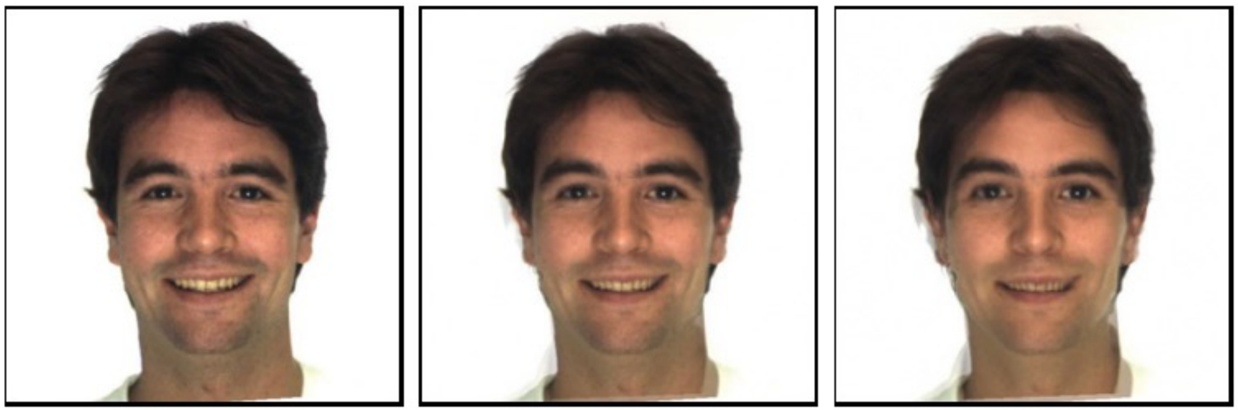
Data-driven Methods: Faces

Portrait of Piotr Gibas © Joaquin Rosales Gomez (2003)

CS194: Intro to Computer Vision and Comp. Photo
Alexei Efros, UC Berkeley, Fall 2022

Morphing & matting

Extract foreground first to avoid artifacts in the background

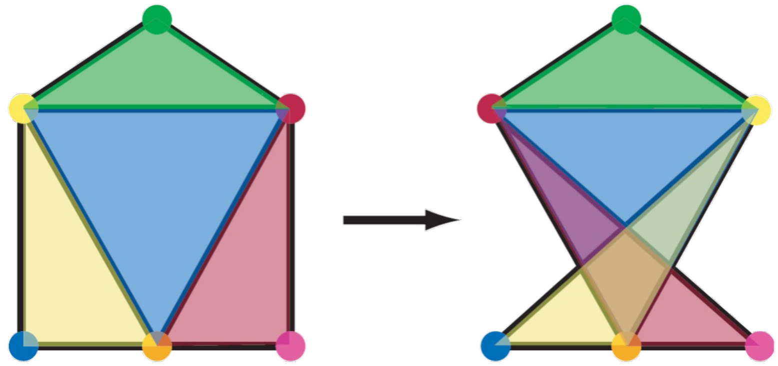


(c) $\alpha = 0.0$ (d) $\alpha = 0.2$ (e) $\alpha = 0.4$

(f) $\alpha = 0.6$ (g) $\alpha = 0.8$ (h) $\alpha = 1.0$

Slide by Durand and Freeman

Other Issues



Beware of folding

- You are probably trying to do something 3D-ish

Morphing can be generalized into 3D

- If you have 3D data, that is!

Extrapolation can sometimes produce interesting effects

- Caricatures

Dynamic Scene (“Black or White”, MJ)

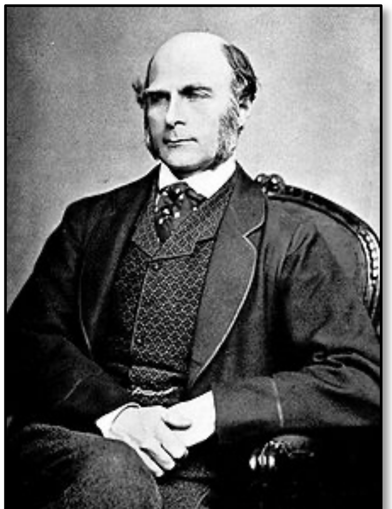
http://www.youtube.com/watch?v=R4kLKv5gtxc

