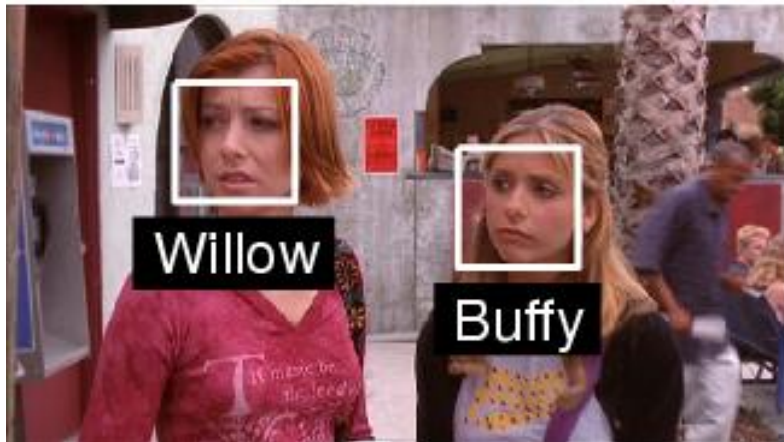


# What is Facial Processing

- One of the most well studied topics in Computer Vision.
- Tons of applications in this human-centric world:
  - Digital photography
  - Person identification and verification
  - Emotions and expressions



Character recognition from TV shows [*Everingham et. al.*]



Female  
Young  
Black hair  
...

Facial attributes [*Kumar et. al.*]

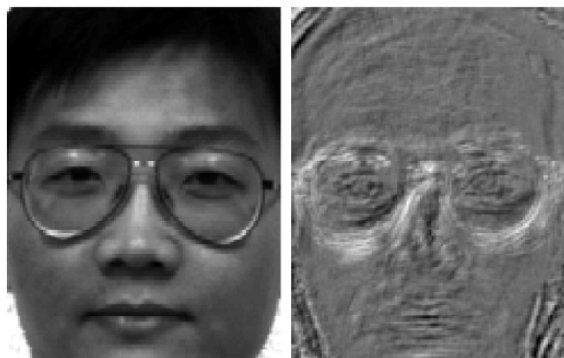
# Human Perception of Faces

- Understanding human perception helps facial processing in Computer Vision.
- Early face recognition systems use the facial landmark distance ratios.
- Who are these people?



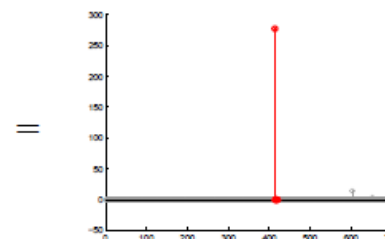
Each face is compressed to be 25% of its original width.

# Major Milestones

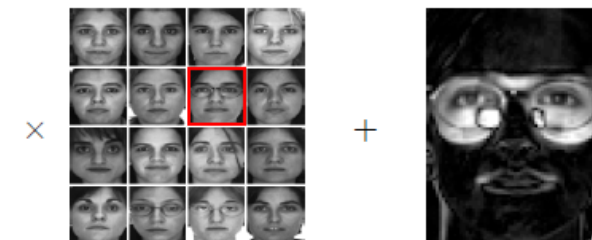


Eigenfaces  
[1991]

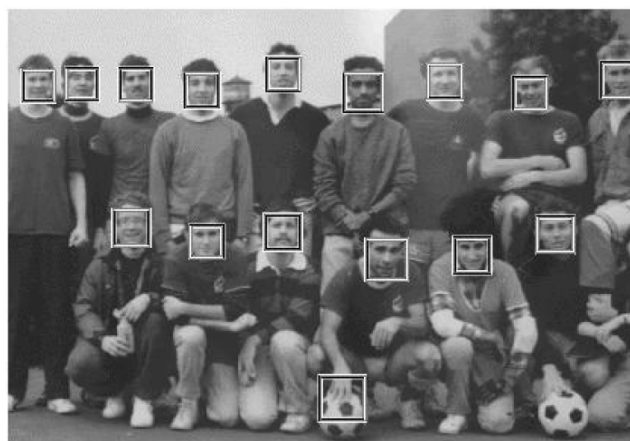
Fisherfaces [1997]



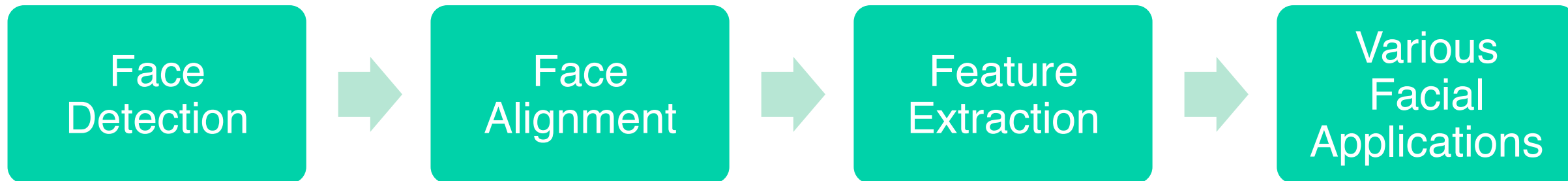
Viola-Jones Face  
Detector [2001]



Sparse Coding  
[2009]



# A Typical Facial Processing Pipeline



# Face Detection

- Human can detect face effortlessly. But also susceptible to occlusions.



