COS 429: COMPUTER VISON

Face Recognition

- Intro to pattern recognition
- Intro to visual recognition
- PCA and Eigenfaces
- LDA and Fisherfaces
- generic object models for faces: the Constellation Model

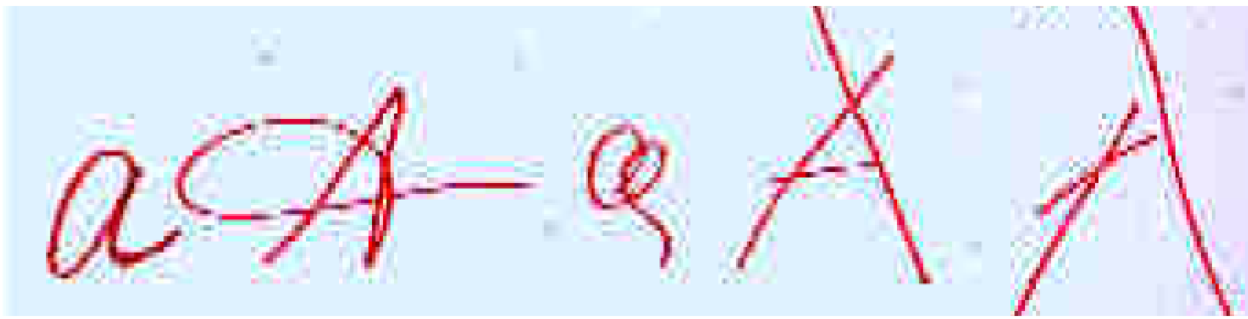
What is a Pattern?

"A pattern is the opposite of chaos; it is an entity vaguely defined, that could be given a name."

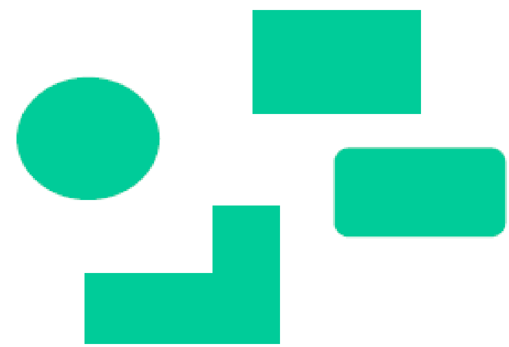
A pattern is an abstract object, such as a set of measurements describing a physical object.

Examples of Patterns

Handwritten Characters

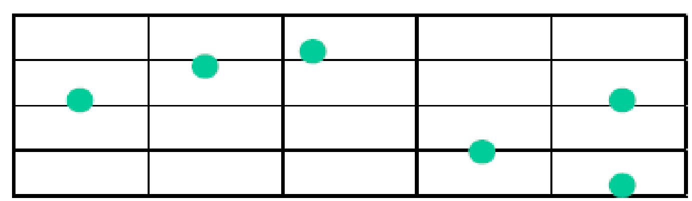


UPC BarCode



Fingerprint

Animal Footprint

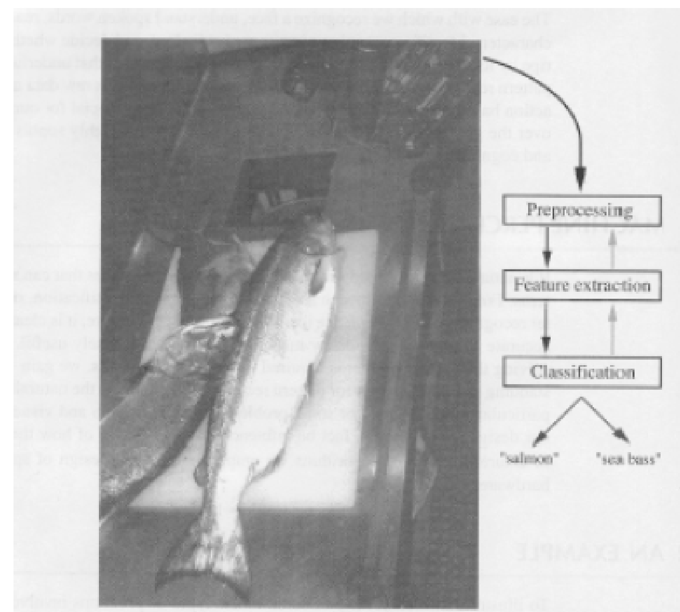


Postnet Bar Code

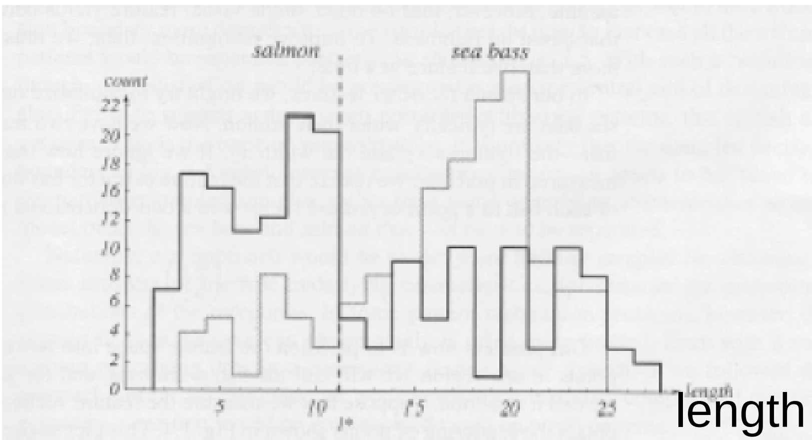
Data Trend

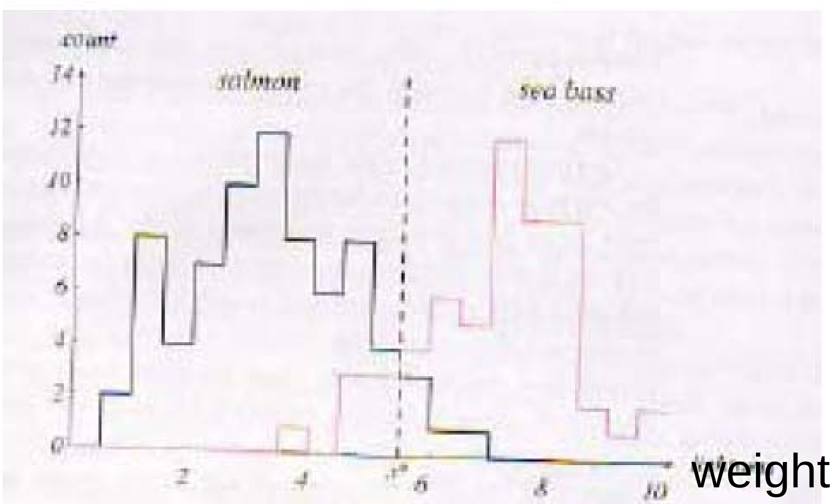
Pattern Recognition Processes

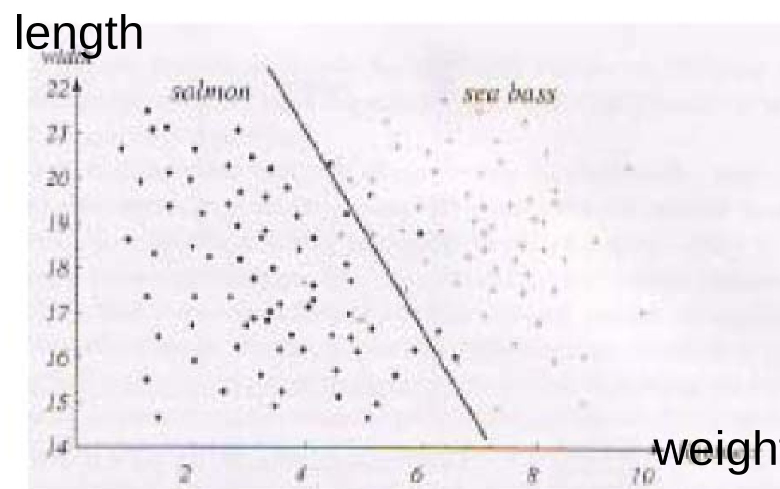
- Objects to be classified are sensed by transducer (camera)
- Signals are preprocessed
- Features are extracted
- Classification is emitted



