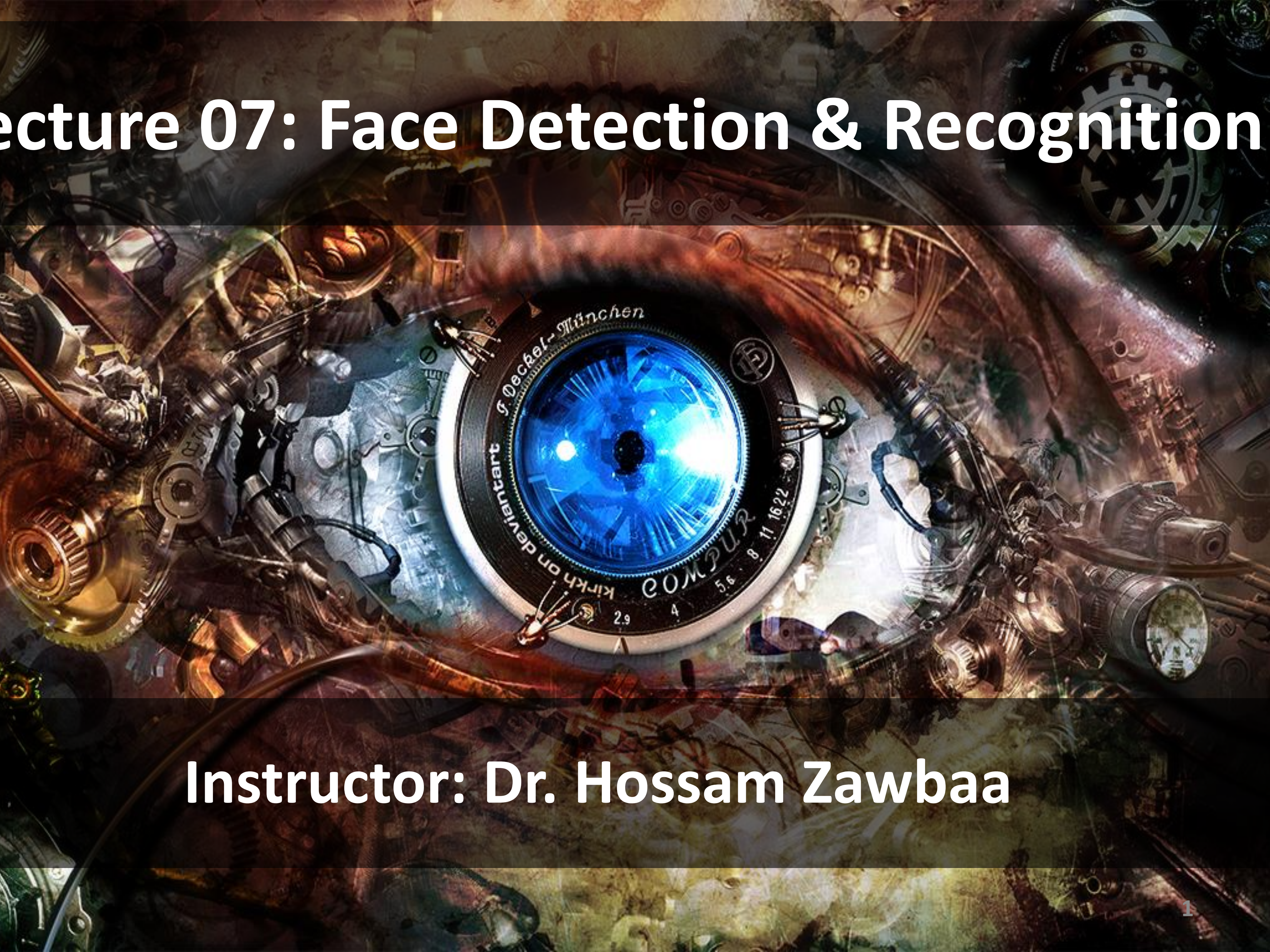
ecture 07: Face Detection & Recognition



Instructor: Dr. Hossam Zawbaa

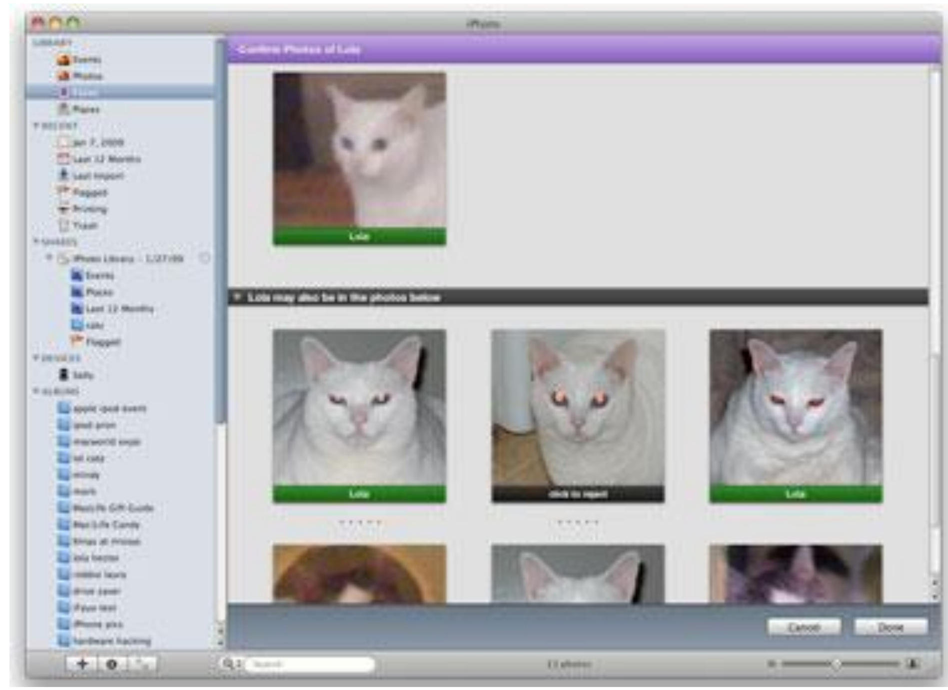
Face detection and recognition

Application: Apple iPhoto

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

Application: Apple iPhoto

- Can be trained to recognize cats!



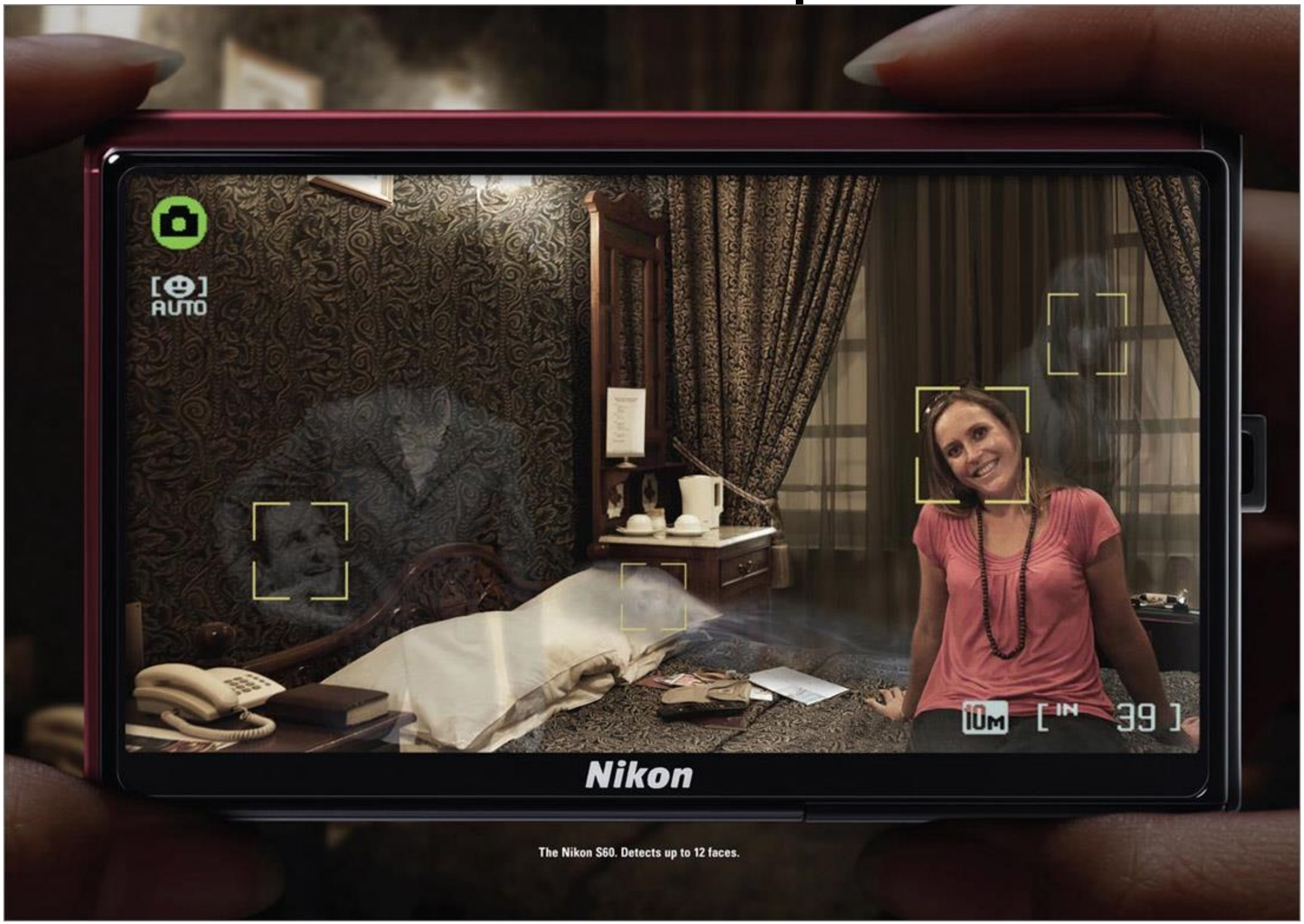
http://www.maclife.com/article/news/iphotos_faces_recognizes_cats