The Power of Averaging

8-hour exposure

© Atta Kim

Image Composites



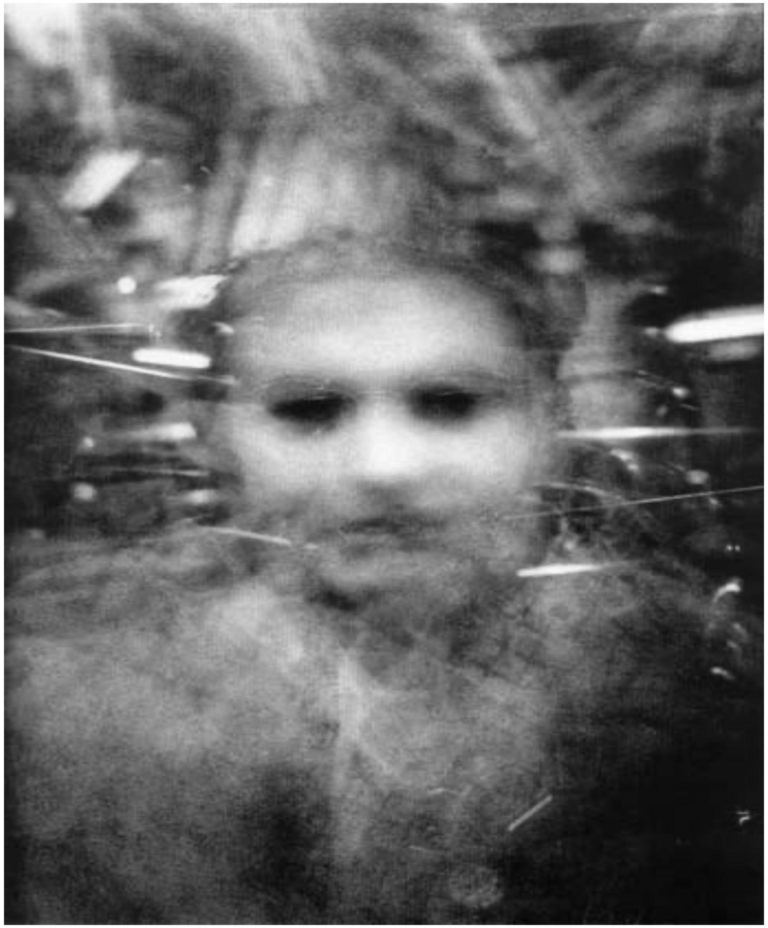
Sir Francis
Galton
1822-1911

Multiple Individuals

Composite

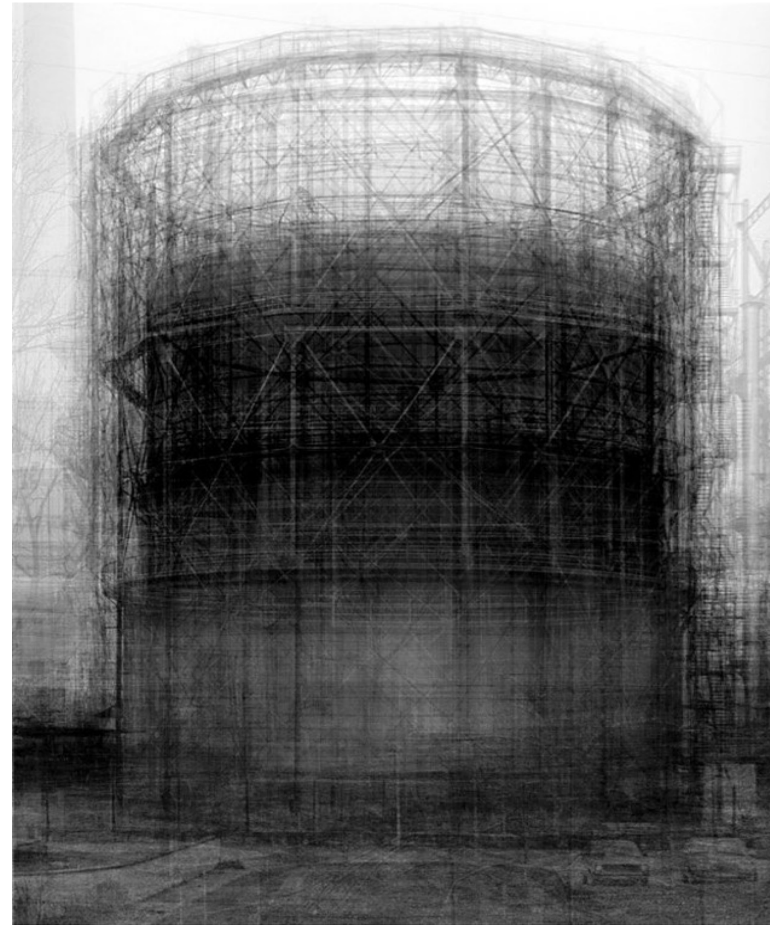
[Galton, "Composite Portraits", Nature, 1878]

Average Images in Art



“60 passagers de 2e classe du metro, entre 9h et 11h” (1985)

Krzysztof Pruszkowski

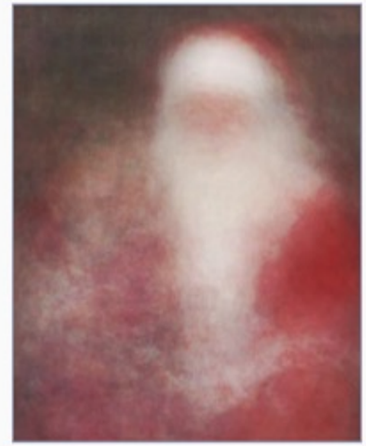


“Spherical type gasholders” (2004)

Idris Khan

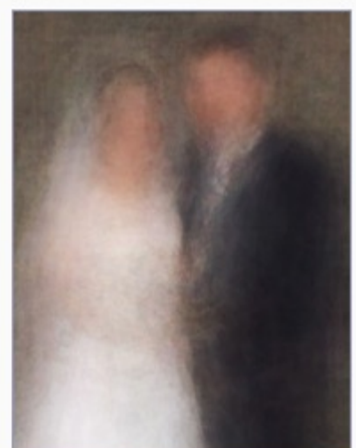
“100 Special Moments” by Jason Salavon

Little Leaguer



Kids with Santa

The Graduate

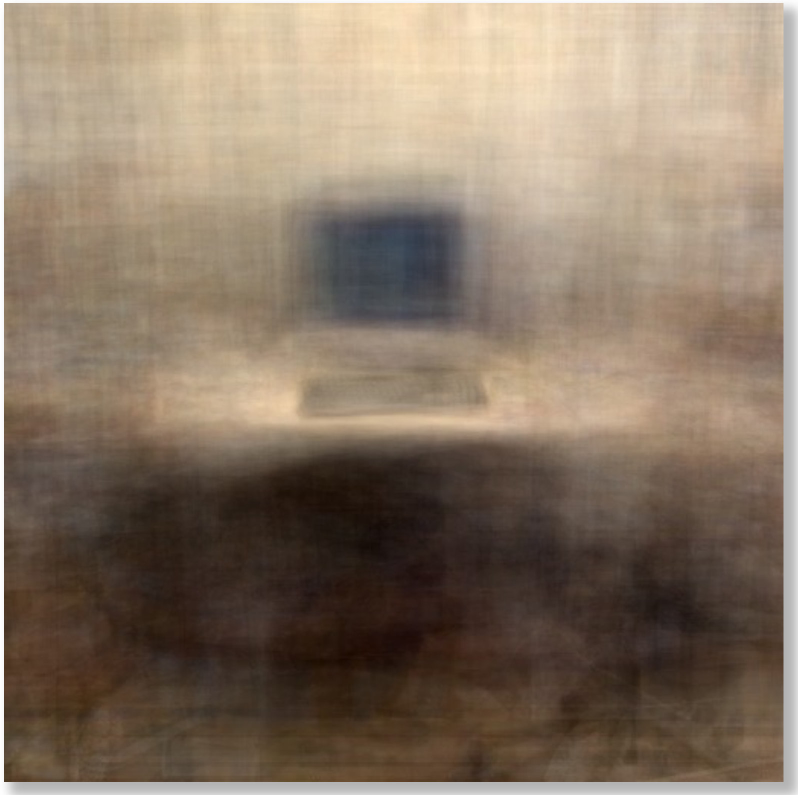


Newlyweds

Why blurry?

Object-Centric Averages by Torralba (2001)

Manual Annotation and Alignment



Average Image

Slide by Jun-Yan Zhu

Computing Means

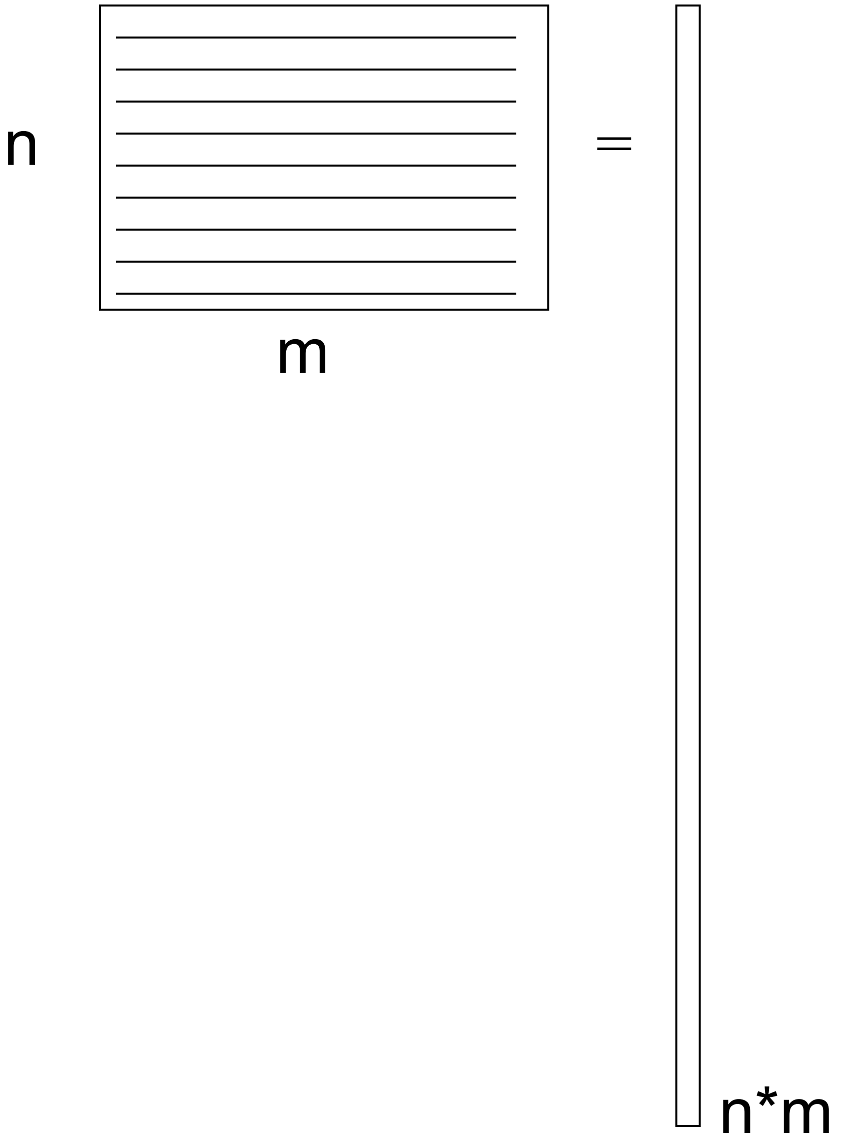
Two Requirements:

