Object Detection by Adaboost Classifier

Boosting

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https://labicvl.github.io/

Further reading:
Viola and Jones, Robust real-time object detector, 2004.
http://www.iis.ee.ic.ac.uk/tkkim/tmp/viola04ijcv.pdf

Chapter 14, C. Bishop, Pattern Recognition and Machine Learning, Springer, 2006.

Object detection

– A single image is given as input, without prior knowledge (except a known target object class, e.g. pedestrian).

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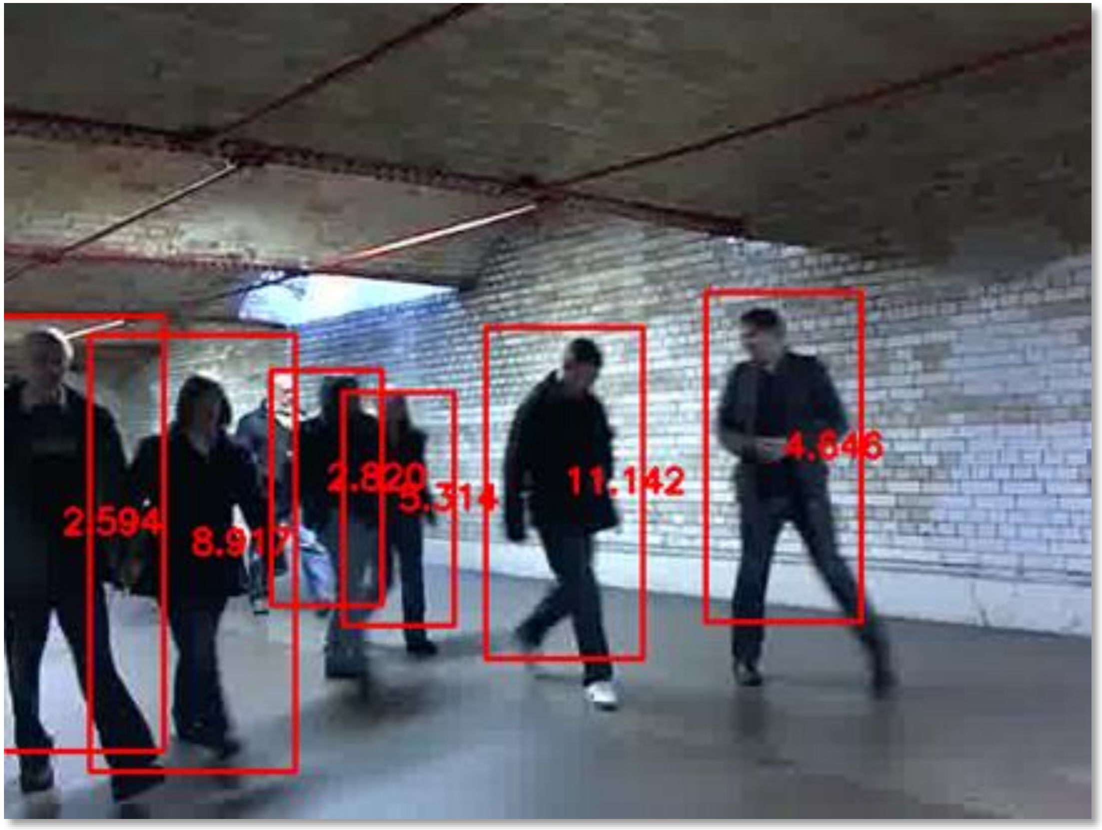
– Output is a set of tight bounding boxes (positions and scales) of instances of the target object class, optionally with confidence scores.

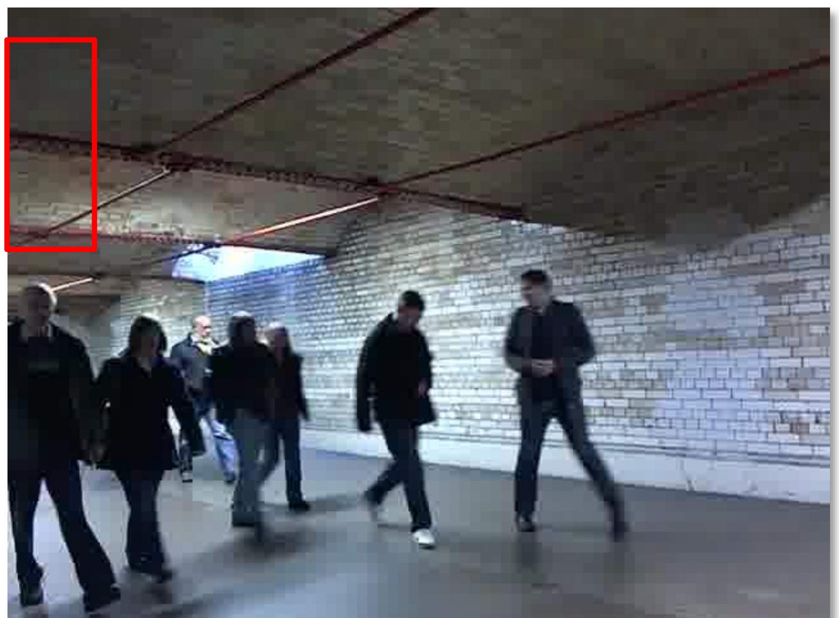


Number of hypotheses (scanning windows)

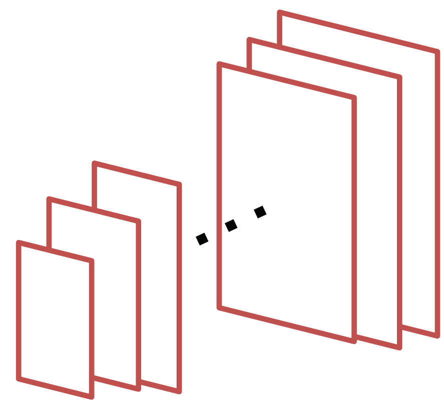
- We scan every scale and every pixel location in the given image.

Number of hypotheses (scanning windows)

- We scan every scale and every pixel location in the given image.
- We end up with a huge number of candidate windows i.e. detection hypotheses.



X



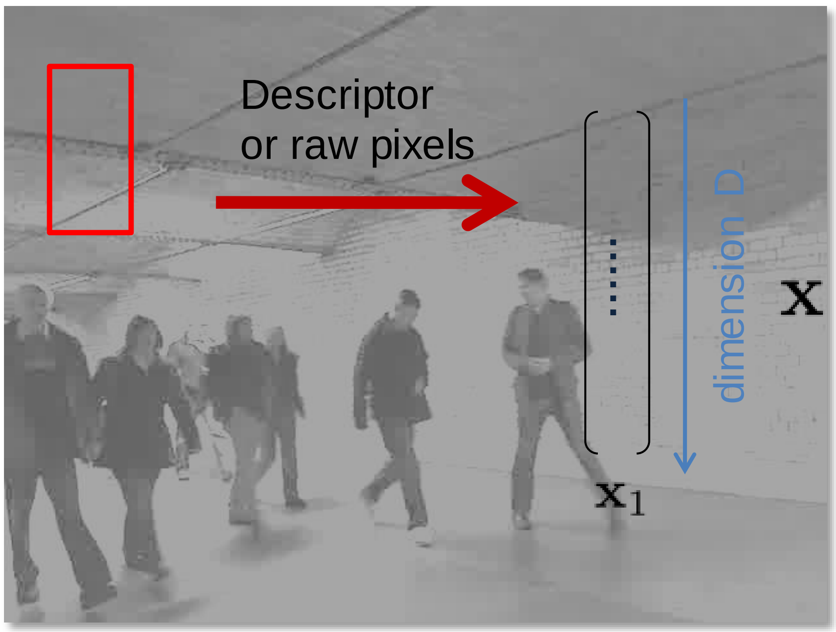
# of scales

# of pixels

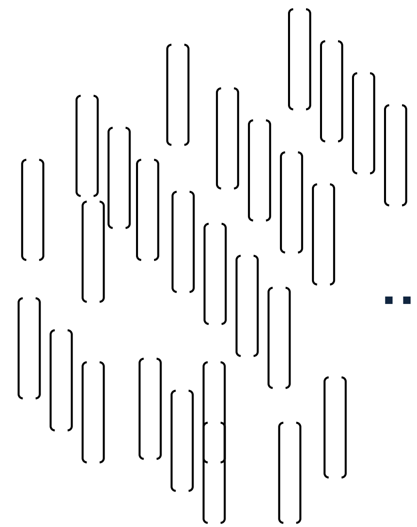
Number of windows: e.g. 747,666

Number of hypotheses (scanning windows)

– Little amount of time is given per a scanning window.
– It requires an extremely fast yet reliable feature/classifier.



