RESEARCH SPOTLIGHTS

Short and to the point, "How to Avoid the Curse of Dimensionality: Scalability of Particle Filters with and without Importance Sampling" is the first of two Research Spotlights articles. The authors—Simone Carlo Surace, Anna Kutschireiter, and Jean-Pascal Pfister—are concerned with the continuous time nonlinear filter problem in which the state and observation variables are D-dimensional diffusion processes representing the solution to a particular stochastic differential equation defined in section 2. The goal in the filtering problem is to approximate a conditional expectation that is defined in terms of a measurable function mapping the observation state to the reals, conditioned on a filtration generated from the observation process. Standard particle filters employ importance sampling to approximate this conditional expectation. At issue is "weight degeneracy," the tendency of the majority of the weights as they evolve to become negligibly small, causing the value of the approximation to worsen. In high-dimensional spaces, the importance weights are more likely to be degenerate, hence the curse of dimensionality (COD) problem. The authors illustrate that the time scale of weight decay will shorten in higher dimensions. They also show numerically that traditional approaches to improve behavior by resampling and improved proposal functions for particle motion cannot circumvent the COD. They present an alternative feedback particle filter (FPF) that does not utilize importance sampling, and they illustrate numerically that it does not suffer from the COD. The authors invite the research community to consider the potential benefits of FPF and similar techniques for use in such high-dimensional applications as data assimilation problems in numerical weather prediction.

The need to model dynamical processes on networks is of paramount importance in a wide range of applications. The second article, "Multistate Dynamical Processes on Networks: Analysis through Degree-Based Approximation Frameworks," by Peter G. Fennell and James P. Gleeson, focuses specifically on multistate dynamical process models and on developing suitably general frameworks in which to analyze these models. Whereas binary state network models allow a node in only one of two states, multistate dynamical processes on networks allow for a larger number of discrete states, thereby enabling modeling of more complex behavior as the authors discuss in some detail in section 2. Focusing on undirected, unweighted networks with a given degree distribution and multistate Markovian dynamical processes that can be described via rate matrix functions, the authors develop three so-called approximation frameworks. These frameworks—the Approximate Master Equation, the Pair Approximation, and the Mean-Field frameworks—are generalized from the methods used for binary-state dynamics. As the authors demonstrate in examples in cooperative disease dynamics and kinetically constrained dynamics, the frameworks differ in their degrees of accuracy, with each having its advantages depending on the goals of the analysis. The authors provide a link to their optimized code that was developed to give numerical solutions to the equations in the frameworks, and invite the research community to test the suitability of their multistate frameworks as an aid in understanding the dynamics in other applications.

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