# OpenCV Object Detection: Theory and Practice

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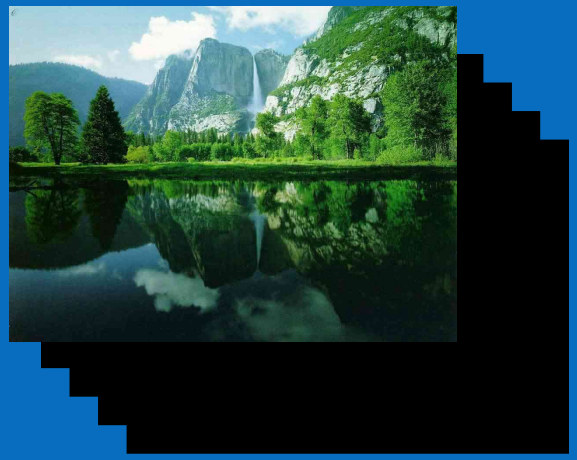
# Agenda

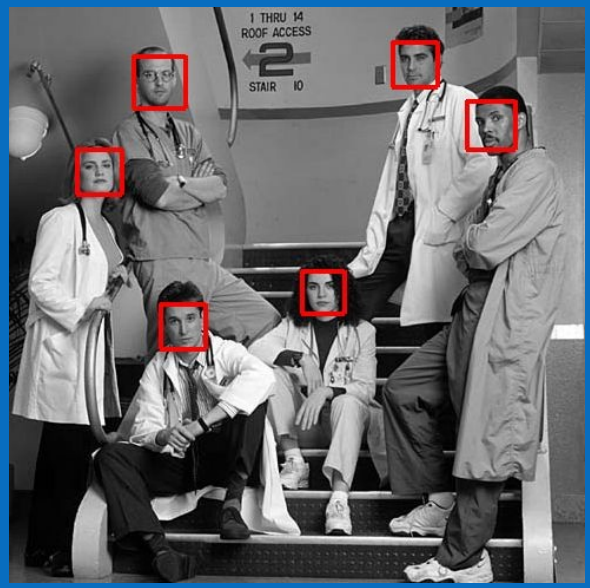
- Quick introduction to object detection
- Basic theory
- History of the approach
- Object detection functions
- Haartraining workflow and tips

# Quick Introduction: Top-level view

“objects”

“non-objects”






opencv/apps/haartraining

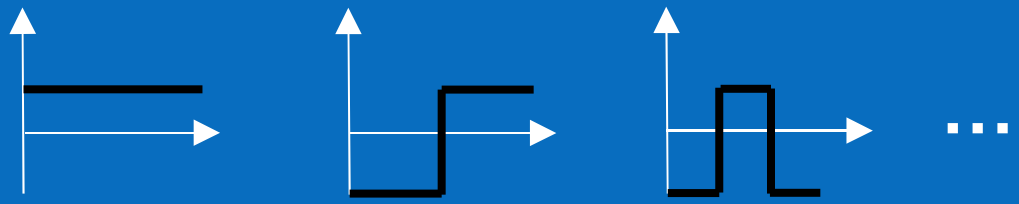
```
<?xml version="1.0" ?>
- <opencv_storage>
  - <haarcascade_frontalface_alt type_id="opencv-haar-classifier">
      <size>20 20</size>
    - <stages>
      - <_>
          <!-- stage 0 -->
        - <trees>
          - <_>
              <!-- tree 0 -->
            - <_>
                <!-- root node -->
              - <feature>
                - <rects>
                    <_>3 7 14 4 -1.</_>
                    <_>3 9 14 2 2.</_>
```

