

# Introduction to Robotics for cognitive science

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# Web page of the subject

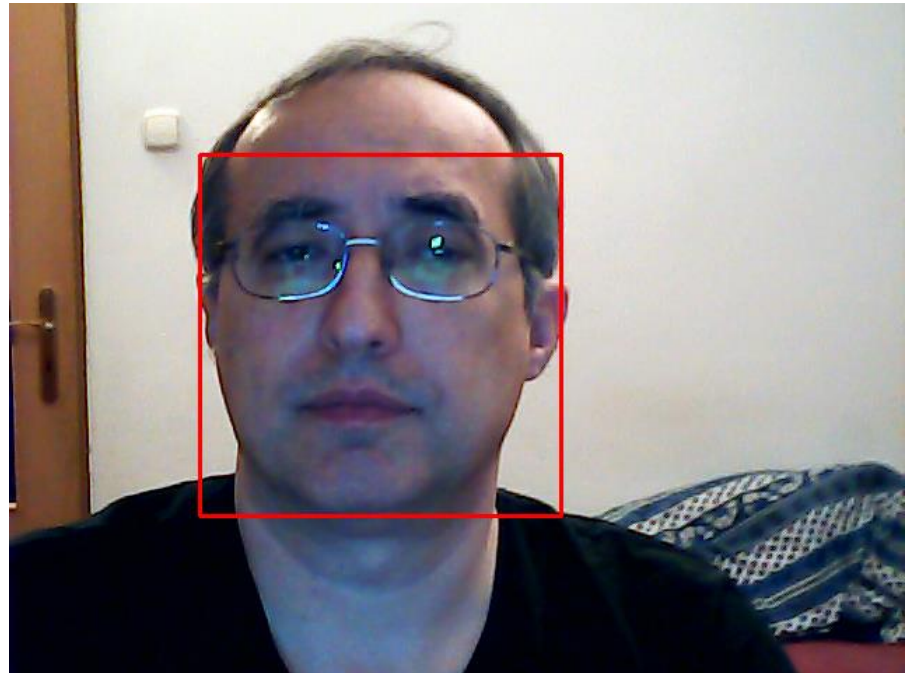
[www.agentspace.org/kv](http://www.agentspace.org/kv)



# More general object detectors

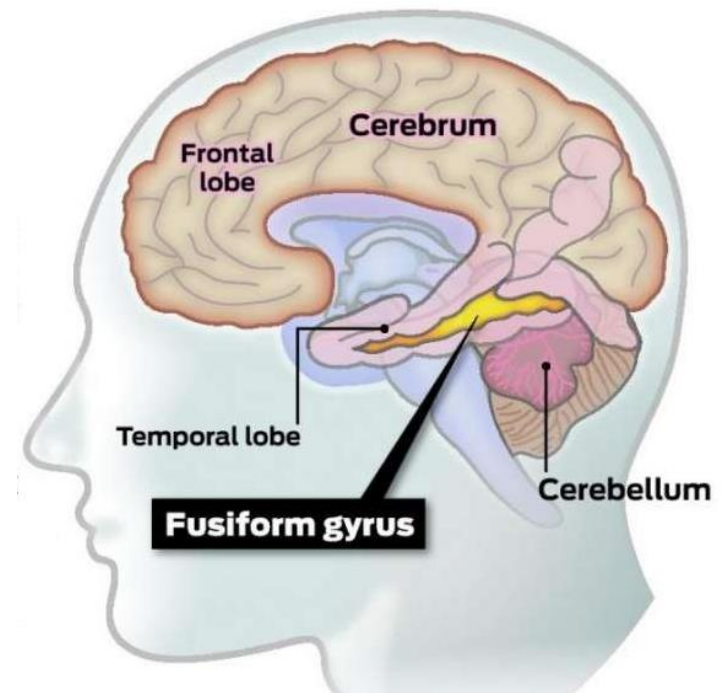
So far we have been detecting and tracking very particular objects, e.g. part of your face

Now we would like to detect a general object, e.g. face (any human face, regardless age, gender or race)



# Face detection in human brain

- Ability to recognize face is strongly stored in our genes and we do not need to learn it (unlike walking on two legs)
- In brain there is anatomic structure responsible particularly for face recognition
- Its malfunction causes no other incapability if it happens to adult, but has serious effects if it is congenital, including no empathy to other people



# Machine Learning

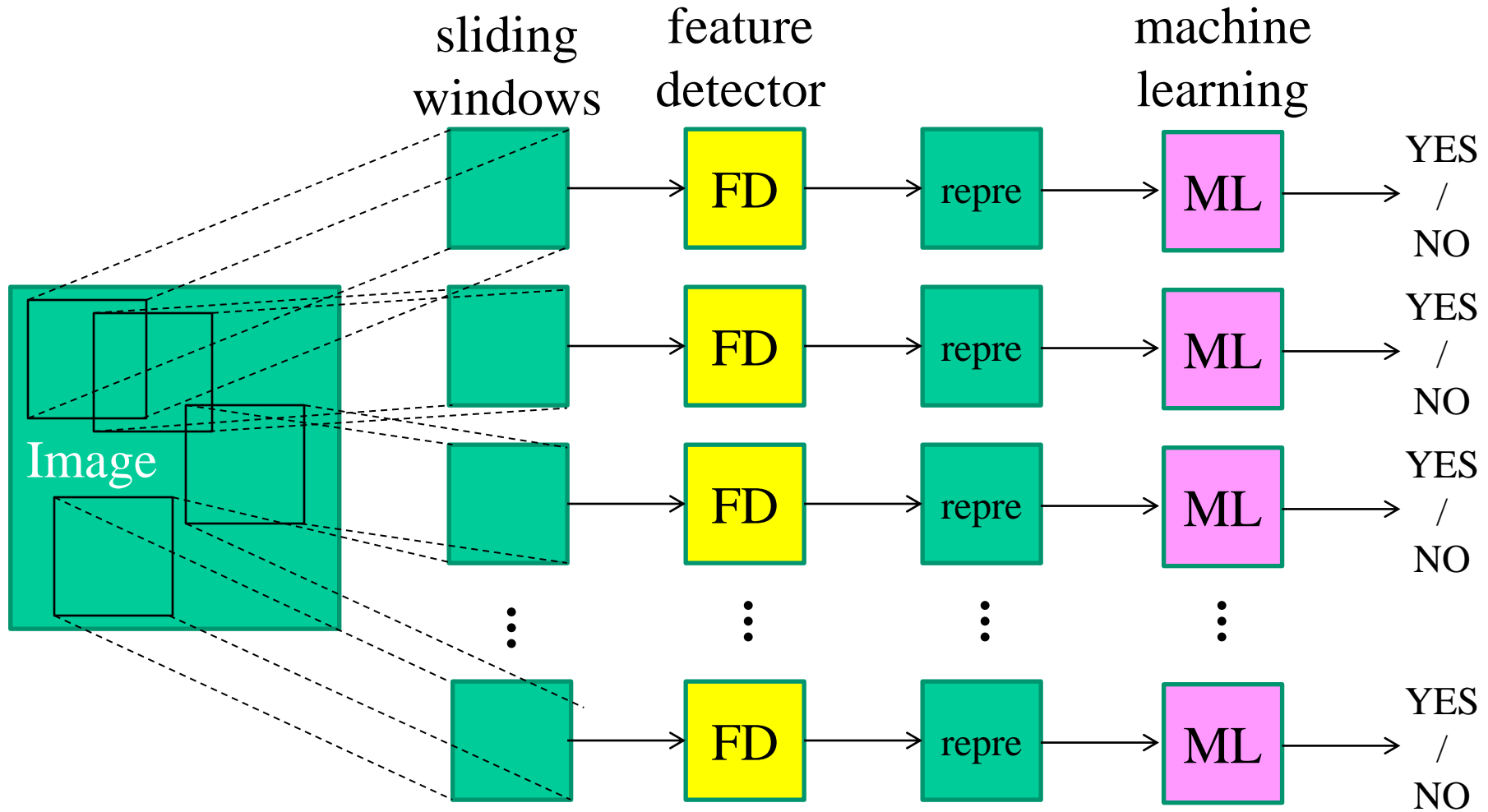
- In robotics, we have to put into robot a **model** (instead of the human genes)
- The model is created from **dataset** by a method of **supervised machine learning**
- Data in the dataset have to be **annotated**
- The typical model is a **classifier**
- Classifier tells category (face: yes or no, animal: cat, dog, elephant, monkey, other)

# Dataset



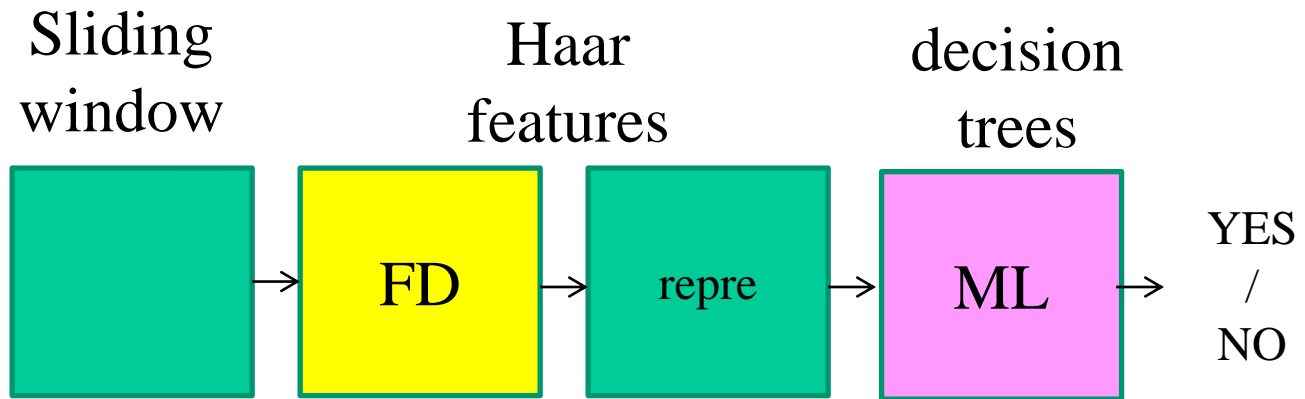
It contains positive and also negative samples

# General schema of classifier based detector



# Viola Jones Algorithm

The first operational face detector [2001]

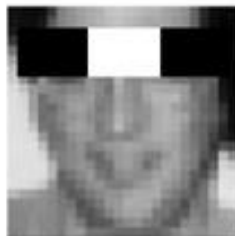
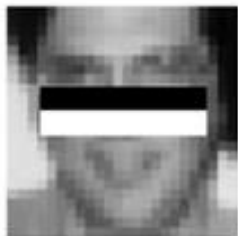




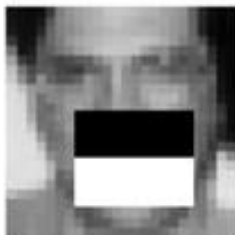
# Haar Features

$$\sum_c \boxed{\phantom{00}} < \sum_c \blacksquare \quad ?$$

Stage 0



Stage 1



...

