Ph.D. Program in Information Engineering

Course Catalogue

A.Y. 2024/2025

Rev. 1.1 - 11/11/2024

Revision History

Revisions with respect to the reference version: 1.0 – 30/10/2024

Rev. 1.1 – 11/11/2024:

- Updated “**Course period”** for some courses, highlighted in yellow

[back to **Summary**]

Summary

General Information

Courses - Transversal Skills Area

Courses - Information Engineering Area

Mathematical and Statistical Methods (IE_MSM)

Bioengineering (IE_BIO)

Electronics (IE_ELE)

Telecommunications (IE_TLC)

[back to **Summary**]

Control Theory and Applications (IE_AUT)

Computer Science (IE_CSC)

Applied Optics (IE_OPT)

[back to **Summary**]

Coursework Requirements

The following requirements are valid for Ph.D. Students starting in November 2024 (40° 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).
- In order 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.

[back to **Summary**]

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 all the lectures of the **Distinguished Lecturer Series** program offered by the Department during the three-year Ph.D. course (if offered)
- Attend at least two **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.

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

within November 22nd *(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, Distinguished Lectures 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.

[back to **Summary**]

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 2024/25 PhD Courses for Google Calendar

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

Class Schedule of 2024/25 PhD Courses

With very few exceptions, classes meet in classrooms and meeting rooms of the Department of Information Engineering, via Gradenigo 6/A, Padova. In order 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.

[back to **Summary**]

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	5
Course period	normally on Wednesday morning from Wednesday 15 January 2025 to Wednesday 26 February 2025.
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (66% minimum of presence) ☐ No
Course unit contents	Entrepreneurship The team and the early decisions From the idea to the market Intellectual Property Rights Business Models The financials of a startup Funding a startup
Learning goals	The course is aimed at those who have undertaken or are undertaking research paths which can result in potential entrepreneurial ventures. The aim of this course is to provide participants with the main elements needed to establish an innovative start-up. Each participant develops and understanding of their propensity to be an entrepreneur, followed by awareness of how ready they are to set up an entrepreneurial project. The course aims to expand participants' ability to embark on an entrepreneurial journey by providing them with greater confidence and competence. By the end of the programme, participants will perceive their entrepreneurial ability to have greatly improved. Main learning goals: • understand the characteristics of a technology and innovation-based start-up;

[back to **Summary**]

	• use feasibility criteria applied to a business idea; • understand the main features of a founding team and the major problems associated with it; • define and evaluate a product and/or service concept; • understand and apply intellectual property protection and related processes; • evaluate the market aspects of a business idea; • design and evaluate business models to be applied to a business idea; • understand and draw up the economic and financial aspects of a start-up; • assess cash flow aspects; • evaluate different options for financing a start-up; • understand what professional investors are interested in and how they assess it.
Teaching methods	frontal lessons
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)	Final evaluation will be based on the discussion of a case study of a technology-based startup.
Suggested readings	
Additional information	

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	03/2025 – 04/2025
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

[back to Summary]

	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.

	[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 2025
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

[back to **Summary**]

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	02/2025 – 04/2025
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

[back to **Summary**]

	☐ 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	• 03/02/2025 • 10/02/2025 • 27/06/2025-30/06/2025
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

[back to **Summary**]

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	03/2025-04/2025
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	Lecures, 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. Statistical Learning for Big Data in Medicine

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Prof. Andrea Facchinetti (Department of Information Engineering, University of Padova), Dr. Martina Vettoretti (Department of Information Engineering, University of Padova)

Important note: course not offered in A.A. 2024/25

IE_BIO 2. Quantitative Neuroimaging: from Microparameters to Connectomics

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructors: Prof. Alessandra Bertoldo, Prof. Mattia Veronese, Department of Information Engineering, University of Padova

Important note: course not offered in A.A. 2024/25

[back to **Summary**]

IE_BIO 3. 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 (% 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, TBC) - 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.

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.

[back to **Summary**]

	The projects will be presented to the whole class, including a peer-to-peer evaluation activity.
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 4. Deep Learning for Biomedical Images

Course Area: Information Engineering

Course unit English denomination	Deep Learning for Biomedical Images
Teacher in charge (if defined)	TBA
Teaching Hours	18
Number of ECTS credits allocated	4
Course period	03/2025 - 06/2025
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 • Transformers, attention principle and its application 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 5. 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	20
Number of ECTS credits allocated	4
Course period	TBD
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.

