Additional Exercises For Convex Optimization Boyd Solutions

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Theory, Algorithms, and Applications with MATLAB CRC Press
The primary goal of this book is to provide a self-contained, comprehensive study of the main ?rst-order methods that are frequently used in solving large-scale problems. First-order methods exploit information on values and gradients/subgradients (but not Hessians) of the functions composing the model under consideration. With the increase in the number of applications that can be modeled as large or even huge-scale optimization problems, there has been a revived interest in using simple methods that require low iteration cost as well as low memory storage. The author has gathered, reorganized, and synthesized (in a unified manner) many results that are currently scattered throughout the literature, many of which cannot be typically found in optimization books. First-Order Methods in Optimization offers comprehensive study of first-order methods with the theoretical foundations; provides plentiful examples and illustrations; emphasizes rates of convergence and complexity analysis of the main first-order methods used to solve large-scale problems; and covers both variables and functional decomposition methods.
Statistical Learning with Sparsity Cambridge University Press
A uniquely pedagogical, insightful, and rigorous treatment of the analytical/geometrical foundations of optimization. The book provides a comprehensive development of convexity theory, and its rich applications in optimization, including duality, minimax/saddle point theory, Lagrange multipliers, and Lagrangian relaxation/nondifferentiable optimization. It is an excellent supplement to several of our books: Convex Optimization Theory (Athena Scientific, 2009), Convex Optimization Algorithms (Athena Scientific, 2015), Nonlinear Programming (Athena Scientific, 2016), Network Optimization (Athena Scientific, 1998), and Introduction to Linear Optimization (Athena Scientific, 1997). Aside from a thorough account of convex analysis and optimization, the book aims to restructure the theory of the subject, by introducing several novel unifying lines of analysis, including: 1) A unified development of minimax theory and constrained optimization duality as special cases of duality between two simple geometrical problems. 2) A unified development of conditions for existence of solutions of convex optimization problems, conditions for the minimax equality to hold, and conditions for the absence of a duality gap in constrained optimization. 3) A unification of the major constraint qualifications allowing the use of Lagrange multipliers for nonconvex constrained optimization, using the notion of constraint pseudonormality and an enhanced form of the Fritz John necessary optimality conditions. Among its features the book: a) Develops rigorously and comprehensively the theory of convex sets and functions, in the classical tradition of Fenchel and Rockafellar b) Provides a geometric, highly visual treatment of convex and nonconvex optimization problems, including existence of solutions, optimality conditions, Lagrange multipliers, and duality c) Includes an insightful and comprehensive presentation of minimax theory and zero sum games, and its connection with duality d) Describes dual optimization, the associated computational methods, including the novel incremental subgradient methods, and applications in linear, quadratic, and integer programming e) Contains many examples, illustrations, and exercises with complete solutions (about 200 pages) posted at the publisher's web site http://www.athenasc.com/convexity.html
Electrical Transmission System Cascades and Vulnerability: An Operations Research Viewpoint SIAM
This book presents a carefully selected group of methods for unconstrained and bound constrained optimization problems and analyzes them in depth both theoretically and algorithmically. It focuses on clarity in algorithmic description and analysis rather than generality, and while it provides pointers to the literature for the most general theoretical results and robust software, the author thinks it is more important that readers have a complete

understanding of special cases that convey essential ideas. A companion to Kelley's book, Iterative Methods for Linear and Nonlinear Equations (SIAM, 1995), this book contains many exercises and examples and can be used as a text, a tutorial for self-study, or a reference. Iterative Methods for Optimization does more than cover traditional gradient-based optimization: it is the first book to treat sampling methods, including the Hooke-Jeeves, implicit filtering, MDS, and Nelder-Mead schemes in a unified way, and also the first book to make connections between sampling methods and the traditional gradient-methods. Each of the main algorithms in the text is described in pseudocode, and a collection of MATLAB codes is available. Thus, readers can experiment with the algorithms in an easy way as well as implement them in other languages.