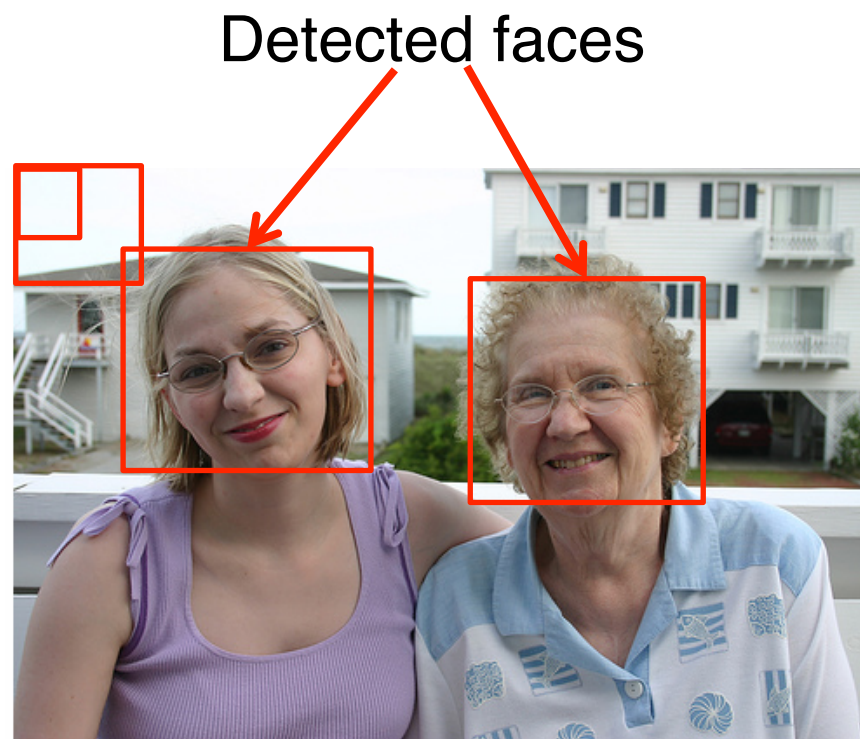
# EE368 Class Project 2003 – Face Detection

- Most groups used skin detector, followed by connected component analysis.



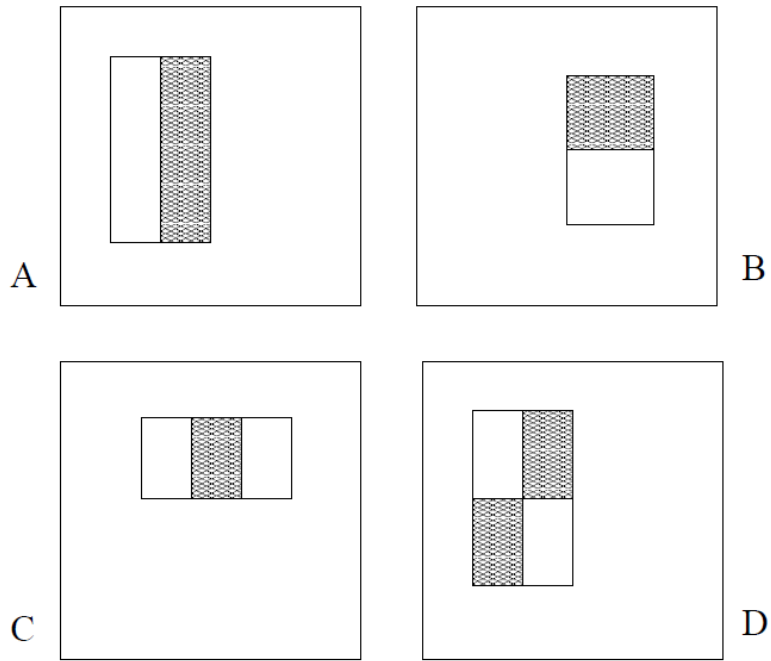
# Face Detection Overview (Viola & Jones, 2001)

- Slide a multi-scale detection window through the image.
- Classify each detection window as face / non-face.



# Face Detection (Viola & Jones, 2001)

- Features: difference between the sum of the pixels within two rectangular regions.
  - Captures prior knowledge about faces.
  - Efficient computation.



# Integral Image

- The value at a point  $(x, y)$  in the integral image is the sum of all the pixels above and to the left of  $(x, y)$

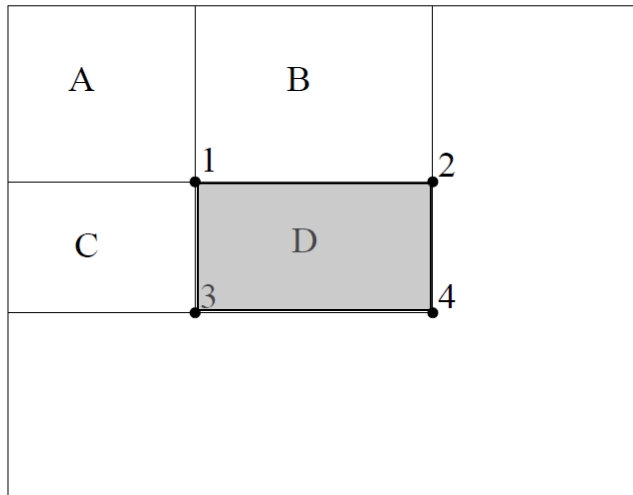
$$I(x, y) = \sum_{x' \leq x, y' \leq y} i(x', y')$$

Image pixels

|   |   |   |   |
|---|---|---|---|
| 2 | 5 | 6 | 2 |
| 3 | 2 | 8 | 4 |
| 6 | 7 | 9 | 1 |
| 1 | 9 | 2 | 4 |

