Learning in Robotics

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SEVENTH FRAMEWORK PROGRAMME

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Overview

- Learning in robotics
  - What and why
  - Case study: Image based visual servoing
- Learning in sensing
  - Bayesian decision theory
  - What is a classifier
  - Some classifiers
  - Combining classifiers
  - What makes a classification task hard?

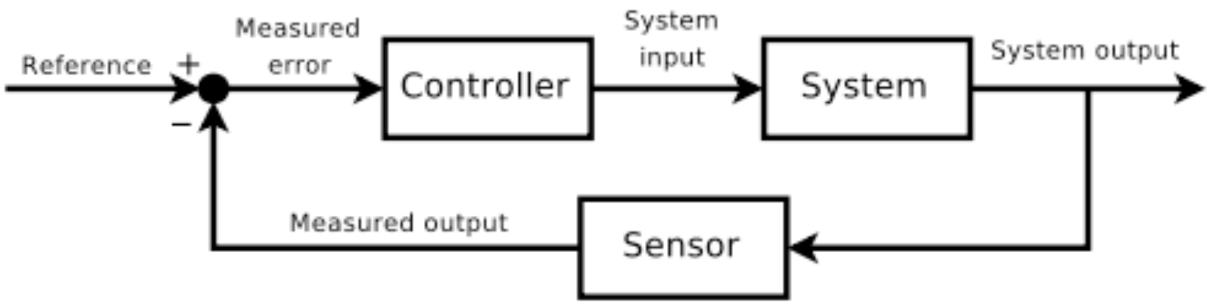
(Bayesian decision theory through classification task hardness: Pattern classification)

What is Learning?

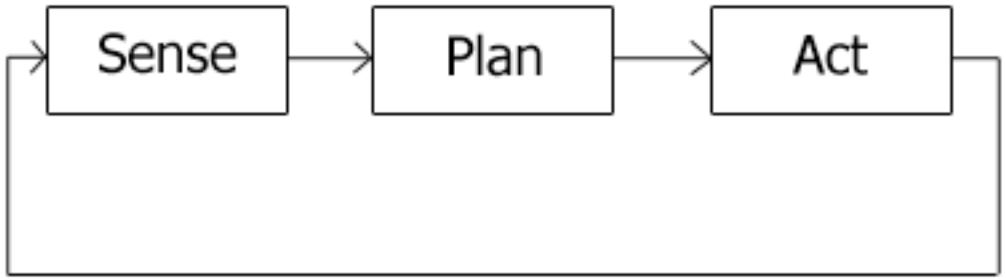
- Webster's Dictionary: "…modification of a behavioral tendency by experience"
- For a robot - and also human:
  - Behavior = Actions
  - Experience = Sensed data

Robot learning

- In all closed loop control, sensing influences actions - but that is not viewed as learning!



- Learning is about modifying the "behavioral tendency" – the mapping from sensing to action



- We have learning opportunities in all three parts

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Robot learning in Sensing

- How to interpret sensor data
  - Object localization
  - Object classification
  - Scene understanding
  - Maps of the world
  - …

} Focus for this presentation (eventually…)

Robot learning in Planning

- How to act to reach a goal
  - Learning from demonstration
    - Sense the actions of a human teacher, and learn to act the same way
  - Reinforcement learning
    - Act and receive feedback, and change the way you act

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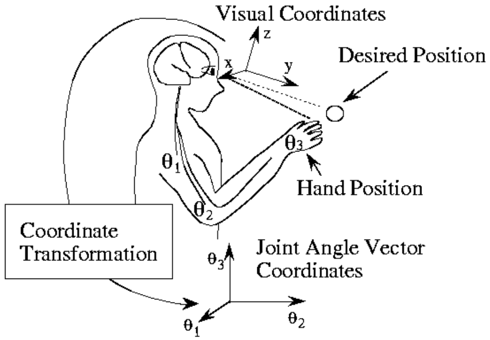
Robot learning in Acting

- Relations between cause and effect
  - How the robot works
    - Kinematics, Dynamics
  - How the world works
    - How humans act and react to robot actions
    - How objects react to robot actions



Why is learning important in robotics?

- Robots are too expensive to only know pre-programmed skills
  - Entirely new skills have to be learned
- Pre-programmed skills are not sufficient in an open, non-deterministic world
  - Task specifications and environmental conditions vary and have to be learned on-line
- Sometimes we do not know how to pre-program the skills!
  - Learning applied off-line
  - Perhaps the most common case of learning for robotics

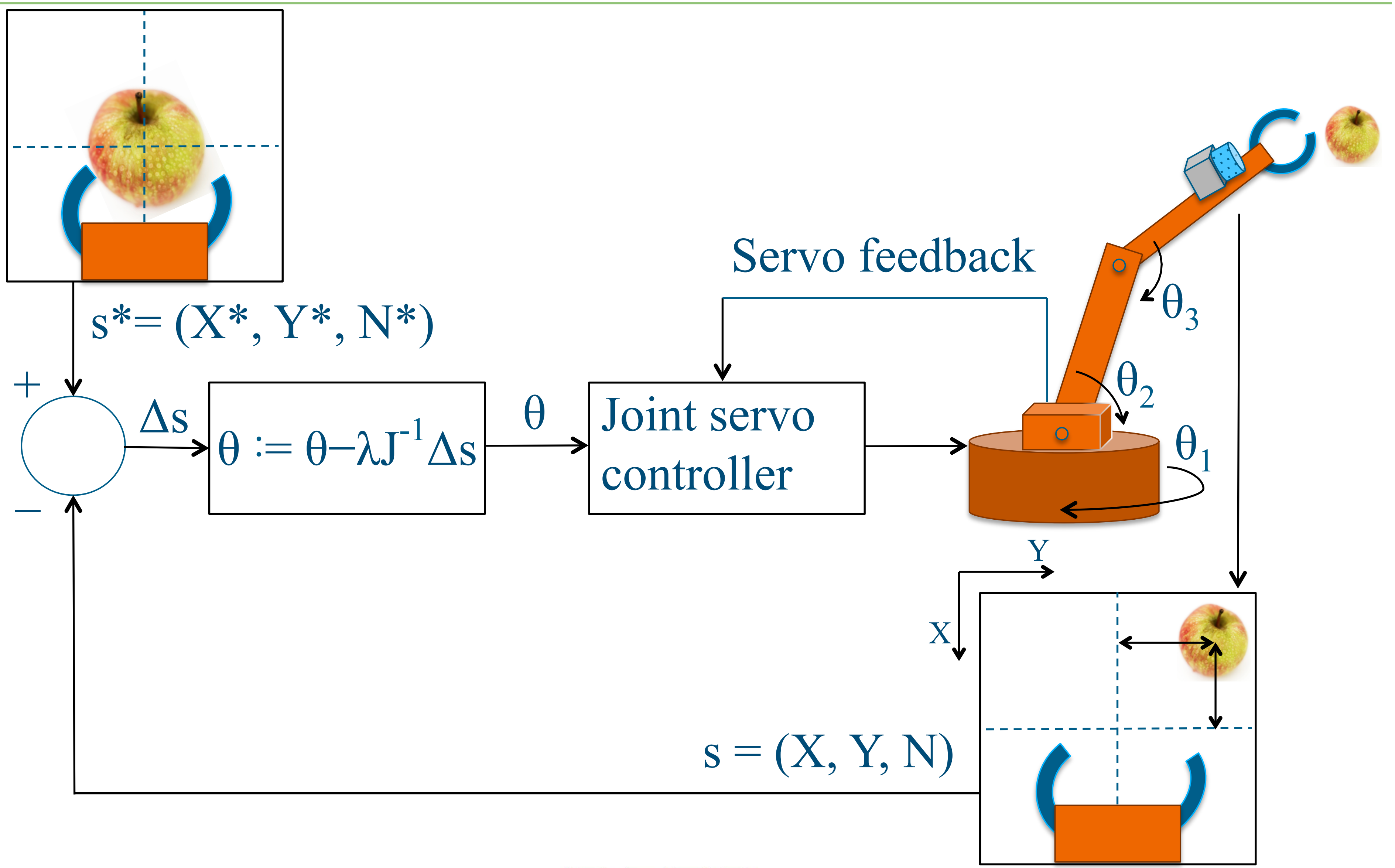
Intertwined learning

- Learning can appear in all parts: Sense, Plan, Act
- However, actions cause changes in sensing, so learning sometimes is intertwined
- One good example is Visual Servoing

Image Based Visual Servoing (IBVS) [13]

- An established technique for vision guided control of robot manipulators and grippers
- Features *s* are extracted from the 2D image (in image coord.system)
  - E.g.: location (X,Y) and area N of centroids for selected image regions
- Target feature values *s** are defined
  - E.g.: (X,Y) at image center, and area N larger than a threshold
- (s-s*) is used as error signal for a controller that drives the joints

Example: Visual servoing for fruit picking



Model-free Image Based Visual Servoing (IBVS)