- Alignment of objects
- Objects must span a subspace

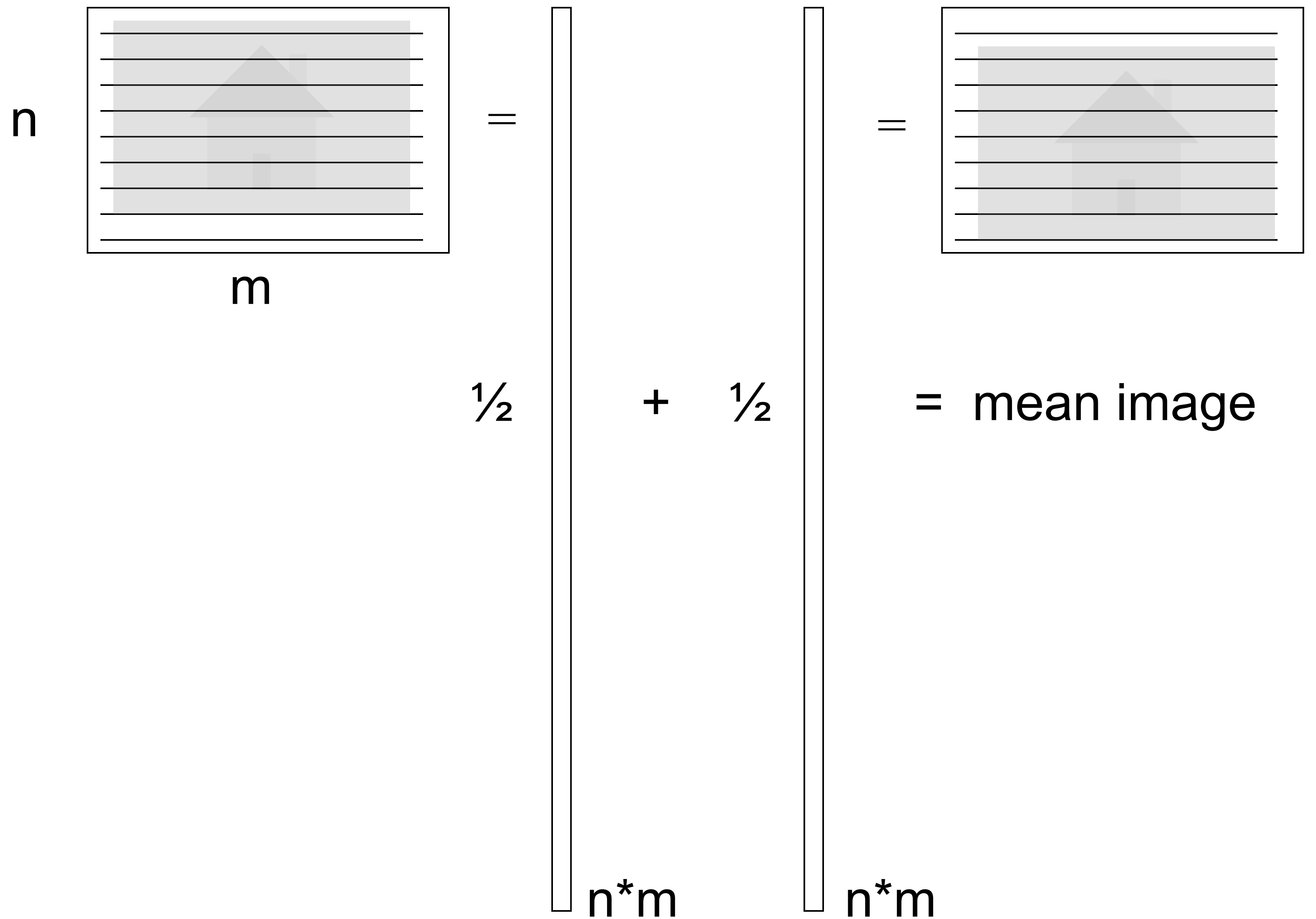
Useful concepts:

- Subpopulation means
- Deviations from the mean

Images as Vectors



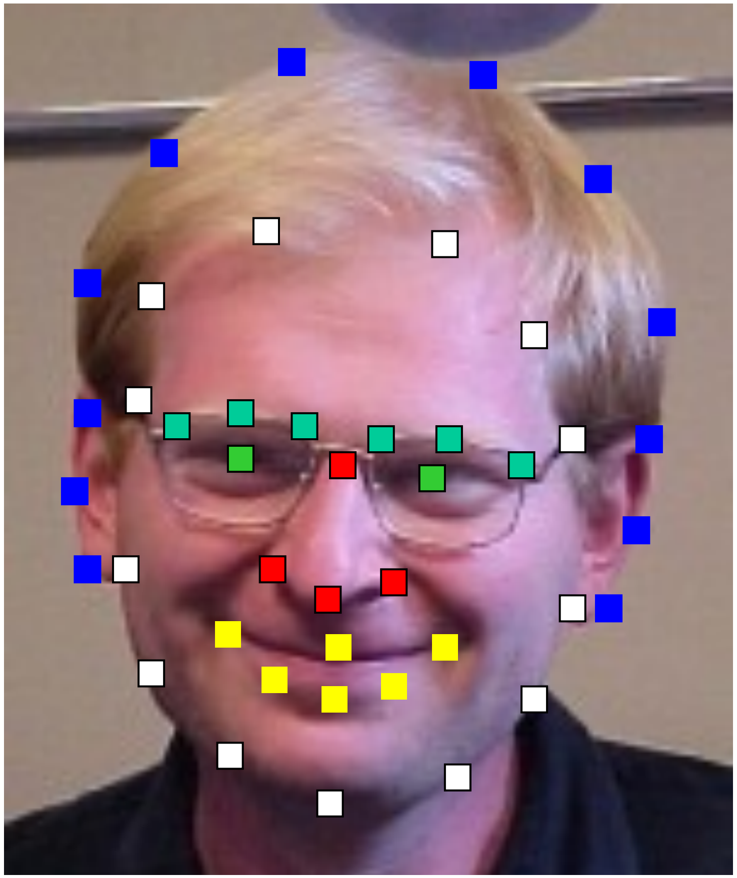
Vector Mean: Importance of Alignment



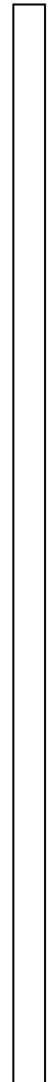
How to align faces?

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

Shape Vector



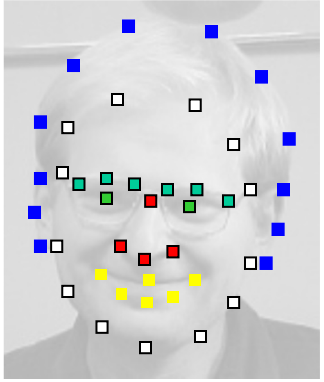
=



43

Provides alignment!

Appearance Vectors vs. Shape Vectors

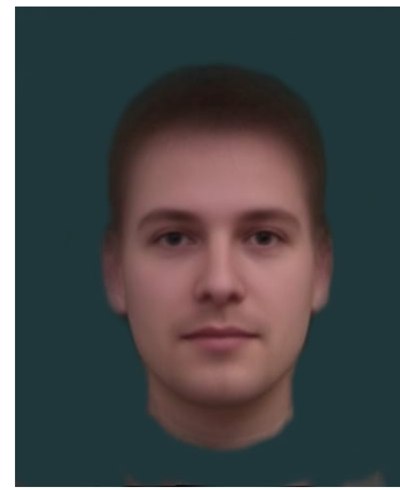
Appearance Vector	 200*150 pixels (RGB)	Vector of 200*150*3 Dimensions
Shape Vector	 43 coordinates (x,y)	Vector of 43*2 Dimensions

- Requires Annotation
- Provides alignment!

