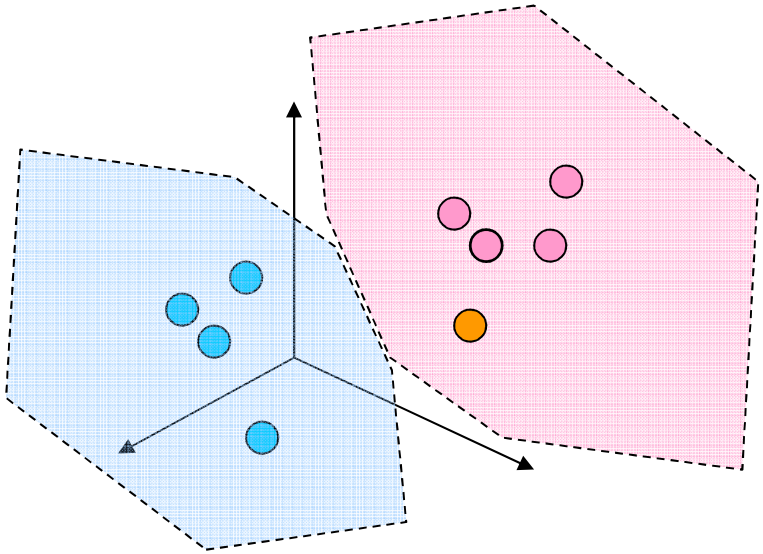
Discriminative classifiers

Query image



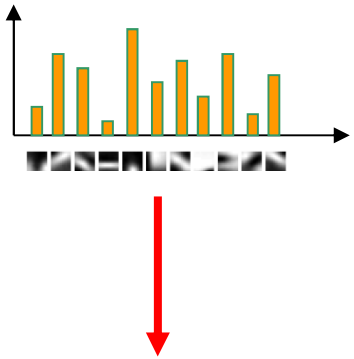
Winning class: pink

Model space



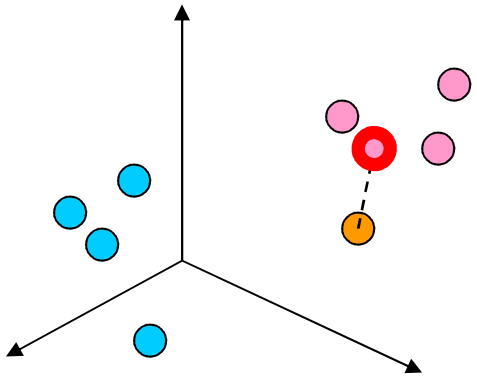
Nearest Neighbors classifier

Query image



Winning class: pink

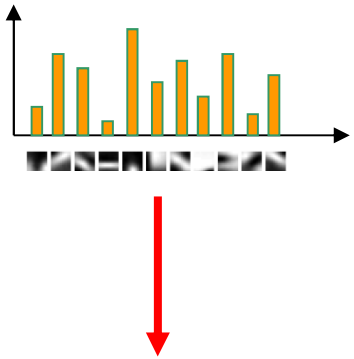
Model space



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

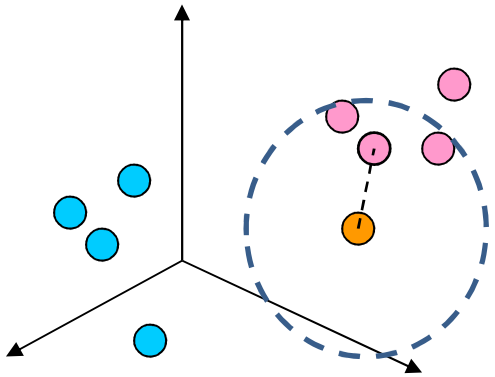
K- Nearest Neighbors classifier

Query image



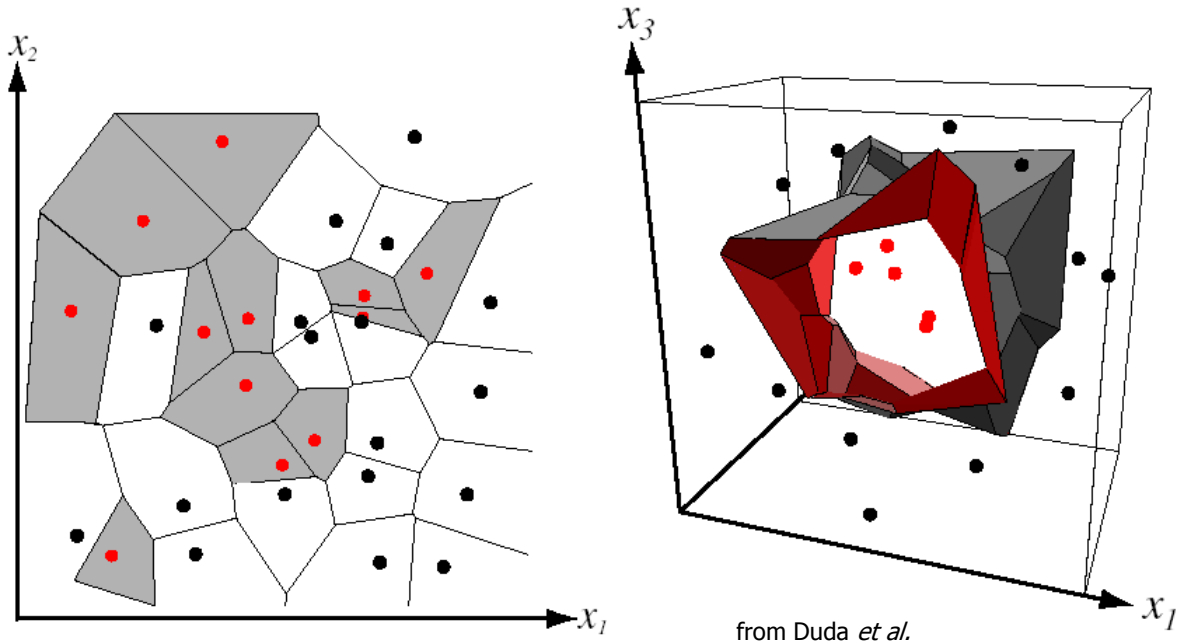
Winning class: pink

Model space



- For a new point, find the k closest points from training data
- Labels of the k points “vote” to classify
- Works well provided there is lots of data and the distance function is good

K- Nearest Neighbors classifier



from Duda *et al.*

- Voronoi partitioning of feature space for 2-category 2-D and 3-D data
- For k dimensions: k-D tree = space-partitioning data structure for organizing points in a *k*-dimensional space
- Enable efficient search
- Nice tutorial: http://www.cs.umd.edu/class/spring2002/cmsc420-0401/pbasic.pdf

Functions for comparing histograms

- L1 distance

$$D(h_1, h_2) = \sum_{i=1}^{N} | h_1(i) - h_2(i) |$$

- χ^2 distance popular

$$D(h_1, h_2) = \sum_{i=1}^{N} \frac{(h_1(i) - h_2(i))^2}{h_1(i) + h_2(i)}$$

- Quadratic distance (*cross-bin*)

$$D(h_1, h_2) = \sum_{i,j} A_{ij} (h_1(i) - h_2(j))^2$$

Jan Puzicha, Yossi Rubner, Carlo Tomasi, Joachim M. Buhmann: Empirical Evaluation of Dissimilarity Measures for Color and Texture. ICCV 1999

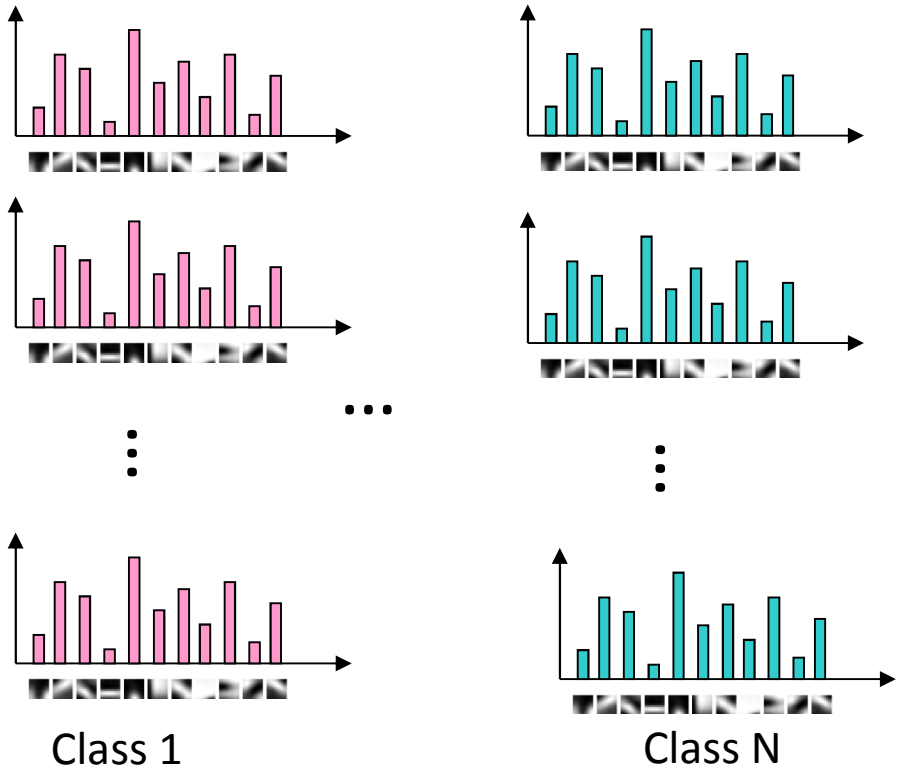
Learning and Recognition

1. Discriminative method:
   - NN
   - SVM

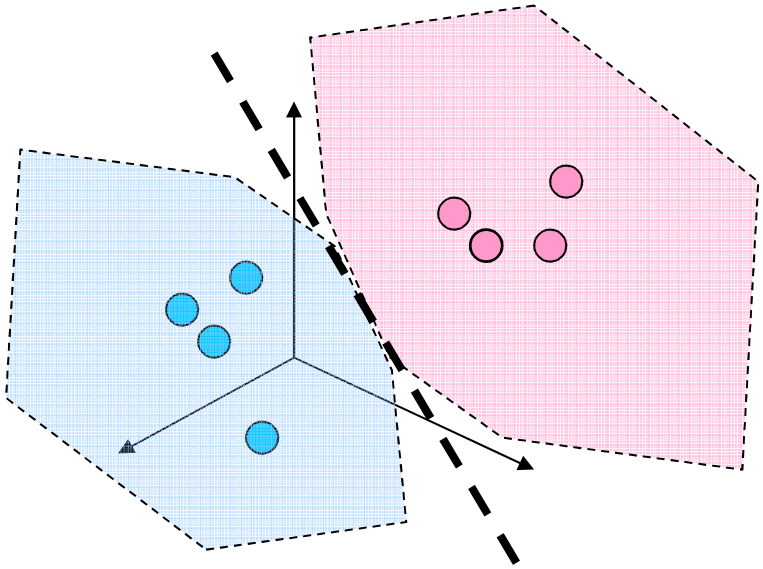
2.Generative method:
   - graphical models

Discriminative classifiers (linear classifier)

category models

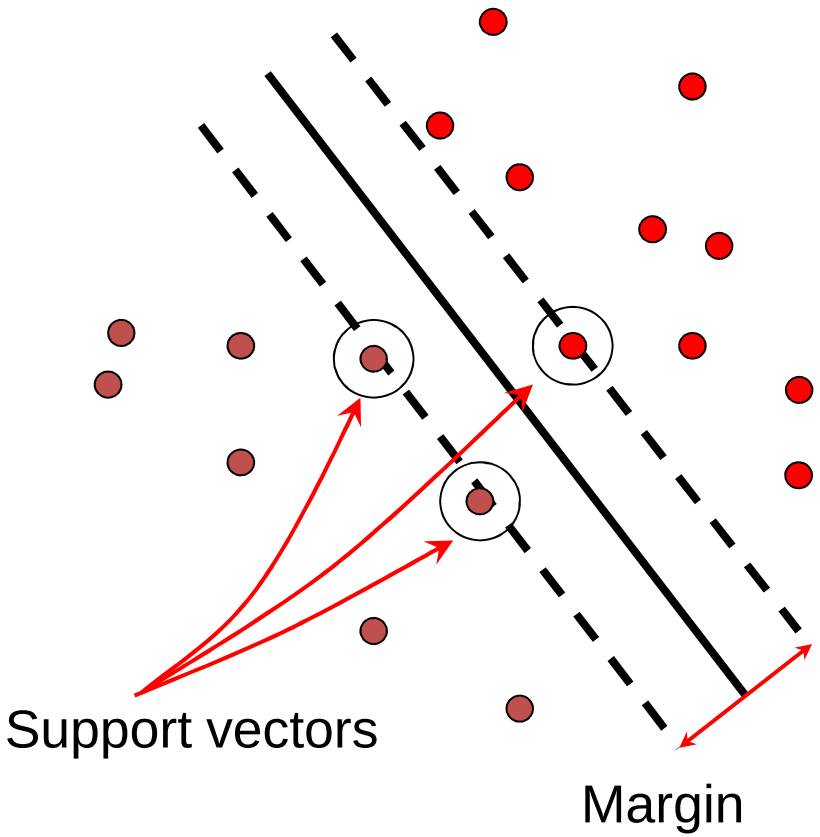


Model space



Support vector machines

- Find hyperplane that maximizes the *margin* between the positive and negative examples



Support vectors: $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

Distance between point and hyperplane: $\frac{|\mathbf{x}_i \cdot \mathbf{w} + b|}{\|\mathbf{w}\|}$

Margin = $2 / \|\mathbf{w}\|$

Solution: $\mathbf{w} = \sum_i \alpha_i y_i \mathbf{x}_i$

Classification function (decision boundary):

$$\mathbf{w} \cdot \mathbf{x} + b = \sum_i \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b$$

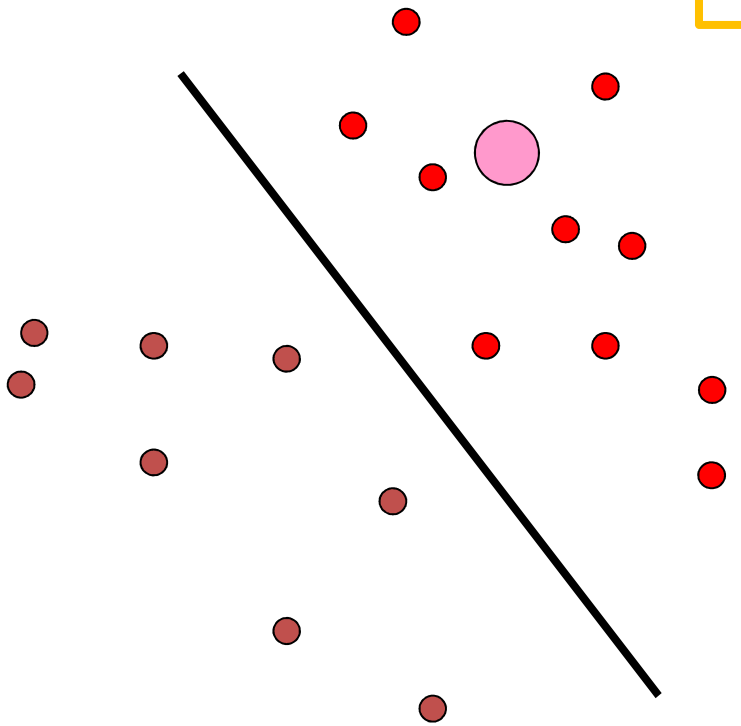
Credit slide: S. Lazebnik

Support vector machines

- Classification

$$\mathbf{w} \cdot \mathbf{x} + b = \sum_i \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b$$

Test point



Margin

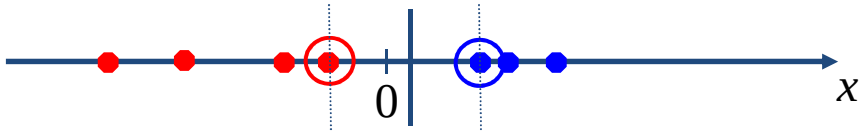
$$if \quad \mathbf{x} \cdot \mathbf{w} + b \geq 0 \rightarrow \quad class\ 1$$

$$if \quad \mathbf{x} \cdot \mathbf{w} + b < 0 \rightarrow \quad class\ 2$$

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

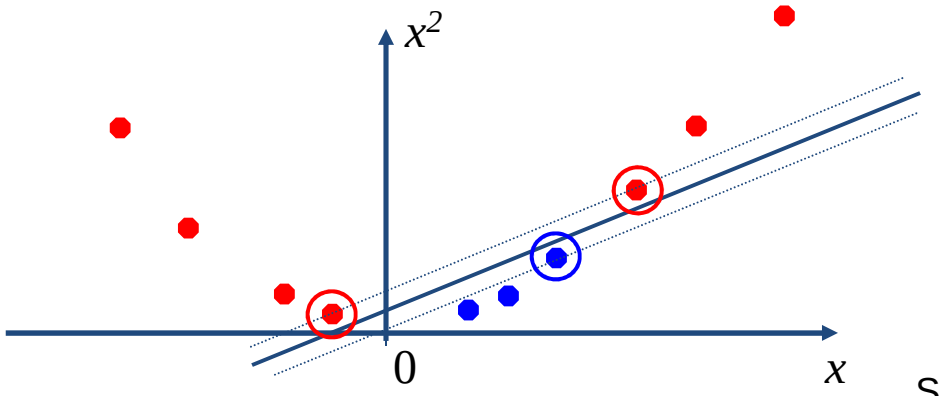
Nonlinear SVMs

- Datasets that are linearly separable work out great:



- But what if the dataset is just too hard?

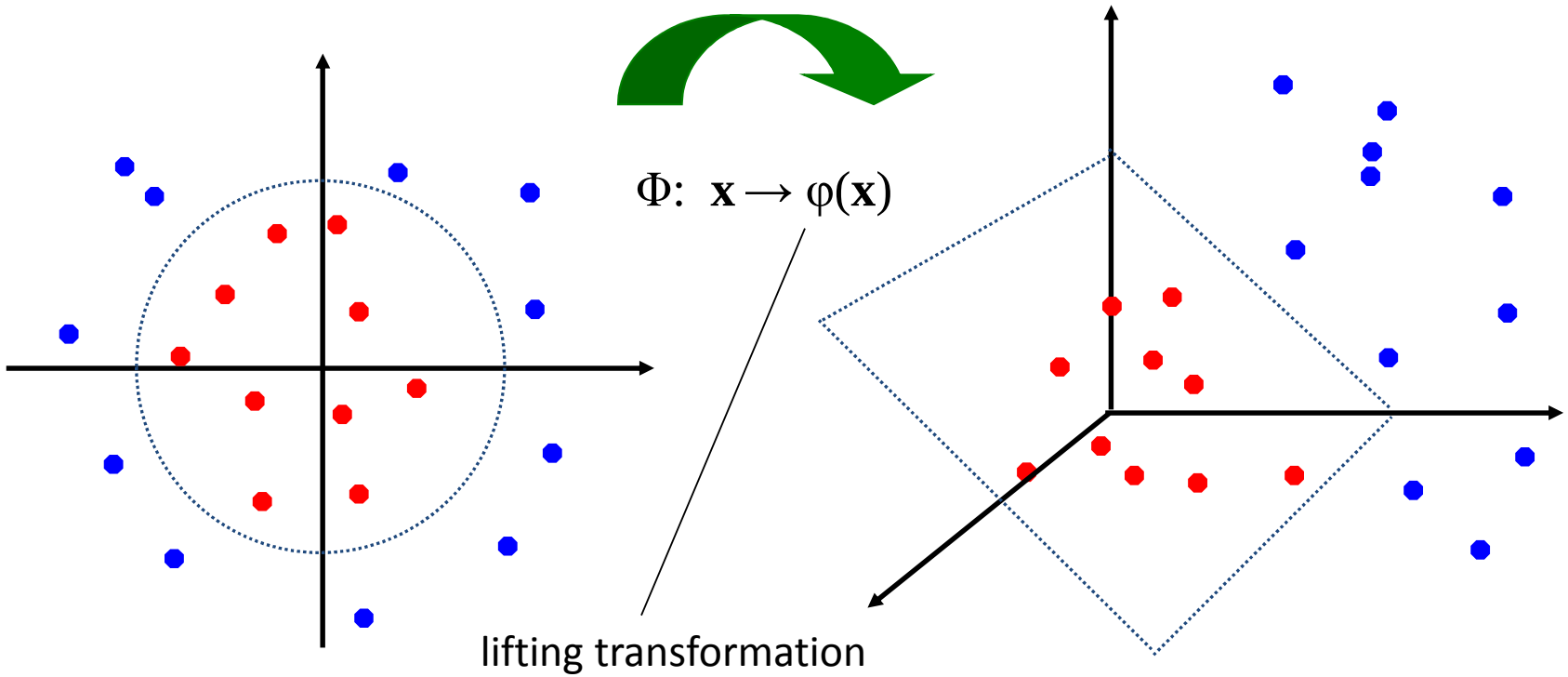
- We can map it to a higher-dimensional space:



Slide credit: Andrew Moore

Nonlinear SVMs

- General idea: the original input space can always be mapped to some higher-dimensional feature space where the training set is separable:



Slide credit: Andrew Moore

Nonlinear SVMs

- Nonlinear decision boundary in the original feature space:

$$\sum_i \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b$$

- *The kernel K* = product of the lifting transformation $\boldsymbol{\varphi}(\mathbf{x})$:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \boldsymbol{\varphi}(\mathbf{x}_i) \cdot \boldsymbol{\varphi}(\mathbf{x}_j)$$

NOTE:

- It is not required to compute $\boldsymbol{\varphi}(\mathbf{x})$ explicitly:
- The kernel must satisfy the "Mercer inequality"

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

Kernels for bags of features

- Histogram intersection kernel:

$$I(h_1, h_2) = \sum_{i=1}^{N} \min(h_1(i), h_2(i))$$

- Generalized Gaussian kernel:

