Course unit English denomination	Applied Multivariate Techniques
SS	STAT-01/A, STAT-01/B
Teacher in charge (if defined)	Livio Finos
Teaching Hours	20
Number of ECTS credits allocated	3
Course period	12/2025-02/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	- Matrix decompositions and Dimensionality Reduction - Multidimensional Scaling and other dimensionality reduction methods - Modern multiple testing approaches - Univariate and Multivariate Permutation testing - Knockoff Methods, Split methods for post-selection inference - Conformal Inference - Summary and insight into further research directions
Learning goals	This course aims to equip students with the knowledge and skills to apply advanced multivariate statistical techniques in real-world data analysis scenarios. By the end of the course, students will be able to: - Understand and implement key matrix decompositions and dimensionality reduction methods for simplifying complex datasets. - Apply various techniques for visualizing and interpreting high-dimensional data, including multidimensional scaling and other modern dimensionality reduction methods. - Learn and apply modern multiple testing approaches, with a focus on controlling the false discovery proportion in high-dimensional settings.
Teaching methods	• Lectures • Laboratories

Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation and until the maximum number of students has been reached
Prerequisites (not mandatory)	
Examination methods (in applicable)	None
Suggested readings	• Course material available from the instructor • Mardia, K. V., Kent, J. T., Bibby, J. M. (1979). Multivariate Analysis. Academic Press
Additional information	

Course unit English denomination	Bayesian Data Analysis and Computation
SS	STAT-01/A
Teacher in charge (if defined)	• Brunero Liseo • Andrea Tancredi
Teaching Hours	18
Number of ECTS credits allocated	3
Course period	05/2026-06/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	- Prior distributions for Bayesian Inference: Objective vs. Subjective - Posterior simulation and Monte Carlo methods - Markov Chain Monte Carlo and other computational methods - Prediction, Model Selection and Testing - MCMC in practice: linear models, generalized linear models and other case studies - Mixture models and hierarchical models - Approximate Bayesian Computation and sequential Monte Carlo methods
Learning goals	Participants will learn posterior simulation techniques using Monte Carlo methods. They will understand and implement Markov Chain Monte Carlo (MCMC) methods for Bayesian analysis, conducting prediction, model selection, and testing. The course will cover practical applications of MCMC in linear and generalized linear models, as well as mixture and hierarchical models. Additionally, participants will gain insights into Approximate Bayesian Computation and sequential Monte Carlo methods for complex models.
Teaching methods	• Lectures • Laboratories
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No

Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation and until the maximum number of students has been reached
Prerequisites (not mandatory)	
Examination methods (in applicable)	None
Suggested readings	• Course material available from the instructors
Additional information	

Course unit English denomination	Bibliography, plagiarism, academic publishing
SS	-
Teacher in charge (if defined)	• Bruno Costantina • Cattarinussi Raffaella • Rubino Elisa • Visentin Michele • Zorzi Michela
Teaching Hours	9
Number of ECTS credits allocated	1
Course period	01/2026-02/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	First module: How to do an effective bibliographic research in Padua University 1. Services and resources. 2. Databases by topics. Second module: Bibliography and Plagiarism 1. Bibliographic citations and citation styles. Plagiarism. 2. Reference management: introduction to Zotero. Integration with LaTeX. Third module: Bibliometrics and academic publishing 1. Introduction to bibliometrics. Academic publishing and Open Access. 2. Padua Research Archive (PRA/IRIS), the institutional repository for academic research.

	Fourth module: Open Science and PhD thesis 1. Institutional repositories for the outputs of research. 2. Management of PhD theses.
Learning goals	Participants will learn how to conduct effective bibliographic research using university resources and topic-specific databases. They will master citation practices, avoid plagiarism, and gain proficiency in using Zotero for reference management and LaTeX integration. The course will cover bibliometrics, academic publishing, and Open Access concepts, alongside navigation of the Padua Research Archive for research outputs. Finally, participants will understand Open Science principles and manage PhD theses within institutional frameworks, enhancing their academic research skills.
Teaching methods	• Lectures and practices
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted until the maximum number of students has been reached.
Prerequisites (not mandatory)	None
Examination methods (in applicable)	None
Suggested readings	Course material available from the instructors
Additional information	Students who have attended the training activity of the master course in Statistical Sciences are exempt from the first two modules.

