A Novel Class of Covariance Functions and Linear-Cost Matrix Computations

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Gaussian processes are the cornerstone of statistical data analysis in many application areas, ranging from geology, computer experiments, uncertainty quantification, to machine learning. A substantial challenge, however, lies in the computation with the covariance matrix that is generated from the covariance function of the process. These matrices are large, dense, and irregularly structured. Examples of the bottleneck computations include square-root factorization, log-determinant, linear system solution, and a large amount of vector operations where the vectors are generated also from the covariance function. In this work, we present a novel class of covariance functions to alleviate the high cost of these computations. The resulting matrix structure is recursively low-rank, which allows for the design of tree data structure and algorithms at an $O(n)$ cost. We demonstrate the effective use of these functions for a number of tasks, including sampling, data fitting, and parameter estimation.

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