Lecture 15: Object recognition: Part-based generative models

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What we will learn today?

- Introduction
- Constellation model
  - Weakly supervised training
  - One-shot learning
- (Problem Set 4 (Q1))

Challenges: intra-class variation

Usual Challenges:

Variability due to:

- View point
- Illumination
- Occlusions

Basic issues

- **Representation**
  - 2D Bag of Words (BoW) models;
  - Part-based models;
  - Multi-view models;
- **Learning**
  - Generative & Discriminative BoW models
  - Generative models
  - Probabilistic Hough voting
- **Recognition**
  - Classification with BoW
  - Classification with Part-based models

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  - Part-based models;
  - Multi-view models (Lecture #19);
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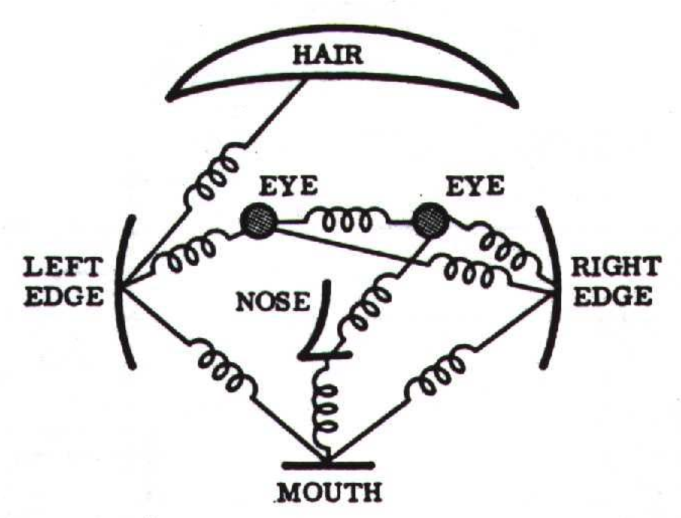
  - Generative models
  - Probabilistic Hough voting
- **Recognition**
  - Classification with BoW
  - Classification with Part-based models

Problem with bag-of-words

- All have equal probability for bag-of-words methods
- Location information is important

Model: Parts and Structure

Parts and Structure Literature



- Fischler & Elschlager 1973

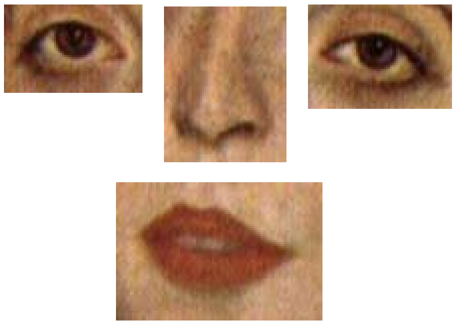
- Yuille '91
- Brunelli & Poggio '93
- Lades, v.d. Malsburg et al. '93
- Cootes, Lanitis, Taylor et al. '95
- Amit & Geman '95, '99
- et al. Perona '95, '96, '98, '00, '03
- Huttenlocher et al. '00
- Agarwal & Roth '02

etc…

The Constellation Model

T. Leung	Representation	Shape statistics – F&G '95 Affine invariant shape – CVPR '98
M. Burl	Detection	CVPR '96 ECCV '98
M. Weber M. Welling	Unsupervised Learning	ECCV '00 Multiple views - F&G '00 Discovering categories - CVPR '00
R. Fergus	Joint shape & appearance learning Generic feature detectors	CVPR '03 Polluted datasets - ECCV '04
L. Fei-Fei	One-Shot Learning Incremental learning	ICCV '03 CVPR '04

Deformations



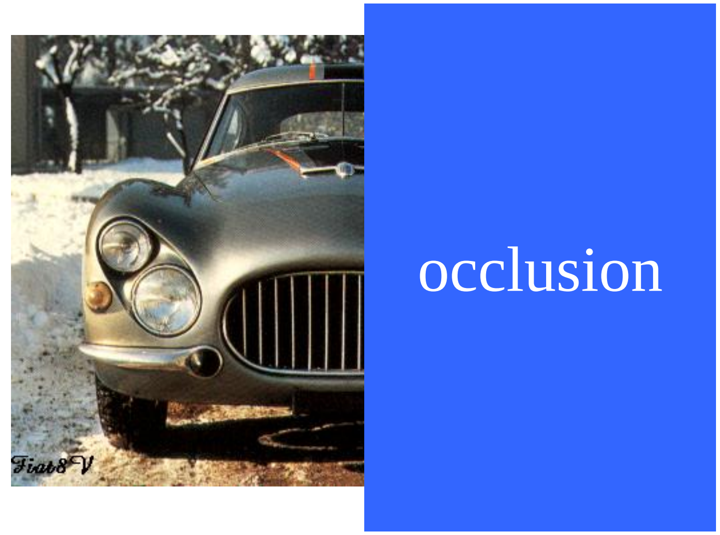
A

B

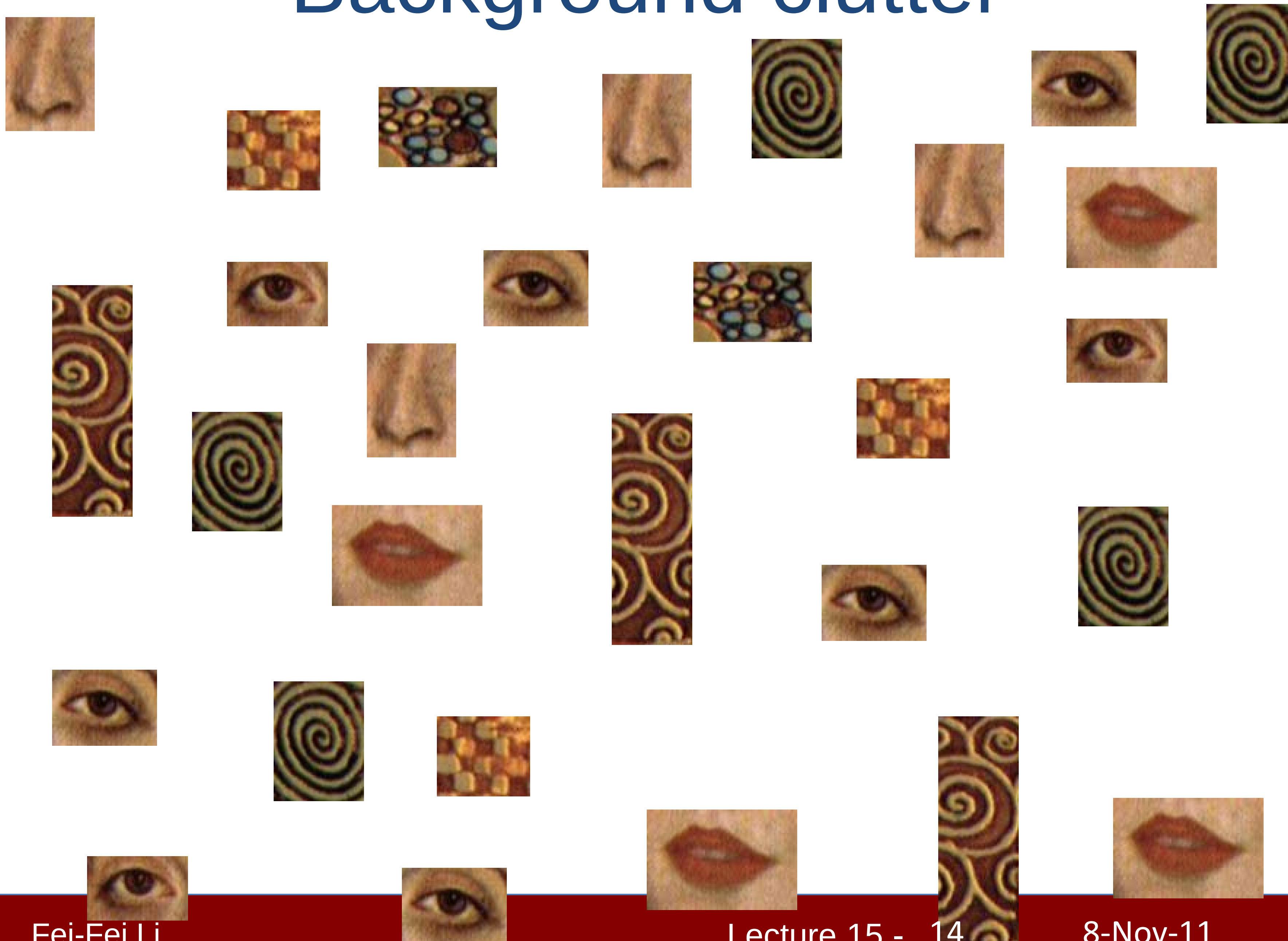
C

D

Presence / Absence of Features



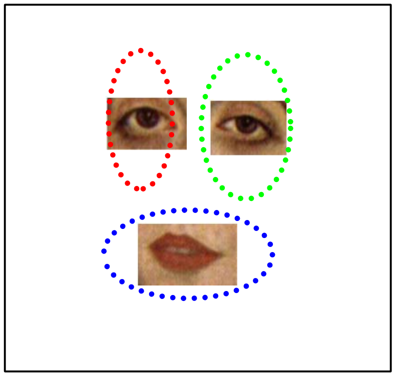
Background clutter



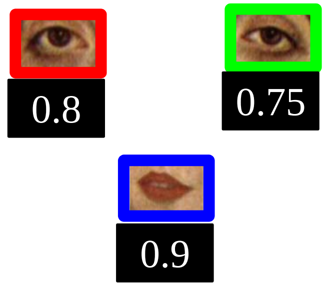
Generative probabilistic model

Foreground model

Gaussian shape pdf

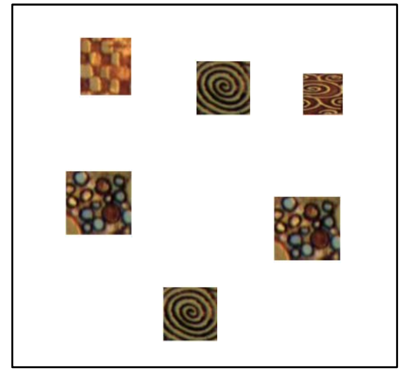


Prob. of detection



Clutter model

Uniform shape pdf



detections

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

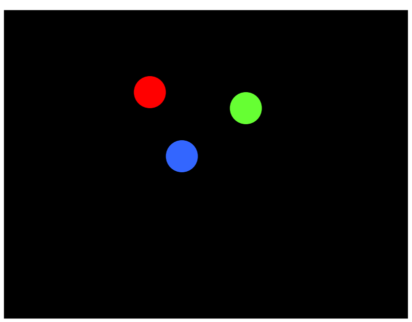
$p_{\text{Poisson}}(N_2|\lambda_2)$

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

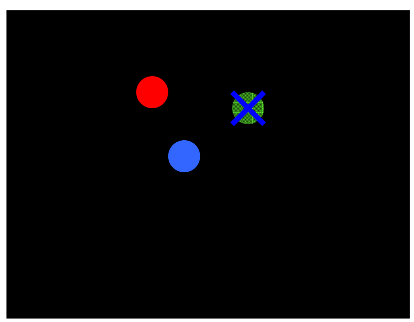
Assumptions: (a) Clutter independent of foreground detections
(b) Clutter detections independent of each other

Example

1. Object Part Positions

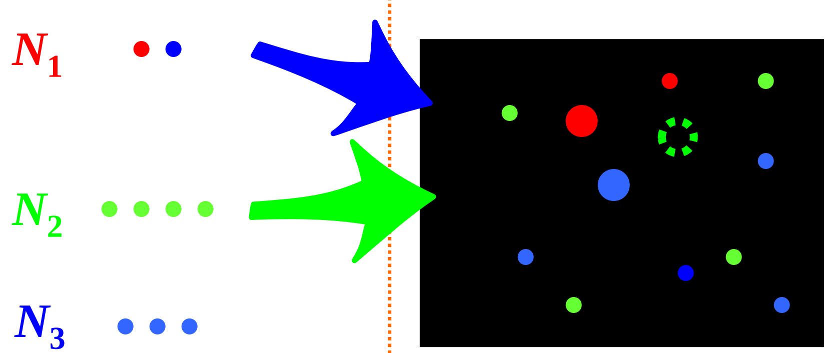


2. Part Absence

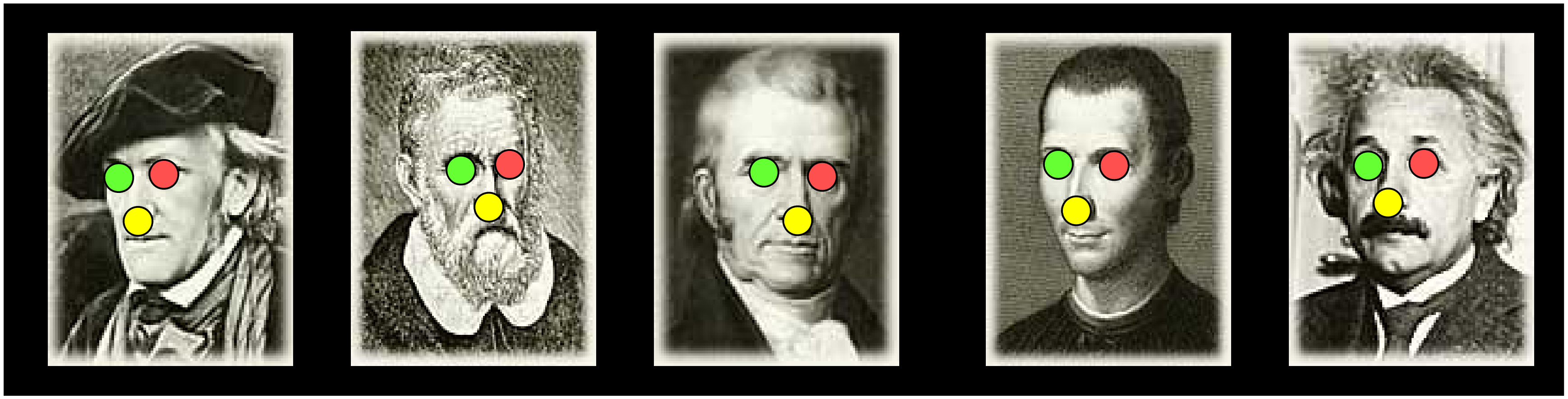


3a. N false detect

3b. Position f. detect

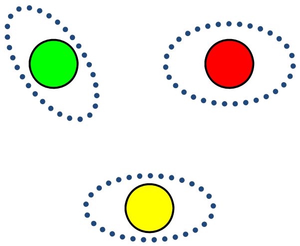


Learning Models `Manually’



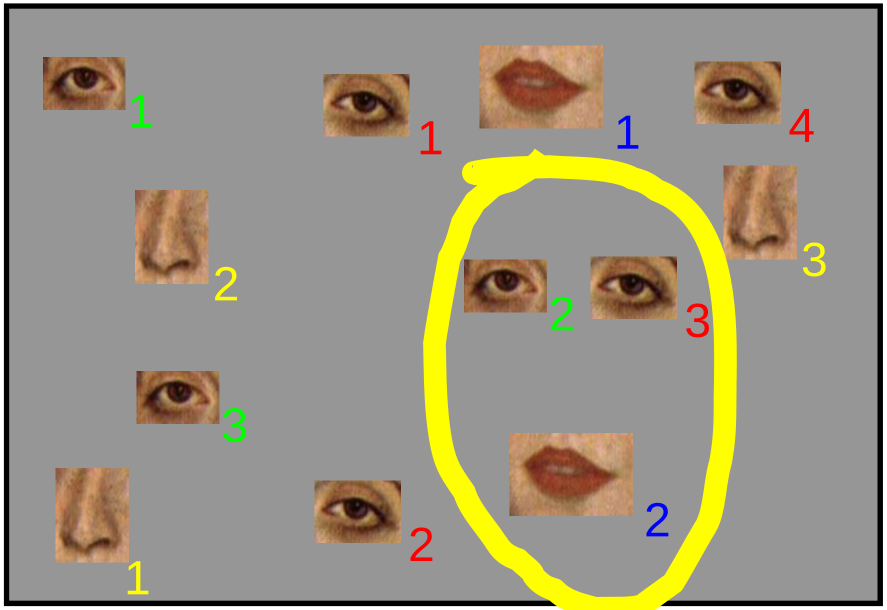
- Obtain set of training images
- Choose parts

- 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: $\dfrac{p(Data \mid Object, Hyp)}{p(Data \mid Clutter, Hyp)}$
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

