Sequential Bayesian Learning

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In various application areas it is crucial to make predictions or decisions based on sequentially incoming observations and previous existing knowledge on the system of interest. The prior knowledge is often given in the form of evolution equations (e.g., ODEs derived via first principles or fitted based on previously collected data), from here on referred to as model. Despite the available observation and prior model information, accurate predictions of the "true" reference dynamics can be very difficult. Common reasons that make this problem so challenging are: (i) the underlying system is extremely complex (e.g., highly nonlinear) and chaotic (i.e., crucially dependent on the initial conditions), (ii) the associate state and/or parameter space is very high dimensional (e.g., worst case 10^8), (iii) observations are noisy, partial in space and discrete in time. In practice these obstacles are combated with a series of approximations (the most important ones being based on assuming Gaussian densities and using Monte Carlo type estimations) and numerical tools that work surprisingly well in some settings. Yet the mathematical understanding of the signal tracking ability of a lot of these methods is still lacking. Additionally, solutions of some of the more complicated problems that require simultaneous state and parameter estimation (including control parameters that can be understood as decisions/actions performed) can still not be approximated in a computationally feasible fashion. Here we will discuss how techniques from the world of machine learning can aid to overcome some of the computational challenges.