
Ph.D. Program in Information Engineering

Course Catalogue

A.Y. 2023/2024

Rev. 1.2 - 23/10/2023

Revision History

Revisions with respect to the reference version: 1.0 – 3/10/2023

Rev. 1.1 – 10/10/2023

- IE_AUT4 Fundamentals of Adaptive Control for Applications: added details for lecturer
- The planned period of lectures has been added for most courses

Rev. 1.2 – 23/10/2023

- The planned period of lectures has been added for all courses not taught by external lecturers

Summary

General Information

Coursework Requirements	5
Course enrollment and attendance	7
Class Schedule	8

Courses - Transversal Skills Area

TSK 1. Entrepreneurship and Startup.....	9
TSK 2. Python Programming for Data Science and Engineering.....	12
TSK 3. Data Visualization	14

Courses - Information Engineering Area

Mathematical and Statistical Methods (IE_MSM)

IE_MSM 1. Statistical Methods	16
IE_MSM 2. Statistics for Engineers.....	17
IE_MSM 3. Computational Inverse Problems	20
IE_MSM 4. Heuristics for Mathematical Optimization.....	21

Bioengineering (IE_BIO)

IE_BIO 1. Statistical Learning for Big Data in Medicine	22
IE_BIO 2. Introduction to Model Predictive Control with Case Studies in Automotive and Biomedicine	23
IE_BIO 3. Fluid mechanics for the functional assessment of cardiovascular devices.....	24
IE_BIO 4. Quantitative Neuroimaging: from Microparameters to Connectomics.....	25
IE_BIO 5. Principles of Synthetic Biology	26
IE_BIO 6. Deep Learning for Biomedical Images	28
IE_BIO 7. Healthcare data management and analytics	29

Electronics (IE_ELE)

IE_ELE 1. Diagnostics of Electron Devices	31
IE_ELE 2. Physics and Operation of Heterostructure-Based Electronic and Optoelectronic Devices	32
IE_ELE 3. Embedded Design with FPGA	34

Telecommunications (IE_TLC)

IE_TLC 1. Machine Learning for Mobile Communication Systems 36

IE_TLC 2. Introduction to Reinforcement Learning 38

IE_TLC 3. Information Theoretic Models in Security 39

IE_TLC 4. A Deep Dive into 5G Network Specifications and its Applications..... 40

IE_TLC 5. Underwater Simulation and Experimentation 42

IE_TLC 6. FPGA Programming for TLC Systems 44

IE_TLC 7. A walkthrough on Generative AI: the evolution of generative strategies from GANs to diffusion models..... 46

Control Theory and Applications (IE_AUT)

IE_AUT 1. Elements of Deep Learning 49

IE_AUT 2. Applied Functional Analysis and Machine Learning..... 51

IE_AUT 3. Applied Linear Algebra..... 53

IE_AUT 4. Fundamentals of Adaptive Control for Applications..... 55

IE_AUT 5. Applied Causal Inference 57

IE_AUT 6. Distributed Machine Learning and Optimization: from ADMM to Federated and multiagent Reinforcement Learning 59

IE_AUT 7. Analysis and Control of Multi-agent Systems 61

IE_AUT 8. Introduction to Harmonic Analysis and Applications..... 64

Computer Science (IE_CSC)

IE_CSC 1. Bayesian Machine Learning 66

IE_CSC 2. Advanced topics in scientific and parallel programming with practical application to the CAPRI HPC infrastructure 68

IE_CSC 3. Domain-Specific Accelerators 70

IE_CSC 4. Learning from Networks 71

Applied Optics (IE_OPT)

IE_OPT 1. Quantum Communication: methods and implementations..... 72

Course Index by Instructor

Alphabetical List of Course Instructors 74

Coursework Requirements

The following requirements are valid for Ph.D. Students starting in October 2023 (39° cycle). In summary, Students shall **take courses for a minimum of 20 credits** 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 homework or project, etc.). **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 20 credits** by the end of the second year.

Specific constraints to earn the minimum of 20 credits of courses:

- C.1 **Transversal Skills Area (TSK)**: at least 5 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 10 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**).
- C.3 **External Courses**: up to a maximum of 5 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 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.

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.
- Attend at least two seminars of the **PhD Educational Week on Transferable Skills (PhDETSWeek)** during their three-year Ph.D. course. The PhDETSWeek is organized by the University of Padova and is typically offered every year. It consists of a series of seminars on transversal topics.

Study plan

Each first-year student **enrolled in the PhD 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 3rd (*NOTE: PhD Students starting their program later than October 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 Educational Week modules should not be included in the program of study. Please, use the [Seminar Certificate of Attendance](#) to collect the signature of the speaker or of a member of the Executive Board attending the event.

Course enrollment and attendance

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

[Course Enrollment Form](#)

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

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

Note for students enrolled in PhD Programs other than Information Engineering

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

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

Class Schedule

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

[Class Schedule of 2023/24 PhD Courses for Google Calendar](#)

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

[Class Schedule of 2023/24 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.

TSK 1. Entrepreneurship and Startup

Course Area: Transversal Skills

Credits: 5 (20 hours)

Instructors: Prof. Moreno Muffatto, Ing. Francesco Ferrati, Dipartimento di Ingegneria Industriale, Università di Padova

e-mail: moreno.muffatto@unipd.it, francesco.ferrati@unipd.it

Notes: the course delivers an Open Badge that can be redeemed at <https://bestr.it/badge/show/2670>

Topics:

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

Entrepreneurship

- Entrepreneurship and Entrepreneurial attitudes
- Entrepreneurship vs Management
- What is a technology based startup
- Venture creation: different options

The team and the early decisions

- The creation of the founders' team
- Types and characteristics of founders' teams
- Founders' decisions and their consequences
- Frequent mistakes and suggestions deriving from experience

From the idea to the market

- Innovation: technologies and markets
- Market size
- Customers profiles
- Value proposition
- Development of the product/service concept

[back to [Summary](#)]

Intellectual Property Rights

- Types of IPR (patent, copyright, trademark)
- The structure of a patent application (description, claims, etc)
- Getting a patent: the patenting process (step by step)
- When to file a patent application: priority date, Patent Cooperation Treaty (PCT)
- Where to protect an invention
- Different IPR strategies

Business Models

- Business models case studies
- Successful and problematic business models
- Revenue streams
- Cost of Customer Acquisition

The financials of a startup

- The structures of the financial statements
- Income Statement
- Balance Sheet
- Cash Flow Statement
- Evaluation of the value of the company

Funding a startup

- New ventures' funding options
- Different sources of funds: Angel Investors and Venture Capital
- Investment companies and funds: how they work
- How and what investors evaluate
- How to present a business idea to investors

References:

- Thomas R. Ittelson (2009), *Financial Statements: A Step-by-Step Guide to Understanding and Creating Financial Reports*, Career Press.
- Ferrati, F. & Muffatto, M. (2021). "Reviewing Equity Investors' Funding Criteria: A Comprehensive Classification and Research Agenda". *Venture Capital*, Vol. 23: No. 2, pp. 1-22.
- Noam Wasserman (2013) *The Founder's Dilemmas: Anticipating and Avoiding the Pitfalls That Can Sink a Startup*, Princeton University Press.