$\mathbf{x} \in \mathbb{R}^D$



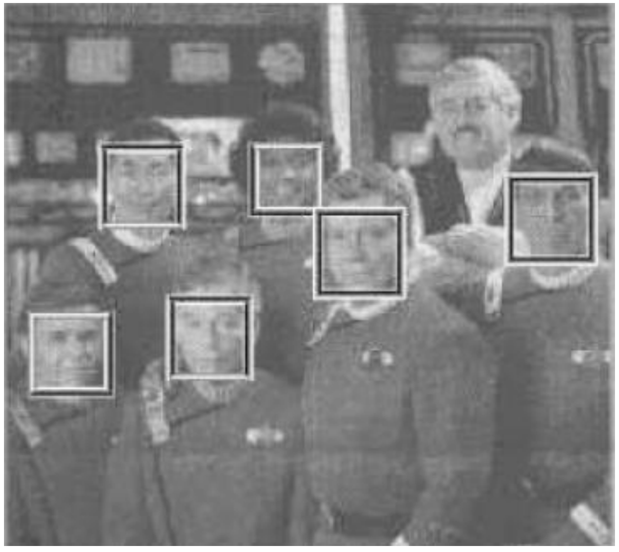
Num of feature vectors:
747,666

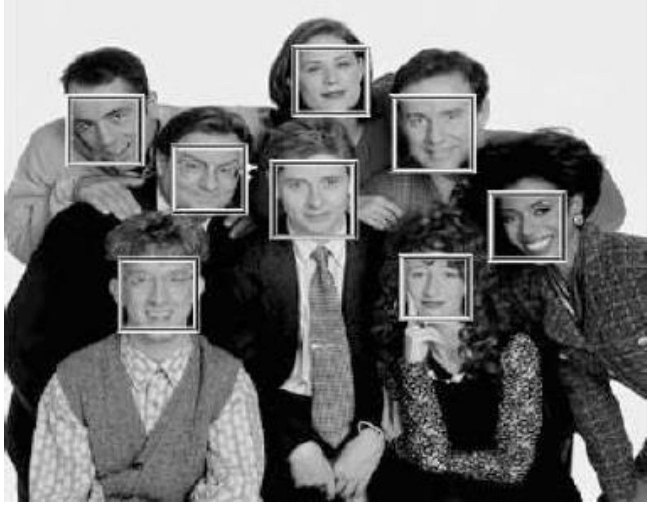
$f : \mathbf{x} \rightarrow t$

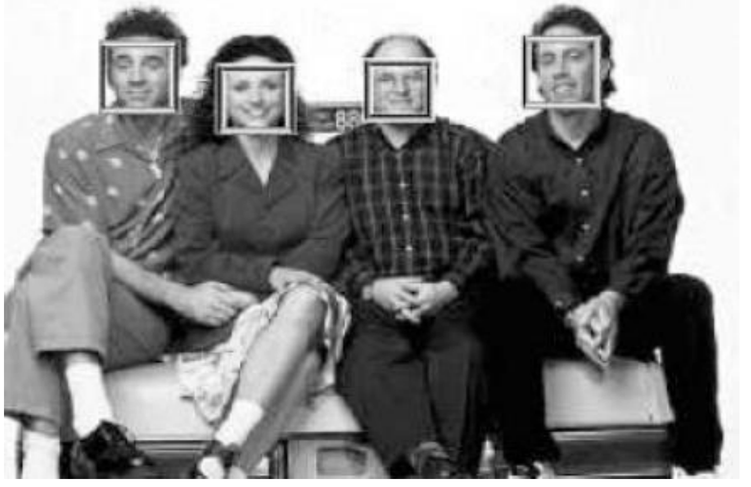
Binary classification: $t \in \{-1,1\}$

Time per window (or vector):
0.00000134 sec
(to process an entire image in e.g. 1 sec)

Examples of face detection



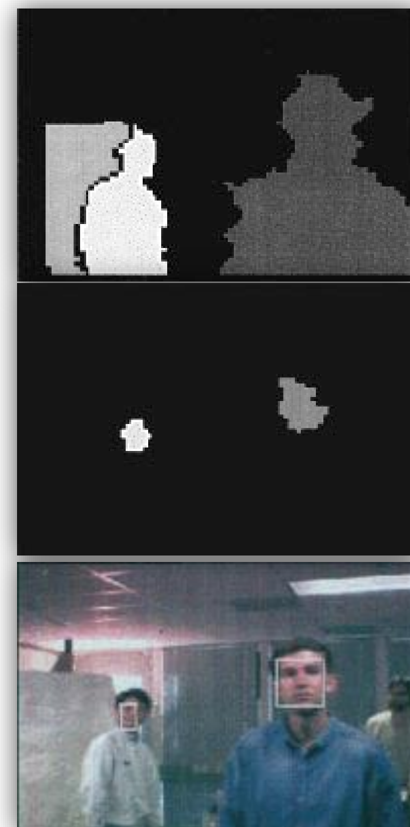


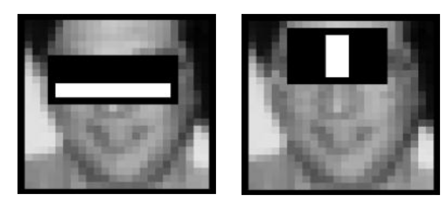


From Viola, Jones, 2001

A brief history for face detection

- Earlier approaches are knowledge-based, feature-based, or template-based.
- More contemporary methods are appearance-based i.e. learning a classifier from examples: e.g.
  - PCA
  - Distribution-based [Sung and Poggio, 1994]
  - Multi-Layer Perceptron [Rowley, Kanade, 1998]
  - Support Vector Machine [Osuna et al., 1997]
- To accelerate speed, the search space is narrowed down by integrating visual cues [Darrell et al, 2000]:
  - Connected pixels from stereo depth data (top).
  - Skin colour (hue) regions (middle).
  - Face pattern detection output (bottom).
- Since Viola &Jones 2001, boosting simple features has been a dominating art:
  - Adaboost classification
  - Weak classifiers: rectangle filter responses





Introduction to boosting classifiers AdaBoost (adaptive boosting)

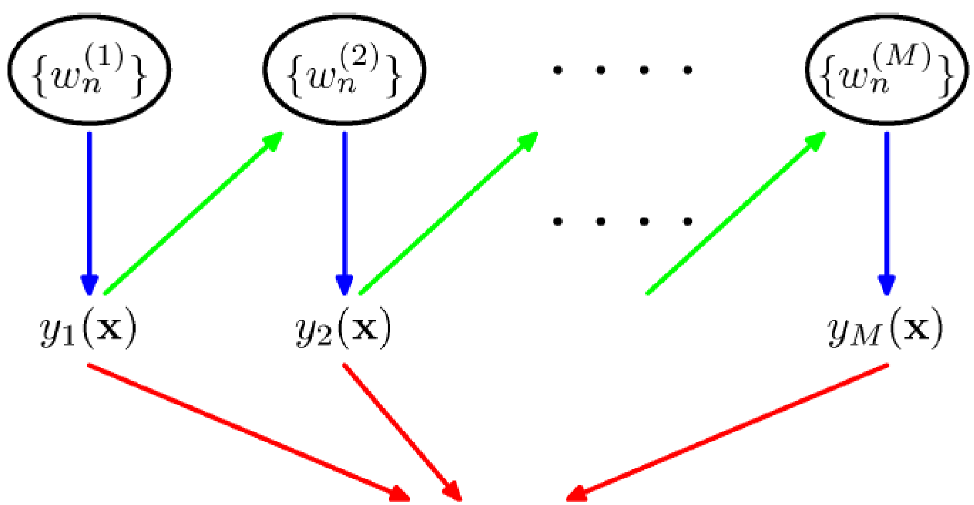
– Boosting gives good results even if the base classifiers have a performance slightly better than *random* guessing.

– Hence, the base classifiers are called *weak classifiers* or *weak learners*.

Boosting

For a two (binary)-class classification problem, we train with

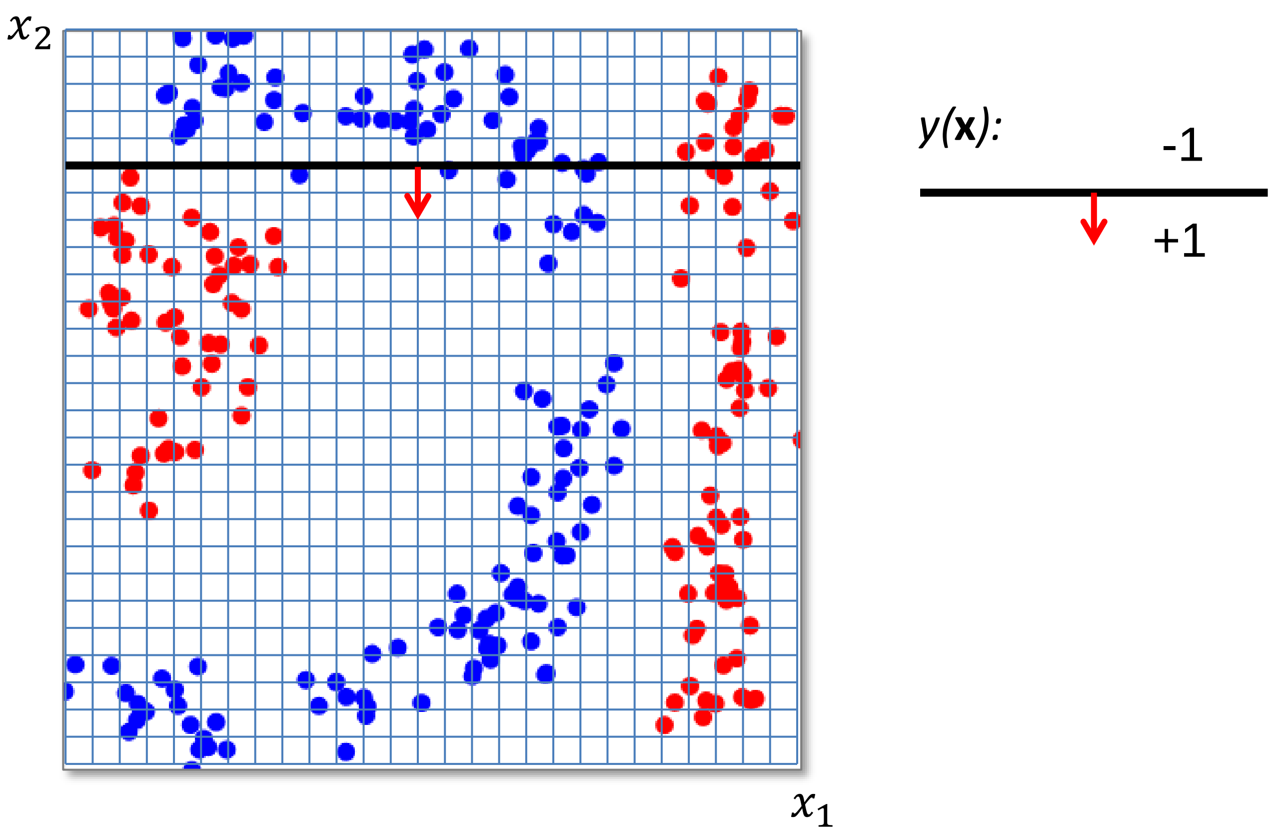
- training data $\mathbf{x}_{1,\ldots,}\ \mathbf{x}_N$
- target variables $t_{1,\ldots,}\ t_N$, where $t_N \in \{-1,1\}$,
- data weight $w_{1,\ldots,}\ w_N$
- weak (base) classifier candidates $y(\mathbf{x}) \in \{-1, 1\}$.



$$Y_M(\mathbf{x}) = \operatorname{sign}\left(\sum_m^M \alpha_m y_m(\mathbf{x})\right)$$

Boosting

– In the example below, the weak learner *y(**x**)* ∈ {-1, 1} is defined as axis-aligned e.g. $[x_i < \tau]$, for any $i \in \{1, \ldots, d\}$, $\mathbf{x} = [x_1, x_2, \ldots, x_d]$.



