Learning to Detect Faces

A Large-Scale Application of Machine Learning

(This material is not in the text: for further information see the paper by
P. Viola and M. Jones, International Journal of Computer Vision, 2004

Viola-Jones Face Detection Algorithm

- Overview :
  - Viola Jones technique overview
  - Features
  - Integral Images
  - Feature Extraction
  - Weak Classifiers
  - Boosting and classifier evaluation
  - Cascade of boosted classifiers
  - Example Results

Viola Jones Technique Overview

- Three major contributions/phases of the algorithm :
  - Feature extraction
  - Learning using boosting and decision stumps
  - Multi-scale detection algorithm

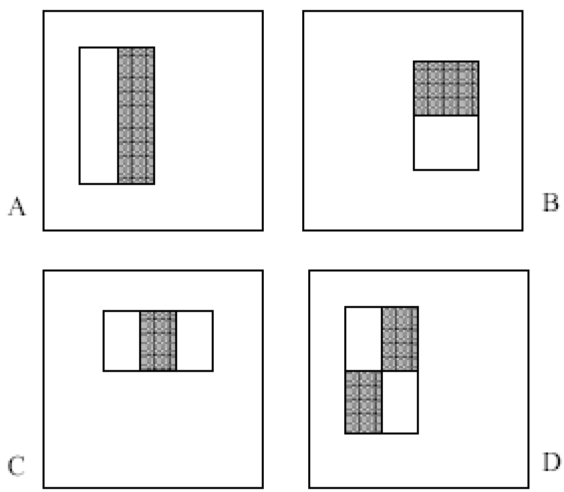
- Feature extraction and feature evaluation.
  - Rectangular features are used, with a new image representation their calculation is very fast.

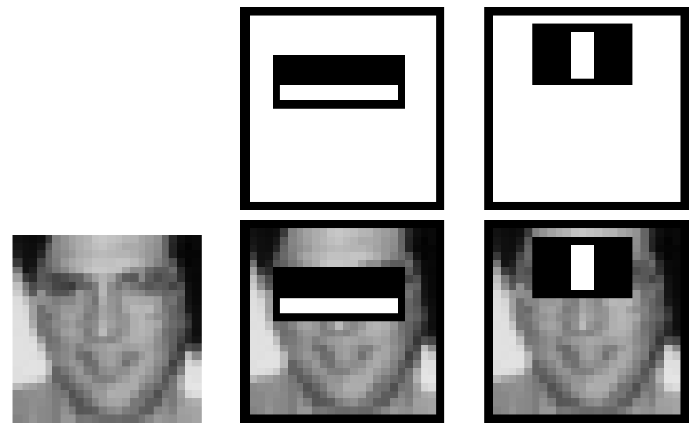
- Classifier learning using a method called boosting

- A combination of simple classifiers is very effective

Features

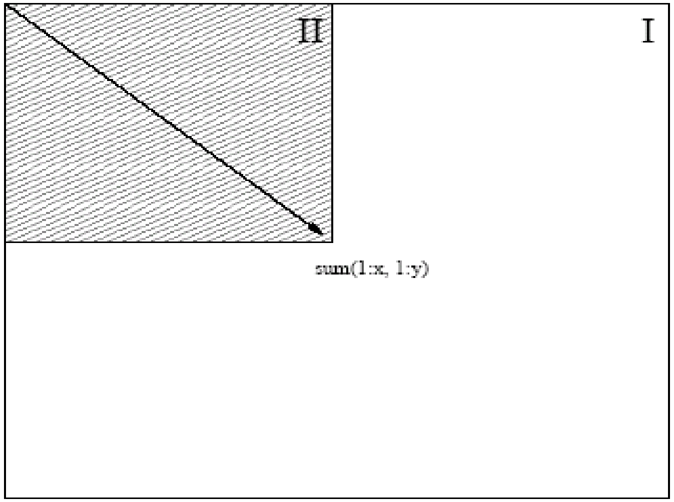
- Four basic types.
  - They are easy to calculate.
  - The white areas are subtracted from the black ones.
  - A special representation of the sample called the **integral image** makes feature extraction faster.





Integral images

- Summed area tables



- A representation that means any rectangle's values can be calculated in four accesses of the integral image.