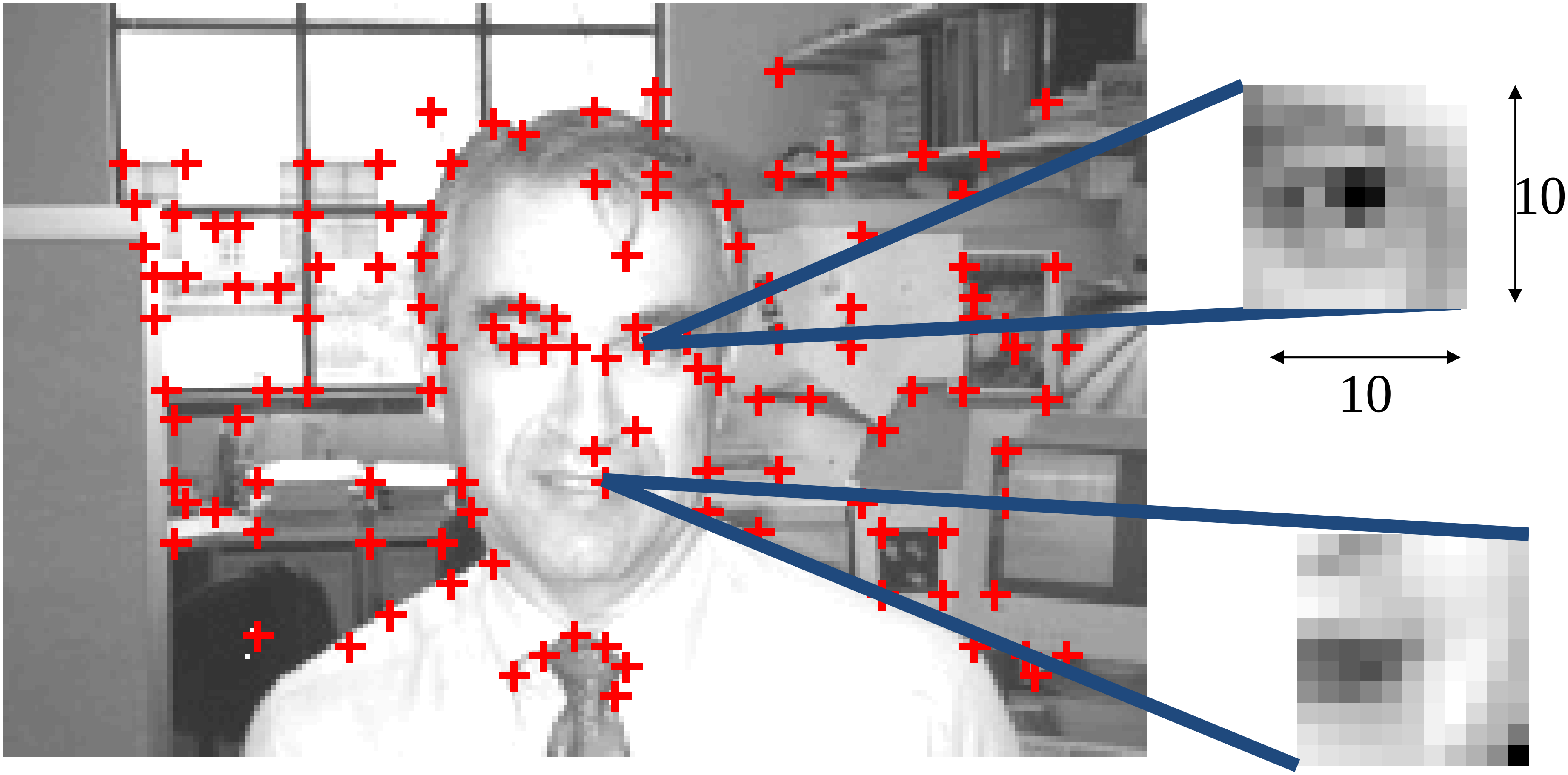
Unsupervised Learning

Weber & Welling et. al.

(Semi) Unsupervised learning

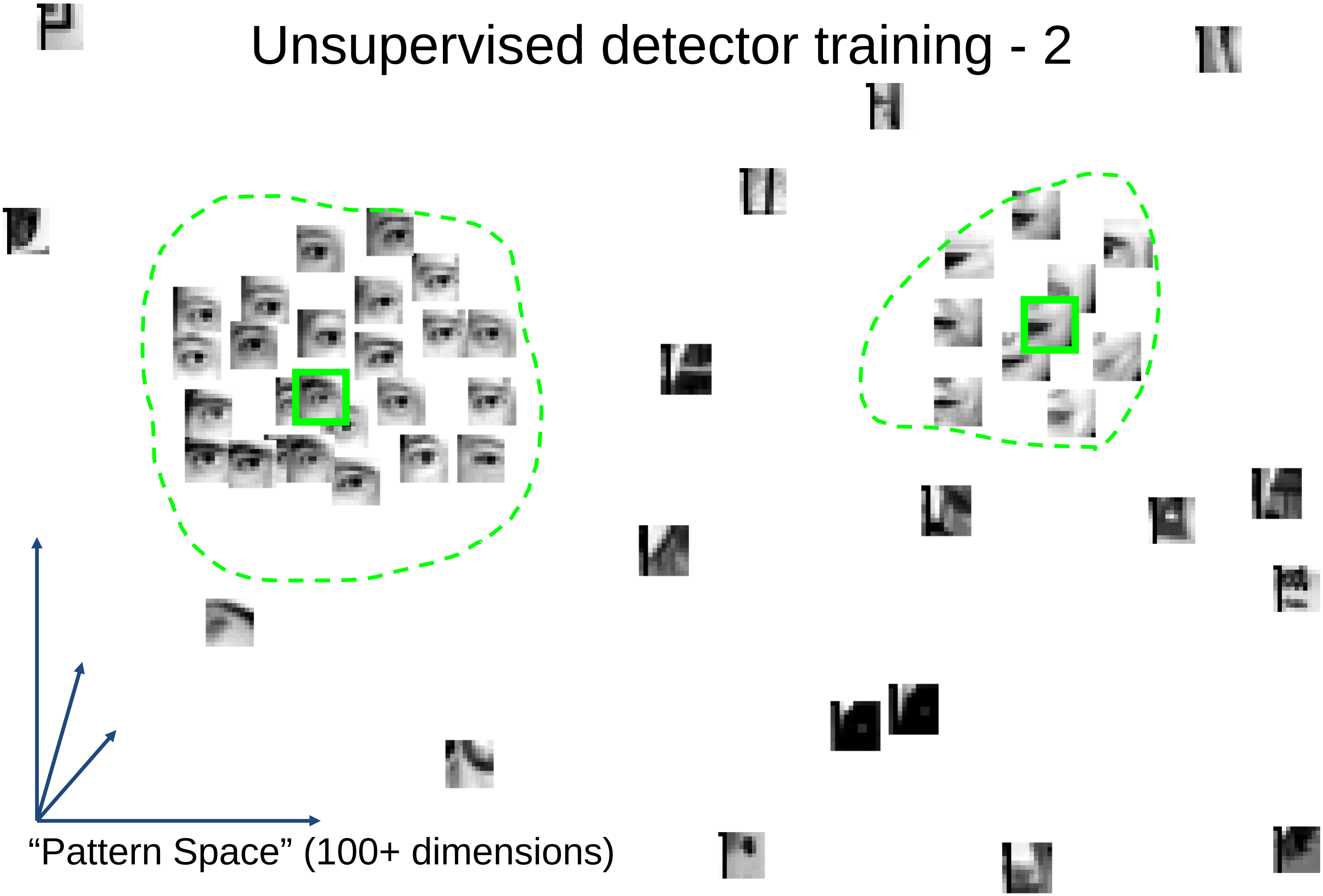
- Know if image contains object or not
- But no segmentation of object or manual selection of features

Unsupervised detector training - 1



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

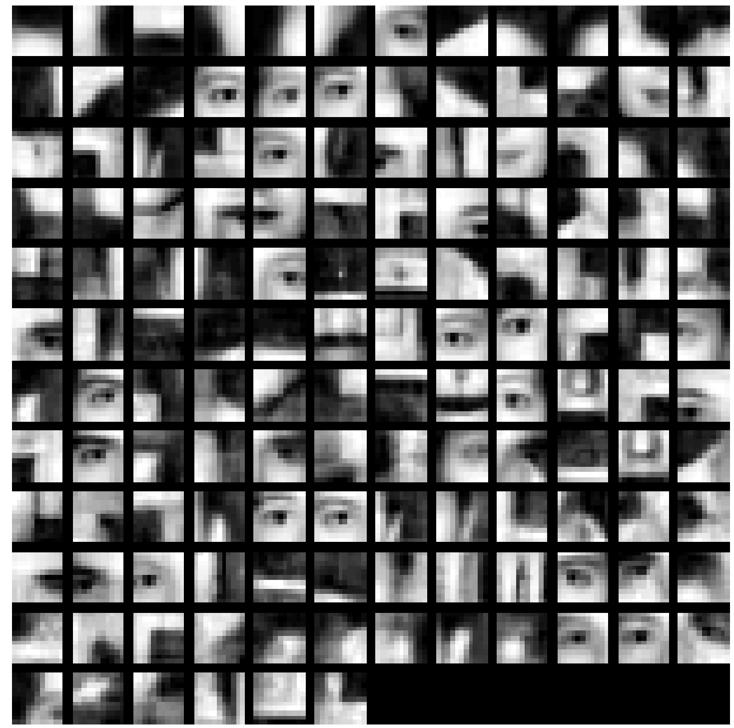
Unsupervised detector training - 2



“Pattern Space” (100+ dimensions)

Unsupervised detector training - 3

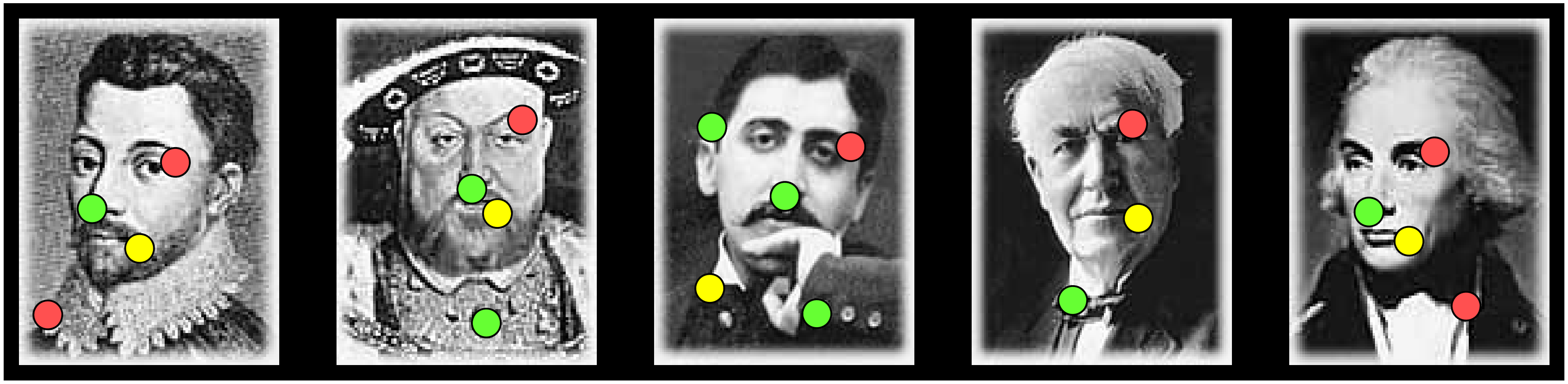
100-1000 images



~100 detectors

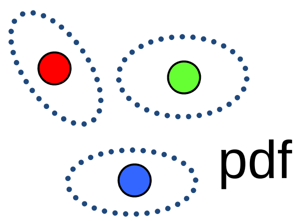
Learning

- 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

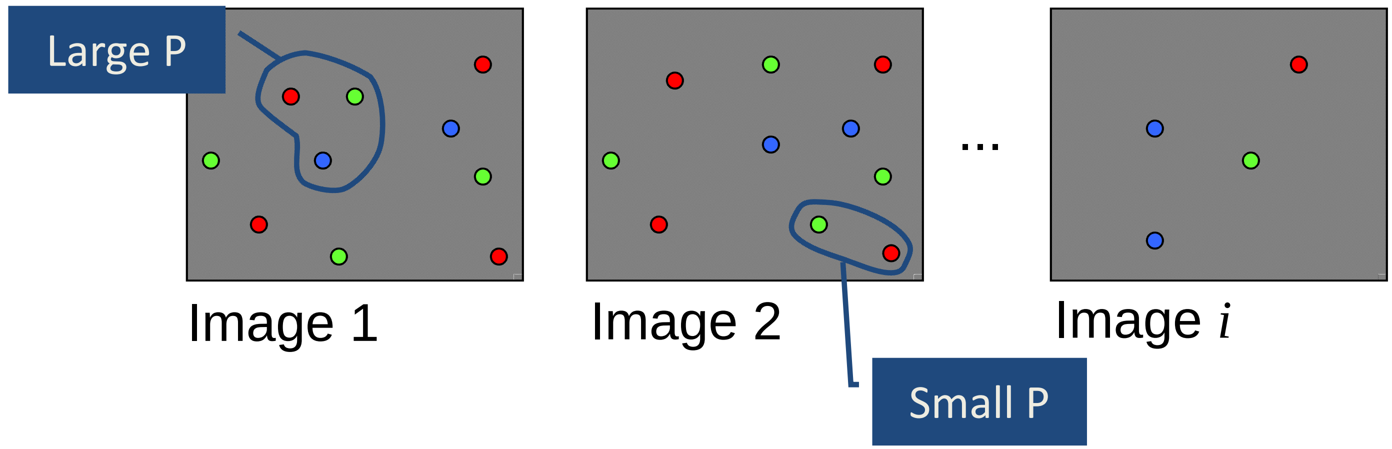


ML using EM

1. Current estimate



2. Assign probabilities to constellations

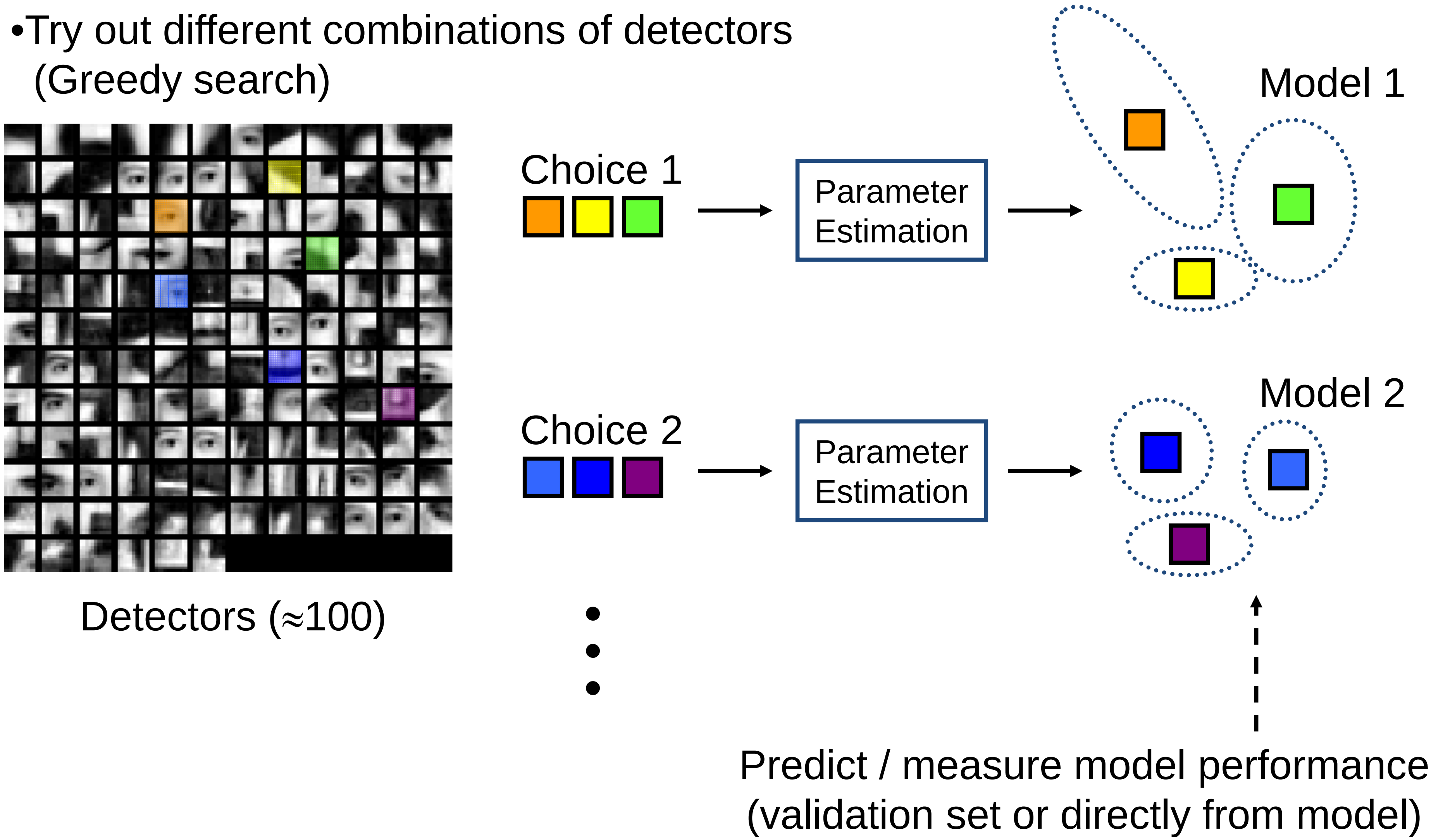


3. Use probabilities as weights to re-estimate parameters. Example: μ

new estimate of μ

Detector Selection

- Try out different combinations of detectors (Greedy search)