Course unit English denomination	Functional Analysis
SS	MATH-03/A
Teacher in charge (if defined)	Annalisa Cesaroni
Teaching Hours	22
Number of ECTS credits allocated	3
Course period	11/2025-01/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	**Measure theory and integration.** Definition of σ-algebras, definition of measures, and measure spaces. Borel σ- algebras and Borel measures. Characterization of σ-finite Borel measures on R in terms of the cumulative distribution function. Definition of the Lebesgue measure on R and R^n. Measurable functions, and random variables. Definition of the Lebesgue integral. Singular measures and absolutely continuous measures with respect to the Lebesgue measure. Density of an absolutely continuous measure. The Lebesgue-Radon-Nikodym decomposition theorem, differentiation of measures. Distribution of random variables (discrete and continuous). **Banach spaces.** L^p spaces and spaces of random variables with finite p-moment. Definition of Banach spaces, norms, metric structure induced by the norm. Young inequality, Holder inequality, Minkowski inequality, with applications, e.g. boundedness of moments of a random variable. Bounded linear operators. **Hilbert spaces.** Hilbert spaces, theorem of orthogonal projection and conditional expectation. Orthonormal basis of a Hilbert space, computation of the orthogonal projection. Linear least square estimator. Fourier series and Fourier transform in L^2. Bounded linear operators in a Hilbert space, adjoint of an operator, eigenvalues, spectrum. Spectral theorem for compact symmetric operators, Hilbert-Schimdt operators. Notion of weak derivative. The Sobolev space H^1.

Learning goals	The aim of the course is to provide basic notions and tools in the (infinite-dimensional) setting of Linear Functional Analysis. The students will acquire knowledge and understanding of many basic tools which are of common use in the analysis of infinite dimensional vector spaces (e.g. the theory of Banach and Hilbert spaces, of linear, bounded, and compact operators), which are of fundamental importance in many branches of applied mathematics, in particular in probability theory and statistics. Moreover the students will be able to solve simple problems requiring manipulation or application of the concepts and results introduced in this course and apply their knowledge in mathematical and statistical domains where functional analytic techniques are relevant.
Teaching methods	• Lectures
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation by the Faculty Board
Prerequisites (not mandatory)	Basics of linear algebra. Basics of calculus.
Examination methods (in applicable)	Written exam on the contents of the course
Suggested readings	• Course material available from the instructor • A. Bressan Lecture notes in Functional Analysis with application to linear partial differential equations . AMS 2012. • G. B. Folland Real Analysis: modern tecniques and their applications. Wiley 1999 (2nd ed)
Additional information	

Course unit English denomination	Kalman Filter and State Space Models
SS	STAT-02/A
Teacher in charge (if defined)	Siem Jan Koopman
Teaching Hours	9
Number of ECTS credits allocated	1
Course period	06/2026-07/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No

Course unit contents	- Introduction
	- Time Series Models
	  - Local Level Model
	  - Unobserved Component Time Series Models
	  - Multivariate Extension, incl. Dynamic Factor Models
	- State Space Methods
	  - Kalman Filter
	  - Observation Weights
	  - Log likelihood Evaluation and Parameter Estimation
	  - Diagnostic Checking
	  - Smoothing
	  - Missing Values and Forecasting
	  - Usage of Principal Components
	- Nonlinear non-Gaussian Extensions
	  - Extended Kalman filter
	  - Dynamic models for discrete data
	  - Stochastic Volatility
	- Conclusion and Discussion

Learning goals	Students will understand the principles of state space models and Kalman Filters, including the necessary mathematical foundations. They will learn to model dynamic systems, design and implement standard and extended Kalman Filters, but also particle filters, and evaluate their performance through diagnostic error analysis. The course will cover real-world applications and software development for implementation.