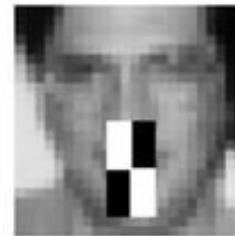
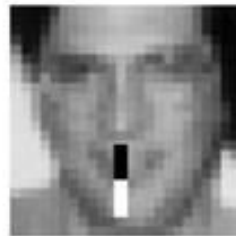
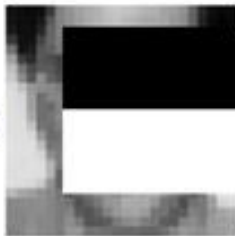
10

more

.

.

Stage 21

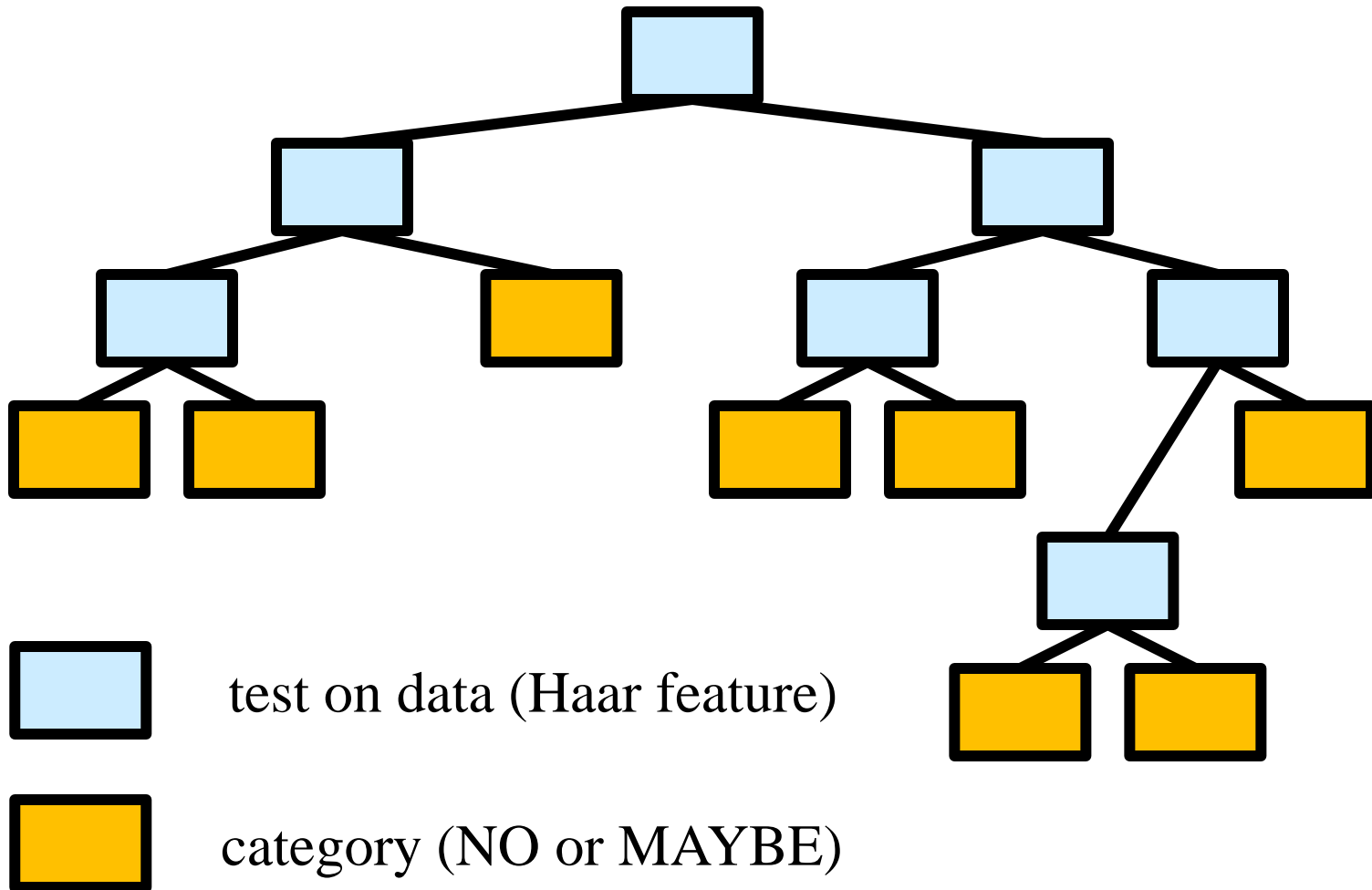


...

