Classifier Case Study: Viola-Jones Face Detector

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.

Most of these slides are from Svetlana Lazebnik

http://www.cs.unc.edu/~lazebnik/spring09/

Face detection

- Basic idea: slide a window across image and evaluate a face model at every location

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
  - To avoid having a false positive in every image image, our false positive rate has to be less than 10^{-6}

The Viola/Jones Face Detector

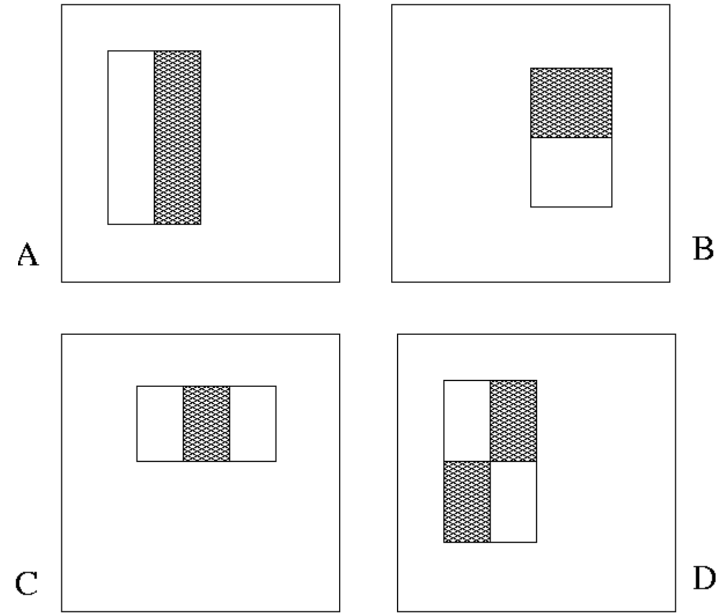
- A seminal approach to real-time object detection
- Training is slow, but detection is very fast
- Key ideas:
  - *Haar-like* image features
  - *Integral images* for fast feature evaluation
  - *Boosting* for feature selection
  - *Attentional cascade* for fast rejection of non-face windows

Image Features

Haar-like filters

Rectangular regions consisting of +1,-1, coefficients

Similar to Haar wavelets

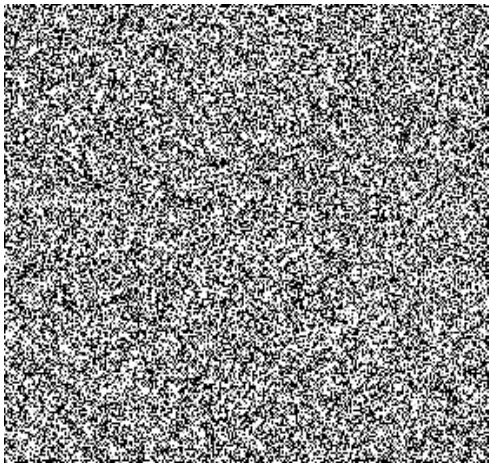


Value =

$\sum$ *(pixels in white area)* – $\sum$ *(pixels in black area)*

Example

When does the filter have high response?



Source
images

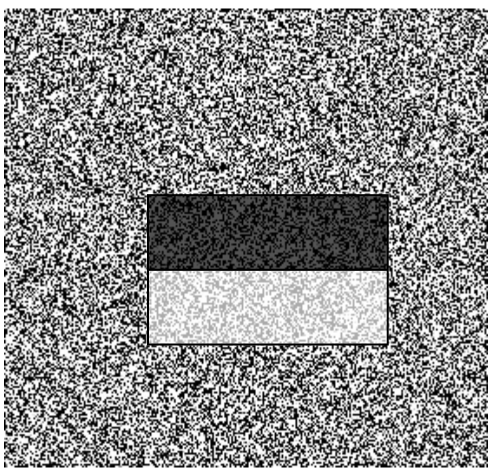
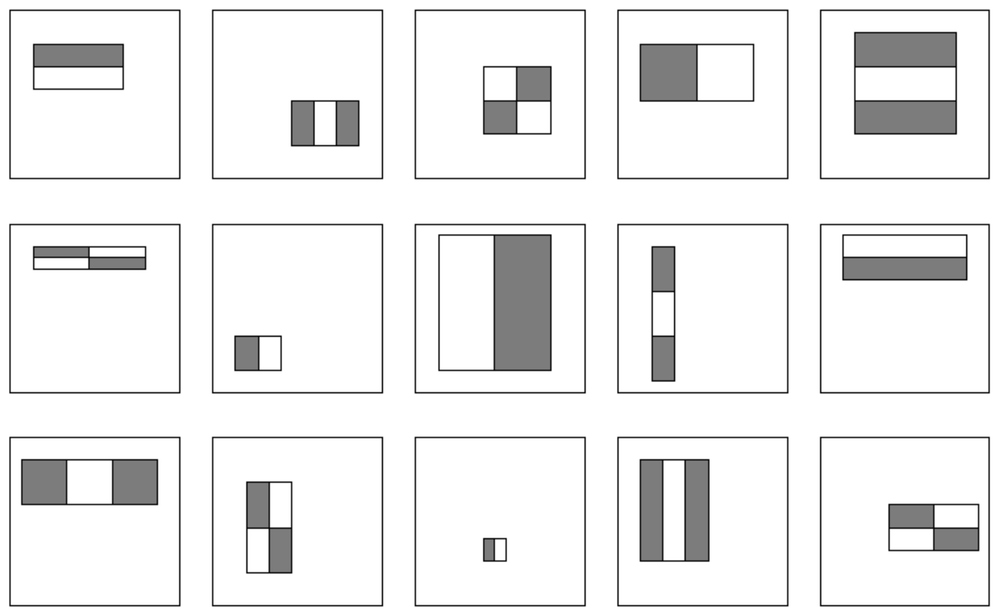


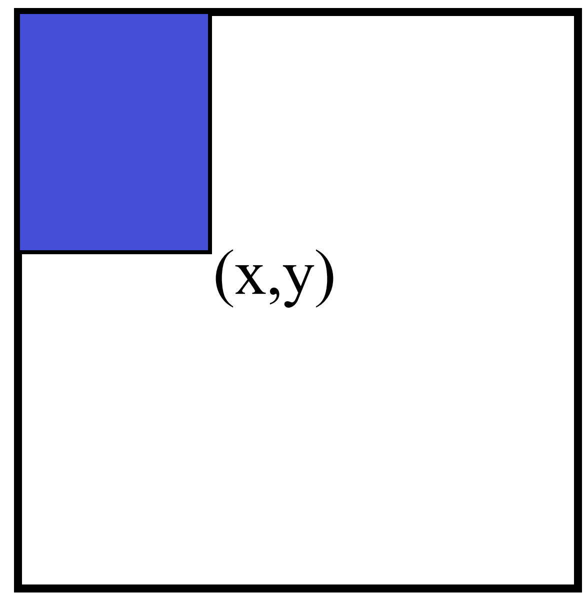
Image Features

- Appropriate combinations of added and subtracted rectangles approximate various derivative filters, e.g. dx, dy, dx dy, dx^2, at different locations and scale.