Schedule and room: (Jan-Mar 2024) please, see [Class Schedule](#)

[back to [Summary](#)]

Enrollment: students planning to attend the course must

1. register via the Moodle platform of the PhD Course in Industrial Engineering (in order to enter the Moodle platform click on “dettagli” of the course at the page <http://www.cdii.dii.unipd.it/corsi>). Registered students that, for any reason, are not able to attend the course, must inform the lecturer;
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](#).

Examination and grading: Attendance is required for at least 70% of the lecture hours (i.e. 14 hours). Final evaluation will be based on the discussion of a case study of a technology-based startup.

TSK 2. Python Programming for Data Science and Engineering

Course Area: Transversal Skills

Credits: 5 (20 hours)

Instructor: Dr. Stefano Tortora, Department of Information Engineering (DEI), University of Padova

e-mail: stefano.tortora@unipd.it

Aim: 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. 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.

Topics:

- Introduction to the Python Programming Language
 - What is different in Python?
 - The Python Language Syntax
- Modules and Packages
 - NumPy and SciPy: Numerical and Scientific Python
 - Pandas: Labeled Column-Oriented Data
 - Matplotlib: MATLAB-style scientific visualization
 - Scikit-learn: Basics of Machine Learning in Python

References:

[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.

Schedule and room: (Mar-Apr 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Backgrounds in computing with some object-oriented programming language: C++, Java, MATLAB, etc. If you are starting from scratch, please have a look at [3] or [4].

Examination and grading: Homework assignments

TSK 3. Data Visualization

Course Area: Transversal Skills

Credits: 5 (20 hours)

Instructor: Dr. Matteo Ceccarelli, Dept. of Information Engineering, University of Padova.

e-mail: matteo.ceccarelli@unipd.it

Aim: Data visualization is a fundamental tool in the researcher's toolbox. Visualizing data allows us to uncover patterns and to understand relationships in the data. Furthermore, visualization can be used to deliver more effectively the results of our analyses.

This course covers topics related to human perception and color theory, to inform our choices in the design of graphics. Furthermore, we will focus on the usage of the Grammar of Graphics to create graphics in a modular way, breaking free from the constraints imposed by the API of commonly used libraries.

We will use ggplot, an implementation of the Grammar of Graphics in the R programming language, but the concepts and techniques we will cover are generally applicable (for instance in a Python environment). A working knowledge of R is therefore not required.

Topics:

- 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
- Beyond basic charts: getting creative with the Grammar of Graphics

References:

[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. 2009

[4] Wickham, H. (2010). *A layered grammar of graphics*. Journal of Computational and Graphical Statistics, 19(1), 3-28

Schedule and room: (starting Mar 2024) please, see [Class Schedule](#)

Enrollment: students must enroll in the course using the Enrollment Form on the PhD Program eLearning platform (requires SSO authentication).

[back to [Summary](#)]

Course requirements:

- basic programming notions

Examination and grading: Homework assignments and final test.

IE_MSM 1. Statistical Methods

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

Credits: 6 (24 hours)

Instructor: Dr. Lorenzo Finesso (formerly of CNR-IEIIT Padova)

e-mail: lorenzo.finesso@unipd.it

Important note: course not offered in A.A. 2023/24

IE_MSM 2. Statistics for Engineers

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

Credits: 5

Number of lectures: total of 40 hours

Instructors: Prof. Luigi Salmaso, Prof. Rosa Arboretti, Prof. Marta Disegna, University of Padova.

e-mail: luigi.salmaso@unipd.it, rosa.arboretti@unipd.it, marta.disegna@unipd.it

Important note: 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.

Outline of lecture and lab: The course is structured into 2 on-campus lectures and a Summer School of 4 days. A total of 40 hours in-person course will be delivered.

The on-campus lectures will take place on Friday the 2nd February 2024 and Friday the 9th February 2024. Classes will take place online in the morning, 9am to 1pm, and in the afternoon, 2pm to 4pm for a total of 6 hours per day.

The Summer School will take place in Villa San Giuseppe, Monguelfo, Bolzano province (<https://www.villasangiuseppemonguelfo.com>) from Tuesday the 25th June 2024 to Friday the 28th June 2024 for a total of 28 hours. The Summer school will start at 2pm on Tuesday and will finish at 1pm on Friday (plus lunch served in Villa San Giuseppe and included in the fees).

Villa San Giuseppe offers a full board accommodation and rooms are of different size. The cost of the Summer School is €150 (To Be Confirmed) for the full board accommodation to be paid on site for the entire period. Students of the PhD Program in Information Engineering are reimbursed the full cost of the School (full board accommodation and travel).

Payment can be made directly in “Villa San Giuseppe”, no need to pre-pay anything in advance.

Aim: The course is an introduction to statistical methods most frequently used for experimentation in Engineering. Lectures are planned both in the classroom and in computer lab also for an introduction to the use of the following statistical software:

- R and BlueSky, both open-source software.
- MINITAB, licensed to University of Padova.

Topics:

1. Elements of univariate statistical methods:
 - a. Elements of descriptive statistics: frequency, indices of synthesis (position, variability and shape) and graphical representations (histogram, boxplot, scatterplot).
 - b. Elements of probability theory: discrete and continuous probability distributions.

- c. Elements of statistical inference: sampling distributions, point and interval estimation, hypothesis testing, One-way ANOVA.
2. Linear and non-linear regression models:
 - a. Simple and multiple linear regression model
 - b. Logit model
3. Machine Learning algorithms:
 - a. Introduction to Supervised Machine Learning algorithms
 - b. Introduction to Unsupervised Machine Learning algorithms
4. DOE: Introduction to Factorial Designs, Two level and general factorial designs. Tutorials in MINITAB.

Examination and grading: Attendance is required for at least 2/3 of the lecture hours. Final evaluation will be based on the discussion of a case study, preferably drawn from the individual PhD project of one of the group members.