- An established technique for vision guided control of robot manipulators and grippers
- Features s are extracted from the 2D image (in image coord.system)
  - E.g.: location (X,Y) and area N of centroids of selected image regions
- Target feature values s* are defined
  - E.g.: (X,Y) at image center, and area N larger than a threshold
- (s-s*) is input as error signal to a controller that drives the joints
- The controller maps this error to changes in joint angles θ

$$s = F(\theta)$$

$$\frac{\partial s}{\partial t} = \frac{\partial F}{\partial \theta}\frac{\partial \theta}{\partial t}$$

$$\dot{s} = J(\theta)\dot{\theta}$$

$$\Delta s \approx J(\theta)\Delta\theta$$

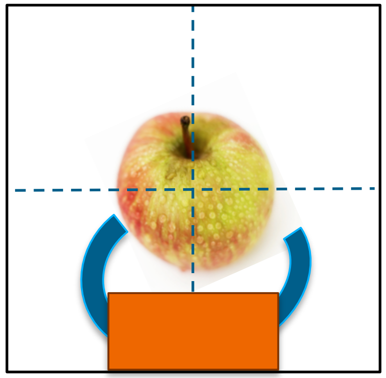
$$\theta := \theta - \lambda \hat{J}^{-1}(s)\Delta s$$

F combines the mapping from *s* to 3D coordinates, and the mapping of 3D coordinates to θ

$J(\theta) = \frac{\partial F}{\partial \theta}$ is the *visual-motor Jacobian*

Learning in model-free IBVS

- Fruit detection (which image area is of interest)
  - For real: refer to Efi, Ehud, Ohad, Yael
  - For the example:
    - Place “fruit” in the gripper
    - Learn the blob colors



$s^* = (X^*, Y^*, N^*)$

- Target feature values
    - Place “fruit” in the gripper
    - Learn X*, Y*, and N* (size) for fruit in gripper
- The visual-motor Jacobian *J*
  - Learned by motor babbling (Broyden's root-finding algorithm)
  - A case of Sensory-motor learning
    - Learning the relation between sensing and acting

$$J = \begin{pmatrix} \frac{\partial X}{\partial \theta_1} & \frac{\partial X}{\partial \theta_2} & \frac{\partial X}{\partial \theta_3} \\ \frac{\partial Y}{\partial \theta_1} & \frac{\partial Y}{\partial \theta_2} & \frac{\partial Y}{\partial \theta_3} \\ \frac{\partial N}{\partial \theta_1} & \frac{\partial N}{\partial \theta_2} & \frac{\partial N}{\partial \theta_3} \end{pmatrix}$$

Demo CRO$^{p}_{b}$S light

Gene modified
Christmas tree

- Features s = (X,Y,N) for detected fruit
- Target features s*=(X*, Y*, N*)
- Δs=(s-s*)
- $J(\theta) = \dfrac{\partial F}{\partial \theta}$

$$s = F(\theta)$$

$$\frac{\partial s}{\partial t} = \frac{\partial F}{\partial \theta}\frac{\partial \theta}{\partial t}$$

$$\dot{s} = J(\theta)\dot{\theta}$$

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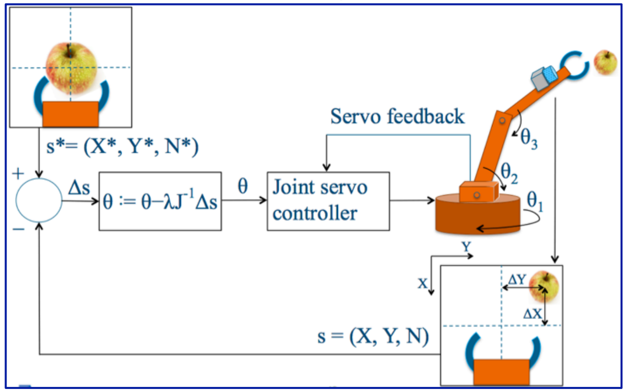
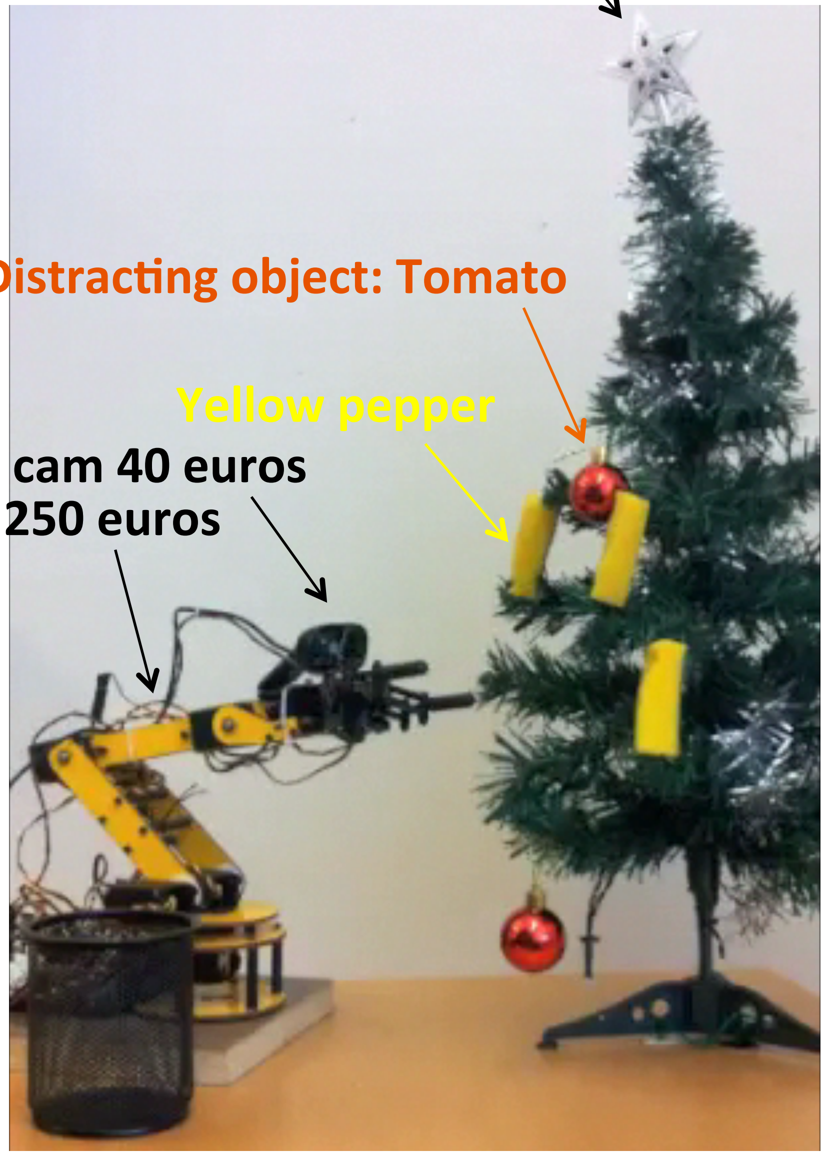


Logitech web cam 40 euros
Lynx robot arm 250 euros



Distracting object: Tomato

Yellow pepper

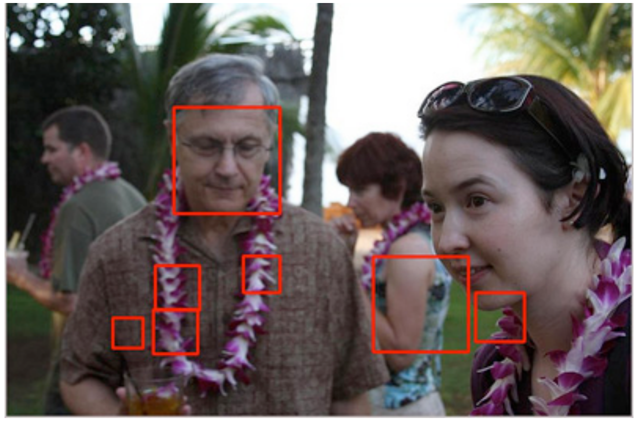
Robot learning in Sensing

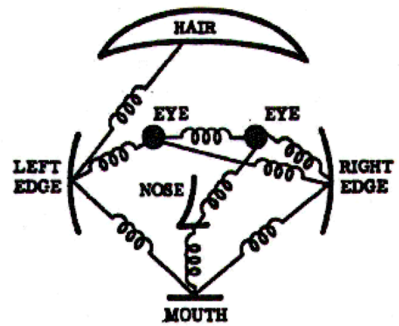
- How to interpret data
  - Object localization
  - Object classification
  - Scene understanding
  - Maps of the world
  - …

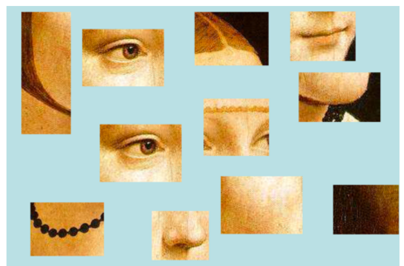
} Focus for the rest of the presentation

Learning for object localization/classification

- Usually based on image data
- Localization by sliding windows
  - Multiple locations and scales
- Feature extraction
  - Edges, Corners, Lines, Circles
  - Histogram of gradients (HOG)
  - Scale-invariant feature transform (SIFT)
- State-of-the-art
  - Part-based methods [1,2]
  - Bag-of-words methods [3,4,5,6]
- In most methods, *Pattern classification* techniques are used to map features to class







