Professor Donald Goldfarb

Brief Bio:

Donald Goldfarb is the Alexander and Hermine Avanessians Professor in the Department of Industrial Engineering and Operations Research at Columbia University. Professor Goldfarb is internationally recognized for his contributions to the field of optimization, and in particular for the development and analysis of efficient and practical algorithms for solving various classes of optimization problems. His most well-known and widely used algorithms include the BFGS quasi-Newton method (QN) for unconstrained optimization, steepest-edge simplex algorithms for linear programming, and the Goldfarb-Idnani algorithm for convex quadratic programming. According to SIAM's president, Nick Higham [SIAM News 2016], Newton and quasi-Newton methods and simplex methods rank first and ninth, respectively among all "algorithms with the greatest influence on the development and practice of science and engineering in the 20th century". The BFGS and steepest-edge algorithms developed by Goldfarb, are the basis for the most successful variants of these classes of methods. Professor Goldfarb has also developed simplex and combinatorial algorithms for network flow problems, and interior-point methods for linear, quadratic and second-order cone programming. His recent work on robust optimization for portfolio selection, and first-order algorithms for image de-noising, compressed sensing and machine learning is also very highly cited.

After obtaining a BChE degree from Cornell University and MA and PhD degrees (also in chemical engineering) from Princeton University, Goldfarb spent two years as a post-doc in applied mathematics at the Courant Institute of Mathematical Sciences of NYU. In 1968, he moved to the City College of New York, where he co-founded the Department of Computer Sciences, serving 14 years on its faculty. During the 1979-80 academic year, Goldfarb was a Visiting Professor in the Department of Computer Science and the School of Operations Research and Industrial Engineering at Cornell University. In 1982, Goldfarb joined the IEOR Department at Columbia, serving as Chair for eighteen years from 1984-2002. He also served as Interim Dean of Columbia's School of Engineering and Applied Science during the 1994-95 and 2012-13 academic years and its Executive Vice Dean during the Spring 2012 semester.

Goldfarb is a SIAM Fellow. He was awarded the 2017 INFORMS John Von Neumann Theory Prize for Fundamental, Sustained Contributions to Theory in Operations Research and the Management Sciences, the Khachiyan Prize in 2013 for Life-time Accomplishments in Optimization and the Prize for Research Excellence in the Interface between OR and CS in 1995 by INFORMS, and was listed in The World's Most Influential Scientific Minds, 2014, as being among the 99 most cited mathematicians between 2002 and 2012. Goldfarb has served as an editor-in-chief of Mathematical Programming, an editor of the SIAM Journal on Numerical Analysis and the SIAM Journal on Optimization, and as an associate editor of Mathematics of Computation, Operations Research and Mathematical Programming Computation.

Current Research:

Professor Goldfarb's current research interests are in the development of algorithms for optimization problems involving a huge number of variables and an enormous amount of data typical of problems that arise in statistical machine learning. Because of the size and amount of data involved in these problems, a major focus of current research in this area has been on first-order and stochastic optimization methods. Initially, Goldfarb's research focused on convex models, such as empirical risk minimization with a logistic loss objective or on problems for which convex relaxations exist whose solutions give the solutions to the original problems with high probability. These problems include robust and stable principal component pursuit models, tensor completion models and inverse covariance selection models, among others.

In terms of algorithmic contributions, Goldfarb has developed fast alternating linearization methods, fast multiple-splitting methods, Bregman iterative algorithms, block-coordinate descent algorithms, proximal methods and conditional gradient (Frank-Wolfe) methods. All of these methods require only the computation of either gradients or subgradients and in many cases, through the use of splitting, involve subproblems that have closed-form solutions. Splitting is a technique that, by defining new variables, allows a complicated function to be decomposed into separate simpler functions and is a very powerful way of solving variational problems, problems in imaging, dictionary learning and other areas, as well as in statistical machine learning. Splitting is commonly used with the alternating direction method of multipliers (ADMM) and several of the above mentioned methods are related to ADMM.

Another focus of Goldfarb's research is the development of algorithms that take advantage of the structure, such as sparsity and group sparsity, low-rankness, and factorizability, inherent in the solutions to the problems of interest.

More recently, Goldfarb's research focus has shifted to stochastic methods, one of whose goals is trying to make use of the curvature of the objective function using only first-order computations. Specifically, he has developed stochastic block BFGS methods, stochastic variants of the Frank-Wolfe method and for nonconvex problems such as those that arise in deep neural network models, and damped BFGS methods. The block BFGS methods are an attempt to make as much use as possible of the information that has been obtained during a sequence of steps, each of which are only based on partial (stochastic) information. He has also developed adaptive quasi-Newton methods for self-concordant functions to avoid performing line searches, which are prohibitively expensive in big data applications.

In all of his work on developing efficient optimization algorithms, Goldfarb thoroughly analyzes their convergence, and often their rate of convergence and complexity.