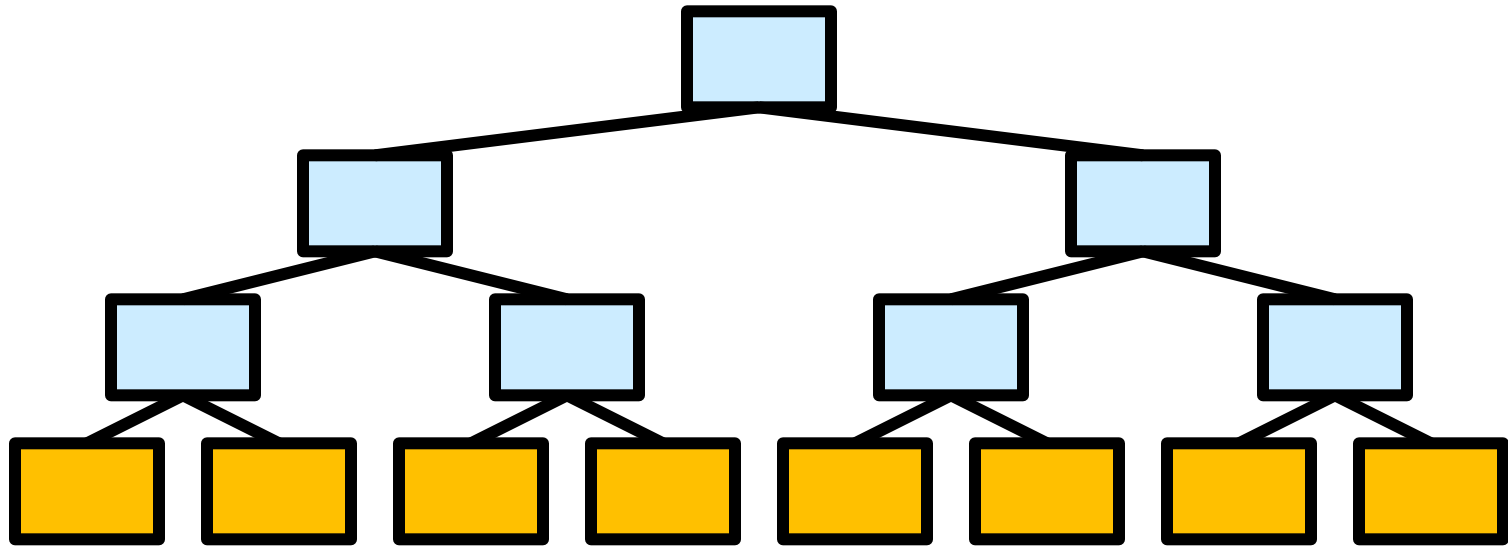
206

more

# Decision tree

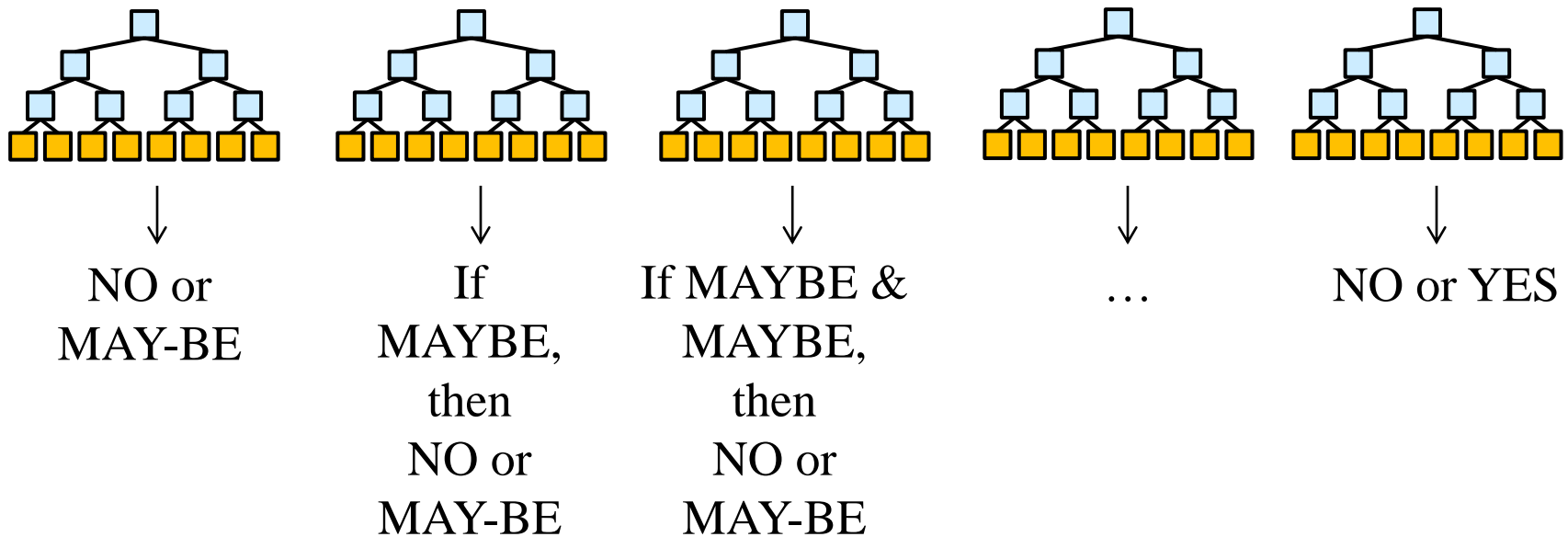


# How to get a good decision tree?



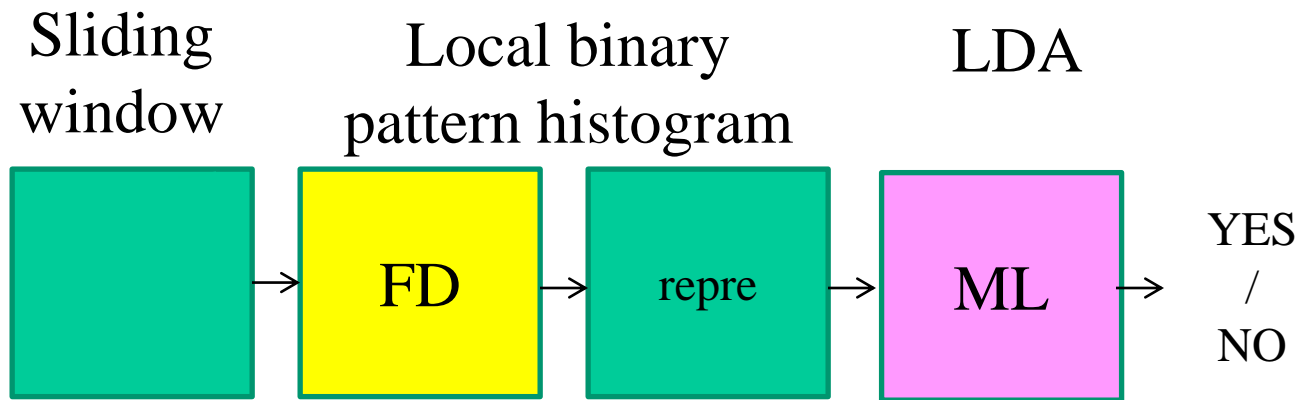
- We generate candidate features and select one that best distinguishes faces from non-faces

# Cascade classifier



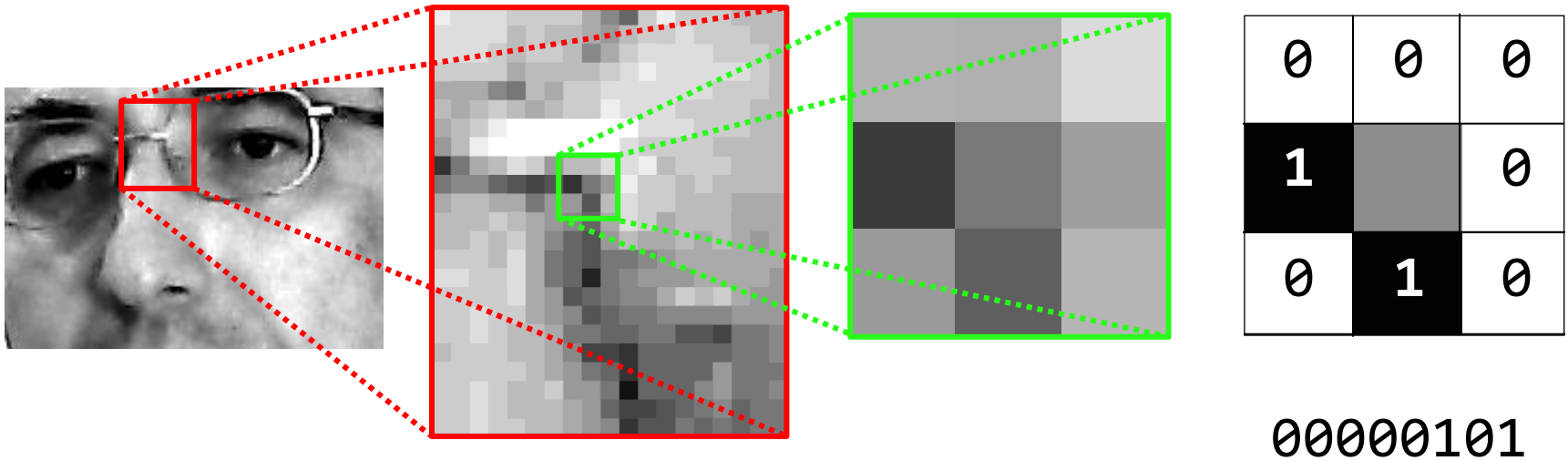
Viola-Jones algorithmus: Haar features + cascade classifier

# LBPH approach

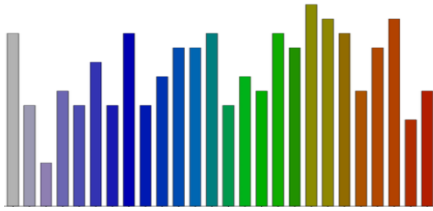


[T. Ojala, M. Pietikäinen, and D. Harwood 1994]

# LBPH Features



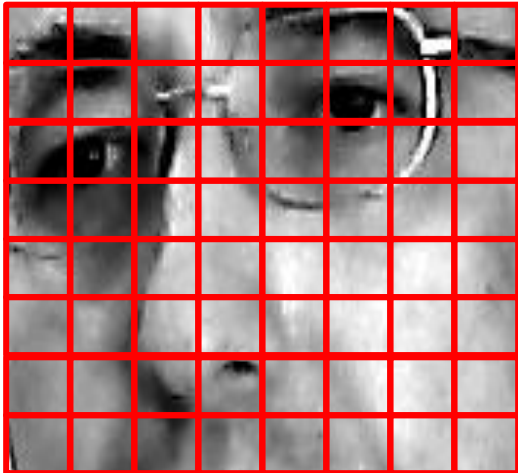
- Each pixel has its LBP
  - 0 .. 255



3F 2E 01 ... FF  
256 bytes

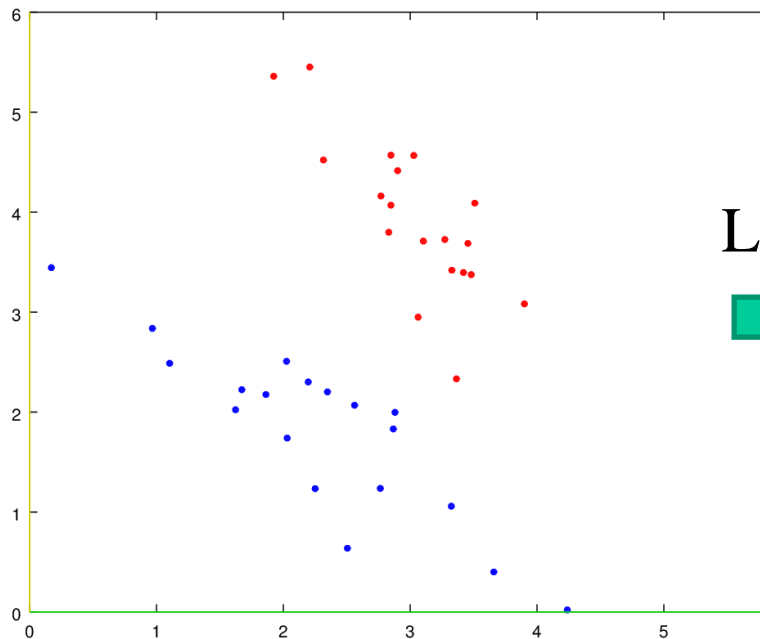
# LBPH Features

- Each region can be associated with histogram of LBP
- Object is represented by set of LPBH

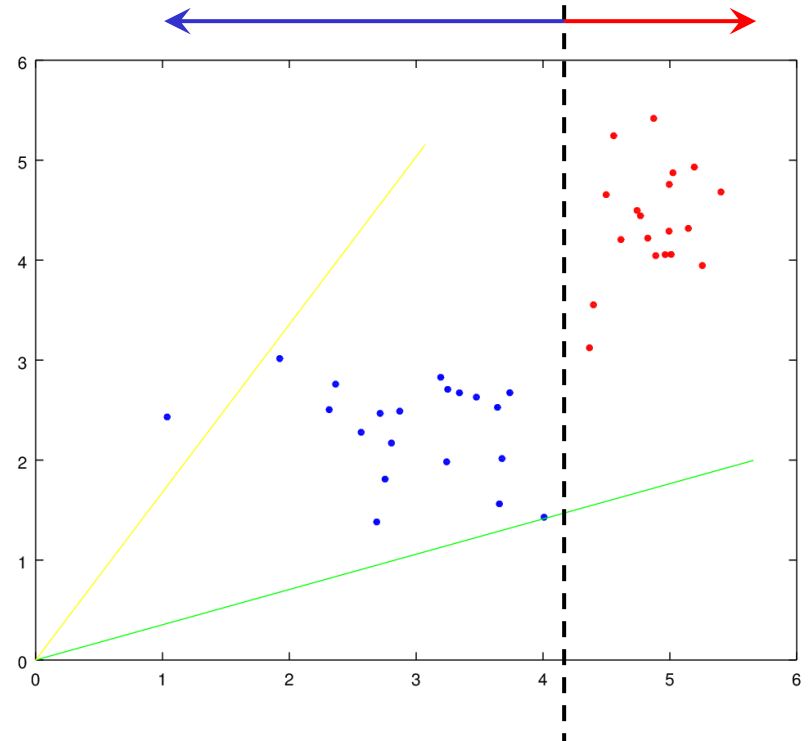
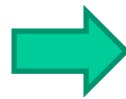