Slide by Kevin Karsch

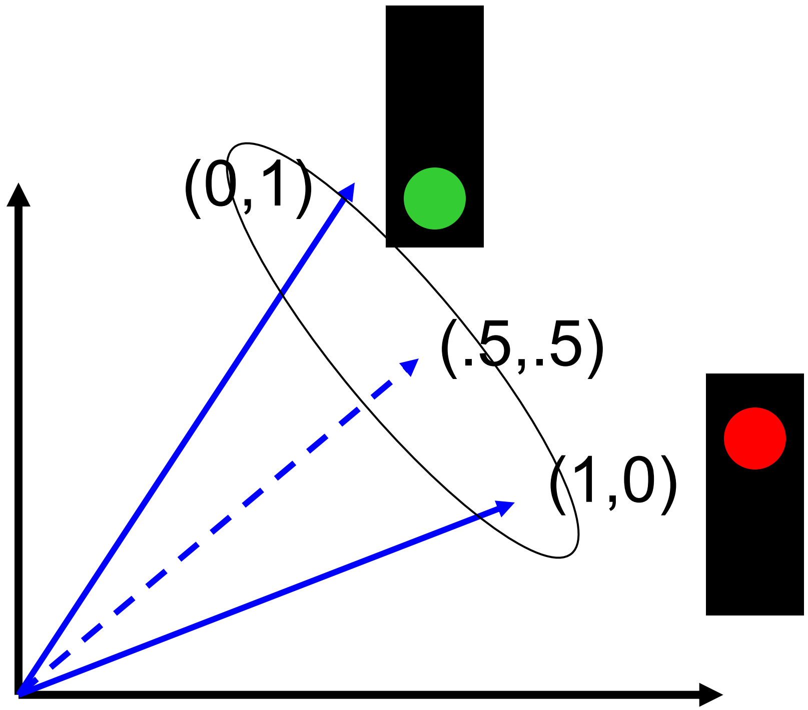
Average Face

1. Warp to mean shape
2. Average pixels



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

Objects must span a subspace



Example

mean

Does not span a subspace

Subpopulation means

Examples:

- Male vs. female
- Happy vs. said
- Angry Kids
- People wearing glasses
- Etc.
- http://www.faceresearch.org