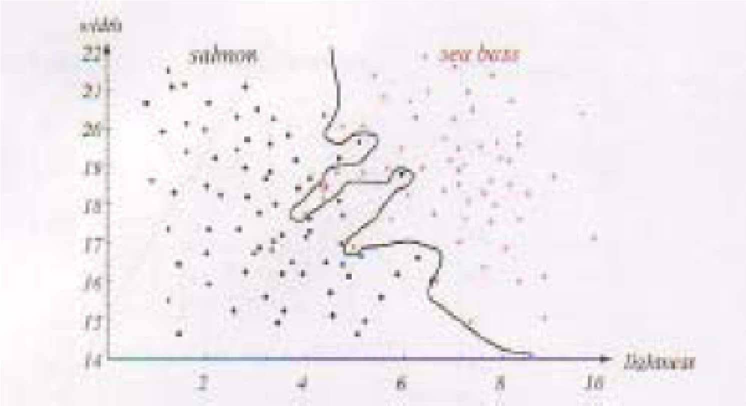
Classification Process

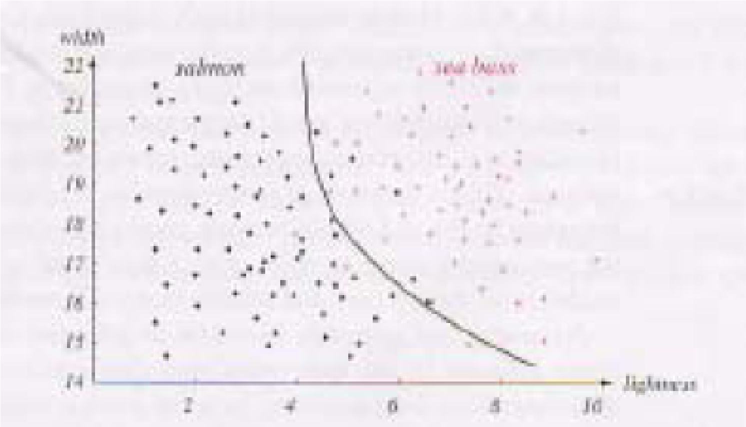






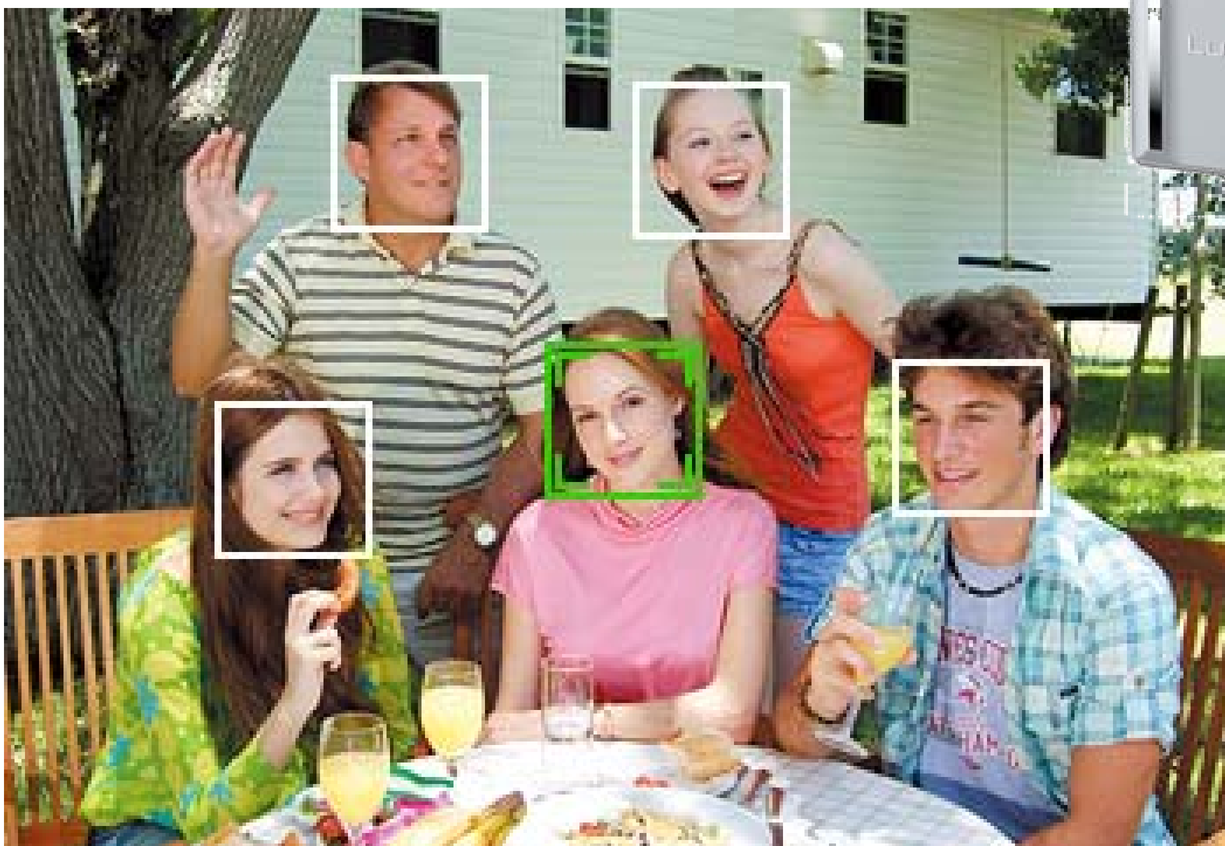
Generalization





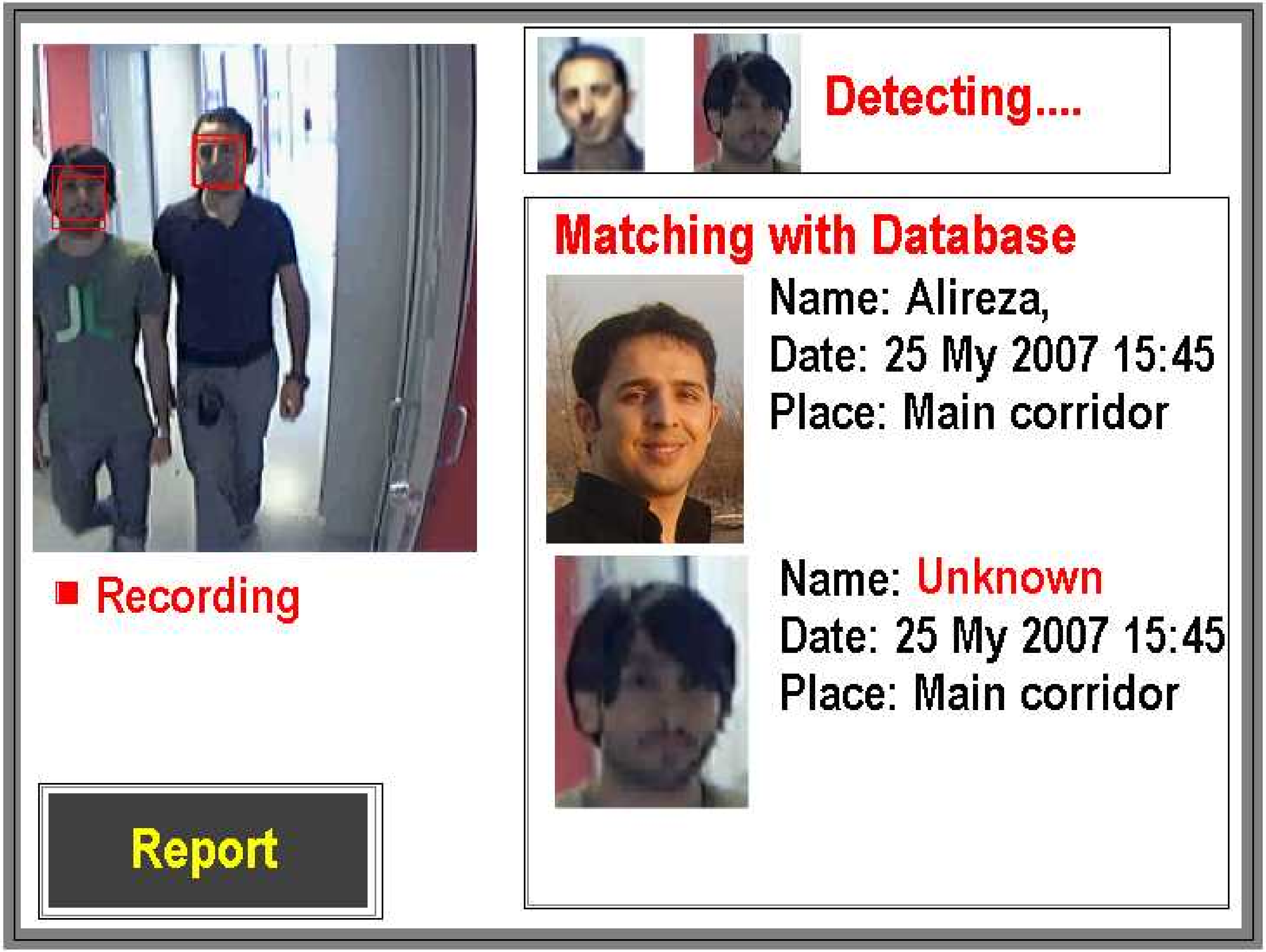
Face Recognition

- Digital photography



Face Recognition

- Digit
- Surv

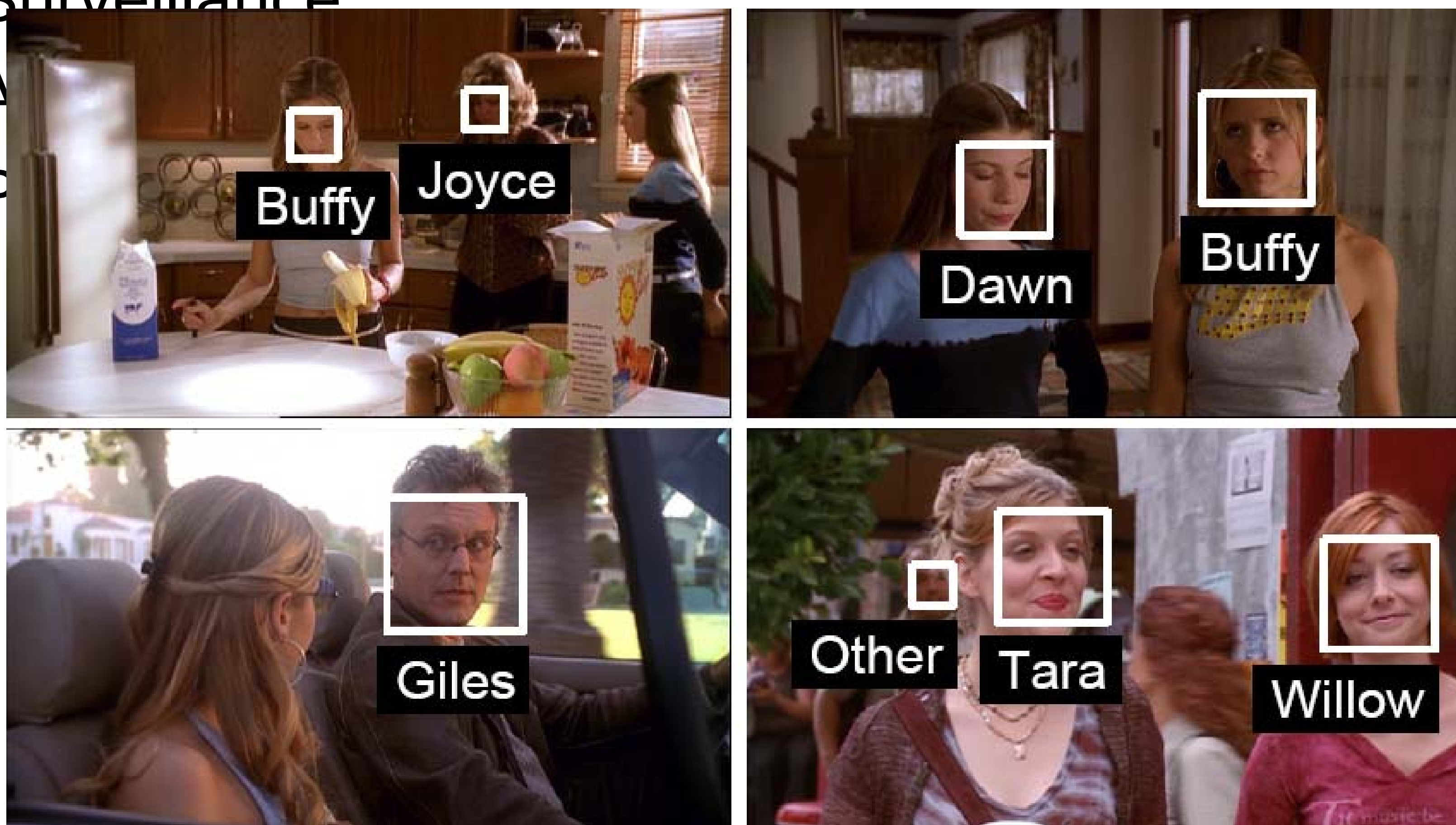


Face Recognition

- Digital photography
- Surveillance
- Album organization

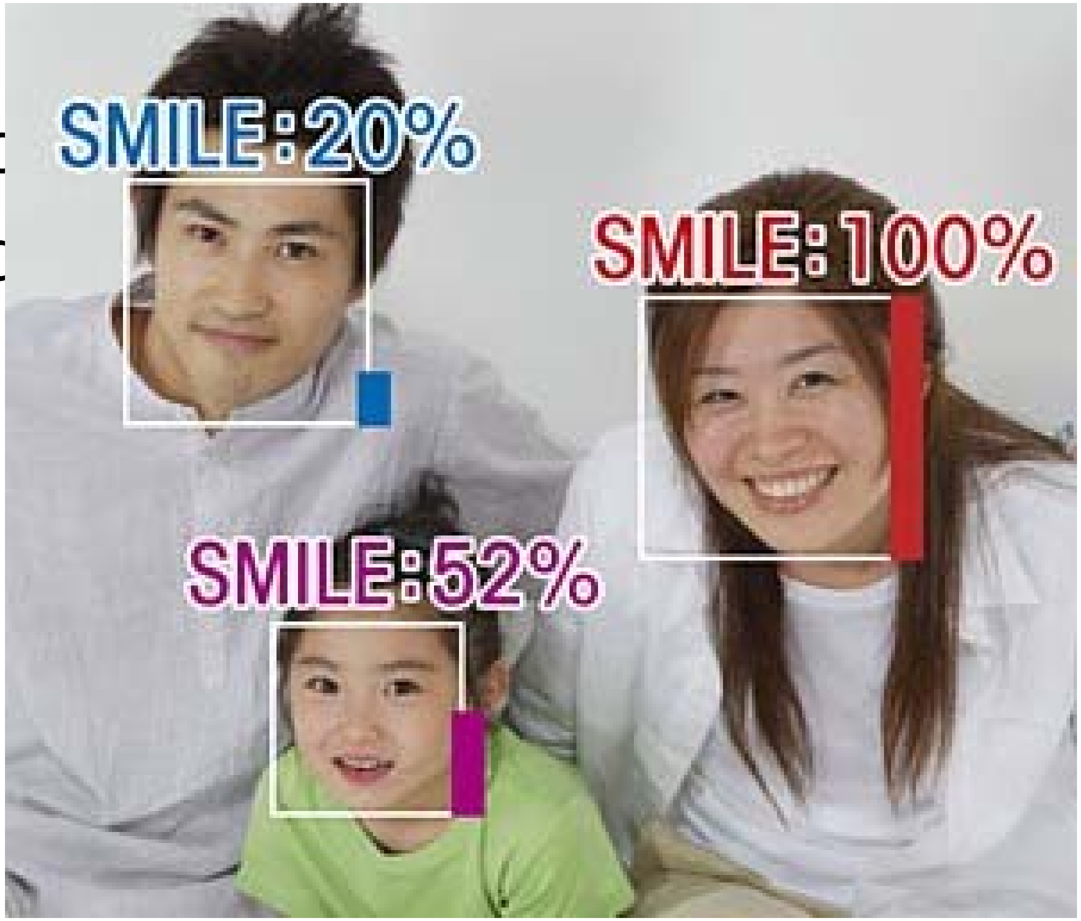
Face Recognition

- Digital photography
- Surveillance
- A
- P



Face Recognition

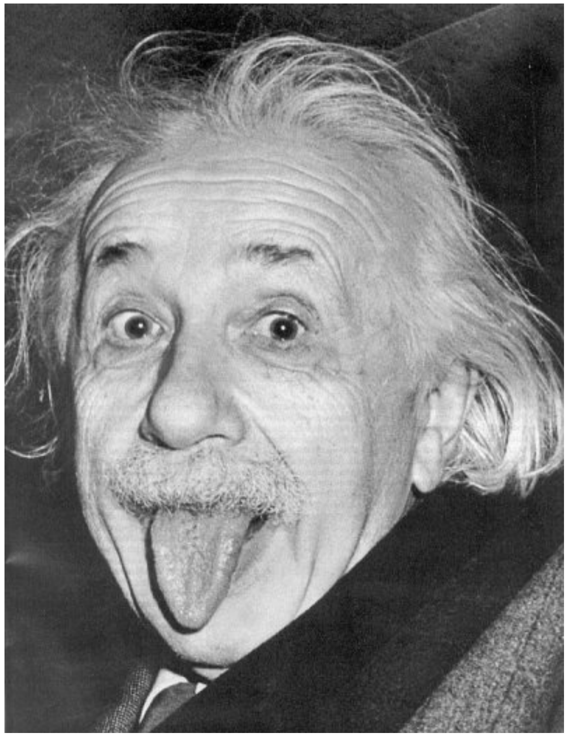
- Digital photography
- Surveillance
- Album organizatio
- Person tracking/id
- Emotions and expressions



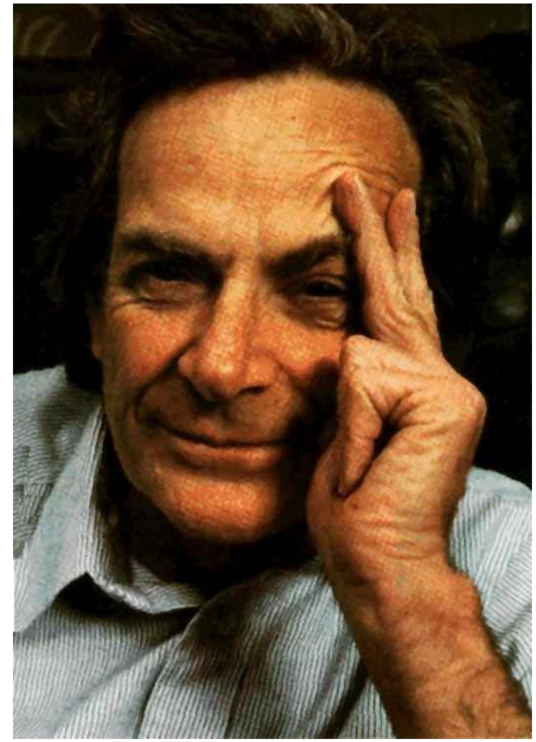
Face Recognition

- Digital photography
- Surveillance
- Album organization
- Person tracking/id.
- Emotions and expressions
- Security/warfare
- Tele-conferencing
- Etc.