# Linear Discriminant Analysis

- Data are represented as point in multidimensional space (fixed number of dimensions)
- The space is reduced and transformed to easy distinguish e.g. data categories

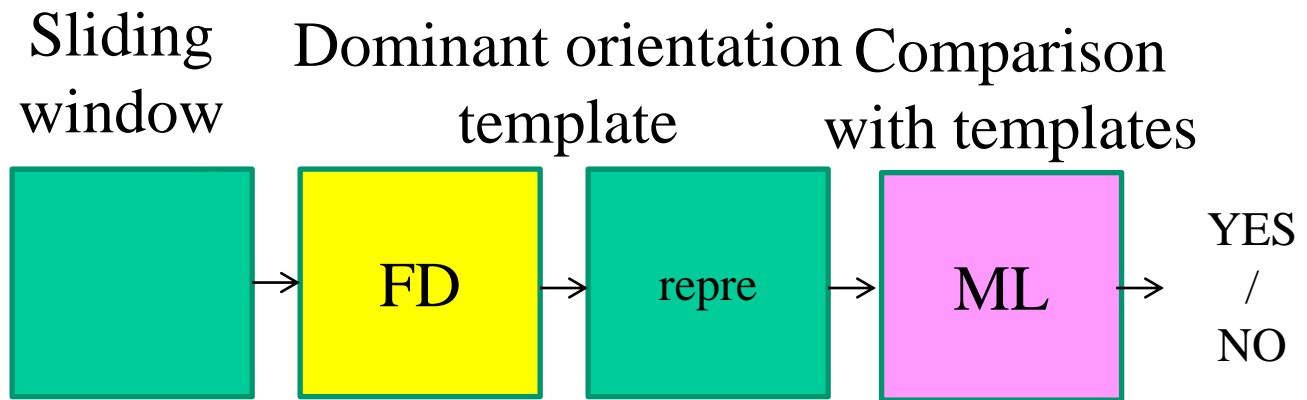


LDA





# Dominant Orientation Templates

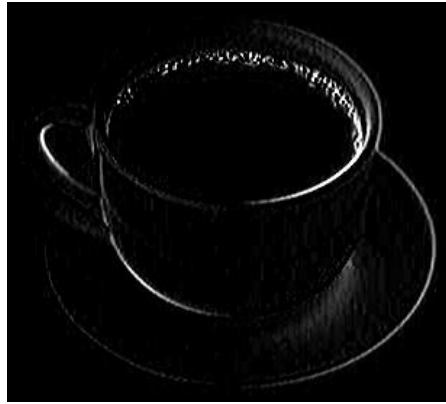


[Hinterstoisser, 2010]

# DOT Features



obraz



dx



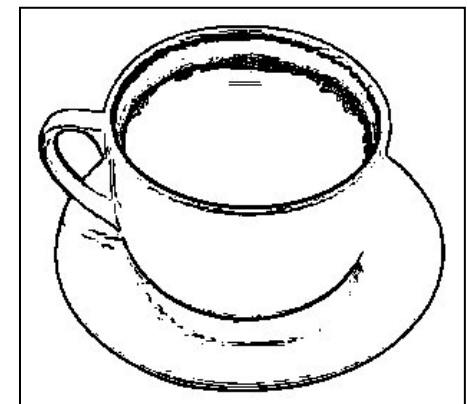
dy



|gradient|

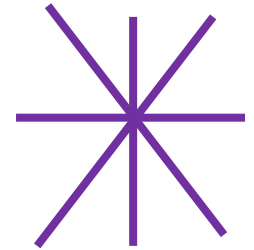
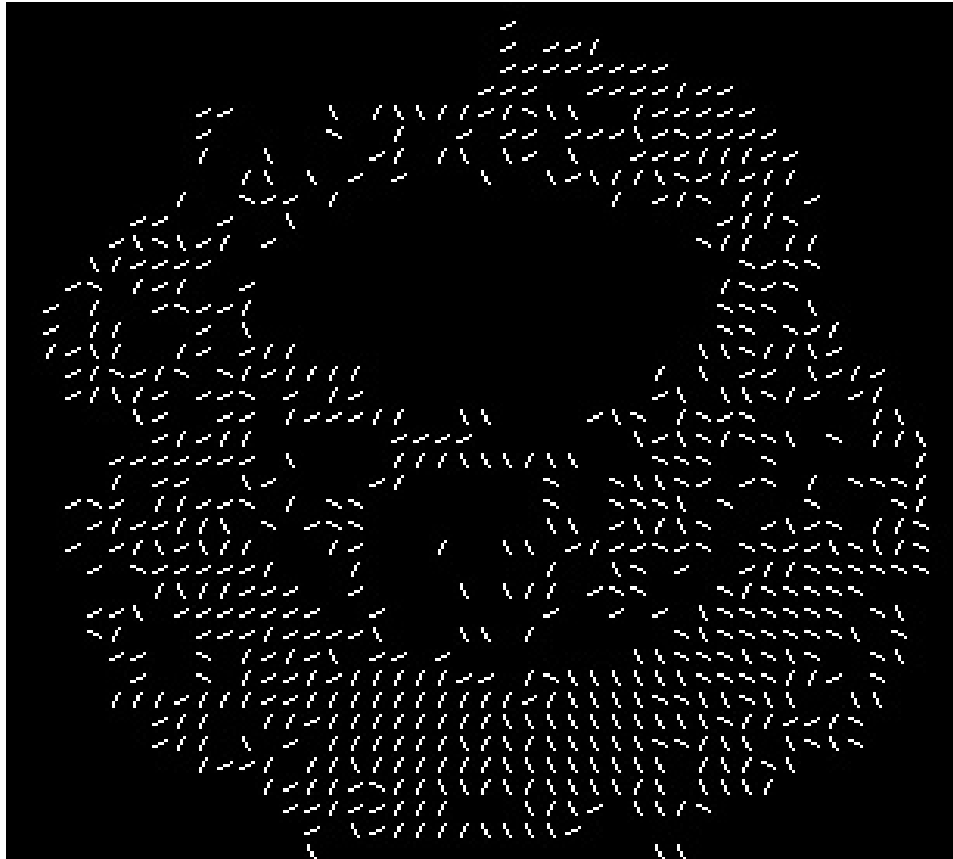
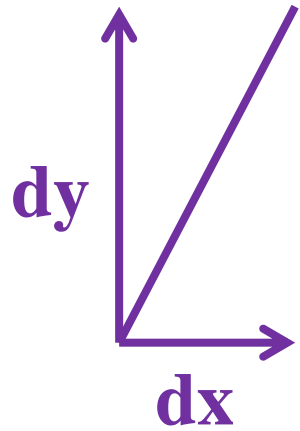