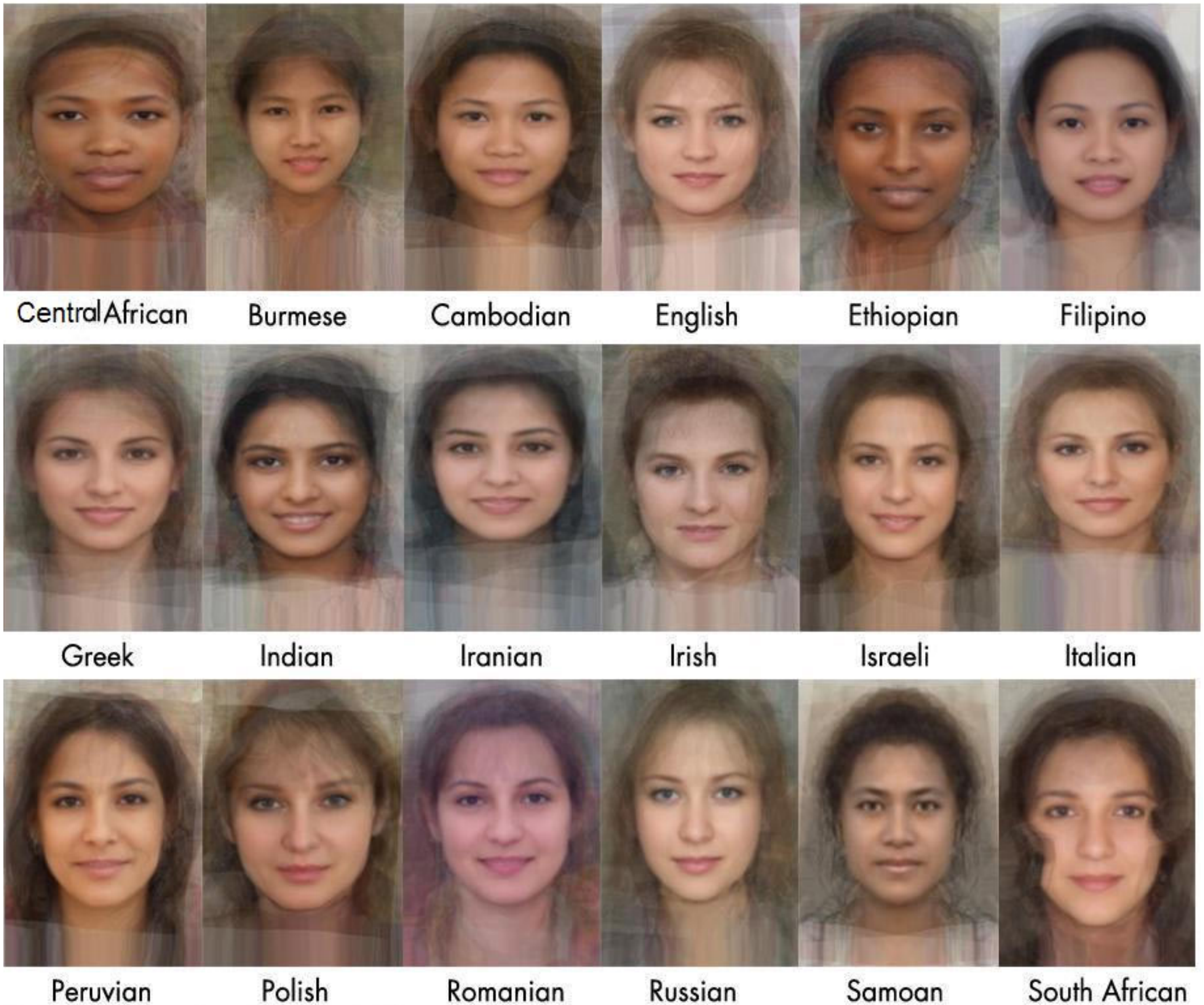
Average female

Average kid

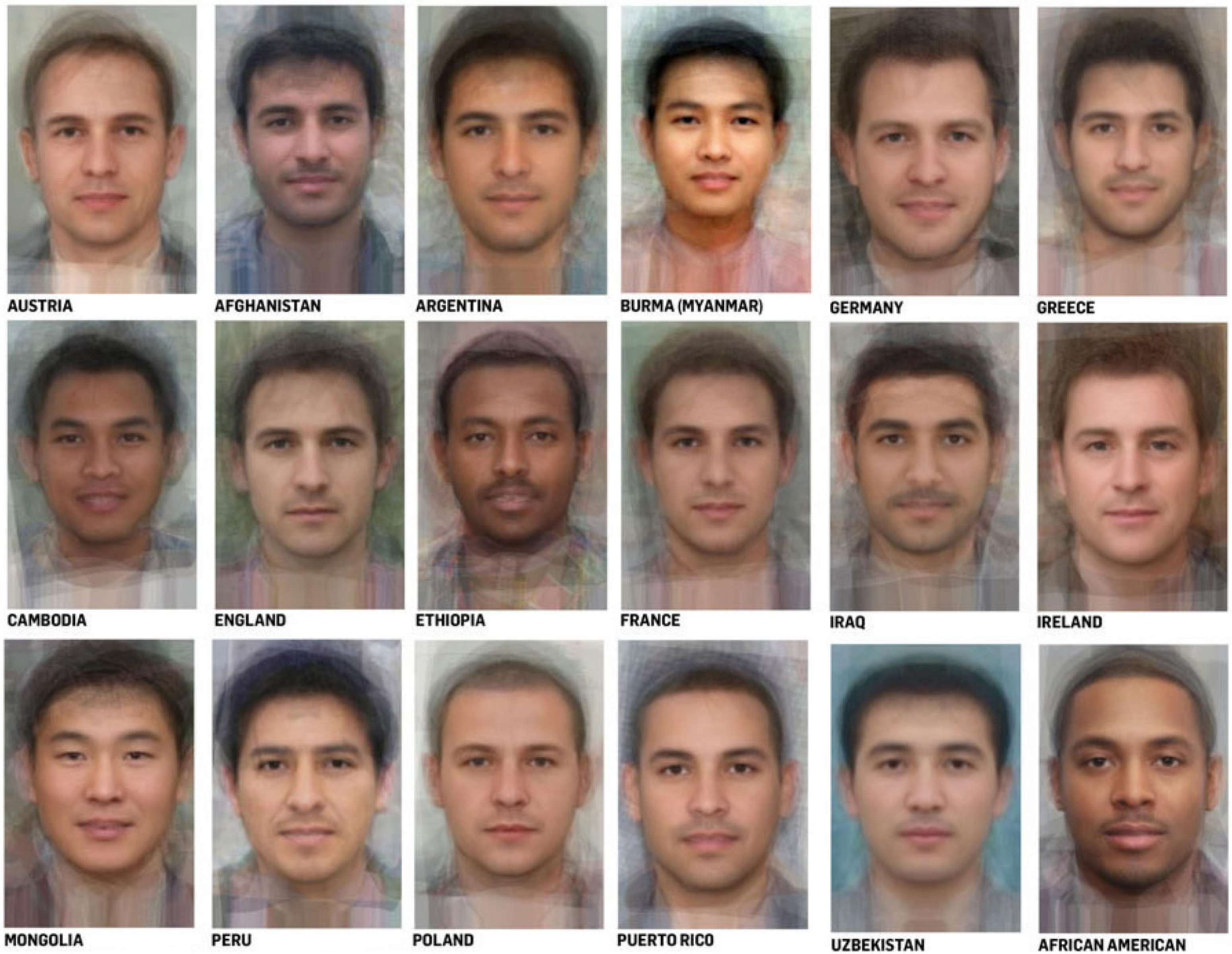
Average happy male

Average male

Average Women of the world



Average Men of the world



Deviations from the mean

Image X

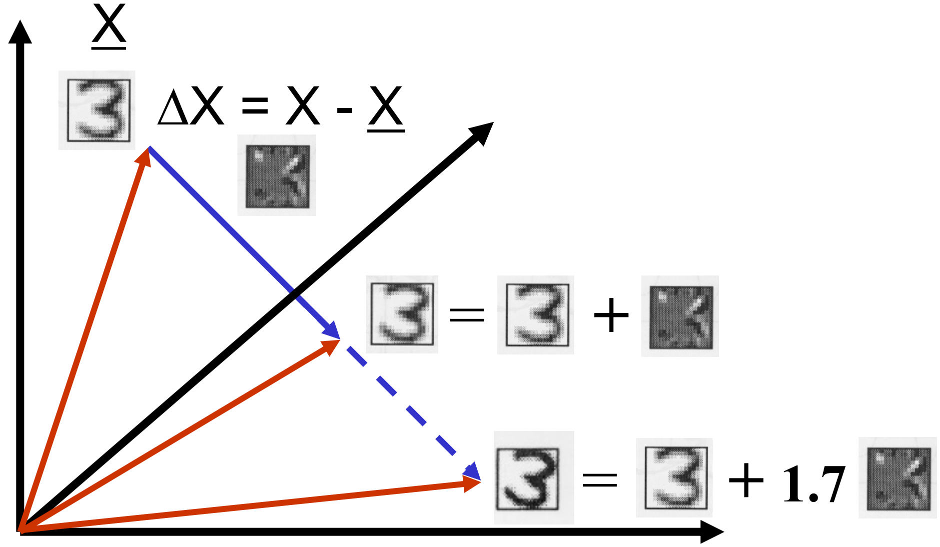
\-

Mean $\underline{X}$

=

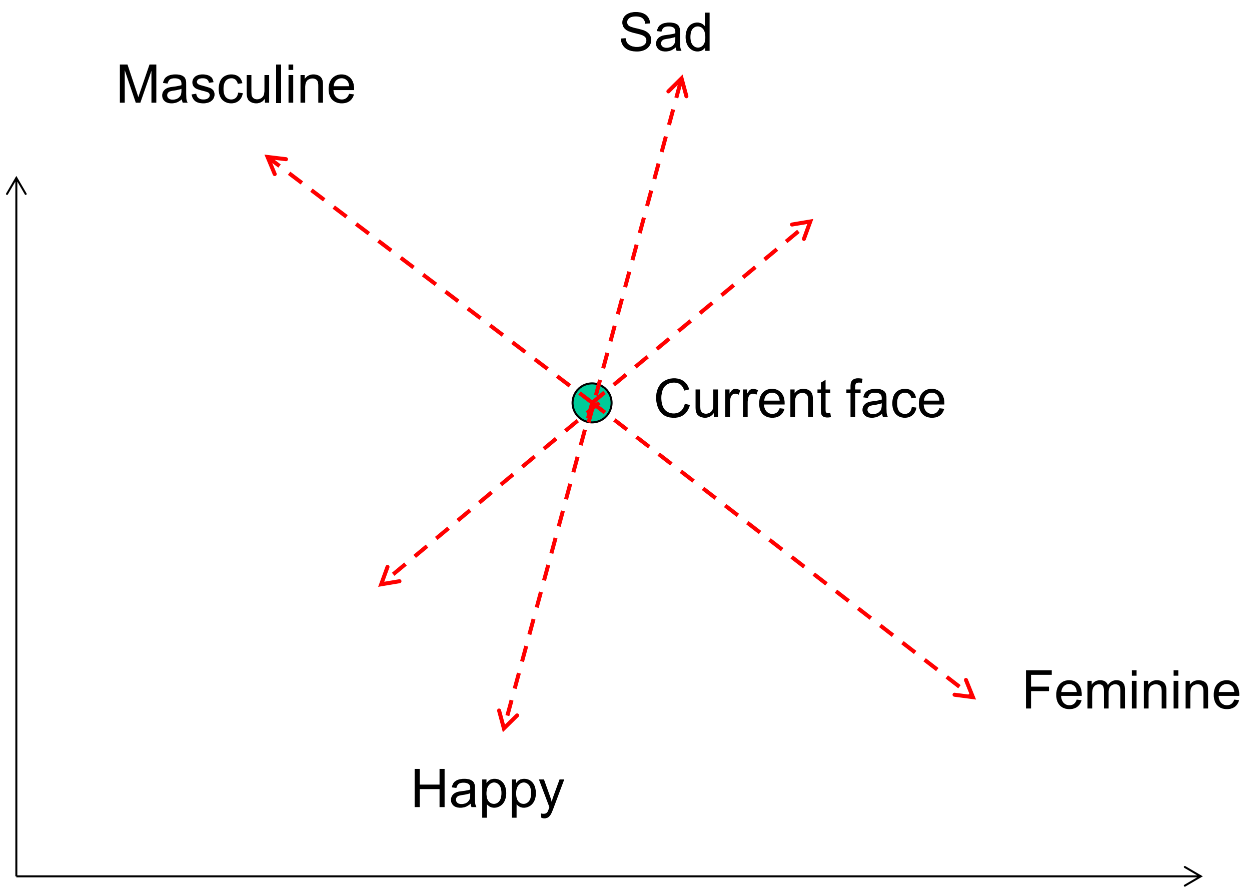
$\Delta X = X - \underline{X}$

Deviations from the mean



Extrapolating faces

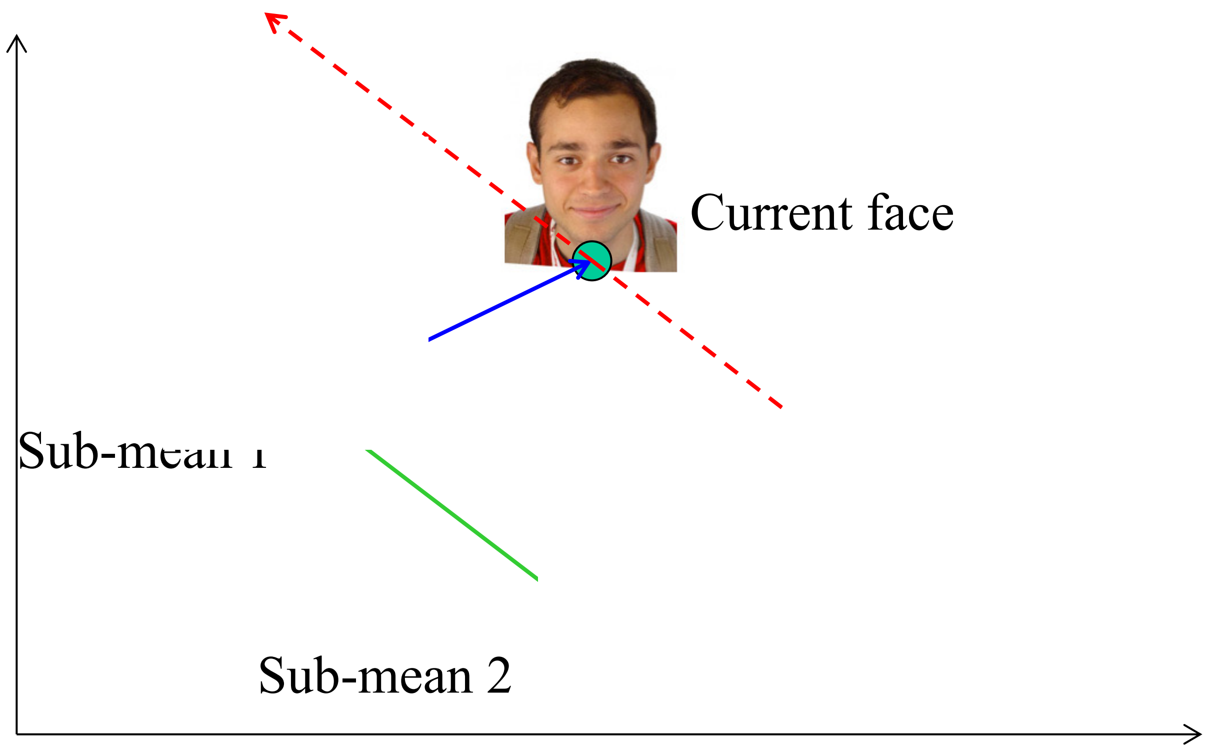
- We can imagine various meaningful directions.



Slide by Kevin Karsch

Manipulating faces

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



Slide by Kevin Karsch