[back to **Summary**]

	•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
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

Course unit English denomination	Physics and Operation of Heterostructure-Based Electronic and Optoelectronic Devices
Teacher in charge (if defined)	Matteo Buffolo, Carlo De Santi, Matteo Meneghini
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	Feb-Mar 2025
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 building high-frequency communication systems, radar, satellite applications and high-efficiency power converters. On the other hand, LEDs and lasers are high-efficiency monochromatic light sources, which can be used both for lighting applications (with significant energy savings), in the biomedical field, and in photochemistry and in the telecommunications sector. A special focus will be given to devices based on gallium nitride (GaN)

[back to **Summary**]

	and gallium oxide (Ga_2O_3), which represent the most promising devices for future power electronics applications. The course will focus on the main aspects related to the physics of heterostructures, on quantum processes in heterostructures, on recombination processes in semiconductors, on carrier transport in heterostructures, on the structure and operating principles of MESFET, HEMT, GIT, on trapping and on reliability in compound semiconductor devices, on the operating principles of LEDs and lasers and on 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 simulating the physics of such devices can 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: • Frontal lessons • Flipped classroom • Classroom discussion • Homework • Classroom exercises • Analysis of the literature

[back to **Summary**]

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 exam 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.

[back to **Summary**]

IE_ELE 2. Embedded Design with FPGA

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructors: Dr. Andrea Stanco and Prof. Daniele Vogrig, Department of Information Engineering, University of Padova

Important note: course not offered in A.A. 2024/25

IE_ELE 3. 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.

[back to **Summary**]

IE_TLC 1. Information Theoretic Models in Security

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Prof. Nicola Laurenti, Department of Information Engineering

Important note: course not offered in A.A. 2024/25

[back to **Summary**]

IE_TLC 2. A Deep Dive into 5G Network Specifications and its Applications

Course Area: Information Engineering

Course unit English denomination	A Deep Dive into 5G Network Specifications and its Applications
Teacher in charge (if defined)	Marco Giordani
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	April 2025 – May 2025 (tentative)
Course delivery method	☐ In presence
Language of instruction	English
Mandatory attendance	☐ 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
	  ○ The Third Generation Partnership Project (3GPP)
	  ○ How to read standardization documents and specifications
	  ○ The 5G NR Radio Access Network (RAN) architecture
	• 5G NR spectrum
	  ○ 5G NR frequencies
	  ○ The millimeter wave spectrum and channel model
	  ○ The Multiple Input Multiple Output (MIMO) technology
	• The 3GPP NR PHY layer
	  ○ 5G NR frame structure
	  ○ 5G NR numerology and resource grid
	  ○ 5G duplexing schemes
	  ○ 5G PHY signals and channels

[back to Summary]

	•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	☐ No
Available for PhD students from other courses	☐ Yes
Prerequisites (not mandatory)	Preliminary knowledge of the ISO/OSI protocol stack
Examination methods (in applicable)	Final project

[back to Summary]

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 3. Underwater Simulation and Experimentation

Course Area: Information Engineering

Course unit English denomination	Underwater Network Simulation and Experimentation
Teacher in charge (if defined)	Filippo Campagnaro
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	10-14 Feb. 2025
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% 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.

[back to **Summary**]

	Topics: • Basics of communication networks and differences between the ISO OSI stack and underwater protocol stack. • Differences between network emulation and simulation with an event-based 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.
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 4. A walkthrough on Generative AI: the evolution of generative strategies from GANs to diffusion models

Course Area: Information Engineering

Course unit English denomination	**A walkthrough on Generative AI: the evolution of generative strategies from GANs to diffusion models**
Teacher in charge (if defined)	Prof. Simone Milani
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	Nov. 2024-Dec. 2024
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence). 70 % ☐ 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.

- 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.

[back to **Summary**]

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

[back to **Summary**]

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.

[back to **Summary**]

IE_TLC 5. 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

[back to **Summary**]

- 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_TLC 6. Advanced Information Theory and Machine Learning (Seminar Series)

Course Area: Information engineering

Credits: 4 (20 hours)

Instructor: Dr. Stefano Rini – 李冕, Dept. of Electrical and Computer Engineering, National Yang-Ming Chiao-Tung University, Taiwan.

e-mail: rini.stefano@gmail.com

Aim: Information theory is a pivotal discipline in understanding and optimizing communication systems and data processing techniques. This course aims to explore the profound impact of information theory on machine learning, presenting it not just as a theoretical study but as a practical lens to enhance machine learning models.

We will delve into fundamental concepts such as entropy, mutual information, and data compression, and extend these concepts to analyze and improve modern machine learning algorithms. The course emphasizes the symbiotic relationship between information theory and machine learning, exploring how principles derived from information theory can lead to more efficient, robust, and interpretable machine learning systems.

Additionally, the course is designed to bridge the gap between theory and application. Each week, students will engage with both the theoretical underpinnings and practical implementations of information theory in machine learning. Through hands-on sessions, students will apply these concepts to various deep learning architectures, gaining insights into their operational mechanisms and limitations.

Topics:

Week 1: Foundations of Information Theory

Lecture 1: Fundamentals of Information Theory

Introducing key concepts such as entropy, mutual information, and channel capacity.