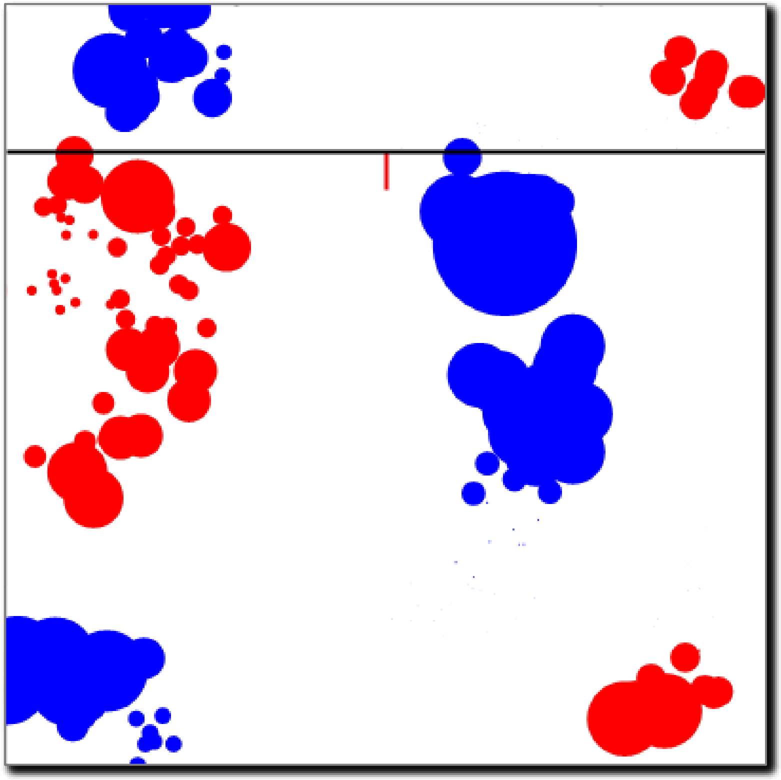
Boosting

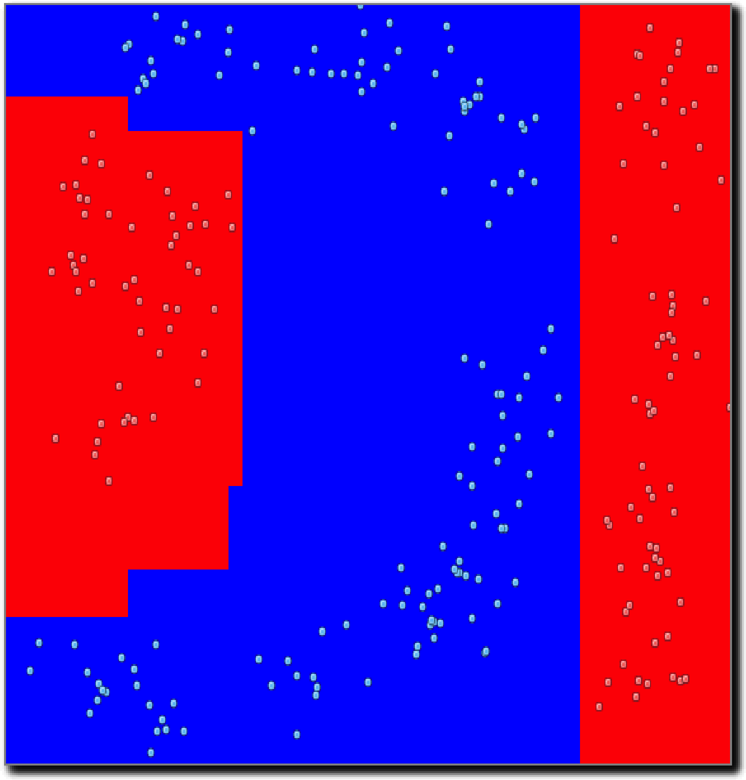
- The algorithm iteratively does

  1) reweighting training samples, by assigning higher weights to previously misclassified samples,

  2) finding the best weakclassifier for the weighted samples.

- Complex nonlinear classification problems are solved by a set of simple weak learners.





50 rounds

AdaBoost (adaptive boosting)

Initialise the data weights $\{w_n\}$ by $w_n^{(1)} = 1/N$ for $n = 1,\dots,N$.

For $m = 1, \dots, M$ $\boxed{\text{: the number of weak classifiers to choose}}$

(a) Learn a classifier $y_m(\mathbf{x})$ that minimises the weighted error, among all weak classifier candidates

$$J_m = \sum_{n=1}^{N} w_n^{(m)} I(y_m(\mathbf{x}_n) \neq t_n)$$

where I is the impulse function.

(b) Evaluate

$$\epsilon_m = \frac{\sum_{n=1}^{N} w_n^{(m)} I(y_m(\mathbf{x}_n) \neq t_n)}{\sum_{n=1}^{N} w_n^{(m)}}$$

AdaBoost (adaptive boosting)

and set

$$\alpha_m = \ln\left\{\frac{1-\epsilon_m}{\epsilon_m}\right\}$$

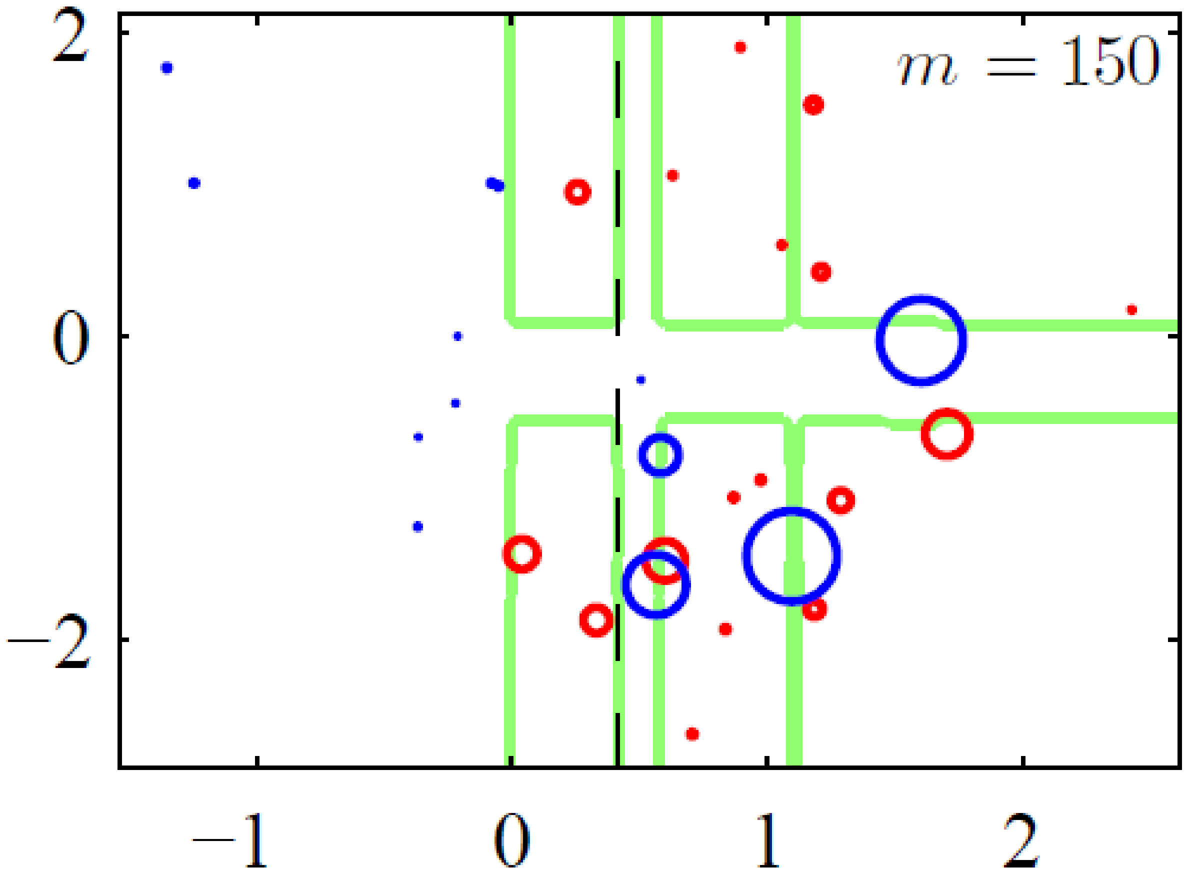
(c) Update the data weights

$$w_n^{(m+1)} = w_n^{(m)} \exp\{\alpha_m I(y_m(\mathbf{x}_n) \neq t_n)\}$$

Make predictions using the final model by

$$Y_M(\mathbf{x}) = \mathbf{sign}\left(\sum_{m=1}^{M} \alpha_m y_m(\mathbf{x})\right)$$

AdaBoost (adaptive boosting)



Boosting as an optimisation framework

– AdaBoost is the sequential minimisation of the exponential error function

$$E = \sum_{n=1}^{N} \exp\{-t_n f_m(\mathbf{x}_n)\}$$

where $t_n \in \{-1, 1\}$ and $f_m(\mathbf{x})$ is a classifier as a linear combination of base classifiers $y_l(\mathbf{x})$

$$f_m(\mathbf{x}) = \frac{1}{2}\sum_{l=1}^{m} \alpha_l y_l(\mathbf{x})$$

– We minimise E with respect to the weight α_l and the parameters of the base classifiers $y_l(\mathbf{x})$.

Boosting as an optimisation framework

– Sequential Minimisation: suppose that the base classifiers $y_1(\mathbf{x})$,. …, $y_{m-1}(\mathbf{x})$ and their coefficients $\alpha_1, \ldots, \alpha_{m-1}$ are fixed, and we minimise only w.r.t. α_m and $y_m(\mathbf{x})$.

– The error function is rewritten by

$$E = \sum_{n=1}^{N} \exp\{-t_n f_m(\mathbf{x}_n)\}$$

$$= \sum_{n=1}^{N} \exp\left\{-t_n f_{m-1}(\mathbf{x}_n) - \frac{1}{2} t_n \alpha_m y_m(\mathbf{x}_n)\right\}$$

$$= \sum_{n=1}^{N} w_n^{(m)} \exp\left\{-\frac{1}{2} t_n \alpha_m y_m(\mathbf{x}_n)\right\}$$

where $w_n^{(m)} = \exp\{-t_n f_{m-1}(\mathbf{x}_n)\}$ are constants.