Teaching methods	• Lectures • Laboratories
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation and until the maximum number of students has been reached
Prerequisites	An intermedaite level of statistical theory, time series models and matrix algebra are required for this course.
Examination methods (in applicable)	None
Suggested readings	• Course material available from the instructor • Commandeur, J. J. F. & Koopman, S. J. (2007). An Introduction to State Space Time Series Analysis. Oxford University Press • Durbin, J. & Koopman, S. J. (2012). Time Series Analysis by State Space Methods. Oxford University Press
Additional information	

UNIVERSITÀ DEGLI STUDI DI PADOVA

SCIENZE STATISTICHE

Course unit English denomination	Probability Theory
SS	MATH-03/B
Teacher in charge (if defined)	Athena Picarelli
Teaching Hours	42
Number of ECTS credits allocated	7
Course period	11/2025-01/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	- Basics on probability spaces and random variables. Independence of random variables. - Conditional distribution and expectations. Characteristic and moment generating functions. Functions of random variables - Order statistics and martingales. Normal distribution theory. - Convergence of random variables and review of limit theorems: Laws of Large Numbers and Central Limit Theorems. - Stochastic processes: general definitions, filtrations, martingales, stopping times. - Discrete time Markov processes: Markov property and transition matrix. Canonical representations. Communication, irreducibility and periods. Stationarity. Convergence to steady state. Renewal equation and renewal theorem. Time to absorption and probability of absorption. - Generalities on continuous-time stochastic processes. Poisson process. Continuous time Markov chains: transition semigroup, infinitesimal generator. Diffusion processes.
Learning goals	The students are supposed to achieve a deep knowledge of probability theory starting from basic concepts to more advanced ones. Objective of the course is to provide theoretical insights on the topics and us them for solving practical exercises.
Teaching methods	Lectures

Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation by the Faculty Board
Prerequisites (not mandatory)	Basic notions on Probability
Examination methods (if applicable)	Written Test
Suggested readings	Course material available from the instructor
Additional information	

Course unit English denomination	Programming Methodologies for Data Analysis
SS	IINF-05/A
Teacher in charge (if defined)	• Luca Di Gaspero • Kevin Roitero
Teaching Hours	30
Number of ECTS credits allocated	5
Course period	11/2025-01/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	The course will be split in a set of conceptual lectures (18h) and a set of guided practice (12h). The detailed topics that will be covered by the course include: - Basic data types, control flow, structured data types (tuples, sets, lists, dictionaries, strings), functions; - Comprehensions and generators; - Functional programming style and higher-order functions (map, filter, reduce); - Input/Output (file manipulation, network access), Exceptions, modules and packages; - Data representation and manipulation libraries (numpy, pandas, json, xml); - Web scraping (playwright); - Data visualization (seaborn/plotly) and dashboards (streamlit/dash); - BigData Platforms (pySpark); - Neural Networks Libraries (PyTorch); - Natural Language Processing (HuggingFace); - HyperParameter tuning (Optuna).
Learning goals	The course aims at providing a comprehensive working knowledge of different computer programming styles using the Python language. After introducing language basics, the course will cover specifically functional programming in Python, which is the fundamental tool of several data- processing libraries and frameworks. Moreover, a few relevant modules from the Python standard library will be introduced, with a particular focus at the data-analysis and machine learning

	ecosystem. Also, we will cover best practices to use programming for executing frequent tasks and will investigate how to use Python in different scenarios, from small scripting tasks to medium-scale projects.
Teaching methods	• Lectures • Laboratories
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation by the Faculty Board
Prerequisites (not mandatory)	Basic programming skills are beneficial but not mandatory for this course.
Examination methods (if applicable)	The assessment will consist of weekly homework assignments and a final written exam. The homework assignments will allow students to apply the concepts learned in class on a regular basis, reinforcing their understanding. The final exam will focus on demonstrating mastery in data processing and wrangling using the tools and techniques covered throughout the course.
Suggested readings	• Course material available from the instructors
Additional information	

Course unit English denomination	Statistical Consulting
SS	STAT-01/A, STAT-01/B, STAT-02/A, STAT-03/A, STAT-03/B
Teacher in charge (if defined)	• Emanuele Aliverti • Mariangela Guidolin
Teaching Hours	30
Number of ECTS credits allocated	5
Course period	03/2026-05/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	Course Description The course allows students to apply commonly encountered statistical methods in the consulting environment. Written and oral communication skills are emphasized (in order to both understand the clients' needs and present the results) and ethical aspects of consulting are introduced. The course provides students with an opportunity to gain practical experience in consulting through various projects with clients. The course immerses students in real world consulting, exposing them to all aspects of statistical data analysis including understanding the applied context and its goals, data collection, data modeling, and presentation of the results. Through a consulting program inside and outside the University, students work with researchers and practitioners from a multitude of disciplines providing recommendations for statistical methodologies appropriate for their problems. Projects are also examined through the lens of ethics underlying data collection, model assumptions, analysis, reproducibility, and reporting of results. Tentative course topics: About consulting classes dedicated to the following topics - Communication - Asking Questions - Managing a Session - Dealing with Difficult Clients

