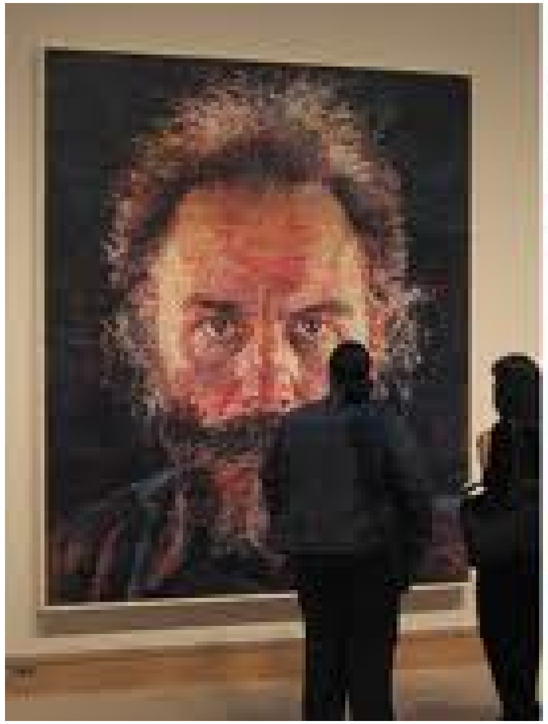
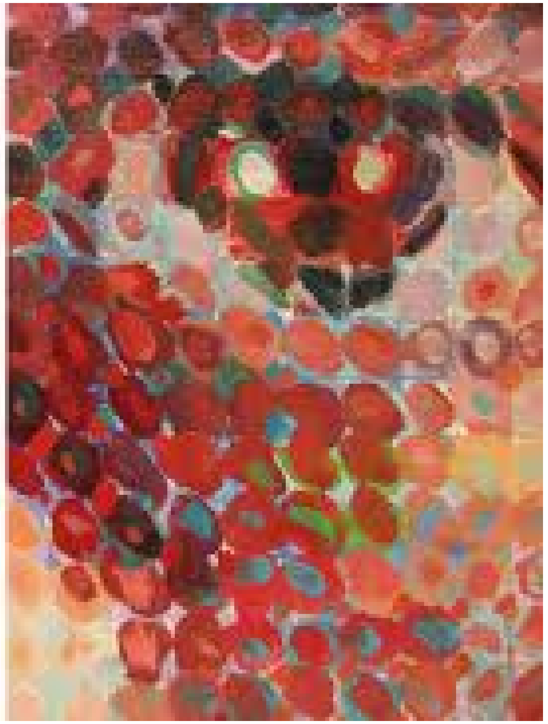
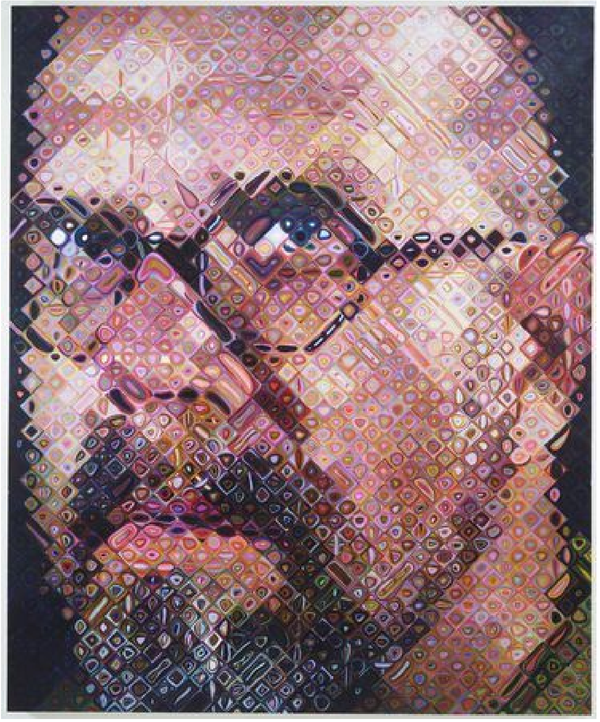
Detection, Recognition, and Transformation of Faces



Lucas by Chuck Close





Chuck Close, self portrait

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

Exams

- Exams handed back after this class or in office hours

Better grade distribution than 2015

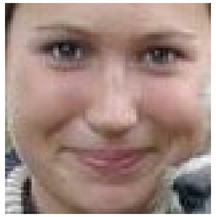
	2015	2017	2019
90 - 100	12%	20%	32%
80 - 89	27%	40%	33%
70 - 79	42%	24%	21%
< 70	19%	17%	15%

Mean: 82%
Median: 84%
Max: 100%

- Go over common mistakes today

Face detection and recognition

Detection

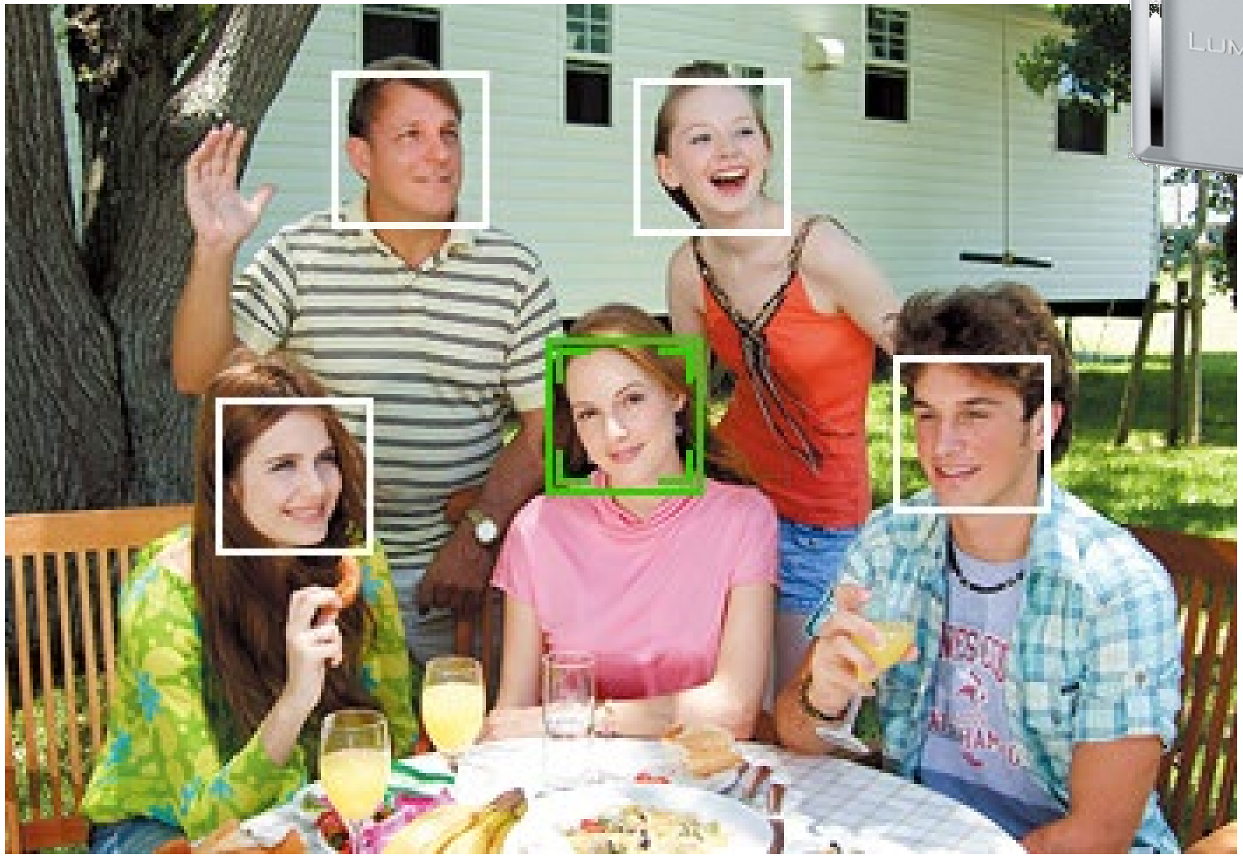


Recognition

“Sally”

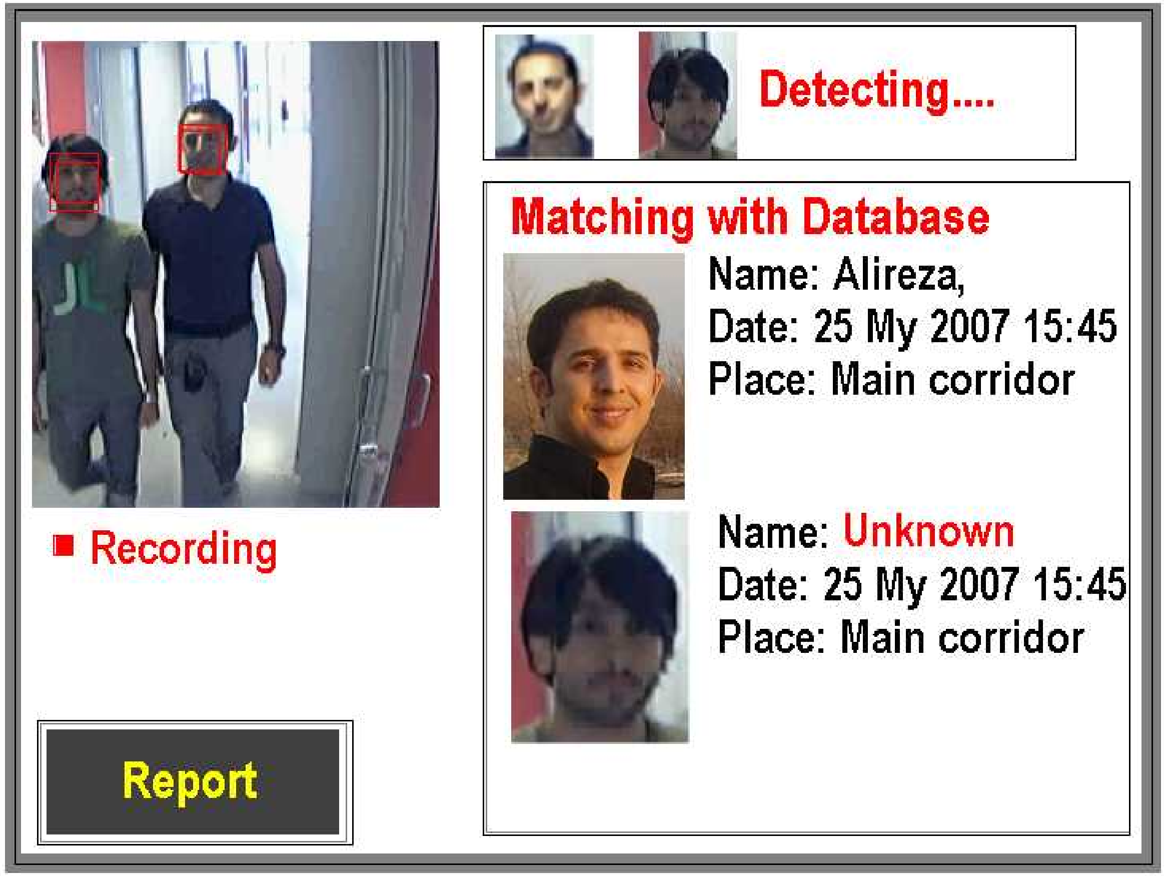
Applications of Face Recognition

- Digital photography



Applications of Face Recognition

- Digital photography
- Surveillance

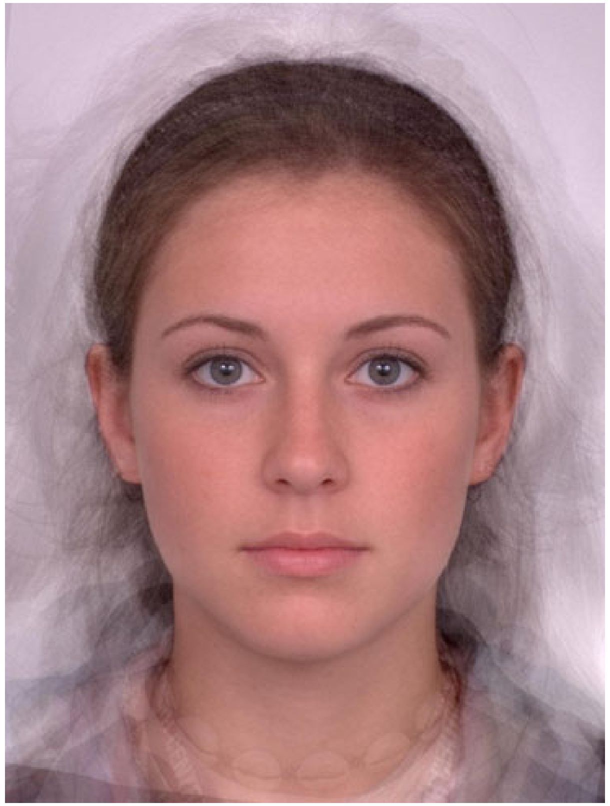


Applications of Face Recognition

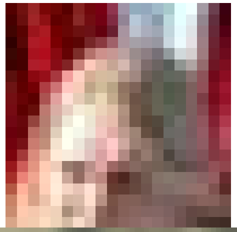
- Digital photography
- Surveillance
- Album organization

