

# Pattern Recognition and Image Analysis

Dr. Manal Helal – Fall 2014  
Lecture 1

# Tentative Course Contents

1. Introduction
2. Random variables, probability definitions
3. Bayesian decision theory
4. The Gaussian classifier
5. The Gaussian mixture model (GMM) and EM algorithm
6. Non-Parametric classifiers (PNN, NNC, and KNN)
7. Hidden Markov models (HMMs)
8. Applications of HMM (OCR, Speech, Face recognition)
9. Neural Network models (linear perceptrons, MLP, RBF)
10. Support Vector Machines (SVM)
11. Clustering (such as K-means)

# Grading

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## ■ Week 7 30%:

- Assignments 10%
- Midterm 20%

## ■ Week 12 30%:

- Assignments 10%
- Project presented in Week 12: 20%

## ■ Final 40%

- Seminar presented in Week 15: 20%
- Final Exam in Week 16: 20%

# Textbook & References

- Pattern Recognition, by S. Theodoridis and K. Koutroumbas , second edition available on moodle,
  - Book Website: <http://cgi.di.uoa.gr/~stpatrec/welcome3d.html>
- MATLAB-based examples accompanying the book: An Introduction to Pattern Recognition, by S. Theodoridis and K. Koutroumbas
- More will be added on moodle as we need them.

# Tools and Datasets

- Matlab Book examples.
- The PRTools MATLAB toolkit ([prtools.org](http://prtools.org))
- Other tools that can be useful such as Apache Mahout.
- Datasets:
  - Public datasets for Statistical Pattern Recognition
    - <http://homepages.inf.ed.ac.uk/rbf/IAPR/researchers/PPRPAGES/pprdat.htm>
  - Machine Learning Repository Centre for Machine Learning and Intelligent Systems
    - <https://archive.ics.uci.edu/ml/datasets.html>
  - Pattern Recognition Tools Datasets
    - <http://www.37steps.com/prtools/examples/datasets/>
  - Pattern Recognition and Neural Networks
    - <http://www.stats.ox.ac.uk/pub/PRNN/>
  - Test Images & Speech Segments:
    - <http://cgi.di.uoa.gr/~stpatrec/welcome3d.html>

# Project topics

## ■ Applications:

- Handwritten Digit Recognizer
- Face Recognition
- Speech Recognition
- Fingerprint Recognition
- Land Cover Identification

## ■ Classifier Implementation:

- Sequential Implementation of Any classifier of your choice and testing it on a dataset of your choice.
- Running a Parallel Implementation of a classifier of your choice, such as on Apache Mahout on a data set of your choice.



# A Course on **PATTERN RECOGNITION**

**Sergios Theodoridis**

**Konstantinos Koutroumbas**

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# PATTERN RECOGNITION Applications

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- Machine vision
- Character recognition (OCR)
- Computer aided diagnosis
- Speech recognition
- Face recognition
- Fingerprint identification
- Biometrics: voice, iris, finger print, face, and gait recognition
- Smell recognition: e-nose, sensor networks
- Image Data Base retrieval
- Data mining
- Bionformatics: DNA sequence identification
- Automatic diacritization
- Defect detection in chip manufacturing
- Network traffic modeling, intrusion detection
- Biomedical signal classification (EEG) (BCI)

❖The task: Assign unknown objects – **patterns** – into the correct class. This is known as **classification**.



# Examples of Patterns

❖ Classification of the type and category of a natural scene or creature



# Examples of Patterns

❖ Face detection, face recognition, emotion classification, etc.