What's 'recognition'?



vs.



Identification or Discrimination

What's 'recognition'?

vs.

Identification or
Discrimination

**Categorization or
Classification**

Wh ’?

Yes, there are faces

No localization

Identification or Discrimination

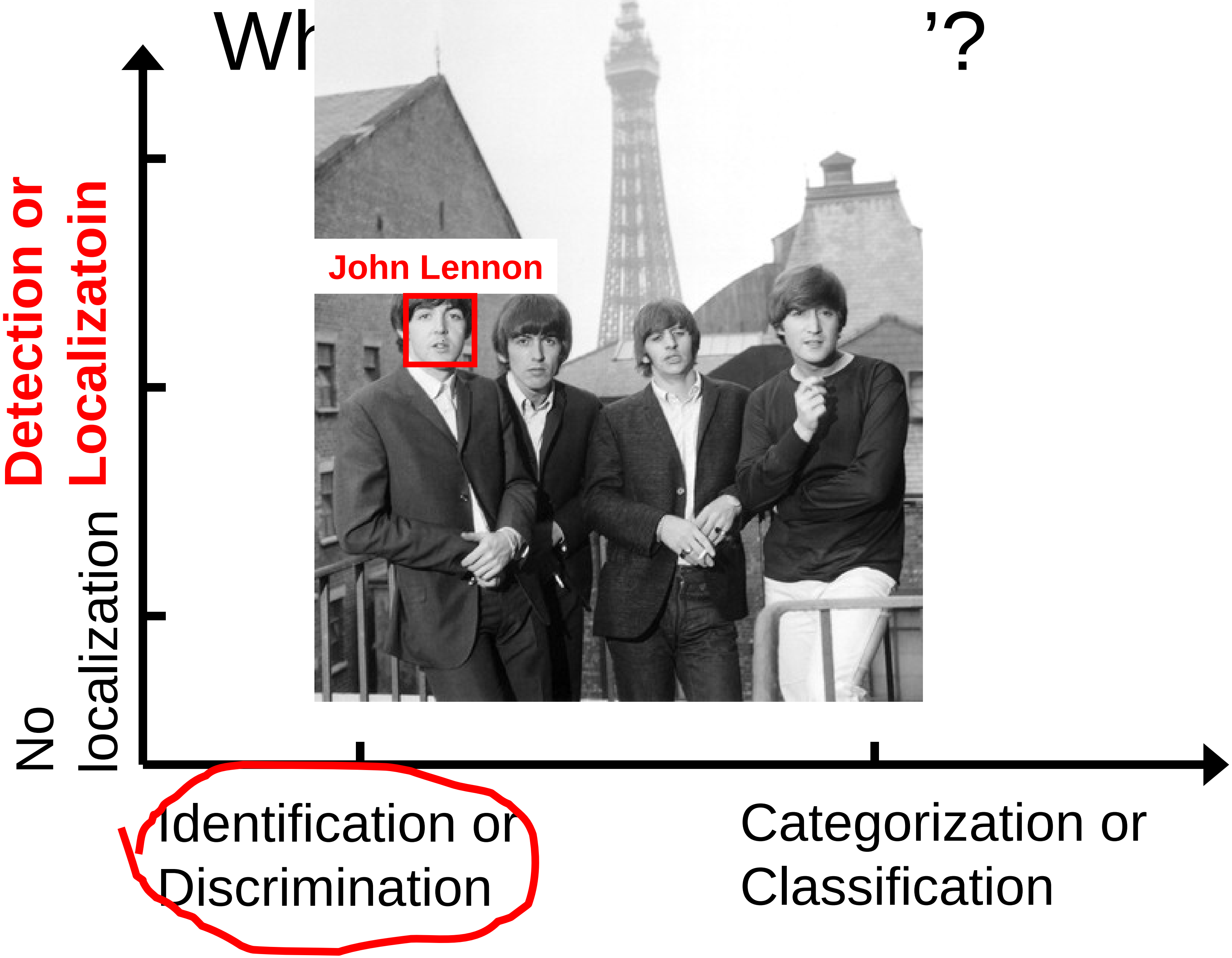
Categorization or Classification

Wh ’?

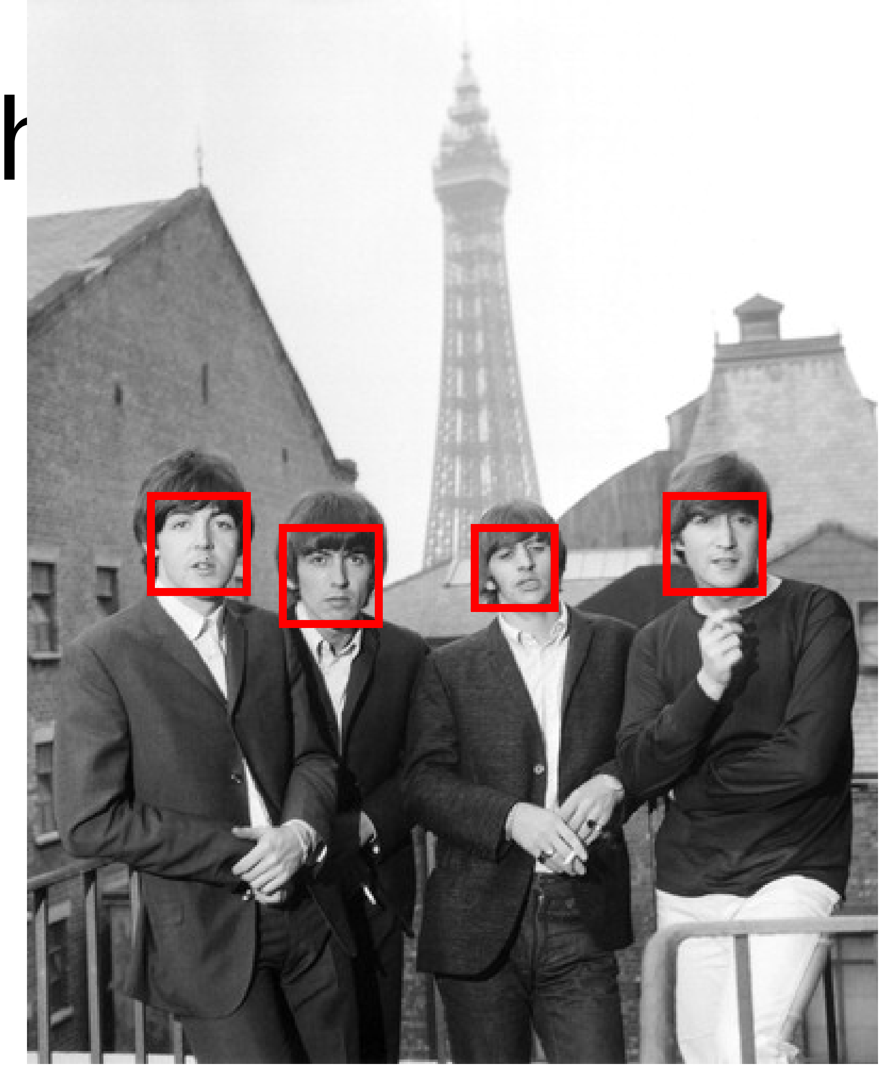
No localization

Identification or Discrimination

Categorization or Classification


Wh
’?
John Lennon
Detection or Localizatoin
No localization
Identification or Discrimination
Categorization or Classification

Wh ’?



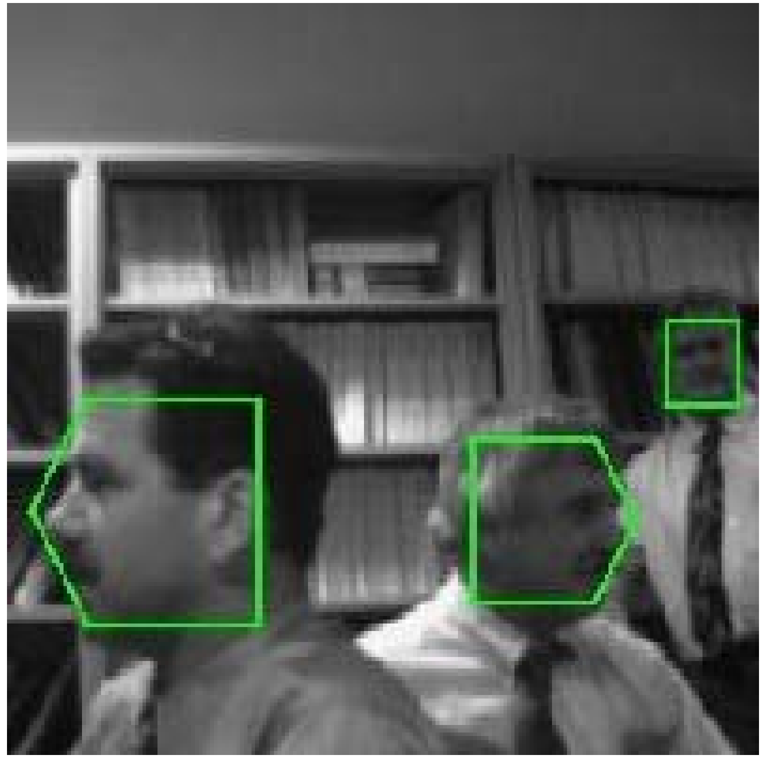
Detection or Localizatoin

No localization

Identification or Discrimination

Categorization or Classification

What's 'recognition'?



