Geophysical Research Abstracts
Vol. 18, EGU2016-13057, 2016
EGU General Assembly 2016

Boosting Bayesian parameter inference of stochastic differential equation models with methods from statistical physics

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Measured time-series of both precipitation and runoff are known to exhibit highly non-trivial statistical properties. For making reliable probabilistic predictions in hydrology, it is therefore desirable to have stochastic models with output distributions that share these properties. When parameters of such models have to be inferred from data, we also need to quantify the associated parametric uncertainty. For non-trivial stochastic models, however, this latter step is typically very demanding, both conceptually and numerically, and always never done in hydrology.
Here, we demonstrate that methods developed in statistical physics make a large class of stochastic differential equation (SDE) models amenable to a full-fledged Bayesian parameter inference.
For concreteness we demonstrate these methods by means of a simple yet non-trivial toy SDE model. We consider a natural catchment that can be described by a linear reservoir, at the scale of observation. All the neglected processes are assumed to happen at much shorter time-scales and are therefore modeled with a Gaussian white noise term, the standard deviation of which is assumed to scale linearly with the system state (water volume in the catchment). Even for constant input, the outputs of this simple non-linear SDE model show a wealth of desirable statistical properties, such as fat-tailed distributions and long-range correlations.
Standard algorithms for Bayesian inference fail, for models of this kind, because their likelihood functions are extremely high-dimensional intractable integrals over all possible model realizations. The use of Kalman filters is illegitimate due to the non-linearity of the model. Particle filters could be used but become increasingly inefficient with growing number of data points.
Hamiltonian Monte Carlo algorithms allow us to translate this inference problem to the problem of simulating the dynamics of a statistical mechanics system and give us access to most sophisticated methods that have been developed in the statistical physics community over the last few decades.
We demonstrate that such methods, along with automated differentiation algorithms, allow us to perform a full-fledged Bayesian inference, for a large class of SDE models, in a highly efficient and largely automatized manner. Furthermore, our algorithm is highly parallelizable.
For our toy model, discretized with a few hundred points, a full Bayesian inference can be performed in a matter of seconds on a standard PC.