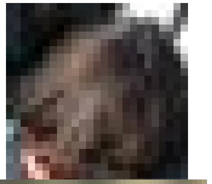
Face detection

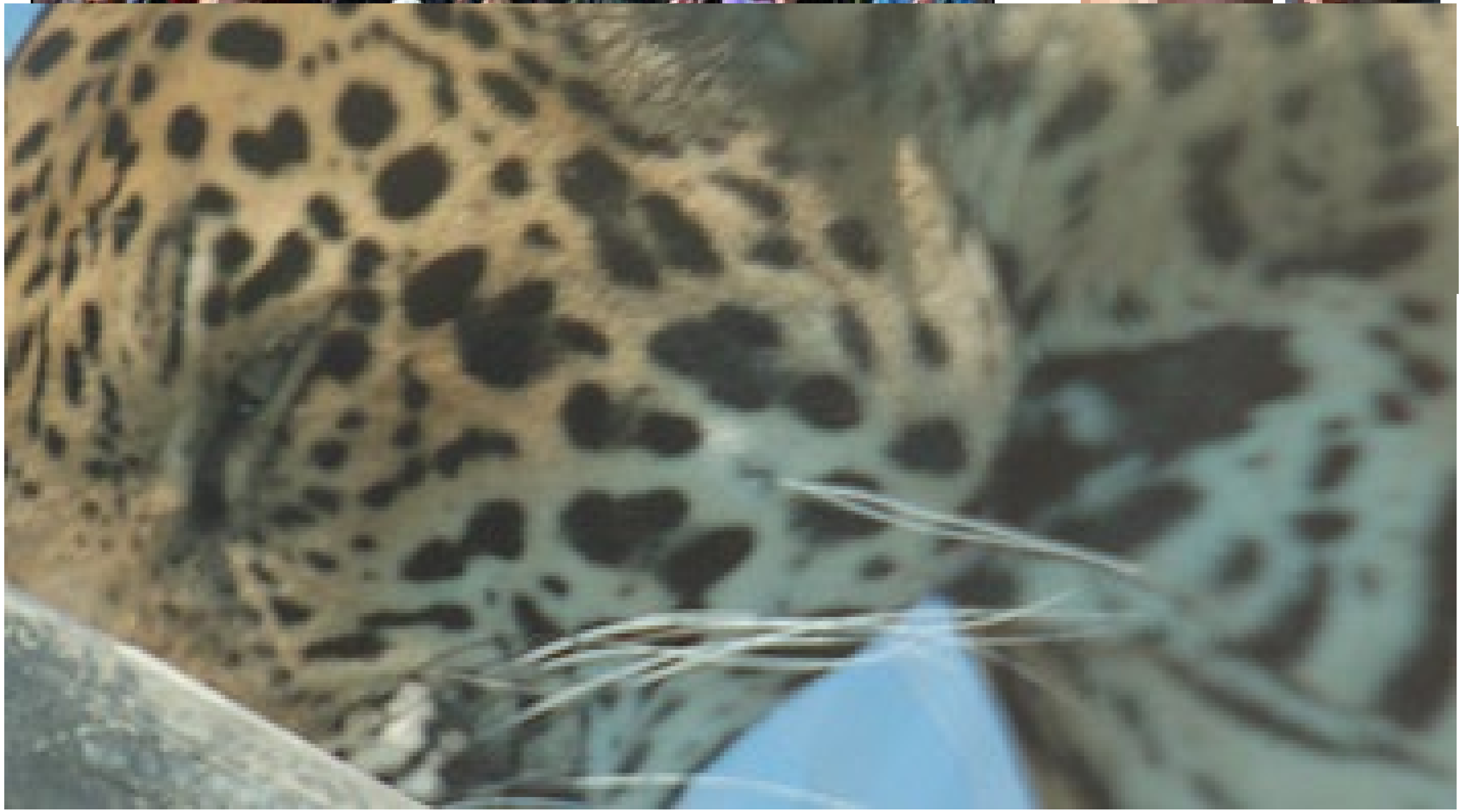
What does a face look like?



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

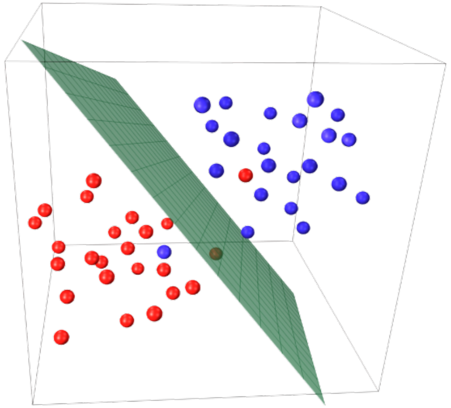
Consumer application: iPhoto 2009

- <u>Things iPhoto thinks are faces</u>

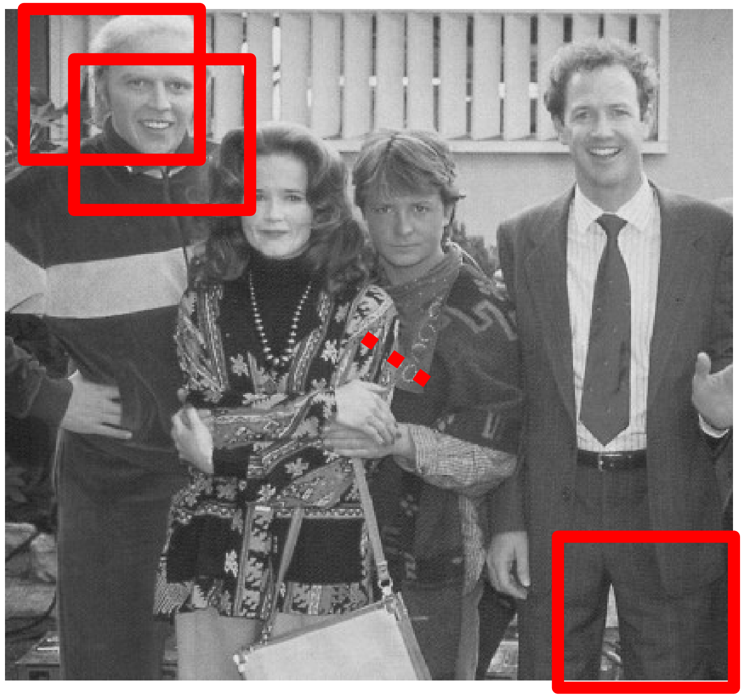
How to find faces anywhere in an image?

- Filter Image with a face?

Train a Filter



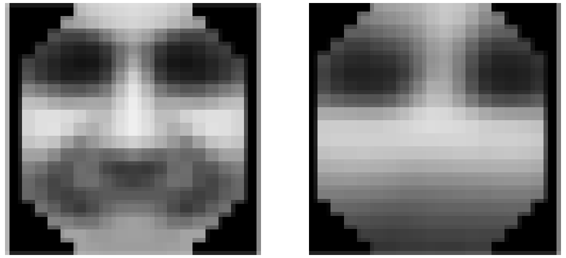
Face detection: sliding windows



Filter/Template

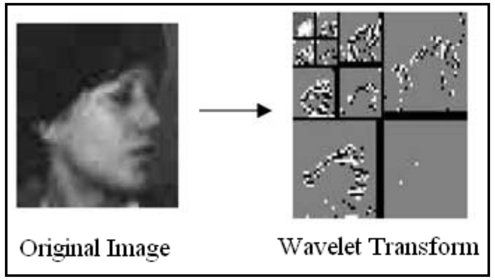
Multiple scales

What features?

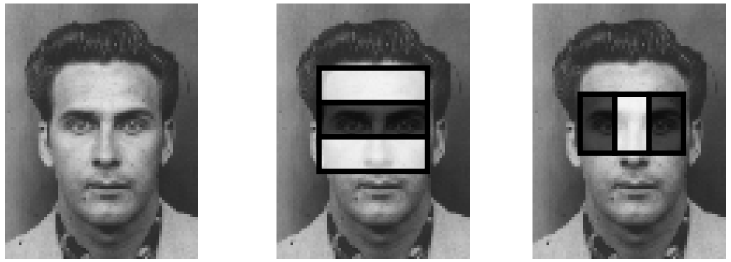


Exemplars
(Sung Poggio 1994)

Intensity Patterns (with NNs)
(Rowley Baluja Kanade 1996)



Edge (Wavelet) Pyramids
(Schneiderman Kanade 1998)

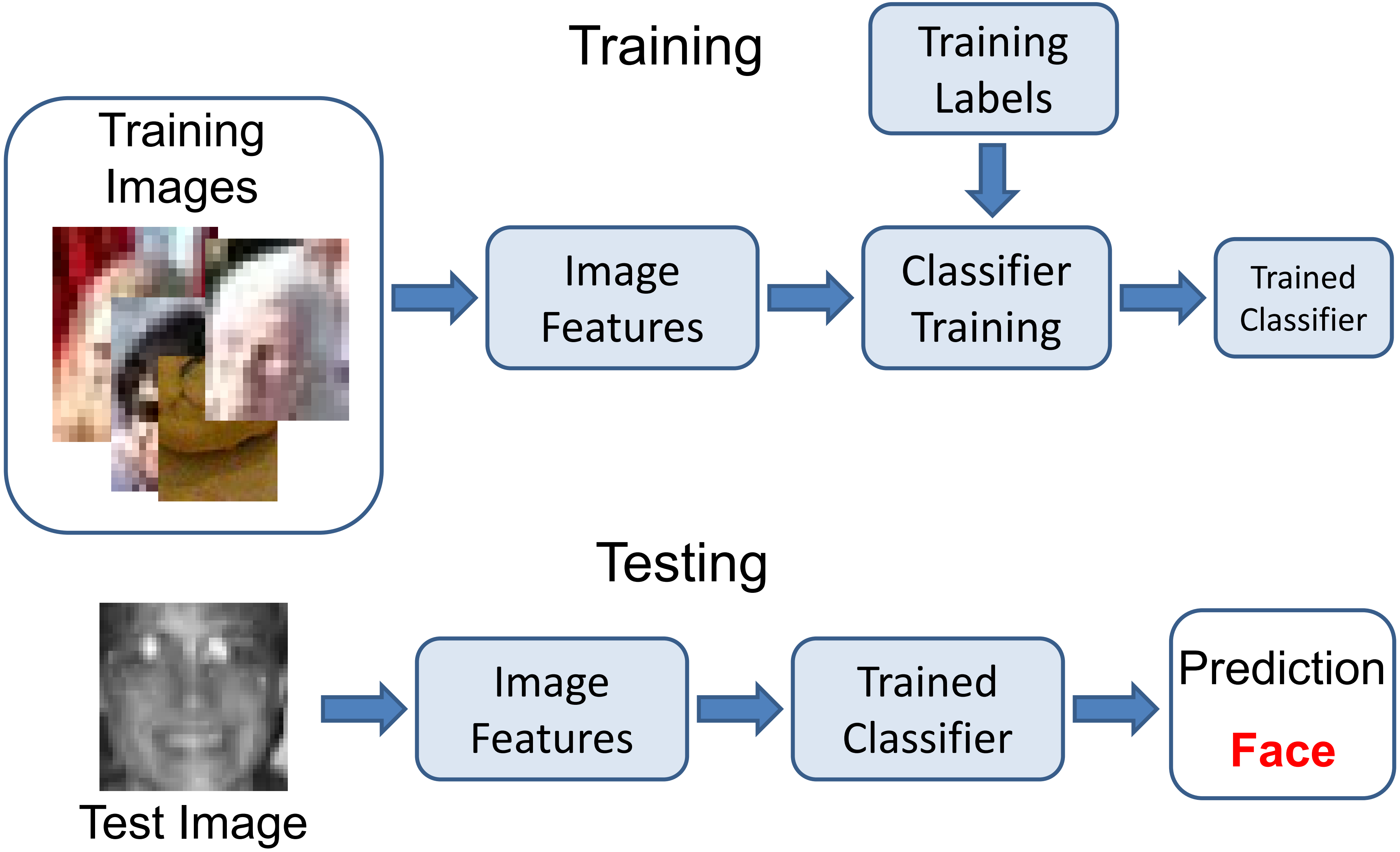


Haar Filters
(Viola Jones 2000)

How to classify?

