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*Total Sensitivity Kernels: Learning Weighted ANOVA Kernels by RKHS Norm Minimization*

Kernel methods with standard isotropic kernels treat all input variables similarly and therefore suffer from the curse of dimensionality. Many high-dimensional functions arising in applications have low effective dimension: their ANOVA (analysis of variance) decomposition is dominated by a few inputs and by main effects and low-order interactions. We introduce total sensitivity kernels (TSKs), a family of weighted ANOVA kernels in which the weights of all ANOVA components are determined by a single sensitivity parameter per input.

All TSKs generate the same function space and differ only in their norms. Since the RKHS norm of the target function governs the approximation term in standard error bounds for kernel ridge regression, we choose the sensitivity parameters by minimizing this norm. We show that the resulting objective is strongly convex. The data-driven approximation, based on minimum-norm interpolation, converges uniformly on compact parameter sets as the number of samples grows. Numerical experiments show substantial improvements over product kernels and unweighted ANOVA kernels, and illustrate that TSKs exploit multivariable structures.

This talk is based on joint work with John Darges (Emory University).