TEACHING GUIDE - 2025-2026

Machine Learning

UGRA_015032

Departments	Data, Analytics, Technology and Artificial Intelligence (DATA), Dept. of Operations, Innovation & Data Sciences
Teaching Languages	English
ECTS	6
Teacher responsible	Maria De-Arteaga - maria.dearteaga@esade.edu

Course Goals

By the end of the course, students will be able to:

- Apply unsupervised learning techniques for dimensionality reduction and clustering: Students will implement and compare methods such as Principal Component Analysis (PCA), and density-based and spectral clustering to explore structure in unlabeled data, reduce dimensionality for visualization or preprocessing, and identify meaningful groupings within datasets.
- Implement and optimize complex ML algorithms: Write efficient implementations (or adapt existing libraries) for algorithms such as ensemble supervised methods, clustering algorithms, and reinforcement learning agents; fine-tune hyperparameters using techniques like grid search, random search, or Bayesian optimization.
- Design and implement active learning workflows: Build machine learning workflows that incorporate active learning loops, including uncertainty-based query strategies, human-in-the-loop data labeling, iterative model retraining, and evaluation of labeling efficiency and model improvement over time.
- Apply ML to real-world scenarios with critical judgment: Analyze a real-world dataset or business problem, select and justify an appropriate ML strategy, train and validate models, and identify potential pitfalls such as data leakage, overfitting, or bias. Present results in a clear, reproducible, and business-relevant format.

Previous knowledge

Students should have a foundational understanding of machine learning concepts, algorithms, and techniques. This includes familiarity with key concepts such as classification and regression, supervised versus unsupervised, as well as model training and evaluation, error measures, and performance metrics. A strong background in statistics and probability theory is also expected, as well as proficiency in linear algebra and calculus, especially in differentiation and optimization techniques. Additionally, this will be a hands-on course, so experience with Python is required; students should be comfortable writing and debugging code. Finally, students are expected to be familiar with data preprocessing, cleaning, and exploratory data analysis (EDA) techniques.

Prerequisits

- Programming with data
- Optimízation and computational modeling
- Introduction to Artificial Intelligence

Teaching methodology

This course will combine a theoretical description of topics and practical implementation. During lecture-style sessions that provide conceptual and theoretical descriptions, students are expected to participate actively; asking clarifying questions and responding to the professor's questions are useful learning strategies. The course will emphasize hands-on experience through practical assignments and projects. For hands-on sessions, students will bring their laptops to class. Laptops in the classroom should only be used for class-related activities.

This course will be managed through a dedicated eCampus website, where students will find all the necessary class materials, including assigned readings and pre-class work, deliverables and exercises, and further references. Students should familiarize themselves with this environment before the start of the course and regularly check for updates.

Description

Course contribution to program

This course is a follow-up to the Introduction to Artificial Intelligence course. It builds upon students' previous knowledge of data structures, algorithmic techniques and computational problem solving to explore additional topics in machine learning, including various supervised and unsupervised learning algorithms, as well as introduction to other machine learning paradigms like active learning and reinforcement learning. This course will expand students' knowledge of various techniques that are applicable to diverse business problems, and it will equip students with the technical knowledge necessary to implement these solutions. By the end of the course, students will have a comprehensive view of different machine learning algorithms, and will be prepared to take the Deep Learning course in their final year. The course will also mature students' ability to think critically about the potential application of machine learning in a given business or organizational setting, which will help students strengthen their leadership and managerial skills. Having an in-depth technical understanding of machine learning will also serve as an important foundation for courses such as AI for Sustainable Leadership and Data and Business Ethics.

Short description

This course is designed to deepen students' understanding of machine learning techniques, building on foundational knowledge acquired in previous courses. Students will gain

conceptual and theoretical understanding of various machine learning algorithms, and will develop the ability to critically analyze their performance and anticipate potential implications of their deployment in a given setting. Practical exercises will enable
students to implement and optimize these algorithms, reinforcing their coding skills, and equipping them with the ability to design and implement complete machine learning pipelines.

Bibliography

Tom Mitchell, Machine Learning, McGraw Hill (Book)
Trevor Hastie, Robert Tibshirani, Jerome Friedman, The Elements of Statistical Learning, Springer (Book)

Burr Settles, Active Learning Literature Survey, University of Wisconsin-Madison Department of Computer Sciences (Article)

Richard S. Sutton and Andrew G. Barto, Reinforcement Learning: An Introduction, Cambridge: MIT press (Book)

Content

#	Topic
1	Ensemble Learning and Bagging Techniques: Students will be introduced to the fundamental concepts of ensemble learning, explaining its importance and the basic idea behind combining multiple models to improve overall performance. Key concepts such as bias-variance trade-off, model diversity, and voting mechanisms will be covered. Students will also delve into bagging (Bootstrap Aggregating) methods, learning how bagging reduces variance and improves model stability, and gaining practical experience implementing and tuning bagging algorithms.
2	Boosting Methods: The course will also cover boosting techniques. Students will theoretically understand how boosting sequentially combines weak learners to form a strong learner, and will engage in practical exercises to implement and optimize boosting models.
3	Advanced clustering approaches: This topic will build on students' statistical knowledge of the basics of clustering. It will cover advanced clustering algorithms to handle distinct data distributions. It will also explore the importance of clustering in unsupervised learning and discuss the implications of choosing different clustering approaches.
4	Reinforcement Learning: Students will be introduced to the reinforcement learning paradigm. Students will understand the general paradigm of selecting actions that maximize a reward in a dynamic environment, and will gain practical experience with at least one reinforcement learning algorithm.
5	Active Learning: Students will be introduced to the active learning paradigm. They will understand the motivation behind reducing labeling costs by selecting the most informative data points for annotation. The course will cover key query strategies, such as uncertainty sampling, query-by-committee, and diversity-based methods. Students will gain practical experience by implementing an active learning loop and evaluating its performance in terms of model improvement and labeling efficiency.

Assessment

Tool	Assessment tool	Category	Weight %
Attendance and punctuality	Attendance. In accordance with ESADE regulations, attendance is mandatory for this course. Students who fail to attend 80% of the course will not be allowed to pass and will be required to sit the retake exam.	Ordinary round	0.00%
Written and/or oral exams	Midterm exam	Ordinary round	20.00%
Written and/or oral exams	Final exam. A minimum grade of 4/10 is required to pass the course.	Ordinary round	40.00%
Individual or team exercises	Assignments: Students will submit several deliverables throughout the course	Retake and ordinary round	25.00%
Group project	Final project: Students will complete a final project in groups	Ordinary round	15.00%
Written and/or oral exams	Retake exam	Retake	75.00%

PROGRAMS

DBAI21-Double Degree in Business Administration and Artificial Intelligence for Business (Undergraduates: Business)

DBAI21 Year 3 (Mandatory)

DBAI23-Double Degree in Business Administration and Artificial Intelligence for Business (Undergraduates: Business)

DBAI23 Year 3 (Mandatory)