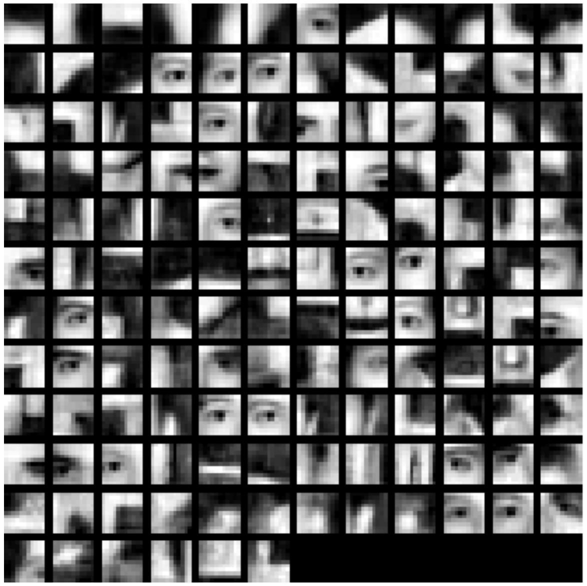


Frontal Views of Faces

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

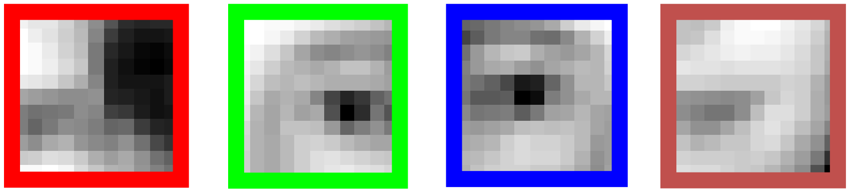
Learned face model

Pre-selected Parts

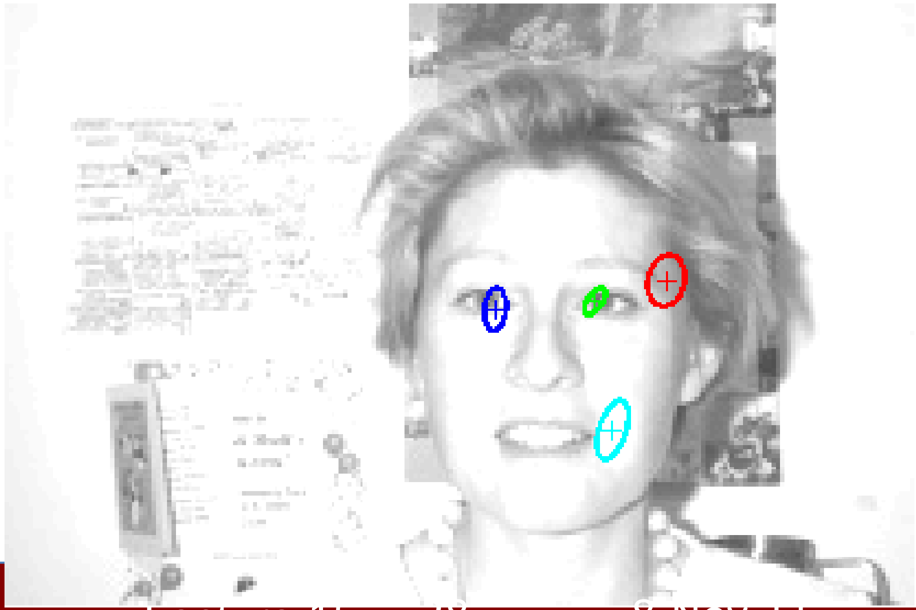


Test Error: 6% (4 Parts)

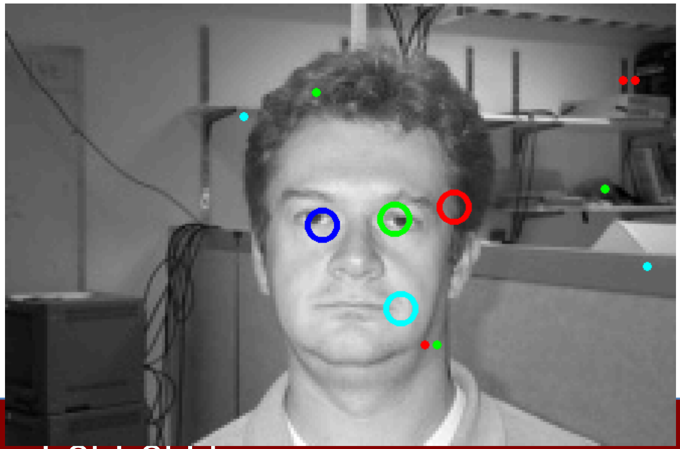
Parts in Model



Model Foreground pdf



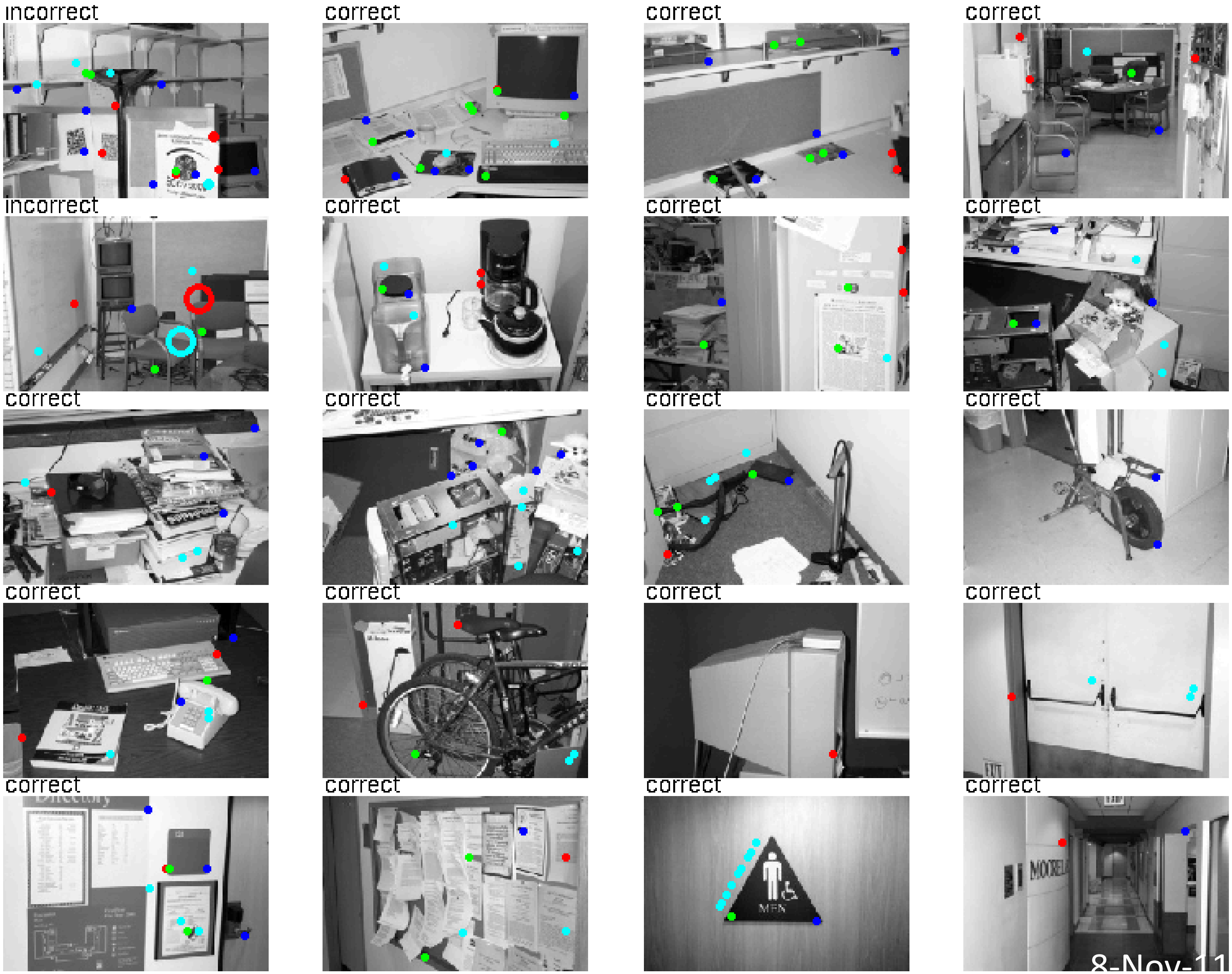
Sample Detection



Face images

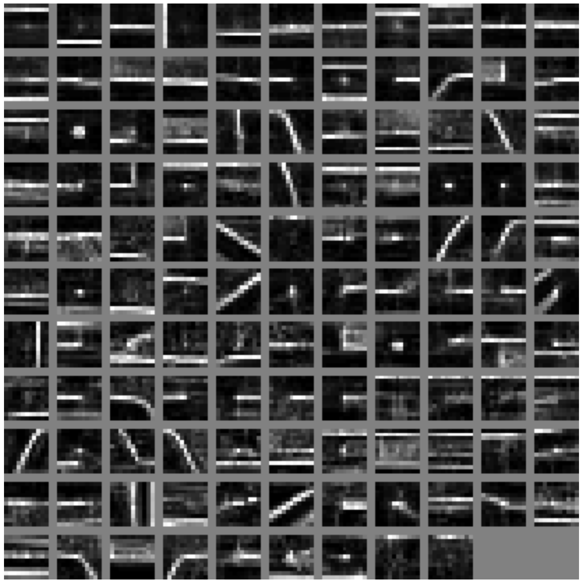

correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
correct
incorrect
incorrect
incorrect

Background images



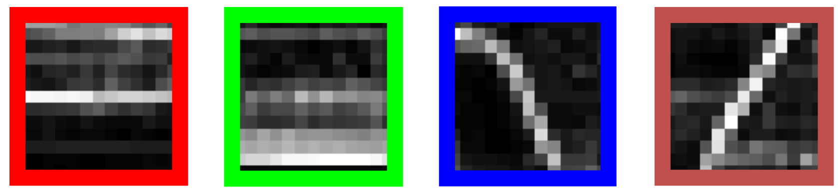
Car from Rear

Preselected Parts

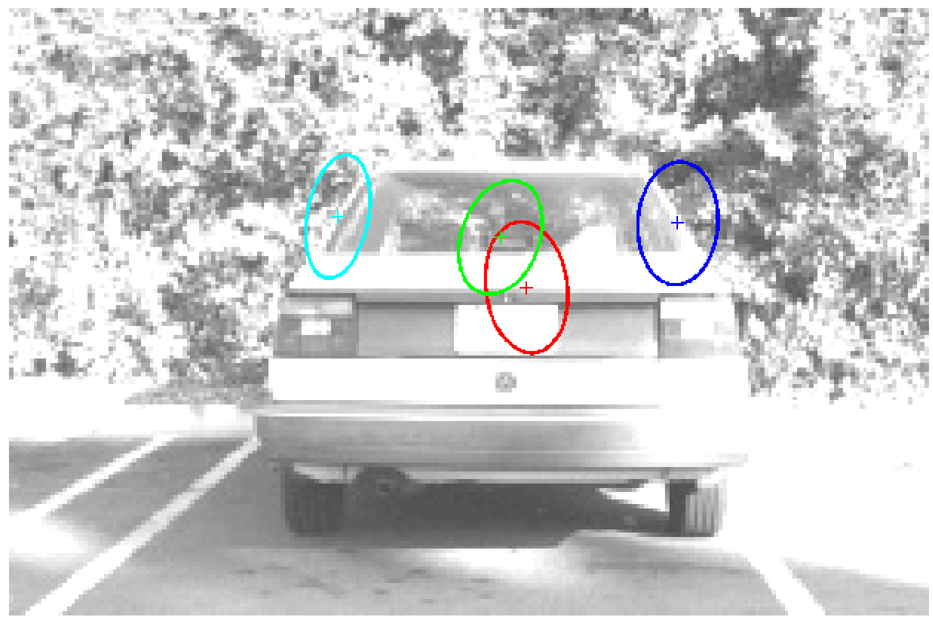


Test Error: 13% (5 Parts)

