Stochastic Programming Optimization When Uncertainty Matters

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Maximize Objective Function Given Constraints. Part 1Solving Combinatorial Optimization Problems with Constraint

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Approximation Algorithms for Stochastic Optimization I

Resource Allocation in Wireless Networks Under Uncertainties: A Stochastic Optimization FrameworkLec 13 : Introduction on Stochastic Optimization Warren Powell, \"A Unified Framework for Handling Decisions and Uncertainty\" Stochastic Programming

~~Optimization When Uncertainty~~

Stochastic Programming: Optimization When Uncertainty Matters Julia L. Higle Dept. of Systems and Industrial Engineering, The University of Arizona, Tucson AZ 85721, julie@sie.arizona.edu Abstract Stochastic Programming (SP) was first introduced by George Dantzig in the 1950s.

~~Stochastic Programming: Optimization When Uncertainty Matters~~

Stochastic Programming (SP) was first introduced by George Dantzig in the 1950's. Since that time, tremendous progress toward an understanding of properties of SP models and the design of algorithmic approaches for solving them has been made. As a result, SP is gaining recognition as a viable approach for large scale models of decisions under uncertainty.

~~Stochastic Programming: Optimization When Uncertainty Matters~~
Stochastic programming is applied when uncertain environment occurs, in this case the uncertain environment refers to the production of renewable energy sources (RES) and its dependence on the ...

~~Stochastic Programming: Optimization When Uncertainty Matters~~
In order to solve stochastic programming problems numeri- cally the (continuous) distribution of the data process should be discretized by generating a nite number of realizations of the data process (the scenarios approach). Size of the de- terministic equivalent problem is proportional to the number of generated scenarios.

~~Stochastic Programming Approach to Optimization Under ...~~

The traditional approach is to model the underlying data process as random (stochastic) and to optimize a specified objective function on average. This raises the questions of controlling the risk, and the uncertainty with respect to the considered probability distributions themselves.

~~Stochastic Programming Approach to Optimization Under ...~~

Under the standard two-stage stochastic programming paradigm, the decision variables of an optimization problem under uncertainty are partitioned into two sets. The first-stage variables are those that have to be decided before the actual realization of the uncertain parameters.

~~Optimization under uncertainty: state-of-the-art and ...~~

A popular impression has arisen that the robust approach, with its focus on the worst case, is better able to control risk while stochastic programming emphasizes expected values. However, the stochastic programming formulation can easily accommodate a risk measure. Moreover, the results of both methods depend strongly on the model for the uncertain parameters either the uncertainty set or the probabilistic scenarios employed in the optimization.

~~stochastic programming - Modeling the uncertainty of the ...~~

In the field of mathematical optimization, stochastic programming is a framework for modeling optimization problems that involve uncertainty. Whereas deterministic optimization problems are formulated with known parameters, real world problems almost invariably include some unknown parameters. When the parameters are known only within certain bounds, one approach to tackling such problems is called robust optimization. Here the goal is to find a solution which is feasible for all such data and o

~~Stochastic programming - Wikipedia~~

Uncertainty: Decisions must often be taken in the face of the unknown. Actions decided upon in the present will have consequences that can't fully be determined until a

~~OPTIMIZATION UNDER UNCERTAINTY~~

Stochastic optimization is the perfect tool for these problems. In other real-world problems, the uncertain parameters being modeled are dependent on the decision variables they change if the decisions change. For example, in a market response model that includes competitor actions in a future period, where your product prices are decision variables, and your competitors product prices are uncertainties, it is quite likely that the uncertainties will depend on the decisions.

Module 10: Stochastic Optimization | solver

Stochastic programming is an optimization model that deals with optimizing with uncertainty. For example, imagine a company that provides energy to households. This company is responsible for delivering energy to households based on how much they demand.

Stochastic programming - optimization

Stochastic optimization (SO) methods are optimization methods that generate and use random variables. For stochastic problems, the random variables appear in the formulation of the optimization problem itself, which involves random objective functions or random constraints.