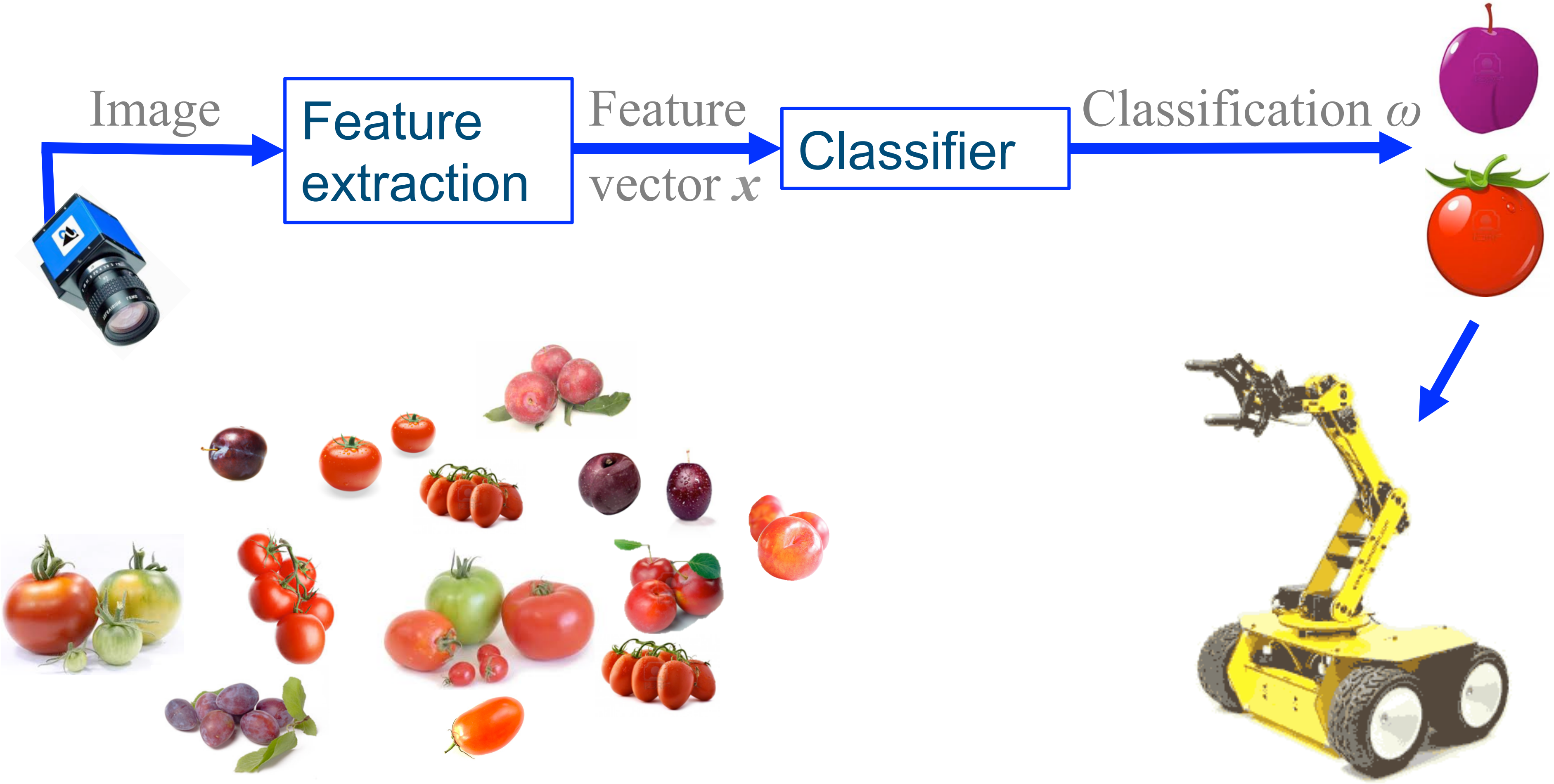
Pattern classification

- One (of a few) central problem statement:

  Given a set of N instances consisting of features $\boldsymbol{x} = (x_1, \ldots, x_d)$ *and a class label* ω *in* $\{\omega_1, \ldots, \omega_c\}$, *construct a classifier that successfully predicts* ω *for new feature vectors*
- Similar to regression, but ω is discrete
- Learning!

Example

Classification of fruit in images



Bayesian decision theory [7]

- A fundamental statistical approach to pattern classification
- ω and $\boldsymbol{x}$ are viewed as stochastic variables (s.v.)
- The unknown class ω is a s.v. with *prior probabilities*

$$P(\omega_1),\ldots, P(\omega_c)$$

- Each feature vector $\boldsymbol{x} = (x_1, \ldots, x_d)$ is a s.v. with *probability density function* $p(\boldsymbol{x}) = (p(x_1), \ldots p(x_d))$
- More useful to look at each class separately: *Class conditional probability density functions* defined as

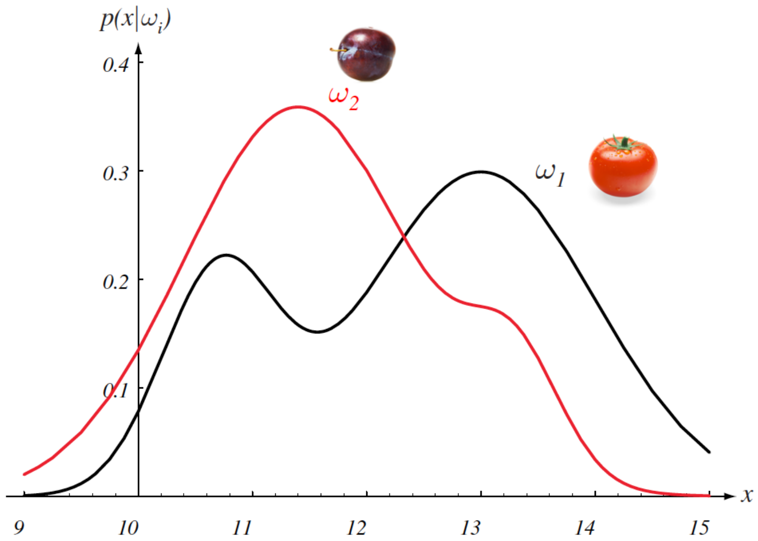
$$p(x_i \mid \omega_j) = p(x_i , \omega_j) / \mathrm{P}(\omega_j)$$

Example:

- The robot
  - should decide if a detected fruit is a plum or tomato
  - measures size (in reality a lot more features: colour, shape, …)
- Two classes: ω_1 (tomatoes) and ω_2 (plums) with priors

$$P(tomato) = 2/3 \quad P(\text{plum}) = 1/3$$

- One feature: $x = size$
- *Class conditional probability density functions* ➔
- Possible interpretation:
  - There are two types of tomatoes; small and big. The size of plums is in between these two types



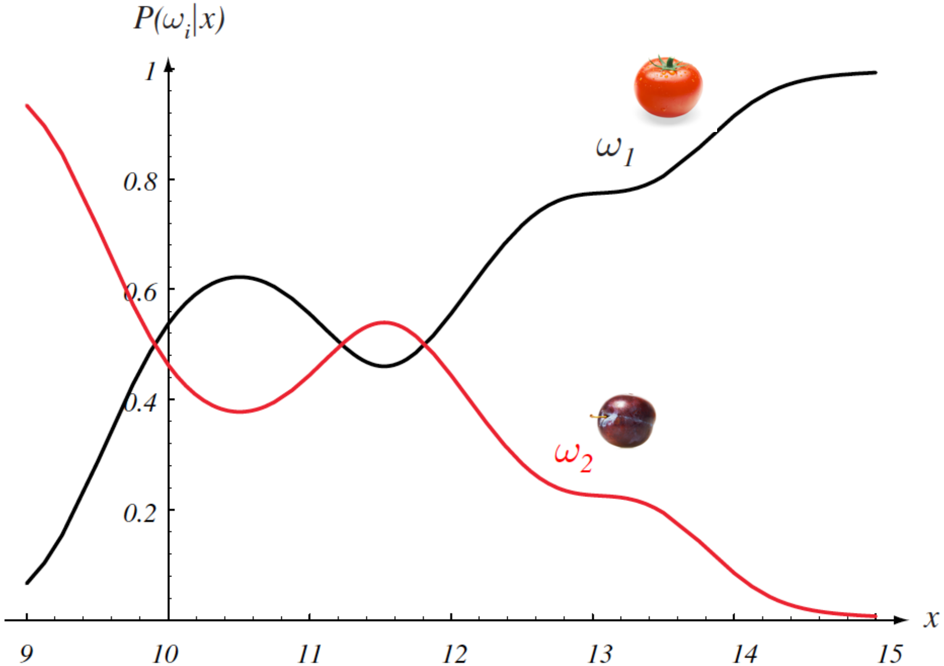
Bayesian decision theory

- We want to predict ω given $\boldsymbol{x}$
- How about this decision rule:
  "Choose the class that is most probable given observation x" ?
- This is expressed by the *posterior probability* $P(\omega_i \mid \boldsymbol{x})$, which is defined by

$$P(\omega_i|\boldsymbol{x}) = \frac{p(\boldsymbol{x},\omega_i)}{p(\boldsymbol{x})}$$

and also related to the *class conditional probabilities* by Bayes rule:

$$P(\omega_i|\boldsymbol{x}) = \frac{p(\boldsymbol{x}\mid\omega_i)P(\omega_i)}{p(\boldsymbol{x})}$$



