IMT SCHOOL FOR ADVANCED STUDIES LUCCA

# PhD Program in "Systems Science"
# Track in "Computer Science and Systems Engineering" (CSSE)

## Course List - A.Y. 2019/20

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

| Key: X=elective | | | |
|---|---|---|---|
| **Course** | **Lecturer(s)** | **Hours** | **Type** |
| Advanced Methods for Complex Systems I | Diego Garlaschelli | 20 | X |
| Advanced Methods for Complex Systems II | Diego Garlaschelli | 20 | X |
| Advanced Methods for Complex Systems III | Diego Garlaschelli | 20 | X |
| Advanced Numerical Analysis | Benedetta Morini; Valeria Simoncini | 20 | X |
| Advanced Topics in Network Theory: Algebraic Concepts in Network Theory | Guido Caldarelli | 10 | X |
| Advanced Topics in Network Theory: Brain Networks | Guido Caldarelli | 10 | X |
| Advanced Topics in Network Theory: Research Topics in Network Theory | Guido Caldarelli | 10 | X |
| Advanced Topics in Network Theory: Topological Concepts in Network Theory | Guido Caldarelli | 10 | X |
| Advanced Topics of Computational Mechanics | Marco Paggi; Pietro Lenarda | 20 | X |
| Advanced Topics of Control Systems: Numerical Methods for Optimal Control | Mario Zanon | 20 | X |
| Applications of Stochastic Processes | Mirco Tribastone | 20 | X |
| Behavioral Economics | Ennio Bilancini | 20 | X |
| Business Model for Emerging Markets | Nicola Lattanzi | 20 | X |
| Computational Contact and Fracture Mechanics | Marco Paggi | 20 | X |
| Computer Programming and Methodology | Mirco Tribastone | 30 | X |
| Computer-Aided Engineering for Virtual Prototyping and Advanced Manufacturing Solutions | Marco Paggi; Andrea Amicarelli | 10 | X |
| Cybersecurity (essentials) | Rocco De Nicola | 10 | X |
| Cybersecurity (advanced topics) | Gabriele Costa | 10 | X |
| Data Science Lab (no exam) | Andrea Morescalchi | 40 | X |
| Econometrics 1 | Paolo Zacchia | 20 | X |
| Econometrics 2 | Armando Rungi | 20 | X |
| Firms, Business Analytics and Managerial Behavior | Nicola Lattanzi | 20 | X |
| Foundations of Probability and Statistical Inference | Irene Crimaldi | 30 | X |
| Funding and Management of Research and Intellectual Property (no exam) | Marco Paggi | 10 | X |
| Game Theory | Ennio Bilancini | 20 | X |
| Identification, Analysis and Control of Dynamical Systems | Alberto Bemporad | 20 | X |
| Introduction to Network Theory | Guido Caldarelli | 10 | X |
| Machine Learning | Giorgio Gnecco | 20 | X |
| Model Predictive Control | Alberto Bemporad | 20 | X |

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|---|---|---|---|
| Modelling and Verification of Reactive Systems | Rocco De Nicola | 20 | X |
| Numerical Methods for the Solution of Partial Differential Equations | Marco Paggi | 20 | X |
| Numerical Optimization | Alberto Bemporad | 20 | X |
| Optimal Control | Giorgio Gnecco | 20 | X |
| Philosophy of Science (no exam) | Gustavo Cevolani | 16 | X |
| Principles of Concurrent and Distributed Programming | Rocco De Nicola; Letterio Galletta | 30 | X |
| Qualitative and Quantitative Formal Methods for Computer Science | Rocco De Nicola; Mirco Tribastone | 20 | X |
| Research Topics in Computer Science | Rocco De Nicola; Mirco Tribastone | 20 | X |
| Scientific Writing, Dissemination and Evaluation (no exam) | TBD | 8 | X |
| Software Verification | Gabriele Costa | 10 | X |
| Stochastic Processes and Stochastic Calculus | Irene Crimaldi | 20 | X |
| Strategies and Business Behavior | Nicola Lattanzi | 20 | X |

