Experiments with Object Detection using Haar-like Features

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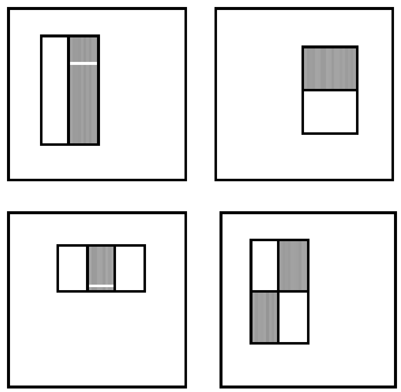
Outline

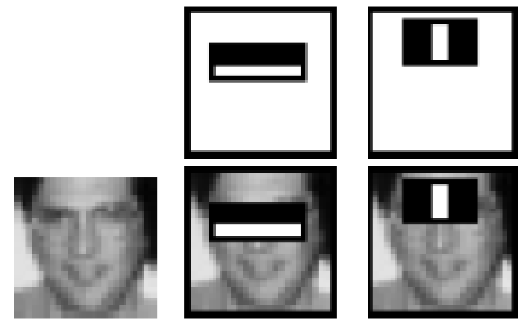
- Background
- A walkthrough of cascade creation
- Visualizing a couple of cascades
- Detecting different types of objects
- Training with a single image
- Incorporating color information to improve performance (for face detection)

The Detector

- Proposed by [Viola, Jones 2001]
- Using boosted cascades of Haar-like features
- Implementation available in OpenCV

Haar-like features





- feature = w_1 x RecSum(r_1) + w_2 x RecSum(r_2)
- Weights can be positive or negative
- Weights are directly proportional to the area
- Calculated at every point and scale

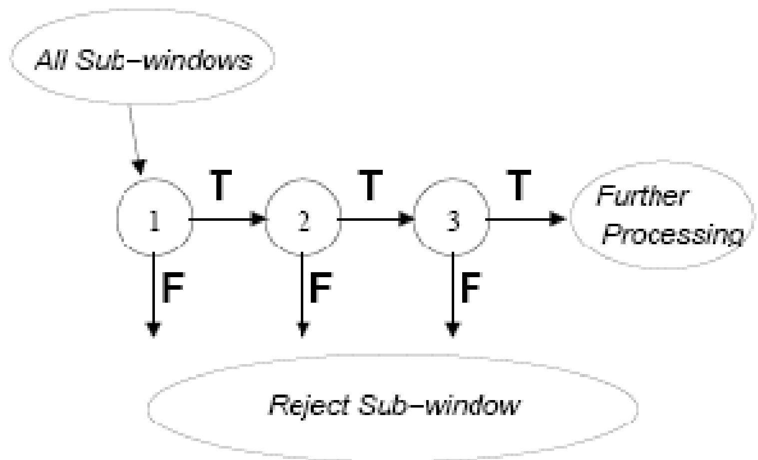
Weak Classifier

- A **weak classifier** ($h(x, f, p, \vartheta)$) consists of
  - feature (f)
  - threshold (ϑ)
  - polarity (p), such that

$$h(x, f, p, \theta) = \begin{cases} 1 & if\ pf(x) < p\theta \\ 0 & otherwise \end{cases}$$

- Requirement
  - Should perform better than random chance

Attentional Cascade



- Initial stages have less features (faster computation)
- More time spent on evaluating more promising sub-windows