Boosting as an optimisation framework

– Denote the set of data points correctly classified by $y_m(\mathbf{x}_n)$ *by* T_m, and those misclassified M_m, then

$$E = e^{-\alpha_m/2} \sum_{n \in \mathcal{T}_m} w_n^{(m)} + e^{\alpha_m/2} \sum_{n \in \mathcal{M}_m} w_n^{(m)}$$

$$= \left(e^{\alpha_m/2} - e^{-\alpha_m/2}\right) \sum_{n=1}^{N} w_n^{(m)} I(y_m(\mathbf{x}_n) \neq t_n) + e^{-\alpha_m/2} \sum_{n=1}^{N} w_n^{(m)}$$

– When we minimise w.r.t. $y_m(\mathbf{x}_n)$, the second term is constant and minimising E is equivalent to

$$J_m = \sum_{n=1}^{N} w_n^{(m)} I(y_m(\mathbf{x}_n) \neq t_n)$$

Boosting as an optimisation framework

– By setting the derivative w.r.t. α_m to 0, we obtain $\alpha_m = \ln\left\{\frac{1-\epsilon_m}{\epsilon_m}\right\}$

where $\epsilon_m = \frac{\sum_{n=1}^{N} w_n^{(m)} I(y_m(\mathbf{x}_n) \neq t_n)}{\sum_{n=1}^{N} w_n^{(m)}}$

– From $E = \sum_{n=1}^{N} w_n^{(m)} \exp\left\{-\frac{1}{2}t_n\alpha_m y_m(\mathbf{x}_n)\right\}$

$$\rightarrow \quad w_n^{(m+1)} = w_n^{(m)} \exp\left\{-\frac{1}{2}t_n\alpha_m y_m(\mathbf{x}_n)\right\}$$

– As $t_n y_m(\mathbf{x}_n) = 1 - 2I(y_m(\mathbf{x}_n) \neq t_n)$

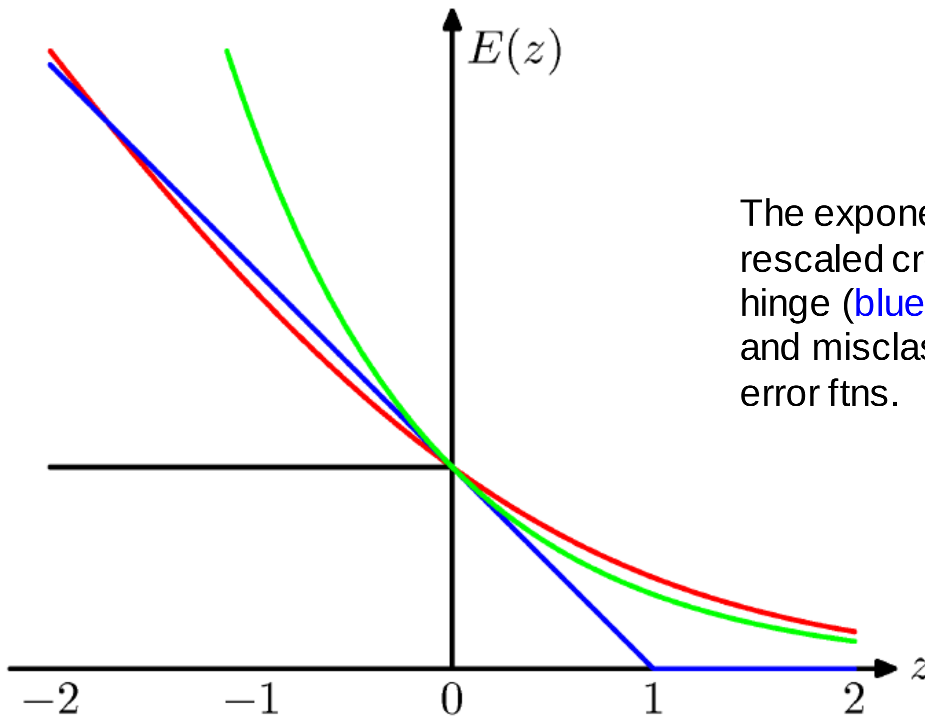
$$w_n^{(m+1)} = w_n^{(m)} \exp(-\alpha_m/2) \exp\{\alpha_m I(y_m(\mathbf{x}_n) \neq t_n)\}$$

– The term *exp*(-α_m/2) is independent of *n*, thus we obtain

$$w_n^{(m+1)} = w_n^{(m)} \exp\{\alpha_m I(y_m(\mathbf{x}_n) \neq t_n)\}$$

Exponential error function

- *Pros:* it leads to simple derivations of Adaboost algorithms.
- *Cons:* it penalises large negative values. It is prone to outliers.



The exponential (green)
rescaled cross-entropy (red)
hinge (blue),
and misclassification (black)
error ftns.

Robust real-time object detector [Viola and Jones 2001]

- A face detection framework that is capable of processing images extremely rapidly while achieving high detection rates.
- Three key components:
  - The first is the introduction of a new image representation called the "Integral Image" which allows the features used by the detector to be computed very quickly.
  - The second is a simple and efficient classifier which is built using the AdaBoost learning algorithm (Freund and Schapire, 1995) to select a small number of critical visual features from a very large set of potential features.
  - The third contribution is a method for combining classifiers in a "cascade" which allows background regions of the image to be quickly discarded while spending more computation on promising face-like regions.

Robust real-time object detector
[Viola and Jones 2001]

– Adaboost classification

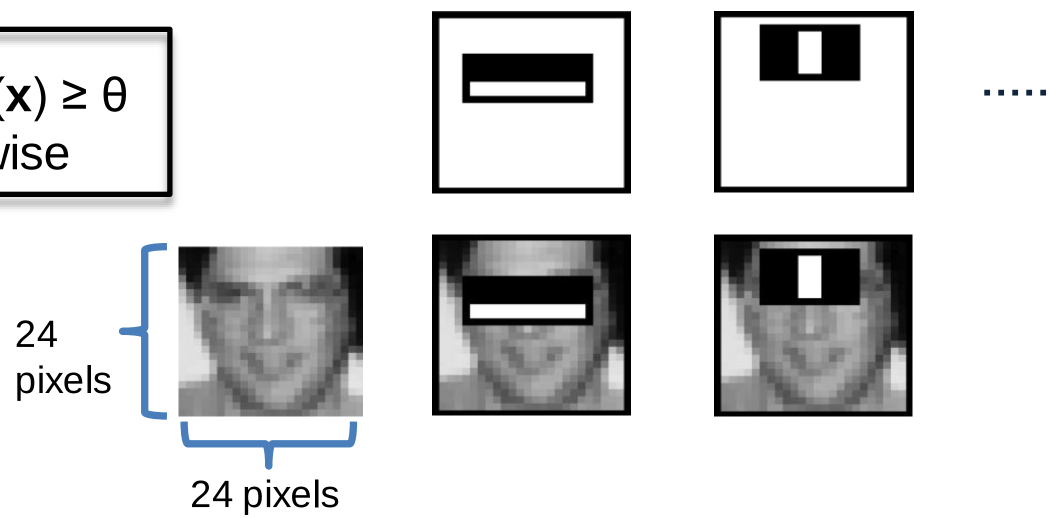
Strong classifier

$$\boxed{\boxed{Y_M(\mathbf{x})} = \text{sign}\left(\sum_{m=1}^{M} \alpha_m \boxed{y_m(\mathbf{x})}\right)}$$

Weak classifier

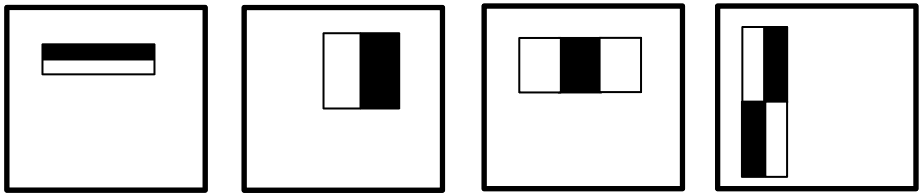
– Weak classifiers: rectangle filter responses **(**160,000 **in total feature pool)**

$$\boxed{y_m(\mathbf{x}) = \begin{cases} +1 & \text{if } \ h_m(\mathbf{x}) \geq \theta \\ -1 & \text{otherwise} \end{cases}}$$



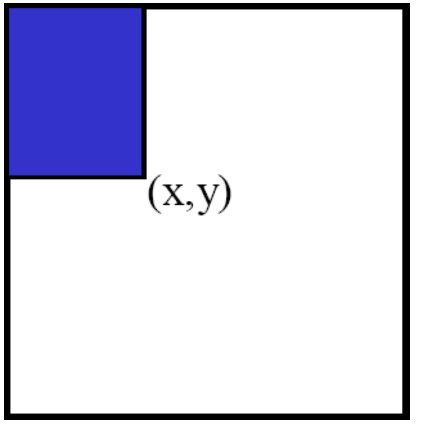
Rectangle features

- Our face detection procedure classifies images based on the value of simple features.
- The simple features used are reminiscent of Haar basis functions which have been used by Papageorgiou et al. 1998.
- More specifically, we use following example of features.
  - The value of a *two-rectangle feature* is the difference between the sum of the pixels within two rectangular regions. The regions have the same size and shape and are horizontally or vertically adjacent.
  - A *three-rectangle feature* computes the sum within two outside rectangles subtracted from the sum in a center rectangle.
  - Finally a *four-rectangle feature* computes the difference between diagonal pairs of rectangles.
- Given that the base resolution of the detector is 24 × 24, the exhaustive set of rectangle features is large, 160,000.



Integral image

- Rectangle features can be computed very rapidly using an intermediate representation for the image which we call the integral image.
- The integral image at location (x,y) contains the sum of the pixels above and to the left of (x,y), inclusive:



$$ii(x,y) = \sum_{x' \le x,\, y' \le y} i(x', y')$$

where $ii(x, y)$ is the integral image and $i(x, y)$ is the original image.

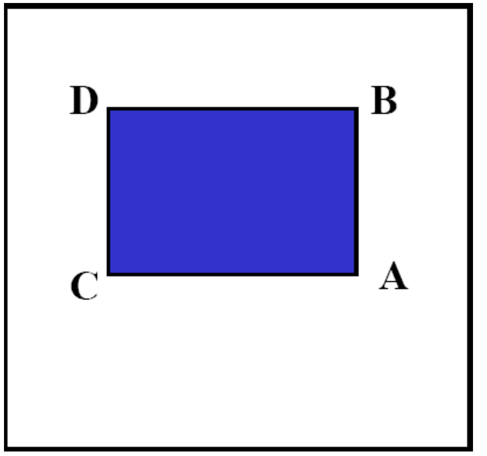
- Using the following pair of recurrences:

$$s(x,y) = s(x, y-1) + i(x,y)$$
$$ii(x,y) = ii(x-1, y) + s(x,y)$$

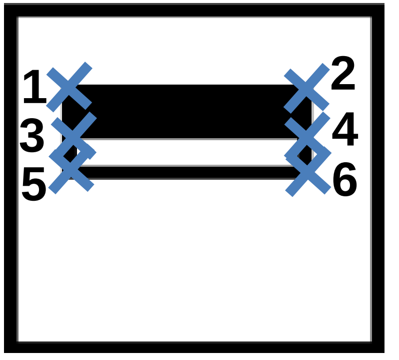
where s(x,y) is the cumulative row sum, s(x,-1)=0, and ii(-1,y)=0, the integral image can be computed in one pass over the original image.

