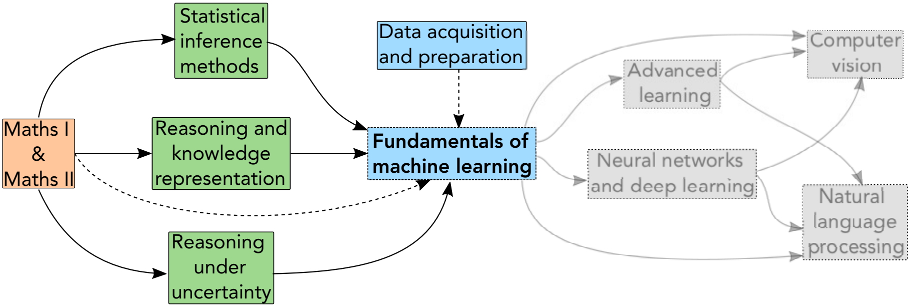
Fundamentos del Aprendizaje Automático

Grado en Ingeniería en Inteligencia Artificial

Departamento de Lenguajes y Sistemas Informáticos
Universidad de Alicante

Curso 2025/2026

Context


Statistical inference methods
Data acquisition and preparation
Maths I & Maths II
Reasoning and knowledge representation
Fundamentals of machine learning
Reasoning under uncertainty
Advanced learning
Computer vision
Neural networks and deep learning
Natural language processing

Objectives

1. Understand the foundations of machine learning.
2. Formalize machine learning problems from a mathematical and statistical perspective.
3. Select, train, and evaluate supervised and unsupervised learning models.
4. Apply data preprocessing techniques and choose appropriate evaluation metrics.
5. Use and interpret model evaluation and validation methods.
6. Critically analyse the results obtained with different algorithms and justify model design and selection decisions.

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Syllabus

1. Introduction to Machine Learning ($\sim$1-2 s.)
   Concepts, taxonomy, historical evolution, areas and applications
2. Computational learning ($\sim$3 s.)
   Decision theory, error probability, empirical risk minimization, model likelihood, under/overfitting, dimensionality
3. Model evaluation ($\sim$2-3 s.)
   Classification and regression scenarios, metrics, cross-validation and model selection
4. Nonparametric and distance-based learning ($\sim$2-3 s.)
   Distance-based classifiers, metrics, k-Nearest neighbor, Voronoi diagram
5. Linear methods and perceptron ($\sim$2-3 s.)
   Linear models, perceptron, activation, gradient, backpropagation
6. Unsupervised learning ($\sim$1-2 s.)
   Clustering, metrics
7. Statistical methods for model comparison($\sim$2 s.)

   Hypothesis testing, statistical significance, pair-wise/multiple comparison, post-hoc analysis

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Practical sessions

- Practical contents to support the understanding of the syllabus
- 3 (+1) labs
- What to do?
  - Different exercises in Python (basic scripts, programs, notebooks)
  - Report (2-3 long)
- Individual development and evaluation of the work
- No exam of the practical sessions

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Calendar

Date	Lesson	Practical content
09/09	T0: Module description T1: Introduction to Machine Learning	-
16/09	T1: Introduction to Machine Learning T2: Computational learning	P0
23/09	T2: Computational learning	P1 (delivery: 28/10)
30/09	T2: Computational learning	
07/10	T3: Model evaluation	
14/10	T3: Model evaluation	
21/10	T4: Nonparametric and distance-based learning	
28/10	T4: Nonparametric and distance-based learning	P2 (delivery: 25/11)
04/11	T4: Nonparametric and distance-based learning T5: Linear methods and perceptron	
11/11	T5: Linear methods and perceptron	
18/11	T5: Linear methods and perceptron	
25/11	T6: Unsupervised learning	P3 (delivery: 23/12)
02/12	T6: Unsupervised learning	
09/12	T7: Statistical methods for model comparison	
16/12	T7: Statistical methods for model comparison	

Evaluation

- Ordinary examination period. Two components:
  - **Final theoretical exam** (50%): written exam
  - **Assignment submission** (50%): practical assignments based on the contents covered in the lab sessions

  Average mark must be ≥ 5, with a **minimum of 4 in each part**; otherwise, failed course

- Extraordinary examination period.
  - **Single theoretical-practical exam** (100%).

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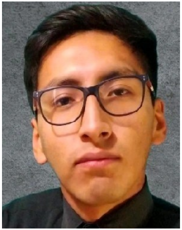
Lecturers

José Javier Valero Mas



Wilson Anthony Mamani Machaca

Bibliography

- Hart, P. E., Stork, D. G., & Duda, R. O. (2001). *Pattern classification*. Hoboken: Wiley.
- Bishop, C. M. (2006). *Pattern recognition and machine learning* (Vol. 4, No. 4, p. 738). New York: springer.
- Murphy, K. P. (2012). *Machine learning: a probabilistic perspective*. MIT press.

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