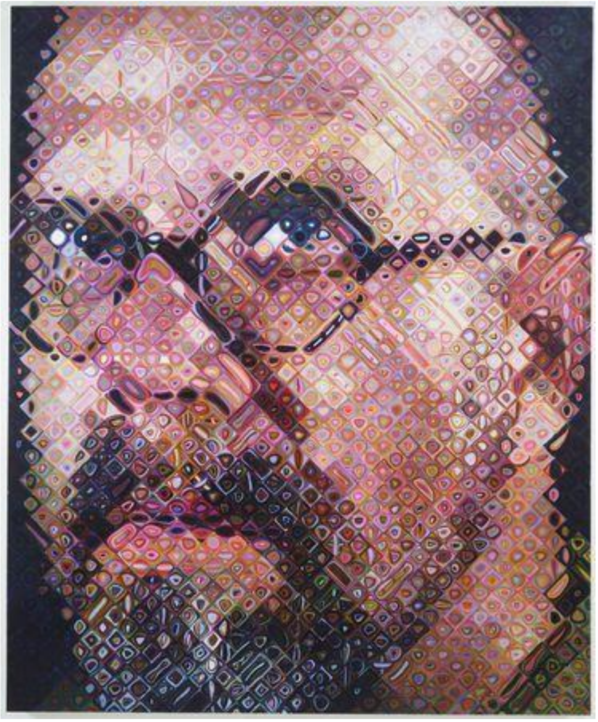
Face Detection and Recognition


Lucas by Chuck Close



Chuck Close, self portrait

Computational Photography

Derek Hoiem, University of Illinois

Lecture by Kevin Karsch

Some slides from Lana Lazebnik, Silvio Savarese, Fei-Fei Li

Administrative stuff

- Final project write-up due Dec 17th 11:59pm
- Presentations Dec 18th 1:30-4:30pm (SC 1214)
- Exams back at end of class

Face detection and recognition

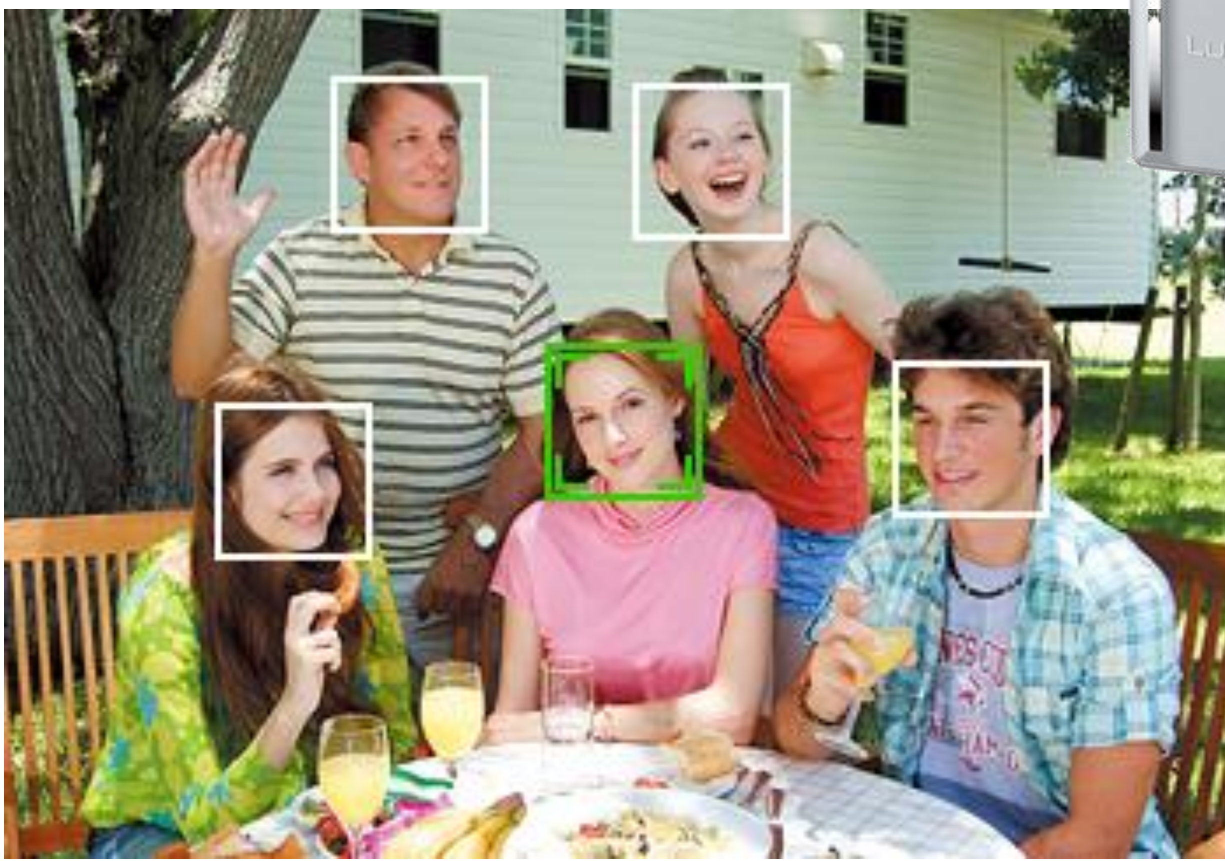
Detection

Recognition

"Sally"

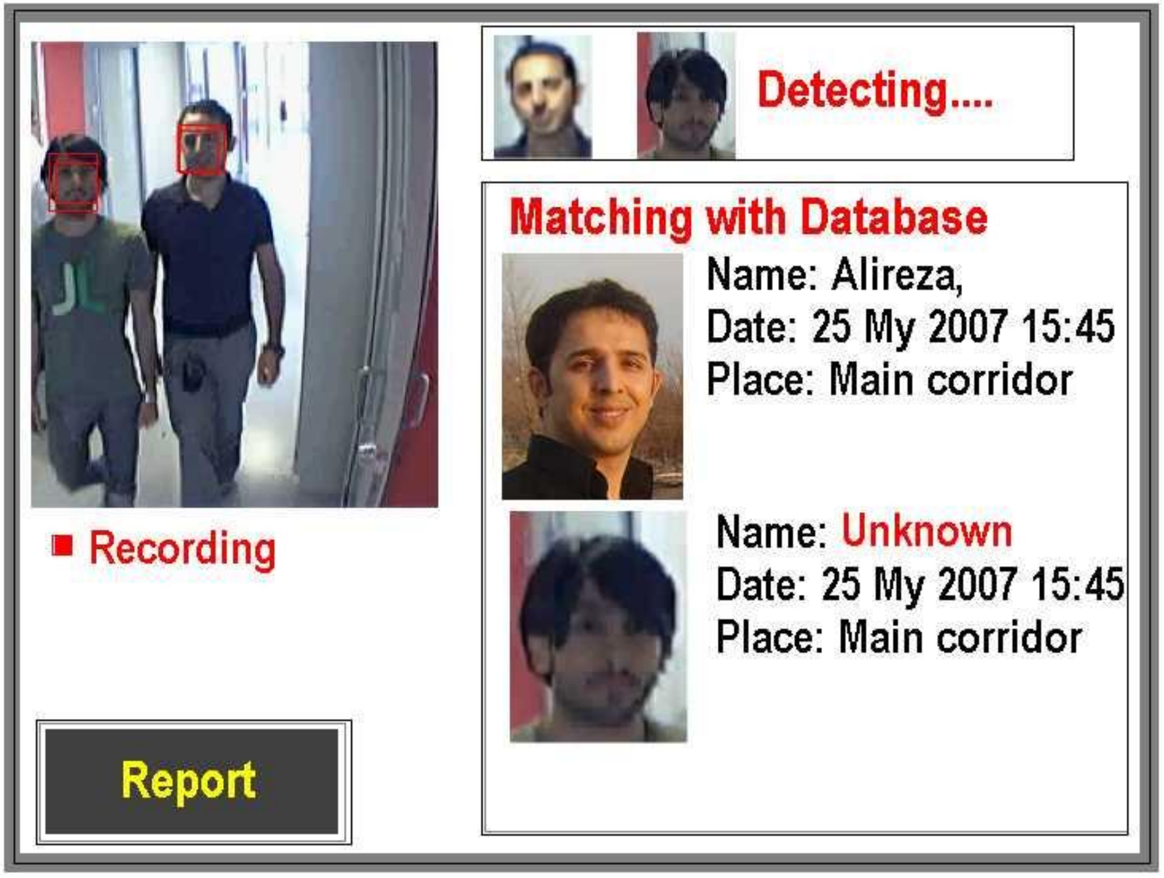
Applications of Face Recognition

- Digital photography



Applications of Face Recognition

- Digital photography
- Surveillance



Applications of Face Recognition

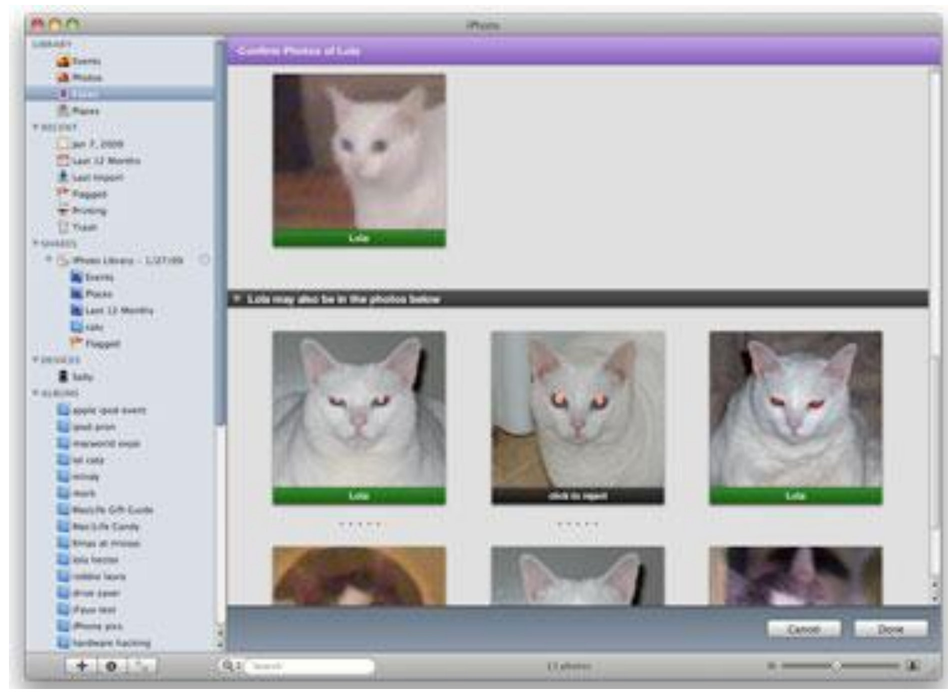
- Digital photography
- Surveillance
- Album organization

Consumer application: iPhoto 2009

http://www.apple.com/ilife/iphoto/

Consumer application: iPhoto 2009

- Can be trained to recognize pets!