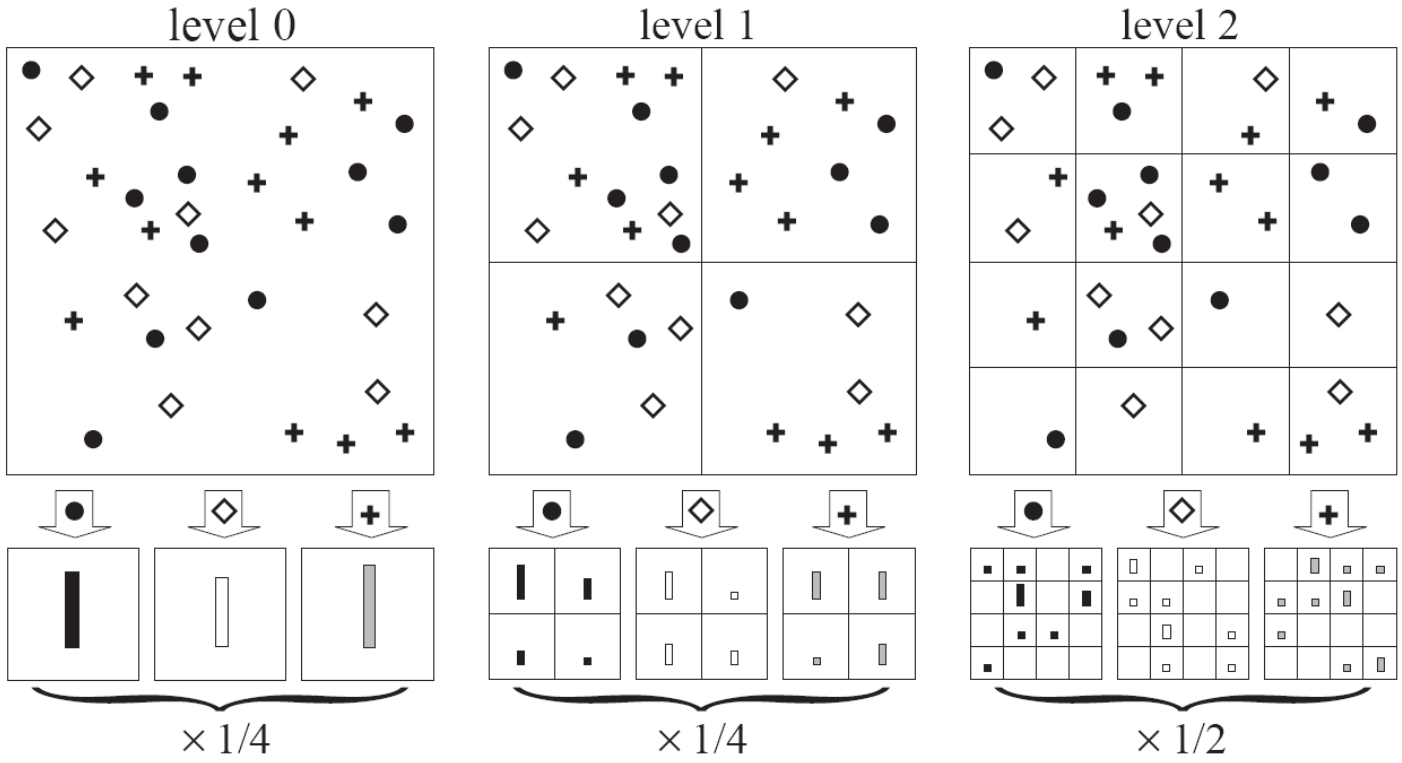
$$K(h_1, h_2) = \exp\left(-\frac{1}{A} D(h_1, h_2)^2\right)$$

- *D* can be Euclidean distance, χ^2 distance etc…

J. Zhang, M. Marszalek, S. Lazebnik, and C. Schmid, Local Features and Kernels for Classifcation of Texture and Object Categories: A Comprehensive Study, IJCV 2007

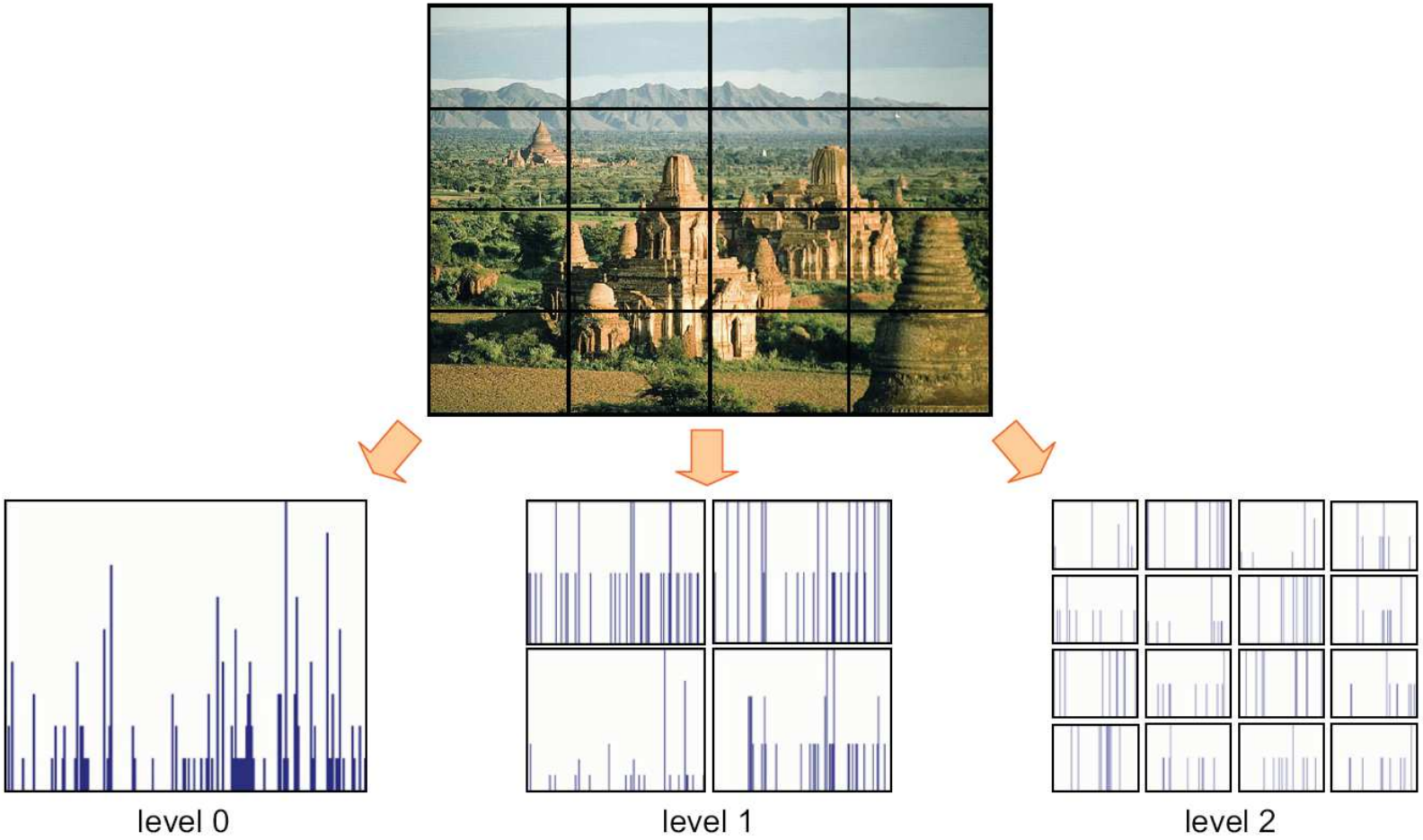
Pyramid match kernel

- Fast approximation of Earth Mover's Distance
- Weighted sum of histogram intersections at mutliple resolutions (linear in the number of features instead of cubic)



K. Grauman and T. Darrell. The Pyramid Match Kernel: Discriminative Classification with Sets of Image Features, ICCV 2005.

Spatial Pyramid Matching



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

What about multi-class SVMs?

- No “definitive” multi-class SVM formulation
- In practice, we have to obtain a multi-class SVM 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

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

- Cons
  - No “direct” multi-class SVM, must combine two-class SVMs
  - Computation, memory
    - During training time, must compute matrix of kernel values for every pair of examples
    - Learning can take a very long time for large-scale problems

Object recognition results

- ETH-80 database of 8 object classes
  (*Eichhorn and Chapelle 2004)*
- Features:
  - Harris detector
  - PCA-SIFT descriptor, *d*=10

Kernel	Complexity	Recognition rate
Match *[Wallraven et al.]*	$O(dm^2)$	84%
Bhattacharyya affinity *[Kondor & Jebara]*	$O(dm^3)$	85%
Pyramid match	$O(dmL)$	84%

Slide credit: Kristen Grauman

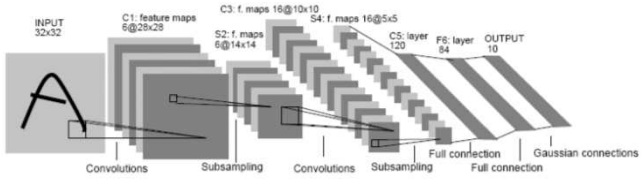
Discriminative models

Nearest neighbor

10^6 examples

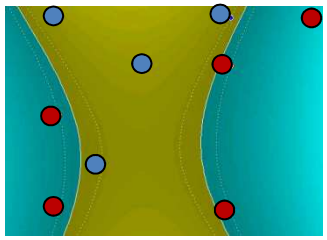
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005...

Neural networks



LeCun, Bottou, Bengio, Haffner 1998
Rowley, Baluja, Kanade 1998
…

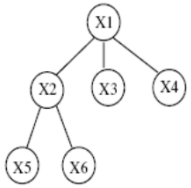
Support Vector Machines



Guyon, Vapnik, Heisele, Serre, Poggio…

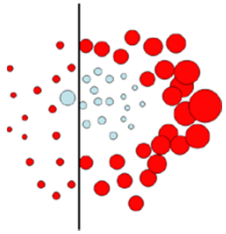
Latent SVM

Structural SVM



Felzenszwalb 00
Ramanan 03…

Boosting



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

Source: Vittorio Ferrari, Kristen Grauman, Antonio Torralba

Learning and Recognition

1. Discriminative method:
   - NN
   - SVM

2. Generative method:
   - graphical models

→ Model the probability distribution that produces a given bag of features

Generative models

1. Naïve Bayes classifier
   - Csurka Bray, Dance & Fan, 2004

2. Hierarchical Bayesian text models (pLSA and LDA)
   - Background: Hoffman 2001, Blei, Ng & Jordan, 2004
   - Object categorization: Sivic et al. 2005, Sudderth et al. 2005
   - Natural scene categorization: Fei-Fei et al. 2005

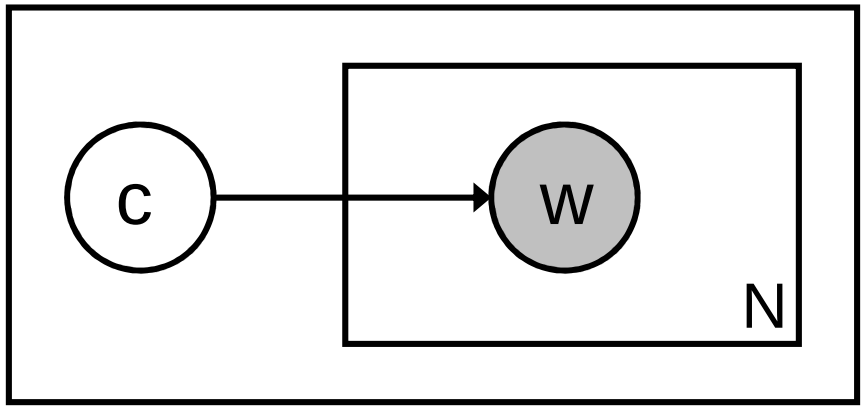
Some notations

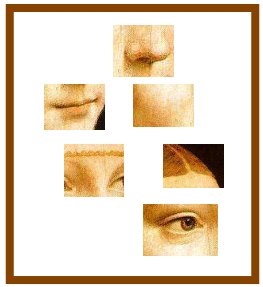
- **w:** a collection of all N codewords in the image

  $\mathbf{w} = [w_1, w_2, \ldots, w_N]$

- c: category of the image

the Naïve Bayes model





Graphical model

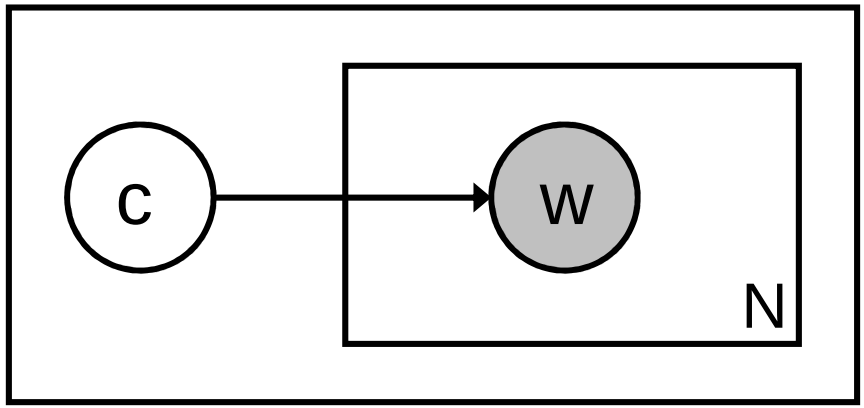
Posterior = $p(c \mid w) \propto p(c)\, p(w \mid c)$

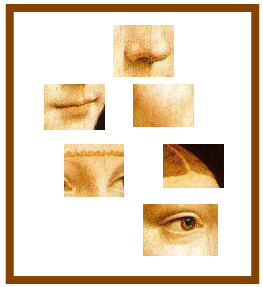
probability
that image **I** is
of category c

Prior prob. of
the object classes

Image likelihood
given the class

the Naïve Bayes model





Graphical model

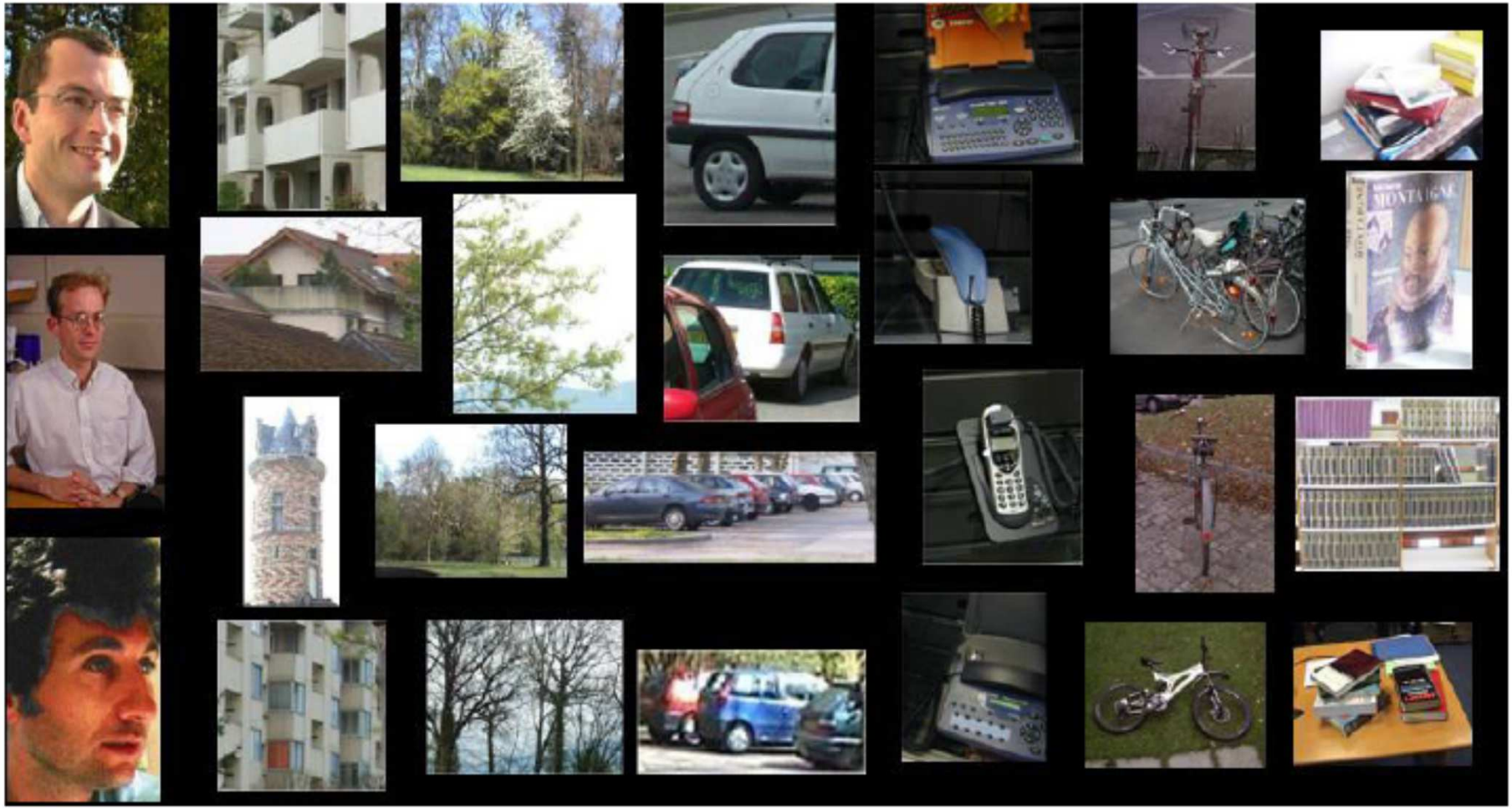
$$c^* = \arg\max_c \; p(c \mid w) \propto p(c)\, p(w \mid c) = p(c) \prod_{n=1}^{N} p(w_n \mid c)$$

Object class decision

Likelihood of ith visual word given the class

Estimated by empirical frequencies of code words in images from a given class

Our in-house database contains 1776 images in seven classes[1]: faces, buildings, trees, cars, phones, bikes and books. Fig. 2 shows some examples from this dataset.



Csurka et al. 2004

Table 1. Confusion matrix and the mean rank for the best vocabulary (*k=1000*).

True classes →	*faces*	*buildings*	*trees*	*cars*	*phones*	*bikes*	*books*
faces	**76**	4	2	3	4	4	13
buildings	2	**44**	5	0	5	1	3
trees	3	2	**80**	0	0	5	0
cars	4	1	0	**75**	3	1	4
phones	9	15	1	16	**70**	14	11
bikes	2	15	12	0	8	**73**	0
books	4	19	0	6	7	2	**69**
Mean ranks	1.49	1.88	1.33	1.33	1.63	1.57	1.57

Csurka et al. 2004

Other generative BoW models

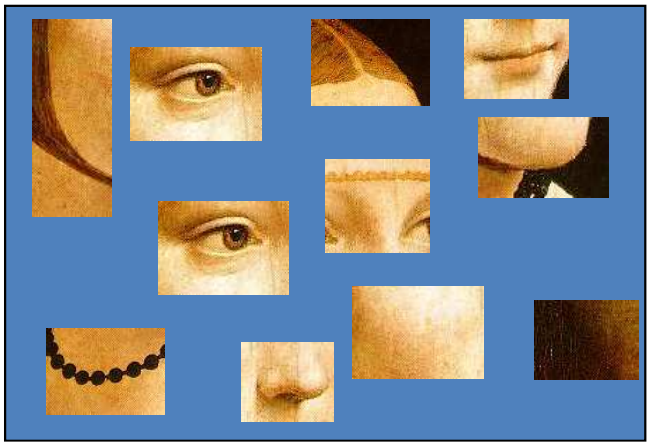
- Hierarchical Bayesian topic models (e.g. pLSA and LDA)
  - Object categorization: Sivic et al. 2005, Sudderth et al. 2005
  - Natural scene categorization: Fei-Fei et al. 2005

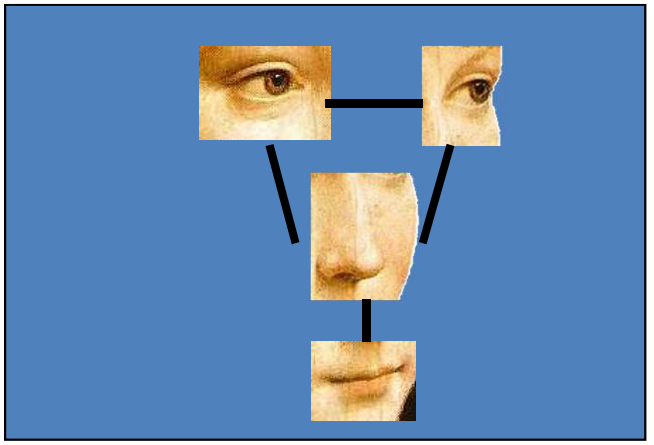
Generative vs discriminative

- Discriminative methods
  - Computationally efficient & fast
- Generative models
  - Convenient for weakly- or un-supervised, incremental training
  - Prior information
  - Flexibility in modeling parameters

Weakness of BoW the models

- No rigorous geometric information of the object components
- It's intuitive to most of us that objects are made of parts – no such information
- Not extensively tested yet for
  - View point invariance
  - Scale invariance
- Segmentation and localization unclear

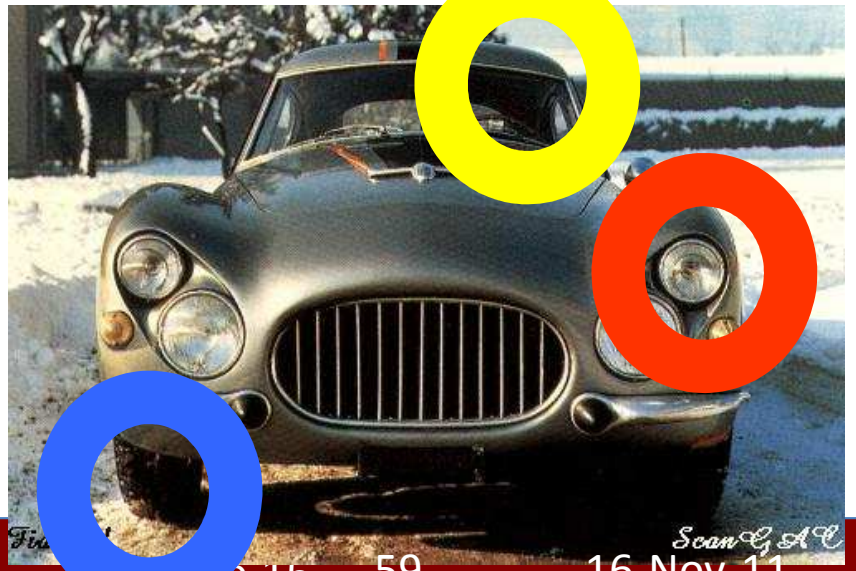




What we will learn today?