For this course you are expected to describe and analyse a case study using the statistical techniques presented during the course or more advanced statistical techniques, when more suitable. You are required to present your case study on a **maximum of 15 slides** by the **30th of September 2024 at 12:00 noon**. The presentation should include: aim of your project, description of the dataset, description of the method, interpretation of the results and final discussion. You should provide both the presentation and the dataset analysed (if possible). You are allowed to work alone or in team of no more than 3 people.

You can upload your project in the “Presentation_2024” Google Drive folder using the following link https://drive.google.com/drive/folders/1b1pryOOP6kf5ABHzghWrxfg8Bl8Zxr8_?usp=share_link

If you have any problem regarding the upload of the files email to marta.disegna@unipd.it

Please state clearly in the presentation the name(s) of the participant(s).

Some projects will be selected for an oral presentation to the class. The selected projects and the data of the presentation will be communicated in September.

Materials (slides, datasets, etc.) of the course is available at the following link:

https://drive.google.com/drive/folders/1aumb-BSnp8DKWKwbl2VUre6m_lvSzPip?usp=share_link

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.

[back to [Summary](#)]

Schedule and room: please, see **Outline of lecture and lab** above or the [Class Schedule](#)

IE_MSM 3. Computational Inverse Problems

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Prof. Fabio Marcuzzi, Dept. of Mathematics, University of Padova.

e-mail: marcuzzi@math.unipd.it

Important note: course not offered in A.A. 2023/24

IE_MSM 4. Heuristics for Mathematical Optimization

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Prof. Domenico Salvagnin

e-mail: dominiqs@gmail.com, domenico.salvagnin@unipd.it

Aim: 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.

Topics:

- 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.

References:

[1] Gendreau, Potvin “Handbook of Metaheuristics”, 2010

[2] Marti, Pardalos, Resende “Handbook of Heuristics”, 2018

Schedule and room: (Feb-Apr 2024) please, see [Class Schedule](#)

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](#).

Course requirements:

- Moderate programming skills (on a language of choice)
- Basics in linear/integer programming.

Examination and grading: Final programming project.

IE_BIO 1. Statistical Learning for Big Data in Medicine

Course Area: Information Engineering

Credits: 5 (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. 2023/24

IE_BIO 2. Introduction to Model Predictive Control with Case Studies in Automotive and Biomedicine

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructors: Prof. Ruggero Carli, Dr. Mattia Bruschetta, Dr. Simone Del Favero, Department of Information Engineering, University of Padova

e-mail : carlirug@dei.unipd.it, mattia.bruschetta@dei.unipd.it, simone.delfavero@unipd.it

Important note: course not offered in A.A. 2023/24

IE_BIO 3. Fluid mechanics for the functional assessment of cardiovascular devices

Course Area: Information Engineering

Credits: 5 (18 hours)

Instructor: Prof. Francesca Maria Susin, Dept. of Civil, Environmental and Architectural Engineering (DICEA)

e-mail: francescamaria.susin@unipd.it

Aim:

The course is aimed at giving a survey of research approaches for the assessment of cardiovascular medical devices. Emphasis will be given to methods and techniques adopted for the analysis of hemodynamic performance of prosthetic heart valves

Topics:

Review of basic fluid mechanics concepts. Definition of hydrodynamic performance of artificial cardiac valves and ventricular assist devices. Local and global approaches in in-vitro and in-silico models. Cardiac overload. Blood particles damage. Pulse duplicator loops and experimental techniques.

References:

Course Slides. Recent literature references will be proposed during lectures.

Schedule and room: (Jan-Feb 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Fundamentals of Fluid Dynamics.

Examination and grading: Homework assignment with final discussion.

IE_BIO 4. 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

e-mail : alessandra.bertoldo@unipd.it, mattia.veronese@unipd.it

Aim: The course aims to give the methodological knowledge necessary to define a directed or non-directed brain network (compartmental models, seed-based analysis, ICA, mutual information, dynamic casual modeling) and its topographic analysis (graph theory).

Topics:

- What is quantitative neuroimaging: methods to quantify PET microparameters and fMRI features (preprocessing, the role of the atlases, input/output models, compartmental models, seed based analysis, ICA);
- Functional and effective connectivity (static and dynamic): correlation, sliding windows, Hidden Markov Models, Dynamic Casual Modeling, Granger and Transfer entropy.
- Metabolic connectivity (static and dynamic): SICE methods & Non-SICE methods (Pearson, Cosine, Euclidean)
- Network theory applied on brain connectivity
- Hands-on: analysis of neuroimaging data to estimate functional connectivity maps and derived graph measures.

References: Lecture notes and a complete list of references will be made available by the Lecturers.

Schedule and room: (starting May 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Basics of modeling, system identification and statistics; basics of Matlab programming.

Examination and grading: Final project consisting in the definition and analysis of a brain network using MRI and/or PET data.

IE_BIO 5. Principles of Synthetic Biology

Course Area: Information Engineering

Credits: 5

Instructor: Dr. Massimo Bellato (Department of Information Engineering, University of Padova)

e-mail: bellato@dei.unipd.it

Aim: The course is intended to provide some insights into Synthetic Biology, providing the student with primary instruments for the design of an engineered biological system.

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 the measurement and characterization techniques 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.

MATLAB simulations and Wet-Lab hands-on (TBC) will be also included.

Topics:

- 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.

References:

- Uri Alon, "An Introduction to Systems Biology Design Principles of Biological Circuits"
- Alberts et al. "The Molecular Biology of the Cell" (6th edition)
- Vijai Singh, "New Frontiers and Applications of Synthetic Biology"

Schedule and room: (Jan-Feb 2024) please, see [Class Schedule](#)

[back to [Summary](#)]

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](#).

Course requirements: ODEs modeling; basics of Matlab programming. Progressed knowledge in molecular biology, bioinformatics, and control theory can be useful but not necessary.

Examination and grading: Final group project consisting of the design of a genetic circuit in a proper host, on an assigned relevant topic. Alternatively, single student journal club activities. The projects will be presented during the last lecture, including a peer-to-peer evaluation activity.

IE_BIO 6. Deep Learning for Biomedical Images

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Dr. Marco Castellaro (Department of Information Engineering, University of Padova)

e-mail: castellaro@dei.unipd.it

Aim: 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.

References:

- A set of lecture notes and a complete list of references will be made available by the Lecturer

Schedule and room: (Jan-Feb 2024) please, see [Class Schedule](#)

Enrollment: **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](#).

Technical details: the course will use the Medical Open Network for Artificial Intelligence (monai.io) framework and the Pytorch ecosystem

Course requirements: Python programming and basic machine learning theoretical background.