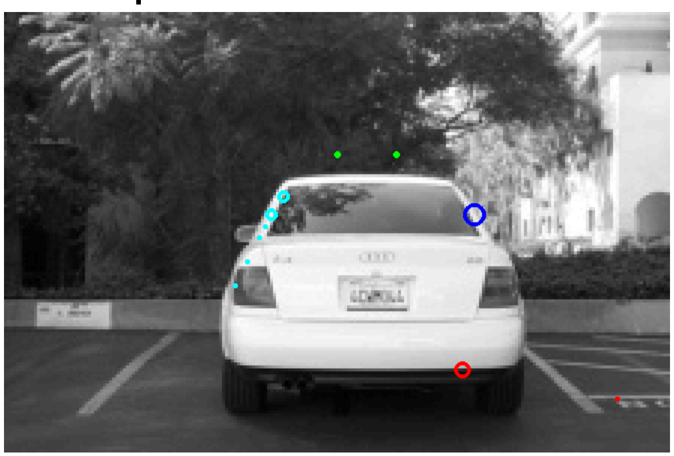
Parts in Model



Model Foreground pdf

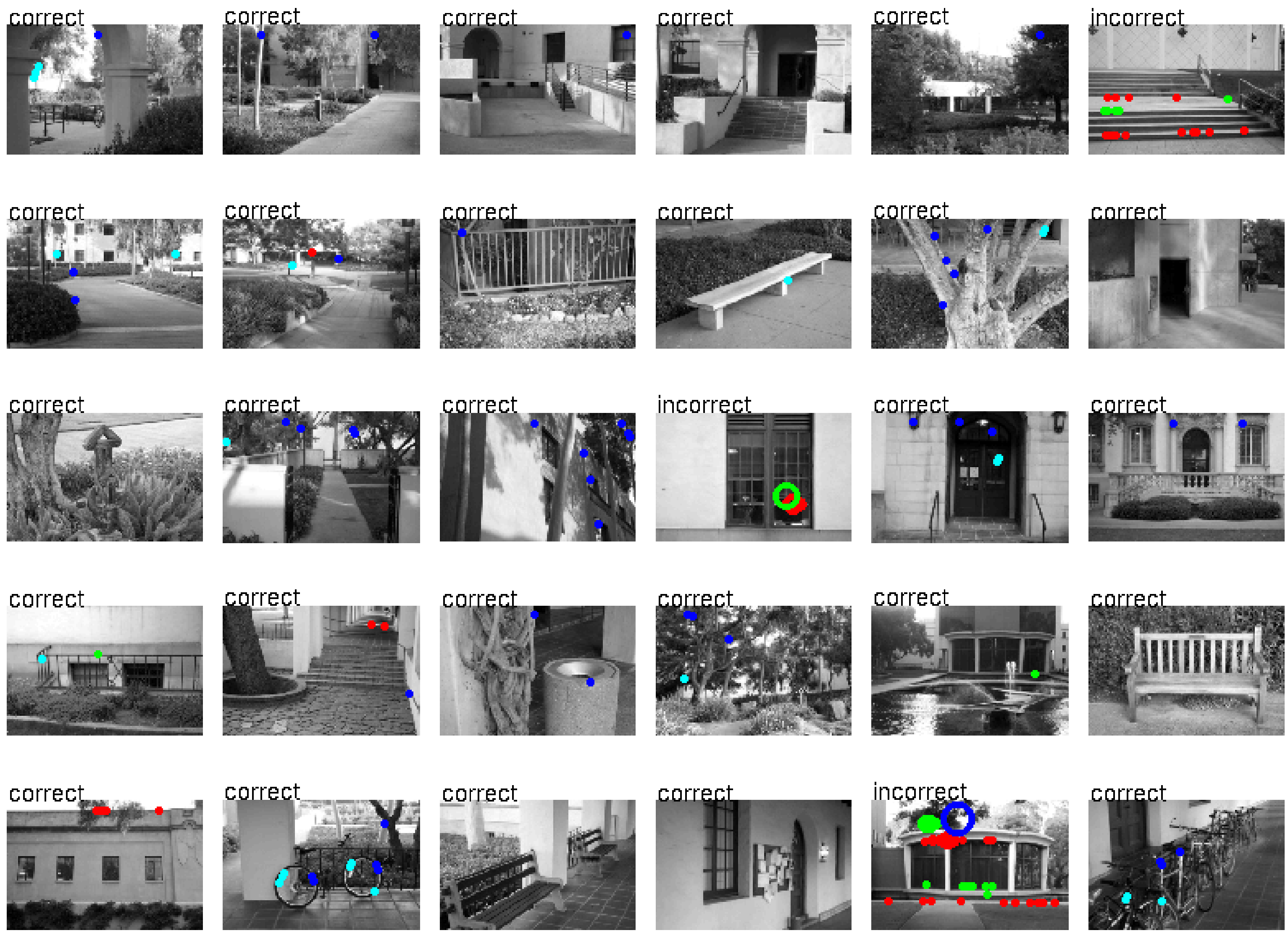


Sample Detection



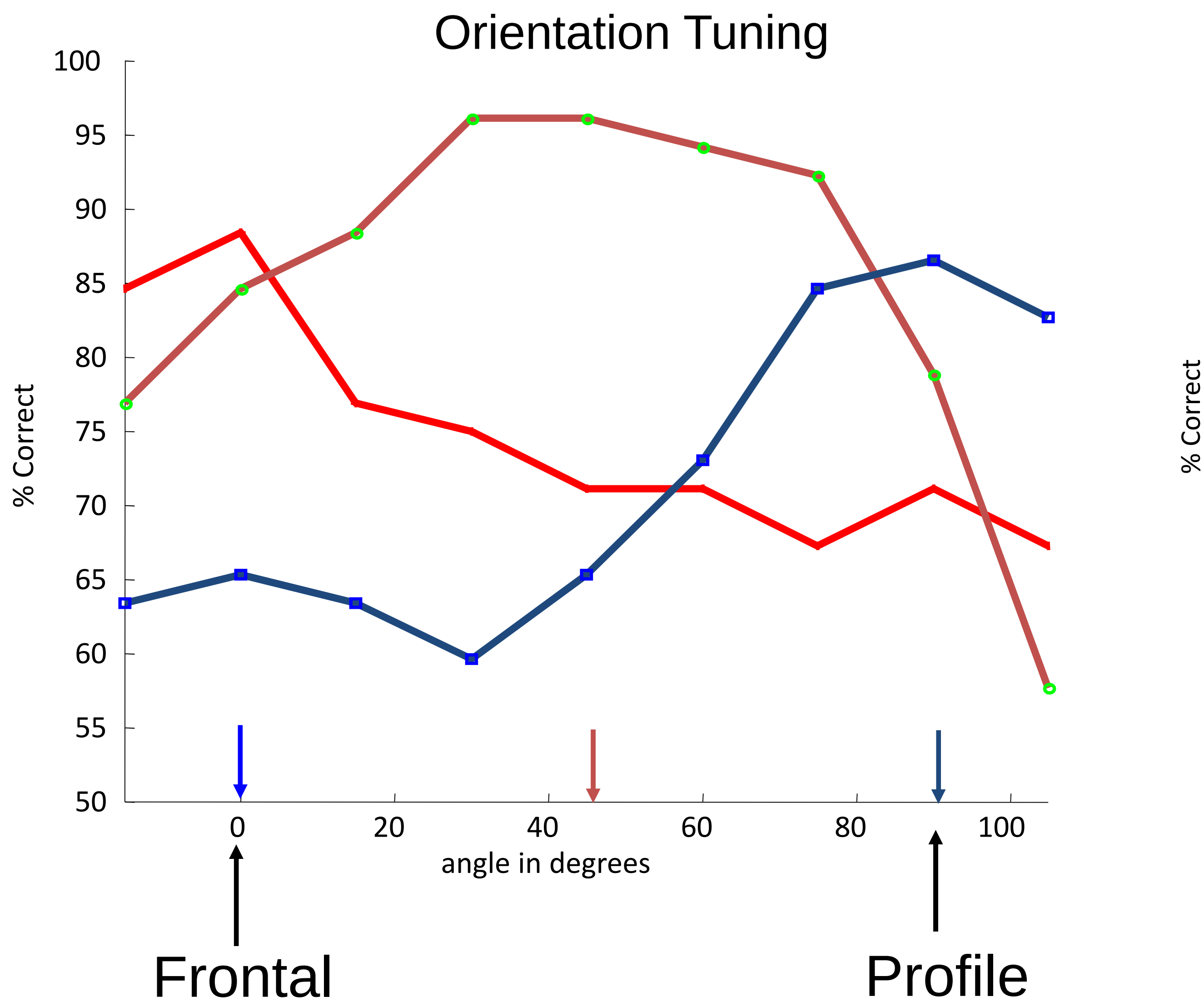
Detections of Cars

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

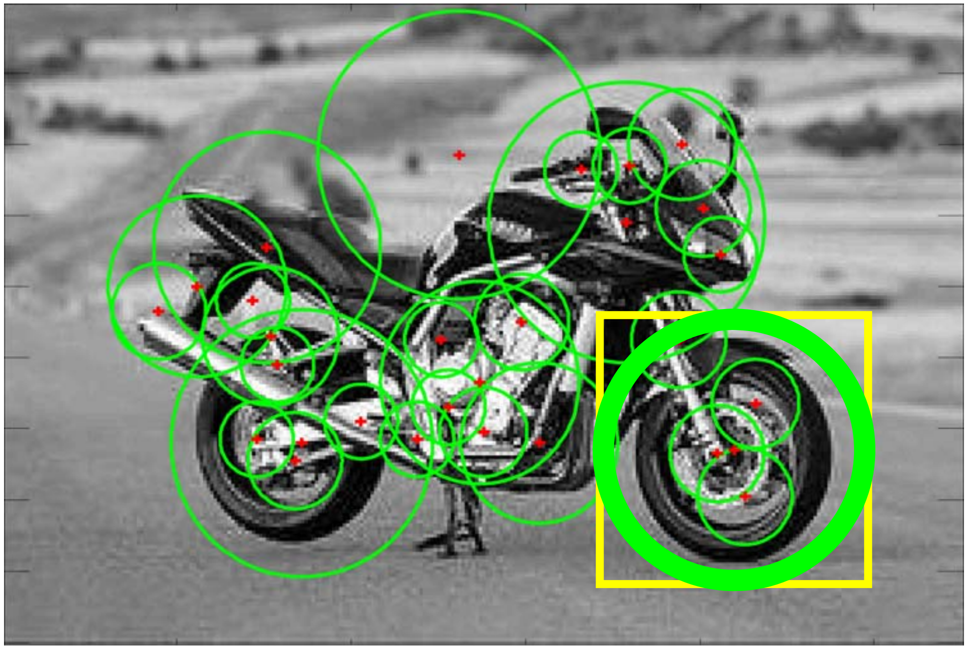
- Would like a fully probabilistic representation of the object

Object categorization

Fergus et. al.

CVPR ’03, IJCV ‘06

Detection & Representation of regions



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

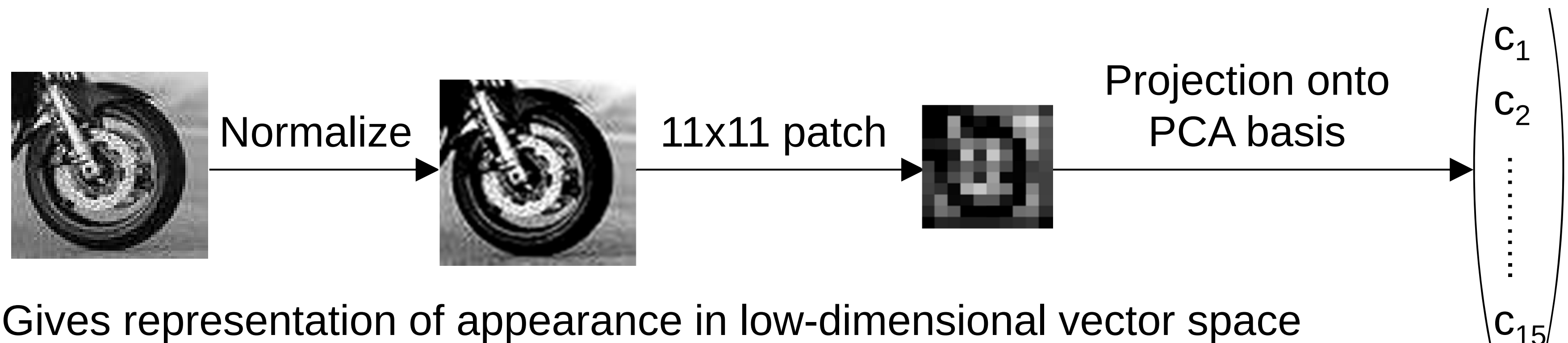
Location

(x,y) coords. of region centre

Scale

Radius of region (pixels)

Appearance



Gives representation of appearance in low-dimensional vector space

Motorbikes example

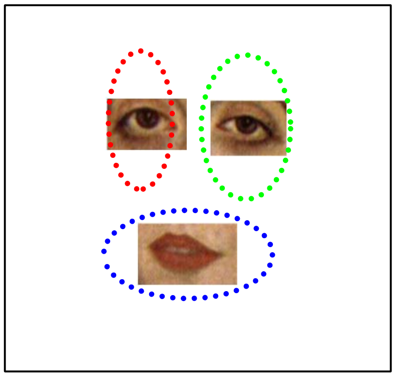
•Kadir & Brady saliency region detector

Generative probabilistic model (2)

