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When Are Nonconvex Optimization Problems Not Scary?

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Eckhart 133, 5734 S. University Avenue

ABSTRACT

Many problems arising from scientific and engineering applications can be naturally formulated as optimization problems, most of which are nonconvex. In theory, obtaining a local minimizer for a general nonconvex problem is computationally hard, never mind the global minimizer. In practice, simple numerical methods often work surprisingly well in finding high-quality solutions for nonconvex problems at hand. In this talk, I will describe our recent effort in bridging the mysterious theory-practice gap for nonconvex optimization. I will highlight a family of nonconvex problems that can be solved to global optimality using simple numerical methods, independent of initialization. This family has the characteristic global structure that (1) all local minimizers are global, and (2) all saddle points have negative directional curvatures. Examples lying in this family cover various applications across machine learning, signal processing, scientific imaging, and more. I will focus on two examples we worked out: learning sparsifying bases for massive data and recovery of complex signals from phaseless measurements. In both examples, the benign global structure allows us to derive novel geometric insights and computational results that are inaccessible from previous methods. In contrast, alternative approaches to solving nonconvex optimization often either entail expensive convex optimization (e.g., solving large-scale semidefinite programs) or require delicate problem-specific initializations. Completing and enriching this framework is an active research endeavor that is being undertaken by several research communities. At the end of the talk, I will discuss open problems to be tackled to move forward.