Pre-requisites	Basics of Probability Theory. Models of Theoretical Physics or Theoretical Physics
Knowledge. Abilities and competences:	After completing the course the student should be able to understand and explain how to use information theory and physical models to analyse data and understand main features of complex systems. In particular, the student will 1) Acquire fundamental knowledge of Bayesian thinking and Information Theory. 2) Acquire the ability to build an appropriate statistical analysis based on the available data of the system 3) Know how to perform Monte Carlo simulations and Information Theory based algorithms to explore high-dimensional dataset 4) Understand the use of Gaussian and Dirichlet processes as well as Approximate Bayesian Computation 5) Connect concepts between Information Theory, Bayesian Statistics and Statistical Mechanics
Modalita' di esame in Inglese:	The first part of the verification of the acquired knowledge will evaluated be through home-works and the participation of the students in the class discussions The second part will takes place through presentation of a small project or exercises and open questions to test the knowledge on basic concepts, the scientific vocabulary, the ability to synthesis and critical discussion on the various topics discussed during the course.
Criteri di valutazione in Inglese:	The criteria used to verify the knowledge and skills acquired are: 1) understanding of the topics covered; 2) critical ability to connect the acquired knowledge; 3) completeness of the acquired knowledge; 4) synthesis ability; 5) understanding of the terminology used 6) ability to use the analytical methodologies and computational techniques illustrated during the course to solve or at least to approach set problems where information theory and Baysian inference plays an important role.
Contenuti in Inglese:	• The program can be summarized as follow Basic Principles o Bayesian Statistics: prior, likelihood, posterior. o The Monte Carlo Paradigm: noise vs. bias.

		- Basic building blocks of samplers: transformations, weighting (importance sampling), acceptance/rejection. Exploring a high-dimensional potential - The Metropolis algorithm (Markov Chain Monte Carlo) - Gibbs sampling: local interactions. - Adaptive (non-Markov) algorithms - Ensemble methods Information Theory - Information Bottleneck, and predictive information. - Diffusion and Information theory: Machine learning kernels and the Green’s function of the Diffusion equation - Partially Observed Markov Decision Processes - Example: application to time series data. Bayesian inference: Letting the model fluctuate around the data - Gaussian Process (GP): Using a path integral to fit data - GP Example: Fitting spherical harmonics to data - GP Example: Guassian Process for Time Series - Dirichlet Process and Information Theory (DP): The probability over probability distributions - Example: Computing the uncertainty in the density estimation of a gas - Example: Unsupervised Clustering of data points Information Geometry - Using Entropy to Understand Probability - Comparing probability distributions: From KL divergence to information geometry - Local structure versus Global symmetries: Hamiltonians or Green’s functions - The manifold of multivariate Gaussian probability distributions - Diffusion on a Manifold: Parametric approximation - The Estimation of the Gradient of a Density Function - Example: manifold learning from time series data. - Example: clustering data The statistics of high-dimensional point clouds - Estimating the dimensionality of the data - Manifold Learning and Local Models in high dimension. - Mixture of Probabilistic PCA - Divide and conquer the manifold: Estimating tangent spaces in high-d data - Stitching together the tangent spaces: Interpolating

	between tangent spaces o Example: Application to data Hamiltonian Dynamics: Beyond random search. o Hamiltonian Monte Carlo (HMC) o HMC for stochastic differential equations: path-integrals and separation of time. Thermodynamics: Entropy and learning. o Approximate Bayesian Computation (ABC) o Simulated Annealing ABC: learning with minimal entropy production [Albert et al. 2014]. o Summary Statistics: Machine Learning of thermodynamic state variables. Statistical Mechanics: Interacting particle systems as inference tool. o Field-theoretic description: Doi-Peliti formalism. o Inference: particle filters and path-integral methods.
Attivita' di apprendimento previste e metodi di insegnamento in Inglese:	The course is organized in lectures whose contents are presented on the slides + blackboard, sometimes with the help of images, diagrams and videos. The teaching is interactive, with questions exercises, and presentation of case studies, in order to promote discussion and critical thinking in the classroom.
Eventuali indicazioni sui materiali di studio in Inglese:	Beyond some suggested books, materials (notes and published papers) will be available to the students in Moodle.
Testi di riferimento:	Girolami, M., & Calderhead, B., *Riemann manifold Langevin and Hamiltonian Monte Carlo methods.* Journal of the Royal Statistical Society: Series B (Statistical Methodology), 73(2), 123-214 (2011). Albert C., Künsch HR., Scheidegger A., *A Simulated Annealing Approach to Approximate Bayes Computations*, Stat. Comput. 6, 1217-1232 (2014). Albert, C., Ulzega, S., Stoop, R. Boosting Bayesian parameter inference of nonlinear stochastic differential equation models by Hamiltonian scale separation. Phys. Rev. E 93 (2016).