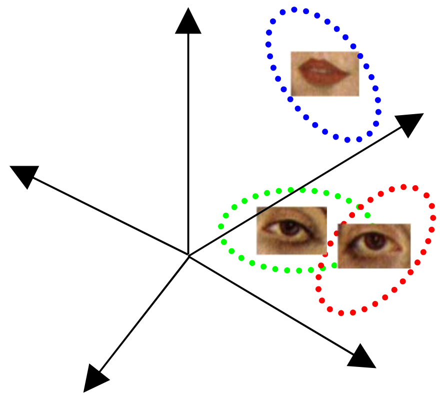
Foreground model

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

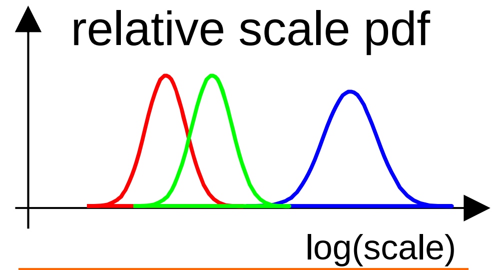
Gaussian shape pdf



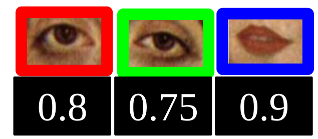
Gaussian part appearance pdf



Gaussian
relative scale pdf

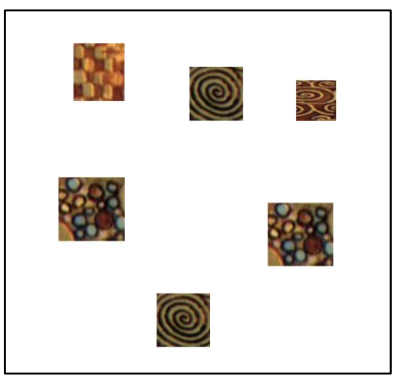


Prob. of detection

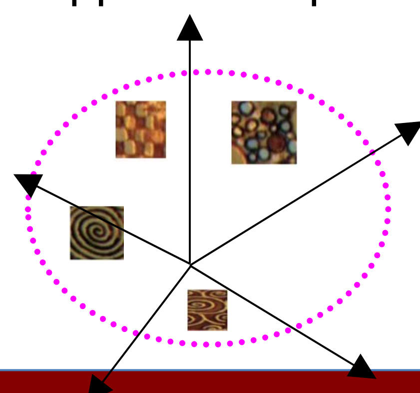


Clutter model

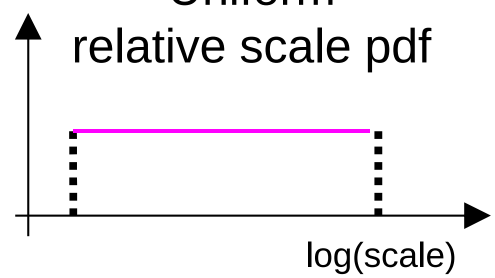
Uniform shape pdf



Gaussian background
appearance pdf



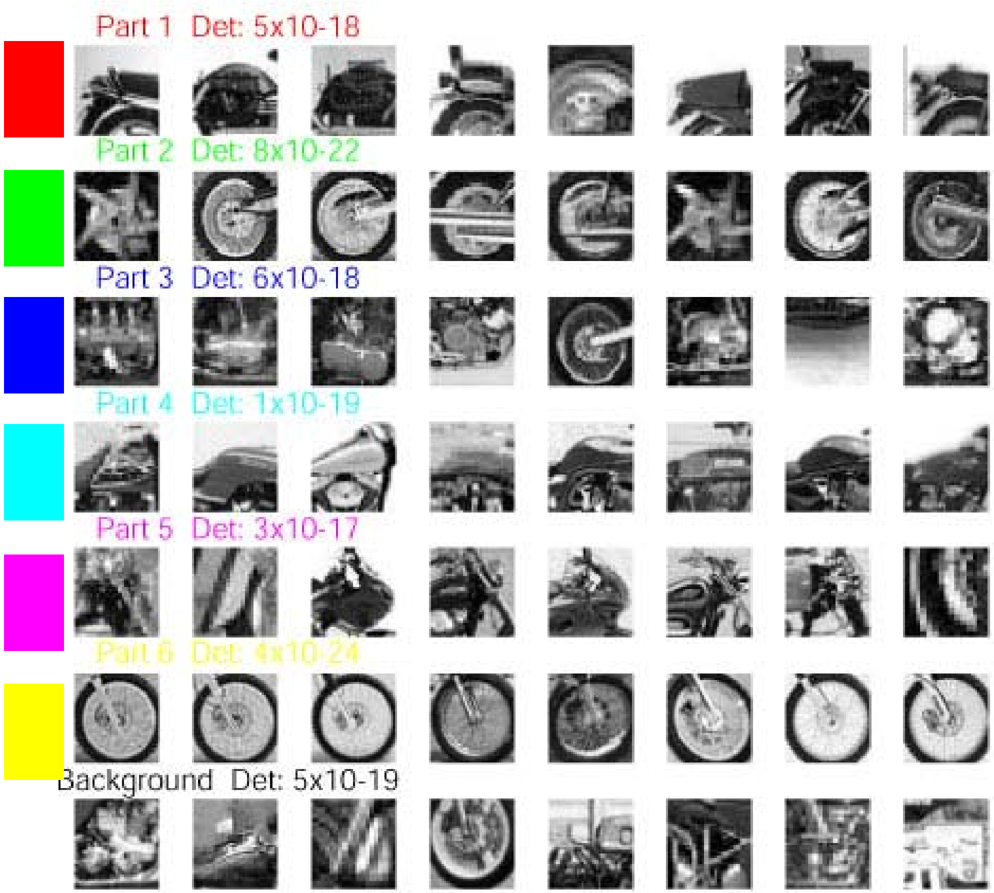
Uniform
relative scale pdf



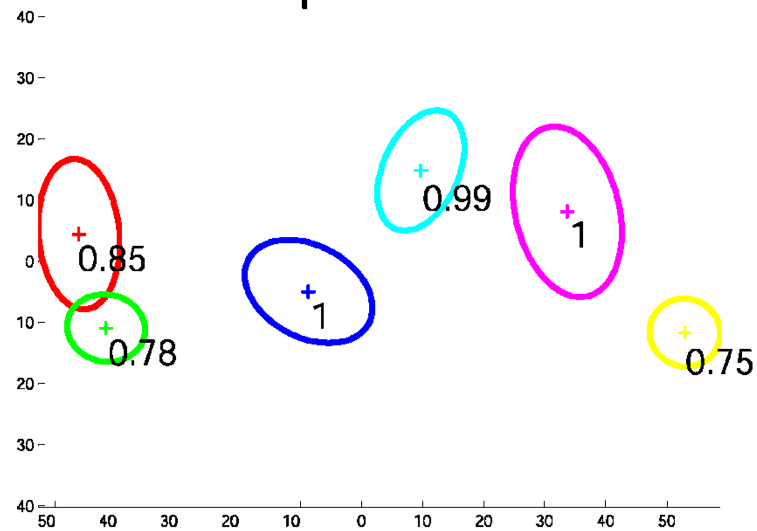
Poission pdf on #
detections

Motorbikes

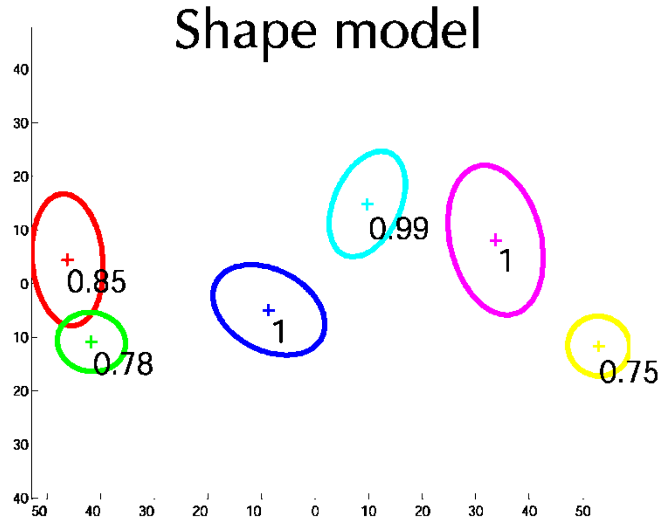
Samples from appearance model



Shape model

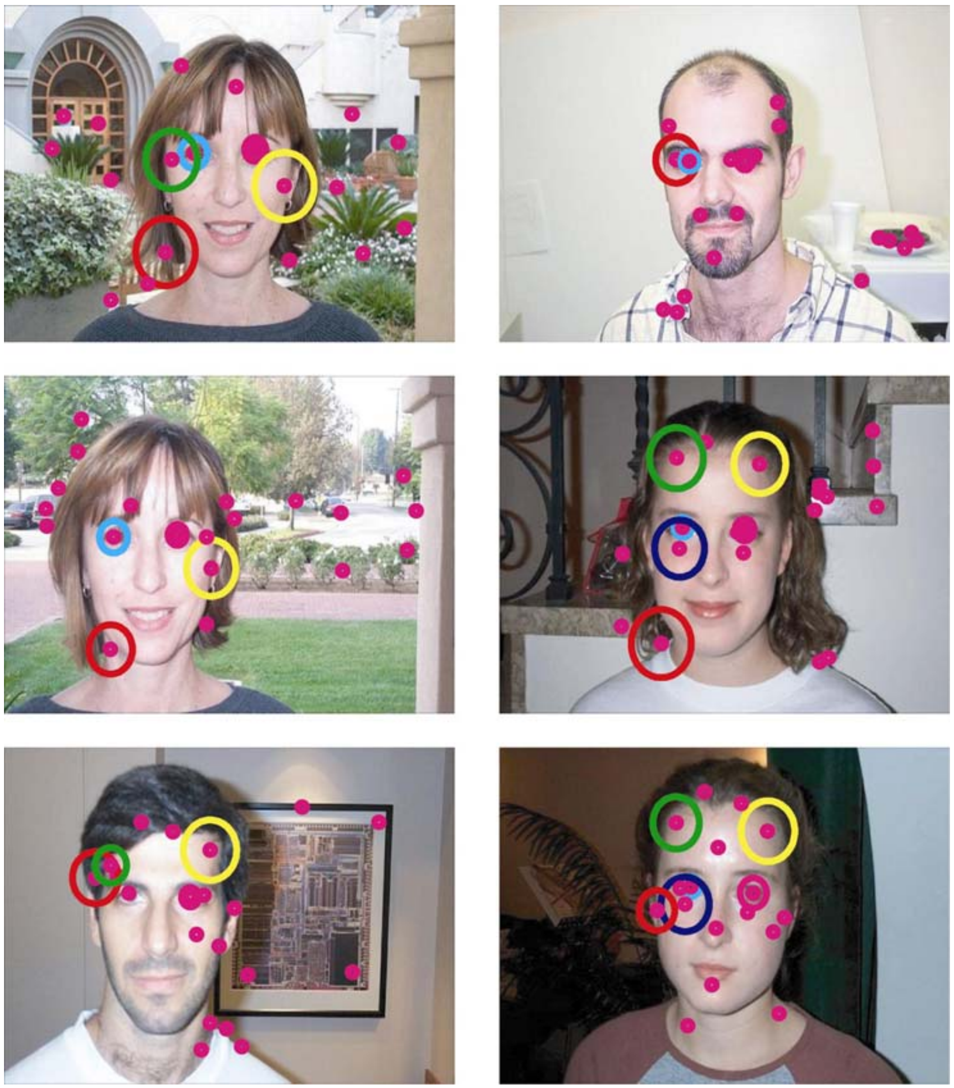


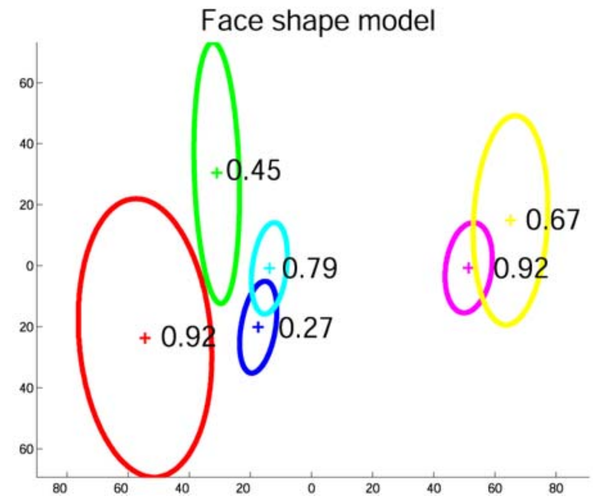
Recognized Motorbikes



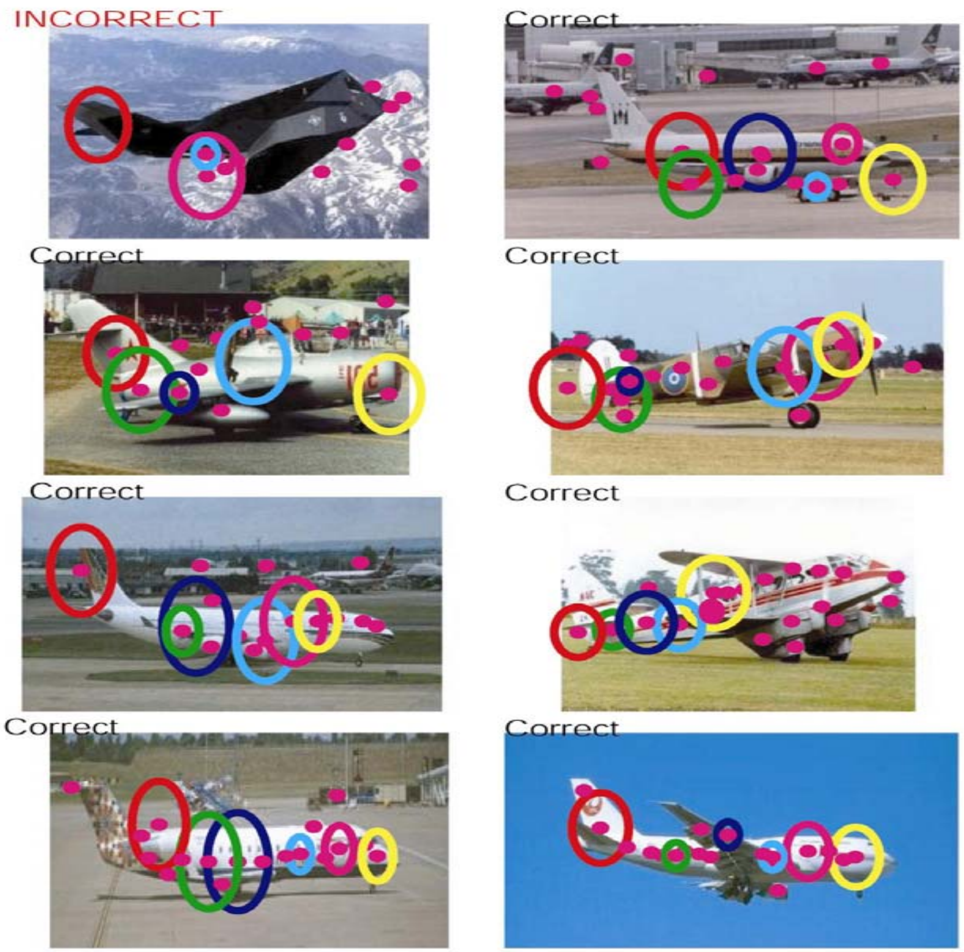
Background images evaluated with motorbike model

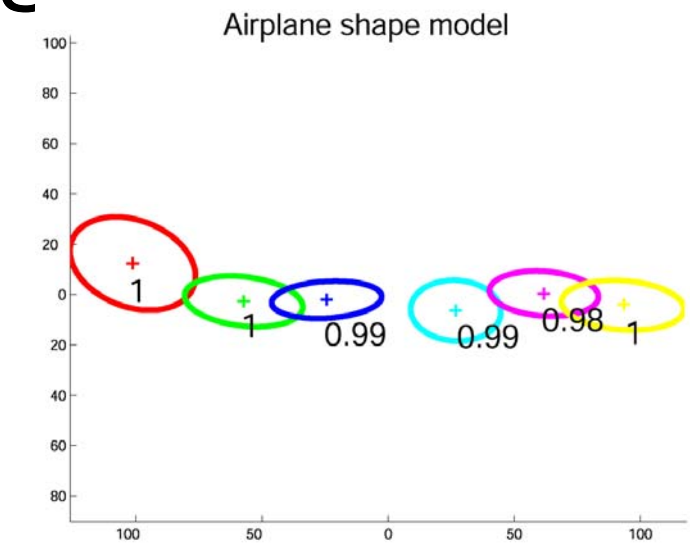
Frontal faces

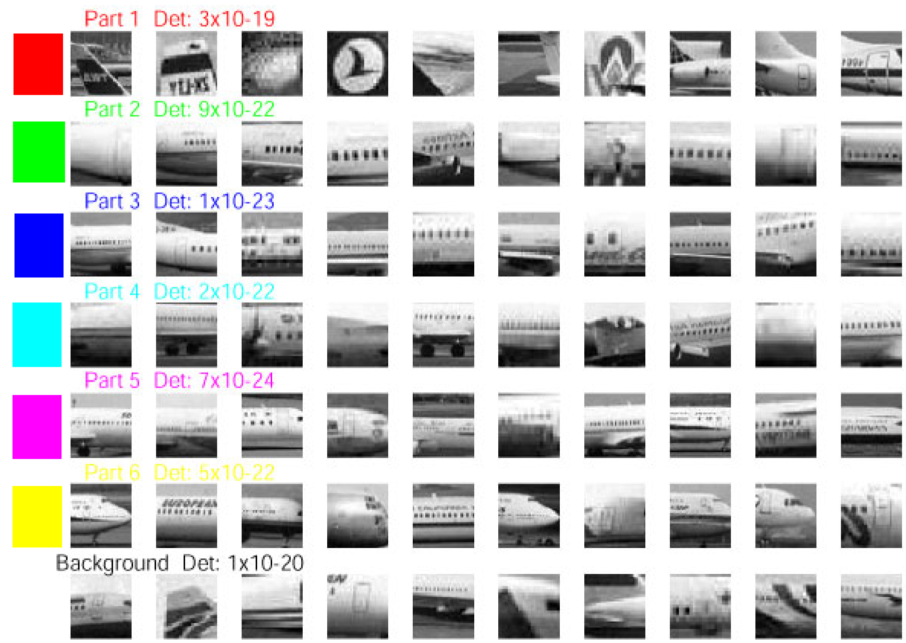




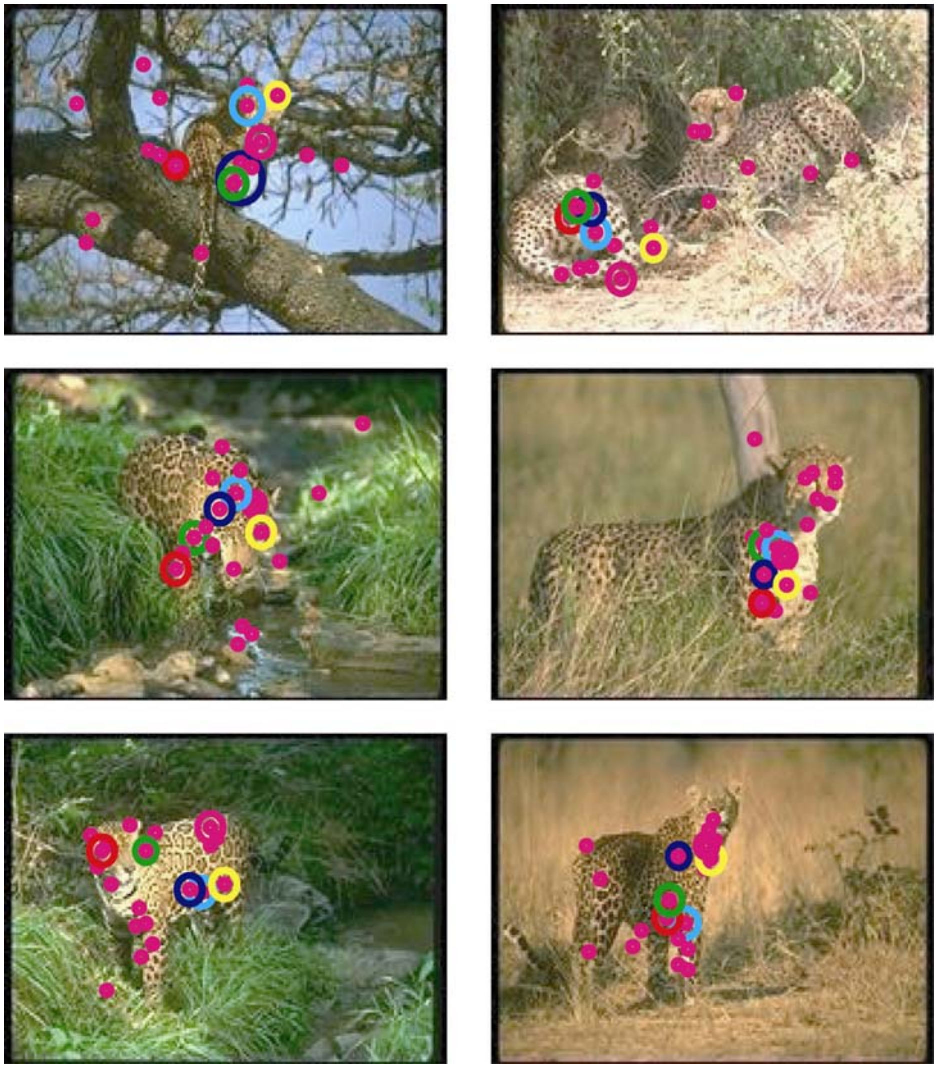
Airplanes

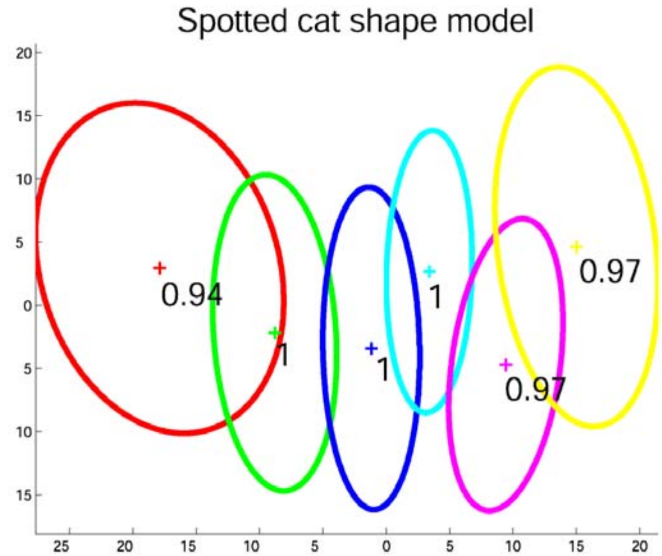

INCORRECT
Correct
Correct
Correct
Correct
Correct
Correct
Correct

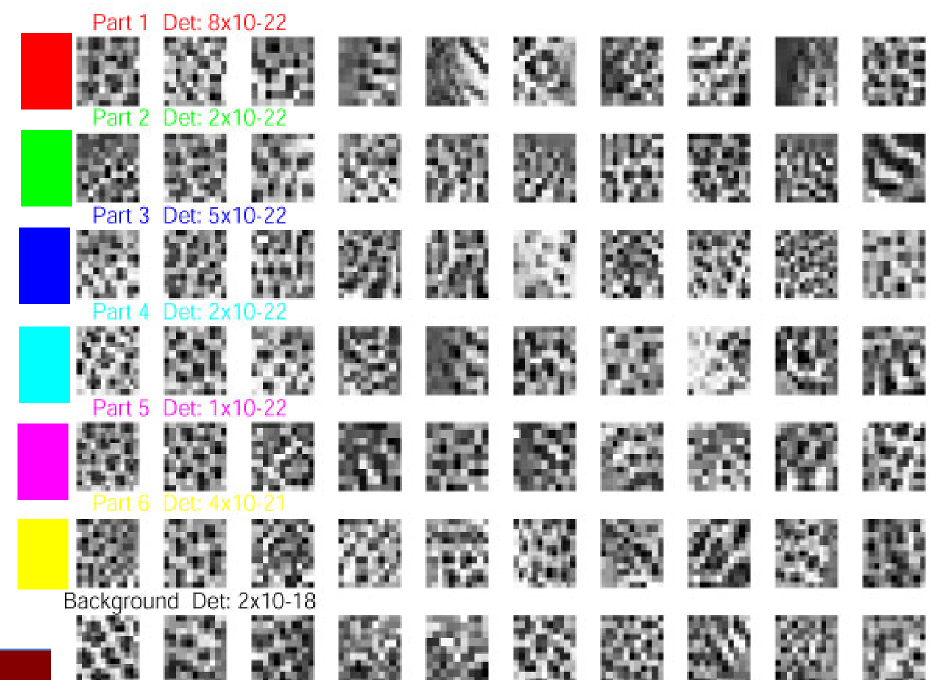

Airplane shape model
100
80
60
40
20
0
20
40
60
80
100
50
0
50
100
1
1
0.99
0.99
0.98
1