Rectangle features

- Using the integral image any rectangular sum can be computed in four array references:
  - The sum of original image values within the rectangle can be computed: Sum = ii(A)-ii(B)-ii(C)+ii(D).
  - This provides the fast evaluation of rectangle-filter responses.



- Clearly the difference between two rectangular sums can be computed in eight references. Since the two-rectangle features defined above involve adjacent rectangular sums they can be computed in six array references.



$h_m(\mathbf{x})$ = (ii(6)-ii(4)-ii(5)+ii(3)) -(ii(4)-ii(2)-ii(3)+ii(1))

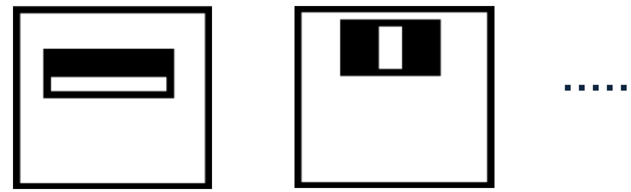
AdaBoost Learning

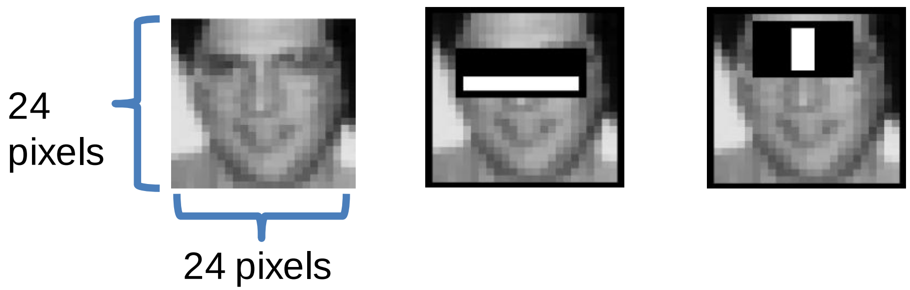
- Given a feature set and a training set of positive and negative images, any machine learning approach could be used to learn a classification function.
- Recall that there are 160,000 rectangle features associated with each image sub-window.
- Even though each feature can be computed very efficiently, computing the complete set is prohibitively expensive.
- The main challenge is to find a very small number of features can be combined to form an effective classifier.
- Here AdaBoost is used both to select the features and to train the classifier (Freund and Schapire, 1995).
- AdaBoost combines a collection of weak classification functions to form a stronger classifier.

AdaBoost Learning

– One practical method is to restrict the weak learner to the classification function depends on a single feature.
– The weak learner $y_m(\mathbf{x})$ is designed to select the single rectangle feature which best separates the positive and negative examples.

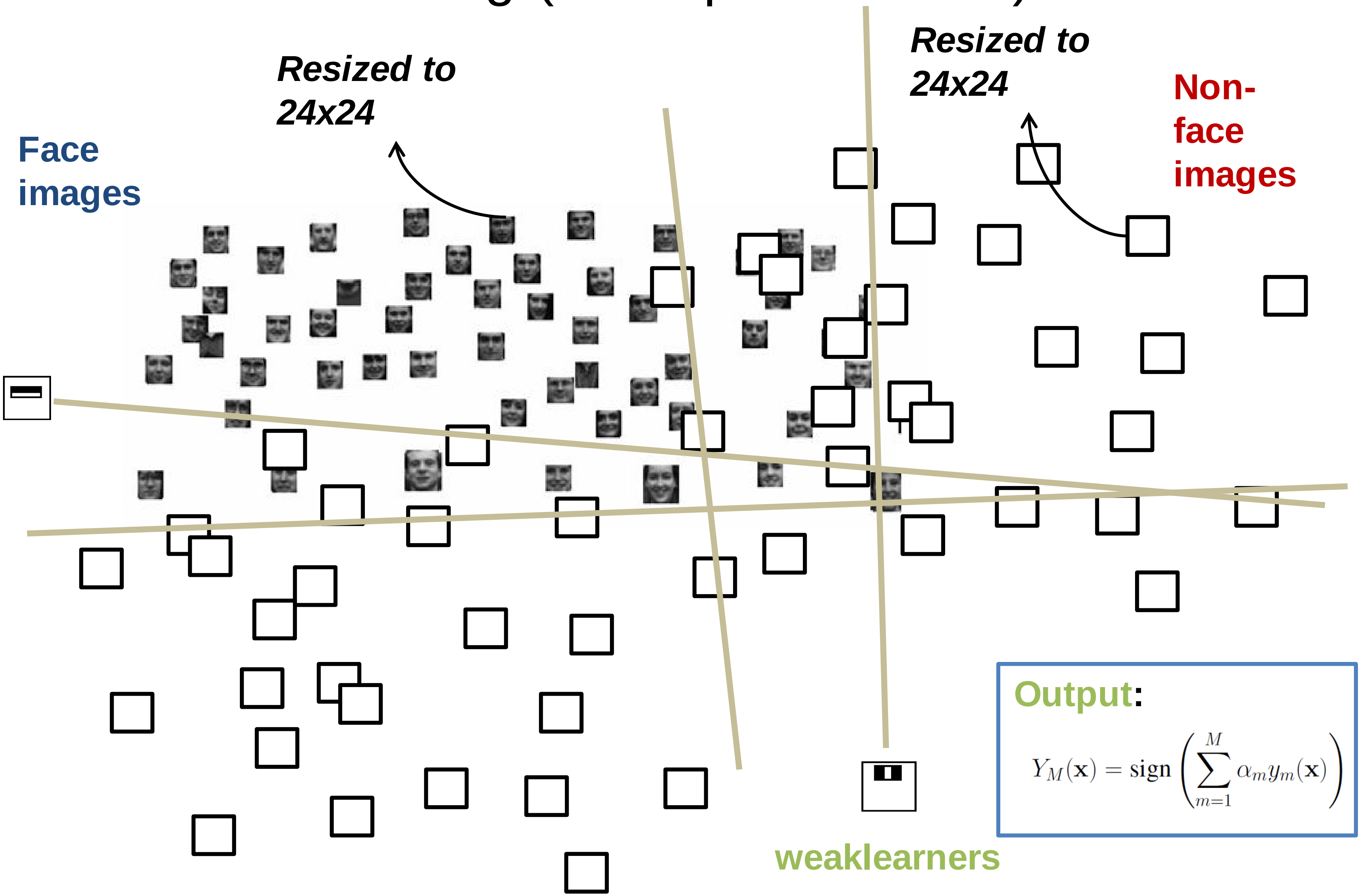
$$y_m(\mathbf{x}) = \begin{cases} +1 & \text{if} \quad h_m(\mathbf{x}) \geq \theta \\ -1 & \text{otherwise} \end{cases}$$





– Here h_m is a rectangle feature, and x is a 24 × 24 pixel sub-window of an image.
– The weak classifiers that we use (thresholded single features) can be viewed as single node decision trees. Such structures are called decision stumps.

Learning (concept illustration)

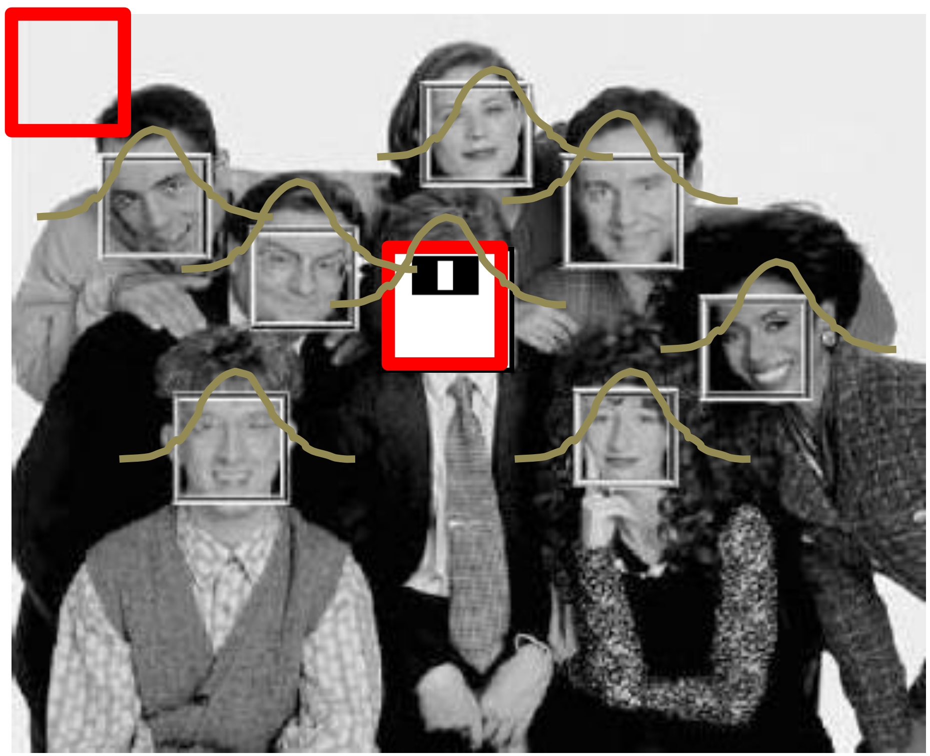


Output:

$$Y_M(\mathbf{x}) = \text{sign}\left(\sum_{m=1}^{M} \alpha_m y_m(\mathbf{x})\right)$$

Evaluation (testing)

- The learnt boosting classifier i.e. $\sum_{m=1}^{M} \alpha_m y_m(\mathbf{x})$ is applied to every scan-window.
- The response map is obtained, then the non-local maxima suppression is performed to detect local maximas.