Integral image

|    |    |    |    |
|----|----|----|----|
| 2  | 7  | 13 | 15 |
| 5  | 12 | 26 | 32 |
| 11 | 25 | 48 | 55 |
| 12 | 35 | 60 | 71 |



1: A

2: A+B

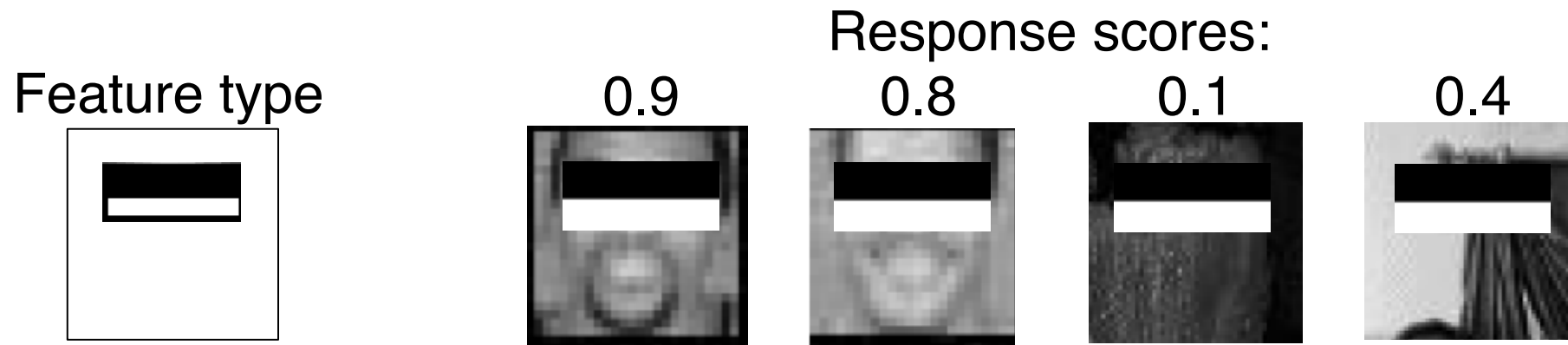
3: A+C

4: A+B+C+D

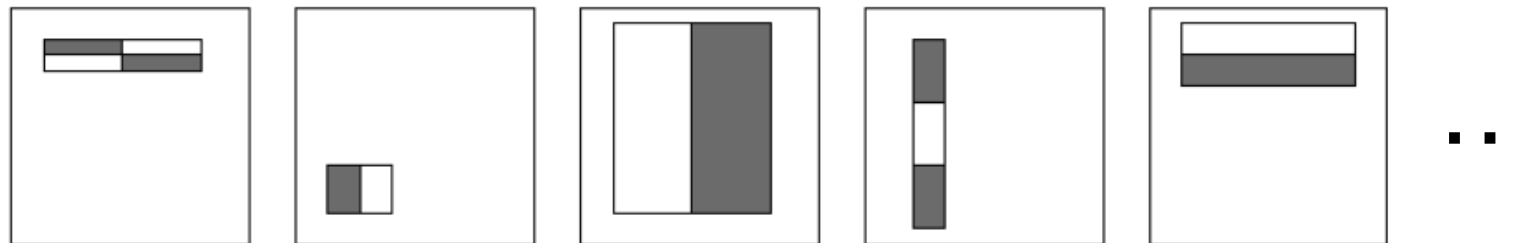
Pixel sum in shade:  $4+1-2-3$

# Face/Non-face Classification

- Objective: classify a detection window as face/non-face.
- For each detection window, compute the feature responses.



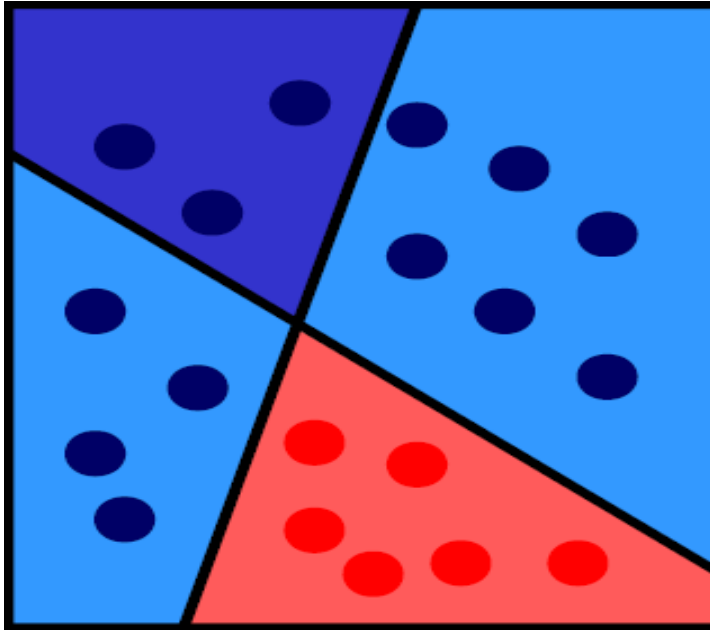
- There are many types of features. Select relevant features for face detection.




