UNIVERSITÀ DEGLI STUDI DI PADOVA

PHD OF NATIONAL INTEREST IN TECHNOLOGIES FOR FUNDAMENTAL RESEARCH IN PHYSICS AND ASTROPHYSICS

EDUCATIONAL OFFER – A.Y. 2024/25

Curriculum: COMPUTING

- Big Data modelling and learning
- Big Data Analysis in Python
- Advanced scientific programming in Matlab
- Programmable System on Chip (SoC) for data acquisition and processing
- Adaptive Optics for Astronomy
- Fundamentals of system engineering and project management for large scientific projects
- Machine Learning for Physics
- Simulation of optical photon propagation for generic scintillator-based detectors
- Computing Methods for Experimental Physics and Data Analysis
- Neural Networks and Deep Learning
- Introduction to Neuromorphic Computing
- Cloud Computing & Big Data
- Cloud Computing & Big Data Lab
- Maximum-entropy methods for complex systems I
- Maximum-entropy methods for complex systems II

- Quantum Artificial Intelligence

Course unit English denomination	Big Data modelling and learning
Teacher in charge (if defined)	Ester Pantaleo Università degli studi di Bari Aldo Moro, Dipartimento di Fisica – Via Amendola, 173 70125, Bari (Italy) ester.pantaleo@uniba.it
Teaching Hours	12
Number of ECTS credits allocated	1,5
Course period	June-July
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	The increasing availability of high dimensional and heterogeneous data samples (big data) makes urgent the development of a scientific background including data science and machine learning techniques, with applications in many fields. This course introduces the fundamental concepts in machine learning. We will explore how supervised and unsupervised learning algorithms including random forests, artificial neural networks, support vector machines and deep learning, can proficiently exploit the knowledge content of big data. After explaining the basic evaluation measures for machine learning algorithms, we will discuss how to handle correlated features, unbalanced data, biases and variances, the curse of dimensionality, confounding features, alternative cross-validation strategies.
Learning goals	-
Teaching methods	Frontal and Remote classes
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☐ No
Available for PhD students from other courses	☐ Yes ☐ No
Prerequisites (not mandatory)	-
Examination methods	80% Case study 20% Presentation of the results

(in applicable)	
Suggested readings	Introduction to Machine Learning - Ethem Alpaydin - MIT Press 2010
Additional information	-

Course unit English denomination	Big Data Analysis in Python
Teacher in charge (if defined)	Gioacchino Vino - gioacchino.vino@infn.it
Teaching Hours	20
Number of ECTS credits allocated	2,5
Course period	February-March
Course delivery method	☐ In presence x Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) x No
Course unit contents	Technologies should go at the same pace of Data sample size and Machine Learning model complexity, in order to keep the execution times acceptable. Python is a language that makes data analysis easier thanks to its large amount of available tools. Advanced Python libraries (e.g. PyTorch, TensorFlow, Keras) are available to speed up specific phases of the Machine Learning application. Big Data and GPU based libraries could provide further improvements in the execution time, distributing and parallelizing computation on a cluster of machines. This course will cover all these topics including some examples of platforms capable to support the data scientist during all Machine Learning lifecycle. This course does not provide any Machine Learning concepts and only focuses on technologies, so please take Machine Learning courses before where basic principles are introduced. Key concepts: Optimization of Python code, numpy, pandas, dask, polars and cuda.
Learning goals	Develop a critical view during the writing and execution of python codes for data analysis
Teaching methods	Presentation of concepts and discussion of hands-on exercises
Course on transversal, interdisciplinary, transdisciplinary skills	x Yes ☐ No
Available for PhD students from other courses	☐ Yes x No

Prerequisites (not mandatory)	C++ programming language
Examination methods (in applicable)	Students are supposed to implement a Data Analysis code in Python with parallel computing modules. A presentation of the work is recommended.
Suggested readings	provided slides
Additional information	none