slope



edges

# Edge orientations (=slopes)



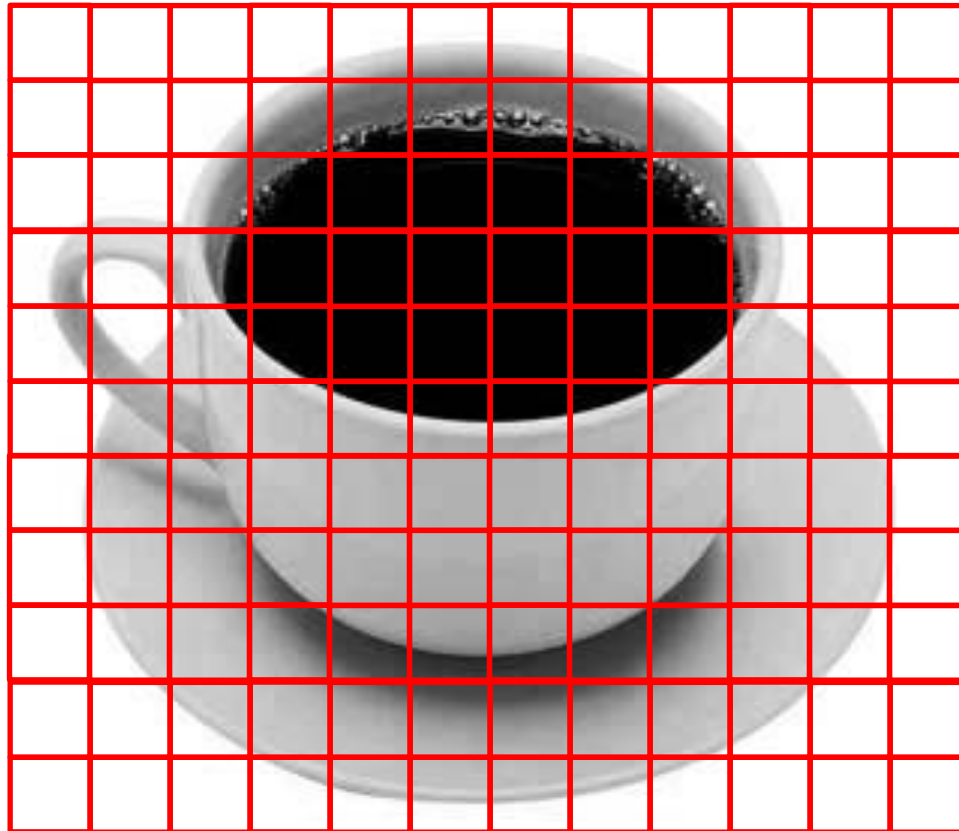
# DOT Templates

- Just clustered dominant orientations will represent the object



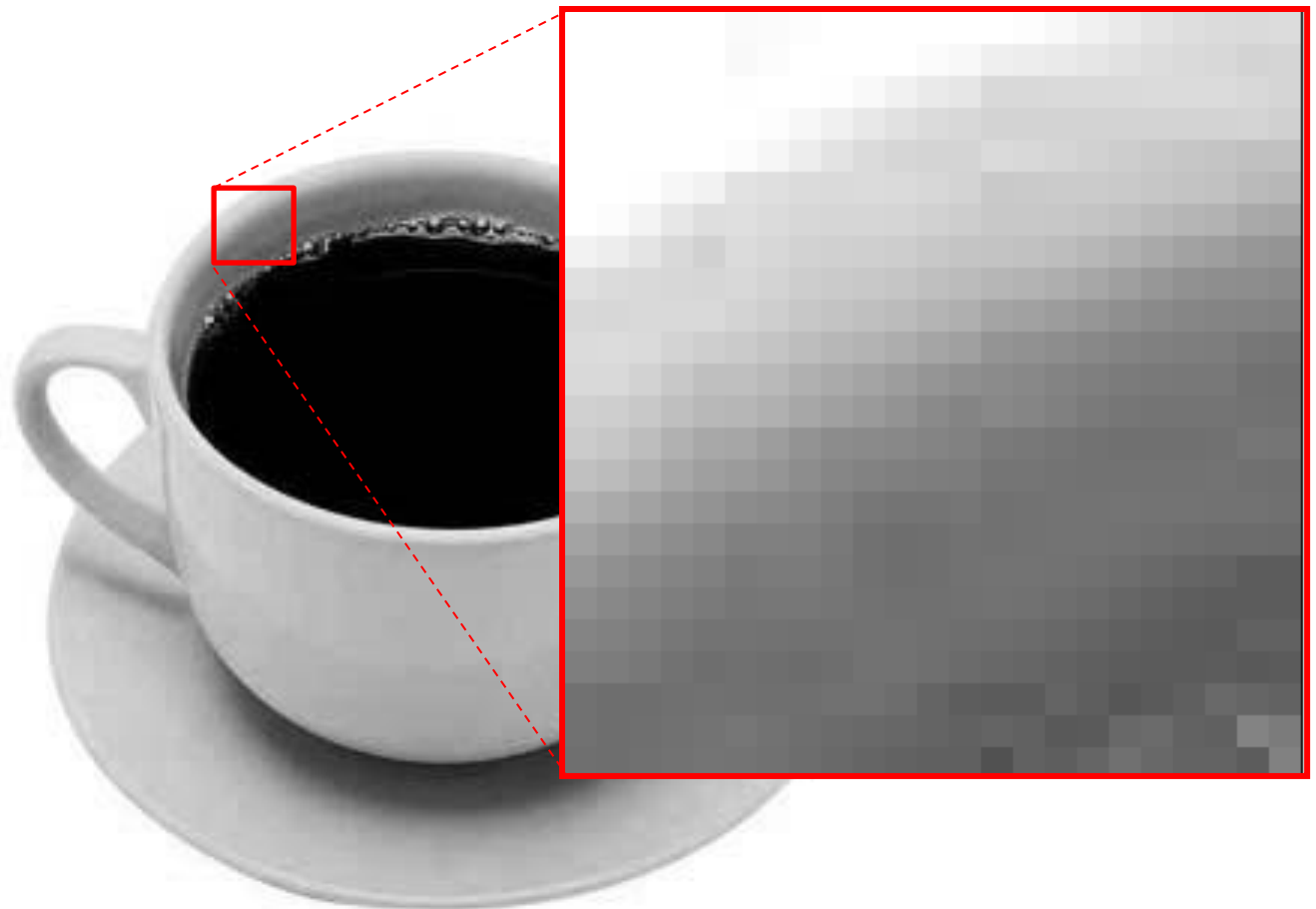
# DOT Templates

- We cover object with set of non-overlapping regions



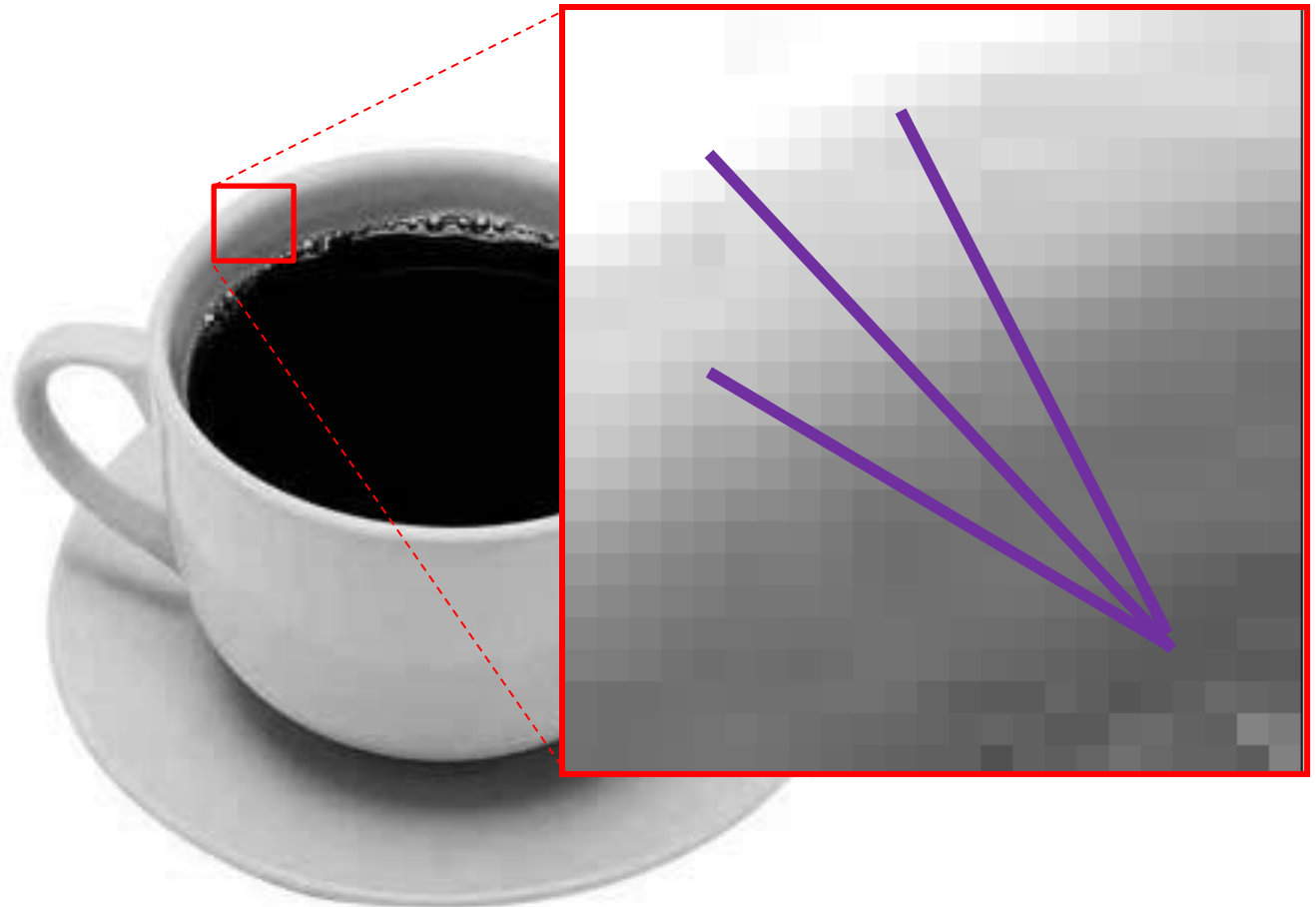
# DOT Templates

- For each pixel we calculate edge slope



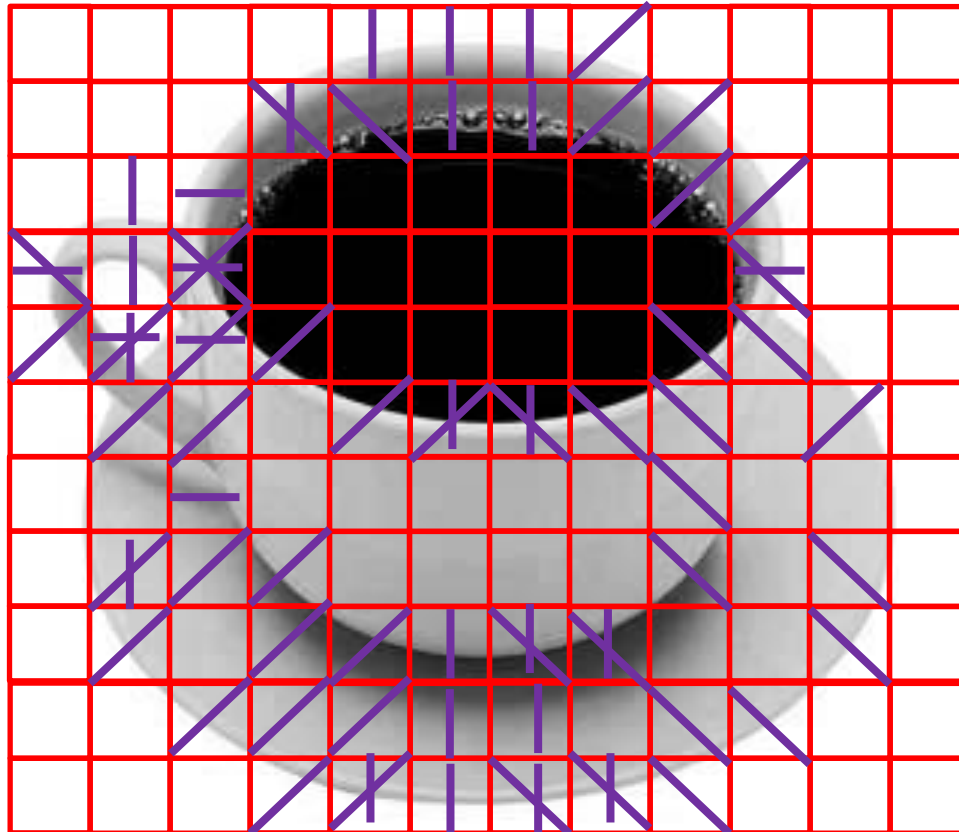
# DOT Templates

- We select prevailing slopes



# DOT Templates

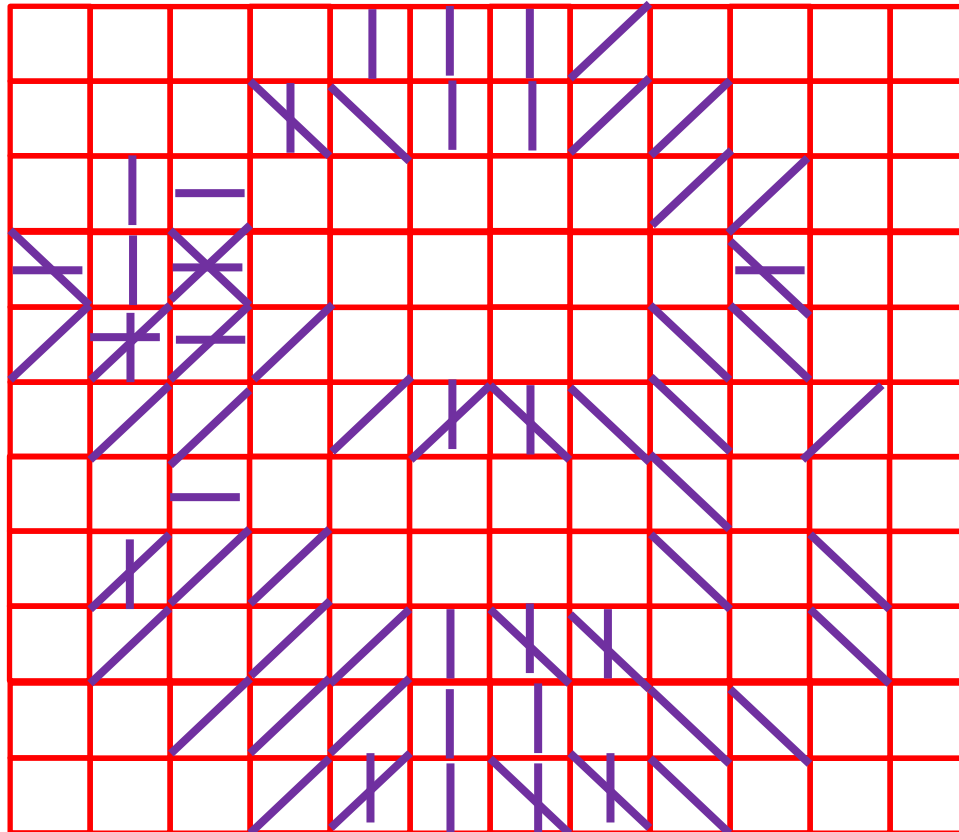