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

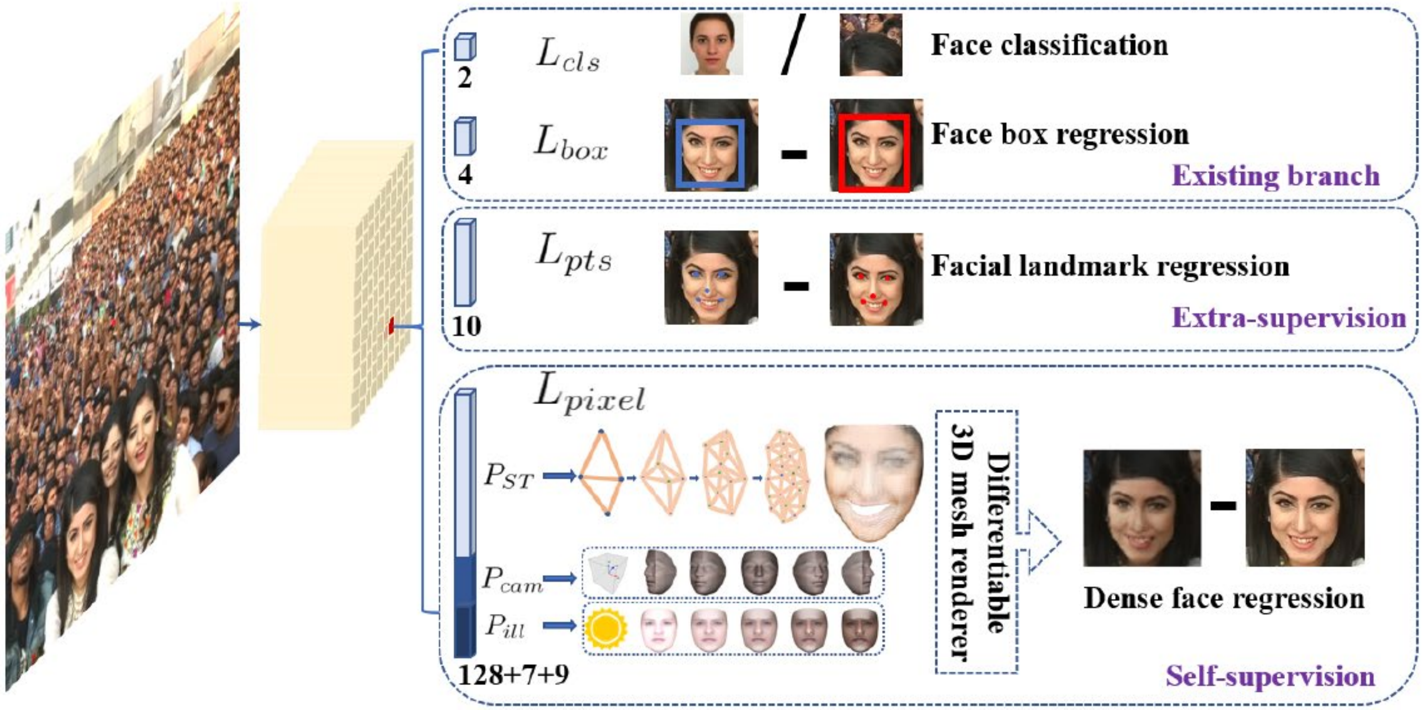
Face classifier



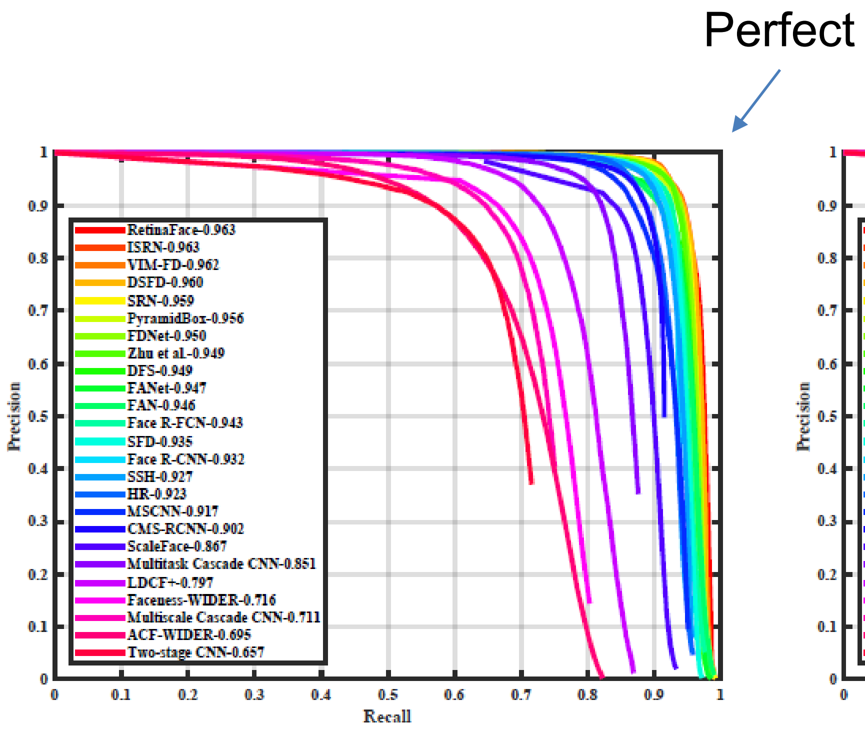
Face Detection: State of the Art

RetinaFace: Single-stage Dense Face Localisation in the Wild

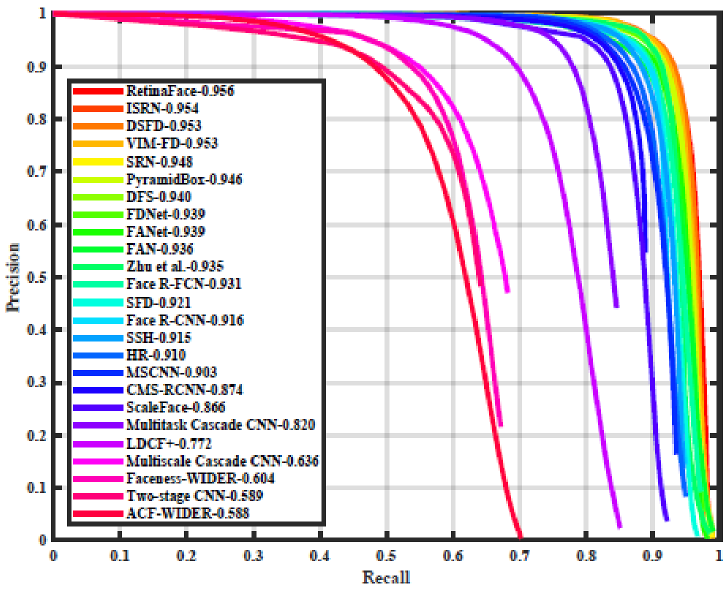
Jiankang Deng * [1,2,4] Jia Guo * [2] Yuxiang Zhou [1]
Jinke Yu [2] Irene Kotsia [3] Stefanos Zafeiriou [1,4]
[1]Imperial College London [2]InsightFace [3]Middlesex University London [4]FaceSoft



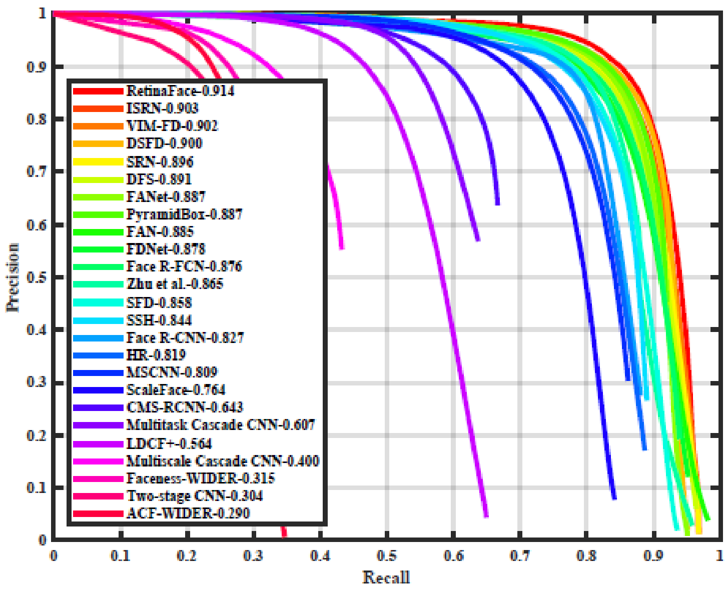
https://arxiv.org/pdf/1905.00641v2.pdf



(d) Test: Easy



(e) Test: Medium



(f) Test: Hard

RetinaFace can find around 900 faces (threshold at 0.5) out of the reported 1151 people

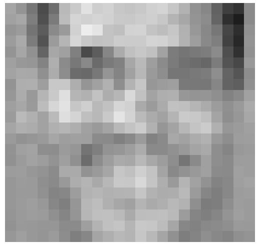
Face recognition

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 technique

1. Treat pixels as a vector



$\rightarrow \mathbf{x}$

2. Recognize face by nearest neighbor

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

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

State-of-the-art Face Recognizers

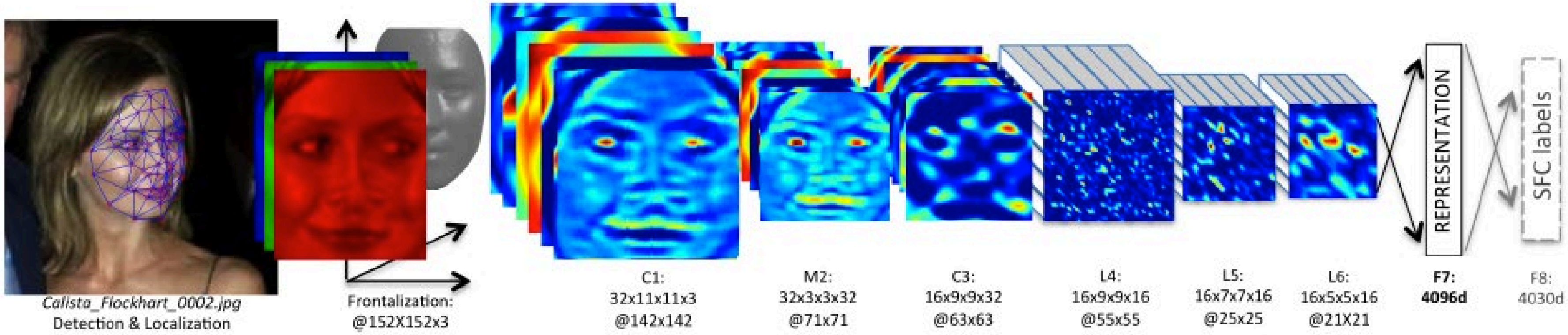
- Most recent research focuses on “faces in the wild”, recognizing faces in normal photos
  - Classification: assign identity to face
  - Verification: say whether two people are the same

- Important steps
  1. Detect
  2. Align
  3. Represent
  4. Classify

DeepFace: Closing the Gap to Human-Level Performance in Face Verification

Yaniv Taigman Ming Yang Marc'Aurelio Ranzato
Facebook AI Research
Menlo Park, CA, USA
{yaniv, mingyang, ranzato}@fb.com

Lior Wolf
Tel Aviv University
Tel Aviv, Israel
wolf@cs.tau.ac.il



<u>DeepFace: Closing the Gap to Human-Level Performance in Face Verification</u>

Taigman, Yang, Ranzato, & Wolf (Facebook, Tel Aviv), CVPR 2014

Following slides adapted from Daphne Tsatsoulis

Face Alignment

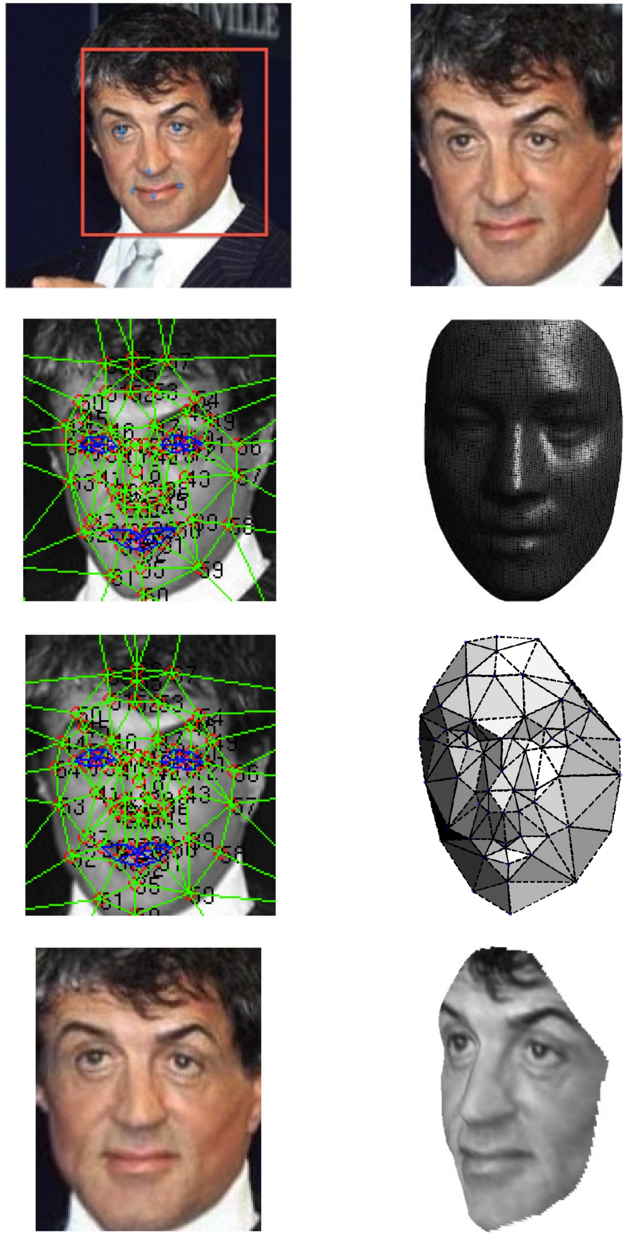
1. Detect a face and 6 fiducial markers using a support vector regressor (SVR)

