Ph.D. Program in Information Engineering

Course Catalogue

A.Y. 2025/2026

06/11/2025

Revision History

Revisions with respect to the reference version: 1.0 – 29/10/2025

Rev. 1.1 – 06/11/2025

- Section "Coursework Requirements": the deadline for the submission of the Study and Research Plan has been updated to November 28th, 2025.

Summary

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Control Theory and Applications (IE_AUT)

Computer Science (IE_CSC)

Applied Optics (IE_OPT)

Coursework Requirements

The following requirements are valid for Ph.D. Students starting in November 2025 (41° cycle). In summary, Students shall **take courses for a minimum of 16 credits** (usually corresponding to 80 hours of lectures) and shall **attend the seminars proposed by the Ph.D. Program**, following the rules detailed below.

Definitions

A **course** is a series of lectures given by an instructor (professor or university researcher), possibly accompanied by laboratory sessions, that includes an assessment of the student knowledge (final exam, graded homeworks or project, etc.). Among courses, some are organized as a Seminar Series, constituted by several lectures on a specific topic. **A course gives credits**.

A **seminar**, in the context of the Ph.D. Program, is typically a talk, or a series of talks, given by an academic researcher or an eminent professional, that does not include an assessment. **A seminar does not give credits**.

Course requirements

- Take Ph.D. courses for **a minimum of 16 credits** by the end of the second year.

Specific constraints to earn the minimum of 16 credits of courses:

C.1 **Transversal Skills Area (TSK)**: at least 4 credits should come from courses belonging to the Transversal Skills area (labeled **TSK** in the course Summary) and to the Mathematical and Statistical Methods area (labeled **IE_MSM**).

C.2 **Information Engineering Area (IE_*)**: students shall earn at least 8 credits by taking courses belonging to the Information Engineering Area (labeled **IE_*** in the course Summary, with * being **MSM**, **BIO**, **ELE**, **TLC**, **AUT**, **CSC**, **OPT**); some Seminar Series, listed on the PhD webpage (phd.dei.unipd.it), can be taken as courses in this area.

C.3 **External Courses**: up to a maximum of 4 credits may be earned by taking external courses (i.e. courses not included in this catalogue) falling in the following categories:

- Courses appearing in the list of external courses approved by the Executive Board. The list of credited external courses is available on the Ph.D. Program main website.
- Additional external courses might be included into the list after submission of a written request signed by the Student and his/her Supervisor. **Only courses including an exam with grading/evaluation are considered.**
- Courses from other Ph.D. School catalogues (provided they include a final exam with grading).
- To get credit recognition for external courses, students shall obtain a certificate stating that the student attended the course and successfully passed the exam. Alternatively, the student may fill a Certification of Attendance with the course data and have it signed by the course instructor.

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Seminar requirements

- Attend the **seminars** promoted by the Ph.D. Program and advertised on the website during the three-year Ph.D. course. Students are expected to **attend a minimum of three seminars during their three-year Ph.D. course**, although it is strongly recommended that they attend more than the minimum number required.
- Attend at least one **Interdisciplinary Training Courses during their three-year Ph.D. course**. The Interdisciplinary Training Courses are organized by the University of Padova and are typically offered every year. They are series of seminars on transversal topics. The list of course is updated throughout the year and is available here: https://www.unipd.it/en/phd-interdisciplinary-teachings

Note: due to some unforeseen circumstance (e.g., occupancy restrictions on other activities), it may happen that a student may not be able to satisfy all requirements, in particular on seminars. In such exceptional cases, it is possible to complete the Ph.D. program without satisfying all constraints, after obtaining the approval of the Coordinator of the Ph.D. Program.

Study plan

Each first-year student **enrolled in the Ph.D. Program in Information Engineering** must fill a tentative study and research plan form and upload it using the following link:

https://phd.dei.unipd.it/study-and-research-plan

by November 28th *(NOTE: PhD Students starting their program later than November 1st shall submit their program of study form within 30 days from their start date)*. The study plan may be subsequently modified by submitting a new form no later than six months before the end of the third year. Seminars and PhD Training Week modules should not be included in the program of study. Please, use the Seminar Certificate of Attendance to collect the signature of the speaker or of a member of the Executive Board attending the event.

Course enrollment and attendance

Unless otherwise indicated in the course syllabus, Students are required to enroll in each course they plan to attend, be it for credits (i.e., taking the final exam) or otherwise, by filling the course enrollment form that can be found at the following link:

Course Enrollment Form

Students are expected to attend classes regularly. Punctuality is expected both from instructors and students. Instructors have to report to the Coordinator of the Ph.D. Program students missing classes without proper excuse.

Instructors shall complete student grading within 30 days after the end of lectures.

Note for students enrolled in PhD Programs other than Information Engineering

PhD Students enrolled in other PhD Programs are welcome to take courses from this Catalogue. External students planning to take a course shall submit a request to be enrolled by sending an e-mail message to: corso.dottorato@dei.unipd.it (PhD Secretariat) **at least two weeks in advance with respect to the date of the course first lecture**. Please note that attendance to a course is typically limited to a maximum number of participants, so the request of enrollment might not be accepted.

External students must be aware that the number of credits awarded by a course and its recognition inside the study plan depend on the rules of the PhD Program the students are enrolled in.

Class Schedule

The class schedule is embedded in the Ph.D. Program Calendar. You may add the Calendar to your Google account through the following link:

Class Schedule of 2025/26 PhD Courses for Google Calendar

You may also visualize the class schedule using any browser through the following link:

Class Schedule of 2025/26 PhD Courses

With very few exceptions, classes meet in classrooms and meeting rooms of the Department of Information Engineering, via Gradenigo 6/A, Padova. To locate the rooms, you may find helpful the map of the Department buildings:

Map of the Department of Information Engineering

Please, always check the class schedule in the calendar to verify the room where the class meets.

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TSK 1. Entrepreneurship and Startup

Course Area: Transversal Skills

Teacher in charge (if defined)	Prof. Moreno Muffatto, Dipartimento di Ingegneria Industriale, Università di Padova; Ing. Francesco Ferrati, Dipartimento di Ingegneria Industriale, Università di Padova e-mail: moreno.muffatto@unipd.it, francesco.ferrati@unipd.it
Teaching Hours	21
Number of ECTS credits allocated	3
Course period	14-21-28 January, 4-11-18-25 February 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (70% minimum of presence) ☐ No
Course unit contents	•characteristics of a technology and innovation-based startup. •characteristics of an effective founding team. •define and evaluate a product and/or service concept. •intellectual property protection and related processes. •evaluate the market aspects of a business idea. •design and evaluate different business models. •understand and develop the financials of a startup. •evaluate cash flow dynamics. •evaluate different options for financing a start-up. •understand what professional investors are interested in and how they assess it.
Learning goals	•Understand the process to develop and Innovation and Entrepreneurship project •identify and articulate the real-world problems your research can address. •select a field and find relevant problems to solve. •translate scientific expertise into practical solutions. •understand how to create an effective team. •engage in team building. •work effectively in a team with individuals from other disciplines, leveraging varied expertise. •understand the fundamentals of entrepreneurship, including

	business models, value propositions, and market analysis. •understand intellectual property rights, patents, and strategies for bringing research-based innovations to market. •use Generative AI (ChatGPT) more efficiently and effectively. • harnessing the synergy of your creative insights and Generative AI (ChatGPT) to shape and refine every outcome of the project. •understand the basics of a startup financials.
Teaching methods	•Formation of interdisciplinary teams and group working •Development of an Innovation and Entrepreneurship Project designed to provide hands-on experience with practical methodologies. •Integration of Generative AI tools (ChatGPT) to enhance and streamline each stage of the development process.
Course on transversal, interdisciplinary, transdisciplinary skills	X Yes ☐ No
Available for PhD students from other courses	X Yes ☐ No
Prerequisites (not mandatory)	
Examination methods (in applicable)	Development of an Innovation and Entrepreneurship project
Suggested readings	Karen Berman and Joe Knight (2008), Financial Intelligence for Entrepreneurs, Harvard Business Publishing. Thomas R. Ittelson (2009), Financial Statements: A Step-by-Step Guide to Understanding and Creating Financial Reports, Career Press. Ferrati, F. & Muffatto, M. (2021). "Reviewing Equity Investors' Funding Criteria: A Comprehensive Classification and Research Agenda". Venture Capital, Vol. 23: No. 2, pp. 1-22. Noam Wasserman (2013) The Founder's Dilemmas: Anticipating and Avoiding the Pitfalls That Can Sink a Startup, Princeton University Press.
Additional information	The course is included in the University's cross-disciplinary doctoral programme. https://www.unipd.it/en/phd-interdisciplinary-teachings Kindly note that the maximum capacity for participants is limited to 80. Participants who have met the requirements in terms of attendance and assignment will be awarded the open badge for the course. https://bestr.it/badge/show/2670

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Schedule and room: see Class Schedule for details

Enrollment: students planning to attend the course must

1. Contact the lecturers for details
2. then, add the course to the list of courses they plan to attend using the Course Enrollment Form (requires SSO authentication) and, if taking the course for credits, to the Study and Research Plan.