cvLoad, cvDetectHaarObjects

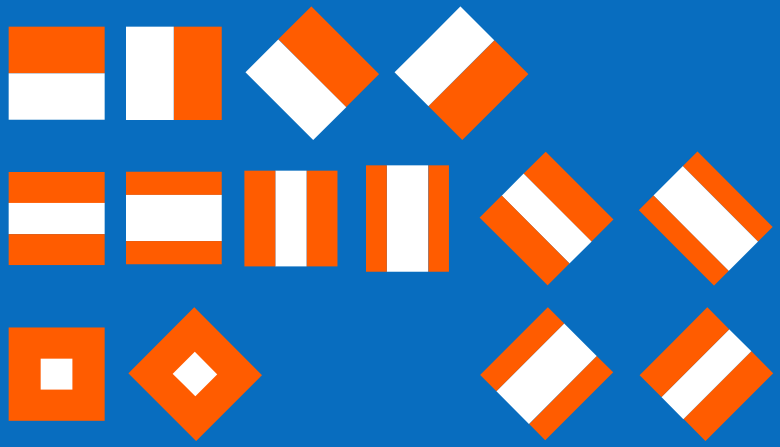
# Basic Theory of Haar-like Object Detectors

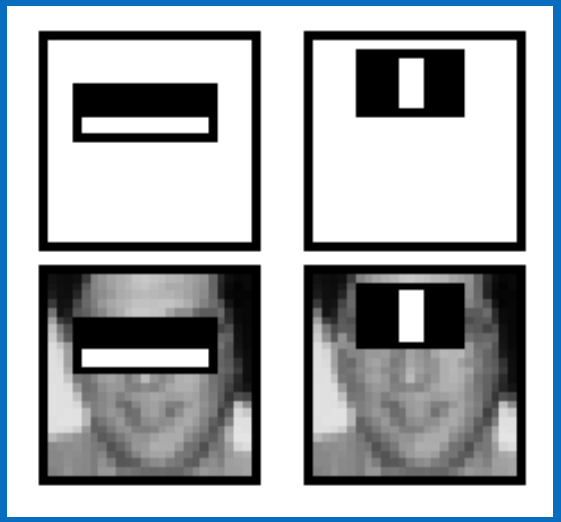
# Why is it called "Haar-like"?

The features are similar to the basis functions in Haar wavelets:



Pool of features used in OpenCV implementation:





Can be scaled => ~130.000 features for 24x24 window

# How are the features computed?

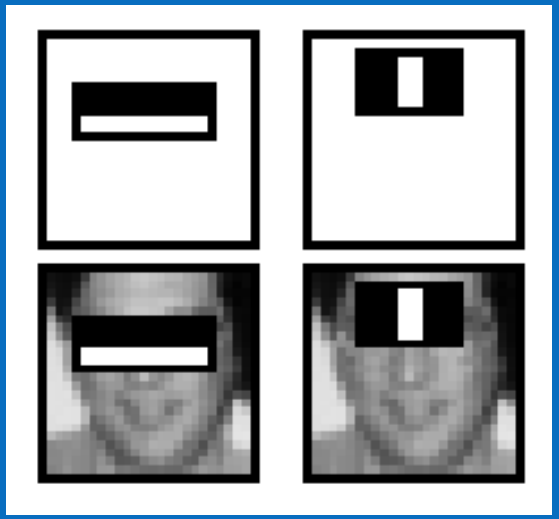
$$feature_{i,k}=w_{i,k,1}*RectSum_{i,k,orange+white}(I)+w_{i,k,2}*RectSum_{i,white}(I)$$

