COURSE DATA

DATA SUBJECT

Code: 46579
Name: Causal inference and machine learning
Cycle: Master's Degree
ECTS Credits: 3
Academic year: 2026-27

STUDY (S)

Degree	Center	Acad. year	Period
2262 - Master's Degree in Data Science	Escola Tècnica Superior d'Enginyeria	1	Second quarter

SUBJECT-MATTER

Degree	Subject-matter	Character
2262 - Master's Degree in Data Science	Causal inference and machine learning	COMPULSORY

COORDINATION

MONTORO PONS JUAN DE DIOS

SUMMARY

Causal Inference and Machine Learning aims to provide a solid understanding of the fundamental concepts and techniques used to estimate causal relationships as well as to explore recent advances with the incorporation of methods based on machine learning. All this is motivated through applications using data from different fields of study, mainly economics but also other areas such as sociology, medicine, epidemiology, biology or ecology.

The course gradually addresses the main aspects of causal inference. It starts from a research design aimed at answering a causal question (effect of a treatment X on the response Y) and the introduction of the differences between the use of experimental and observational data. Specifically, we explore the distinction between data obtained through controlled experiments and data in which the researcher lacks control over the generation process. Empirical research using quantitative methods and machine learning relies mostly on observational data, such as data collected from an organization's internal records, from instruments designed for specific purposes (surveys), or generated through online activity to name just a few. In this context, the strengths and weaknesses of each data type are discussed and the main challenge associated with the use of observational data to test causal relationships, i.e. the problem iof identification, is examined. This arises from the difficulty of estimating precise and unbiased causal relationships using non-experimental data that, in the absence of a theoretical model and an adequate empirical strategy, only provides correlations.

From a theoretical perspective, complementary approaches for the modeling of causal relationships are proposed. We introduce DAGs (Directed Acyclic Graphs) as a tool to represent and visualize the causal structure of a model and help in its identification strategy. Additionally, the potential outcomes model explores the idea of the contrast between observed outcomes and those that would have been observed under different treatment conditions (counterfactuals). The latter allows us to identify the problem of causal inference as a missing value problem and connects it with recent developments in machine learning.

Next, we introduce different techniques for the estimation of causal effects under the assumption of selection on observables. Here we deal with those methods that seek to mitigate bias in observational data stemming from the existence of confounders (observed variables that influence both the response and the treatment). Specifically, parametric methods such as regression, and semi-parametric/non-parametric methods such as matching or propensity score weighting are discussed.

The catalogue of techniques for selection on observables is expanded with machine learning methods, which make it possible to model complex relationships between variables flexibly and to incorporate, where appropriate, unstructured data into the estimation of causal effects. In this context, double machine learning combines predictive algorithms with causal identification strategies to estimate average effects. In addition, metalearners extend this approach to the estimation of heterogeneous effects, exploring how treatment impacts vary across units or groups. Finally, causal trees and causal forests provide specific tools to detect, characterise, and analyse this heterogeneity in causal effects.

The last block of the subject deals with selection techniques on unobservables, a situation in which there are latent traits affecting treatment and outcome (or, to put it differently, there are confounders that cannot be measured). This is a complex methodological challenge that requires the introduction of additional hypotheses for the estimation of causal effects. The validity of the results is based on the plausibility of these restrictions and on an appropriate validation strategy. This part includes designs whose origin is in econometrics: instrumental variables, selection models, fixed effects, differences in differences, and regression discontinuity designs. Likewise, the literature on machine learning offers flexible alternatives for solving the problem, such as instrumental forests.

PREVIOUS KNOWLEDGE

RELATIONSHIP TO OTHER SUBJECTS OF THE SAME DEGREE

There are no specified enrollment restrictions with other subjects of the curriculum.

OTHER REQUIREMENTS

There are no prerequisites.

COMPETENCES / LEARNING OUTCOMES

2262 - Master's Degree in Data Science

Be able to assess the need to complete their technical, scientific, language, computer, literary, ethical, social and human education, and to organise their own learning with a high degree of autonomy.

