PhD Program in “Systems Science”
Track in “Computer Science and Systems Engineering” (CSSE)

Course List - A.Y. 2019/20
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<td>Identification, Analysis and Control of Dynamical Systems</td>
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<td>Modelling and Verification of Reactive Systems</td>
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<td>Giorgio Gnecco</td>
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<td>Philosophy of Science (no exam)</td>
<td>Gustavo Cevolani</td>
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<td>Research Topics in Computer Science</td>
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<td>Scientific Writing, Dissemination and Evaluation (no exam)</td>
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<td>Stochastic Processes and Stochastic Calculus</td>
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<td>Strategies and Business Behavior</td>
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Learning Outcomes:
Students will learn how to: identify the properties of real-world complex systems that defeat traditional tools of analysis across different disciplines and research fields; design advanced methods to empirically characterise, mathematically model and computationally simulate those properties.

Abstract:
This interdisciplinary course aims at introducing rigorous tools from statistical physics, information theory and probability theory for investigating real-world complex systems arising in different fields of research. First, some key aspects of complexity encountered in physical, biological, social, economic and technological systems will be reviewed. Then, emphasis will be put on the construction of theoretical models based on the concept of constrained randomness, i.e. the maximisation of the entropy subject to suitable constraints. This will lead to the introduction of maximum-entropy models that serve as mathematical benchmarks for the properties of highly heterogeneous systems. Special cases of interest for this first part of the course include statistical ensembles of time series and correlation matrices with given properties. Applications to pattern detection in econophysics and neuroscience will be discussed. Full mathematical derivations of the models, as well as methods of statistical inference and model selection for data analysis will be provided.

Lecture Contents:
- Introduction
- From Complexity to Thermodynamics
- From Thermodynamics to Statistical Physics
- Entropy in Probability Theory
- Entropy in Information Theory
- Empirical patterns in univariate time series
- Empirical patterns in multivariate time series
- Community detection for correlation matrices

Teaching Method: Combination of frontal lectures, blackboard discussions and students' presentations.

Bibliography: References to relevant research papers are gradually provided during the lectures. Lecture slides and other course materials are regularly distributed to the students.

Final Exam:
Consists of students’ presentations of research papers, around which the professor organises a critical discussion with the rest of the class, towards the end of the course. No additional time slot for the exam is therefore scheduled.

Prerequisites: Solid mathematical background, scientific curiosity, logical rigor, interest in
multidisciplinarity, passion for theory.
Advanced Methods for Complex Systems II  
Diego Garlaschelli  
20 hours

Learning Outcomes:
Students will learn how to: identify the properties of real-world complex systems that defeat traditional tools of analysis across different disciplines and research fields; design advanced methods to empirically characterise, mathematically model and computationally simulate those properties.

Abstract:
The second part of the course “Advanced Methods for Complex Systems” focuses on advanced practical applications of the concepts introduced in the first part. In particular, emphasis will be put on the successful areas of pattern detection and network modelling. Network pattern detection is the identification of robust empirical patterns (like scale-invariance, clustering, assortativity, reciprocity, motifs, etc.) that are widespread across real-world networks and that deviate systematically from some null hypothesis formalised in terms of a suitable random graph model. The models introduced in part 1 will then be used here for pattern detection purposes. Similarly, they will be used for modelling the properties of real networks in terms of explanatory factors. The course will include a combination of recent and ongoing research in the NETWORKS unit at IMT Lucca, thereby offering directions for possible PhD projects in this area.

Lecture Contents:
- Complex networks: robust empirical properties
- Maximum-entropy network ensembles
- Networks with given degree sequence
- Maximum likelihood parameter estimation in network ensembles
- Pattern detection in networks
- Reciprocity and the Reciprocal Configuration Model
- The International Trade Network (econometric vs network modelling)

Teaching Method: Combination of frontal lectures, blackboard discussions and students' presentations.

Bibliography:
References to relevant research papers are gradually provided during the lectures. Lecture slides and other course materials are regularly distributed to the students.

Final Exam:
The final consists of students’ presentations of research papers, around which the professor organises a critical discussion with the rest of the class, towards the end of the course. No additional time slot for the exam is therefore scheduled.

Prerequisites: Solid mathematical background, scientific curiosity, logical rigor, interest in multidisciplinarity, passion for theory. Successful completion of the course "Advanced Methods for
Advanced Methods for Complex Systems III
Diego Garlaschelli
20 hours

Learning Outcomes:
Students will learn how to: identify the properties of real-world complex systems that defeat traditional tools of analysis across different disciplines and research fields; design advanced methods to empirically characterise, mathematically model and computationally simulate those properties.

Abstract:
The course focuses on the problem of network reconstruction from partial topological information and on the different physical and mathematical properties found when the input information is treated as a “soft” or a “hard” constraint.
On the side of applications, emphasis will be put on the reconstruction of financial and interbank networks from node-specific properties, with the purpose of improving stress tests and systemic risk estimates in real markets and offering better tools to policy makers. The methods recently found by central banks to be the best-performing reconstruction techniques will be reviewed in detail.
On the side of theory, the surprising breakdown of the equivalence of statistical ensembles constructed from soft and hard constraints will be discussed. We will show how this breakdown affects all models of complex systems encountered throughout the three parts of the course. Finally, we discuss deep implications for data compression, information theory and combinatorial enumeration.

Lecture Contents:
- From binary networks to weighted networks: the Weighted Random Graph
- The Weighted Configuration Model
- The Enhanced Configuration Model
- The Enhanced Gravity Model
- Network reconstruction in various settings
- Adaptive Networks
- Breaking of ensemble equivalence
- Relative entropy between ensembles
- Weak and strong ensemble nonequivalence
- Applications to combinatorial enumeration and data compression

Teaching Method: Combination of frontal lectures, blackboard discussions and students' presentations.

Bibliography:
References to relevant research papers are gradually provided during the lectures. Lecture slides and other course materials are regularly distributed to the students.

Final Exam:
The final consists of students’ presentations of research papers, around which the professor organises a critical discussion with the rest of the class, towards the end of the course. No additional time slot for the
exam is therefore scheduled.

**Prerequisites:**
Solid mathematical background, scientific curiosity, logical rigor, interest in multidisciplinarity, unlimited passion for theory. Successful completion of the courses “Advanced Methods for Complex Systems 1” and “Advanced Methods for Complex Systems 2”
**Advanced Numerical Analysis**  
*Benedetta Morini; Valeria Simoncini*  
*20 hours*

**Learning Outcomes:**
At the end of the course the student will be able to use dense and sparse linear system solvers for medium to large size problems in standardly used scientific computational environment. The student will be able to select the appropriate methodology depending on the application considered, while being able to tailor general methods to the given problem.

**Abstract:**
Lecturers: prof. B. Morini, UniFI, prof. V. Simoncini, uniBO. We present an introduction to numerical linear algebra methods for solving algebraic linear systems, with particular focus on algorithms and their application. In particular, modern methods for dense and sparse matrices will be discussed, and state-of-the-art iterative methods for large problems will be introduced. The students will have the opportunity to test the discussed methods during computer lab sessions, working on real data.