Application: Apple iPhoto

- Things iPhoto thinks are faces

Funny Nikon ads

"The Nikon S60 detects up to 12 faces."



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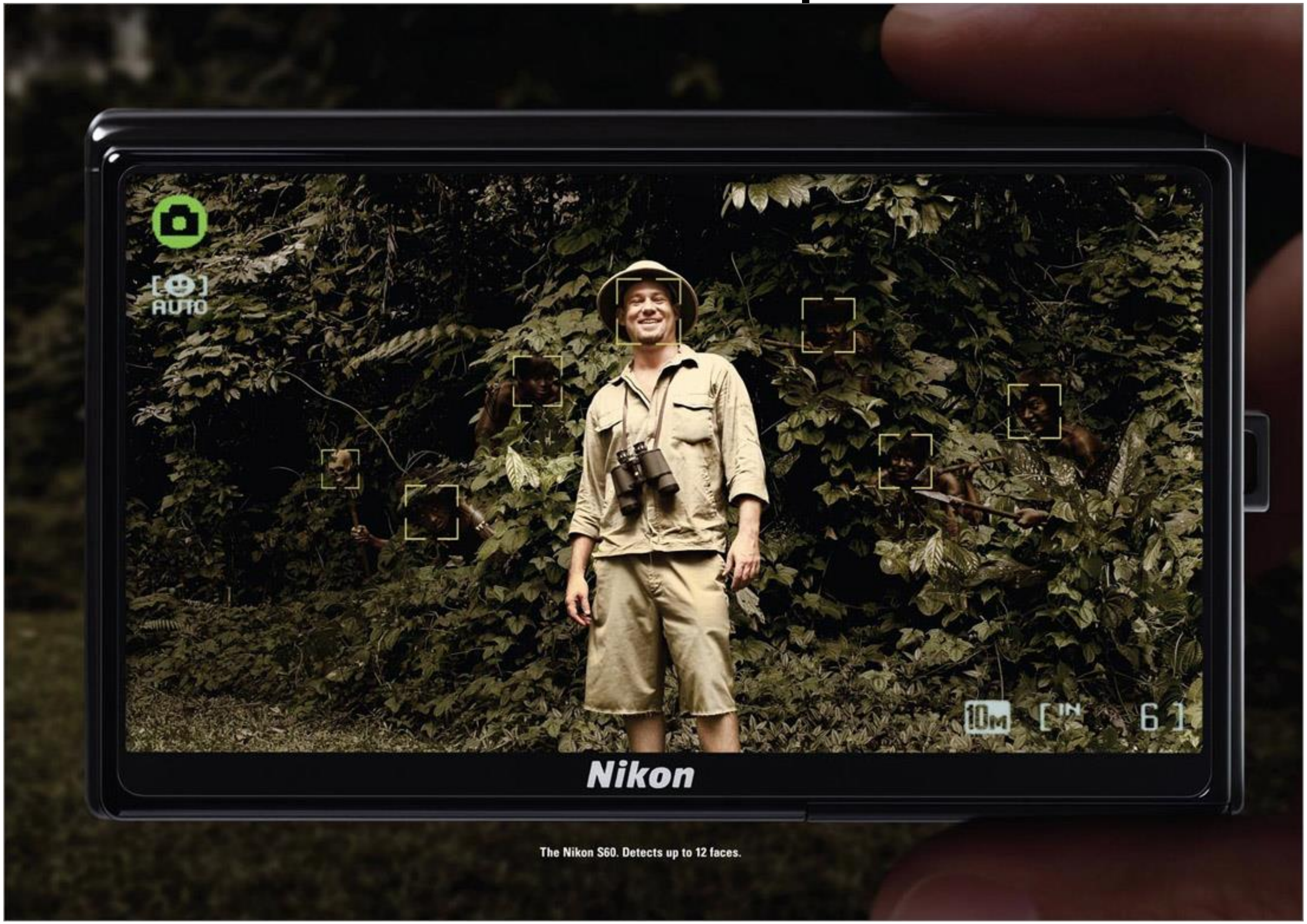


Challenges of face detection

- **Sliding window detector** must *evaluate tens of thousands of location/scale combinations*
- **Faces are rare**: 0–10 per image
  - For *computational efficiency*, we should *try to spend as little time as possible on the non-face windows*
  - A **megapixel image has ~10^6 pixels** and a **comparable number of candidate face locations**

The Viola/Jones Face Detector

- An approach to real-time object detection
- Training is slow, but detection is very fast
- Key ideas
  1. **Integral images** for fast feature evaluation
  2. **Boosting** for feature selection
  3. **Attentional cascade** for fast rejection of non-face windows

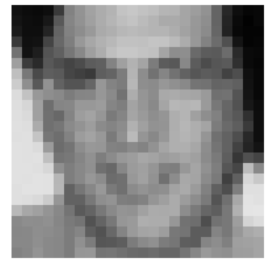
P. Viola and M. Jones. *Rapid object detection using a boosted cascade of simple features.* CVPR 2001.

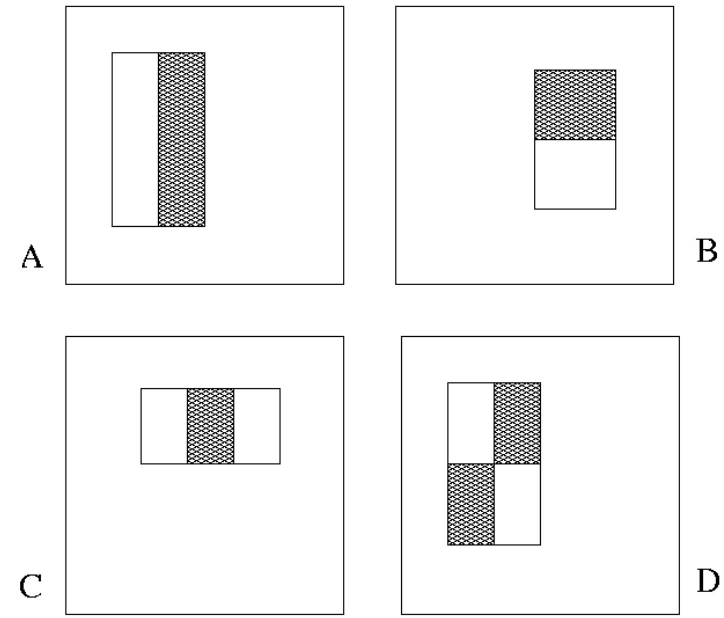
P. Viola and M. Jones. *Robust real-time face detection.* IJCV 57(2), 2004.

~8000 citations!

