London meeting on Computational Statistics
11-13 June 2024

Location: G01 Lankester Lecture Theatre, Medawar Building, University College London (lectures). North Cloisters (poster session). Roberts Foyer G02 (lunches/coffee breaks)

Sponsors: EPSRC (via New Investigator Award EP/V055380/1), UCL Institute for Mathematical and Statistical Sciences (IMSS).

Contact: Samuel Livingstone (samuel.livingstone@ucl.ac.uk).

Program

Title: Learned harmonic mean estimation of the marginal likelihood with normalizing flows

Abstract: TBA

17:00 Giacomo Zanella

Title: Zero-order parallel sampling

Abstract: Finding effective ways to exploit parallel computing in order to speed up MCMC convergence is an important problem in Bayesian computation and related disciplines. Here we consider the zero-order (aka derivative-free) version of the problem, where we assume that (a) the gradient of the target distribution is unavailable (either for theoretical, practical or computational reasons) and (b) we can metric defined using a reproducing kernel Hilbert space (RKHS), with properties determined by the choice of kernel. For good test power, particularly when the data clusters are not well separated, or when the employed model is misspecified.

11:50 Nick Whiteley

Title:

parametrisation of) the covariance matrix can be modelled additively, via parametric or spline-based smooth effects. We will focus particularly on the modified Cholesky decomposition and we will show how the sparsity of the corresponding derivative system aids scalabili

Title: Tuning pseudo-marginal Metropolis-Hastings: a vase or two faces?

Abstract: The general applicability and ease of use of the pseudo-marginal Metropolis-Hastings (PMMH) algorithm, and particle Metropolis-Hastings in particular, makes it a popular method for inference on discretely observed Markovian stochastic processes. It substitutes realisations of unbiased estimators of the posterior into both the numerator and denominator of the Metropolis-Hastings acceptance ratio. The more accurate the estimator (enacted, for example, by increasing the number of particles in an underlying particle filter), the better the algorithm mixes. However, increased accuracy comes at an increased computational cost, and tuning the algorithm involves a trade off between these factors. Two independent papers, both published in 2015, suggested choosing the number of particles so that the variance of the logarithm of the estimator of the posterior at a fixed sensible parameter value is approximately 1. This advice does not hold for a single, simple importance sampling estimator, but it has been widely and successfully adopted when using products of such estimators or using particle filters. We provide simple examples which demonstrate that the 2015 advice cannot be correct for a general particle filter or a product. We explore the asymptotic variance associated with the PMMH algorithm and provide a remarkably simple bound which leads to alternative advice. In most situations our guidance and the early advice closely coincide - the picture is both a vase and two faces. We then extend the analysis to the correlated pseudo-marginal method.

17:00 Bob Carpenter

Title: GIST: Gibbs self-tuning for locally adaptive Hamiltonian Monte Carlo

Abstract: We present a novel and flexible framework for localized tuning of Hamiltonian Monte Carlo samplers by sampling the algorithm's tuning parameters conditionally based on the position and momentum at each step. For adaptively sampling path lengths, we show that randomized Hamiltonian Monte Carlo, the No-U-

Title: Diffusion Schrödinger Bridge Matching

Abstract: Solving transport problems, i.e. finding a map transporting one given distribution to another, has numerous applications in machine learning. Novel mass transport methods motivated by generative modeling have recently been proposed, e.g. Denoising Diffusion Models (DDMs) and Flow Matching Models (FMMs) implement such a transport through a Stochastic Differential Equation (SDE) or an Ordinary Differential Equation (ODE). However, while it is desirable in many applications to approximate the deterministic dynamic Optimal