Cascade Creation - Walkthrough

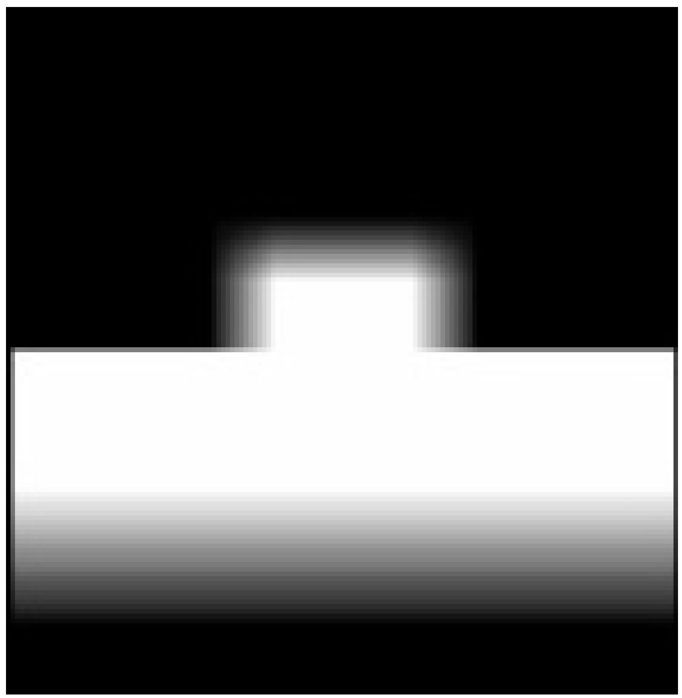
Positive Samples

200 distorted versions of a synthetic image

Cascade Creation - Walkthrough

Positive Samples

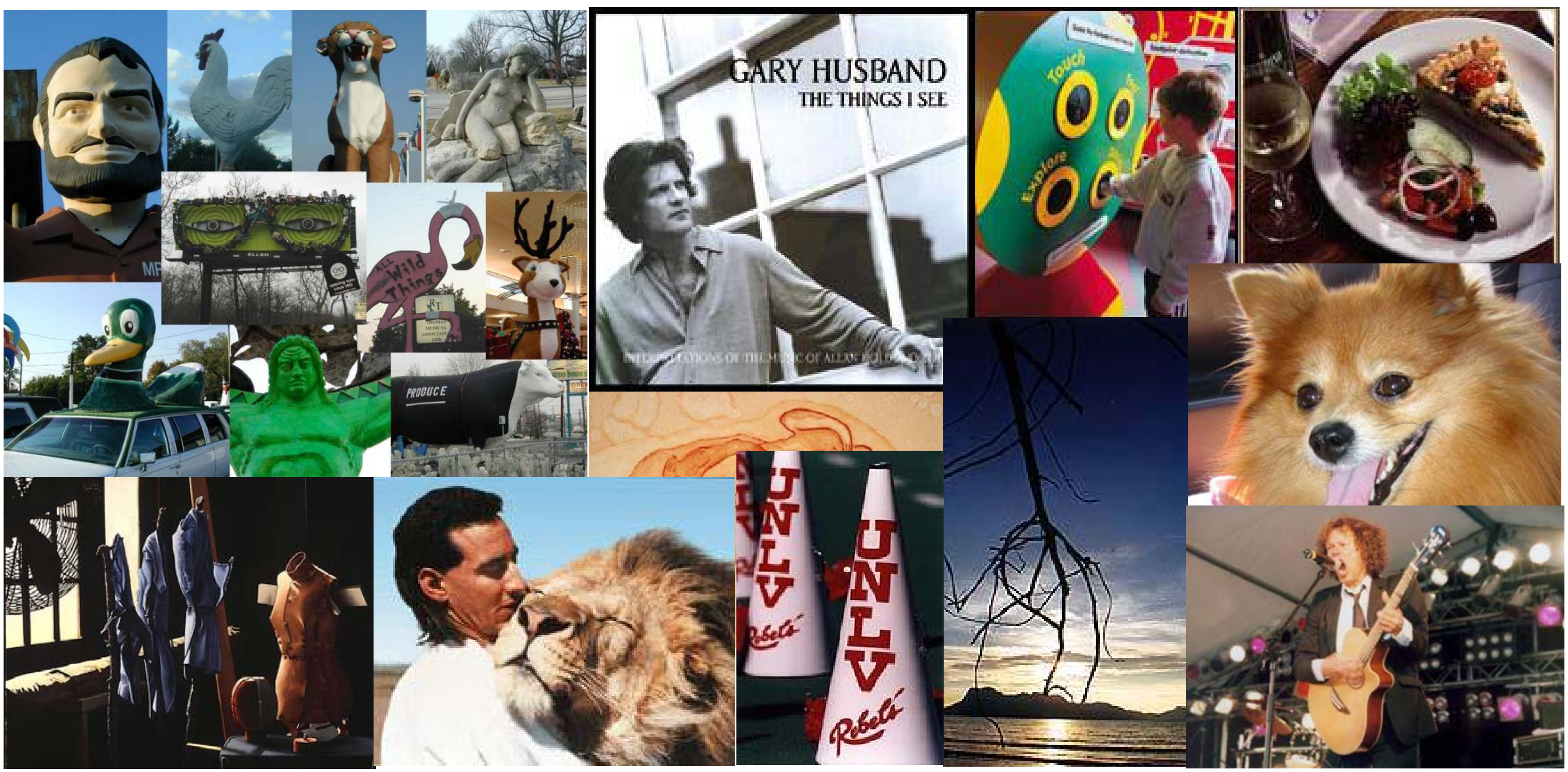
200 distorted versions of a synthetic image



Cascade Creation - Walkthrough

Negative Samples

100 images from BACKGROUND_Google category of Caltech 101 dataset



Cascade Creation - Walkthrough

- Input Parameters
  - d = Minimum acceptable detection rate per layer (0.995)
  - f = Maximum acceptable false positive rate per layer (0.5)
  - F_{target} = Target overall false positive rate
    - Or maximum number of stages in the cascade
    - For nStages = 14, $F_{target} = f^{nStages} = 6.1$ e-5

Cascade Creation - Walkthrough

$F_0 = 1$
$i = 0$
while $F_i > F_{target}$ and $i < nStages$

    $i = i + 1$
    Train Classifier for stage i

        Initialize Weights
        Normalize Weights
        Pick the (next) best weak classifier
        Update Weights
        Evaluate f_i
        if $f_i > f$

            go back to Normalize Weights

        Combine weak classifiers to form the strong stage classifier
        Evaluate F_i
        If $F_i > F_{target}$, N = set of negative samples that are labeled positive by current detector

Cascade Creation - Walkthrough

F_i = False alarm rate of the cascade with i stages

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Weight for each

positive sample	0.5/m
negative sample	0.5/n

m – number of positive samples (200)
n – number of negative samples (100)

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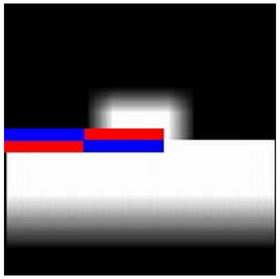
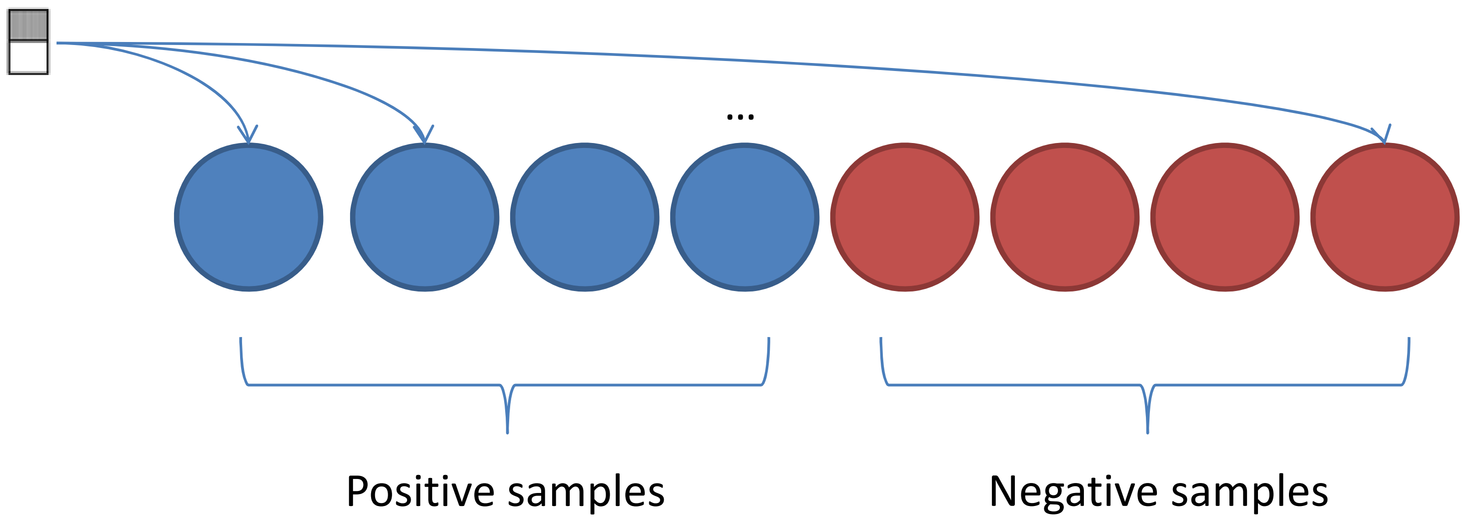
The one with minimum error

$$\epsilon_t = min_{f,p,\theta} \sum_t w_t \left| h(x_t, f, p, \theta) - y_t \right|$$

