Prof. Dr. Ronny Hartanto



Objective:

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Given some input data $x \in F$, predict the target values $y \in L$ according to some performance measure P.

The input data space *F* is also called "feature space".

Supervised Learning has two phases:

 Training period: Receive a set of input data with corresponding target values:

$$(x_i, y_i), i = 1, ..., n$$

Test period: Receive a set of input data without target values.

$$x_i$$
, $i = 1, ..., m$

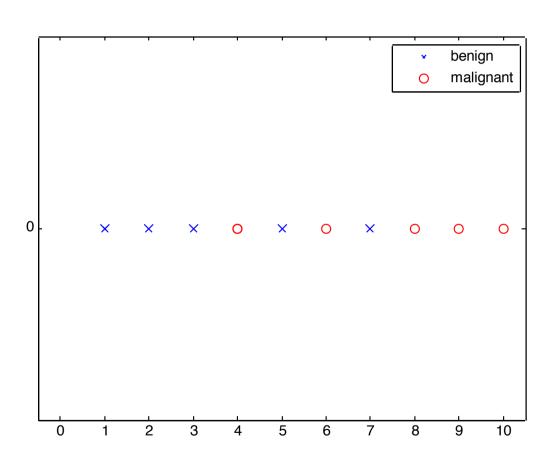


Example:

Wisconsin breast cancer database (<u>link</u>)

F: Tumor size (integer numbers from 1 to 10)

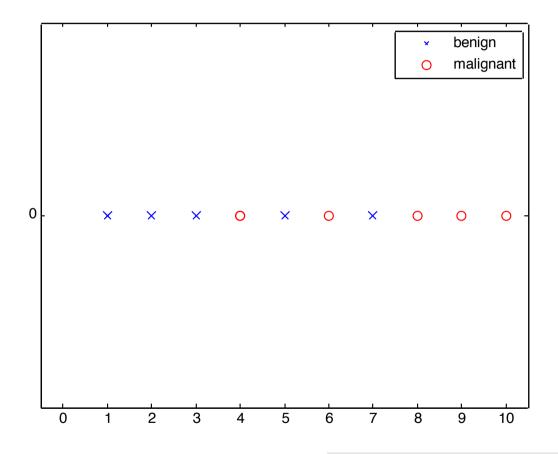
L: {"benign", "malignant"} or { x, o}, or {0,1}.





Exercise:

Write down the 10 samples that you see here into a table (Example: the leftmost data point is (1,0)).



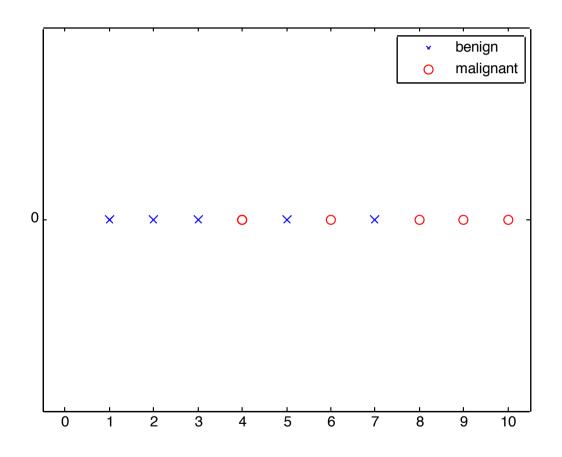


Classification:

If the target space consists of finite discrete values, the learning task is also called classification:

"Assign the most probable class label"

A function $f: F \to L$ is called a *classifier function* in this case.

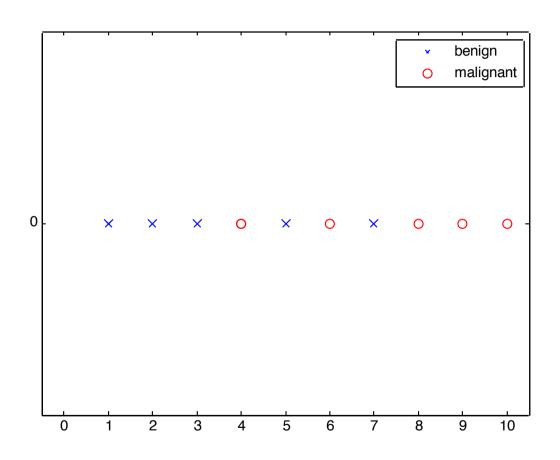




Test period:

Suppose you have a new data point (e.g. the size of an unknown new tumor is 7).

What y value do you predict? Why?



