Gaussian Process Regression: Innovations and Applications

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Fast Gaussian Process Calibration of Computer Models with Large Ensembles

Statistical model calibration of computer models is commonly done in a wide variety of scientific endeavours. In the end, this exercise amounts to solving an inverse problem and a form of regression. Gaussian process model are very convenient in this setting as non-parametric regression estimators and provide sensible inference properties. However, when the data structures are large, fitting the model becomes difficult. In this work, new methodology for calibrating large computer experiments is presented. We proposed to perform the calibration exercise by modularizing a hierarchical statistical model with approximate emulation via local Gaussian processes. The approach is motivated by an application to radiative shock hydrodynamics.

JASON LOEPPKY, University of British Columbia

Comparing Simulated Emission from Molecular Clouds using Gaussian Process Regression

The process of star formation is the fundamental agent at determining how a galaxy evolves over the course of the Universe. Decades of observation of star-forming regions suggest that several different physical effects shape the star formation process: gravitation, magnetism, chemistry, and radiation. However, it is not understood exactly how these effects shape the star formation process. Large-scale, multi-physics computer simulations are routinely used to model the process of star formation. The simulations are computationally expensive and produce a three dimensional model that can only be compared statistically to observations. In this talk we will explore the use of a GP regression as a tool for providing a sensitivity analysis of various metrics used to compare astronomical data sets.

MARTIN LYSY, University of Waterloo

Parameter Inference for Diffusion Processes via Gaussian Process Regression

Diffusion processes are used to model a wealth of stochastic phenomena in the natural sciences, engineering, and finance. For many such processes, the likelihood function is only available for continuous-time data. Since actual data recordings are discrete, parameter inference is typically achieved by integrating over the missing paths between observations. However, most Markov chain Monte Carlo algorithms used to this end impose a formidable computational burden. Here, we propose an Importance Sampling approach to the missing path imputation via Gaussian Process Regression. To account for the highly non-Gaussian nature of these paths, both model-free and model-dependent features are included in the variance function. The methodology is illustrated with several financial and biological examples.