Stochastic optimization - Wikipedia

The Stochastic Programming Society (SPS) is a world-wide group of researchers who are developing models, methods, and theory for decisions under uncertainty. SPS promotes the development and application of stochastic programming theory, models, methods, analysis, software tools and standards, and encourages the exchange of information among practitioners and scholars in the area of stochastic programming.

~~Stochastic Programming Society | Stochastic Programming ...~~
Buy Shape Optimization Under Uncertainty From A Stochastic Programming Point Of View 2009 by Held, Harald (ISBN: 9783834809094) from Amazon's Book Store. Everyday low prices and free delivery on eligible orders.

~~Shape Optimization Under Uncertainty From A Stochastic ...~~
Stochastic programming has been widely utilized to capture the uncertain nature of real world optimization problems in many different aspects. These models, however, often fall short in adequately capturing the stochasticity introduced by the interactions within a system or a society involving human beings or sub-systems.

~~An Optimization Via Agent-Based Simulation Framework to ...~~
Topology optimization under uncertainty (TOuU) often defines objectives and constraints by statistical moments of geometric and physical quantities of interest. Most traditional TOuU methods use gradient-based optimization algorithms and rely on accurate estimates of the statistical moments and their gradients, e.g., via adjoint calculations.

~~Topology optimization under uncertainty using a stochastic ...~~
Stochastic programming is an approach for modeling optimization problems that involve uncertainty. Whereas deterministic optimization problems are formulated with known pa- rameters, real world problems almost invariably include parameters which are

unknown at the time a decision should be made.

~~A Tutorial on Stochastic Programming~~

In this paper, a linear multi-stage stochastic optimization model was developed to optimize the future power generation mix of a region or country by minimizing the total discounted cost, while also considering a number of constraints related to the peak and consumption demand, renewable energy potential limit, renewable energy penetration targets, annual construction limit, fuel diversity, CO 2,eq emission targets and carbon pricing policy. The model took into account the uncertainty of ...

Optimization problems are relevant in many areas of technical, industrial, and economic applications. At the same time, they pose challenging mathematical research problems in numerical analysis and optimization. Harald Held considers an elastic body subjected to uncertain internal and external forces. Since simply averaging the possible loadings will result in a structure that might not be robust for the individual loadings, he uses techniques from level set based shape optimization and two-stage stochastic programming. Taking advantage of the PDE□s linearity, he is able to compute solutions for an arbitrary number of scenarios without significantly increasing the computational effort. The author applies a gradient method using the shape derivative and the topological gradient to minimize, e.g., the compliance and shows that the obtained solutions strongly depend on the initial guess, in particular its topology. The stochastic programming perspective also allows incorporating risk measures into the model which might be a more appropriate objective in many practical applications.

This rapidly developing field encompasses many disciplines including operations research, mathematics, and probability. Conversely, it is being applied in a wide variety of subjects ranging from agriculture to financial planning and from industrial engineering to computer networks. This textbook provides a first course in stochastic programming suitable for students with a basic knowledge of linear programming, elementary analysis, and probability. The authors present a broad overview of the main themes and methods of the subject, thus helping students develop an intuition for how to model uncertainty into mathematical problems, what uncertainty changes bring to the decision process, and what techniques help to manage uncertainty in solving the problems. The early chapters introduce some worked examples of stochastic programming, demonstrate how a stochastic model is formally built, develop the properties of stochastic programs and the basic solution techniques used to solve them. The book then goes on to cover approximation and sampling techniques and is rounded off by an in-depth case study. A well-paced and wide-ranging introduction to this subject.