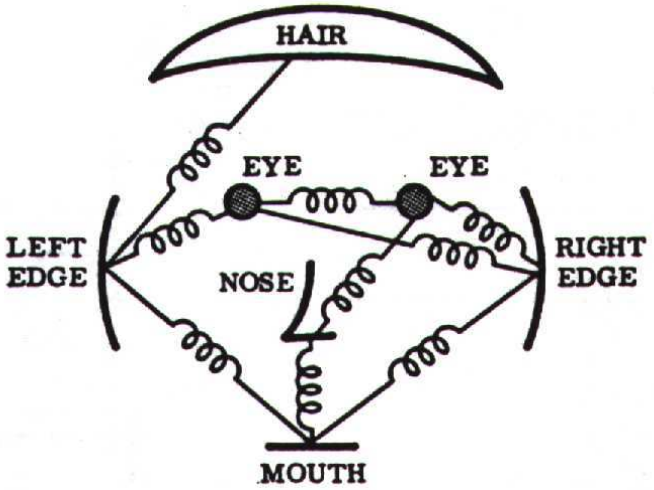
- Bag of Words model (Problem Set 4 (Q2))
  - Basic representation
  - Different learning and recognition algorithms
- Constellation model
  - Weakly supervised training
  - One-shot learning (supplementary materials)
- (Problem Set 4 (Q1))

Model: Parts and Structure



Parts and Structure Literature

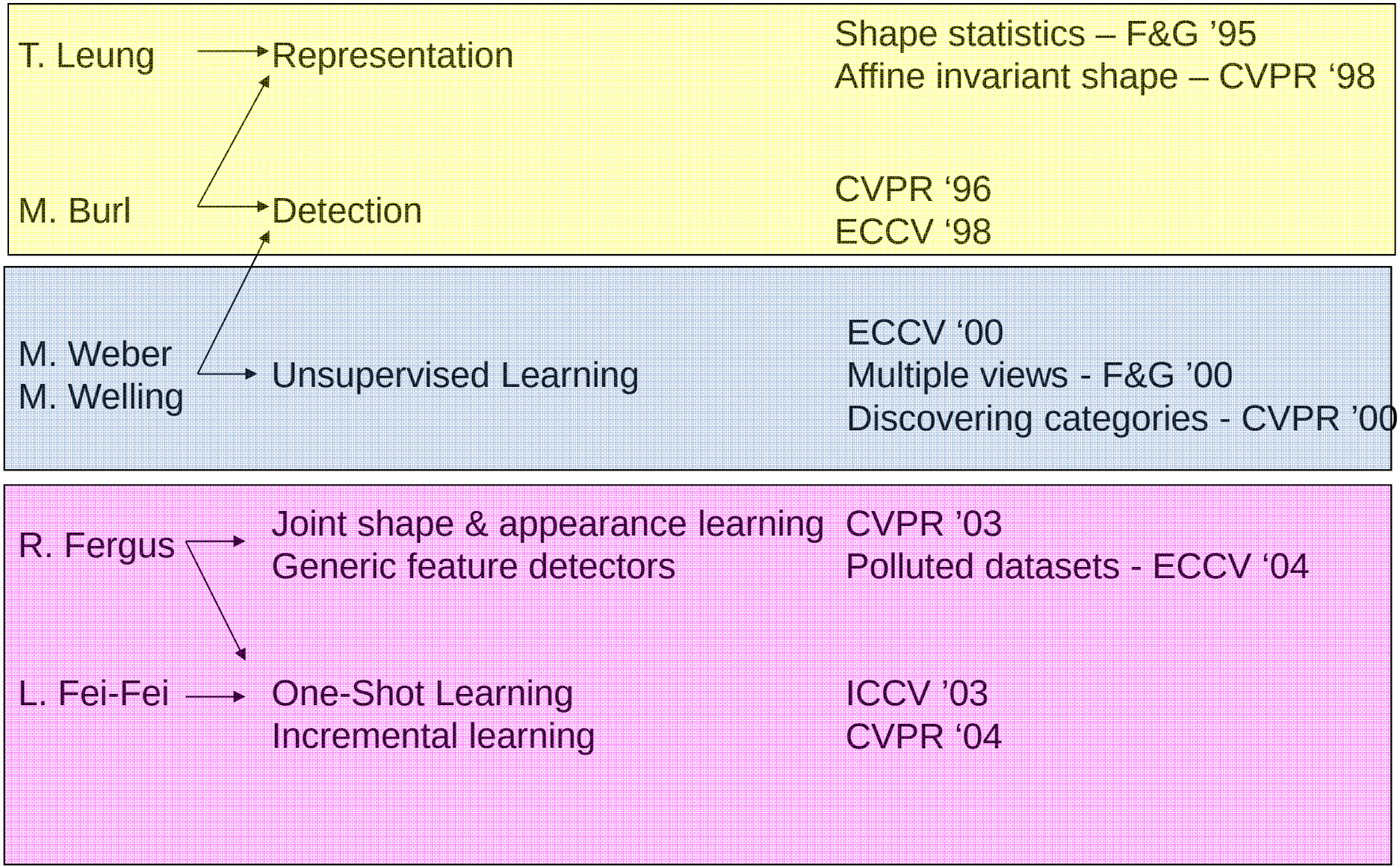
- Fischler & Elschlager 1973



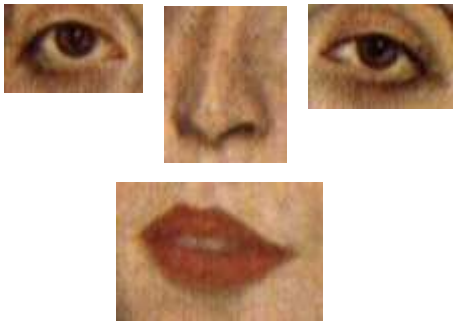
- Yuille ‘91
- Brunelli & Poggio ‘93
- Lades, v.d. Malsburg et al. ‘93
- Cootes, Lanitis, Taylor et al. ‘95
- Amit & Geman ‘95, ‘99
- et al. Perona ‘95, ‘96, ’98, ’00, ‘03
- Huttenlocher et al. ’00
- Agarwal & Roth ’02

etc…

The Constellation Model



Deformations



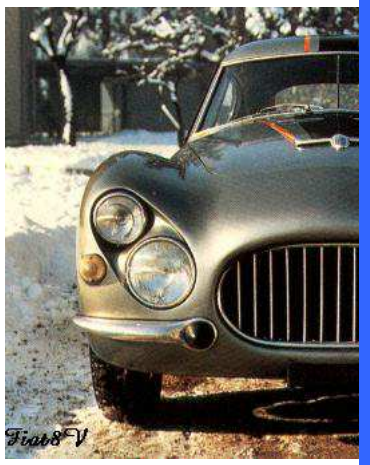
A

B

C

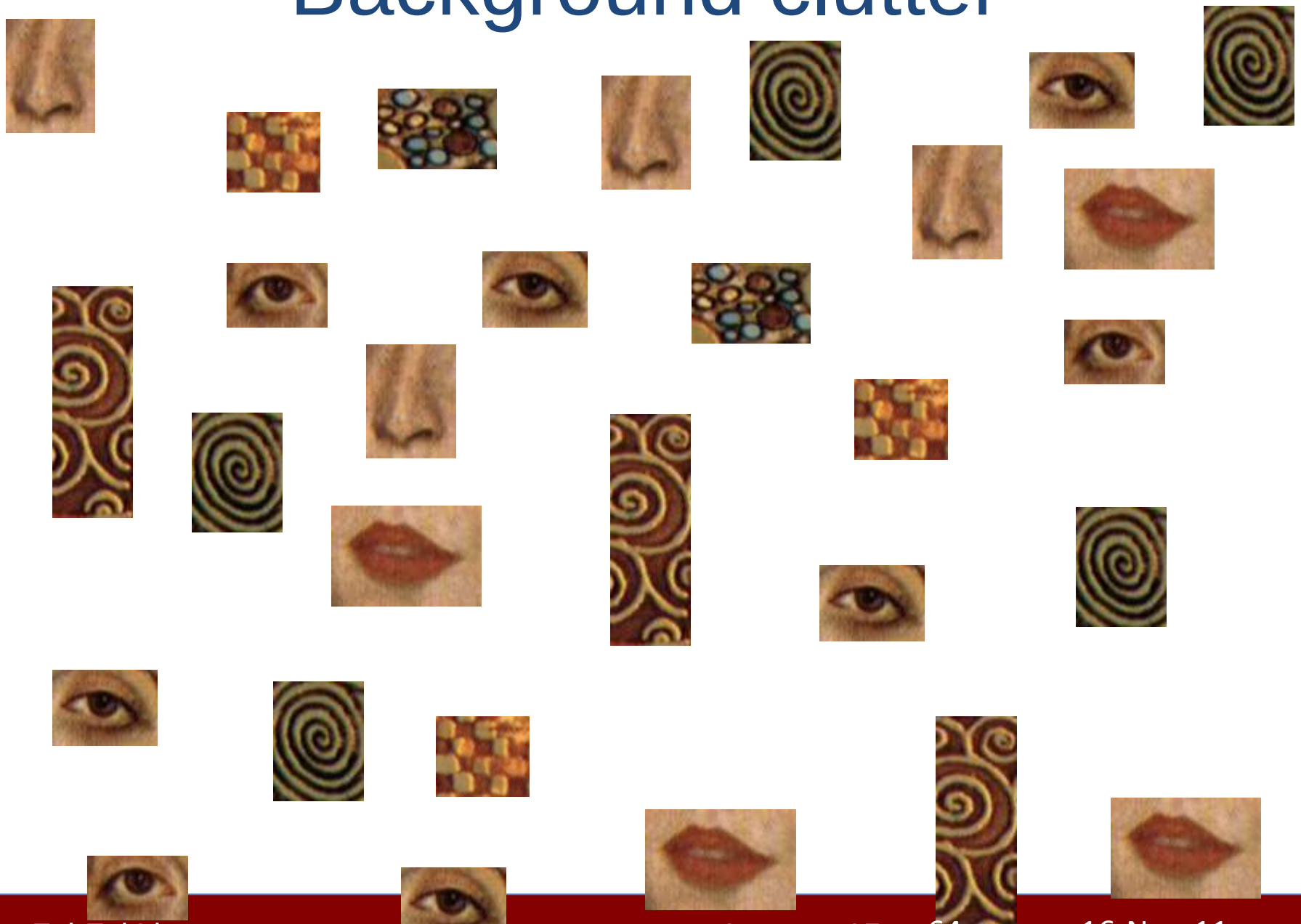
D

Presence / Absence of Features



occlusion

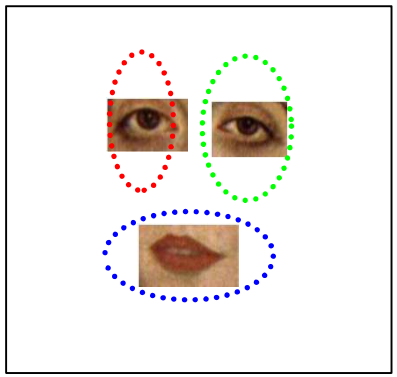
Background clutter



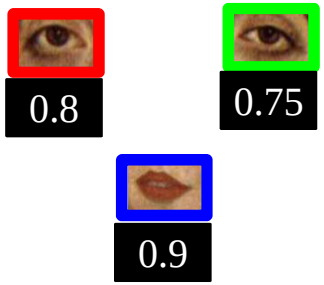
Generative probabilistic model

Foreground model

Gaussian shape pdf

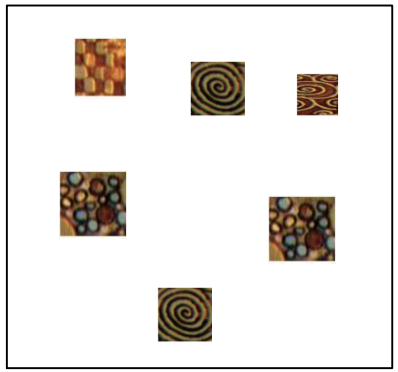


Prob. of detection



Clutter model

Uniform shape pdf



detections

$p_{\text{Poisson}}(N_1|\lambda_1)$

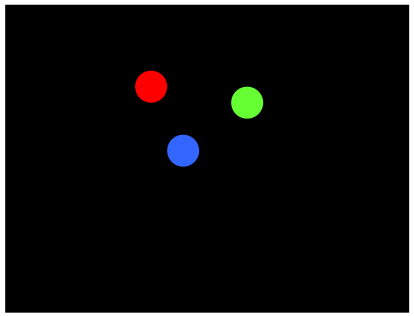
$p_{\text{Poisson}}(N_2|\lambda_2)$

$p_{\text{Poisson}}(N_3|\lambda_3)$

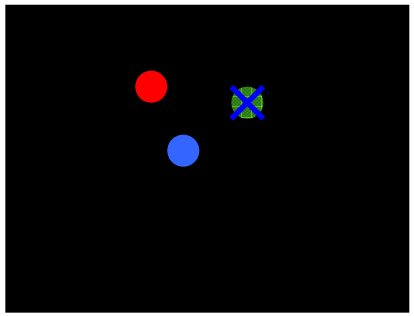
Assumptions: (a) Clutter independent of foreground detections
(b) Clutter detections independent of each other

Example

1. Object Part Positions

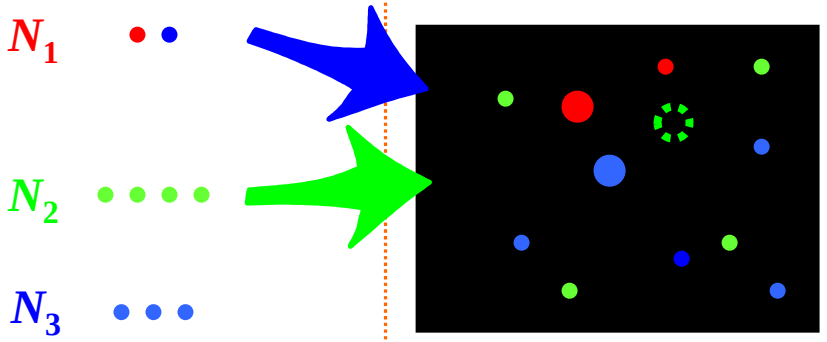


2. Part Absence

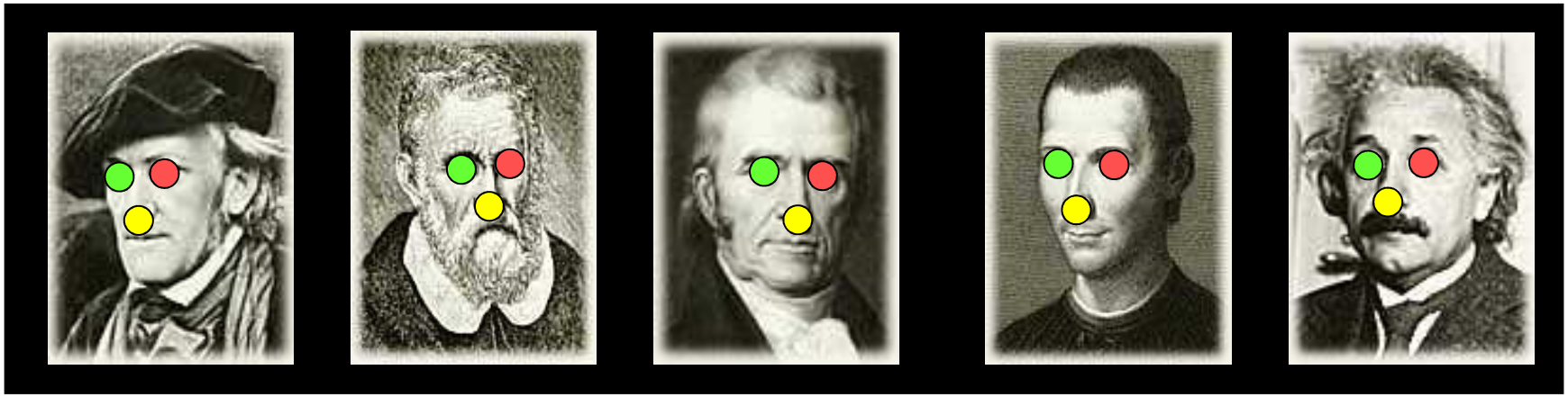


3a. N false detect

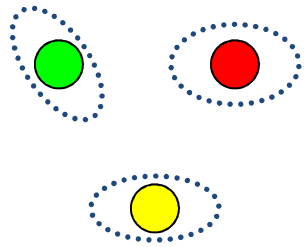
3b. Position f. detect



Learning Models `Manually'

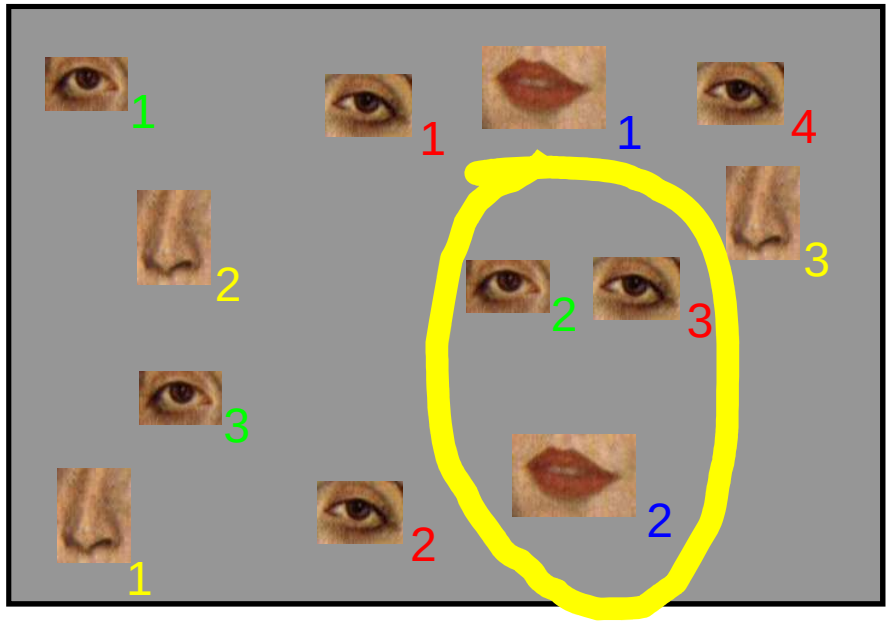


- Obtain set of training images
- Choose parts
- Label parts by hand, train detectors
- Learn model from labeled parts



Recognition

1. Run part detectors exhaustively over image



$$h = \begin{pmatrix} 0 \ldots N_1 \\ 0 \ldots N_2 \\ 0 \ldots N_3 \\ 0 \ldots N_4 \end{pmatrix} \qquad \text{e.g. } h = \begin{pmatrix} 2 \\ 3 \\ 0 \\ 2 \end{pmatrix}$$

2. Try different combinations of detections in model
   - Allow detections to be missing (occlusion)

3. Pick hypothesis which maximizes:

$$\frac{p(Data \mid Object, Hyp)}{p(Data \mid Clutter, Hyp)}$$

4. If ratio is above threshold then, instance detected

So far…..

- Representation
  - Joint model of part locations
  - Ability to deal with background clutter and occlusions

- Learning
  - Manual construction of part detectors
  - Estimate parameters of shape density

- Recognition
  - Run part detectors over image
  - Try combinations of features in model
  - Use efficient search techniques to make fast

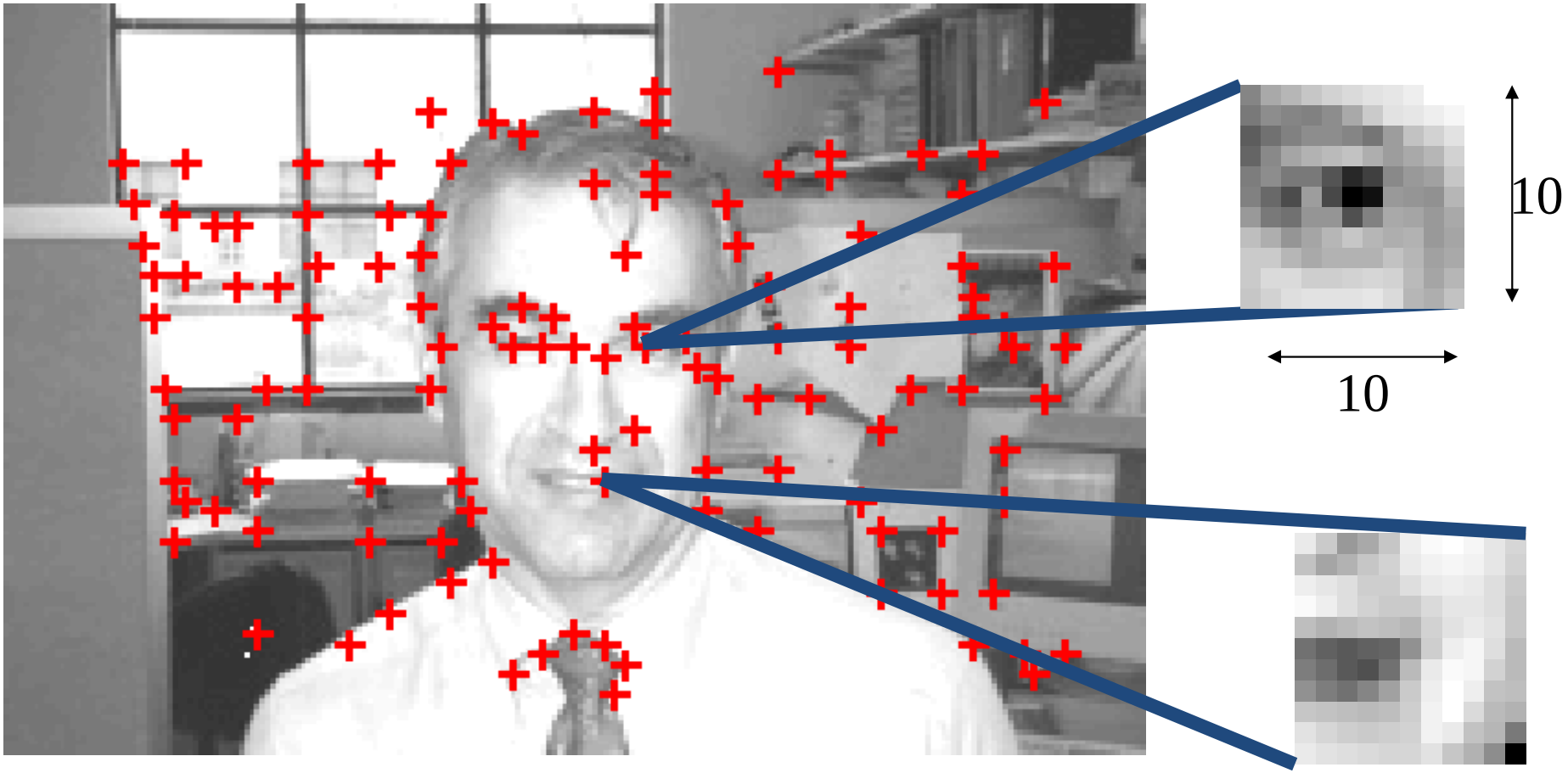
Unsupervised Learning

Weber & Welling et. al.