Convex Analysis and Optimization MIT Press

Proximal Algorithms discusses proximal operators and proximal algorithms, and illustrates their applicability to standard and distributed convex optimization in general and many applications of recent interest in particular. Much like Newton's method is a standard tool for solving unconstrained smooth optimization problems of modest size, proximal algorithms can be viewed as an analogous tool for nonsmooth, constrained, large-scale, or distributed versions of these problems. They are very generally applicable, but are especially well-suited to problems of substantial recent interest involving large or high-dimensional datasets. Proximal methods sit at a higher level of abstraction than classical algorithms like Newton's method: the base operation is evaluating the proximal operator of a function, which itself involves solving a small convex optimization problem. These subproblems, which generalize the problem of projecting a point onto a convex set, often admit closed-form solutions or can be solved very quickly with standard or simple specialized methods. Proximal Algorithms discusses different interpretations of proximal operators and algorithms, looks at their connections to many other topics in optimization and applied mathematics, surveys some popular algorithms, and provides a large number of examples of proximal operators that commonly arise in practice.

Convex Analysis and Nonlinear Optimization Now Pub

The study of Euclidean distance matrices (EDMs) fundamentally asks what can be known geometrically given onlydistance information between points in Euclidean space. Each point may represent simply locationor, abstractly, any entity expressible as a vector in finite-dimensional Euclidean space.The answer to the question posed is that very much can be known about the points;the mathematics of this combined study of geometry and optimization is rich and deep.Throughout we cite beacons of historical accomplishment.The application of EDMs has already proven invaluable in discerning biological molecular conformation.The emerging practice of localization in wireless sensor networks, the global positioning system (GPS), and distance-based pattern recognitionwill certainly simplify and benefit from this theory.We study the pervasive convex Euclidean bodies and their various representations.In particular, we make convex polyhedra, cones, and dual cones more visceral through illustration, andwe study the geometric relation of polyhedral cones to nonorthogonal bases biorthogonal expansion.We explain conversion between halfspace- and vertex-descriptions of convex cones,we provide formulae for determining dual cones,and we show how classic alternative systems of linear inequalities or linear matrix inequalities and optimality conditions can be explained by generalized inequalities in terms of convex cones and their duals.The conic analogue to linear independence, called conic independence, is introducedas a new tool in the study of classical cone theory; the logical next step in the progression:linear, affine, conic.Any convex optimization problem has geometric interpretation.This is a powerful attraction: the ability to visualize geometry of an optimization problem.We provide tools to make visualization easier.The concept of faces, extreme points, and extreme directions of convex Euclidean bodiesis explained here, crucial to understanding convex optimization.The convex cone of positive semidefinite matrices, in particular, is studied in depth.We mathematically interpret, for example,its inverse image under affine transformation, and we explainhow higher-rank subsets of its boundary united with its interior are convex.The Chapter on "Geometry of convex functions",observes analogies between convex sets and functions:The set of all vector-valued convex functions is a closed convex cone.Included among the examples in this chapter, we show how the real affinefunction relates to convex functions as the hyperplane relates to convex sets.Here, also, pertinent results formultidimensional convex functions are presented that are largely ignored in the literature;tricks and tips for determining their convexityand discerning their geometry, particularly with regard to matrix calculus which remains largely unsystematizedwhen compared with the traditional practice of ordinary calculus.Consequently, we collect some results of matrix differentiation in the appendices.The Euclidean distance matrix (EDM) is studied,its properties and relationship to both positive semidefinite and Gram matrices.We relate the EDM to the four classical axioms of the Euclidean metric;thereby, observing the existence of an infinity of axioms of the Euclidean metric beyondthe triangle inequality. We proceed byderiving the fifth Euclidean axiom and then explain why furthering this endeavoris inefficient because the ensuing criteria (while describing polyhedra)grow linearly in complexity and number.Some geometrical problems solvable via EDMs,EDM problems posed as convex optimization, and methods of solution arepresented;\eg, we generate a recognizable isotonic map of the United States usingonly comparative distance information (no distance information, only distance inequalities).We offer a new proof of the classic Schoenberg criterion, that determines whether a candidate matrix is an EDM. Our proofrelies on fundamental geometry; assuming, any EDM must correspond to a list of points contained in some polyhedron(possibly at its vertices) and vice versa.It is not widely known that the Schoenberg criterion implies nonnegativity of the EDM entries; proved here.We characterize the eigenvalues of an EDM matrix and then devisea polyhedral cone required for determining membership of a candidate matrix(in Cayley-Menger form) to the convex cone of Euclidean distance matrices (EDM cone); \ie,a candidate is an EDM if and only if its eigenspectrum belongs to a spectral cone for EDM^N.We will see spectral cones are not unique.In the chapter "EDM cone", we explain the geometric relationship betweenthe EDM cone, two positive semidefinite cones, and the elliptope.We illustrate geometric requirements, in particular, for projection of a candidate matrixon a positive semidefinite cone that establish its membership to the EDM cone. The faces of the EDM cone are described,but still open is the question whether all its faces are exposed as they are for the positive semidefinite cone.The classic Schoenberg criterion, relating EDM and positive semidefinite cones, isrevealed to be a discretized membership relation (a generalized inequality, a new Farkas''''''-like lemma)between the EDM cone and its ordinary dual. A matrix criterion for membership to the dual EDM cone is derived thatis simpler than the Schoenberg criterion.We derive a new concise expression for the EDM cone and its dual involvingtwo subspaces and a positive semidefinite cone."Semidefinite programming" is reviewedwith particular attention to optimality conditionsof prototypical primal and dual conic programs,their interplay, and the perturbation method of rank reduction of optimal solutions(extant but not well-known).We show how to solve a ubiquitous platonic combinatorial optimization problem from linear algebra(the optimal Boolean solution x to Ax=b)via semidefinite program relaxation.A three-dimensional polyhedral analogue for the positive semidefinite cone of 3X3 symmetricmatrices is introduced; a tool for visualizing in 6 dimensions.In "EDM proximity"we explore methods of solution to a few fundamental and prevalentEuclidean distance matrix proximity problems; the problem of finding that Euclidean distance matrix closestto a given matrix in the Euclidean sense.We pay particular attention to the problem when compounded with rank minimization.We offer a new geometrical proof of a famous result discovered by Eckart \& Young in 1936 regarding Euclideanprojection of a point on a subset of the positive semidefinite cone comprising all positive semidefinite matriceshaving rank not exceeding a prescribed limit rho.We explain how this problem is transformed to a convex optimization for any rank rho.

