

The Viola/Jones face detector

• Training data

↳ 5000 faces

• All frontal

- 300 million non-faces

• 9400 non-face image

- faces are normalized

• Scale, Translation

• Variants

- Across individual

- Illumination

- Pose (rotation both in plane and out)

• Properties

• Each image contains 10-50 thousand locs/scales

• faces are rare 0-50 per image

• Extremely small # of false positives: 10^{-6}

• Adaboost!

• Given a set of weak classifiers, originally: $h_j(x) \in \{+1, -1\}$

• Iteratively combine classifier, $C(x) = \theta \left(\sum_t h_t(x) + b \right)$

• Training error converge 0 so quickly.

• Test error is related to training margin.

Boosted face detector! Image feature

$$h_t(x_t) = \begin{cases} \alpha_t & \text{if } f_t(x_t) > \theta_t \\ \beta_t & \text{otherwise} \end{cases} \quad \left| \begin{array}{l} \rightarrow 60,000 \text{ features} \\ \text{to choose from} \end{array} \right.$$
$$C(x) = \Theta \left(\sum_t h_t(x) + b \right)$$

Integral image!

The integral image compute a value at each pixel (x, y) that is the sum of pixel values above and to the left of (x, y) .

- This can be quickly be computed in one pass through the image.

Computing sum within rectangle!

- The sum of original image value within the rectangle can be computed: $\text{sum} = A - B - C + D$

feature selection!

• for each round of boosting

- Evaluate each rectangle filter on each example.
- Sort example by filter values
- Select best threshold for each filter (min z)
- Select best filter/threshold (= feature)
- Reweight examples

- m filters, τ threshold, N examples, 2 learning time

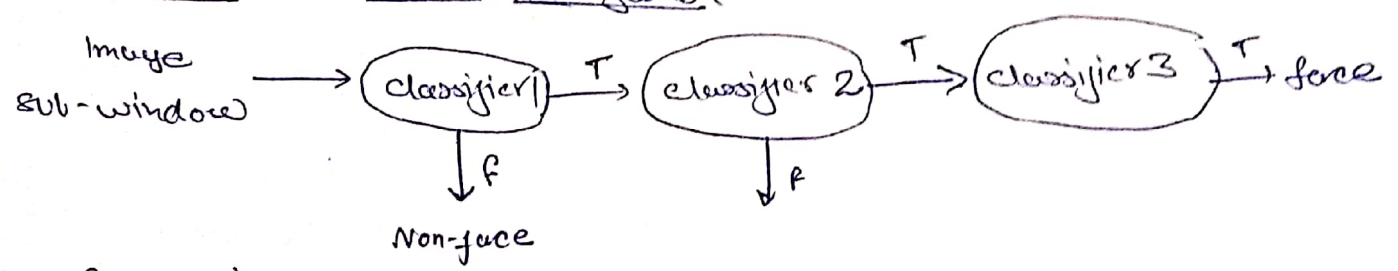
- $O(m \tau L(m \tau N))$ Naive wrapper method.

- $O(mN)$ Adaboost feature select.

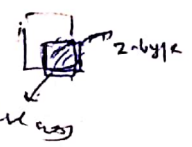
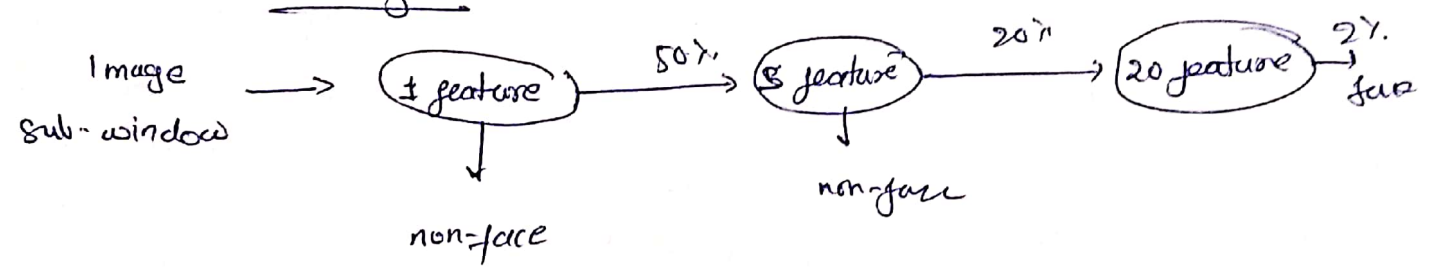
Building fast classifier:-

- Given a nested set of classifier hypothesis classes.

Computation Rule Minimization



Cascaded classifier



Review

Color :-

- Spectrum of illumination and surface
- Human color perception (trichromacy)
- metamerism light, Grassman's laws
- RGB and CIE color spaces
- Uniform color space
- Detection of specularities
- Color constancy

Invariant feature:-

- Scale invariance, using image pyramid
- Orientation selection
- Local region descriptor (vector formation)
- matching with nearest and 2nd nearest neighbors
- object recognition
- Panorama stitching

Classifier:-

- Bayes risk, loss funⁿ
- Histogram-based classifier
- Kernel density estimation
- Nearest-neighbor classifier
- Neural network

Grassman's laws:-

- Grassman's law describe empirical results about how the perception of mixture of colored light composed of different spectral power distributions can be algebraically related to one another in a color matching context.

modern interpretation:-

1st law:- Two colored light appear different if they are differ in either dominant wavelength, luminance or purity.

Corollary: For every colored light there exist a light with a complementary color such that a mixture of both light either desaturates for more intense component or give uncolored (grey/white) light.

2nd law: The appearance of mix of light made from two component changes if either component changes.

Corollary: A mix- of two colored light that are non-complementary result in a mixture that varies in hue with relative intensities of each light and in saturation acc. the distance b/w the hue of light.

3rd level These are light with different spectral power distribution but appear identical.

Corollary I:- Such identical appearing light must have identical effects when added to a mixture of light.

Corollary II:- Such identical effects when subtracted (i.e., filtered) from a mixture of light.

9th level The intensity of mixture of light is the sum of intensities of each component known as Abney's law:-

$$R = \int_0^{\infty} I(\lambda) \bar{r}(\lambda) d\lambda$$

$$G = \int_0^{\infty} I(\lambda) \bar{g}(\lambda) d\lambda$$

$$B = \int_0^{\infty} I(\lambda) \bar{b}(\lambda) d\lambda$$