**Lecture Contents:**
A) Basics and small scale linear systems (10 hours, prof. Benedetta Morini)

1. General considerations on matrices  
   Matrices: definitions and properties; norm of matrices  
   The condition number of a matrix  
   Sparse matrices and sparse formats (sparsity, structure, functionals)  
   The role of the PDE discretization (e.g., parameter dependence)

2.a Direct methods for general linear systems  
   Factorizations: definitions and properties  
   Factorization algorithms  
   Cost and numerical stability  
   Least-squares solution

2.b Direct methods for sparse linear systems  
   Factorizations of banded matrices  
   Ordering strategies to minimize the fill-in of a matrix  
   Solution of sparse triangular systems  
   Sparse matrices in Matlab: memorization and handling  
   Predefined functions for the direct solution of systems

B) Numerical solution of large-scale linear systems (10 hours, prof. Valeria Simoncini)

Vector spaces and Galerkin projection  
Krylov subspace methods (CG, MINRES, GMRES, IDR family)
Structured linear algebra problems
Preconditioning: incomplete decompositions
Algebraic multigrid methods (short intro)
Methods for Saddle point linear systems
Numerical experiments with Matlab and the IFISS package

Teaching Method:
Lectures with slides, also available online. Computer lab sessions.

Bibliography:
- Yousef Saad, Iterative solution of large linear systems, SIAM, 2003 (book)

Final Exam:
Oral presentation on a selected project possibly related to the student’s interests.

Prerequisites:
Basics knowledge on Mathematical Analysis, linear algebra and Geometry.
Learning Outcomes:
Manipulation of adjacency matrices and algorithms connected

Abstract:
we shall provide the definitions of the algebraic concepts lying at the core of network theory and shall introduce the principles of network analysis with Python. This module is propaedeutic for modules 3, 4, 5.

Lecture Contents:
Binary, undirected networks: basic definitions; spectral properties; functions of the adjacency matrix. Other network representations (directed, weighted, bipartite, multiplex networks) and generalization of the results above. Other representations of network data (5h)
Python: Jupiter notebook; variables, lists, dictionaries; loops (for, while); functions; files management; errors (2h)
NumPy: arrays and functions; spectral properties; other representations for large datasets (3h)

Teaching Method:
Slides and Lab

Bibliography:
● G. Caldarelli Scale-Free Networks OUP (2007) (made available to students).
● Easley, Kleinberg “Networks Crowds and Markets” CUP (2010)
● http://barabasilab.neu.edu/networksciencebook/
● G. Caldarelli A. Chessa Data Science and Complex Networks OUP (made available to students)

Final Exam:
The candidate will work in the classroom and we shall assign a “pass” or “retake” vote at the end of the course.

Prerequisites: Introduction Course
Advanced Topics in Network Theory: Brain Networks
Guido Caldarelli
10 Hours

Learning Outcomes:
to be able to know the functioning of the various measuring instruments and to be able to correlate and model different measures on brain activity. We also want to teach brain structure and areas of interests

Abstract:
we shall provide the tools to measure and analyze the different kinds of networks that can be defined when studying the human brain (e.g. the functional and the structural one).

Lecture Contents:
Physics of the measuring instruments, structure of the Brain, connectome, networks from time series

Teaching Method:
slides and working in groups on pc

Bibliography:
- Easley, Kleinberg "Networks Crowds and Markets" CUP (2010)
- http://barabasilab.neu.edu/networksciencebook/
- Other texts will be suggested in the various lectures (basic biblio in this list)

Final Exam:
The candidate will work in the classroom and we shall assign a "pass" or "retake" vote at the end of the course.

Prerequisites:
Introduction to Complex Networks
Advanced Topics in Network Theory: Research Topics in Network Theory
Guido Caldarelli
10 hours

Learning Outcomes:
To be able to select stat-of-the-art problems in the area of complex networks

Abstract:
we shall review the latest developments in research concerning the field of network theory. This module
requires module 2. The course “Advanced Methods for Complex Systems I”
is suggested as a prerequisite.

Lecture Contents:
The Exponential Random Graph Model: constrained entropy maximization; parameter estimation;
computing expectations and errors; a quick look at perturbation theory for networks ( 2h )
Hypothesis testing on networks: projecting and filtering bipartite networks; early-warning signals
detection; community detection techniques for correlation matrices (asset graph, MSF,
dendrogram-cutting, the Masuda approach, random matrix theory-based techniques) ( 3h )
Network reconstruction; applications to the World Trade Web; comparison between network models and
econometric models; applications to financial networks; link prediction ( 3h )

Teaching Method:
slides and working on pc

Bibliography:
• G. Caldarelli Scale-Free Networks OUP (2007) (made available to students). • Easley, Kleinberg
• http://barabasilab.neu.edu/networksciencebook/
• Other texts will be suggested in the various lectures (basic biblio in this list)

Final Exam:
The candidate will work in the classroom and we shall assign a “pass” or “retake” vote at the end of the
course.

Prerequisites:
Introduction to Network Theory.
Advanced Topics in Network Theory: Topological Concepts in Network Theory
Guido Caldarelli
10 Hours

Learning Outcomes:
To be able to work on graphs as for example to be able to detect centrality and communities structures

Abstract:
we shall introduce the definitions of the main topological quantities of interest in network theory and their implementation in Python.

Lecture Contents:
Centrality metrics: degree; closeness; betweenness; eigenvector; Katz; hub/authority; PageRank (2h)
Exercises in Python + NetworkX (2h)
Mesoscale structures detection: Girvan-Newman algorithm and modularity; spectral methods; Louvain; the limitations of modularity; surprise; block-model fitting; community detection for bipartite networks; core-periphery structure; bow-tie structure (6h)

Teaching Method:
Slides and lab

Bibliography:
- Easley, Kleinberg “Networks Crowds and Markets” CUP (2010)
- http://barabasilab.neu.edu/networksciencebook/
- G. Caldarelli A. Chessa Data Science and Complex Networks OUP (made available to students)

Final Exam:
the candidate will work in the classroom and we shall assign a “pass” or “retake” vote at the end of the course.

Prerequisites:
This module requires module 2 (Algebraic properties) and Introduction to Networks.
Learning Outcomes:
Overview of interdisciplinary frontier research topics where computational methods can be profitably applied as predictive simulation tools. Nonlinear coupled problems in solid mechanics and fluid dynamics problems in biomechanics will be the main object of the lectures.

Abstract:
This course covers advanced topics of computational mechanics, with special emphasis on nonlinear coupled problems in solid mechanics and fluid dynamics. This course aims at providing an overview of frontier research topics in emerging interdisciplinary areas where computational methods can be profitably applied as predictive simulation tools.

Lecture Contents:
The course content covers the following topics:
- Advanced techniques for solid mechanics and fluid dynamics;
- Coupled problems in biomechanics;
- Coupled problems for renewable energy applications;
- Computational methods for the prediction of the evolution of discrete mechanical systems and interdisciplinary analogies (traffic networks, economic networks, etc.)

Teaching Method:
Lectures using powerpoint slides.

Bibliography:
Selection of scientific articles published in international journals.

Final Exam:
An application of the taught methodologies to a problem relevant for the PhD research is welcome. Alternatively, the student is requested to deliver a short presentation/discussion on the content of an article based on methodologies related to those presented in the course.

Prerequisites:
Numerical Method for the Solution of Partial Differential Equations
Advanced Topics of Control Systems: Numerical Methods for Optimal Control  
Mario Zanon  
20 Hours

Learning Outcomes:  
The students will learn how to properly formulate and solve an optimal control problem using state-of-the-art techniques.

Abstract:  
Many control and estimation tasks seek at minimizing a given cost while respecting a set of constraints, which belongs to the class of problems denoted as Optimal Control (OC). The most practical approach to solve OC problems is via direct methods, which consists in discretizing the problem to obtain a Nonlinear Program (NLP) which is then solved using one of the many available approaches. The course will be introduced by an overview of the available classes of algorithms for OC and place direct methods in this context. The core of the course is structured around the following two main parts.