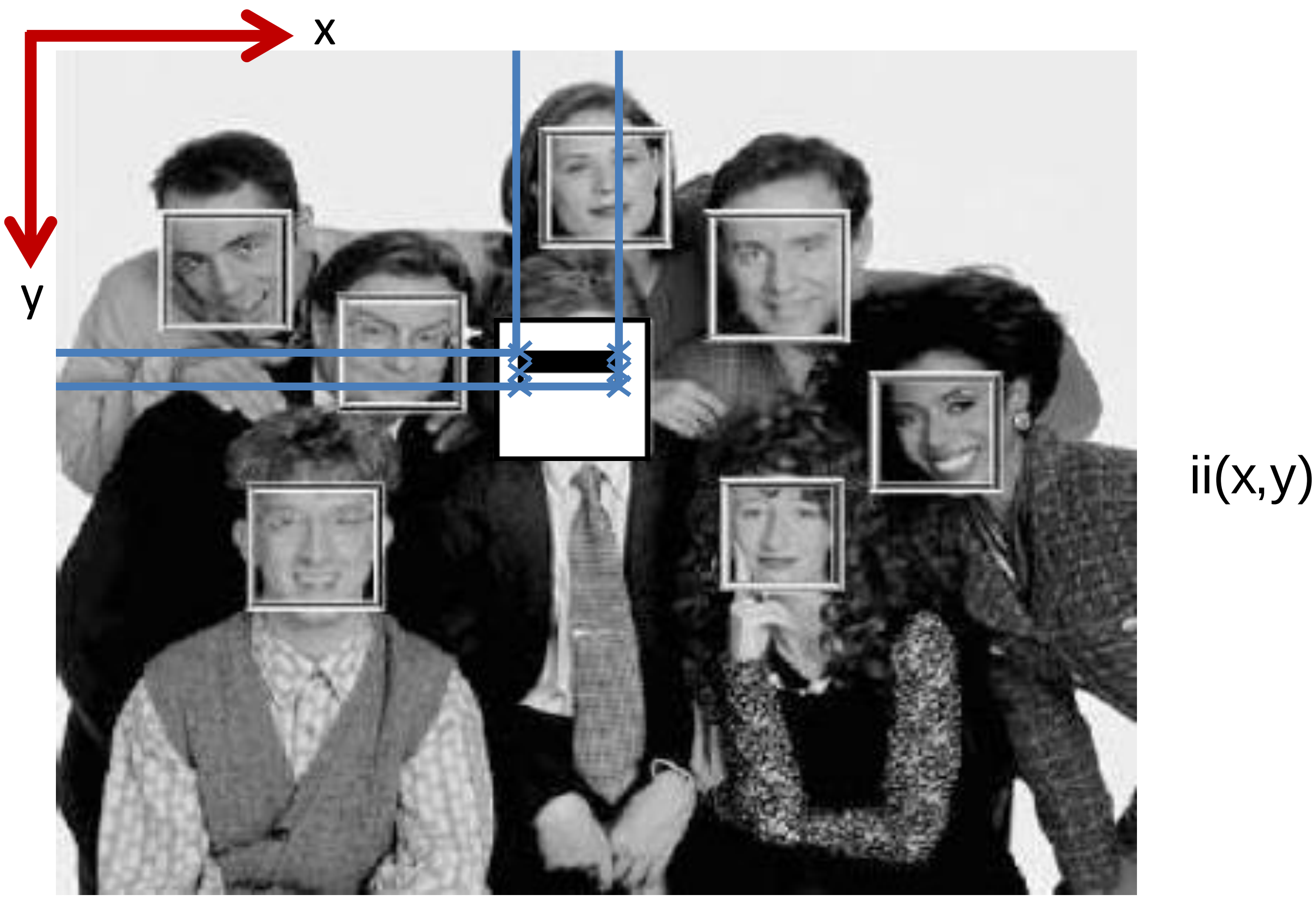


Non-local maxima suppression is carried out to detect faces.

response map

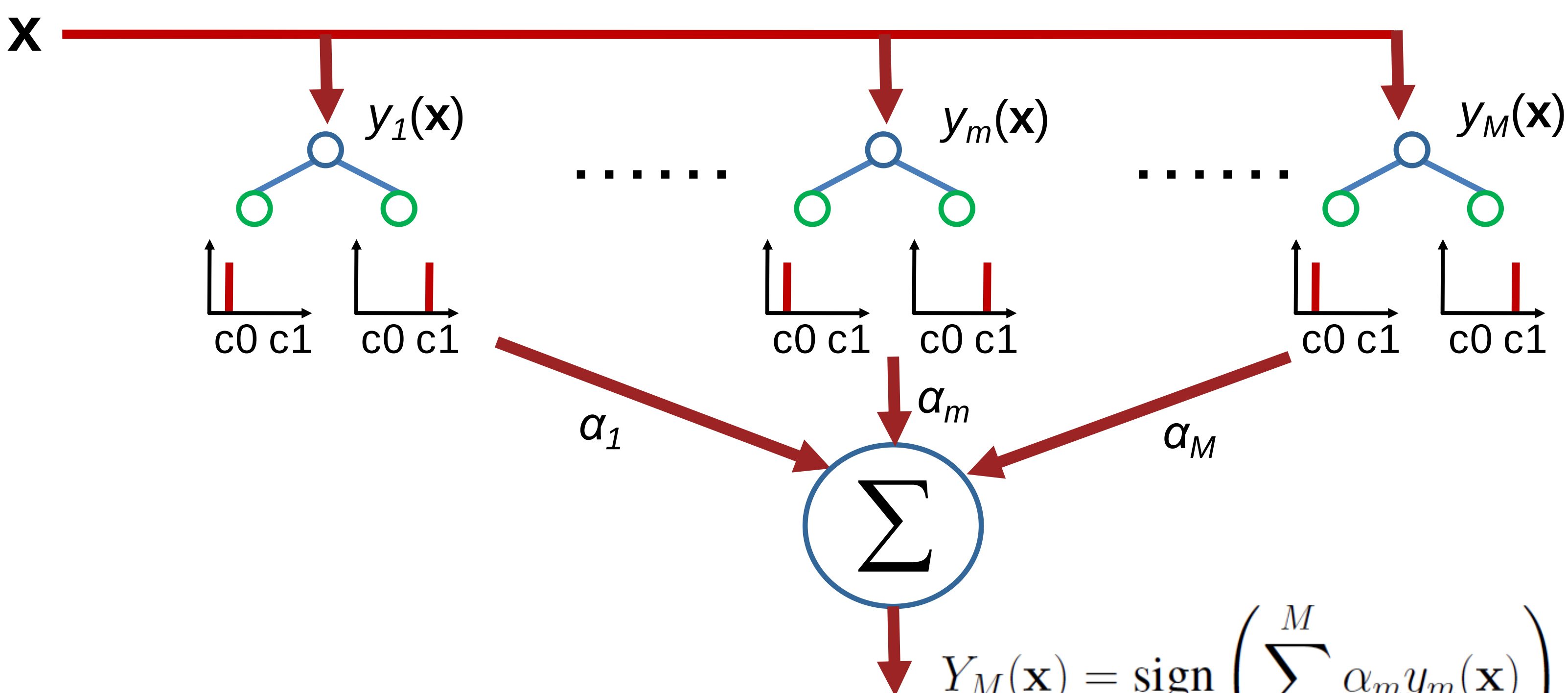
Evaluation (testing)

- The boosting evaluation time is greatly accelerated using the Integral image.
- Each weak classifier is computed using a small number of array references on the integral image.



Boosting (very shallow network)

– The strong classifier $Y_M(\mathbf{x})$ as boosted decision stumps has a flat structure.



$$Y_M(\mathbf{x}) = \operatorname{sign}\left(\sum_{m=1}^{M} \alpha_m y_m(\mathbf{x})\right)$$

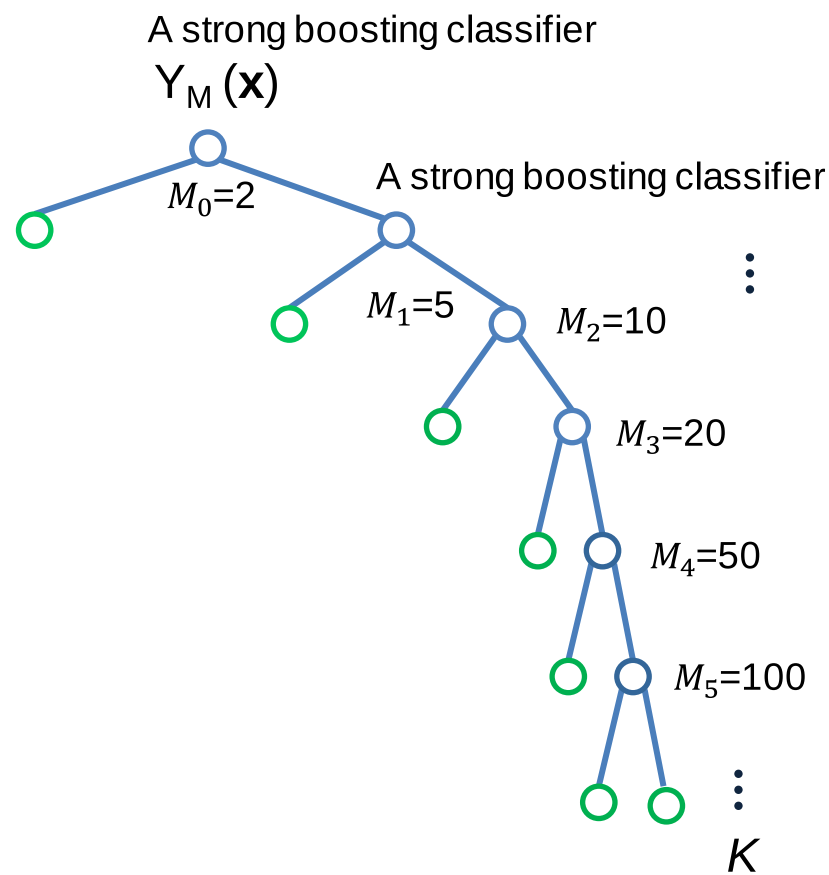
– Cf. Decision “ferns” has been shown to outperform “trees” [Zisserman et al, 07] [Fua et al, 07].

Boosting - continued

- Good generalisation is achieved by a flat structure.
- It does sequential optimisation.
- It provides fast evaluation on top of the Integral image.
- However, its run-time speed is sub-optimal.

A cascade of classifiers

- A cascade of classifiers achieves increased detection performance while radically reducing computation time.
- The key insight is that smaller, and therefore more efficient, boosted classifiers reject many of the negative sub-windows while detecting almost all positive instances.
- Simpler classifiers are used to reject the majority of sub-windows before more complex classifiers are to achieve low false positive rates.
- Stages in the cascade are constructed by AdaBoost.
- It is very imbalanced tree structured.



A cascade of classifiers

– The detection system requires good detection rate and extremely low false positive rates.

– False positive rate and detection rate are

$$F = \prod_{i=0}^{K} f_i \qquad D = \prod_{i=0}^{K} d_i$$

where f_i is the false positive rate and d_i is the detection rate of i-th classifier on the examples that get through to it.