TSK 2. Python Programming for Data Science and Engineering

Course Area: Transversal Skills

Course unit English denomination	Python programming for Data Science and Engineering
Teacher in charge (if defined)	Stefano Tortora
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	03/2026 – 04/2026
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	Python is an easy-to-learn and powerful high-level language and it is becoming more and more popular for scientific applications such as machine learning, statistics, manipulating and transforming data, but also computer vision and robotics. Topics: •Introduction to the Python Programming Language oWhat is different in Python? oThe Python Language Syntax and Data Structures •Modules and Packages oNumPy and SciPy: Numerical and Scientific Python

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	oPandas: Labeled Column-Oriented Data oMatplotlib: MATLAB-style scientific visualization oScikit-learn: Basics of Machine Learning in Python
Learning goals	Acquired knowledge: the first objective of the course is to become familiar with Python syntax, environments and basic libraries. Secondly, the learner will be guided in performing basic inferential data analyses and introduced to the application of common machine learning algorithms. Acquired skills: the students will learn practically how to structure a complex project in Python through the guided execution of 5 assignments. In addition, they will learn how to handle and organize a group project through the subdivisions into small groups (max 3 people) for the handover of the assignments.
Teaching methods	- Lectures - Laboratory exercises - Group projects
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Backgrounds in computing with some object-oriented programming language: C++, Java, MATLAB, etc.
Examination methods (in applicable)	Homework assignments and final presentation
Suggested readings	[1] J. VanderPlas, “A Whirlwind Tour of Python”, O’Reilly Media Inc. 2016. [Online: https://www.oreilly.com/programming/free/files/a-whirlwind-tour-of-python.pdf] [2] J. VanderPlas, “Python Data Science Handbook: Essential Tools for Working with Data” O’Reilly Media Inc. 2017.

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	[3] B. Miles, "Begin to Code with Python", Pearson Education, Inc. 2018. [Online: https://aka.ms/BeginCodePython/downloads] [4] Z. Shaw, "Learn Python the Hard Way", Addison-Wesley. 2014. [5] A. Géron, "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems", O'Reilly Media Inc. 2019.
Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

TSK 3. Data Visualization

Course Area: Transversal Skills

Course unit English denomination	Data Visualization
Teacher in charge (if defined)	Matteo Ceccarello
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	January/February 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (60% minimum of presence) ☐ No
Course unit contents	• The Grammar of Graphics • Human perception and color theory • The ggplot implementation of the Grammar of Graphics • Case studies: how to visualize data from different perspectives • Avoiding pitfalls in scientific data visualization
Learning goals	PhD students will be able to choose the most appropriate visualization idiom to visualize the data at hand. Furthermore, they will be able to make use of graphical marks and colors to improve the effectiveness of their visualizations.
Teaching methods	Lectures, guided exercises, individual exercises, peer feedback, case studies.
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No

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Prerequisites (not mandatory)	Basic computer programming experience
Examination methods (in applicable)	Project-based exam
Suggested readings	1. Healy K. Data Visualization, a practical introduction. Princeton University Press. https://socviz.co 2. Wickham H., Grolemund G. R for Data Science. O'Reilly. https://r4ds.had.co.nz/ 3. Ware C., Visual thinking for design. Elsevier. 4. Wickham, H. (2010). A layered grammar of graphics. Journal of Computational and Graphical Statistics, 19(1), 3-28.
Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

TSK 4. Geopolitics of ICT in an unpredictably changing world

Course Area: Transversal Skills

Course unit English denomination	Geopolitics of ICT in an unpredictably changing world
Teacher in charge (if defined)	Alessandro Paccagnella (DEI), David Burigana (SPGI)
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	11/2025 – 12/2025
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (80% minimum of presence) ☐ No
Course unit contents	Information and communication technologies are one of the fundamental backbones of the world, based on a formidable scientific and technological development starting from the end of WWII. In this course we follow the ICT technological evolution, in particular its enabling technology – microelectronics - in parallel with the evolution of the international context from the Cold war period to the globalization time, and then in the current de/post-globalized world. From the viewpoint of International Relations, we present the current geopolitical frame that is characterized by a strong comeback of the power politics among countries, where the multilateral approach (i.e., United Nations) appears embroiled in a crisis difficult to overcome. Superpowers (US and China) as well as powers (Russia, India, Brazil, South Africa, United Arab Emirates) are gaining ground; some regional experiences (UE, ASEAN) still resist, while other (western) countries preserve with difficulty their influence

	and presence in the world (France, UK). Other countries instead are playing a strategic role owing to their techno-scientific capabilities, in particular in the ICT sector: South Korea, Taiwan, Singapore, Japan, Israel, to a lesser extent Germany. Others, such as Vietnam, aim to join this group, despite its troubled colonial past. Italy may find its role as a bridge of dialogue among powers. In this complex frame a new gold rush is occurring for the leadership, or at least a significant participation, in the Advanced High Technologies for ICT, which are continuously gaining momentum. In this course we take as a reference the case of semiconductors, which are at the center of a global competition where polarization in alliances is enhancing barriers and mutual distrust. The evolution of Moore's law toward the "more Moore" and "more than Moore" options is spurring massive investments at private and government levels, with the 2022 EU Chips act and the CHIPS for America act being just the most renown actions taking place these days. The recent chip crisis during the pandemic has increased the level of hostility, favoring increasing levels of embargo towards China of the most advanced technologies (such as IC design tools or EUV photolithographic machines) from the Western bloc, that today appears more and more as a military alliance. De-risking, re-shoring, friendly-shoring are widespread keywords leading to reacquiring at least part of the technological sovereignty lost by western countries in the first two decades of the XXI century.
Learning goals	By joining the geopolitical and sci-tech perspectives, the student will be able to identify actors and dynamics that have made ICTs a crucial asset of the foreign policy. Starting from the analysis of the geopolitical and technological situations, the student will assess the relations between experts/advisors and the political decision makers in the international projection of national strategies.
Teaching methods	The course will be based on lectures and discussion. The course will involve also some selected witnesses and actors that will interact with the class, that will be also involved in a simulation of a negotiation in a multinational arena.
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes the course is open to all UNIPD PhD students

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	☐ No
Prerequisites (not mandatory)	The course can be taken by any student interested. Basic knowledge of ICT technologies, as acquired in the previous degrees, would facilitate communication, as well as some fundamental notions about the world history of the XX and XXI centuries, that will be nevertheless summarized during the lectures.
Examination methods (in applicable)	simulation of a negotiation in a multinational arena, final presentation.
Suggested readings	Will be given during the lectures
Additional information	-

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_MSM 1. Statistics for Engineers

Course Area: Information Engineering (may also be taken as Transversal Skills course)

Course unit English denomination	Statistics for Engineers
Teacher in charge (if defined)	• Salmaso Luigi • Disegna Marta • Arboretti Rosa
Teaching Hours	42
Number of ECTS credits allocated	7
Course period	• February 2026 • End of June 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (90% minimum of presence) ☐ No
Course unit contents	In this course will be developed the following topics: 1) introduction to descriptive statistics; 2) introduction to inferential statistics; 3) introduction to linear and non-linear regression models; 4) introduction to supervised and unsupervised Machine Learning algorithms; 5) Design of Experiments.
Learning goals	The course develops in participants the statistical skills necessary to handle and analyse data of various kinds, including data from the doctoral project they are developing. Students will acquire both theoretical and practical knowledge to independently develop statistical analysis. During the course, students will gain basic skills to correctly use some user-friendly statistical software. Additionally, the

	course enables students to acquire the skills to effectively and correctly present and interpret statistical analysis.
Teaching methods	Frontal lessons, group works, workshops, case studies.
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 final evaluation will be based on the discussion of two projects developed individually or in teams of no more than three people. Students are expected to describe and analyse one or two case studies using the statistical techniques presented during the course.
Suggested readings	Materials (slides, datasets, etc.) of the course will be provided by the course leaders.
Additional information	The course is structured into 2 online (February) and a Summer School of 4 days (June). The Summer School will take place in Villa San Giuseppe, Monguelfo, Bolzano province. During the course an introduction to the use of the following statistical software will be presented: • R and BlueSky, both open-source software. • MINITAB, licensed to University of Padova.

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan. Please note that enrollment in this specific course is reserved to Students of the Ph. D. Program in Information Engineering. Students of other Ph.D. Programs please refer to their Program secretariat.

Schedule and room: see **Course period** above or the Class Schedule

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IE_MSM 2. Heuristics for Mathematical Optimization

Course Area: Information Engineering (may also be taken as Transversal Skills course)

Course unit English denomination	Heuristics for Mathematical Optimization
Teacher in charge (if defined)	Salvagnin Domenico
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	03/2026-04/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	Italian
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	• Mathematical optimization problems (intro). • Heuristics vs exact methods for optimization (intro). • General principle of heuristic design (diversification, intensification, randomization). • Local search-based approaches. • Genetic/population-based approaches. • The subMIP paradigm. • Applications to selected combinatorial optimization problems: TSP, QAP, facility location, scheduling.
Learning goals	Make the students familiar with the most common mathematical heuristic approaches to solve mathematical/combinatorial optimization problems. This includes general strategies like local

	search, genetic algorithms and heuristics based on mathematical models.
Teaching methods	Lectures, group projects
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	• Moderate programming skills (on a language of choice) • Basics in linear/integer programming.
Examination methods (in applicable)	Final programming project
Suggested readings	[1] Gendreau, Potvin "Handbook of Metaheuristics", 2010 [2] Marti, Pardalos, Resende "Handbook of Heuristics", 2018
Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_BIO 1. Principles of Synthetic Biology

Course Area: Information Engineering

Course unit English denomination	Principles of Synthetic biology
Teacher in charge (if defined)	Massimo Bellato
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	June
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (75% minimum of presence) ☐ No
Course unit contents	- Introduction to Synthetic Biology: Definitions, aims, DBTL (Design, Build, Test, Learn) cycle, boundaries, and case studies. - Basics of molecular biology and genetics: Essential review of cellular biology and microbiology, genetic parts and modules, living chassis, molecular tools. - Cloning DNA genetic circuits into bacterial cells (wet-lab activity) - Measuring synthetic biology: Instrumentation, data analysis, and modeling - Notable genetic circuits and motifs: genetic feedback loops, toggle switches, oscillators, and perfect adaptation via antithetic integral control. - Additional material depending on the class interests

Learning goals	The course is intended to provide some insights into Synthetic Biology, providing the student knowledge and primary instruments for the design of engineered biological systems. More specifically, the genetic markup of a cell can be modified by inserting rationally designed genetic circuits (as happens for electric devices, but with modules composed of DNA instead of resistors and capacitors) to generate novel biological functions with predictable outcomes. Therefore, the course will be focused on stimulating a cross-field mindset, to apply engineering principles and methodologies to the biological world; analogously, "biological parts" as "engineerable toolkits" will be explained. The basic biological knowledge required to understand how to engineer a living cell will be provided at the beginning of the course, including basic mathematical modeling of molecular kinetics and the Central Dogma. The second part will focus on measurement and characterization techniques, for rational experimental design, including data analysis approaches and tools used in this realm. Lastly, advanced topics on engineered biological systems and culture control techniques will be faced including bi-stability, feed forward/feed-back regulations, and perfect adaptation in gene expression and bioreactor setups. Additional specific aspects (e.g., optogenetics and FBA, will also be faced depending on students' specific interests).
Teaching methods	Lectures, Wet lab with practical hands-on, Students presentations
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	ODEs modeling; basics of Matlab programming. Prior knowledge in molecular biology, bioinformatics, and control theory can be useful but not necessary. Students are required to complete the "HIGH-RISK ACTIVITIES (12 hours) – Laboratory activities" security course from https://elearning.unipd.it/formazione/course/index.php?categoryid=40 to access the laboratory space.
Examination methods (in applicable)	Final group project consisting of the design of a genetic circuit in a proper host, on a relevant topic. Alternatively, single student journal club activities. The projects will be presented to the whole class, including a peer-to-peer evaluation activity.