NLP solvers:  
This part of the course first establishes a sound theoretical background on the characterization of local minima (maxima) by introducing geometric optimality concepts and relating them to the first- and second-order conditions for optimality, i.e. the Karush-Kuhn-Tucker conditions, constraint qualifications and curvature conditions. Second, the theoretical concepts will be used to analyze the most successful algorithms for derivative-based nonconvex optimization, i.e. Sequential Quadratic Programming and Interior Point Methods, both based on Newton's method. Since there does not exist a plug-and-play NLP solver, attention will be devoted to giving the students a solid understanding of the mechanisms underlying the algorithms so as to endow them with the ability to formulate the problem appropriately and choose the adequate algorithm for each situation.

Discretization techniques:  
This second part of the course covers the most successful discretization approaches, i.e. single-shooting, multiple-shooting and collocation. All mentioned approaches rely on the simulation of dynamical systems, for which a plethora of algorithms have been developed. The students will be explained the features of the different classes of algorithms, with particular attention on the numerical efficiency, simulation accuracy and sensitivity computation. Finally, the structure underlying the NLP obtained via direct methods for OC will be analyzed in order to understand the immense benefits derived from developing dedicated structure-exploiting OC solvers.

Advanced Topics:  
The course will be concluded by two lectures on parametric sensitivities, path-following methods and Nonlinear Model Predictive Control (NMPC) with considerations on stability, tuning and real-time solvers.

Lecture Contents:  
The following lectures are divided by topic in the order in which they will be presented. Some lecture
requires more than 2 hours and some other requires less. Altogether, the 9 lectures require 20 hours of teaching, which will be supported by 10 hours of supervision for the solution of the assignments.

1. Introduction to optimal control
2. Nonlinear Programming: optimality characterization
3. Newton's method and algorithms for nonconvex optimization
4. Shooting methods
5. Numerical integration with sensitivities
6. Collocation methods
7. Structure of discretized optimal control problems
8. Parametric sensitivity and path-following
9. Nonlinear Model Predictive Control

Teaching Method:
Lectures and exercise sessions

Bibliography:
L. Biegler. Nonlinear Programming, MOS-SIAM Series on Optimization 2010
J. C. Butcher Numerical Methods for Ordinary Differential Equations, Wiley 2016

Final Exam:
Solution of all the assignments

Prerequisites:
Basic knowledge in dynamical systems and linear algebra. Some knowledge on numerical optimization and simulation can be helpful but is not required.
Applications of Stochastic Processes
Mirco Tribastone
20 Hours

Learning Outcomes:
To provide students with basic tools for the modeling and analysis of systems using stochastic processes.

Abstract:
This course offers an introduction to stochastic processes as a practical modelling tool for the quantitative analysis of systems. It covers the fundamentals of Markov chains, and presents algorithms and state-of-the-art software applications and libraries for their numerical solution and simulation. The class of Markov Population Processes is presented, with its most notable applications to as diverse disciplines as chemistry, ecology, systems biology, health care, computer networking, and electrical engineering. Finally, the course will examine the computational issues arising from the modelling of large-scale systems, reviewing effective approximation methods based ordinary differential equation (fluid) limits, moment-closure techniques, and hybrid models.

Lecture Contents:
Introductions to discrete- and continuous-Markov chains; examples (Page Rank, reaction networks, queuing networks); Markov population processes; stochastic simulation algorithms; fluid approximations of Markov population processes; software tools for analysing Markov chains.

Teaching Method:
Blackboard and slides.

Bibliography:
Bibliographic material will consist of research articles distributed throughout the course.

Final Exam:
Student may choose between the presentation of a research paper or the development of project

Prerequisites:
None
Learning Outcomes:
The goal of the course is to provide an all-purpose introduction to behavioral economics as well as to offer hooks and suggestions for cutting-edge research projects concerning bounded rationality and prosocial behavior.

Abstract:
The course is a self-contained presentation and discussion of state-of-the-art research in behavioral economics, an area merging economics and psychology for the purpose of modelling and predicting human decision-making and behavior.

Lecture Contents:
1. What is Behavioral Economics? An economist’s take on surprising human behaviors, with a reference to why psychologists and neuroscientists are hardly surprised
2. Rationality with cognitive bounds: Searching for predictable mistakes
3. Beyond homo economicus: Searching for predictable other-regarding preferences
4. A case study in behavioral game theory: Cognitive foundations of human prosociality
5. A discussion on methods: Experiments by economists in the lab and in the field, with a reference to how psychologists and neuroscientists would disagree

Teaching Method:
Frontal lectures

Bibliography:

Final Exam:
A 10-page essay applying behavioral economics to a phenomenon decided by the student

Prerequisites:
The course is self-contained, but basic knowledge of microeconomics and choice theory are welcome.
Learning Outcomes:
Students will learn how to observe and evaluate business behavior, as well as how to locate sources of potential competitive advantage. They will also learn the base to identify organizational barriers and corporate behaviors that sustain or challenge manager decisions and execution of strategies.

Abstract:
The course is based on key business concepts that will support students develop the expertise required to understand and evaluate business behaviors, firms’ strategies and financial results. The course is composed of three modules: "Firms, business analytics and managerial behavior", "Business Behavior and Behavioral Strategy", "Business model for emerging markets". The course will describe the decision-making in competitive markets as well as in emerging markets at the business unit level, in which many key strategic choices and actions are formulated and undertaken. The essential “tool-kit” that combines a broad understanding of strategies, businesses and market dynamics and the new challenges of businesses in today’s world.

Lecture Contents:
Business Model for Emerging Markets
1. What makes the economy emerging and the market new?
2. Fintech challenge: centralized economy versus decentralized economy? Decentralized organizations and business models? DAO, DAC and others
3. Digital Economy: effects and implications on business modeling, business plan and business reporting
4. Family business and Italian SMSB: “Made in a recognizable place”
5. A business model for a global value chain approach in a Digital Economy. The smile curve: where value is added along supply chains
6. The new Silk Road - Belt and Road: Avoiding Errors, Discovering Opportunities
7. Creation of needs, emerging behaviors and business dynamics: the interaction of neuroscience and technology for business and strategy (joint E. Ricciardi)
8. Zombie Economy and Zombie Firms: The Emerging Phenomena
9. Network approach for Business modeling and decision making process
10. The role and function of studies in management science and business strategy. The emerging scenario.

Teaching Method:
Lectures, discussions, business cases, presentations.

Bibliography:
Suggested readings will be provided for each topic.

Final Exam: Critical paper presentations in at least four groups.
Prerequisites:
Basic knowledge of business economics.
Learning Outcomes:
The course provides a comprehensive overview of theory and numerics for the understanding and simulation of frontier research topics relevant for the design of innovative materials and structures.

Abstract:
This course provides an overview on the theories of contact and fracture mechanics relevant for a wide range of disciplines ranging from materials science to engineering. Introducing their theoretical foundations, the physical aspects of the resulting nonlinearities induced by such phenomena are emphasized. Numerical methods (FEM, BEM) for their approximate solution are also presented together with a series of applications to real case studies.

Lecture Contents:
The course covers the following topics:
- Hertzian contact between smooth spheres;
- the Cattaneo-Mindlin theory for frictional contact;
- numerical methods for the treatment of unilateral contact constraints;
- contact between rough surfaces;
- fundamentals of linear elastic fracture mechanics;
- the finite element method for crack propagation;
- nonlinear fracture mechanics and the cohesive zone model;
- interface finite elements;
- applications of fracture mechanics to materials science, retrofitting of civil/architectonic structures, composite materials;
- fatigue.

