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Random subspace trust-region algorithm for high-dimensional convex-constrained derivative-free optimization

Model-based derivative-free optimization (DFO) methods are one major class of DFO methods widely used in practice. However, these methods are known to struggle in high dimensions. Recent research tackles this issue by searching for decreases in low-dimensional subspaces sampled randomly in each iteration. This talk proposes a random subspace trust-region algorithm for general convex-constrained DFO problems. We provide a new subspace sampling technique that guarantees that the subspace preserves the first-order criticality measure by a certain percentage with a fixed probability. We define a new class of models that can be constructed using only feasible points in the subspace. Based on these new theoretical results, an almost-sure global convergence and a worst-case complexity analysis of our algorithm are presented. Numerical experiments demonstrate the strong performance of our algorithm in high dimensions.