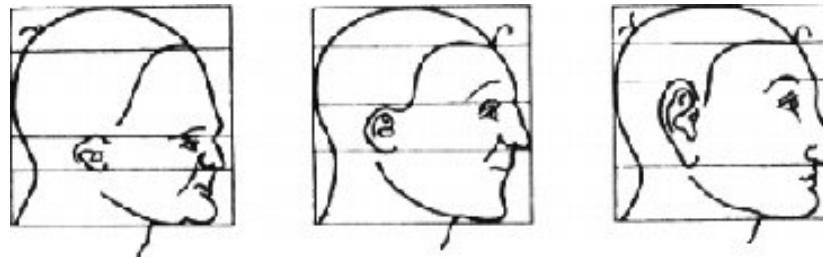


# Examples of Patterns: Car-plate Recognition



# Examples of Patterns

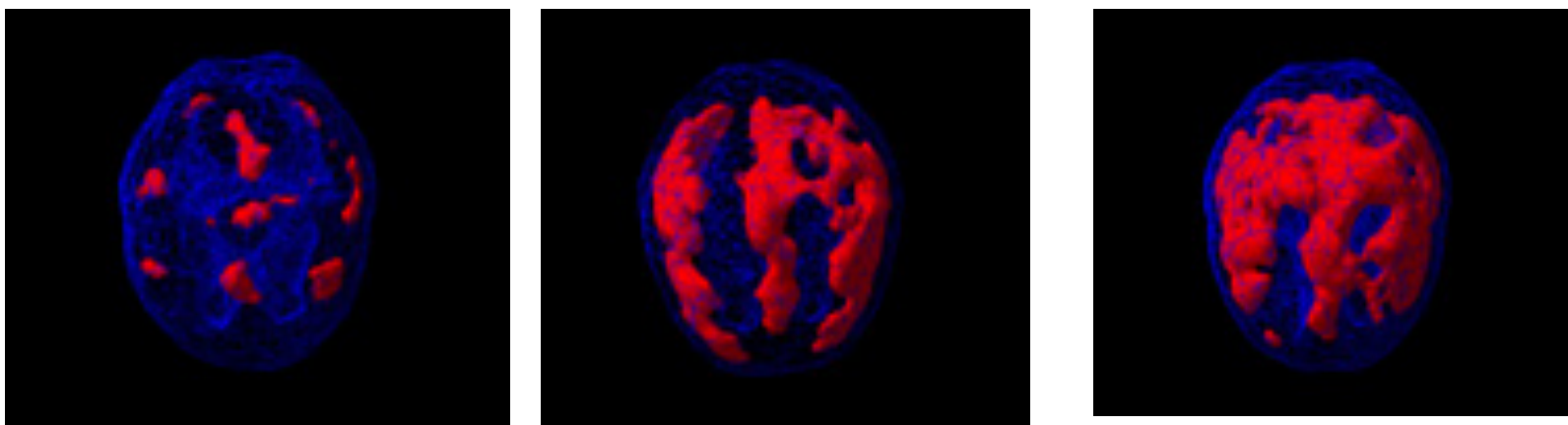
## ❖Pattern discovery and association



❖Statistics show connections between the shape of one's face (adults) and his/her Character. There is also evidence that the outline of children's face is related to alcohol abuse during pregnancy.

# Examples of Patterns

❖Patterns of brain activities:



❖We may understand patterns of brain activity and find relationships between brain activities, cognition, and behaviors

# Examples of Patterns

❖ Patterns with variations:

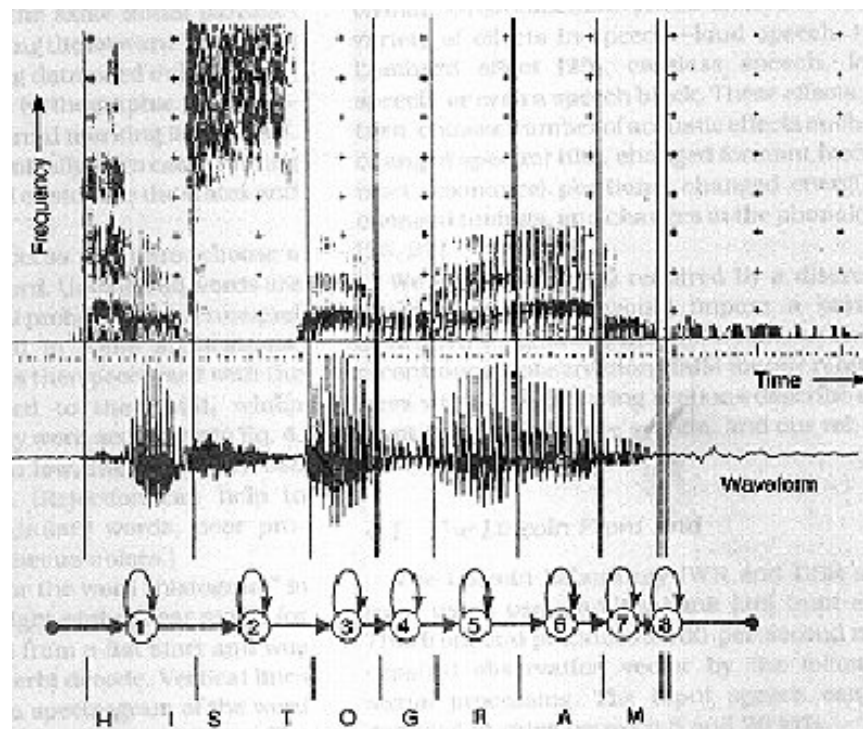
1. Expression –geometric deformation
2. Lighting --- photometric deformation
3. 3D pose transform
4. Noise and occlusion





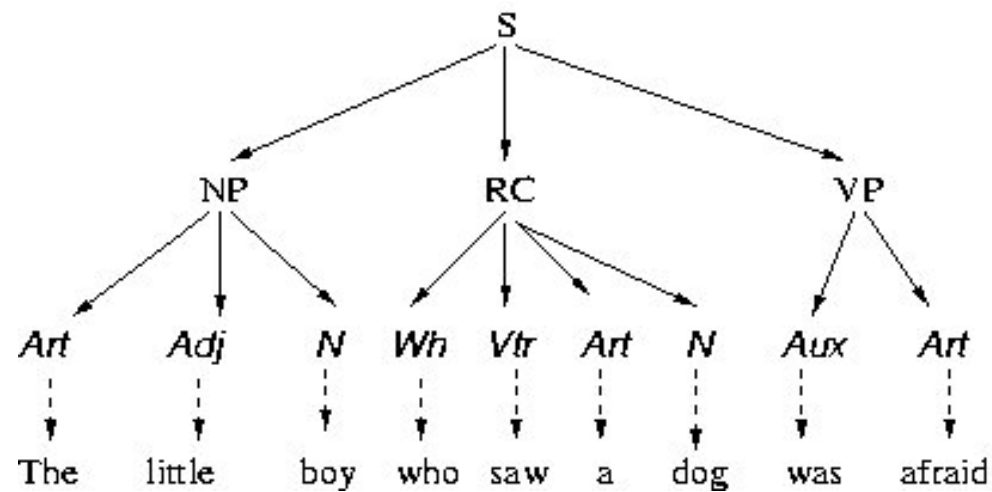
# Examples of Patterns

## ❖ Speech signal and Hidden Markov model



# Examples of Patterns

❖ Natural language and stochastic grammar.



❖ Building Automaton and parsing languages will not be covered in this course.



❖ **Features:** These are measurable quantities obtained from the patterns, and the classification task is based on their respective values.