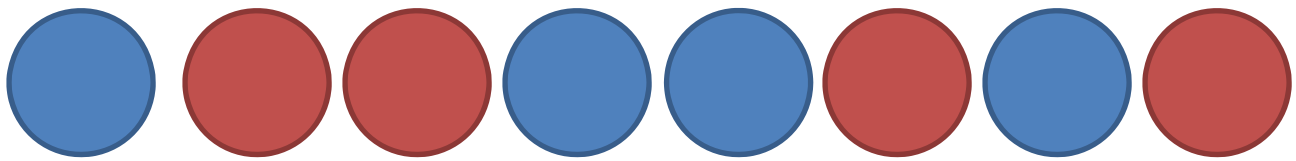


$\epsilon_t = 0.005$

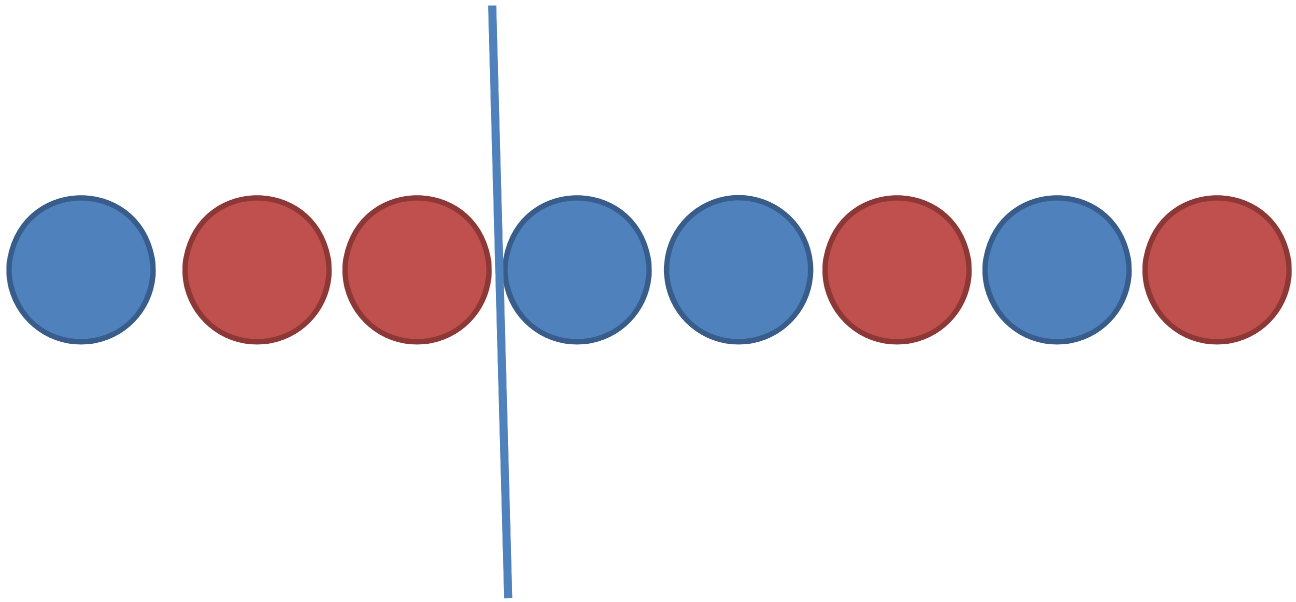
Error minimization



Error minimization



Error minimization



Sum of weights of
T^+: All +ve examples
T^-: All -ve examples
S+: +ve examples below the current one
S-: -ve examples below the current one

$e_1 = S^+ + (T^- - S^-)$
$e_2 = S^- + (T^+ - S^+)$

$\mathbf{e = min(e_1, e_2)}$

Cascade Creation - Walkthrough

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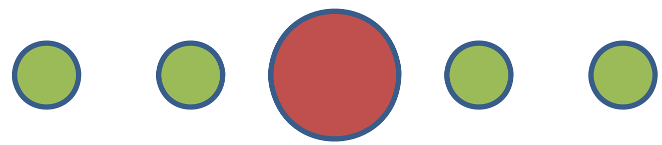
$$w_{t+1,i} = w_{t,i}\,\beta_t^{1-e_i}$$

$e_i = 0$, if example x_i is classified correctly
$e_i = 1$, otherwise

$$\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$$



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f_i = number of negative samples that were detected by this stage/ total number of negative samples
= 1/100

Cascade Creation - Walkthrough

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How far will you go to get down to f?

Cascade Creation - Walkthrough

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$$C(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & otherwise \end{cases}$$

$$\alpha_t = \log \frac{1}{\beta_t} \qquad \beta_t = \frac{\epsilon_t}{1 - \epsilon_t}$$

Cascade Creation - Walkthrough

$F_0 = 1$

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Add another stage?