Fast Computation of Pixel Sums

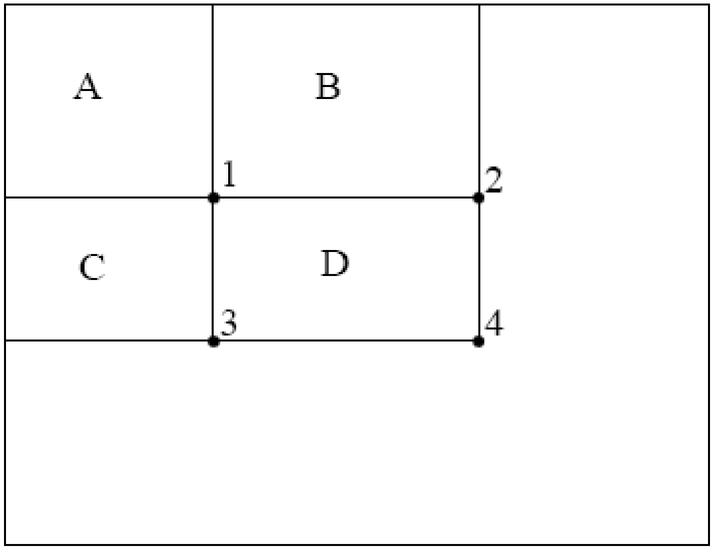
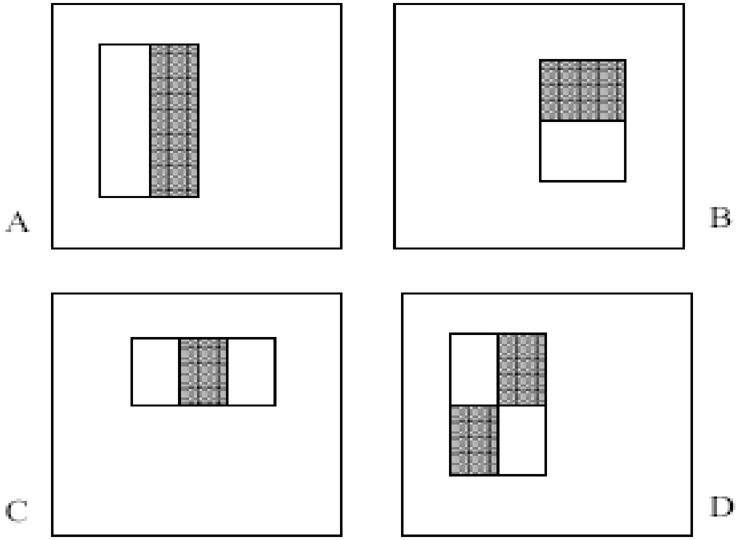


Figure 3: The sum of the pixels within rectangle D can be computed with four array references. The value of the integral image at location 1 is the sum of the pixels in rectangle A. The value at location 2 is $A + B$, at location 3 is $A + C$, and at location 4 is $A + B + C + D$. The sum within D can be computed as $4 + 1 - (2 + 3)$.

Feature Extraction

- Features are extracted from sub windows of a sample image.
  - The base size for a sub window is 24 by 24 pixels.
  - Each of the four feature types are scaled and shifted across all possible combinations
    - In a 24 pixel by 24 pixel sub window there are ~160,000 possible features to be calculated.



Learning with many features

- We have 160,000 features – how can we learn a classifier with only a few hundred training examples without overfitting?

- Idea:
  - Learn a single very simple classifier (a “weak classifier”)
  - Classify the data
  - Look at where it makes errors
  - Reweight the data so that the inputs where we made errors get higher weight in the learning process
  - Now learn a 2nd simple classifier on the weighted data
  - Combine the 1st and 2nd classifier and weight the data according to where they make errors
  - Learn a 3rd classifier on the weighted data

  - ... and so on until we learn T simple classifiers

  - Final classifier is the combination of all T classifiers

  - This procedure is called “Boosting” – works very well in practice.

“Decision Stumps”

- Decision stumps = decision tree with only a single root node
  - Certainly a very weak learner!

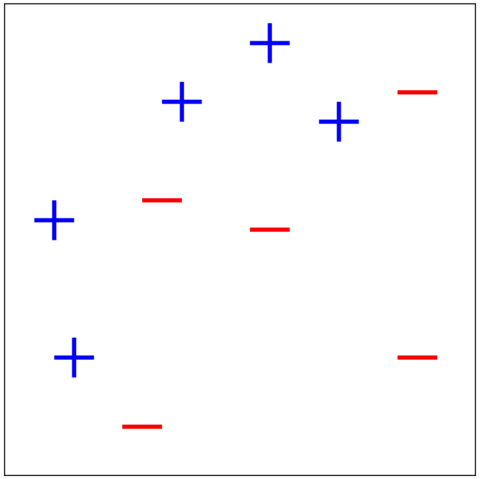
  - Say the attributes are real-valued
  - Decision stump algorithm looks at all possible thresholds for each attribute
  - Selects the one with the max information gain
  - Resulting classifier is a simple threshold on a single feature
    - Outputs a +1 if the attribute is above a certain threshold
    - Outputs a -1 if the attribute is below the threshold

  - Note: can restrict the search for to the n-1 “midpoint” locations between a sorted list of attribute values for each feature. So complexity is n log n per attribute.