Manipulating Facial Appearance through Shape and Color

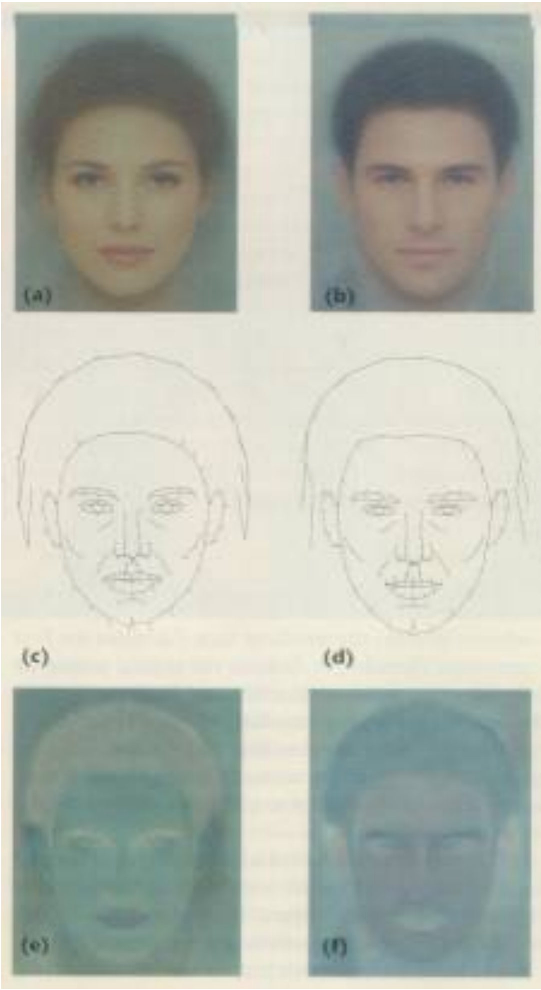
Duncan A. Rowland and David I. Perrett
St Andrews University

IEEE CG&A, September 1995

Face Modeling

Compute *average* faces
(color and shape)

Compute *deviations* between male and female (vector and color differences)

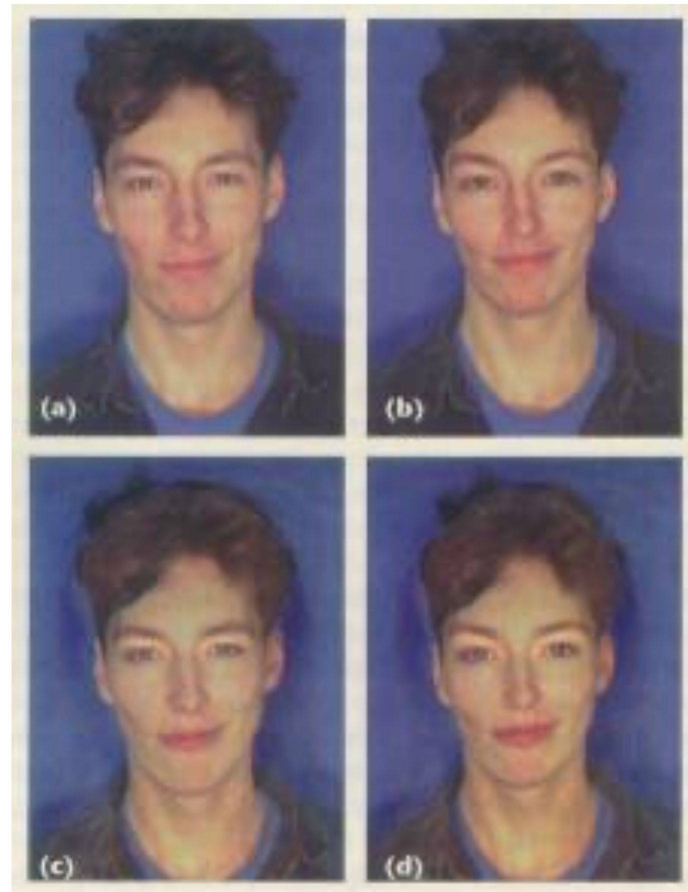


Changing gender

Deform shape and/or color of an input face in the direction of "more female"

original

shape



color

both

Enhancing gender

more same **original** androgynous more opposite

Changing age

Face becomes “rounder” and “more textured” and “grayer”