Image Features

"Rectangle filters"

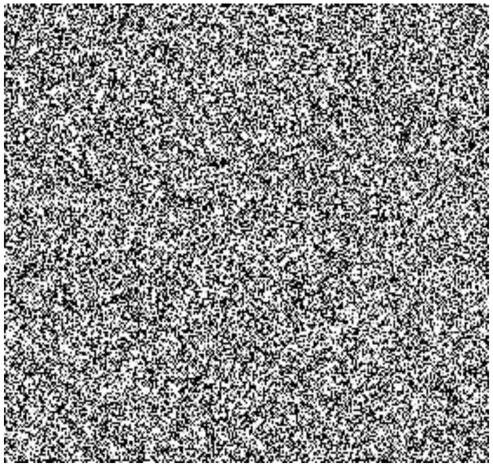




Value =

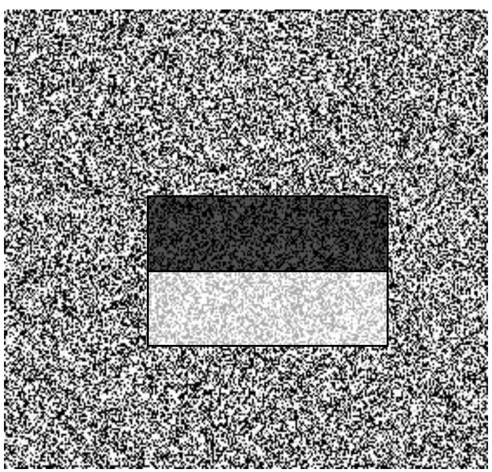
∑ (pixels in white area) –
∑ (pixels in black area)

Example



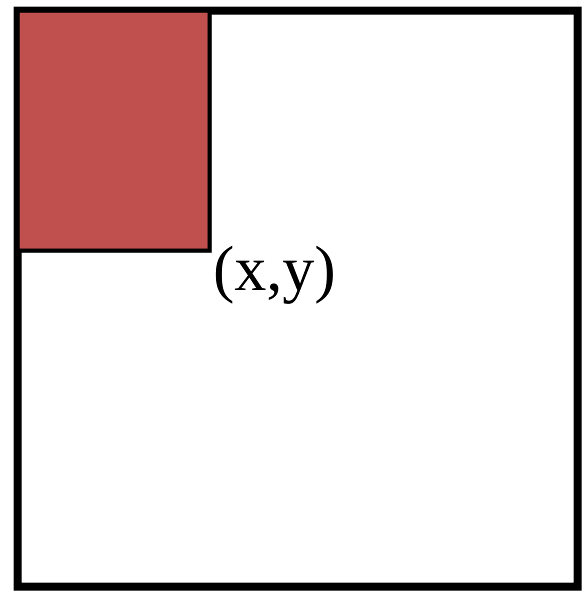
Source

Result

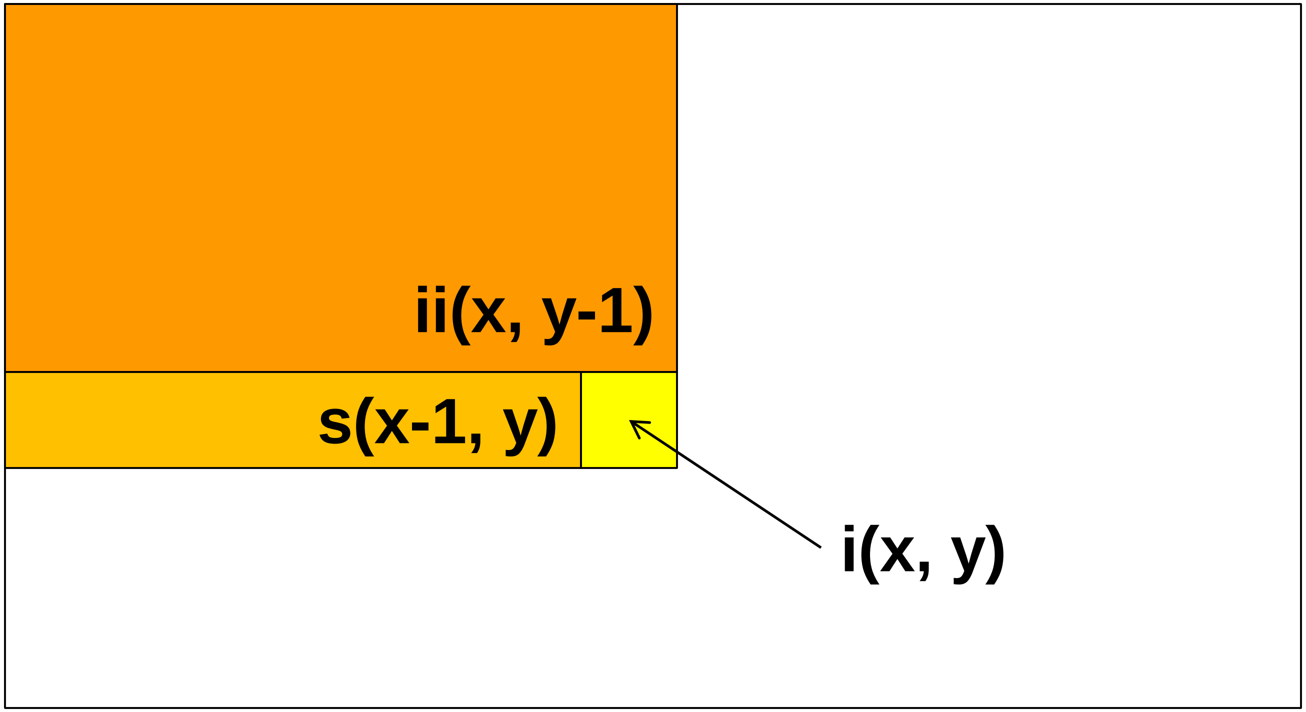


Fast computation with integral images

- The *integral image* computes a value at each pixel (x, y) that is the sum of the pixel values above and to the left of (x,y), inclusive
- This can quickly be computed in one pass through the image



Computing the integral image



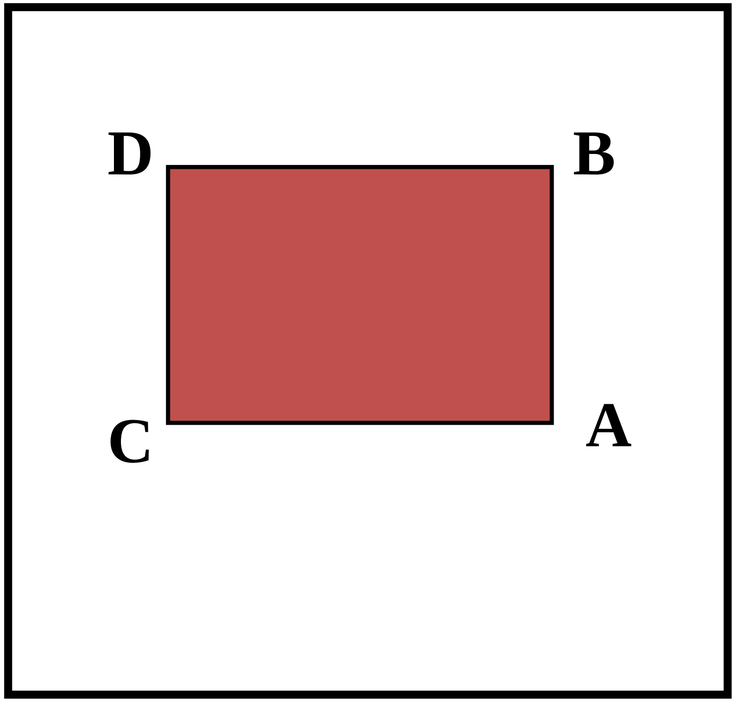
- Cumulative row sum: $s(x, y) = s(x-1, y) + i(x, y)$
- Integral image: $ii(x, y) = ii(x, y-1) + s(x, y)$

MATLAB: `ii = cumsum(cumsum(double(i)), 2);`

Computing sum within a rectangle

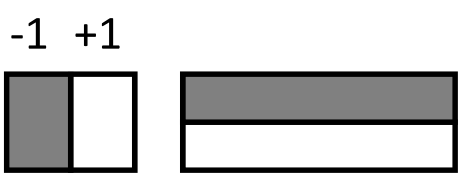
- Let A,B,C,D be the values of the integral image at the corners of a rectangle
- Then, **the sum of original image values** within the rectangle can be computed as:

  sum = A – B – C + D

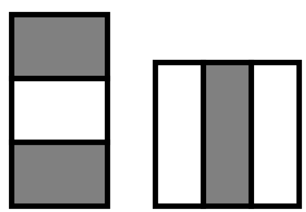


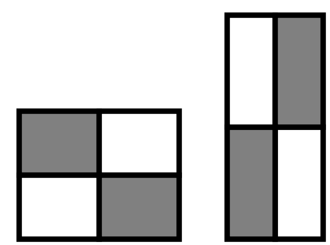
Features that are fast to compute

- "**Haar-like features**"
  - Differences of sums of intensity
  - **Thousands, computed at various positions and scales** within detection window