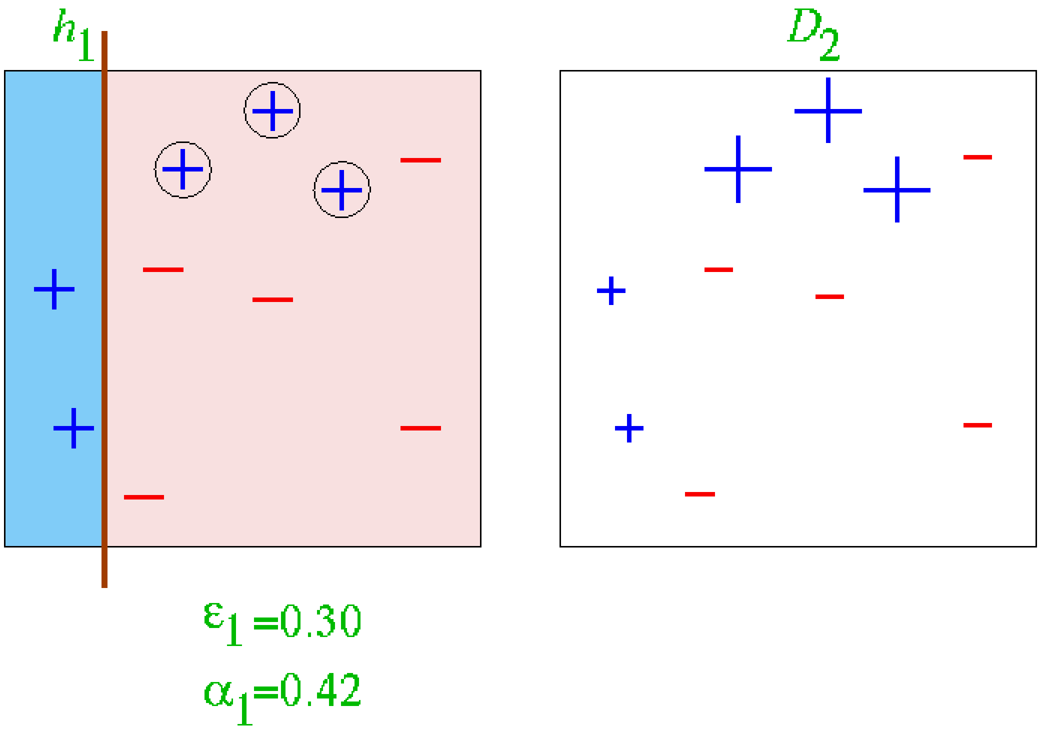
  - Note this is exactly equivalent to learning a perceptron with a single intercept term (so we could also learn these stumps via gradient descent and mean squared error)

