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Regression-Based Covariance Functions for Nonstationary Spatial Modeling

Abstract

In Gaussian process (GP) models for spatial data, the covariance function is typically assumed to belong to a parametric class of stationary covariance models. Various authors have proposed methods for relaxing the second-order stationarity assumption in GP models using constructive techniques for specifying valid parametric and nonparametric covariance functions. While these approaches are elegant in their flexibility, model fitting can be problematic due to the high dimensionality of the parameter space and weak identifiability of model parameters. To overcome these issues, we build on the growing literature of covariate-driven nonstationary spatial modeling. We propose a Bayesian model for continuously-indexed spatial data based on a flexible covariance regression structure for a convolution-kernel covariance matrix, which allows the components of the convolution-kernel matrix to vary smoothly over space according to spatially-varying covariate information. We explore the properties of this model, including a description of the implied spatially-varying covariance function, and demonstrate that our parsimonious model provides a compromise between stationary and overly parameterized nonstationary models that do not perform well in practice. We illustrate our approach through simulation and an analysis of precipitation data.

This is based on joint work with Mark Risser.

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