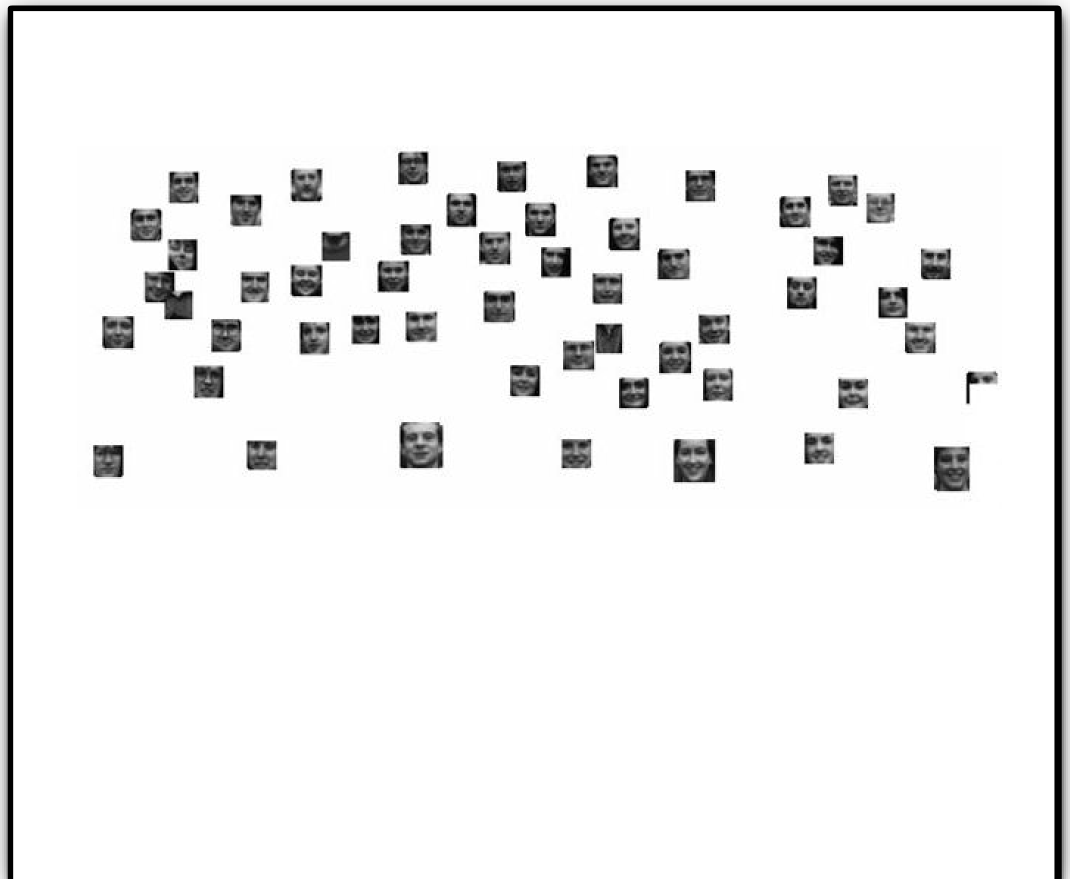
– The expected number of features (or weaklearners) evaluated is

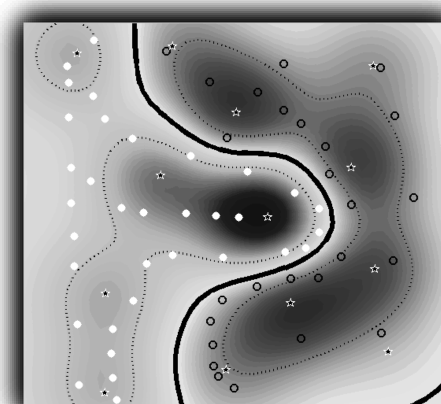
$$M = M_0 + \sum_{i=1}^{K} \left(M_i \prod_{j<i} p_j \right)$$

where p_j is the proportion of windows input to j-th classifier, and M_i is the number of weaklearners of i-th classifier.

Object detection by a cascade of classifiers

– It speeds up object detection by coarse-to-fine search.





Romdhani et al. ICCV01

Receiver operating characteristic (ROC)

– Boosting classifier score (prior to the binarisation) is compared with a threshold.

$$\sum_{m=1}^{M} \alpha_m y_m(\mathbf{x})$$

≥ Threshold → Class 1 (face)

< Threshold → Class -1 (no face)

– The ROC curve is drawn by the false negative rate against the false positive rate at various threshold values:

- False positive rate (FPR) = FP/N
- False negative rate (FNR) = FN/P

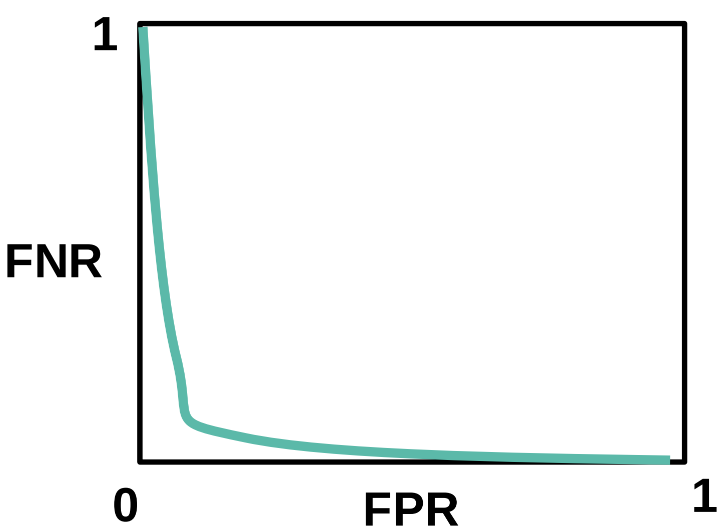
where

P positive instances,

N negative instances,

FP false positive cases, and

FN false negative cases.



Multiclass object detection

[Torralba et al PAMI 07]

– A boosting algorithm, originally designed for binary class problems, has been extended to multi-class problems.

Multiclass object detection

[Torralba et al PAMI 07]

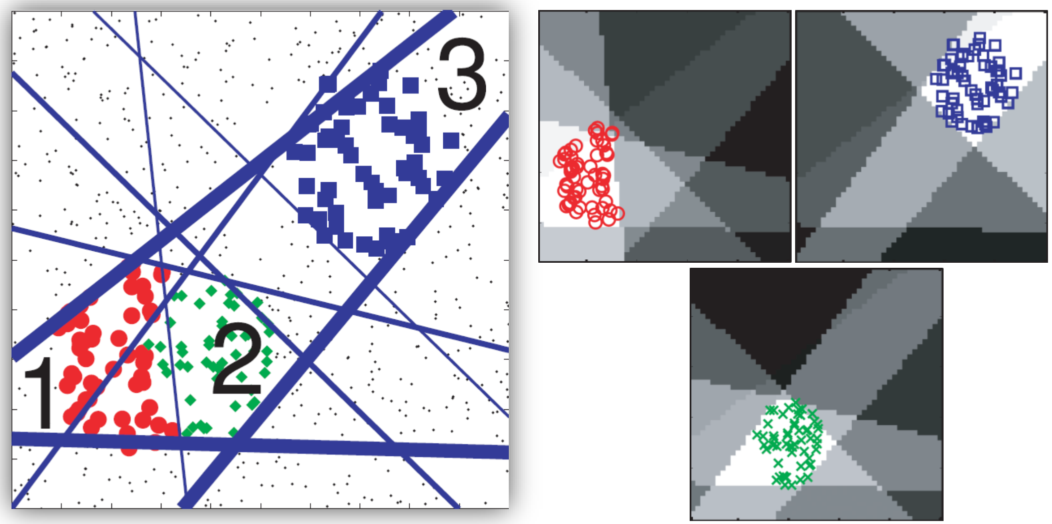
- Multi-view or multi-category object detection
- Images exhibit multi-modality.
- A single boosting classifier is not sufficient.
- Manual labeling sub-categories.

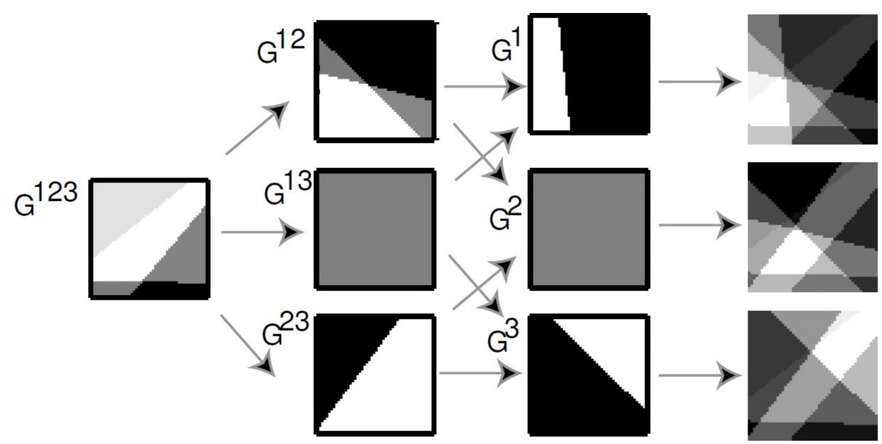
From Torralba et al 07

Multiclass object detection [Torralba et al PAMI 07]

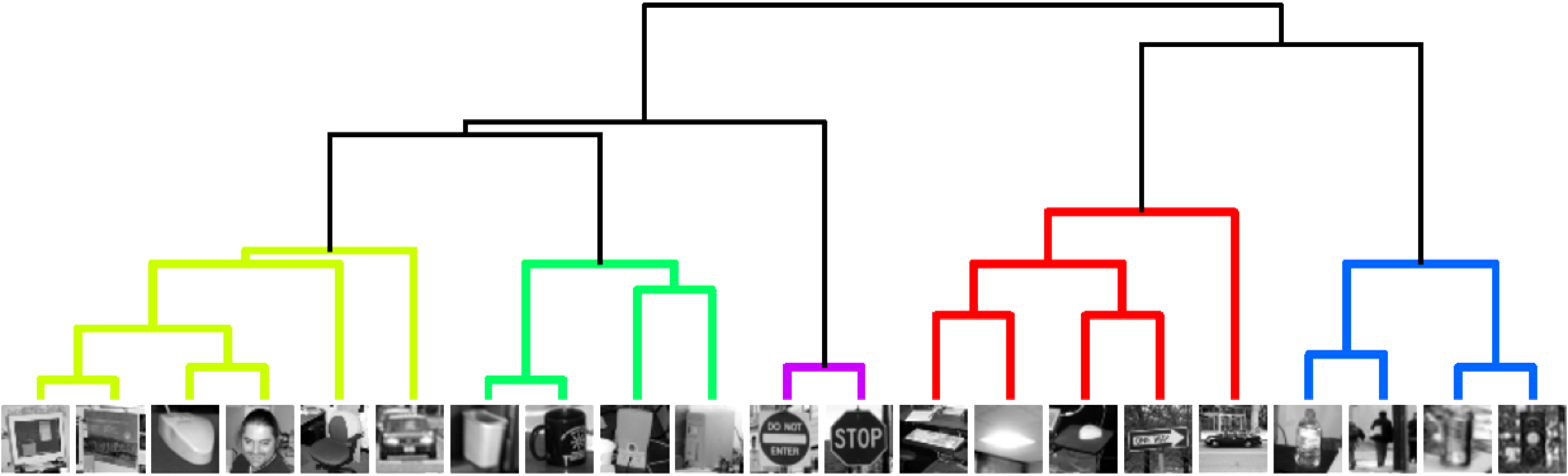
- (automatic) Learning multiple boosting classifiers by sharing features.