Teaching Method:
Lectures using blackboard and powerpoint slides.

Bibliography:

Final Exam:
An application of the taught methodologies to a problem of interest for the PhD student's research is recommended. Alternatively, a topic for the exam can be suggested by the lecturer.

Prerequisites:
Numerical Methods for the Solution of Partial Differential Equations
Learning Outcomes:
This course aims to provide students with basic principles and methodologies of computer programming using Python. It is aimed particularly to students without a computer science background. The main objective is to develop the necessary skills to effectively read, write, and maintain computer programs. It provides background for facilitating the understanding of advanced programming classes as well as the proficiency with domain-specific software libraries and tools.

Abstract:
The course will cover the basic principles of programming, starting from the interaction between programs and the environment (memory, input/output) in which they execute. It will discuss: fundamental programming constructs (conditional statements, loops); how to effectively structure code using functions; recursion; object-oriented programming; basics of functional programming; memory management for programs (garbage collection). The Python programming language will be used to demonstrate these concepts and to develop simple illustrative programs that will be presented throughout the course.

Lecture Contents:
Introduction to computer architectures; programming; variables; data structures and Python sequences; memory management; conditional statements; for and while loops; functions; basics of object-oriented programming; basics of functional programming.

Teaching Method:
Blackboard; slides; programming tutorials

Bibliography:
M. Lutz. Learning Python, O'Reilly.

Final Exam:
Group project

Prerequisites:
None.
Learning Outcomes:
Overview of Computer-Aided Engineering (CAE) software for solid and fluid dynamics; CAD-CAE integration software; overview of fast prototyping solutions with examples of high industrial relevance.

Abstract:
This course aims at introducing doctoral students to the state-of-the-art of methods and tools of Computer-Aided Engineering (CAE), which refers to the broad use of computer software to aid in engineering design tasks. It encompasses finite element analysis (FEA), computational fluid dynamics (CFD), analysis tools for industrial process simulation, multi-physics simulation software for smart systems, and also platforms allowing the integration with control and optimization for the product or process. This field is one of the pillars of Industry 4.0, since it allows for virtual testing and virtual and rapid prototyping of materials, components and processes, reducing the time to market of new products and leading to higher levels of performance and reliability.

Lecture Contents:
The course covers the following content:
- Overview of Computer-Aided Engineering software, with special focus on finite element analysis and computational fluid dynamics tools.
- Overview of techniques for CAD-CAE integration, including isogeometric finite elements.
- Overview of 3D prototyping techniques.
- Introduction to CFD Smoothed Particle Hydrodynamics software (SPHERA).
- High-performance computing techniques for the analysis of industrial problems.

Teaching Method:
Powerpoint presentations.

Bibliography:
Handouts are provided to the participants.

Final Exam:
The final exams consists of an application of one of the taught methodologies to a case study of interest for the PhD students’ research.

Prerequisites:
It could be useful to attend the course on Numerical Methods for the Solution of Partial Differential Equations. However, the present course is self-contained.
Learning Outcomes:
Theory and practice of network, web and host security attacks and defence.

Abstract:
The course is structured in two modules. The first module is introductory to cybersecurity in general and teaches methods for navigating securely and for defending assets and privacy. It can be beneficial for any student and does not assume any prior technical knowledge. The second module covers some advanced topics in cybersecurity such as security protocols, usage control, vulnerability analysis and web and mobile security.

Lecture Contents:

Teaching Method:
Blackboard; slides.

Bibliography:
Handouts with the slides, introductory books, research papers.

Final Exam:
Programming project and oral presentation.

Prerequisites:
Basic knowledge of Formal Methods and Software Verification.
**Learning Outcomes:**
Methods for navigating securely and for defending assets and privacy.

**Abstract:**
The course is structured in two modules. The first module is introductory to cybersecurity in general and teaches methods for navigating securely and for defending assets and privacy. It can be beneficial for any student and does not assume any prior technical knowledge. The second module covers some advanced topics in cybersecurity such as security protocols, usage control, vulnerability analysis and web and mobile security.

**Lecture Contents:**

**Teaching Method:**
Blackboard; slides.

**Bibliography:**
Handouts with the slides, introductory books, research papers.

**Final Exam:**
No exam.

**Prerequisites:**
No prerequisite.
Learning Outcomes:
(1) Knowledge of the most relevant functionalities in Stata to carry out data management and exploratory analysis
(2) To achieve autonomy in application of econometric techniques to real data

Abstract:
The aim of this course is to provide students with fundamentals of Stata language to conduct data management and exploratory analysis, and implement a variety of econometric techniques to address typical research questions in Economics.

Lecture Contents:
Lectures will cover the following topics:
– Introduction to Stata, descriptive statistics, fundamentals of inference
– OLS regression
– Non-linear models (binary, multinomial, count outcomes)
– Panel methods (pooled OLS, Fixed Effects, Random Effects, First Difference, Generalized Least Squares)
– Impact Evaluation (Randomized experiments, Matching, Difference-in-differences, Instrumental Variables, Regression Discontinuity Design)

Teaching Method:
Computer-based

Bibliography:
Cameron, A. C., P. K. Trivedi (2009) Microeconometrics Using Stata. Stata Press

Final Exam:
Not required

Prerequisites:
Basic Statistics.
Econometrics I
Paolo Zacchia
20 Hours

Learning Outcomes:
The objective of the course is to provide a firm understanding of the core theory of Econometrics at the graduate level.

Abstract:
This course provides a general introduction to modern econometrics. Following a review of fundamental concepts of probability theory, the course illustrates the fundamental linear and non-linear models at the core of econometrics, under the unifying framework of Maximum Estimation. Emphasis is placed upon the concepts of structure, identification, causality; their mutual relationships; as well as their connection to the actual econometric practice.

Lecture Contents:
1) Probability Review
2) Asymptotics Review
3) Structure, Identification and Causality
4) The Linear Regression Model
5) Least Squares Estimation
6) Endogeneity and Instrumental Variables
7) Simultaneous Equations Model
8) Introduction to Maximum Estimation
9) Maximum Likelihood Estimation
10) Generalized Method of Moments

Teaching Method:
Traditional frontal instruction accompanied by optional practice hours

Bibliography:
A. Colin Cameron and Pravin K. Trivedi (2005), Microeconometrics: Methods and Applications, Cambridge University Press
William H. Greene (2012), Econometric Analysis, Pearson
Other notes and scientific articles will be distributed in class

Final Exam:
The assessment is based upon a final written exam (for about 70% of the final grade) as well as on two extensive problem sets (for about the remaining 30%).

Prerequisites:
Multivariate calculus, linear algebra, graduate-level probability and statistical inference.
Learning Outcomes:
The objective is to develop a critical understanding of the iterative research process leading from real economic issues to the choice of the best tools available from the analyst kit.

Abstract:
This course covers the most important topics of modern microeconometrics. A variety of methods are illustrated with a hands-on-tool approach combining theory and practice. The objective is to develop a critical understanding of the iterative research process leading from real economic issues to the choice of the best tools available from the analyst kit. The assessment is based on the production of a short empirical project (50%), a written exam (30%) and the presentation/replication of a published scientific article (20%).