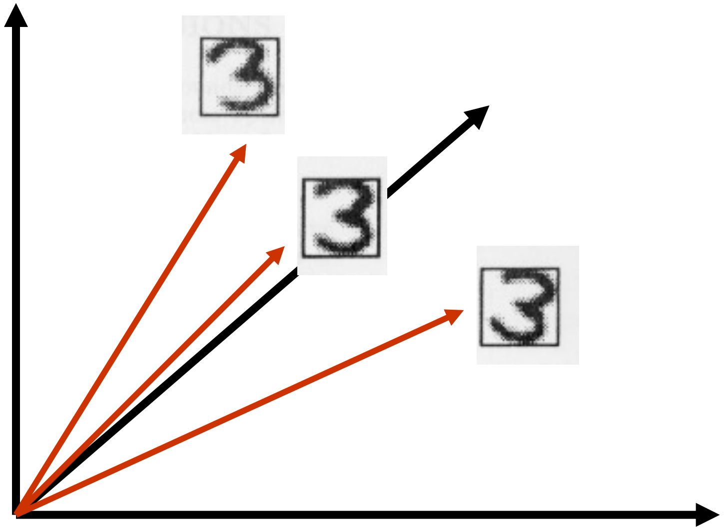
original

shape

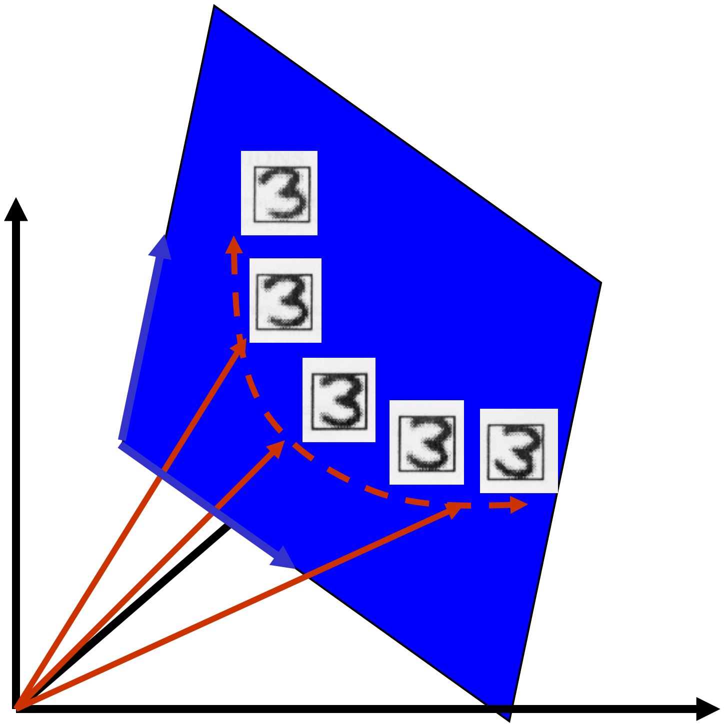
color

both

Back to the Subspace



Linear Subspace: convex combinations



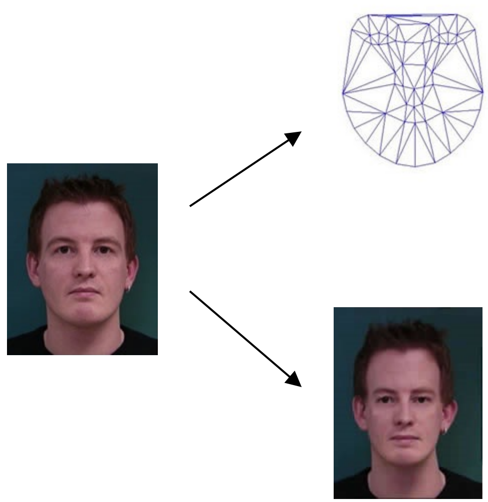
Any new image X can be obtained as weighted sum of stored "basis" images.

$$X = \sum_{i=1}^{m} a_i X_i$$

Our old friend, change of basis! What are the new coordinates of X?

The Morphable Face Model

The actual structure of a face is captured in the shape vector **S** = $(x_1, y_1, x_2, \ldots, y_n)^T$, containing the (x, y) coordinates of the n vertices of a face, and the appearance (texture) vector **T** = $(R_1, G_1, B_1, R_2, \ldots, G_n, B_n)^T$, containing the color values of the mean-warped face image.



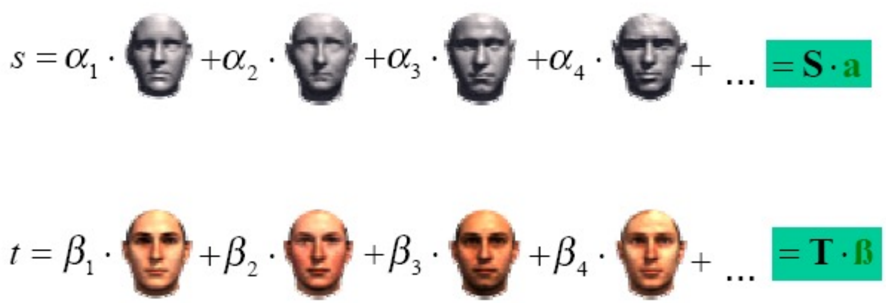
Shape S

Appearance T

The Morphable face model

Again, assuming that we have ***m*** such vector pairs in full correspondence, we can form new shapes $\mathbf{S}_{model}$ and new appearances $\mathbf{T}_{model}$ as:

$$\mathbf{S}_{model} = \sum_{i=1}^{m} a_i \mathbf{S}_i \qquad \mathbf{T}_{model} = \sum_{i=1}^{m} b_i \mathbf{T}_i$$



If number of basis faces ***m*** is large enough to span the face subspace then:

<u>Any new</u> face can be represented as a pair of vectors

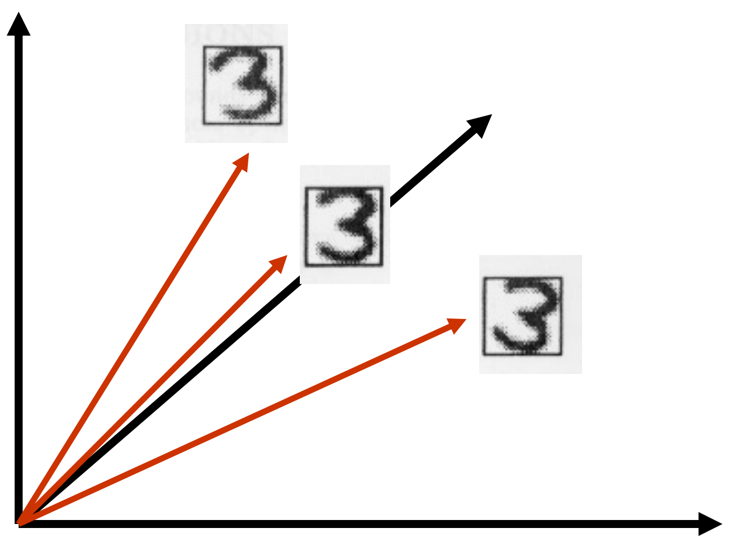
$(\alpha_1, \alpha_2, \ldots, \alpha_m)^T$ and $(\beta_1, \beta_2, \ldots, \beta_m)^T$!

Issues:

1. How many basis images is enough?
2. Which ones should they be?
3. What if some variations are more important than others?
    - E.g. corners of mouth carry much more information than haircut

Need a way to obtain basis images automatically, in order of importance!

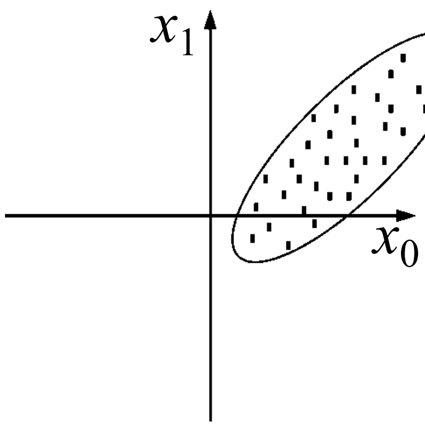
But what's important?