Examination and grading: 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.

IE_BIO 7. Healthcare data management and analytics

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Dr. Enrico Longato (Department of Information Engineering, University of Padova)

Email: enrico.longato@dei.unipd.it

Aim:

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.

Topics:

- A refresher on the bare necessities of python programming: numpy, pandas, and matplotlib.
- Interfacing with R for access to libraries for advanced biostatistics and clinical data management.
- Typical workflows for healthcare data preprocessing.
- Missing values and data imputation.
- Patient disposition and characteristics: creating a “Table 1” for different study types.
- Implementing basic experimental frameworks for classification and regression on healthcare data.
- Understanding and communicating model performance.
- Presenting your results.

References:

- Lectures notes and code snippets made available by the Lecturer
- 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>

Schedule and room: (Mar-Apr 2024) please, see [Class Schedule](#)

Enrollment: **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](#)]

Course requirements: basic knowledge of any programming language, basics of probability theory and/or statistics.

Examination and grading: Final project consisting of the end-to-end analysis of a healthcare or clinical dataset from raw data ingestion to results presentation.

IE_ELE 1. Diagnostics of Electron Devices

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Prof. Giovanna Mura, Department of Electrical and Electronic Engineering (DIEE), 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 or catastrophic failure and to provide corrective actions able to solve the problem. It is a proactive tool with three fundamental tasks: 1) Technical/scientific: 2) Technological 3) Economical. The purpose of this course is to teach what Failure Analysis should be and should do, to show how and why it often does not, to state that F.A. has Logics and has Rules.

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

Several case studies will be proposed with the aim to demonstrate that if sometimes Failure Analysis looks unclear or not problem solving is merely because it was badly conducted.

Topics:

1. Reverse engineering
2. Failure modes and failure mechanisms
3. Principles and fundamental methods in Electron Microscopy
4. Methodology for the Failure Analysis

References: Failure Analysis of Integrated Circuits - Tools and Techniques, Springer International Series - Lawrence C. Wagner.

Slides

Schedule and room: (starting Apr 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Electron Devices, Microelectronics, Optoelectronics devices.

Examination and grading: Written test/ presentation of a report at the end of the course.

IE_ELE 2. Physics and Operation of Heterostructure-Based Electronic and Optoelectronic Devices

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructors: Prof. Matteo Meneghini, Dr. Carlo De Santi, DEI, University of Padova, Dott. Matteo Buffolo

e-mail: matteo.meneghini@unipd.it, carlo.desanti@unipd.it, matteo.buffolo.1@unipd.it

Aim: 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) represent excellent devices for the realization of high frequency communication systems, radars, satellite applications, and high efficiency power converters. On the other hand, LEDs and lasers are high-efficiency monochromatic light sources, that can be used both for lighting applications (with a considerable energy saving), in the biomedical field, and in in photochemistry. Special focus will be given to Gallium Nitride (GaN) based devices, that represent the most promising devices for future power electronics applications. This course will focus on the main aspects related to the physics of heterostructures, on the recombination processes in semiconductors, on carrier transport in heterostructures, on the structure and operating principles of MESFET, HEMTs, GITs, on the trapping and reliability in compound semiconductor devices, on the operating principles of LEDs and lasers, and on parasitics and reliability in LEDs and lasers. An overview of real applications highlighting the capabilities of these devices will also be given.

Topics:

- physics of heterostructures, band diagrams, carrier transport in heterostructures;
- recombination processes in semiconductors; properties of compound semiconductors;
- basic structure of heterojunction transistors, MESFET, HEMT, GIT; parasitics and reliability in HEMTs, LEDs and lasers;
- operating principles of LEDs and lasers;
- fabrication and development of nitride-based devices
- methods for advanced characterization of heterojunction based devices; applications of GaN based HEMTs, LEDs and lasers;
- modeling of semiconductor-based devices

References:

Umesh Mishra, Jasprit Singh, Semiconductor Device Physics and Design, Springer, 2008

Ruediguer Quay, Gallium Nitride Electronics, Springer 2008.

Tae-Yeon Seong, Jung Han, Hiroshi Amano, Hadis Morkoc, III-Nitride Based Light Emitting Diodes and Applications, Springer 2013

S. Pearton (ed.), GaN and ZnO-based Materials and Devices, Springer Series in Materials Science, Vol. 156 (2012). Berlin: Springer-Verlag. DOI: 10.1007/978-3-642-23521-4_7

Schedule and room: (Feb-Mar 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Introductory course of device physics: Microelectronics, Optoelectronic and Photovoltaic Devices.

Examination and grading: homeworks assigned during the course.

IE_ELE 3. Embedded Design with FPGA

Course Area: Information Engineering

Credits: 5 (20 hours)

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

e-mail: andrea.stanco@dei.unipd.it, vogrig@dei.unipd.it

Aim: The course aims at teaching how to practically use System-on-a-Chip (FPGA+CPU) as a potentially application to academic research topics. 75% of the course will be held in a dedicated laboratory to deal with the programming of a [Pynq-Z1](#) board.

Topics:

- Recap on basic of Digital Design. Digital Design Flow (HDL language and HLS). Introduction to VHDL program language.
- Introduction to FPGA and Zynq SoC.
- Introduction to Vivado System Design environment. Time domains, time violations, metastability, system constraints.
- Introduction to SDK environment
- Information exchange between processor and programmable logic. Hardware and Software interrupts.
- Communication between SoC and the outside world.
- [PYNQ](#) (Python on Zynq) project as example of how to make easier the design embedded systems
- Case studies

References:

[1] Xilinx, Vivado Design Suite User Guide, UG893 (v2019.1), https://www.xilinx.com/support/documentation/sw_manuals/xilinx2019_1/ug893-vivado-ide.pdf

[2] Xilinx, Xilinx Software Development Kit (SDK) User Guide, https://www.xilinx.com/support/documentation/sw_manuals/xilinx2015_1/SDK_Doc/index.html

Other material will be pointed out in class and available online for download

Schedule and room: (Jan-Feb 2024) please, see [Class Schedule](#)

[back to [Summary](#)]

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](#).

Course requirements: Basic knowledge of digital electronics. Knowledge of program language (e.g. C/C++). No VHDL knowledge or experience on FPGAs is required.

Examination and grading: Homework assignments and final project.