Bayesian decision theory

- The decision rule can be written

$$\omega_{MAP} = \arg\max_i P(\omega_i|\boldsymbol{x})$$

  and is called *Maximum a posteriori probabilities* (MAP) or Bayes decision rule

- It can be shown that it minimizes the risk of miss classification: $P(Error \mid x)$
- The idea can easily be extended to take different miss classification costs into account

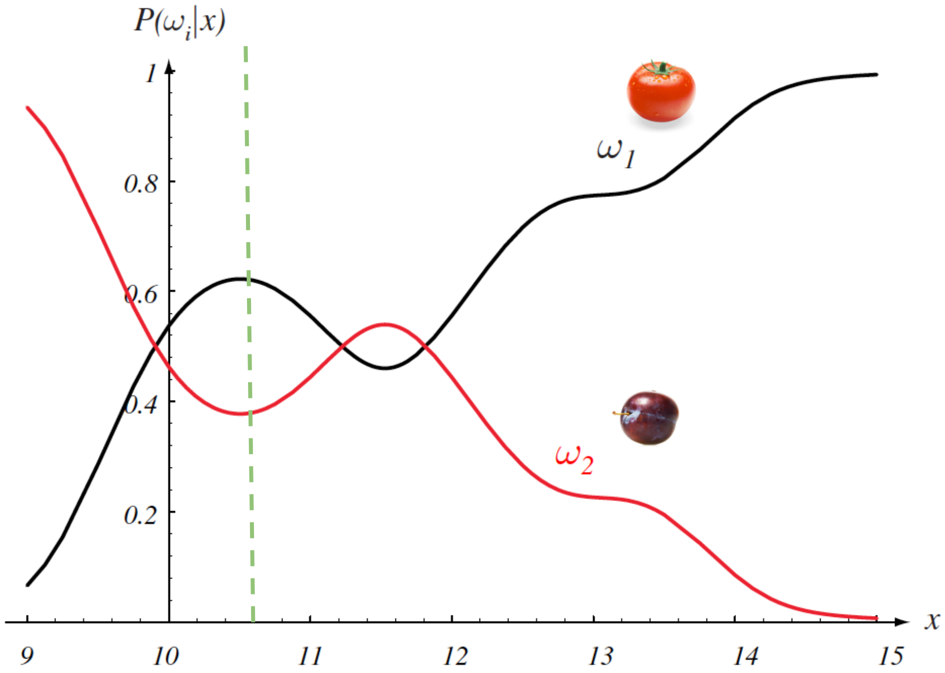
Back to the example

- Given an observed size *x*, we predict the fruit ω_i with maximum $P(\omega_i|x)$
- For observed *size* =10.6:

  $P(tomato|14)=0.62$

  $P(plum|14)=0.38$

  The fruit is a tomato!!



- Simple principle, but we need to know all $P(\omega_i|x)$
- Often they can be estimated from the data (LEARNING!)
- Some classifiers, like KNN and ANN, do exactly that!

Other formulations of MAP

- Reformulation with Bayes rule:

$$P(\omega_i|\boldsymbol{x}) = \frac{p(\boldsymbol{x}\,|\,\omega_i)P(\omega_i)}{p(\boldsymbol{x})}$$

- $p(x)$ is independent of i and does not affect the MAP decision

$$\omega_{MAP} = \arg\max_i p(\boldsymbol{x}|\omega_i)\, P(\omega_i)$$

- Same decision as for $P(\omega_i \,|\, \boldsymbol{x})$, but different methods for the estimation

Classifiers as discriminant functions

- The posterior probabilities can be seen as functions of $\boldsymbol{x}$

$$g_i(\boldsymbol{x}) = P(\omega_i \mid \boldsymbol{x}) \text{ or}$$

$$g_i(\boldsymbol{x}) = p(\boldsymbol{x} \mid \omega_i)\, P(\omega_i)$$

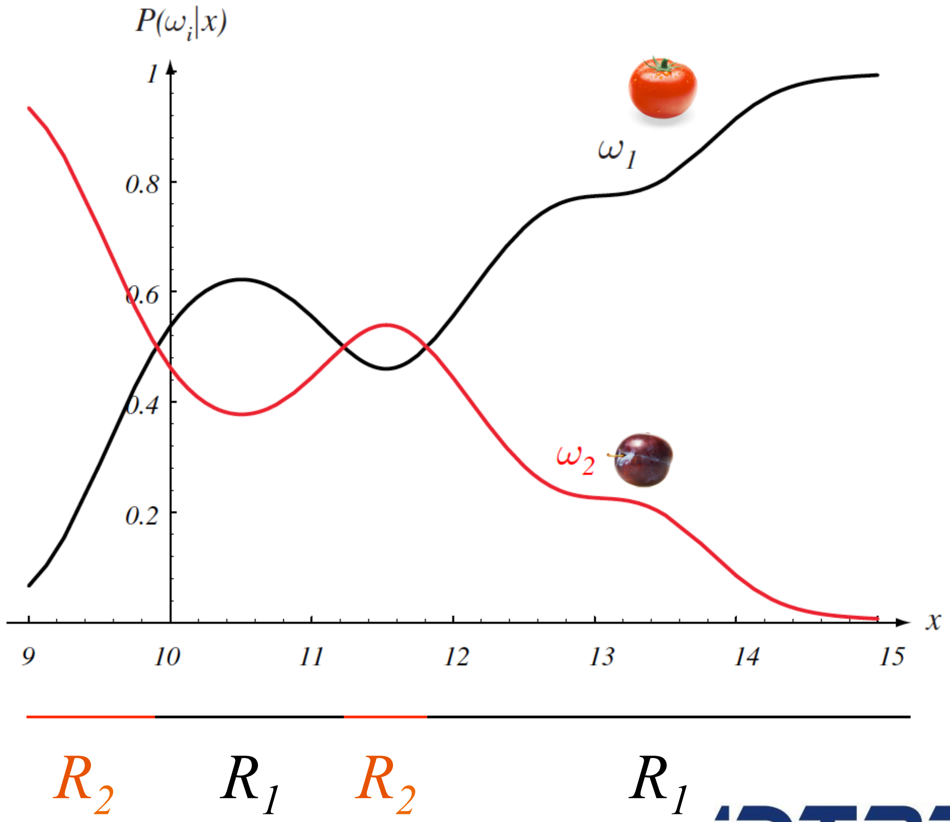
- A classifier can be described as a set of *discriminant functions* $g_i(\boldsymbol{x})$, $i = 1, \ldots, c$.
- The classifier assigns a feature vector $\boldsymbol{x}$ to ω_i iff

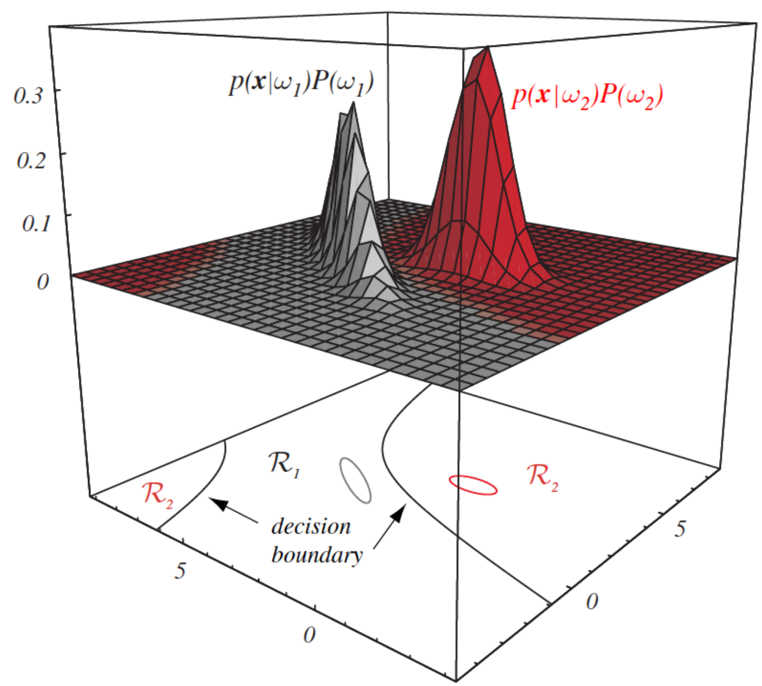
$$g_i(\boldsymbol{x}) > g_j(\boldsymbol{x}) \text{ for all } j \neq i$$

- "Lines" along which $g_i(\boldsymbol{x}) = g_j(\boldsymbol{x})$ are the decision boundaries
- Learning a classifier ↔ finding discriminant functions or decision boundaries that optimize some chosen objective

Decision boundaries and decision regions

- Decision boundaries separate input space in *decision regions*
- *Decision regions* R_i, $i=1,\ldots,c$, are the set of points in feature space where we decide ω_i
- The decision regions need not be simply connected