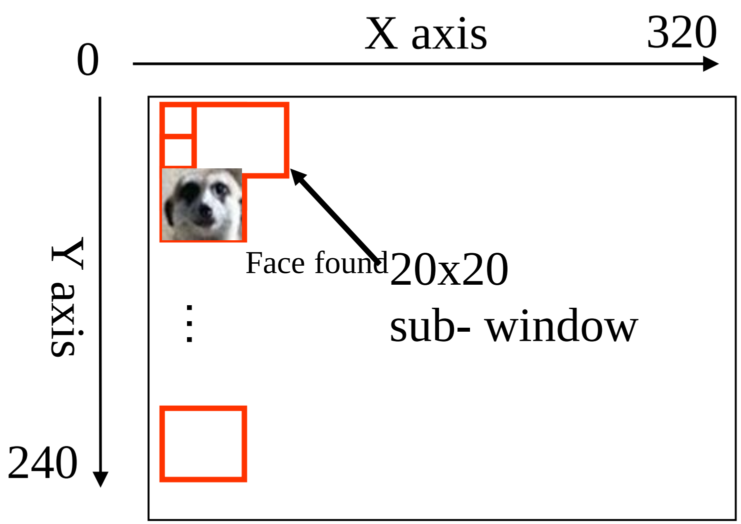


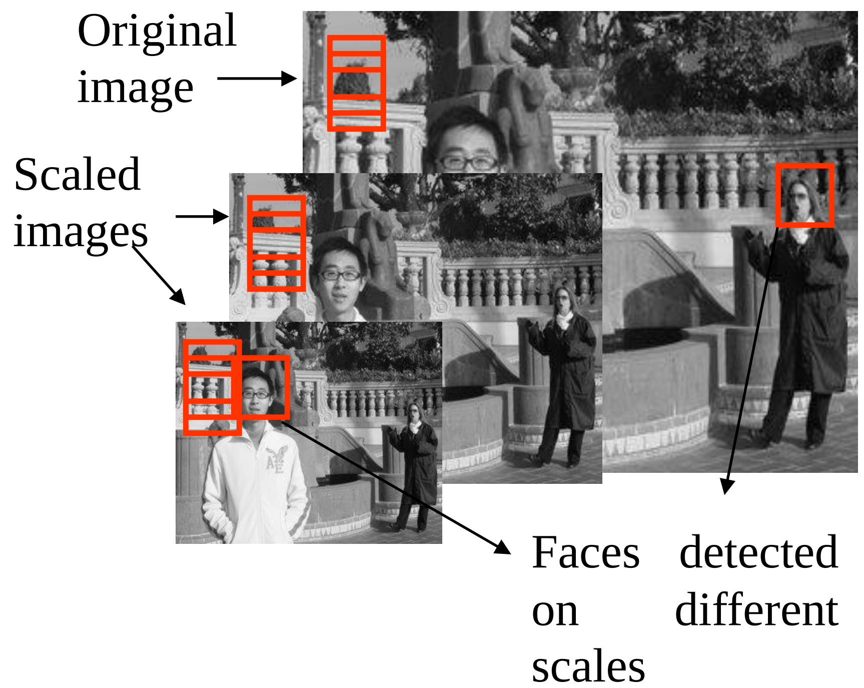
Two-rectangle features


Three-rectangle features


Etc.

Haar-Feature based object detection algorithm



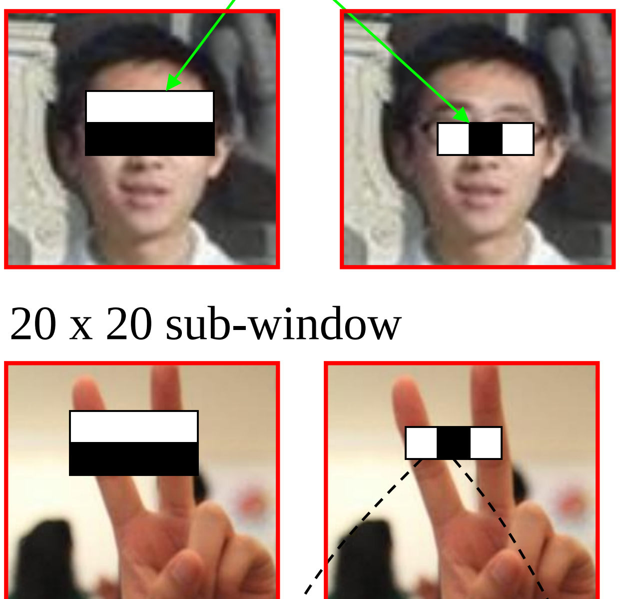


Movement of sub-window

(320 – 20) * (240 – 20) = **66,000** sub-windows

Face detection in sub-window

Facial Haar ***features***



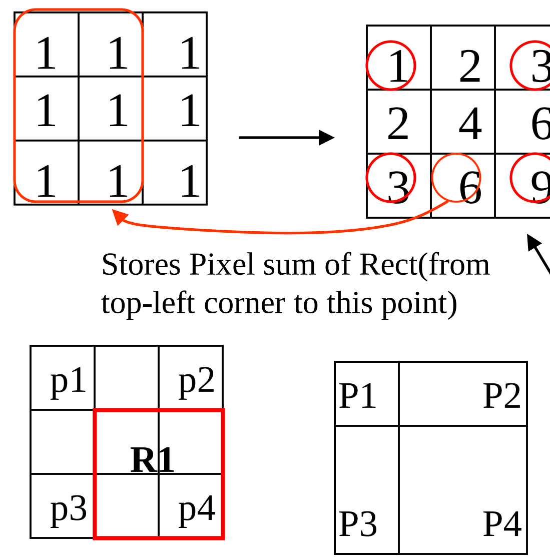
20 x 20 sub-window

Pass

Fail

Original image

Integral Image



Stores Pixel sum of Rect(from top-left corner to this point)

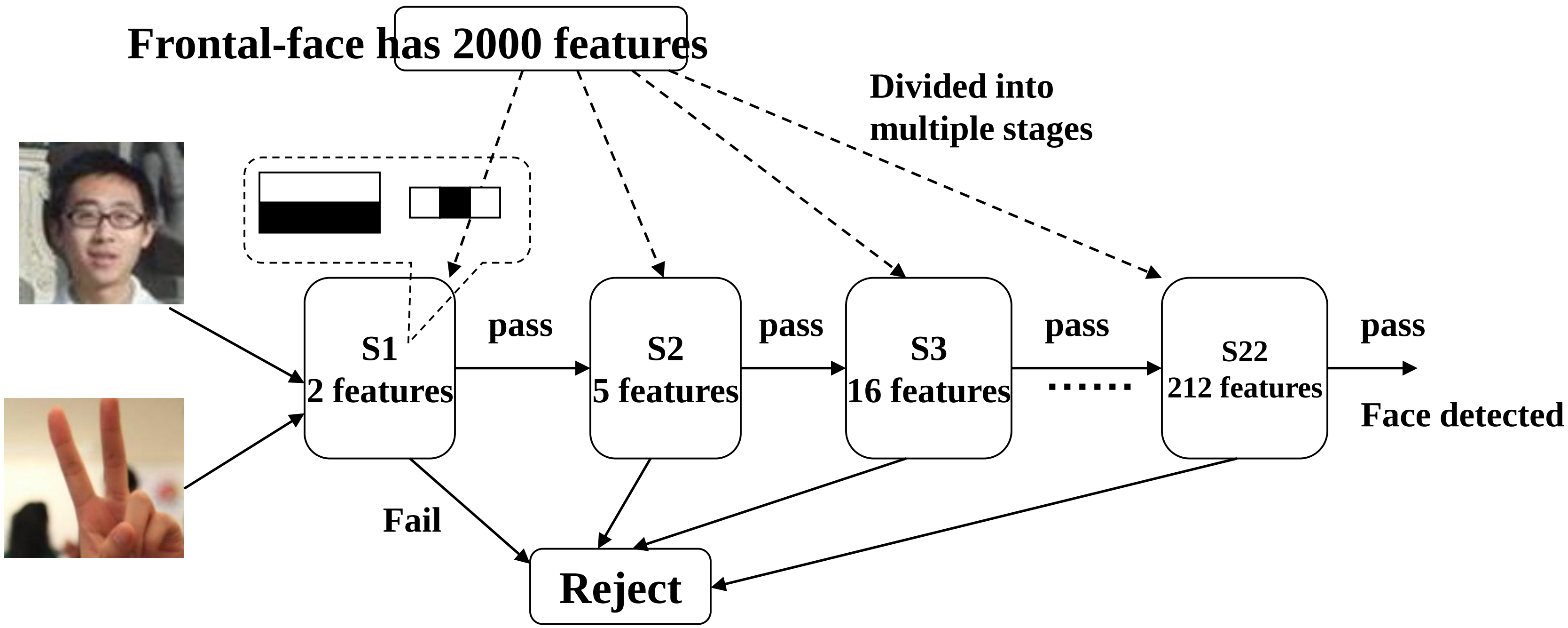
Need 4 corner values

Pixel_Sum(R1) =
P4 - P2 - P3 + P1 = 4

Calculate Haar-feature value:

Pixel_Sum(Rect_W) – Pixel_Sum(Rect_B)