**Weights are compensated:**

$$w_{i,k,1}*Area_{i,k,orange+white}+w_{i,k,2}*Area_{i,k,white}=0$$

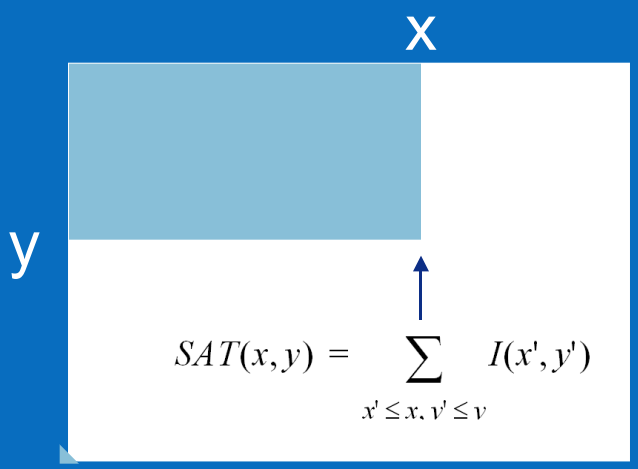
$$w_{i,k,2}=-3*w_{i,k,1}$$

$$w_{i,k,2}=-9*w_{i,k,1}$$

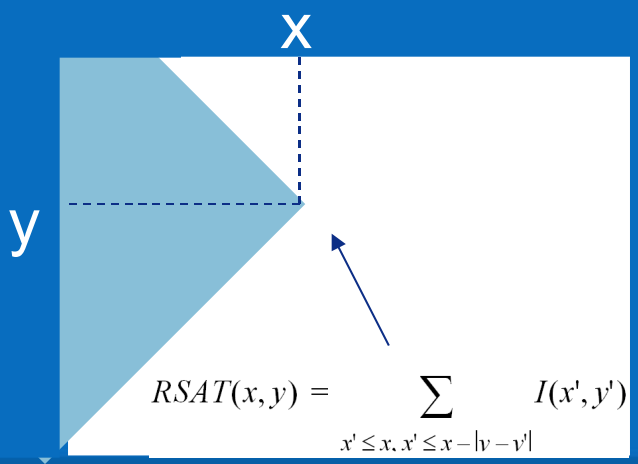


# Rapid Computation

**First, integral images (SAT, RSAT) are computed,**
**Then the features can be computed in O(1)**



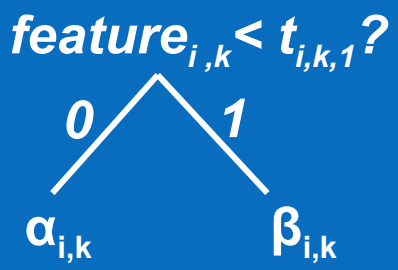

$$RecSum(r) = SAT(x-1,y-1)+SAT(x+w-1,y+h-1) - SAT(x-1,y+h-1)-SAT(x+w-1,y-1)$$



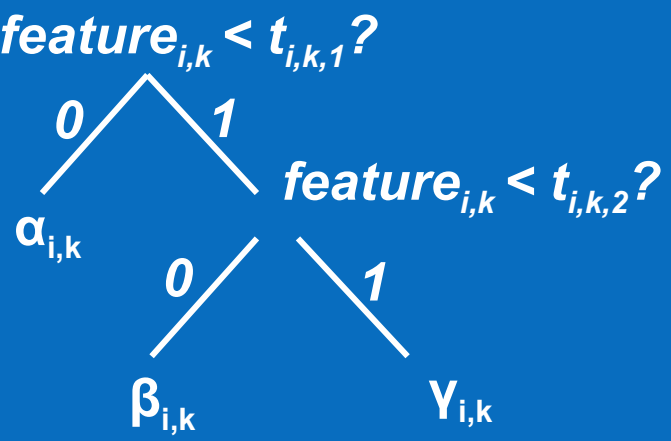

$$RecSum(r) = RSAT(x+w,y+w)+RSAT(x-h,y+h) - RSAT(x,y)-RSAT(x+w-h,y+w+h)$$

# Weak classifiers

**1-split decision tree (stump)**




**2-split decision tree**




**…**

**$t_{i,k}$ and the values at leaves are found using L.Brieman CART™ algorithm**

# Making weak classifiers stronger: DAB etc.

## Discrete Adaboost (DAB) (Freund, Schapire, 1996)

1. Given $N$ examples $(x_1,y_1),\ldots,(x_N,y_N)$ with $x\in \Re^k, y_i\in\{-1,1\}$
2. Start with weights $w_i = 1/N$, $i = 1, \ldots, N$.
3. Repeat for $m = 1, \ldots, M$
   (a) Fit the classifier $f_m(x)\in\{-1,1\}$ using weights $w_i$ on the training data $(x_1,y_1),\ldots,(x_N,y_N)$.
   (b) Compute $err_m = E_w[1_{(y\neq f_m(x))}]$, $c_m = \log((1-err_m)/err_m)$.
   (c) Set $w_i \leftarrow w_i \cdot \exp(c_m \cdot 1_{(y_i\neq f_m(x_i))})$, $i = 1, \ldots, N$, and renormalize weights so that $\sum_i w_i = 1$.
4. Output the classifier $sign\left[\sum_{m=1}^{M} c_m \cdot f_m(x)\right]$