IE_TLC 1. Machine Learning for Mobile Communication Systems

Course Area: Information Engineering

Credits: 5 (20 hours)

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

e-mail: paolo.dini@cttc.es

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

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

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

Topics:

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

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

References:

- [1] Anwer Al-Dulaimi, Xianbin Wang, Chih-Lin I, 5G Networks: Fundamental Requirements, Enabling Technologies, and Operations Management, October 2018, Wiley-IEEE Press
- [2] R. Boutaba, M.A. Salahuddin, N. Limam, et al., A comprehensive survey on machine learning for networking: evolution, applications and research opportunities, Elsevier J. Internet Serv Appl (2018) 9: 16
- [3] Richard Sutton, Andrew G. Barto, Reinforcement Learning: An Introduction, MIT press, 2017
- [4] Christopher M. Bishop, Pattern Recognition and Machine Learning, Springer, 2006
- [5] Ian Goodfellow, Yoshua Bengio, Aaron Courville, Deep Learning, MIT press

Schedule and room: lecture dates and hours will be published on [Class Schedule](#) when available.

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](#).

Course requirements: Basic knowledge of probability theory, random processes, python scripting.

Examination and grading: Each student will develop a final project, possibly related to his/her research activity, addressing some topic presented in the Course.

Course requirements: Basic knowledge of probability theory, random processes, data analysis, python scripting.

Examination and grading: Each student will develop a final project, possibly related to his/her research activity, addressing some topic presented in the Course.

IE_TLC 2. Introduction to Reinforcement Learning

Course Area: Information Engineering

Credits: 5 (18 hours)

Instructor: Dr. Juan José Alcaraz Espín, Associate Professor, Technical University of Cartagena, Spain.

e-mail: juan.alcaraz@upct.es

Important note: course not offered in A.A. 2023/24

IE_TLC 3. Information Theoretic Models in Security

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Prof. Nicola Laurenti, Department of Information Engineering

e-mail: nil@dei.unipd.it

Important note: course not offered in A.A. 2023/24

IE_TLC 4. A Deep Dive into 5G Network Specifications and its Applications

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Prof. Marco Giordani

e-mail: marco.giordani@unipd.it

Aim: This course will provide a comprehensive overview of the 3GPP NR standardization activities for 5G cellular networks. The first part of the course will be dedicated to the overview of the 3GPP NR PHY layer, focusing on the renovated NR frame structure, the NR spectrum (including the millimeter wave spectrum and channel model), the MIMO technology, the duplexing schemes, and the NR PHY signals and channels. The second part of the course will review the 3GPP NR MAC procedures, from scheduling to resource allocation, with a focus on beam and mobility management. To conclude, the course will provide guidelines towards the design and dimensioning of 5G applications.

Topics:

- 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
- 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

References:

- [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.

Schedule and room: (Mar-Apr 2024) please, see [Class Schedule](#).

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](#).

Course requirements: Preliminary knowledge of the ISO/OSI protocol stack.

Examination and grading: Final project.

IE_TLC 5. Underwater Simulation and Experimentation

Course Area: Information Engineering

Credits: 5 (20 hours) - Winter School, intensive course

Instructor: Prof. Filippo Campagnaro

e-mail: filippo.campagnaro@unipd.it

Aim: The winter school will last one week and will focus on the challenges imposed by the underwater communication channel, where WiFi, 2/3/4/5G and other radio frequency transmissions are strongly attenuated and cannot be used. An underwater network simulation and experimentation tool, called DESERT Underwater, will be used to test and evaluate the performance of underwater networks. Every day will be split into two parts, a theoretical part where the students will attend frontal lessons to learn the concepts and procedures to perform network simulations and develop software modules, and an experimental part where the student will be required to implement the code, run simulation experiments and analyze the results.

Required equipment (for all): laptop with GNU/Linux OS (recommended Ubuntu LTS), a Linux virtual machine.

Topics:

- Basics of communication networks and differences between the ISO OSI stack and underwater protocol stack.
 - Understand when simulation results are statistically relevant.
 - Definition of Confidence Interval (CI).
- 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

References:

[back to [Summary](#)]

- [1] Filippo Campagnaro, Roberto Francescon, Federico Guerra, Federico Favaro, Paolo Casari, Roe 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] EvoLogics Underwater Acoustic Modems <https://evologics.de/acoustic-modems>
- [6] Alberto Signori, Filippo Campagnaro, Michele Zorzi, Modeling the Performance of Optical Modems in the DESERT Underwater Network Simulator, IEEE Ucomms 2018
- [7] Filippo Campagnaro, Roberto Francescon, Paolo Casari, Roe Diamant and Michele Zorzi Multimodal Underwater Networks: Recent Advances and a Look Ahead WUWNet17

Schedule and room: (Jan-Feb 2024) please, see [Class Schedule](#).

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](#).

Course requirements: Basics of Probability Theory. Basics of R Programming.

Examination and grading: Homework assignments and final project.

IE_TLC 6. FPGA Programming for TLC Systems

Course Area: Telecommunication Engineering

Credits: 5 (20 hours)

Instructor: Prof. Jesus Omar Lacruz Jucht

e-mail: jesusomar.lacruz@imdea.org

Aim: The course will introduce fundamentals of hardware design for FPGAs, starting from the design flow, then covering the fundamentals of hardware design and verification using hardware description languages (HDL). The basis of quantization and fixed-point arithmetic are covered as well as their impact in area / timing constrained designs. IP integration is addressed as an important tool to manage large designs from a top-level perspective. The design of communication sub-systems is addressed from a practical perspective, using FPGA devices in laboratory classes.

Topics:

- Introduction to programmable hardware
 - FPGA fundamentals
 - Role in communication systems
 - FPGA evolution
 - Design flow and tools
- Fundamentals of hardware design and verification
 - High-level hardware description languages (Vivado HLS)
 - Quantization and finite precision arithmetic
 - Area / timing constrained designs
 - Hardware verification
- Communication sub-systems
 - Transmitter and receiver architectures
 - Design examples
 - IP integration
 - Evaluation using hardware devices

References:

- [1] D. Allan, et-al., Software Design Radios with Zynq Ultrascale+ RFSoc, Strathclyde Academic Media, 2023.
- [2] AMD Xilinx, UG902 Vivado Design Suite User Guide: High Level Synthesis, 2021.
- [3] S. Brown and Z. Branesic, Fundamentals of Digital Design Logic with VHDL design, Mc Graw Hill, 2009.
- [4] U. Meyer-Baese, Digital Signal Processing with Field Programmable Gate Arrays, Springer, 2014.

[back to [Summary](#)]

Schedule and room: the schedule will be shared when available; please, see [Class Schedule](#)

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](#).

Course requirements: Basics of digital logic. Basic communication systems. Basic of MATLAB.