Two ways of constructing classifiers

- Estimating discriminant functions

$$g_{\mathrm{i}}(\boldsymbol{x}) = P(\omega_i \mid \boldsymbol{x}) \text{ or}$$

$$g_i(\boldsymbol{x}) = p(\boldsymbol{x} \mid \omega_i)\, P(\omega_i)$$

- Estimating optimal decision boundaries

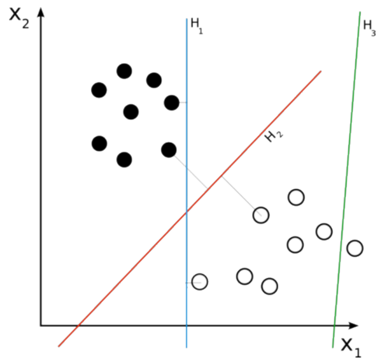
Constructing classifiers by estimating discriminant functions

- Parametric methods
  - Assume a parameterized form of $p(\boldsymbol{x} \mid \omega_i)$ or $P(\omega_i \mid \boldsymbol{x})$ and estimate the parameters from data
- Non-parametric methods
  - Estimate from data
    - Naïve Bayes : $g_i(\boldsymbol{x}) = p(\boldsymbol{x}|\omega_i)\ P(\omega_i)$
    - k-NN : $g_i(\boldsymbol{x}) = P(\omega_i \mid \boldsymbol{x})$

Constructing classifiers

by estimating optimal decision boundaries

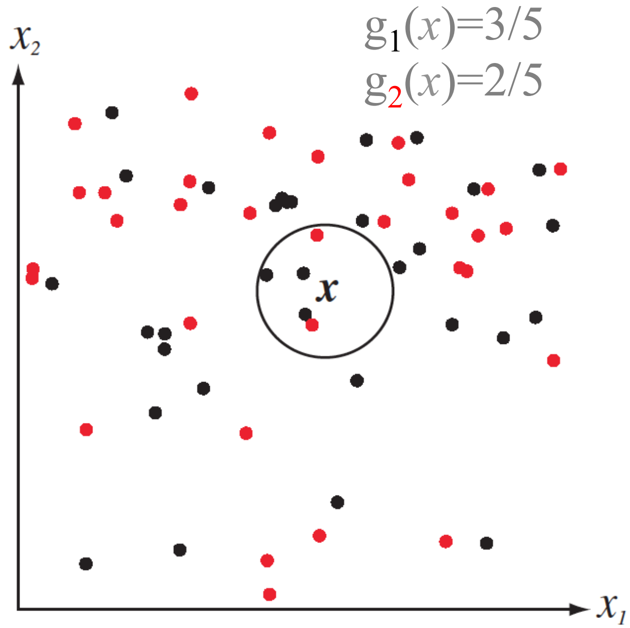
- Parametric methods
  1. Assume a parameterized form of decision boundary
  2. Estimate parameters
  - Perceptrons
  - LDA
  - Support vector machines (SVM)



- Non-parametric methods
  - Neural networks

k-nearest-neighbor classifier (k-NN)

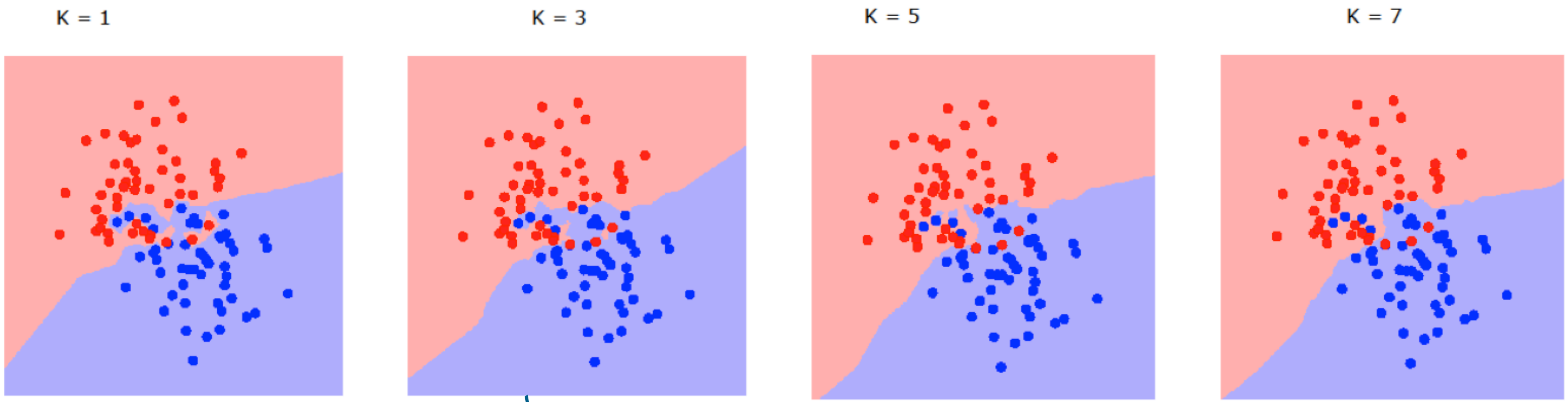
- Estimates discriminant function $g_i(\boldsymbol{x}) = P(\omega_i \mid \boldsymbol{x})$
  - find the k nearest neighbors to $\boldsymbol{x}$
  - $P(\omega_i \mid \boldsymbol{x})$ = #(neighbors with class=i)/k

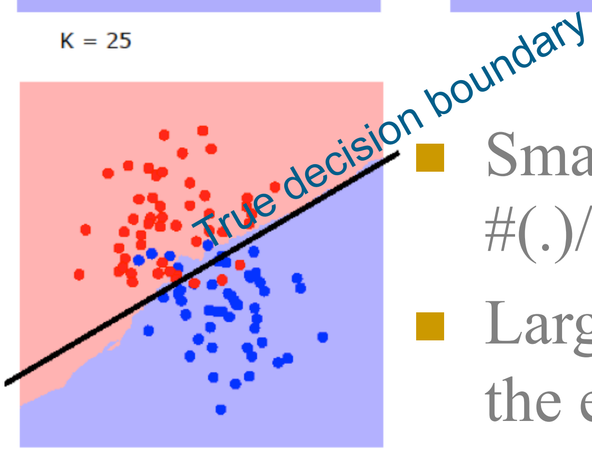


- As before: $\omega = \arg\max_i g_i(\boldsymbol{x})$
  i.e. predict the most frequent class
- Not always good probability estimates, but the decision rule only the ordering of discriminant functions $g_i(\boldsymbol{x})$

k-nearest-neighbor classifier (k-NN)

- Piecewise linear decision boundary
- Larger k gives smoother decision boundary





- Small k : all k neighbors are close to $\boldsymbol{x}$ ➔ #(.)/k is close to $P(\omega_i \mid \boldsymbol{x})$
- Large k : more data in the calculation ➔ the estimate #(.)/k is more reliable
- k can be determined by cross-validation

Pictures from R. H. Lathrop Univ. of California

Combining several classifiers [12]

3 reasons why this may be a good idea

H: All classifier hypotheses that can be learned with the method

f: the correct hypothesis

<u>Statistical argument</u>

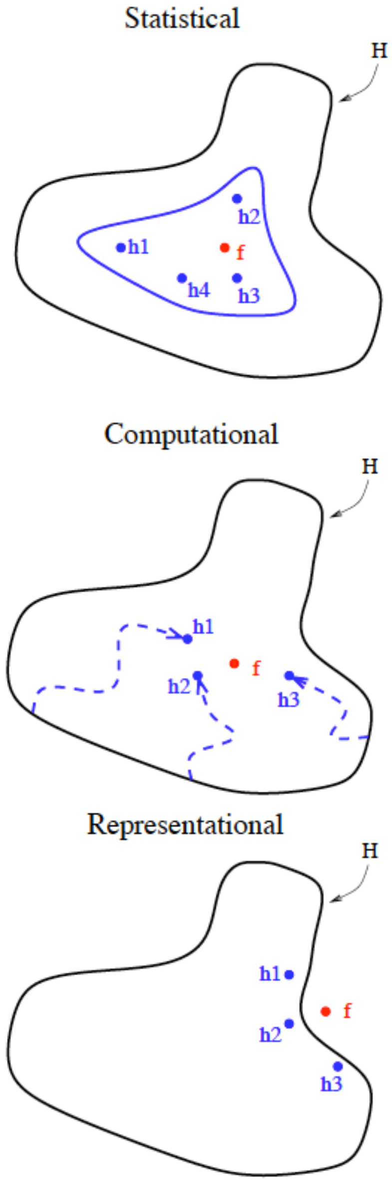
With limited data, we may find different hypotheses h1, h2, h3,… by using different subsets of the data. Averaging increases the chance of being close to f.

<u>Computational argument</u>

Learning, often a search, may get stuck in local minima. Averaging the result from several starting points increases the chance of being close to f.

<u>Representational</u>

F may be outside H. Averaging may expand H.