**The Boosting Theorem (paraphrased): "*As long as weak classifiers are better than random, with sufficiently large M boosted classifier may become as good as you wish*"**

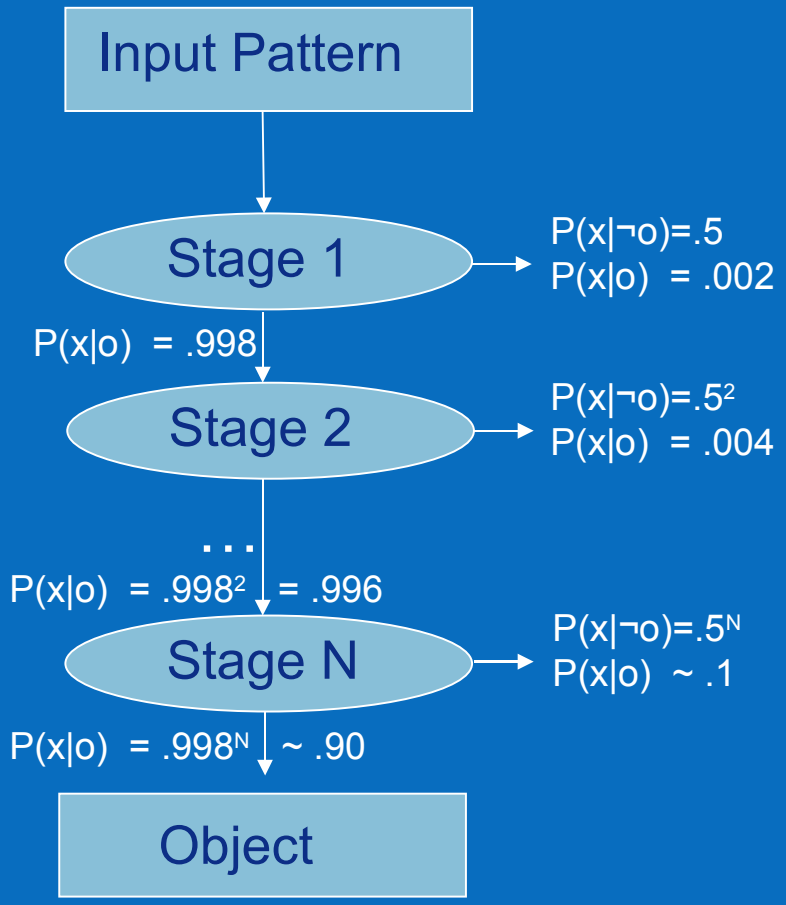
**There are also Real Adaboost (RAB), Logitboost (LB) and Gentle Adaboost (GAB) implemented in OpenCV, and many other variants.**