Course unit English denomination	Advanced scientific programming in Matlab
Teacher in charge (if defined)	Paolo Bardella, Stefano Scialò
Teaching Hours	30
Number of ECTS credits allocated	6
Course period	January/February 2025
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	1.5h: introduction to MATLAB, with particular attention on the improvements introduced in the latest versions 1.0h: source Control systems integrated in MATLAB (git) 1.5h: MATLAB internals: data structures, JIT, numerical libraries 3.0h: object oriented programming in MATLAB 3.0h: optimization of MATLAB code, use of the Code Profiler 3.0h: MEX files for the execution of C/C++ and Fortran code in MATLAB. MATLAB C code generator 3.0h parallel computing in MATLAB: introduction to parallel computing, commands parfor, spmd, advantages and limitations. 3.0h: GPUs in MATLAB: introduction to GPUs and gpuarray command 3.0h: optimization of I/O in MATLAB, control of hardware 3.0h: fundamentals of machine learning in MATLAB; Big data and tall arrays 1.0h: alternatives to MATLAB: python, Arrayfire, Gnu Scientific library, Octave, Scilab 4.0h: projects' presentation
Learning goals	The course aims to provide advanced skills in scientific programming, and to teach sound methodologies for the development of reliable, optimized and maintainable codes. During this course, many common methods used in Scientific Computing will be presented, with particular attention to the most recent programming techniques in MATLAB. At the end of the course, the student will have expanded his/her knowledge of MATLAB and will be able to choose the best approach for the solution of numerical problem he/she will face.
Teaching methods	Lectures
Course on transversal, interdisciplinary,	☒ Yes ☐ No

transdisciplinary skills	
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Basic knowledge of MATLAB language.
Examination methods (in applicable)	Presentation of group activity on the optimization of existing MATLAB code proposed by the students.
Suggested readings	Slides provided by the teachers, video recordings of the lessons, suggested texts on specific topics.
Additional information	-

Course unit English denomination	Programmable System on Chip (SoC) for data acquisition and processing
Teacher in charge (if defined)	Andrea Fabbri
Teaching Hours	20
Number of ECTS credits allocated	4
Course period	
Course delivery method	☐ In presence ☒ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	The course will introduce the latest generation programmable devices (FPGA and ACAP) describing their characteristics and main modules (DDR management, integrated processors, DSP, AI engine…) and their interaction. Use cases will then be presented and a classroom project will be carried out aimed at learning the methodologies for using these complex systems in the field of data acquisition systems (DAQ) for physics and astrophysics equipment.
Learning goals	The main objective is to give the student a vision of the tools currently available on the market that can be used in the context of complex data acquisition systems. The student will be provided with the methodologies for the architectural design of such systems through the use of such platforms and hints on the relative programming methods.
Teaching methods	The course includes an introductory part in which the basic concepts related to the needed functionality of an acquisition systems. Moreover, the components integrated within a modern FPGA will be discussed and recalled. Two case studies will then be viewed in the classroom as an example of complex acquisition systems based on programmable devices.
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	-

Examination methods (in applicable)	Oral interview (By appointment)
Suggested readings	handouts provided by the teacher
Additional information	-

Course unit English denomination	Adaptive Optics for Astronomy
Teacher in charge (if defined)	Carmelo Arcidiacono (INAF-Arcetri)
Teaching Hours	12
Number of ECTS credits allocated	1,5
Course period	March-June 2025
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	Inglese
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	Adaptive optics (AO) is an advanced technology used to improve the quality of images obtained from astronomical telescopes by correcting distortions caused by the Earth's atmosphere in real time. Without AO, the scintillation and flicker effect caused by atmospheric turbulence blurs images, significantly limiting the ability to resolve fine details of astronomical objects. AO has revolutionised modern astronomy, enabling observations impossible with conventional telescopes. The PhD course 'Astronomical Observations with Adaptive Optics' will provide an in-depth understanding of how AO works and its applications in astronomy. Students will explore the fundamental concepts and mechanisms behind these technologies and will be introduced to the tools used to measure and correct atmospheric wavefront distortions.
Learning goals	- Understanding the physical and technical principles of adaptive optics Students will gain a solid understanding of the mechanisms by which adaptive optics corrects atmospheric distortions in real time, improving the quality of astronomical images. - Designing and implementing simple adaptive optics systems At the end of the course, students will be able to design basic AO systems, understanding how to select and configure the necessary components, such as deformable mirrors and wavefront sensors. - Using adaptive optics systems to conduct astronomical observations Students will be able to apply AO principles to improve the quality of astronomical observations, exploiting technology to overcome limitations imposed by the Earth's atmosphere. - Interpret and analyse data obtained with AO systems Skills will be provided to understand and reduce data acquired through AO observations, enabling students to analyse high-resolution astronomical images and draw valid scientific conclusions. - Knowing the practical applications of AO in modern astronomy

	Students will learn to identify the different areas of astronomical research that benefit from the use of AO, such as the study of planetary surfaces, the resolution of stars in star clusters and the observation of active galactic nuclei.
Teaching methods	Lectures Guided discussions Individual or group projects
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Physics I and Physics II (Optics)
Examination methods (in applicable)	At the student's request
Suggested readings	Slides and links recommended by the lecturer
Additional information	-