Cascade Creation - Walkthrough

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    $i = i + 1$

    Train Classifier for stage i

        Initialize Weights

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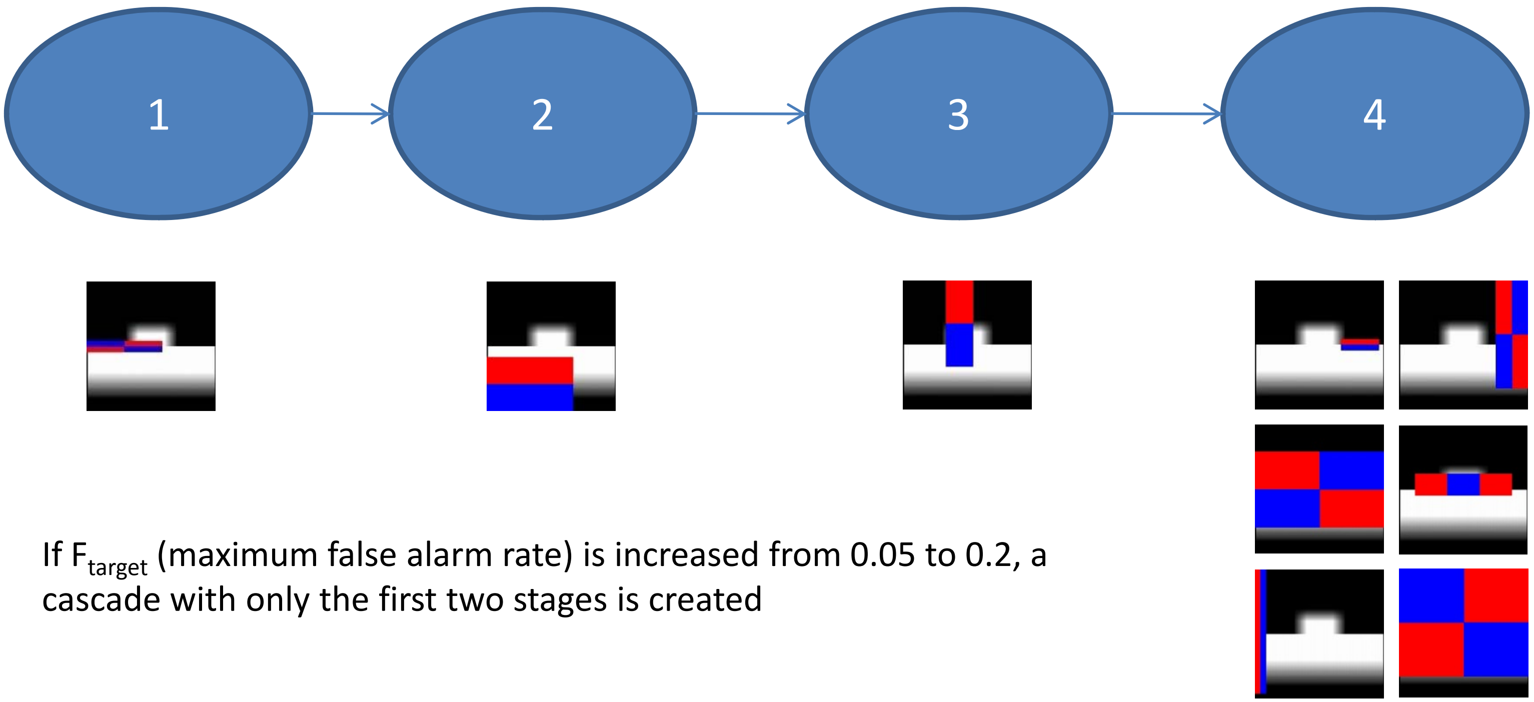
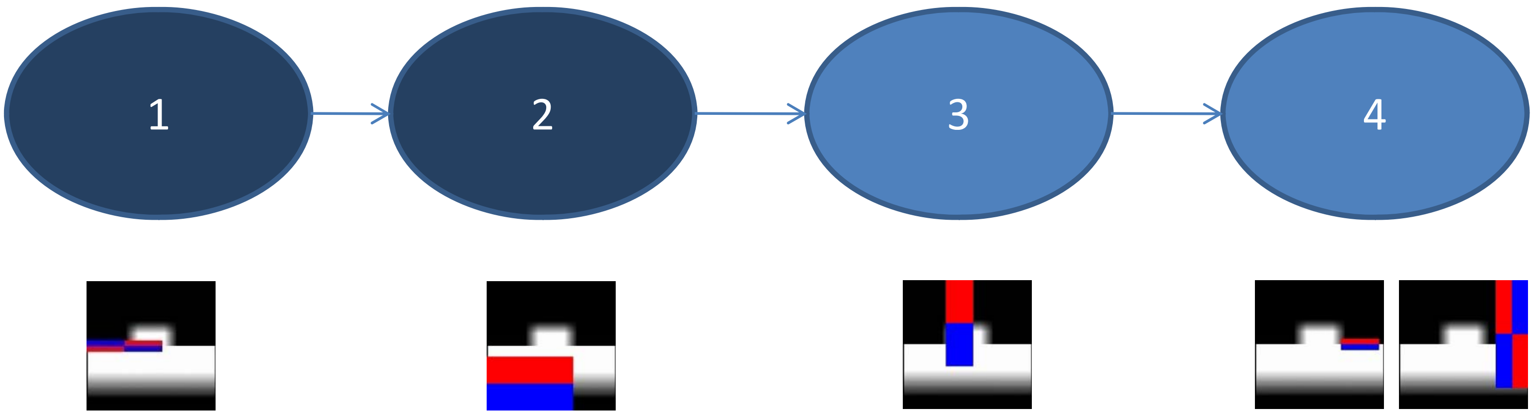
Trim the negative samples

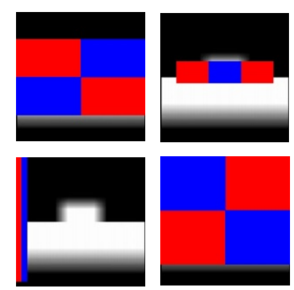
Resulting Cascade



If F_{target} (maximum false alarm rate) is increased from 0.05 to 0.2, a cascade with only the first two stages is created

Resulting Cascade



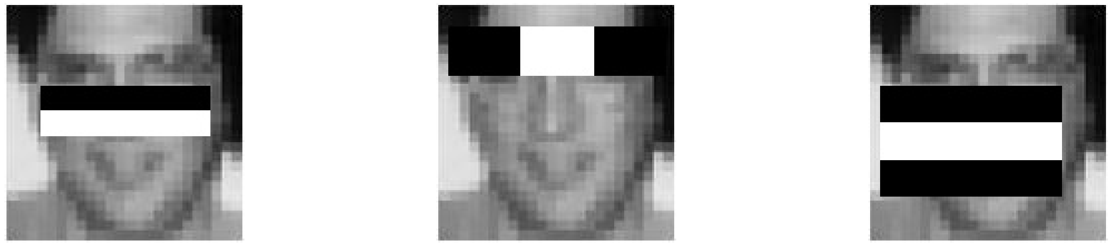


If F_{target} (maximum false alarm rate) is increased from 0.05 to 0.2, a cascade with only the first two stages is created

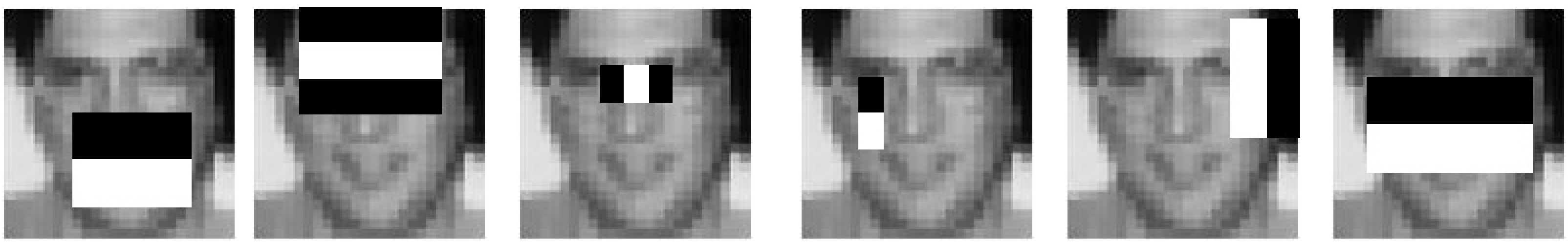
Which features actually get selected?