	- Research ethics - Legal aspects, privacy and confidentiality - Consulting from Start to Finish Practical sessions of consulting Students, teachers, researchers and professionals from inside and outside the University are assigned a team of `student consultants', who hold an intake meeting with the client and find out the details of their project and consulting request. Then, the consulting team presents the project to the class and the class discusses the problem and comes up with suggestions. The consulting team then reports the suggestions back to the client.
Learning goals	The overall objectives of the statistical consulting course are: - to provide doctoral students with practical consulting and communication skills, such as how to present results verbally and in a written report, and - how to work cooperatively with other researchers and/or practitioners
Teaching methods	● Lectures ● Group homework ● Student's written and oral presentations ● Problem solving ● Project work ● Feedback ● Assessment activities during the course ● Develop collaborative and supportive peer relationships
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☐ Yes ☒ No
Prerequisites (not mandatory)	
Examination methods (in applicable)	The evaluation of students' performance will be based on two key components: their active engagement throughout the course and the quality of their contributions to the case studies. Active participation includes involvement in class discussions, group work, and collaboration on consulting tasks. The case studies will serve as practical assessments, where students are expected to apply statistical methods to real-world problems, demonstrate critical thinking, and presentation skills.
Suggested readings	● Course material available from the instructors
Additional information	

Course unit English denomination	Statistical Models
SS	STAT-01/A, STAT-01/B, STAT-02/A, STAT-03/A, STAT-03/B
Teacher in charge (if defined)	• Bruno Scarpa • Mauro Bernardi • Stefano Mazzuco • Davide Risso
Teaching Hours	90
Number of ECTS credits allocated	15
Course period	02/2026-06/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	*What is a statistical model* *Nonparametric statistics* – Nonparametric estimation of functions – Nonparametric regression – Nonparametric classification – Multivariate nonparametric regression *Experimental design* – Basic techniques – Modern techniques *Statistical models for high-dimensional data* – Extensions of lasso – Inference in the context of the lasso – Graphical models *Reproducible research and R best practices* *Random effects, multilevel models, hierarchical models* – Linear and generalized mixed models inference

	– Bayesian and frequentist estimators – Hierarchical nonparametric methods – Nonlinear mixed models *Models for dependent observations* Gaussian process regression; – Modelling time series – Dynamic autoregressive models; – Bayesian inference for autoregressive models; – Prior shrinkage and variable selection; – Factor analysis In each topic there will be a focus to analytical development of models and to computational methods (introduction to optimization theory, convex optimization and duality, MCMC algorithms, variational methods).
Learning goals	The course aims to provide students with an advanced understanding of statistical modeling, from the development of models, through their estimation using both Bayesian and frequentist approaches, to their application in interpretation, knowledge enhancement, and prediction. Problem-solving skills are strengthened through weekly homework, assigned to small groups and subsequently discussed with the entire class. Students are also introduced to the study of various bibliographic sources, including books and scientific articles. Enhancing writing and presentation skills is also part of the program.
Teaching methods	• Lectures • Group homework • Student's written and oral presentations (posters) • Problem solving • Project work • Feedback • Assessment activities during the course • Develop collaborative and supportive peer relationships
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation by the Faculty Board
Prerequisites (not mandatory)	• Linear models and their generalizations: generalized linear models (GLM), nonlinear models, models for ordinal and categorical data, maximum likelihood estimation principle and its properties, least squares estimation paradigms and their penalised generalizations, Lasso, Ridge, etc., (Davison 2003, ch. 8, 10; Agresti 2015, ch. 1–8).