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Suggested readings	Teacher slides and linked references. Additional useful books: “Uri Alon, An Introduction to Systems Biology Design Principles of Biological Circuits”, “ Alberts et al. The Molecular Biology of the Cell (6th edition)” and “Vijai Singh, New Frontiers and Applications of Synthetic Biology”
Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_BIO 2. Deep Learning for Biomedical Images

Course Area: Information Engineering

Course unit English denomination	Deep Learning for Biomedical Images
Teacher in charge	Casterllaro Marco
Teaching Hours	18
Number of ECTS credits allocated	4
Course period	04/2026 - 06/2026
Course delivery method	☐ In presence ☐ Remotely X Blended
Language of instruction	Italian
Mandatory attendance	☐ Yes (% minimum of presence) ☐ No
Course unit contents	The rapid evolution of deep learning in the field of computer vision provided state-of-the-art solutions for classical tasks such as object detection, classification, segmentation, and activity recognition. Besides, medical imaging is the ideal candidate model for the application of complex deep neural network (DNN) or Convolutional neural network (CNN) and more recent introduced Transformers architectures. In this course the teacher will provide students the knowledge and the practical skills to understand the most recent networks and to use them in the field of biomedical imaging. Topics: • Introduction to biomedical images (DICOM/Nifti standards) • Introduction to Pytorch and Monai (Medical Open Network for Artificial Intelligence) • Pre-processing, transform and data augmentation • Case studies: DNN and CNN architectures for image classification, segmentation, and image reconstruction • Training procedures, algorithms, and strategies • Transfer learning and fine tuning

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	• Transformers, attention principle and its application to biomedical images analysis tasks. • Foundational models and their applications to biomedical images analysis tasks.
Learning goals	The learning goal of the deep learning for biomedical images course is to equip students with the knowledge and practical skills necessary to comprehend and utilize the latest deep neural network. Through topics such as data pre-processing, deep neural network and convolutional neural networks architectures, training, transfer learning and fine-tuning procedures, the course aims to empower students to address complex challenges in medical image analysis using cutting-edge deep learning methodologies.
Teaching methods	Two/third frontal lessons and one/third laboratory and coding activity
Course on transversal, interdisciplinary, transdisciplinary skills	X Yes ☐ No
Available for PhD students from other courses	X Yes ☐ No
Prerequisites **(not mandatory)**	Basic programming skills with Python language and basic theoretical knowledge of machine learning.
Examination methods **(in applicable)**	The examination will be based on a team-work to implement a deep learning based task to be applied to a real dataset of biomedical images.
Suggested readings	
Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_BIO 3. Healthcare data management and analytics

Course Area: Information Engineering

Course unit English denomination	Healthcare data management and analytics
Teacher in charge (if defined)	Enrico Longato
Teaching Hours	18
Number of ECTS credits allocated	4
Course period	March-June 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	The analysis and management of healthcare data present a set of often underestimated practical challenges when attempting to go from the raw data to the communication of scientific results of clinical significance. In this course, we will go over some of the main difficulties in healthcare data management and analytics (e.g., heterogeneity of the data, lack of centralised programming resources), and present tried-and-true, first-line solutions specifically scoped for the biomedical context. The course will follow a learn-by-doing approach with lectures accompanied by hands-on programming sessions in python. •A refresher on the bare necessities of python programming: numpy, pandas, object oriented programming refresher, reading and writing from/to files and databases.

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	•Interfacing with R for access to libraries for advanced biostatistics and clinical data management. •Typical workflows for healthcare data preprocessing including missing data imputation. •Patient disposition and characteristics: creating a "Table 1." •Implementing basic experimental frameworks for classification and regression on healthcare data. •Probability theory recap and statistical testing. •Understanding and communicating model performance and specifics.
Learning goals	•Developing complete pipelines for the management and analysis of healthcare or clinical data. •Python programming basics, including interfacing with the R programming language, for the solution of clinical or healthcare data analytics problems •Knowledge and ability to apply the fundamentals of probability theory, inferential statistics, and machine learning
Teaching methods	• Frontal lectures • Hands-on labs • Live coding • Case studies
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☐ Yes ☒ No
Prerequisites **(not mandatory)**	• Basic knowledge of any programming language • Basics of probability theory and/or statistics
Examination methods **(in applicable)**	Final project consisting of the end-to-end analysis of a healthcare or clinical dataset from raw data ingestion to results presentation.
Suggested readings	T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning : Data Mining, Inference, and Prediction. in Springer Series in Statistics. New York, NY: Springer-Verlag New York, 2009. Available online at: https://hastie.su.domains/ElemStatLearn/download.html

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Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_ELE 1. Physics and Operation of Heterostructure-Based Electronic and Optoelectronic Devices

Course Area: Information Engineering

Teacher in charge (if defined)	Carlo De Santi
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	February-March 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	This course provides an introduction to the physics and operating principles of advanced electronic and optoelectronic devices based on compound semiconductors. These devices are particularly important for several applications: high electron mobility transistors (HEMTs) are excellent devices for the realization of high-frequency communication systems, radar, satellite applications and high-efficiency power converters. On the other hand, LEDs and lasers are highly efficient monochromatic light sources, which can be used for lighting applications (with significant energy savings), in the biomedical field, as well as in photochemistry and telecommunications. A special focus will be given to devices based on gallium nitride (GaN) and gallium oxide (Ga2O3), which represent the most promising devices for future applications in power electronics. The course will focus on the main aspects related to the physics of heterostructures, quantum processes in heterostructures, recombination processes in semiconductors, carrier transport in heterostructures, structure and operating principles of MESFET,

	HEMT, GIT, trapping and reliability in compound semiconductor devices, operating principles of LEDs and lasers and parasitic effects in LEDs and lasers. An overview of real applications will also be provided, highlighting the possibilities offered by these devices. Finally, an overview of the modern approach to the simulation of the physics of such devices may be provided.
Learning goals	The course aims to provide skills and competences relating to the physics and operation of heterostructure devices and their modeling. Specific topics may include, among others: • Future developments of microelectronic technologies • Elements of quantum mechanics • Properties of heterostructures • Compound semiconductors • Defects in semiconductors • Operating principles of heterostructure devices (e.g. LEDs, lasers, heterostructure transistors, ...) • Modeling of heterostructure devices • Basic principles of numerical simulation • Optoelectronic devices for silicon-photonics
Teaching methods	Different teaching methodologies will be applied, in order to develop both methodological aspects and experimental skills. Specific methodologies may include: • Lectures • Flipped classroom • Classroom discussion • Homework • Classroom exercises • Literature analysis
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No

Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites **(not mandatory)**	
Examination methods **(in applicable)**	Examination methods may include: • Evaluation of homework • Evaluation of presentations prepared by students • Practical exercises and related report
Suggested readings	Teaching material provided by teachers via the course Moodle
Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_ELE 2. Embedded Design with FPGA

Course Area: Information Engineering

Teacher in charge (if defined)	Dr. Andrea Stanco and Prof. Daniele Vogrig, Department of Information Engineering, University of Padova ; Dr. A. Triossi, Department of Physics and Astronomy, University of Padova
Teaching Hours	24
Number of ECTS credits allocated	5
Course period	February-March 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (at least 4 lab-lessons out of 7) ☐ No
Course unit contents	•Recap on the basics of Digital Design. Digital Design Flow (HDL language and HLS). Introduction to VHDL program language. •Introduction to FPGA and Zynq SoC. •Introduction to Vivado System Design environment. Time domains, time violations, metastability, system constraints, time-to-digital converter (TDC) •Introduction to SDK environment •Information exchange between processor and programmable logic. Hardware and Software interrupts. •Communication between SoC and the outside world. •PYNQ (Python on Zinq) project as example of how to make easier the design embedded systems •Several case studies including a time-to-digital converter (TDC)

Learning goals	The course aims at teaching how to practically use System-on-a-Chip (FPGA+CPU) technology as a potential application to academic research topics.
Teaching methods	The course fully supports a hands-on and practical approach to deliver a more effective comprehension of the challenges and issues related to the SoC/FPGA design. The course includes 5 lectures and 7 lab-lessons that will be held in a dedicated laboratory using the boards Pynq-Z1 and Pynq-Z2
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Basic knowledge of digital electronics. Knowledge of program language (e.g. C/C++). No VHDL knowledge or experience on FPGAs is required.
Examination methods (in applicable)	Final project (abstract+presentation) about the application of FPGA/SoC to an academic research topic.
Suggested readings	1. Hubert Kaeslin "Top-Down Digital VLSI Design: From Architectures to Gate-Level Circuits and FPGAs", Morgan Kaufmann, 2014 2. Xilinx, Vivado Design Suite User Guide, UG893 (v2019.1), https://www.xilinx.com/support/documentation/sw_manuals/xilinx2019_1/ug893-vivado-ide.pdf 3. Xilinx, Xilinx Software Development Kit (SDK) User Guide, https://www.xilinx.com/support/documentation/sw_manuals/xilinx2015_1/SDK_Doc/index.html
Additional information	The course is divided in 5 standard lessons and 7 "hands-on" laboratory lessons.