Numerical Optimization SIAM

A groundbreaking introduction to vectors, matrices, and least squares for engineering applications, offering a wealth of practical examples.

Proximal Algorithms Walter de Gruyter GmbH & Co KG

Flexible graduate textbook that introduces the applications, theory, and algorithms of linear and nonlinear optimization in a clear succinct style, supported by numerous examples and exercises. It introduces important realistic applications and explains how optimization can address them.

Problem Complexity and Method Efficiency in Optimization Athena Scientific

Specialists working in the areas of optimization, mathematical programming, or control theory will find this book invaluable for studying interior-point methods for linear and quadratic programming, polynomial-time methods for nonlinear convex programming, and efficient computational methods for control problems and variational inequalities. A background in linear algebra and mathematical programming is necessary to understand the book. The detailed proofs and lack of "numerical examples" might suggest that the book is of limited value to the reader interested in the practical aspects of convex optimization, but nothing could be further from the truth. An entire chapter is devoted to potential reduction methods precisely because of their great efficiency in practice.

Foundations of Optimization SIAM

Non-convex Optimization for Machine Learning takes an in-depth look at the basics of non-convex optimization with applications to machine learning. It introduces the rich literature in this area, as well as equips the reader with the tools and techniques needed to apply and analyze simple but powerful procedures for non-convex problems. Non-convex Optimization for Machine Learning is as self-contained as possible while not losing focus of the main topic of non-convex optimization techniques. The monograph initiates the discussion with entire chapters devoted to presenting a tutorial-like treatment of basic concepts in convex analysis and optimization, as well as their non-convex counterparts. The monograph concludes with a look at four interesting applications in the areas of machine learning and signal processing, and exploring how the non-convex optimization techniques introduced earlier can be used to solve these problems. The monograph also contains, for each of the topics discussed, exercises and figures designed to engage the reader, as well as extensive bibliographic notes pointing towards classical works and recent advances. Non-convex Optimization for Machine Learning can be used for a semester-length course on the basics of non-convex optimization with applications to machine learning. On the other hand, it is also possible to cherry pick individual portions, such the chapter on sparse recovery, or the EM algorithm, for inclusion in a broader course. Several courses such as those in machine learning, optimization, and signal processing may benefit from the inclusion of such topics.