(Semi) Unsupervised learning

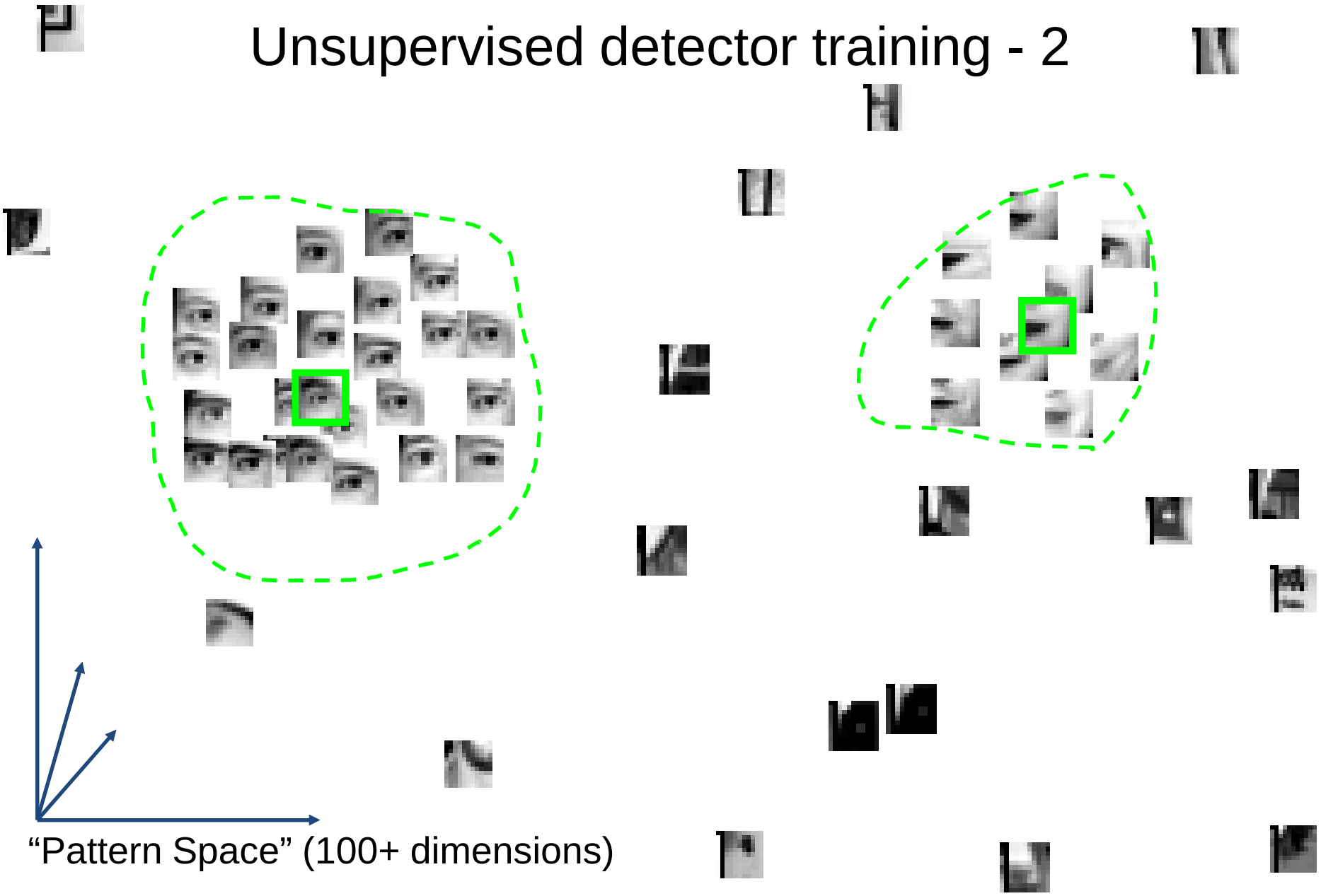
- Know if image contains object or not
- But no segmentation of object or manual selection of features

Unsupervised detector training - 1

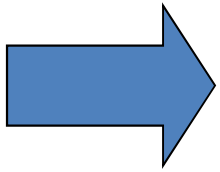


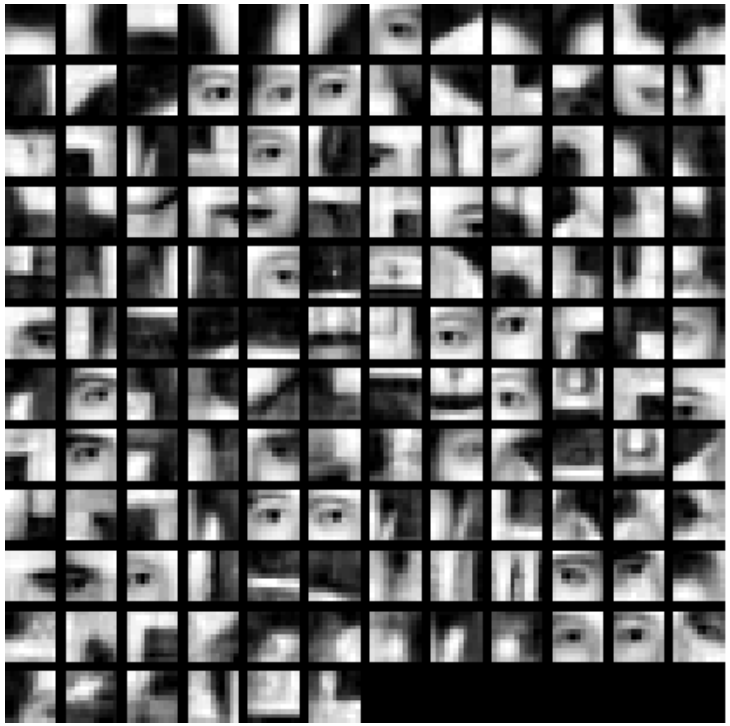
- Highly textured neighborhoods are selected automatically
- produces 100-1000 patterns per image

Unsupervised detector training - 2



Unsupervised detector training - 3



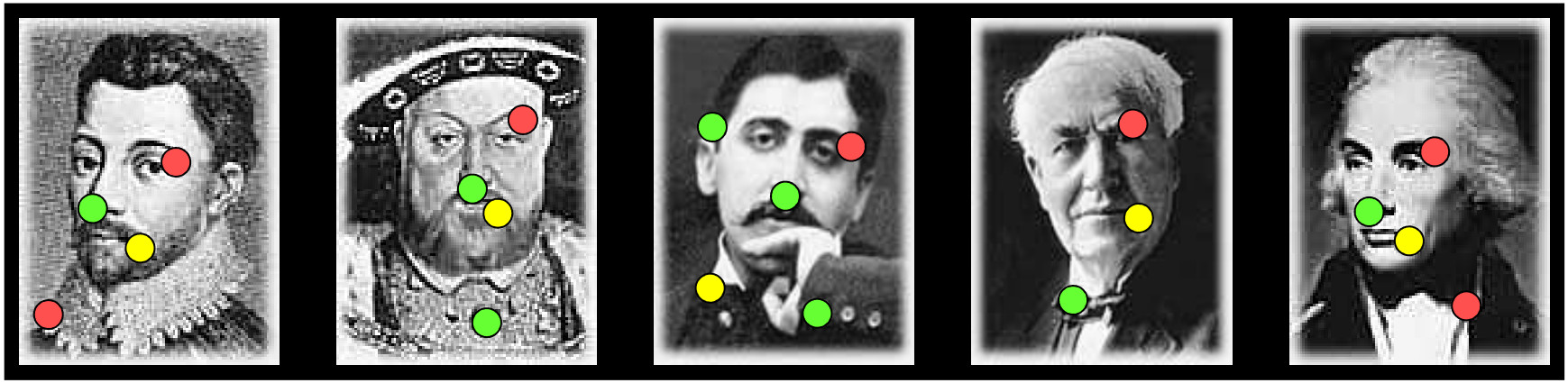


100-1000 images

~100 detectors

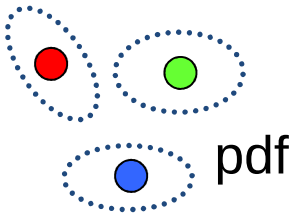
Learning

- Take training images. Pick set of detectors. Apply detectors.
- Task: Estimation of model parameters
- Chicken and Egg type problem, since we initially know neither:
  - Model parameters
  - Assignment of regions to foreground / background
- Let the assignments be a hidden variable and use EM algorithm to learn them and the model parameters

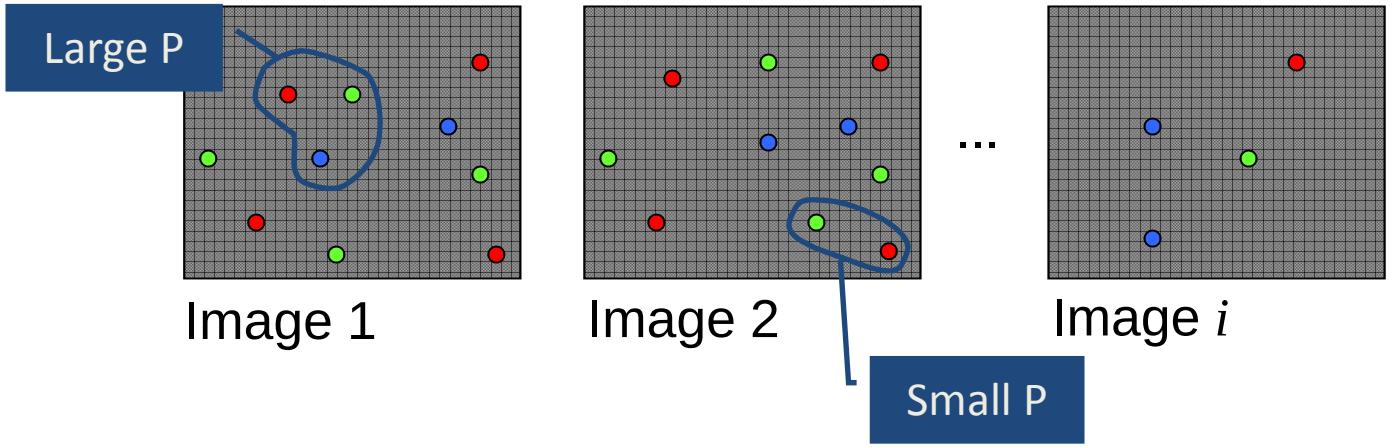


ML using EM

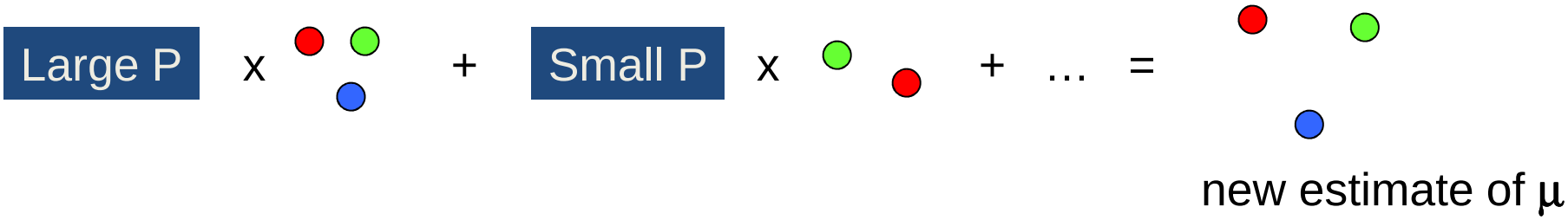
1. Current estimate



2. Assign probabilities to constellations

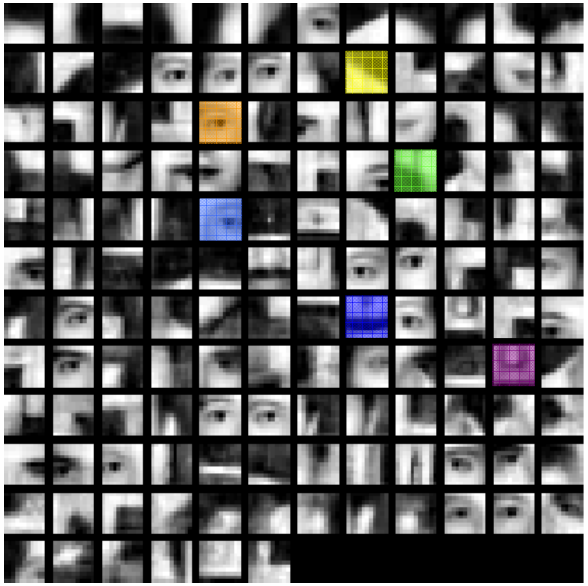


3. Use probabilities as weights to re-estimate parameters. Example: μ



Detector Selection

- Try out different combinations of detectors (Greedy search)



Detectors (≈100)

Choice 1 → Parameter Estimation → Model 1

Choice 2 → Parameter Estimation → Model 2

•
•
•

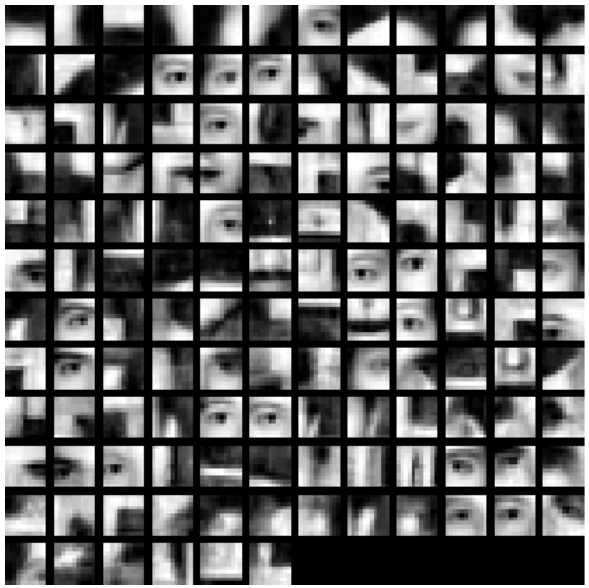
Predict / measure model performance (validation set or directly from model)

Frontal Views of Faces

- 200 Images (100 training, 100 testing)
- 30 people, different for training and testing

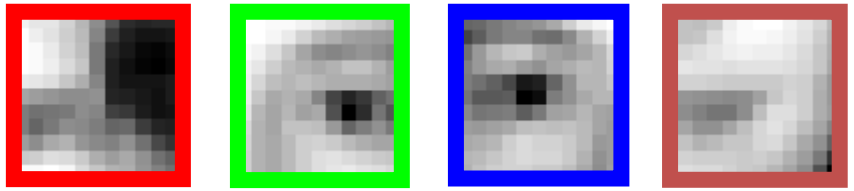
Learned face model

Pre-selected Parts

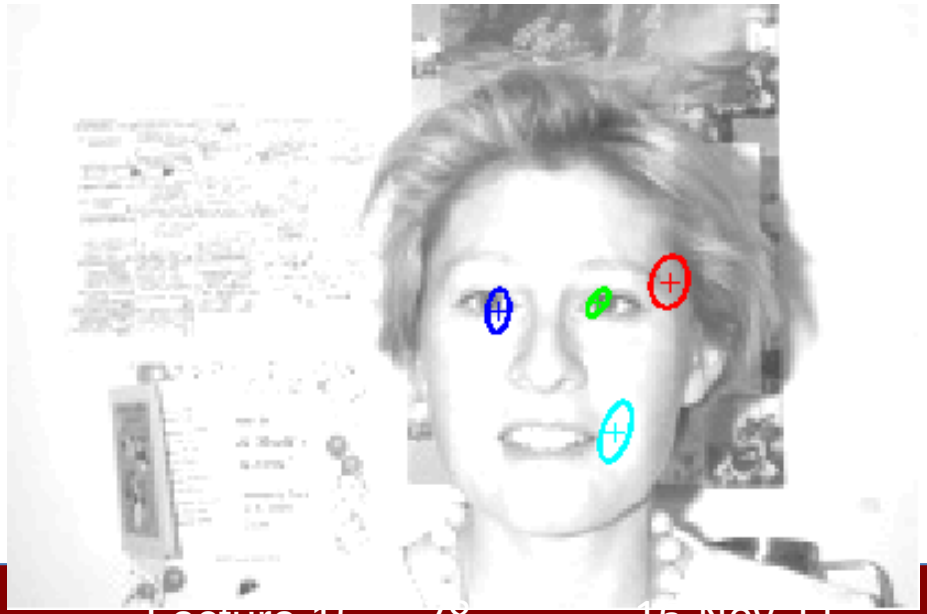


Test Error: 6% (4 Parts)

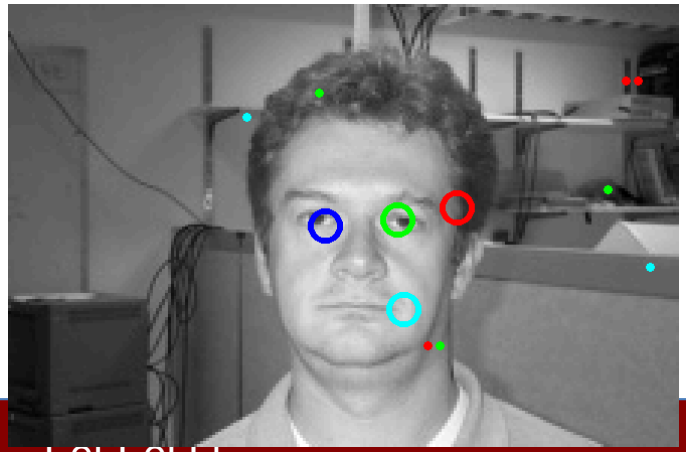
Parts in Model



Model Foreground pdf



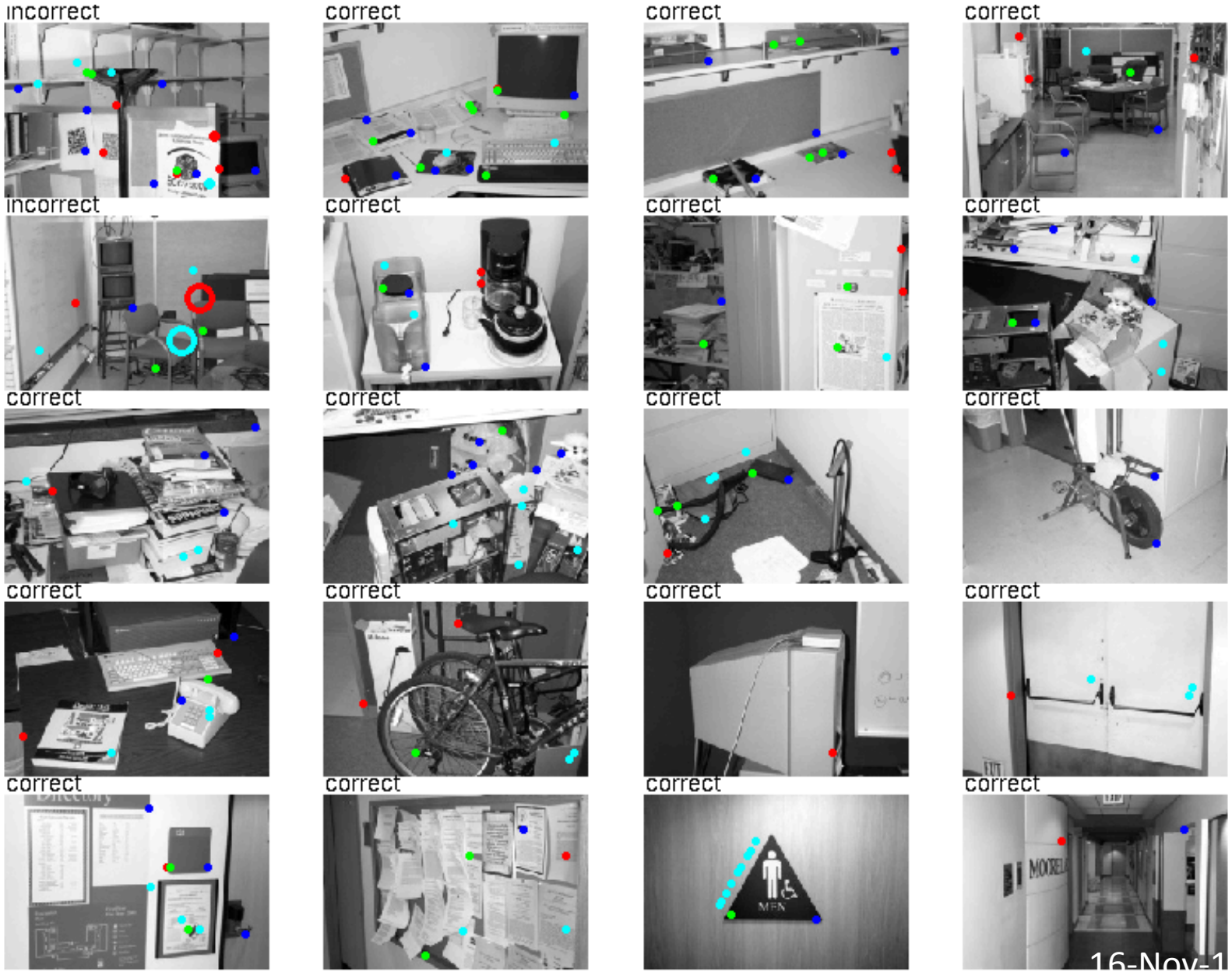
Sample Detection



Face images

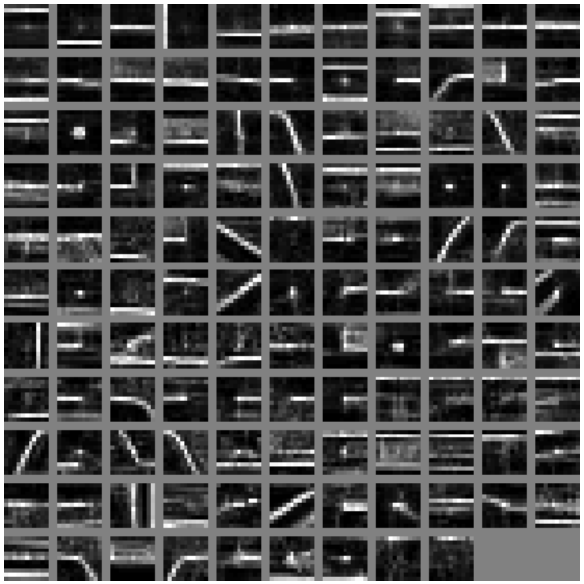

correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
incorrect
incorrect
incorrect

Background images



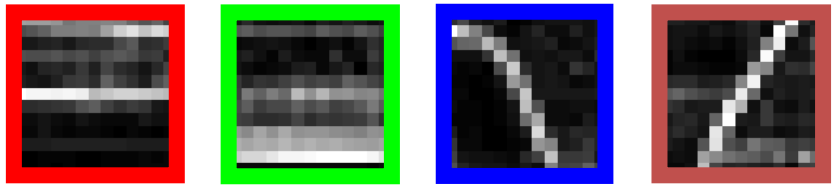
Car from Rear

Preselected Parts

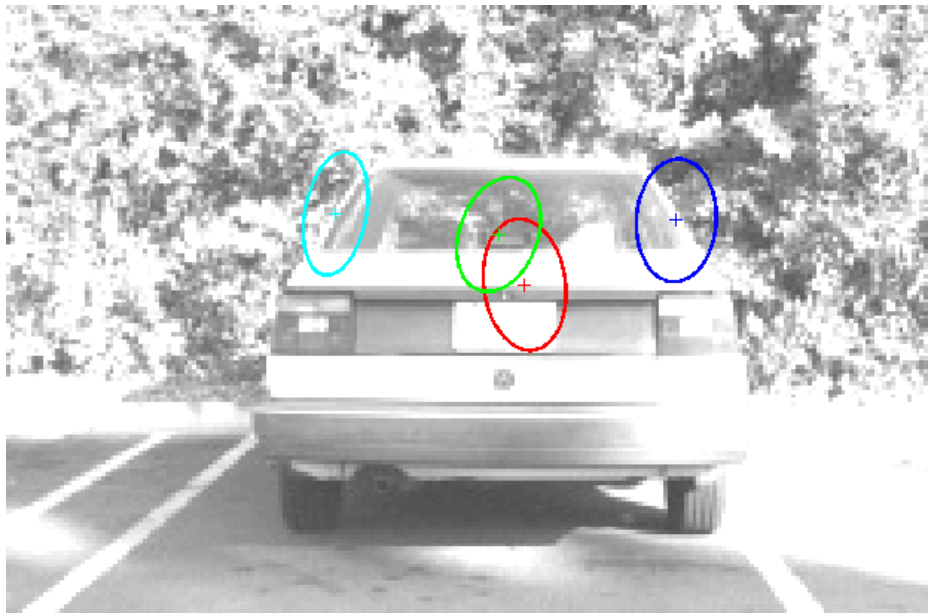


Test Error: 13% (5 Parts)