Lecture Contents:
1) Introduction to Microeconometrics
   i) Heterogeneity and Microdata
   ii) The Potential Outcome Model
   iii) Exogeneity and Identification
   iv) Parametric, Semiparametric and Non-parametric Models
   v) The Local Polynomial Regression Model
   vi) The Kernel Density Estimation

2) Survey Design, Sampling and Variance
   i) Survey design and Sampling Techniques
   ii) The Heckman Correction
   iii) One-way and Two-way Analysis of Variance
   iv) Analysis of Covariance

3) Linear Panel Models
   i) Pooled Models
   ii) The Fixed Effects Estimator
   iii) The Random Effects Estimator
   iv) Mixed Models
   v) GMM Estimators for Panel Data
   vi) Application: Firms, Productivity and Technical Change (Industrial Organization)

4) The Evaluation Problem
   i) Randomized Experiments
   ii) Matching Models
   iii) The Difference-in-difference Estimators
iv) Instrumental Variables
v) Regression Discontinuity Design
vi) Models with Control Functions
vii) Application: Evaluation of Active Labor Markets Programs (Labor economics)

5) Repeated Measures and Longitudinal Designs
i) Experiments and Quasi-experiments
ii) Longitudinal Designs and Repeated Measures
iii) Between-subjects Hypothesis Testing
iv) Application: Behaviorally Motivated Policies (Behavioral/Experimental Economics)

6) Multinomial Models
i) A Review of Logit and Probit Models
ii) The Multinomial Logit Model
iii) The Conditional Logit Model
iv) The Nested Logit Model
v) The Ordered Probit Model
vi) Application: Location Choices and Agglomeration Economies (Economic Geography)

7) Models for Count Data
i) Poisson Regression Model
ii) Negative Binomial Regression Model
iii) Hurdle Models
iv) Application: Technology Diffusion with Patent Data (Economics of Innovation)

8) Survival/Duration Models
i) On Censoring and Truncation
ii) The Kaplan-Meier Curve
iii) The Cox Regression Model
iv) The Weibull Model
v) Application: Market Access for Pharmaceutical Products (Health Economics)

9) Special seminar: Econometrics and Machine learning

Teaching Method:
Hands-on-tool approach combining theory and practice.

Bibliography:
Cameron and Trivedi (2005), Microeconometrics: Methods and Applications, Cambridge University Press.
Cameron and Trivedi (2010), Microeconometrics using Stata, Stata Press.
Angrist and Pischke (2009), Mostly Harmless Econometrics, Princeton University Press
Final Exam:
The assessment is based on the production of a short empirical project (50%), a written exam (30%) and the presentation/replication of a published scientific article (20%).

Prerequisites:
Foundations of Probability and Statistics; Econometrics I.
Learning Outcomes:
Students will learn how to observe and evaluate business behavior, as well as how to locate sources of potential competitive advantage. They will also learn the base to identify organizational barriers and corporate behaviors that sustain or challenge manager decisions and execution of strategies.

Abstract:
The course is based on key business concepts that will support students develop the expertise required to understand and evaluate business behaviors, firms’ strategies and financial results. The course is composed of three modules: "Firms, business analytics and managerial behavior", "Business Behavior and Behavioral Strategy", "Business model for emerging markets". The course will describe the decision-making in competitive markets as well as in emerging markets at the business unit level, in which many key strategic choices and actions are formulated and undertaken. The essential “tool-kit” that combines a broad understanding of strategies, businesses and markets dynamics and the new challenges of businesses in today’s world.

Lecture Contents:
Firms, business analytics and managerial behavior
1. Firm as a system of choices and decisions in progress: theory
2. The system of forces in a business organization: efficiency in production and effectiveness in results
3. Business performance and ways to represent: quantitative and qualitative languages in accounting. The Financial conditions and the Profit and Loss prospect
4. The fundamental role of Human Being. Human capital and intellectual capital: evolution and analysis
5. Technological progress, occupations and skills in a business combination: the analysis
6. The financial statement. How to read and comprehend performances and results in a business organization: methodology and tools
7. The financial statement. How to read and comprehend performances and results in a business organization: methodology and tools
8. Strategy, forecast simulation versus predictive simulation, Business analytics
9. Entrepreneurship and management in a complex scenario
10. Neuroscience, brain and business

Teaching Method:
Lectures, discussions, business cases, presentations.

Bibliography:
Suggested readings will be provided for each topic.
Final Exam:
Critical paper presentations in at least four groups.

Prerequisites:
Basic knowledge of business economics.
Foundations of Probability and Statistical Inference
Irene Crimaldi
30 Hours

Learning Outcomes:
By the end of this course, students will:
- have the ability to employ the fundamental tools of Probability Theory in order to solve different kinds of problems,
- have the fundamental concepts of Statistical Inference in order to perform various kinds of statistical analysis,
- appreciate the importance of mathematical formalization in solving probabilistic problems and in performing statistical analysis,
- be able to independently read mathematical and statistical literature of various types and be life-long learners who are able to independently expand their probabilistic and statistical expertise when needed.

Abstract:
This course covers the fundamental concepts of probability and statistical inference. Some proofs are sketched or omitted in order to have more time for examples, applications and exercises.

Lecture Contents:
This course deals with the following topics:
- probability space, random variable, expectation, variance, cumulative distribution function, discrete and absolutely continuous distributions,
- random vector, joint and marginal distributions, joint cumulative distribution function, covariance,
- conditional probability, independent events, independent random variables, conditional probability density function, order statistics,
- multivariate Gaussian distribution, copula functions,
- probability-generating function, Fourier transform/characteristic function,
- types of convergence and some related important results,
- Mathematical Statistics (point estimation, interval estimation, hypothesis testing, linear regression, introduction to Bayesian statistics).

Teaching Method:
Frontal teaching

Bibliography:
- Slides and other material provided by the lecturer

**Final Exam:**
Written test

**Prerequisites:**
No
Funding and Management of Research and Intellectual Property

Marco Paggi

10 Hours

Learning Outcomes:
How to write a research/mobility project proposal; fundamentals on the management of intellectual property rights.

Abstract:
The long seminar aims at providing an overview of funding opportunities for PhD students’ mobility, post-docs, and researchers (Erasmus+ scheme; scholarships by the Alexander von Humboldt Foundation; initiatives by the Deutscher Akademischer Austausch Dienst; scholarships offered by the Royal Society in UK; bilateral Italy-France exchange programmes; Fulbright scholarships; Marie Curie actions; grants for researchers provided by the European Research Council). For each funding scheme, specific hints on how to write a proposal are given. In the second part of the long seminar, fundamentals on the management of intellectual property rights (copyright transfer agreements, open access, patents, etc.) are provided.

Lecture Contents:
- Overview of funding schemes to support research mobility;
- Fundamentals of Intellectual Property Rights (patents, copyrights, etc.)

Teaching Method:
Powerpoint slides

Bibliography:
Handouts are provided to the participants.

Final Exam:
This long seminar has no final exam.

Prerequisites:
None
Learning Outcomes:
The goal is to equip students with an in-depth understanding of the main concepts and tools of game theory in order to enable them to successfully pursue research related to strategic behavior.

Abstract:
The course begins by providing a detailed discussion of the state of the art approach to the modeling of strategic situations as games. Then, basic solution concepts and their main refinements will be reviewed. Finally, prominent applications concerning incomplete and asymmetric information will be presented.

Lecture Contents:
Game concepts covered:
Dominance and iterative dominance, rationalizability, Nash equilibrium, subgame perfect Nash equilibrium, trembling hand perfect Nash equilibrium, weak perfect Bayes-Nash equilibrium, sequential equilibrium, perfect Bayes-Nash equilibrium, out-of-equilibrium beliefs refinements.

The discussion of all theoretical concepts will be accompanied by representative applications from economics and the social and behavioral sciences.