Linear Matrix Inequalities in System and Control Theory Athena Scientific

Examines in detail those topics in convex geometry that are concerned with Euclidean space Enriched by numerous examples, illustrations, and exercises, with a good bibliography and index Requires only a basic knowledge of geometry, linear algebra, analysis, topology, and measure theory Can be used for graduates courses or seminars in convex geometry, geometric and convex combinatorics, and convex analysis and optimization

Princeton University Press

Praise for the Third Edition ". . . guides and leads the reader through the learning path . . . [e]xamples are stated very clearly and the results are presented with attention to detail." —MAA Reviews Fully updated to reflect new developments in the field, the Fourth Edition of Introduction to Optimization fills the need for accessible treatment of optimization theory and methods with an emphasis on engineering design. Basic definitions and notations are provided in addition to the related fundamental background for linear algebra, geometry, and calculus. This new edition explores the essential topics of unconstrained optimization problems, linear programming problems, and nonlinear constrained optimization. The authors also present an optimization perspective on global search methods and include discussions on genetic algorithms, particle swarm optimization, and the simulated annealing algorithm. Featuring an elementary introduction to artificial neural networks, convex optimization, and multi-objective optimization, the Fourth Edition also offers: A new chapter on integer programming Expanded coverage of one-dimensional methods Updated and expanded sections on linear matrix inequalities Numerous new exercises at the end of each chapter MATLAB exercises and drill problems to reinforce the discussed theory and algorithms Numerous diagrams and figures that complement the written presentation of key concepts MATLAB M-files for implementation of the discussed theory and algorithms (available via the book's website) Introduction to Optimization, Fourth Edition is an ideal textbook for courses on optimization theory and methods. In addition, the book is a useful reference for professionals in mathematics, operations research, electrical engineering, economics, statistics, and business.

Convex Optimization Theory MIT Press

It was in the middle of the 1980s, when the seminal paper by Kar markar opened a new epoch in nonlinear optimization. The importance of this paper, containing a new polynomial-time algorithm for linear op timization problems, was not only in its complexity bound. At that time, the most surprising feature of this algorithm was that the theoretical pre diction of its high efficiency was supported by excellent computational results. This unusual fact dramatically changed the style and direc tions of the research in nonlinear optimization. Thereafter it became more and more common that the new methods were provided with a complexity analysis, which was considered a better justification of their efficiency than computational experiments. In a new rapidly develop ing field, which got the name "polynomial-time interior-point methods", such a justification was obligatory. Afteralmost fifteen years of intensive research, the main results of this development started to appear in monographs [12, 14, 16, 17, 18, 19]. Approximately at that time the author was asked to prepare a new course on nonlinear optimization for graduate students. The idea was to create a course which would reflect the new developments in the field. Actually, this was a major challenge. At the time only the theory of interior-point methods for linear optimization was polished enough to be explained to students. The general theory of self-concordant functions had appeared in print only once in the form of research monograph [12].