Examination and grading: Homework assignments.

IE_TLC 7. A walkthrough on Generative AI: the evolution of generative strategies from GANs to diffusion models

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Prof. Simone Milani

e-mail: simone.milani@dei.unipd.it

Aim: The course will introduce fundamental strategies in Generative AI overviewing different architectures from GANs to the most recent diffusion models.

Topics:

- **Introduction to Generative AI and strategies**
 - Fundamentals, basics, fields of applications, open issues and problems.
 - Example of generative AI applications: ChatGPT, DALL-E, Stable-diffusion, Mid-journey.
 - A taxonomy of deep generative models. Maximum likelihood problems. Explicit and implicit density approaches.
- **Bringing randomness into neural networks: the Variational Autoencoder.**
 - Basic principles: regularizing an AE, statistical characterization, operation implementation.
 - Issues and limitations.
- **Becoming adversarial: from adversarial neural networks to generative adversarial networks (GANs).**
 - Network training as a non-cooperative game.
 - Convergence to equilibrium. Stability points.
 - Training procedure for a GAN.
 - Vanishing gradients, convergence problems, mode collapse.
- **Optimizing a GAN.**
 - Evaluation and optimization of GAN's output. Inception Score. Frechet Inception Distance.
 - Other kinds of GANs: conditional GANs, adversarial autoencoders, Cycle GANs, Style GAN, GAN for time series.
- **Detecting a GAN.**
 - Why GAN-generated images/video are not like the real ones and how this can help to improve their quality.
 - 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).
- Approximating continuous domain functions with neural networks.
- 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.
 - What makes a good 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.

References:

- [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>

Schedule and room: (Mar-Apr 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Basics of Probability Theory and Deep Learning. Basics of Python Programming.

Examination and grading: Final project.

IE_AUT 1. Elements of Deep Learning

Course Area: Information Engineering

Credits: 6 (24 hours)

Instructor: Dr. Gian Antonio Susto

e-mail: gianantonio.susto@dei.unipd.it

Aim: 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.
- Elements of Deep Reinforcement Learning.
- Unsupervised Learning: Generative Adversarial Neural Networks and Autoencoders.
- Laboratory sessions in Colab.
- Hot topics in current research.

References:

- [1] Arjovsky, M., Chintala, S., & Bottou, L. (2017). Wasserstein GAN. CoRR, abs/1701.07875.
- [2] Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural Machine Translation by Jointly Learning to Align and Translate. CoRR, abs/1409.0473.
- [3] I. Goodfellow, Y. Bengio, A. Courville 'Deep Learning', MIT Press, 2016
- [4] Goodfellow, I.J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A.C., & Bengio, Y. (2014). Generative Adversarial Nets. NIPS.
- [5] Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural computation, 9 8, 1735-80.
- [6] Kalchbrenner, N., Grefenstette, E., & Blunsom, P. (2014). A Convolutional Neural Network for Modelling Sentences. ACL.
- [7] Krizhevsky, A., Sutskever, I., & Hinton, G.E. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Commun. ACM, 60, 84-90.
- [8] LeCun, Y. (1998). Gradient-based Learning Applied to Document Recognition.

[back to [Summary](#)]

[9] Mikolov, T., Sutskever, I., & Chen, K. (2013). Representations of Words and Phrases and their Compositionality.

[10] Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y., & Manzagol, P. (2010). Stacked Denoising Autoencoders: Learning Useful Representations in a Deep Network with a Local Denoising Criterion. Journal of Machine Learning Research, 11, 3371-3408.

[11] Zaremba, W., Sutskever, I., & Vinyals, O. (2014). Recurrent Neural Network Regularization. CoRR, abs/1409.2329.

Schedule and room: (starting Jan 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Basics of Machine Learning and Python Programming.

Examination and grading: Final project.

IE_AUT 2. Applied Functional Analysis and Machine Learning

Course Area: Information Engineering

Credits: 7 (28 hours)

Instructor: prof. Gianluigi Pillonetto

e-mail: giapi@dei.unipd.it

Aim: The course is intended to give a survey of the basic aspects of functional analysis, machine learning, regularization theory and inverse problems.

Topics: 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.

References:

- [1] G. Pillonetto, T. Chen, A. Chiuso, G. De Nicolao, L. Ljung. Regularized System Identification – learning dynamic models from data, Springer Nature 2022
- [2] W. Rudin. Real and Complex Analysis, McGraw Hill, 2006
- [3] C.E. Rasmussen and C.K.I. Williams. Gaussian Processes for Machine Learning. The MIT Press, 2006
- [4] H. Brezis, Functional analysis, Sobolev spaces and partial differential equations, Springer 2010
- [5] G. Pillonetto, A. Aravkin, D. Gedon, L. Ljung, A.H. Ribeiro and T.B. Schön, Deep networks for system identification: a Survey, eprint 2301.12832 arXiv, 2023

Schedule and room: (Nov-Dec 2023) please, see [Class Schedule](#)

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](#)]

Course requirements: The classical theory of functions of real variable: limits and continuity, differentiation and Riemann integration, infinite series and uniform convergence. The arithmetic of complex numbers and the basic properties of the complex exponential function. Some elementary set theory. A bit of linear algebra.

Examination and grading: Two tests.

IE_AUT 3. Applied Linear Algebra

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructors: Prof. Luca Schenato, Dipartimento di Ingegneria dell'informazione, Università di Padova (<http://automatica.dei.unipd.it/people/schenato.html>)

e-mail: schenato@dei.unipd.it

Aim: We study concepts and techniques of linear algebra that are important for applications with special emphasis on the topics: solution of systems of linear equations with particular attention to the analysis of the backward error and computational cost of the basic algorithms and matrix equation. A wide range of exercises and problems will be an essential part of the course and constitute homework required to the student.

Topics:

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 subspace
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, numerical conditionings

Objectives:

- Theory: formal proofs of many results (theorem-proof type problems)
- Algorithms: understanding of most commonly used algorithm used in MATLAB and Python for Linear Algebra
- Implementation: MATLAB implementation of algorithms and performance evaluation on Big Data

References:

Textbooks and Internet Notes:

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

Schedule and room: (Nov-Dec 2023) please, see [Class Schedule](#)

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](#).

Course requirements: A good working knowledge of basic notions of linear algebra as for example in [1]. Some proficiency in MATLAB.

Examination and grading: Grading is based on Homeworks, Written final exam, Short presentation based on a recent paper of Linear Algebra Algorithms for Big Data.

IE_AUT 4. Fundamentals of Adaptive Control for Applications

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.