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



Origins of integral images

Note idea of cumulative distributions in probability theory

$$D(x) = P(X \le x) = \int_{-\infty}^{x} P(\xi)\, d\xi,$$

Then P(a <= X <= b) = D(b)-D(a) $= \int_{a}^{b} P(\xi)\, d\xi,$

Similarly, a multivariate distribution function can be defined if outcomes depend on n parameters:

$$D(a_1, \ldots, a_n) \equiv P(x_1 \le a_1, \ldots, x_n \le a_n).$$

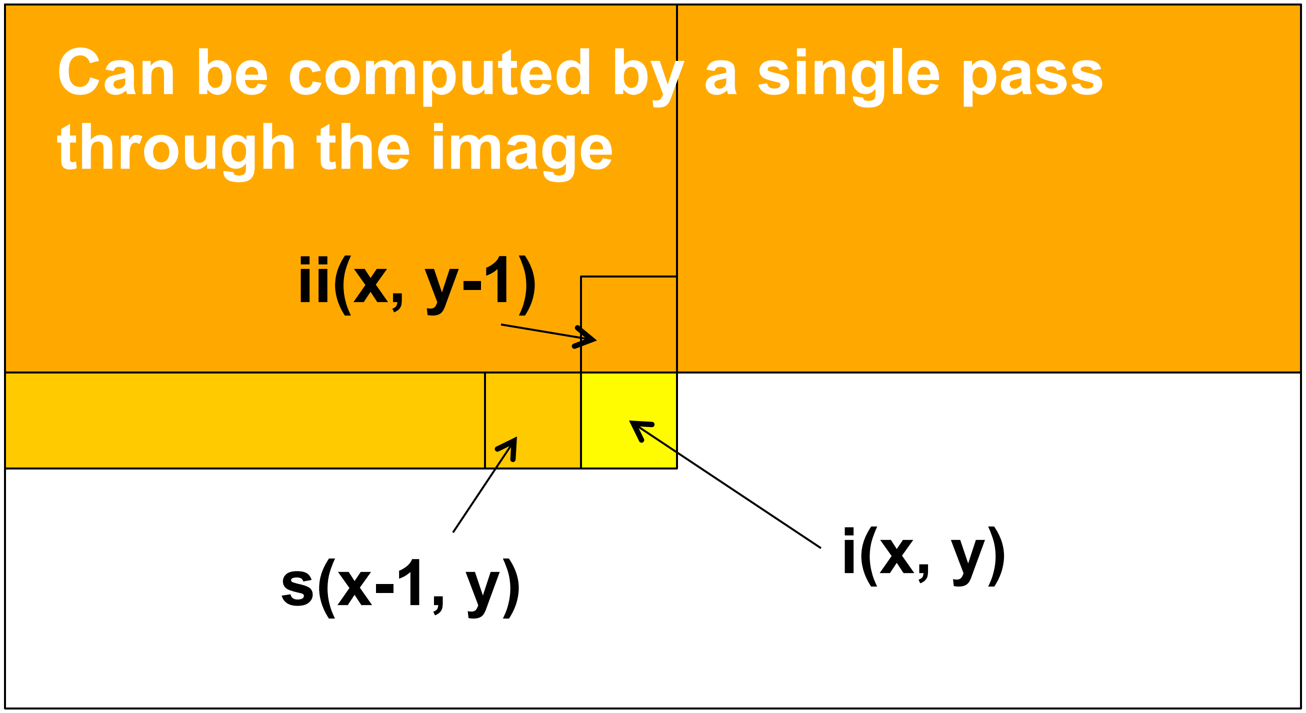
The probability content of a closed region can be found much more efficiently than by direct integration probability density function $P(x)$ by appropriate evaluation of the distribution function at all possible ex defined on the region (Rose and Smith 1996; 2002, p. 193). For example, for a bivariate distribution fur $D(x, y)$, the probability content in the region $x_1 \le x \le x_2$, $y_1 \le y \le y_2$ is given by

$$P(x_1 \le x \le x_2, y_1 \le y \le y_2) = \int_{x_1}^{x_2} \int_{y_1}^{y_2} P(x, y)\, dy\, dx,$$

but can be computed much more efficiently using

$$P(x_1 \le x \le x_2, y_1 \le y \le y_2) = D(x_1, y_1) - D(x_1, y_2) - D(x_2, y_1) + D(x_2, y_2).$$

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)

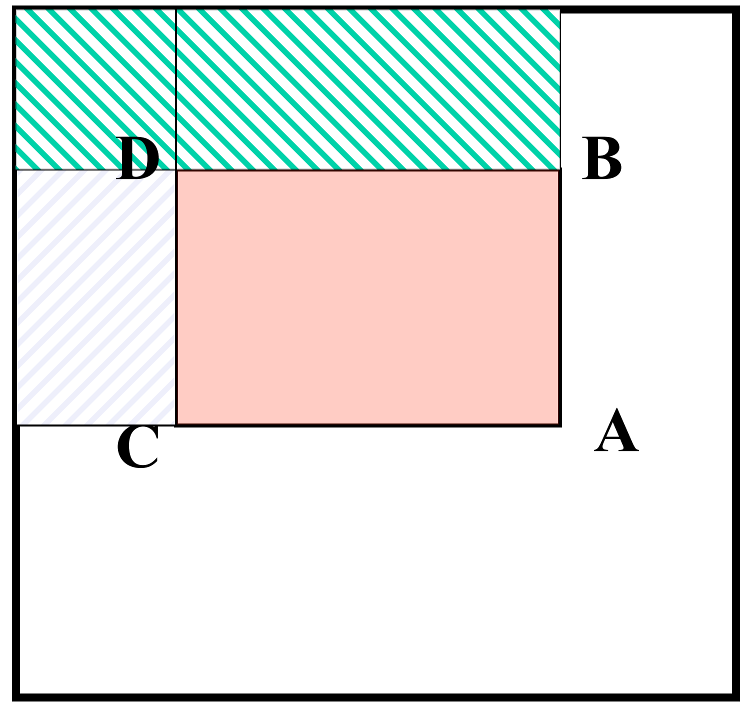
MATLAB: ii = cumsum(cumsum(double(i)), 2);

Computing sum within a rectangle

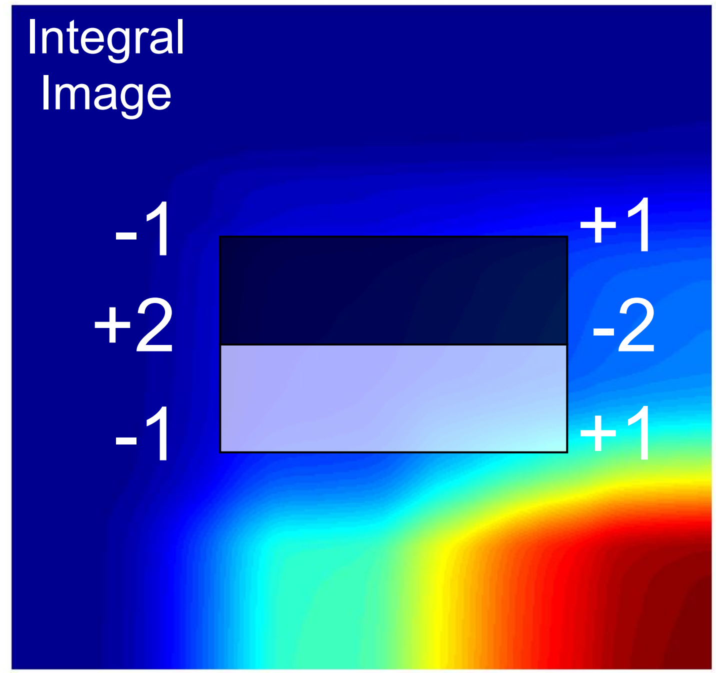
- Let A,B,C,D be the values of the integral image at the corners of a rectangle
- Then the sum of original image values within the rectangle can be computed as:

Sum = A - B - C + D

- Only 3 additions are required for any size of rectangle!