Cascade decision process



Fail any stage will reject current sub-window

- Fast classifiers early in cascade
- Slow classifiers later, but most examples don’t get there

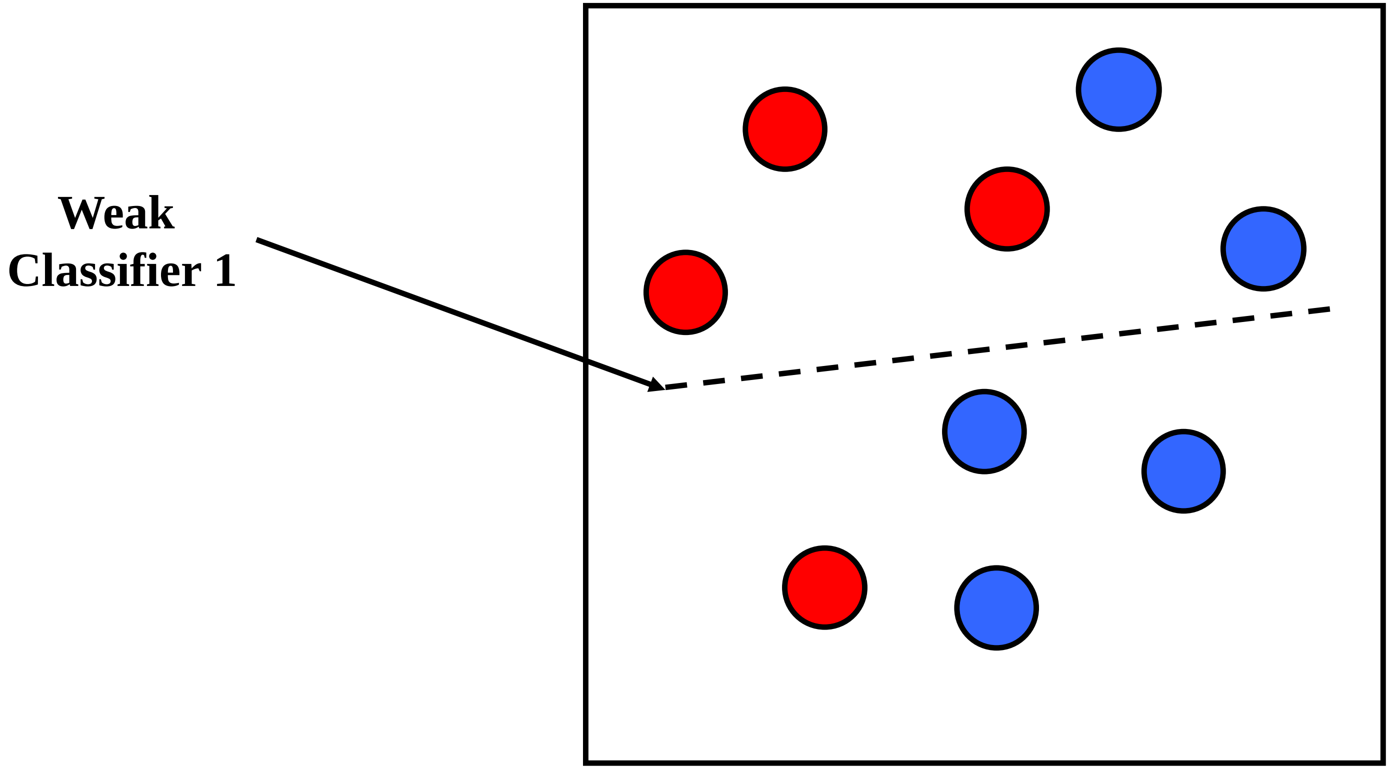
Training procedure

- Initially, weight each training example equally
- In each boosting round:
  - **Find the weak learner** that achieves the lowest *weighted* training error
  - **Increase the weights of training examples misclassified** by current weak learner
- **Compute final classifier** as linear **combination of all weak learners** (weight of each learner is directly proportional to its accuracy).

Y. Freund and R. Schapire, A short introduction to boosting, *Journal of Japanese Society for Artificial Intelligence*, 14(5):771-780, September, 1999.

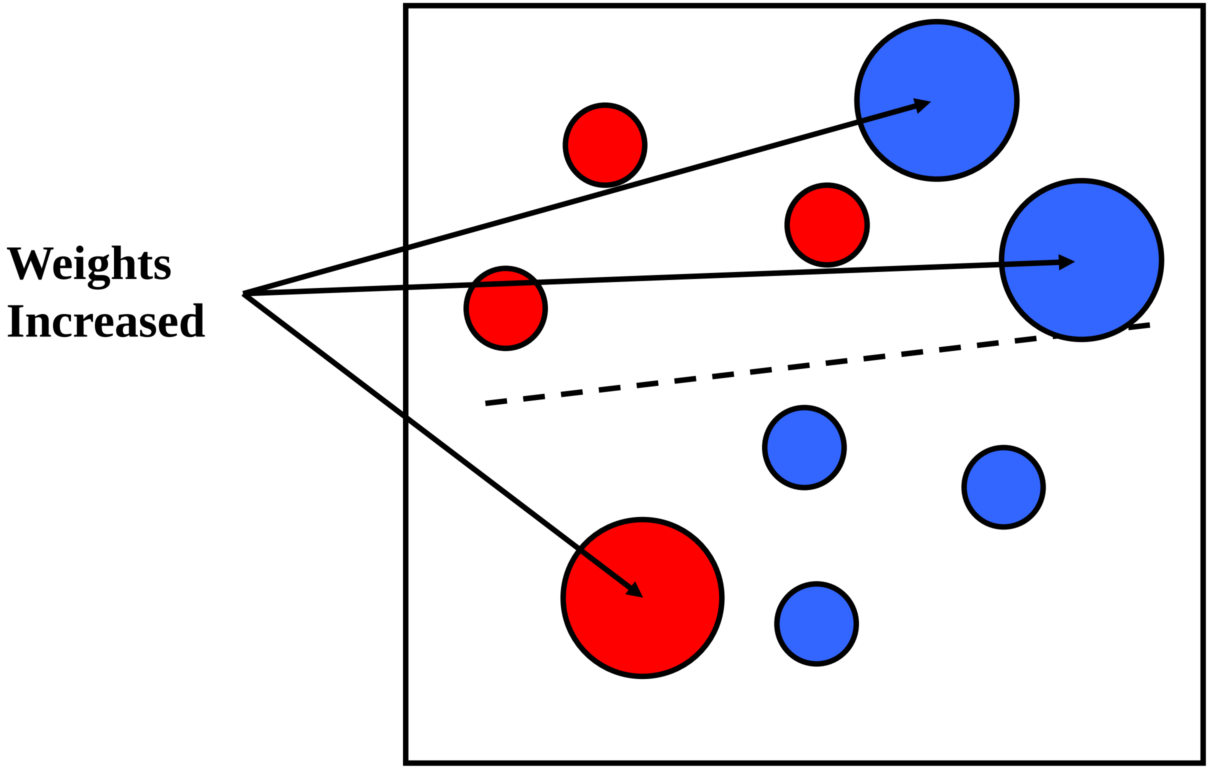
Boosting intuition

- *Boosting* is a classification scheme that combines *weak learners* into a more accurate *ensemble classifier*