Boosting Example

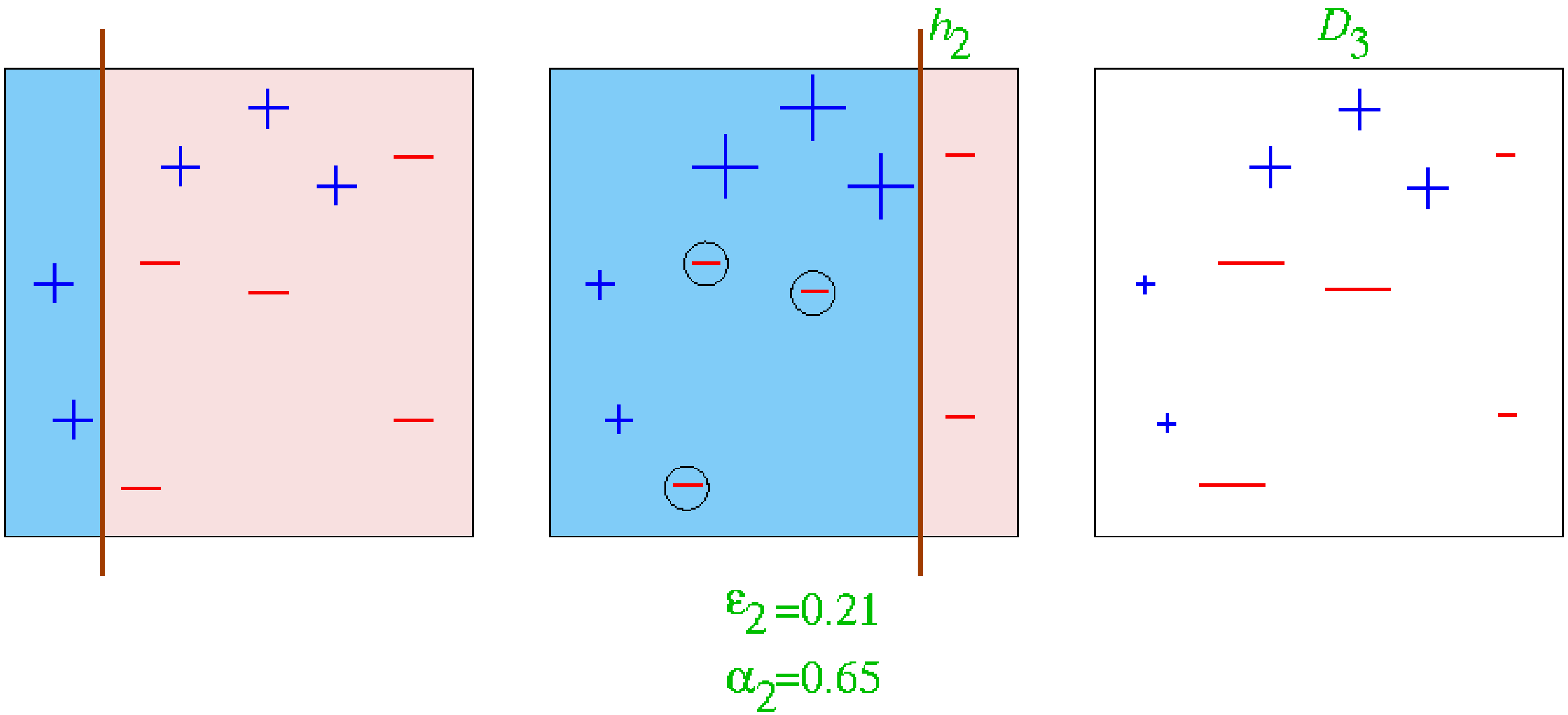
D_1



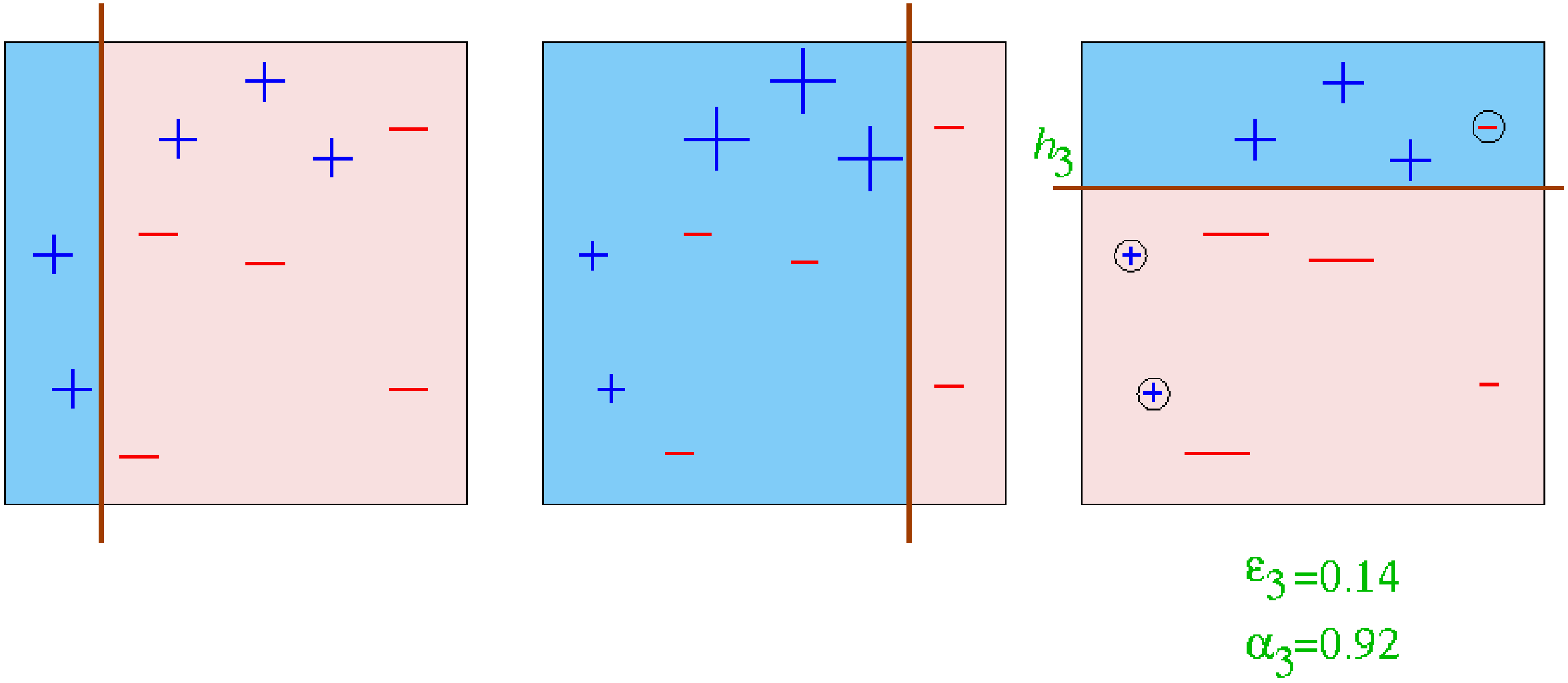
First classifier



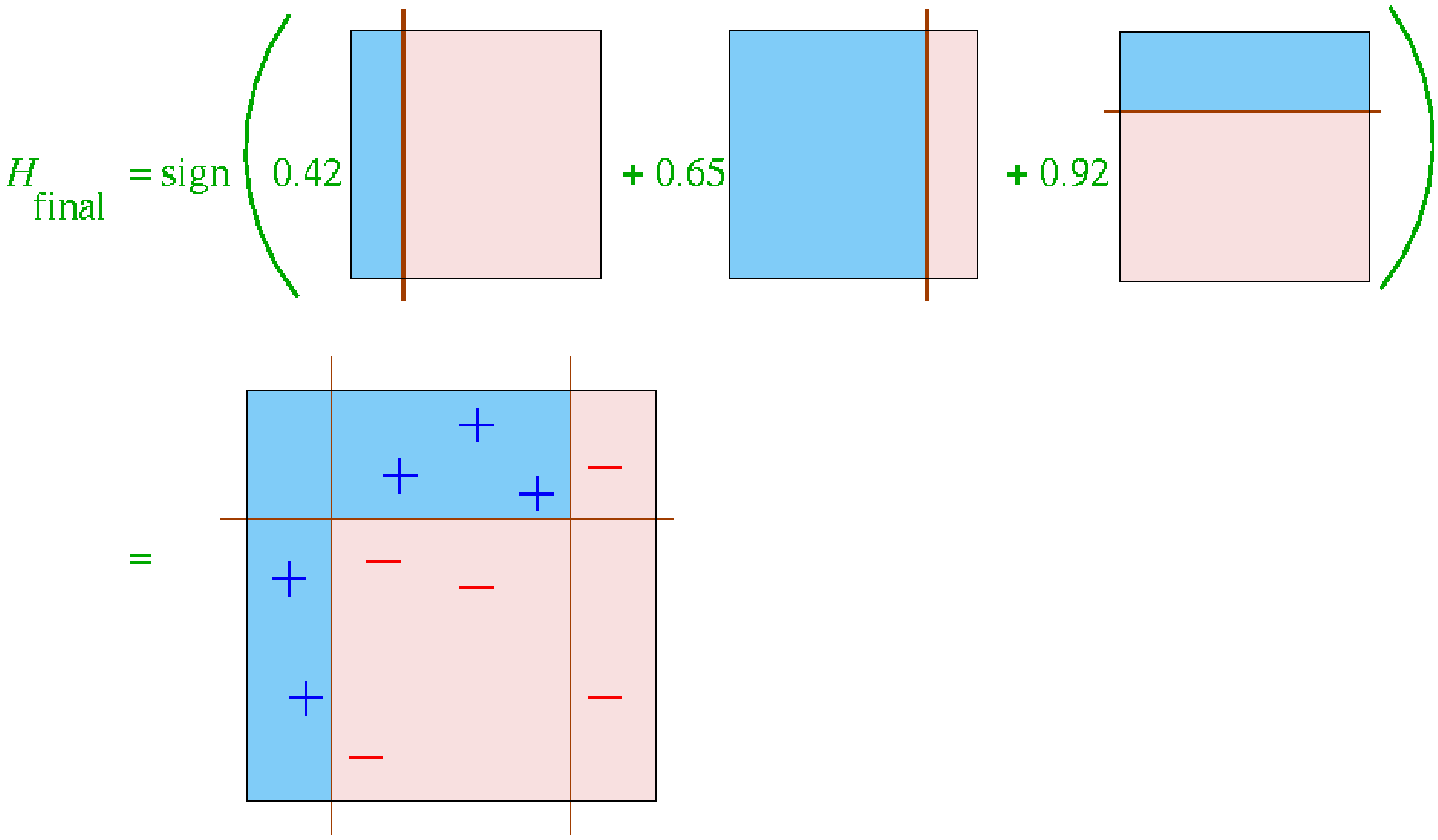
First 2 classifiers



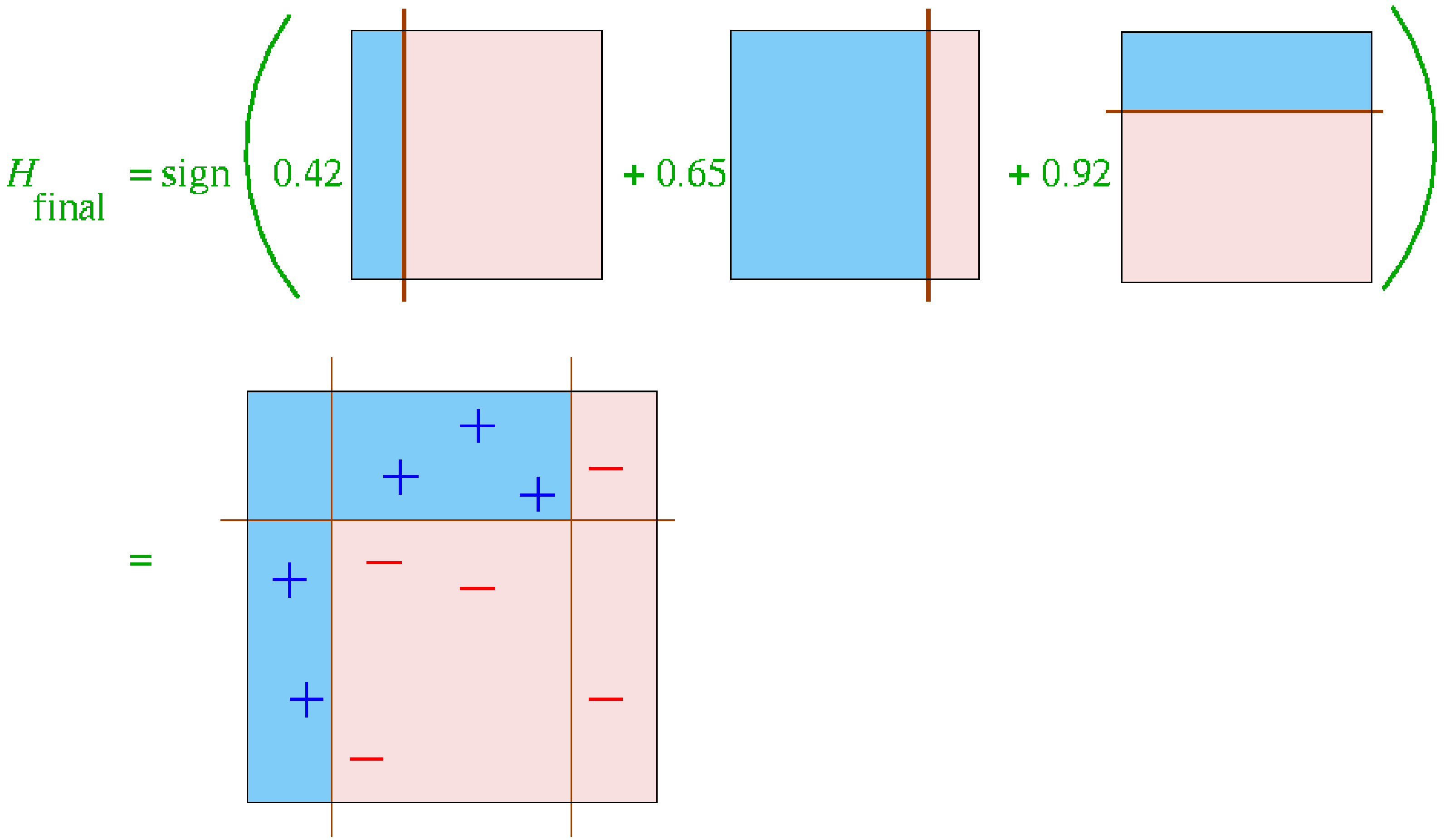
First 3 classifiers



Final Classifier learned by Boosting



Final Classifier learned by Boosting



Boosting with Decision Stumps