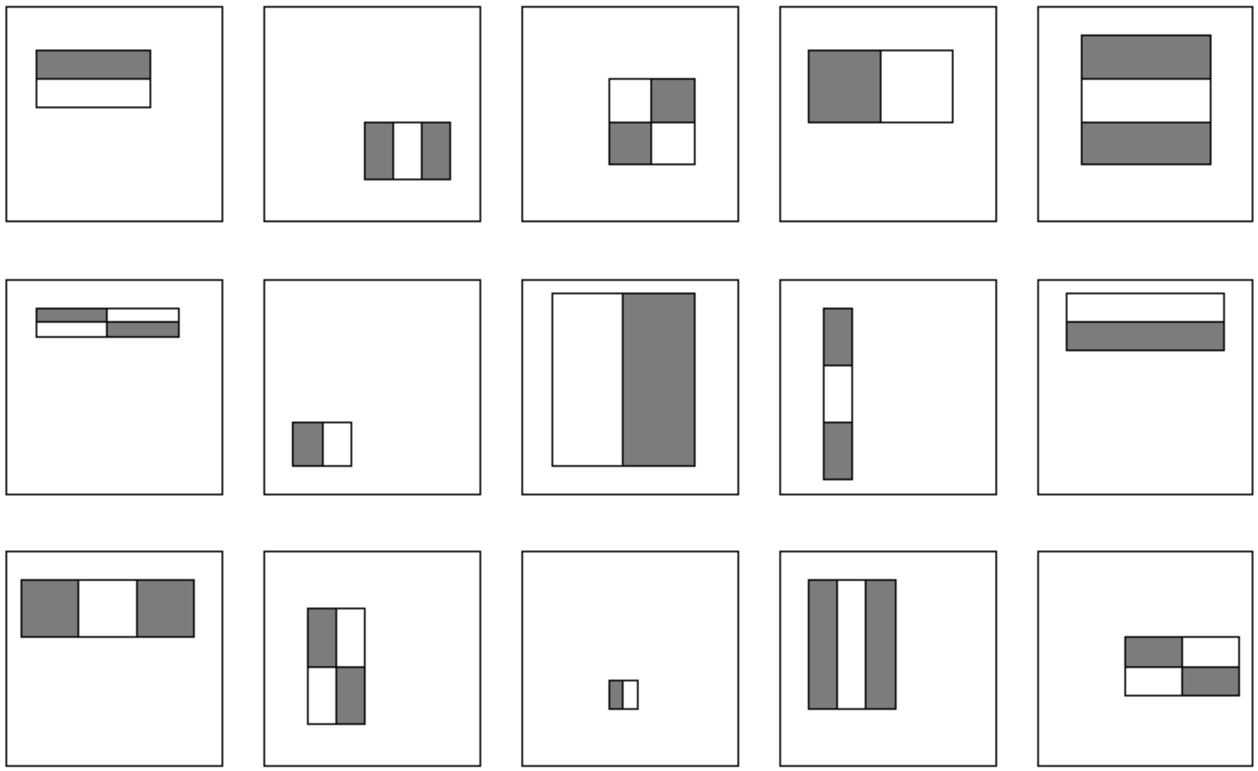


Example



Feature selection

- For a 24x24 detection region, the number of Haar features considered is ~160,000!



Feature selection

- For a 24x24 detection region, the number of Haar features considered is ~160,000!
- At test time, it is impractical to evaluate the entire feature set
- Can we create a good classifier using just a small subset of all possible features?
- How to select such a subset?

Boosting

- Boosting is a classification scheme that works by combining *weak learners* into a more accurate *ensemble* classifier
  - A weak learner need only do better than chance
- Training consists of multiple *boosting rounds*
  - During each boosting round, we select a weak learner that does well on examples that were hard for the previous weak learners
  - "Hardness" is captured by weights attached to training examples

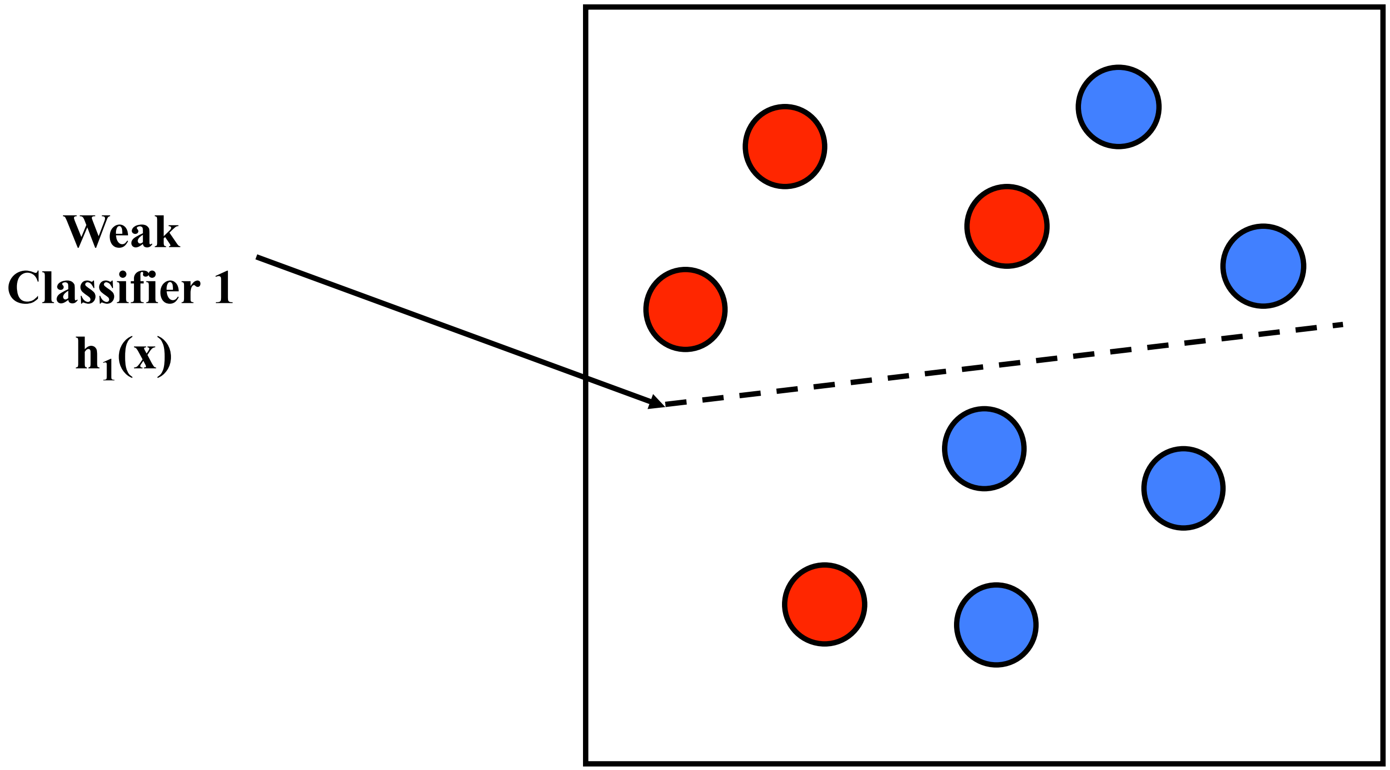
Y. Freund and R. Schapire, A short introduction to boosting, *Journal of Japanese Society for Artificial Intelligence*, 14(5):771-780, September, 1999.

Training procedure

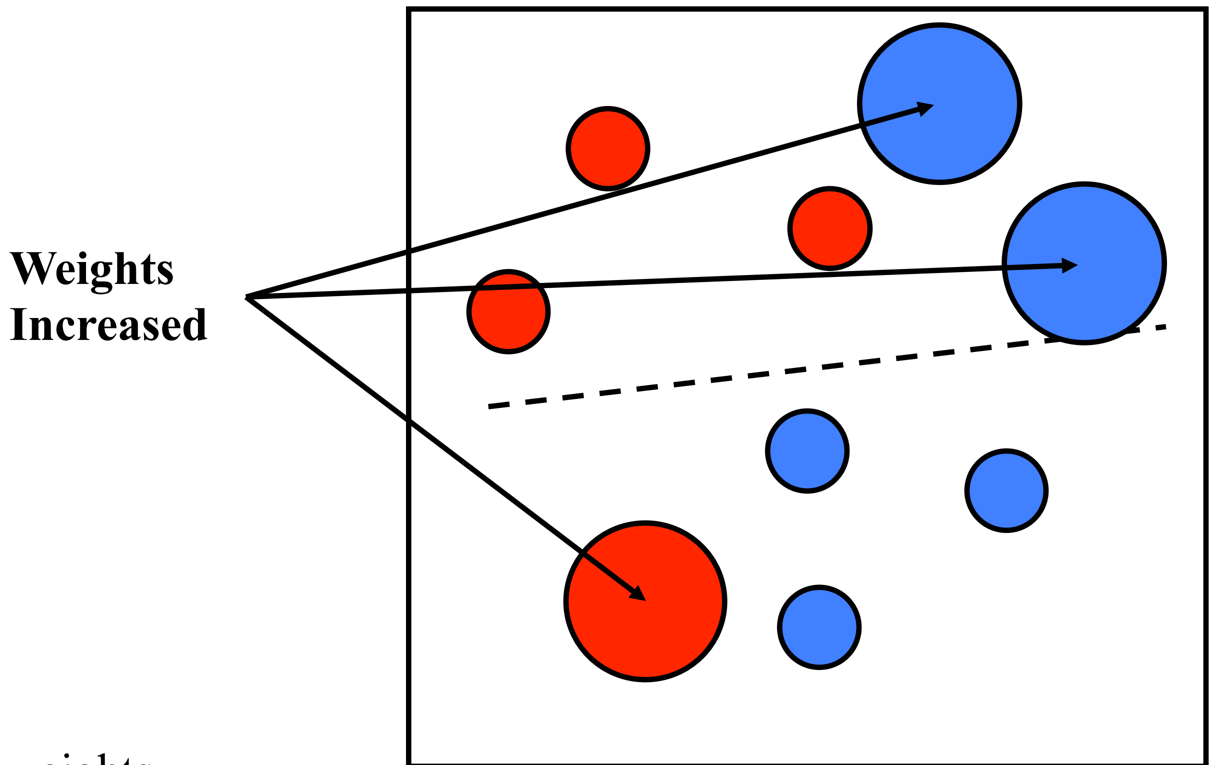
- Initially, weight each training example equally
- In each boosting round:
  - Find the weak learner that achieves the lowest *weighted* training error
  - Raise the weights of training examples misclassified by current weak learner
- Compute final classifier as linear combination of all weak learners (weight of each learner is directly proportional to its accuracy)
- Exact formulas for re-weighting and combining weak learners depend on the particular boosting scheme (e.g., AdaBoost)