SCHOOL FOR ADVANCED STUDIES LUCCA

**Advanced Methods for Complex Systems I**
**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:**
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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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

Complex Systems 1”

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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"

SCHOOL FOR ADVANCED STUDIES LUCCA

**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:**
-Philip E. Gill, Walter Murray, Margaret H. Wright, Numerical linear algebra and optimization, v.1 Numerical Linear Algebra and Optimization, Addison-Wesley Pub. Co., Advanced Book Program, 1991 (book)
-Timothy A. Davis, Direct Methods for Sparse Linear Systems, SIAM, Series Fundamentals of Algorithms, 2006 (book)
- Yousef Saad, Iterative solution of large linear systems, SIAM, 2003 (book)
- V. Simoncini and D. Szyld, Recent computational developments in Krylov Subspace methods for linear systems, Num.Lin.Alg.w/Appl 2007, v.14 pp.1-59

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Advanced Topics in Network Theory: Algebraic Concepts in Network Theory**
**Guido Caldarelli**
**10 Hours**

**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://www.cs.cornell.edu/home/kleinber/networks-book/
- 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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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:**

- G. Caldarelli Scale-Free Networks OUP (2007) (made available to students).
- Easley, Kleinberg "Networks Crowds and Markets" CUP (2010) http://www.cs.cornell.edu/home/kleinber/networks-book/
- 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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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 "Networks Crowds and Markets" CUP (2010) http://www.cs.cornell.edu/home/kleinber/networks-book/
• 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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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:**

- G. Caldarelli Scale-Free Networks OUP (2007) (made available to students). • Easley, Kleinberg "Networks Crowds and Markets" CUP (2010)
- http://www.cs.cornell.edu/home/kleinber/networks-book/
- 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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Advanced Topics of Computational Mechanics**
**Marco Paggi, Pietro Lenarda**
**20 Hours**

**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

SCHOOL FOR ADVANCED STUDIES LUCCA

**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. Betts. Practical Methods for Optimal Control Using Nonlinear Programming, Advances in Design and Control 2010
L. Biegler. Nonlinear Programming, MOS-SIAM Series on Optimization 2010
J. Nocedal and S. Wright. Numerical Optimization, Springer 2006
S. Boyd and L. Vandenberghe. Convex Optimization, University Press 2004
M. Bierlaire. Optimization: principles and algorithms, EPFL Press 2015
J. Guddat, F. Guerra Vazquez, H. Th. Jongen. Parametric Optimization: Singularities, Pathfollowing and Jumps, Springer 1990
J. C. Butcher Numerical Methods for Ordinary Differential Equations, Wiley 2016
E. Hairer, S. P. Nørsett, and G. Wanner. Solving Ordinary Differential Equations I, Springer 1993
E. Hairer ,and G. Wanner. Solving Ordinary Differential Equations II, Springer 1996

**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.

SCHOOL FOR ADVANCED STUDIES LUCCA

**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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Behavioral Economics**
**Ennio Bilancini**
**20 Hours**

**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:**
Dhami, Sanjit. The foundations of behavioral economic analysis. Oxford University Press, 2016.

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Business Model for Emerging Markets**
**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:**
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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Computational Contact and Fracture Mechanics**
**Marco Paggi**
**20 Hours**

**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:**
M. Paggi, D. Hills (2020) Modeling and Simulation of Tribological Problems in Technology, Springer, https://link.springer.com/book/10.1007/978-3-030-20377-1

**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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Computer Programming and Methodology**
**Mirco Tribastone**
**30 Hours**

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Computer-Aided Engineering for Virtual prototyping and Advanced Manufacturing Solutions**
**Marco Paggi, Andrea Amicarelli**
**10 Hours**

**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.

SCHOOL FOR ADVANCED STUDIES LUCCA

**Cybersecurity (Advanced Topics)**
**Gabriele Costa**
**10 Hours**

**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:**
Security Protocols: Specification and Verification. Usage Control policy models. Vulnerability Analysis of Binary Code. Web and mobile security attacks and defence: SQL injection, cross-site scripting, command injection, permission systems.

