



## Course guide

### 200900 - ML - Machine Learning

**Last modified:** 12/06/2023

**Unit in charge:** School of Mathematics and Statistics  
**Teaching unit:** 723 - CS - Department of Computer Science.  
715 - EIO - Department of Statistics and Operations Research.

**Degree:** MASTER'S DEGREE IN ADVANCED MATHEMATICS AND MATHEMATICAL ENGINEERING (Syllabus 2010). (Optional subject).  
MASTER'S DEGREE IN STATISTICS AND OPERATIONS RESEARCH (Syllabus 2013). (Optional subject).

**Academic year:** 2023    **ECTS Credits:** 7.5    **Languages:** English

#### LECTURER

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**Coordinating lecturer:** LUIS ANTONIO BELANCHE MUÑOZ

**Others:** Segon quadrimestre:  
LUIS ANTONIO BELANCHE MUÑOZ - A  
PEDRO FRANCISCO DELICADO USEROS - A

#### PRIOR SKILLS

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The student should have knowledge of fundamental mathematical and statistical topics, such as linear algebra, calculus, probability distributions, optimization algorithms and basic multivariate statistical methods.

#### REQUIREMENTS

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The student should have knowledge of basic machine learning concepts. These concepts can be acquired simultaneously, for example being enrolled in the "Statistical Learning" subject offered in the MESIO master. It is not recommended that the student acquires this knowledge from the course itself.

#### DEGREE COMPETENCES TO WHICH THE SUBJECT CONTRIBUTES

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**Specific:**

MAMME-CE2. MODELLING. Formulate, analyse and validate mathematical models of practical problems by using the appropriate mathematical tools.

MAMME-CE4. CRITICAL ASSESSMENT. Discuss the validity, scope and relevance of these solutions; present results and defend conclusions.

#### TEACHING METHODOLOGY

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**On-Site Learning:** On-site learning will be organized into theoretical-practical sessions. All these sessions will be held in a standard classroom; students should bring their own laptops to the classroom. Lectures will normally combine a 75% of expository classes and a 25% of guided practical work. In the expository part of the sessions, the theoretical aspects are presented, discussed and accompanied by practical examples, using slides that will be previously supplied to the student. The fundamental work environment of the practical part of the sessions will be R, of which an intermediate knowledge is presumed (use of the environment and basic programming).

**Off-Site Learning:** Off-site learning will consist of the study and resolution of (mainly practical) problems that the student should turn in throughout the course. Some of these exercises will require completion of programming tasks in R and preparation of short reports using RMarkdown (or a similar tool).



## LEARNING OBJECTIVES OF THE SUBJECT

Upon completion of the course, the student should have acquired advanced competences on general topics and techniques for statistical machine learning (particularly for regularization-based learning algorithms) as well as for unsupervised learning, particularly data visualization. The student should be able to produce machine learning solutions for many complex problems, including those in which a reduction of dimension is necessary, those where the data comes as variables of different mixed types, or those where the number of variables greatly exceeds the number of observations, such as problems typically found in genomics.

## STUDY LOAD

Type	Hours	Percentage
Hours large group	60,0	32.00
Self study	127,5	68.00

**Total learning time:** 187.5 h

## CONTENTS

### Introduction to unsupervised learning

**Description:**

Definition and illustrative examples of unsupervised learning

**Full-or-part-time:** 2h

Theory classes: 2h

### Nonlinear dimensionality reduction

**Description:**

- Principal curves.
- Local Multidimensional Scaling.
- ISOMAP.
- t-Stochastic Neighbor Embedding.
- Applications

**Full-or-part-time:** 8h

Theory classes: 4h

Laboratory classes: 4h

### Dimensionality reduction with sparsity

**Description:**

- Matrix decompositions, approximations, and completion.
- Sparse Principal Components and Canonical Correlation.
- Applications

**Full-or-part-time:** 8h

Theory classes: 4h

Laboratory classes: 4h



### Gentle introduction to machine learning

**Description:**

Introduction to Bayesian thinking for machine learning. Learning by solving a regularized problem. Illustrative example.

**Full-or-part-time:** 5h

Theory classes: 2h

Practical classes: 3h

### Learning in functional spaces

**Description:**

Reproducing kernel Hilbert spaces. The representer theorem. Example 1: Kernel ridge regression. Example 2: The Perceptron and the kernel Perceptron.