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

Boosting illustration

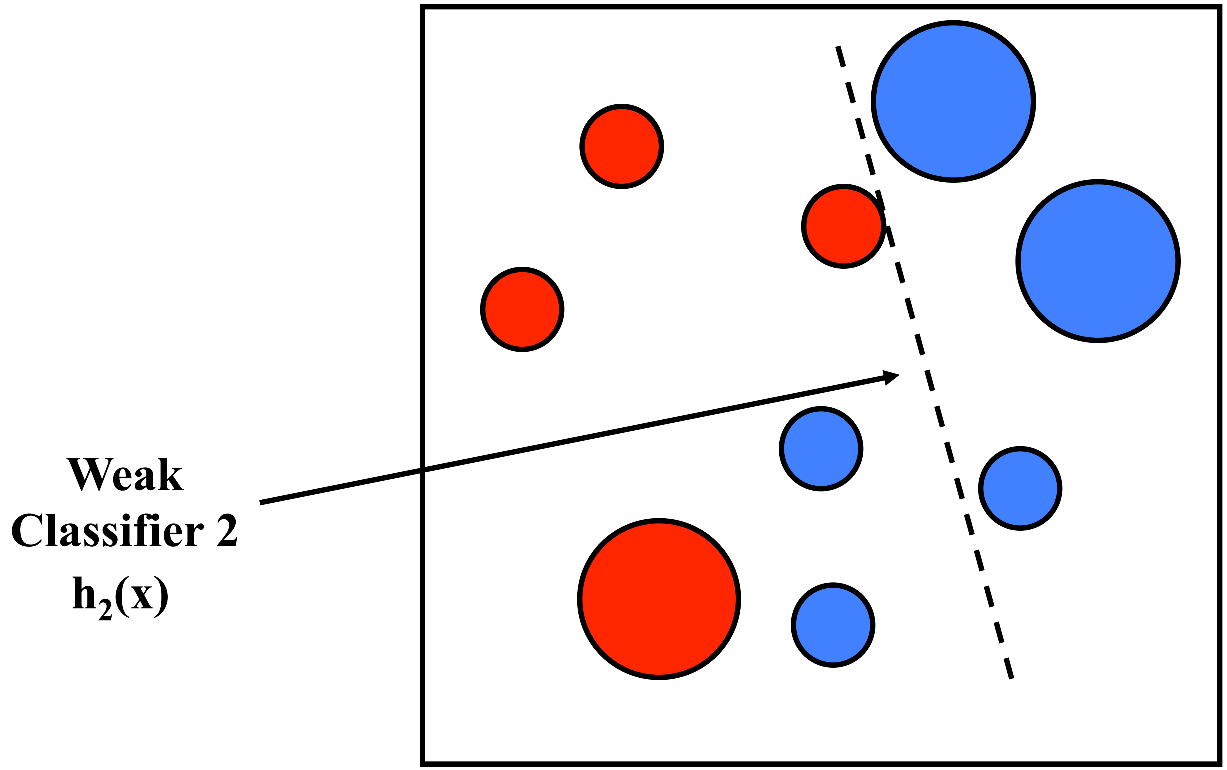


Boosting illustration

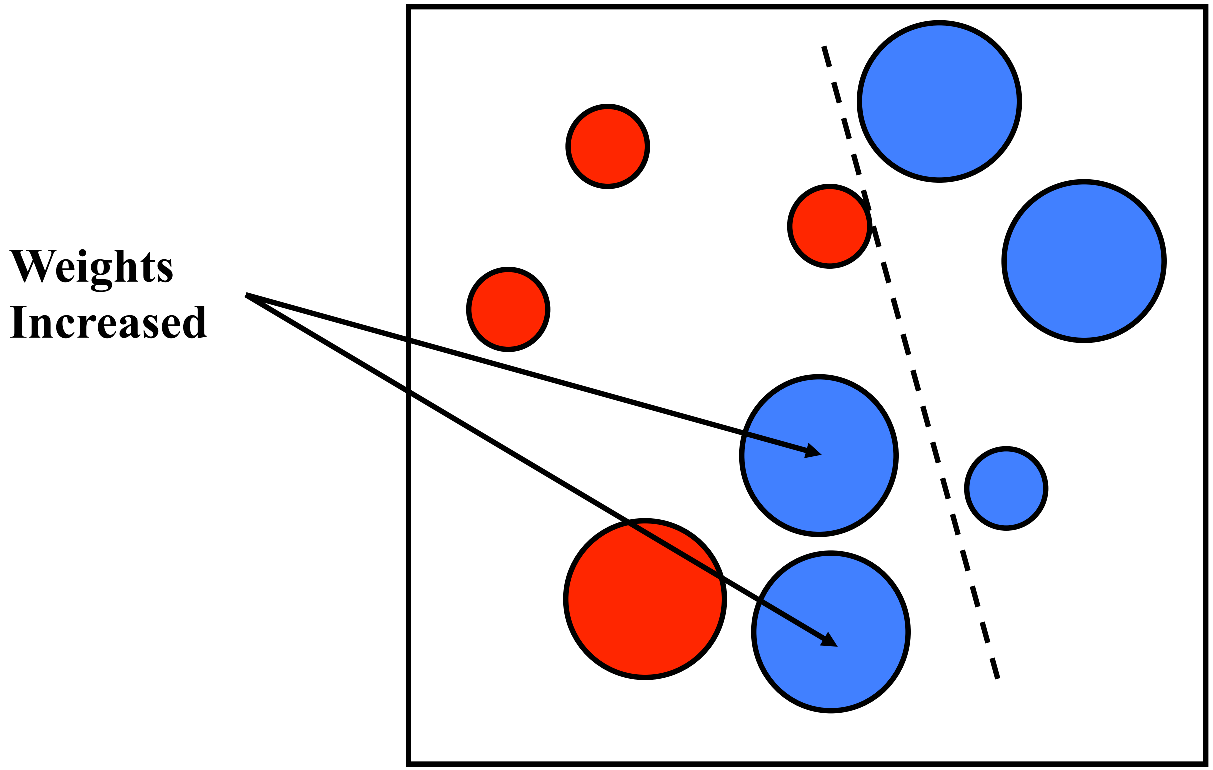


Increasing the weights
forces subsequent classifiers
to focus on residual errors

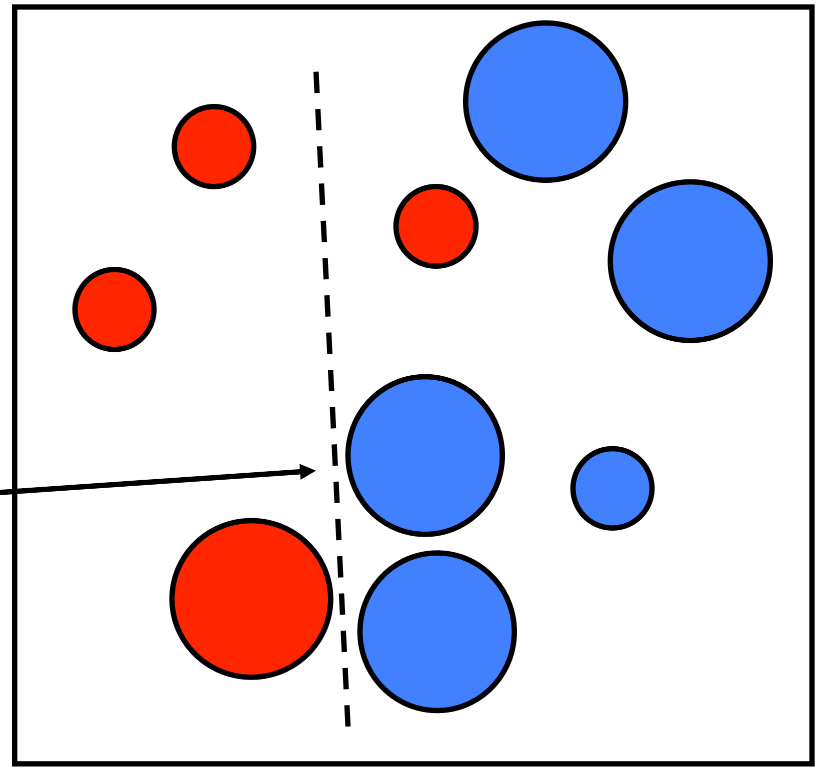
Boosting illustration



Boosting illustration



Boosting illustration

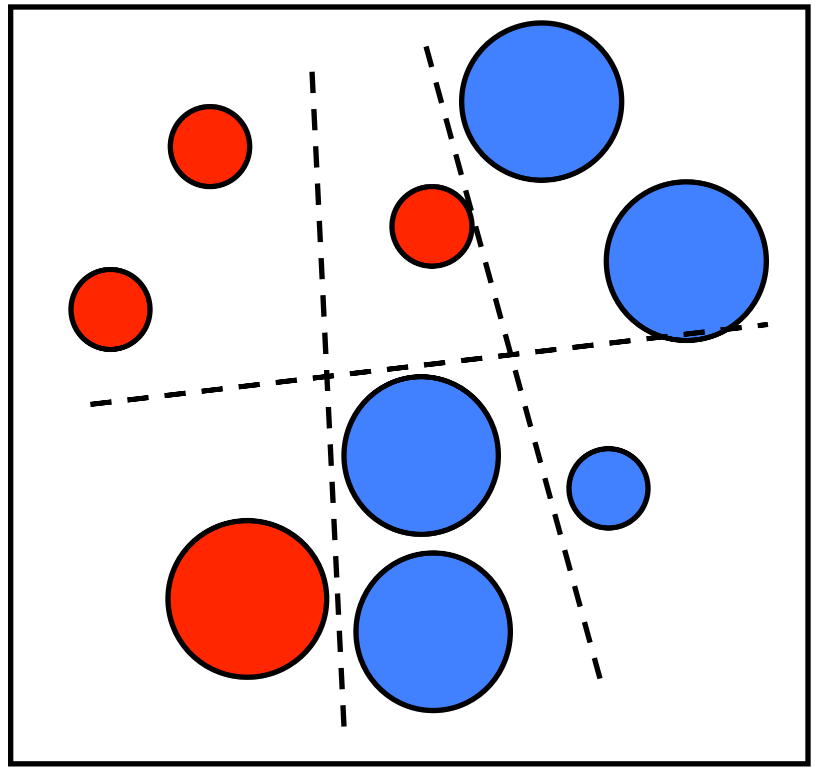


Weak Classifier 3
$h_3(x)$

Boosting illustration

Final classifier is a weighted combination of the weak classifiers

$$h(\mathbf{x}) = \text{sign}\left(\sum_{j=1}^{M} \alpha_j h_j(\mathbf{x})\right)$$



Boosting