Schedule and room: see Class Schedule for details

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Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_ELE 3. Power Electronic Converters for Micro Grid Applications

Course Area: Information Engineering

Teacher in charge (if defined)	Simone Buso, Paolo Mattavelli, Giorgio Spiazzi, Department of Information Engineering, University of Padova
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	Spring 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (at least 4 lab-lessons out of 7) ☐ No
Course unit contents	Power electronic converter applications for micro dc, ac and hybrid grids. Stability analysis in high converter density power distribution grids. High efficiency topologies for dc-dc bidirectional bridging functions. Digital control techniques for high performance switching converters.
Learning goals	Familiarize with micro grid converter applications. Learning to apply stability analysis techniques for grid connecting and grid connected converters. Understanding design criteria and performance goals for high efficiency bidirectional converters. Learning how to use of digital control techniques to achieve stability and performance goals in high performance converter applications.
Teaching methods	Lectures, working groups, design homework assignments

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Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Power electronics course from the Master Degree in Electronic Engineering.
Examination methods (in applicable)	Final presentation of design assignment outcomes
Suggested readings	Lesson notes and topic related papers (indicated by the instructor after each lesson).
Additional information	The course is divided into two modules: 5 lectures and 7 laboratories.

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_ELE 4. AI-Enhanced Measurement: Concepts and Uncertainty

Course Area: Information Engineering

Teacher in charge (if defined)	Federico Tramarin, Department of Management and Engineering, University of Padova
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	May-June 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes ☐ No (even though in-presence attendance is highly recommended)
Course unit contents	The course explores the conceptual and methodological relationship between Artificial Intelligence (AI), Machine Learning (ML), and Measurement Science, with a focus on uncertainty estimation, interpretation and validation. It examines how AI techniques can support measurement processes while accounting for both aleatoric and epistemic uncertainty. Topics include: •Foundations of measurement science, statistical interpretation of measurement results, from classic modelling approaches to AI-enhanced measurement •Probabilistic and Bayesian frameworks and their extension to data-driven models. •Fundamental principles of measurement uncertainty, propagation, and probabilistic interpretation.

	•Uncertainty quantification in ML regression and classification, including Gaussian processes, deep ensembles, and calibration methods. •Interpretability, reliability, and trustworthiness of AI-assisted measurement systems. •Emerging challenges such as robustness, traceability, standardization, and the design of explainable, trustworthy AI-driven measurement architectures. The course provides students with a solid conceptual understanding of how AI can enhance measurement systems while rigorously addressing uncertainty, preparing them to critically evaluate and apply AI-based methods in practical measurement contexts.
Learning goals	•Describe how Machine Learning and AI impact measurement processes, including indirect and data-driven approaches. •Identify and distinguish between aleatoric and epistemic uncertainty in both sensors and AI models. •Evaluate methodologies for uncertainty quantification in ML regression and classification. •Critically assess the reliability, calibration, and interpretability of AI-assisted measurement systems. •Recognize challenges related to robustness, traceability, standardization, and trust in AI-enhanced measurement systems.
Teaching methods	Frontal interactive lessons.
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Basic knowledge of Measurement and Instrumentation (bachelor and master's degree level). Basic knowledge of supervised learning (regression and classification).
Examination methods (in applicable)	Short essay and oral presentation

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Suggested readings	Lesson notes and topic related papers (indicated by the instructor after each lesson).
Additional information	The course is divided into two modules: 5 lectures and 7 laboratories.

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_ELE 5. Diagnostics of Electron Devices (Seminar Series)

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Prof. Giovanna Mura, Dept. of Electrical and Electronic Engineering, University of Cagliari.

e-mail: gmura@diee.unica.it

Aim: This course provides an overview of the Failure Analysis techniques for the diagnostics of electron devices. Failure Analysis is the process of analyzing the failed electron devices to determine the reason for degraded performance/catastrophic failure and provide corrective actions to fix the problem. It is a proactive tool with three fundamental tasks: 1) Technical/scientific, 2) Technological, and 3) Economical. This course aims to teach what Failure Analysis should be and should do, to show how and why it often does not, and to state that F.A. has Logic and Rules.

Microscopy, in its several forms (optical, electron, scanning, transmission, emission, ionic) and tools is the playground for practical F.A., and its fundamentals will be described. Device basic technology, working principle and failure physics are the other pillars of a successful study.

Several case studies will be proposed to demonstrate if Failure Analysis looks unclear or if there is no problem-solving because it was badly conducted.

Topics:

- Reverse Engineering
- Failure modes and mechanisms
- Principles and fundamental methods in Electron Microscopy
- Methodology for the Failure Analysis, Case studies
- Counterfeit electronics: taxonomy, detection and avoidance

References:

[1] Failure Analysis of Integrated circuits - tool and techniques L.C.Wagner - Kluwer Academic Publishers

Course requirements:

- Electron devices, Microelectronics, Optoelectronic devices

Examination and grading: Homework assignments and final report.

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

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IE_TLC 1. A Deep Dive into 5G Network Specifications and its Applications

Course Area: Information Engineering

Teacher in charge	Marco Giordani
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	April 2026 – May 2026 (tentative)
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes ☒ No (even though in-presence attendance is highly recommended)
Course unit contents	This course will provide a comprehensive overview of the 3GPP NR standardization activities for 5G cellular networks. • Introduction on 5G cellular networks • 3GPP NR: the new standard for 5G cellular networks o The Third Generation Partnership Project (3GPP) o How to read standardization documents and specifications o The 5G NR Radio Access Network (RAN) architecture • 5G NR spectrum o 5G NR frequencies o The millimeter wave spectrum and channel model o The Multiple Input Multiple Output (MIMO) technology • The 3GPP NR PHY layer o 5G NR frame structure o 5G NR numerology and resource grid o 5G duplexing schemes o 5G PHY signals and channels

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	• The 3GPP NR MAC layer
	  ○ 5G MAC signals and channels
	  ○ Beam/mobility management in 5G NR
	  ○ Scheduling and resource allocation in 5G NR
	• Guidelines for proper design and dimensioning of 5G applications

Learning goals	By the end of the course, students will be provided with: • An overview of the main features of 5G networks, with a focus on the standard specifications and innovations developed for 3GPP NR. • An understanding of the main innovations introduced by 3GPP NR specifications for the PHY layer, focusing on the renovated NR frame structure, the NR spectrum, the MIMO technology, the duplexing schemes, and the NR PHY signals and channels. • An understanding of the main innovations introduced by 3GPP NR specifications for the MAC layer, from scheduling to resource allocation, with a focus on beam and mobility management. • An understanding of the complex and interesting trade-offs to be considered when designing PHY/MAC protocol solutions for 5G cellular networks by examining a wide set of parameters based on 3GPP NR considerations and agreements.
Teaching methods	The course consists of classroom lectures and student group activities. Several textbooks are suggested. Notes, slides, articles and additional study material will also be provided during the course. The material will be made available on the course STEM webpage.
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Preliminary knowledge of the ISO/OSI protocol stack
Examination methods (in applicable)	Final project

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Suggested readings	1. 3GPP, "NR and NG-RAN Overall Description - Release 15," TS 38.300, 2018. 2. P. Marsch, Ö Bulakci, O. Queseth, M. Boldi (Ed.), "5G System Design: Architectural and Functional Considerations and Long Term Research," Wiley, 2018. 3. D. Chandramouli, R. Liebhart, J. Pirskanen (Ed.), "5G for the Connected World," Wiley, 2019. 4. M. Polese, M. Giordani, and M. Zorzi, "3GPP NR: the cellular standard for 5G networks," 5G-Italy White Book: a Multiperspective View of 5G, 2018. 5. E. Dahlman, S. Parkvall, J. Skold, "5G NR: The next generation wireless access technology," Academic Press, 2020.
Additional information	N/A

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_TLC 2. Underwater Simulation and Experimentation

Course Area: Information Engineering

Teacher in charge (if defined)	Filippo Campagnaro
Teaching Hours	18
Number of ECTS credits allocated	4
Course period	January-Februray 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (75% minimum of presence) ☐ No
Course unit contents	The course will last one week and will focus on the challenges imposed by the underwater communication channel, where WiFi, 2/3/4/5G and other radio frequency transmissions are strongly attenuated and cannot be used. An underwater network simulation and experimentation tool, called DESERT Underwater, will be used to test and evaluate the performance of underwater networks. Every day will be split into two parts, a theoretical part where the students will attend frontal lessons to learn the concepts and procedures to perform network simulations and develop software modules, and an experimental part where the student will be required to implement the code, run simulation experiments and analyze the results. Required equipment (for all): laptop with GNU/Linux OS (recommended Ubuntu LTS), a Linux virtual machine. Topics: • Basics of communication networks and differences between the ISO OSI

	• stack and underwater protocol stack. • Differences between network emulation and simulation with an eventbased scheduler • The DESERT Underwater simulation and experimentation framework. • Underwater acoustic networks: Acoustic physical layers, Multipath, • Acoustic Noise, Propagation delay and impact to MAC layers. • Underwater optical and EM communication, and multimodal networks: • Underwater EM channel, Underwater optical channel, Underwater • multimodal networks • From simulation to sea experiment: use of real modems with DESERT • Exercises: at the end of each day, a guided assignment is provided
Learning goals	Understand when simulation and experimental results are statistically relevant, understand the challenges of communicating underwater, learn how to use advanced features of the Linux operating system for telecommunications tasks, learn how to interpreter the underwater channel conditions and see how theory can be used to predict the underwater network performance.
Teaching methods	Frontal interactive lessons, seminars, hands on exercises and assignments
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Basic of Linux and C++, basic of computer networks, basic of probability theory.