Parts in Model



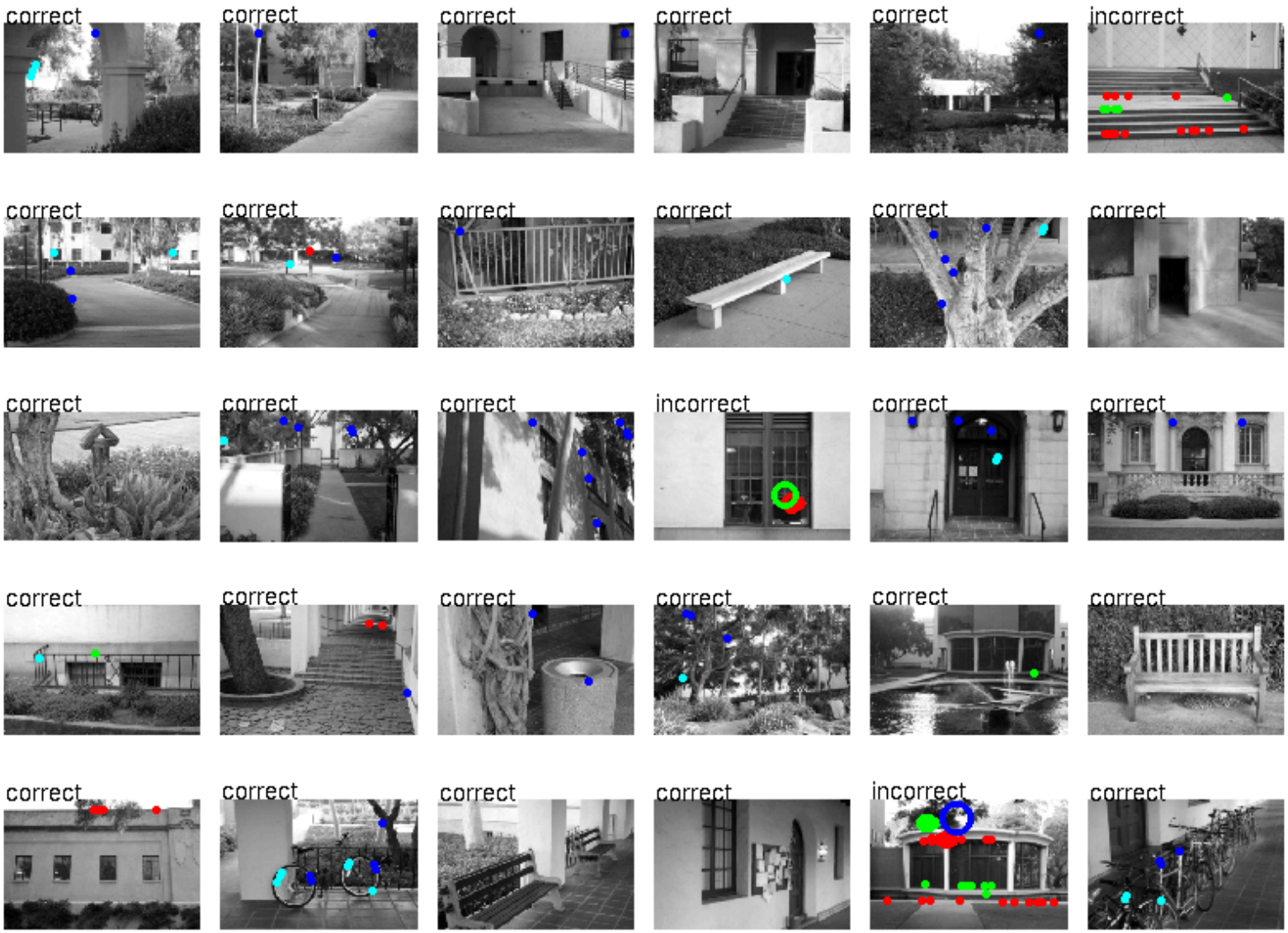
Model Foreground pdf



Sample Detection

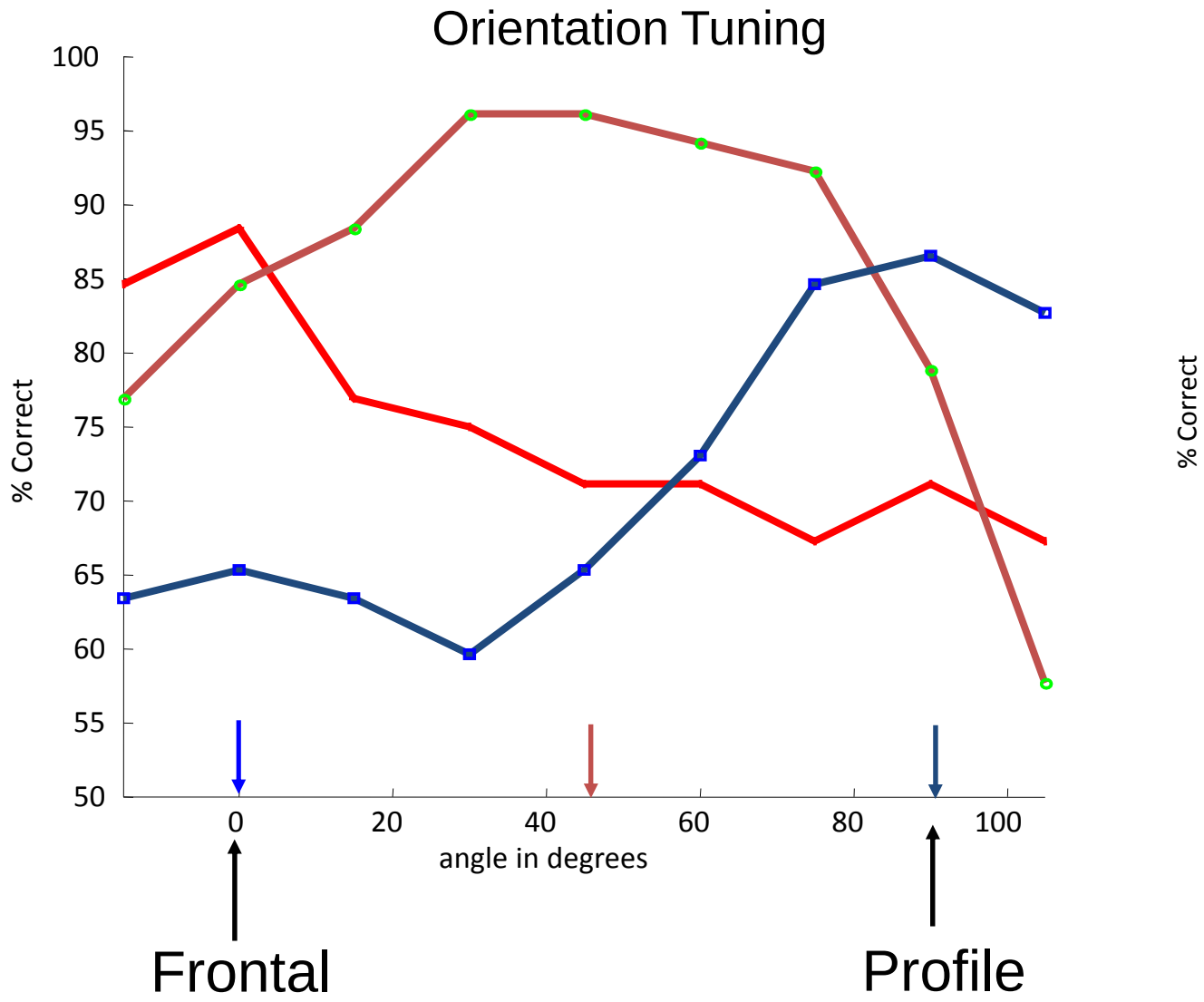
Detections of Cars

Background Images



3D Object recognition – Multiple mixture components

3D Orientation Tuning



So far (2)…..

- Representation
  - Multiple mixture components for different viewpoints
- Learning
  - Now semi-unsupervised
  - Automatic construction and selection of part detectors
  - Estimation of parameters using EM
- Recognition
  - As before

- Issues:

  -Learning is slow (many combinations of detectors)

  -Appearance learnt first, then shape

Issues

- Speed of learning
  - Slow (many combinations of detectors)
- Appearance learnt first, then shape
  - Difficult to learn part that has stable location but variable appearance
  - Each detector is used as a cross-correlation filter, giving a hard definition of the part's appearance

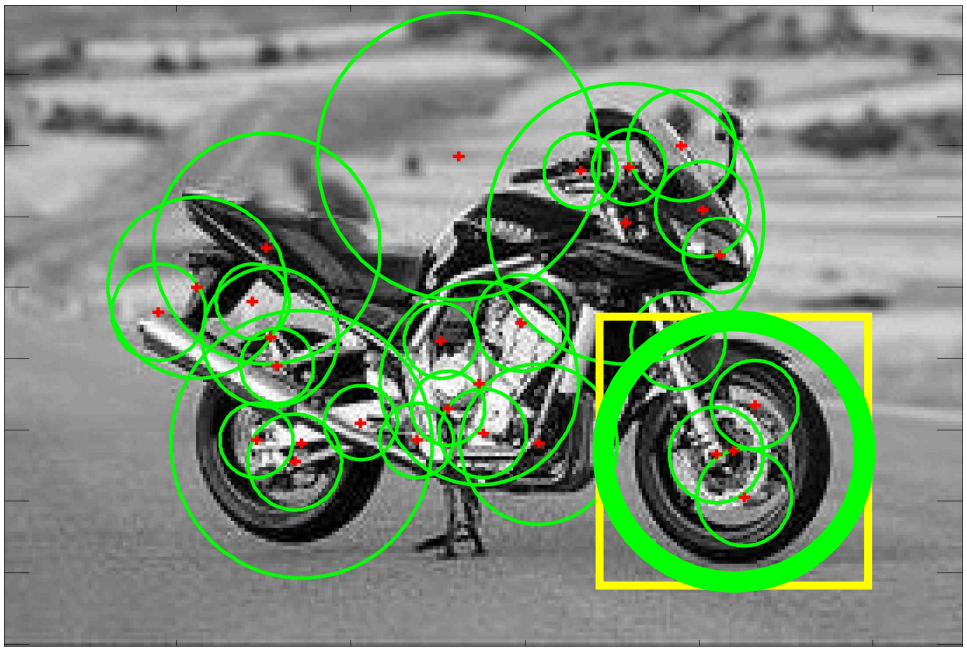
- Would like a fully probabilistic representation of the object

Object categorization

Fergus et. al.

CVPR ’03, IJCV ‘06

Detection & Representation of regions



- Find regions within image
- Use salient region operator (Kadir & Brady 01)

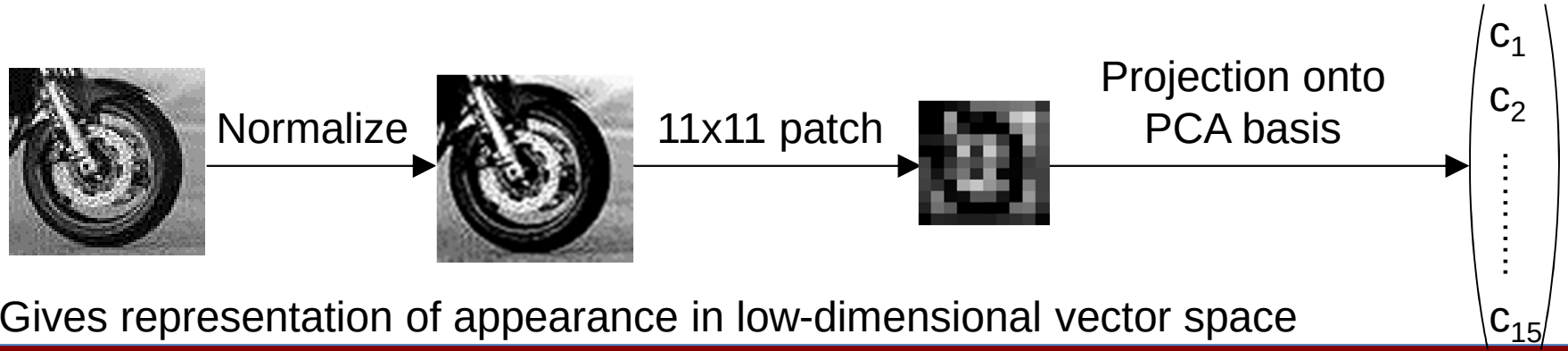
Location

(x,y) coords. of region centre

Scale

Radius of region (pixels)

Appearance



Gives representation of appearance in low-dimensional vector space

Motorbikes example

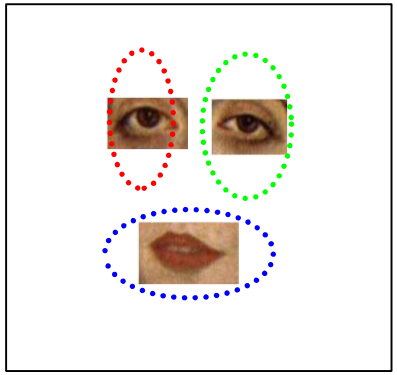
•Kadir & Brady saliency region detector

Generative probabilistic model (2)

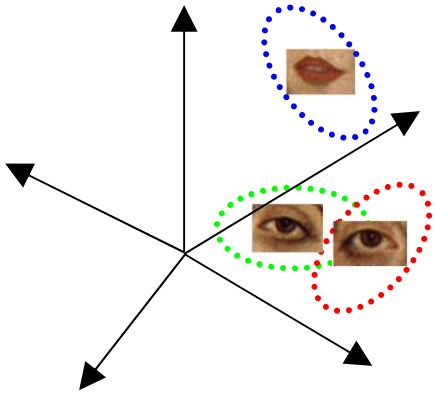
Foreground model

based on Burl, Weber et al. [ECCV '98, '00]

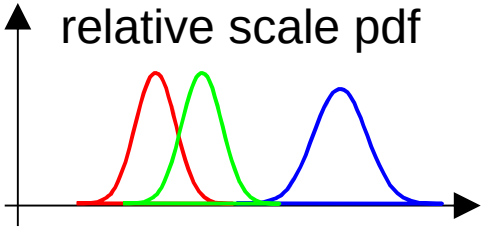
Gaussian shape pdf



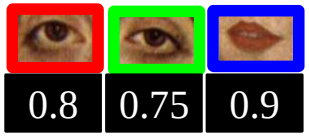
Gaussian part appearance pdf



Gaussian relative scale pdf

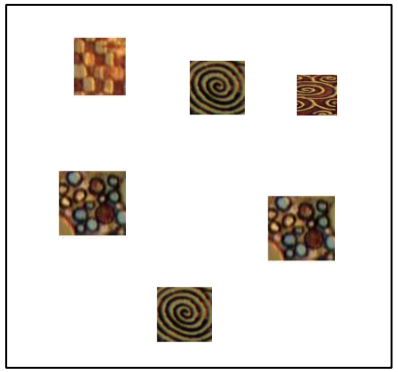


Prob. of detection

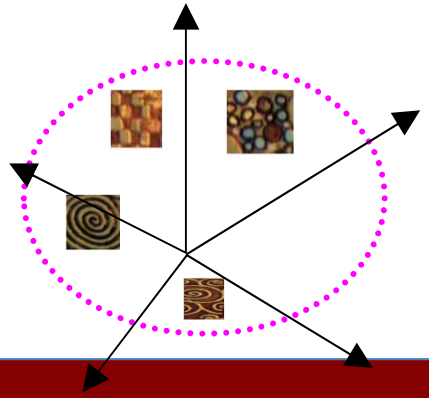


Clutter model

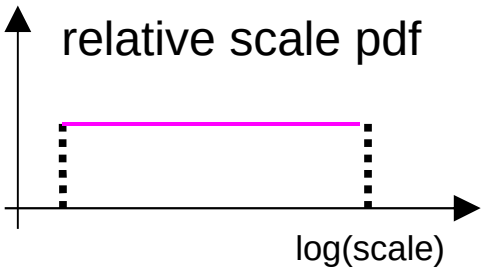
Uniform shape pdf



Gaussian background appearance pdf



Uniform relative scale pdf

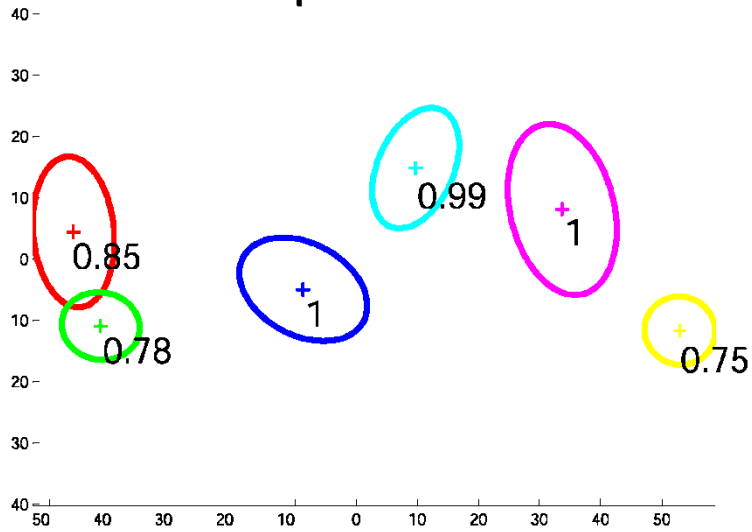


Poission pdf on # detections

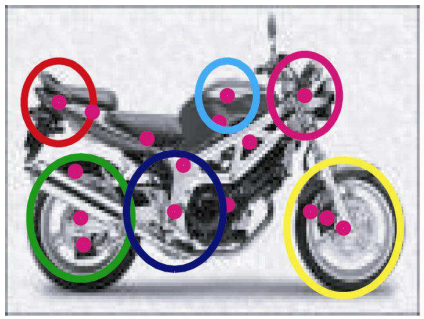
Motorbikes

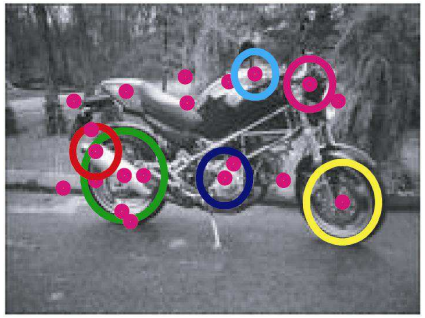
Samples from appearance model

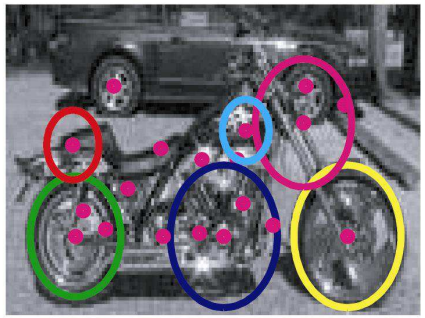
Shape model

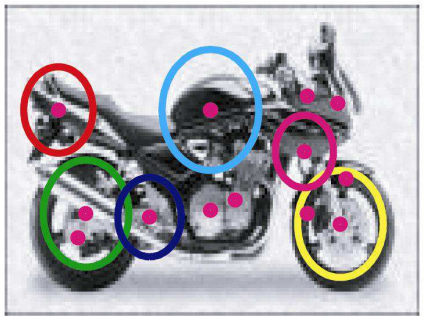


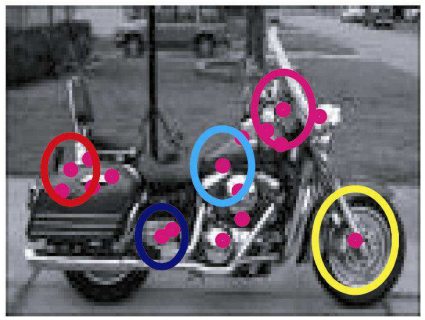
Recognized Motorbikes

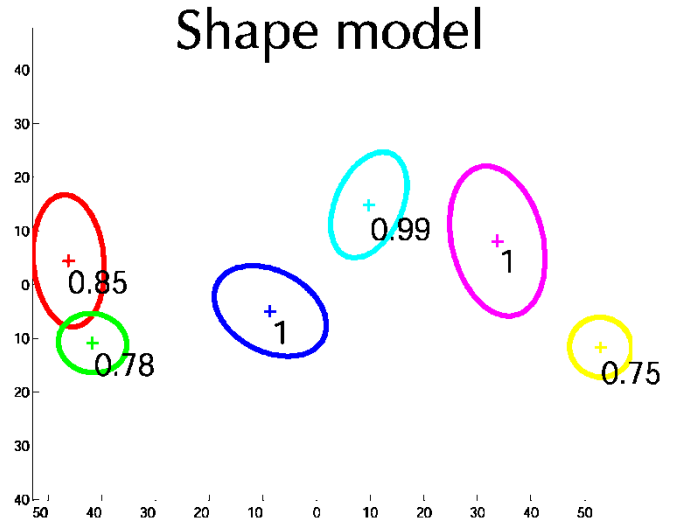






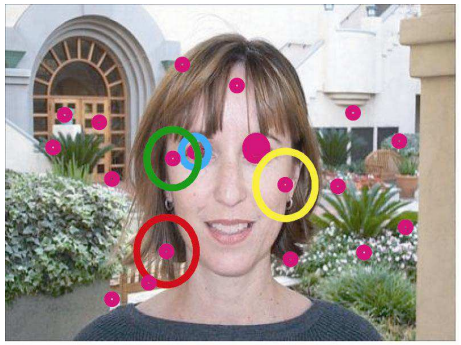


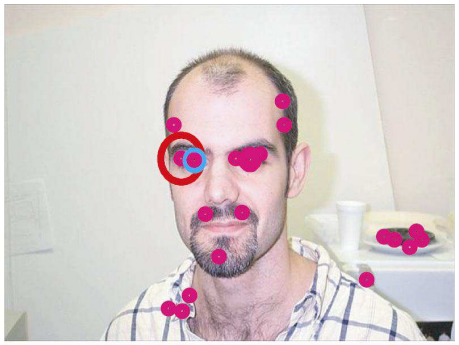


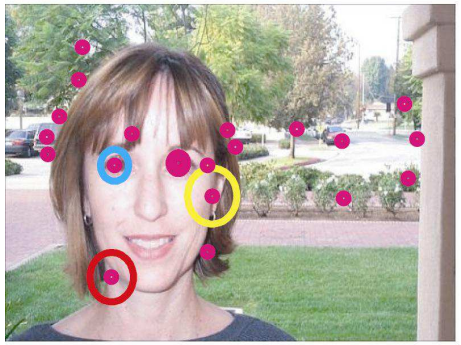


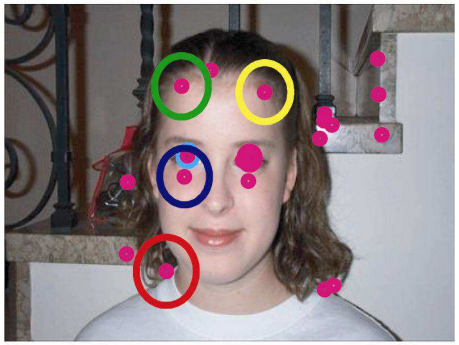
Background images evaluated with motorbike model