Boosting is a type of greedy method for minimizing average loss over a training set by adding new features/classifiers one at a time.

- Advantages of boosting
  - Integrates classification 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
  - Often doesn’t work as well as SVM (especially for many-class problems)

Boosting for face detection

- Weak learners here are defined based on thresholded Haar features

value of Haar feature

$$h_t(x) = \begin{cases} +1 & \text{if } p_t f_t(x) > p_t \theta_t \\ -1 & \text{otherwise} \end{cases}$$

window

parity
+1/-1

threshold

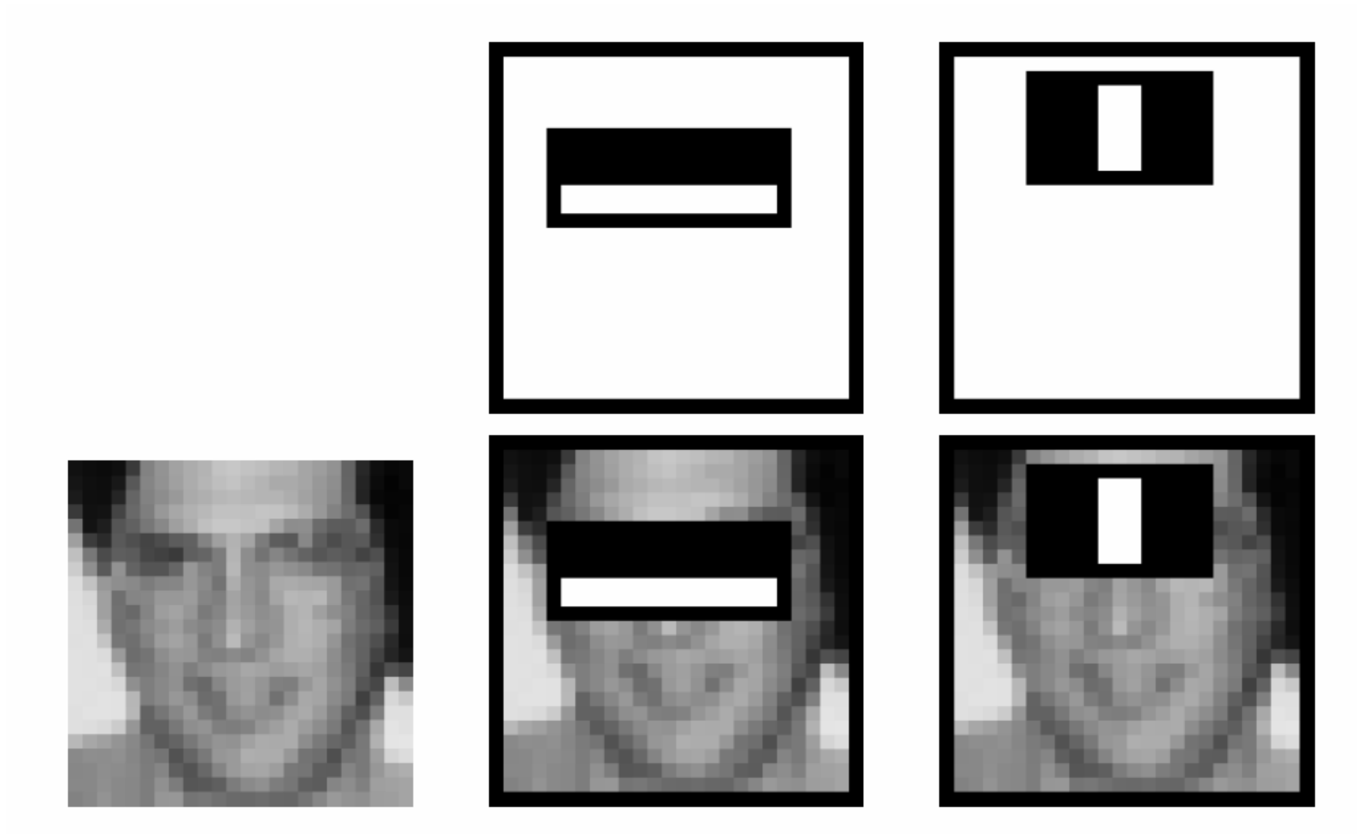
Note: the parity value just serves to change the direction of the threshold to be either less that or greater than, as appropriate.