An Introduction to Continuous Optimization John Wiley & Sons

The book is devoted to the study of approximate solutions of optimization problems in the presence of computational errors. It contains a number of results on the convergence behavior of algorithms in a Hilbert space, which are known as important tools for solving optimization problems. The research presented in the book is the continuation and the further development of the author's (c) 2016 book Numerical Optimization with Computational Errors, Springer 2016. Both books study the algorithms taking into account computational errors which are always present in practice. The main goal is, for a known computational error, to find out what an approximate solution can be obtained and how many iterates one needs for this. The main difference between this new book and the 2016 book is that in this present book the discussion takes into consideration the fact that for every algorithm, its iteration consists of several steps and that computational errors for different steps are generally, different. This fact, which was not taken into account in the previous book, is indeed important in practice. For example, the subgradient projection algorithm consists of two steps. The first step is a calculation of a subgradient of the objective function while in the second one we calculate a projection on the feasible set. In each of these two steps there is a computational error and these two computational errors are different in general. It may happen that the feasible set is simple and the objective function is complicated. As a result, the computational error, made when one calculates the projection, is essentially smaller than the computational error of the calculation of the subgradient. Clearly, an opposite case is possible too. Another feature of this book is a study of a number of important algorithms which appeared recently in the literature and which are not discussed in the previous book. This monograph contains 12 chapters. Chapter 1 is an introduction. In Chapter 2 we study the subgradient projection algorithm for minimization of convex and nonsmooth functions. We generalize the results of [NOCE] and establish results which has no prototype in [NOCE]. In Chapter 3 we analyze the mirror descent algorithm for minimization of convex and nonsmooth functions, under the presence of computational errors. For this algorithm each iteration consists of two steps. The first step is a calculation of a subgradient of the objective function while in the second one we solve an auxiliary minimization problem on the set of feasible points. In each of these two steps there is a computational error. We generalize the results of [NOCE] and establish results which has no prototype in [NOCE]. In Chapter 4 we analyze the projected gradient algorithm with a smooth objective function under the presence of computational errors. In Chapter 5 we consider an algorithm, which is an extension of the projection gradient algorithm used for solving linear inverse problems arising in signal/image processing. In Chapter 6 we study continuous subgradient method and continuous subgradient projection algorithm for minimization of convex nonsmooth functions and for computing the saddle points of convex-concave functions, under the presence of computational errors. All the results of this chapter has no prototype in [NOCE]. In Chapters 7-12 we analyze several algorithms under the presence of computational errors which were not considered in [NOCE]. Again, each step of an iteration has a computational errors and we take into account that these errors are, in general, different. An optimization problems with a composite objective function is studied in Chapter 7. A zero-sum game with two-players is considered in Chapter 8. A predicted decrease approximation-based method is used in Chapter 9 for constrained convex optimization. Chapter 10 is devoted to minimization of quasiconvex functions. Minimization of sharp weakly convex functions is discussed in Chapter 11. Chapter 12 is devoted to a generalized projected subgradient method for minimization of a convex function over a set which is not necessarily convex. The book is of interest for researchers and engineers working in optimization. It also can be useful in preparation courses for graduate students. The main feature of the book which appeals specifically to this audience is the study of the influence of computational errors for several important optimization algorithms. The book is of interest for experts in applications of optimization to engineering and economics.

Springer Science & Business Media

Optimization is an important tool used in decision science and for the analysis of physical systems used in engineering. One can trace its roots to the Calculus of Variations and the work of Euler and Lagrange. This natural and reasonable approach to mathematical programming covers numerical methods for finite-dimensional optimization problems. It begins with very simple ideas progressing through more complicated concepts, concentrating on methods for both unconstrained and constrained optimization.

Nonlinear Programming Convex Optimization

In this book the authors reduce a wide variety of problems arising in system and control theory to a handful of convex and quasiconvex optimization problems that involve linear matrix inequalities. These optimization problems can be solved using recently developed numerical algorithms that not only are polynomial-time but also work very well in practice; the reduction therefore can be considered a solution to the original problems. This book opens up an important new research area in which convex optimization is combined with system and control theory, resulting in the solution of a large number of previously unsolved problems.

Statistical Inference Via Convex Optimization Springer Science & Business Media

An accessible introduction to convex algebraic geometry and semidefinite optimization. For graduate students and researchers in mathematics and computer science.

Introduction to Online Convex Optimization SIAM

This treatment focuses on the analysis and algebra underlying the workings of convexity and duality and necessary/sufficient local/global optimality conditions for unconstrained and constrained optimization problems. 2015 edition.

Interior-point Polynomial Algorithms in Convex Programming John Wiley & Sons

A comprehensive introduction to the tools, techniques and applications of convex optimization.

Iterative Methods for Optimization John Wiley & Sons

Optimization models play an increasingly important role in financial decisions. This is the first textbook devoted to explaining how recent advances in optimization models, methods and software can be applied to solve problems in computational finance more efficiently and accurately. Chapters discussing the theory and efficient solution methods for all major classes of optimization problems alternate with chapters illustrating their use in modeling problems of mathematical finance. The reader is guided through topics such as volatility estimation, portfolio optimization problems and constructing an index fund, using techniques such as nonlinear optimization models, quadratic programming formulations and integer programming models respectively. The book is based on Master's courses in financial engineering and comes with worked examples, exercises and case studies. It will be welcomed by applied mathematicians, operational researchers and others who work in mathematical and computational finance and who are seeking a text for self-learning or for use with courses.

Optimization Methods in Finance John Wiley & Sons

Convex OptimizationCambridge University Press