Bayesian Computation for High-Dimensional Statistical Models (27 August – 21 September 2018)
Closing Workshop, 19 – 21 September 2018

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Reversible Proposal MCMC with Heavy-tailed Target Distributions

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ABSTRACT

We will discuss Markov chain Monte Carlo methods for heavy-tailed target probability distributions, based on a reversible proposal transition kernel. We will study the dimensionality effect using the high-dimensional asymptotic analysis of Roberts, Gelman, and Gilks. We also study ergodic properties for heavy-tailed target distributions.
Unbiased inference for discretely observed hidden Markov model diffusions

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**ABSTRACT**

In this talk we discuss an importance sampling (IS) type estimator for Bayesian joint inference on the model parameters and latent states of a class of hidden Markov models (HMMs). We are interested in the class of HMMs for which the hidden state dynamics is a diffusion process and noisy observations are obtained at some number of points in time. We suppose that the diffusion dynamics can not be simulated exactly and hence one must time-discretise the diffusion. Our approach is based on particle marginal Metropolis–Hastings (PMMH), particle filters (PFs), and randomised multilevel Monte Carlo (rMLMC). The estimator is built upon a single run of PMMH using a coarse discretisation of the model. The consequent IS type correction is based on a single-term rMLMC estimator using output from a PF developed for level difference integral estimation. The resulting IS type estimator leads to inference without a bias from the time-discretisation. We give convergence results, such as a central limit theorem, and recommend allocations for algorithm inputs. A nice advantage of our method is its general applicability, as it does not rely on exact simulation of the diffusion. The method is also highly parallelisable, and likely computationally efficient in many situations. We demonstrate the method on two examples from the literature. This talk is based on [1].

**References**

An Overview of Parallel and Distributed MCMC Methods

CHENG LI
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ABSTRACT

Standard posterior sampling algorithms, such as Markov chain Monte Carlo (MCMC), face major challenges in scaling up to massive datasets with large numbers of observations. In this talk, we focus on the divide-and-conquer (d&c) strategy that has been popularized in the past few years. The d&c Bayesian methods typically consist of three steps: (i) partition the full datasets into many non-overlapping subsets; (ii) run MCMC in parallel on all subsets using stochastic approximations; (iii) combine subset posterior samples into a global approximation to the true posterior distribution. We survey the various d&c Bayesian methods, and discuss their ideas, properties and practical implementation. Our comparisons cover both theoretical analysis and numerical experiments on some commonly used statistical models.
Gaussian Variational Approximation with Structured Covariance Matrices

DAVIDNOTT
National University of Singapore

ABSTRACT

Variational approximation methods provide a scalable alternative to Markov chain Monte Carlo methods in Bayesian computational problems. In this talk we consider approximations to a posterior distribution from a Gaussian family, when the model parameter is high-dimensional. Learning a Gaussian variational approximation is very challenging in high dimensions, because the number of parameters in the variational posterior covariance matrix grows quadratically with the number of model parameters, which makes the variational optimization a very high-dimensional one unless further restrictions are made. In this talk, we consider imposing sparsity in the precision matrix of such an approximation to reflect appropriate conditional independence structure in the model, which allows the Gaussian variational distribution to be both flexible and parsimonious. The sparsity is achieved through parameterization in terms of the Cholesky factor, and efficient stochastic gradient methods are developed for the optimization. Alternative methods for structuring the covariance matrix of the posterior based on factor models will also be discussed briefly, and our approaches will be illustrated using generalized linear mixed models and state-space models for time series.
Hamiltonian Descent Methods for Optimization

Arnaud Doucet, Chris Maddison, Daniel Paulin, and Yee Whye Teh

University of Oxford, UK

ABSTRACT

Hamiltonian dynamics is widely used for sampling. In this talk, we will introduce a new convex optimization method based on Hamiltonian dynamics, and show that it has convergence properties that improve upon existing methods in the literature.
Utilising Inference in State-space Models with Multiple Paths from Conditional Sequential Monte Carlo

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ABSTRACT

We consider a state-space model \( \{X_t, Y_t\}_{t \geq 1} \) with a static parameter \( \theta \) governing its transition and observation probability laws. Our work concerns Bayesian inference of \( \theta \) given \( Y_{1:n} \) for some \( n \geq 1 \). When the state-space model is non-linear or non-Gaussian, the inference is utilised with sequential Monte Carlo (SMC). In particular, in the Metropolis-within-particle Gibbs algorithm, an iteration consists of (i) updating the sample for \( X_{1:n} \) via a conditional SMC (cSMC), which is followed by (ii) a Metropolis-Hastings update for \( \theta \)\cite{1}. Retaining one path from the samples in the cSMC involved in Metropolis-within-particle Gibbs may seem to be wasteful. A natural question is whether it is possible to make use of multiple, even all possible, trajectories and average out the corresponding acceptance ratios. We show that this is possible via the use of asymmetric acceptance ratios. The proposed schemes reduce asymptotic variance at a cost that can be parallelised. This is a part of the work in\cite{2} where the use of asymmetric acceptance ratios in Metropolis-Hastings algorithm is studied in more generally.

