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# Mean Field Variational Bayesian Data Assimilation

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Current data assimilation schemes propose a range of approximate solutions to the classical data assimilation problem, particularly state estimation. Broadly there are three main active research areas: ensemble Kalman filter methods which rely on statistical linearization of the model evolution equations, particle filters which provide a discrete point representation of the posterior filtering or smoothing distribution and 4DVAR methods which seek the most likely posterior smoothing solution. In this paper we present a recent extension to our variational Bayesian algorithm which seeks the most probably posterior distribution over the states, within the family of non-stationary Gaussian processes.

Our original work on variational Bayesian approaches to data assimilation sought the best approximating time varying Gaussian process to the posterior smoothing distribution for stochastic dynamical systems. This approach was based on minimising the Kullback-Leibler divergence between the true posterior over paths, and our Gaussian process approximation. So long as the observation density was sufficiently high to bring the posterior smoothing density close to Gaussian the algorithm proved very effective, on lower dimensional systems. However for higher dimensional systems, the algorithm was computationally very demanding. We have been developing a mean field version of the algorithm which treats the state variables at a given time as being independent in the posterior approximation, but still accounts for their relationships between each other in the mean solution arising from the original dynamical system.

In this work we present the new mean field variational Bayesian approach, illustrating its performance on a range of classical data assimilation problems. We discuss the potential and limitations of the new approach. We emphasise that the variational Bayesian approach we adopt, in contrast to other variational approaches, provides a bound on the marginal likelihood of the observations given parameters in the model which also allows inference of parameters such as observation errors, and parameters in the model and model error representation, particularly if this is written as a deterministic form with small additive noise. We stress that our approach can address very long time window and weak constraint settings. However like traditional variational approaches our Bayesian variational method has the benefit of being posed as an optimisation problem. We finish with a sketch of the future directions for our approach.