- And this our template ...





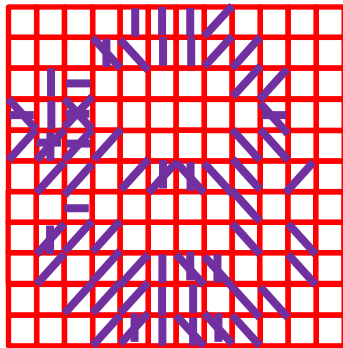
# DOT Templates

- ... which represent the object

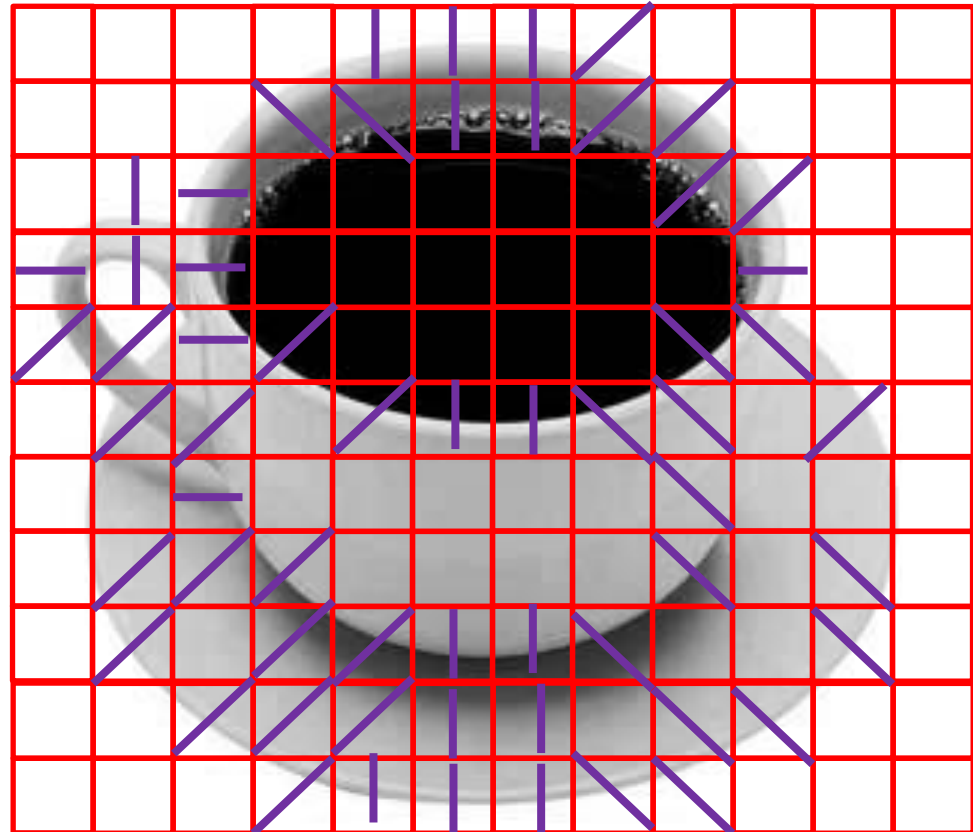


# Searching for object

- For each place we calculate one dominant orientation for each region



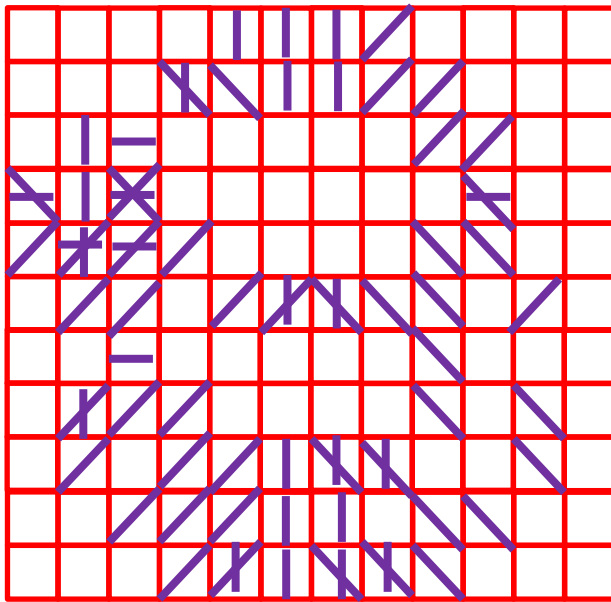
template



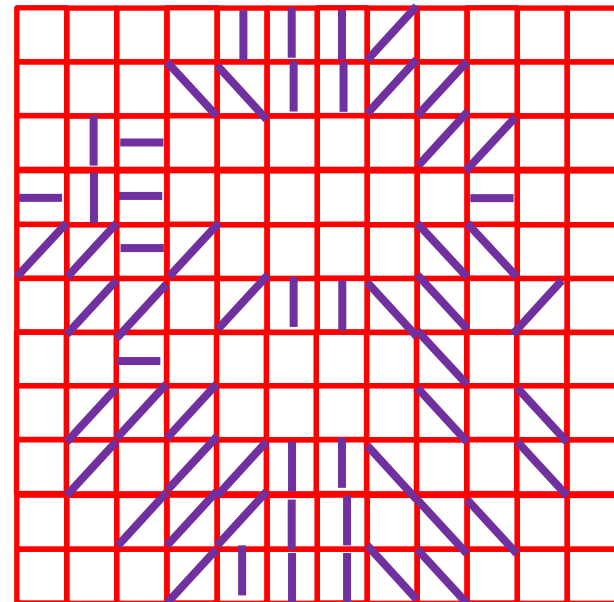
image

# Comparison with templates

- If the image matches template, we have found the object



template

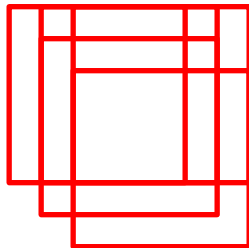
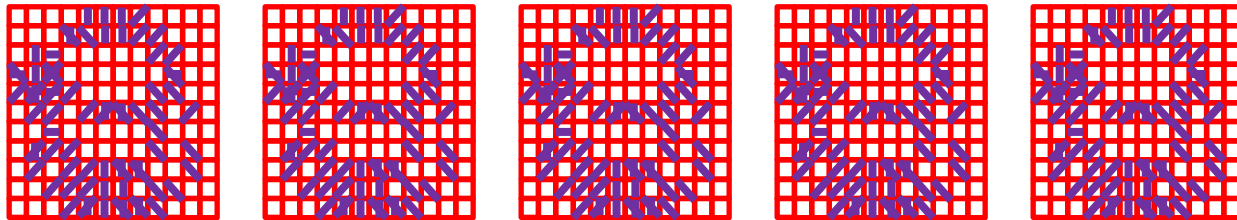