❖ **Feature vectors:** A number of features

$$x_1, \dots, x_l,$$

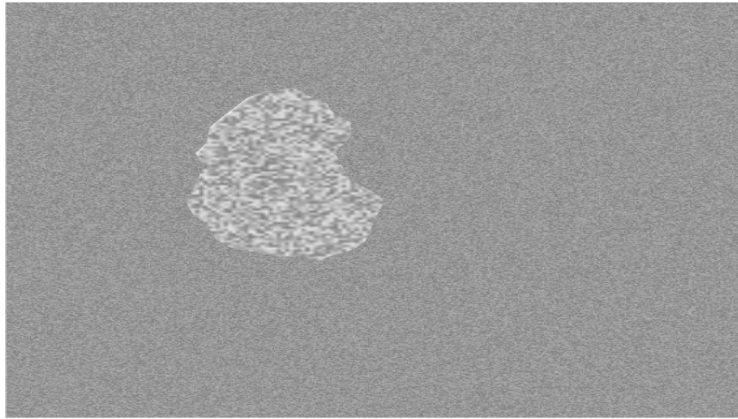
constitute the feature vector

$$\underline{x} = [x_1, \dots, x_l]^T \in R^l$$

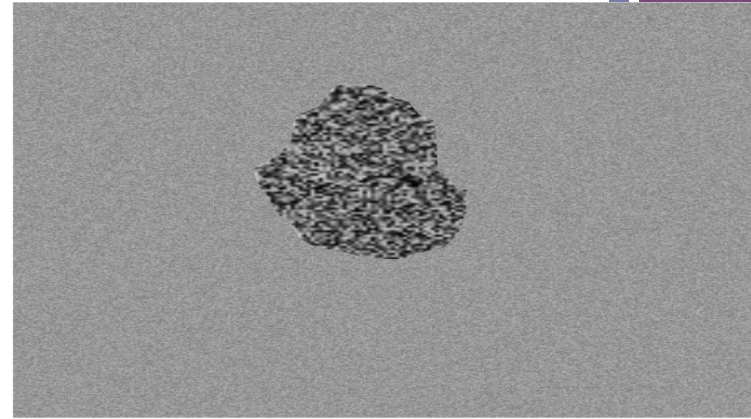
Feature vectors are treated as **random vectors**.

An example:

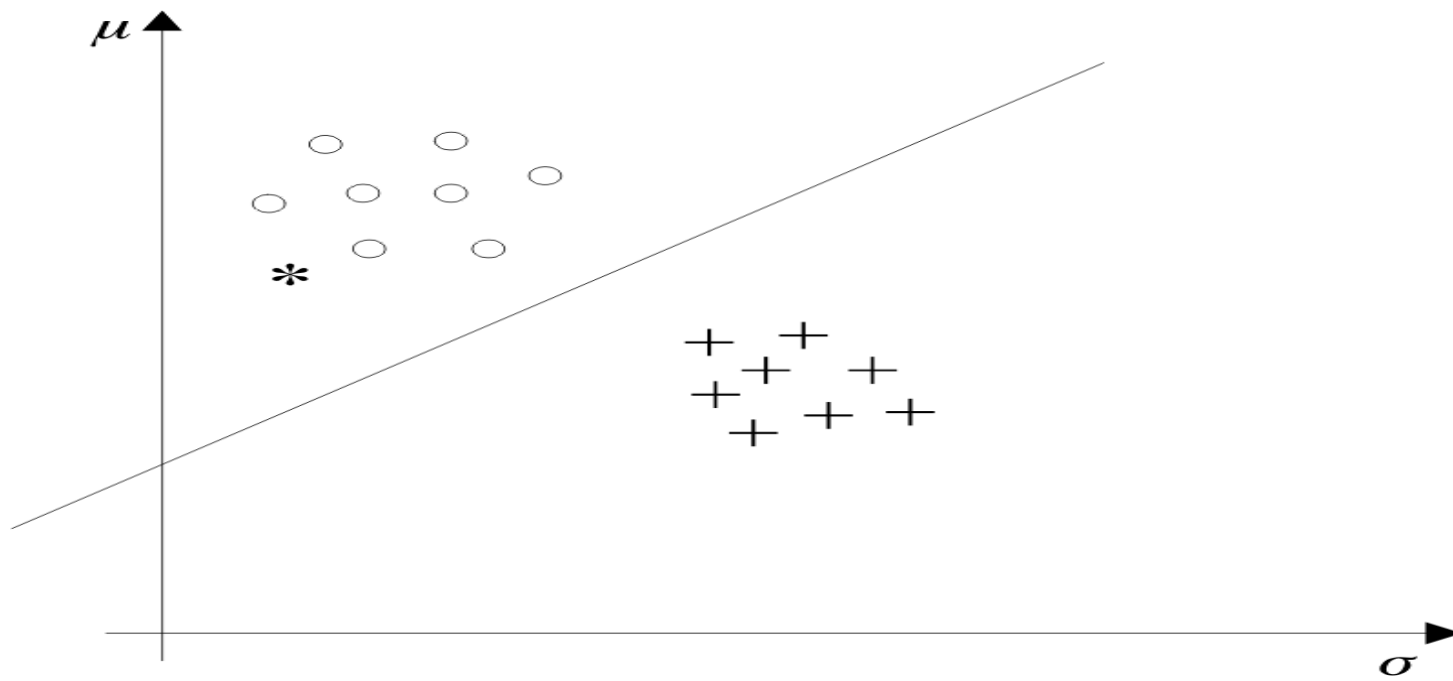
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(a)