- Viola-Jones algorithm
  - With K attributes (e.g., K = 160,000) we have 160,000 different decision stumps to choose from

  - At each stage of boosting
    - given reweighted data from previous stage
    - Train all K (160,000) single-feature perceptrons
    - Select the single best classifier at this stage
    - Combine it with the other previously selected classifiers
    - Reweight the data
    - Learn all K classifiers again, select the best, combine, reweight
    - Repeat until you have T classifiers selected

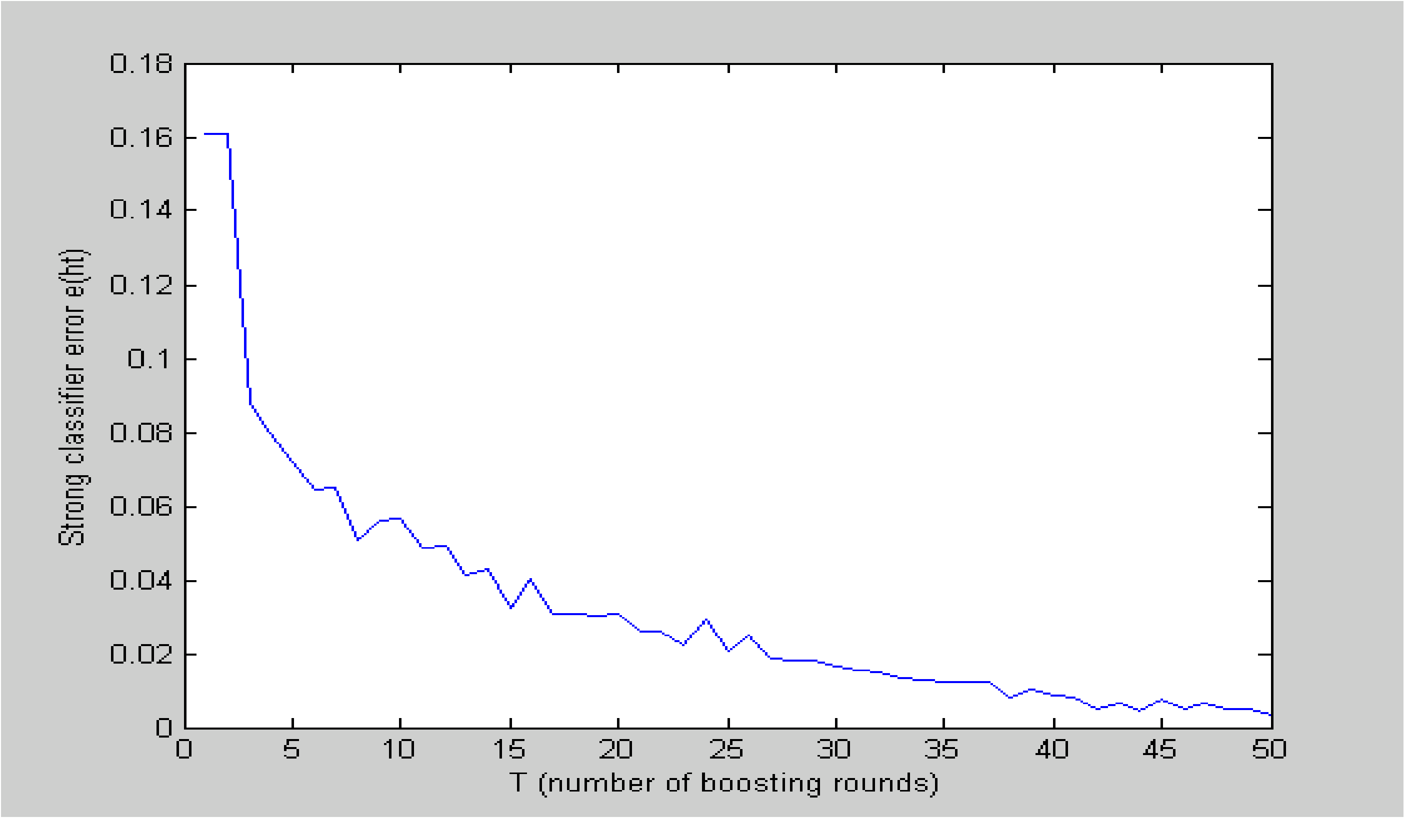
  - Very computationally intensive
    - Learning K decision stumps T times
    - E.g., K = 160,000 and T = 1000

How is classifier combining done?

