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Chair's Column

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With this inaugural issue, the INFORMS Optimization Society is publishing a new newsletter: "INFORMS OS Today." It is a great pleasure to welcome Shabbir Ahmed (sahmed@isye.gatech.edu) as its Editor. Our plan is to start by publishing one issue each Spring. At some point we may add a Fall issue. Please let us know what you think about the newsletter.

The current issue features articles by the 2010 OS prize winners: George Nemhauser (Khachiyan Prize for Life-time Accomplishments in Optimization), Zhi-Quan (Tom) Luo (Farkas Prize for Mid-career Researchers), Anthony Man-Cho So (Prize for Young Researchers), and Shiqian Ma (Student Paper Prize). Each of these articles describes the prize-winning work in a compact form.

Also, in this issue, we have announcements of key activities for the OS: Calls for nominations for the 2011 OS prizes, a call for nominations of candidates for OS officers, and the 2012 OS Conference (to be held at the University of Miami, February 24–26, 2012). I want to emphasize that one of our most important activities is our participation at the annual INFORMS meetings, the next one being at the Charlotte Convention Center, Charlotte, North Carolina, November 13–16, 2011. Our participation at that meeting is centered on the OS sponsored clusters. The clusters and cluster chairs for that meeting mirror our list of Vice Chairs:

- Steven Dirkse, Computational Optimization and Software (sdirkse@gams.com)
- Oleg A. Prokopyev, Global Optimization (prokopyev@engr.pitt.edu)
- Oktay Günlük, Integer Programming (gunluk@us.ibm.com)
- Miguel Anjos, Linear Programming and Complementarity (miguel-f.anjos@polymtl.ca)
- Mauricio Resende, Networks (mgcr@research.att.com)
- Frank E. Curtis, Nonlinear Programming (frank.e.curtis@gmail.com)
- Huseyin Topaloglu, Stochastic Programming (ht88@cornell.edu)

Their hard work is the means by which we have a strong presence within INFORMS — and we *should* have a strong presence which reflects the OS membership of about 1000! Please contact any of the Vice Chairs to get involved.

Additionally for the Charlotte meeting, jointly with the INFORMS Computing Society, the OS is co-sponsoring a mini-cluster on “Surrogate and derivative-free optimization.” Please contact either of the co-chairs for this cluster, Nick Sahinidis (sahinidis@cmu.edu) and Christine Shoemaker (cas12@cornell.edu) to get involved.

Pietro Belotti is the new OS webmaster, and he will be pleased to get your feedback on our revamped website: `www.informs.org/Community/Optimization-Society`.

Finally, I would like to take this opportunity to thank our Most-Recent Past Chair Nick Sahinidis, and our Secretary/Treasurer Marina Epelman for making my job as Chair an enjoyable experience.

All of the OS officers and I look forward to seeing you next at Charlotte in November — in particular, at the OS Business Meeting which is always a great opportunity to have a couple of glasses of wine and catch up with members of our community.

Hooked on Optimization

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This article is based on a presentation I gave at a session sponsored by the Optimization Society at the INFORMS 2010 annual meeting where I had the great honor of being chosen as the first recipient of the Khachiyan Prize for Life-time Accomplishments in Optimization. I would like to thank the prize committee members Martin Grötschel, Arkadi Nemirovski, Panos Pardalos and Tamás Terlaky and my friends and colleagues Bill Cook, Gérard Cornuéjols and Bill Pulleyblank who nominated me.

I was first introduced to optimization in a course in operations research taught by Jack Mitten when I was an M.S. student in chemical engineering at Northwestern University in 1958. Chemical processes are a great source of optimization problems, but at that time not much was being done except for the use of linear programming for blending problems in the petro-chemical industry. When I learned about dynamic programming in this course and saw the schematic diagram of a multi-time period inventory problem, I realized that it sort of looked like a flow diagram for a multi-stage chemical process, which I would now think of as a path in a graph. The difference was that the serial structure would not suffice for many chemical processes. We needed more general graph structures that included feedback loops or directed cycles. So Jack Mitten, also a chemical engineer by training, and I embarked on how to extend dynamic programming type decomposition to more general structures. I realized that I needed to learn more about optimization than fluid flow, so after completing my Master’s degree I switched to the I.E. department with its fledgling program in operations research for my PhD, and this work on dynamic programming became my thesis topic. I quickly learned about the trial and tribulations of research and publication. As my work was about to be completed, I submitted a paper on it and was informed rather quickly that there was another paper in process on the same topic written by the very distinguished chemical engineer/mathematician Rutherford (Gus) Aris, a professor at the University of Minnesota. Aris was an Englishman, and a true scholar and gentleman. He was also a noted calligrapher and a professor of classics. After recovering from the initial shock of this news, I carefully read Aris' paper on dynamic programming with feedback loops, and discovered a fundamental flaw in his algorithm. It took some time to convince him of this, and we ultimately co-authored a paper [2], which was essentially my algorithm. This was a good introduction to the fact that the academic world was not an ivory tower. It also motivated by first book, *Introduction to Dynamic Programming* [19].