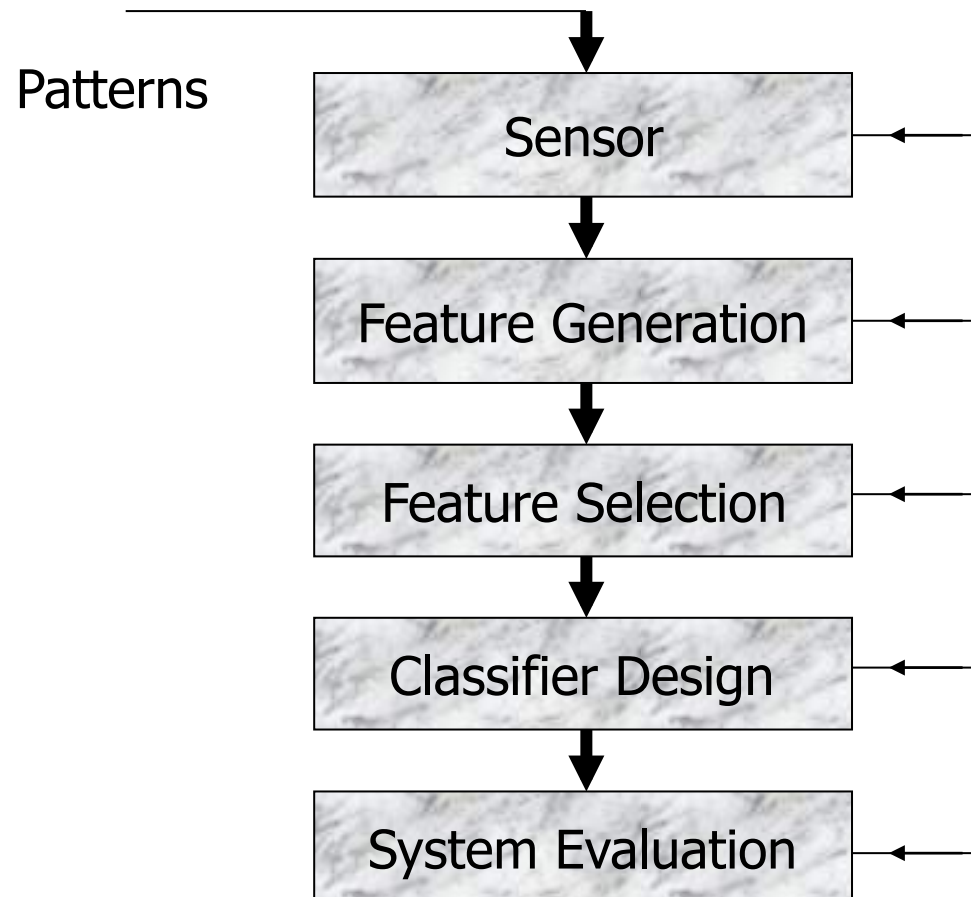


(b)



- The **classifier** consists of a **set of functions**, whose values, computed at  $x$ , determine the class to which the corresponding pattern belongs

- Classification system overview



# PR Different Paradigms

- Template matching and nearest neighbor approach
- Statistical techniques
- Syntactic (Structural) techniques
- Neural networks and SVMs
- HMMs
- Hybrid approaches

# Two Schools of Thinking

## 1. *Generative methods:*

Bayesian school, pattern theory.