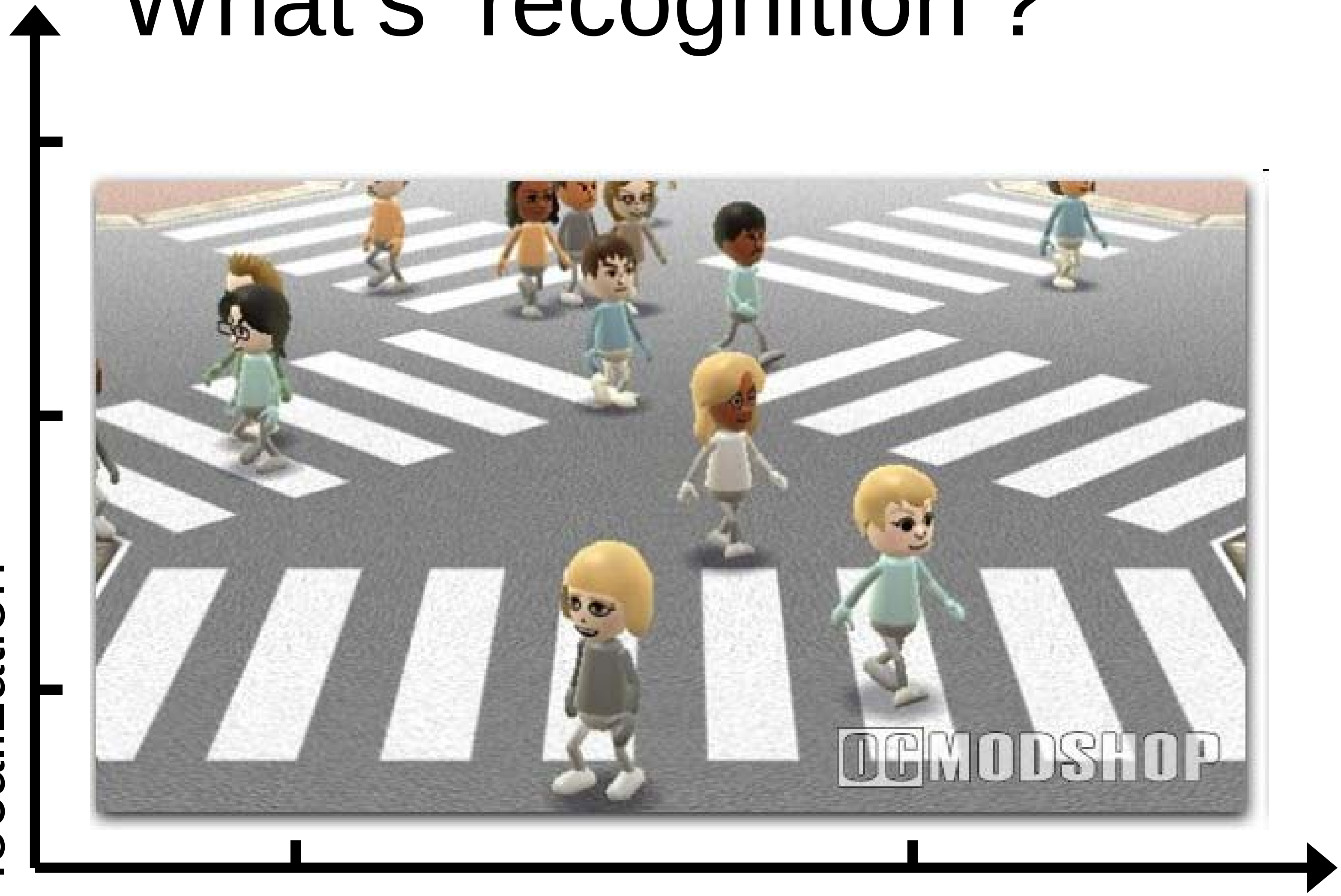
Detection or Localizatoin

No localization

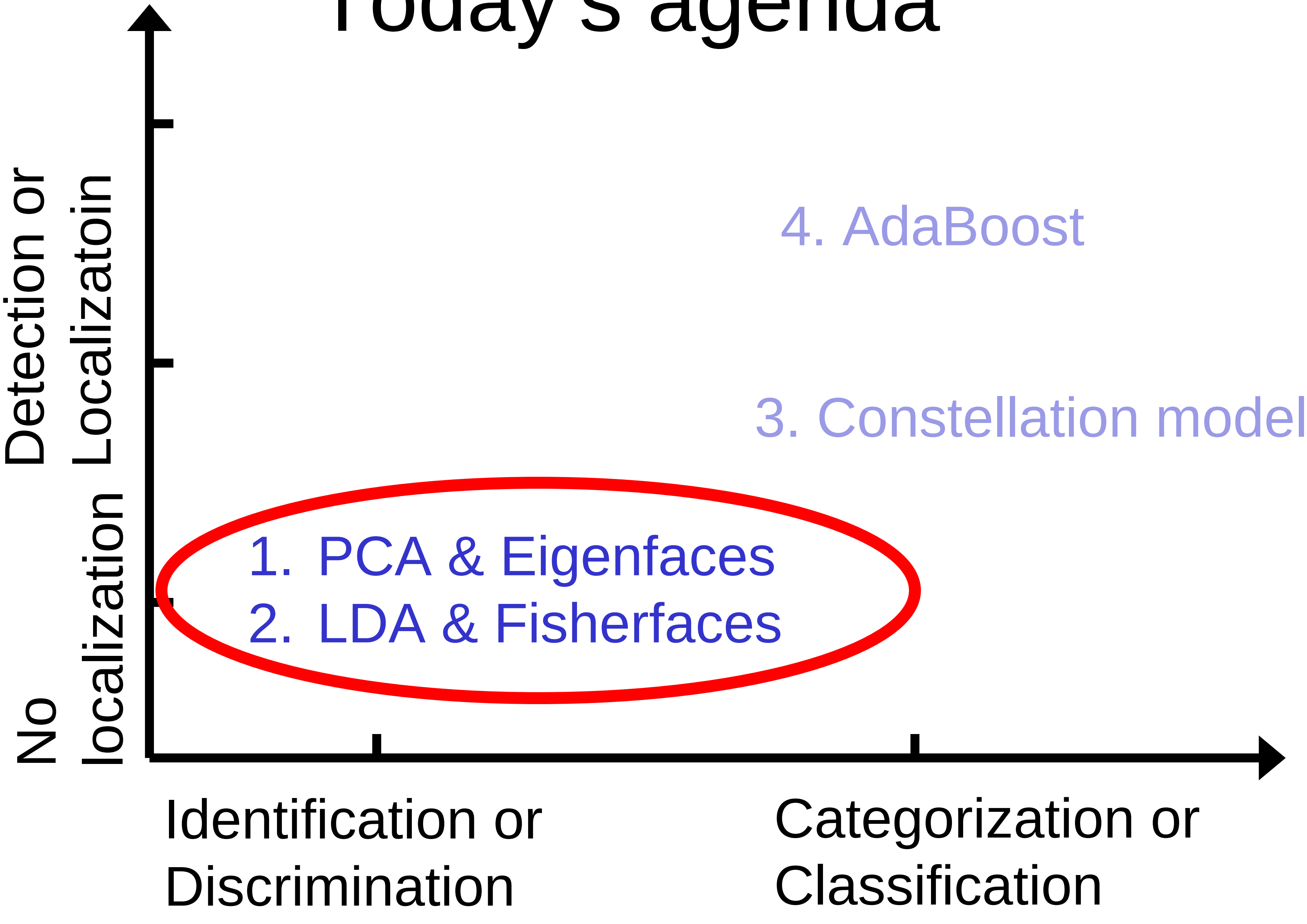
Identification or Discrimination

Categorization or Classification

What’s ‘recognition’?



Today’s agenda



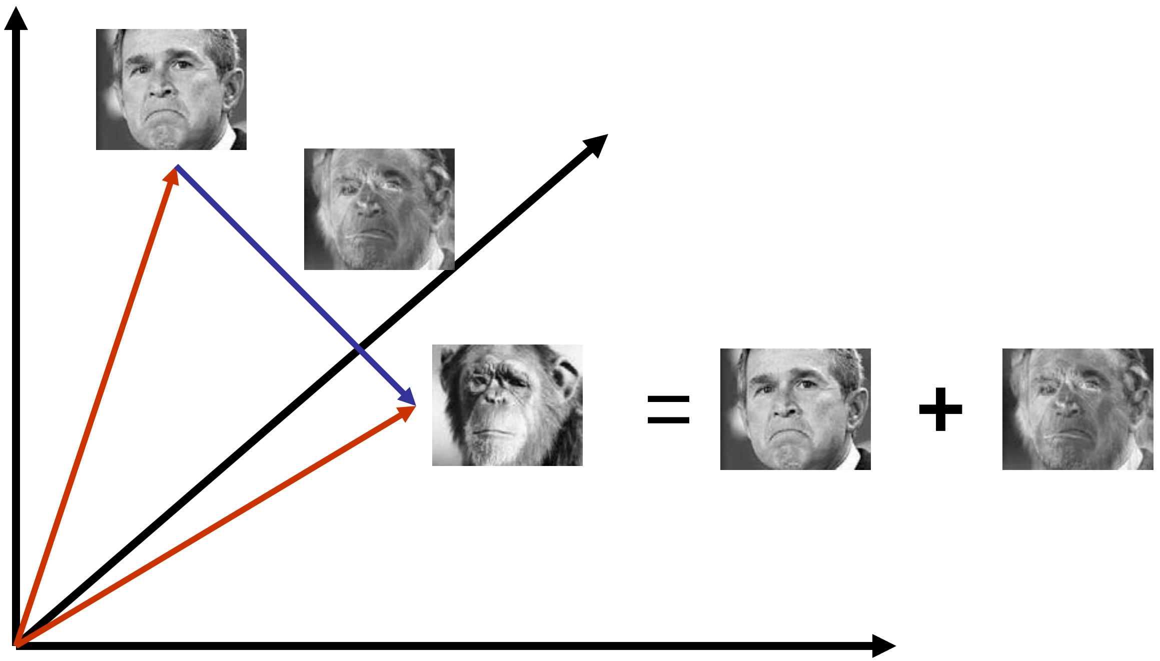
Eigenfaces and Fishfaces

- Introduction
- Techniques
  - Principle Component Analysis (PCA)
  - Linear Discriminant Analysis (LDA)
- Experiments

References:

1. Turk and Penland, Eigenfaces for Recognition, 1991
2. Belhumeur, Hespanha and Kriegman, Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection

The Space of Faces



- An image is a point in a high dimensional space
  - An N x M image is a point in R^{NM}
  - We can define vectors in this space as we did in the 2D case

[Thanks to Chuck Dyer, Steve Seitz, Nishino]

Key Idea

- Images in the possible set $\chi = \{\hat{x}_{RL}^{P}\}$ are highly correlated.

- So, compress them to a low-dimensional subspace that captures key appearance characteristics of the visual DOFs.

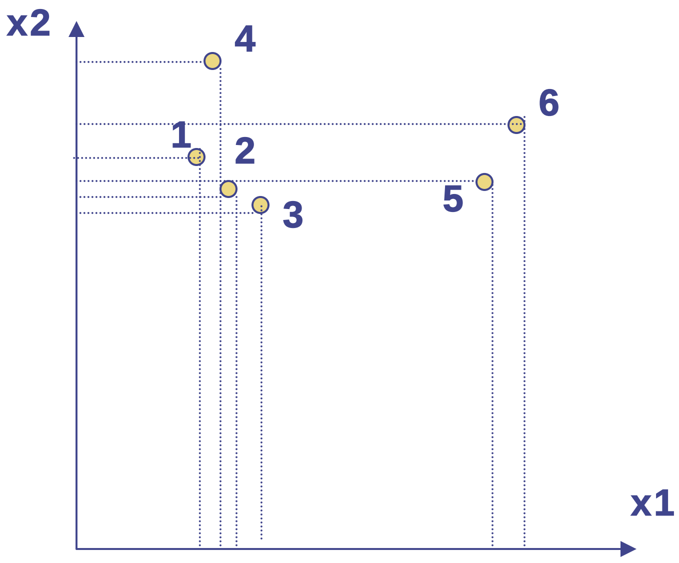
- EIGENFACES: [Turk and Pentland]

USE PCA!

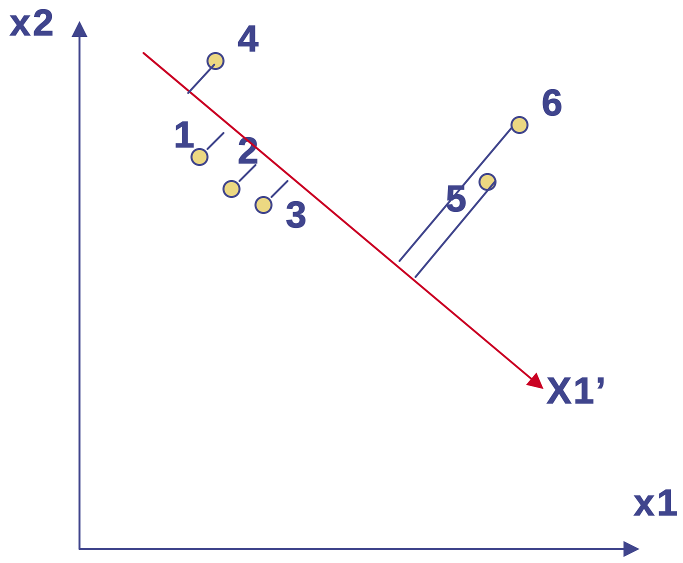
Principal Component Analysis (PCA)

- PCA is used to determine the most representing features among data points.
  - It computes the p-dimensional subspace such that the projection of the data points onto the subspace has the largest variance among all p-dimensional subspaces.