Instructors: Prof. Andrea Serrani, The Ohio State University <https://ece.osu.edu/people/serrani.1>

Email: serrani.1@osu.edu

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).
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

Schedule and room: (starting Jun 2024) please, see [Class Schedule](#)

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](#).

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.

IE_AUT 5. Applied Causal Inference

Course Area: Information Engineering

Credits: 4 (16 hours)

Instructor: Prof. Reza Arghandeh, Department of Computer Science, Electrical Engineering and Mathematical Sciences, Western Norway University of Applied Sciences, Bergen, Norway

e-mail: rajo@hvl.no

This course is an overview of applied causal inference. The course starts with an introduction to causal inference. Then, we talk about moving from observation to intervention. We learn about directed acyclic graphs and non-parametric structural equation models to create causal models. Furthermore, we use various realistic examples to understand better the concepts we introduced in each chapter. By the end of this course, students will be able to develop familiarity with causal models for investigating a wide range of questions about the world works.

Goals:

- Information-era literacy: learning to be informed citizens, consumers, and hopefully producers of information.
- Understand sources of bias in data (a big challenge in data science).
- Understand the importance of the causal discovery.
- Understand the basics of causal models.
- Ask causal questions:
 - for the sake of science
 - for better decision-making in daily life.

Learning Objectives:

- Understand the difference of causal inference with statistics and machine learning.
- Translate scientific questions and background knowledge into a causal model.
- Understand properties of causal models.
- Begin to develop familiarity with the uses of causal models for investigating a wide range of questions about the real world.

References:

1. Github page: https://github.com/Ci2Lab/Applied_Causal_Inference_Course
2. Elements of Causal Inference, Book, 2017 (open access)
<https://mitpress.mit.edu/books/elements-causal-inference>
3. Causal Inference What If, Book, 2020 (open access)
<https://www.hsph.harvard.edu/miguel-hernan/causal-inference-book/>

Schedule and room: May/June 2023. Lectures exact dates and times will be published in [Class Schedule](#) as soon as they are fixed by the instructor.

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](#).

Course requirements: familiarity with basic statistics. Knowledge of graph theory also helps, but it is not a requirement.

Examination and grading: a final presentation or a take-home exam.

IE_AUT 6. Distributed Machine Learning and Optimization: from ADMM to Federated and multiagent Reinforcement Learning

Course Area: Information Engineering

Credits: 5 (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 decomposition, 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: Multiagent reinforcement learning, safe (constrained) reinforcement learning and its applications to data-driven multiagent control, inverse 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. Vandenberghe, *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.

Schedule and room: May/June 2023. Lectures exact dates and times will be published in [Class Schedule](#) as soon as they are fixed by the instructor.

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](#).

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.

IE_AUT 7. Analysis and Control of Multi-agent Systems

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Dr. Marco Fabris, Department of Information Engineering, University of Padova, Italy

e-mail: marco.fabris.1@unipd.it

Aim:

Multi-agent systems (MASs), or networked dynamic systems (NDS), 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 interagent 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.

Topics:

- 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 both in continuous and discrete time, firstly for unweighted graphs and then for weighted digraphs.
- Lecture 4. 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.

- Lectures 9-10. Bearing-based formation control. Bearing rigidity. A bearing-only formation controller. Bearing-based formation maneuvering.

References:

- [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 and A. Cenedese, "Optimal Time-Invariant Distributed Formation Tracking for Second-Order Multi-Agent Systems", arXiv preprint arXiv:2307.12235 (2023).
- [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.

Further potentially relevant recent papers will be referred to and distributed during the lectures.

Schedule and room: (Oct-Dec 2023) please, see [Class Schedule](#)

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](#).

Course requirements: Linear Algebra and basic Calculus

[back to [Summary](#)]

Examination and grading: 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

IE_AUT 8. Introduction to Harmonic Analysis and Applications

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Dr. Valentina Ciccone, Mathematical Institute, Universität Bonn, Germany

e-mail: ciccone@math.uni-bonn.de

Aim:

The first part of the course aims to provide some basics in classical Fourier and Harmonic Analysis. The second part of the course will focus on modern applications of Harmonic Analysis, and in particular of the Harmonic Analysis of Boolean functions, to machine learning and theoretical computer science. Boolean functions are a basic tool in theoretical computer science, learning theory, and more, which can be studied by means of analytic tools, in particular using Fourier analysis. We will see some basic concepts and techniques in the subject as well as applications in machine learning.

Topics:

- Part I: Fourier transform of L^1 functions, basic properties, Riemann-Lebesgue lemma, inversion formula. Schwartz functions class, Fourier transform of L^p functions, $1 < p \leq 2$. Plancherel's theorem. Glimpse of distribution theory, an application to the analysis of signals. Heisenberg uncertainty principle. Convolution and Young's inequality for convolution. If time permits: Hausdorff-Young inequality, Beckner's sharp Hausdorff-Young inequality, and hypercontractivity.
- Part II: Boolean functions and their Fourier expansion, spectral structure and learning. Probably Approximately Correct (PAC) learning. If time permits: an application of hypercontractivity in theoretical computer science.

References:

- [1] W. Beckner, Inequalities in Fourier Analysis, Annals of Mathematics, 102 (1975), 159-182
- [2] R. O'Donnell, Analysis of Boolean Functions, arXiv preprint arXiv:2105.10386 (2021)
- [3] G. B. Folland, Fourier analysis and its applications, American Mathematical Society, 2009

Schedule and room: (starting May 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Calculus I and II, basic real and functional analysis, basic probability theory.

[back to [Summary](#)]

Examination and grading: Homework assignments with final discussion

IE_CSC 1. Bayesian Machine Learning

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Prof. Giorgio Maria Di Nunzio

e-mail: dinunzio@dei.unipd.it

Aim: The course will introduce fundamental topics in Bayesian reasoning and how they apply to machine learning problems. In this course, we will present pros and cons of Bayesian approaches and we will develop a graphical tool to analyse the assumptions of these approaches in classical machine learning problems such as classification and regression.