2. Iteratively scale, rotate, and translate image until it aligns with a target face

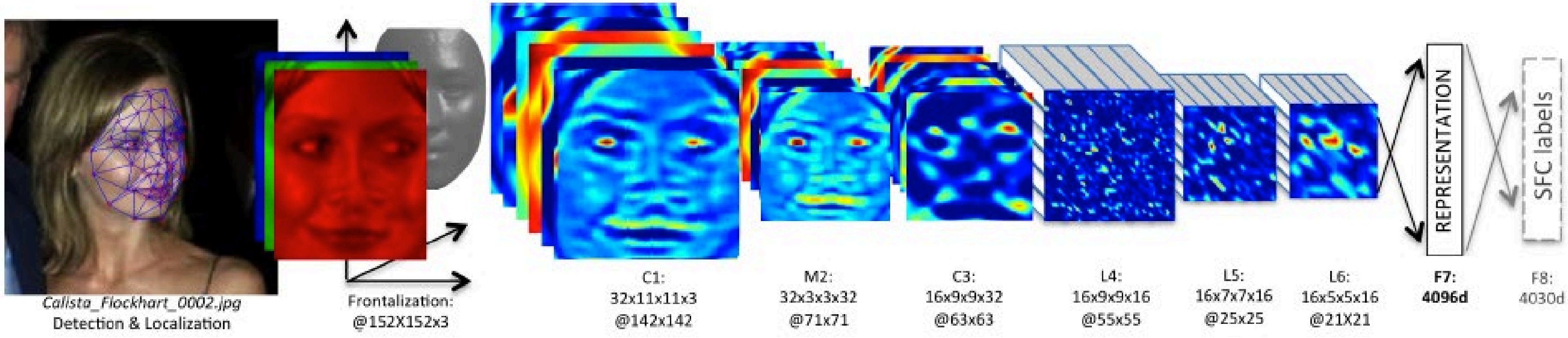
3. Localize 67 fiducial points in the 2D aligned crop

4. Create a generic 3D shape model by taking the average of 3D scans from the USF Human-ID database and manually annotate the 67 anchor points

5.Fit an affine 3D-to-2D projection and use it to frontally warp the face



Train DNN classifier on aligned faces



Architecture (deep neural network classifier)

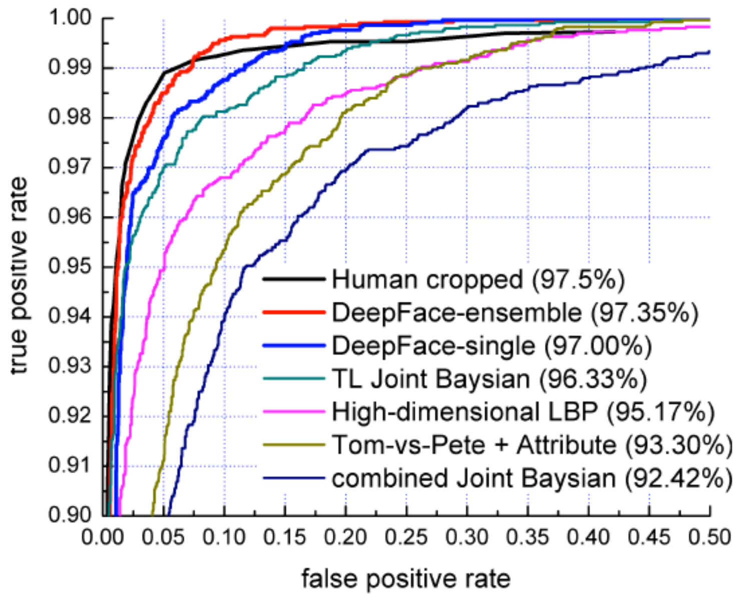
- Two convolutional layers (with one pooling layer)
- 3 locally connected and 2 fully connected layers
- > 120 million parameters

Train on dataset with 4400 individuals, ~1000 images each

- Train to identify face among set of possible people

Face matching (verification) is done by comparing features at last layer for two faces

Results: Labeled Faces in the Wild Dataset



Method	Accuracy ± SE	Protocol
Joint Bayesian [6]	0.9242 ±0.0108	restricted
Tom-vs-Pete [4]	0.9330 ±0.0128	restricted
High-dim LBP [7]	0.9517 ±0.0113	restricted
TL Joint Bayesian [5]	0.9633 ±0.0108	restricted
DeepFace-single	**0.9592** ±0.0029	unsupervised
DeepFace-single	**0.9700** ±0.0028	restricted
DeepFace-ensemble	**0.9715** ±0.0027	restricted
DeepFace-ensemble	**0.9735** ±0.0025	unrestricted
Human, cropped	0.9753	

Performs similarly to humans!

(note: humans would do better with uncropped faces)

Experiments show that alignment is crucial (0.97 vs 0.88) and that deep features help (0.97 vs. 0.91)

Transforming faces

Figure-centric averages

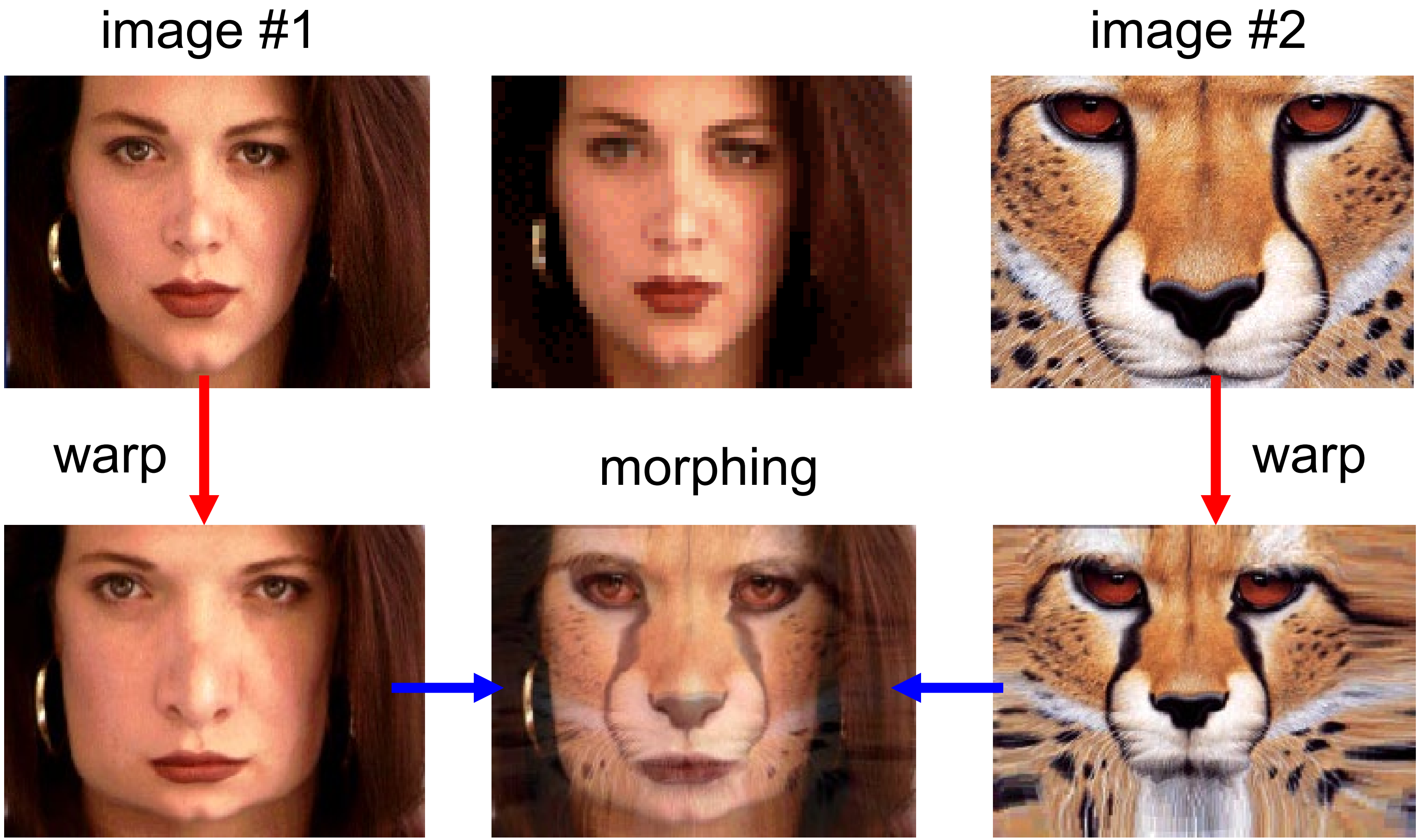
- Need to Align
  - Position
  - Scale
  - Orientation

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.

How do we average faces?

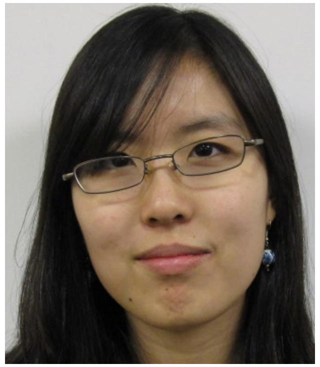
http://www2.imm.dtu.dk/~aam/datasets/datasets.html

Morphing



Cross-Dissolve vs. Morphing

Average of
Appearance Vectors



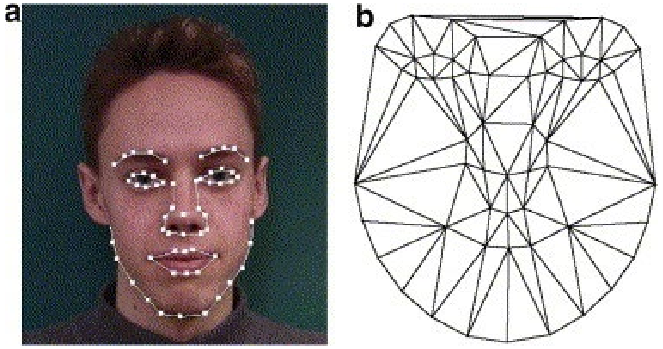
Average of
Shape Vectors

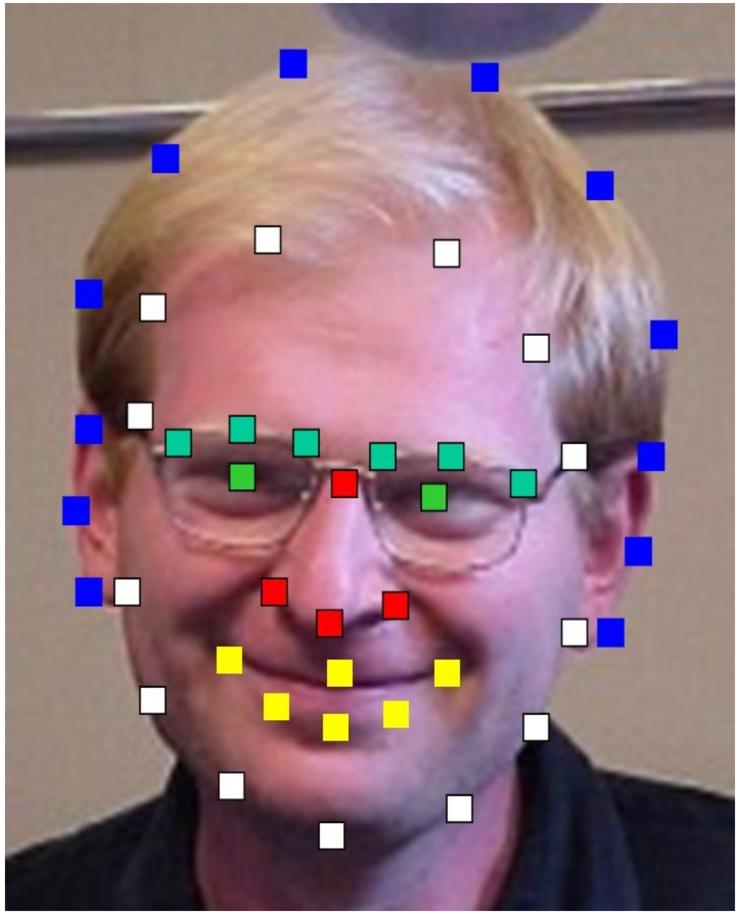
http://www.faceresearch.org/demos/vector

Images from James Hays

Aligning Faces

- Need to Align
  - Position
  - Scale
  - Orientation
  - Key-points
- The more key-points, the finer alignment





Images from Alyosha Efros

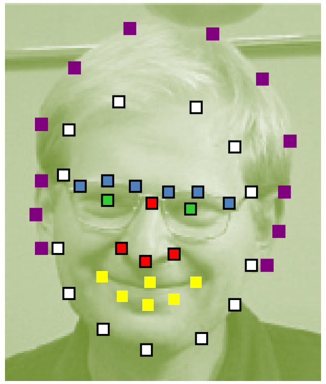
Appearance Vectors vs. Shape Vectors

Appearance Vector

200*150 pixels (RGB)

Vector of 200*150*3 Dimensions

Shape Vector

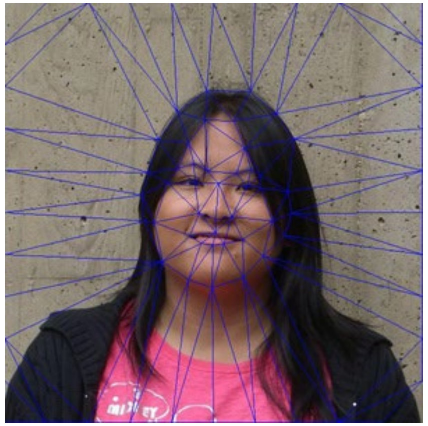


43 coordinates (x,y)