In 1961 I became an Assistant Professor in the department of Operations Research and Industrial Engineering at Johns Hopkins University. My first student Bill Hardgrave and I were trying to understand why the traveling salesman (TSP) problem seemed so much harder to solve than the shortest path problem (SPP). We thought we might have had a breakthrough when we figured out how to reduce the TSP to the longest path problem (LPP). Perhaps this was an early example of a polynomial reduction. But in our minds it was not, as is currently done, for the purpose of proving NP-hardness, a concept that would only appear more than a decade later. Our idea was that the LPP was closer to the SPP, so maybe we could solve the TSP by finding an efficient algorithm for the LPP. Being engineers, we liked the notion of physical models and especially the string model of Minty for solving the SPP - pull from both ends, and the first path to become tight is a shortest path. For the longest path build the graph with rubber bands instead of string - pull from both ends, and the last rubber band to remain slack is an edge of the longest path. Now you could proceed recursively. We actually built these rubber band models for graphs with up to about eight nodes, and our conjecture seemed to hold for our examples. However we were never able to prove the conjecture as we were unable to describe the physical model mathematically. Nevertheless, the work was published in *Operations Research* [15], my first of many papers in the journal of which I became the editor several years later. We also submitted the paper to the 4th International Symposium on Mathematical Programming held in 1962, but it was rejected. So I didn't get to one of these meetings until the 8th one in 1973. But I haven't missed one since then, and I wonder if I hold the record for consecutive attendance at these conferences.

George L. Nemhauser

Being an engineer, I tended to learn about optimization techniques and the underlying mathematics only as I needed to solve problems. My first real involvement with integer programming (IP), other than teaching a little about cutting planes and branch-and-bound, came from a seminar presentation on school districting. This was around the time when congressional districting at the state level was being examined by the federal courts. Many states, my current home state of Georgia was one of the worst, had congressional districts that were way out of balance with respect to the principle of "one man, one vote." The average congressional district should have had a population of around 400,000 then, but in Georgia they ranged from about 100,000 to nearly 800,000. The Supreme Court had just declared such districting plans to be unconstitutional, and redistricting was a hot topic. I had recently read a paper on solving vehicle routing problems using a set partitioning model, and it was easy to see that set partitioning was the right model for districting.

The difficulty was to describe feasible districts by population, compactness, natural boundaries and possibly political requirements. These districts would be constructed from much smaller population units such as counties in rural areas and smaller geographical units in urban areas. The cost of a district would be its population deviation from the mean given by the state's population divided by the number of congressional districts; i.e. the population of a perfect district. Given the potential districts, we then have the set partitioning problem of choosing a minimum cost set of districts such that each population unit is in exactly one district. My student, Rob Garfinkel worked on this districting problem for his doctoral research. Rob had been a programmer before beginning his graduate studies, and he made great use of his machine language programming skills in implementing our implicit enumeration algorithm [9]. Of course, our solutions were suboptimal since we generated all of our candidate districts up front. Branch-and-price hadn't entered my mind then.

Soon after that work was completed, in 1969 I left Hopkins for Cornell determined to learn more and do more IP. I was convinced that IP modeling was very robust for operations research applications but the models were hard to solve. One of the difficulties in getting students involved in integer programming was the absence of an IP book that could serve as a text for graduate students and also as a reference for researchers. Fortunately when I moved to Cornell, Garfinkel took a position at the University of Rochester only 90 miles from Ithaca, and we began collaborating on our book *Integer Programming* which was published in 1972 [10].

Also, motivated by the set partitioning work, I got my first NSF grant in IP, which was to study theory and algorithms for set packing, partitioning and covering. I worked with my student Les Trotter on polyhedral structure and algorithms for the node packing and independent set problem [22]. Our work was influenced by Ray Fulkerson who joined the Cornell faculty a couple of years after I did and taught us, among other things, the beautiful theory connecting perfect graphs and the class of IPs known as node packing. While Ray was not computationally oriented, he had insight on what made integer programs hard and gave us the family of Steiner triple set covering problems that are now part of the MIPLIB library of IP test problems and still remain difficult to solve [8]. Ray also started the cooperation between Cornell and Waterloo where Jack Edmonds and his students were doing exciting work on matroids, matching and other combinatorial optimization problems. I first met Bill Cunningham, Bill Pulleyblank and Vašek Chvátal when they were graduate students at Waterloo.

I became interested in transportation and especially using optimization to solve equilibrium problems of traffic assignment. Together with my student Deepak Merchant, we wrote the first papers on dynamic traffic assignment [18].

Marshall Fisher visited Cornell in 1974, and together with my student Gérard Cornuéjols, we worked on a facility location problem that was motivated by a problem of locating bank accounts so that companies could maximize the time they could hold money they owed and hence their cash flow. I think this was some of the early work on the analysis of approximation algorithms that is now so popular, and we were fortunate to receive the Lanchester prize for a paper we published on it [5].

I began my long and very fruitful collaboration with Laurence Wolsey in the fall of 1975 when I was the research director of the Center for Operations Research and Econometrics (CORE) at the University of Louvain. In generalizing the facility location analysis, Laurence, Marshall and I figured out that submodularity was the underlying principle [7]. Laurence and I wrote several papers during this period, but nothing on computational integer programming. I think that was typical of the 1970s. We just didn't have the software or the hardware to experiment with computational ideas. At the time I think it was fair to say that from a practical standpoint branch-and-bound was it.