(OpenCV's default frontal face cascade)

Stage 0



Stage 1



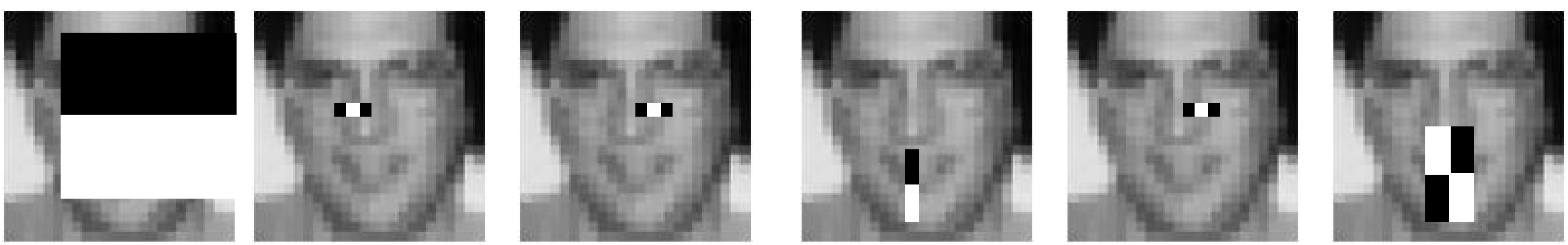
…

10 more

.

.

Stage 21



…

206 more

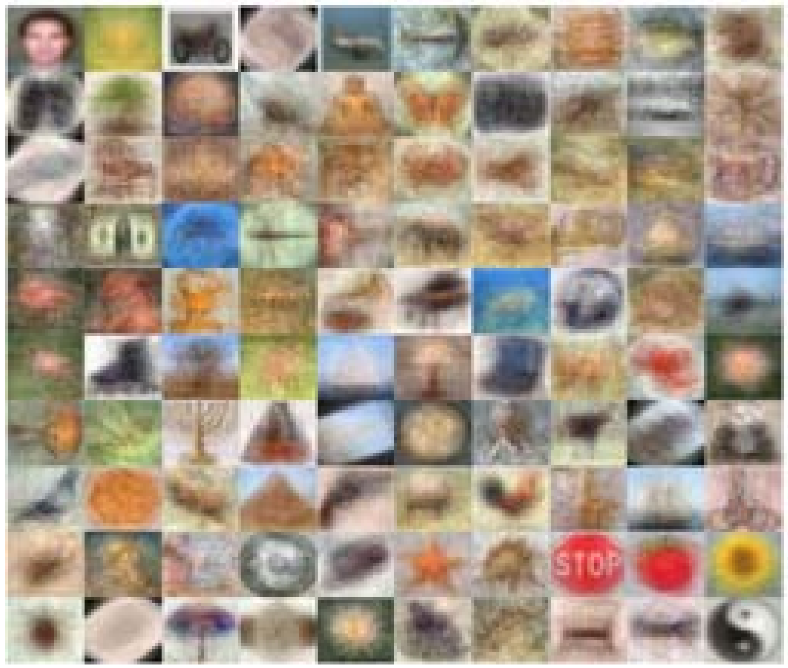
Caltech 101 dataset

- 101 categories
- 40 to 800 images per category
- Each image is roughly 300x200 pixels





Regularity in Images



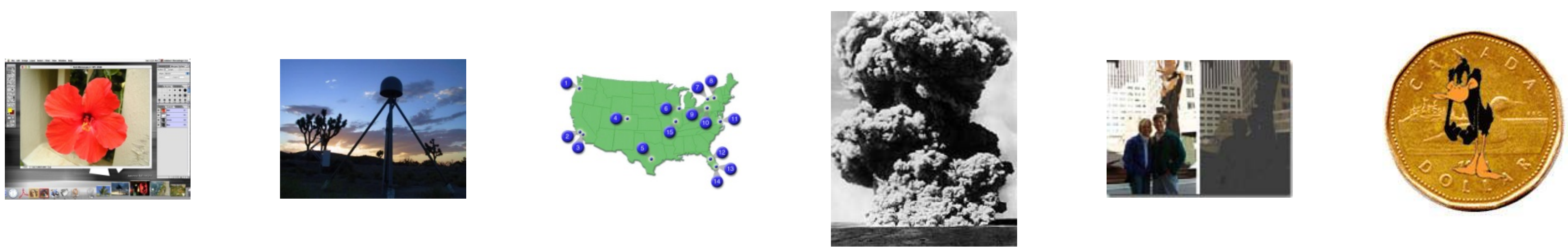
"Most images have little or no clutter. The objects tend to be centered in each image. Most objects are presented in a stereotypical pose."

Detecting different types of objects

1. Train a cascade from:

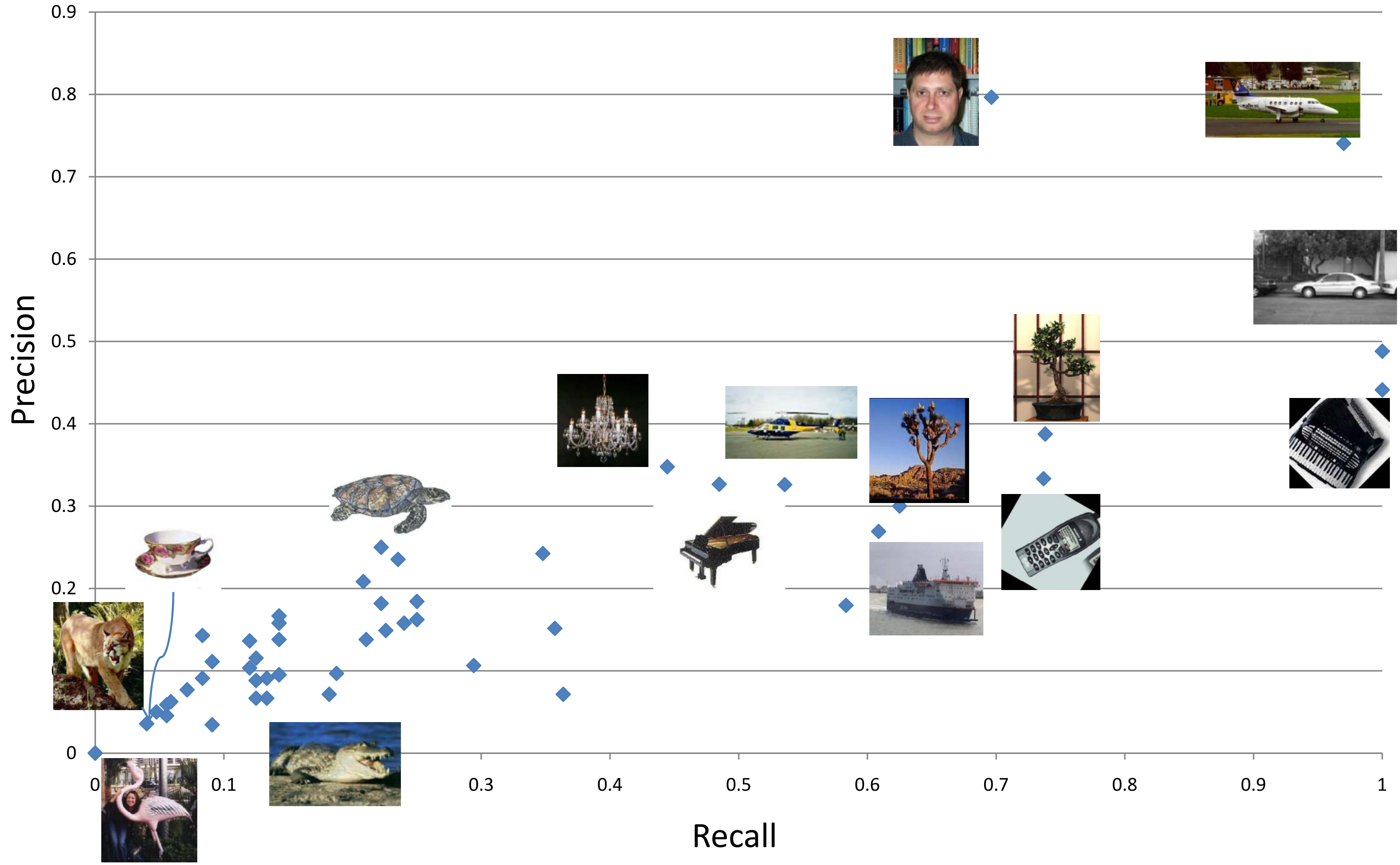
Positive Samples (60% of images from Faces_easy category)