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Cybersecurity (Essentials)**
**Rocco De Nicola**
**10 Hours**

**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:**
Introduction to Cybersecurity, examples of different kinds of attacks. Best practice for malware detection and for password management. Secure and privacy preserving Internet and mobile usage. Introduction to Discretionary, Mandatory, Role-based Access Control Models. Basic concepts of cryptography: Symmetric and Asymmetric Encryption, Public-Key Encryption, Message Authentication, Digital Signatures.

**Teaching Method:**
Blackboard; slides.

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

**Final Exam:**
No exam.

**Prerequisites:**
No prerequisite.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Data Science Lab**
**Andrea Morescalchi**
**40 Hours**

**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:**
Angrist, J. D., and J. S. Pischke (2008) Mostly harmless econometrics: An empiricist's companion. Princeton University Press.
Cameron, A. C., P. K. Trivedi (2009) Microeconometrics Using Stata. Stata Press
Wooldridge, J. M. (2010) Econometric Analysis of Cross Section and Panel Data. MIT Press.

**Final Exam:**
Not required

**Prerequisites:**
Basic Statistics.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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
Marno Verbeek (2012), A Guide to Modern Econometrics, Wiley
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.

**Econometrics II**
**Armando Rungi**
**20 Hours**

**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.

**Firms, Business Analytics and Managerial 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 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.

SCHOOL FOR ADVANCED STUDIES LUCCA

**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
- R. Durrett, Elementary Probability for Applications, Cambridge Univ. press (2009)
- S. M. Ross, Introduction to Probability Models, Academic press (2003)
- M. Mitzenmacher, E. Upfal, Probability and Computing, Cambridge Univ. press (2005)
- O. Kallenberg, Foundations of Modern Probability, Springer (1997)
- S. M. Ross, Introductory Statistics, Elsevier (2010)
- K. V. Mardia, J. T. Kent, J. M. Bibby, Multivariate analysis. Academic press (1979)

- R. B. Nelsen, An Introduction to Copulas, Springer Series in Statistics (2006)
- P. K. Trivedi, D. M. Zimmer, Copula modeling: an introduction for practitioners (2005)

**Final Exam:**
Written test

**Prerequisites:**
No

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Game Theory**
**Ennio Bilancini**
**20 Hours**

**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:**
Mas-Colell A, Whinston MD, Green JR. Microeconomic theory. New York: Oxford university press

**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.

SCHOOL FOR ADVANCED STUDIES LUCCA

**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:**
Introduction to dynamical systems. Linear systems in continuous time. Lagrange's formula and modal analysis. Stability of linear systems. Linearization. Stability of nonlinear systems. Discrete-time linear systems. Discrete-time linear systems: equilibria, stability, Z-transform, transfer function. Steady-state analysis and DC gain. Closed-loop control concept, PID control. Reachability analysis, state-feedback control, observability analysis. State estimator, dynamic compensator. Linear quadratic regulator. Kalman filtering, LQG control. System identification: identification of autoregressive models, recursive least squares for systems identification, model selection criteria.

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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://www.cs.cornell.edu/home/kleinber/networks-book/
- http://barabasilab.neu.edu/networksciencebook/


**Final Exam:**
essay by students

**Prerequisites:**
basic of mathematics

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Markov Processes**
**(Sant'Anna School for Advanced Studies - Pisa)**
**Irene Crimaldi**
**12 Hours**

**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
- S. M. Ross, Introduction to Probability Models, Academic press (2003)
- G. Grimmett, D. Stirzaker, Probability and Random Processes, Oxford Univ. Press, third ed. (2001)
- W. Woess, Denumerable Markov chains, EMS textbooks in Mathematics (2009).
- N. Lanchier, Stochastic Modeling, Springer (2017)
- O. Kallenberg, Foundations of Modern Probability, Springer (1997)

**Final Exam:**
Without exam

**Prerequisites:**
Basics of probability theory

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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 8: A comparison of approximation error bounds for neural networks and linear approximators.
Lecture 9: Application of neural networks to optimal control problems.
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.