[Slide credit: L. Fei-fei]

# AdaBoost [Freund & Schapire 97]

Feature space



$$= \alpha_1 \times h_1 + \alpha_2 \times h_2$$


## Input

- Set of labeled training samples
- Weight distribution over samples

## Algorithm

for n=1 to N // number of classifiers

- train a classifier using samples and weight distribution

- calculate error
- calculate classifier weight
- update sample weights

end

## Result

$$H(\mathbf{x}) = \text{sign} \left( \sum_{n=1}^N \alpha_n h_n(\mathbf{x}) \right)$$

# Feature Selection by Adaboost

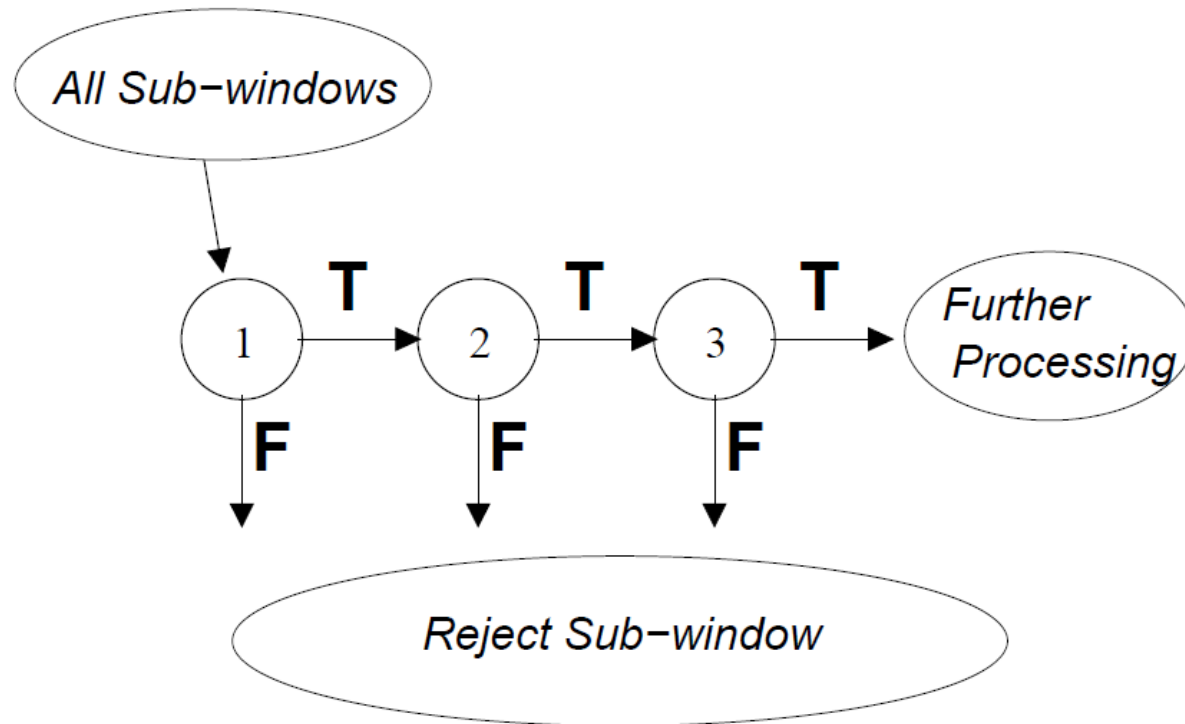
- The top two features selected by Adaboost:



- To achieve good performance, Adaboost needs to select many features.
  - Computationally expensive!
  - An idea: Quickly rule out the windows that are highly unlikely to be faces. Gradually refine detection.

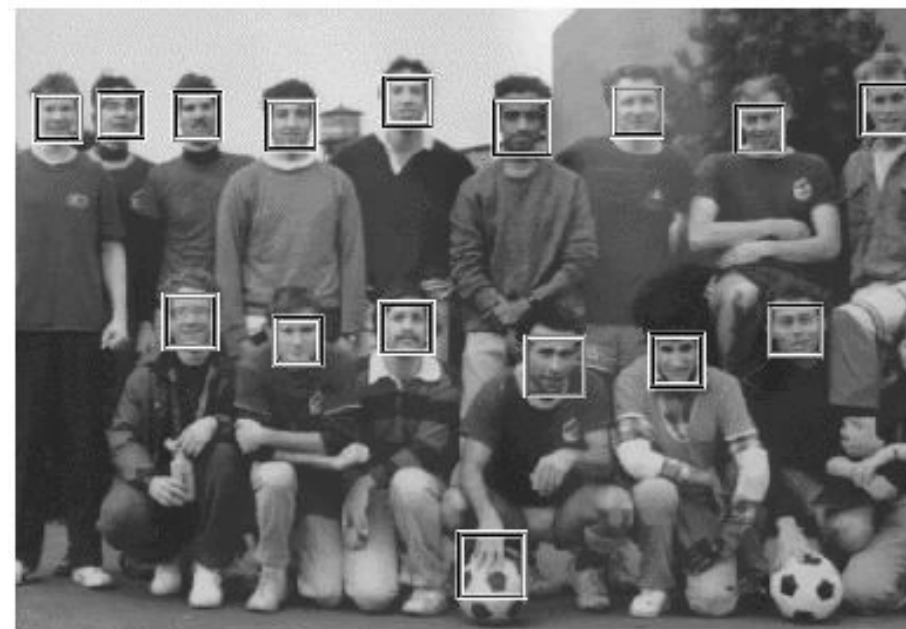
# Cascaded Detection

- Each node is a layer of detection with a few number of features.
- At each detection layer, the threshold is tuned such that no face is missed.
- Detection windows that are highly non-face will be rejected at early stage.