References

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Multilevel Monte Carlo and Transport Maps

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ABSTRACT

The multilevel Monte Carlo approach has proved useful in applications where solutions of diverse computational cost and accuracy are available; the most straightforward example being given by varying discretizations of SDEs. However, the success of this approach is conditioned on the ability to produce highly-correlated samples between adjacent levels, which can be difficult in many cases. In this talk, I will show how transport maps can be used to address this challenge and I will demonstrate the performance of this approach on SDE-related inference problems as well as on smoothing problems for hidden Markov models.
Spatially smooth local ensemble transform particle filtering

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ABSTRACT

State inference in spatially-extended dynamical systems is a challenging problem with significant practical applications such as numerical weather prediction. Particle filters (PFs) while having attractive theoretical properties require infeasibly large ensemble sizes for accurate inference in high-dimensional spatial models. Localisation approaches, which exploit low dependence between state variables at spatially distant points by performing local state updates, offer a potential resolution to this issue. Naively applying the resampling step of the PF update locally can however produce implausible spatially discontinuous states. The ensemble transform PF replaces resampling with linear transformation by an optimal transport (OT) map and can be localised by computing OT maps for every spatial mesh point. The resulting scheme is however computationally intensive for dense meshes and still produces non-smooth states. In this talk I will present a new local ensemble transform PF method which computes a fixed number of OT maps independent of the mesh resolution and smoothly interpolates these maps across space, reducing the computation required while also ensuring state particles retain spatial smoothness properties. I will illustrate the performance of the proposed approach compared to alternative methods in several nonlinear spatiotemporal models, including a challenging two-dimensional stochastic Navier-Stokes example.
Bayesian Changepoint Detection in Cyber-security

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ABSTRACT

Changepoint models have numerous applications within statistical cyber-security: Examples include determining the genealogy of a malware executable; providing flexible models for densities and intensities of normal computer network traffic; and, of course, network anomaly detection to potentially reveal the presence of a network intrusion. This talk will review changepoint inferential tools, and demonstrate how these tools can be applied and adapted in the cyber context.
Bayesian Inference for Multiple Gaussian Graphical Models with Application to Metabolic Association Networks

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ABSTRACT

We investigate the effect of cadmium (an environmental pollutant) on the correlation structure of a number of urinary metabolites using Gaussian graphical models (GGMs). Differential networks, which highlight changes in metabolite interactions under different experimental conditions, are constructed using the fitted GGMs. Analysis of such networks can reveal differences in the underlying biological reactions caused by cadmium exposure. We consider Bayesian inference and propose using the multiplicative (Chung-Lu random graph) model as a prior on the graphical space. In this model, each edge is chosen independently with probability equal to the product of the connectivities of the end nodes. This class of prior is parsimonious yet highly flexible; it can be used to encourage sparsity or graphs with a pre-specified degree distribution when such prior knowledge is available. We extend the multiplicative model to multiple GGMs linking the probability of edge inclusion through logistic regression and demonstrate how this leads to joint inference for multiple GGMs. A sequential Monte Carlo (SMC) algorithm is developed for estimating the posterior distribution of the graphs.
Localization for MCMC

XIN TONG

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ABSTRACT

We investigate how ideas from covariance localization in numerical weather prediction can be used to construct effective Markov chain Monte Carlo (MCMC) methods for sampling high-dimensional distributions with banded covariance and precision matrices. The main idea is to exploit banded structure during problem formulation and numerical solution. In particular, we propose to solve high-dimensional Bayesian inverse problems with nearly banded structure (i.e., small off-diagonal elements) by first replacing the problem with a banded version, and then solving the modified problem using a Metropolis-within-Gibbs sampler that exploits this banded structure. We discuss conditions under which posterior moments of the modified problem are close to those of the original problem. Under the same conditions, the convergence rate of an associated sampler is independent of dimension. We present our ideas in the context of Gaussian problems, where mathematical formulations are precise and for which convergence analysis can be made rigorous.
Piecewise Deterministic MCMC

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ABSTRACT
Non-reversible Markov chain Monte Carlo schemes based on piecewise deterministic Markov processes have been recently introduced in applied probability, automatic control, physics and statistics. Although these algorithms demonstrate experimentally good performance and are accordingly increasingly used in a wide range of applications, our theoretical understanding of their properties is still far from complete. I will give an overview of recent progress in this direction.
A Defensive Marginal Particle Filtering Method for Data Assimilation

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ABSTRACT

The Particle filtering (PF) method is a popular approach to estimate the states of dynamical systems from noisy and indirect data in a Bayesian framework. A major limitation of the standard PF method is that the dimensionality of the state space increases as the time proceeds which may cause degeneracy of the algorithm. A possible approach to alleviate the degeneracy issue is to compute the marginal posterior distribution at each time step, which leads to the so-called marginal PF method. In this work we propose a defensive marginal PF method which constructs an importance sampling distribution in the marginal space by combining the standard PF and the EnKF approach. With numerical examples we demonstrate that the proposed method has competitive performance against many existing algorithms.
Anytime Monte Carlo

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ABSTRACT

A Monte Carlo algorithm typically simulates some prescribed number of samples, taking some random real time to complete the computations necessary. This work considers the converse: to impose a real-time budget on the computation, so that the number of samples simulated is random. To complicate matters, the real time taken for each simulation may depend on the sample produced, so that the samples themselves are not independent of their number, and a length bias with respect to compute time is apparent. This is especially problematic when a Markov chain Monte Carlo (MCMC) algorithm is used and the final state of the Markov chain—rather than an average over all states—is required. The length bias does not diminish with the compute budget in this case. It occurs, for example, in sequential Monte Carlo (SMC) algorithms. We propose an anytime framework to address the concern, using a continuous-time Markov jump process to study the progress of the computation in real time. We show that the length bias can be eliminated for any MCMC algorithm by using a multiple chain construction. The utility of this construction is demonstrated on a large-scale $SMC^2$ implementation, using four billion particles distributed across a cluster of 128 graphics processing units on the Amazon EC2 service. The anytime framework imposes a real-time budget on the MCMC move steps within $SMC^2$, ensuring that all processors are simultaneously ready for the resampling step, demonstrably reducing wait times and providing substantial control over the total compute budget.