**Full-or-part-time:** 8h

Theory classes: 4h

Practical classes: 4h

### The support vector machine for classification, regression and novelty detection

**Description:**

The support vector machine (SVM) is the flagship in kernel methods. Its versions for classification, regression and novelty detection are explained and demonstrated.

**Full-or-part-time:** 6h

Theory classes: 4h

Practical classes: 2h

### Kernel functions in $\mathbb{R}^d$

**Description:**

Description and demonstration of fundamental kernel functions in  $\mathbb{R}^d$ . Polynomial and Gaussian kernels. General properties of kernel functions.

**Full-or-part-time:** 4h

Theory classes: 2h

Practical classes: 2h

### Kernel functions for different data types

**Description:**

Some kernel functions for different data types are presented and demonstrated, such as text, trees, graphs, categorical variables, and others.

**Full-or-part-time:** 6h

Theory classes: 4h

Practical classes: 2h



### Other kernel-based learning algorithms

**Description:**

Additional kernel-based learning methods are explained, such as kernel PCA and kernel FDA. These are illustrated in several application examples. Finally, recent research on the fusion of deep neural networks and kernel functions will be presented, if time permits.

**Full-or-part-time:** 5h

Theory classes: 3h

Practical classes: 2h

### Advanced ideas and techniques in kernel-based learning methods

**Description:**

Other advanced methods are briefly introduced, such as the RVM and GPs. Nyström acceleration and random Fourier features. Introduction to the idea of Deep Kernel Learning

**Full-or-part-time:** 2h

Theory classes: 2h

## GRADING SYSTEM

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The grading method will be based in two basic marks, as follows:

- 1) Practical work done throughout the course: 50%
- 2) Final exam: 50%

The practical work will consist in a term project as well as several exercises, all of which can be done in groups (their format will be specified onsite), but the exam is completed as an individual task.

## EXAMINATION RULES.

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The precise format for the exam will be specified with sufficient advance. It may include restrictions on the allowed knowledge sources, such as written notes, books, internet connection, etc.



## BIBLIOGRAPHY

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### Basic:

- Hastie, Trevor; Tibshirani, Robert; Wainwright, Martin. Statistical learning with sparsity : the lasso and generalizations [on line]. CRC raton, 2015 [Consultation: 28/06/2023]. Available on : <https://ebookcentral-proquest-com.recursos.biblioteca.upc.edu/lib/upcatalunya-ebooks/detail.action?pq-origsite=primo&docID=4087701>. ISBN 78149871216.
- Bishop, Christopher M. Pattern recognition and machine learning. New York: Springer, cop. 2006. ISBN 9780387310732.
- Vapnik, Vladimir Naumovich. The Nature of statistical learning theory. 2nd ed. New York ; Barcelona [etc.]: Springer, cop. 2000. ISBN 9780387987804.
- Kung, S. Y. Kernel methods and machine learning [on line]. Cambridge University Press, 2014 [Consultation: 28/06/2023]. Available on : <https://www-cambridge-org.recursos.biblioteca.upc.edu/core/books/kernel-methods-and-machine-learning/4B52092A98E1553A26EB5271D832D29E>. ISBN 9781107024960.
- Schölkopf, Bernhard; Smola, Alexander J. Learning with Kernels : support vector machines, regularization, optimization, and beyond. Cambridge ; London: The MIT Press, cop. 2002. ISBN 9780262194754.
- Hastie, Trevor; Tibshirani, Robert; Friedman, Jerome. The Elements of statistical learning : data mining, inference, and prediction [on line]. 2nd ed. New York, NY: Springer New York, 2009 [Consultation: 28/06/2023]. Available on : <https://link-springer-com.recursos.biblioteca.upc.edu/book/10.1007/978-0-387-84858-7>. ISBN 9780387848587.

### Complementary:

- Smola, Alexander J. Advances in large margin classifiers [on line]. Cambridge, Mass: MIT Press, 2000 [Consultation: 28/06/2023]. Available on : <https://ebookcentral-proquest-com.recursos.biblioteca.upc.edu/lib/upcatalunya-ebooks/detail.action?pq-origsite=primo&docID=5966303>. ISBN 9780262194488.