Vector of 43*2 Dimensions

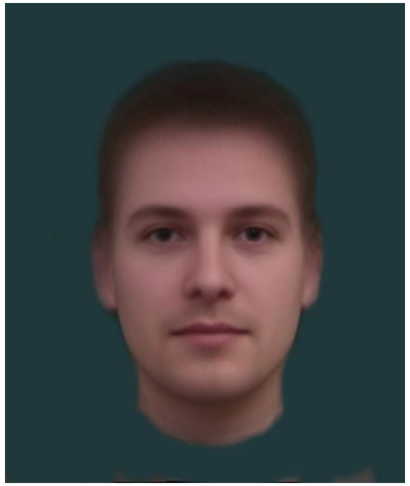
Average of two Faces

1. Input face keypoints
2. Pairwise average keypoint coordinates
3. Triangulate the faces
4. Warp: transform every face triangle
5. Average the pixels

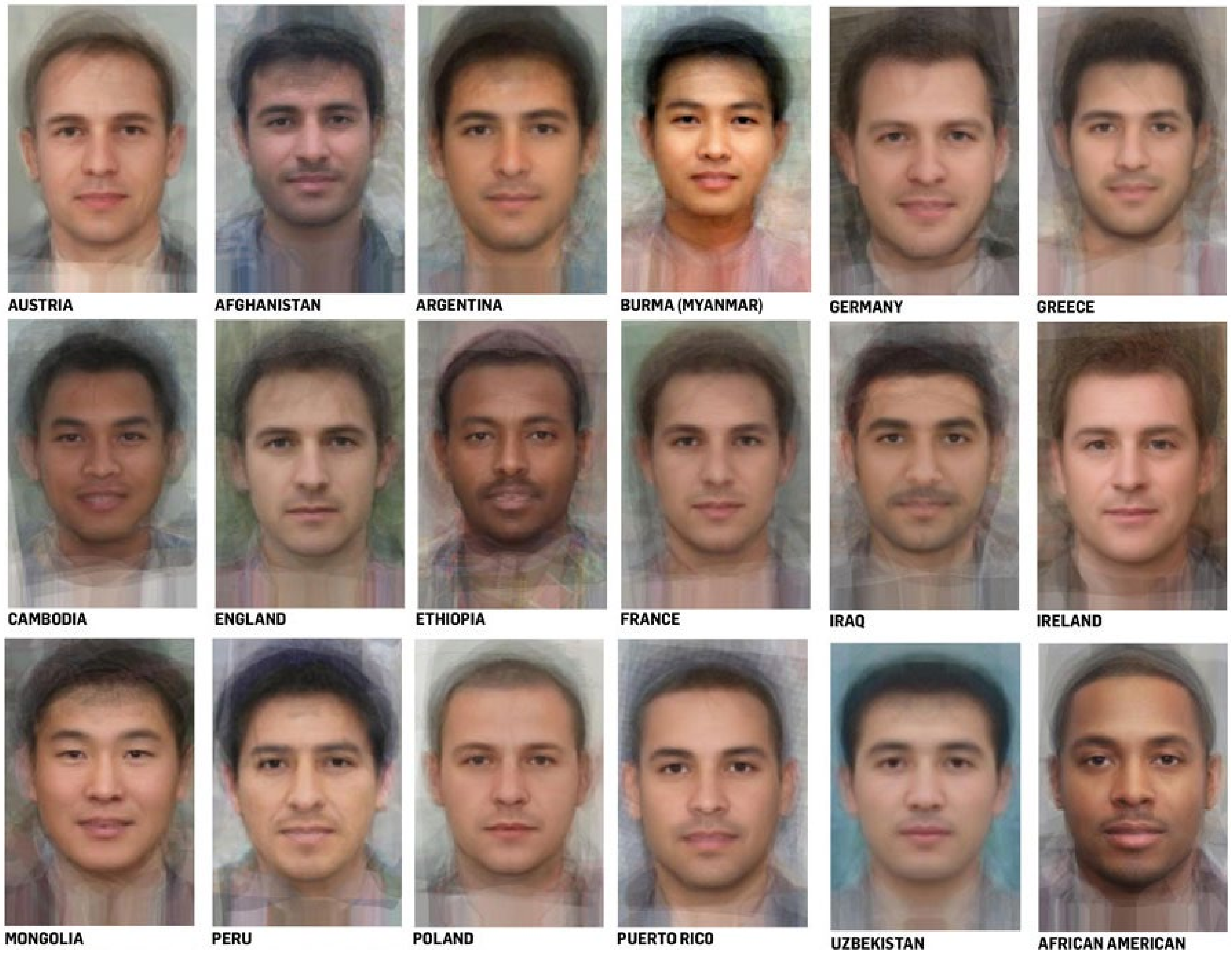

Average of multiple faces

1. Warp to mean shape
2. Average pixels

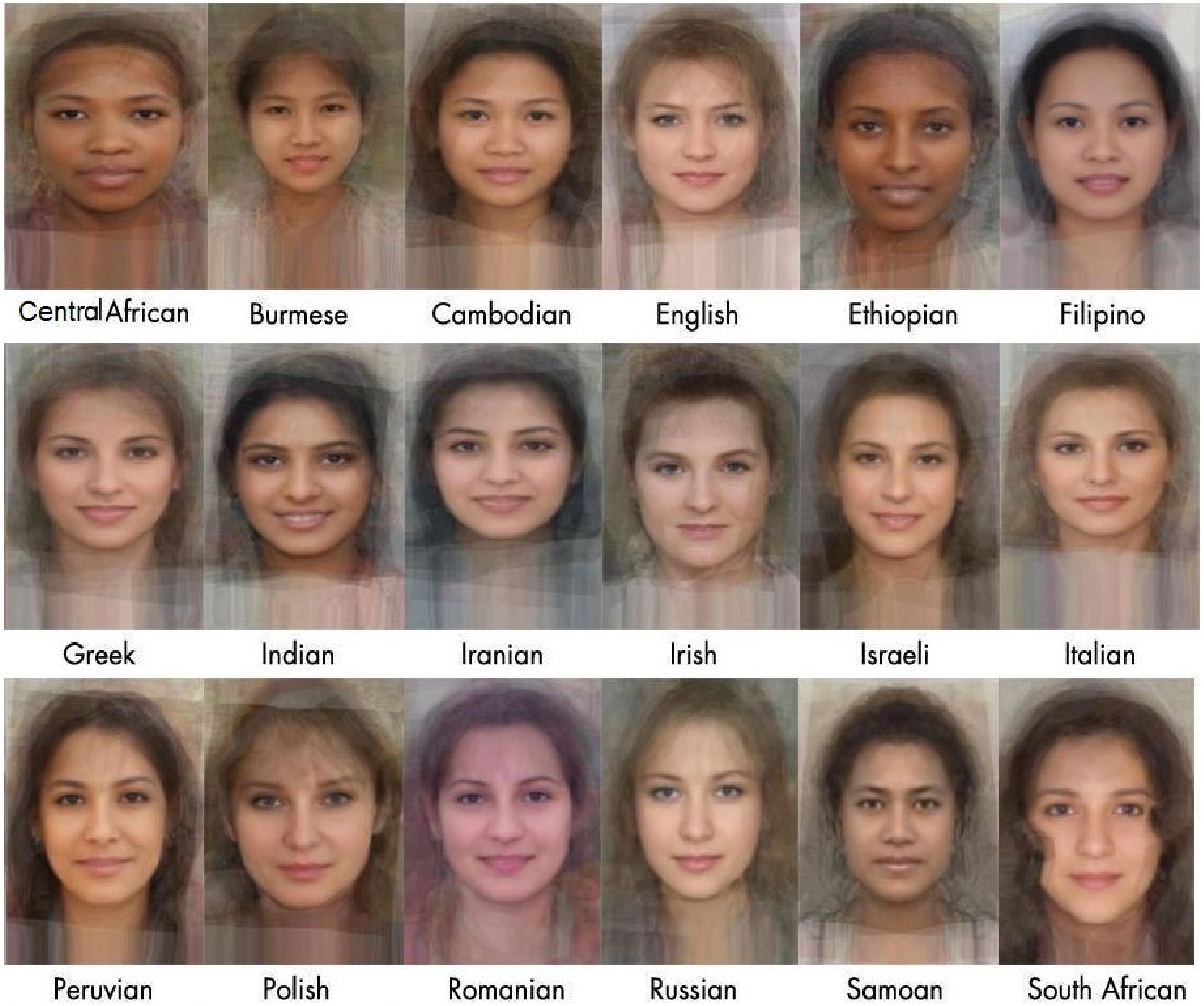


http://graphics.cs.cmu.edu/courses/15-463/2004_fall/www/handins/brh/final/

Average Men of the world



Average Women of the world



Subpopulation means

Other Examples:

- Average Kids
- Happy Males
- Etc.

Average female

Average kid

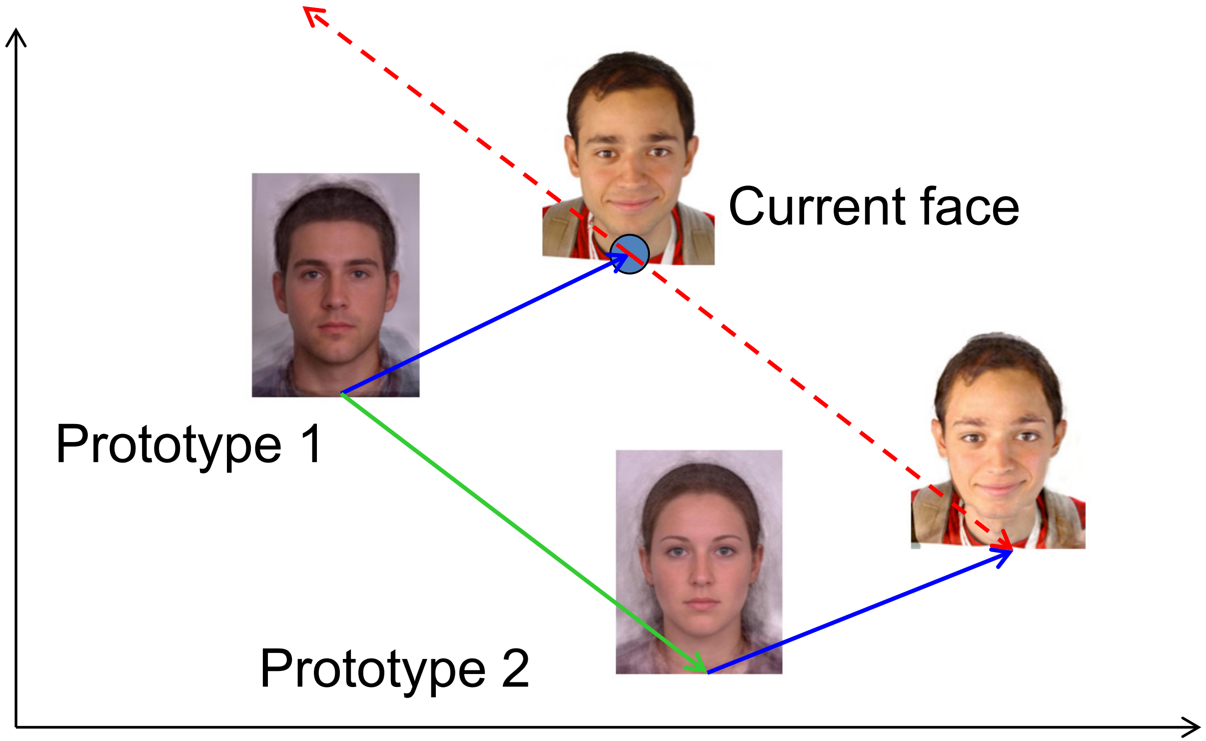
Average happy male

Average male

Manipulating faces

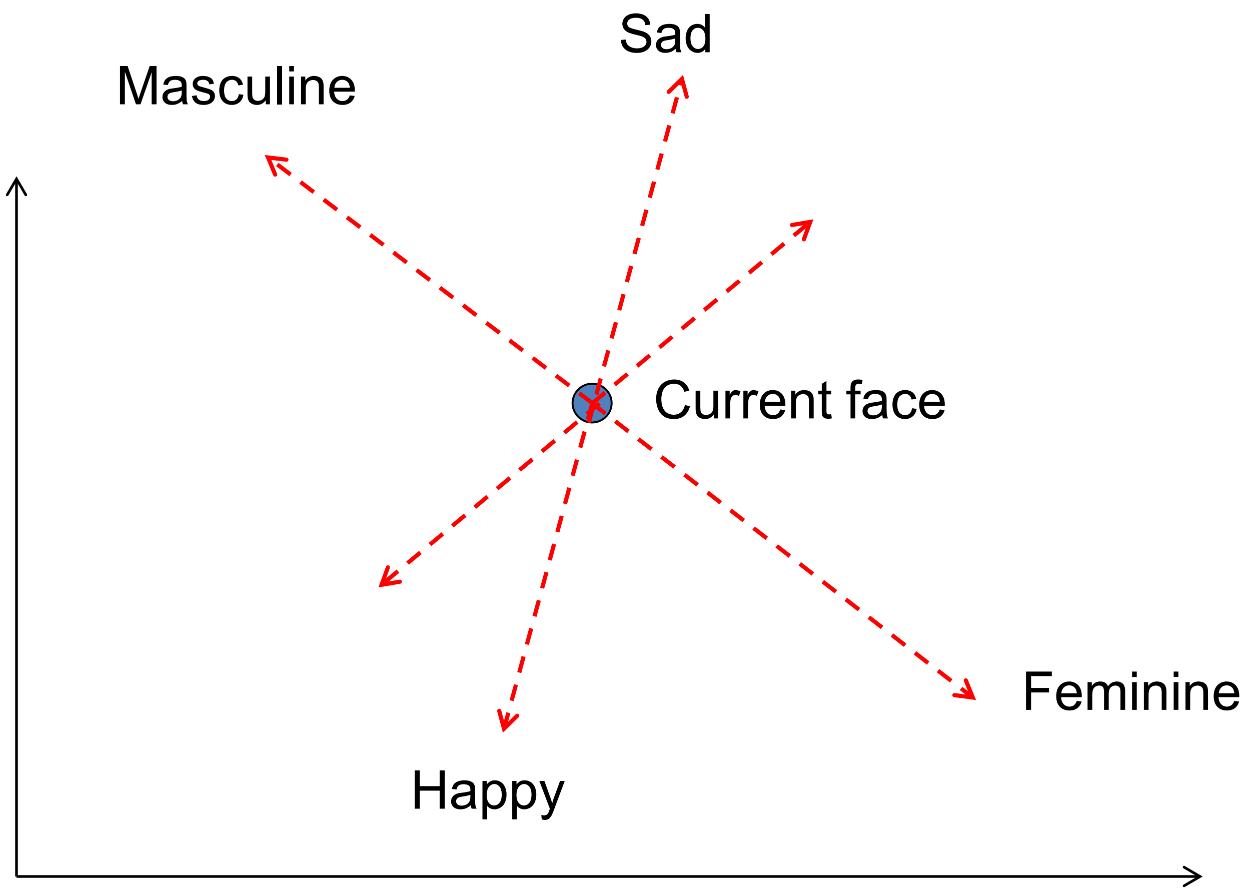
How can we make a face look more female/male, young/old, happy/sad, etc.?