	● Basic treatment of linear models with random effects (multi-level, hierarchical models) (Gelman and Hill, 2007, ch. 11–14). ● Introduction to nonparametric modelling: trade-off bias-variance, univariate smoothing methods (local regression, loess, regression splines, smoothing splines, etc.), standard nonparametric modesl such as, regression trees, additive models, random forests, bagging, boosting and neural networks, (Azzalini and Scarpa, 2012). ● Univariate and multivariate time series analysis: univariate ARMA models, stationary and non-stationary vector autoregressive models, cointegration analysis, introduction to state space modelling, introduction to spectral analysis (Brockwell and Davis 2016; Lutkepohl 2005, ch 1–8). *References* Agresti, A. (2015). *Foundations of linear and generalized linear models*. John Wiley & Sons, Inc., Hoboken, NJ. Azzalini, A. and Scarpa, B. (2012). *Data analysis and data mining. An introduction*. Oxford University Press, Oxford. Brockwell, P. J. and Davis, R. A. (2016). *Introduction to time series and forecasting*. Springer, third edition. Davison, A. C. (2003). *Statistical models*, Cambridge University Press, Cambridge. Gelman, A. and Hill, J. (2007). *Data analysis using regression and multi- level/hierarchical models*, Cambridge University Press, New York. Lutkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer.
Examination methods (in applicable)	Homework, final written exam, poster preparation and presentation.
Suggested readings	● Course material available from the instructors
Additional information	

UNIVERSITÀ DEGLI STUDI DI PADOVA

SCIENZE STATISTICHE

Course unit English denomination	Sampling Theory
SS	STAT-01/A
Teacher in charge (if defined)	Pier Francesco Perri
Teaching Hours	13
Number of ECTS credits allocated	2
Course period	02/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	The problem of estimating the population mean is discussed starting from sampling with varying probabilities and emphasis will be given to the use of auxiliary variables at the estimation stage through the regression and calibration estimators. Moreover, the problem of reducing nonsampling errors due to untruthful response and nonresponse will be introduced and discussed in the context of surveys on sensitive issues. Contents: - First and second order inclusion probabilities - Sampling with varying probabilities and some selection schemes - Estimation of the population mean through the Hansen-Hurwitz estimator and the Horvitz-Thompson estimator - Sample size determination - Stratified and cluster samplings: design and estimation - Estimation with auxiliary information: ratio, regression and calibration estimators - Surveying sensitive issues by indirect questioning techniques - The nonresponse - Brief overview with R
Learning goals	The short course aims at providing basic notions on sampling theory and practice for finite population. At the end of the lessons, students should be able to:

	- Select a representative sample of the population taking into account the aims of the survey, the information available and the budget constraints. - Evaluate the advantages and disadvantages arising from the use of a sampling design - Prevent and correct nonsampling errors stemming from untruthful responses and nonresponse.
Teaching methods	• Lectures
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation and until the maximum number of students has been reached
Prerequisites (not mandatory)	
Examination methods (in applicable)	None
Suggested readings	• Course material available from the instructor • Chaudhuri A., Chistofides T.C. (2013). Indirect Questioning in Sample Survey. Springer • Cochran W.G. (1977). Sampling Techniques. Wiley. • Conti P.L., Marrella D. (2012). Campionamento da Popolazioni Finite. Il Disegno Campionario. Springer • Heeringa S.G., West B.T., Berglund P.A. (2010). Applied Survey Data Analysis. CRC Press • Lohr S.L. (2022). Sampling: Design and Analysis. . CRC Press • Lu Y., Lohr S.L (2022). R Companion for Sampling: Design and Analysis. CRC Press • Lumley T. (2010). Complex surveys: A Guide to Analysis Using R. Wiley • Särndal C. E., Lundström S. (2005). Estimation in Surveys with Nonresponse. Wiley • Särndal C. E., Swensson B., Wretman, J. (1992). Model Assisted Survey Sampling. Springer • Tillè, Y. (2020). Sampling and Estimation from Finite Populations. Wiley • Valliant R., Dever J.A., Kreuter F. (2018). Practical Tools for Designing and Weighting Survey Samples. Springer

	- Wu C., Thompson M.E. (2020). Sampling: Theory and Methods. Springer
Additional information	