Negative Samples (60% of images in Background_Google category)



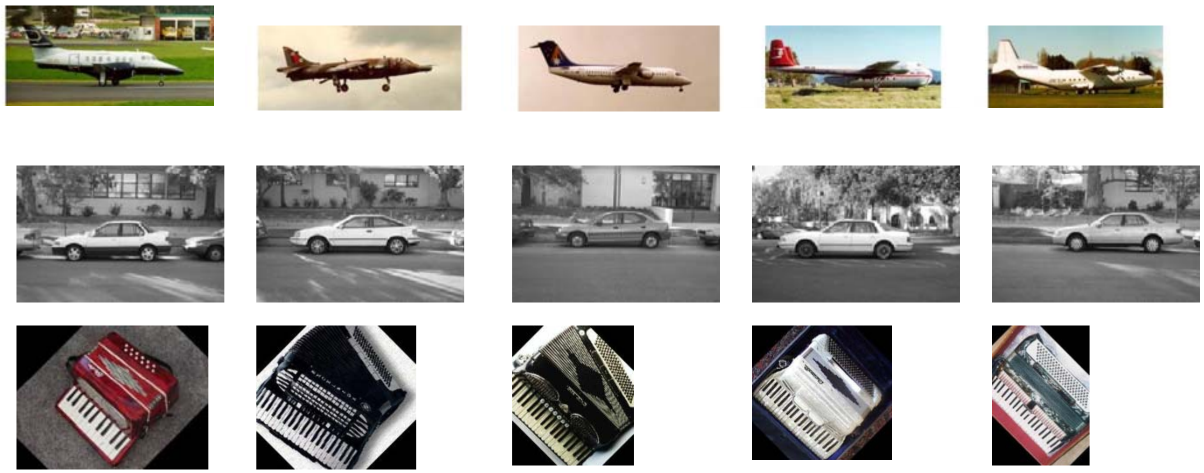
2. Test on the rest of the images from Faces_easy and Background_Google categories
3. Repeat with another category

Detecting different types of objects

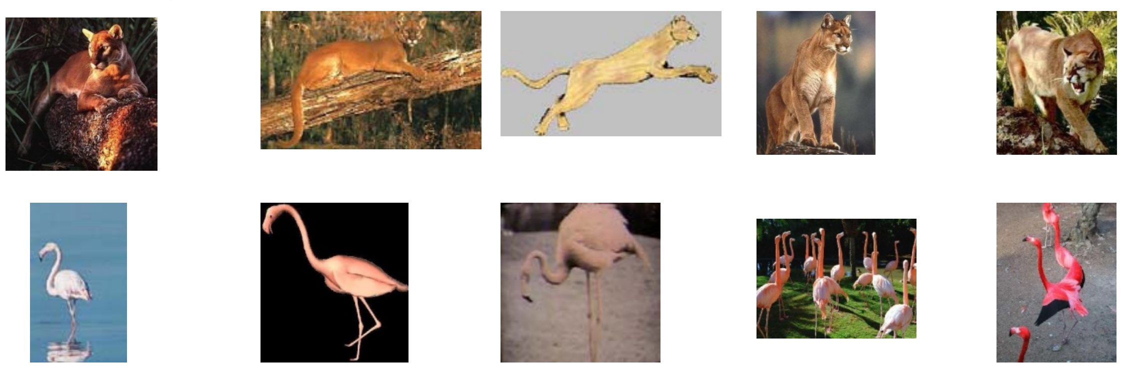


Variation in Training Images

High accuracy categories

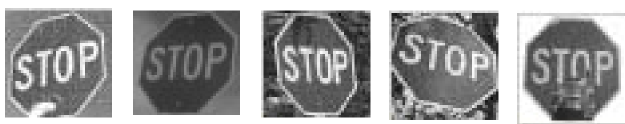


Low accuracy categories

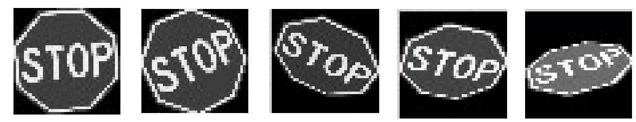


Training with a Single Image

Hand label ROI in 40/64 images

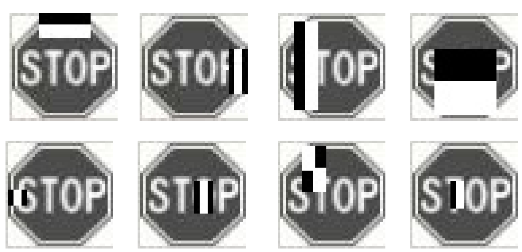


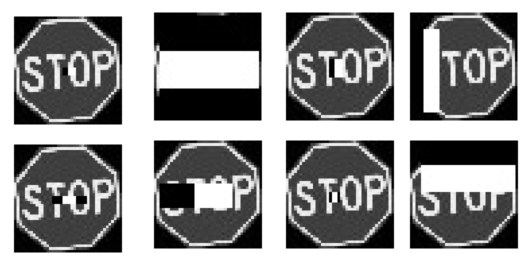
Generate 1000 random distortions of a representative image