With shape/texture analogies!



Manipulating faces

We can imagine various meaningful directions



Averaging and transformation demos

http://www.faceresearch.org/demos

State-of-the-art in Face Fakery

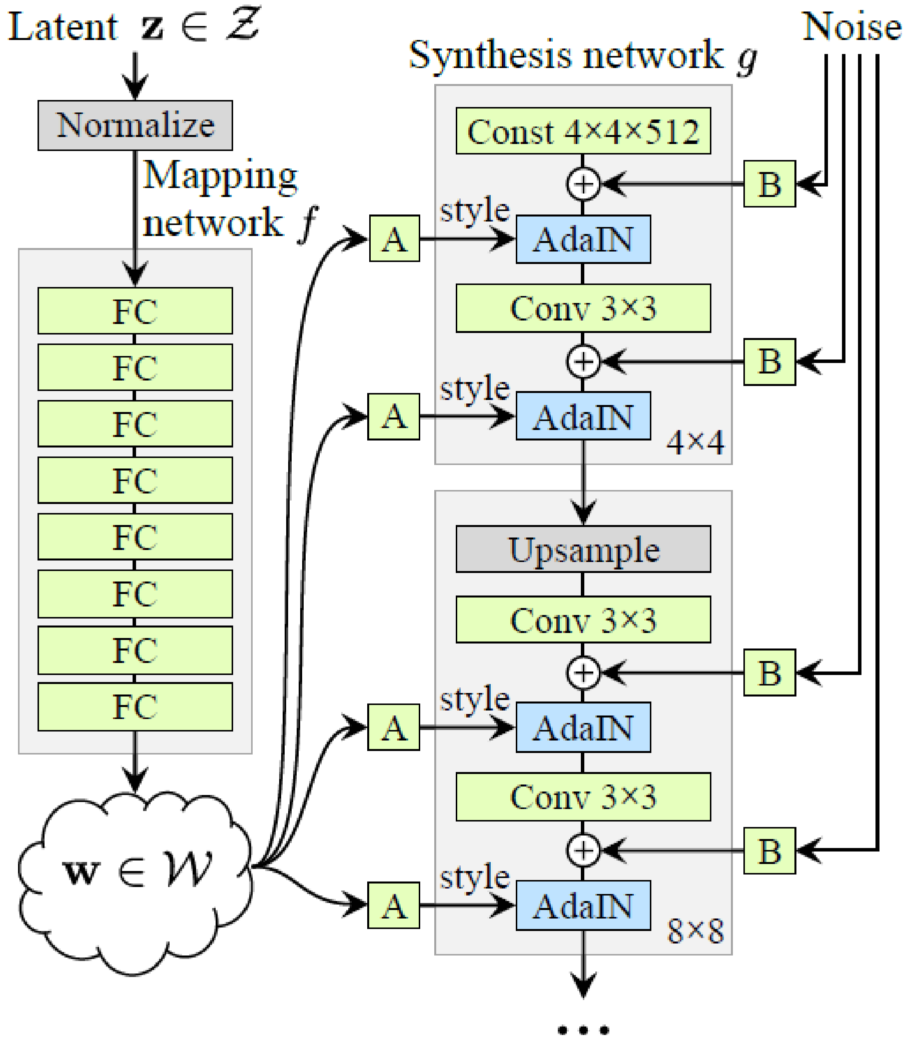
A Style-Based Generator Architecture for Generative Adversarial Networks

Tero Karras
NVIDIA
tkarras@nvidia.com

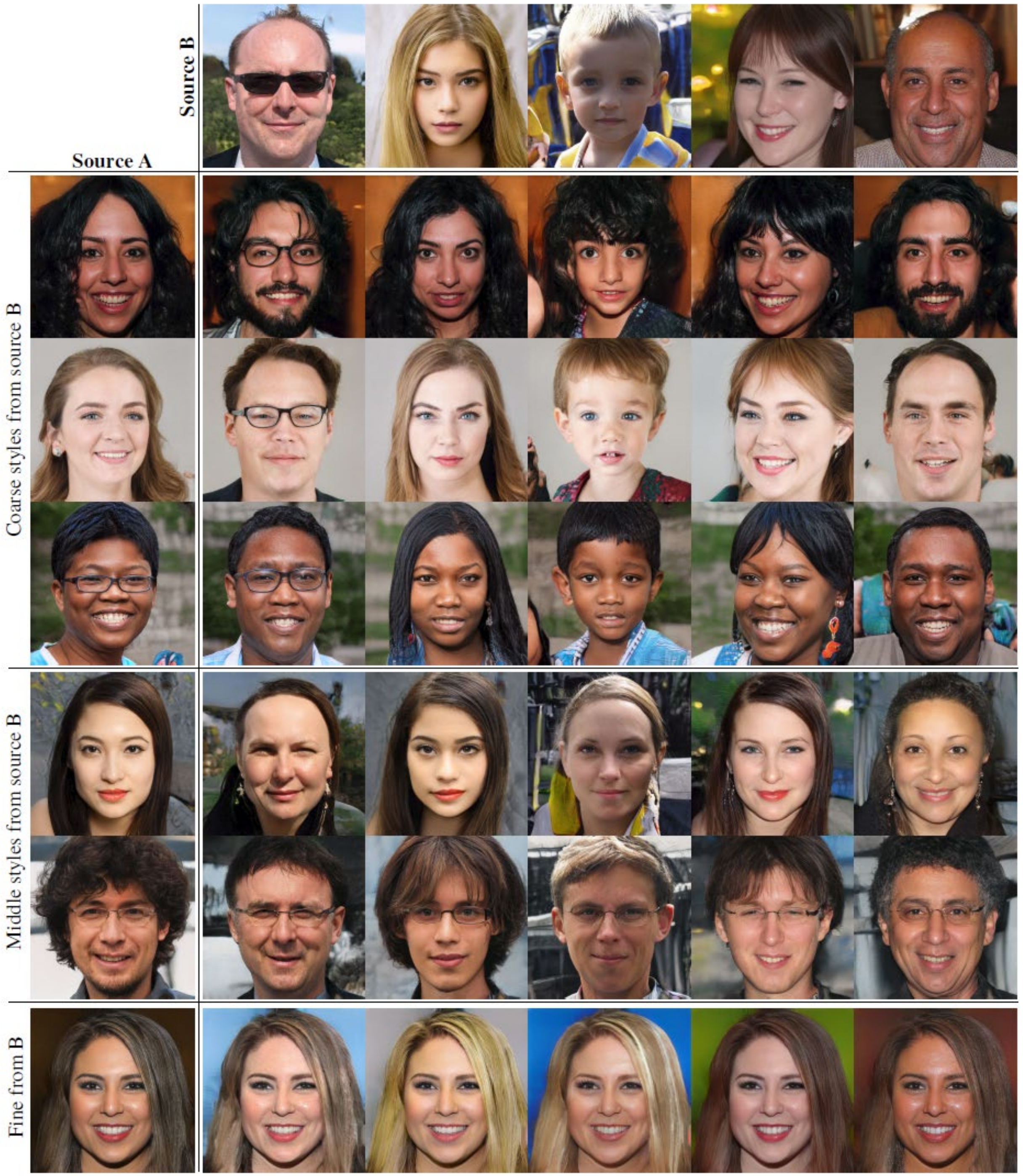
Samuli Laine
NVIDIA
slaine@nvidia.com

Timo Aila
NVIDIA
taila@nvidia.com

CVPR 2019 (Best Paper Honorable Mention)



1024x1024



4x4 - 8x8

16x16 - 32x32

64x64 - 1024x1024

Making people say what you want

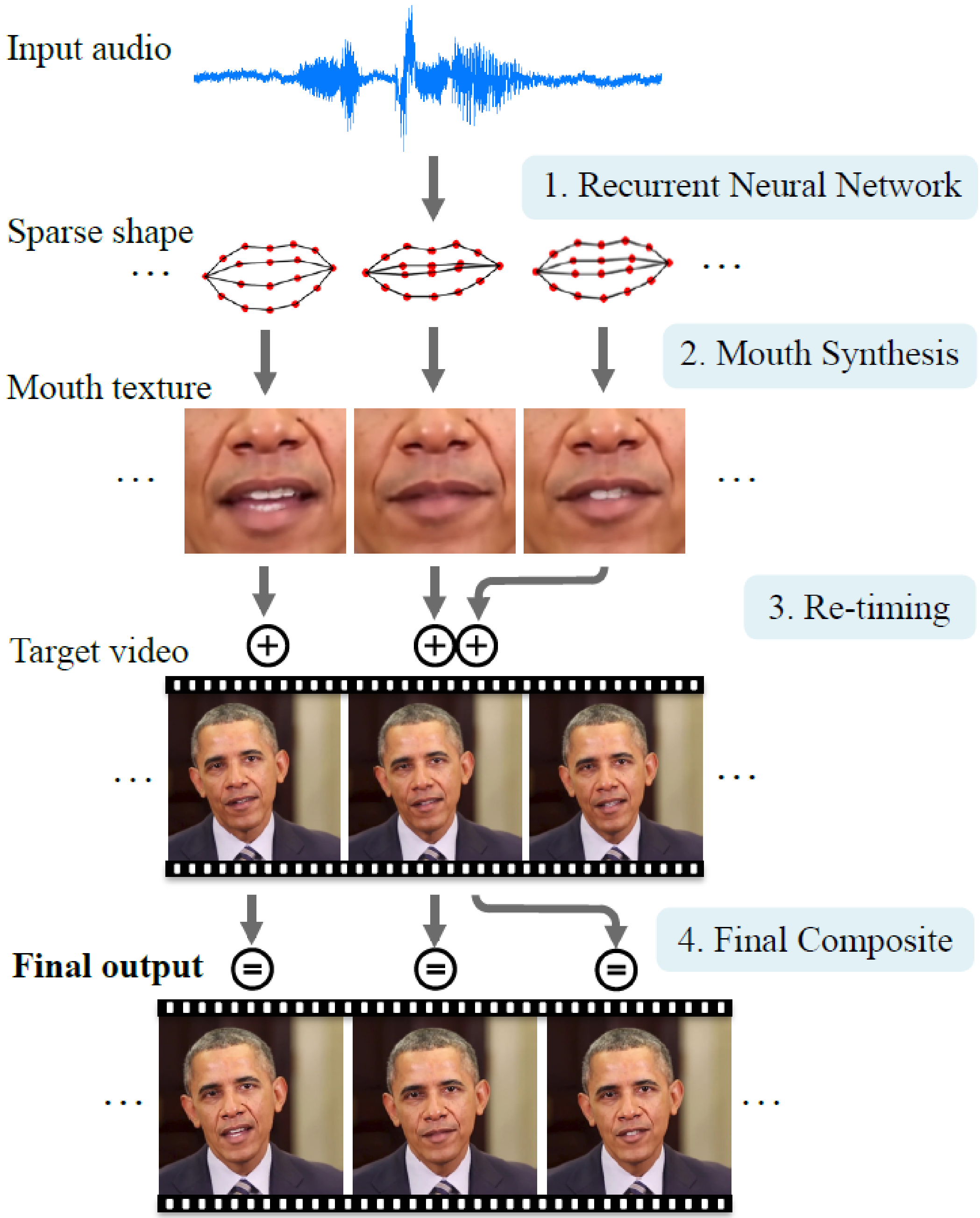
Synthesizing Obama: Learning Lip Sync from Audio

SUPASORN SUWAJANAKORN, STEVEN M. SEITZ, and IRA KEMELMACHER-SHLIZERMAN, University of Washington

Output Obama Video

Fig. 1. Given input Obama audio and a reference video, we synthesize photorealistic, lip-synced video of Obama speaking those words.

