Fast Gaussian Process Regression for Smooth Functions using Lattice and Digital Sequences with Matching Kernels

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Gaussian process regression (GPR) provides a principled way to update a distribution governing potential functions modeling data. Classic GPR models cost $\mathcal{O}(n^3)$ to fit to n data points which prohibits their application in big data regimes. However, this cost can be reduced to $\mathcal{O}(n \log n)$ by pairing lattice or digital sequences with shift-invariant or digitally-shift-invariant kernels respectively. A connection is made between kernel parameter optimization during GPR and the weighted tensor product Reproducing Kernel Hilbert Spaces (RKHSs) studied in QMC. We discuss specific forms on shift-invariant kernels whose RKHS contains periodic functions of arbitrary smoothness. We also propose a new class of digitally-shift-invariant kernels whose RKHS contains (optionally periodic) functions of arbitrary smoothness. Examples and software are shown which implement the theory.