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Examination methods (in applicable)	Homework assignments.
Suggested readings	[1] Filippo Campagnaro, Roberto Francescon, Federico Guerra, Federico Favaro, Paolo Casari, Roee Diamant, Michele Zorzi, "The DESERT Underwater Framework v2: Improved Capabilities and Extension Tools, IEEE Ucomms 2016 [2] Paolo Casari, Cristiano Tapparello, Federico Guerra, Federico Favaro, Ivano Calabrese, Giovanni Toso, Saiful Azad, Riccardo Masiero, Michele Zorzi, Open-source Suites for the Underwater Networking Community: WOSS and DESERT Underwater, IEEE Network SI "Open source for networking," 2014 [3] DESERT Underwater - DEsign, Simulate, Emulate and Realize Test-beds for Underwater network protocols https://desert-underwater.dei.unipd.it/ [4] Milica Stojanovic, On the relationship between capacity and distance in an underwater acoustic communication channel, ACM SIGMOBILE Mobile Computing and Communications Review, Volume 11, Issue 4, October 2007, pp 34–43 [5] Alberto Signori, Filippo Campagnaro, Michele Zorzi, Modeling the Performance of Optical Modems in the DESERT Underwater Network Simulator, IEEE Ucomms 2018 [6] Filippo Campagnaro, Roberto Francescon, Paolo Casari, Roee Diamant and Michele Zorzi Multimodal Underwater Networks: Recent Advances and a Look Ahead, WUWNet 2017
Additional information	This will be an intensive course and will last one week

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_TLC 3. Generative Artificial Intelligence: Foundations and Recent Trends

Course Area: Information Engineering

Teacher in charge (if defined)	Prof. Simone Milani
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	November 2025-December 2025
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (70% minimum of presence). ☐ No
Course unit contents	**Introduction to Generative AI and strategies** ○ Fundamentals, basics, fields of applications, open issues and problems. ○ Example of generative AI applications. **Bringing randomness into neural networks: the Variational Autoencoder**. ○ Basic principles: regularizing an AE, statistical characterization, operation implementation. **Becoming adversarial: from adversarial neural networks to generative adversarial networks (GANs).** ○ Network training as a non-cooperative game. ○ Convergence to equilibrium. Stability points. ○ Vanishing gradients, convergence problems, mode collapse. ○ Evaluating and optimizing GANs ○ Other kinds of GANs. **Detecting a GAN**.

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	○ GAN-revealing footprints: physical, noise, motion-related, signal-related, statistical. Improving quality by composite loss function. **Overfitting a network**. ○ Building a neural implicit representation (NIR). ○ Creating an overfitted networks: convergence issues, initialization, quantization and compression of network weights. ○ Entropy layers versus classical quantization+coding. **Going iterative: diffusion models**. ○ Basic definition of diffusion process: forward diffusion and reverse diffusion. ○ Diffusion process as Markov chains. ○ Forward diffusion via stochastic differential equations. Generative reverse stochastic diffusion. ○ Sampling issues. **Tips and tricks for diffusion models**. ○ Accelerated Sampling, Conditional Generation, and Beyond. ○ A simple implementation of a diffusion model. ○ Accelerated diffusion models. Variational diffusion models. Critical sampling. Progressive distillation. Conditional diffusion models. Latent diffusion models. **Application of diffusion models**. ○ Image Synthesis, Text-to-Image, Controllable Generation, Image Editing, Image-to-Image, Super-resolution, Segmentation, Video Synthesis, Medical Imaging, 3D Generation. **Combining transformers into diffusion models**: **diffusion transformers**. ○ Basics principles of transformers. ○ Attention layers. Positional encoding. Application of transformers to DM. ○ The GLIDE architecture. ○ Application to LLMs.
Learning goals	The course will introduce fundamental strategies in Generative AI overviewing different architectures from GANs to the most recent diffusion models. Students will have the opportunity to understand the building blocks of these solutions and verify their performances, as well as their advantages and disadvantages. In the end, we will discuss a possible application of these solutions in their field of research.
Teaching methods	Frontal lectures, moodle quizzes, demos and video tutorials

Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Previous basic knowledge on Probability, Machine Learning and Deep Learning
Examination methods (in applicable)	Oral presentation
Suggested readings	[1] Ian Goodfellow and Yoshua Bengio and Aaron Courville, "Deep learning", MIT Press 2016, https://www.deeplearningbook.org/ [2] Jonathan Ho and Ajay Jain and Pieter Abbeel, Denoising Diffusion Probabilistic Models, 2020, https://arxiv.org/pdf/2006.11239.pdf [3] Richard O. Duda, Peter E. Hart, David G. Stork, Pattern Classification (2nd Edition), Wiley-Interscience, 2000 [4] Nichol, Alex & Dhariwal, Prafulla. (2021). Improved Denoising Diffusion Probabilistic Models. https://arxiv.org/pdf/2102.09672.pdf [5] David J. C. MacKay, Information Theory, Inference and Learning Algorithms, Cambridge University Press, 2003 (freely available and supporting material at http://www.inference.phy.cam.ac.uk/mackay/ [6] Ian Goodfellow, NIPS 2016 Tutorial: Generative Adversarial Networks, 2016, https://arxiv.org/pdf/1701.00160.pdf [7] Zhiqin Chen and Hao Zhang. 2019. Learning Implicit Fields for Generative Shape Modeling. ***arXiv:1812.02822 [cs]*** (September 2019). [8] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, Illia Polosukhin, Attention is all you need, Proc of Advances in Neural Information Processing Systems (NIPS 2017), https://arxiv.org/pdf/1706.03762.pdf
Additional information	

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Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_TLC 4. Machine Learning for Mobile Communication Systems (Seminar Series)

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Dr. Paolo Dini, Senior Researcher, Centre Tecnologic de Telecomunicacions de Catalunya

e-mail: paolo.dini@cttc.es

Aim: The course will introduce the requirements, scenarios and architectures for the next-generation mobile edge computing platforms, together with their challenges and open issues. We will discuss the central role played by the historical data exchanged among the different network entities and how to distribute computing operations across them to enable automatic and energy efficient extraction of context information and network control.

The core focus of the course is the application of Machine Learning (ML) tools to solve identified mobile networking and computing problems. Moreover, we will discuss how to enable ML-based services at the edge. It will be explained what the usage models are and what they imply in terms of stability, convergence and optimality guarantees. For this, fundamentals of Reinforcement Learning and Artificial Neural Networks / Deep Learning will be given. Moreover, Multi-task Learning, Knowledge Transfer Learning, Continual Learning and Federated Learning paradigms for networked systems will be introduced.

Finally, several ML algorithms will be tailored for specific case studies. We will examine the automatic control of base station operation modes to solve the Energy-Quality of Service trade-off; and how to build models for mobile traffic prediction, classification and anomaly detection using real data from mobile operators. The course covers Supervised, Unsupervised, Semi-Supervised and Reinforcement Learning applications to mobile networking and computing.

Topics:

- Introduction of next-generation mobile edge computing platforms
  - data-centric scenario and architecture
  - multi-access edge computing and distributed learning
  - vertical markets and services
  - energy sustainability issues
- Identification of machine learning tools for mobile networking and computing
- Fundamentals of Artificial Neural Network architectures
  - Multi-layer perceptron
  - Recurrent neural networks
  - Convolutional neural networks
  - Auto-encoders

- Distributed Learning in networked systems
    - Multi-task learning
    - Knowledge Transfer learning
    - Continual learning
    - Federated learning (including centralized and decentralized architectures)
- Fundamentals of Reinforcement Learning
    - Dynamic Programming
    - Temporal-Difference methods
    - Deep-Reinforcement Learning
- Mobile traffic characterization and modeling
    - Applications of Artificial Neural Networks
    - Traffic prediction, classification and anomaly detection
- Mobile network on-line optimization methods
    - Applications of Reinforcement Learning
    - Multi-agent Reinforcement Learning

References:

[1] Anwer Al-Dulaimi, Xianbin Wang, Chih-Lin I, 5G Networks: Fundamental Requirements, Enabling Technologies, and Operations Management, October 2018, Wiley-IEEE Press

[2] R. Boutaba, M.A. Salahuddin, N. Limam, et al., A comprehensive survey on machine learning for networking: evolution, applications and research opportunities, Elsevier J. Internet Serv Appl (2018) 9: 16

[3] Richard Sutton, Andrew G. Barto, Reinforcement Learning: An Introduction, MIT press, 2017

[4] Christopher M. Bishop, Pattern Recognition and Machine Learning, Springer, 2006

[5] Ian Goodfellow, Yoshua Bengio, Aaron Courville, Deep Learning, MIT press

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_AUT 1. Applied Functional Analysis and Machine Learning: from Regularization to Deep Networks