Teaching Method:
Frontal lectures

Bibliography:

Final Exam:
1/3 assignments, 1/3 final written exam, 1/3 essay

Prerequisites:
The course is self-contained, but being familiar with basic concepts from calculus, linear algebra, and probability theory is quite helpful.
Identification, Analysis and Control of Dynamical Systems  
Alberto Bemporad  
20 Hours

Learning Outcomes:  
Getting familiar with analyzing, controlling, estimating, and identifying dynamical systems, with emphasis on linear dynamical systems in state-space form.

Abstract:  
The course provides an introduction to dynamical systems, with emphasis on linear systems in state-space form. After introducing the basic concepts of stability, controllability and observability, the course covers the main techniques for the synthesis of stabilizing controllers (state-feedback controllers and linear quadratic regulators) and of state estimators (Luenberger observer and Kalman filter). The course also briefly covers data-driven approaches of parametric identification to obtain models of dynamical systems from a set of data.

Lecture Contents:  

Teaching Method:  
Lecture slides and blackboard

Bibliography:  
Lecture slides available on http://cse.lab.imtlucca.it/~bemporad/intro_control_course.html

Final Exam:  
Typically a small research project, or discussion about a paper on a subject related to the course, or oral exam.

Prerequisites:  
Linear algebra and matrix computation, calculus and mathematical analysis.
Introduction to Network Theory
Guido Caldarelli
10 Hours

Learning Outcomes:
Being able to understand the basic concepts and theoretical frameworks in complex network theory

Abstract:
The course will provide an introduction to the mathematical basis of Complex Networks and their use to describe, analyze and model a variety of physical and economic situations.

Lecture Contents:
LECTURE 01 Graph Theory Introduction
LECTURE 02 Properties of Complex Networks I
LECTURE 03 Properties of Complex Networks II
LECTURE 04 Communities
LECTURE 05 Different kind of Graphs
LECTURE 06 Ranking
LECTURE 07 Static Models of Graphs
LECTURE 08 Dynamical Models of Graphs
LECTURE 09 Fitness Models
LECTURE 10 Financial Networks

Teaching Method:
Slides

Bibliography:
• G. Caldarelli Scale-Free Networks OUP (2007) (made available to students).
• Easley, Kleinberg "Networks Crowds and Markets” CUP (2010)
• http://barabasilab.neu.edu/networksciencebook/

Final Exam:
essay by students

Prerequisites:
basic of mathematics
Learning Outcomes:
By the end of this course, students will:
- be familiar with Markov processes in discrete and continuous time,
- be able to employ the fundamental tools of Markov Processes Theory in order to solve different kinds of problems,
- appreciate the importance of mathematical formalization in solving probabilistic problems,
- be able to independently read mathematical and statistical literature of various types.

Abstract:
This course covers the fundamental results regarding Markov processes. Some proofs are sketched or omitted in order to have more time for examples, applications and exercises.

Lecture Contents:
This course deals with the following topics:
- Markov chains (definitions and basic properties, classification of states, invariant measure, stationary distribution, ergodic limit theorem, random walk and Gambler’s ruin problem);
- Poisson process (definition, properties and applications);
- Markov processes with continuous time (definitions, Markov property, generator, forward Kolmogorov equations, stationary probability distribution);
- Birth-Death processes and queues.

Teaching Method:
Frontal teaching

Bibliography:
- Slides and other material provided by the lecturer

Final Exam:
Without exam

Prerequisites:
Basics of probability theory
Machine Learning
Giorgio Gnecco
20 Hours

Learning Outcomes:
At the end of the course, the student will have a basic knowledge of a quite-large set of commonly-used machine-learning techniques.

Abstract:
The course provides an introduction to basic concepts in machine learning. Topics include: learning theory (bias/variance tradeoff, Vapnik-Chervonenkis dimension and Rademacher complexity, cross-validation); supervised learning (linear regression, logistic regression, support vector machines); unsupervised learning (clustering, principal and independent component analysis); semisupervised learning (Laplacian support vector machines); online learning (perceptron algorithm); hidden Markov models.

Lecture Contents:
Lecture 1: Introduction to supervised learning and regression.
Lecture 2: Classification problems.
Lecture 3: Online learning: the perceptron learning algorithm and the LQG online learning framework.
Lecture 4: Unsupervised learning.
Lecture 5: Introduction to statistical learning theory.
Lecture 6: Structural risk minimization and support vector machines.
Lecture 7: A joint application of econometrics and machine learning: trade-off between sample size and precision of supervision.
Lecture 10: Connection between supervised learning and reinforcement learning.

Moreover, the teacher will illustrate some of the methods above, based on MATLAB implementations.

Teaching Method:
The teacher will project slides on the screen (a copy of the slides and of the MATLAB code will be provided to the students).

Bibliography:
The following books are related to the course. They can be useful as a supplementary material.


The following are slides/lectures notes from related courses.


The following reference reports commented MATLAB code for some of the machine-learning techniques examined in the course.


Final Exam:
The student will prepare slides for a short seminar (20-30 minutes) on a topic related to machine learning. The topic of the seminar will be either proposed by the teacher or chosen by the student. The date of the seminar will be agreed between the student and the teacher. The seminar will take place either in the teacher's office or in the classroom (in case several students will decide to have their seminars in the same day).

Prerequisites:
Calculus.
Model Predictive Control
Alberto Bemporad
20 Hours

Learning Outcomes:
Knowledge of the theory and practice of Model Predictive Control (MPC) of constrained linear, linear time-varying, nonlinear, stochastic, and hybrid dynamical systems, and of the numerical optimization methods required for the implementation of MPC.

Abstract:
Model Predictive Control (MPC) is a well-established technique for controlling multivariable systems subject to constraints on manipulated variables and outputs in an optimized way. Following a long history of success in the process industries, in recent years MPC is rapidly expanding in several other domains, such as in the automotive and aerospace industries, smart energy grids, and financial engineering. The course is intended for students who want to learn the theory and practice of Model Predictive Control (MPC) of constrained linear, linear time-varying, nonlinear, stochastic, and hybrid dynamical systems, and numerical optimization methods for the implementation of MPC. The course will make use of the MPC Toolbox for MATLAB developed by the teacher and co-workers (distributed by The MathWorks, Inc.) for basic linear MPC, and of the Hybrid Toolbox for explicit and hybrid MPC.

Lecture Contents:
General concepts of Model Predictive Control (MPC). MPC based on quadratic programming. General stability properties. MPC based on linear programming. Models of hybrid systems: discrete hybrid automata, mixed logical dynamical systems, piecewise affine systems. MPC for hybrid systems based on on-line mixed-integer optimization. Multiparametric programming and explicit linear MPC, explicit solutions of hybrid MPC. Stochastic MPC: basic concepts, approaches based on scenario enumeration. Linear parameter- and time-varying MPC and applications to nonlinear dynamical systems. Selected applications of MPC in various domains, with practical demonstration of the MATLAB toolboxes.

Teaching Method:
Lecture slides and blackboard

Bibliography:
Lecture slides available on http://cse.lab.imtlucca.it/~bemporad/mpc_course.html


A. Bemporad and M. Morari, Control of systems integrating logic, dynamics, and constraints, Automatica, vol. 35, no. 3, pp. 407–427, 1999


**Final Exam:**
Typically a small research project, or discussion about a paper on a subject related to the course, or oral exam.

**Prerequisites:**
Linear algebra and matrix computation, linear control systems, numerical optimization.
Modelling and Verification of Reactive Systems
Rocco De Nicola
20 Hours

Learning Outcomes:
Students will learn how to approach the design and verification of computing systems consisting of many interacting components and to tackle one of the key scientific challenges in computer science, namely the design and development of computing systems that do what they are expected to do, and do so reliably.