- Tree structure speeds up the evaluation (testing) time.



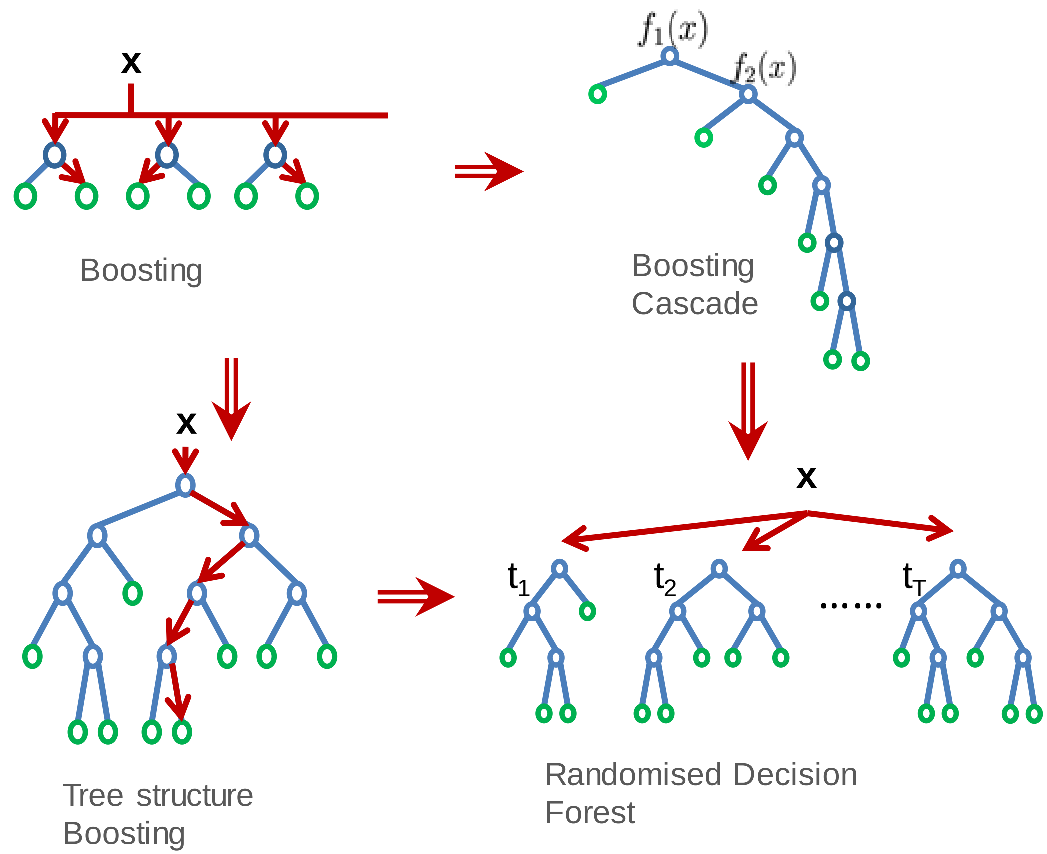


Multiclass object detection
[Torralba et al PAMI 07]

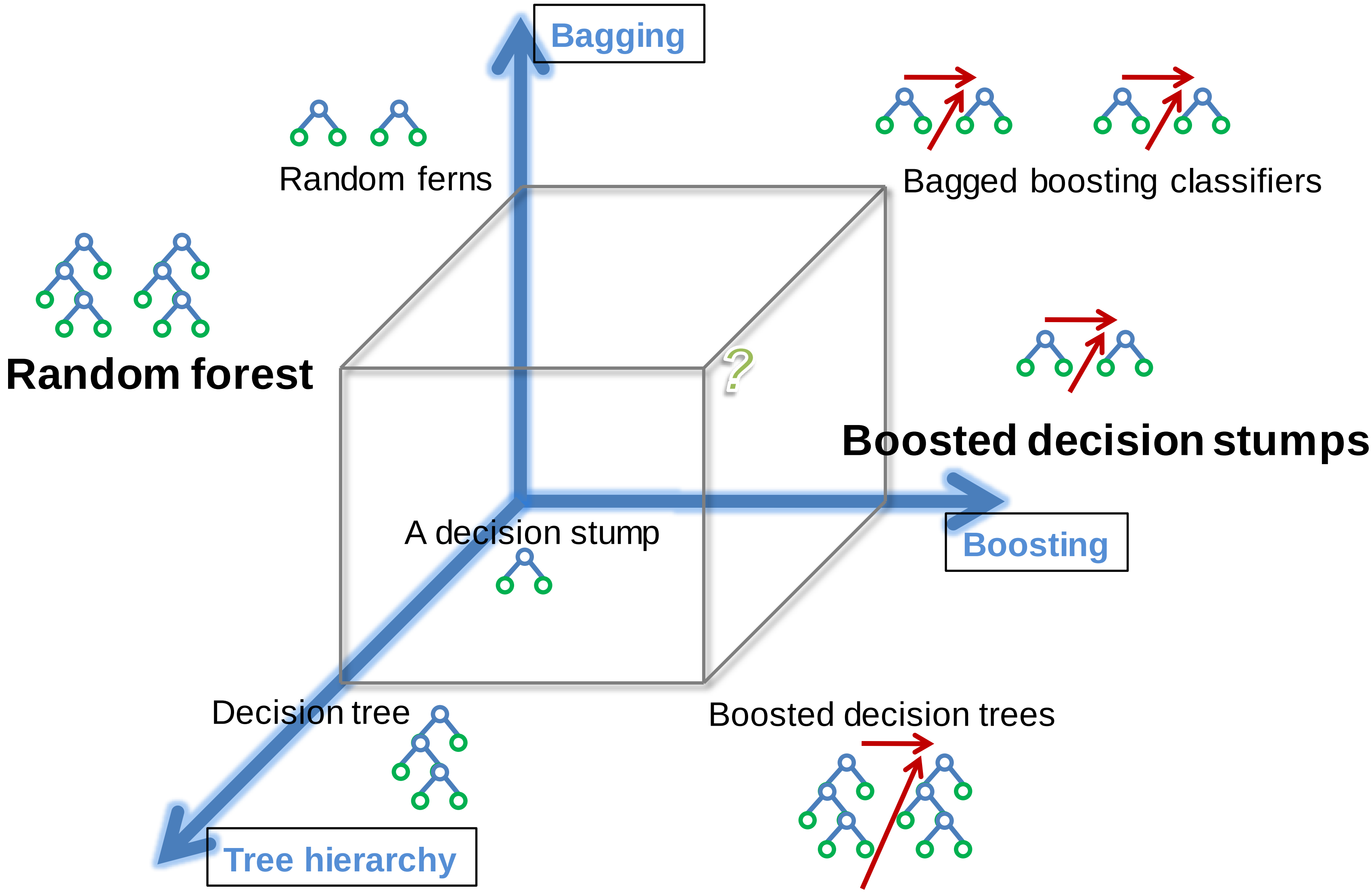


Boosting classifiers and decision forests

- Boosting can be seen in a flat structure.
- Boosting cascade designed to accelerate run-time is a highly imbalanced tree.
- Tree-structured boosting classifiers have been studied to tackle multi-class problems.



Boosting classifiers and decision forests



Summary

Random Forest

- Pros
  - Generalization through random samples/features
  - Extremely fast classification
  - Highly scalable in training
  - Inherently multi-classes
- Cons
  - Inconsistency
  - Difficulty for adaptation

Boosting Decision Stumps

- Pros
  - Generalisation by a flat structure
  - Fast classification
  - Optimisation framework
- Cons
  - Slower than RF
  - Slow training

See more in Yin, Crinimisi, CVPR07, and Belle et al, ICPR08

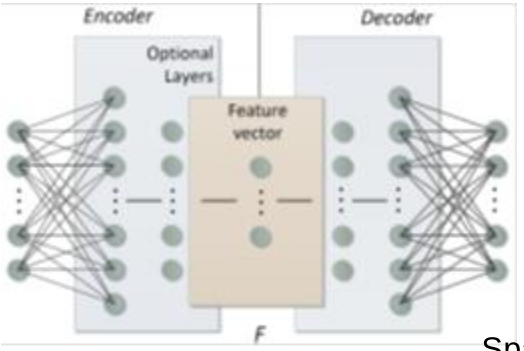
Deep Convolutional Neural Networks and Decision Forests

Connectivity (memory)

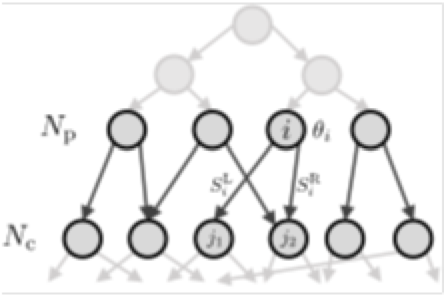
- CNN is fully connected.
- Memory used in decision trees grows exponentially with depth.
- Decision Jungle (ensembles of directed acyclic graphs) allows multiple paths.

Data representation

- DF requires a set of features manually defined.
- Neural Decision Forests jointly tackles data representation and discriminative learning, using randomized Multi-Layer Perceptrons as split nodes.
- Hough Networks (cf. Hough Forest) (Riegler et al. BMVC14) jointly perform classification and regression.



Sparse Autoencoders



Decision Jungle (Shotton et al. NIPS13)

NDF (Bulo et al. CVPR14/ICCV15)