Course unit English denomination	Fundamentals of system engineering and project management for large scientific projects
Teacher in charge (if defined)	Marco Xompero / Runa Briguglio
Teaching Hours	12
Number of ECTS credits allocated	1,5
Course period	spring 2025
Course delivery method	x In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	x Yes (100% minimum of presence) ☐ No
Course unit contents	Today, scientific research projects are carried out by large international teams and involve a multi-disciplinary approach. In add, specific tools are requested: to organize the team-work, to meet the deadlines, to define a common language and comprehension across all the elements in the project. The system engineer and the project manager are key-figures in the organizational chart. System engineering is an approach for successful systems, focusing on the early analysis of the user needs, then proceeding with design synthesis and system validation considering the complete problem. Project management, in parallel, is related to the organizational aspects: the definition of who will be doing what and how, the creation and optimization of a project calendar, based on the activities prioritization and their conflicts, the identification and management of risks, and much more. The class is intended to provide PhD students with a basic package to understand the project's working mechanisms.
Learning goals	Project planning System management
Teaching methods	Slides and group work, analysis of use cases. The course is organized as a 2, 3 days workshop in Florence
Course on transversal, interdisciplinary,	x☐ Yes No

transdisciplinary skills	
Available for PhD students from other courses	☐ Yes x No
Prerequisites (not mandatory)	None
Examination methods (in applicable)	class work, organization of a custom project.
Suggested readings	None. References will be given during the classes
Additional information	https://sites.google.com/inaf.it/syseng-phdnazionale/home-page

Course unit English denomination	Machine Learning for Physics
Teacher in charge (if defined)	Pierluigi Bortignon
Teaching Hours	24
Number of ECTS credits allocated	3
Course period	Second semester (March – June)
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☐ Yes (% minimum of presence) ☒ No
Course unit contents	Regression. Classification. Supervised learning. Unsupervised learning. Reinforcement learning. Function approximation, Model, Hyper-parameters, Generalization, Regularization. Decision trees (bagging, boosting, random forest). Artificial neural network, the Multi LayerPerceptron, Gradient descent techniques. Deep networks. Convolutional networks. Recursive networks. Autoencoders. Transfer learning. Keras toolset.
Learning goals	The course has the objective to introduce the theoretical concept of Machine Learning. It creates abilities and competences on how to use the most common machine learning architectures used in physics.
Teaching methods	The course will have half of the lectures as frontal lectures on theoretical aspects of the machine learning and half of the lectures as hands-on session where the most common architecture will be used with simple dataset together in class.
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Basic understanding of statistics and programming.
Examination methods (in applicable)	The evaluation will be based on a data analisys project on a dataset agreed with the teacher that uses one or more of the machine learning techniques studies in class.

Suggested readings	Introduction to Statistical Learning. G. James. Springer edition Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow - Aurelien Gerontoiatrie - O'Reilly (2nd edition)
Additional information	-

Course unit English denomination	SIMULATION OF OPTICAL PHOTON PROPAGATION FOR GENERIC SCINTILLATOR-BASED DETECTORS
Teacher in charge (if defined)	Dott. Davide Serini (INFN Sezione di Bari)
Teaching Hours	16
Number of ECTS credits allocated	2
Course period	2 Semester (May-July)
Course delivery method	☐ In presence ☒ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	Scintillator materials are widely used in particle physics for ion identification and energy measurements. Next-generation space missions will employ plastic scintillator detectors (PSDs) equipped with the new Silicon Photomultipliers (SiPMs) technology to read out the scintillator light emission. Scintillator based detectors are also widely used for radiation monitoring for environmental or industrial purposes. This course aims to provide the student with knowledge of radiation measurements and detection techniques. It will also provide the student the capability to implement a dedicated MC simulation of the performances of a generic scintillator-based detector using the GEANT 4 toolkit with hands-on sessions. ***Part 1 (Theoretical)***: Absorption of radiation in scintillation materials. Light yield, organic and inorganic scintillators. Quenching effect and Birk's Law. Optical coupling. Solid state photodetectors: the Silicon Photomultiplier (SiPMs). Scintillator-based detectors application for space missions and for radiation environmental monitoring. ***Part 2 (Hands-on sessions)*** : An introduction to GEANT4 simulation toolkit. Make your own optical simulation project: the geometry, the physic list and the optical processes. Sensitive detector and optical photon hit. An introduction to ROOT toolkit: how to read the simulation results. Each topic will be correlated to progressive exercises aimed to make the student able to implement a complete simulation tool.
Learning goals	Understand the base classes to implement a generic simulation using the Geant4 toolkit. Understand the operating principles of detectors based on scintillators and photosensors. Implement a simple simulation involving optical processes.
Teaching methods	Lectures with slides support. Progressive exercises aimed to make the student able to implement a complete simulation tool.