image

# What about translation of regions?

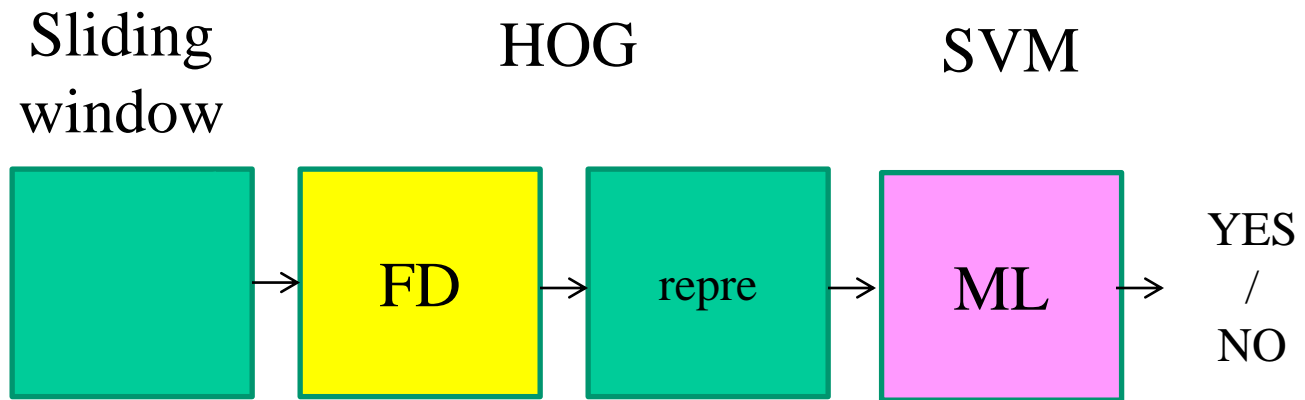
- No problem we prepare more templates for various translations, even various viewpoints, but same size

templates

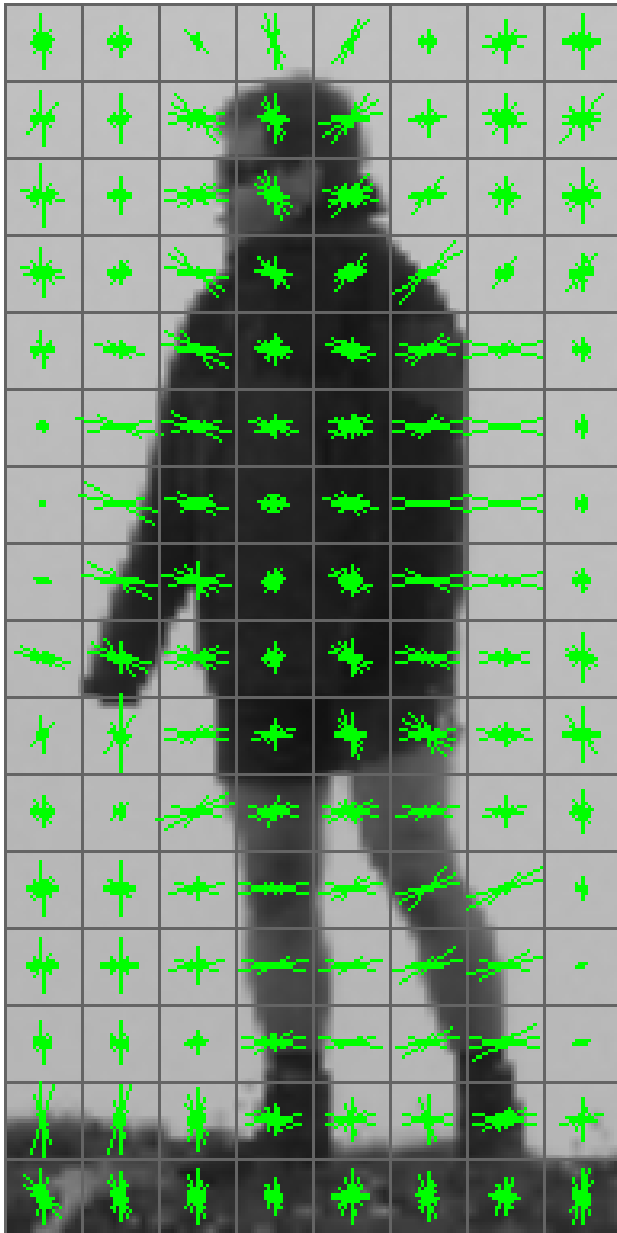


- Then we try all parts of image with variable size

# Histogram of Gradients



[Dalal, Triggs, 2005]

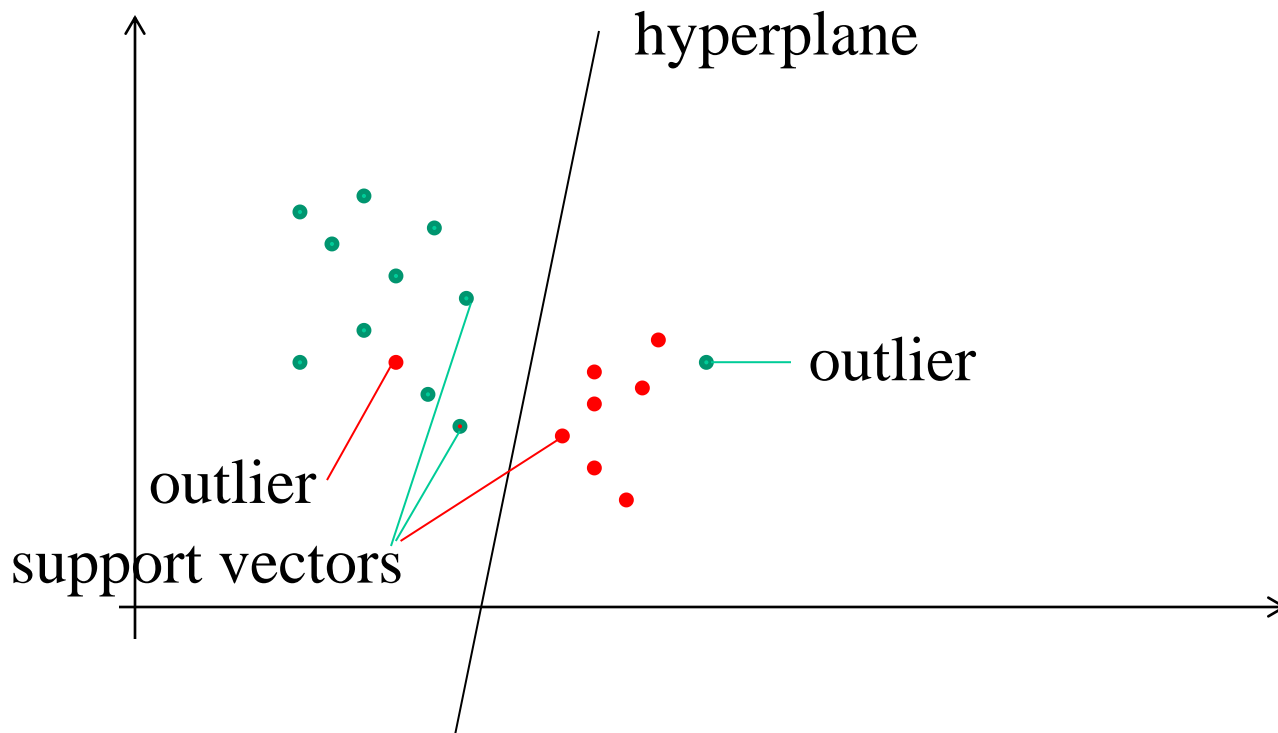


# HOG features

- Instead of few dominant slopes we take their histogram

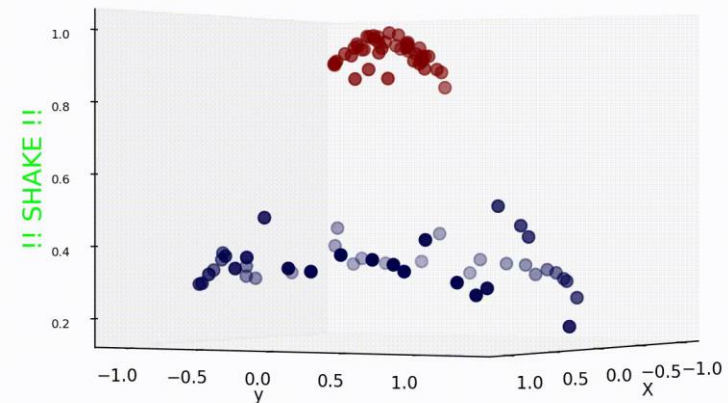
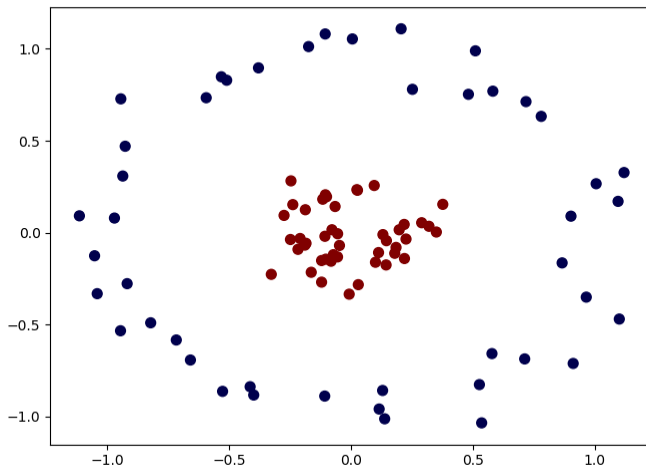
# (Linear) Support Vector Machine

- Fast and good method which can handle outliers by maximalization of so called soft margin



# SVM Kernel trick

- SVM expand dimension of data by application of a kernel to enable separation by hyperplane



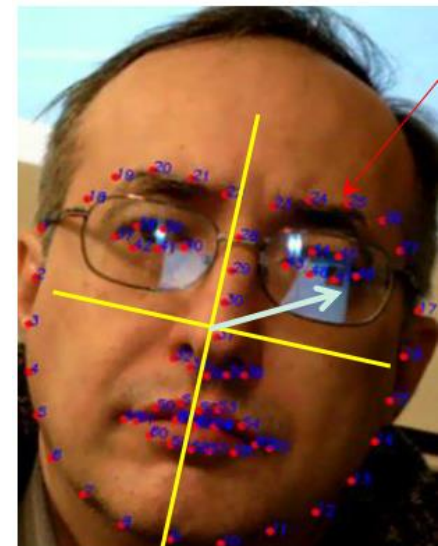
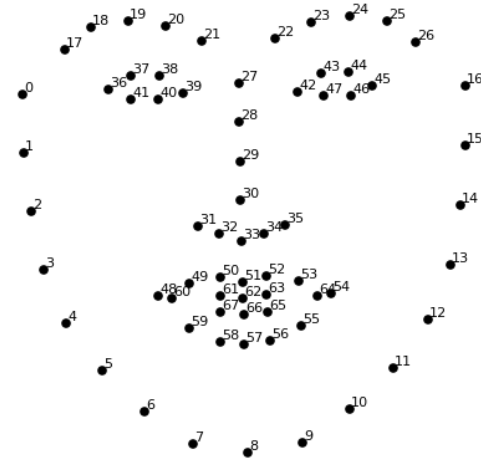
[\[more details\]](#)