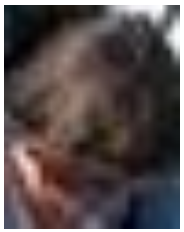
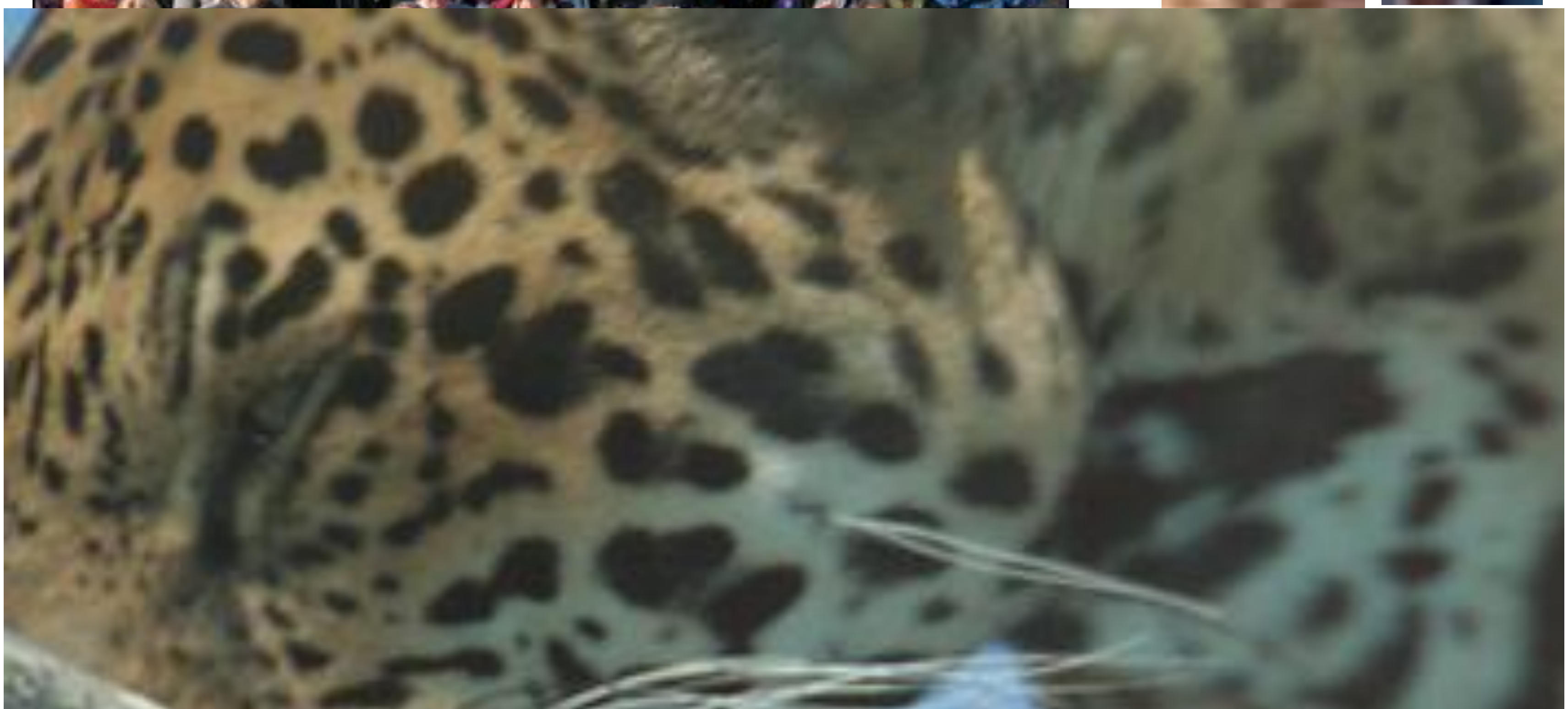


http://www.maclife.com/article/news/iphotos_faces_recognizes_cats

What does a face look like?

What does a face look like?



What makes face detection hard?

Expression

What makes face detection hard?

Viewpoint

What makes face detection hard?

Occlusion

What makes face detection and recognition hard?

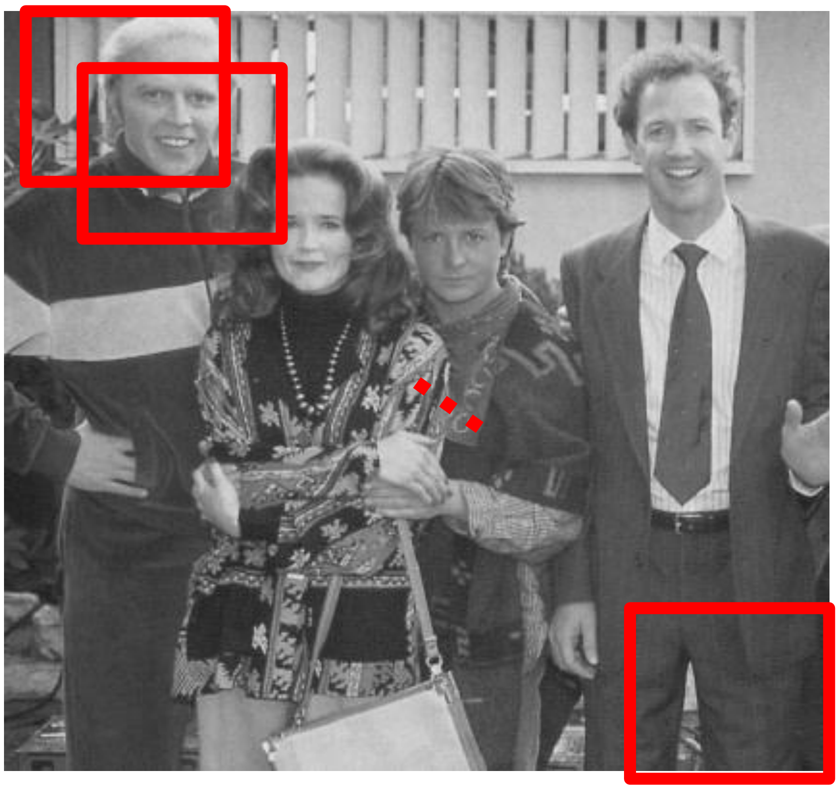
Coincidental textures

Consumer application: iPhoto 2009

- Things iPhoto thinks are faces

How to find faces anywhere in an image?