# Cascade of Classifiers

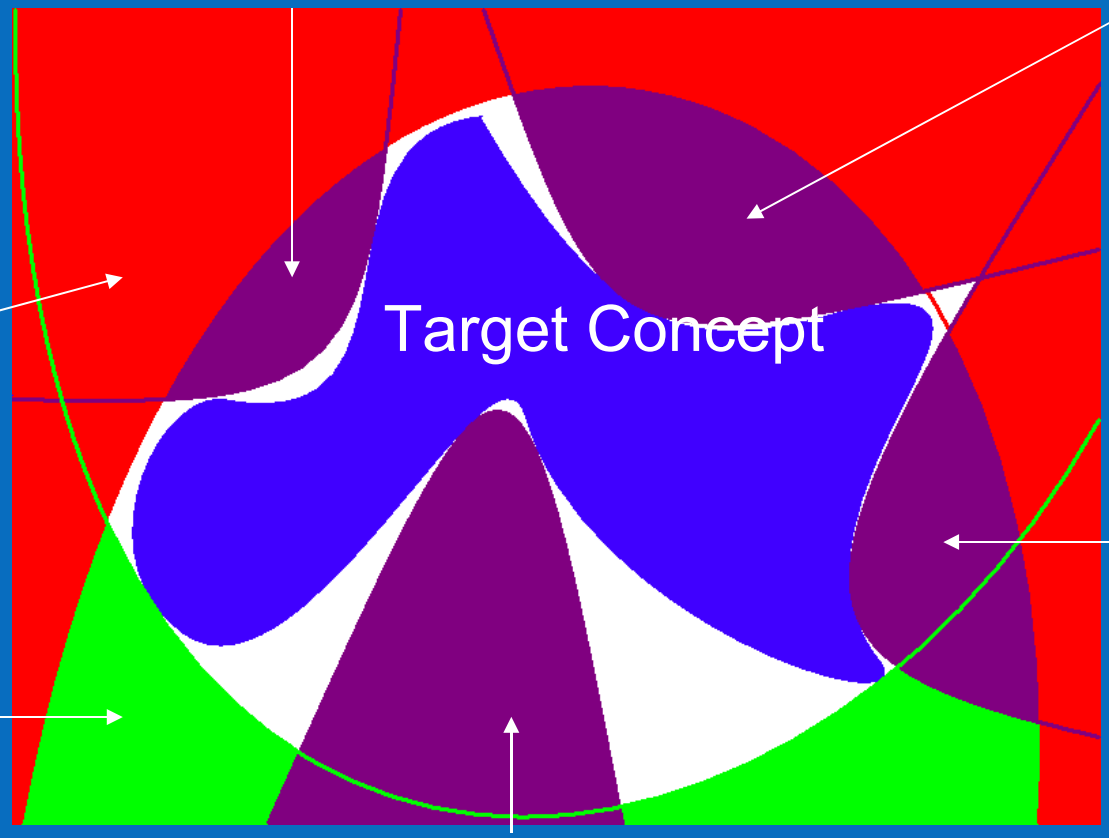
Premise:

Size of feature pool (>100000) exceeds what any reasonable classifier can handle

Cascade of classifiers (special kind of decision tree) can outperform a single stage classifier because it can use more features at the same average computational complexity



# Cascade Concept

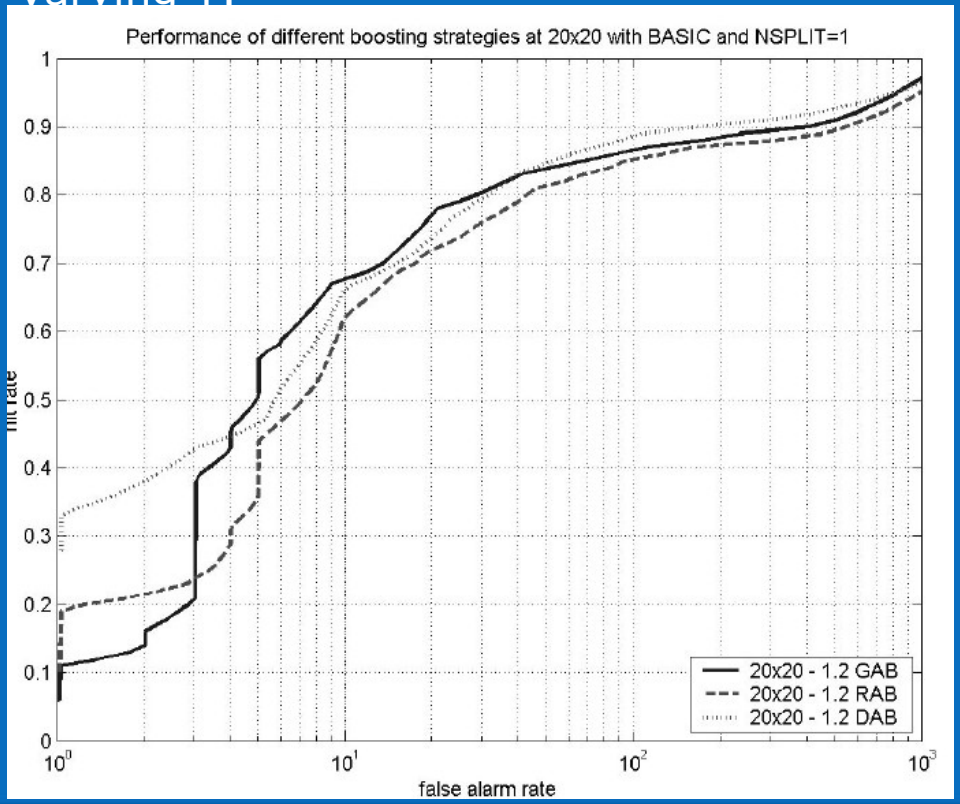


# Tuning global thresholds: ROC curves

Classical boosting algorithms give: $F(x)=\text{sign}\ \Sigma_{m=0,M-1}c_m f_m(x)$