- 1). Define patterns and regularities (graph spaces),
- 2). Specify likelihood model for how signals are generated from hidden structures
- 3). Learning probability models from ensembles of signals
- 4). Inferences.

## 2. *Discriminative methods:*

The goal is to tell apart a number of patterns, say 100 people in a company, 10 digits for zip-code reading. These methods hit the discriminative target directly, without having to understand the patterns (their structures) or to develop a full mathematical description.

For example, we may tell someone is speaking English or Chinese in the hallway without understanding the words he is speaking.

❖ “You should not solve a problem to an extent more than what you need”

# Levels of task

❖ For example, there are many levels of tasks related to human face patterns

1. Face authentication (hypothesis test for one class)
2. Face detection (yes/no for many instances).
3. Face recognition (classification)
4. Expression recognition (smile, disgust, surprise, angry)  
    identifiability problem.

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5. Gender and age recognition
  6. Face sketch and from images to cartoon  
    --- needs generative models.
  7. Face caricature

... ..

The simple tasks 1-4 may be solved effectively using discriminative methods,  
but the difficult tasks 5-7 will need generative methods.

# Schools and Streams

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❖ Schools for pattern recognition can be divided in three axes:

❖ Axis I: generative vs discriminative

(Bayesian vs non-Bayesian)

(--- modeling the patterns or just want to tell them apart)

❖ Axis II: deterministic vs stochastic

(logic vs statistics)

(have rigid regularity and hard thresholds or have soft constraints on regularity and soft thresholding)

❖ Axis III: representation---algorithm---implementation

❖ Examples:

Bayesian decision theory, neural networks, syntactical pattern recognition (AI),  
decision trees, Support vector machines, boosting techniques,

- **Supervised – unsupervised** pattern recognition:  
The two major directions
  - **Supervised:** Patterns whose class is known a-priori are used for training.
  - **Unsupervised:** The number of classes is (in general) unknown and no training patterns are available.



# BAYES DECISION THEORY

Introduction

# CLASSIFIERS BASED ON BAYES DECISION THEORY

- Statistical nature of feature vectors

$$\underline{x} = [x_1, x_2, \dots, x_l]^T$$

$$\omega_1, \omega_2, \dots, \omega_M$$

- Assign the pattern represented by feature vector to the **most probable** of the available classes

$$\text{That is } \underline{x} \longrightarrow \omega_i : \underset{\text{maximum}}{P(\omega_i | \underline{x})}$$

Known as M conditional probabilities (***a posteriori probabilities***)

Posterior probability  $\propto$  Likelihood  $\times$  Prior probability

- Computation of **a-posteriori** probabilities

- Assume known

- **a-priori** probabilities

$$P(\omega_1), P(\omega_2), \dots, P(\omega_M)$$

if  $N$  is the total number of available training patterns, and  $N_1, N_2$  of them belong to  $\omega_1$  and  $\omega_2$  respectively, then  $P(\omega_1) \approx N_1/N$  and  $P(\omega_2) \approx N_2/N$ .

$$p(\underline{x}|\omega_i), i = 1, 2, \dots, M$$

class-conditional probability density functions. This is also known as the **likelihood of**

$$\underline{x} \text{ w.r. to } \omega_i.$$

# Example

Suppose there is a mixed school having 60% boys and 40% girls as students. The girls wear trousers or skirts in equal numbers; the boys all wear trousers. An observer sees a (random) student from a distance; all the observer can see is that this student is wearing trousers. What is the probability this student is a girl?