Course Area: Information Engineering

Teacher in charge (if defined)	Gianluigi Pillonetto
Teaching Hours	24
Number of ECTS credits allocated	5
Course period	November - December 2025
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (80% minimum of presence) ☐ No
Course unit contents	Review of some notions on metric spaces and Lebesgue integration: Metric spaces. Open sets, closed sets, neighborhoods. Convergence, Cauchy sequences, completeness. Completion of metric spaces. Review of the Lebesgue integration theory. Lebesgue spaces. Banach and Hilbert spaces: Finite dimensional normed spaces and subspaces. Compactness and finite dimension. Bounded linear operators. Linear functionals. The finite dimensional case. Normed spaces of operators and the dual space. Weak topologies. Inner product spaces and Hilbert spaces. Orthogonal complements and direct sums. Orthonormal sets and sequences. Representation of functionals on Hilbert spaces. Reproducing kernel Hilbert spaces, inverse problems and regularization theory: Representer theorem. Reproducing Kernel Hilbert Spaces (RKHS): definition and basic properties. Examples of RKHS. Function estimation problems in RKHS. Tikhonov regularization. Support vector regression and classification. Extensions of the

	theory to deep kernel-based networks: multi-valued RKHSs and the concatenated representer theorem.
Learning goals	The course is intended to give a survey of the basic aspects of functional analysis, machine learning, regularization theory and inverse problems. At the end of the course, the student will have the methodological tools to tackle various machine learning problems in both regression and classification (estimation of functions from scattered and noisy data) starting from very general hypothesis spaces.
Teaching methods	Blackboard lectures and various questions posed to students regarding previous lessons
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	The classical theory of functions of real variable: limits and continuity, differentiation and Riemann integration, infinite series and uniform convergence. Some elementary set theory and linear algebra.
Examination methods (if applicable)	Two written exams, one in the middle of the course and the other at the end
Suggested readings	[1] G. Pillonetto, T. Chen, A. Chiuso, G. De Nicolao, L. Ljung. Regularized System Identification –learning dynamic models from data, Springer Nature 2022 [2] W. Rudin. Real and Complex Analysis, McGraw Hill, 2006 [3] C.E. Rasmussen and C.K.I. Williams. Gaussian Processes for Machine Learning. The MIT Press, 2006 [4] H. Brezis, Functional analysis, Sobolev spaces and partial differential equations, Springer 2010 [5] G. Pillonetto, A. Aravkin, D. Gedon, L. Ljung, A.H. Ribeiro and T.B. Schön, Deep networks for system identification: a Survey, eprint 2301.12832 arXiv, 2023

	In addition, written notes will be made available to the students.
Additional information	None

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_AUT 2. Elements of Deep Learning (Seminar Series)

Course Area: Information Engineering

Course unit English denomination	Elements of Deep Learning
Teacher in charge (if defined)	Davide Dalle Pezze
Teaching Hours	24
Number of ECTS credits allocated	5
Course period	19/01/2026-27/02/2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	The course will serve as an introduction to Deep Learning (DL) for students who already have a basic knowledge of Machine Learning. The course will move from the fundamental architectures (e.g. CNN, RNN, and Transformer) to hot topics in Deep Learning research. Topics: •Introduction to Deep Learning: context, historical perspective, differences with respect to classic Machine Learning. •Feedforward Neural Networks (stochastic gradient descent and optimization). •Convolutional Neural Networks.

	•Neural Networks for Sequence Learning. •Elements of Deep Natural Language Processing. •Elements of Deep Reinforcement Learning. •Unsupervised Learning: Generative Adversarial Neural Networks and Autoencoders. •Advanced topics of Deep Learning. •Emerging trends in current research.
Learning goals	The course will serve as an introduction to Deep Learning (DL) for students who already have a basic understanding of Machine Learning. The course will move from fundamental architectures (e.g., CNN, RNN, and Transformer) to advanced topics and emerging trends in Deep Learning.
Teaching methods	In class lectures
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites **(not mandatory)**	Basic Machine Learning
Examination methods **(in applicable)**	Project based on the topics covered during the course or summary of scientific papers on advanced topics not covered directly during the course. Both the project and the summary will then be presented and discussed with the lecturer and the other students.
Suggested readings	- 'Dive into Deep Learning' https://d2l.ai/ - 'Deep Learning' https://www.deeplearningbook.org/ - Understanding Deep Learning https://udlbook.github.io/udlbook/ - slides from the lecturer

Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_AUT 3. Causal Intelligence: From AI Inference to Reasoning (Seminar Series)

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Prof. Reza Arghandeh Department of Computer Science, Electrical engineering and Mathematical Sciences, Western Norway University of Applied Sciences. Profile: https://www.hvl.no/en/employee/?user=Reza.Arghandeh

e-mail: reza.arghandeh@hvl.no

Aim: This course provides an in-depth introduction to the theory and applications of causal inference, with a focus on understanding cause-and-effect relationships in data. The course covers foundational concepts such as correlation, association, and the limitations of traditional statistical methods. Students will explore advanced topics including Directed Acyclic Graphs (DAGs), Structural Causal Models (SCMs), interventions, and counterfactual analysis. By the end of the course, students will be able to model causal relationships and perform causal discovery using real-world datasets.

Topics:

1. **Introduction to Causality:**
   - Correlation vs. causation
   - Observational vs. experimental data
   - Examples from different domains
2. **Ladder of Causality:**
   - Judea Pearl's framework: associations, interventions, and counterfactuals
   - Biases and statistical paradoxes
3. **Graphical Causal Models:**
   - Directed Acyclic Graphs (DAGs)
   - d-Separation and conditional independence
   - Building and analyzing causal graphs
4. **Structural Causal Models (SCMs):**
   - Defining and using SCMs
   - Interventions and counterfactual queries
5. **Causal Model Discovery from Data:**
   - Constraint-based and score-based discovery methods
   - Real-world applications in economics, healthcare, and AI

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References:

Most topics will be drawn from recent research articles (selection below). The FairML book [1] serves as a foundational textbook.

[1] Barocas, Solon, Moritz Hardt, and Arvind Narayanan. Fairness and machine learning: Limitations and opportunities. MIT press, 2023.

[2] Hort, Max, et al. "Bias mitigation for machine learning classifiers: A comprehensive survey." ACM Journal on Responsible Computing (2023).

[3] Zhao, D., Andrews, J. T., Papakyriakopoulos, O., & Xiang, A. (2024). Position: Measure Dataset Diversity, Don't Just Claim It. ICML 2024

[4] Buolamwini, J., & Gebru, T. (2018, January). Gender shades: Intersectional accuracy disparities in commercial gender classification. In Conference on fairness, accountability and transparency (pp. 77-91). PMLR.

[5] Hardt, Moritz, Eric Price, and Nati Srebro. "Equality of opportunity in supervised learning." Advances in neural information processing systems 29 (2016).

[6] Agarwal, Alekh, et al. "A reductions approach to fair classification." International conference on machine learning. PMLR, 2018.

[7] Bandy, Jack. "Problematic machine behavior: A systematic literature review of algorithm audits." Proceedings of the acm on human-computer interaction 5.CSCW1 (2021): 1-34.

[8] Chouldechova, Alexandra. "Fair prediction with disparate impact: A study of bias in recidivism prediction instruments." Big data 5.2 (2017): 153-163.

[9] Selbst, Andrew D., et al. "Fairness and abstraction in sociotechnical systems." Proceedings of the conference on fairness, accountability, and transparency. 2019.

[10] Weerts, Hilde, et al. "Algorithmic unfairness through the lens of EU non-discrimination law: Or why the law is not a decision tree." Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency. 2023.

Period: TBD

Course requirements: Basic knowledge of statistics and programming (preferably Python) is recommended.

Examination and grading: 1-3 Homework assignments and a Group-based Final project

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_AUT 4. Distributed Machine Learning and Optimization: from ADMM to Federated and Multiagent Reinforcement Learning (Seminar Series)

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Prof. Subhrakanti Dey, Signals and Systems, Uppsala University, Sweden

e-mail: Subhra.Dey@signal.uu.se

Aim:

The aim of this course is to introduce postgraduate students to the topical area of Distributed Machine Learning and Optimization. As we enter the era of Big Data, engineers and computer scientists face the unenviable task of dealing with massive amounts of data to analyse and run their algorithms on. Often such data reside in many different computing nodes which communicate over a network, and the availability and processing of the entire data set at one central place is simply infeasible. One needs to thus implement distributed optimization techniques with communication-efficient message passing amongst the computing nodes. The objective remains to achieve a solution that can be as close as possible to the solution to the centralized optimization problem. In this course, we will start with distributed optimization algorithms such as the **Alternating Direction Method of Multipliers (ADMM),** and discuss its applications to both convex and non-convex problems. We will then explore **distributed statistical machine learning methods, such as Federated Learning as well as consensus based fully distributed algorithms**. The final topic will be based on **multi-agent reinforcement learning and its applications to safe (constrained) data-driven (model free) control in a multi-agent setting.** This course will provide a glimpse into this fascinating subject, and will be of relevance to graduate students in Electrical, Mechanical and Computer Engineering, Computer Science students, as well as graduate students in Applied Mathematics and Statistics, along with students dealing with large data sets and machine learning applications to Bioinformatics.

Topics:

- Lectures 1-3: Precursors to distributed optimization algorithms: parallelization and decomposition of optimization algorithms (dual de- composition, proximal minimization algorithms, augmented Lagrangian and method of multipliers), The Alternating Direction Method of Multipliers (ADMM): (Algorithm, convergence, optimality conditions, applications to machine learning problems)

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- Lectures 5-7: Applications of distributed optimization to distributed machine learning, Federated Learning, fully distributed, consensus based methods under communication constraints
- Lectures 8-10: Introduction to reinforcement learning, safe (constrained) reinforcement learning and its applications to data-driven multiagent control, Federated and multiagent reinforcement learning

References:

[1] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, *Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers*, Foundations and Trends in Machine Learning, 3(1):1122, 2011.

[2] Dimitri Bertsekas and John N. Tsitsiklis, *Parallel and Distributed Computation: Numerical Methods*, Athena Scientific, 1997.

[3] S. Boyd and L. Vandenverghe, *Convex Optimization*, Cambridge University Press.

[4] R. Sutton and A. G. Barto, *Reinforcement Learning*, 2nd Edition, Bradford Books.

[5] D. Bertsekas, *Rollout, Policy Iteration and Distributed Reinforcement Learning*, Athena Scientific, 2020.