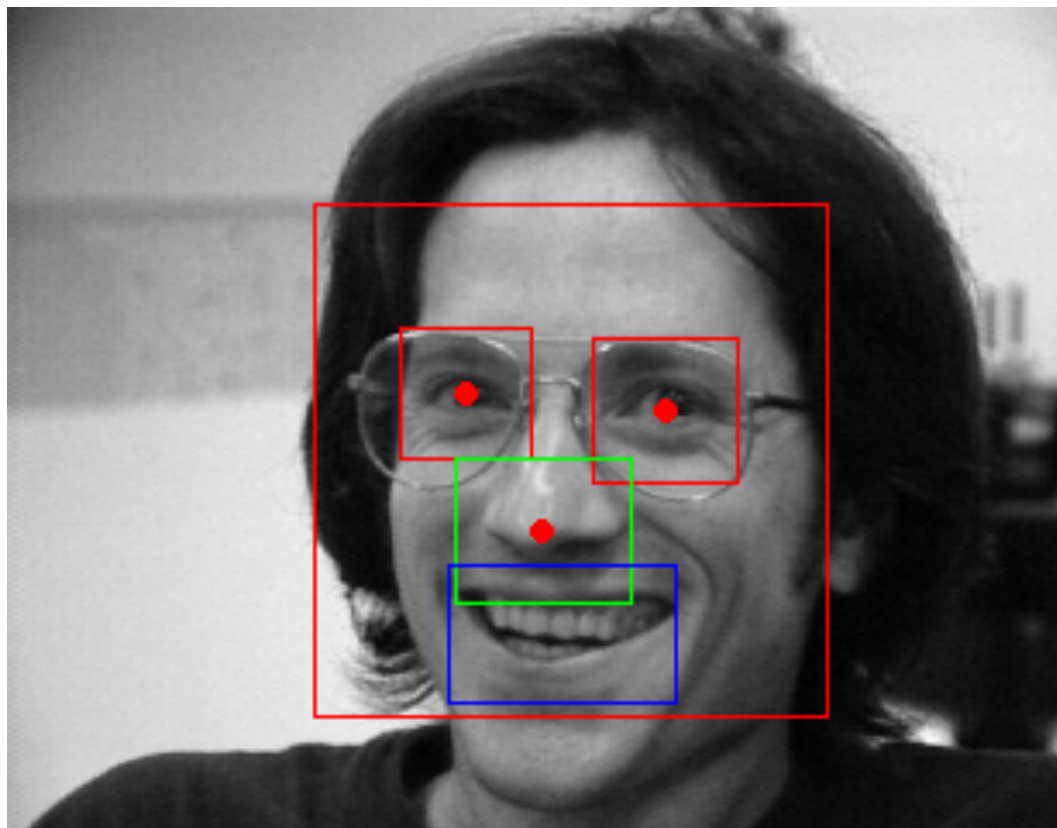
# Face Detection Examples

- 700 MHz Intel Pentium III
  - Training: a 38 layer cascaded classifier was trained in “weeks”.
  - Testing: 384×288 pixel image in about 0.067 seconds.



# Facial Landmark Detection

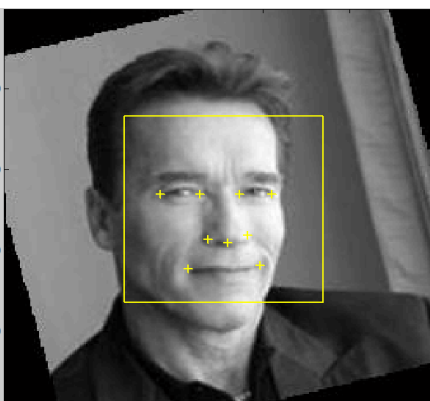
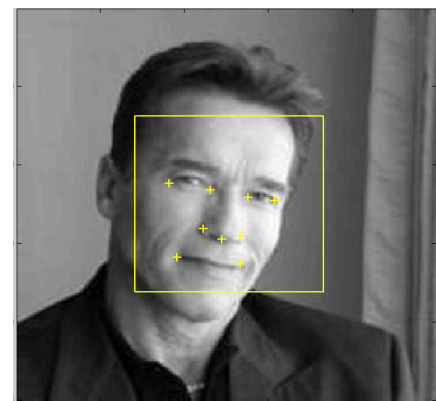
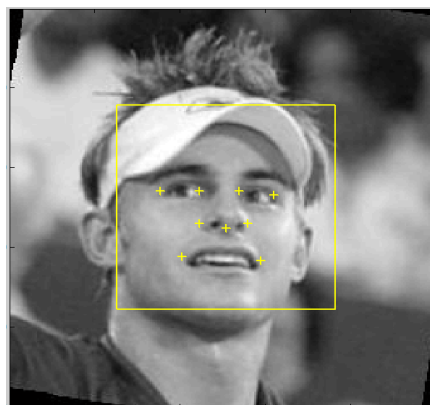
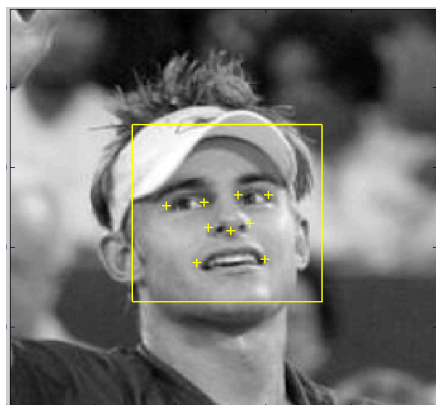
- The Viola-Jones face detector can also be used for generic object detection.
- Finding the facial landmarks (eyes, nose, mouth, etc.).