Capacidad de organización y planificación de actividades de investigación, desarrollo y consultoría en el área de ciencia de datos.

Diseñar y poner en marcha soluciones basadas en análisis de datos teniendo en cuenta los requisitos específicos para cada aplicación.

Extraer conocimiento de conjuntos de datos en diferentes formatos.

Modelar la dependencia entre una variable respuesta y varias variables explicativas, en conjuntos de datos complejos, mediante técnicas de aprendizaje máquina, interpretando los resultados obtenidos.

Ser capaces de acceder a herramientas de información (bibliográficas y de empleo) y utilizarlas apropiadamente.

Ser capaces de asumir la responsabilidad de su propio desarrollo profesional y de su especialización en uno o más campos de estudio, aplicando los conocimientos adquiridos en la identificación de salidas profesionales y yacimientos de empleo.

Students should be able to integrate knowledge and address the complexity of making informed judgments based on incomplete or limited information, including reflections on the social and ethical responsibilities associated with the application of their knowledge and judgments.

Students should communicate conclusions and underlying knowledge clearly and unambiguously to both specialized and non-specialized audiences.

Students should demonstrate self-directed learning skills for continued academic growth.

Students should possess and understand foundational knowledge that enables original thinking and research in the field.

DESCRIPTION OF CONTENTS

1. Introduction to causal inference

• Pure prediction problems vs. causal inference problems
• Experimental data and observational data
• The problem of identification
• Directed Acyclic Graphs (DAGs)
• The model of potential results (Rubin's model)
• Types of causal effects
• Identification strategies

2. Selection on observables

• Selection on observables and identification: parametric and non-parametric methods
• Matching
• Propensity score matching
• Diagnosis
• Doubly robust estimation
• Inverse probability weighting

3. Causality and machine learning

• Causal inference and prediction
• Double machine learning (DML)
• Use of metalearners for the estimation of heterogeneous effects
• Causal trees and causal forests
• Other machine learning developments applied to causal inference

4. Selection on unobservables

• Selection models
• Instrumental variables
• Panel data: fixed effects and random effects.
• Panel data: differences in differences
• Discontinuity regression
• Machine learning developments in selection on unobservables

WORKLOAD

PRESENCIAL ACTIVITIES

Activity	Hours
Theory	19,00
Theoretical and practical classes	2,00
Laboratory	9,00
Total hours	**30,00**

NON PRESENCIAL ACTIVITIES

Activity	Hours
Attendance at other activities	0,00

Individual or group project	15,00
Independent study and work	10,00
Preparation of lessons	10,00
Preparation for assessment activities	10,00
Resolution of case studies	0,00
Total hours	**45,00**

TEACHING METHODOLOGY

Theoretical activities. Expository development of the subject with the participation of the student in the resolution of specific questions. Carrying out individual evaluation questionnaires.

Practical activities. Learning through problem solving, exercises and case studies through which skills are acquired on different aspects of the subject.

Work in laboratory and/or computer classroom. Learning by carrying out activities carried out individually or in small groups and carried out in computer classrooms.

EVALUATION

1. One or several tests that will consist of both theoretical-practical questions and problems (30%)
2. Evaluation of the practical activities from the elaboration of works/reports, oral presentations and e-learning tools of the University (60%).
3. Evaluation based on the participation and degree of involvement of the student in the teaching-learning process, taking into account regular attendance at the planned face-to-face activities and the resolution of questions and problems proposed periodically (10%).

In the second examination call:
Section 1 will be reassessed through an objective test identical to the one in the first call.
For section 2, students who have not achieved the full grade corresponding to the continuous assessment may recover it by taking an additional test. This test will be held on a date to be determined, coinciding with the second call exam or at a later time, and will consist of an oral presentation by the student of one of the practical assignments submitted during the course, selected at random, followed by a Q&A session on its content. Passing this test will allow the student to recover a maximum of 50% of the continuous assessment grade; it is not possible to obtain the full grade through this test.
The grades obtained in section 3 will be retained for both calls of the academic year in which they were awarded, given that their evaluation is only possible during the teaching period.

REFERENCES

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