Boosting for face detection

- For each round of boosting:
  - Evaluate each rectangle filter on each example
  - Select best threshold for each filter
  - Select best filter/threshold combination as weak learner
  - Reweight examples
- Computational complexity of learning: $O(MNK)$
  - M rounds, N examples, K features

Boosting for face detection

- First two features selected by boosting:

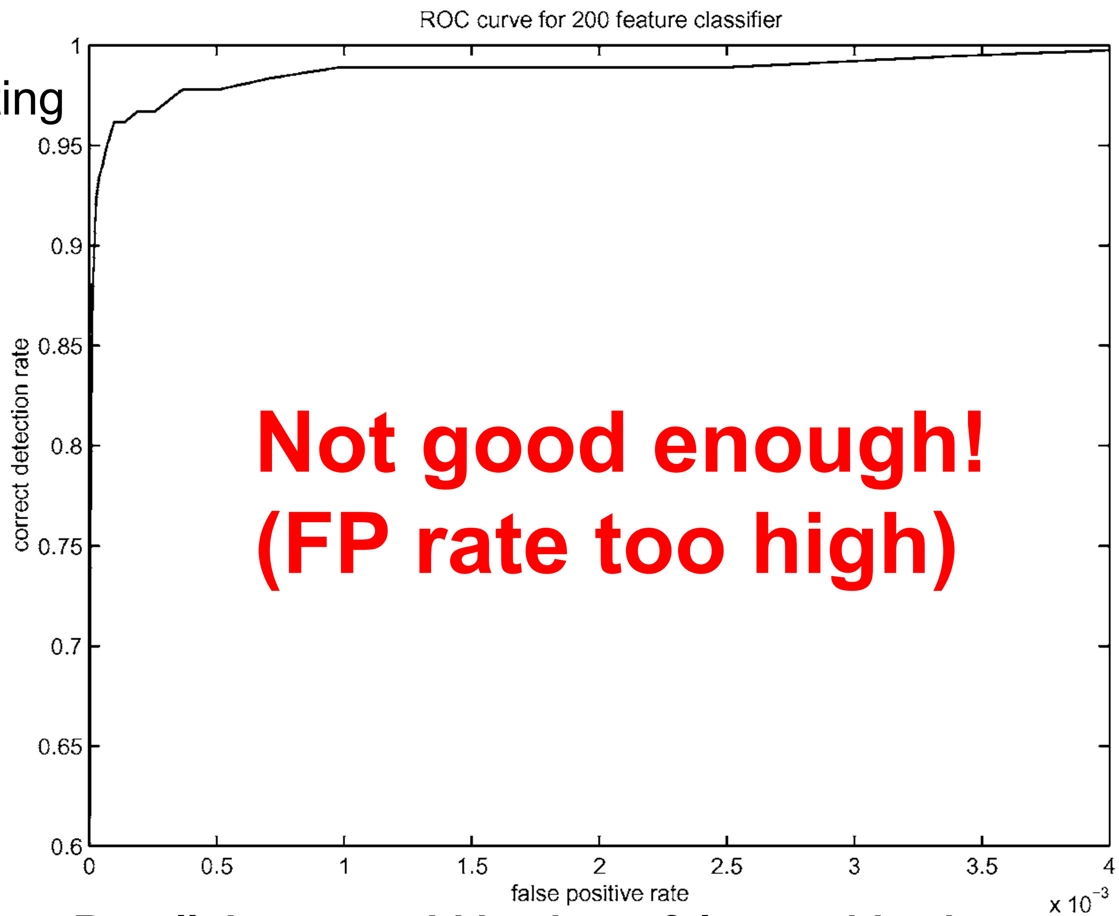


This feature combination can yield 100% detection rate and 50% false positive rate

Boosting for face detection

- A 200-feature classifier can yield 95% detection rate and a false positive rate of 1 in 14084

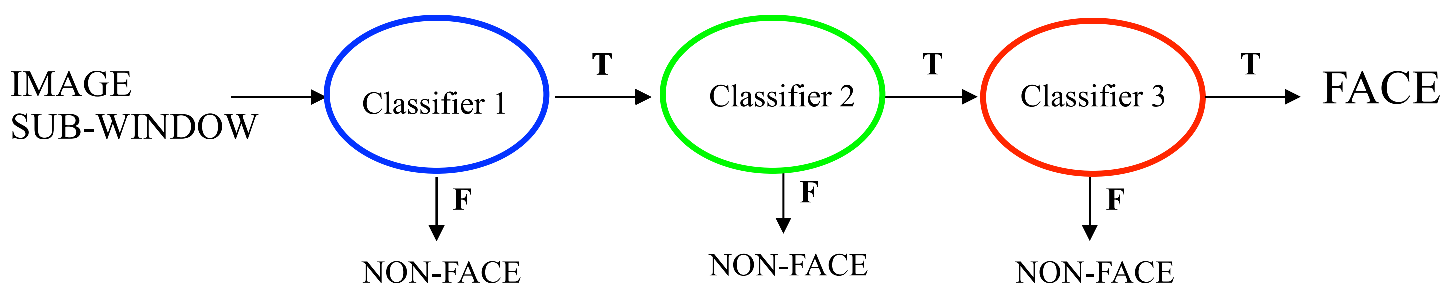
Receiver operating characteristic (ROC) curve



Recall that to avoid having a false positive in every image, our false positive rate has to be less than 10^{-6}

Attentional cascade

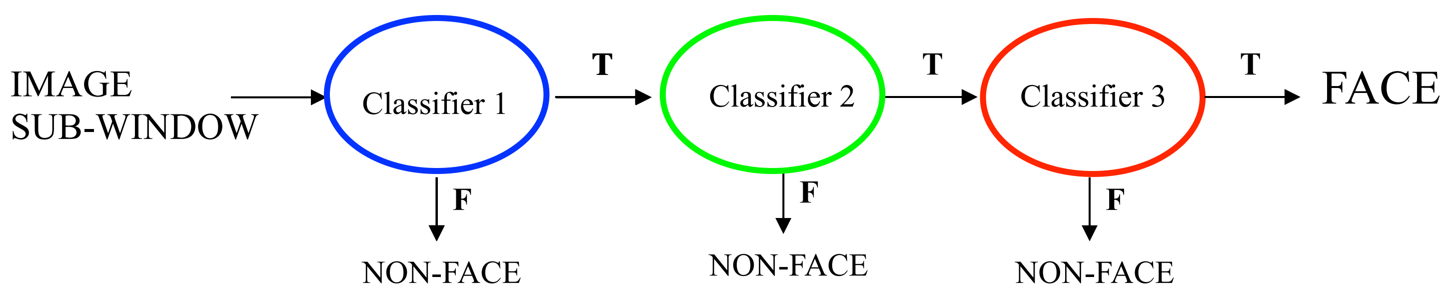
- We start with simple classifiers which reject many of the negative sub-windows while detecting almost all positive sub-windows
- Positive response from the first classifier triggers the evaluation of a second (more complex) classifier, and so on
- A negative outcome at any point leads to the immediate rejection of the sub-window



Attentional cascade

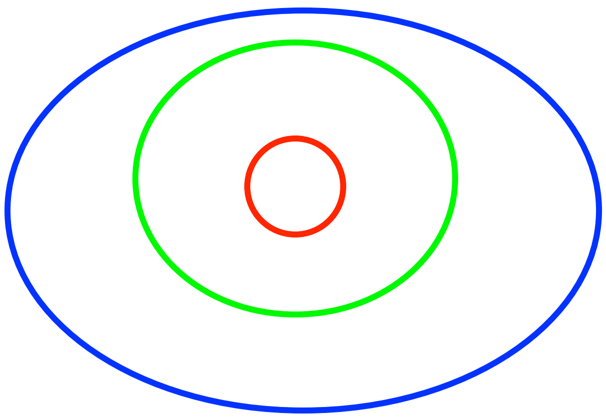
- Cascading classifiers solves several problems:

- Improves speed by early rejection of nonface regions by simple classifiers
- Reduces false positive rates