	The course can be fully attended online through live Zoom lectures. Course materials, including lectures, example codes, and exercises, will be shared via a common repository accessible to all students. A comprehensive guide for installing all the necessary software will be provided before starting the course. Communication within the class will be managed through a dedicated mailing list.
Course on transversal, interdisciplinary, transdisciplinary skills	☐ Yes ☒ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Basic knowledge of C++ programming
Examination methods (in applicable)	Exercise sessions. Development of a simple project and discussion with an oral presentation.
Suggested readings	- G. F. Knoll, "Radiation Detection and Measurement", ed. Wiley - Lecture notes. - Geant4 User's Documents page. - Root User's manual.
Additional information	

Course unit English denomination	Computing Methods for Experimental Physics and Data Analysis
Teacher in charge (if defined)	Andrea Rizzi, Alessandra Retico (Pisa)
Teaching Hours	40
Number of ECTS credits allocated	-
Course period	November-December
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	Lectures for PhD students focus on the design of neural networks for the analysis of scientific data; the development of analysis projects in the context of particle physics or medical physics. 3 modules: Fundamentals (python, git, ...) Advanced (Parallelism, Machine Learning) Specific module: High Energy Physics/C++/Root Medical Physics/Image Processing/Matlab
Learning goals	By the end of the course, the student will be familiar with the following tools for scientific calculation and data analysis: advanced unix shell commands for automating operations python language and main system modules python libraries for scientific calculation tools for software management and documentation tools for machine learning and neural network development specific tools for applications in particle physics and/or medical physics
Teaching methods	lectures (theory) and exercises/hands-on
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No

Prerequisites (not mandatory)	A minimum knowledge of how a computer works is necessary. It would also be advisable to have knowledge, even rudimentary, of programming in high languages (e.g. C, or python)
Examination methods (in applicable)	verification of acquired knowledge through specific questions in the oral examination on the basis of a scientific calculation project realised and presented by the students
Suggested readings	Slides and articles/books provided by lecturers
Additional information	andrea.rizzi@unipi.it, alessandra.retico@pi.infn.it

Course unit English denomination	Neural Networks and Deep Learning
Teacher in charge (if defined)	Giorgio Carlo Buttazzo (SantAnna Pisa)
Teaching Hours	60
Number of ECTS credits allocated	-
Course period	January-May
Course delivery method	☐ In presence ☒ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	This course includes four modules: the first module (20 hours) focuses on the theoretical foundations of neural networks; the second module (20 hours) focuses on deep neural networks; the third module (20 hours) covers more advanced topics and the latest research trends; the fourth module (30 hours) covers practical and implementation issues.
Learning goals	By the end of the course, the student will have become familiar and comfortable with the theory and practical implementation of deep neural networks.
Teaching methods	lectures (theory) and exercises/hands-on
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Fundamentals of python and machine learning
Examination methods (in applicable)	Final project
Suggested readings	http://retis.sssup.it/~giorgio/courses/neural/nn.html

Additional information	http://retis.sssup.it/~giorgio/courses/neural/nn.html

Course unit English denomination	Introduction to Neuromorphic Computing
Teacher in charge (if defined)	Andrea Duggento ((andrea.duggento@uniroma2.eu, Univ. Tor Vergata, Roma)
Teaching Hours	12
Number of ECTS credits allocated	-
Course period	March
Course delivery method	☐ In presence ☒ Online
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	The mammalian brain is a very sophisticated, highly efficient biocomputer from which technology has begun to draw inspiration for developing artificial neural networks. However, this biology to-technology translation is still in its infancy. Spiking neural networks based on neuromorphic architectures are emerging as a more biologically-inspired artificial minds which will likely underlie next-generation AI paradigms. This course will explore the biological – in silico correspondence at all levels, introducing key concepts of neuronal membrane potential dynamics, neuroanatomy and chemical neuromodulation, neural tissue energy demands, theory of evolution and principles of cognition. For each topic, its state-of-the-art neuromorphic engineering application counterpart will be presented. All major aspects of spiking neural network applications will be introduced, from training strategies (including principles of reinforcement learning, synaptic plasticity and multi-agent evolutionary artificial neural networks) to software and hardware implementation, e.g. including CMOS neuromorphic chips and memristor-based neuromorphic computers. Lecture 1: Introduction, membrane potential, synapses, and chemical neuromodulation Lecture 2: Spiking neural network in silico: models and simulation environments Lecture 3: Hard-wired spiking neural network: CMOS vs Memristors Lecture 4: Synaptic plasticity, neuromodulation strategies and learning. Lecture 5: Chemical-modulated reinforcement learning and evolution: from biology to engineering
Learning goals	By the end of the course, the student is expected to have acquired: A basic understanding of the biological mechanisms that have inspired the field of neuromorphic engineering. The ability to conceptualise biologically plausible mechanisms in a neural simulation with learning capabilities.
Teaching methods	Lectures will be blackboard-based for analytical and qualitative concepts, while slides will be used to illustrate applications
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No

Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Key concepts of Machine Learning
Examination methods (in applicable)	The student will prepare a seminar on a topic to be agreed upon
Suggested readings	- Principles of Neural Science, Sixth Edition, by Eric R. Kandel et Al., 2021 - Neuromorphic Engineering; The Scientist's, Algorithm Designer's, and Computer Architect's Perspectives on Brain-Inspired Computing, by Elishai Ezra Tsur, 2021 - Neuroscience, by D Purves et Al., 2018 - Selected articled from scientific literature.
Additional information	Monday 10/03/2025, 8:00-10:00. Tuesday 11/03/2025, 8:00-10:30. Thursday 13/03/2025, 8:00-10:30. Monday 17/03/2025, 8:00-10:30. Tuesday 18/03/2025, 8:00-10:30. Students who wish to attend the course are invited to contact the lecturer to enrol in the course.

Course unit English denomination	Cloud Computing & Big Data
Teacher in charge (if defined)	Tommaso Cucinotta (SantAnna Pisa)
Teaching Hours	30
Number of ECTS credits allocated	-
Course period	November-December
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	This course provides an overview of the challenges to be faced and the technical solutions to be adopted in building real-time, distributed, replicated, large-scale and fault-tolerant cloud services. These systems must be able to handle millions or billions of requests per second with industrial-grade reliability, availability and performance, and are composed of thousands of components distributed on millions of machines worldwide. The course focuses on the design, development and operations of scalable software systems, including the processing and analysis of big data, which are increasingly used for the intensive computations required to train large machine learning and artificial intelligence models, where the huge volume of data to be handled requires the use of highly distributed algorithms. The course also covers basic concepts on network architectures for cloud computing infrastructures and data centres.
Learning goals	related to big data, and will be able to master the key concepts that characterise them. This constitutes a fundamental element in the background of a software engineer or computer scientist who will deal with modern distributed software systems, both in industry and academia, ranging from high-performance systems to the cloud and even (increasingly connected) embedded systems.
Teaching methods	Slides and digital blackboard
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Students should have a basic knowledge of software, computer architectures, distributed systems and communication protocols.

Examination methods (in applicable)	Oral exam
Suggested readings	TBD
Additional information	tommaso.cucinotta@santannapisa.it

Course unit English denomination	Cloud Computing & Big Data Lab
Teacher in charge (if defined)	Tommaso Cucinotta (SantAnna Pisa)
Teaching Hours	30
Number of ECTS credits allocated	-
Course period	Flexible, to be agreed with the students, starting mid-April.
Course delivery method	☒ In presence ☐ Remotely ☐ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	This is a practical and applied course that follows the Cloud Computing & Big Data course. In this course, students will put into practice the theoretical/abstract concepts acquired in the general course on Cloud Computing & Big Data. During practical sessions, we will delve into concepts such as: machine virtualisation and operating system-level virtualisation on Linux; network virtualisation on Linux; programming abstractions for cloud and distributed computing; elasticity in practice; programming frameworks for big data; command-line interface for major public cloud services; and popular open-source cloud platforms.
Learning goals	Students will gain a unique insight into the world of cloud computing and big data related technologies, and will be able to master the key tools for their use. This constitutes a fundamental element in the background of a software engineer or computer scientist who will deal with modern distributed software systems, both in industry and academia, ranging from high-performance systems to the cloud and even (increasingly connected) embedded systems.
Teaching methods	Slides and digital blackboard
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Students must have attended the general Cloud Computing & Big Data course and must have a good command of shell programming and scripting on Linux.