D. P. Bertsekas and J. N. Tsitsiklis: "Neuro-Dynamic Programming," Athena Scientific, 1996
C. J. C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition," Data Mining and Knowledge Discovery, vol. 2, pp. 121-167, 1998

S. Mendelson, "A Few Notes on Statistical Learning Theory," in S. Mendelson, A. J. Smola (Eds.): Advanced Lectures on Machine Learning, Lectures Notes in Artificial Intelligence, vol. 2600, pp. 1-40, Springer, 2003
S. Shalev-Shwartz and S. Ben-David, "Understanding Machine Learning: From Theory to Algorithms," Cambridge University Press, New York, USA, 2014
J. Shawe-Taylor and N. Cristianini, "Kernel Methods for Pattern Analysis," Cambridge University Press, New York, USA, 2004
R. S. Sutton and A. G. Barto, "Reinforcement Learning: An Introduction," MIT Press, Cambridge, USA, 1998
C. Szepesvári: "Algorithms for Reinforcement Learning," Morgan & Claypool, 2010
S. Theodoridis and K. Koutroumbas, "Pattern Recognition," Academic Press, San Diego, USA, 2009
V. N. Vapnik, "Statistical Learning Theory," Wiley-Interscience, New York, USA, 1998

The following are slides/lectures notes from related courses.

D. P. Bertsekas: slides for the course "Approximate Dynamic Programming," CEA, Cadarache, 2012, available online at http://www.athenasc.com/ADP_Short_Course_Complete.pdf
T. Jebara, Lecture notes for the course "Machine Learning 4771," Columbia University, 2015, http://www.cs.columbia.edu/~jebara/4771/handouts.html
A. Ng: lecture notes for the course "Machine Learning," Stanford, 2017, available online at http://cs229.stanford.edu/notes

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

P. Kim, "MATLAB Deep Learning With Machine Learning, Neural Networks and Artificial Intelligence," Apress, 2017

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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, M. Morari, V. Dua, and E.N. Pistikopoulos, The explicit linear quadratic regulator for constrained systems, Automatica, vol. 38, no. 1, pp. 3–20, 2002

A. Bemporad, A multiparametric quadratic programming algorithm with polyhedral computations based on nonnegative least squares, IEEE Trans. Automatic Control, vol. 60, no. 11, pp. 2892–2903, 2015.

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

F.D. Torrisi and A. Bemporad, HYSDEL — A tool for generating computational hybrid models, IEEE Trans. Contr. Systems Technology, vol. 12, no. 2, pp. 235–249, Mar. 2004

D. Bernardini and A. Bemporad, Stabilizing model predictive control of stochastic constrained linear systems, IEEE Trans. Automatic Control, vol. 57, no. 6, pp. 1468–1480, 2012

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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:**
- A. Quarteroni, Numerical Models for Differential Problems, Second Ed. Springer, 2013.
- K.-J. Bathe, Finite Element Procedures, Pearson College Div, 2005.
- N. Hilber, O. Reichmann, C. Schwab, C. Winter, Computational Methods for Quantitative Finance, Springer, 2013.

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Numerical Optimization**
**Alberto Bemporad**
**20 Hours**

**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:**
Course introduction. Basic definitions in optimization (function, constraints, minima, convexity). Linear programming (LP), quadratic programming (QP), mixed-integer programming (MIP), optimization taxonomy. LP models. Convex functions and sets, convexity recognition. Constrained least squares, QP, LASSO. Second-order cone programming, semidefinite programming, geometric programming. First order necessary conditions. Optimality conditions. Sensitivity. Duality. Dual functions for LP and QP. Example from machine learning: support vector regression. Proximal operator, proximal point and proximal gradient methods, gradient projection methods for quadratic programming. Proximal operator calculus. Convex conjugate function. Alternating direction method of multipliers (ADMM), ADMM for quadratic programs, ADMM for LASSO problems, consensus ADMM for separable functions. Stochastic gradient descent methods. Unconstrained nonlinear optimization: gradient descent methods, line search, Gauss-Newton method for unconstrained nonlinear optimization. Interior-point methods.