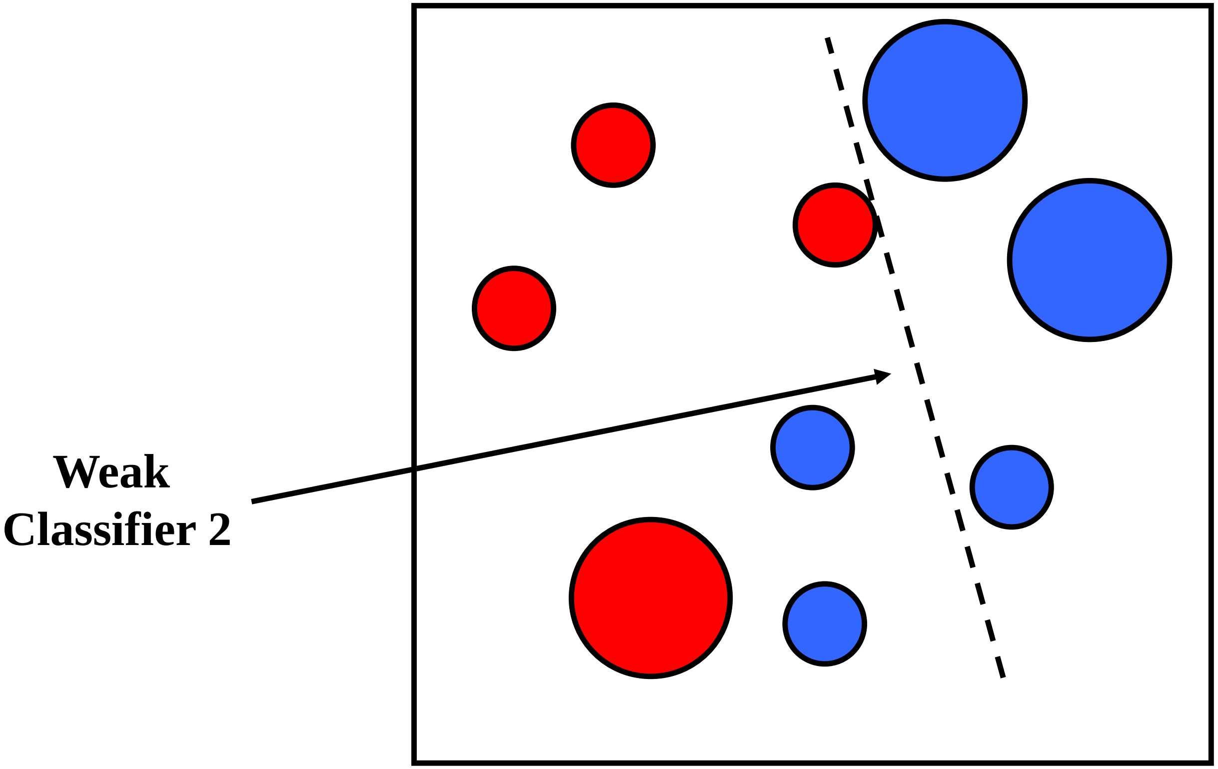


Slide credit: Paul Viola

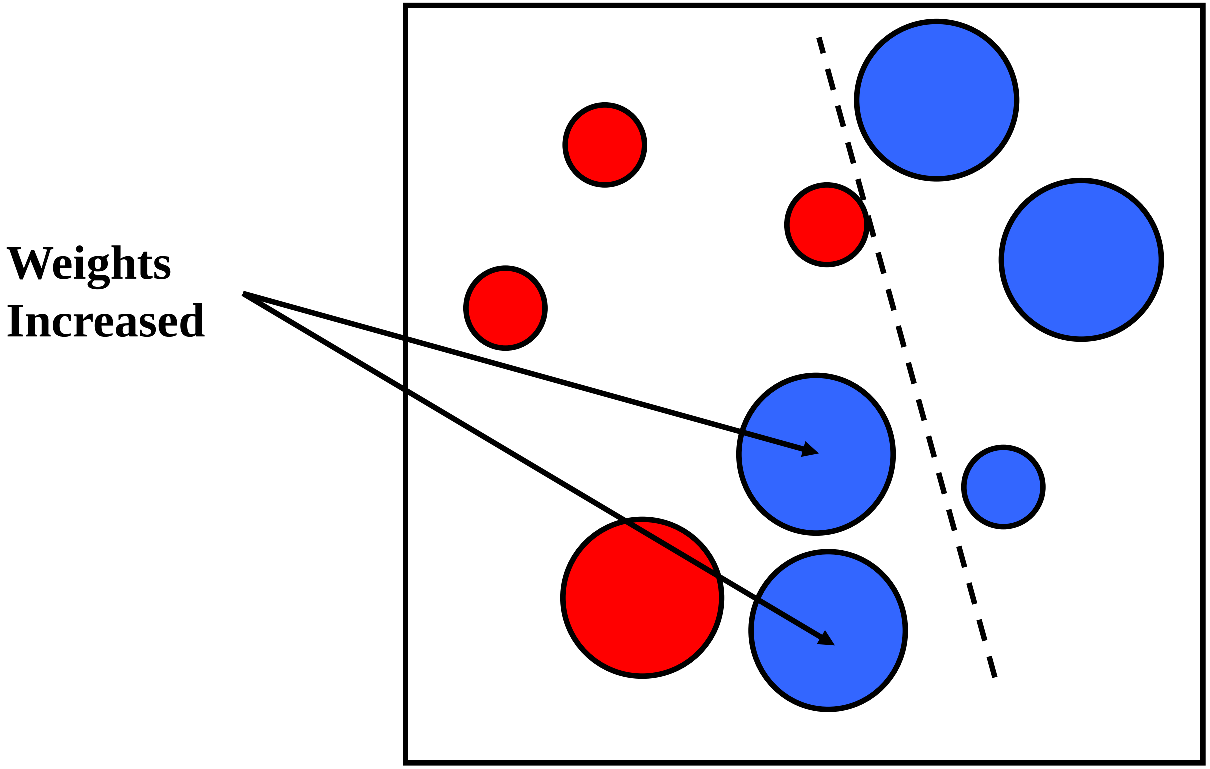
Boosting illustration



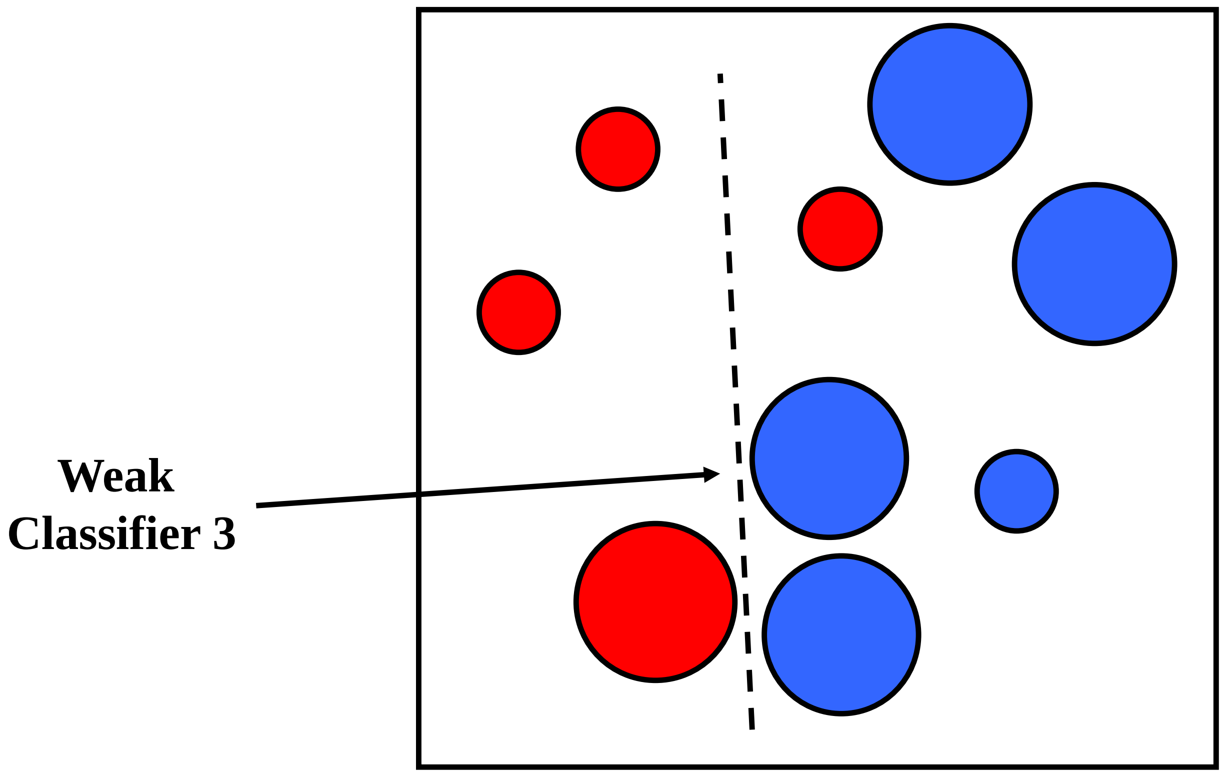
Boosting illustration



Boosting illustration

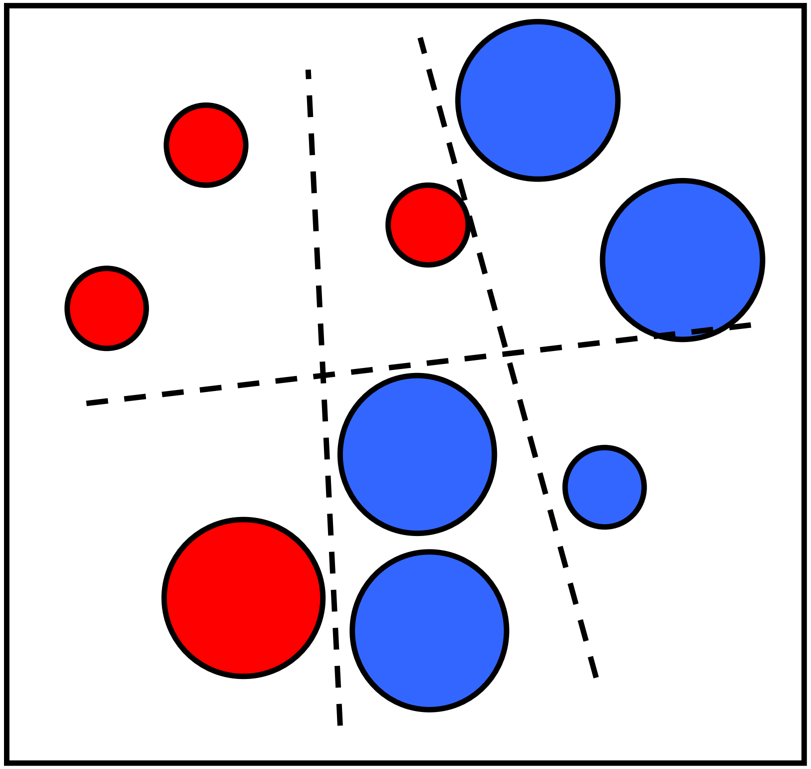


Boosting illustration



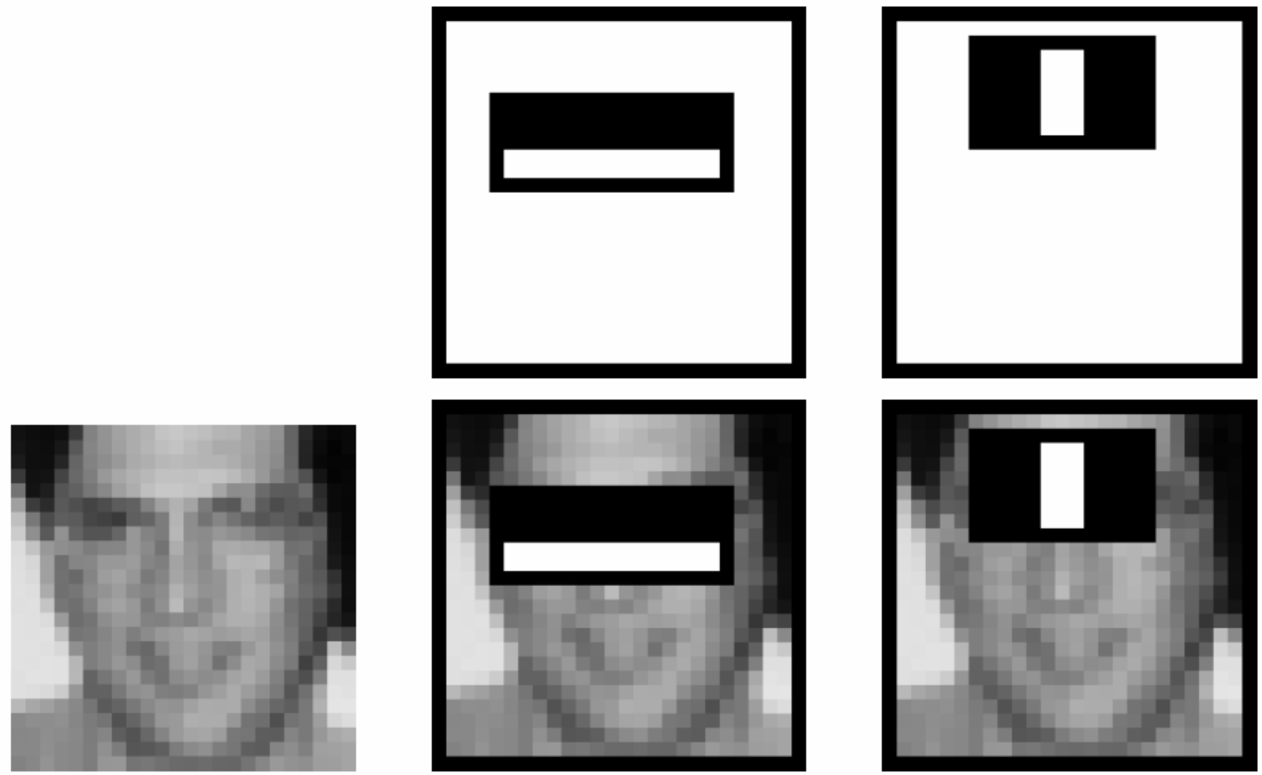
Boosting illustration

Final classifier is a combination of weak classifiers



Boosting for face detection

- First two features selected by boosting:

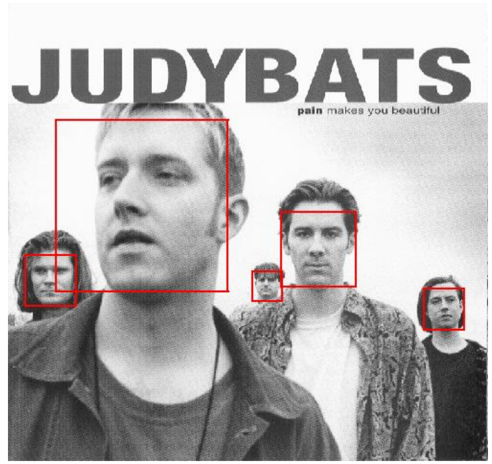


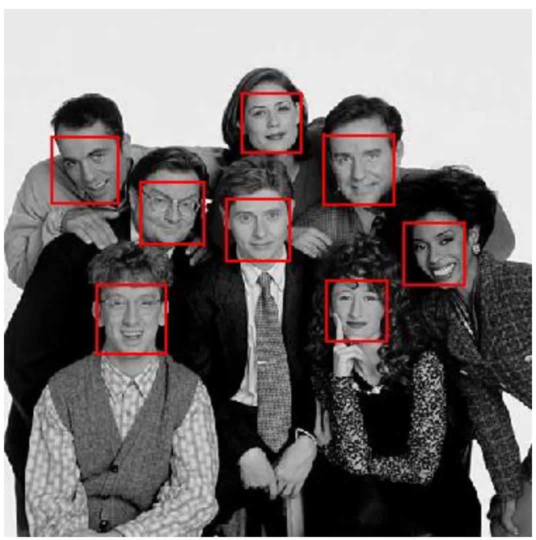
