

INTERNATIONAL CONFERENCE ON CONTINUOUS OPTIMIZATION



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Weierstrass Institute for
Applied Analysis and Stochastics

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Michael Hintermüller (Chair of the Organizing Committee)

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NON	NON
Wed.1 H 0105	Wed.1 H 1012
Geometry in Non-Convex Optimization (Part I)	Nonlinear Optimization Methods and Their Global Rates of Convergence
Organizers: Nicolas Boumal, André Uschmajew, Bart Vander-eycken	Organizer: Geovani Grapiglia
Chair: André Uschmajew	Chair: Geovani Grapiglia
Suvrit Sra, MIT	Oliver Hinder, Stanford Univ. (joint work with Yair Carmon, John Duchi, Aaron Sidford)
Riemannian optimization for some problems in probability and statistics	The complexity of finding stationary points of nonconvex functions
Non-convex optimization is typically intractable. This intractability can be surmounted if the problem possesses enough structure. This talk focuses on “geodesic convexity” as this structure. This hidden convexity not only yields proofs not only of tractability but also suggests practical algorithmic approaches. I will highlight several examples from machine learning and statistics, where non-Euclidean geometry plays a valuable role in obtaining efficient solutions to fundamental tasks (e.g., eigenvector computation, gaussian mixtures, Wasserstein barycenters, etc.).	We investigate the complexity of finding stationary points of smooth (potentially) nonconvex functions. We provide both new algorithms, adapting Nesterov’s accelerated methods to the nonconvex setting (achieving faster convergence than gradient descent), and fundamental algorithm-independent lower bounds on the complexity of finding stationary points. Our bounds imply that gradient descent and cubic-regularized Newton’s method are optimal within their natural function classes.
Nick Vannieuwenhoven, KU Leuven (joint work with Paul Breiding)	Philippe L. Toint, University of Namur (joint work with Stefania Bellavia, Coralia Cartis, Nick Gould, Gianmarco Gurioli, Bendetta Morini)
Riemannian optimization for computing canonical polyadic decompositions	Recent results in worst-case evaluation complexity for smooth and non-smooth, exact and inexact, nonconvex optimization
The canonical tensor rank approximation problem consists of approximating a real-valued tensor by one of low canonical rank, which is a challenging non-linear, non-convex, constrained optimization problem, where the constraint set forms a non-smooth semi-algebraic set. We discuss Riemannian optimization methods for solving this problem for small-scale, dense tensors. The proposed method displayed up to two orders of magnitude improvements in computational time for challenging problems, as measured by the condition number of the tensor rank decomposition.	We present a review of results on the worst-case complexity of minimization algorithm for nonconvex problems using potentially high-degree models. Global complexity bound are presented that are valid for any model’s degree and any order of optimality, thereby generalizing known results for first- and second-order methods. An adaptive regularization algorithm using derivatives up to degree p will produce an ϵ -approximate q -th order minimizer in at most $O(\epsilon^{(p+1)/(p-q+1)})$ evaluations. We will also extend these results to the case of inexact objective function and derivatives.
Nicolas Boumal, Princeton University	Ernesto G. Birgin, Universidade de São Paulo (joint work with J. M. Martínez)
Complexity of optimization on manifolds, and cubic regularization	A Newton-like method with mixed factorizations and cubic regularization and its usage in an Augmented Lagrangian framework
Unconstrained optimization can be framed generally within the framework of optimization on Riemannian manifolds. Over the years, standard algorithms such as gradient descent, trust regions and cubic regularization (to name a few) have been extended to the Riemannian setting, with excellent numerical success. I will show how, under appropriately chosen assumptions, their worst-case iteration complexity analyses carry over seamlessly from the Euclidean to the Riemannian case, then I will discuss finer points related to these assumptions.	A Newton-like method for unconstrained minimization is introduced that uses a single cheap factorization per iteration. Convergence and complexity results, even in the case in which the subproblems’ Hessians are far from being Hessians of the objective function, are presented. When the Hessian is Lipschitz-continuous, the proposed method enjoys $O(\epsilon^{-3/2})$ evaluation complexity for first-order optimality and $O(\epsilon^{-3})$ for second-order optimality. The usage of the introduced method for bound-constrained minimization and for nonlinear programming is reported.