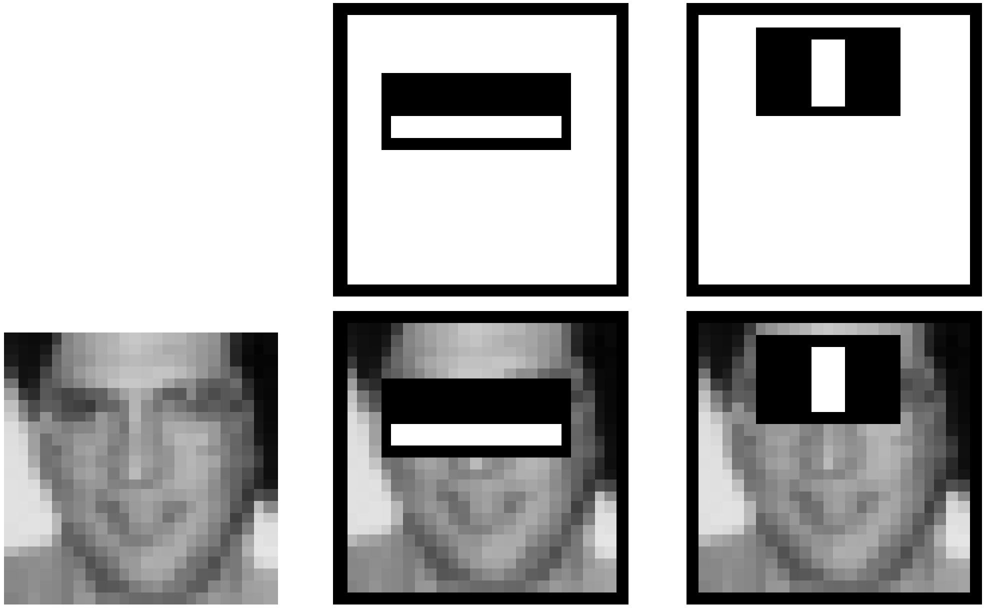
- At each stage we select the best classifier on the current iteration and combine it with the set of classifiers learned so far

- How are the classifiers combined?
  - Take the weight*feature for each classifier, sum these up, and compare to a threshold (very simple)
  - Boosting algorithm automatically provides the appropriate weight for each classifier and the threshold
  - This version of boosting is known as the AdaBoost algorithm
  - Some nice mathematical theory shows that it is in fact a very powerful machine learning technique

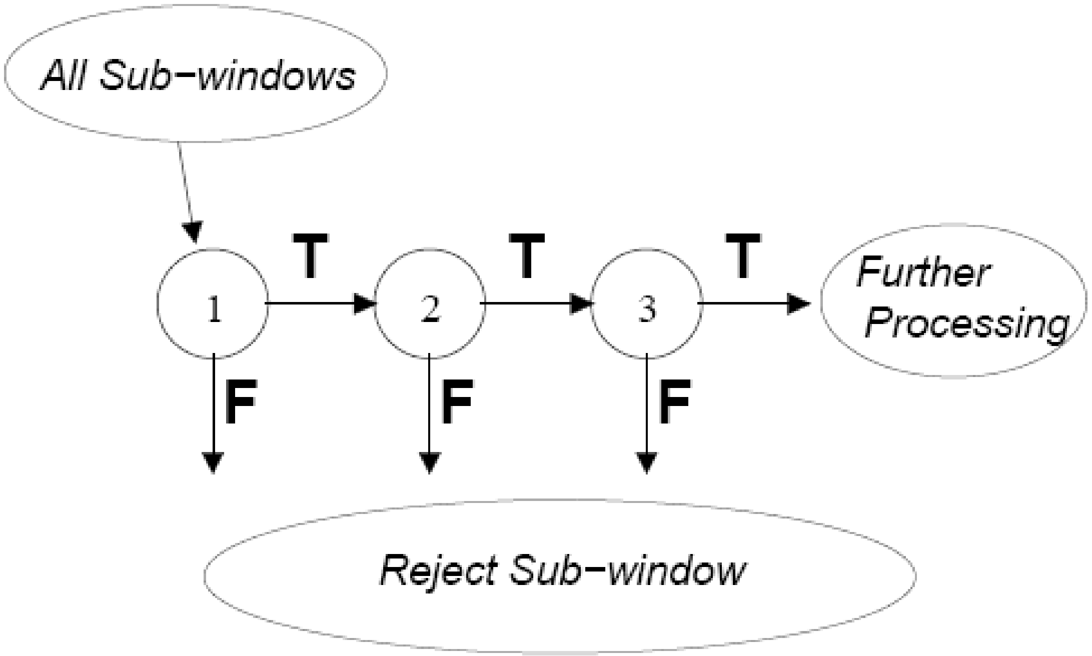
Reduction in Error as Boosting adds Classifiers