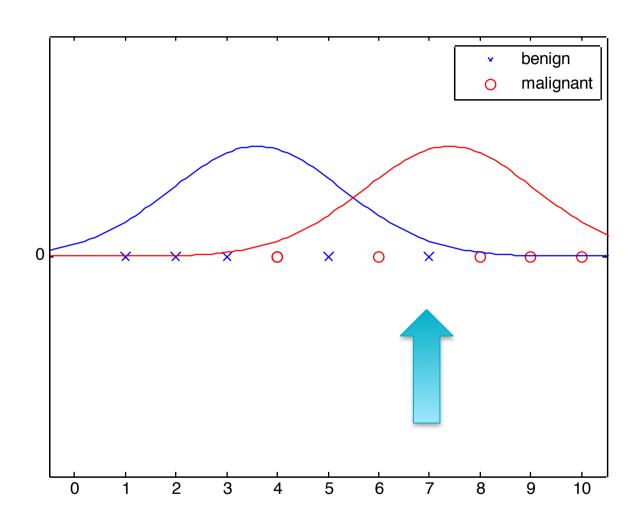


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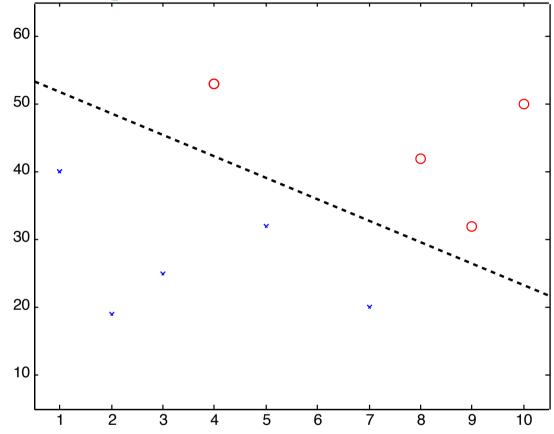
We can use findings and models from statistics.

Assumption: tumor sizes of each class are normally distributed, with equal variance.

According to these probability distributions, we should opt for "malignant".







Also in multiple dimensions: The assumptions

- Normal distributions
- 2. Equal Covariance matrices

lead to a *linear* classifier function.

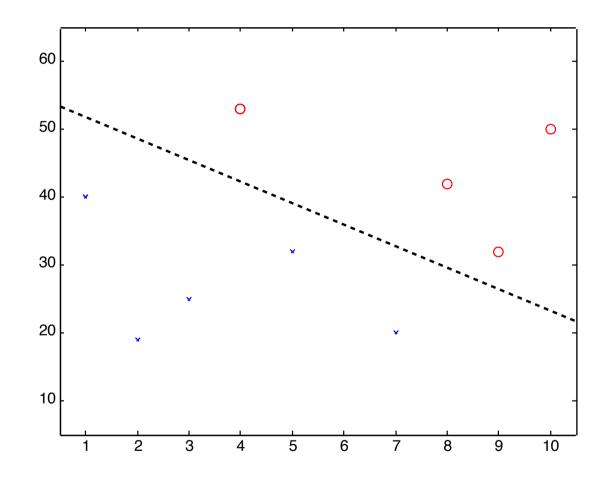
$$f(x) = \begin{cases} 1, & \text{if } a_1x_1 + \dots + a_mx_m + c > 0 \\ 0, & \text{otherwise.} \end{cases}$$



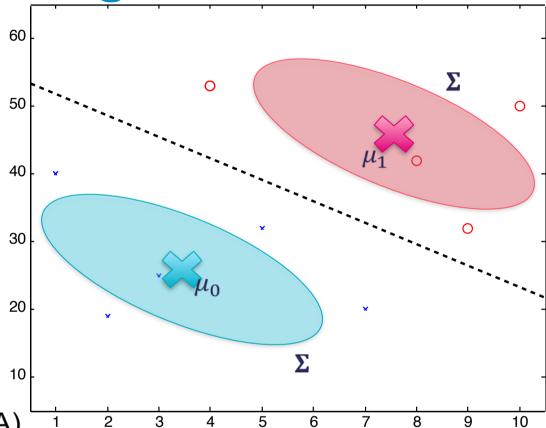
Observation:

Using more dimensions may lower the classification error.

The Wisconsin breast
cancer dataset
contains multiple
features, such as
clump thickness,
uniformity of cell size,
cell shape,...







Linear Discriminant Analysis (LDA) 1 2 3 4 5 6 7 8 9
Algorithm:

- Estimation of the class means μ_0 and μ_1
- Estimation of the "within-class" scatter matrix $\Sigma = \frac{\Sigma_0 + \Sigma_1}{2}$, where $\Sigma_j = \frac{1}{|D_j 1|} \sum_{i \in D_j} (x_i \mu_j) (x_i \mu_j)^t$



Linear Discriminant Analysis (LDA)

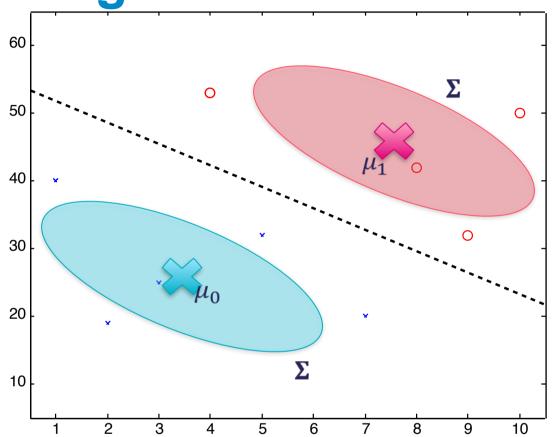
Algorithm:

 The separating hyperplane has the equation

$$w^t(x - x_0) = 0$$

where

$$w = \Sigma^{-1}(\mu_1 - \mu_0)$$
$$x_0 = \frac{(\mu_1 + \mu_0)}{2}$$





Exercise:

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Suppose the training data on the right are given.

- 1. Draw the data into a diagram.
- 2. Calculate the class means μ_0 and μ_1
- Derive the classifier parameters w and x_0
- Draw the separating hyperplane.
- How would you label the point (3,2)?

Hint: The inverse of the scatter matrix is

$$\Sigma^{-1} = \begin{pmatrix} 0.34 & -0.43 \\ -0.43 & 1.26 \end{pmatrix}$$

X 1	X 2	у
1	1.5	0
2	4	0
6	4	0
2	0	+1
4.5	0.5	+1
6	0.5	+1
6	2	+1