We replace it with: $F(x)=\text{sign}\ [\Sigma_{m=0,M-1}c_m f_m(x) - T] \Rightarrow$

Instead of a fixed classifier we may choose an optimal balance between the hit-rate and false alarms by varying T:



# Finding objects of different sizes in an image

*window_size* = $window\_size_0$

*scale* = 1

*faces* = {}

while *window_size* ≤ *image_size* do

  *classifier_cascade* = $classifier\_cascade_0$ scaled by *scale*

  *dX* = *scale*

  *dY* = *scale*

  for 0 ≤ *Y* < *image_height* – *window_height* do

    for 0 ≤ *X* < *image_height* – *window_height* do

      *region_to_test* = {0 ≤ *x* < *X* + *window_width*; 0 ≤ *y* < *Y* + *window_width*}

      if *classifier_cascade(region_to_test)* == 1 then

        *faces* = *faces* ∪ {*region_to_test*}

      end if

      *X* = *X* + *dX*

    end for

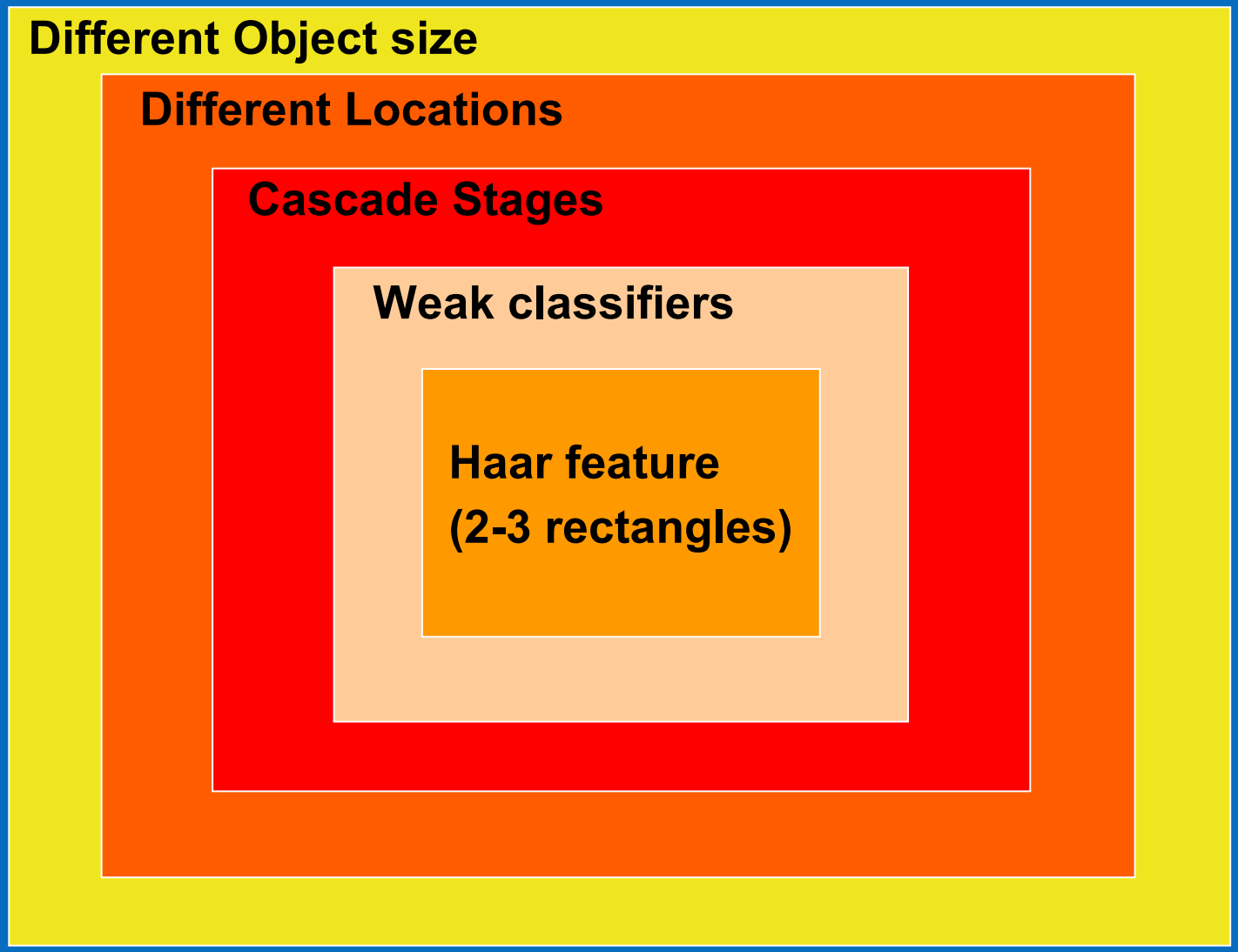
    *Y* = *Y* + *dY*

  end for

  *scale* = *scale* × *C* /* C – some constant, e.g. 1.1 or 1.2 */

end while

# Algorithm Structure




1 THRU 14
ROOF ACCESS
2
STAIR 10
Examples

# History and the previous works

- C. Papageorgiou, M. Oren, and T. Poggio. A general framework for Object Detection. In *International Conference on Computer Vision*, 1998. Introduced Haar-like features + boosted classifiers for face detection.
- Paul Viola and Michael J. Jones. Rapid Object Detection using a Boosted Cascade of Simple Features. IEEE CVPR, 2001. Simplified features computed in O(1) using integral images, multi-stage classifiers.
- Rainer Lienhart and Jochen Maydt. An Extended Set of Haarlike Features for Rapid Object Detection. IEEE ICIP 2002, Vol. 1, pp. 900-903, Sep. 2002. Tilted features and algorithm tuning (GAB, ROC optimization …).

----- Recent improvements (under consideration) ------

Floatboost, more efficient feature selection …

