Kernel Machines with Hard Shape Constraints*

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Abstract

Shape constraints (such as non-negativity, monotonicity, convexity or super-modularity) play a central role in a large number of successful applications in statistics and machine learning. Imposing these shape requirements however in a hard way can be extremely challenging. Typically the task is tackled in a soft fashion (at finite many points) or for highly restricted function classes (such as polynomials or polynomial splines). I am going to present a technique which allows encoding hard affine shape constraints on function derivatives into the flexible framework of kernel machines; the approach relies on a tightened second-order cone constrained reformulation that can be readily implemented in convex solvers. The efficiency of the method is illustrated in joint quantile regression (with applications in economics and in the analysis of aircraft trajectories), in the reconstruction problem of convoy trajectories, and in a safety-critical control task (piloting an underwater vehicle avoiding obstacles).

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