Illustration of PCA

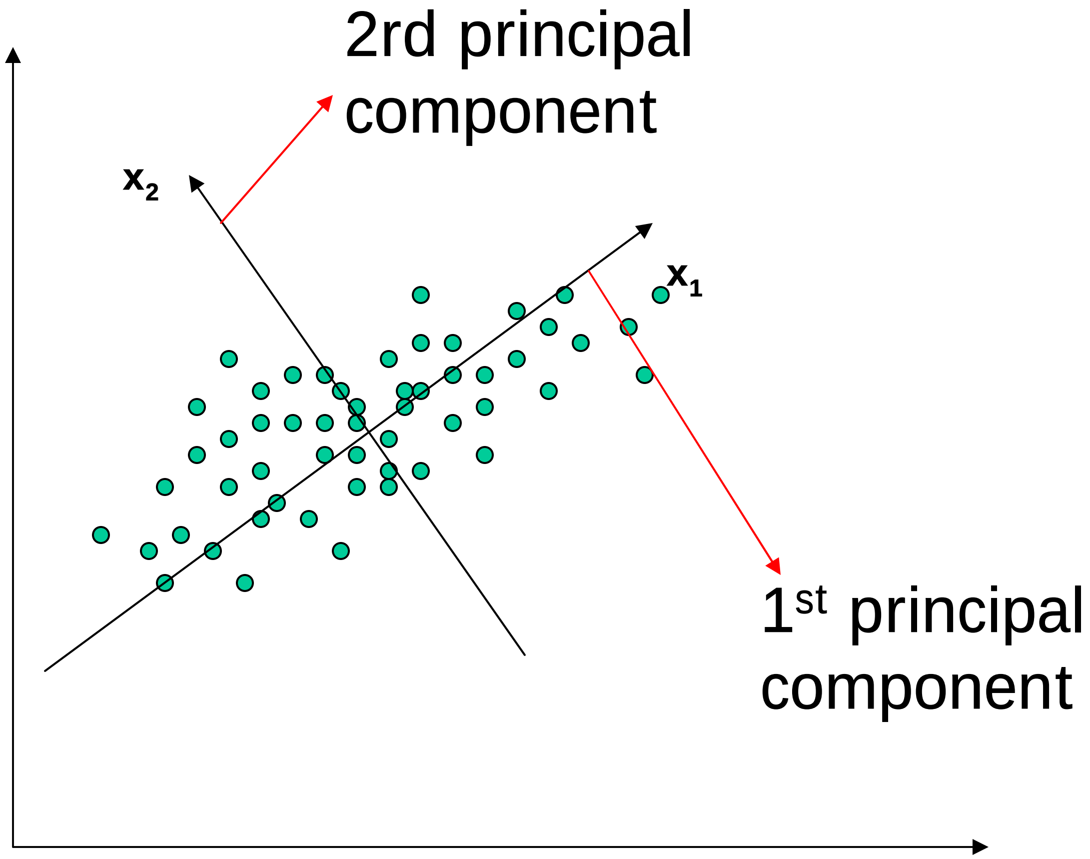


One projection



PCA projection

Illustration of PCA



Go to the handout…

Mathematical Formulation

Find a transformation, W,

$$\mathbf{y}_k = W^T \mathbf{x}_k \qquad k = 1, 2, \ldots, N$$

m-dimensional | **Orthonormal** $W \in \mathbb{R}^{n \times m}$ | **n-dimensional**

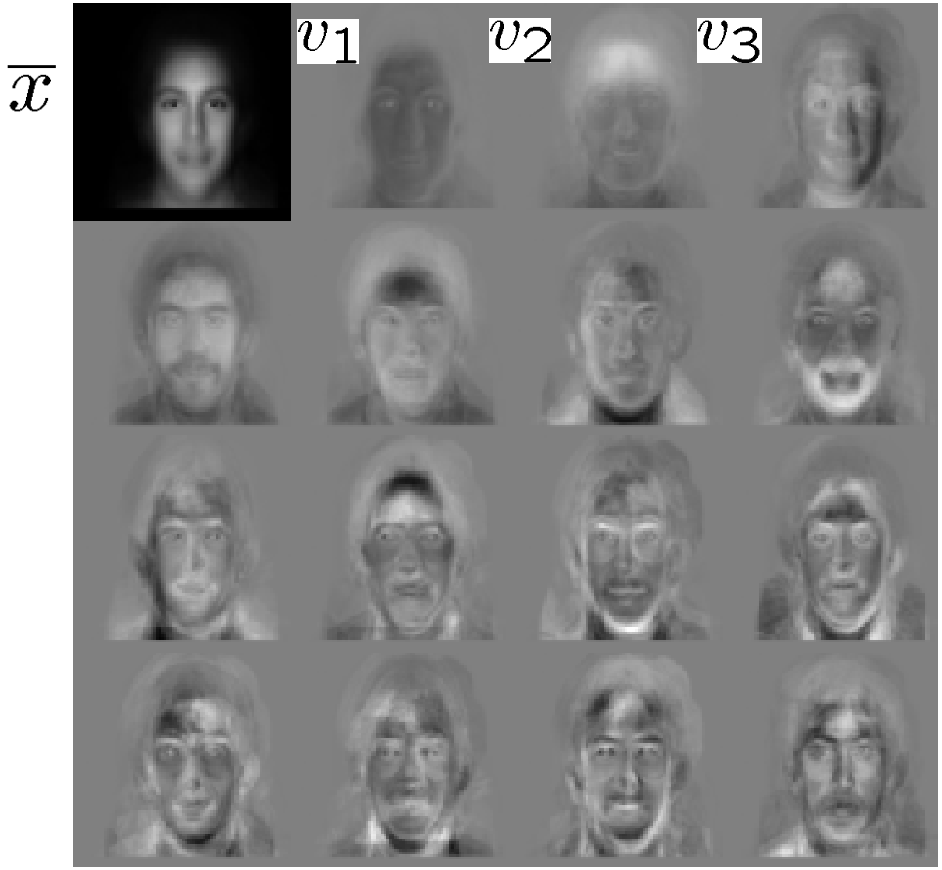
Total scatter matrix: $$S_T = \sum_{k=1}^{N} (\mathbf{x}_k - \mu)(\mathbf{x}_k - \mu)^T$$

$$W_{opt} = \arg\max_W \left| W^T S_T W \right| = \begin{bmatrix} \mathbf{w}_1 & \mathbf{w}_2 & \ldots & \mathbf{w}_m \end{bmatrix}$$

W_{opt} corresponds to m eigen-vectors of S_T

Eigenfaces

- PCA extracts the eigenvectors of **A**
  - Gives a set of vectors $\mathbf{v_1}$, $\mathbf{v_2}$, $\mathbf{v_3}$, ...
  - Each one of these vectors is a direction in face space
    - what do these look like?

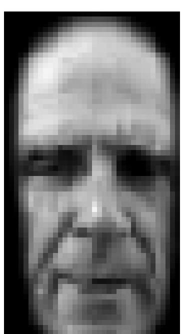


Projecting onto the Eigenfaces

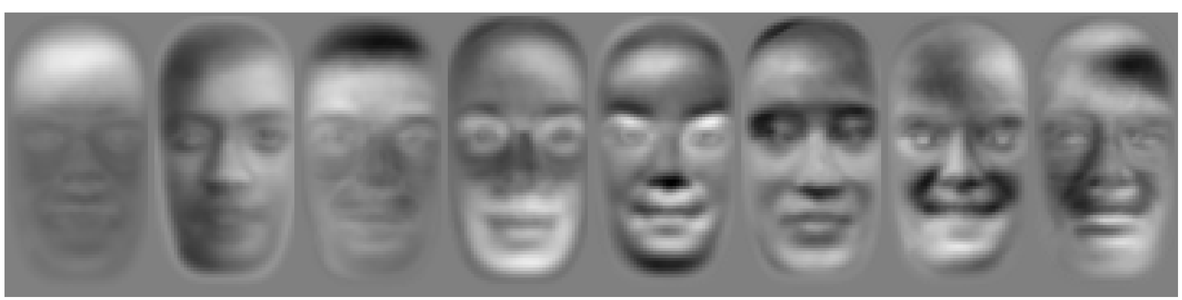
- The eigenfaces $\mathbf{v_1}$, ..., $\mathbf{v_K}$ span the space of faces
  - A face is converted to eigenface coordinates by

$$\mathbf{x} \rightarrow (\underbrace{(\mathbf{x}-\overline{\mathbf{x}}) \cdot \mathbf{v}_1}_{a_1},\ \underbrace{(\mathbf{x}-\overline{\mathbf{x}}) \cdot \mathbf{v}_2}_{a_2}, \ldots,\ \underbrace{(\mathbf{x}-\overline{\mathbf{x}}) \cdot \mathbf{v}_\mathbf{K}}_{a_K})$$

$$\mathbf{x} \approx \overline{\mathbf{x}} + a_1\mathbf{v_1} + a_2\mathbf{v_2} + \ldots + a_K\mathbf{v_K}$$



$\mathbf{x}$

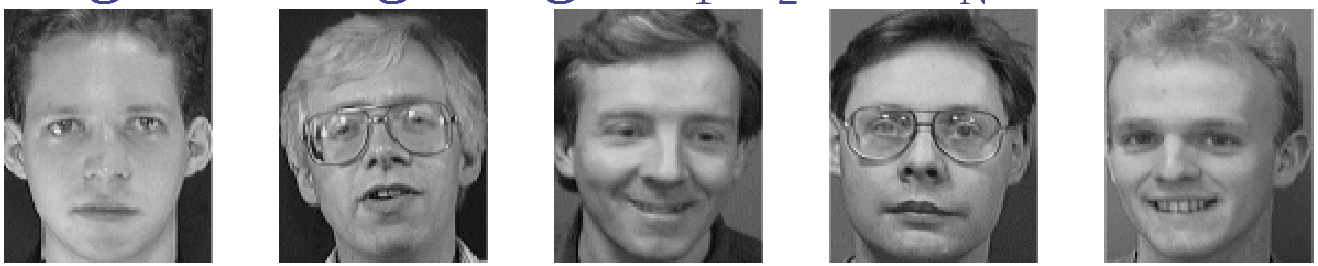


$a_1\mathbf{v_1}$ $a_2\mathbf{v_2}$ $a_3\mathbf{v_3}$ $a_4\mathbf{v_4}$ $a_5\mathbf{v_5}$ $a_6\mathbf{v_6}$ $a_7\mathbf{v_7}$ $a_8\mathbf{v_8}$

Algorithm

Training

1. Align training images $x_1, x_2, \ldots, x_N$



Note that each image is formulated into a long vector!

2. Compute average face $u = 1/N \sum x_i$

3. Compute the difference image $\varphi_i = x_i - u$

Algorithm

4. Compute the covariance matrix (total scatter matrix)

$$S_T = 1/N \sum \varphi_i \varphi_i^T = BB^T, B=[\varphi_1, \varphi_2 \ldots \varphi_N]$$

5. Compute the eigenvectors of the covariance matrix , W

Testing

1. Projection in Eigenface

   Projection $\omega_i = W(X - x)$, $W = \{eigenfaces\}$

2. Compare projections

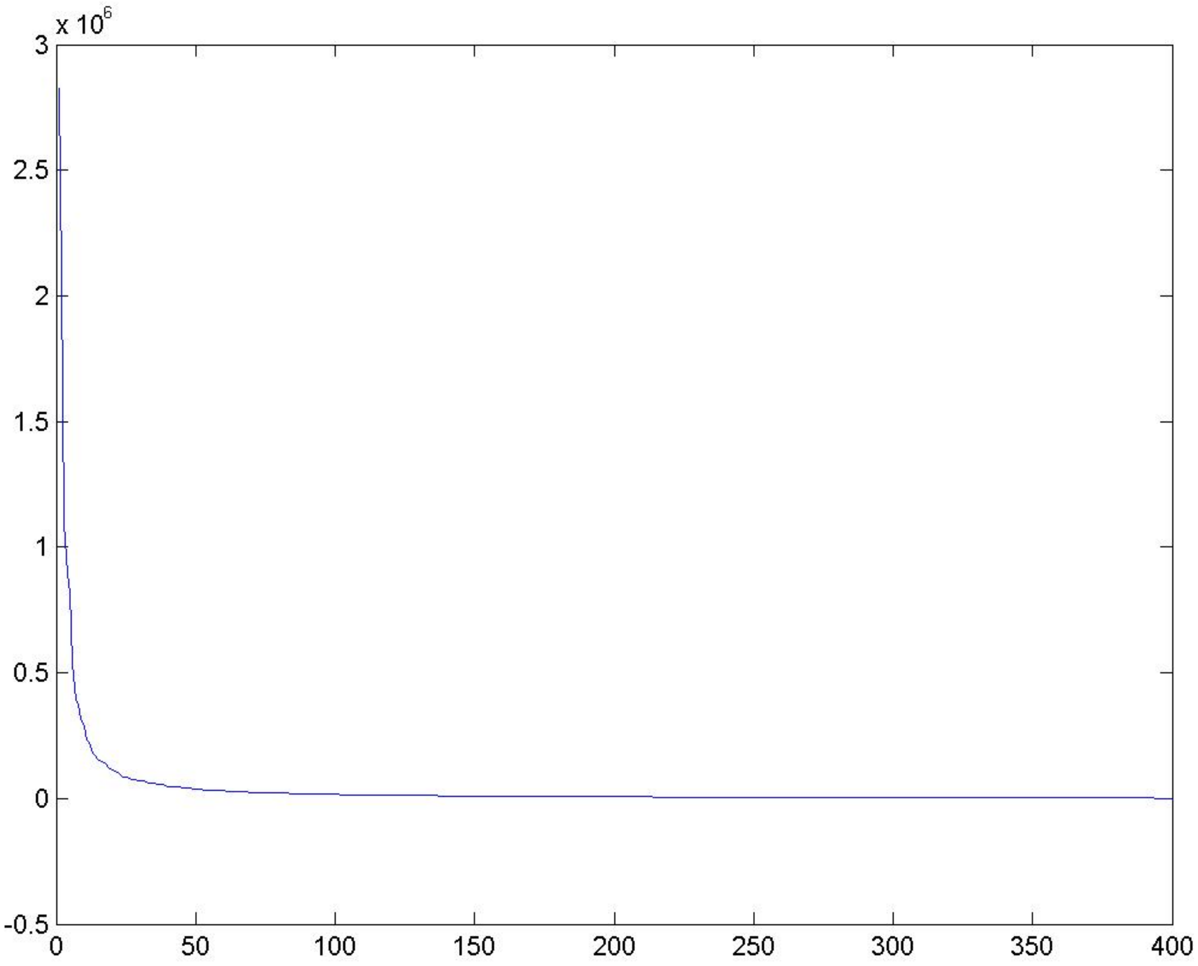
Illustration of Eigenfaces

- The visualization of eigenvectors:

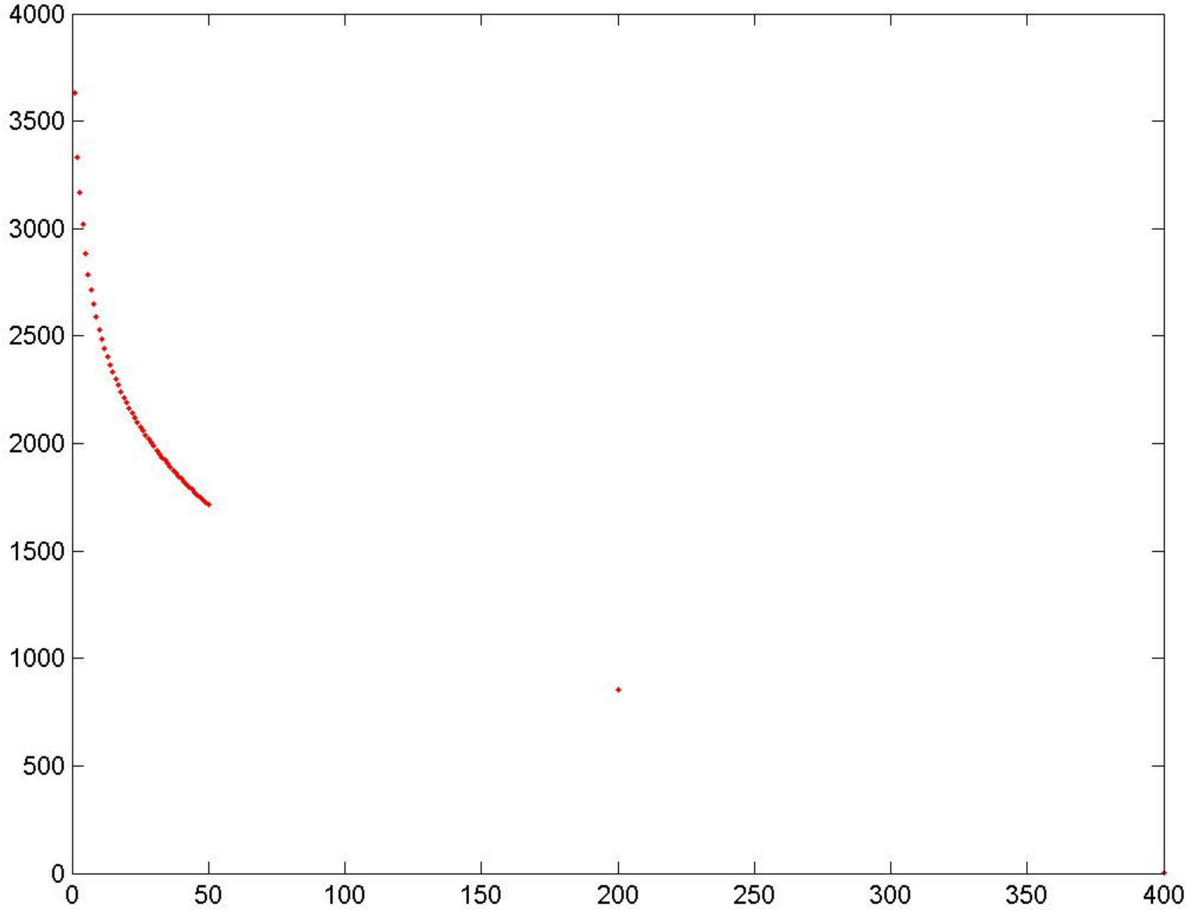
These are the first 4 eigenvectors from a training set of 400 images (ORL Face Database). They look like faces, hence called Eigenface.

Eigenfaces look somewhat like generic faces.

Eigenvalues



Reconstruction and Errors



imensionality.

ıd hence less

Summary for PCA and Eigenface

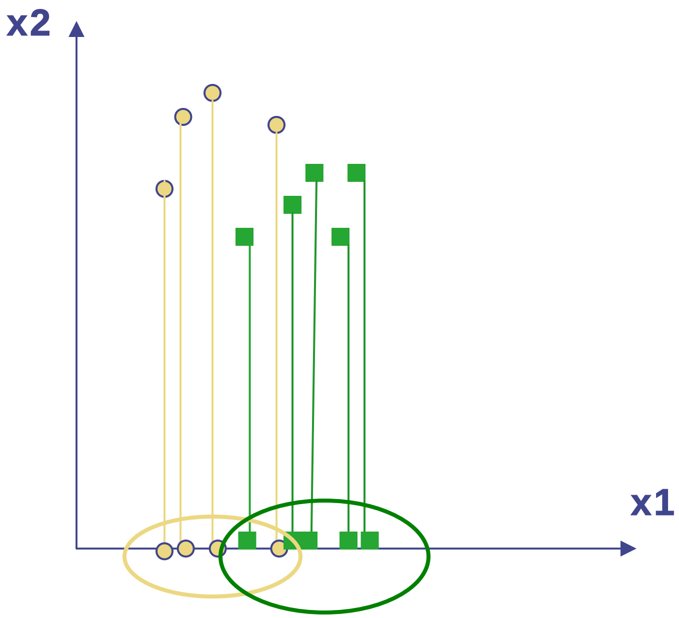
- Non-iterative, globally optimal solution
- PCA projection is **optimal for reconstruction** from a low dimensional basis, but **may NOT be optimal for discrimination…**

Linear Discriminant Analysis (LDA)

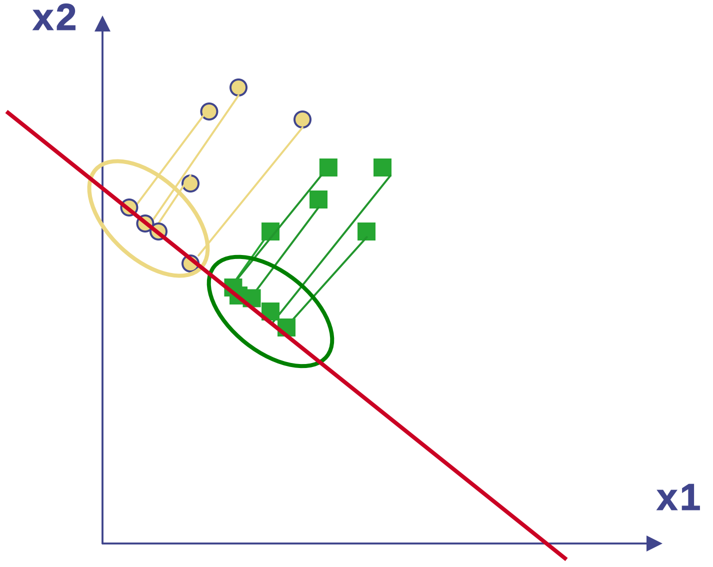
- Using Linear Discriminant Analysis (LDA) or Fisher's Linear Discriminant (FLD)
- Eigenfaces attempt to maximise the scatter of the training images in face space, while Fisherfaces attempt to maximise the **between class scatter**, while minimising the **within class scatter**.

Illustration of the Projection

- Using two classes as example:

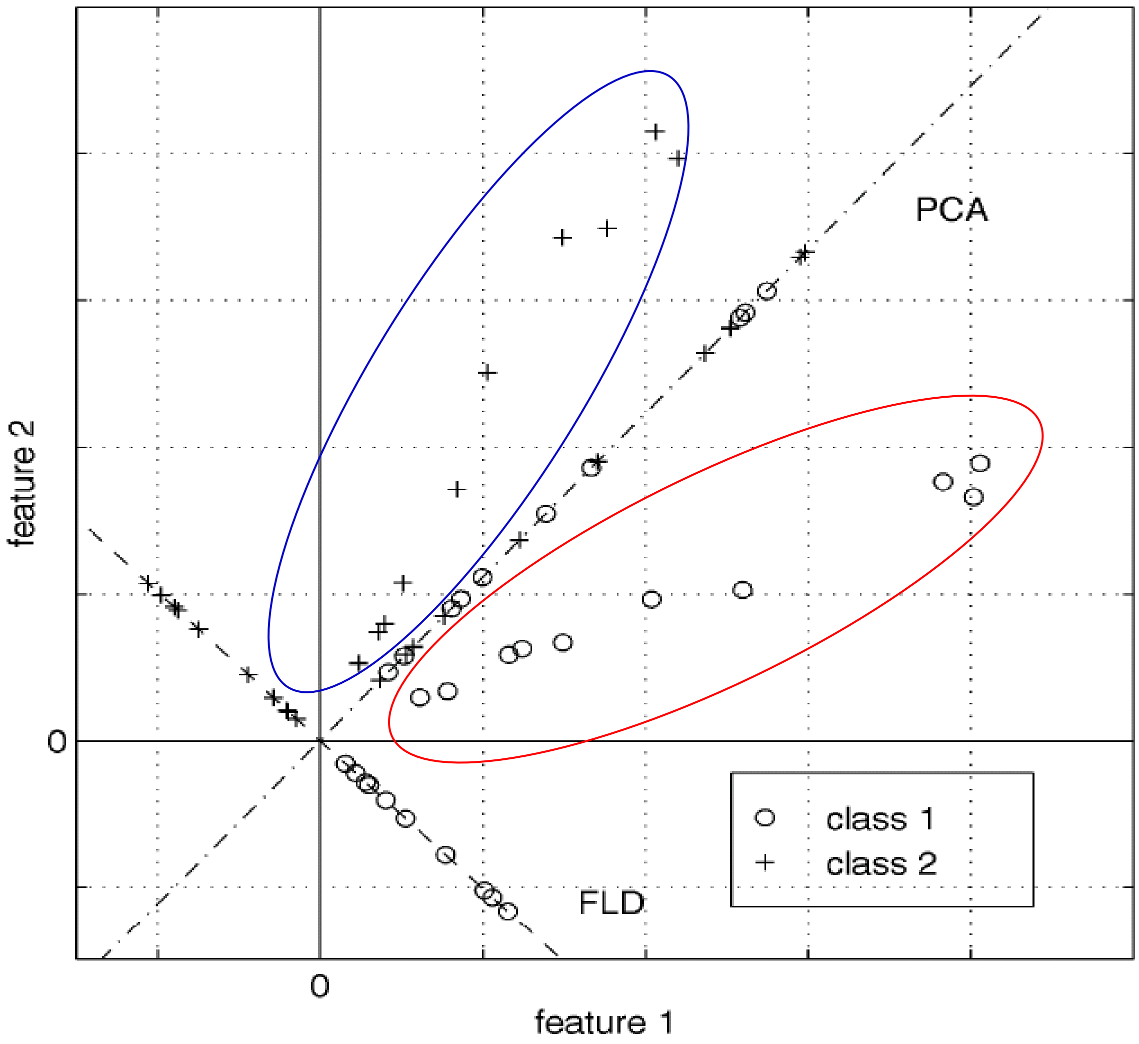


Poor Projection



Good Projection

Comparing with PCA



Variables

- N Sample images: $\{x_1, \Lambda\ , x_N\}$
- c classes: $\{\chi_1, \Lambda\ , \chi_c\}$

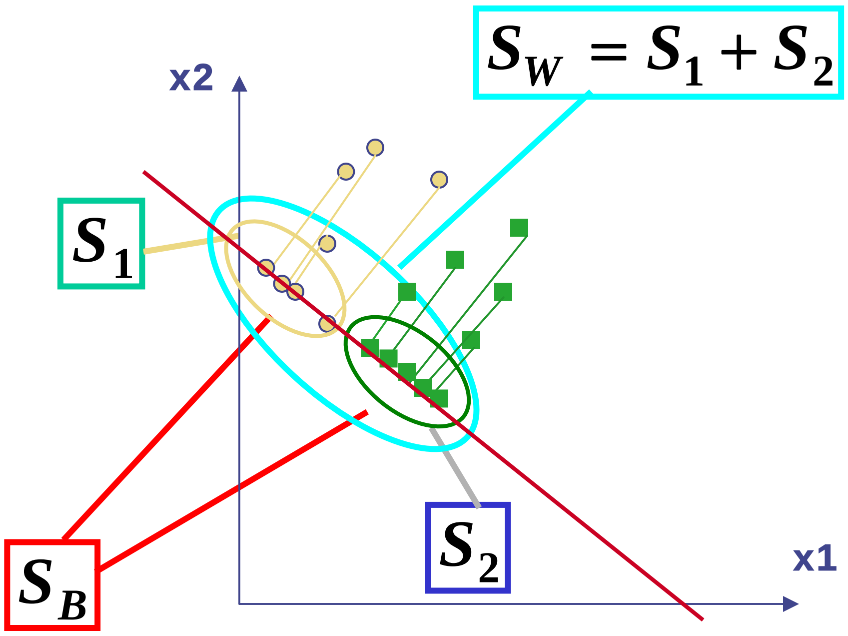
- Average of each class: $\mu_i = \frac{1}{N_i} \sum_{x_k \in \chi_i} x_k$