# Detecting Objects with OpenCV

# Object detection within OpenCV package

opencv/

- apps/haartraining/ - haartraining application
- apps/haartraining/doc – haartraining user guide
- cv/include/ - data structures and object detection functions.
- cv/src/cvhaar.cpp – detection algorithm source code
- data/haarcascades – pre-trained classifiers (read the license!)
- samples/c/facedetect.c – object detection demo

# Object Detection Sample

```
#include "cv.h"
#include "highgui.h"
int main( int argc, char** argv )
{
    static CvMemStorage* storage = cvCreateMemStorage(0);
    static CvHaarClassifierCascade* cascade = 0;
    if( argc != 3 || strncmp( argv[1], "--cascade=", 10 ))
        return -1;
    cascade = (CvHaarClassifierCascade*)cvLoad( argv[1] + 10 );
    CvCapture* capture = cvCaptureFromAVI( argv[2] );
    if( !cascade || !capture ) return -1;
    cvNamedWindow( "Video", 1 );
    for(;;) {
        IplImage* frame = cvQueryFrame( capture ), *img;
        if( !frame )
            break;
        img = cvCloneImage(frame); img->origin = 0;
        if( frame->origin ) cvFlip(img, img);
        cvClearMemStorage( &storage );
        CvSeq* faces = cvHaarDetectObjects( img, cascade, storage,
           1.1, 2, CV_HAAR_DO_CANNY_PRUNING, cvSize(20, 20) );
        for( int i = 0; i < (faces ? faces->total : 0); i++ ) {
            CvRect* r = (CvRect*)cvGetSeqElem( faces, i );
            cvRectangle( img, cvPoint(r->x,r->y),
                cvPoint(r->x+r->width,r->y+r->height),
                   CV_RGB(255,0,0), 3 );
        }
        cvShowImage( "Video", img );
        cvReleaseImage( &img );
        if( cvWaitKey(10) >= 0 ) break;
    }
    cvReleaseCapture( &capture );
    return 0;
}
```


```
./facedetect --cascade=opencv/data/haarcascades/haarcascade_frontalface_alt2.xml screetcar.avi
```