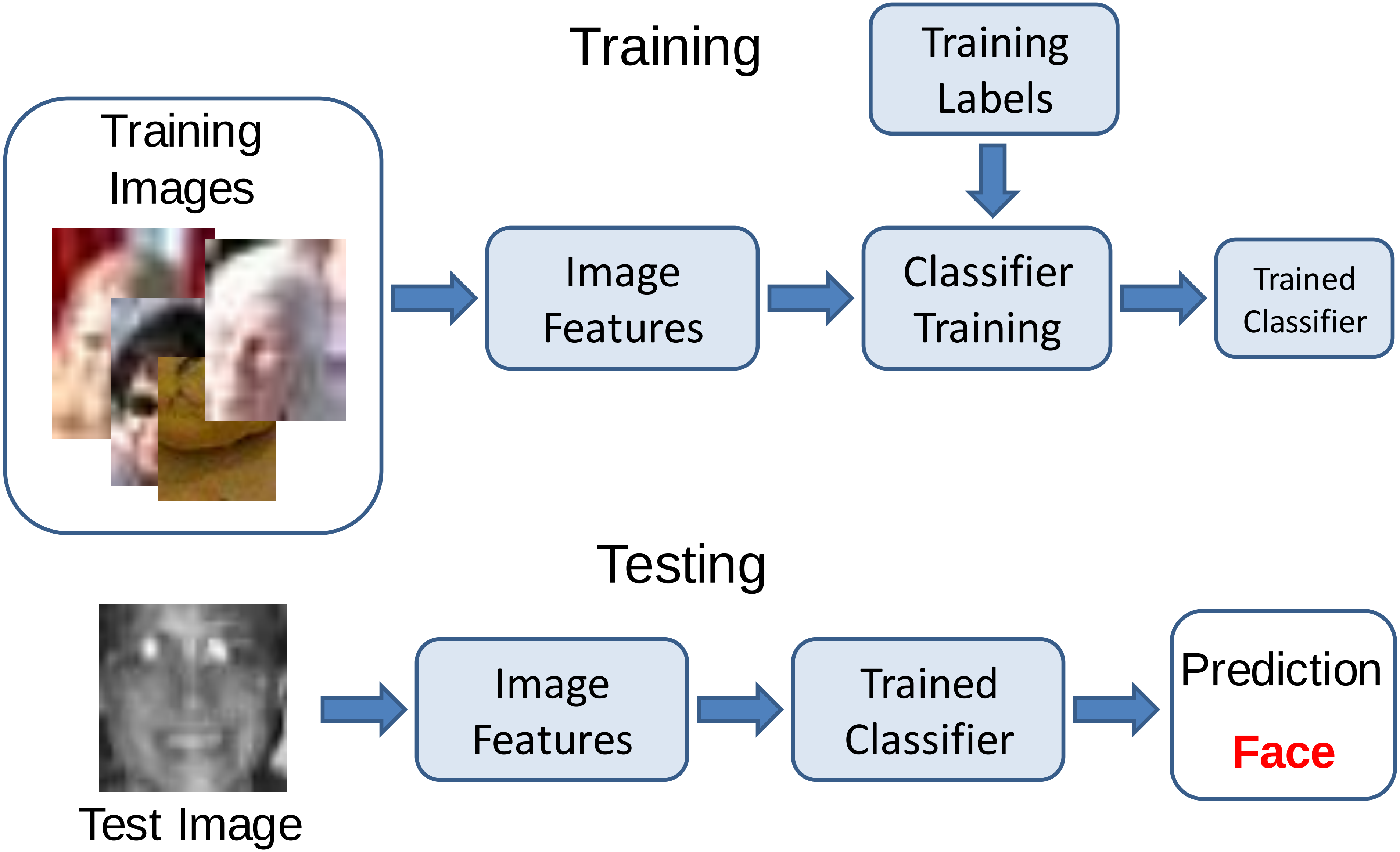
Face detection: sliding windows



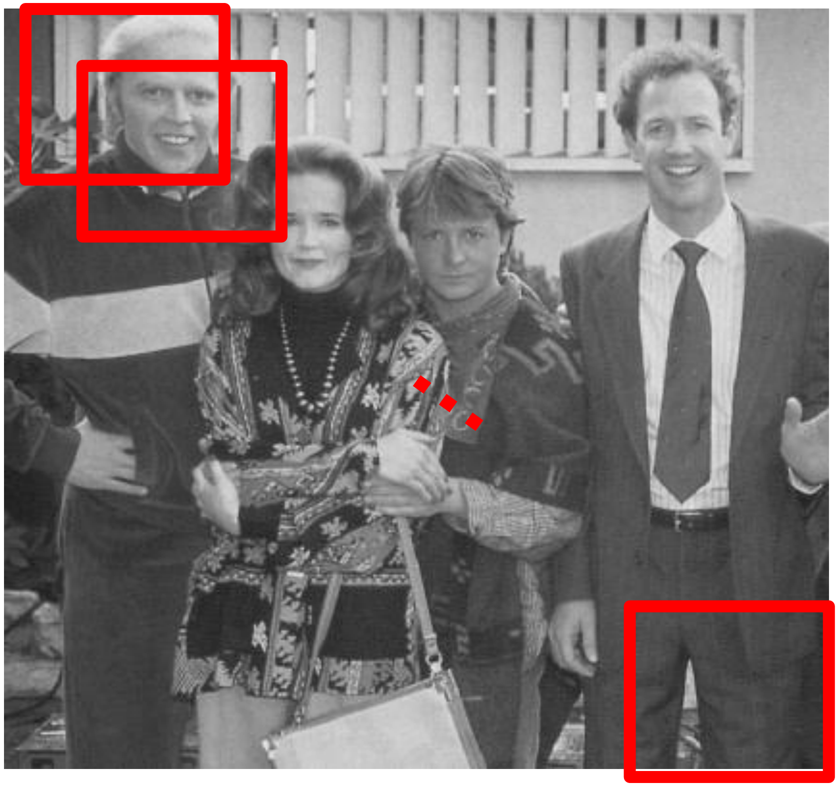
Face or **Not Face**

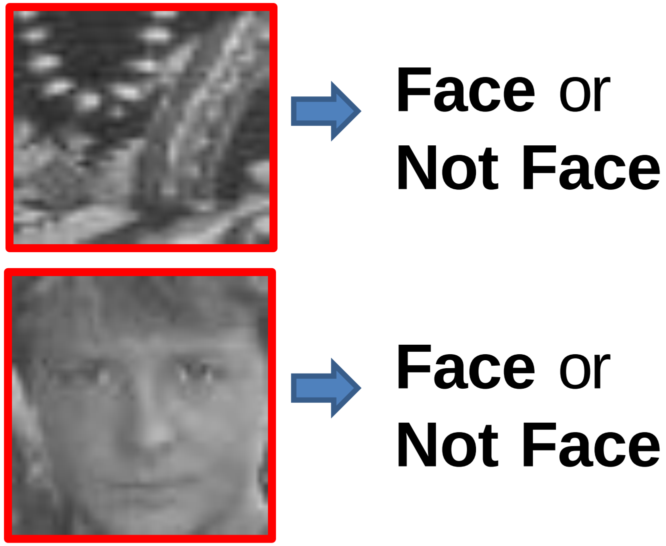
How to deal with multiple scales?

Face classifier

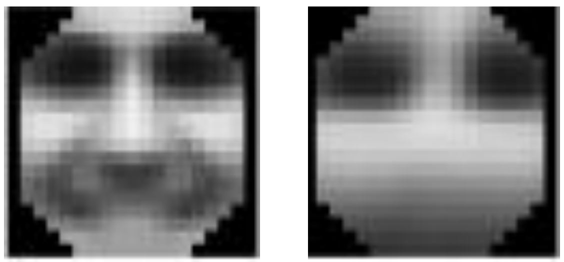


Face detection



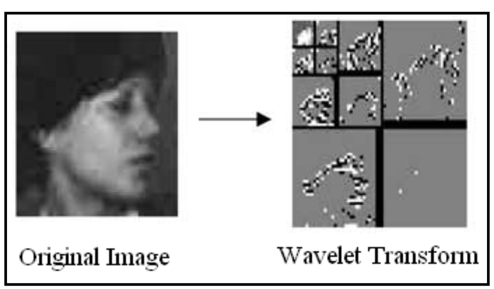


What features?



Exemplars
(Sung Poggio 1994)

Intensity Patterns (with NNs)
(Rowely Baluja Kanade1996)



Edge (Wavelet) Pyramids
(Schneiderman Kanade 1998)

Haar Filters
(Viola Jones 2000)

How to classify?

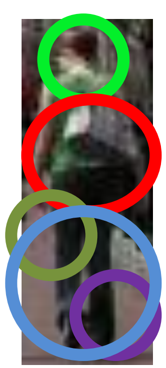
- Many ways
  - Neural networks
  - Adaboost
  - SVMs
  - Nearest neighbor

Statistical Template

- Object model = log linear model of parts at fixed positions

$$+3 +2 -2 -1 -2.5 = -0.5 \overset{?}{>} 7.5$$

Non-object



$$+4 +1 +0.5 +3 +0.5 = 10.5 \overset{?}{>} 7.5$$

Object

Training multiple viewpoints

Train new detector for each viewpoint.

Results: faces

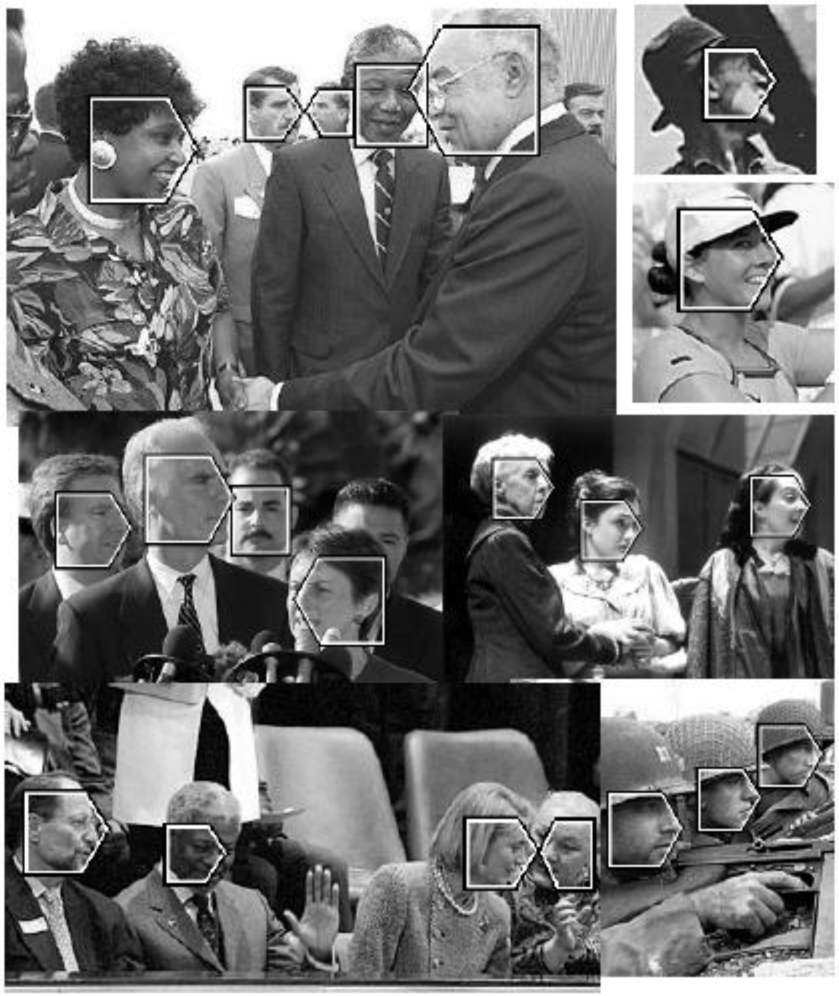


Table 1. Face detection with out-of-plane rotation

γ	Detection (all faces)	Detection (profiles)	False Detections
0.0	92.7%	92.8%	700
1.5	85.5%	86.4%	91
2.5	75.2%	78.6%	12

208 images with 441 faces, 347 in profile

Face recognition

Face recognition

- Typical scenario: few examples per face, identify or verify test example
- What's hard: changes in expression, lighting, age, occlusion, **viewpoint**
- Basic approaches (all nearest neighbor)
  1. Project into a new subspace (or kernel space) (e.g., "Eigenfaces"=PCA)
  2. Measure face features
  3. Make 3d face model, compare shape+appearance (e.g., AAM)