However, beginning in the late 1970s and early 1980s a new era of computational integer programming based on integrating polyhedral combinatorics with branch-and-bound was born. As Laurence Wolsey and I saw, and participated in these exciting developments, we thought that the field needed a new integer programming book so that researchers would have good access to the rapid changes that were taking place. I think we first talked about this project in the late 1970s but I was chairman of the OR department at Cornell and didn't have the time until I had my sabbatical leave in 1983-84 at CORE. We worked very hard on the book that academic year not realizing that it would take us five more years to complete it [23]. We were honored when in 1989 it received the Lanchester prize. We tried not to get too distracted by all of the unsolved problems that arise in the process of putting results from papers into a book. But we couldn't resist studying the basic question of finding for mixed-integer problems the analog of Chvátal's rounding for pure integer programming. Solving that question led to what we called mixed-integer rounding, which has become a key tool for deriving cuts based on structure for mixed-integer programs [24].

After returning from CORE, I spent one more year at Cornell and then moved to Georgia Tech. By this time I really wanted to work on some real problems and to apply integer programming in practice. Ellis Johnson came to Tech soon thereafter having played a leadership role in the development of IBM's OSL code for mixed integer programming. Thanks to Ellis, IBM provided support for us to teach MIP short courses to people from industry using OSL. This opened up tremendous research opportunities with industry and led to long-term relations with several airlines and other companies mainly with supply chain optimization problems [1, 14, 16, 26]. These projects with industry generated many PhD dissertations including those of Pam Vance, Dan Adelman, Greg Glockner, Ladislav Lettowsky, Diego Klabjan, Andrew Schaefer, Jay Rosenberger and Jeff Day. Martin Savelsbergh and Cindy Barnhart joined our faculty and participated actively in our collaborations with industry. Some of this work led us to thinking about column generation in integer programming and to branch-and-price [4]. During this period, as Georgia Tech Faculty Representative for Athletics, I got involved with Mike Trick in sports scheduling. Our first work was scheduling basketball for the Atlantic Coast Conference [21]. Later on we formed a company called the Sports Scheduling Group, and we now, together with my student Kelly Easton, schedule major league baseball as well as several other sports conferences

OSL had a much better MIP solver than earlier commercial codes using some of the new technology like lifted cover cuts. But the ability to experiment with new ideas for cuts, branching, preprocessing and primal heuristics was still missing. My student Gabriel Sigismondi and I began the development of a MIP research code that was a branch-and-bound shell that would call an LP solver and would give the user all of the LP information needed to write subroutines for cuts, branching, etc. Martin Savelsbergh joined us from the Netherlands as a postdoc and became the key person in the creation of our research code called MINTO [20], which for many years was the code widely used by researchers in integer programming to evaluate the implementation of their theoretical results. Many of the ideas from MINTO, developed with Martin, were incorporated in the earlier releases of CPLEX's MIP code. In fact our student, Zhonghau Gu, became the key person in the development of the MIP code for subsequent releases of CPLEX and GUROBI. Several of my Georgia Tech students, including Alper Atamtürk, Ismael de Farias, Zhonghau Gu, Andrew Miller, Jean-Philippe Richard and Juan Pablo Vielma produced many new results in integer programming [3, 6, 11, 25, 27].

More recently, I have been collaborating with my colleague Shabbir Ahmed. Together with students, Yongpei Guan, Jim Luedtke and Juan Pablo Vielma, we have been making some progress on polyhedral aspects of stochastic integer programming [12, 13, 17].

I have been extremely fortunate throughout my academic career to have worked with an incredible group of PhD students and postdocs. I owe them a great debt, and they help keep me a young 73. So I would like to end this note by recognizing all of my graduated PhD students and postdoctoral associates by listing all of their names.

PHD STUDENTS

1961-69 Johns Hopkins (11): Bill Hardgrave, Hugh Bradley, Mike Thomas, Zev Ulmann, Gil Howard, Hank Nuttle, Dennis Eklof, Robert Garfinkel, Gus Widhelm, Joe Bowman, Sherwood Frey.

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POST DOCTORAL STUDENTS (6):
Ram Pandit, Natashia Boland, Petra Bauer, Emilie Danna, Bram Verweij, Menal Güzelsoy.

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First Order Methods for Large Scale Optimization: Error Bounds and Convergence Analysis

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1. Preamble

Needless to say, I am deeply honored by the recognition of the 2010 Farkas prize. Over the years, my research has been focused on various algorithmic and complexity issues in optimization that are strongly motivated by engineering applications. I think the 2010 Farkas prize is, more than anything, a recognition of this type of interdisciplinary optimization work.

Of course, doing research is not so much about winning a prize as it is about having fun, especially if you have an opportunity to work with smart colleagues and students. In this regard, I have been blessed. Collaborations with brilliant people like Paul Tseng and Jos Sturm had been a real source of inspiration. I am really fortunate to have worked closely with my professors at MIT, John Tsitsiklis and Dimitri Bertsekas, and later with colleagues like Jong-Shi Pang, Yinyu Ye and Shuzhong Zhang. They have taught me many things. Their energy and wisdom have shaped my research and enriched my academic life. To all of them and to the prize committee, I am deeply grateful.

If I have to pick one individual that had the most impact on my research over the last 20 years, it would be my close friend Paul Tseng, with whom I had published 20 journal papers. That amounts to one joint paper per year, for 20 years! This in itself is a true testament of the depth and breadth of our collaboration. It is to the fond memories of Paul that I dedicate this article.