# Object detection functions

- CvHaarClassifierCascade* cascade = (CvHaarClassifierCascade*)cvLoad(<classifier_filename.xml>);
- CvSeq* face_rects = cvHaarDetectObjects(image, cascade, memory_storage, scale_factor, min_neighbors, flags, min_size);
  - scale – classifier cascade scale factor. typically, 1.1 or 1.2 (10% and 20%, respectively)
  - min_size – starting minimum size of objects. By specifying large enough minimum size one can speedup processing a lot!

  Let's look at the other parameters …

# min_neighbors: clustering output rectangles

min_neighbors=0

min_neighbors=2

# flags

CV_HAAR_DO_CANNY_PRUNING (reject regions with too few or too many edges inside (parameters are tuned for faces!)):

| Image size | Scale factor | Classifier calls (naïve algorithm) | Classifier calls (with pruning) |
|---|---|---|---|
| 160x120 | 1.2 | 32000 | 8000 |
| 320x240 | 1.2 | 180000 | 50000 |
| 640x480 | 1.2 | 850000 | 200000 |
| 160x120 | 1.1 | 55000 | 20000 |
| 320x240 | 1.1 | 300000 | 90000 |
| 640x480 | 1.1 | 1500000 | 390000 |

So, the pruning techniques decrease number of calls to classifier by 60-80%.

CV_HAAR_FIND_BIGGEST_OBJECT:

**Decreases the processing time by factor of 10(!)**
**when you need to find at most 1 face (the biggest one)**

# Haartraining

# Haartraining use:

1. Put all the positive samples in a directory, prepare textual description (info file) in a special format, e.g.:

   **Directory with positive samples:**

   mydir/positive/

   face1.jpg

   face2.jpg

   my_family.png

   …

   **Info file (e.g. my_info.dat)**:

```
mydir/positive/face1.jpg  1  140 100 45 45
mydir/positive/face2.jpg 1 10 20 50 50
mydir/positive/my_family.png  4  100 200 50 50   50 30 25 25 …
```

1. Run opencv/bin/createsamples.exe:

createsamples –vec pos_samples.vec –info my_info.dat –w <width> -h <height>

createsamples can also generate a set of positive samples out of a single image.
See the reference in opencv/apps/haartraining/doc.

# Haartraining use:

1. Now prepare collection of negative samples and another corresponding text file:

   **Directory with negative samples:**

   mydir/negative/

   my_house.jpg

   beijing_view.jpg

   riverside.png

   …

   Background info file **(e.g. bg.txt)**:

```
mydir/negative/my_house.jpg
mydir/negative/beijing_view.jpg
mydir/negative/riverside.jpg
```

1. Now run opencv/bin/haartraining.exe:

haartraining –vec pos_samples.vec –bg bg.txt –w <width> -h <height> -data my_classifier_dir –nsplits 1 –nstages 15 –npos N1 –nneg N2 –mem <mem_buf_size>

See the reference for detailed description of haartraining parameters

# Haartraining tips

- Get the fastest machine with a lot of memory (few gig's), and specify large enough buffer size using –mem option of haartraining
- Build OpenMP-enabled haartraining (or use precompiled one from OpenCV distribution)
- Haartraining resumes training automatically starting from the last trained stage.
- Positive samples: take care of proper alignment, avoid a lot of background; the smaller is standard deviation => easier for classifier to learn; consider training several classifiers instead of a single almighty one.
- Negative samples: make sure you have enough large-resolution background images (a big percentage of background images is rejected by first few stages => those images can not be used on later stages).
- Choose the optimal object size for haartraining. Play with the other parameters (set of haar features, type of boosting algorithm, number of splits in weak classifier etc.) too. See "**Empirical Analysis of Detection Cascades of Boosted Classifiers for Rapid Object Detection"** technical report by R.Lienhart et al for empirical study of face detection classifier.