Simple idea

1. Treat pixels as a vector

$\to \mathbf{x}$

2. Recognize face by nearest neighbor

$\to \mathbf{y}_1 \ldots \mathbf{y}_n$

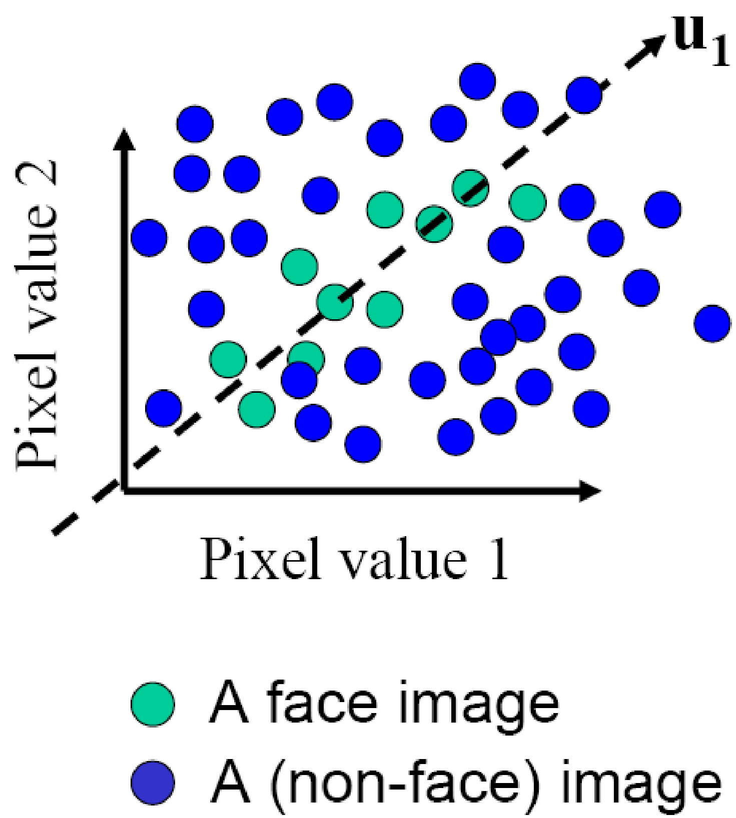
$$k = \underset{k}{\operatorname{argmin}} \left\| \mathbf{y}_k{}^T - \mathbf{x} \right\|$$

The space of all face images

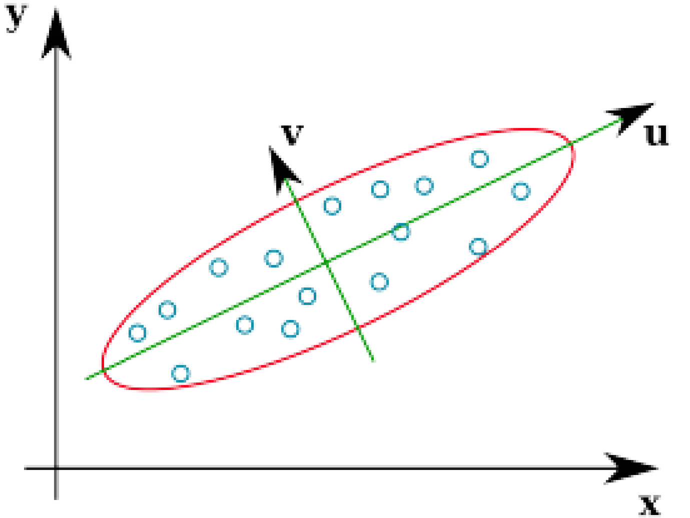
- When viewed as vectors of pixel values, face images are extremely high-dimensional
  - 100x100 image = 10,000 dimensions
  - Slow and lots of storage
- But very few 10,000-dimensional vectors are valid face images
- We want to effectively model the subspace of face images

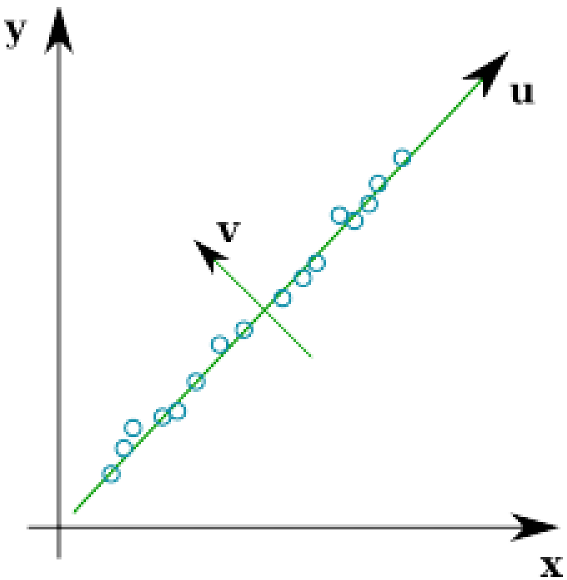
The space of all face images

- Eigenface idea: construct a low-dimensional linear subspace that best explains the variation in the set of face images



Principle Component Analysis (PCA)





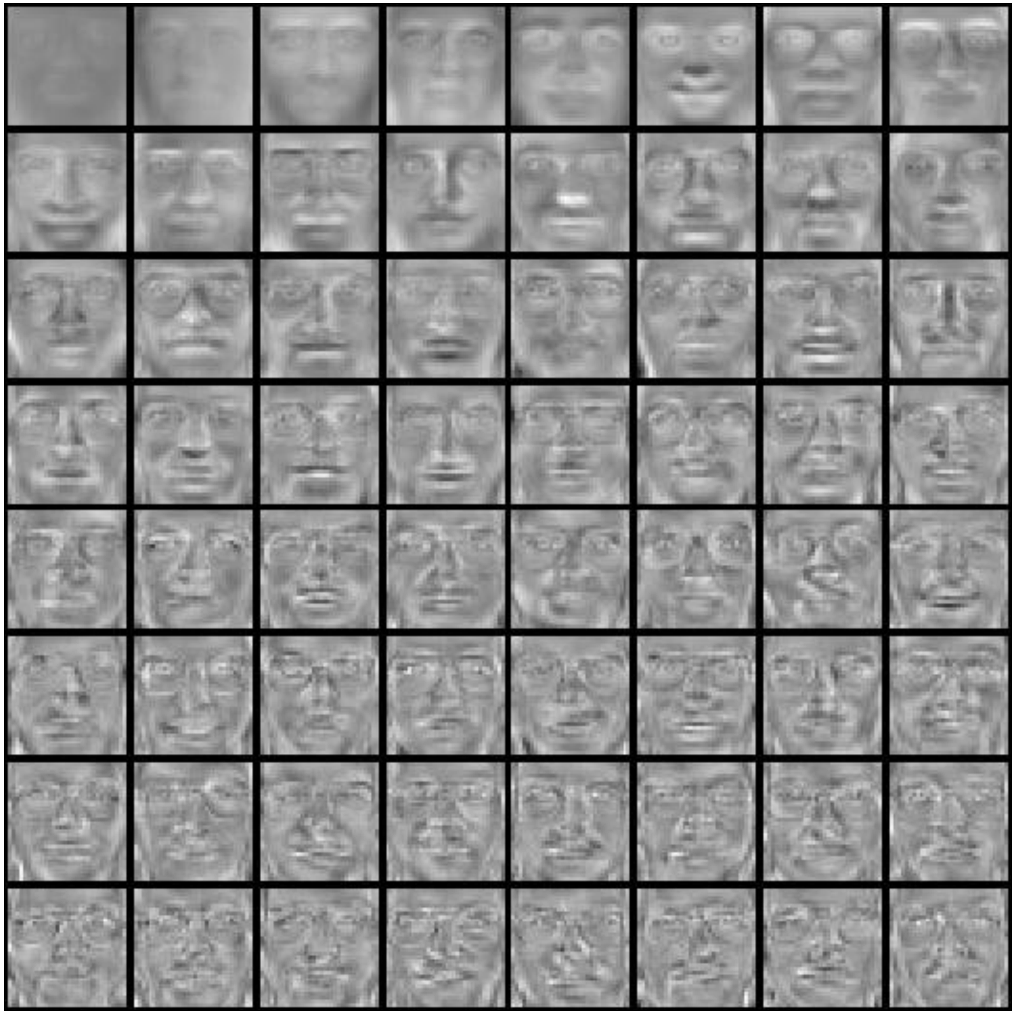
Eigenfaces example

- Training images
- $\mathbf{x}_1,\ldots,\mathbf{x}_N$

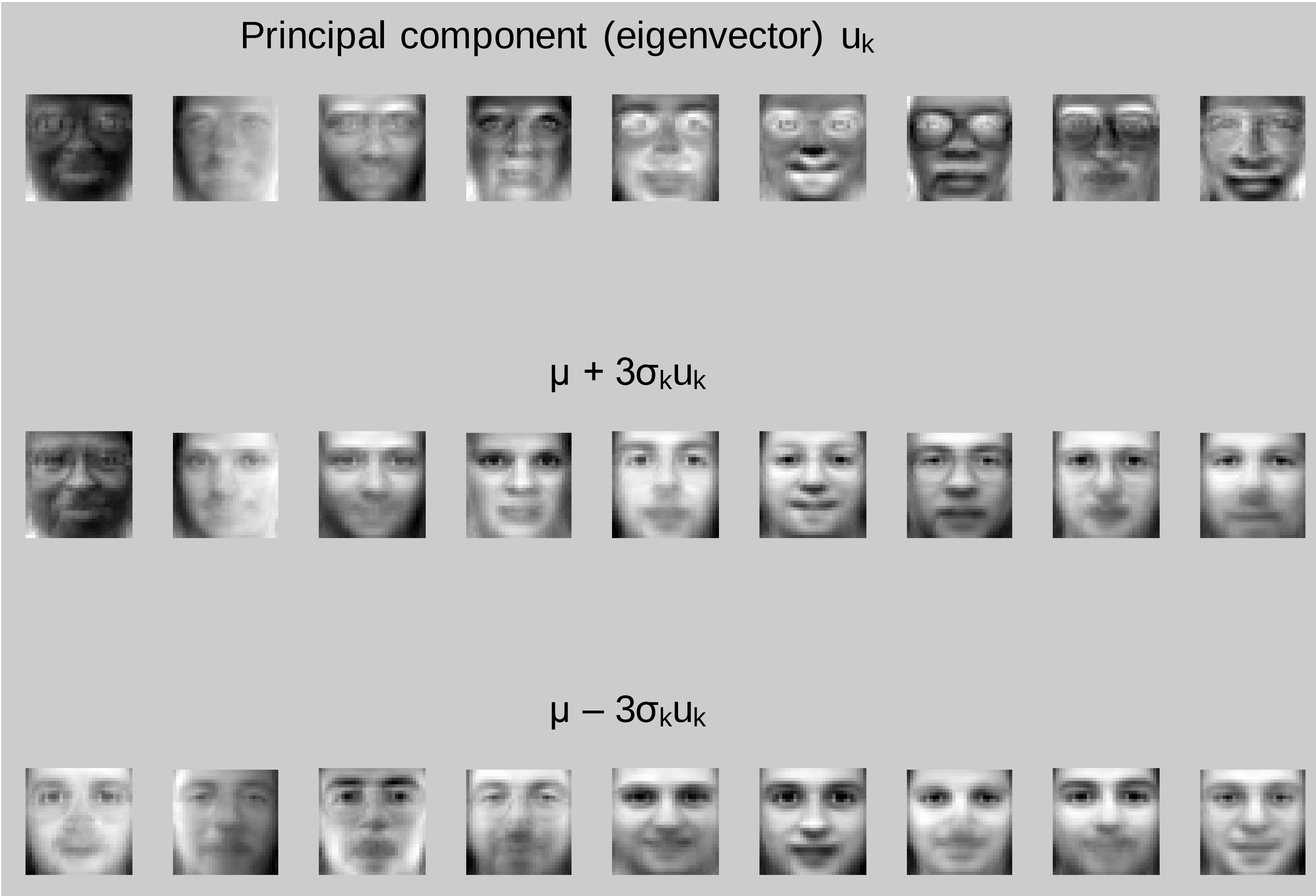
Eigenfaces example

Mean: μ

Top eigenvectors: $u_1,\ldots u_k$



Visualization of eigenfaces



Representation and reconstruction

- Face **x** in "face space" coordinates:

$$\mathbf{x} \rightarrow [\mathbf{u}_1^{\mathrm{T}}(\mathbf{x} - \mu), \ldots, \mathbf{u}_k^{\mathrm{T}}(\mathbf{x} - \mu)]$$
$$= \quad w_1, \ldots, w_k$$

Representation and reconstruction

- Face **x** in "face space" coordinates:

$$\mathbf{x} \rightarrow [\mathbf{u}_1^{\mathrm{T}}(\mathbf{x} - \mu), \ldots, \mathbf{u}_k^{\mathrm{T}}(\mathbf{x} - \mu)]$$
$$= \quad w_1, \ldots, w_k$$

- Reconstruction:

 =  + 

$\hat{x} = \mu + w_1u_1+w_2u_2+w_3u_3+w_4u_4+ \ldots$

Reconstruction

P = 4

P = 200

P = 400

After computing eigenfaces using 400 face images from ORL face database

Recognition with eigenfaces

Process labeled training images

- Find mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$
- Find k principal components (eigenvectors of $\boldsymbol{\Sigma}$) $\mathbf{u}_1,\ldots\mathbf{u}_k$
- Project each training image $\mathbf{x}_i$ onto subspace spanned by principal components:
  $(w_{i1},\ldots,w_{ik}) = (\mathbf{u}_1^T(\mathbf{x}_i - \boldsymbol{\mu}), \ldots , \mathbf{u}_k^T(\mathbf{x}_i - \boldsymbol{\mu}))$

Given novel image $\mathbf{x}$

- Project onto subspace:
  $(w_1,\ldots,w_k) = (\mathbf{u}_1^T(\mathbf{x} - \boldsymbol{\mu}), \ldots , \mathbf{u}_k^T(\mathbf{x} - \boldsymbol{\mu}))$
- Optional: check reconstruction error $\mathbf{x} - \hat{\mathbf{x}}$ to determine whether image is really a face
- Classify as closest training face in k-dimensional subspace

M. Turk and A. Pentland, Face Recognition using Eigenfaces, CVPR 1991

PCA

- General dimensionality reduction technique

- Preserves most of variance with a much more compact representation
  - Lower storage requirements (eigenvectors + a few numbers per face)
  - Faster matching

- What are the problems for face recognition?

Limitations

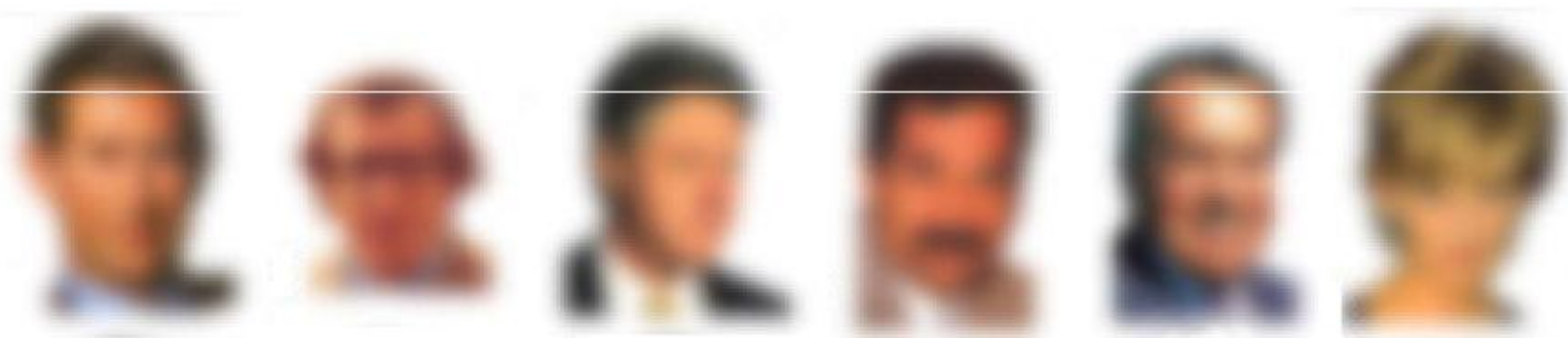
Global appearance method: not robust to misalignment, background variation

Face recognition by humans

Face recognition by humans: 20 results (2005)

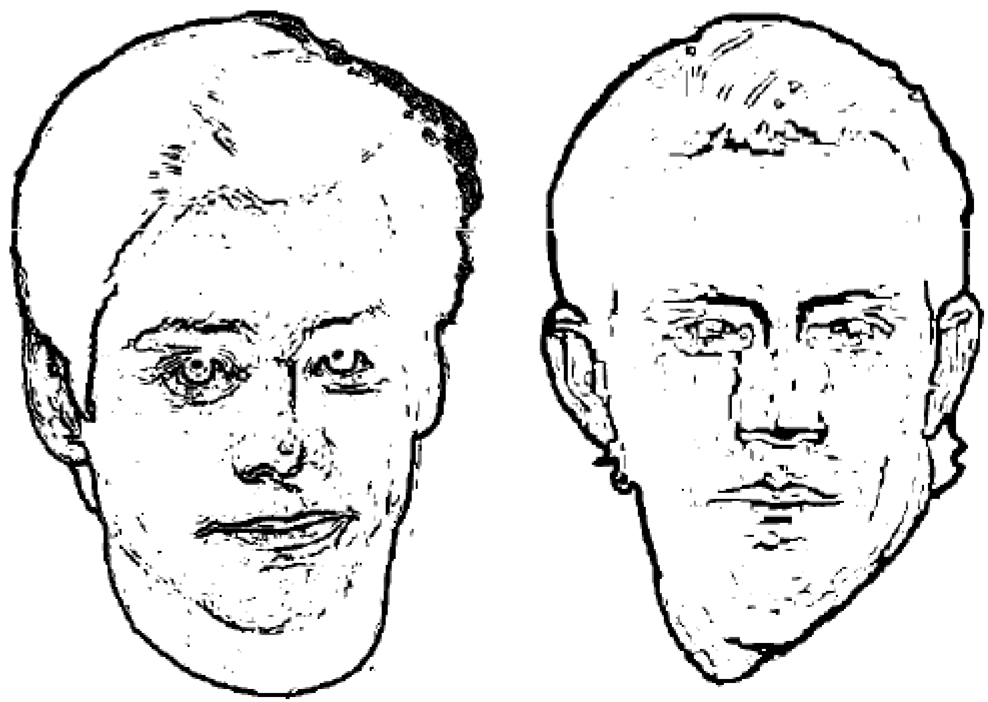
Result 1

- Humans can recognize faces in extremely low resolution images.



Result 3

- High-frequency information by itself does not lead to good face recognition performance

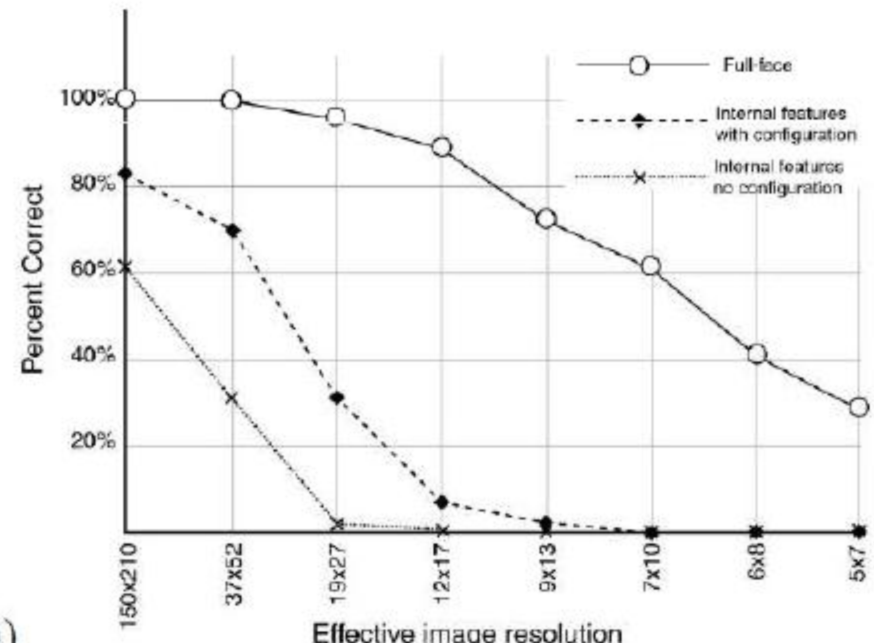


Result 5

- Eyebrows are among the most important for recognition

Result 6

- Both internal and external facial cues are important and they exhibit non-linear interactions