In 1989 while I was finishing up my Ph.D thesis at MIT, Paul Tseng, then a postdoc with Bertsekas, posed an open question to me as a challenge: establish the convergence of the matrix splitting algorithm for convex QP with box constraints. We worked really hard for a few months and eventually settled this question. The set of techniques we developed for solving this problem turned out to be quite useful for a host of other problems and algorithms. This then led to a series of joint papers [1-7] published in the early part of 1990's in which we developed a general framework for the convergence analysis of first order methods for large scale optimization. This framework is broad, and allows one to establish linear rate of convergence in the absence of strong convexity. Most interestingly, some of this work has a direct bearing on the L_1-regularized sparse optimization found in many contemporary applications such as compressive sensing and imaging processing. In the following, I will briefly outline this algorithmic framework and the main analysis tools (i.e., error bounds), and mention their connections to the compressive sensing applications.

2. A General Framework

Let $f : \Re^n \mapsto \Re$ be a continuously differentiable function whose gradient is Lipschitz continuous on some nonempty closed convex set X in $\Re^n$. We are

Zhi-Quan Luo and Paul Tseng

interested in finding a stationary point of f over X, i.e., a point $x \in \Re^n$ satisfying

$$x = [x - \nabla f(x)]_X^+,$$

where $[\cdot]_X^+$ denotes the orthogonal projection onto X. We assume throughout that $\inf_{x \in X} f(x) > -\infty$ and that the set of stationary points, denoted by $\bar{X}$, is nonempty.

We consider a class of feasible descent methods that update the iterates according to

$$x^{r+1} := [x^r - \alpha^r \nabla f(x^r) + e^r]_X^+, \; r = 0, 1, ... \quad (1)$$

where e^r is a sufficiently small "error" vector satisfying

$$\|e^r\| \le \kappa_1 \|x^{r+1} - x^r\|, \quad \kappa_1 > 0,$$

and the step size α^r can be chosen either as a suitable constant, via the exact line search or by the Armijo rule. This is a broad class that includes a gradient projection algorithm of Goldstein and Levitin and Polyak, a certain matrix splitting algorithm for convex QP, coordinate descent methods, the extragradient method of Korpelevich, and the proximal minimization algorithm of Martinet, among others. The aforementioned methods have been studied extensively. Unfortunately, the existing analysis (prior to 1990) typically requires some nondegeneracy assumption on the problem (such as uniqueness of the solution) which does not hold for many "real-world" problems.

A new line of analysis was introduced by Tseng and myself whose key lies in a certain *error bound* which estimates the distance to the solution set $\bar{X}$ from an $x \in X$ near $\bar{X}$: for every $\upsilon \ge \inf_{x \in X} f(x)$ there exist scalars $\delta > 0$ and $\tau > 0$ such that

$$\mathrm{dist}(x, \bar{X}) \le \tau \|x - [x - \nabla f(x)]_X^+\|, \quad (2)$$

for all $x \in X$ with $f(x) \le \upsilon$ and $\|x - [x - \nabla f(x)]_X^+\| \le \delta$. In addition, we make a mild assumption on f and X regarding the "proper" separation of the isocost surfaces of f on the solution set $\bar{X}$: there exists a scalar $\epsilon > 0$ such that

$$x, \; y \in \bar{X}, \; f(x) \ne f(y) \; \Rightarrow \; \|x - y\| \ge \epsilon. \quad (3)$$

This condition holds whenever f takes on only a finite number of values on $\bar{X}$ or whenever the connected components of $\bar{X}$ are properly separated from each other. In particular, it holds automatically when f is convex.

By using the error bound (2) and the isocost surface separation condition (3), it has been shown that a sequence generated by iterations of the form (1) converges at least linearly to a stationary point in $\bar{X}$ (even if $\bar{X}$ is not a singleton). This result implies, as an immediate consequence, linear rate of convergence for, respectively, the extragradient method, the proximal minimization algorithm, and the coordinate descent method. A nice feature of these convergence results is that they do not require any nondegeneracy assumption on the problem.

We summarize below the known sufficient conditions for both (2) and (3) to hold.

(a) (Strongly convex case). f is strongly convex.

(b) (Quadratic case). f is quadratic. X is a polyhedral set.

(c) (Composite case). $f(x) = \langle q, x \rangle + g(Ex), \; \forall x$, where E is an $m \times n$ matrix with no zero column, q is a vector in $\Re^n$, and g is a strongly convex differentiable function in $\Re^m$ with ∇g Lipschitz continuous in $\Re^m$. X is a polyhedral set.

(d) (Dual functional case).

$$f(x) = \langle q, x \rangle + \max_{y \in Y} \{\langle Ex, y \rangle - g(y)\} \quad \forall x,$$

where Y is a polyhedral set in $\Re^m$, E is an $m \times n$ matrix with no zero column, q is a vector in $\Re^n$, and g is a strongly convex differentiable function in $\Re^m$ with ∇g Lipschitz continuous in $\Re^m$. X is a polyhedral set.

3. L_1-regularized Minimization

In contemporary applications of large scale convex optimization, we are interested in the L_1-regularized convex QP:

$$\min_{x \in \Re^n} f(x) = \lambda \|x\|_1 + \frac{1}{2}\|Ax - b\|^2, \quad (4)$$

where $\lambda > 0$ is a constant, A is an $m \times n$ matrix, and b is a vector in $\Re^m$. The optimization problem (4) arises naturally in compressive sensing applications where the goal is to obtain a sparse solution to a large but under-determined linear system $Ax = b$. Notice that if matrix A has full column rank, then $f(x)$ is strictly convex. However, in practical applications (e.g., compressive sensing), A is a fat matrix (i.e., $m \ll n$) and the objective function $f(x)$ may not be strictly convex, so there can be multiple optimal solutions for (4).