Abstract:
The aim of this course is to introduce models for the formal description of computing systems, with an emphasis on parallel, reactive and possibly real-time systems, and the techniques for system verification and validation that accompany them. As an important component of the course, we shall introduce industrial-strength software tools for modelling and analyzing the behaviour of (real-time) reactive systems.

Lecture Contents:
Finite state automata, Kripke structures, Labelled transition systems
Operators for Modelling composition of concurrent systems as labelled transition systems. First part: sequentialization, nondeterministic composition, parallelism, abstraction, recursion.
Behavioural Equivalences for labeled transition systems. Strong and weak variants of trace, testing and bisimulation equivalences.
Alternative approaches to the semantics of Concurrent systems. ACP and Axiomatic Semantics. CSP and Denotational semantics.
A calculus of Communicating Systems (CCS) and its operational and Axiomatic Semantics.
Logics for Specifying properties of concurrent Systems. Hennessy Milner Logic (HML) and Bisimulation. HML with recursion and fixed-point theory.
Temporal and Modal Logics and Model Checking techniques

Teaching Method:
Blackboard and Slides

Bibliography:
Handouts with the slides, some introductory books and web resources with software tools

Final Exam:
Specification and Verification project and presentation in the classroom

Prerequisites:
Basics of formal methods and of sequential and concurrent programming
Numerical Methods for the Solution of Partial Differential Equations  
Marco Paggi  
20 Hours

**Learning Outcomes:**
Ability to solve numerically a problem related to a physical system and predict its response. The physical system can be embedded within an optimization problem, for instance, or it can be part of a complex system (biological, mechanical, thermo-mechanical, chemical, or even financial) you are interested in predicting its behaviour and evolution over time.

**Abstract:**
The course introduces numerical methods for the approximate solution of initial and boundary value problems governed by linear and nonlinear partial differential equations (PDEs) used to describe physical systems. The fundamentals of the finite difference method and the finite element method are introduced step-by-step in reference to exemplary model problems taken from heat conduction, linear elasticity, and pricing of stock options in finance. Notions on numerical differentiation, numerical integration, interpolation, and time integration schemes are provided. Special attention is given to the implementation of the numerical schemes in finite element analysis programmes for fast intensive computations.

**Lecture Contents:**
- Numerical differentiation schemes  
- Numerical interpolation schemes  
- Numerical integration schemes  
- Time integration algorithms  
- Newton-Raphson incremental-iterative schemes for nonlinear problems  
- Finite difference method  
- Finite element method

**Teaching Method:**
Blackboard. Handouts are also provided.

**Bibliography:**

**Final Exam:**
An application of the taught methodologies to one case study of relevance for the PhD student's research is recommended. Alternatively, a topic to investigate can be suggested by the lecturer.

**Prerequisites:** The course is self-contained. Fundamentals of algebra are required.
Learning Outcomes:
Learn how to model optimal decision problems as optimization problems and how to solve them using numerical optimization packages. By learning the basic theory behind the most used numerical optimization methods (optimality conditions, sensitivity, duality) and understanding how the algorithms work, the student will be able to formulate real-life optimization problems and to choose the most appropriate algorithms to solve them, or to develop new optimization algorithms or adapt existing ones to solve them.

Abstract:
Optimization plays a key role in solving a large variety of decision problems that arise in engineering (design, process operations, embedded systems), data science, machine learning, business analytics, finance, economics, and many others. This course focuses on formulating optimization models and on the most popular numerical methods to solve them, including active-set methods for linear and quadratic programming, proximal methods and ADMM, stochastic gradient, interior-point methods, line-search methods for unconstrained nonlinear programming.

Lecture Contents:

Teaching Method:
Lecture slides and blackboard.

Bibliography:
Lecture slides available on http://cse.lab.imtlucca.it/~bemporad/optimization_course.html

**Final Exam:**
Typically a small research project, or discussion about a paper on a subject related to the course, or oral exam.

**Prerequisites:**
Linear algebra and matrix computation, calculus and mathematical analysis.
**Learning Outcomes:**
At the end of the course, the student will be able to formulate optimal control problems and will know a wide range of techniques that can be applied for solving such problems.

**Abstract:**
The course provides an overview of optimal control theory for the deterministic and stochastic cases. Both discrete-time and continuous-time problems are considered.

**Lecture Contents:**
- An overview of optimal control problems.
- An economic example of an optimal control problem: the cake-eating problem.
- Dynamic programming and Bellman’s equations for the deterministic discrete-time case.
- Reachability/controllability and observability/reconstructability for time-invariant linear dynamical systems.
- The Hamilton-Jacobi-Bellman equation for continuous-time deterministic optimal control problems.
- Pontryagin’s principle for continuous-time deterministic optimal control problems.
- LQ optimal control in discrete time for deterministic problems.
- Application of dynamic programming to stochastic and infinite-horizon optimal control problems in discrete time.
- LQ optimal control in discrete time for stochastic problems and Kalman filter.
- Introduction to approximate dynamic programming and reinforcement learning.
- An economic application of optimal control: a dynamic limit pricing model of the firm.

**Teaching Method:**
The teacher will project slides on the screen (a copy of the slides will be provided to the students).

**Bibliography:**
The following books are related to the course. They can be useful as a supplementary material.


The following are slides/lectures notes from related courses.


**Final Exam:**
The student will prepare slides for a short seminar (20-30 minutes) on a topic related to optimal control. The topic of the seminar will be either proposed by the teacher or chosen by the student. The date of the seminar will be agreed between the student and the teacher. The seminar will take place either in the teacher’s office or in the classroom (in case several students will decide to have their seminars in the same day).
Prerequisites:
Matrix algebra, calculus.
Learning Outcomes:
On completing the course, the students will have an enhanced capacity of understanding and evaluating past and current debates about the reliability, the rationality and the limits of science. They can assess the scope and limits of scientific knowledge and appreciate the differences and relations between science and other scientific endeavours. They understand why and to what extent science is rational and often successful, and what is its role in guiding decision-making in modern societies.

Abstract:
The course provides an introduction to the basic concepts and problems in the philosophical analysis of scientific reasoning and inquiry. We will focus on some central patterns of reasoning and argumentation in science and critically discuss their features and limitations. Topics covered include the nature of theory and evidence, the logic of theory testing, and the debate about the aims of science and the trustworthiness of scientific results. We shall discuss classical examples and case studies from the history and practice of science to illustrate the relevant problems and theoretical positions. Students will freely engage in brainstorming on these topics and are welcome to propose examples, problems, and methods from their own disciplines.

Lecture Contents:
The topic of each lesson will be decided at the beginning of the course on the basis of student’s feedback; the following is a tentative list subject to change.

Lecture 1. Presentation of the course. Discussion and choice of specific topics. What is science?
Lecture 2. How many sciences? The method(s) of science. Exact and inexact sciences.
Lecture 3 Theories, models, data. Experiments and observations.
Lecture 4. Inferences in science. Falsification, confirmation, disconfirmation.
Lecture 6. History of science and scientific progress. The aim(s) of science.
Lecture 7. Science, truth, and reality.
Lecture 8. Recap, verification and general discussion.

Teaching Method:
Mixture of lectures and discussion seminar.

Bibliography:
We won't have a textbook or a proper reading list. Relevant readings will be shared on Google Drive. The following are suggestions for background readings and possible topics of discussion.


**Final Exam:**
Active contribution from the participants is a prerequisite for passing the course.

**Prerequisites:**
None.
Principles of Concurrent and Distributed Programming
Rocco De Nicola, Letterio Galletta
30 Hours

Learning Outcomes:
A good understanding of the problems connected to concurrent programming and a good knowledge of the different approaches to modelling communication among distributed components and safe resource sharing. Students will also learn how to write simple concurrent programs.