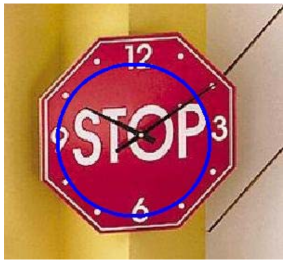
Negative samples taken from *BACKGROUND_Google* category of Caltech 101

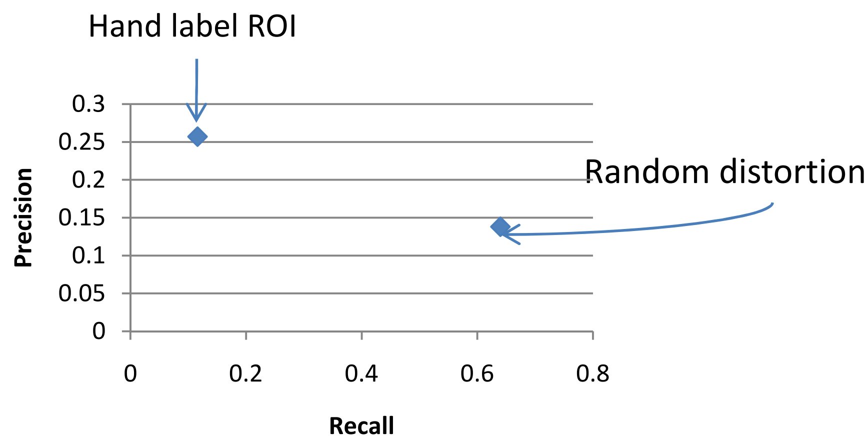
Some features that get selected

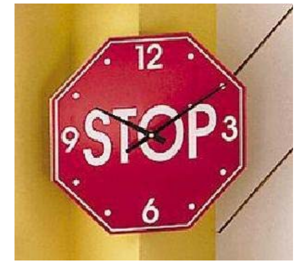




Performance





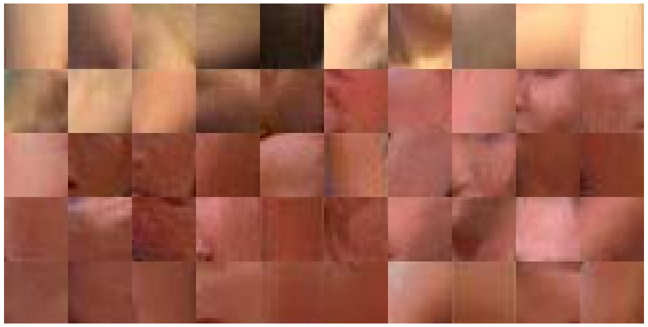


Hand label ROI

Random distortions

Skin Color Approximation

- To filter results of face detector
- Derived from [Bradsky 1998]
- Template Image
  - Patches of faces of different subjects under varying lighting conditions