Relevant recent research papers will be referred to and distributed during the lectures.

Period: TBD

Course requirements: Advanced calculus, and probability theory and random processes.

Examination and grading: A project assignment for students in groups of 2 requiring about 20 hours of work.

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_CSC 1. Bayesian Machine Learning

Course Area: Information Engineering

Course unit English denomination	Bayesian Machine Learning
Teacher in charge (if defined)	Giorgio Maria Di Nunzio
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	February – March 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	The course on Bayesian Machine Learning aims to introduce students to Bayesian reasoning and its application to common machine learning problems such as classification and regression. It covers key concepts including the mathematical framework of supervised and unsupervised learning, Bayesian decision theory with a focus on classification techniques like minimum-error-rate and decision surfaces, and estimation methods such as Maximum Likelihood Estimation, Expectation Maximization, Maximum A Posteriori, and Bayesian approaches. Additionally, the course explores graphical models, including Bayesian networks and two-dimensional visualization, and concludes with methods for evaluating model accuracy. A graphical tool will be developed to analyze the assumptions underlying Bayesian methods in these contexts.

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Learning goals	The learning goals of the course on Bayesian Machine Learning are: understand the fundamentals of Bayesian reasoning and how they apply to classical machine learning problems such as classification and regression; analyze the assumptions of Bayesian approaches in machine learning by developing and utilizing a graphical analysis tool; gain familiarity with graphical models, including the construction and interpretation of Bayesian networks and two-dimensional visualizations; critically assess the pros and cons of Bayesian methods compared to other approaches in machine learning; evaluate the performance of machine learning models** using various accuracy measures.
Teaching methods	The course on Bayesian Machine Learning will use a combination of flipped-classroom methods, slides, and Python Jupyter notebooks to support both theoretical understanding and practical skills. Slides will introduce key topics, with in-class time dedicated to collaborative problem-solving, and hands-on learning using Jupyter notebooks with live demonstrations and visualizations of Bayesian concepts.
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	None
Examination methods (in applicable)	Participation and interaction in course activities. Presentation of a case study (scientific article) or collaborative work on a research topic relevant to the course.
Suggested readings	[1] J. Kruschke, Doing Bayesian Data Analysis: A Tutorial Introduction With R and Bugs, Academic Press 2010 [2] Christopher M. Bishop, Pattern Recognition and Machine Learning (Information Science and Statistics), Springer 2007 [3] Richard O. Duda, Peter E. Hart, David G. Stork, Pattern Classification (2nd Edition), Wiley-Interscience, 2000

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	[4] Yaser S. Abu-Mostafa, Malik Magdon-Ismail, Hsuan-Tien Lin, Learning from Data, AMLBook, 2012 (supporting material available at http://amlbook.com/support.html) [5] David J. C. MacKay, Information Theory, Inference and Learning Algorithms, Cambridge University Press, 2003 (freely available and supporting material at http://www.inference.phy.cam.ac.uk/mackay/ [6] David Barber, Bayesian Reasoning and Machine Learning, Cambridge University Press, 2012 (freely available at http://web4.cs.ucl.ac.uk/staff/D.Barber/pmwiki/pmwiki.php?n= [7] Kevin P. Murphy, Machine Learning: A Probabilistic Perspective, MIT Press, 2012 (supporting material http://www.cs.ubc.ca/ murphyk/MLbook/) [8] Richard McElreath, Statistical Rethinking, CRC Presso, 2015 (supporting material https://xcelab.net/rm/statistical-rethinking/)
Additional information	None

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_CSC 2. Advanced Scientific and Parallel Programming with HPC Infrastructures

Course Area: Information Engineering

Course unit English denomination	Advanced scientific and parallel programming with HPC infrastructures
Teacher in charge (if defined)	Giacomo Baruzzo
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	January – March 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	1. How to use a computing server [Lecture 1-2] • Introduction to High Performance Computing (HPC hardware and architectures, HPC software, supercomputers) • Job scheduling (slurm; writing a job; running, stopping and querying status of a job) • UNIPD HPC queuing system and policy (hardware and architecture; access to UNIPD HPC server; execution queue; how to choose queue) 2. Software Containerization and Singularity [Lecture 3] • Overview of containerization (definition of containers and container daemon; Singularity and Docker software; containers vs virtual machines; advantages: re-usability and

	reproducibility, flexibility, efficiency; disadvantages: learning curve) • Using container that have already been defined (running, stopping, and resuming containers; containers options and flags) • Defining new containers (new containers from scratch; extending existing containers) • Sharing containers and the container repository (browsing and adding a container to the repository; guidelines for creating and documenting containers to be shared) 3. Version control and git [Lecture 4] • Basic operations (create a git repository, staging and committing changes, repository status and history, work with branches) • Advanced operations and remote repository (clone a remote repository, work with a remote repository, GUI for git, git web-based hosting services) 4. Parallel architectures and multi-process/parallel programming [Lecture 5-8] • Introduction to parallel programming models and architectures (basic definitions; shared vs distributed memory architectures; threading: CPU and GPU; shared memory programming; message passing programming; performance metrics) • Parallel programming languages and frameworks (multi-threading; OpenMP; MPI; CUDA) 5. Hands on examples and projects [Lecture 9-10] • a simple parallel software for data analysis / machine learning / numerical analysis • students' proposals
Learning goals	Basic skills for working with remote servers, developing and deploying parallel software on containerized computing environments. Fundamental knowledge of modern computer architecture and key parallel programming paradigms, including multi-threading, OpenMP, MPI, and CUDA, with practical examples (primarily in Python and C++). Essential knowledge on accessing and interacting with remote servers, managing remote resources, and handling job scheduling. Understanding the principles of software version control and software containerization from a user perspective, with hands-on examples using Git and Singularity, respectively.

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	Competency in utilizing at least one of the HPC infrastructures provided by UNIPD.
Teaching methods	Frontal lessons, group project
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No The course is open to all PhD students, with priority given to students enrolled in the offering PhD program (PhD Program in Information Engineering). The total number of guaranteed spots is 60. The possibility of accommodating more students will be considered only after classroom assignments are finalized.
Prerequisites (not mandatory)	Basics usage of tools for run/develop of scientific software (preferable Linux platforms).
Examination methods (if applicable)	Each student or group is required to develop a small (possibly parallel) containerized software application that relates to their research field and incorporates concepts covered in the course. The containerized software must be executed and its performance profiled on the HPC server used during the course.
Suggested readings	Eijkhout V. (2022) “The Science of Computing” (https://theartofhpc.com/istc.html) Eijkhout V. (2022) “Parallel Programming for Science and Engineering” (https://theartofhpc.com/pcse.html) Eijkhout V. (2022) “Introduction to Scientific Programming” (https://theartofhpc.com/isp.html) Eijkhout V. (2022) “HPC Carpentry” (https://theartofhpc.com/isp.html) Grama, A., Kumar, V., Gupta, A., & Karypis, G. (2003). “Introduction to parallel computing”. Addison Wesley (ISBN: 0-201-64865-2) Parhami, B. (1999). “Introduction to parallel processing: algorithms and architectures”. Springer (ISBN 0-306-45970-1)

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Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_CSC 3. Introduction to Modern Cryptography

Course Area: Information Engineering

Teacher in charge	Alessandro Languasco
Teaching Hours	24
Number of ECTS credits allocated	5
Course period	Spring semester 2026
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (75% minimum of presence) ☒ No
Course unit contents	First definition of a cryptosystem. Some historical examples. Fundamental crypto algorithms. Shannon’s perfect cipher. A review about symmetric methods (historical ones, DES, AES). Asymmetric methods based on primality/factoring and discret log problems. Known attacks to some of the most used public key cryptosystems. How to use a public key system to build a digital signature algorithm. Digital Signatures with RSA and discrete log. Authentication protocols (Kerberos, Needham-Schroeder) and public key systems. Key exchange in three steps (Diffie-Hellman key exchange protocol), secret splitting, secret sharing, secret broadcasting, timestamping.
Learning goals	We present some of the main features about what a Modern Cryptosystem is. In particular we will focus on showing the internal characteristics of some of the now used public key cryptosystems. We will overview the methods based on the primality/factorization and on the discrete logarithm problems. The focus will be on the actual implementation and its feasibility in terms of both time and space, while taking care of the needed mathematical concepts (congruences, finite fields) and explaining them along the course as needed. As a final topic, we will show how to use a public key system in an authentication/identification protocol. The goal of the course will be to evaluate pros and cons of the cryptographic choices performed in designing such protocols.
Teaching methods	Frontal lectures

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Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites **(not mandatory)**	none
Examination methods **(in applicable)**	a seminar on a related topic. For example (but on others of common interest we can agree upon): The Secure Hash Algorithm (SHA); other hash algorithms; primality algorithms; factoring algorithms; discrete log algorithms; homomorphic cryptography; elliptic curves cryptography; compression and hash functions; probabilistic cryptography; digital currencies, electronic voting.
Suggested readings	Books: 1) Languasco-Zaccagnini, “Manuale di Crittografia”, Hoepli, 2015. 2) Knospe, “A course in Cryptography”, AMS, 2019. 3) Schneier, “Applied Cryptography, Protocols, Algorithms, and Source Code in C”, Wiley, 1993.
Additional information	

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_CSC 4. Privacy Preserving Information Access (Seminar Series)

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Dr. Guglielmo Faggioli, Università degli Studi di Padova

E-mail: guglielmo.faggioli@unipd.it;

Aim: The course introduces PhD students to the concept of Privacy, emphasizing its ethical, legal, and economic importance in managing user data. It explores privacy's role in cybersecurity across various domains, such as click logs, medical data, and geospatial information.

After covering the General Data Protection Regulation (GDPR), the course focuses on privacy techniques from microdata protection, differential privacy, and geomasking. Topics include k-Anonymity, l-Diversity, t-Closeness, and Differential Privacy mechanisms, along with industry examples like RAPPOR, Private CMS, and LDP. Geomasking methods, including Metric Differential Privacy, conclude the course.