This feature combination can yield 100% detection rate and 50% false positive rate

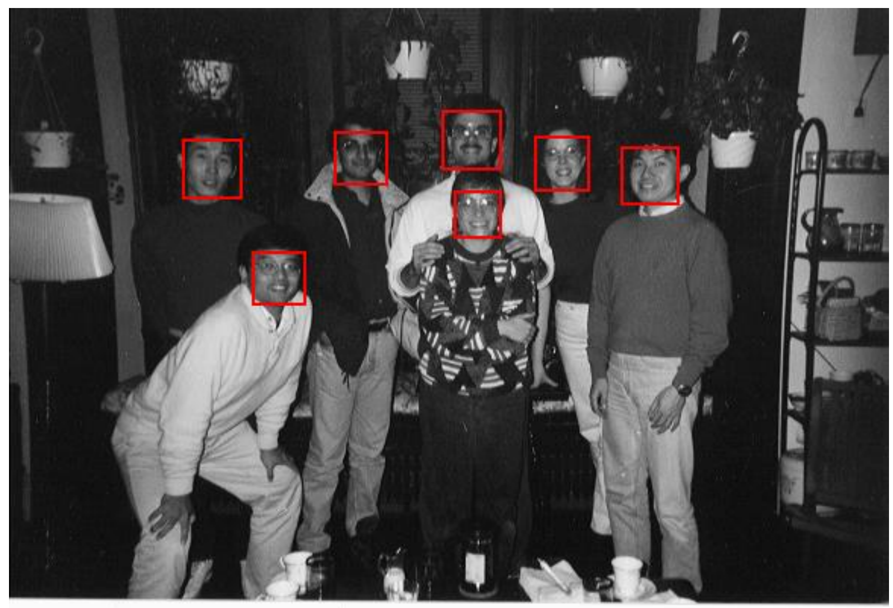
Boosting vs. SVM (ANN)

- Advantages of boosting
  - Integrates classifier training with feature selection
  - Complexity of training is linear instead of quadratic in the number of training examples
  - Flexibility in the choice of weak learners, boosting scheme
  - Testing is fast
  - Easy to implement
- Disadvantages
  - Needs many training examples
  - Training is slow
  - Often doesn’t work as well as SVM or ANN (especially for many-class problems)