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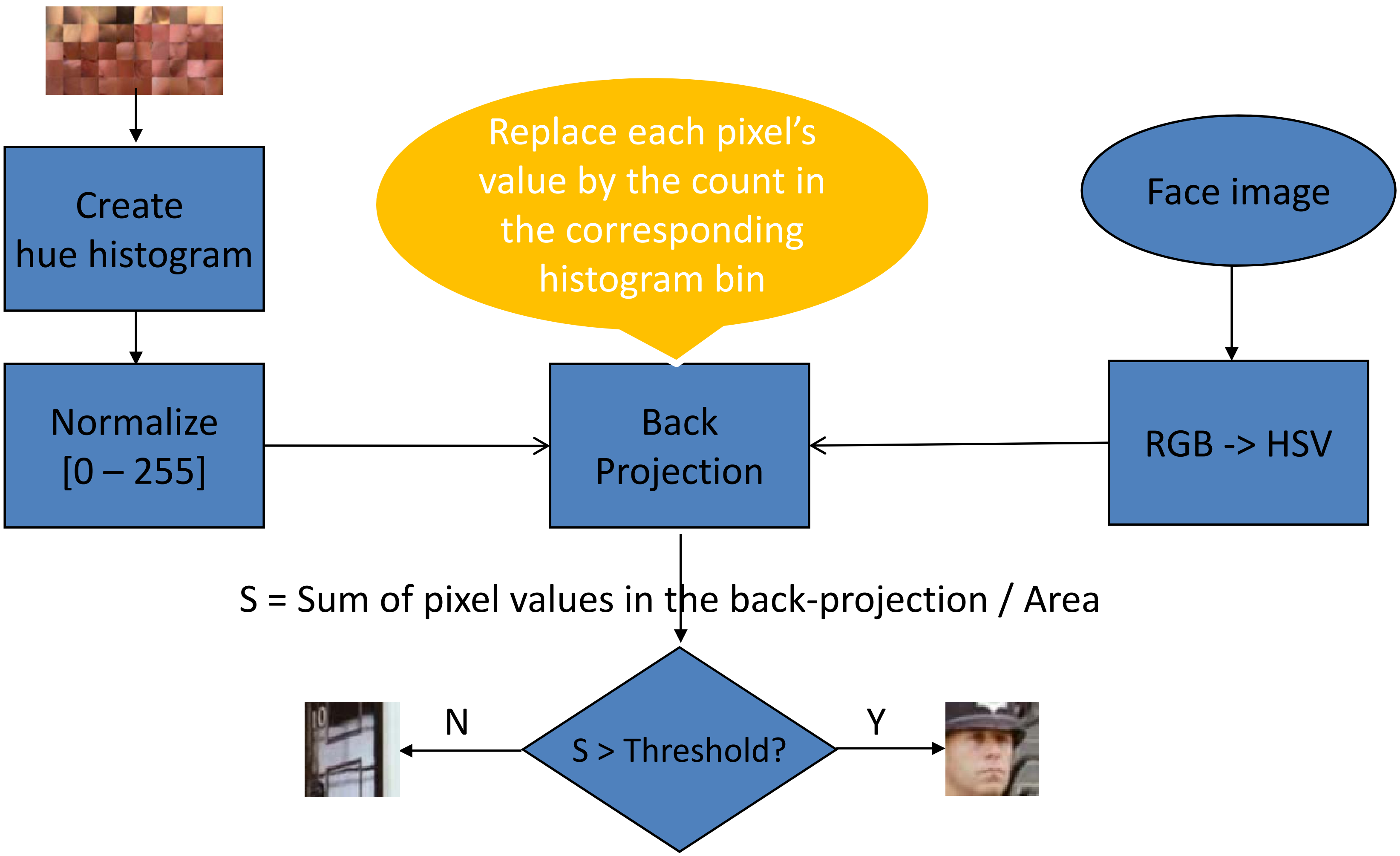
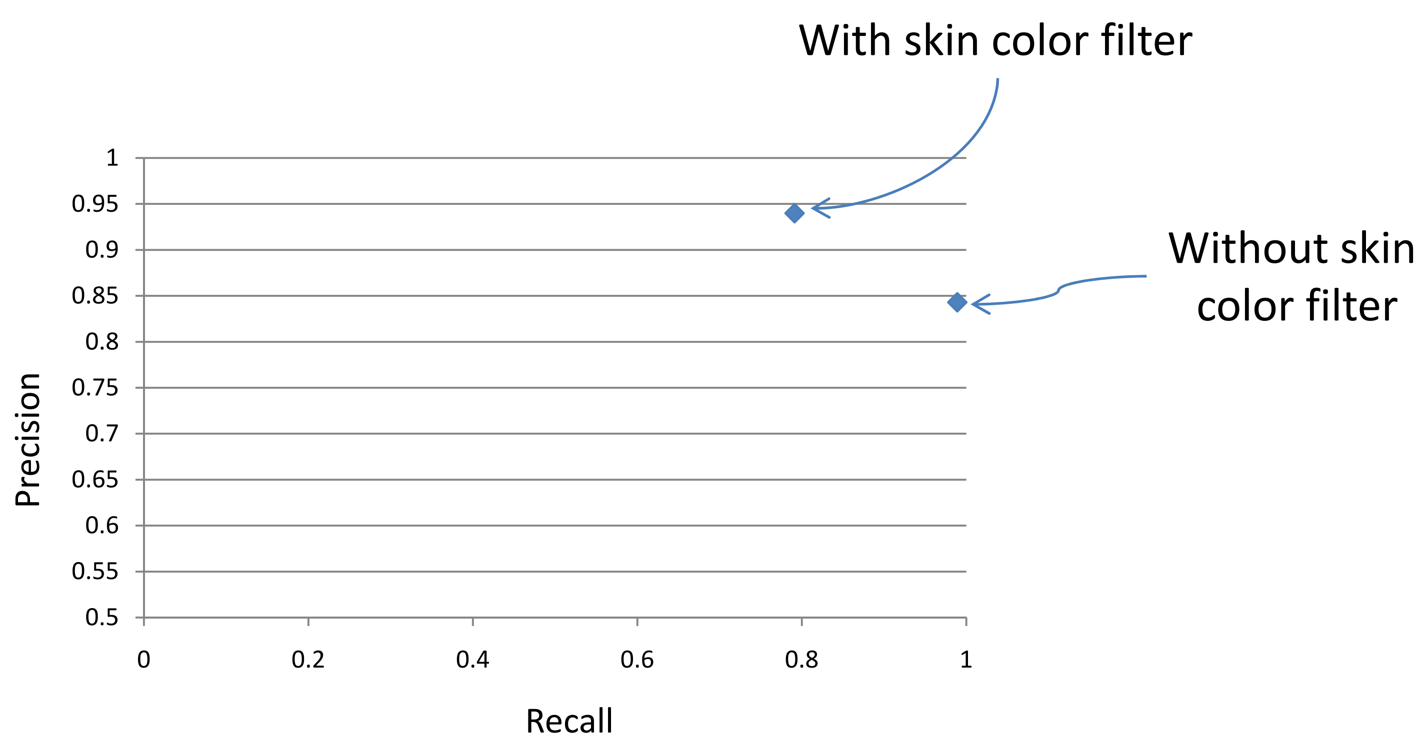
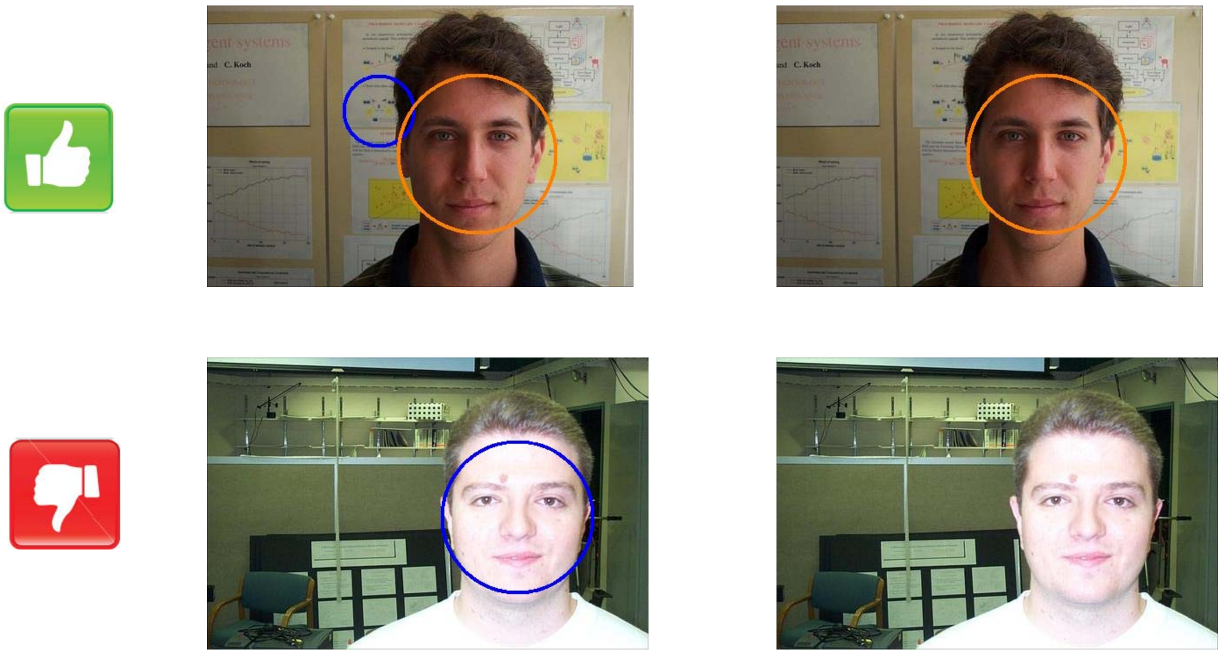


Result



Evaluated on 435 face images in the Caltech 101 dataset

When does it help?



Without skin filter

With skin filter

Lessons

1. Viola Jones' technique worked pretty well for faces and some other categories like airplanes and car_sides.
2. Did not work well with some categories. Accuracy depends largely on the amount of variation in training and test images. It also depends on the amount of background clutter in the training images.
3. In some cases, the training algorithm is not able to go below the maximum false alarm rate of a layer, even with a very large number of features.
4. Selected features for the first few stages are more "intuitive" than the later ones.
5. Skin color can be used to increase the precision of face detection at the cost of recall. Dependent on illumination.
6. Training classifiers is slow! Let OpenCV use as much memory as you have.