The main difference between (4) and the problem in Section 2 is the inclusion of a non-smooth term $\|x\|_1$ in the objective function. Can we extend the rate of convergence analysis framework described in Section 2 to this non-smooth setup? The answer is positive. In particular, Paul Tseng in 2001 (before the L_1-minimization became a hot research topic) showed a general result [8] for the coordinate descent method as long as the non-smooth term is separable across variables. Specialized to (4), Paul's result implies that each limit point generated by the coordinate descent algorithm for solving (4) is a global optimal solution. Recently, we have further strengthened this result to show that the entire sequence of iterates converge linearly to a global optimal solution (4) without any nondegeneracy assumption.

More generally, Paul Tseng considered [9] a class of proximal gradient method for minimizing over a convex set X an objective function $f(x) = f_1(x) + f_2(x)$, where both f_1 and f_2 are convex, but f_2 might be non-smooth. He showed that as long as the local error bound holds around the optimal solution set, the global linear convergence can be expected even in this non-smooth setup. Remarkably, Paul was able to establish a local error bound for the Group Lasso case where $f(x) = \lambda \sum_{J \in \mathcal{J}} \|x_J\|_2 + \frac{1}{2}\|Ax - b\|^2$. Here $\mathcal{J}$ is a partition of $\{1, 2, ..., n\}$ and x_J is a subvector of x with components taken from $J \in \mathcal{J}$. It is likely that this framework can be further extended to other types of non-smooth convex optimization problems/algorithms used for recovering sparse or low-rank solutions.

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Probability Inequalities for Sums of Random Matrices and Their Applications in Optimization

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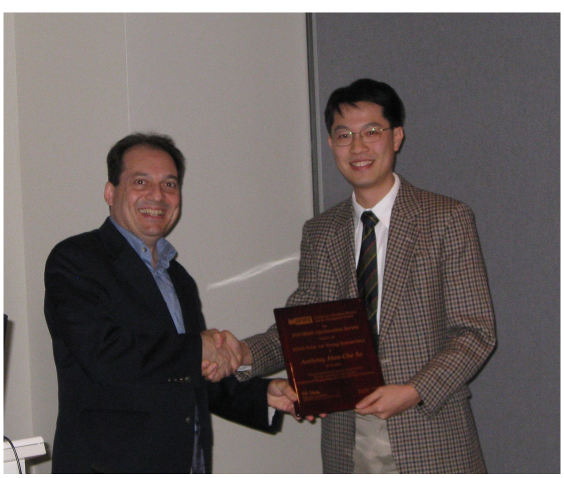
In this article, I will highlight the main ideas in my recent work *Moment Inequalities for Sums of Random Matrices and Their Applications in Optimization* (accepted for publication in *Mathematical Programming*, 2009) and discuss some of the recent developments.

The story begins with a groundbreaking work of Nemirovski [4], which revealed a close relationship between the theoretical properties of a host of optimization problems and the behavior of a sum of certain random matrices. Indeed, Nemirovski showed that the construction of so–called safe tractable approximations of certain chance constrained linear matrix inequalities, as well as the analysis of a semidefinite relaxation of certain non–convex quadratic optimization problems, can be achieved by answering the following question:

Question (Q) *Let $\xi_1, \ldots, \xi_h$ be independent mean zero random variables, each of which is either (i) supported on $[-1, 1]$, or (ii) normally distributed with unit variance. Furthermore, let $Q_1, \ldots, Q_h$ be arbitrary $m \times n$ matrices satisfying $\sum_{i=1}^h Q_i Q_i^T \preceq I$ and $\sum_{i=1}^h Q_i^T Q_i \preceq I$. Under what conditions on $t > 0$ will we have an exponential decay of the tail probability $\Pr\left(\left\|\sum_{i=1}^h \xi_i Q_i\right\|_\infty \geq t\right)$? Here, $\|A\|_\infty$ denotes the spectral norm of the $m \times n$ matrix A.*



Nick Sahinidis presenting the 2010 Young Researcher Prize to Anthony Man–Cho So

In a technical *tour de force*, Nemirovski showed that whenever $t \geq \Omega((m+n)^{1/6})$, the aforementioned tail probability will have an exponential decay. Moreover, he conjectured that the same result would hold for much smaller values of t, namely, for $t \geq \Omega(\sqrt{\ln(m+n)})$. As argued in [4], the threshold $\Omega(\sqrt{\ln(m+n)})$ is in some sense the best one could hope for. Moreover, if the above conjecture is true, then it would immediately imply improved performance guarantees for various optimization problems. Therefore, there is great interest in determining the validity of this conjecture.

As it turns out, the behavior of the matrix–valued random variable $S_h \equiv \sum_{i=1}^h \xi_i Q_i$ has been extensively studied in the functional analysis and probability theory literature. One of the tools that is particularly useful for addressing Nemirovski's conjecture is the so–called Khintchine–type inequalities. Roughly speaking, such inequalities provide upper bounds on the p–norm of the random variable $\|S_h\|_\infty$ in terms of suitable normalizations of the matrices $Q_1, \ldots, Q_h$. Once these bounds are available, it is easy to derive tail bounds for $\|S_h\|_\infty$ using Markov's inequality. In my work, I showed that the validity of Nemirovski's conjecture is in fact a simple consequence of the so–called non–commutative Khintchine's inequality in functional analysis [3] (see also [1]). Using this result, I was then able to obtain the best known performance guarantees for a host of optimization problems.