# Face Alignment

## ■ Face alignment:

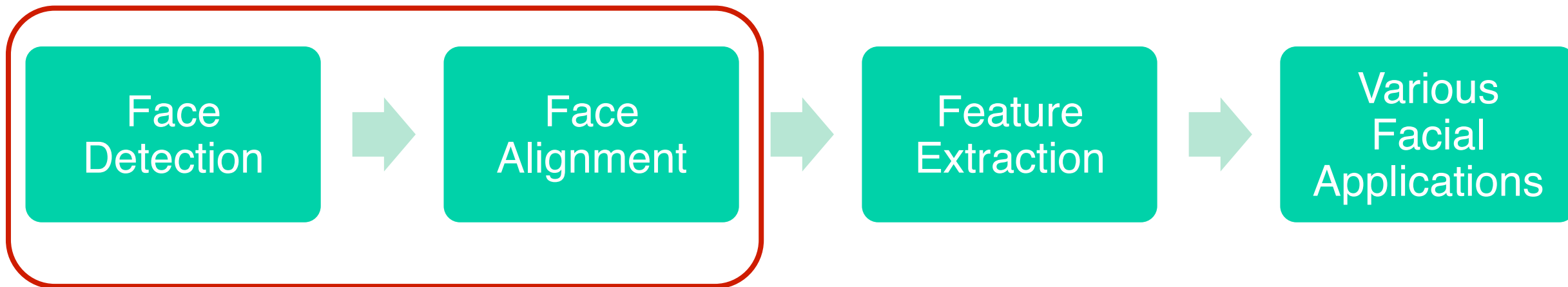
- Detect face landmarks.
- Apply similarity transform to align the faces (usually done by aligning eye locations).



Recap: Similarity transform

$$\mathbf{x}' = \begin{bmatrix} s \cdot \cos \theta & -s \cdot \sin \theta & t_x \\ s \cdot \sin \theta & s \cdot \cos \theta & t_y \end{bmatrix} \underline{\mathbf{x}}$$

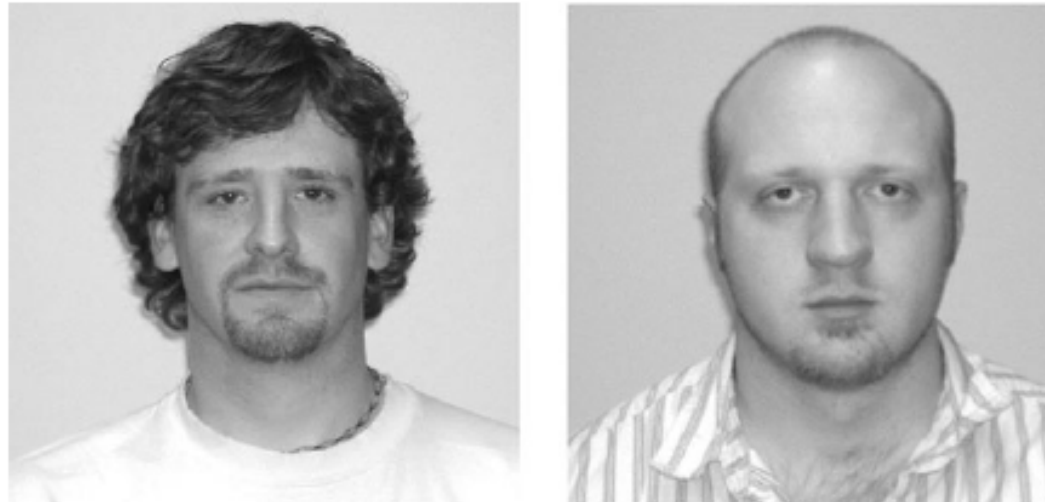
# A Typical Facial Processing Pipeline



What we have discussed.

# A Case Study – The Hidden Sides Names

- Psychology studies: Human has facial stereotypes about names.
- Questions:
  - Is there a relation between a person's first name and facial appearance?
  - Can we use this name-face relation for practical applications?