Modern decision models increasingly involve parameters that are unknown or uncertain. Uncertainty is typically modeled by probability distribution over possible realizations of some random parameters. In presence of high dimensional multivariate random variables, estimating the joint probability distributions is difficult, and optimization models are often simplified by assuming that the random variables are independent. Although popular, the effect of this heuristic on the solution quality was little understood. This thesis centers around the following question: "How much can the expected cost increase if the random variables are arbitrarily correlated?" We introduce a new concept of Correlation Gap to quantify this increase. For given marginal distributions, Correlation Gap compares the expected value of a function on the worst case (expectation maximizing) joint distribution to its expected value on the independent (product) distribution. Correlation gap captures the "Price of Correlations" in stochastic optimization -- using a distributionally robust stochastic programming model, we show that a small correlation gap implies that the efficient heuristic of assuming independence is actually robust against any adversarial correlations, while a large correlation gap suggests that it is important to invest more in data collection and learning correlations. Apart from decision making under uncertainty, we show that our upper bounds on correlation gap are also useful for solving many deterministic optimization problems like welfare maximization, k-dimensional matching and transportation problems, for which it captures the performance of randomized algorithmic techniques like independent random selection and independent randomized rounding. Our main technical results include upper and lower bounds on correlation gap based on the properties of the cost function. We demonstrate that monotonicity and submodularity of function implies a small correlation gap. Further, we employ techniques of cross-monotonic cost-sharing schemes from game theory in a novel manner to provide a characterization of non-submodularity functions with small correlation gap. Results include small constant bounds for cost functions resulting from many popular applications such as stochastic facility location, Steiner tree network design, minimum spanning tree, minimum makespan scheduling, single-source rent-or-buy network design etc. Notably, we show that for many interesting functions, correlation gap is bounded irrespective of the dimension of the problem or type of marginal distributions. Additionally, we demonstrate the tightness of our characterization, that is, small correlation gap of a function implies existence of an "approximate" crossmonotonic cost-sharing scheme. This observation could also be useful for enhancing the understanding of such schemes, and may be of independent interest.

Consisting of two parts, this book presents papers describing publicly available stochastic programming systems that are operational. It presents a diverse collection of application papers in areas such as production, supply chain and scheduling, gaming, environmental and pollution control, financial modeling, telecommunications, and electricity.

This text presents a multi-disciplined view of optimization, providing students and researchers with a thorough examination of algorithms, methods, and tools from diverse areas of optimization without introducing excessive theoretical detail. This second edition includes additional topics, including global optimization and a real-world case study using important concepts from each chapter.

Introduction to Applied Optimization is intended for advanced undergraduate and graduate students and will benefit scientists from diverse areas, including engineers.

This book provides an essential introduction to Stochastic Programming, especially intended for graduate students. The book begins by exploring a linear programming problem with random parameters, representing a decision problem under uncertainty. Several models for this problem are presented, including the main ones used in Stochastic Programming: recourse models and chance constraint models. The book not only discusses the theoretical properties of these models and algorithms for solving them, but also explains the intrinsic differences between the models. In the book□s closing section, several case studies are presented, helping students apply the theory covered to practical problems. The book is based on lecture notes developed for an Econometrics and Operations Research course for master students at the University of Groningen, the Netherlands - the longest-standing Stochastic Programming course worldwide.

Optimization problems involving stochastic models occur in almost all areas of science and engineering, such as telecommunications, medicine, and finance. Their existence compels a need for rigorous ways of formulating, analyzing, and solving such problems. This book focuses on optimization problems involving uncertain parameters and covers the theoretical foundations and recent advances in areas where stochastic models are available. In Lectures on Stochastic Programming: Modeling and Theory, Second Edition, the authors introduce new material to reflect recent developments in stochastic programming, including: an analytical description of the tangent and normal cones of chance constrained sets; analysis of optimality conditions applied to nonconvex problems; a discussion of the stochastic dual dynamic programming method; an extended discussion of law invariant coherent risk measures and their Kusuoka representations; and in-depth analysis of dynamic risk measures and concepts of time consistency, including several new results.

This thesis addresses the topic of decision making under uncertainty, with particular focus on financial markets. The aim of this research is to support improved decisions in practice, and related to this, to advance our understanding of financial markets.