Of course, this is not the end of the story. In fact, it is clear from recent developments that the behavior of a sum of random matrices plays an important role in the design and analysis of many optimization algorithms. One representative example is the analysis of the nuclear norm minimization heuristic (see, e.g., [6] and the references therein). Furthermore, there has been some effort in developing easy–to–use recipes for deriving tail bounds on the spectral norm of a sum of random matrices [5, 7]. In a recent work [2], we applied such recipes to construct safe tractable approximations of chance–constrained linear matrix inequalities with dependent perturbations. Our results generalize the existing ones in several directions and further demonstrate the relevance of probability inequalities for matrix–valued random variables in the context of optimization.

In summary, recent advances in probability theory have yielded many powerful tools for analyzing matrix–valued random variables. These tools will be invaluable as we tackle matrix–valued random variables that arise quite naturally in many optimization problems.

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Fast Multiple Splitting Algorithms for Convex Optimization

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Our paper "Fast Multiple Splitting Algorithms for Convex Optimization" [3] considers alternating direction type methods for minimizing the sum of $K (K \geq 2)$ convex functions $f_i(x), i = 1, \ldots, K$:

$$\min_{x \in \mathbb{R}^n} F(x) \equiv \sum_{i=1}^{K} f_i(x). \tag{1}$$

Many problems arising in machine learning, medical imaging and signal processing etc., can be formulated as minimization problems of the form of (1). For example, the robust principal component analysis problem can be cast as minimizing the sum of two convex functions (see [2]):

$$\min_{X \in \mathbb{R}^{m \times n}} \|X\|_* + \rho \|M - X\|_1, \tag{2}$$

where $\|X\|_*$ is the nuclear norm of X, which is defined as the sum of the singular values of X, $\|Y\|_1 := \sum_{ij} |Y_{ij}|$, $M \in \mathbb{R}^{m \times n}$ and $\rho > 0$ is a weighting parameter. As another example, one version of the compressed sensing MRI problem can be cast as minimizing the sum of three convex functions (see [5]):

$$\min_{x \in \mathbb{R}^n} \alpha TV(x) + \beta \|Wx\|_1 + \tfrac{1}{2}\|Ax - b\|^2, \tag{3}$$

where $TV(x)$ is the total variation function, W is a wavelet transform, $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$ and $\alpha > 0, \beta > 0$ are weighting parameters. Although these problems can all be reformulated as conic programming problems, (e.g., (2) can be reformulated as a semidefinite programming problem and (3) can be reformulated as a second-order cone programming problem), polynomial-time methods such as interior-point methods are not practical for these problems because they are usually of huge size. However, these problems have a common property: although it is not easy to minimize the sum of the f_i's, it is relatively easy to solve problems of the form

$$\min_{x\in\mathbb{R}^n} \tau f_i(x) + \tfrac{1}{2}\|x-z\|_2^2$$

for each of the functions $f_i(x)$ for any $\tau > 0$ and $z \in \mathbb{R}^n$. Thus, alternating direction type methods that split the objective function and minimize each function f_i alternatingly can be effective for these problems.

The main contribution of [3] is two classes of alternating direction type methods, which are called multiple splitting algorithms (MSA) in [3], with provable iteration complexity bounds for obtaining an ϵ-optimal solution. For the unconstrained problem

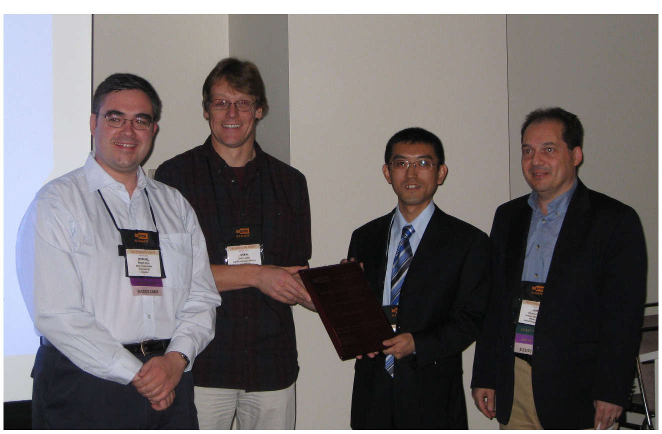
$$\min_x \quad f(x), \tag{4}$$

x is called an ϵ-optimal solution to (4) if $f(x) \le f(x^*) + \epsilon$, where x^* is an optimal solution to (4). Iteration complexity results for gradient methods have been well studied in the literature. It is known that if one applies the classical gradient method with step length τ_k

$$x^{k+1} := x^k - \tau_k \nabla f(x^k) \tag{5}$$

to solve (4), an ϵ-optimal solution is obtained in $O(1/\epsilon)$ iterations under certain conditions. In [6], Nesterov proposed techniques to accelerate (5). One of his acceleration techniques implements the following at each iteration:

$$\left\{\begin{array}{lll} x^{k+1} & := & y^k - \tau_k \nabla f(y^k) \\ y^{k+1} & := & x^k + \frac{k-1}{k+2}(x^k - x^{k-1}). \end{array}\right. \tag{6}$$



(Left to right) Miguel Anjos, Sven Leyffer, Shiqian Ma and Nick Sahinidis

Nesterov proved that the iteration complexity of (6) is $O(1/\sqrt{\epsilon})$ for obtaining an ϵ-optimal solution [6, 7]. He also proved that $O(1/\sqrt{\epsilon})$ is the best bound one can get if one uses only first-order information.