**Teaching Method:**
Lecture slides and blackboard.

**Bibliography:**
Lecture slides available on http://cse.lab.imtlucca.it/~bemporad/optimization_course.html
J. Nocedal and S.J. Wright. NumericalOptimization. Springer, 2nd edition,2006.
M.S. Bazaraa, H.D. Sherali,and C.M. Shetty. NonlinearProgramming-Theory and Algorithms.
John Wiley & Sons, Inc., NewYork, 3rd edition, 2006.
S. Boyd and L. Vandenberghe. Convex Optimization. Cambridge University Press, New York, NY, USA, 2004. http://www.stanford.edu/~boyd/cvxbook.html.

H.P. Williams. Model Building in Mathematical Programming. John Wiley & Sons, 5th edition, 2013."

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Optimal Control**
**Giorgio Gnecco**
**20 Hours**

**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.

D. Acemoglu: Introduction to modern economic growth, Princeton University Press, 2009.
J. Adda and L. W. Cooper: Dynamic economics: quantitative methods and applications, MIT Press, 2003.
P. J. Antsaklis and A. N. Michel: A linear systems primer, Birkhäuser, 2007.
M. Athans and P. L. Falb: Optimal control, Dover, 2007.
M. Bardi and I. Capuzzo-Dolcetta: Optimal control and viscosity solutions of Hamilton-Jacobi-Bellman equations, Birkhäuser, 2008.
D. P. Bertsekas: Dynamic programming and optimal control, vols. 1 and 2, Athena Scientific, 1995.
D. P. Bertsekas and S. E. Shrieve: Stochastic optimal control: the discrete-time case, Academic Press, 1978.

M. R. Caputo: Foundations of dynamic economic analysis: optimal control theory and applications, Cambridge University Press, 2005.
F. Cugno and L. Montrucchio: Scelte intertemporali: teoria e modelli (in Italian), Carocci Editore, 1998.
A. de la Fuente: Mathematical methods and models for economists, Cambridge University Press, 2000.
H. P. Geering: Optimal control with engineering applications, Springer-Verlag, 2007.
M. Gopal: Modern control system theory, New Age International Publishers, 2005.
S. Ross: Applied probability models with optimization applications, Dover, 1970.
S. Ross: Introduction to stochastic dynamic programming, Academic Press, 1983.
J. Rust: Numerical Dynamic Programming in Economics, in Handbook of Computational Economics, H. M. Amman, D. A. Kendrick, and J. Rust (ed.), 1996.
E. D. Sontag: Mathematical control theory: deterministic finite dimensional systems, Springer, 1998.
N. L. Stokey, R. E. Lucas, and E. C. Prescott: Recursive methods in economic dynamics, Harvard University Press, 1989.
C. Szepesvári: Algorithms for reinforcement learning, Morgan & Claypool, 2010.

The following are slides/lectures notes from related courses.

D. P. Bertsekas: slides for the course "Approximate dynamic programming", CEA, Cadarache, 2012, available online at
http://www.athenasc.com/ADP_Short_Course_Complete.pdf.
J. Cho: lecture notes for the course "Linear systems and control", Michigan State University, Michigan, US, 2010, available online at http://www.egr.msu.edu/classes/me851/jchoi/.
J. Le Ny: lecture notes for the course "Dynamic programming and stochastic control", University of Pennsylvania, 2009, available online at
http://www.professeurs.polymtl.ca/jerome.le-ny/teaching/
DP_fall09/notes/.
A. Ng: lecture notes for the course "Machine Learning", Stanford, 2017, available online at
http://cs229.stanford.edu/notes/cs229-notes12.pdf.
J. R. Norris: lecture notes for the course "Optimization and Control", Cambridge, UK, 2007, available online at
http://www.statslab.cam.ac.uk/~james/Lectures/.
B. Van Roy: lecture notes for the course "Reinforcement Learning", Stanford, 2013, available online at
http://www.stanford.edu/class/msande338/ScribeLec3.pdf.
R. Weber: lecture notes for the course "Optimization and Control", Cambridge, UK, 2013, available online at www.statslab.cam.ac.uk/~rrw1/oc/.