Output of Face Detector

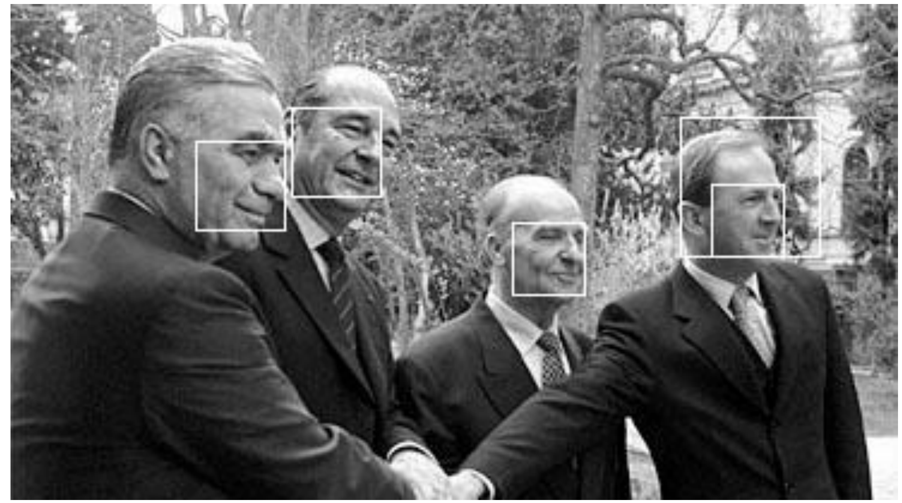






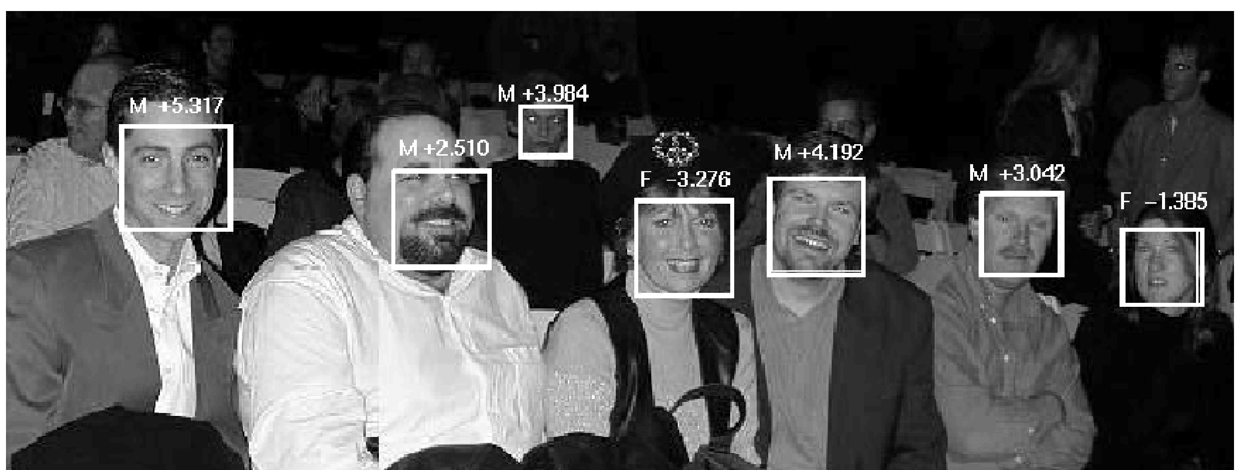
Other detection tasks

Facial Feature Localization

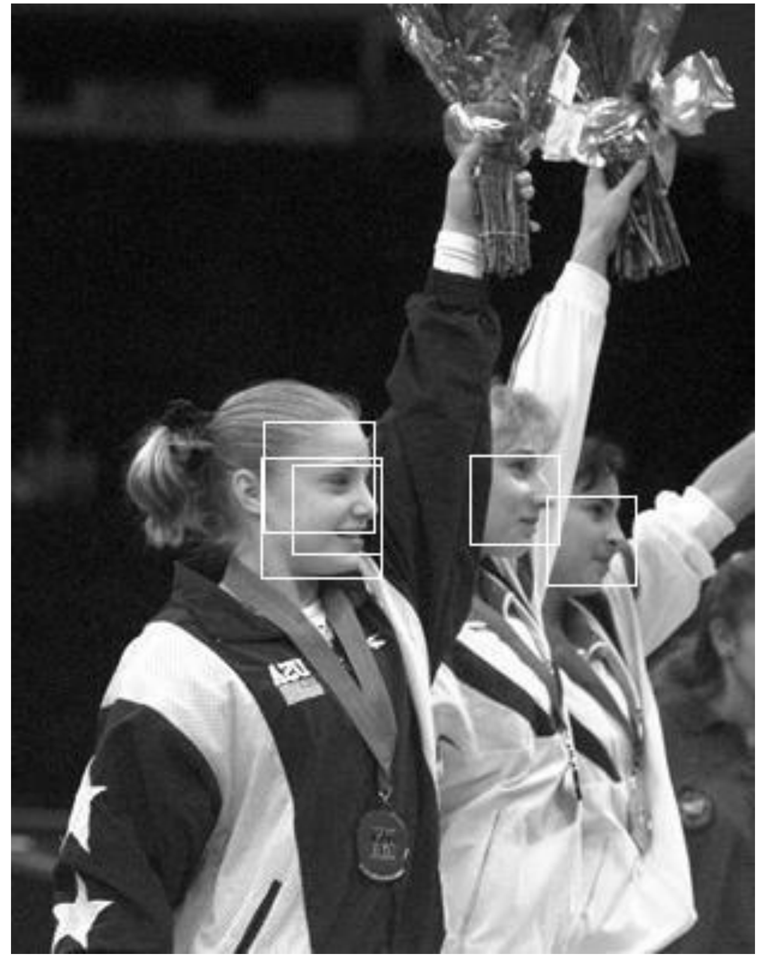


Profile Detection

Male vs. female



Profile Detection



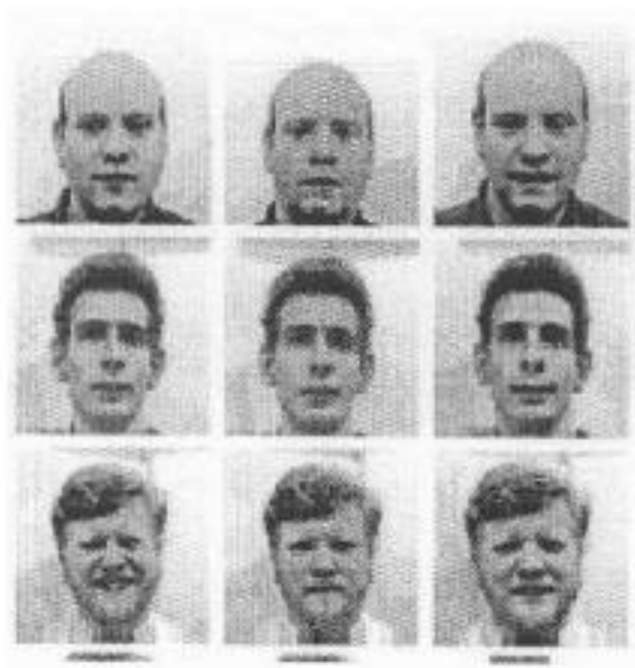
Face Detection and Tracking

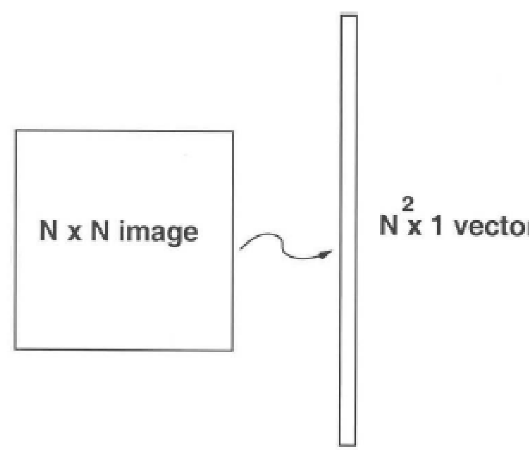
Face Recognition

- Computation of low-dimensional basis (i.e.,eigenfaces):

Step 1: obtain face images $I_1, I_2, \ldots, I_M$ (training faces)

(**very important:** the face images must be *centered* and of the same *size*)





Step 2: represent every image I_i as a vector Γ_i

Face Recognition

- Computation of the eigenfaces

Step 3: compute the average face vector Ψ:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i$$

Step 4: subtract the mean face:

$$\Phi_i = \Gamma_i - \Psi$$

Step 5: compute the covariance matrix C:

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T \quad (N^2 \mathrm{x} N^2 \text{ matrix})$$

$$\text{where } A = [\Phi_1\ \Phi_2 \cdots \Phi_M] \quad (N^2 \mathrm{x} M \text{ matrix})$$

Face Recognition

- Computation of the eigenfaces

Step 6: compute the eigenvectors u_i of AA^T ⇨ $AA^T u_i = \lambda_i u_i$

Step 7: keep only K eigenvectors (corresponding to the K largest eigenvalues)

Face Recognition

Training images

Face Recognition

Mean: μ

Top eigenvectors: $u_1,\ldots u_k$