Lecture 2: Theoretical Computer Science Background

Discussing the underpinnings of information theory in computer science, including algorithmic information theory.

Week 2: Hypothesis Testing and Classification

Lecture 3: Hypothesis Testing & Classification 1

Basic principles of hypothesis testing and its application to machine learning.

Lecture 4: Hypothesis Testing & Classification 2

Advanced techniques and classification algorithms informed by information theory.

Week 3: Data Compression Techniques and Practical Implementations

Lecture 5: Data Compression & Autoencoders 1

Exploring data compression schemes and their implementation in autoencoders.

Lecture 6: Data Compression & Autoencoders 2

Deep dive into autoencoder architectures and their optimization using information theoretic principles.

Week 4: Information Optimization

Lecture 7: Mutual Information Estimation 1

Techniques for estimating mutual information in various data settings.

Lecture 8: Mutual Information Maximization

Methods to maximize mutual information for feature selection and model improvement.

Week 5: Advanced Information Theoretic Applications

Lecture 9: Empirical Risk Minimization 1

The role of information theory in minimizing empirical risk within machine learning frameworks.

Lecture 10: Empirical Risk Minimization 2

Continuing exploration on minimizing risk and improving model accuracy through theoretical insights.

References

1. **Fundamentals of Information Theory**

   Book: Cover, T. M., & Thomas, J. A. (2006). *Elements of Information Theory* (2nd ed.). Wiley-Interscience.
   A foundational text covering the fundamental concepts of information theory, including entropy, mutual information, and channel capacity.
2. **Theoretical Computer Science Background**

   Book: Arora, S., & Barak, B. (2009). *Computational Complexity: A Modern Approach*. Cambridge University Press.
   Provides insights into computational complexity theory, which underpins many concepts in theoretical computer science relevant to information theory.
3. **Hypothesis Testing & Classification**

   Book: Shao, J. (2003). Mathematical Statistics (2nd ed.). Springer.
   Chapters on hypothesis testing provide a deep understanding of statistical decision theory.
   Book: Duda, R. O., Hart, P. E., & Stork, D. G. (2000). *Pattern Classification* (2nd ed.). Wiley-Interscience.
   Covers methods and theories behind classification algorithms, including statistical pattern recognition.
4. **Data Compression & Autoencoders**

   Book: Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
   Chapter on autoencoders discusses data compression using deep learning models.
   Conference Paper: Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the Dimensionality of Data with Neural Networks. *Science*, 313(5786), 504–507.

[back to **Summary**]

Introduces the concept of using autoencoders for dimensionality reduction and data compression.

5. **Mutual Information Estimation & Maximization**
   Article: Kraskov, A., Stögbauer, H., & Grassberger, P. (2004). Estimating Mutual Information. *Physical Review E*, 69(6), 066138.
   Discusses methods for estimating mutual information from data samples.
   Conference Paper: Belghazi, M. I., Baratin, A., Rajeshwar, S., et al. (2018). Mutual Information Neural Estimation. In *Proceedings of the 35th International Conference on Machine Learning* (pp. 531–540).
   Presents neural network-based approaches for estimating and maximizing mutual information.
6. **Empirical Risk Minimization**
   Book: Vapnik, V. N. (1998). *Statistical Learning Theory*. Wiley-Interscience.
   Introduces the principles of empirical risk minimization and its applications in machine learning.
   Article: Bottou, L., & Bousquet, O. (2008). The Tradeoffs of Large Scale Learning. In *Advances in Neural Information Processing Systems* (pp. 161–168).
   Discusses the practical aspects and trade-offs involved in empirical risk minimization for large datasets.
7. **Additional Resources**
   Information Bottleneck Principle:
   Tishby, N., Pereira, F. C., & Bialek, W. (2000). The Information Bottleneck Method. *arXiv preprint arXiv:physics/0004057*.
   Introduces the information bottleneck method for extracting relevant information in signal processing and machine learning tasks.
   Variational Inference and Autoencoders:
   Kingma, D. P., & Welling, M. (2014). Auto-Encoding Variational Bayes. In *Proceedings of the 2nd International Conference on Learning Representations (ICLR)*.
   Describes variational autoencoders and their role in unsupervised learning and generative models.
   Expectation-Maximization Algorithm:
   Moon, T. K. (1996). The Expectation-Maximization Algorithm. *IEEE Signal Processing Magazine*, 13(6), 47–60.
   Provides an in-depth explanation of the EM algorithm and its applications in statistical models.
   Deep Learning Architectures:
   LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep Learning. *Nature*, 521(7553), 436–444.
   An overview of deep learning techniques and architectures relevant to the practical sessions.
   Compressed Sensing:
   Candès, E. J., & Wakin, M. B. (2008). An Introduction to Compressive Sampling. *IEEE Signal Processing Magazine*, 25(2), 21–30.
   Explains the principles of compressed sensing, which relate to data compression topics in the course.