SIGGRAPH 2017

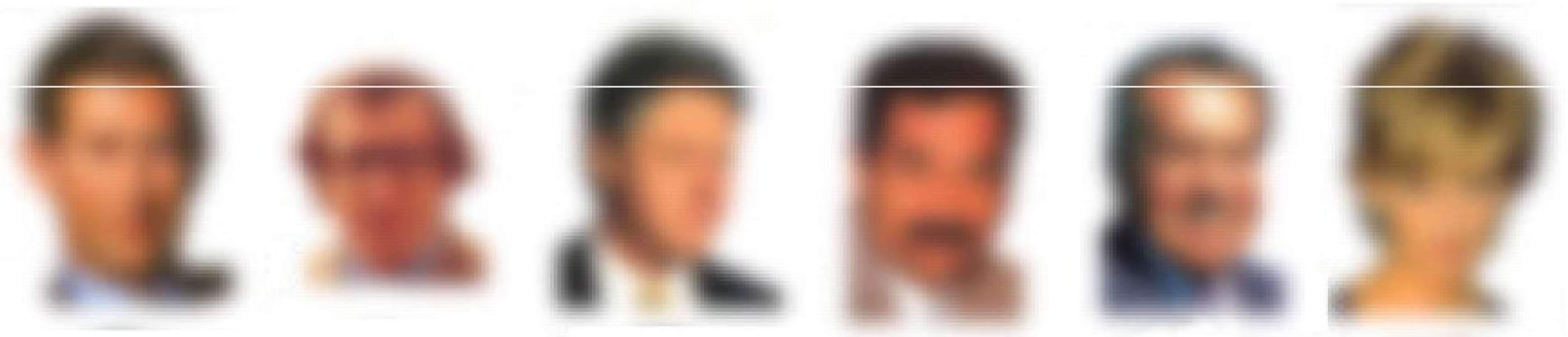


Input audio
1. Recurrent Neural Network
Sparse shape
2. Mouth Synthesis
Mouth texture
3. Re-timing
Target video
4. Final Composite
Final output

Human Perception

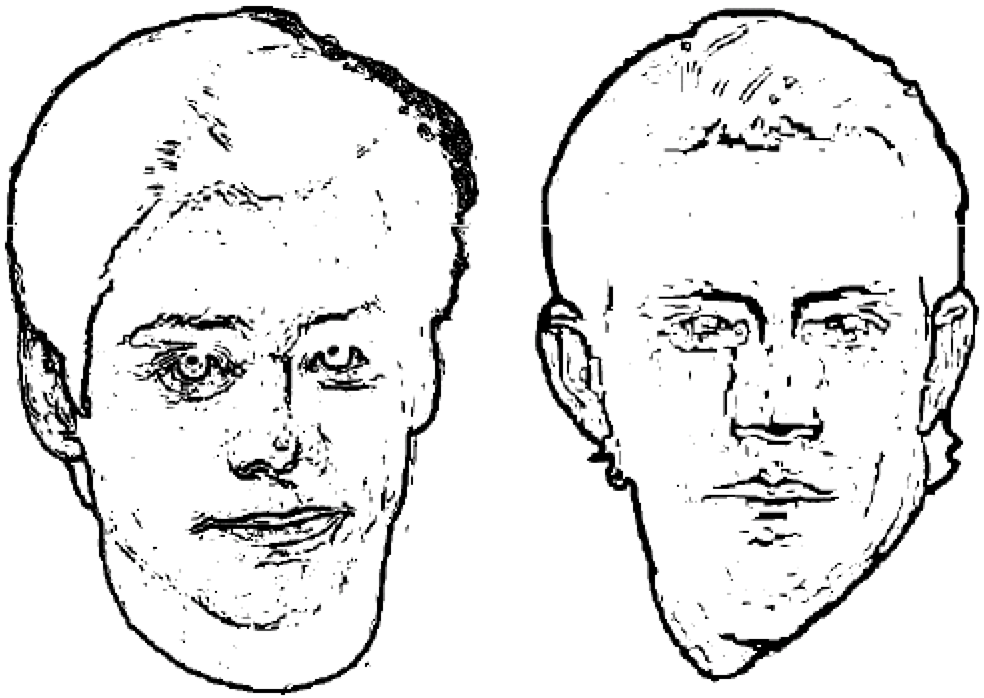
Result 1

- Humans can recognize faces in extremely low resolution images.



Result 3

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

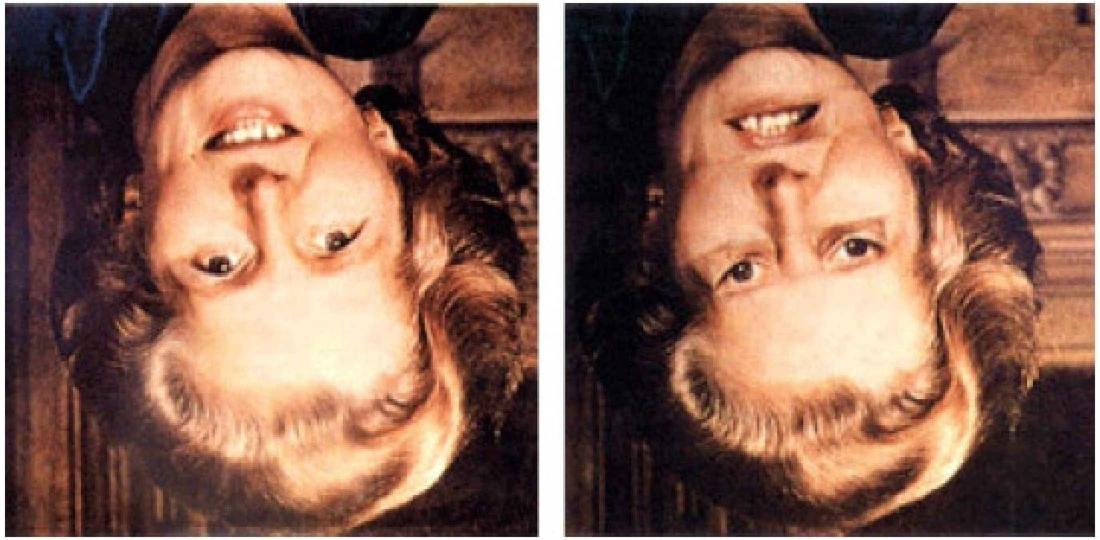


Result 5

- Eyebrows are among the most important for recognition

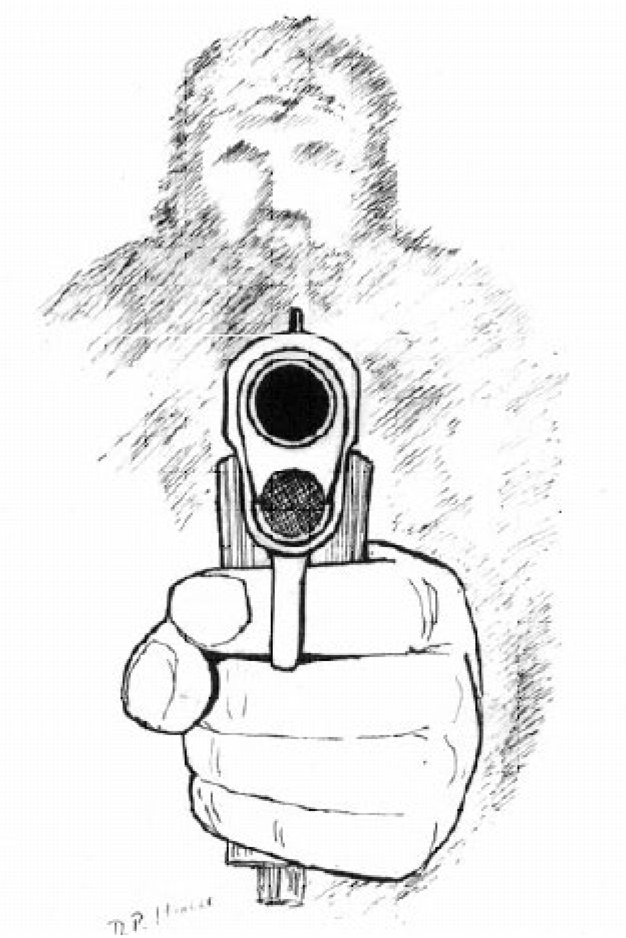
Result 8

- Vertical inversion dramatically reduces recognition performance



Result 20

- Human memory for briefly seen faces is rather poor



Things to remember

- Face Detection: train face vs. non-face model and scan over multi-scale image
- Face Recognition: detect, align, compute features, and compute similarity
- Represent faces with an appearance vector and a shape vector
- Can transform faces by moving shape vector in a given direction and warping
- Deep network methods enable more flexible mixing and generation

Next lectures

- Motion magnification

- Cutting edge and ICES forms

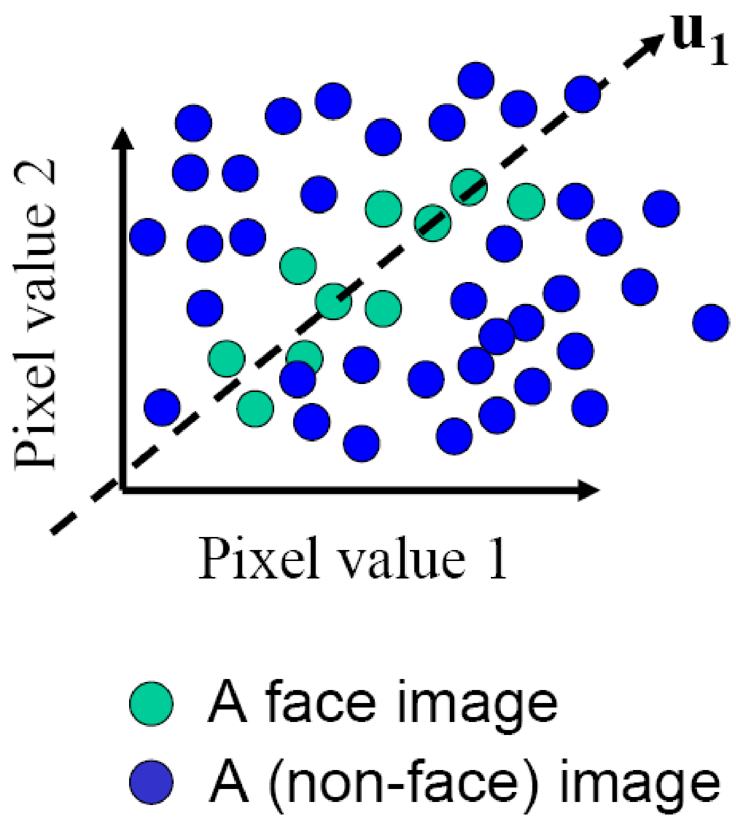
Old slides

How to represent variations?

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

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

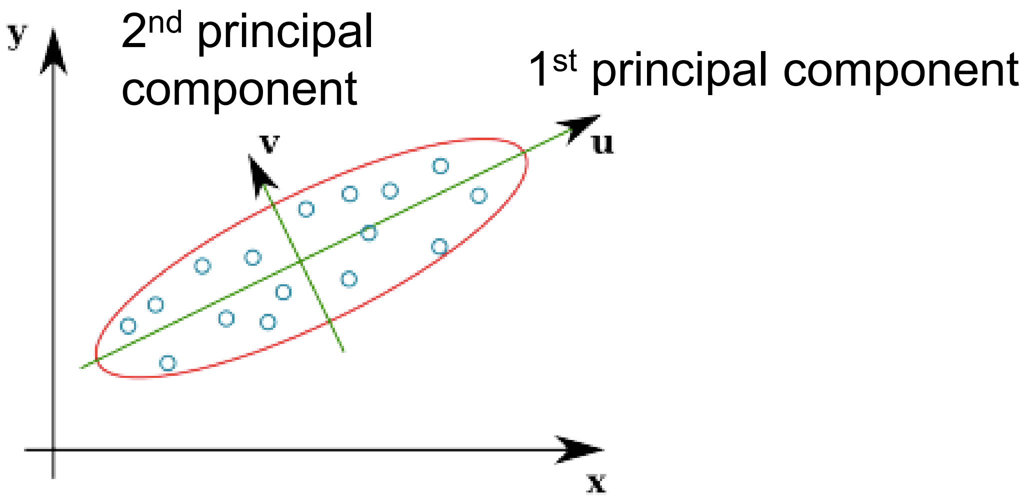


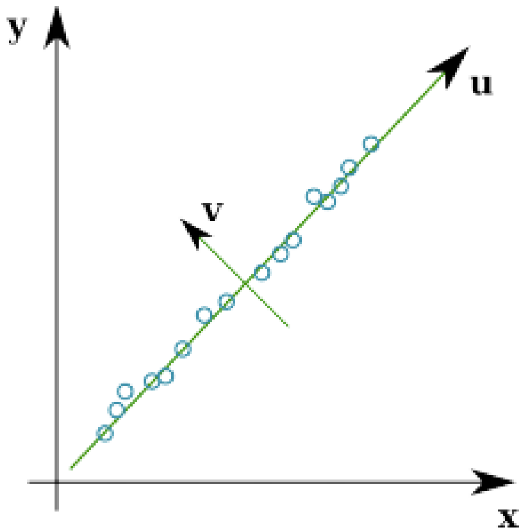
PCA

- General dimensionality reduction technique
  - Finds major directions of variation
- Preserves most of variance with a much more compact representation
  - Lower storage requirements (eigenvectors + a few numbers per face)
  - Faster matching/retrieval

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
  - The most variation is in the first basis vector
  - The second most, in the second vector that is orthogonal to the first vector
  - The third…





Principal Component Analysis (PCA)