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

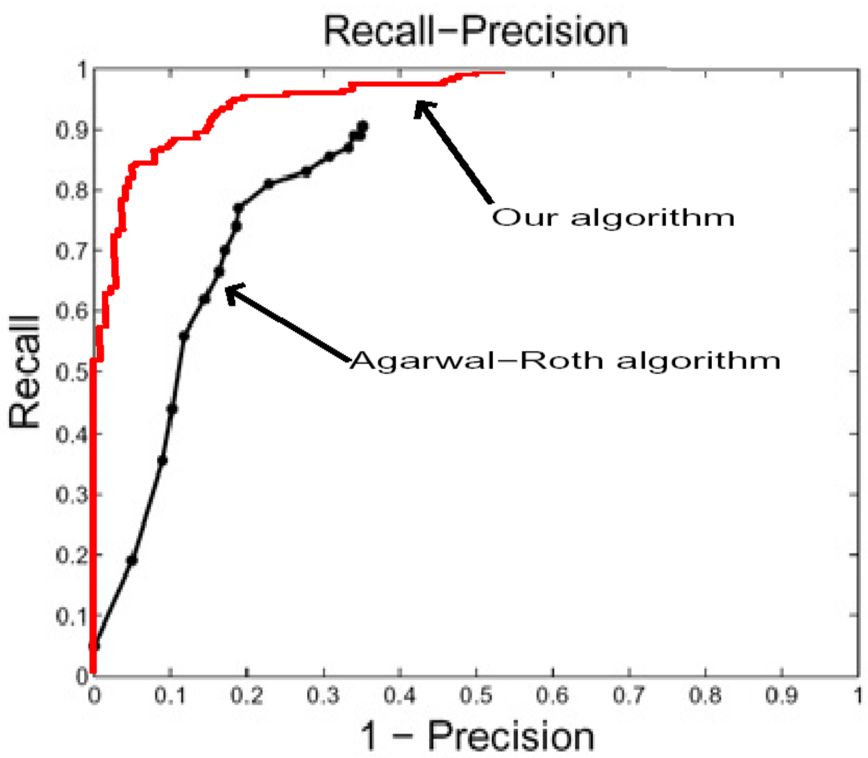
% equal error rate

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

S. Savarese, 2003


P. Buegel, 1562

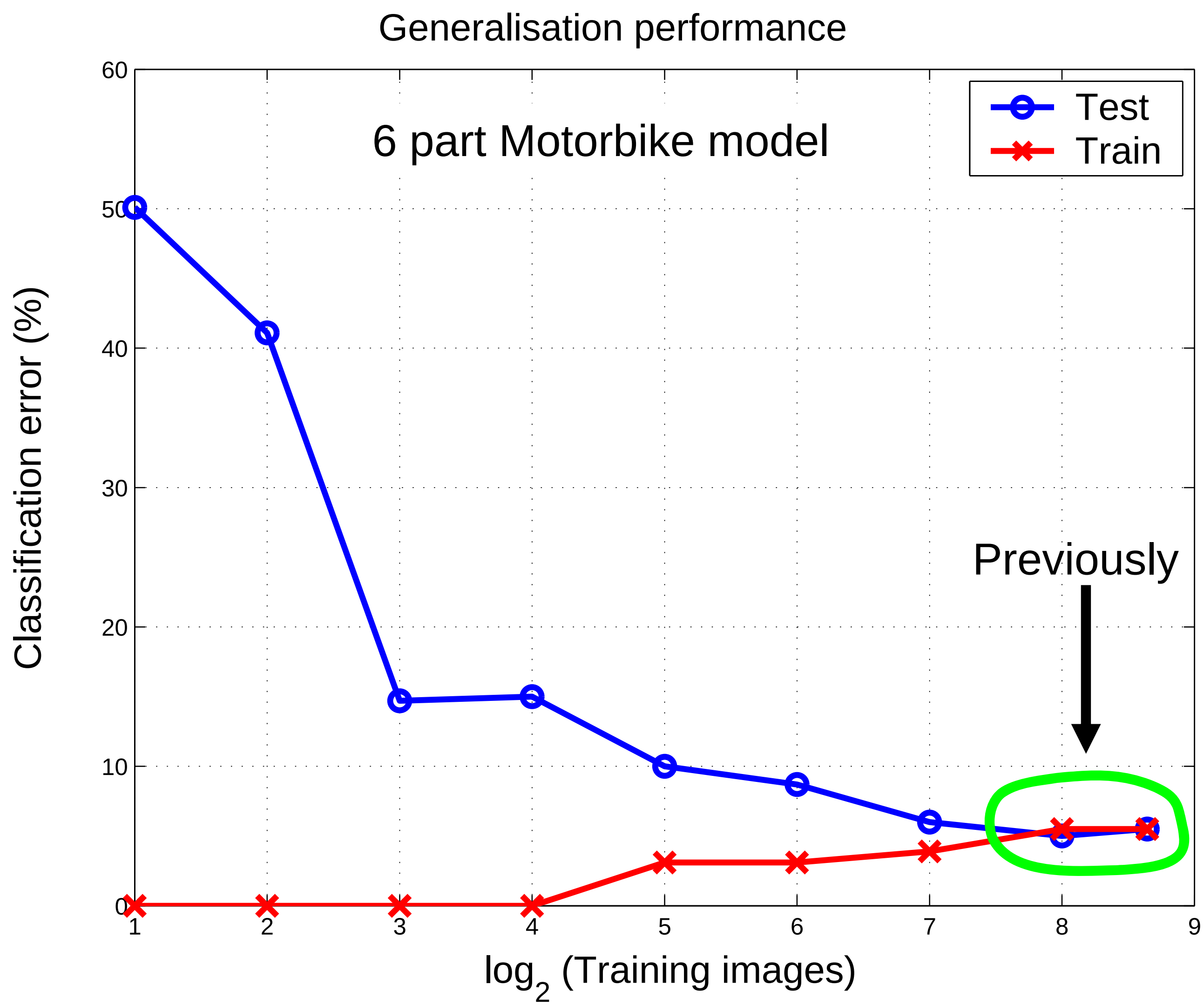
One-Shot learning

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



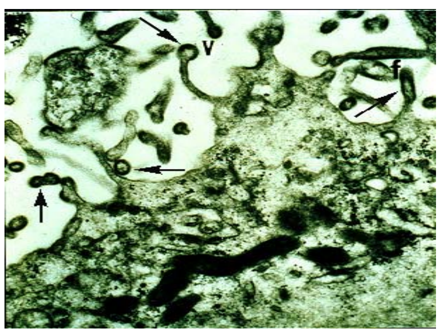
How do we do better than what statisticians have told us?

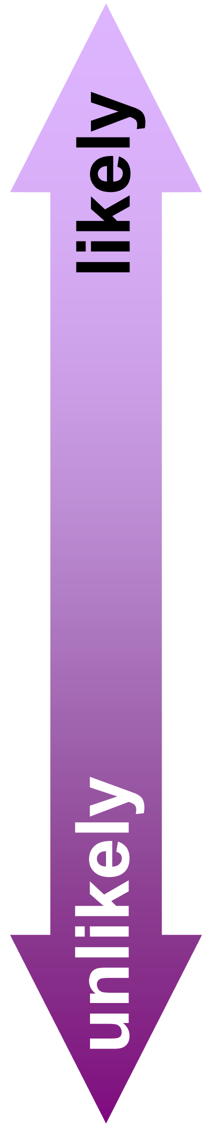
- Intuition 1: use Prior information
- Intuition 2: make best use of training information

Prior knowledge: means

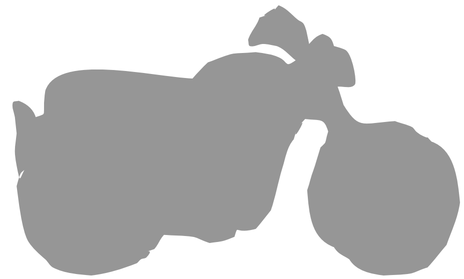
Appearance

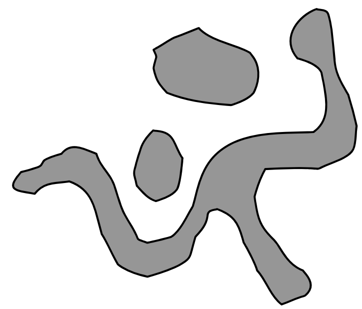




Shape






Bayesian framework

$\boxed{\text{P(object | test, train)}}$ vs. P(clutter | test, train)

Bayes Rule

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

Expansion by parametrization

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

Bayesian framework

$\boxed{\text{P(object | test, train)}}$ vs. P(clutter | test, train)

Bayes Rule

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

Expansion by parametrization

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

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

Bayesian framework

$$\boxed{P(\text{object} \mid \text{test}, \text{train})} \text{ vs. } P(\text{clutter} \mid \text{test}, \text{train})$$

Bayes Rule

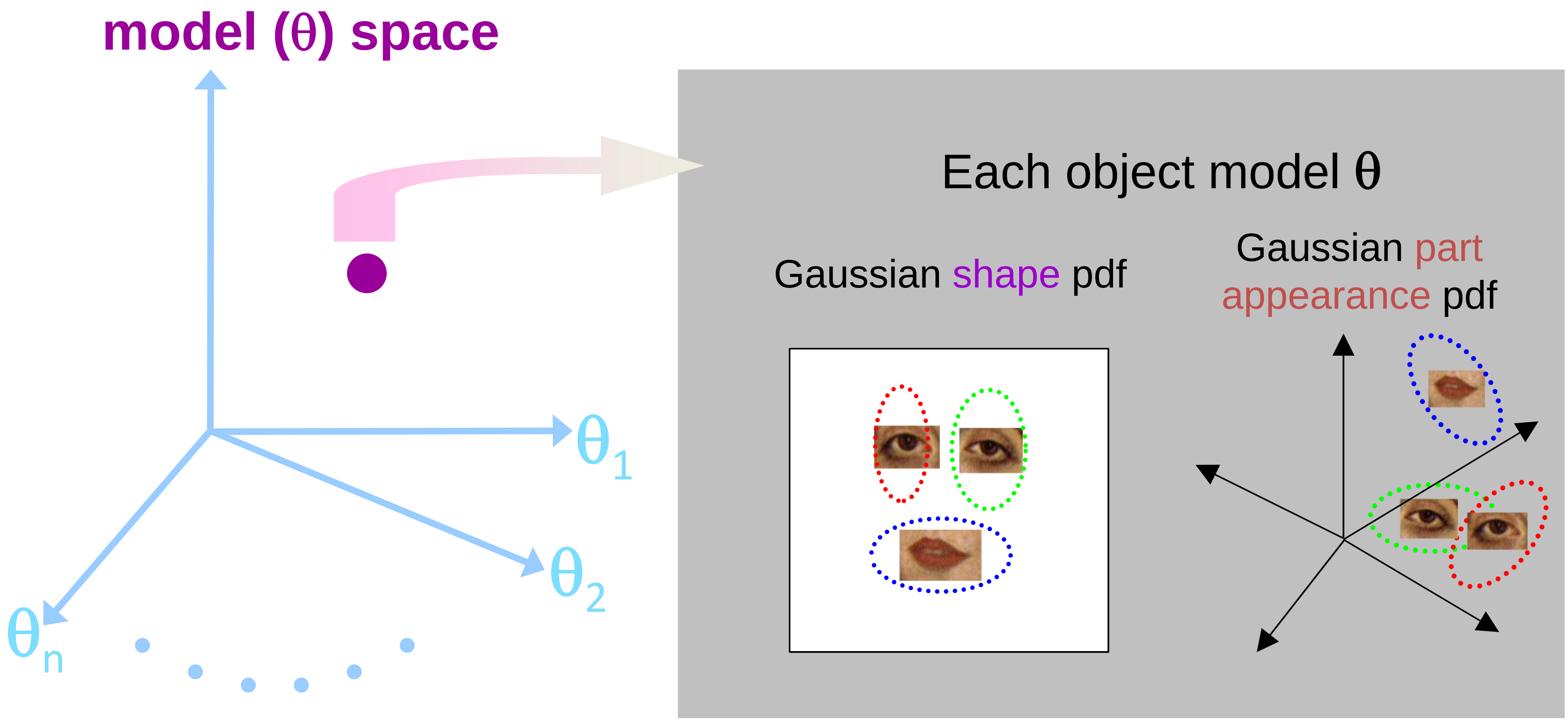
$$\boxed{p(\text{test} \mid \text{object}, \text{train})}\, p(\text{object})$$

Expansion by parametrization

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

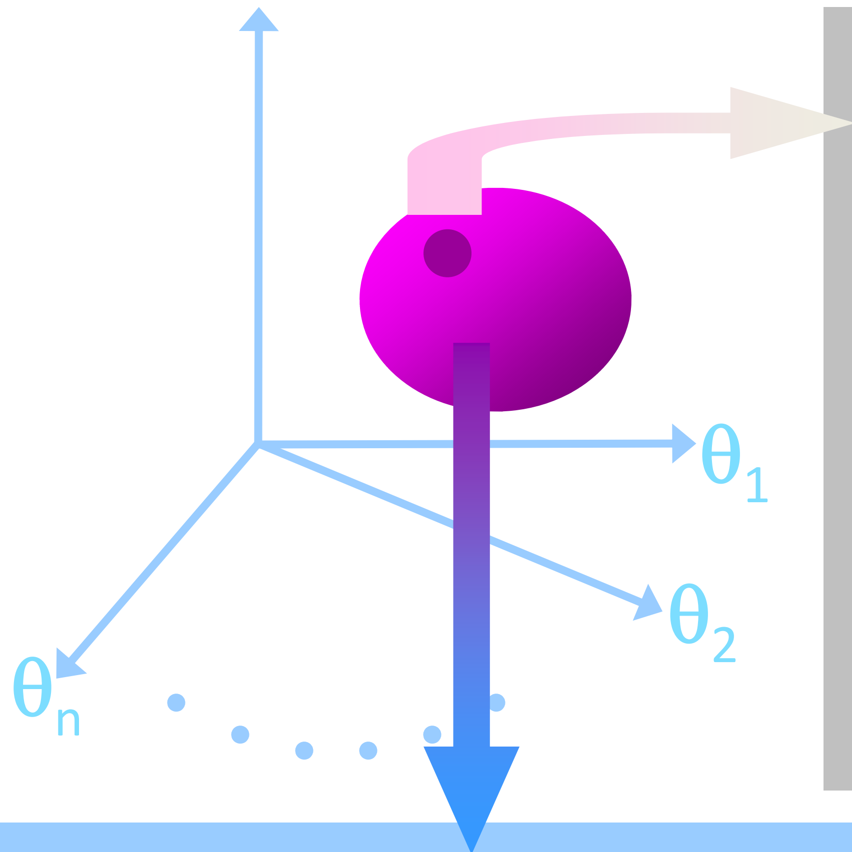
One-Shot learning: $\boxed{p(\text{train} \mid \theta, \text{object})\, p(\theta)}$

Model Structure



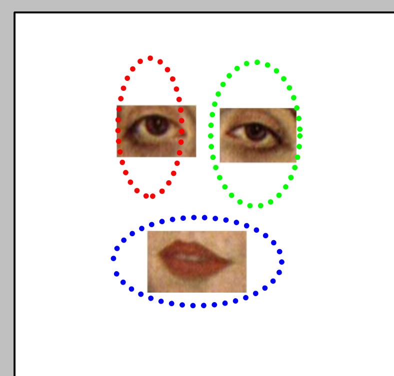
Model Structure

model (θ) space

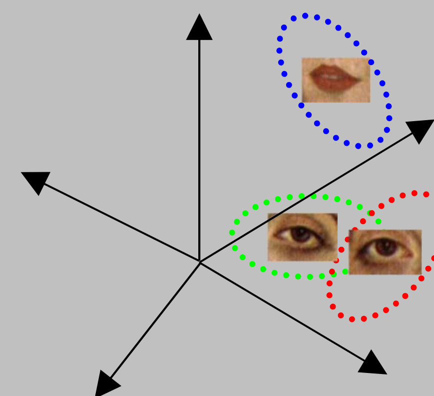


Each object model θ

Gaussian shape pdf



Gaussian part appearance pdf



model distribution: p(θ)