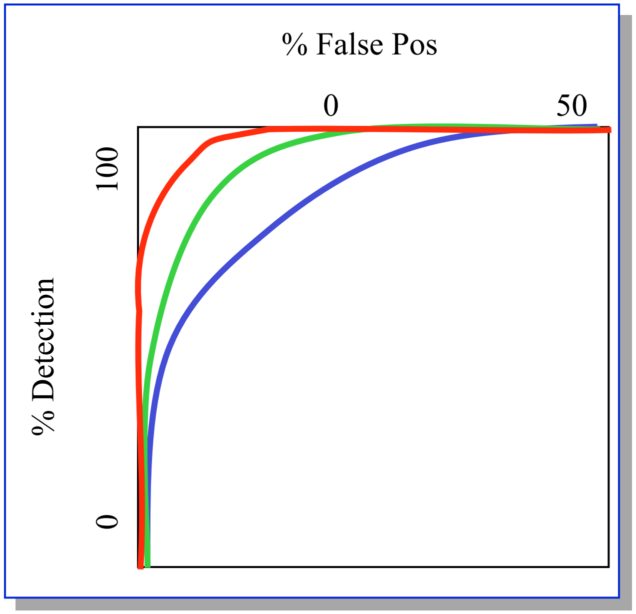


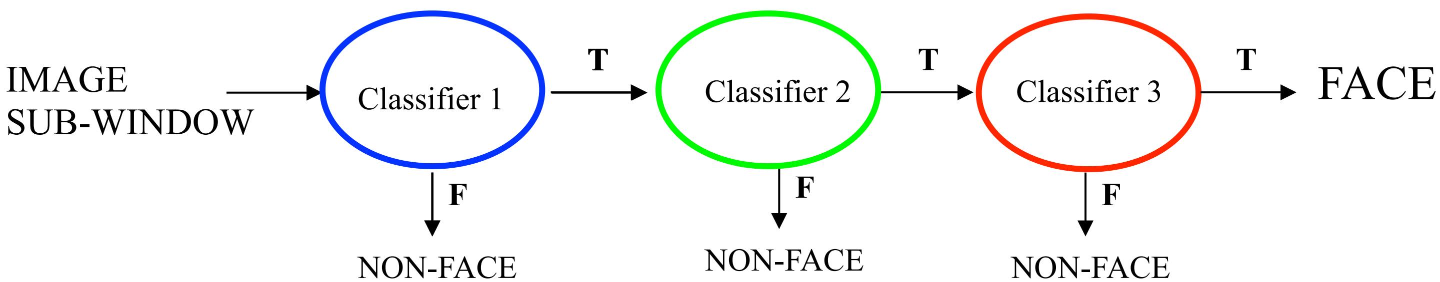
Attentional cascade

- Chain classifiers that are progressively more complex and have lower false positive rates:



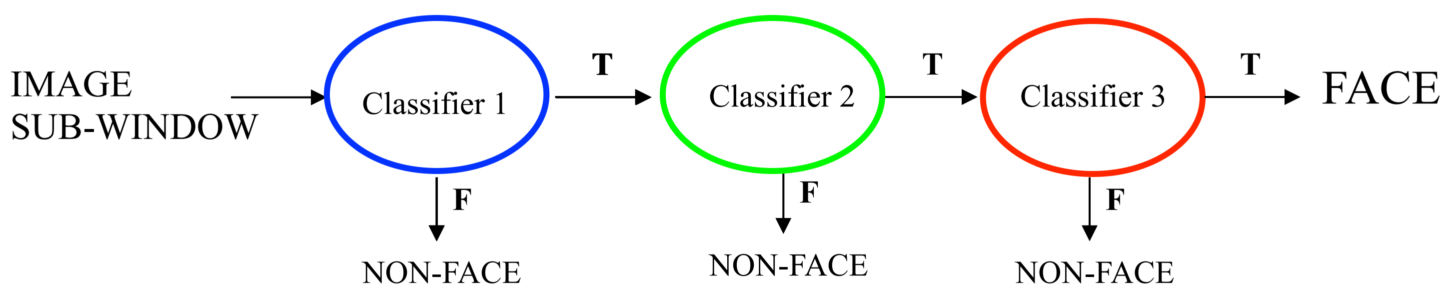
Receiver operating characteristic





Attentional cascade

- The detection rate and the false positive rate of the cascade are found by multiplying the respective rates of the individual stages
- A detection rate of 0.9 and a false positive rate on the order of 10^{-6} can be achieved by a 10-stage cascade if each stage has a detection rate of 0.99 ($0.99^{10} \approx 0.9$) and a false positive rate of about 0.30 ($0.3^{10} \approx 6\times10^{-6}$)



Training the cascade

- Set target detection and false positive rates for each stage
- Keep adding features to the current stage until its target rates have been met
  - Need to lower AdaBoost threshold to maximize detection (as opposed to minimizing total classification error)
  - Test on a *validation set*
- If the overall false positive rate is not low enough, then add another stage
- Use false positives from current stage as the negative training examples for the next stage

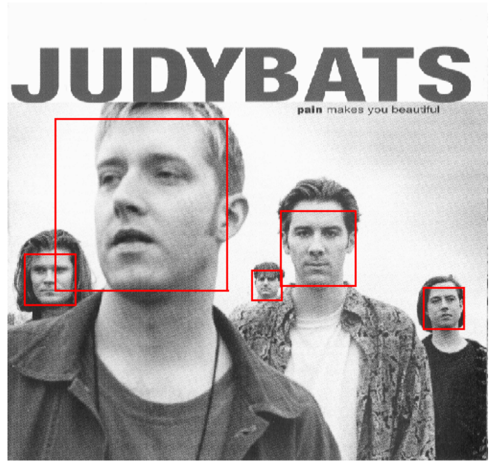
The implemented system

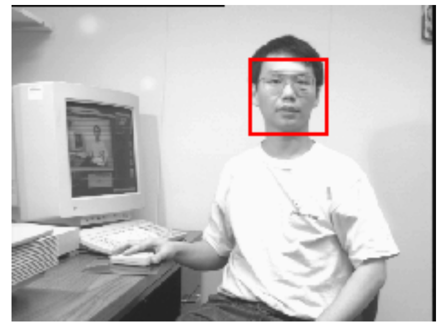
- Training Data
  - 5000 faces
    - All frontal, rescaled to 24x24 pixels
  - 300 million non-faces
    - 9500 non-face images
  - Faces are normalized
    - Scale, translation
- Many variations
  - Across individuals
  - Illumination
  - Pose

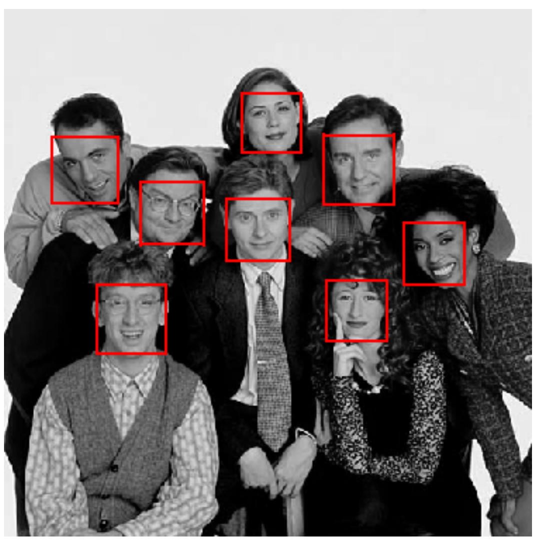
System performance

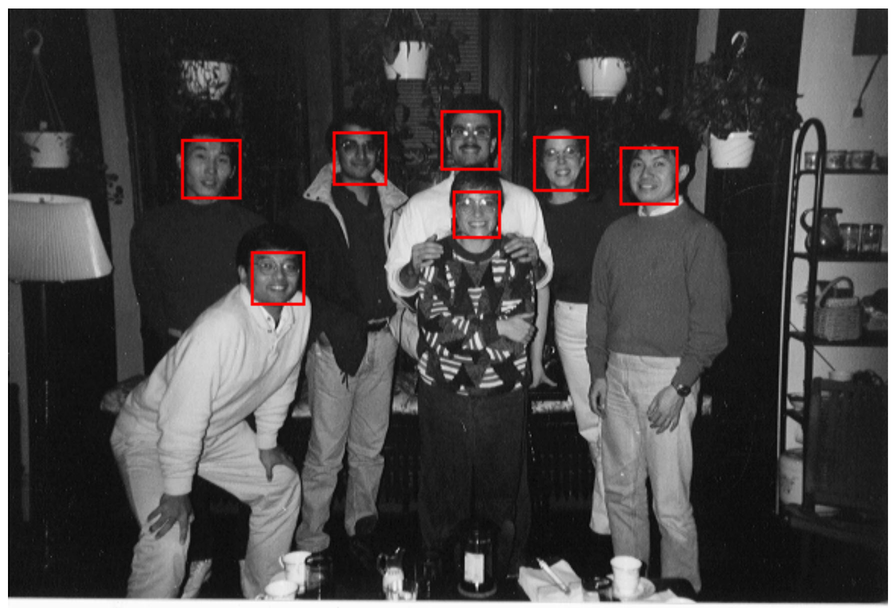
- Training time: “weeks” on 466 MHz Sun workstation
- 38 layers, total of 6061 features
- Average of 10 features evaluated per window on test set
- “On a 700 Mhz Pentium III processor, the face detector can process a 384 by 288 pixel image in about .067 seconds”
    - 15 Hz
    - 15 times faster than previous detector of comparable accuracy (Rowley et al., 1998)