Useful Features Learned by Boosting



A Cascade of Classifiers



Detection in Real Images

- Basic classifier operates on 24 x 24 subwindows

- Scaling:
  - Scale the detector (rather than the images)
  - Features can easily be evaluated at any scale
  - Scale by factors of 1.25

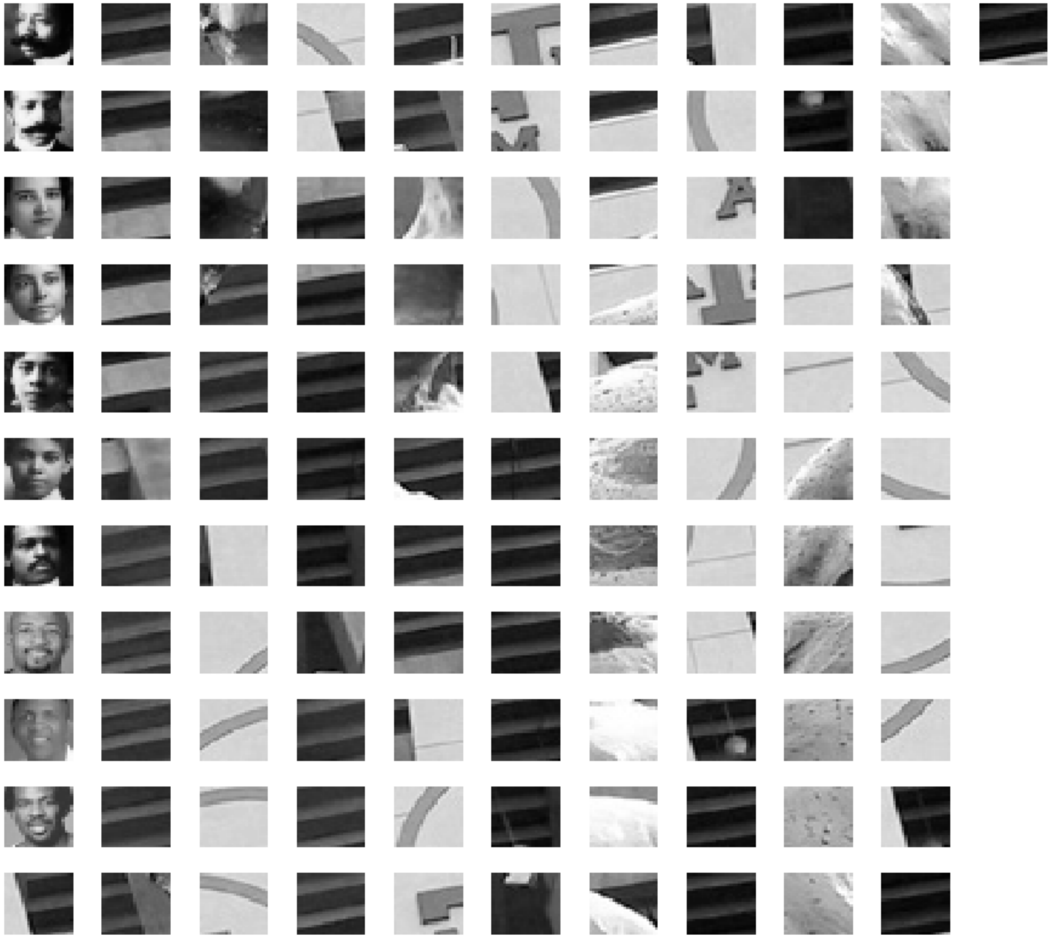
- Location:
  - Move detector around the image (e.g., 1 pixel increments)

- Final Detections
  - A real face may result in multiple nearby detections
  - Postprocess detected subwindows to combine overlapping detections into a single detection

Training

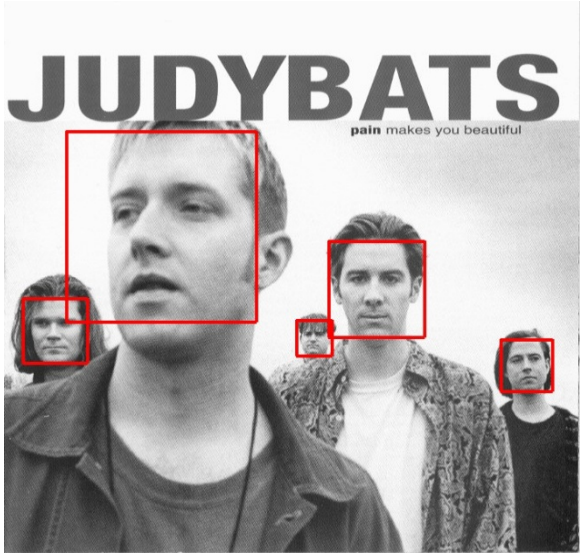
- Examples of 24x24 images with faces

Small set of 111 Training Images



Sample results using the Viola-Jones Detector

- Notice detection at multiple scales



More Detection Examples

Practical implementation

- Details discussed in Viola-Jones paper
- Training time = weeks (with 5k faces and 9.5k non-faces)
- Final detector has 38 layers in the cascade, 6060 features
- 700 Mhz processor:
  - Can process a 384 x 288 image in 0.067 seconds (in 2003 when paper was written)