- Total average: $\mu = \frac{1}{N} \sum_{k=1}^{N} x_k$

Scatters

- Scatter of class i: $\boxed{S_i = \sum_{x_k \in \chi_i} (x_k - \mu_i)(x_k - \mu_i)^T}$
- Within class scatter: $\boxed{S_W = \sum_{i=1}^{c} S_i}$
- Between class scatter: $\boxed{S_B = \sum_{i=1}^{c} |\chi_i| (\mu_i - \mu)(\mu_i - \mu)^T}$
- Total scatter: $\boxed{S_T = S_W + S_B}$

Illustration



Mathematical Formulation (1)

- After projection: $\boxed{y_k = W^T x_k}$

- Between class scatter (of y's): $\boxed{\tilde{S}_B = W^T S_B W}$
- Within class scatter (of y's): $\boxed{\tilde{S}_W = W^T S_W W}$

Mathematical Formulation (2)

- The desired projection:

$$\boxed{W_{opt} = \arg\max_{W} \frac{\left|\tilde{S}_B\right|}{\left|\tilde{S}_W\right|} = \arg\max_{W} \frac{\left|W^T S_B W\right|}{\left|W^T S_W W\right|}}$$

- How is it found ? → Generalized Eigenvectors

$$\boxed{S_B w_i = \lambda_i S_W w_i \qquad\qquad i = 1,\ldots,m}$$

- Data dimension is much larger than the number of samples $n >> N$
- The matrix S_W is singular: $\boxed{Rank(S_W) \leq N - c}$

Fisherface (PCA+FLD)

- Project with PCA to $N - c$ space $\boxed{z_k = W_{pca}^T x_k}$

$$\boxed{W_{pca} = \arg\max_{W} \left| W^T S_T W \right|}$$

- Project with FLD to $c - 1$ space $\boxed{y_k = W_{fld}^T z_k}$

$$\boxed{W_{fld} = \arg\max_{W} \frac{\left| W^T W_{pca}^T S_B W_{pca} W \right|}{\left| W^T W_{pca}^T S_W W_{pca} W \right|}}$$

Illustration of FisherFace

- Fisherface

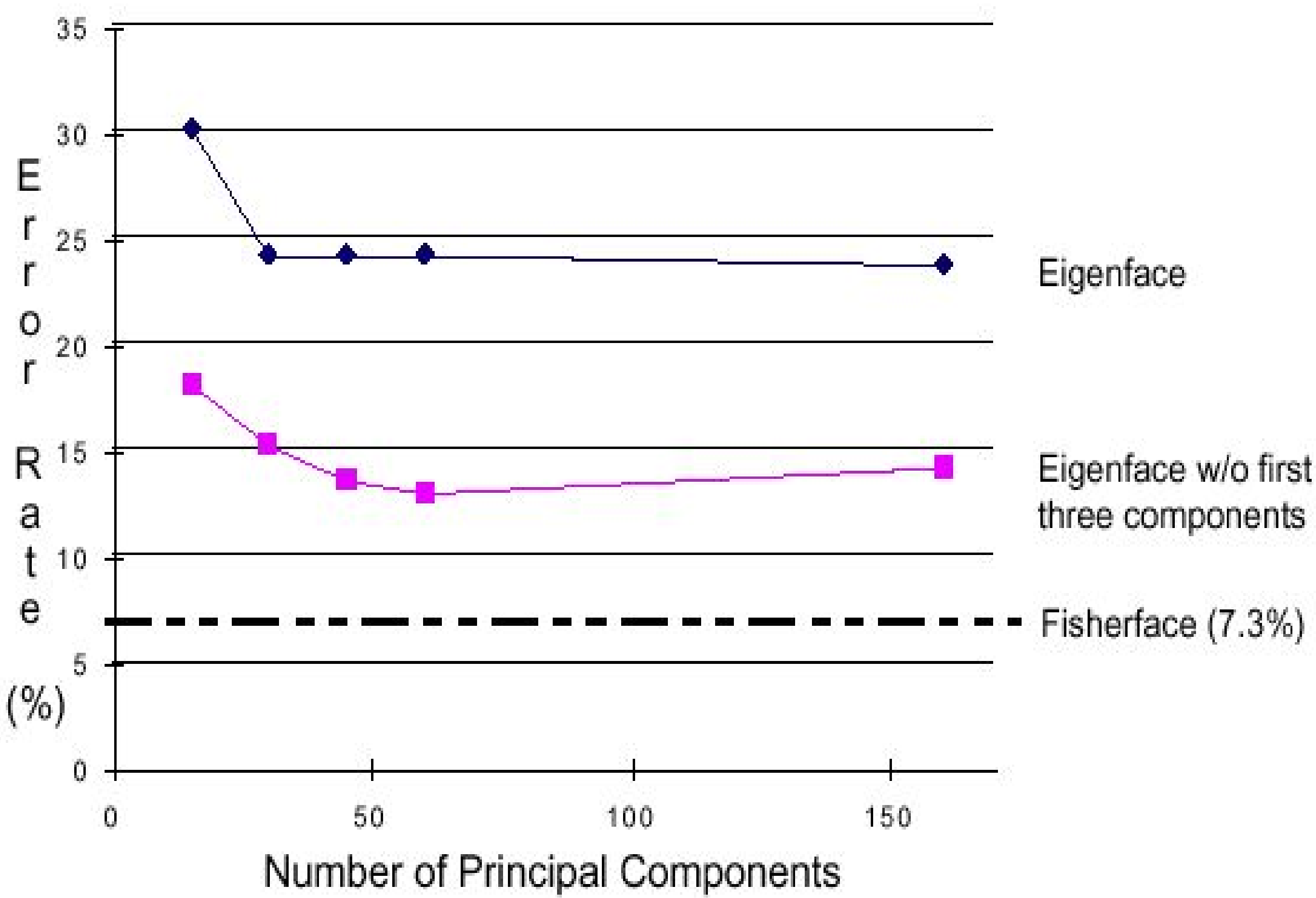
Results: Eigenface vs. Fisherface (1)

- Input: 160 images of 16 people
- Train: 159 images
- Test: 1 image

- Variation in Facial Expression, Eyewear, and Lighting

With glasses | Without glasses | 3 Lighting conditions | 5 expressions

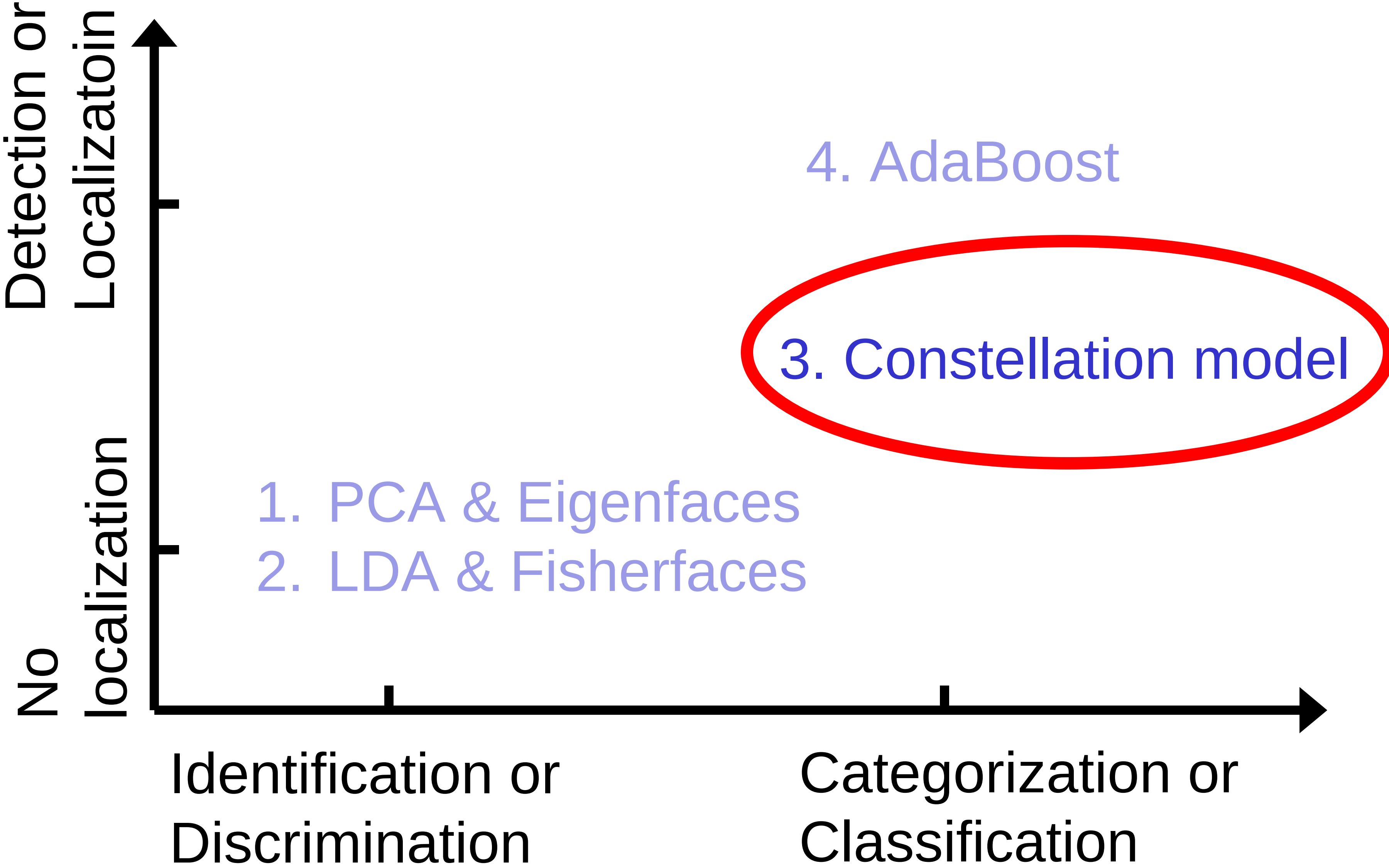
Eigenface vs. Fisherface (2)



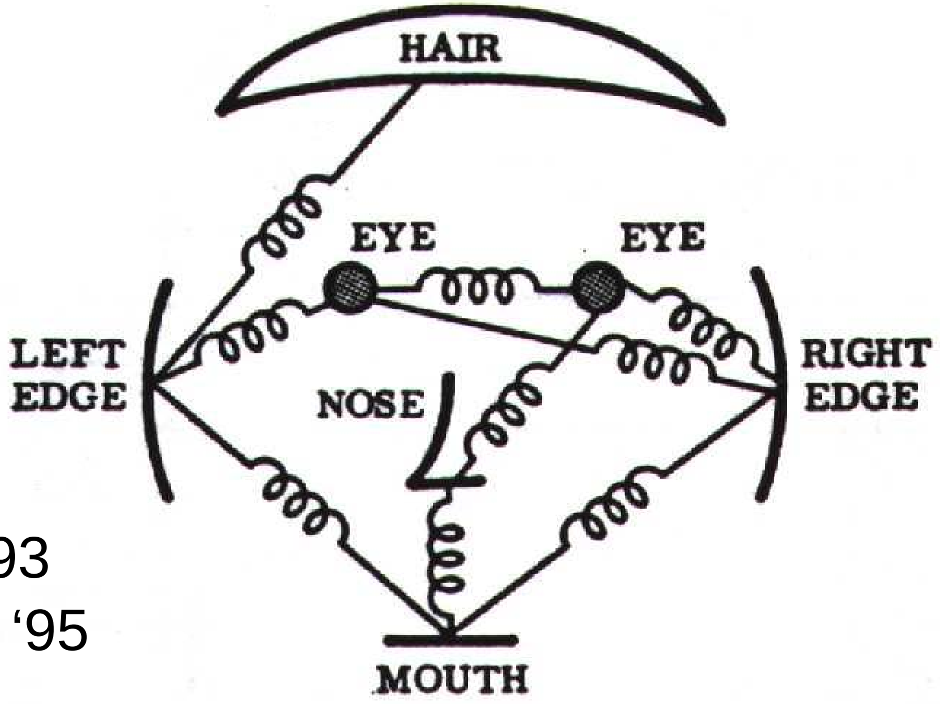
discussion

- Removing the first three principal components results in better performance under variable lighting conditions
- The Firsherface methods had error rates lower than the Eigenface method for the small datasets tested.