Topics:

- Introduction of classical machine learning problems.
 - Mathematical framework
 - Supervised and unsupervised learning
- Bayesian decision theory
 - Two-category classification
 - Minimum-error-rate classification
 - Bayes decision theory
 - Decision surfaces
- Estimation
 - Maximum Likelihood Estimation
 - Expectation Maximization
 - Maximum A Posteriori
 - Bayesian approach
- Graphical models
 - Bayesian networks
 - Two-dimensional visualization
- Evaluation
 - Measures of accuracy

References:

- [1] J. Kruschke, Doing Bayesian Data Analysis: A Tutorial Introduction With R and Bugs, Academic Press 2010
- [2] Christopher M. Bishop, Pattern Recognition and Machine Learning (Information Science and Statistics), Springer 2007
- [3] Richard O. Duda, Peter E. Hart, David G. Stork, Pattern Classification (2nd Edition), Wiley-Interscience, 2000

[back to [Summary](#)]

[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 Press, 2015 (supporting material <https://xcelab.net/rm/statistical-rethinking/>)

Schedule and room: (starting Feb 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Basics of Probability Theory. Basics of R Programming.

Examination and grading: Homework assignments and final project.

IE_CSC 2. Advanced topics in scientific and parallel programming with practical application to the CAPRI HPC infrastructure

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Giacomo Baruzzo, Department of Information Engineering, University of Padova

e-mail: giacomo.baruzzo@unipd.it

Aim: Provide basic skills for working on remote servers, using/developing parallel software and deploying it on a containerized computer server. The course gives basic introduction to modern computer architecture and to the most important parallel programming paradigms: Multi-threading, OpenMP, MPI and CUDA with examples (mostly Python and C++). The course covers basic tools to access and to interact with remote servers, to manage remote resources, and to manage jobs. The course introduces principles of software containerization from the perspective of users, providing practical examples of Singularity/Docker. The concepts discussed are applied to simple case of studies involving writing and/or running parallel programs using the CAPRI HPC infrastructure (256 cores, 6TB shared RAM and 2 GPU Nvidia P100) recently acquired by the University of Padova for research activities.

Topics:

1. How to use a computing server (application to CAPRI)
 - a. Introduction to High Performance Computing (HPC hardware and architectures, HPC software, supercomputers)
 - b. Job scheduling (slurm; writing a job; running, stopping and querying status of a job)
 - c. The CAPRI queuing system and policy (CAPRI hardware and architecture; access to CAPRI and projects; execution queue; how to choose queue)
2. Containerization (Singularity)
 - a. 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)
 - b. Using container that have already been defined (running, stopping, and resuming containers; containers options and flags)
 - c. Defining new containers (new containers from scratch; extending existing containers)
 - d. 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 (git)
 - a. Basic operations (create a git repository, staging and committing changes, repository status and history, work with branches)
 - b. 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
 - a. 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)
 - b. Parallel programming languages and frameworks (multi-threading; OpenMP; MPI; CUDA)
5. Hands on example (a simple parallel software for data analysis / machine learning / numerical analysis; students' proposals)

References:

- Eijkhout, V. (2013). Introduction to High Performance Scientific Computing. Lulu. com.
- Grama, A., Kumar, V., Gupta, A., & Karypis, G. (2003). Introduction to parallel computing. Pearson Education.
- Parhami, B. (2006). Introduction to parallel processing: algorithms and architectures. Springer Science & Business Media.
- Ad-hoc material by Lecturer

Schedule and room: (Jan-Feb 2024) please, see [Class Schedule](#)

Course requirements: Basics usage of tools for run/develop of scientific software (preferable unix/linux platforms)

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](#).

Examination and grading: Each student must produce a small parallel and containerized software (either predefined or custom built container) related to her/his research field. Each student can either a) write a simple parallel software with one of the programming paradigm presented during the course using a language of choice or b) choose a (possibly parallel) software typically used in the research activity. Containerized software must run on the CAPRI server.

IE_CSC 3. Domain-Specific Accelerators

Course Area: Information Engineering

Credits: 5 (20 hours)

Instructor: Carlo Fantozzi

e-mail: carlo.fantozzi@unipd.it

Important note: Not offered in a.a. 2023/24

IE_CSC 4. Learning from Networks

Course Area: Information Engineering

Credits: 5 (10 lectures, 2 hours each)

Instructor: Prof. Fabio Vandin

e-mail: fabio.vandin@unipd.it

Important note: Not offered in a.a. 2023/24

IE_OPT 1. Quantum Communication: methods and implementations

Credits: 5 (20 hours)

Instructors: Dr. Marco Avesani, University of Padova

e-mail: marco.avesani@unipd.it

Aim: The course aims at giving an introduction to 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.

Topics:

- Elements of quantum communication and Quantum Key Distribution
- Entropies in Quantum Information
- Discrete-variable (DV) Quantum Key Distribution: methods and protocols
- Security definitions and security proofs
- Finite key analysis for BB84 and practical QKD
- Numerical tools for QKD
- Experimental DV-QKD: time bin and polarization encodings
- Free-space QKD implementations
- Attacks on QKD

References:

[1]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.

[2]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.

[3]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.

Schedule and room: (Apr-May 2024) please, see [Class Schedule](#)

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](#).

Course requirements: Linear Algebra. Basics of Quantum Information and Quantum Optics may help

[back to [Summary](#)]

Examination and grading: Oral test on the contents of the course, with the possibility of presenting an essay on a topic, agreed with the teachers.

Alphabetical List of Course Instructors

[Alcaraz](#) Juan Jose

[Arboretti](#) Rosa

[Arghandeh](#) Reza

[Avesani](#) Marco

[Baruzzo](#) Giacomo

[Bellato](#) Massimo

[Bertoldo](#) Alessandra

[Bruschetta](#) Mattia

[Campagnaro](#) Filippo

[Carli](#) Ruggero

[Castellaro](#) Marco

[Ceccarello](#) Matteo

[Cicccone](#) Valentina

[Del Favero](#) Simone

[De Santi](#) Carlo

[Dey](#) Subhrakanti

[Di Nunzio](#) Giorgio

[Dini](#) Paolo

[Disegna](#) Marta

[Fabris](#) Marco

[Facchinetti](#) Andrea

[Fantozzi](#) Carlo

[Ferrati](#) Francesco

[Finesso](#) Lorenzo

[Giordani](#) Marco

[Lacruz](#) Jesus Omar

[Laurenti](#) Nicola

[Longato](#) Enrico

[Marcuzzi](#) Fabio

[Meneghini](#) Matteo

[Milani](#) Simone

[Muffatto](#) Moreno

[Mura](#) Giovanna

[Pillonetto](#) Gianluigi

[Salmaso](#) Luigi

[Salvagnin](#) Domenico

[Schenato](#) Luca

[Serrani](#) Andrea

[Stanco](#) Andrea

[Susin](#) Francesca

[Susto](#) Gian Antonio

[Tortora](#) Stefano

[Vandin](#) Fabio

[Veronese](#) Mattia

[Vettoretti](#) Martina

[Vogrig](#) Daniele