- kernels are selected so that distance in the expanded space can be calculated directly in the original space

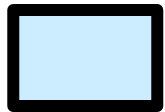
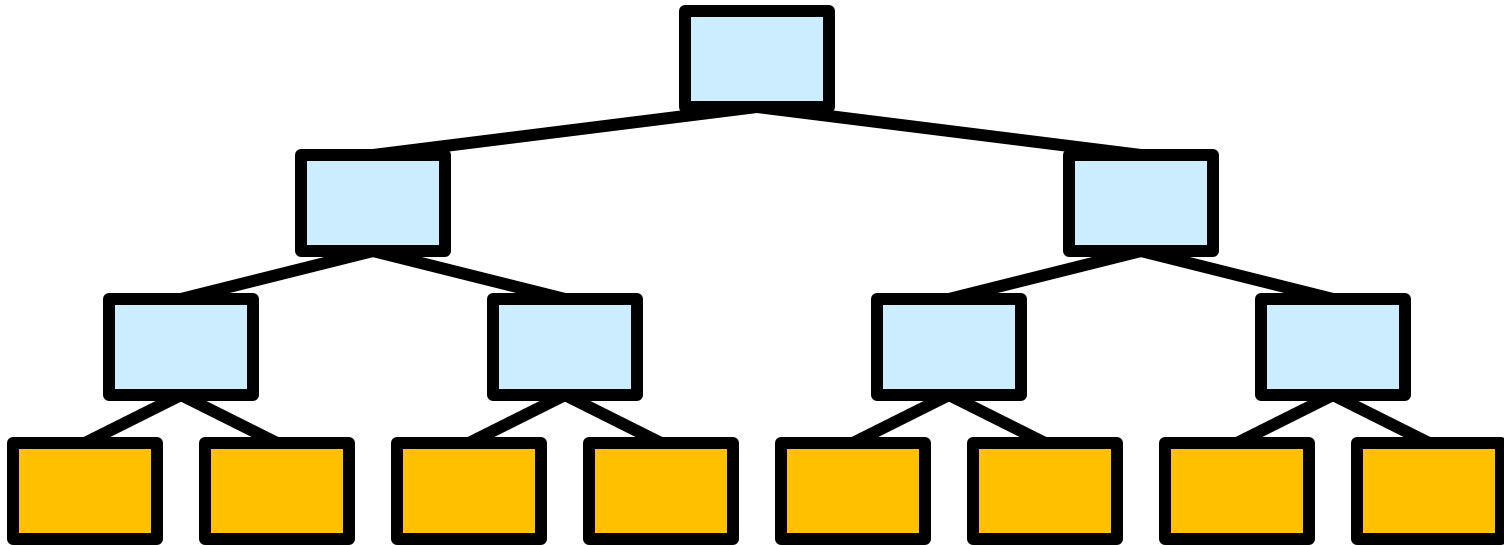


# Regression

- Analogically to classification we can have model of regression, which does not provide category but value.
- E.g. Kazemi facial landmark detector employs cascade regressor based on decision trees (and feature detector is pure selection of pixel on position relative to average face landmarks). So we put average face features on the image and regressor tells us how to move them to the right position



# Weak Regressor

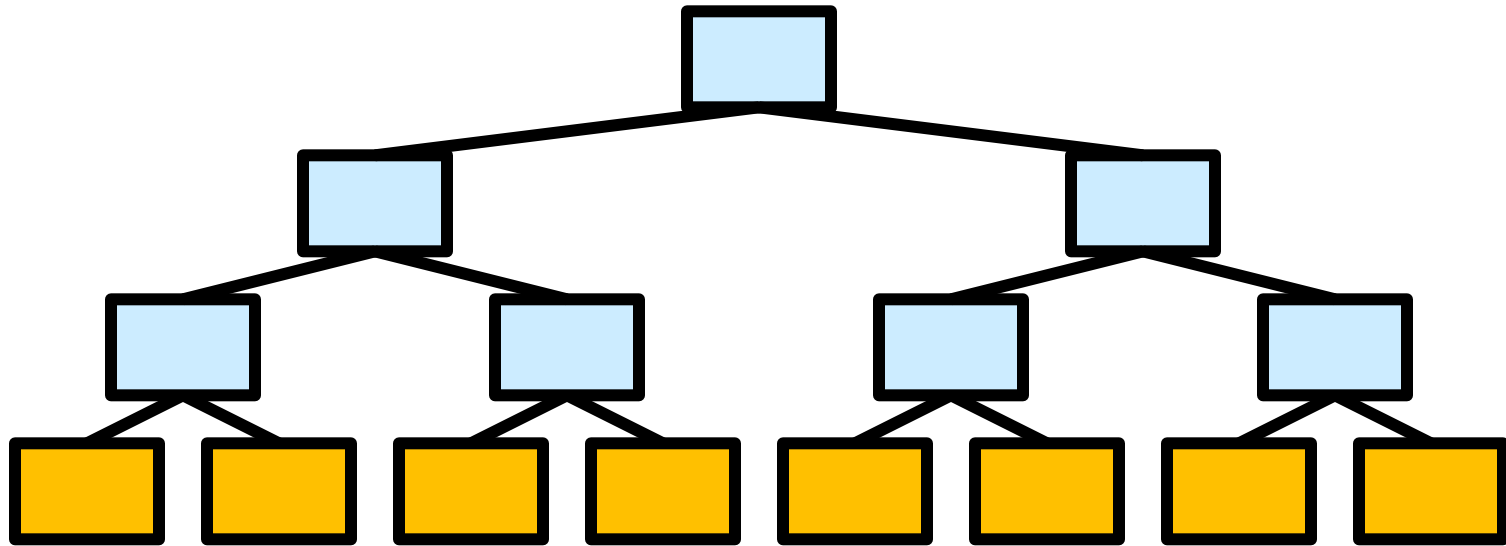


test on data



value

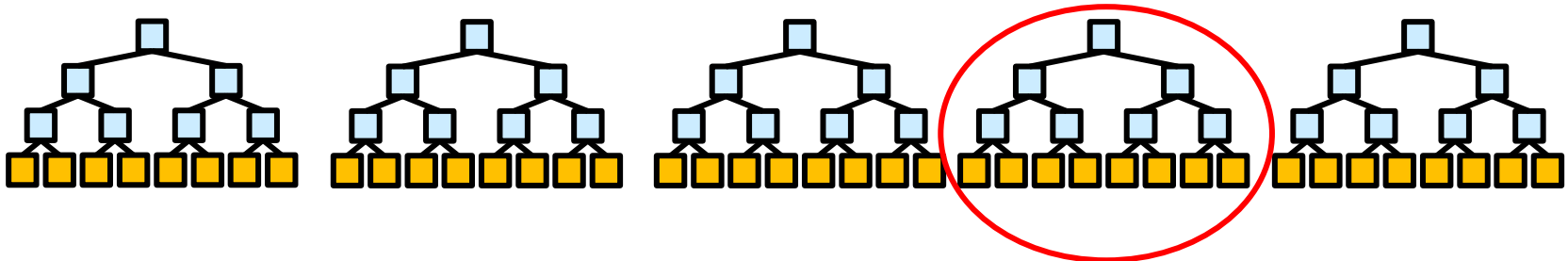
# How to get a regression tree?



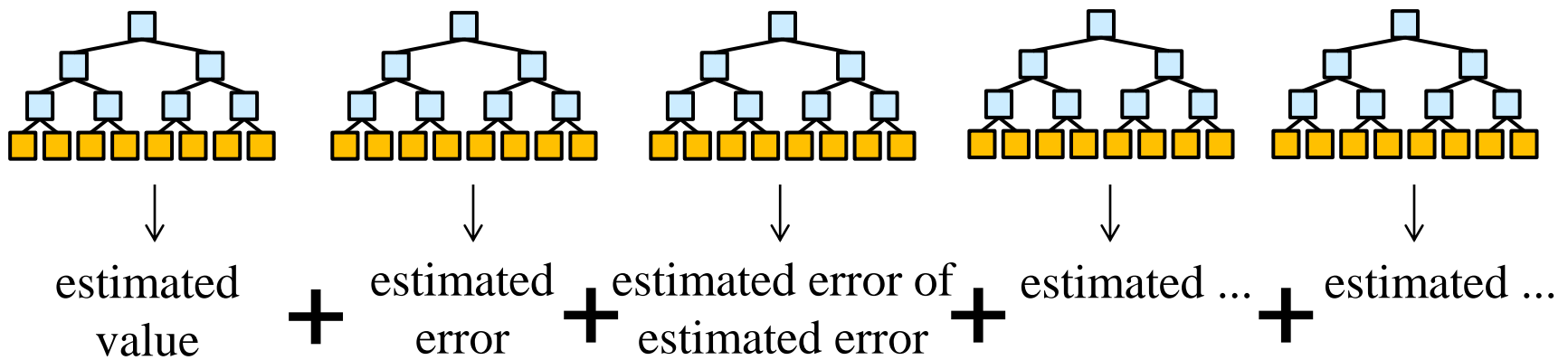
- We specify depth, e.g. 3
- In the inner nodes we test a feature (successful test – left, failed test – right)
- In the list we report: average value from samples in dataset which falls in that list

# How to find a good tree?

1. Generating splitting tests we generate randomly more features and select such a one which splits the samples to sets with significant size and lowest variation in each set
2. We generate more trees and select the lowest error of classification



# Gradient boosting



We can join more weak regressors by gradient boosting method

# Cascade regressor

Kazemi regressor:

- 10 cascades
- 500 regression trees
- features based on comparison of two pixels from 400 pixels selected from image 128x128
- 20 trials for choosing features