[back to **Summary**]

Accessing the References

Most references are available through academic databases such as IEEE Xplore, SpringerLink, or arXiv.
Books can be accessed through university libraries or purchased from academic publishers.

Course requirements: basic programming notions

Examination and grading: in-class presentation and 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 1. Elements of Deep Learning

Course Area: Information Engineering

Course unit English denomination	Elements of Deep Learning
Teacher in charge (if defined)	Gian Antonio Susto
Teaching Hours	24
Number of ECTS credits allocated	5
Course period	18/11/2024-16/12/2024
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 and RNN) 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.

[back to **Summary**]

	•Elements of Deep Reinforcement Learning. •Unsupervised Learning: Generative Adversarial Neural Networks and Autoencoders. •Laboratory sessions in Colab. •Hot topics 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 and RNN) to hot topics in Deep Learning research.
Teaching methods	In class lectures and programming lectures with notebooks (commented and partially solved)
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Basic Machine Learning and basic programming
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/ - Notebook colab and 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.

[back to **Summary**]

IE_AUT 2. Applied Functional Analysis and Machine Learning: from Regularization to Deep Networks

Course Area: Information Engineering

Course unit English denomination	Applied functional analysis and machine learning
Teacher in charge (if defined)	Gianluigi Pillonetto
Teaching Hours	28
Number of ECTS credits allocated	6
Course period	November-december 2024
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% 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

[back to **Summary**]

	[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 3. Applied Linear Algebra

Course Area: Information Engineering

Course unit English denomination	Applied Linear Algebra
Teacher in charge (if defined)	Prof. Luca Schenato
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	Fall
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	1. Vectors: inner products, norms, main operations (average, standard deviation, ...) 2. Matrices: matrix-vector and matrix-matrix multiplication, Frobenius norm, 3. Complexity, sparsity 4. Special matrices: Diagonal, Upper Triangular, Lower triangular, Permutation (general pair), inverse and orthogonal 5. A square and invertible: LU decomposition (aka gaussian elimination), LU-P decomposition, Cholesky decomposition 6. Ax=b via LU-P decomposition: forward and backward substitution 7. (sub)Vector spaces: definitions, span, bases (standard, orthogonal, orthonormal), dimension, direct sum, orthogonal complement, null space, orthogonal complement theorem 8. Gram-Smith orthogonalization and QR decomposition (square and invertible A, general non-square) 9. Ax=b via QR decomposition. LU-P vs QR 10. Linear maps: image space, kernel, column and row rank

	11. Fundamental Theorem of Linear Algebra (Part I): rank-nullity Theorem, the 4 fundamental subspaces 12. Eigenvalues/eigenvector and Shur decomposition 13. Projection matrices: oblique and orthogonal, properties 14. Positive semidefinite matrices: properties and quadratic functions square root matrix 15. Properties of A'A and AA' and Polar decomposition 16. Singular Value Decomposition: proofs and properties 17. Pseudo-inverse: definition and relation to SVD 18. Fundamental Theorem of Linear Algebra (Part II): special orthogonal basis for diagonalization 19. Least-Squares: definition, solution and algorithms 20. Ill-conditioned problems vs stability of algorithms, numerical conditioning of algorithms, regularization
Learning goals	This class provides concepts and techniques of linear algebra that are important for applications from solution of systems of linear equations to optimization. Particular attention is placed on the to analysis of the numerical stability and computational cost of the basic algorithms and matrix equation decompositions. A wide range of exercises and problems are essential part of the course.
Teaching methods	• Theory: formal proofs of many results (theorem-proof type problems) • Algorithms: understanding of most commonly used algortithm used in MATLAB and Python for Linear Algebra • Implementation: MATLAB implementation of algorithms and performance evaluation on Big Data
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	A good working knowledge of basic notions of linear algebra. Some proficiency in MATLAB.
Examination methods (in applicable)	Grading is based on homework sets and a written final exam

[back to **Summary**]

Suggested readings	1. S. Boyd, L. Vanderberghe, "**Introduction to Applied Linear Algebra**", Cambridge University Press, 2018 2. G. Strang, "**The Fundamental Theorem of Linear Algebra**", *The American Mathematical Monthly*, vol. 100(9), pp. 848-855, 1993 3. G. Strang, "**Linear Algebra and Learning From Data",** Wellesley - Cambridge Press, 2019
Additional information	PDF notes are provided by the instructor via Moodle classroom

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. Analysis and Control of Multi-agent Systems

Course Area: Information Engineering

Course unit English denomination	Analysis and Control of Multi-agent Systems
Teacher in charge (if defined)	Fabris Marco
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	November 12th, 2024 – December 13th, 2024 (10 lectures)
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No