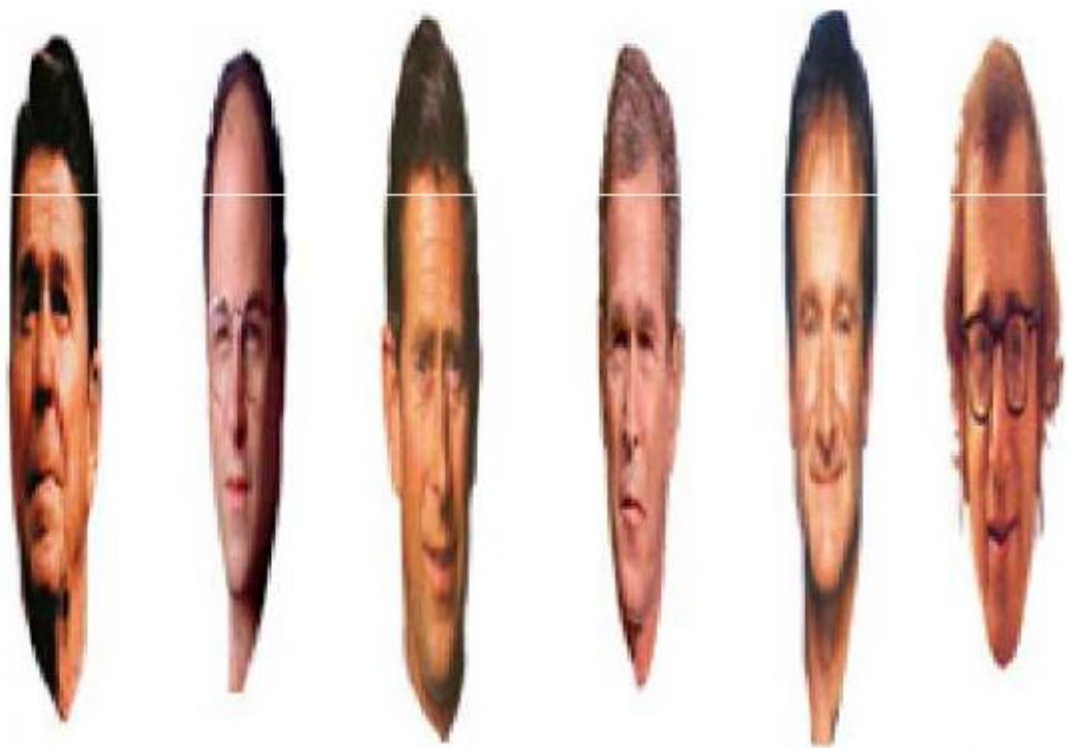


(a)

(b)

Result 7

- The important configural relations appear to be independent across the width and height dimensions



Result 8

- Vertical inversion dramatically reduces recognition performance

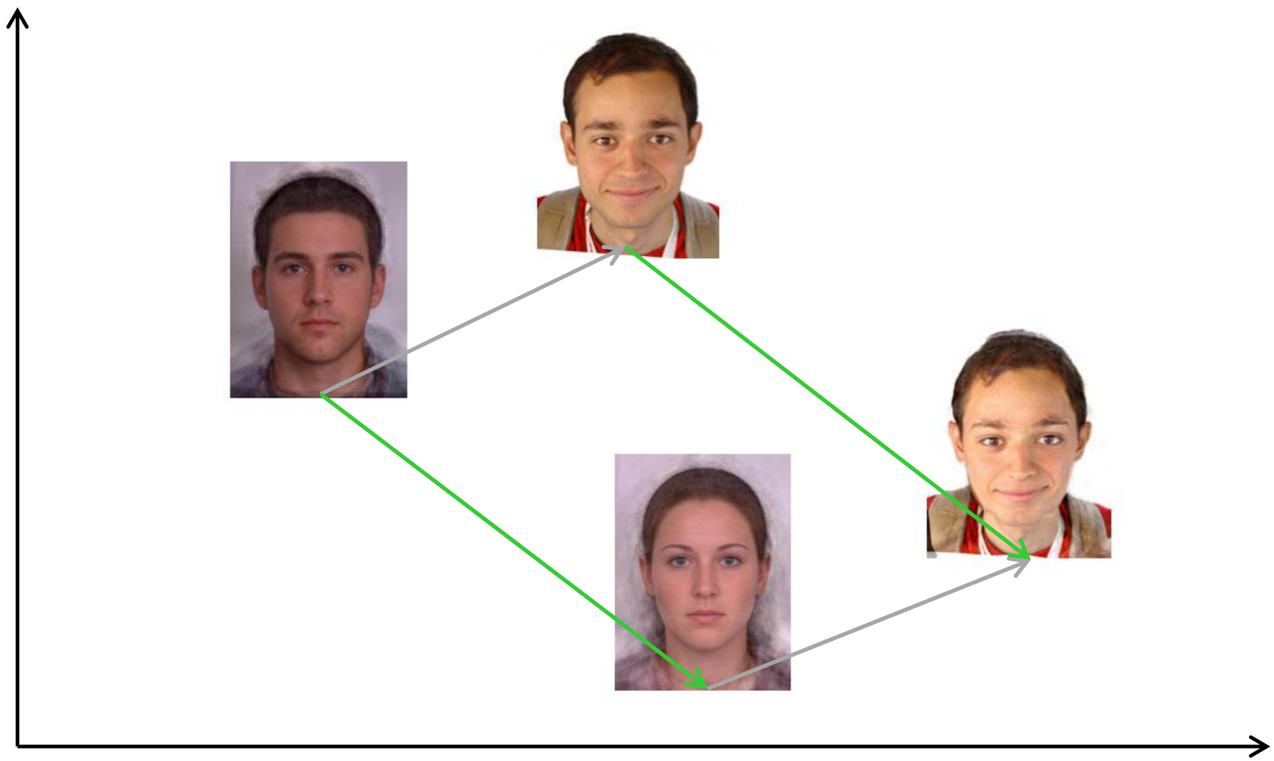
Result 12

- Contrast polarity inversion dramatically impairs recognition performance, possibly due to compromised ability to use pigmentation cues

Result 20

- Human memory for briefly seen faces is rather poor

Fun with Faces



Many slides from Alyosha Efros

Photos From faceresearch.org

The Power of Averaging

The Power of Averaging

8-hour exposure

© Atta Kim

Figure-centric averages

Antonio Torralba & Aude Oliva (2002)
Averages: Hundreds of images containing a person are averaged to reveal regularities in the intensity patterns across all the images.