Output of Face Detector on Test Images



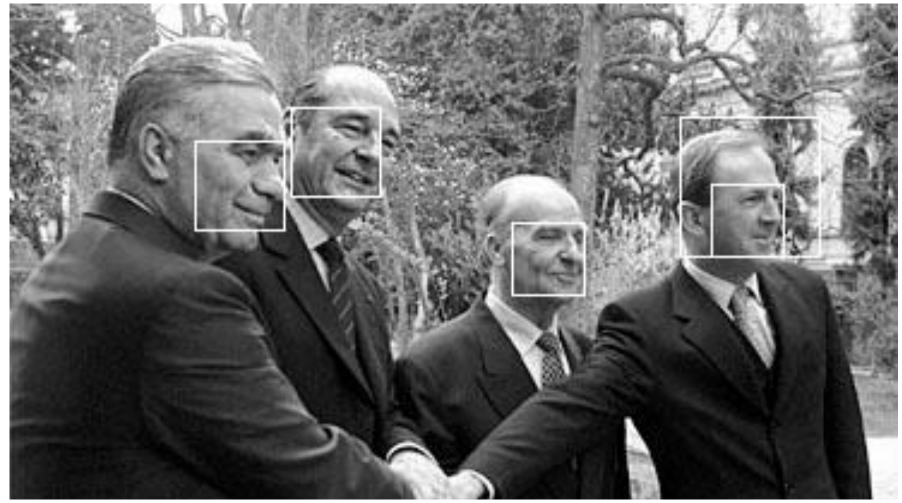






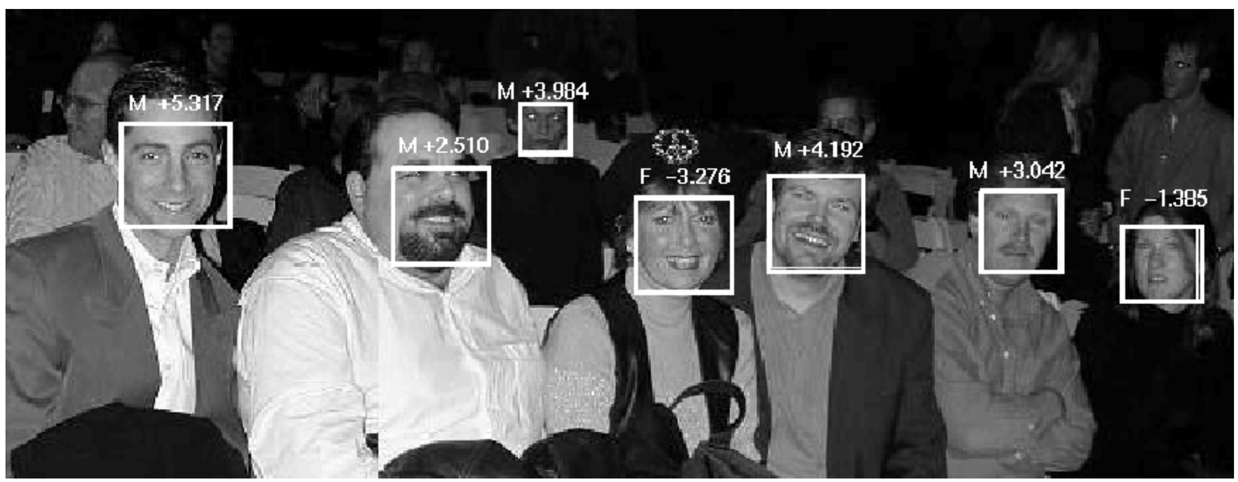
Other detection tasks

Facial Feature Localization

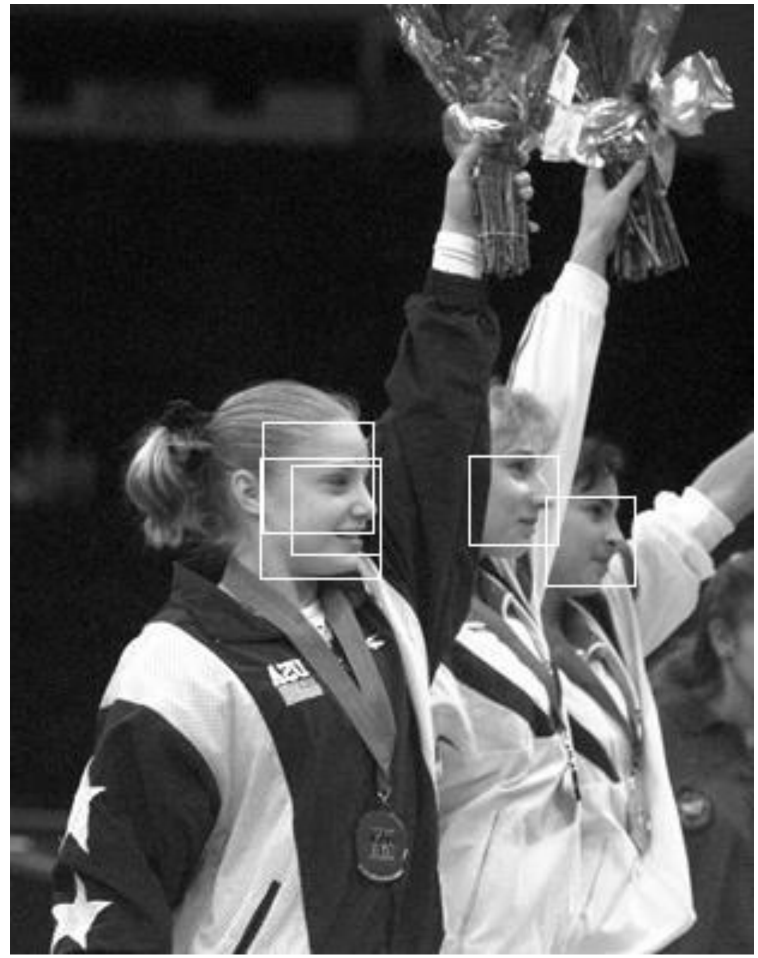


Profile Detection

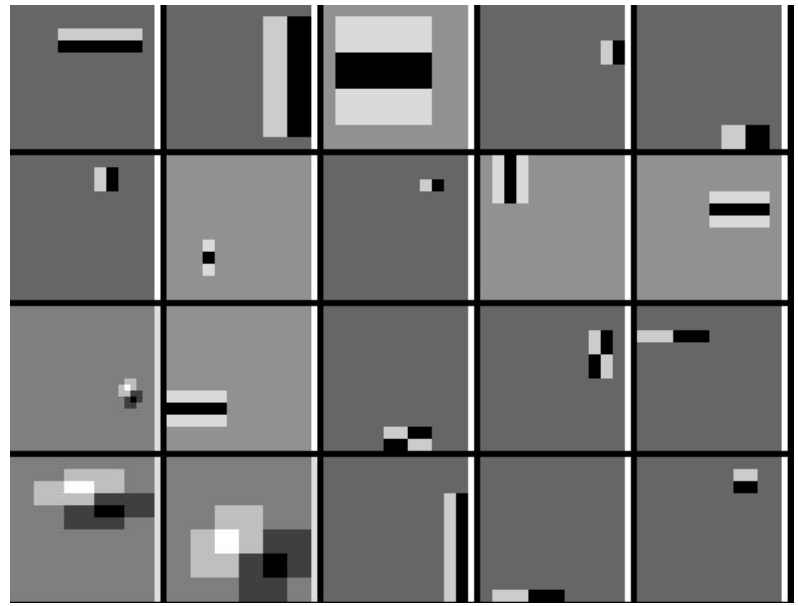
Male vs.
female



Profile Detection



Profile Features



Summary: Viola/Jones detector

- Haar features
- Integral images for fast computation
- Boosting for feature selection
- Attentional cascade for fast rejection of negative windows