Course unit contents

Multi-agent systems (MASs), or networked dynamic systems (NDSs), are systems composed of dynamic agents that interact with each other over an information exchange network. These systems can be used to perform team objectives with applications ranging from formation flying to distributed computation. Challenges associated with these systems are their analysis and synthesis, arising due to their decoupled, distributed, large-scale nature, and due to limited inter-agent sensing and communication capabilities. This course provides an introduction to these systems via tools from graph theory, dynamic systems and control theory. The course will cover a variety of modeling techniques for different types of networked systems and proceed to show how their properties, such as stability, performance and security, can be analyzed. The course will also explore techniques for designing these systems. The course will also cover novel applications by presenting recent

	results obtained in the secure-by-design consensus and optimal time-invariant formation tracking. • Lecture 1. Introduction to MASs, synchronization and coordination, illustration of the course goals. Modeling NDSs and related examples such as opinion dynamics, wireless sensing networks, robot rendezvous, cyclic pursuit. • Lecture 2. Elements of graph theory: basic notation and algebraic graph theory. • Lecture 3. Consensus theory: the linear agreement protocol in continuous time, firstly for unweighted graphs and then for weighted digraphs. • Lecture 4. Consensus theory: the linear agreement protocol in discrete time. Secure-by-design linear agreement protocol against edge-weight perturbations seen as an application of the small-gain theorem. • Lecture 5. The nonlinear agreement protocol along with examples such as coupled oscillators and the Kuramoto model. Passivity as a tool to analyze stability of the nonlinear agreement protocol. • Lectures 6-7. Formation control: gradient dynamics and potential-based control. Rigidity theory. A distance-based formation controller and its stability analysis. • Lecture 8. The optimal time-invariant formation tracking (OIFT) problem as an application of the Pontryagin's Maximum Principle. Distributed OIFT. • Lecture 9. Bearing-based formation control. Bearing rigidity. A bearing-only formation controller. Bearing-based formation maneuvering. • Lecture 10. Bearing-based localization, concluding remarks and advanced topics.
Learning goals	By the end of this course, PhD students will have acquired the following • Knowledge: Core principles of MASs, including synchronization, coordination, consensus protocols, and modeling using graph theory, dynamic systems and control theory. They will also learn advanced topics like secure consensus, formation control, optimal time-invariant formation tracking and rigidity theory. • Skills: Ability to analyze the stability, performance, and security of certain multi-agent protocols, design distributed controllers, and

	apply techniques like potential-based control and Pontryagin's Maximum Principle to solve real-world coordination problems. • Competences: Proficiency in designing and analyzing complex MASs, and applying theoretical knowledge to practical, large-scale dynamic systems. Students will also develop the ability to present and critically assess research papers in the field of multi-agent systems, demonstrating clear communication and analytical thinking skills.
Teaching methods	The course will primarily use traditional frontal lectures to deliver core concepts and theories by means of detailed slides on the topics. In addition, students will present research papers on MASs to the class during their exams, fostering peer learning. During presentations, other students will actively listen, providing feedback and engaging in discussions to enhance understanding and critical thinking.
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No The course is open, but the number of seats can be defined only after the assignment of classrooms. In addition, priority will be given to PhD students of the PhD program providing the course.
Prerequisites (not mandatory)	Linear algebra and Calculus
Examination methods (in applicable)	Oral presentation of either any topic contained in the references [2], [3], [5], [6], [9], [10] or any other related work in the scientific literature that may also include the own student's research.
Suggested readings	The following references, along with additional sources, will be consulted. • [1] D. Zelazo's Ph.D. course "Analysis and Control of Multi-agent systems", held at the Department of Information Engineering (UniPD), 2019. • [2] F. Bullo with the contribution of Jorge Cortés, Florian Dörfler, and Sonia Martínez, "Lectures on Networked Systems", Vol. 1. No. 3. Seattle, DC, USA: Kindle Direct Publishing, 2020. • [3] M. Mehran and M. Egerstedt, "Graph theoretic methods in multiagent networks", Princeton University Press, 2010.

	[4] R. A. Horn and C. R. Johnson, “Matrix Analysis”, Cambridge University Press, 1990. [5] C. Godsil and G. Royle, “Algebraic Graph Theory”, Springer, 2009. [6] F. R. K. Chung, “Spectral graph theory”, Vol. 92. American Mathematical Soc., 1997. [7] M. Fabris and D. Zelazo, “Secure consensus via objective coding: Robustness analysis to channel tampering”, IEEE Transactions on Systems, Man, and Cybernetics: Systems 52.12 (2022): 7885-7897. [8] M. Fabris and D. Zelazo, “A Robustness Analysis to Structured Channel Tampering over Secure-by-design Consensus Networks”, IEEE Control Systems Letters, 2023. [9] W. Ren and R. Beard, “Distributed Consensus in Multi-Vehicle Cooperative Control”, Springer, 2008. [10] H. S. Ahn, “Formation control”, Springer International Publishing, 2020. [11] M. Fabris, A. Cenedese and J. Hauser, "Optimal time-invariant formation tracking for a second-order multi-agent system", 18th European Control Conference (ECC). IEEE, 2019. [12] M. Fabris, G. Fattore and A. Cenedese, “Optimal Time-Invariant Distributed Formation Tracking for Second-Order Multi-Agent Systems”, Europan Journal of Control, 2024. [13] S. Zhao and D. Zelazo, “Bearing rigidity and almost global bearing-only formation stabilization” IEEE Transactions on Automatic Control 61.5 (2015): 1255-1268.
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 5. Quantum Probability, Information and Dynamics (course + Seminar Series)