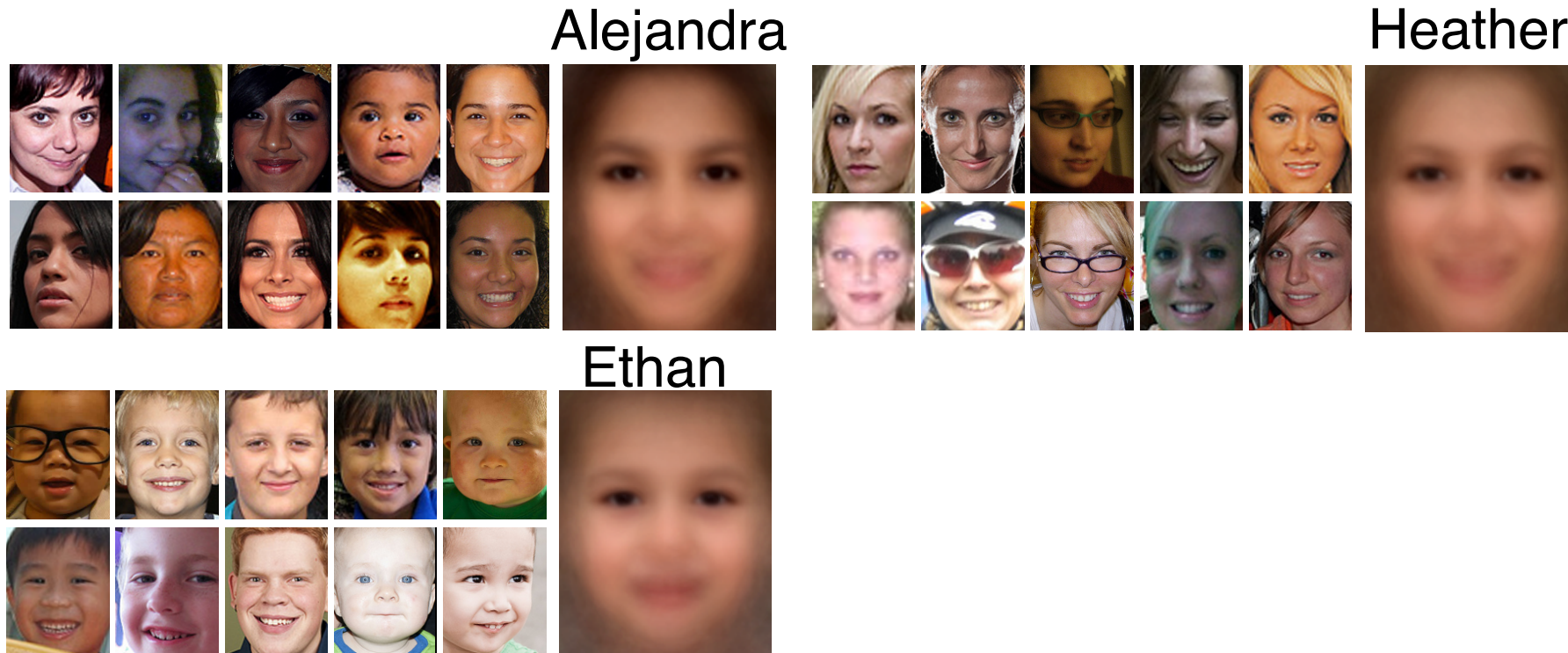


Who is Tim and who is Bob?

*[Lea et. al., 07]*

# What's Behind the Names?

- Gender, age, and possibly many other hidden factors.
- **Can we guess the name of an unseen person?**
  - Surprisingly, machine can do far better than chance.



# System Overview

- The data:
  - 100 popular names in the United States.
  - 800 faces for each name.
  - The data is collected for FREE from image tags with careful filtering to reject noisy tags.
- Use Support Vector Machines to train a set of name classifiers.
- For an input face, generate a ranked list of names.



**Multi-  
Feature  
SVMs**



## **Ranked Name List**

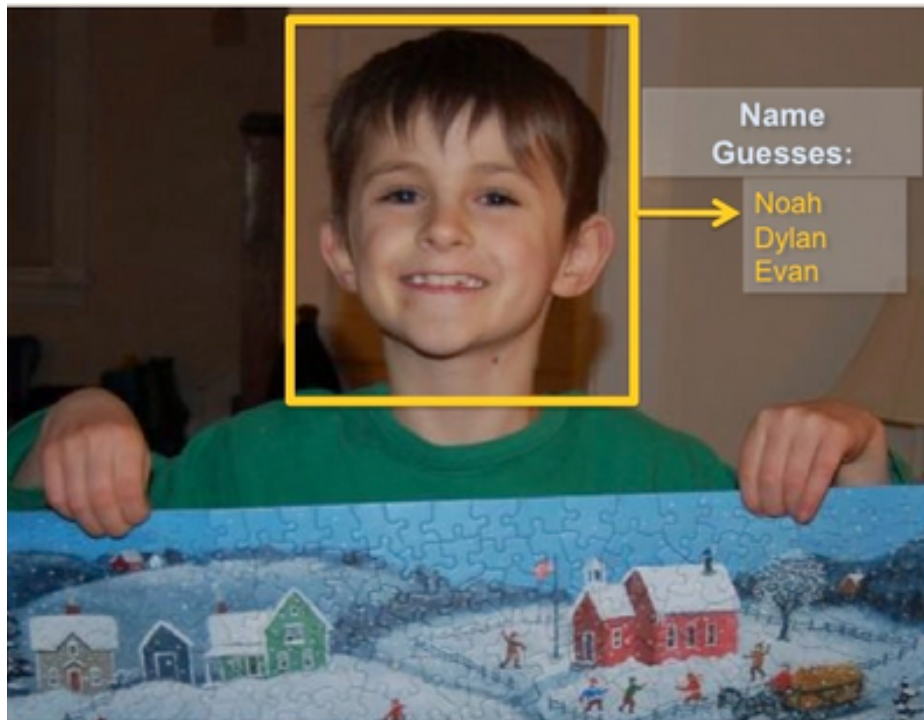
**Lisa  
Sarah  
Christina  
Jennifer**

**⋮**

*[Chen et. al., 2013]*

# Name Guessing

- Our findings:
  - Face appearance and first names are correlated.
  - Machine can guess names at an accuracy far better than random.



Name guessing among 100 names

| Method       | Top-1 Accuracy |
|--------------|----------------|
| Our approach | 4.17%          |
| Random guess | 1.00%          |

# Applications of Name Models

- For a given face, generate a ranked list of names that best fit the facial appearance.
- This ranked list of names provide important information about the person, especially gender and age.

Probably female.