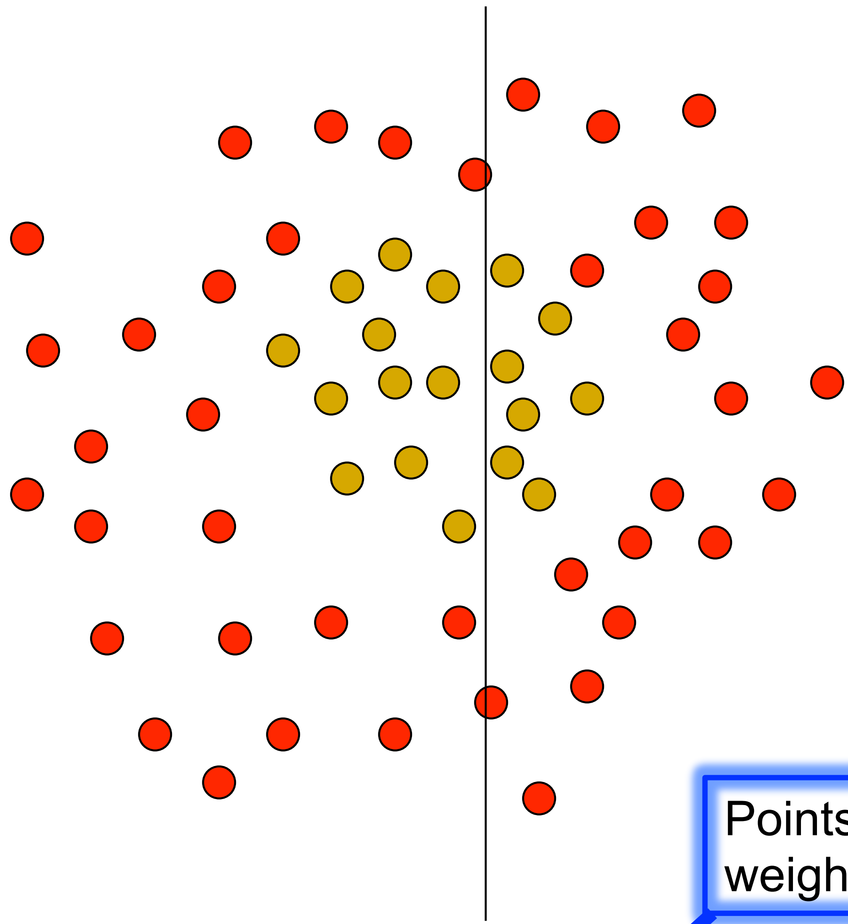
Combining several classifiers

- Several approaches
  - Voting for several classifiers (hypotheses)
  - Modifying the training data
- AdaBoost [8,9]
  - Create a sequence of simple "weak" classifiers
  - Each new classifier
    - is typically fast to train, e.g. a decision tree, "decision stump", or a linear classifier
    - must be a bit better (or worse…) than random guessing
    - focuses on the hard cases by weighting training data
  - Output: a weighted sum of all created classifiers

Example AdaBoost

- figures from Antonio Torralba@MIT

Each data point $\mathbf{x}_i$ has a class label $y_i = \begin{cases} +1 \text{ (red)} \\ -1 \text{ (yellow)} \end{cases}$



Weak classifiers $h_t(\mathbf{x})$: Lines performs (at least) slightly better than chance.

$h_t(\mathbf{x})=+1$ for points on one side of the line and -1 on the other

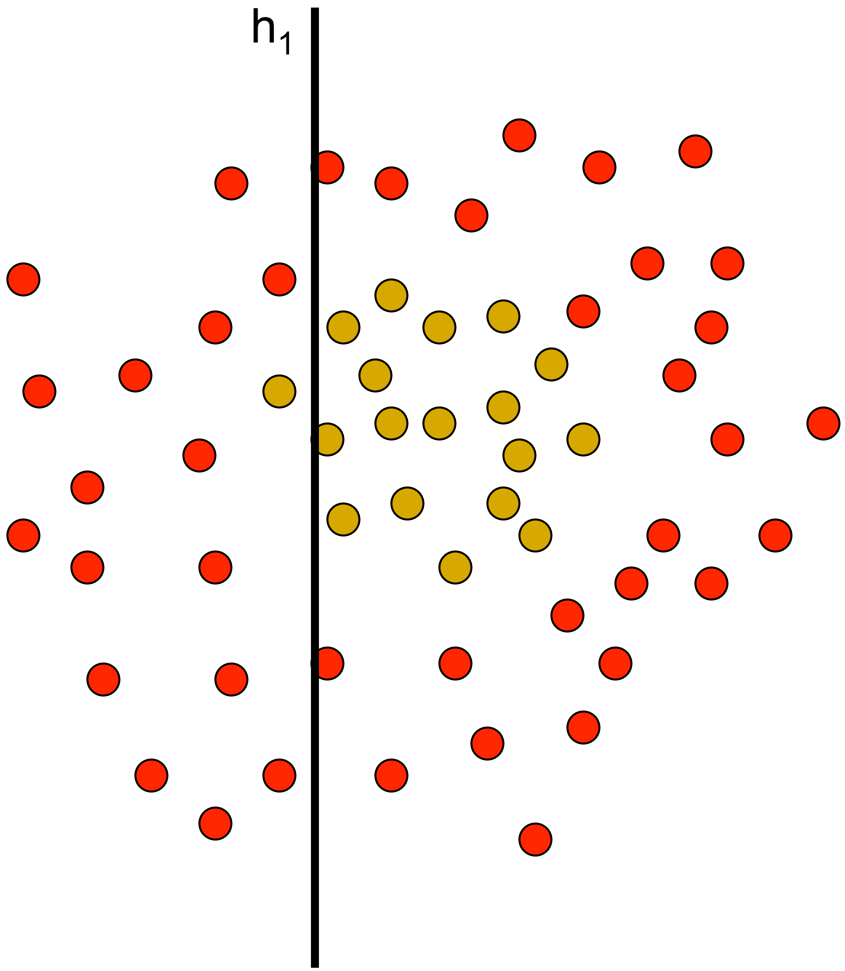
Learning means Finding parameters defining the best h_t

Each data point has an initial weight (size) $w_i=1$

Points with high weights count more

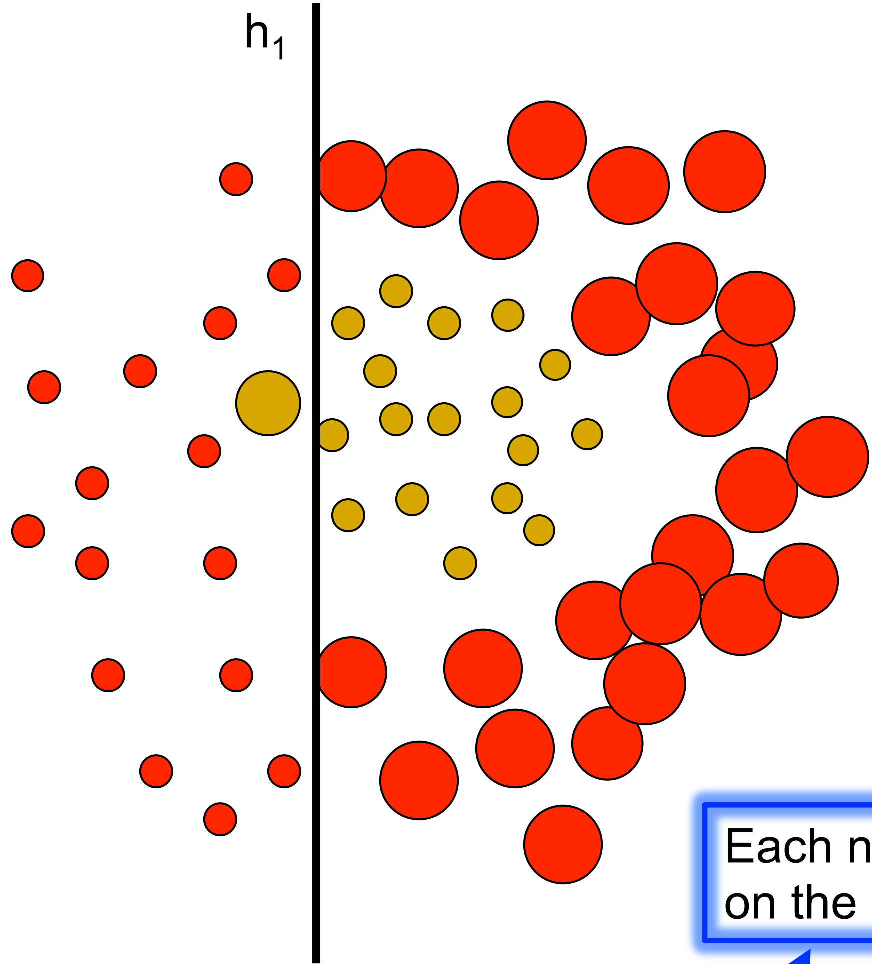
Learn a weak classifier h_1 that maximizes the weighted performance

Example AdaBoost



Update the weights: Increase w_i if $h_t(\mathbf{x}_i) \neq y_i$,decrease if $h_t(\mathbf{x}_i) = y_i$