**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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Philosophy of Science**
**Gustavo Cevolani**
**16 Hours**

**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 5. Science, pseudoscience, junk science. Trust and objectivity in science. The role of experts.
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.

- Curd, Martin and J. A. Cover, eds. (1998). Philosophy of science: the central issues. New York: W.W. Norton.

- Godfrey-Smith, Peter (2003). Theory and Reality: An Introduction to the Philosophy of Science. University of Chicago Press.
- Okasha, Samir (2016). Philosophy of Science: A Very Short Introduction. Oxford
University Press.
- Oldroyd, D. R. (1986). The Arch of Knowledge: An Introductory Study of the History of the Philosophy and Methodology of Science. Methuen.
- Hempel, C. G. (1966). Philosophy of Natural Science. Prentice Hall.
- Salmon, Wesley C. (2017). The Foundations of Scientific Inference. Pittsburgh, Pa: University of Pittsburgh Press.
- Popper, Karl (1963). Conjectures and Refutations: The Growth of Scientific Knowledge. Routledge.
- Sprenger, Jan and S. Hartmann (2019). Bayesian Philosophy of Science. OUP Oxford.

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

**Prerequisites:**
None.

SCHOOL FOR ADVANCED STUDIES LUCCA

**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:**
Basics of Computer Architectures. Concurrent Programming Styles: Iterative versus Recursive Parallelism
Algorithms for guaranteeing mutual exclusion and implementing critical sections. Fair and unfair solutions.
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 e 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.

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Qualitative and Quantitative Formal Methods for Computer Science**
**Rocco de Nicola, Mirco Tribastone**
**20 Hours**

**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:**
Basic elements of discrete mathematics. Syntax of Programming Languages and different approaches to their Semantics. Labelled transition Systems, Inference Systems and Induction Principles.
Regular Expressions as a first programming language and their Denotational, Operational and Axiomatic Semantics.
Operational and Denotational Semantics of simple programming languages and their correspondence.
Domain theory and fixed points. Total and Partial Functions. Complete Partial Orders, Continuity, Tarski theorem.
Basics of probability theory. Discrete and continuous-time Markov chains. Introductions to queuing networks.

**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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Research Topics in Computer Science**
**Rocco De Nicola, Mirco Tribastone**
**20 Hours**

**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 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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**Scientific Writing, Dissemination and Evaluation**
**TBD**
**8 Hours**

Course description will be available soon.

SCHOOL FOR ADVANCED STUDIES LUCCA

**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

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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
- S. M. Ross, Introduction to Probability Models, Academic press (2003)
- M. Mitzenmacher, E. Upfal, Probability and Computing, Cambridge Univ. press (2005)
- J. Jacod, P. Protter, Probability Essentials, Springer (2000)
- N. Lanchier, Stochastic Modeling, Springer (2017)
- G. Grimmett, D. Stirzaker, Probability and Random Processes, Oxford Univ. Press, third ed. (2001)
- W. Woess, Denumerable Markov chains, EMS textbooks in Mathematics (2009).
- D. Williams, Probability with martingales, Cambridge Univ. Press (1991)
- I. Karatzas, S. E. Shreve, Brownian motion and stochastic calculus, Springer (1991)

- O. Kallenberg, Foundations of Modern Probability, Springer (1997)
- C. W. Gardiner, Handbook of Stochastic Methods, Springer (2004)
- T. Björk, Arbitrage Theory in Continuous Time, Oxford Univ. Press (2009)
- U. Garibaldi, E. Scalas, Finitary probabilistic methods in econophysics, Cambridge Univ. Press (2010)

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

**Prerequisites:**
Basics of probability theory and statistical inference

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

**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.