Abstract:
The objective of the course is to introduce the basics of concurrent and distributed programming through an illustration of concepts and techniques related to modelling systems in which there are more components that are simultaneously active and need to coordinate and compete for the use of shared resources. By means of an hands-on approach, at the end of the course students will be able to write and evaluate concurrent programs using different programming languages.

Lecture Contents:
Linguistic constructs for concurrent programming: Semaphores and Monitors.
Indirect Communication via Shared Memory and Direct Communication via Message Passing. Linguistic constructs for distributed programming: Rendez-Vous and Remote Procedure Calls.
Controlled Communication via shared tuple spaces and pattern matching. The coordination language LINDA.
Different approaches to model and program domain specific languages for network aware programming, service oriented computing, autonomic computing, collective adaptive systems,
How different programming languages deal with Concurrency, Parallelism, Mutual exclusion, Atomicity and Communication: Google Go language and Python, C++, C# and Erlang.
All the lectures about the above topics will be accompanied by practical lectures aiming at showing how the illustrated theory can be mapped on JAVA.

Teaching Method:
Blackboard; slides.

Bibliography:
Handouts with the slides, introductory books, research papers

Final Exam:
Programming Project and oral presentation

Prerequisites:
Elementary knowledge of programming with a simple programming language.
Learning Outcomes:
Students will learn the basic notions necessary for modelling and specifying computer systems using formal methods.

Abstract:
The course will be structured in two parts, one concentrating on the qualitative aspects of formal methods, the other on the quantitative one. Overall the course offers an introduction to core topics in formal methods for the functional specification and analysis of systems. Students will be exposed to basic models of computation and formal approaches to specifying the semantics of programming languages such as operational and denotational semantics. Moreover, they will learn about models for quantitative Analysis such as Markov chains and other stochastic models.

Lecture Contents:

Teaching Method:
Slides and blackboard

Bibliography:
Handouts with the slides and some introductory books. Research papers distributed throughout the course.

Final Exam:
Take home exam and students presentation

Prerequisites:
None
Learning Outcomes:
Students will get acquainted with research methods in computer science, and will have a thorough presentation of "hot" research topics by leading scientists.

Abstract:
Students will be exposed to research methods in computer science, including publication strategies and a classification of its main outlets (workshops, conferences, and journals). Students will also receive a broad perspective on the major sub-fields of computer science (e.g., programming languages, verification, software engineering, security, ...) by means of guest lectures delivered by leading experts in the respective areas.

Lecture Contents:
There will be some introductory lectures on how to write, referee and present a paper and a series of two hours lectures on important research topics by leading scientists presenting first their area of research and then going into the details of some of their more recent achievements.

Teaching Method:
Seminars with discussions with the students prompted by the course coordinator.

Bibliography:
Research Papers

Final Exam:
None

Prerequisites:
None
Scientific Writing, Dissemination and Evaluation
TBD
8 Hours

Course description will be available soon.
Software Verification
Gabriele Costa
10 Hours

Learning Outcomes:
Understanding of the formal verification of programs and knowledge of some advanced techniques for checking the correctness of the software

Abstract:
Software is everywhere and it should behave as expected to avoid dramatic consequences. The reasons behind misbehaving software are manifold. On the one hand, developers may make errors when writing the source code. On the other hand, execution platforms can be exposed when the code includes unexpected behavior. All these cases lay in the scope of software verification, i.e., the discipline studying how to check that a piece of code is correct or flawless. During this course, we will present software verification methodologies from the perspective of both the developer and the user. Moreover, the lectures will be integrated by demonstrations of software tools that implement the theoretical approaches.

Lecture Contents:
Overview and Preliminaries
Type systems and type safety
Deductive-style Analysis
Abstract Interpretation
Bounded Model Checking
Satisfiability-based decision procedures
Untrusted third-party software verification
Dynamic analysis and testing
Static analysis techniques

Teaching Method:
Lectures in classroom

Bibliography:
Slides and other material provided by the teacher

Final Exam:
Individual project or presentation

Prerequisites:
Formal methods and theory of programming languages
Stochastic Processes and Stochastic Calculus
Irene Crimaldi
20 Hours

Learning Outcomes:
By the end of this course, students will:
- be familiar with some important stochastic processes,
- be familiar with Ito stochastic calculus,
- be able to identify appropriate stochastic process model(s) for a given research problem,
- appreciate the importance of mathematical formalization in solving probabilistic and statistical problems,
- be able to independently read mathematical and statistical literature of various types and be life-long learners who are able to independently expand their probabilistic and statistical expertise when needed.

Abstract:
This course aims at introducing some important stochastic processes and Ito stochastic calculus. Some proofs are sketched or omitted in order to have more time for examples, applications and exercises.

Lecture Contents:
This course deals with the following topics:
- Markov chains (definitions and basic properties, classification of states, invariant measure, stationary distribution, ergodic limit theorem, cyclic classes, passage problems);
- conditional expectation and conditional variance;
- martingales (definitions and basic properties, Burkholder transform, stopping theorem and some applications, predictable compensator and Doob decomposition, some convergence results, game theory, random walks, urn models);
- Wiener process (definitions, some properties, Donsker theorem, Kolmogorov-Smirnov test)
- Ito calculus (Ito stochastic integral, Ito processes and stochastic differential, Ito formula, stochastic differential equations, Ornstein-Uhlenbeck process, Geometric Brownian motion, Feynman-Kac Representation formula).

Teaching Method:
Frontal teaching

Bibliography:
- Slides and other material provided by the lecturer
- D. Williams, Probability with martingales, Cambridge Univ. Press (1991)

**Final Exam:**
Seminar with a short written report on the topic of the seminar

**Prerequisites:**
Basics of probability theory and statistical inference
Strategies and Business Behavior
Nicola Lattanzi
20 Hours

Learning Outcomes:
Students will learn how to observe and evaluate business behavior, as well as how to locate sources of potential competitive advantage. They will also learn the base to identify organizational barriers and corporate behaviors that sustain or challenge manager decisions and execution of strategies.

Abstract:
The course is based on key business concepts that will support students develop the expertise required to understand and evaluate business behaviors, firms’ strategies and financial results. The course is composed of three modules: "Firms, business analytics and managerial behavior", "Business Behavior and Behavioral Strategy", "Business model for emerging markets".
The course will describe the decision-making in competitive markets as well as in emerging markets at the business unit level, in which many key strategic choices and actions are formulated and undertaken. The essential “tool-kit” that combines a broad understanding of strategies, businesses and market dynamics and the new challenges of businesses in today’s world.

Lecture Contents:
Strategies and Business Behavior
1 Market and strategy: volatility and development
2 What strategic management is
3 A focus on specific firms and competitive advantage
4 The extraordinary life of patterns and trends: how to learn for a business organization? (1)
5 The extraordinary life of patterns and trends: how to learn for a business organization? (2)
6 Cyber-time and cyber-space for humans and virtual humans: business dynamics and organizations
7 Business behavior and patterns of innovation
8 Behavioral strategy: rational approach, heuristic system and cognitive biases
9 Business behavior and behavioral strategy: fundamentals and case study. A short view on a critical business behavior
10 Data Science for business: network theory for strategy and management

Teaching Method:
Lectures, discussions, business cases, presentations.

Bibliography:
Suggested readings will be provided for each topic.

Final Exam:
Critical paper presentations in at least four groups.
Prerequisites:
Basic knowledge of business economics.