Stochastic optimization provides the tools to determine optimal decisions in uncertain environments, and the optimality conditions of these models produce insights into how financial markets work. To be more concrete, a great deal of financial theory is based on optimality conditions derived from stochastic optimization models. Therefore, an important part of the development of financial theory is to study stochastic optimization models that step-by-step better capture the essence of reality. This is the motivation behind the focus of this thesis, which is to study methods that in relation to prevailing models that underlie financial theory allow additional real-world complexities to be properly modeled. The overall purpose of this thesis is to develop and evaluate stochastic optimization models that support improved decisions under uncertainty on financial markets. The research into stochastic optimization in financial literature has traditionally focused on problem formulations that allow closed-form or `exact' numerical solutions; typically through the application of dynamic programming or optimal control. The focus in this thesis is on two other optimization methods, namely stochastic programming and approximate dynamic programming, which open up opportunities to study new classes of financial problems. More specifically, these optimization methods allow additional and important aspects of many real-world problems to be captured. This thesis contributes with several insights that are relevant for both financial and stochastic optimization literature. First, we show that the modeling of several real-world aspects traditionally not considered in the literature are important components in a model which supports corporate hedging decisions. Specifically, we document the importance of modeling term premia, a rich asset universe and transaction costs. Secondly, we provide two methodological contributions to the stochastic programming literature by: (i) highlighting the challenges of realizing improved decisions through more stages in stochastic programming models; and (ii) developing an importance sampling method that can be used to produce high solution quality with few scenarios. Finally, we design an approximate dynamic programming model that gives close to optimal solutions to the classic, and thus far unsolved, portfolio choice problem with constant relative risk aversion preferences and transaction costs, given many risky assets and a large number of time periods.

The aim of stochastic programming is to find optimal decisions in problems which involve uncertain data. This field is currently developing rapidly with contributions from many disciplines including operations research, mathematics, and probability. At the same time, it is now being applied in a wide variety of subjects ranging from agriculture to financial planning and from industrial engineering to computer networks. This textbook provides a first course in stochastic programming suitable for students with a basic knowledge of linear programming, elementary analysis, and probability. The authors aim to present a broad overview of the main themes and methods of the subject. Its prime goal is to help students develop an intuition on how to model uncertainty into mathematical problems, what uncertainty changes bring to the decision process, and what techniques help to manage uncertainty in solving the problems. In this extensively updated new edition there is more material on methods and examples including several new approaches for discrete variables, new results on risk measures in modeling and Monte Carlo sampling methods, a new chapter on relationships to other methods including approximate dynamic programming, robust optimization and online methods. The book is highly illustrated with chapter summaries and many examples and exercises. Students, researchers and practitioners in operations research and the optimization area will find it particularly of interest. Review of First Edition: "The discussion on modeling issues, the large number of examples used to illustrate the material, and the breadth of the coverage make 'Introduction to Stochastic Programming' an ideal textbook for the area." (Interfaces, 1998)

This book examines application and methods to incorporating stochastic parameter variations into the optimization process to decrease expense in corrective measures. Basic types of deterministic substitute problems occurring mostly in practice involve i) minimization of the expected primary costs subject to expected recourse cost constraints (reliability constraints) and remaining deterministic constraints, e.g. box constraints, as well as ii) minimization of the expected total costs (costs of construction, design, recourse costs, etc.) subject to the remaining deterministic constraints. After an introduction into the theory of dynamic control systems with random parameters, the major control laws are described, as open-loop control, closed-loop, feedback control and open-loop feedback control, used for iterative construction of feedback controls. For approximate solution of optimization and control problems with random parameters and involving expected cost/loss-type objective, constraint functions, Taylor expansion procedures, and Homotopy methods are considered, Examples and applications to stochastic optimization of regulators are given. Moreover, for reliability-based analysis and optimal design problems, corresponding optimization-based limit state functions are constructed. Because of the complexity of concrete optimization/control problems and their lack of the mathematical regularity as required of Mathematical Programming (MP) techniques, other optimization techniques, like random search methods (RSM) became increasingly important. Basic results on the convergence and convergence rates of random search methods are presented. Moreover, for the improvement of the sometimes very low convergence rate of RSM, search methods based on optimal stochastic decision processes are presented. In order to improve the convergence behavior of RSM, the random search procedure is embedded into a stochastic decision process for an optimal control of the probability distributions of the search variates (mutation random variables).

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