- **conjugate distribution of p(train|θ,object)**

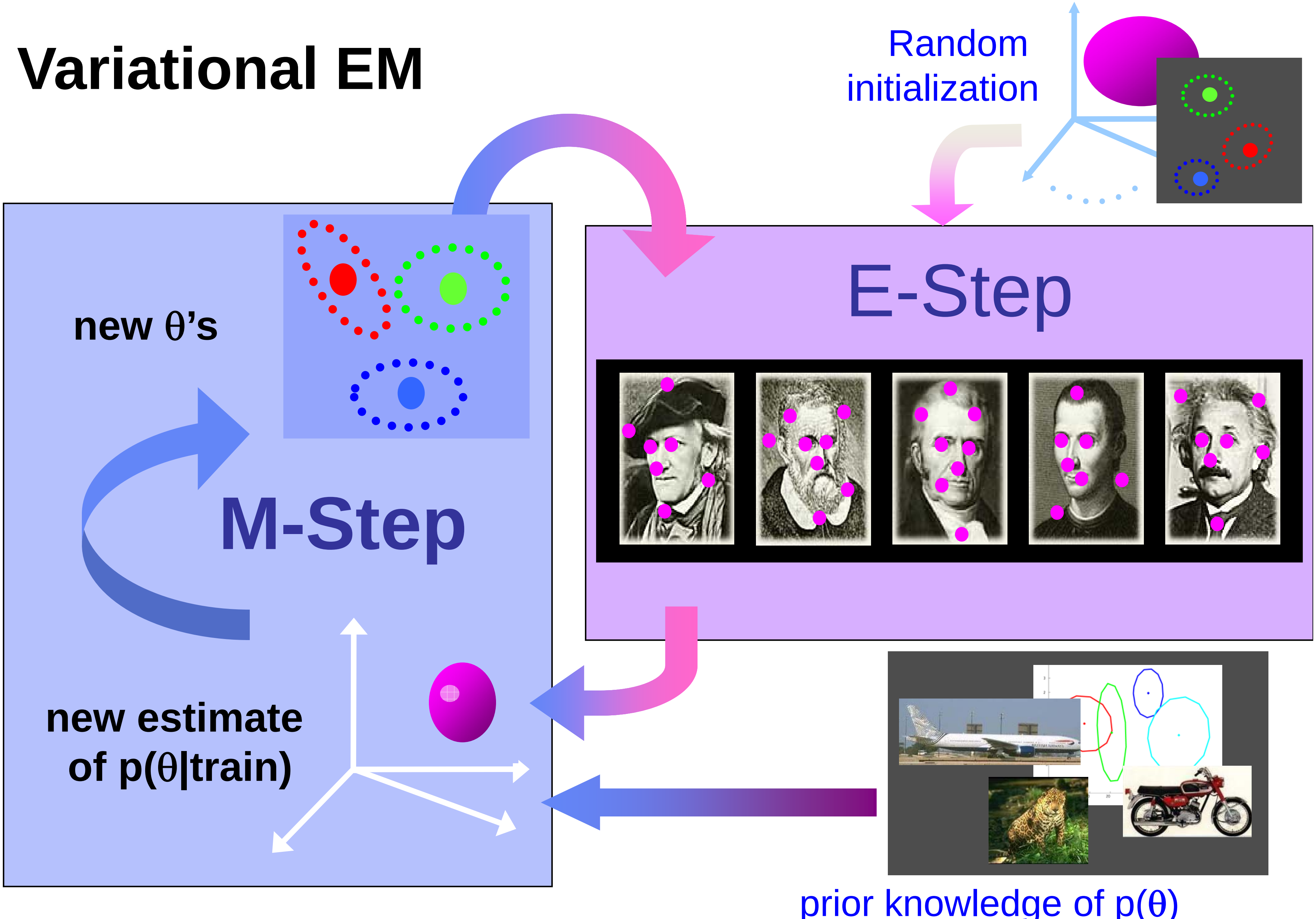
Learning Model Distribution

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

- 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

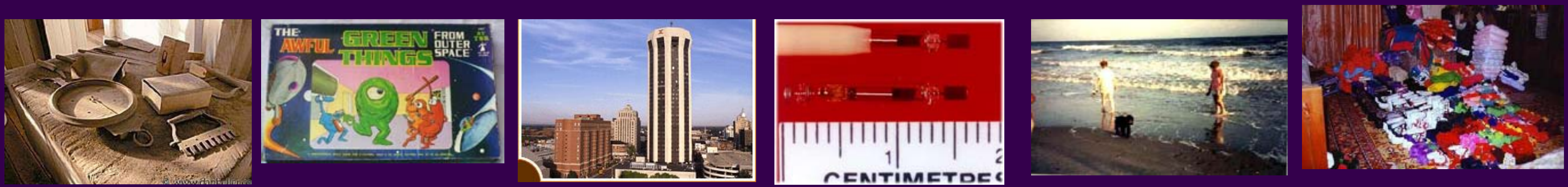
Datasets

faces

airplanes

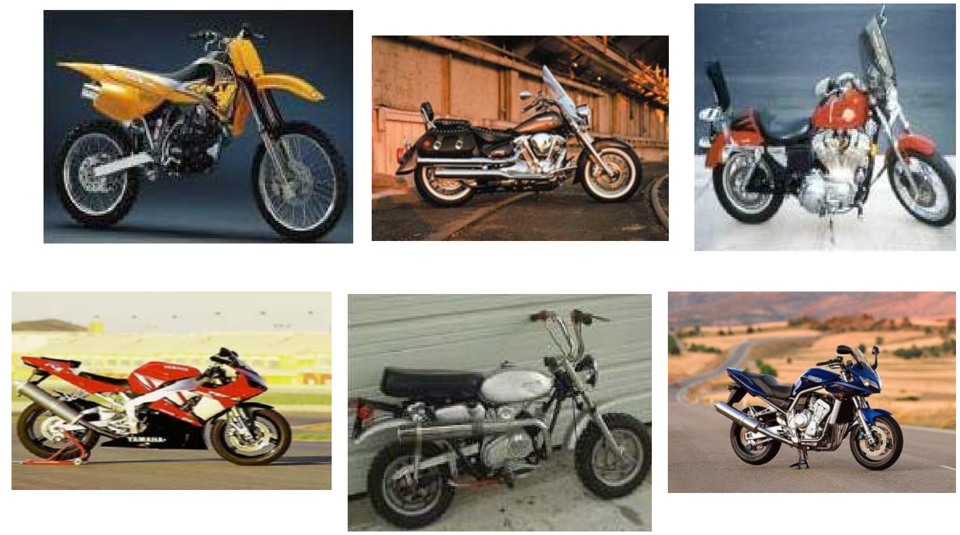
spotted cats

motorbikes



Faces

Motorbikes



Airplanes

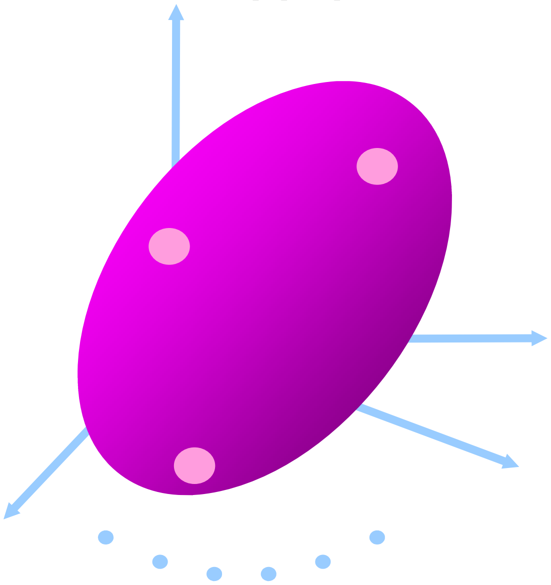
Spotted cats

Experiments: obtaining priors


airplanes


spotted cats


motorbikes



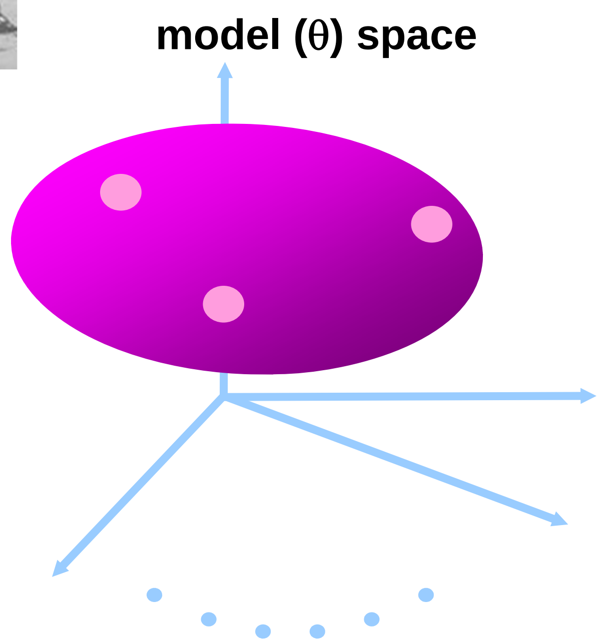

faces

Experiments: obtaining priors

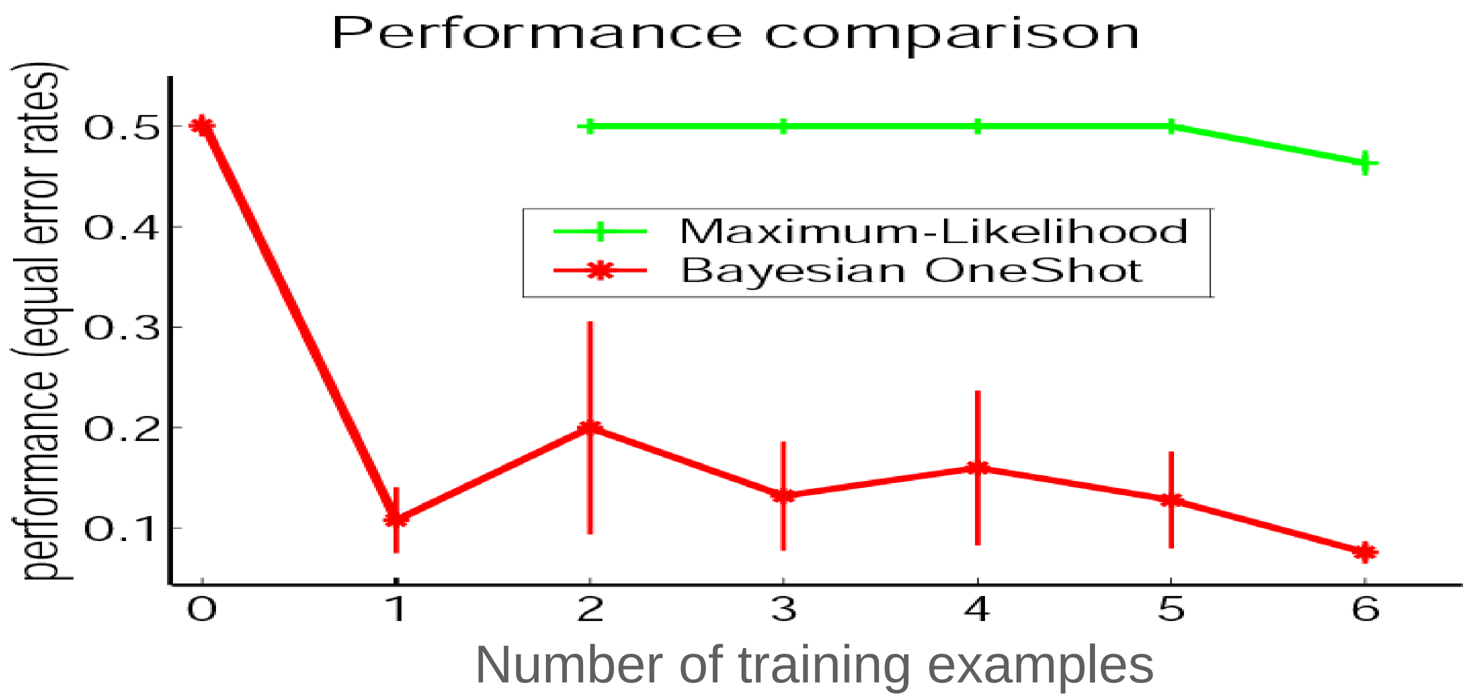
airplanes

faces

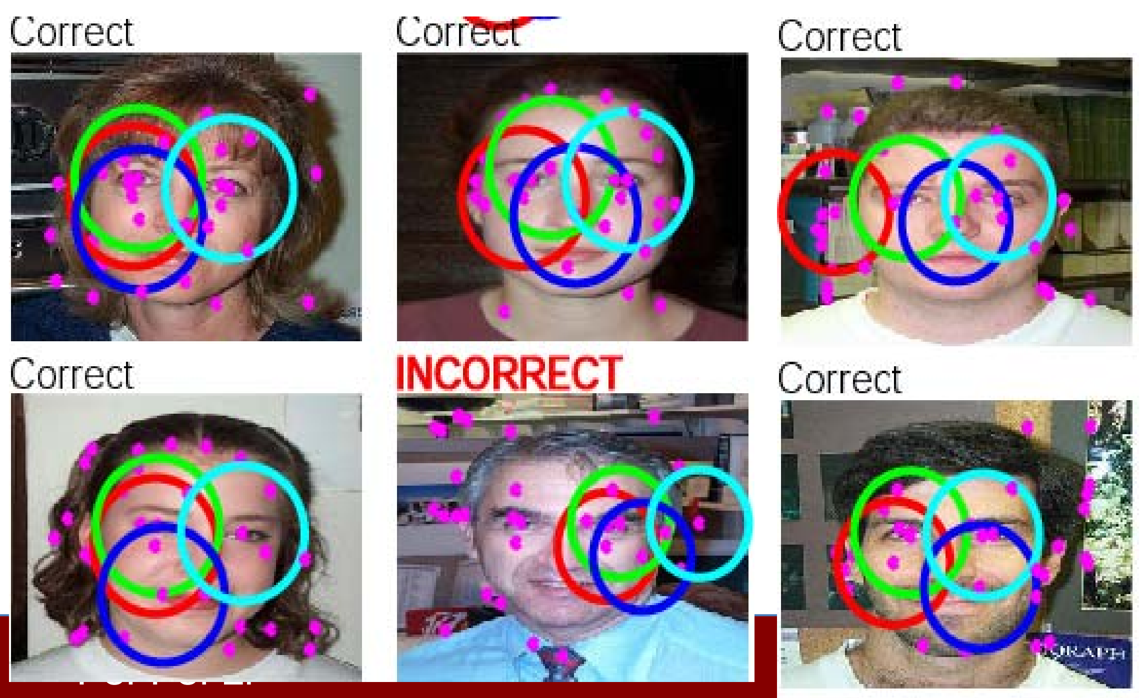
motorbikes

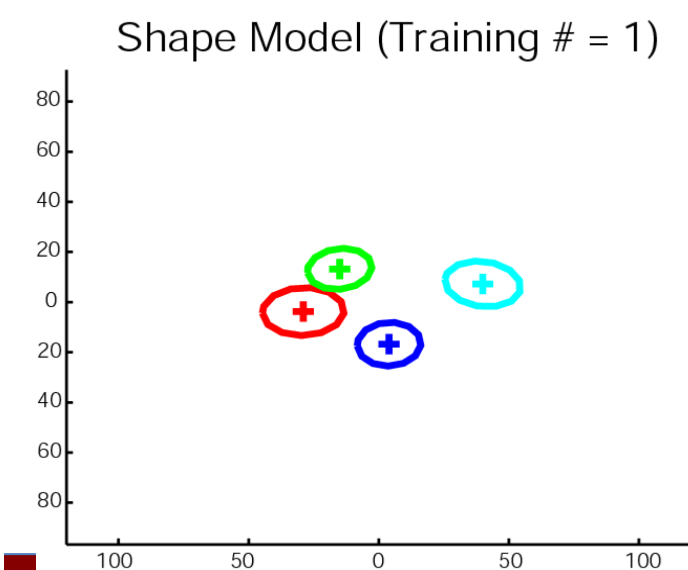


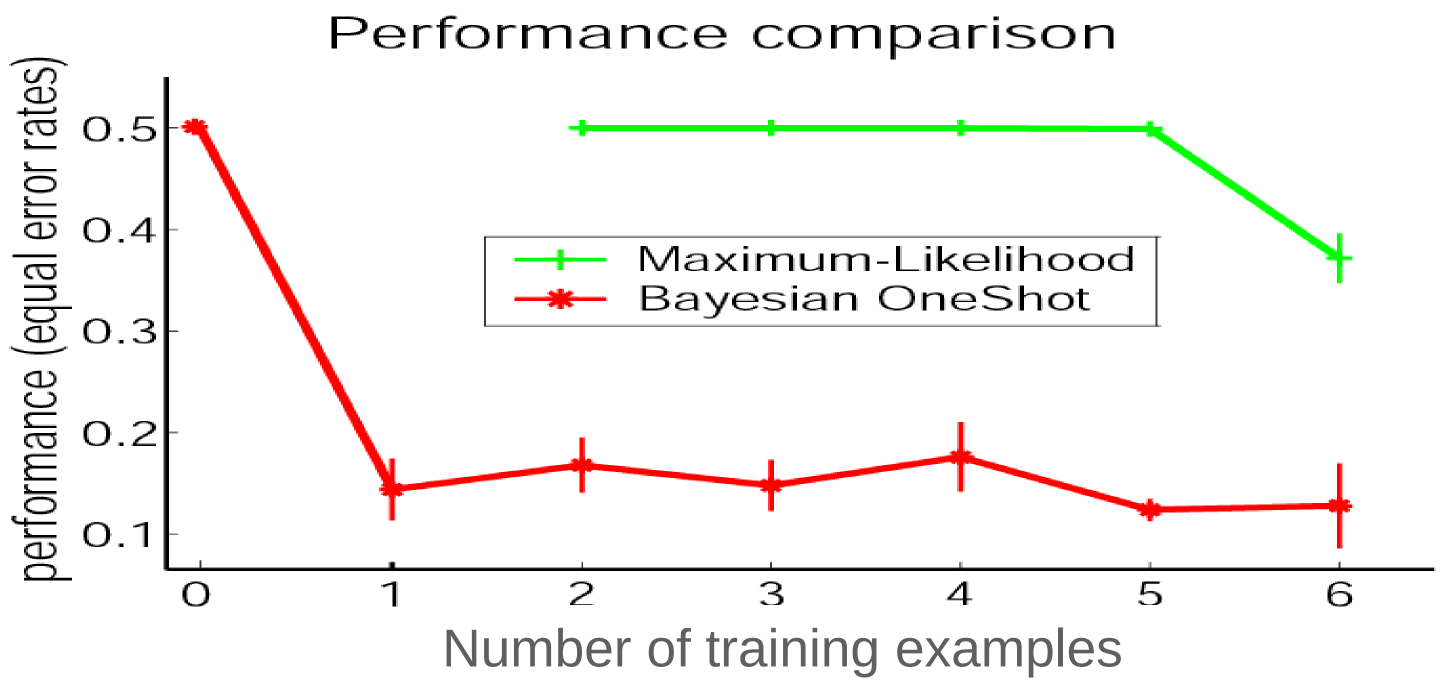
spotted cats


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

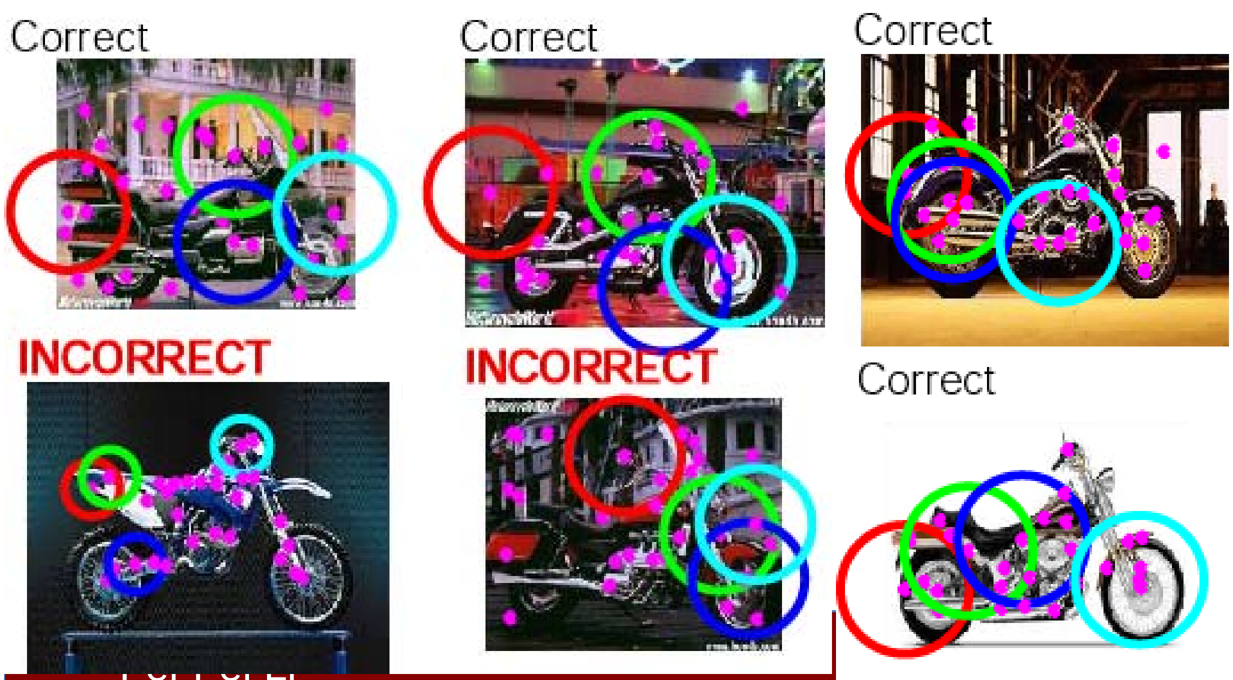

Correct
Correct
Correct
Correct
INCORRECT
Correct


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

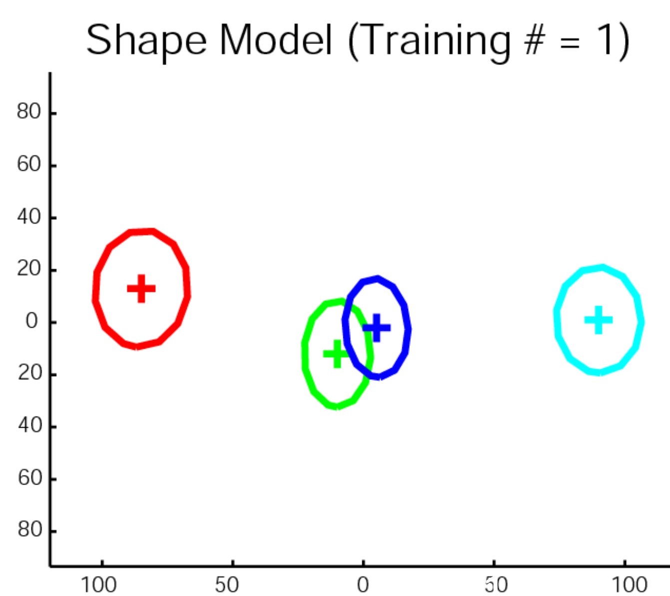


Performance comparison
performance (equal error rates)
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
Maximum-Likelihood
Bayesian OneShot
Number of training examples