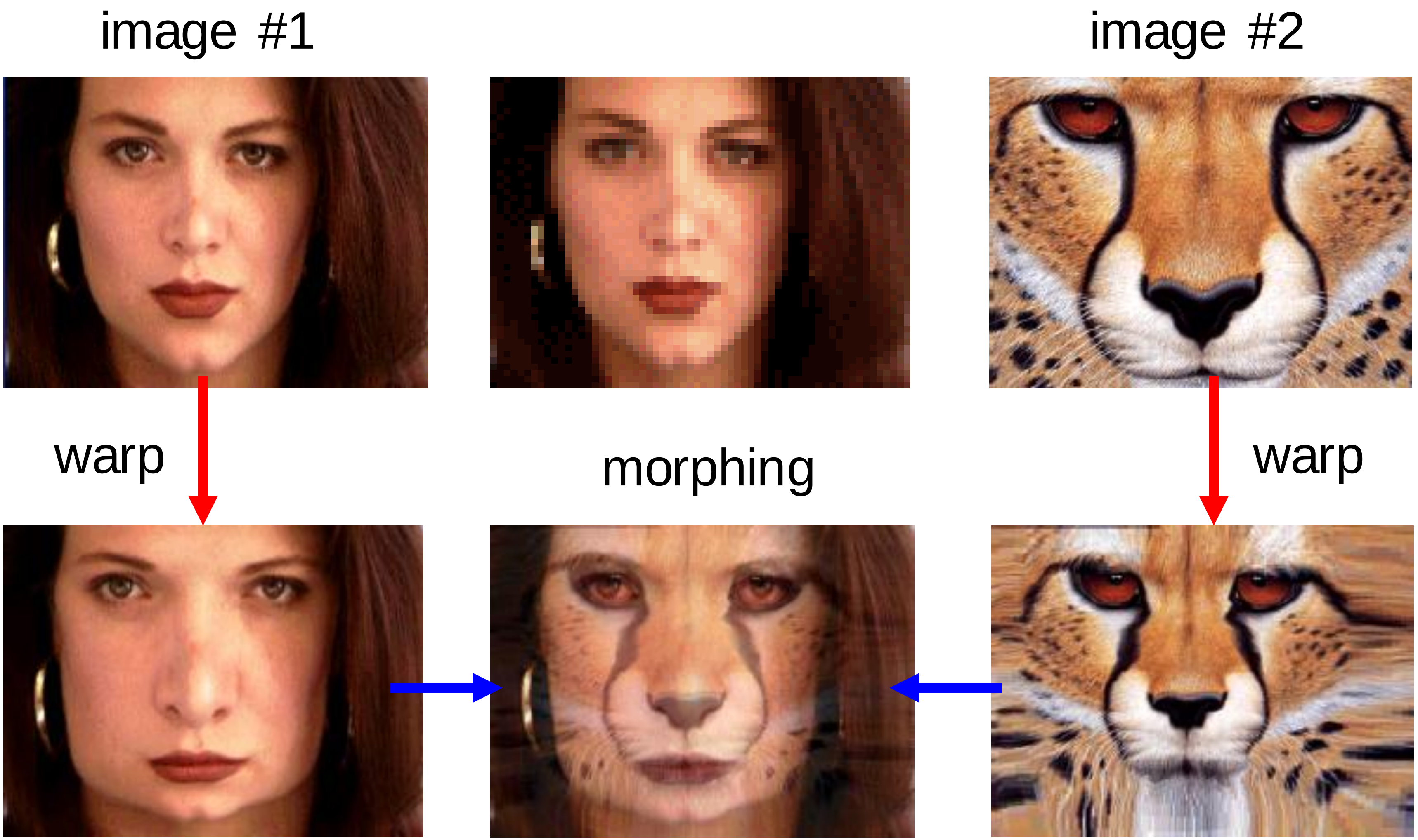
More by Jason Salavon

More at: http://www.salavon.com/

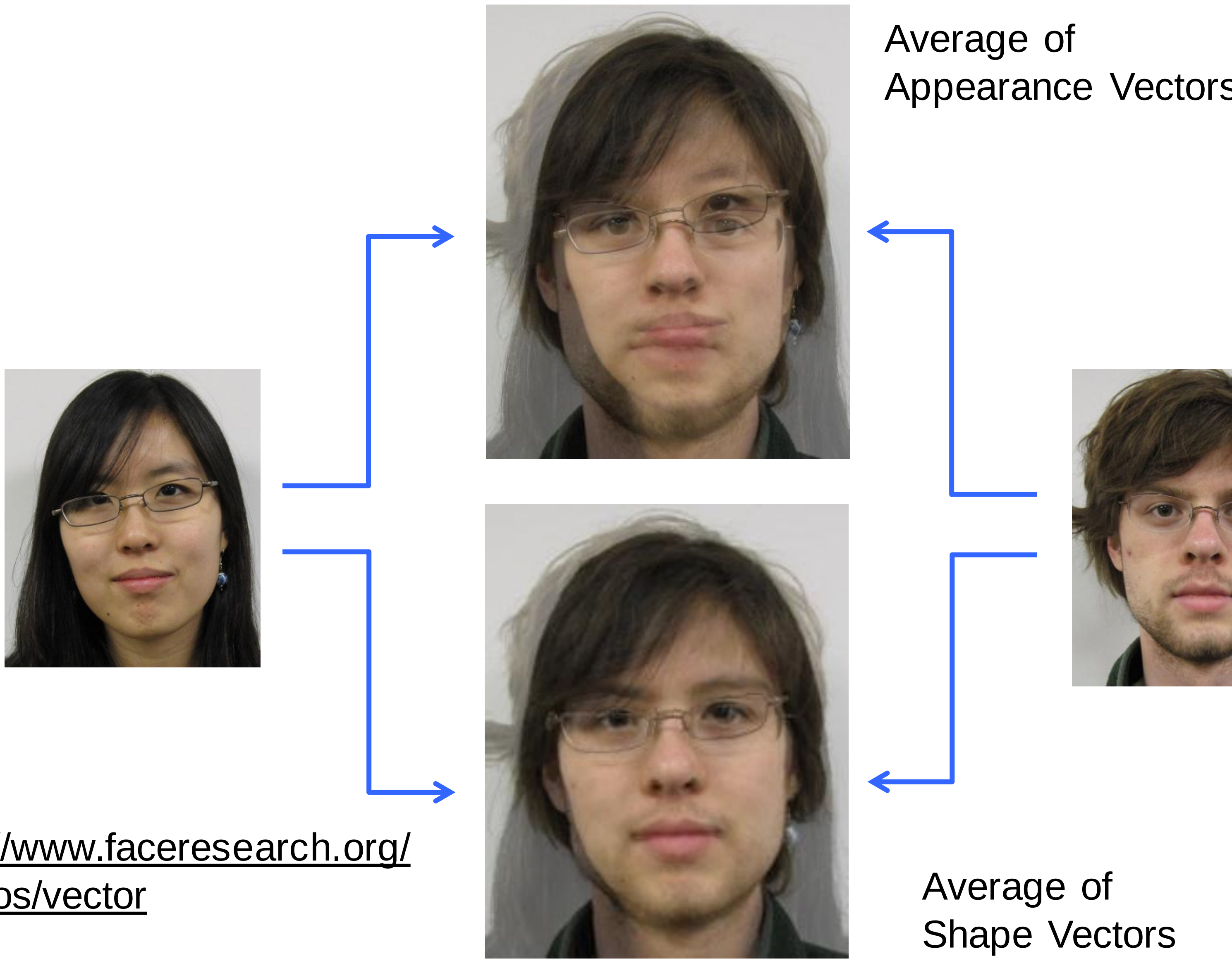
How do we average faces?

http://www2.imm.dtu.dk/~aam/datasets/datasets.html

Morphing



Cross-Dissolve vs. Morphing



http://www.faceresearch.org/demos/vector

Images from James Hays

Average of multiple Face

1. Warp to mean shape
2. Average pixels

http://www.faceresearch.org/demos/average

http://graphics.cs.cmu.edu/courses/15-463/2004_fall/www/handins/brh/final/

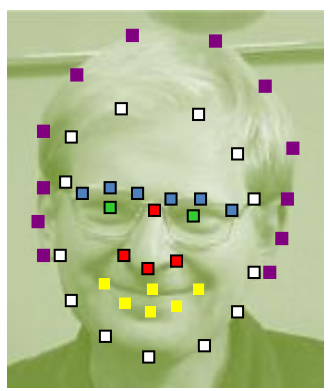
Appearance Vectors vs. Shape Vectors

Appearance Vector

200*150 pixels (RGB)

Vector of 200*150*3 Dimensions

Shape Vector

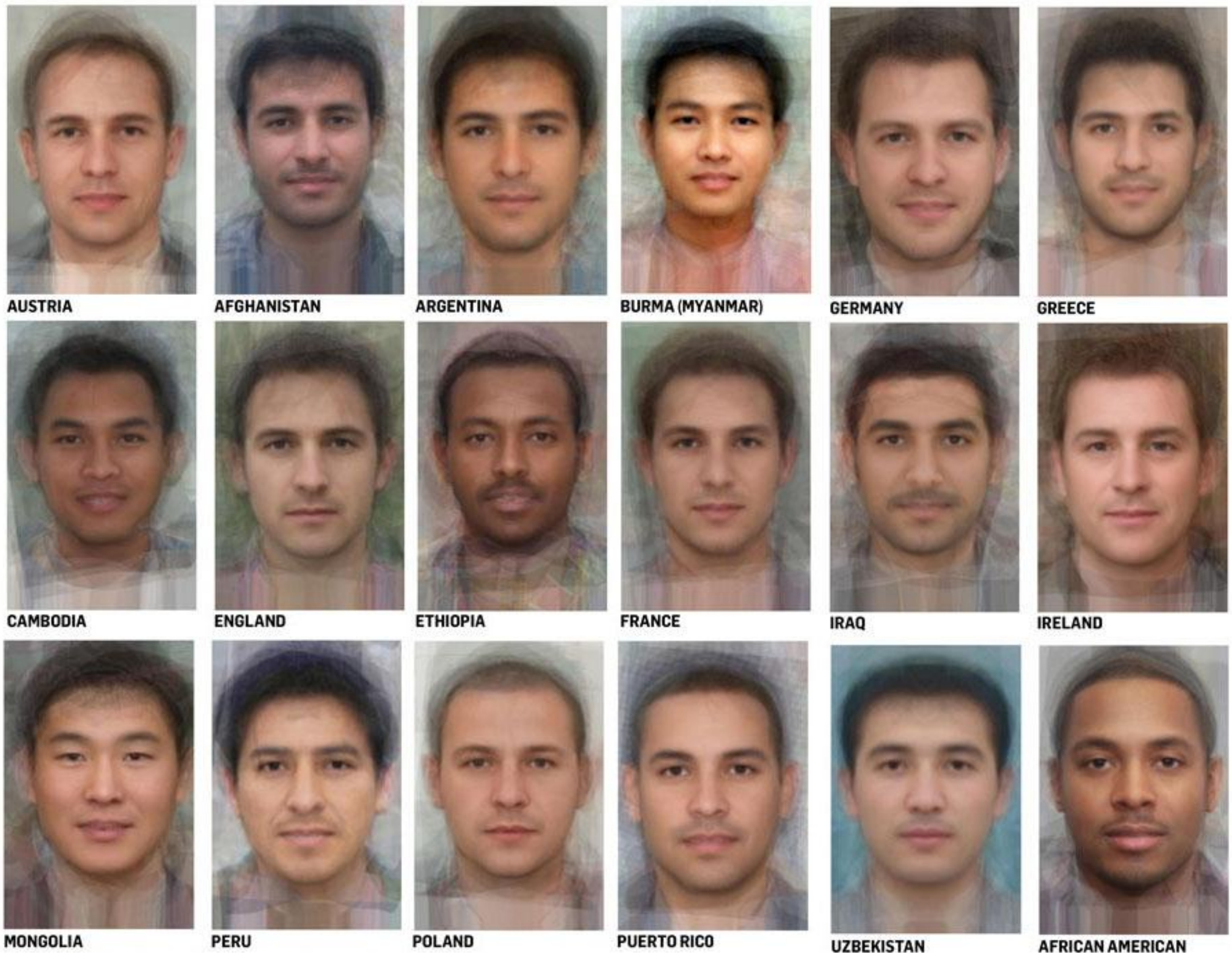


43 coordinates (x,y)

