ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ
ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

ΣΧΟΛΗ ΕΠΙΣΤΗΜΩΝ & ΤΕΧΝΟΛΟΓΙΑΣ ΤΗΣ ΠΛΗΡΟΦΟΡΙΑΣ
SCHOOL OF INFORMATION SCIENCES & TECHNOLOGY

ΤΜΗΜΑ ΣΤΑΤΙΣΤΙΚΗΣ
DEPARTMENT OF STATISTICS

ΚΥΚΛΟΣ ΣΕΜΙΝΑΡΙΩΝ ΣΤΑΤΙΣΤΙΚΗΣ ΟΚΤΩΒΡΙΟΣ – ΔΕΚΕΜΒΡΙΟΣ 2014

Λουκία Μελιγκοτσίδου
Τμήμα Μαθηματικών
Πανεπιστήμιο Αθηνών

Particle MCMC and Augmentation Schemes

ΤΕΤΑΡΤΗ 10/12/2014
11:30 – 12:30

ΑΙΘΟΥΣΑ 607, 6^{ος} ΟΡΟΦΟΣ,
ΚΤΙΡΙΟ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ
(ΕΥΕΛΠΙΔΩΝ & ΛΕΥΚΑΔΟΣ)

ΠΕΡΙΛΗΨΗ (ΣΤΑ ΑΓΓΛΙΚΑ)

Markov chain Monte Carlo (MCMC) methods are frequently used to sample from high dimensional distributions, such as those arising in complex Bayesian problems. However, standard MCMC algorithms may suffer from poor mixing and convergence, especially in cases that highly correlated variables are sampled independently and/or the proposal densities are not efficient. Particle MCMC methods have been recently introduced to deal with such problems, in particular with Bayesian inference for a large class of sophisticated models, such as state space models, where there is an unobserved stochastic process. Alternative (sequential) Monte Carlo methods, called particle filters, can be more efficient for inference about the unobserved process given known parameter values, but struggle when dealing with unknown parameters. The idea of particle MCMC is to embed a particle filter within an MCMC algorithm. The particle filter will then update the unobserved process given a specific value for the parameters, and MCMC moves will be used to update the parameter values. In our work we show how particle MCMC can be generalised beyond this through data augmentation schemes. Our key idea is to introduce new latent variables into the model. We then use the MCMC moves to update the latent variables, and the particle filter to propose new values for the parameters and stochastic process given the latent variables. A generic way of defining these latent variables is to model them as pseudo-observations of the parameters or of the stochastic process. By choosing the amount of information these latent variables have about the parameters and the stochastic process we can often improve the mixing of the particle MCMC algorithm by trading off the Monte Carlo error of the particle filter and the mixing of the MCMC moves.

The talk will provide an introduction to particle MCMC methods and discuss augmentation schemes and their application to a simple state-space model.

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ΤΜΗΜΑ ΣΤΑΤΙΣΤΙΚΗΣ — DEPARTMENT OF STATISTICS

AUEB STATISTICS SEMINAR SERIES OCTOBER– DECEMBER 2014

Loukia Meligkotsidou

Department of Mathematics
University of Athens

Particle MCMC and Augmentation Schemes

Wednesday 10/12/2014
11:30 – 12:30

ROOM 607, 6th FLOOR,
POSTGRADUATE STUDIES BUILDING
(EVELPIDON & LEFKADOS)

ABSTRACT

Markov chain Monte Carlo (MCMC) methods are frequently used to sample from high dimensional distributions, such as those arising in complex Bayesian problems. However, standard MCMC algorithms may suffer from poor mixing and convergence, especially in cases that highly correlated variables are sampled independently and/or the proposal densities are not efficient. Particle MCMC methods have been recently introduced to deal with such problems, in particular with Bayesian inference for a large class of sophisticated models, such as state space models, where there is an unobserved stochastic process. Alternative (sequential) Monte Carlo methods, called particle filters, can be more efficient for inference about the unobserved process given known parameter values, but struggle when dealing with unknown parameters. The idea of particle MCMC is to embed a particle filter within an MCMC algorithm. The particle filter will then update the unobserved process given a specific value for the parameters, and MCMC moves will be used to update the parameter values. In our work we show how particle MCMC can be generalised beyond this through data augmentation schemes. Our key idea is to introduce new latent variables into the model. We then use the MCMC moves to update the latent variables, and the particle filter to propose new values for the parameters and stochastic process given the latent variables. A generic way of defining these latent

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