Our MSA algorithms are based on the idea of splitting the objective function into K parts and applying a linearization technique to minimize each function f_i plus a proximal term, alternatingly. The basic version of MSA iterates the following updates:

$$\left\{\begin{array}{ll} x^i_{(k+1)} := p_i(w^i_{(k)}, \ldots, w^i_{(k)}), & \forall i = 1,\ldots,K \\ w^i_{(k+1)} := \frac{1}{K}\sum_{j=1}^K x^j_{(k+1)}, & \forall i = 1,\ldots,K, \end{array}\right. \tag{7}$$

with initial points $w^1_{(0)} = \ldots = w^K_{(0)} = x_0$, where

$$\begin{array}{ll} & p_i(v^1,\ldots,v^{i-1},v^{i+1},\ldots,v^K) \\ := & \arg\min_u Q_i(v^1,\ldots,v^{i-1},u,v^{i+1},\ldots,v^K), \end{array}$$

$$\begin{array}{ll} & Q_i(v^1,\ldots,v^{i-1},u,v^{i+1},\ldots,v^K) \\ := & f_i(u) + \sum_{j=1,j\neq i}^K \tilde{f}_j(u,v^j) \end{array}$$

and

$$\tilde{f}_i(u,v) := f_i(v) + \langle \nabla f_i(v), u-v\rangle + \frac{1}{2\mu}\|u-v\|^2.$$

Notice that $Q_i(v^1,\ldots,v^{i-1},u,v^{i+1},\ldots,v^K)$ is an approximation to $F(u)$ that keeps the function $f_i(u)$ unchanged and linearizes the other functions $f_j(u), j \neq i$ while adding proximal terms.

The following theorem gives the iteration complexity result for Algorithm MSA.

Theorem 1 *Suppose x^* is an optimal solution to problem (1). Assume f_i's are smooth functions and their gradients are Lipschitz continuous with Lipschitz constants $L(f_i)$, i=1,...,K. If $\mu \le 1/\max_i\{L(f_i)\}$, then the sequence $\{x^i_{(k)}, w^i_{(k)}\}_{i=1}^K$ generated by MSA (7) satisfies:*

$$\min_{i=1,\ldots,K} F(x^i_{(k)}) - F(x^*) \le \frac{(K-1)\|x_0 - x^*\|^2}{2\mu k}.$$

Thus (7) produces a sequence that converges in objective function value. Also, when $\mu \ge \beta/\max_i\{L(f_i)\}$ where $0 < \beta \le 1$, to get an ϵ-optimal solution, the number of iterations required is $O(1/\epsilon)$.

The proof of this theorem basically follows an argument used by Beck and Teboulle in [1] for proving the iteration complexity of the Iterative Shrinkage/Thresholding Algorithm.

A fast version of MSA (FaMSA) is also presented in [3]. Under the same assumptions as in Theorem 1, the iteration complexity bound of FaMSA is improved to $O(1/\sqrt{\epsilon})$ while the computational effort in each iteration is almost the same as in MSA.

To the best of our knowledge, the iteration complexity results for MSA and FaMSA are the first ones of this type that have been given for alternating direction methods involving three or more directions (i.e., functions).

Our theorems require the functions to be smooth to prove the complexity. However, if any of the functions are not smooth as is the case in (2) and (3), we can use the smoothing technique proposed by Nesterov in [8] to smooth them. This smoothing technique also guarantees that the gradients of the smoothed functions are Lipschitz continuous.

The numerical results in [3] show that the multiple splitting algorithms are much faster than the classical interior-point method for solving some randomly created Fermat-Weber problems. Also, since the multiple splitting algorithms in [3] are all Jacobi type algorithms, their performance should be even better if they can be implemented in a parallel computing environment.

Gauss-Seidel type alternating linearization methods are studied in another paper [4].

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Nominations for Society Prizes Sought

The Society awards four prizes, now annually, at the INFORMS annual meeting. We seek nominations and applications for each of them, due by **June 30, 2011**. Details for each of the prizes, including eligibility rules and past winners, can be found by following the links from `http://www.informs.org/Community/Optimization-Society/Prizes`.

Each of the four awards includes a cash amount of US$ 1,000 and a citation certificate. The award winners will be invited to give a presentation in a special session sponsored by the Optimization Society during the INFORMS annual meeting in Charlotte, NC in November 2011 (the winners will be responsible for their own travel expenses to the meeting).

The **Khachiyan Prize** is awarded for outstanding life-time contributions to the field of optimization by an individual or team. The topic of the contribution must belong to the field of optimization in its broadest sense. Recipients of the INFORMS John von Neumann Theory Prize or the MPS/SIAM Dantzig Prize in prior years are not eligible for the Khachiyan Prize. The prize committee for the Khachiyan Prize is as follows:

- George Nemhauser (Chair)
  george.nemhauser@isye.gatech.edu
- Tamás Terlaky
- Yurii Nesterov
- Lex Schrijver

Nominations and applications for the Khachiyan Prize should be made via EasyChair `https://www.easychair.org/conferences/?conf=ioskp2011`. Please direct any inquiries to the prize-committee chair.