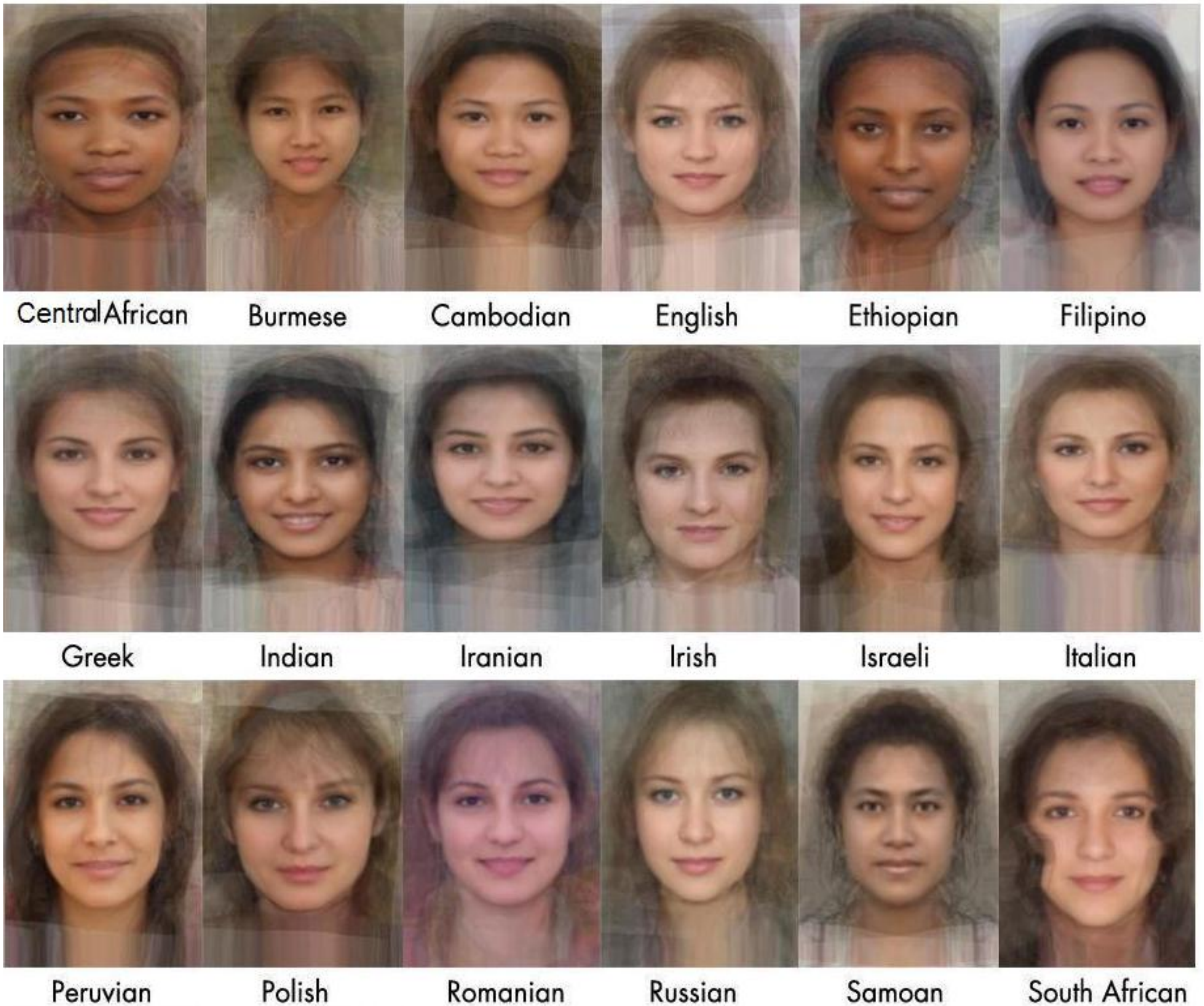
Vector of 43*2 Dimensions

- Requires Annotation
- Provides alignment!

Average Men of the world



Average Women of the world



Subpopulation means

- Other Examples:
  - Average Kids
  - Happy Males
  - Etc.
  - http://www.faceresearch.org

Average female

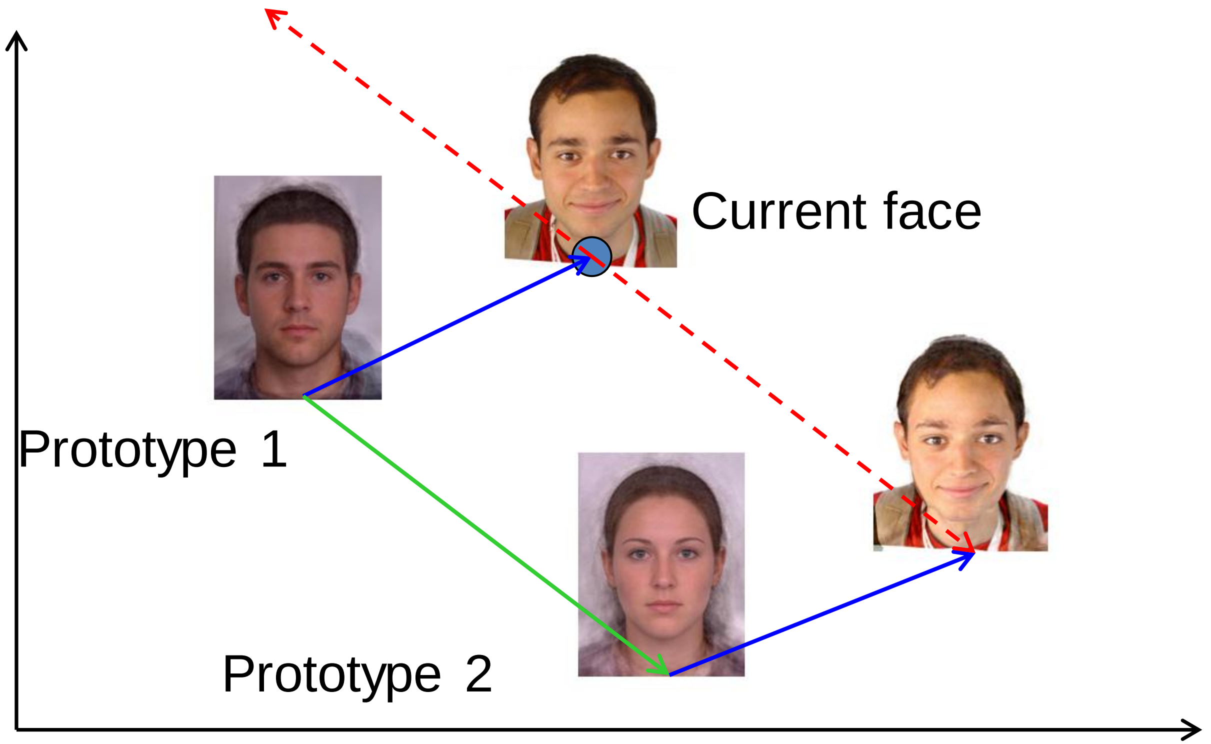
Average kid

Average happy male

Average male

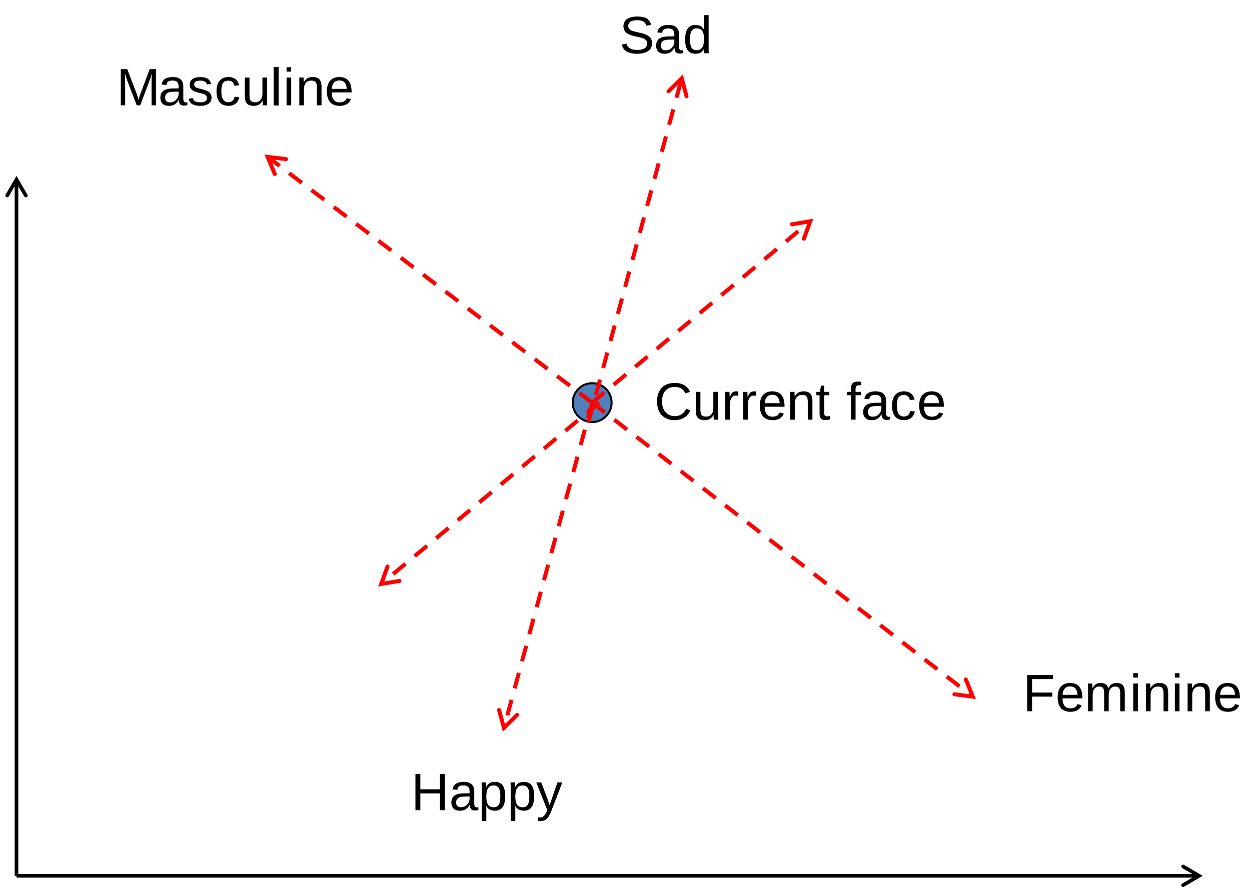
Manipulating faces

- How can we make a face look more female/male, young/old, happy/sad, etc.?
- http://www.faceresearch.org/demos/transform



Manipulating faces

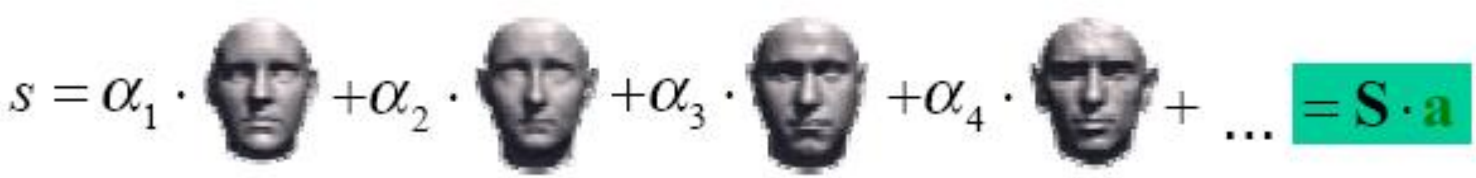
- We can imagine various meaningful directions.



Face Space

- How to find a set of directions to cover all space?

- We call these directions **Basis**
- If number of basis faces is large enough to span the face subspace:
- Any new face can be represented as a linear combination of basis vectors.



Midterm results + review

Midterm results + review

Mean = 87

Median = 90

Std dev = 7.5