UNIVERSITÀ DEGLI STUDI DI PADOVA

SCIENZE STATISTICHE

Course unit English denomination	Theory and Methods of Inference
SS	STAT-01/A
Teacher in charge (if defined)	• Alessandra Salvan • Nicola Sartori
Teaching Hours	64
Number of ECTS credits allocated	10
Course period	03/2026-06/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (100% minimum of presence, apart from exceptional absences that must be justify in advance) ☐ No
Course unit contents	• Statistical models and uncertainty in inference. Paradigms of inference: the Bayesian and frequentist paradigms. Model specification in Bayesian and frequentist inference. Frequentist evaluation of uncertainty and distribution problems. Simulation. Asymptotic approximations and delta method. • Generating functions, moment approximations, transformations. Moments, cumulants and generating functions. Edgeworth and Cornish-Fisher expansions. Notations $O_p(\cdot)$ and $o_p(\cdot)$. Approximations of moments and transformations. Laplace approximation. • Data and model reduction. Dominated statistical models and density factorizations. Sufficiency. Distribution constant statistics. Completeness. Data and model reduction with nuisance parameters. • Exponential and group families. Exponential families and exponential tilting. Mean value mapping and variance function. Multiparameter exponential families. Sufficiency and completeness in exponential families. Marginal and conditional distributions. Exponential dispersion families. Generalized linear models. Groups of transformations. Orbits and maximal invariants. Simple group families. Composite group families. • Likelihood inference. Observed and expected likelihood quantities, exact properties. Observed likelihood quantities in exponential and group families.

	Examples with various models and observation schemes: grouped data, censored data, sequential sampling, stochastic processes. Invariance properties. Likelihood and sufficiency. Expected quantities and exact sampling properties. Universal bounds. Orthogonal parameters and mixed parameterization in exponential families. Reparameterizations. Ancillary statistics. Conditional inference in scale and location families. Consistency. First-order asymptotics and related inference procedures. Profile likelihood. Asymptotically equivalent forms and one-sided versions. First-order asymptotic theory in exponential families. Non-regular models. Approximate conditional inference and higher-order asymptotics. ● Bayesian inference. Asymptotic approximations. Non-informative priors. Empirical Bayes methods. Inference based on the posterior distribution: point estimation and credibility regions, hypothesis testing and the Bayes factor. Prediction. Linear models. ● Likelihood and Bayesian inference in R. Scalar and vector parameter examples. Parameters of interest and profile likelihood. Likelihood and parametric bootstrap. EM algorithm. Bayesian inference (basics). ● Estimating equations and pseudo-likelihoods. Misspecification. Estimating equations. Quasi likelihood. Pseudo-likelihoods. Composite likelihood. Empirical likelihood. Conditional and marginal likelihood in exponential and group families. Profile and integrated likelihoods. ● Decision paradigms. Statistical decision problems. Optimality in estimation. Optimal tests and confidence regions. Procedures with finite sample optimality properties in exponential and group families.
Learning goals	The course aims at offering students an advanced understanding of the theory of statistical inference, both Bayesian and frequentist, with emphasis on unifying ideas as well as on specific aspects. Problem solving abilities are strengthened with weekly homework, assigned to small groups and subsequently discussed with all the students. Students are also introduced to the study of various bibliographic sources, including scientific articles. Enhancing writing and presentation skills is also part of the programme.
Teaching methods	● Lectures ● Group homework ● Student's written and oral presentations ● Problem solving ● Project work ● Feedback ● Assessment activities during the course ● Develop collaborative and supportive peer relationships
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No

Available for PhD students from other courses	☒ Yes ☐ No Students from other PhD courses may be admitted subject to CV evaluation by the Faculty Board
Prerequisites (not mandatory)	First year Master courses at the level of the courses Probability Theory and Statistics (Advanced) at the Department of Statistical Sciences
Examination methods (in applicable)	Homework, final written exam, written and oral presentation rewiewing recent research papers
Suggested readings	● Course material available on the course web page ● Davison, A. C., Statistical Models. Cambridge University Press, 2003 ● Pace, L., Salvan, A., Principles of Statistical Inference, from a Neo-Fisherian Perspective. World Scientific Publishing Company, 1997 ● Severini, T. A., Likelihood Methods in Statistics. Oxford University Press, 2000 ● Severini, T. A., Elements of Distribution Theory. Cambridge University press, 2005 ● Young, G. A., Smith, R. L., Essentials of Statistical Inference. Cambridge University Press, 2005
Additional information	