The event G is that the student observed is a girl, and the event T is that the student observed is wearing trousers. To compute  $P(G|T)$ , we first need to know:

$$P(G) = 0.4$$

$$P(B) = 0.6$$

$$P(T|G) = 0.5$$

$$P(T|B) = 1$$

$$P(T) = P(T|G)P(G) + P(T|B)P(B) = 0.5 \times 0.4 + 1 \times 0.6 = 0.8$$

$$\text{Therefore: } P(G|T) = P(T|G)P(G) / P(T) = 0.5 \times 0.4 / 0.8 = 0.25$$

- The Bayes rule ( $M=2$ )

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

where

$$p(\underline{x}) = \sum_{i=1}^2 p(\underline{x} | \omega_i) P(\omega_i)$$

❖ The Bayes classification rule (for two classes  $M=2$ )

- Given  $\underline{x}$  classify it according to the rule

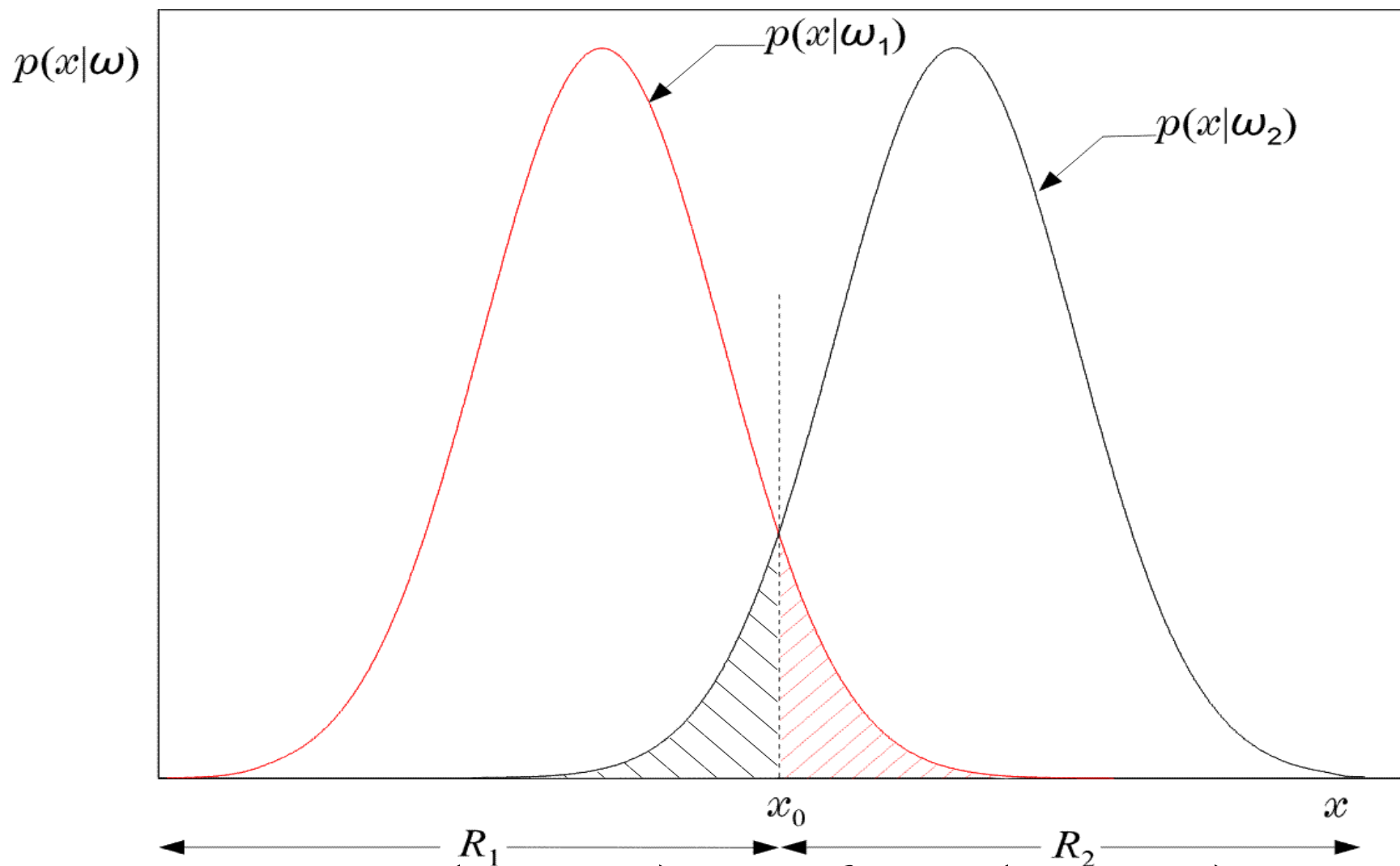
$$\begin{aligned} \text{If } P(\omega_1|\underline{x}) > P(\omega_2|\underline{x}) \quad \underline{x} &\rightarrow \omega_1 \\ \text{If } P(\omega_2|\underline{x}) > P(\omega_1|\underline{x}) \quad \underline{x} &\rightarrow \omega_2 \end{aligned}$$