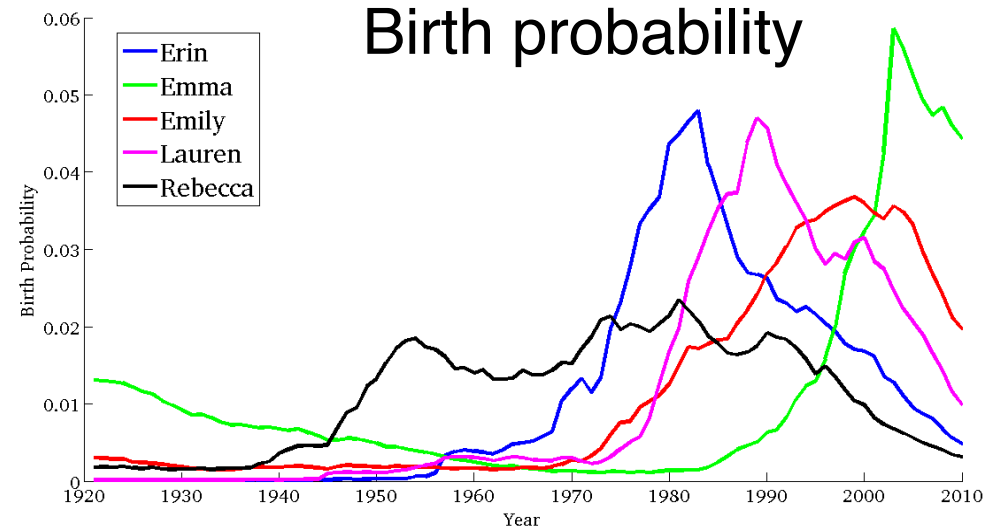


## Ranked name list

Erin  
Emma  
Emily  
Lauren  
Rebecca

⋮

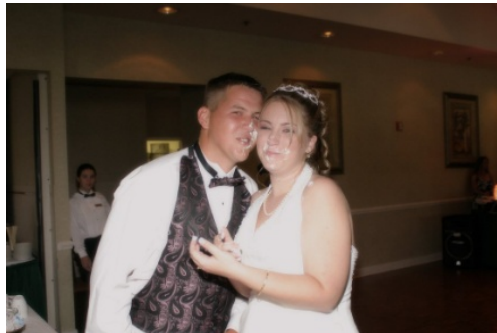
Probably born after 1970.



[source: US social security administration]

# Gender Recognition From Faces

- We declare female if the majority of the top-5 names are female.
- Extremely simple but achieve state-of-the-art performance.
- Advantage: no gender labels required to perform gender recognition!



|                          | Classification accuracy |
|--------------------------|-------------------------|
| <b>Gender-from-names</b> | <b>90.4%</b>            |
| Kumar (PAMI 2011)        | 86.4%                   |
| Random prior             | 52.4%                   |

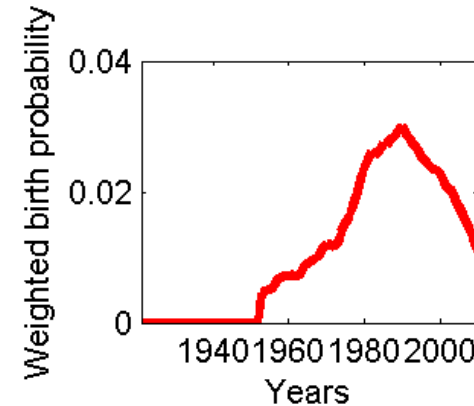
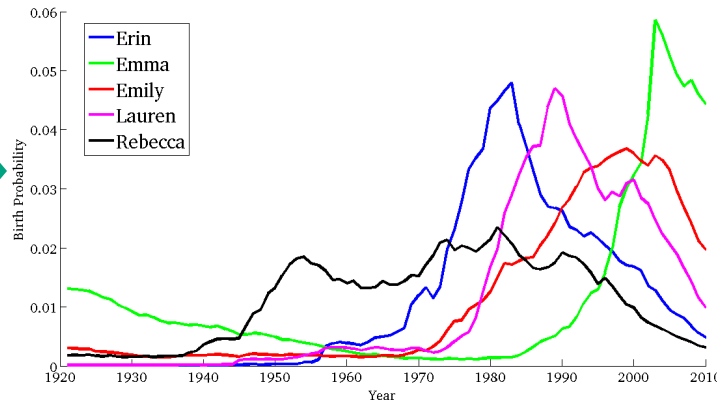
# Age Estimation From Names

- Given a face, generate a ranked list of 100 names.
- Combine the birth probability curves by weighted product.
- Achieves very competitive result without any age labels!



## Ranked name list

Erin  
Emma  
Emily  
Lauren  
Rebecca  
⋮



Predicted age category: 13-19

Combined birth probability

# Thank you!

[hchen2@stanford.edu](mailto:hchen2@stanford.edu)

# Additional Slides

# Human Perception of Faces

- Human are good at recognizing faces, but not always!
- The Thatcher Effect



# Is Face Recognition Dead?

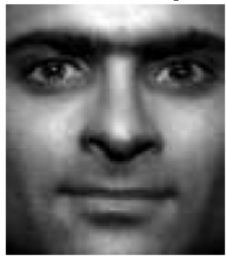
Yes (on well aligned frontal faces)

Noise corrupted



30%

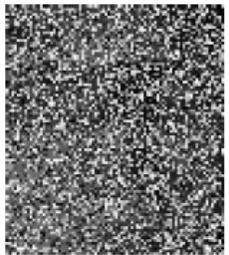
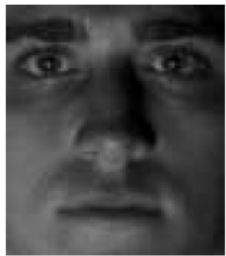
Reconstructed by  
sparse representation



**~100% accuracy  
up to 60% of  
pixel corruption!**



50%



70%



*[Wright et. al.  
2009]*

No (faces in the wild)

**Pubfig Dataset**



Anna Paquin



Audrey Tautou



Barack Obama



Clive Owen



Cristiano Ronaldo



Daniel Craig

**78.65%** face verification accuracy  
*[Kumar et al. 2009]*