Examination methods (in applicable)	Programming project and oral examination
Suggested readings	TBD
Additional information	tommaso.cucinotta@santannapisa.it

Course unit English denomination	Maximum-entropy methods for complex systems I
Teacher in charge (if defined)	Diego GARLASCHELLI (IMT Lucca)
Teaching Hours	20
Number of ECTS credits allocated	-
Course period	Second semester
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	This interdisciplinary course aims to introduce rigorous tools from statistical physics, information theory and probability theory to investigate the complex real-world systems that emerge in different fields of research. Initially, some key aspects of complexity encountered in physical, biological, social, economic and technological systems will be examined. Subsequently, the focus will be on the construction of theoretical models based on the concept of constrained randomness, i.e. entropy maximisation subject to appropriate constraints. This will lead to the introduction of maximum entropy models, which serve as mathematical references for the properties of highly heterogeneous complex systems. Cases of special interest include statistical sets of complex networks and multivariate time series with given properties. Comparisons between model results and empirical properties will be systematically presented. Comprehensive mathematical derivations of the models will be provided, as well as statistical inference methods, model selection and computer codes for parameter estimation on empirical data.
Learning goals	-
Teaching methods	Slides and digital blackboard
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Solid mathematical training, scientific curiosity, interest in multidisciplinarity, passion for theory

Examination methods (in applicable)	Oral exam
Suggested readings	TBD
Additional information	diego.garlaschelli@imtlucca.it; phd@imtlucca.it

Course unit English denomination	Maximum-entropy methods for complex systems II
Teacher in charge (if defined)	Tiziano Squartini (IMT Lucca)
Teaching Hours	20
Number of ECTS credits allocated	-
Course period	Second semester
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	The second part of the Advanced Methods for Complex Systems course focuses on advanced practical applications of the concepts introduced in the first part. In particular, emphasis will be placed on the successful areas of pattern detection and reconstruction of networks from partial information. Pattern detection in networks consists of identifying robust empirical patterns (such as scale invariance, clustering, assortativity, reciprocity, recurring patterns, etc.) that are widespread in real-world networks and that systematically deviate from certain null hypotheses formalised in terms of an appropriate random graph model. The models introduced in Part I will therefore be used here for pattern detection purposes. The problem of community detection will also be addressed, with an emphasis on the differences between finding communities in network data and in correlation matrices constructed from time series databases (e.g. financial or neural series). The problem of reconstructing networks from partial topological information will be addressed by focusing on reconstructing financial and interbank networks from specific node properties, with the aim of improving stress tests and estimates of systemic risk in real markets and providing better tools for policy makers. The statistical physics methods that central banks have recently identified as the best reconstruction techniques will be examined in detail.
Learning goals	-
Teaching methods	Slides and digital blackboard
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No

Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Solid mathematical training, scientific curiosity, interest in multidisciplinarity, successful completion of the Advanced Methods for Complex Systems I course.
Examination methods (in applicable)	Oral exam
Suggested readings	-
Additional information	tiziano.squartini@imtlucca.it; phd@imtlucca.it

Course unit English denomination	Quantum Artificial Intelligence
Teacher in charge (if defined)	Filippo Caruso (Università di Firenze)
Teaching Hours	10
Number of ECTS credits allocated	-
Course period	March-April
Course delivery method	☐ In presence ☐ Remotely ☒ Blended
Language of instruction	English
Mandatory attendance	☒ Yes (% minimum of presence) ☐ No
Course unit contents	Quantum Artificial Intelligence (Quantum AI) is a very young but rapidly evolving field of research, combining AI with the enormous power of quantum computers, now available via the cloud and even on the market. This intensive short course sheds light on this new Quantum AI framework by presenting an overview of the basic elements of quantum computing and quantum machine learning, where supervised and unsupervised learning algorithms, reinforcement learning and generative AI models can be generalised to the quantum world by running them on real and very powerful quantum processing units.
Learning goals	Knowledge of the basic elements of quantum computing and quantum machine learning, understanding the differences and advantages over classical machine learning
Teaching methods	Slides and digital blackboards
Course on transversal, interdisciplinary, transdisciplinary skills	☒ Yes ☐ No
Available for PhD students from other courses	☒ Yes ☐ No
Prerequisites (not mandatory)	Basic knowledge of mathematical analysis and linear algebra
Examination methods (in applicable)	project and oral interview

Suggested readings	Machine Learning With Quantum Computers, M. Schuld and F. Petruccione, Springer Nature 2021.
Additional information	filippo.caruso@unifi.it