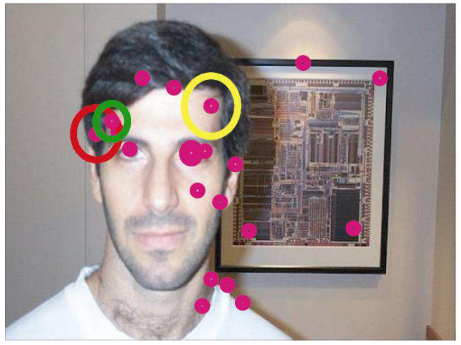
Frontal faces

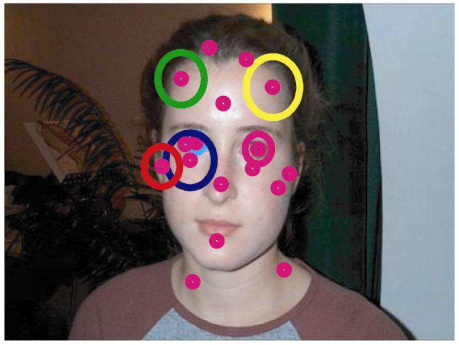


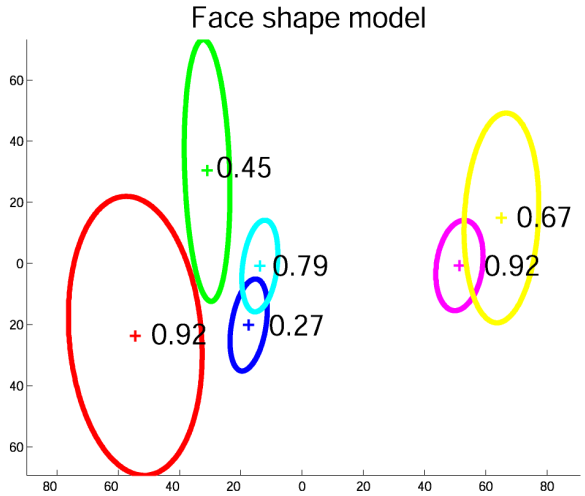


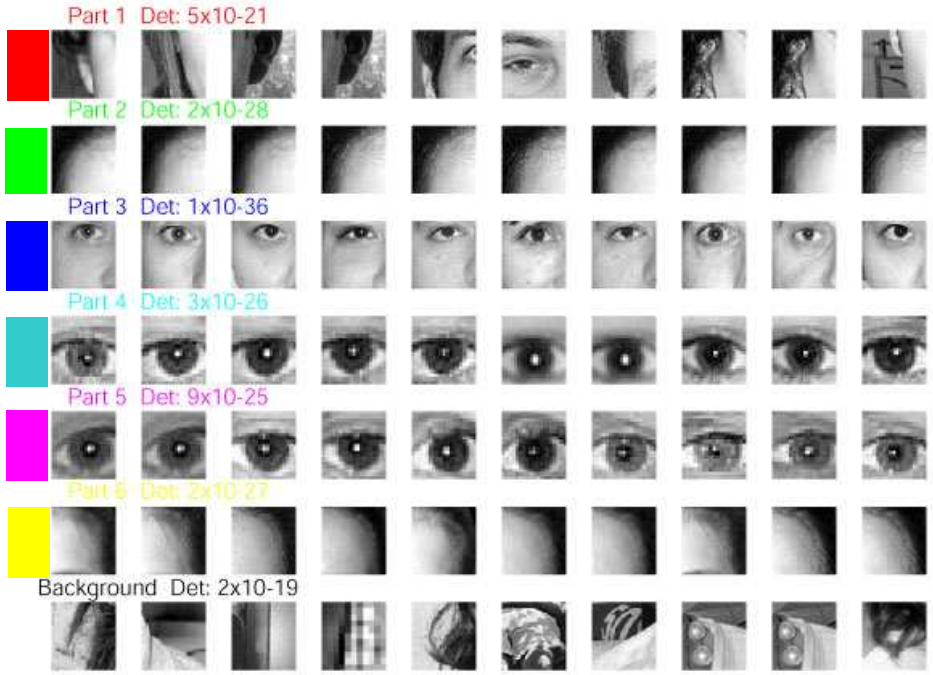




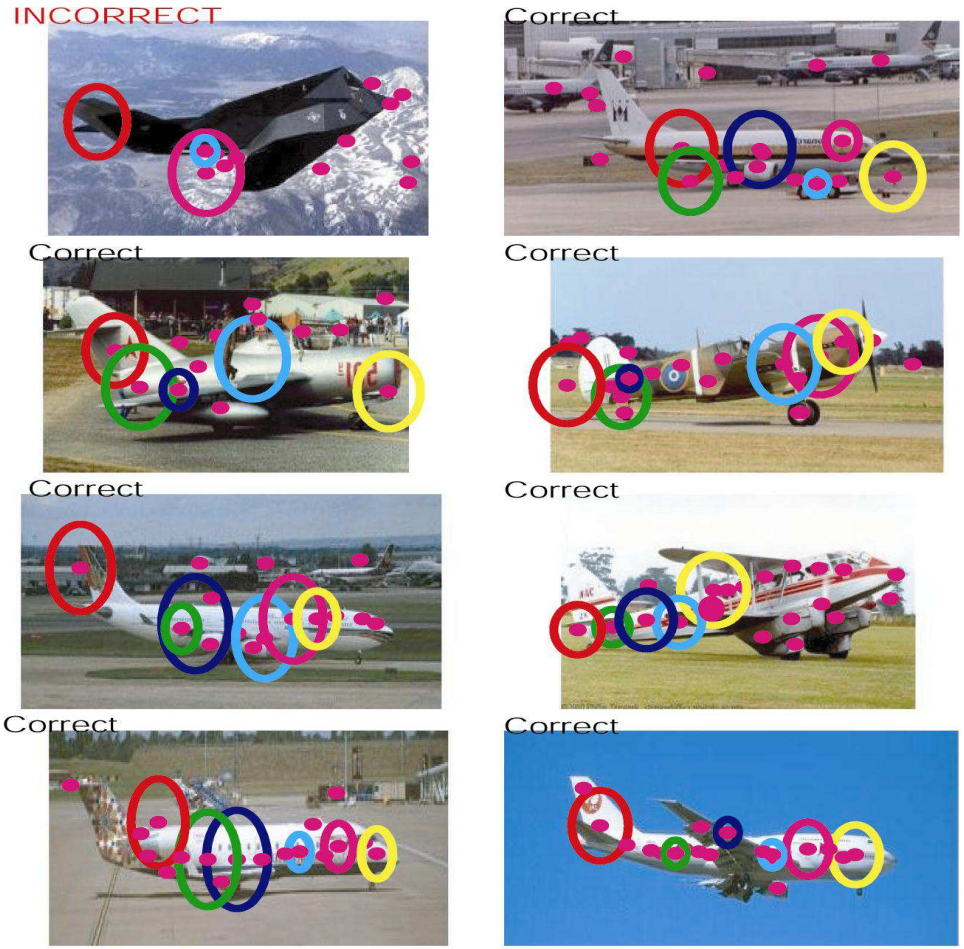


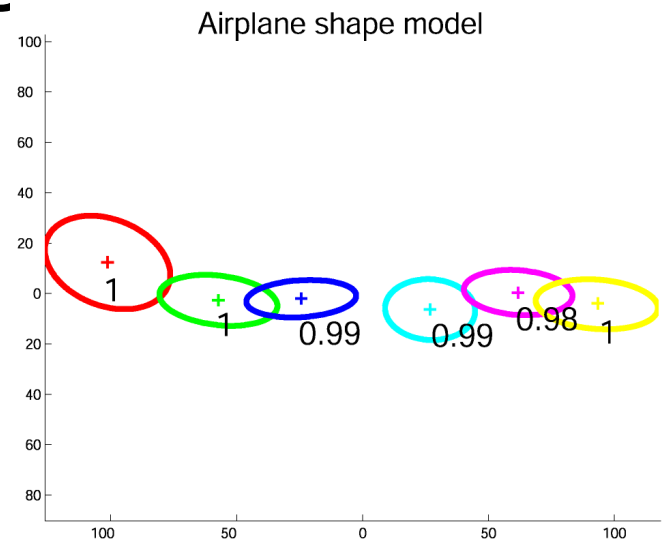


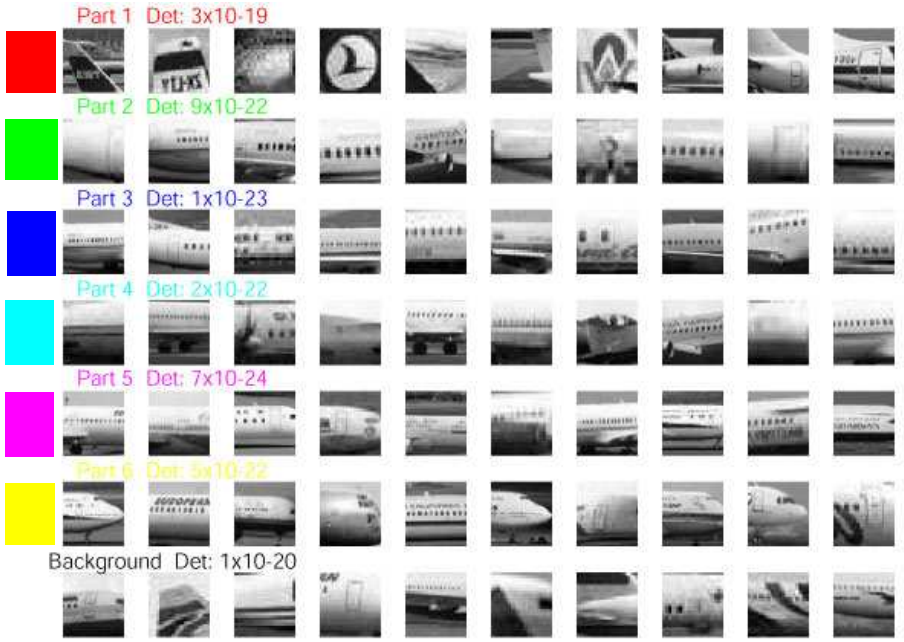




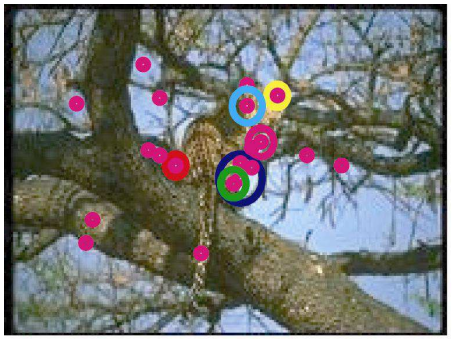
Airplanes

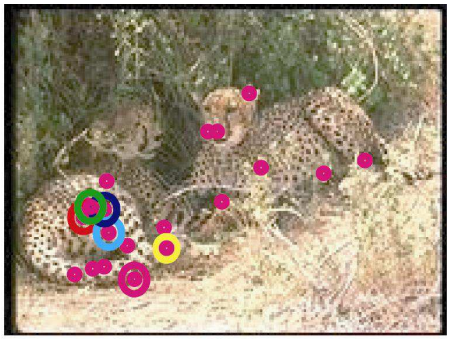

INCORRECT
Correct
Correct
Correct
Correct
Correct
Correct
Correct

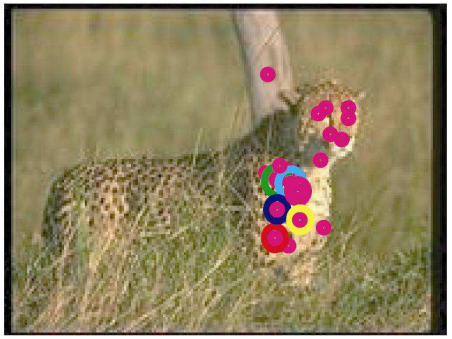

Airplane shape model
100
80
60
40
20
0
20
40
60
80
100
50
0
50
100
1
1
0.99
0.99
0.98
1

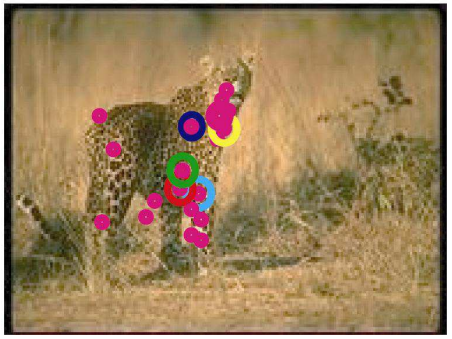

Part 1 Det: 3x10-19
Part 2 Det: 9x10-22
Part 3 Det: 1x10-23
Part 4 Det: 2x10-22
Part 5 Det: 7x10-24
Part 6 Det: 5x10-22
Background Det: 1x10-20

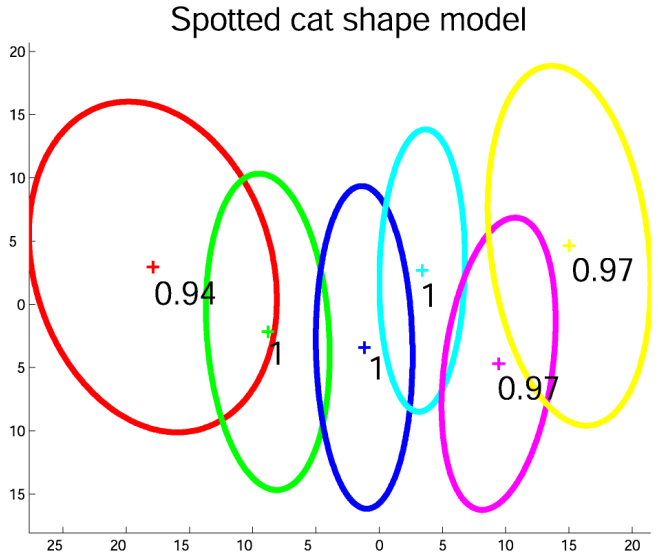
Spotted cats

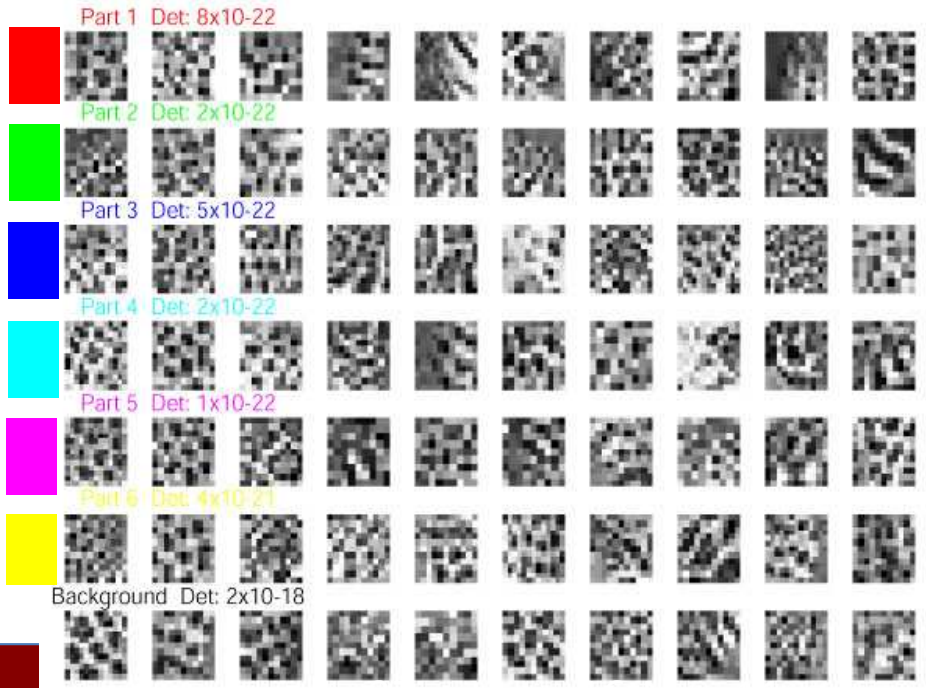












Summary of results

Dataset	Fixed scale experiment	Scale invariant experiment
Motorbikes	7.5	6.7
Faces	4.6	4.6
Airplanes	9.8	7.0
Cars (Rear)	15.2	9.7
Spotted cats	10.0	10.0

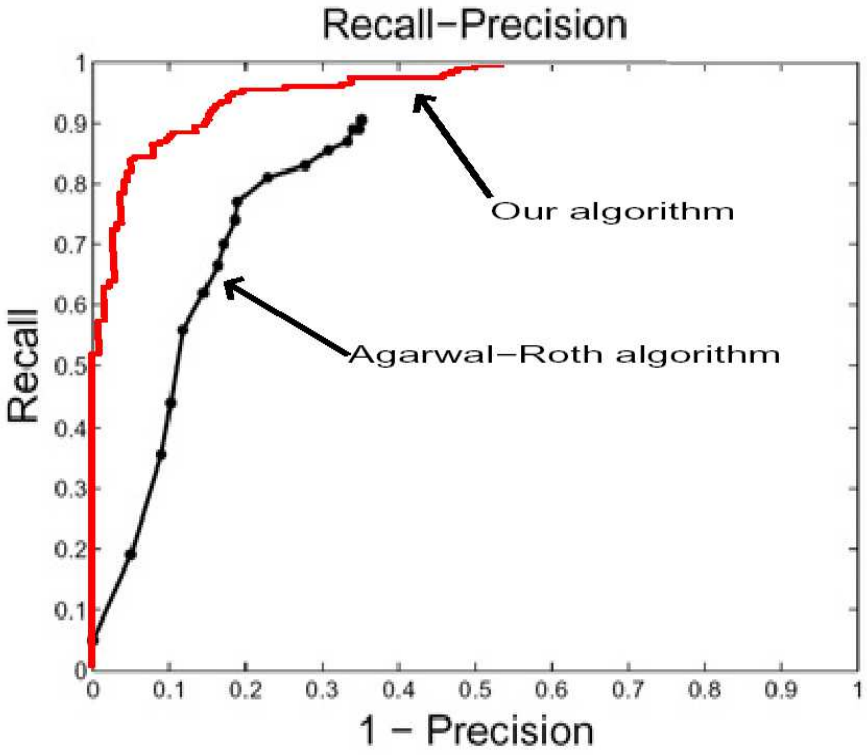
% equal error rate

Note: Within each series, same settings used for all datasets

Comparison to other methods

Dataset	Ours	Others	
Motorbikes	7.5	16.0	Weber et al. [ECCV '00]
Faces	4.6	6.0	Weber
Airplanes	9.8	32.0	Weber
Cars (Side)	11.5	21.0	Agarwal Roth [ECCV '02]

% equal error rate



Why this design?

- Generic features seem to well in finding consistent parts of the object
- Some categories perform badly – different feature types needed
- Why PCA representation?
  - Tried ICA, FLD, Oriented filter responses etc.
  - But PCA worked best
- Fully probabilistic representation lets us use tools from machine learning community

What we have learned today?

- Bag of Words model (Problem Set 4 (Q2))
  - Basic representation
  - Different learning and recognition algorithms
- Constellation model
  - Weakly supervised training
  - One-shot learning (supplementary materials)
- (Problem Set 4 (Q1))

Supplementary materials

- One-Shot learning using Constellation Model

S. Savarese, 2003

P. Buegel, 1562

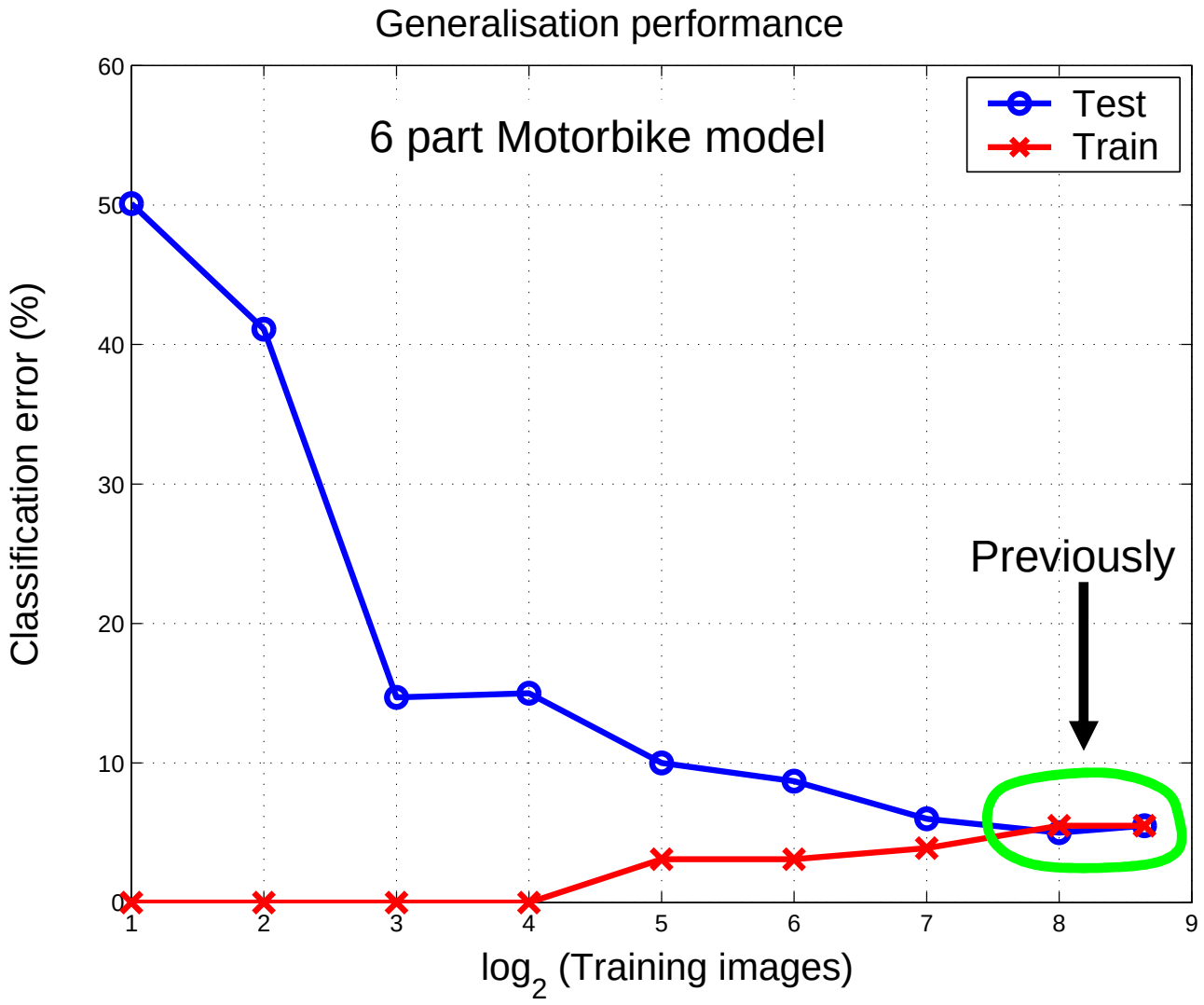
One-Shot learning

Fei-Fei et. al.

ICCV ’03, PAMI ‘06

Algorithm	Training Examples	Categories
Burl, et al. Weber, et al. Fergus, et al.	200 ~ 400	Faces, Motorbikes, Spotted cats, Airplanes, Cars
Viola et al.	~10,000	Faces
Schneiderman, et al.	~2,000	Faces, Cars
Rowley et al.	~500	Faces

Number of training examples



How do we do better than what statisticians have told us?