- Equivalently: classify  $\underline{x}$  according to the rule

$$p(\underline{x}|\omega_1)P(\omega_1)(><)p(\underline{x}|\omega_2)P(\omega_2)$$

- For equiprobable classes the test becomes

$$p(\underline{x}|\omega_1)(><)P(\underline{x}|\omega_2)$$



$R_1(\rightarrow \omega_1)$  and  $R_2(\rightarrow \omega_2)$

If  $\underline{x} \in R_1 \Rightarrow \underline{x} \text{ in } \omega_1$

If  $\underline{x} \in R_2 \Rightarrow \underline{x} \text{ in } \omega_2$

# THE GAUSSIAN PROBABILITY DENSITY FUNCTION

The multidimensional Gaussian pdf has the form

$$p(x) = \frac{1}{(2\pi)^{l/2} |S|^{1/2}} \exp\left(-\frac{1}{2}(x - m)^T S^{-1}(x - m)\right)$$

where  $m = E[x]$  is the mean vector,  $S$  is the covariance matrix defined as  $S = E[(x - m)(x - m)^T]$ ,  $|S|$  is the determinant of  $S$ .

Often we refer to the Gaussian pdf as the *normal* pdf and we use the notation  $N(m, S)$ . For the 1-dimensional case,  $x \in \mathbb{R}$ , the above becomes

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x - m)^2}{2\sigma^2}\right)$$

where  $\sigma^2$  is the variance of the random variable  $x$ .



# Matlab Exercise 1

- Compute the value of a Gaussian pdf,  $N(m, S)$ , at  $x_1 = [0.2, 1.3]^T$  and  $x_2 = [2.2, -1.3]^T$ , where

$$m = [0, 1]^T, S = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

- **Solution.** Use the function *comp\_gauss\_dens\_val* to compute the value of the Gaussian pdf. Specifically, type

```
m=[0 1]'; S=eye(2);  
x1=[0.2 1.3]';  
x2=[2.2 -1.3]';  
pg1=comp_gauss_dens_val(m,S,x1);  
pg2=comp_gauss_dens_val(m,S,x2);
```

- The resulting values for *pg1* and *pg2* are 0.1491 and 0.001, respectively.

# Matlab Exercise 2

- Consider a 2-class classification task in the 2-dimensional space, where the data in both classes,  $\omega_1$ ,  $\omega_2$ , are distributed according to the Gaussian distributions  $N(m_1, S_1)$  and  $N(m_2, S_2)$ , respectively. Let:

$$m_1 = [1, 1]^T, m_2 = [3, 3]^T, S_1 = S_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Assuming that  $P(\omega_1) = P(\omega_2) = 1/2$ , classify  $x = [1.8, 1.8]^T$  into  $\omega_1$  or  $\omega_2$ .

- **Solution.** Utilize the function `comp_gauss_dens_val` by typing

```
P1=0.5;
P2=0.5;
m1=[1 1]'; m2=[3 3]'; S=eye(2); x=[1.8 1.8]';
p1=P1*comp_gauss_dens_val(m1,S,x);
p2=P2*comp_gauss_dens_val(m2,S,x);
```

- The resulting values for  $p_1$  and  $p_2$  are 0.042 and 0.0189, respectively, and  $x$  is classified to  $\omega_1$  according to the Bayesian classifier.