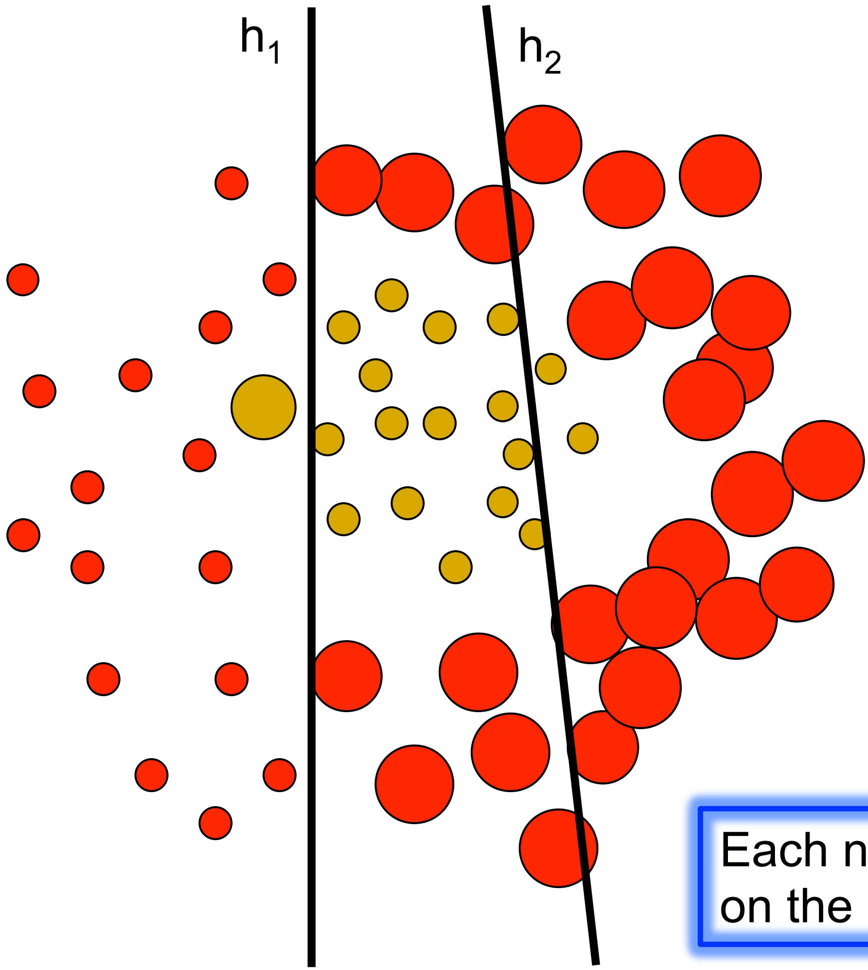
Example AdaBoost



Each new classifier will focus on the “hard” cases

Learn a **new** weak classifier h_2 that maximizes the weighted performance

Example AdaBoost



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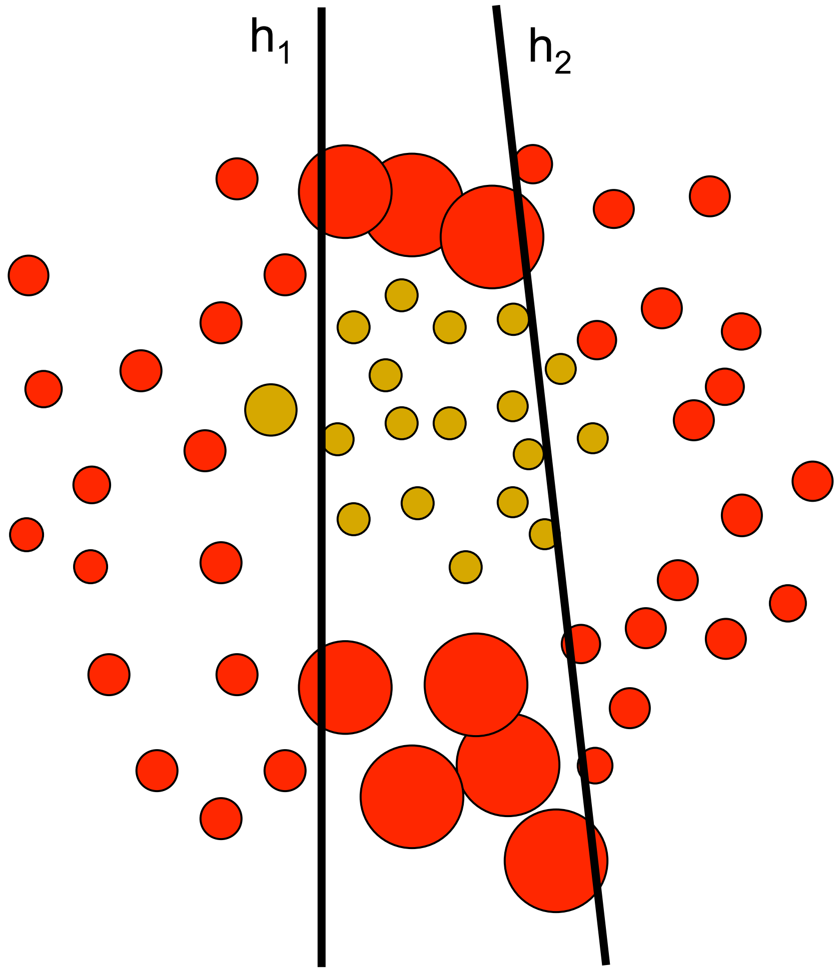