- Intuition 1: use Prior information
- Intuition 2: make best use of training information

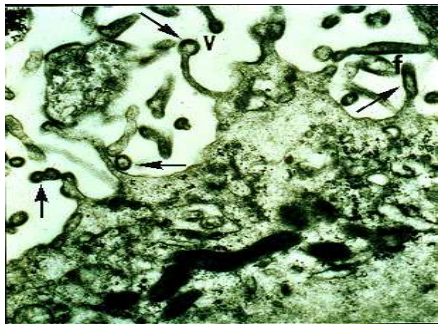
Prior knowledge: means

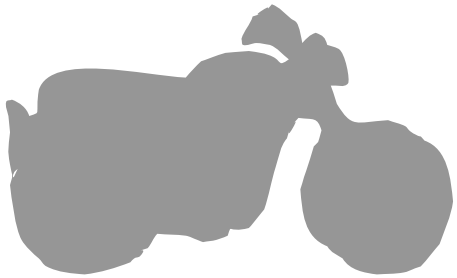
Appearance

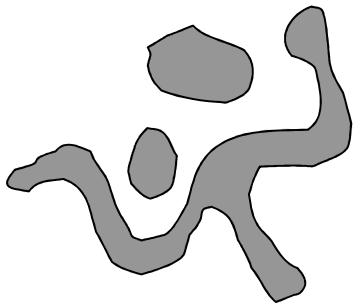
Shape

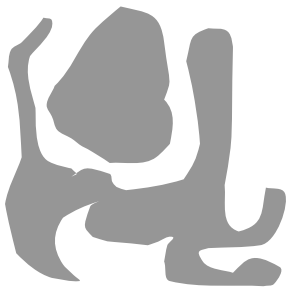
likely

unlikely









Bayesian framework

P(object | test, train) vs. P(clutter | test, train)

Bayes Rule

$$p(\text{test} \mid \text{object}, \text{train}) \; p(\text{object})$$

Expansion by parametrization

$$\int p(\text{test} \mid \theta, \text{object}) \; p(\theta \mid \text{object}, \text{train}) \; d\theta$$

Bayesian framework

P(object | test, train) vs. P(clutter | test, train)

Bayes Rule

$$p(\text{test} \mid \text{object}, \text{train}) \; p(\text{object})$$

Expansion by parametrization

$$\int p(\text{test} \mid \theta, \text{object}) \; p(\theta \mid \text{object}, \text{train}) \; d\theta$$

Previous Work: $\delta\left(\theta^{\text{ML}}\right)$

Bayesian framework

P(object | test, train) vs. P(clutter | test, train)

Bayes Rule

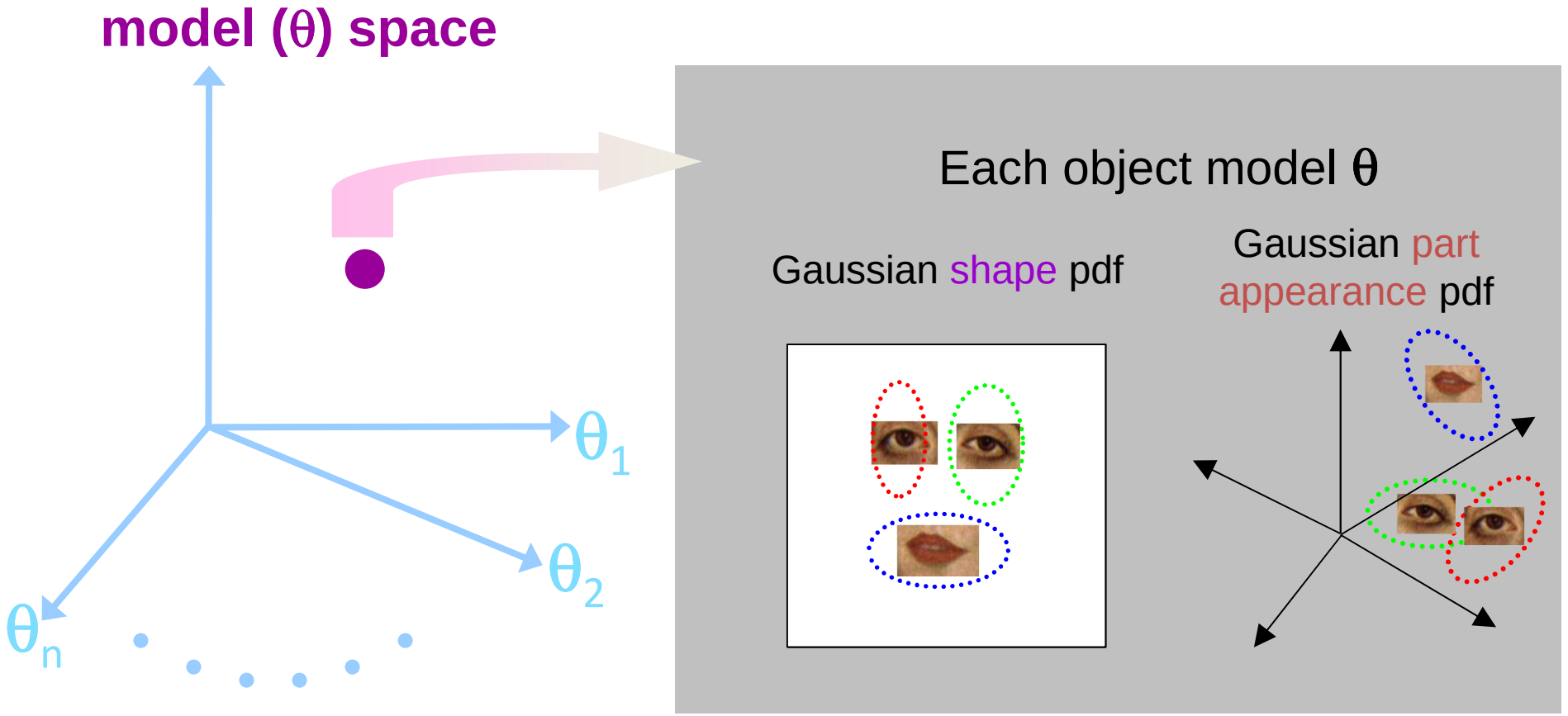
$$p(\text{test} \mid \text{object}, \text{train})\; p(\text{object})$$

Expansion by parametrization

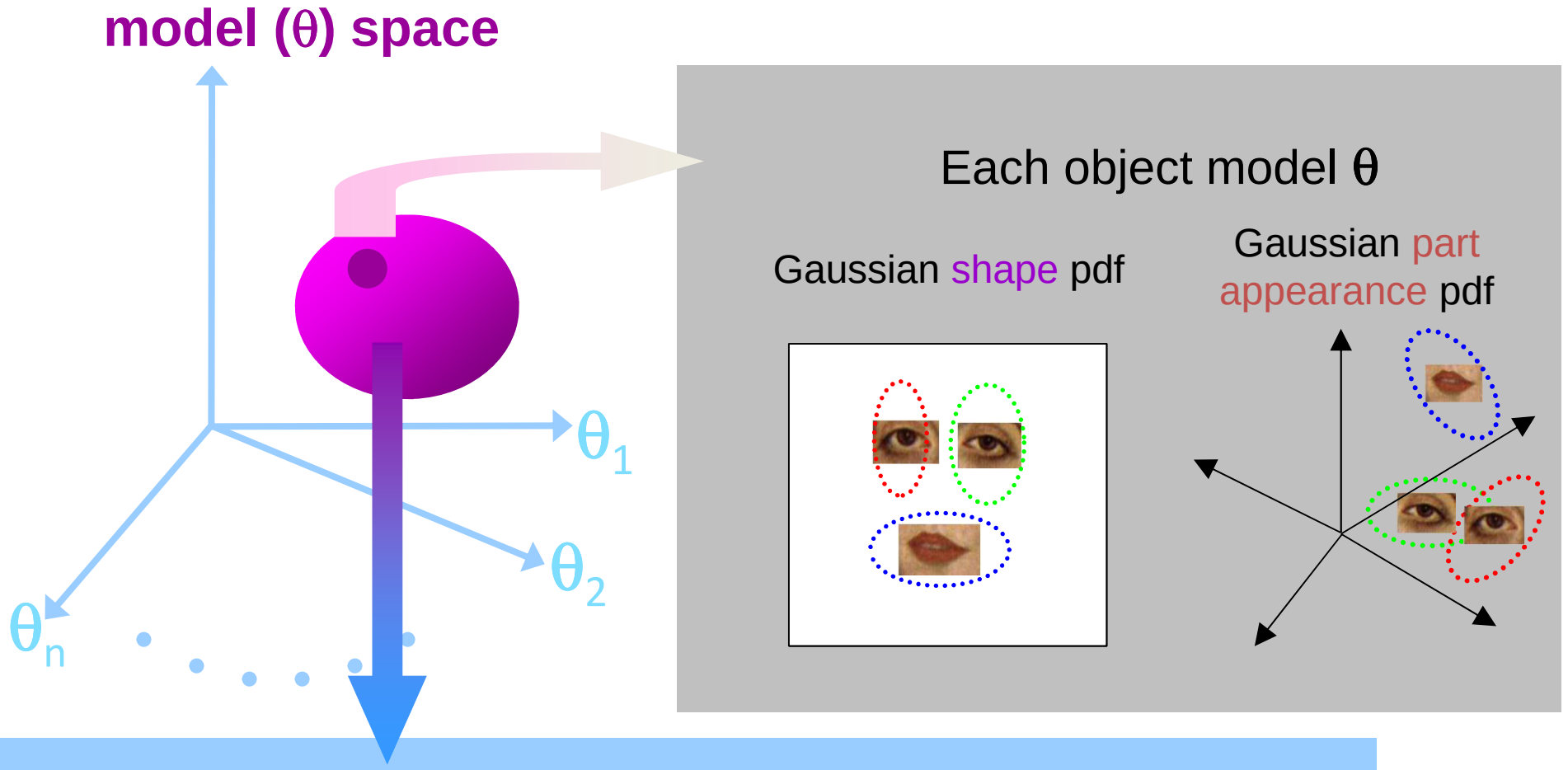
$$\int p(\text{test} \mid \theta, \text{object})\; p(\theta \mid \text{object}, \text{train})\; d\theta$$

One-Shot learning: $p(\text{train} \mid \theta, \text{object})\, p(\theta)$

Model Structure



Model Structure

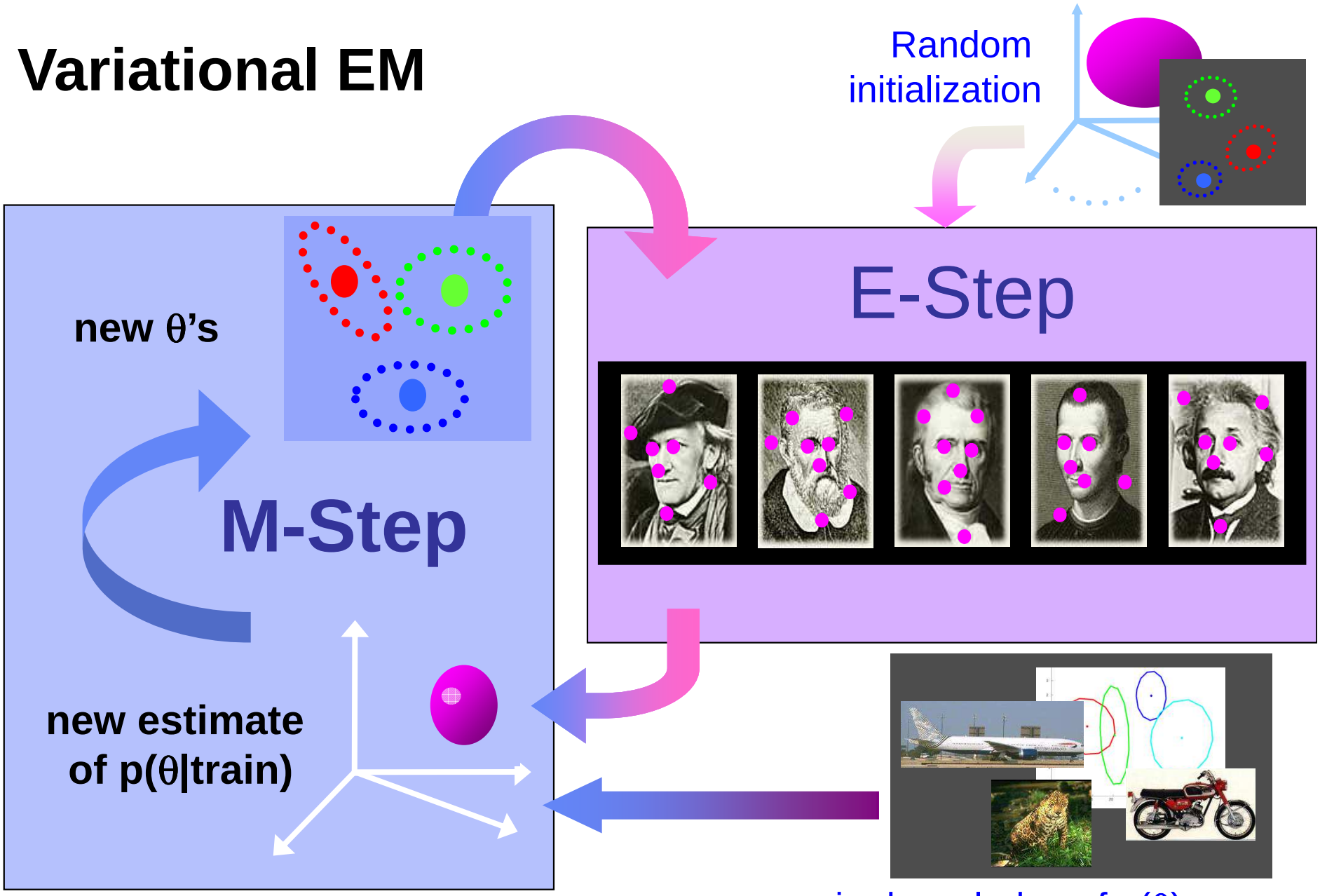


Learning Model Distribution

$$p(\theta|\text{object, train}) \propto p(\text{train}|\theta, \text{object})\, p(\theta)$$

- use Prior information
- Bayesian learning
  - marginalize over theta
    - ❖ **Variational EM (Attias, Hinton, Minka, etc.)**

Variational EM



Experiments

Training:

1- 6 randomly

drawn images

Testing:

50 fg/ 50 bg images

object present/absent

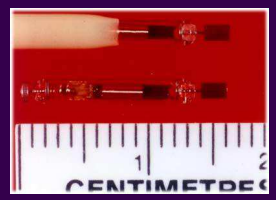
Datasets

faces

airplanes

spotted cats

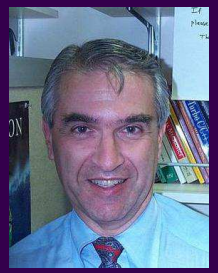
motorbikes



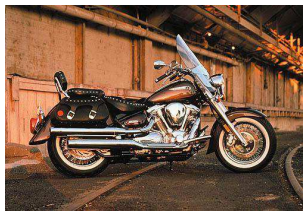
Faces








Motorbikes



Airplanes






Spotted cats



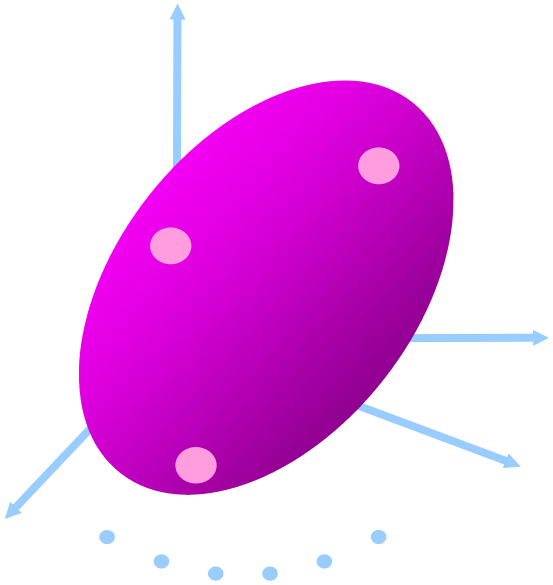



Experiments: obtaining priors

airplanes

spotted cats

motorbikes



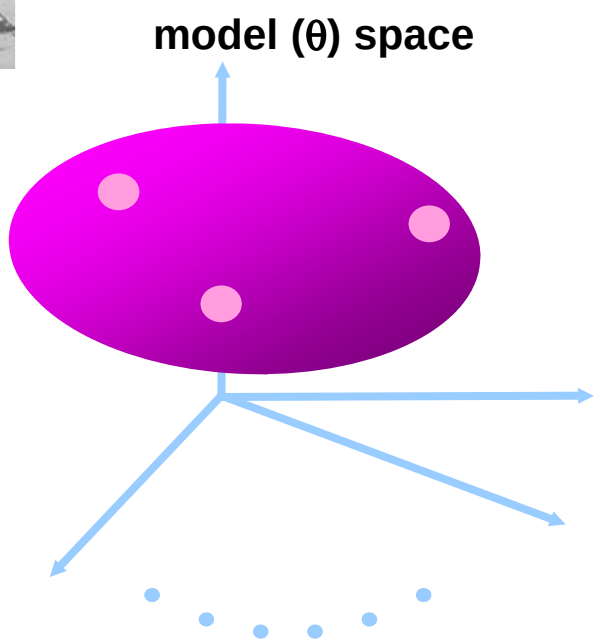
faces

Experiments: obtaining priors

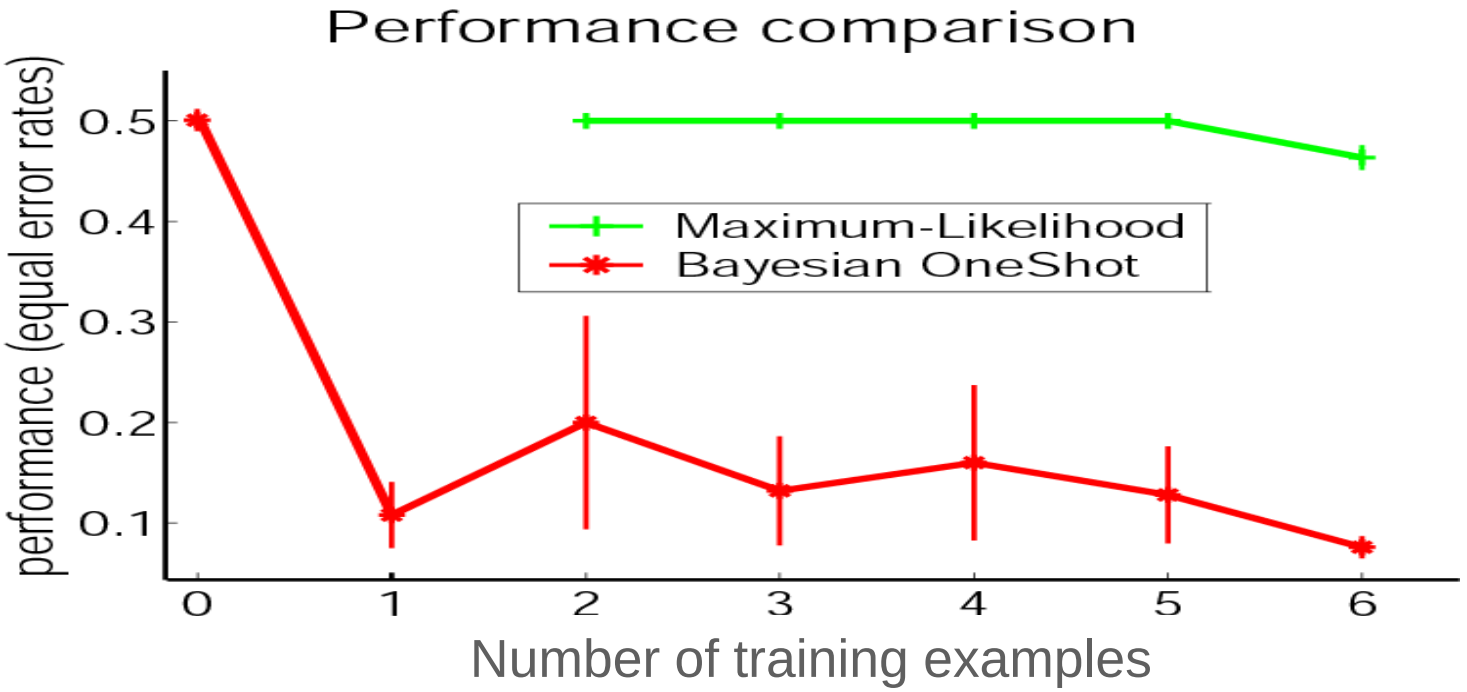
airplanes

faces

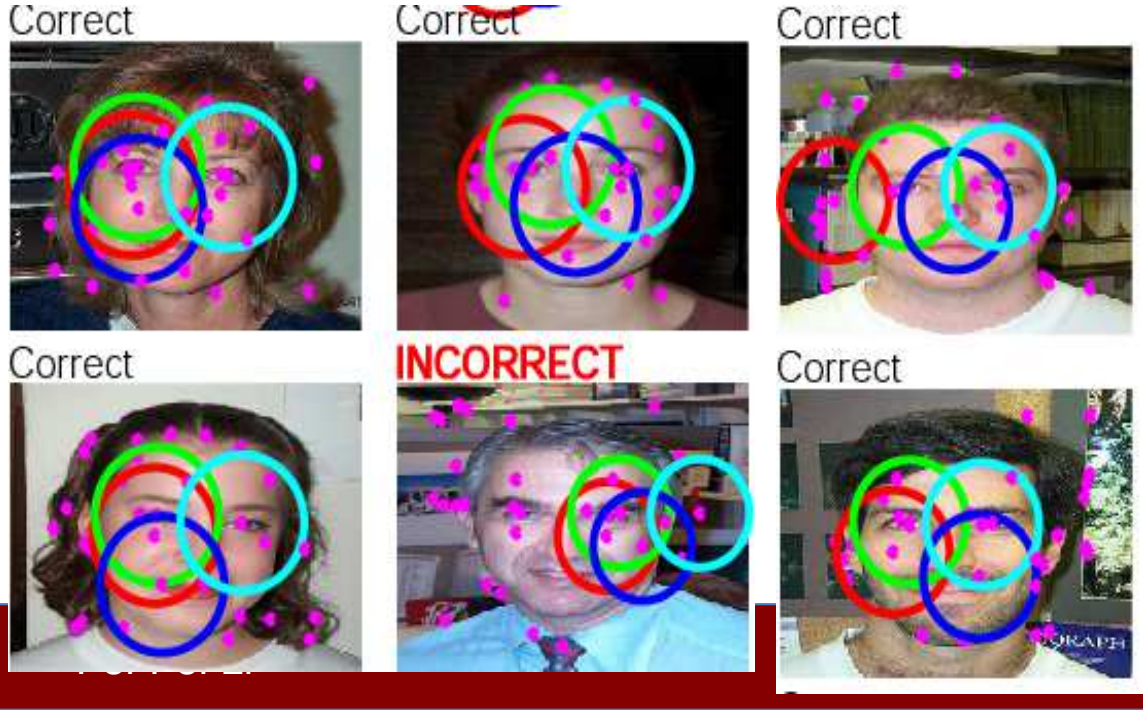
motorbikes

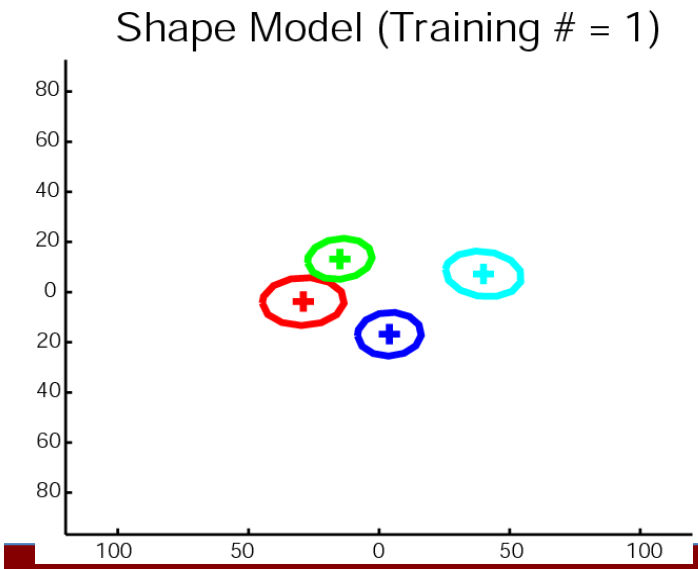


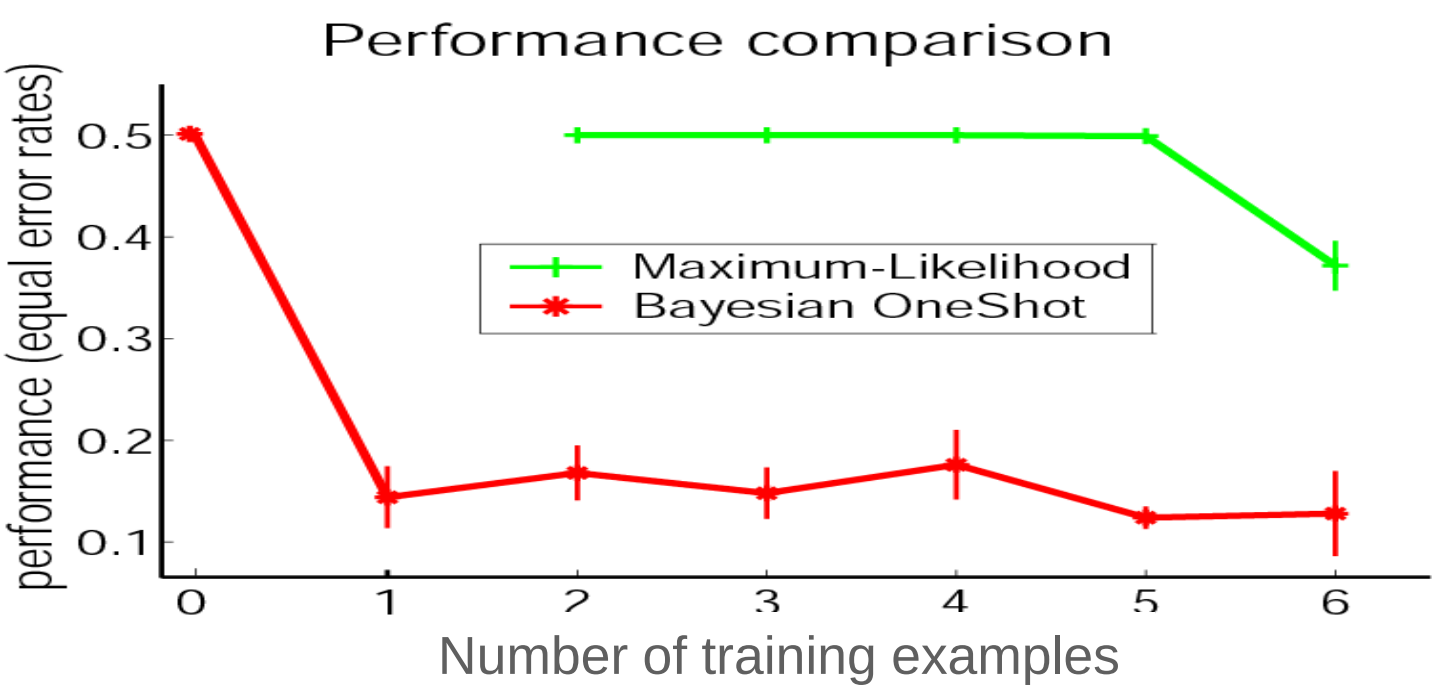
spotted cats


Performance comparison
performance (equal error rates)
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
Number of training examples
Maximum-Likelihood
Bayesian OneShot


Part 1
Part 2
Part 3
Part 4


Correct
Correct
Correct
Correct
INCORRECT
Correct


Shape Model (Training # = 1)
80
60
40
20
0
20
40
60
80
100
50
0
50
100

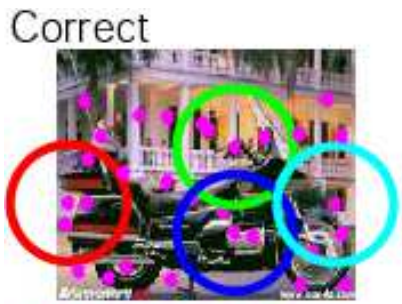

Performance comparison
performance (equal error rates)
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
Number of training examples
Maximum-Likelihood
Bayesian OneShot


Part 1

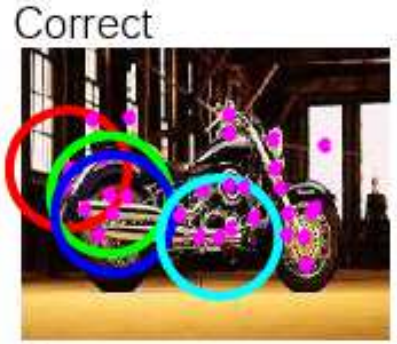

Part 2


Part 3


Part 4


Correct

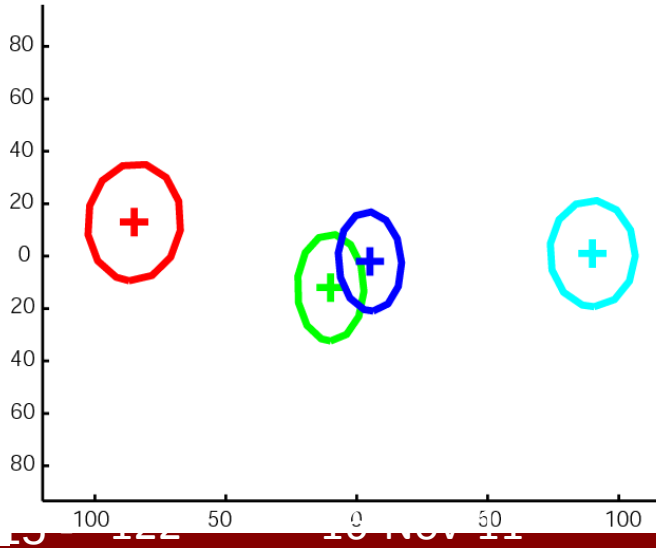

Correct

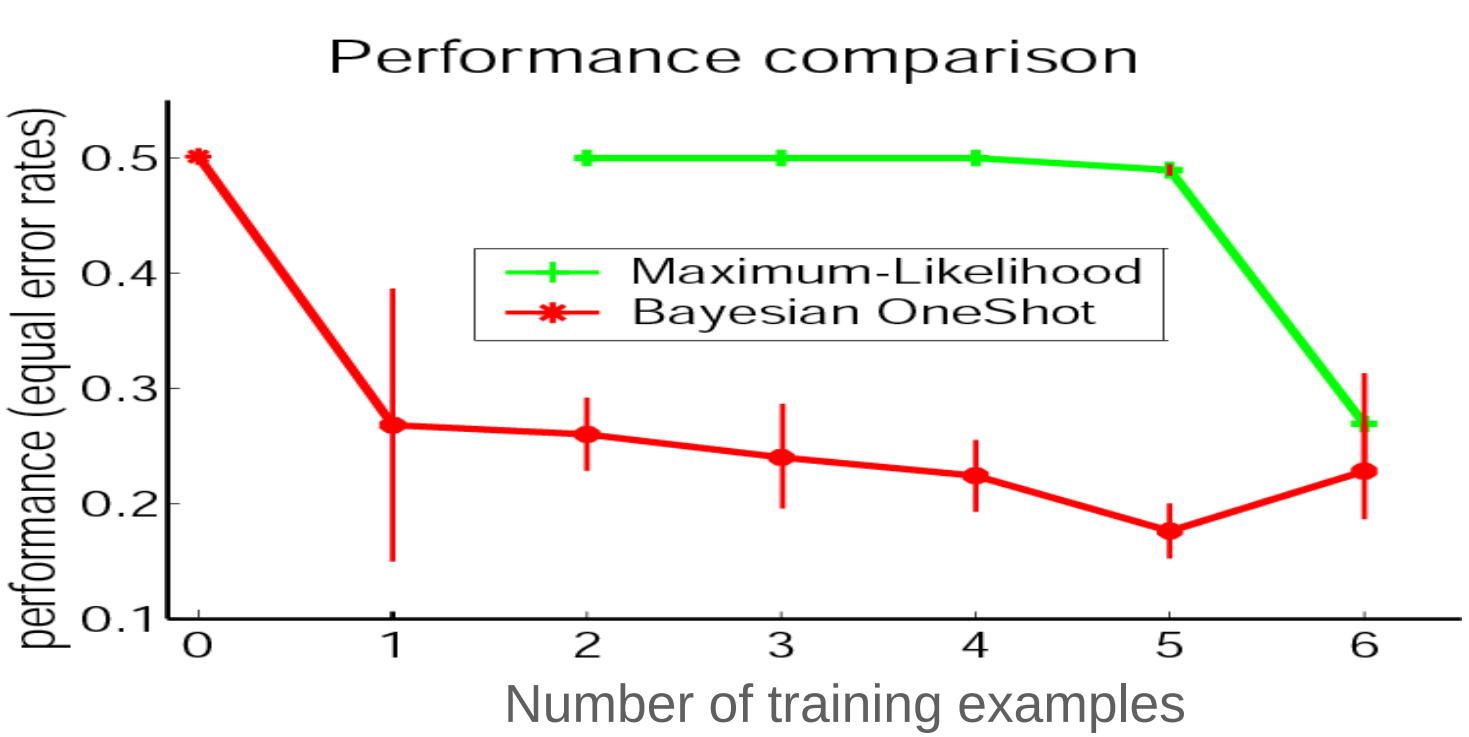

Correct

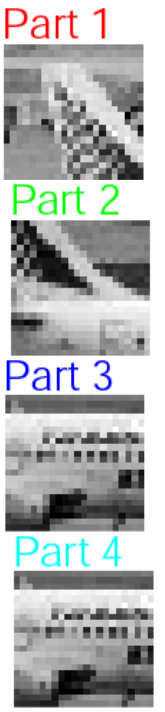

INCORRECT

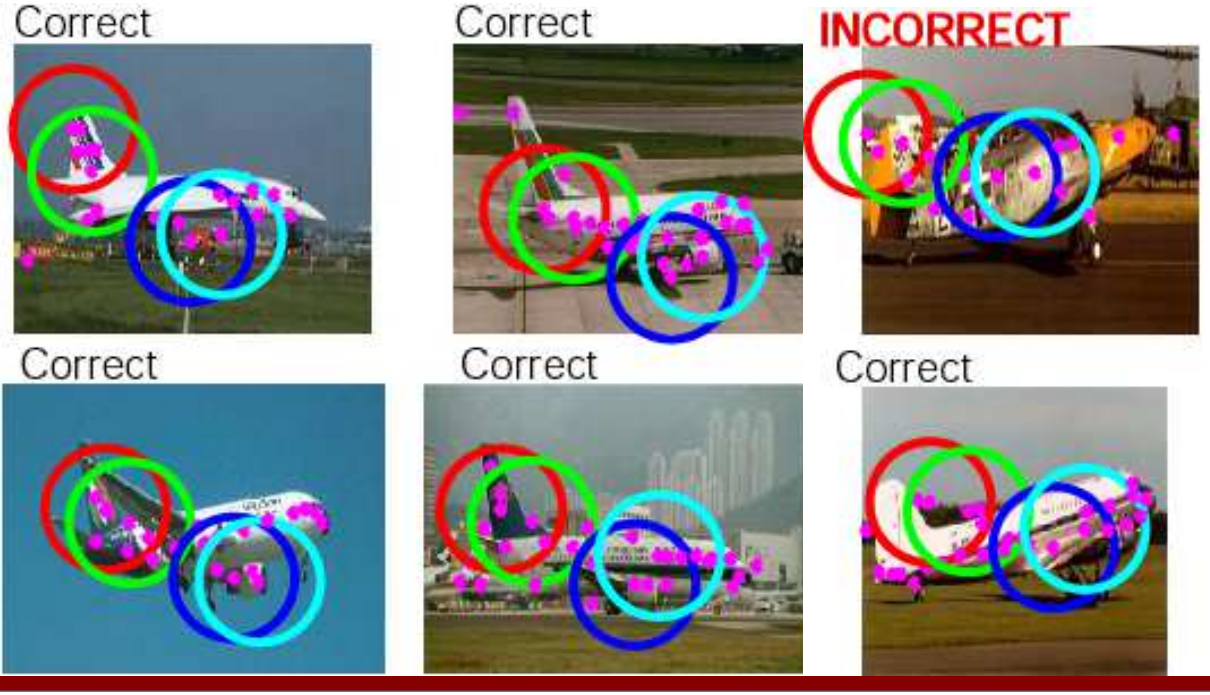

INCORRECT

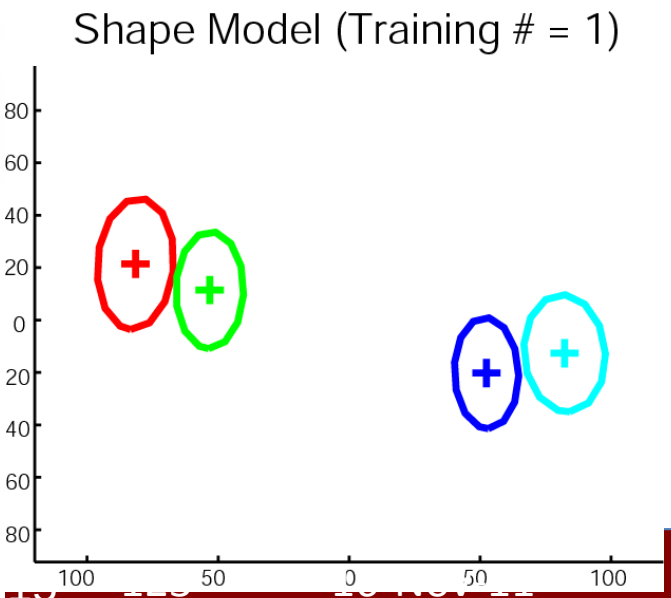

Correct

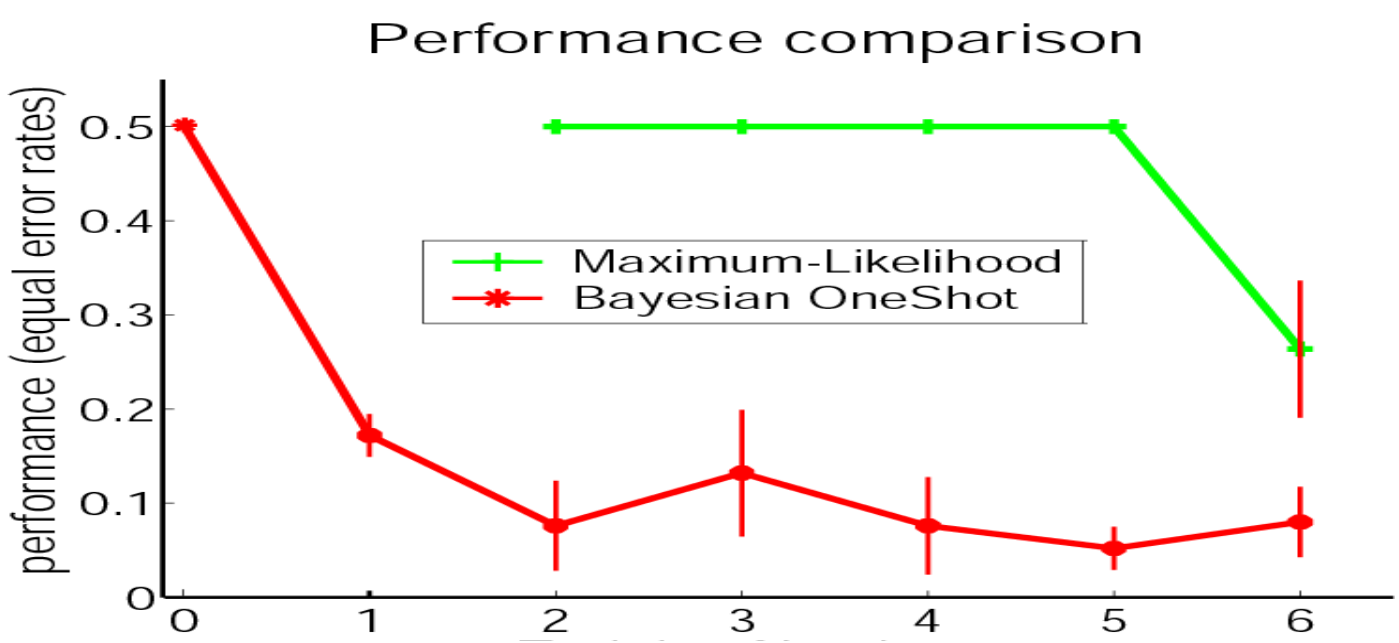

Shape Model (Training # = 1)
80
60
40
20
0
20
40
60
80
100
50
0
50
100


Performance comparison
performance (equal error rates)
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
Number of training examples
Maximum-Likelihood
Bayesian OneShot

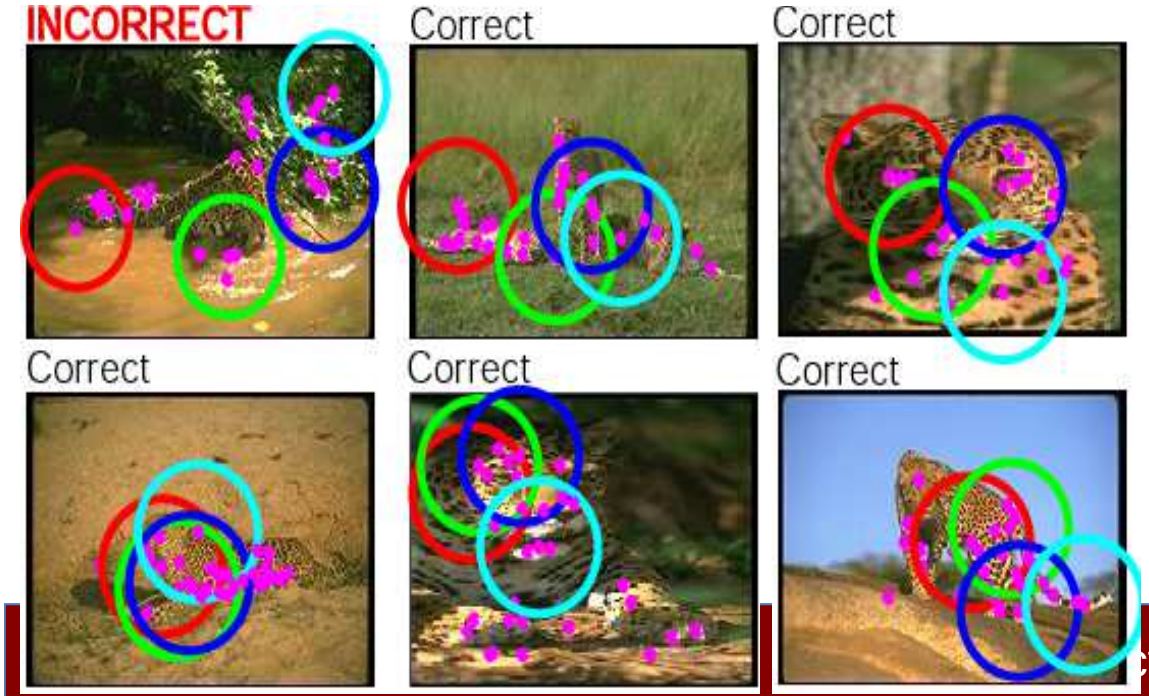

Part 1
Part 2
Part 3
Part 4

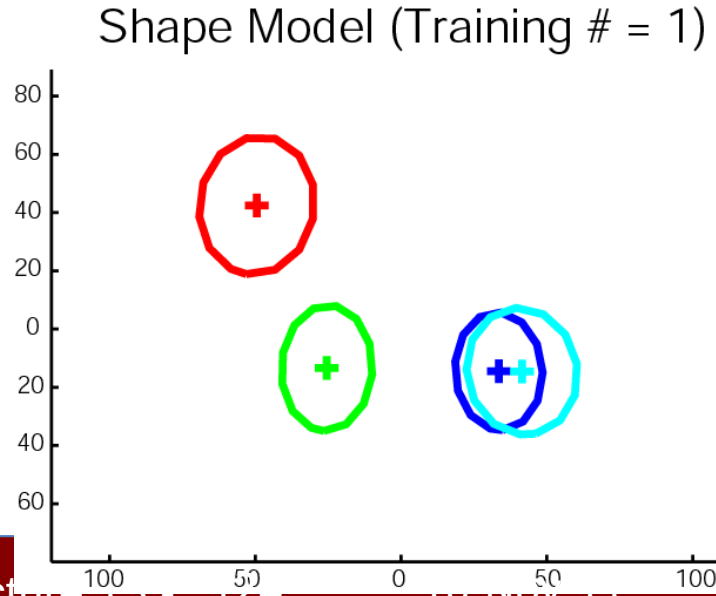

Correct
Correct
INCORRECT
Correct
Correct
Correct


Shape Model (Training # = 1)
80
60
40
20
0
20
40
60
80
100
50
0
50
100


Performance comparison
performance (equal error rates)
0.5
0.4
0.3
0.2
0.1
0
0
1
2
3
4
5
6
Maximum-Likelihood
Bayesian OneShot
Number of training examples


Part 1
Part 2
Part 3
Part 4


INCORRECT
Correct
Correct
Correct
Correct
Correct


Shape Model (Training # = 1)
80
60
40
20
0
20
40
60
100
50
0
50
100

Algorithm	Training Examples	Categories	Results(error)
Burl, et al. Weber, et al. Fergus, et al.	200 ~ 400	Faces, Motorbikes, Spotted cats, Airplanes, Cars	5.6 - 10 %
Viola et al.	~10,000	Faces	7-21%
Schneiderman, et al.	~2,000	Faces, Cars	5.6 – 17%
Rowley et al.	~500	Faces	7.5 – 24.1%
Bayesian One-Shot	1 ~ 5	Faces, Motorbikes, Spotted cats, Airplanes	8 – 15 %