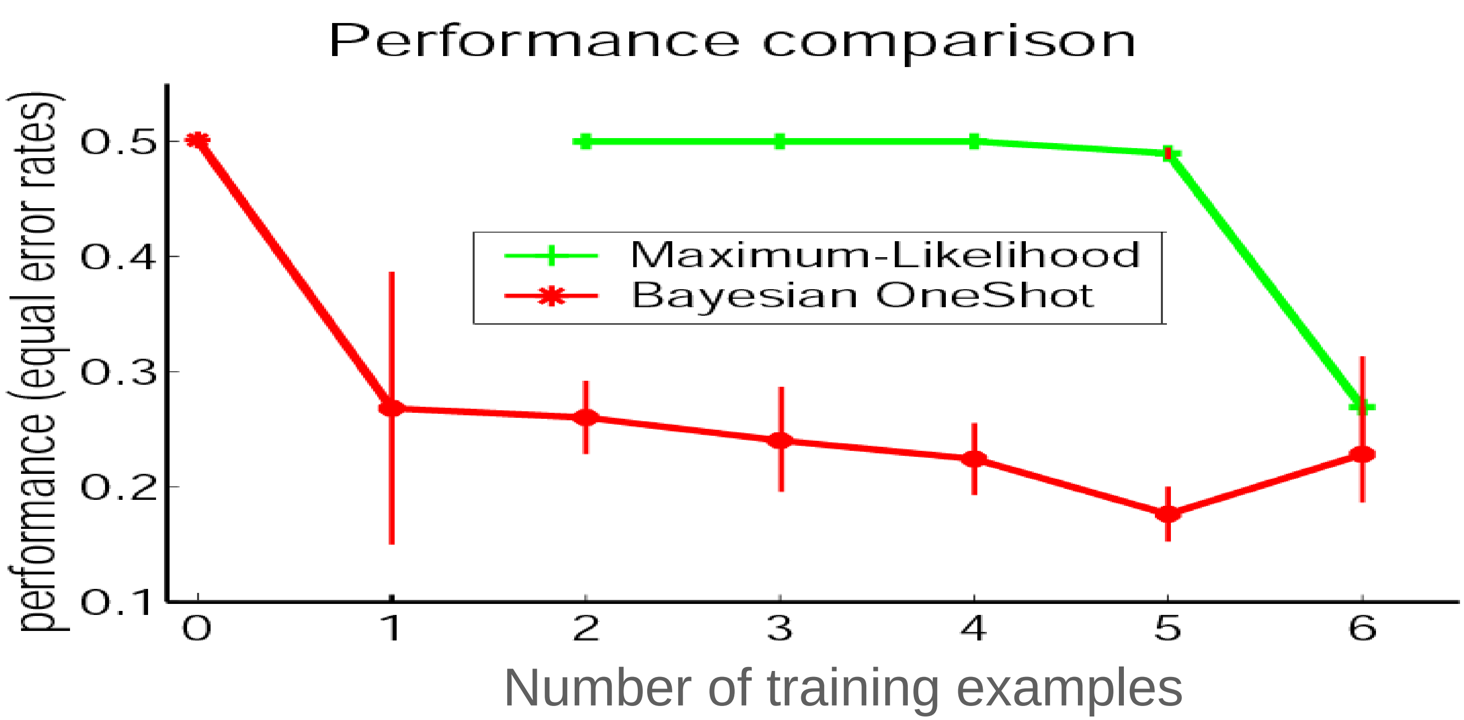
Part 1
Part 2
Part 3
Part 4

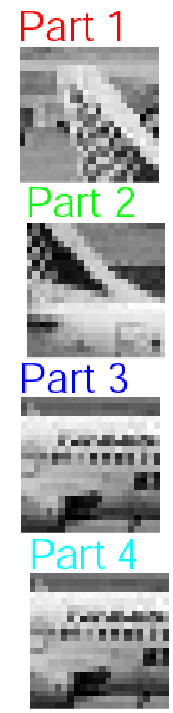


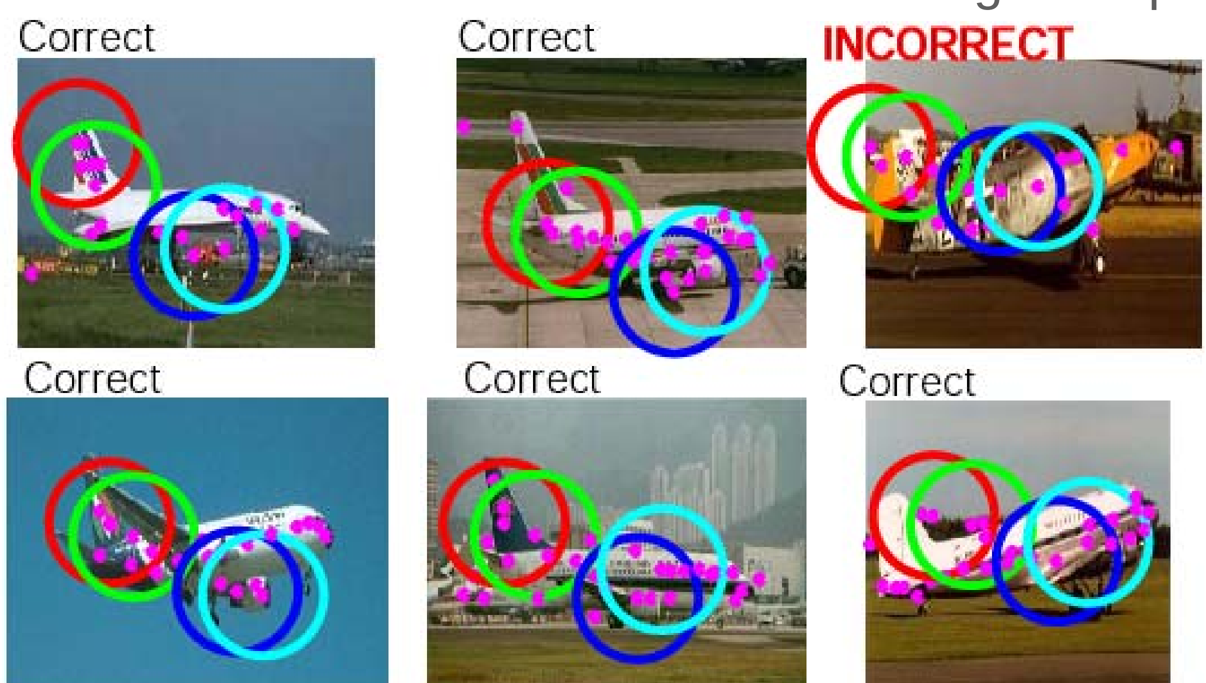
Correct
Correct
Correct
INCORRECT
INCORRECT
Correct

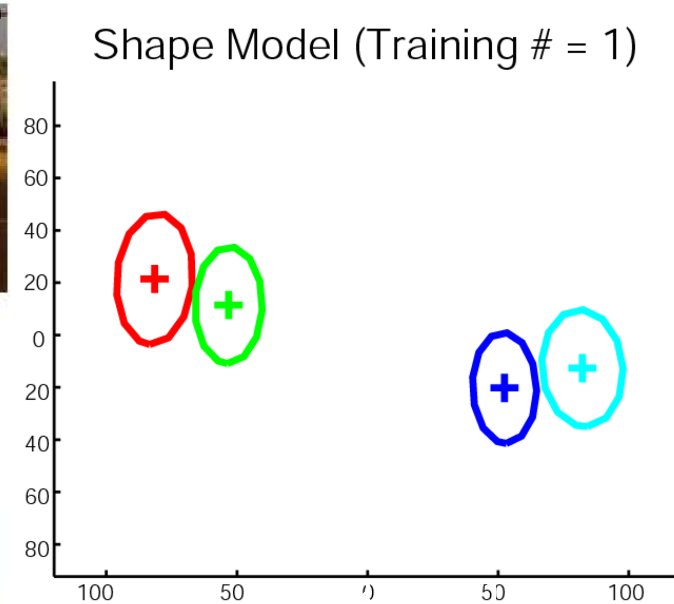


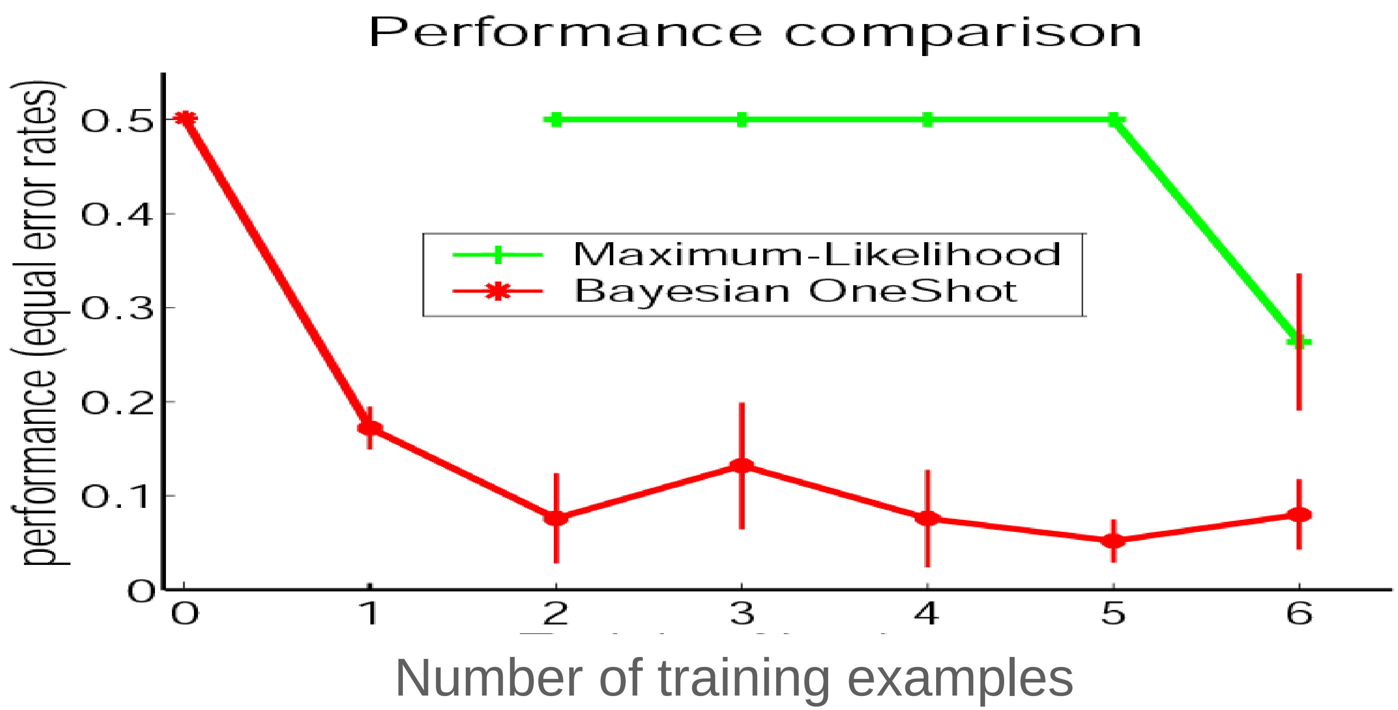
Shape Model (Training # = 1)
80
60
40
20
0
20
40
60
80
100
50
0
50
100

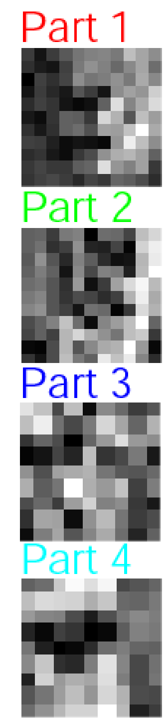

Performance comparison
performance (equal error rates)
0.5
0.4
0.3
0.2
0.1
Maximum-Likelihood
Bayesian OneShot
0
1
2
3
4
5
6
Number of training examples

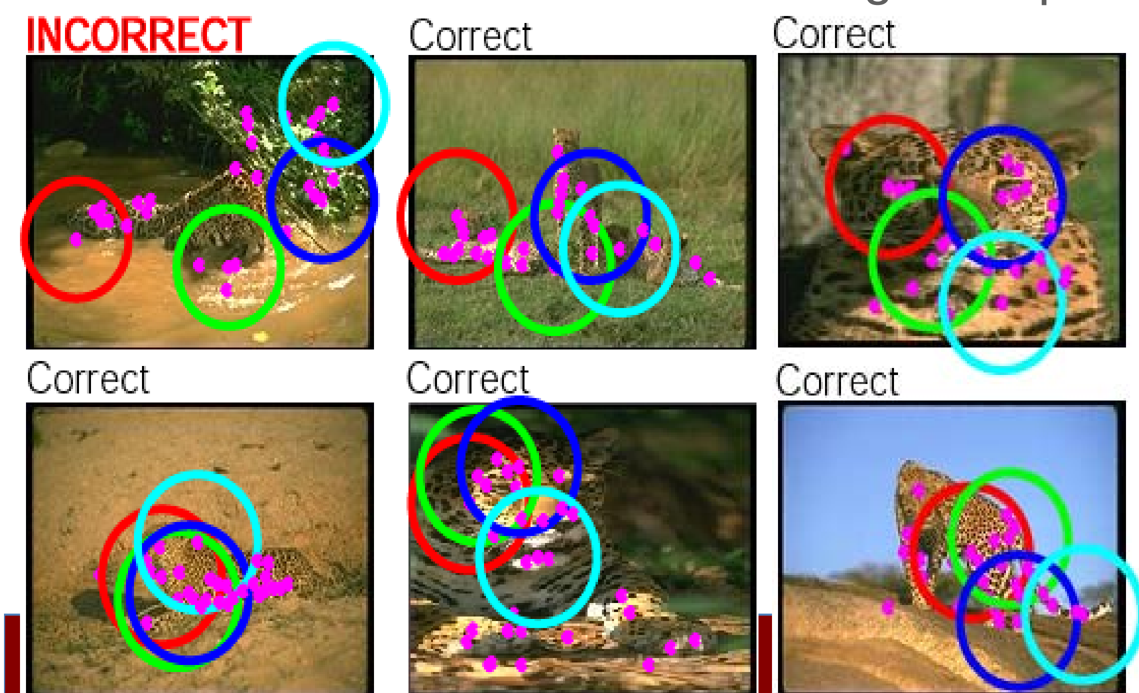

Part 1
Part 2
Part 3
Part 4

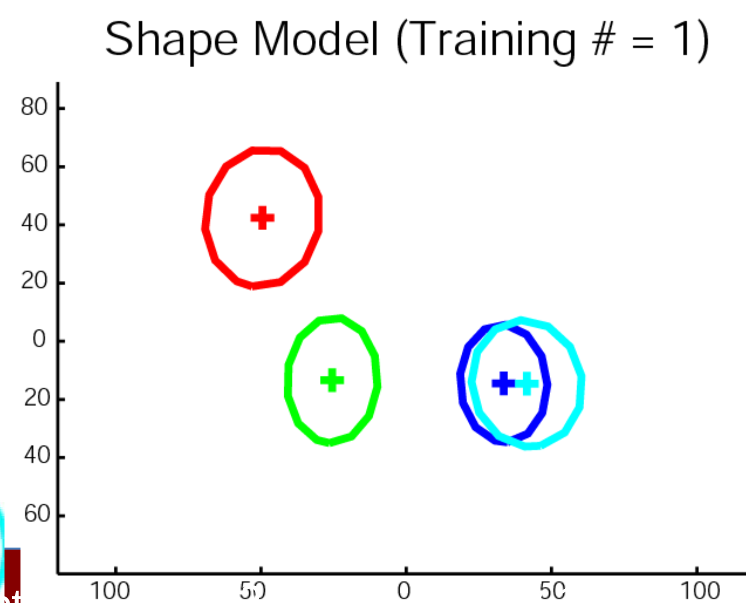

Correct
Correct
INCORRECT
Correct
Correct
Correct


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


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

What we have learned today?

- Introduction
- Constellation model
  - Weakly supervised training
  - One-shot learning
- (Problem Set 4 (Q1))