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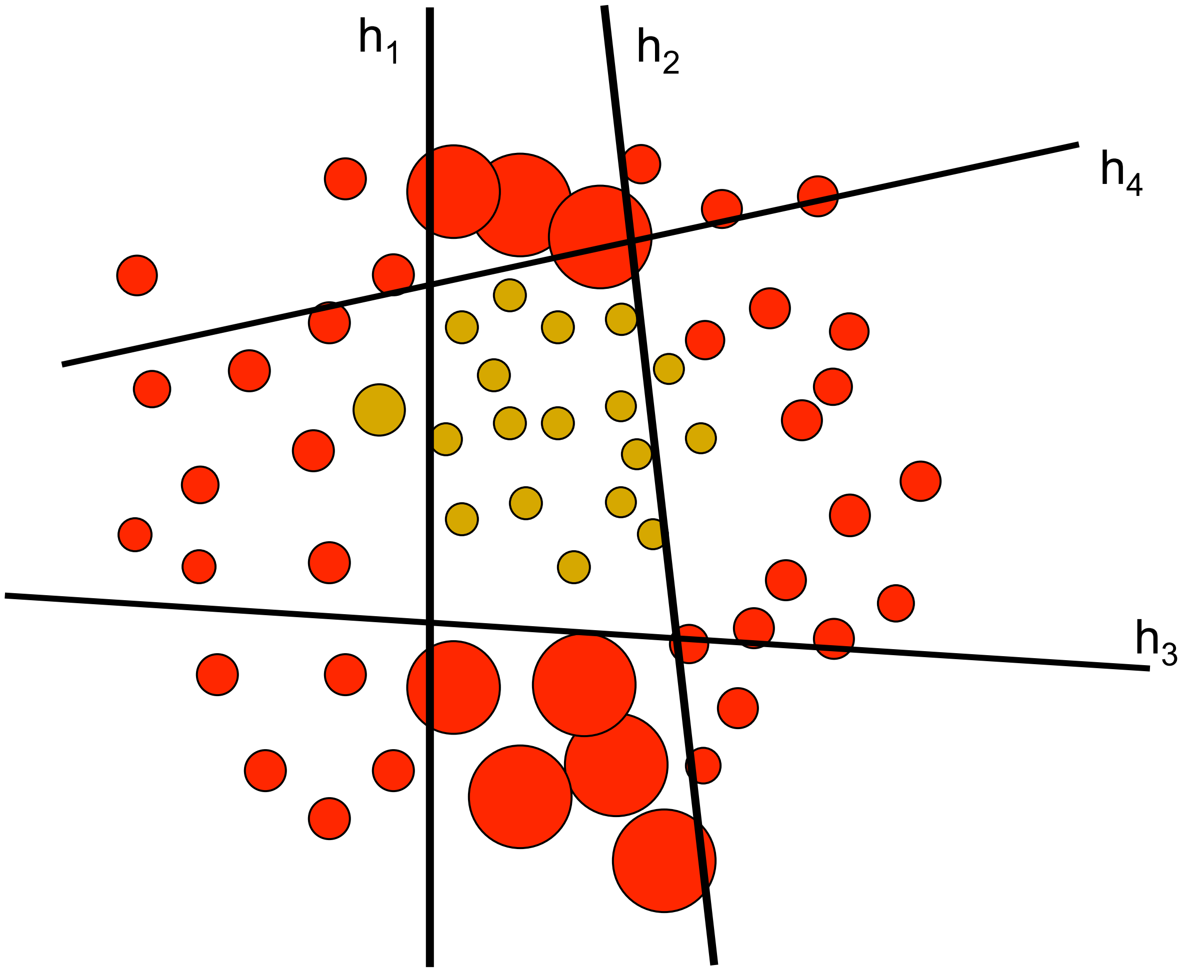
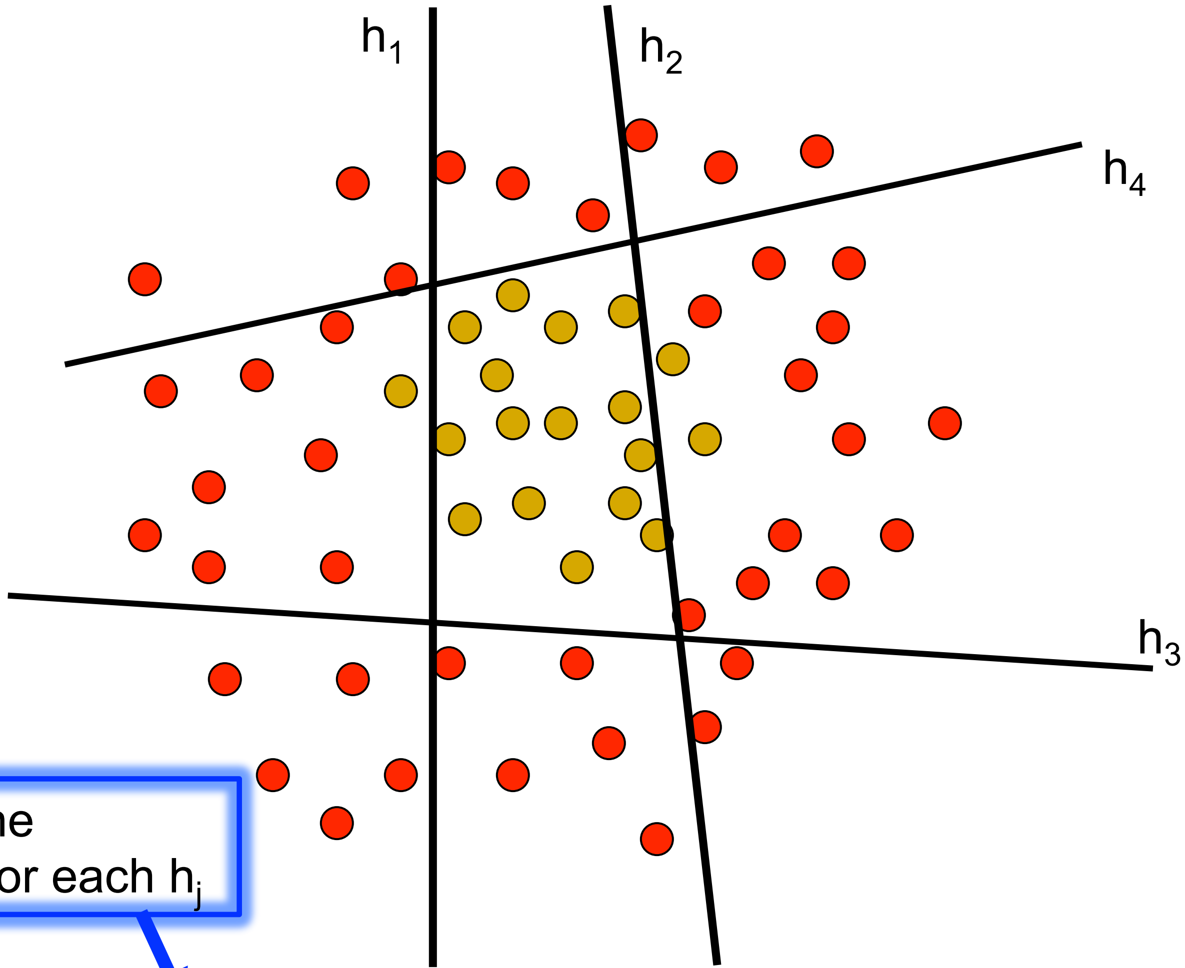
Example AdaBoost



Learn **new** weak classifiers h_3 and h_4 that maximize the weighted performance

Example AdaBoost



Weights are the performance for each h_j

Final classification: A weighted sum of all weak classifiers $h_1 h_{2,} h_{3,} h_4$

AdaBoost

- Very impressive (accurate and fast) performance
  - Used in Viola-Jones face detector
- Simple
  - “just 10 lines of code” [R. Schapire] (actually correct!)
- Solid theoretical foundation
- The inventors R. Schapire and Y. Freund won the 2003 Gödel Prize for the algorithm

INTRO

Just 10 lines of code

$D = \{(x_1,y_1),\dots,(x_n,y_n)\}$, k_{max}, $w_i = 1/n$, $j = 1,\dots,n$

for $k=1$ to k_{max}

  Train weak learner C_k using D sampled according to w_i

  E_k = training error of C_k measured on D using w_i

  $a_k = 1/2 \ln[(1- E_k)/ E_k]$ (performance for classifier C_k)

  if $f_k(x_i) = y_i$ (correct classification)

    $w_i = w_i e^{-a_k}$ (increase weight)

  else

    $w_i = w_i e^{a_k}$ (decrease weight)

end

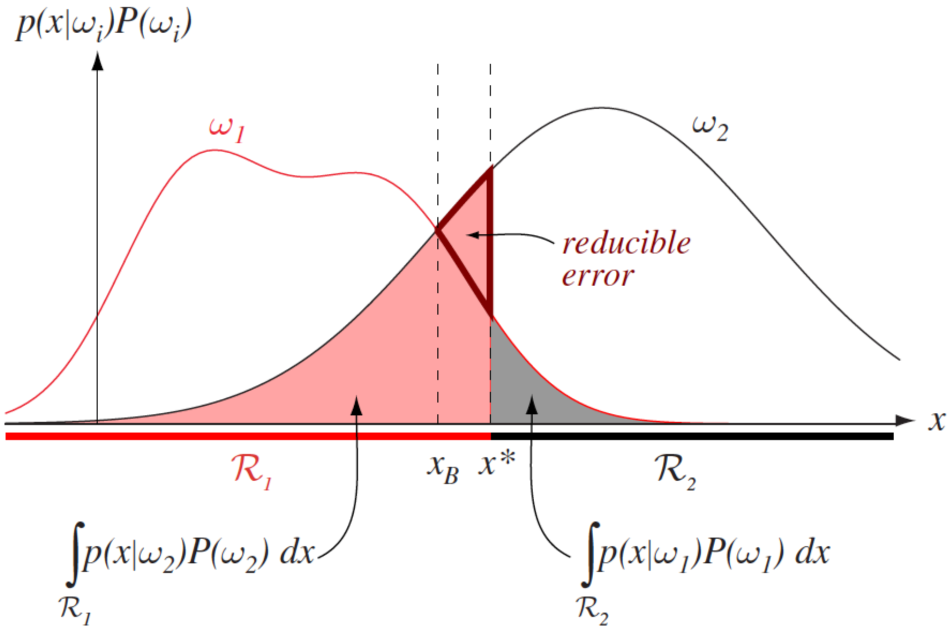
Final classifier: $\sum_{k=1}^{k_{max}} a_k C_k(x)$

What makes a classification task hard?

- Overlapping posterior probabilities $P(\omega_i \mid \boldsymbol{x})$
  - The classes are not uniquely determined by the features
  - Leads to inherent class ambiguity[11]
  - Even with training data covering all combinations of features, classification errors will occur!
- Complexity of the decision boundary
  - The optimal decision boundary needs a long description (Kolmogorov complexity)
  - Complexity typically grows with dimensionality
  - Harder to predict the boundary with little data
  - Extreme example:
    The class labels are assigned randomly
    - No generalization possible - no other way than to use training data as a look-up table
    - Is a problem even with infinite data and no class ambiguity

Class ambiguity

- The Bayes decision assumes full knowledge of all probabilities
- Assume we have a sub optimal decision boundary **x*** separating decision regions R_1 and R_2
- Two possible errors:
  - Predicting ω_2 when real class is ω_1
  - Predicting ω_1 when real class is ω_2



- $$P(error) = P(\mathbf{x} \in \mathcal{R}_2, w_1) + P(\mathbf{x} \in \mathcal{R}_1, w_2) = P(\mathbf{x} \in \mathcal{R}_2 | w_1) P(w_1) + P(\mathbf{x} \in \mathcal{R}_1 | w_2) P(w_2)$$
$$= \int_{\mathcal{R}_2} p(\mathbf{x}|w_1)\, P(w_1)\, d\mathbf{x} + \int_{\mathcal{R}_1} p(\mathbf{x}|w_2)\, P(w_2)\, d\mathbf{x}.$$
- Minimum error achieved for $\mathbf{x}^*=\mathbf{x}_B$ is called the *Bayes error rate*
  - It depends on the class ambiguity
  - It can not be reduced by ANY classifier or data set using the given features

iNTRO

No Free Lunch Theorem [10]

- "Any two algorithms are equivalent when their performance is averaged across all possible problems" (Wolpert)
- Without assumptions on the task, no classifier is superior to any other (including random guesses)!

- Some assumptions – like continuity - are quite valid irl
- Mainly a theoretical result, but gives valuable insight
- There is no "best" classifier (SVM is not "better" than kNN)
- Choose classifier that suits the task – just like you chose your lunch






- But remember - there is always a price to pay

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