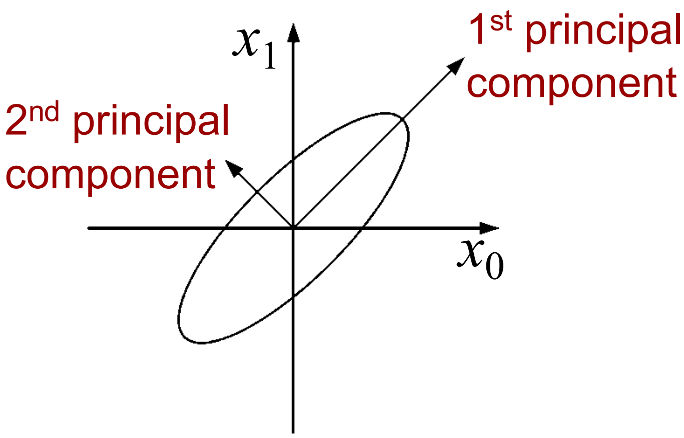


Principal Component Analysis

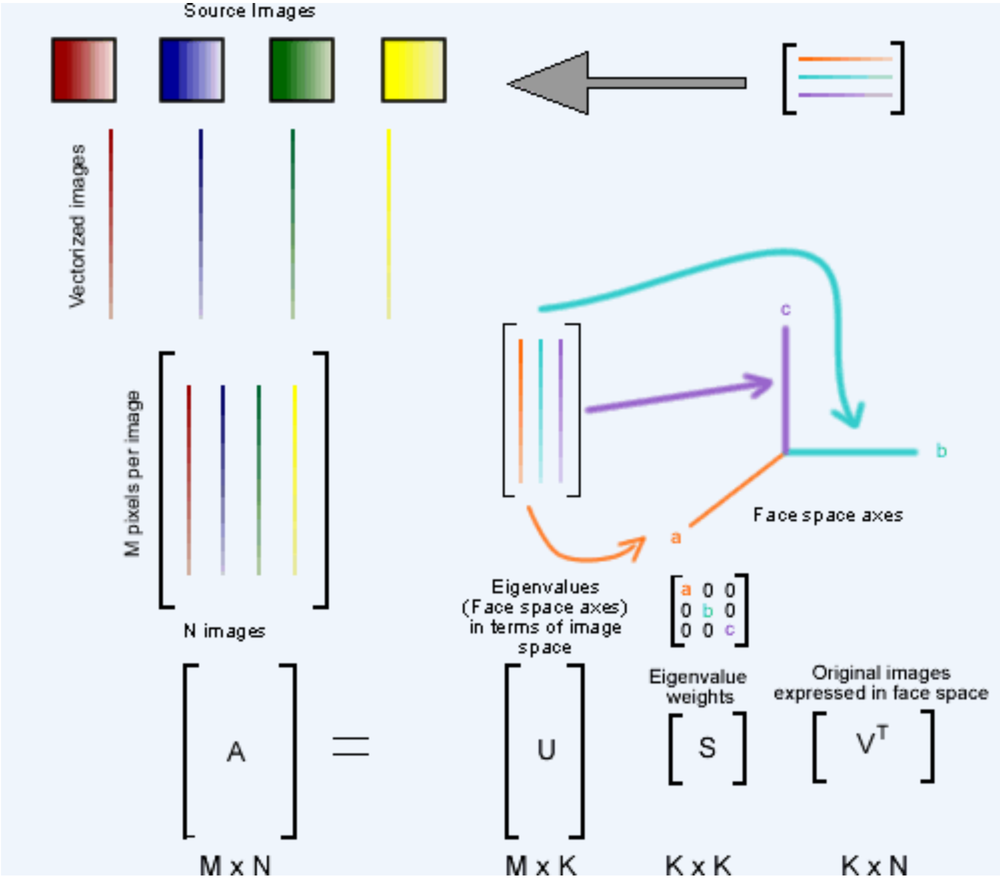
Given a point set $\{\vec{\mathrm{p}}_j\}_{j=1\ldots P}$, in an M-dim space, PCA finds a basis such that

- coefficients of the point set in that basis are uncorrelated
- first $r < M$ basis vectors provide an approximate basis that minimizes the mean-squared-error (MSE) in the approximation (over all bases with dimension r)





PCA via Singular Value Decomposition



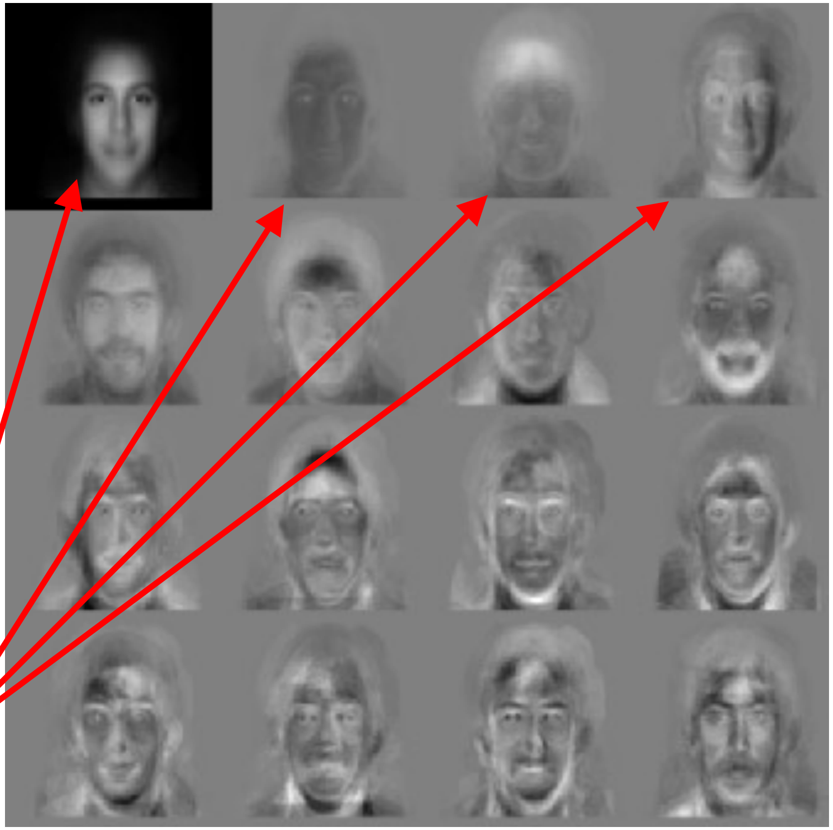
[u,s,v] = svd(A);

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

EigenFaces

First popular use of PCA on images was for modeling and recognition of faces *[Kirby and Sirovich, 1990, Turk and Pentland, 1991]*

- Collect a face ensemble
- Normalize for contrast, scale, & orientation.
- Remove backgrounds
- Apply PCA & choose the first N eigen-images that account for most of the variance of the data.



First 3 Shape Basis

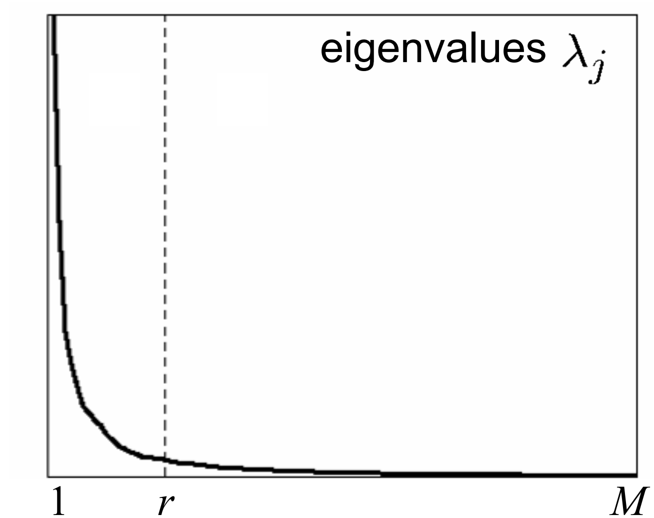
Mean appearance

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

Principal Component Analysis

Choosing subspace dimension r:

- look at decay of the eigenvalues as a function of r
- Larger r means lower expected error in the subspace data approximation



Using 3D Geometry: Blanz & Vetter, 1999

http://www.youtube.com/watch?v=jrutZaYoQJo

Pop Quiz!!

DSP: you can take 15 min more

https://tinyurl.com/2t3etz39