Course Area: Information Engineering

Course unit English denomination	**Quantum Probability, Information and Dynamics**
Teacher in charge	Francesco Ticozzi, Tommaso Grigoletto
Teaching Hours	16 + 4 (4 for seminars specific to the PhD course)
Number of ECTS credits allocated	3 +1 (1 for seminars specific to the PhD course)
Course period	November 2024 – January 2025
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	Main topics: **Quantum Theory as a Probability Theory**: Densities, observable quantities, measurements in a non-commutative setting. Composite systems and entanglement. Partial trace and marginal densities. (4h) **Quantum Dynamical Systems**: Unitary dynamics, open quantum systems and quantum operations. Kraus representation theorem. Examples for two-level systems. Quantum dynamical semigroup and completely positive generators, and their representations. (4h) **Stability Analysis**: Basic stability properties, existence and structure of the invariant sets. Elements of Lyapunov-type analysis and natural Lyapunov functions. (4h)

[back to **Summary**]

	Applications: Noiseless encodings of quantum information; Preparation of states, subspaces and subsystems; Feedback master equations and their control. (4h)
Learning goals	The course aims to provide a modern introduction to (finite-dimensional) quantum theory from the viewpoint of probability, accessible without a background in physics. Some key properties of quantum Markov dynamics will be presented in detail, providing a detailed analysis of a widely used class of models of interest in quantum information and quantum control. Some key applications will be presented, illustrating the application of the mathematical tools developed to problems of information protection and state preparation.
Teaching methods	In class lectures, group work, students presentations
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites **(not mandatory)**	Probability theory, linear algebra, differential equations
Examination methods	Homework and final project
Suggested readings	Lecture notes, provided by the instructor
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.

[back to **Summary**]

IE_AUT 6. Advanced Topics on Model Predictive Control

Course Area: Information Engineering

Course unit English denomination	Advanced topics on Model Predictive Control
Teacher in charge (if defined)	Proff. Mattia Bruschetta, Ruggero Carli, Simone Del Favero, Department of Information Engineering, University of Padova
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	02/2025-03/2025
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	Topics: 1.Review of linear MPC, offset-free tracking and disturbance rejection. 2.Nonlinear MPC: Linearization on trajectories, Direct methods for NLP, Condensing, Sequential Quadratic Programming, Real Time Iteration Scheme. Case study: Virtual driver/rider 3.Learning based NMPC (LbNMPC): using learning dynamics approach based on Guassian Regression and NN. Case study: Furuta inverted pendulum and virtual rider. Live demo of LbMATMPC toolbox
Learning goals	Get confidence with advanced methodological tools for the application of linear and nonlinear Model Predictive Control (MPC).

[back to **Summary**]

Teaching methods	Frontal lectures
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites **(not mandatory)**	The course is tailored to students with a solid background on control system engineering or who have already attended basic course on MPC. Course requirements: Linear Algebra, system theory or foundation of MPCE
Examination methods **(in applicable)**	Homework assignments and take home exam.
Suggested readings	Slides and notes
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 7. Applied Causal Inference (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

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: April/June 2025

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.

[back to **Summary**]

IE_AUT 8. 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)

- 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: June-July 2025

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_AUT 9. Fundamentals of Adaptive Control for Applications (Seminar Series)

Course Area: Information Engineering

Credits: 4 (20 hours)

Instructor: Prof. Andrea Serrani

e-mail: serrani.1@osu.edu

Aim: The course aims at giving an in-depth treatment of classic and recent methodologies for adaptive control of linear and nonlinear models that are relevant in applications, with emphasis on robotics and aerospace systems.