Today's agenda



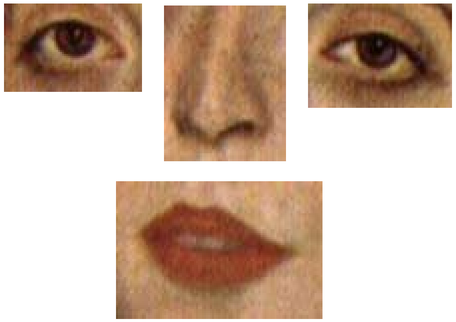
Parts and Structure Literature



- 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

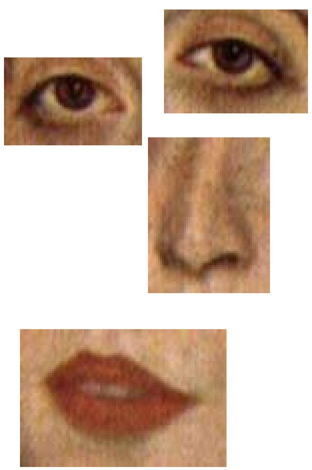
etc…

Deformations



A

B

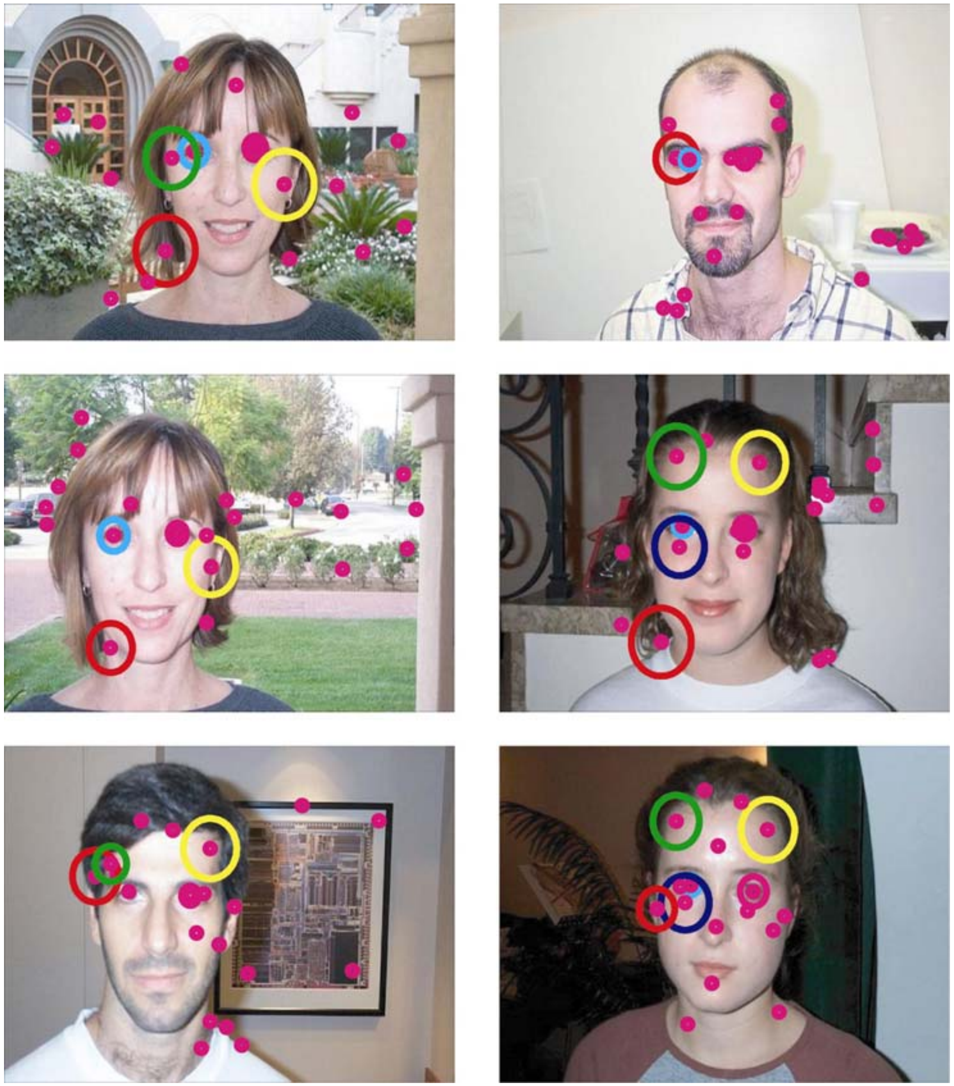


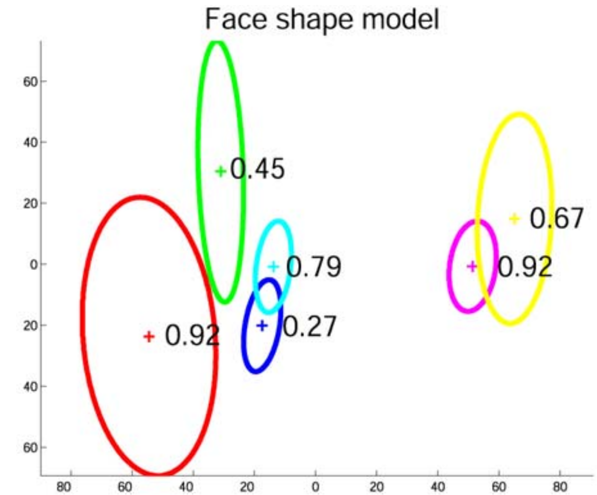
C

D

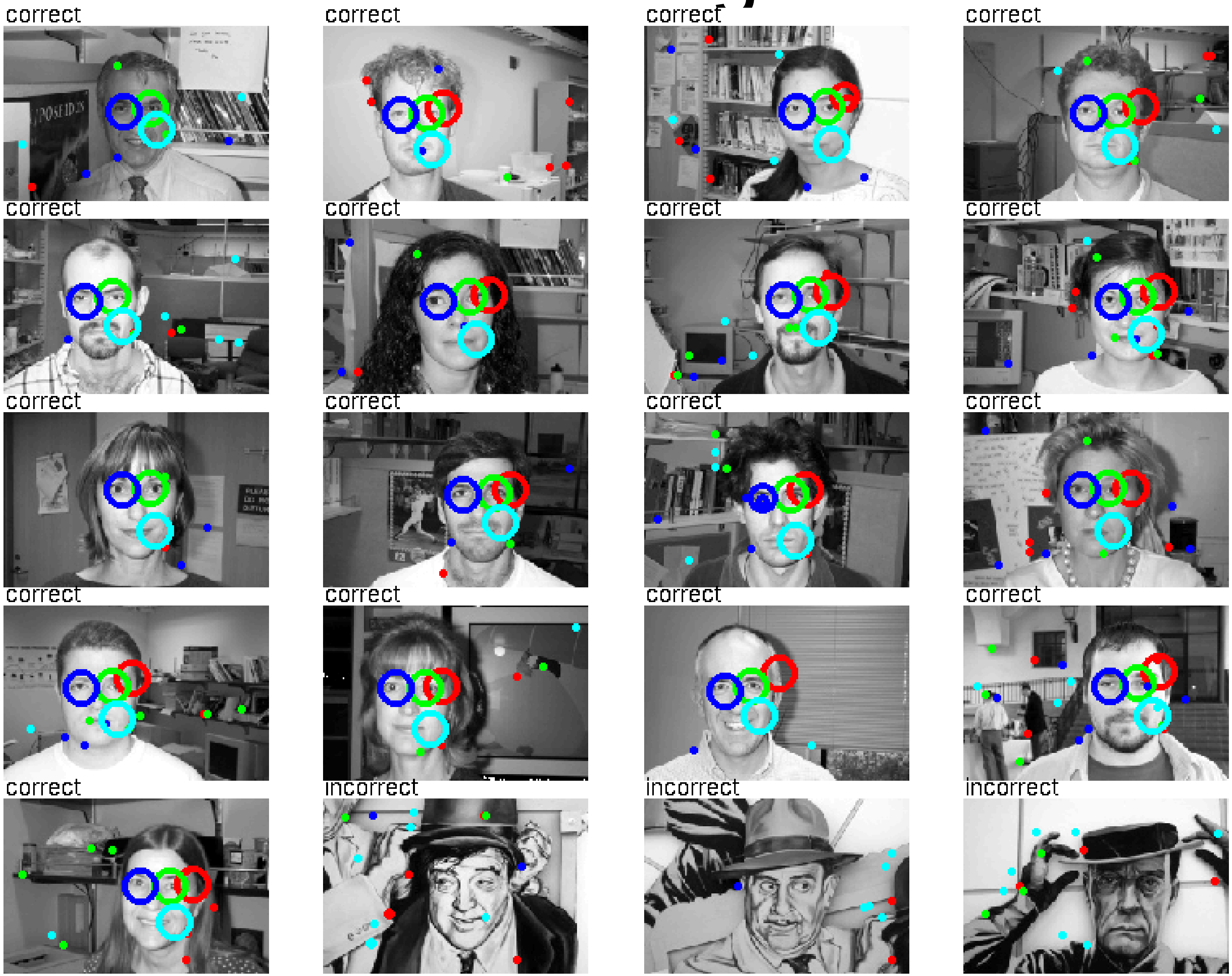
Background clutter

Frontal faces





Face images


correct
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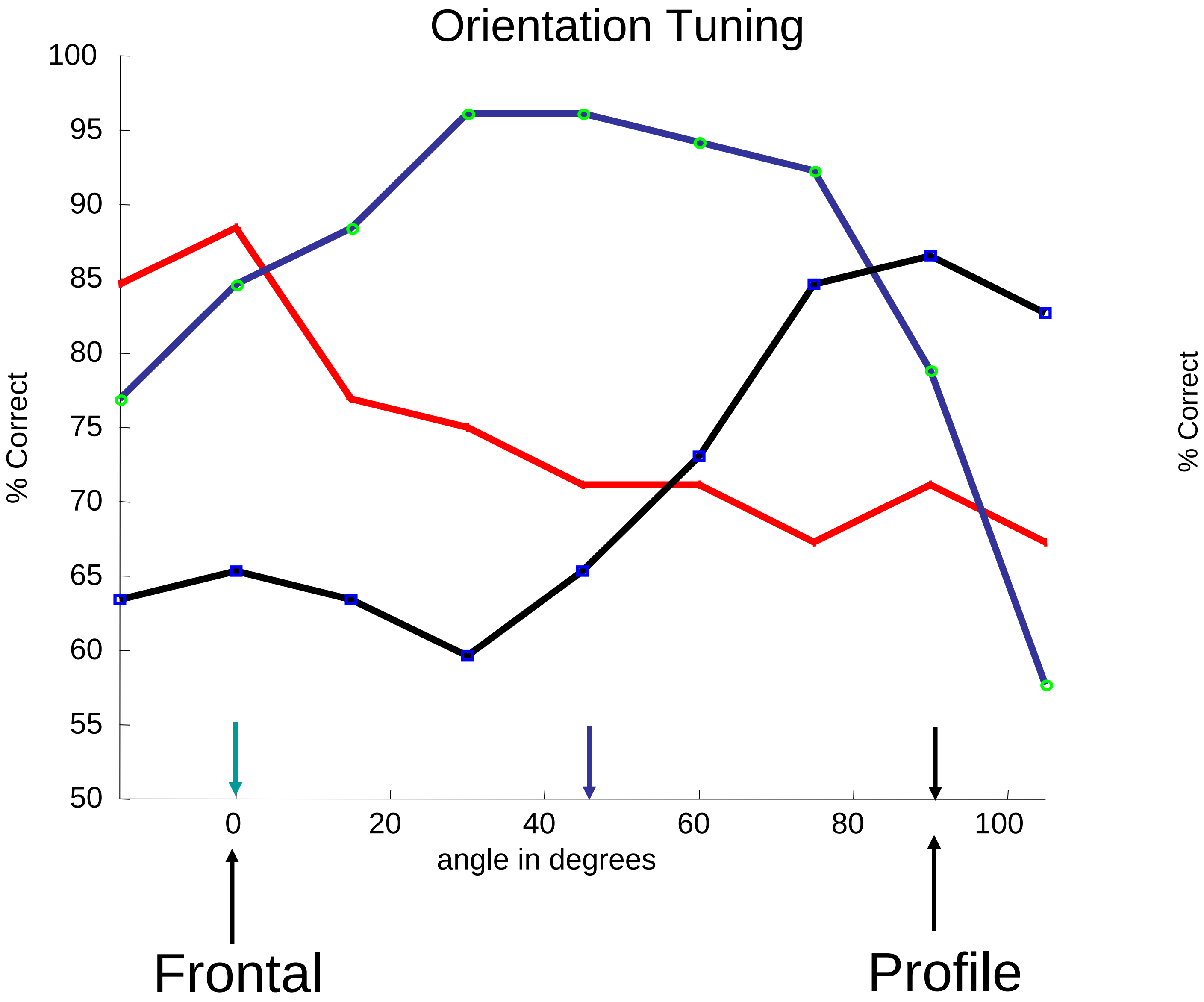
3D Object recognition – Multiple mixture components

3D Orientation Tuning



Thursday this week