- Given: N data points $\mathbf{x_1}, \ldots, \mathbf{x_N}$ in R^d

- We want to find a new set of features that are linear combinations of original ones:

$$u(\mathbf{x}_i) = \mathbf{u}^T(\mathbf{x}_i - \boldsymbol{\mu})$$

(**μ**: mean of data points)

- Choose unit vector **u** in R^d that captures the most data variance

Forsyth & Ponce, Sec. 22.3.1, 22.3.2

Principal Component Analysis

- Direction that maximizes the variance of the projected data:

Maximize $$\frac{1}{N}\sum_{i=1}^{N} \underbrace{\mathbf{u}^{\mathrm{T}}(\mathbf{x}_i - \mu)}_{\text{Projection of data point}}(\mathbf{u}^{\mathrm{T}}(\mathbf{x}_i - \mu))^{\mathrm{T}}$$ subject to ||**u**||=1

$$= \mathbf{u}^{\mathrm{T}} \underbrace{\left[1/N \sum_{i=1}^{N} (\mathbf{x}_i - \mu)(\mathbf{x}_i - \mu)^{\mathrm{T}} \right]}_{\text{Covariance matrix of data}} \mathbf{u}$$

$$= \mathbf{u}^{\mathrm{T}} \Sigma \mathbf{u}$$

The direction that maximizes the variance is the eigenvector associated with the largest eigenvalue of Σ (can be derived using Raleigh's quotient or Lagrange multiplier)

PCA in MATLAB

```
x=rand(3,10);%10 3D examples

mu=mean(x,2);
x_norm = x-repmat(mu,[1 n]);
x_covariance = x_norm*x_norm';
[U, E] = eig(x_covariance)
```

```
U =
     0.74 0.07 -0.66
     0.65 0.10  0.74
    -0.12 0.99 -0.02
```

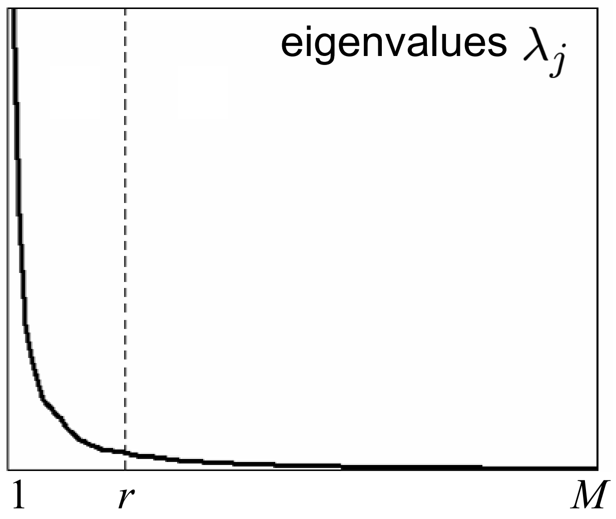
```
E =
     0.27    0    0
        0 0.63    0
        0    0 0.94
```

Principal Component Analysis

First $r < M$ basis vectors provide an approximate basis that minimizes the mean-squared-error (MSE) of reconstructing the original points

Choosing subspace dimension r:

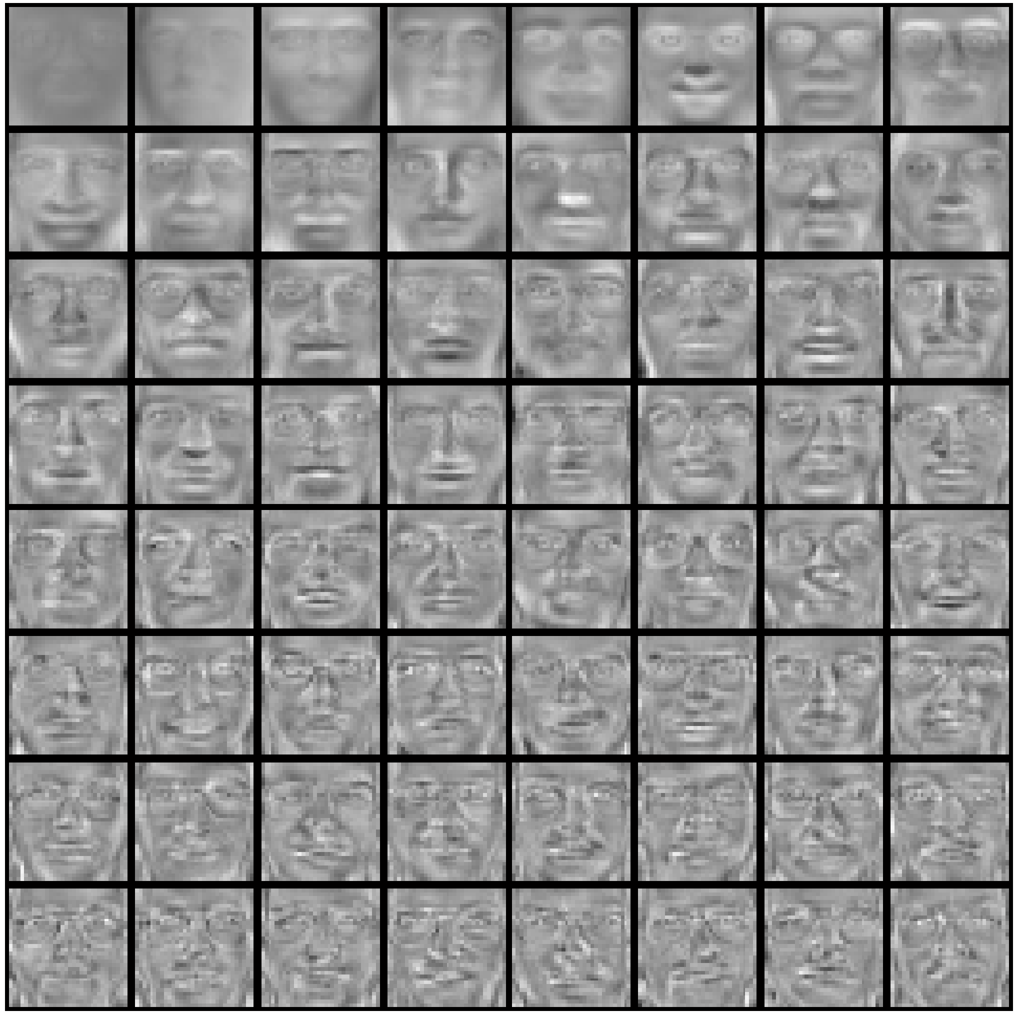
- look at decay of the eigenvalues as a function of r
- Larger r means lower expected error in the subspace data approximation



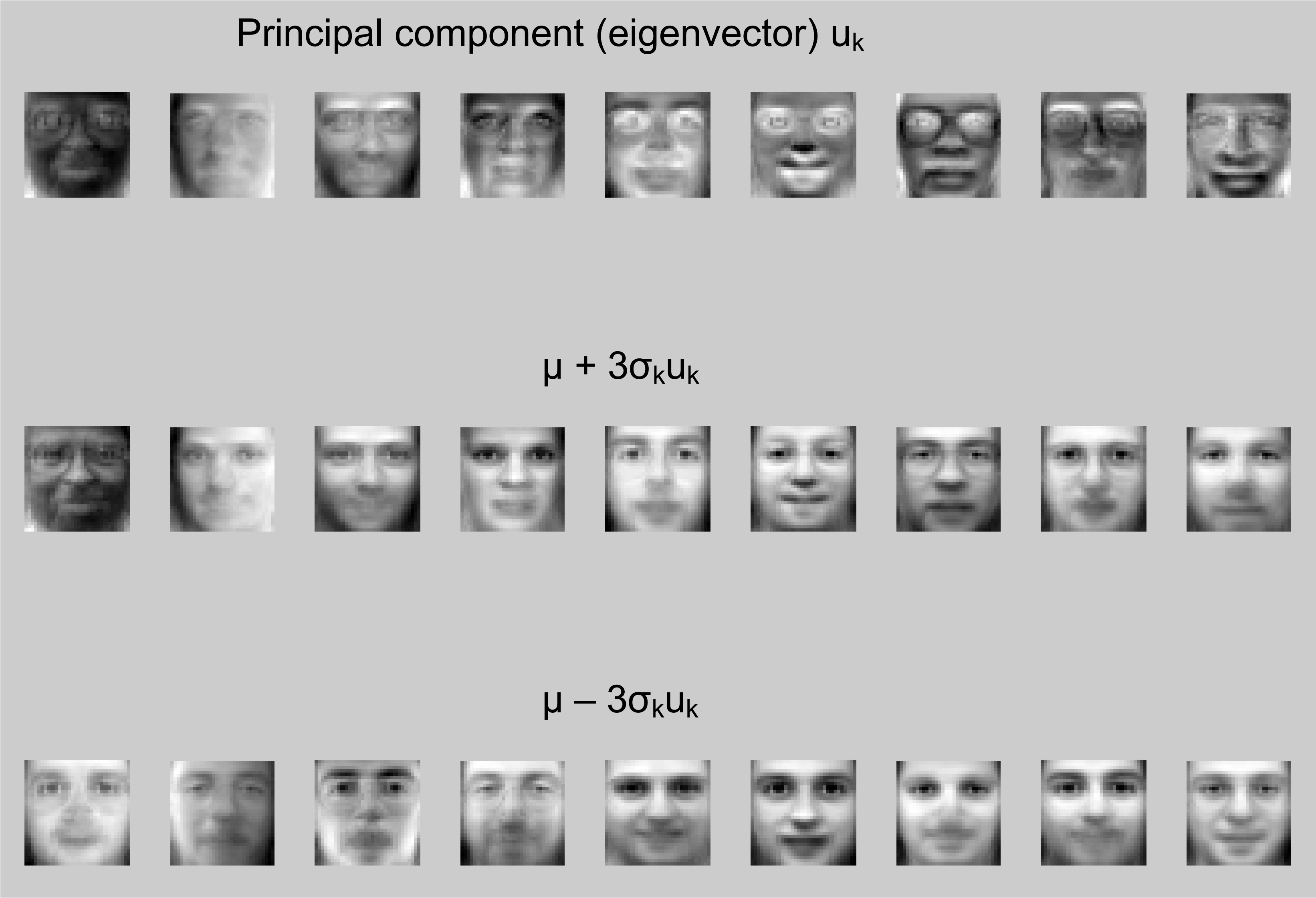
Eigenfaces example (PCA of face images)

Mean: μ

Top eigenvectors: $u_1, \ldots u_k$



Visualization of eigenfaces (appearance variation)

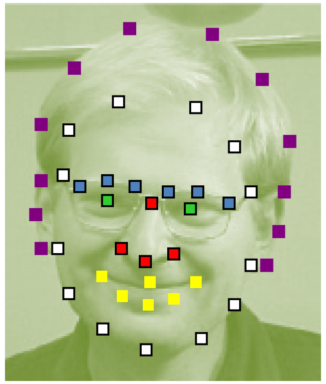


Can represent face in appearance or shape space

Appearance
Vector

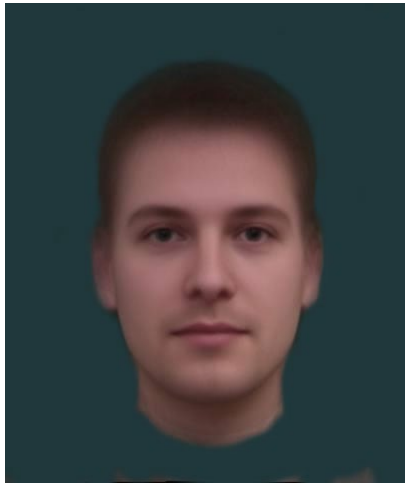
200*150 pixels (RGB)

Shape
Vector

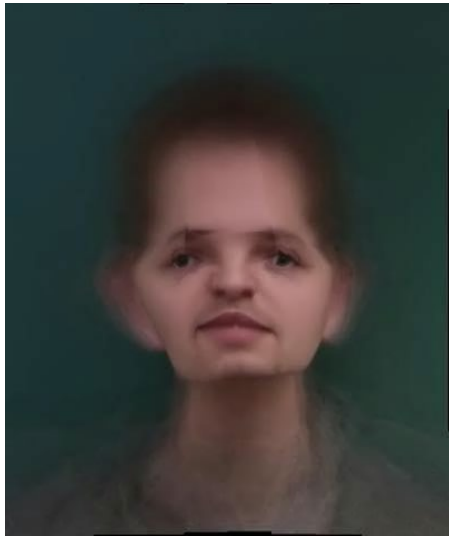


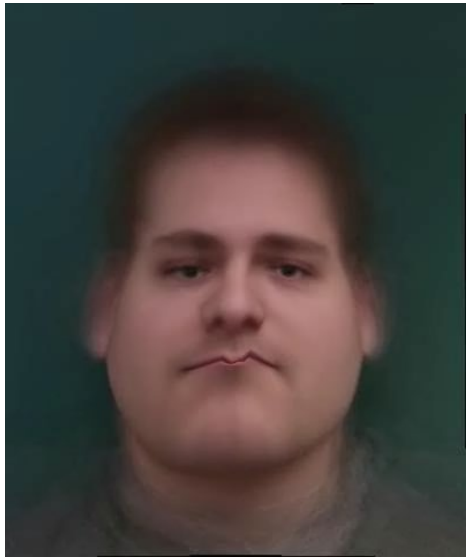
43 coordinates (x,y)

First 3 Shape Bases with PCA



Mean appearance





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