Topics:

1. **Overview of Adaptive Control Systems.** Direct and indirect adaptive control. The principle of certainty-equivalence. Model uncertainty and robustness issues. Motivating example: Attitude control of a rigid satellite. Introduction to stability analysis of adaptive control systems.
2. **Tools.** Stability concepts and Lyapunov theorems. LaSalle/Yoshizawa theorem. Passivity theory. Hill-Moylan conditions. Zero-state detectability. Input-to-state stability. Ultimate boundedness. Positive and strictly positive realness. Kalman-Yakubovich-Popov lemmas.
3. **Stability of Adaptive Control Systems.** The standard form of passivity-based adaptive control systems. Uniform observability. The role of persistence of excitation. Exponential convergence vs. exponential stability and uniform asymptotic stability.
4. **Robust Redesign of Adaptive Controllers.** Robustness of adaptive systems. Leakage, dead-zone and projection-based robustification techniques. Small-gain theorems.
5. **Model Reference Adaptive Control of LTI Models**. Parameterization of certainty-equivalence controllers. State-feedback MRAC schemes. Output-feedback MRAC for systems with relative degree one. Uniform global asymptotic stability of MRACs.
6. **Harmonic Disturbance Rejection:** Adaptive feedforward and adaptive internal model design.
7. **Applications:** Attitude control. Anti-windup redesign. Longitudinal aircraft dynamics. Backstepping techniques. Control of robot manipulators: Slotine-Li controller. Reconfigurable Control**:** Gradient-based dynamic control allocation.

References:

1. Notes (available to registered students).

[back to **Summary**]

2. Isidori, A., Marconi, L., & Serrani, A. (2003). Robust Autonomous Guidance: An Internal Model Approach. Springer Science & Business Media. Appendix A-C (available to registered students).

Additional References:

1. P. Ioannou and J. Sun. Robust Adaptive Control. Prentice Hall, Upper Saddle River, NJ, 1996. (Reprinted by Dover Publishing)
2. M. Krstic, I. Kanellakopoulos, P.V. Kokotovic. Nonlinear and Adaptive Control Design. John Wiley and Sons, 1995

Period: May-June 2025.

Course Requirements: A beginning graduate-level or advanced undergraduate-level course in linear or nonlinear systems theory is required. Previous exposure to adaptive control theory is desirable but not essential. Familiarity with the basic concepts of Lyapunov stability theory is highly desirable.

Examination and Grading: Take-home exam or individual project assignment.

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 2025
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.
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

[back to **Summary**]

	[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 [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 2025
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.

[back to **Summary**]

	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)

[back to **Summary**]

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. Methods for Scalable Graph Analytics

Course Area: Information Engineering

Course unit English denomination	**Methods for Scalable Graph Analytics**
Teacher in charge (if defined)	Stefano Marchesin and Leonardo Pellegrina
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	11/2024 – 12/2024
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	This course presents algorithms and statistical techniques to efficiently analyze large-scale graph data, typical of modern applications. In these settings, standard approaches do not scale due to the sheer size of the networks of interest to the analysis. Therefore, the focus will be on scalable sampling and randomized strategies and their application to processing massive graphs. We will also cover how to adapt and extend the presented tools to real-world application domains (e.g., biomedical, pharmaceutical, news, …). The course is divided into two modules, described in detail below. **Module 1: Efficient Graph Pattern Mining (Leonardo Pellegrina, 10 hours)** This module aims to introduce a selection of key graph analytics problems and scalable algorithmic techniques that can be applied to large graphs. Extensions of the presented techniques to different problems and settings will be discussed.

	Topics: ● Introduction: graph analytics at scale ● Probabilistic tools: Chernoff-Hoeffding concentration bounds ● Identifying communities: the Densest Subgraph problem (exact, approximation, and sampling-based algorithms) ● Node importance metrics: centrality measures (exact and sampling-based algorithms) ● Finding influential nodes: Centrality Maximization ● Mining subgraphs: the Color Coding technique **Module 2: Efficient Graph Quality Evaluation (Stefano Marchesin, 10 hours)** This module aims to introduce statistical methods for evaluating large-scale graph data. Participants will gain an understanding of various sampling and estimation strategies to efficiently evaluate the quality of massive graph datasets. We will also cover how to choose the most appropriate strategies and tools depending on the application scenario. **Topics:** ● Introduction to knowledge graphs ● Scalability challenges of large-scale graph data ● Statistical methods for graph sampling (random, clustering, and stratification) ● Point estimators ● Confidence intervals design ● Evaluation methods and metrics ● Case studies and real-world applications ● Hand-on sessions based on Python (alternatives: R, Matlab)
Learning goals	Achieve confidence with fundamental probabilistic tools to design and analyze randomized and sampling-based algorithms. Gain expertise on the application of these techniques to solve problems involving large-scale graphs. Develop practical hands-on experience on handling large real-world networked data.
Teaching methods	Frontal lectures, presentation and discussion of practical scenarios and case studies, practical hands-on demonstrations.
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No

