Geophysical Research Abstracts
Vol. 18, EGU2016-18498, 2016
EGU General Assembly 2016

Bayesian Attractor Learning

Wim Wiegerinck (1), Christiaan Schoenaker (1), and Gregory Duane (2)

(1) SNN, Donders Institute for Brain, Cognition and Behaviour, Radboud University Nijmegen, Nijmegen, Netherlands, (2) Geophysical Institute, University of Bergen, Norway

Recently, methods for model fusion by dynamically combining model components in an interactive ensemble have been proposed. In these proposals, fusion parameters have to be learned from data. One can view these systems as parametrized dynamical systems.

We address the question of learnability of dynamical systems with respect to both short term (vector field) and long term (attractor) behavior. In particular we are interested in learning in the imperfect model class setting, in which the ground truth has a higher complexity than the models, e.g. due to unresolved scales. We take a Bayesian point of view and we define a joint log-likelihood that consists of two terms, one is the vector field error and the other is the attractor error, for which we take the L1 distance between the stationary distributions of the model and the assumed ground truth.

In the context of linear models (like so-called weighted supermodels), and assuming a Gaussian error model in the vector fields, vector field learning leads to a tractable Gaussian solution. This solution can then be used as a prior for the next step, Bayesian attractor learning, in which the attractor error is used as a log-likelihood term. Bayesian attractor learning is implemented by elliptical slice sampling, a sampling method for systems with a Gaussian prior and a non Gaussian likelihood. Simulations with a partially observed driven Lorenz 63 system illustrate the approach.