We will use Python for coding and discussion prompts for interactive sessions.

Topics:

Ethical, legal, and economic considerations about Privacy
GDPR
Macrodata Protection
Microdata Protection
K-anonymity
Differential Privacy
Geomasking

References:

[1] Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation) (Text with EEA relevance)

[2] Cisco. Cisco 2024 Consumer Privacy Survey (2024). https://www.cisco.com/c/en/us/about/trust-center/consumer-privacy-survey.html

[3] Alissa Cooper: A survey of query log privacy-enhancing techniques from a policy perspective. ACM Trans. Web 2(4): 19:1-19:27 (2008)

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[4] Bradley A. Malin, Khaled El Emam, Christine M. O'Keefe: Biomedical data privacy: problems, perspectives, and recent advances. J. Am. Medical Informatics Assoc. 20(1): 2-6 (2013)

[5] Song Gao, Jinmeng Rao, Xinyi Liu, Yuhao Kang, Qunying Huang, Joseph App: Exploring the effectiveness of geomasking techniques for protecting the geoprivacy of Twitter users. J. Spatial Inf. Sci. 19: 105-129 (2019)

[6] Valentina Ciriani, Sabrina De Capitani di Vimercati, Sara Foresti, Pierangela Samarati: Microdata Protection. Secure Data Management in Decentralized Systems 2007: 291-321

[7] Latanya Sweeney: k-Anonymity: A Model for Protecting Privacy. Int. J. Uncertain. Fuzziness Knowl. Based Syst. 10(5): 557-570 (2002)

[8] Ashwin Machanavajjhala, Daniel Kifer, Johannes Gehrke, Muthuramakrishnan Venkitasubramaniam: L-diversity: Privacy beyond k-anonymity. ACM Trans. Knowl. Discov. Data 1(1): 3 (2007)

[9] Ninghui Li, Tiancheng Li, Suresh Venkatasubramanian: t-Closeness: Privacy Beyond kAnonymity and l-Diversity. ICDE 2007: 106-115

[10] Cynthia Dwork, Aaron Roth: The Algorithmic Foundations of Differential Privacy. Found. Trends Theor. Comput. Sci. 9(3-4): 211-407 (2014)

[11] Úlfar Erlingsson, Vasyl Pihur, Aleksandra Korolova: RAPPOR: Randomized Aggregatable Privacy-Preserving Ordinal Response. CCS 2014: 1054-1067

[12] Apple Differential Privacy Team. Learning with privacy at scale. Apple Mach. Learn. J, 1(8):1–25, 2017.

Course requirements: Basic notions of statistics, machine learning, and programming

Examination and grading: Final project.

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_CSC 5. Advanced Techniques in Bioinformatics (Seminar Series)

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructors:

- Dr. Giulia Cesaro, Department of Information Engineering, University of Padova.
- Dr. Alexander Monzon, Department of Biomedical Sciences, University of Padova.

e-mail: alexander.monzon@unipd.it; giulia.cesaro@unipd.it

Aim: This course provides students with advanced computational tools to analyze complex biological data and model biological systems across multiple scales, from high-dimensional omics datasets to three-dimensional protein structures. The learning outcomes of the course are:

- Understand the structure, complexity, and challenges of major omics data types.
- Learn how to reduce and interpret high-dimensional data using linear and nonlinear approaches.
- Apply systems-level modeling to represent molecular and cellular interactions, and explore dynamic behaviors through computational simulations
- Integrate information across multiple omics layers to gain a holistic understanding of biological systems.
- Use and critically assess AI tools for protein structure prediction and validation.
- Leverage protein language models for embeddings, annotation, and downstream tasks.
- Understand principles of protein design and basics of ensemble/dynamics analysis.

Topics:

- Introduction to omics data: from biology to data
- High-dimensional data: from linear to nonlinear dimensionality reduction
- Modeling biological systems (complex networks, agent based modelling)
- Multi-omics data integration (matrix factorizations, variational autoencoders)
- Introduction to three dimensional data: Proteins
- 3D biomolecular data: protein structure basics, coordinates, validation metrics (pLDDT/PAE/Ramachandran).
- Protein structure prediction: recent AI methods (concepts behind AlphaFold-like/ESMFold-like pipelines), MSA vs single-sequence, limitations.
- Protein language models: embeddings (ESM/ProtT5 family), zero-/few-shot tasks, annotation, mutational scoring.
- Protein design: sequence-to-structure, inverse folding concepts; design constraints and risks.
- Protein dynamics & ensembles: conformational heterogeneity, experimental restraints (NMR/SAXS/smFRET), ensemble analysis pipelines.

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References:

[1] McInnes, L., Healy, J., & Melville, J. (2018). UMAP: uniform manifold approximation and projection for dimension reduction. arXiv. *arXiv preprint arXiv:1802.03426*, *10*.

[2] Kepes, Francois. *Biological networks*. Vol. 3. World Scientific, 2007.

[3] Soheilypour, M., & Mofrad, M. R. (2018). Agent-based modeling in molecular systems biology. *BioEssays*, *40*(7), 1800020.

[4] Baião, Ana R., et al. "A technical review of multi-omics data integration methods: from classical statistical to deep generative approaches." *arXiv preprint arXiv:2501.17729* (2025).

[5] J. Dauparas et al. ,Robust deep learning–based protein sequence design using ProteinMPNN.Science378,49-56(2022).DOI:10.1126/science.add2187

[6] Zeming Lin et al. ,Evolutionary-scale prediction of atomic-level protein structure with a language model.Science379,1123-1130(2023).DOI:10.1126/science.ade2574

[7] Jumper, J., Evans, R., Pritzel, A. et al. Highly accurate protein structure prediction with AlphaFold. Nature 596, 583–589 (2021). https://doi.org/10.1038/s41586-021-03819-2

Course requirements: Basic notions of machine learning, statistics and programming

Examination and grading: Final project on either a relevant research paper from the literature or a project to be carried out by the student.

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_CSC 6. Automated Planning (Seminar Series)

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Dr. Andrea Orlandini, National Research Council of Italy (CNR-ISTC)

e-mail: andrea.orlandini@istc.cnr.it;

Aim: Artificial intelligence (AI) refers to systems designed by humans that, given a complex goal, act in the physical or digital world by perceiving their environment, interpreting the collected structured or unstructured data, reasoning on the knowledge derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can also be designed to learn to adapt their behaviour by analysing how the environment is affected by their previous actions.

This course presents “Artificial Intelligence Automated Planning” and introduces models and resolution techniques for both "classic" and temporal planning problems, involving scheduling aspects. Different methodologies for the synthesis of action plans will be presented, as well as aspects related to uncertainty in planning domains. Furthermore, some applications and samples will be presented and discussed, also in relation to the control of autonomous robots.

Topics:

- Basic concepts of Automated Planning
- Modeling and classical solving approaches
- State-space and Plan-space planning
- Planning graph techniques
- Planning and Heuristics
- HTN and Temporal Planning

References:

Most topics are considered in well known textbooks.

[1] **Automated Planning: Theory and Practice** Ghallab, Nau, Traverso. MIT press New edition freely available on the web: https://projects.laas.fr/planning/

[2] Artificial Intelligence: A Modern Approach. Russell and Norvig. Pearson. https://aima.eecs.berkeley.edu/

Course requirements: Basic notions of logics, data structures, algorithms

Examination and grading: Final project.

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

IE_OPT 1. Quantum Communication: methods and implementations

Course Area: Information Engineering

Teacher in charge	Dr. Avesani Marco
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	Spring 2026
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	• Elements of quantum communication and Quantum Key Distribution (QKD) • Entropies in quantum information • Discrete variable QKD • Safety definitions and tests • Finite key analysis for the BB84 protocol and practical implementations (decoy technique) • Numerical methods for estimating the rate of secure key generation • Experimental realizations: polarization coding and time-bin • Free space QKD implementations • QKD Attacks
Learning goals	The course aims to introduce the theoretical methods and experimental techniques used in the context of quantum communication. The main topic of the course will be the Quantum Key Distribution (QKD), which

	offers the possibility to present in a modern way both the theoretical (protocols, security tests) and experimental (sources, detection technologies, implementation schemes and realizations) aspects that characterize quantum communication technologies. At the end of the course the student will know the basics of quantum technologies, both from a theoretical and experimental point of view, and will be able to understand scientific articles in the field of quantum communications and QKD.
Teaching methods	Frontal lessons
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Good knowledge of linear algebra is required. Basic knowledge of Quantum Mechanics and Quantum Optics can be useful.
Examination methods (in applicable)	Oral exam on the contents of the course, with the possibility of presenting an in-depth study agreed with the teachers.
Suggested readings	• R. Wolf, "Quantum Key Distribution: An Introduction with Exercises (Lecture Notes in Physics)", 1st Ed., Springer (2021) • S. Pirandola et al., «Advances in quantum cryptography», Adv. Opt. Photonics, vol. 12, n. 4, pagg. 1012–1236, dic. 2020, doi: 10.1364/AOP.361502 • N. Gisin, G. Ribordy, W. Tittel, H. Zbinden, e N. Gisin, «Quantum cryptography», Rev Mod Phys, vol. 74, n. 1, pagg. 145–195, mar. 2002, doi: 10.1103/RevModPhys.74.145 • V. Scarani et al., «The security of practical quantum key distribution», Rev. Mod. Phys., vol. 81, n. 3, pagg. 1301–1350, 2009, doi: 10.1103/RevModPhys.81.1301
Additional information	Additional material (notes, slides, etc.) will be made available by the teacher.

Schedule and room: see Class Schedule for details

Enrollment: add the course to the list of courses you plan to attend using the Course Enrollment Form (requires SSO authentication) and, if you are taking the course for credits, to the Study and Research Plan.

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