	The course is open to all UNIPD Ph.D. students.
Prerequisites (not mandatory)	Basics of algorithmics and data structures. Basics of probability theory. Basic programming languages (e.g., R, Python, or Java).
Examination methods (in applicable)	Oral presentation of either a related research work from the literature (or from the students' research activities) or a project to be carried out by the student. The project may consist of the practical application and experimental evaluation of some of the techniques presented in the course to a network from some domain.
Suggested readings	Lecture slides, notes, and relevant recent papers on scalable graph analytics will be referred to and distributed during the lectures. **References (module 1):** • Mitzenmacher, M., and Upfal, E. Probability and computing: Randomization and probabilistic techniques in algorithms and data analysis. *Cambridge university press*, 2017. • Mitzenmacher, M., Pachocki, J., Peng, R., Tsourakakis, C., and Xu, S. C. Scalable large near-clique detection in large-scale networks via sampling. *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)*, 2015. • Lanciano, T., Miyauchi, A., Fazzone, A., and Bonchi, F. A Survey on the Densest Subgraph Problem and its Variants. *ACM Computing Surveys*, 2024. • Bonchi, F., De Francisci Morales, G., and Riondato, M. Centrality measures on big graphs: Exact, approximated, and distributed algorithms. *Proceedings of the 25th international conference companion on world wide web (WWW)*, 2016. • Mahmoody, A., Charalampos E. T., and Upfal, E. Scalable betweenness centrality maximization via sampling. *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (KDD)*, 2016. • Alon, N., Yuster, R., and Zwick, U. 1994. Color-coding: a new method for finding simple paths, cycles and other small subgraphs within large graphs. *Proceedings of the Twenty-Sixth Annual ACM Symposium on theory of Computing (STOC)*, 1994. **References (module 2):** • A. Agresti and B. A. Coull (1998). Approximate is Better than "Exact" for Interval Estimation on Binomial Proportions, *The American Statistician*. • L. D. Brown, T. T. Cai, and A. DasGupta (2001). Interval Estimation for a Binomial Proportion, *Statistical Science*. • G. Casella and R. L. Berger (2002). Statistical Inference, *Thomson Learning*.

	• W. G. Cochran (1977). Sampling Techniques, *Wiley*. • J. Gao, X. Li, Y. E. Xu, B. Sisman, X. L. Dong, and J. Yang (2019). Efficient Knowledge Graph Accuracy Evaluation. *VLDB 2019*. • Y. Qi, W. Zheng, L. Hong, and L. Zou (2022). Evaluating Knowledge Graph Accuracy Powered by Optimized Human-Machine Collaboration. *KDD* 2022.
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. Fairness, Accountability, and Transparency in AI (Seminar Series)

Course Area: Information Engineering

Credits: 4 (18 hours)

Instructor: Dr. Alessandro Fabris, Max Planck Institute for Security and Privacy

e-mail: alessandro.fabris@mpi-sp.org

Aim: social and technological aspects concur in determining who benefits from and who is harmed by algorithms that have increasingly important roles for human lives. Algorithmic Fairness, supported by Accountability and Transparency (FAccT), is an interdisciplinary field of study that analyzes algorithmic decision-making through diverse lenses that revolve around three questions. (1) Do algorithms benefit people equally? (2) If not, why? (3) And how can we rectify undesirable disparities?

This course covers sources of bias in AI, fairness measures, mitigation approaches, and auditing strategies presented in FAccT literature and tangential fields spanning computer science, philosophy, law, and social sciences.

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

Topics:

- The need for fairness & ethics in AI
- Sources of bias
- Measures and mismeasures of fairness
- Bias mitigation
- Auditing algorithms
- What does the law have to do with it
- A broader look at AI ethics

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).

[back to **Summary**]

[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.

Course requirements: Basic notions of 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_OPT 1. Quantum Communication: methods and implementations

Credits: 4 (20 hours)

Course unit English denomination	Quantum Communication: methods and implementations
Teacher in charge (if defined)	• Dr. Avesani Marco • Dr. Francesco Vedovato
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	Spring 2025
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 •Entropies in Quantum Information •Discrete-variable (DV) Quantum Key Distribution •Security definitions and security proofs •Finite key analysis for BB84 and practical QKD (decoy technique)

[back to **Summary**]

	•Numerical tools for QKD rate estimation •Experimental DV-QKD: time bin and polarization encodings •Free-space QKD implementations •Attacks on QKD
Learning goals	The course aims at introducing the methods and experimental techniques used in quantum communication. The main topic of the course will be Quantum Key Distribution since it offers the possibility to present a modern perspective on both theoretical (protocols, security proofs) and practical tools (source and detectors technologies, implementation schemes, and realizations) using the framework of photonic quantum communication technologies. At the end of the course, the student will know the basic principle of quantum communication technologies, from both the theoretical and experimental perspectives, and will be able to understand scientific papers in the field of quantum communication and quantum key distribution.
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 formalism and Quantum Optics may be helpful
Examination methods (in applicable)	Oral test on the contents of the course, with the possibility of presenting an essay on a topic, 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 provided by the teachers during the course.