UNIVERSITÀ DEGLI STUDI FIRENZE

FLORENCE center for DATA SCIENCE

ABSTRACTS

Seminar D ^{2} Seminar Series

Florence Center for Data Science 'Double' Seminar Series

Claudio Durastanti - Department of Basic and Applied Sciences for Engineering (SBAI), Sapienza University

Title: Spherical Poisson Waves

Abstract: During this talk, we will discuss a model of Poisson random waves defined in the sphere, to study Quantitative Central Limit Theorems when both the rate of the Poisson process (that is, the expected number of the observations sampled at a fixed time) and the energy (i.e., frequency) of the waves (eigenfunctions) diverge to infinity. We consider finite-dimensional distributions, harmonic coefficients and convergence in law in functional spaces, and we investigate carefully the interplay between the rates of divergence of eigenvalues and Poisson governing measures.

Cecilia Viscardi - Department of Statistics, Computer Science, Applications "G. Parenti", University of Florence

Title: Likelihood-free Transport Monte Carlo (joint with Dr Dennis Prangle, University of Bristol)

Abstract: Approximate Bayesian computation (ABC) is a class of methods for drawing inferences when the likelihood function is unavailable or computationally demanding to evaluate. Importance sampling and other algorithms using sequential importance sampling steps are state-of-art methods in ABC. Most of them get samples from tempered approximate posterior distributions defined by considering a decreasing sequence of ABC tolerance thresholds. Their efficiency is sensitive to the choice of an adequate proposal distribution and/or forward kernel function. We present a novel ABC method addressing this problem by combining importance sampling steps and optimization procedures. We resort to Normalising Flows (NFs) to optimize proposal distributions over a family of densities to transport particles drawn at each step towards the next tempered target. Therefore, the combination of sampling and optimization steps allows tempered distributions to get efficiently closer to the target posterior. Finally, we show the performance of our method on examples that are a common benchmark for likelihood-free inference.