The **Farkas Prize** is awarded for outstanding contributions to the field of optimization by a researcher or a team of researchers. The contribution may be a published paper, a submitted and accepted paper, a series of papers, a book, a monograph, or software. The author(s) must have been awarded their terminal degree within twenty five calendar years preceding the year of the award. The prize committee for the Farkas Prize is as follows:

- Gérard Cornuéjols (Chair)
  gc0v@andrew.cmu.edu
- Alexander Shapiro
- David Shmoys
- Stephen Wright

Nominations and applications for the Farkas Prize should be made via email to the prize-committee chair. Please direct any inquiries to the prize-committee chair.

The **Prize for Young Researchers** is awarded to one or more young researcher(s) for an outstanding paper in optimization that is submitted to and accepted, or published in a refereed professional journal. The paper must be published in, or submitted to and accepted by, a refereed professional journal within the four calendar years preceding the year of the award. All authors must have been awarded their terminal degree within eight calendar years preceding the year of award. The prize committee for the Prize for Young Researchers is as follows:

- Jim Renegar (Chair)
  renegar@cornell.edu
- Dan Bienstock
- Endre Boros
- Tom McCormick

Nominations and applications for the Prize for Young Researchers should be made via email to the prize-committee chair. Please direct any inquiries to the prize-committee chair.

The **Student Paper Prize** is awarded to one or more student(s) for an outstanding paper in optimization that is submitted to and received or published in a refereed professional journal within three calendar years preceding the year of the award. Every nominee/applicant must be a student on the first of January of the year of the award. Any coauthor(s) not nominated for the award should send a letter indicating that the majority of the nominated work was performed by the nominee(s). The prize committee for the Student Paper Prize is as follows:

- Matthias Köppe (Chair)
  mkoeppe@math.ucdavis.edu
- Katya Scheinberg
- Jean-Philippe Richard

Nominations and applications for the Student Paper Prize should be made via email to the prize-committee chair. Please direct any inquiries to the prize-committee chair.

Nominations of Candidates for Society Officers Sought

Nick Sahinidis will have completed his term as Most-Recent Past-Chair of the Society at the conclusion of the 2011 annual INFORMS meeting. Jon Lee is continuing as Chair through 2012. Marina Epelman will have completed her (extended) term as Secretary/Treasurer, also at the conclusion of the INFORMS meeting. The Society is indebted to Nick and Marina for their work.

We would also like to thank four Society Vice-Chairs who will be completing their two-year terms at the conclusion of the INFORMS meeting: Miguel Anjos, Steven Dirkse, Oktay Günlük and Mauricio Resende.

We are currently seeking nominations of candidates for the following positions:

- **Chair-Elect**
- **Secretary/Treasurer**
- **Vice-Chair for Computational Optimization and Software**
- **Vice-Chair for Integer Programming**
- **Vice-Chair for Linear Programming and Complementarity**
- **Vice-Chair for Networks**

Self nominations for all of these positions are encouraged.

To ensure smooth transition of the chairmanship of the Society, the Chair-Elect is elected and serves a one-year term before assuming a two-year position as Chair; thus this is a three-year commitment. As stated in the Society Bylaws, "The Chair shall be the chief administrative officer of the OS and shall be responsible for the development and execution of the Society's program. He/she shall (a) call and organize meetings of the OS, (b) appoint ad hoc committees as required, (c) appoint chairs and members of standing committees, (d) manage the affairs of the OS between meetings, and (e) preside at OS Council meetings and Society membership meetings."

According to Society Bylaws, "The Secretary/Treasurer shall conduct the correspondence of the OS, keep the minutes and records of the Society, maintain contact with INFORMS, receive reports of activities from those Society Committees that may be established, conduct the election of officers and Members of Council for the OS, make arrangements for the regular meetings of the Council and the membership meetings of the OS. As treasurer, he/she shall also be responsible for disbursement of the Society funds as directed by the OS Council, prepare and distribute reports of the financial condition of the OS, help prepare the annual budget of the Society for submission to INFORMS. It will be the responsibility of the outgoing Secretary/Treasurer to make arrangements for the orderly transfer of all the Society's records to the person succeeding him/her." The Secretary/Treasurer shall serve a two-year term.

According to Society Bylaws, "The main responsibility of the Vice Chairs will be to help INFORMS Local Organizing committees identify cluster chairs and/or session chairs for the annual meetings. In general, the Vice Chairs shall serve as the point of contact with their sub-disciplines." Vice Chairs shall serve two-year terms.

Please send your nominations or self-nominations to Marina Epelman (mepelman@umich.edu), including contact information for the nominee, by Sunday, **July 31, 2011**. Online elections will begin in mid-August, with new officers taking up their duties at the conclusion of the 2011 annual INFORMS meeting.

Announcing the Fourth INFORMS Optimization Society Conference

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The School of Business Administration at the University of Miami is pleased to host the Fourth INFORMS Optimization Society conference to take place on the Coral Gables campus of the University of Miami, February 24–26, 2012. The theme of the conference is "Optimization and Analytics: New Frontiers in Theory and Practice." The Conference Co-Chairs are Anuj Mehrotra and Michael A. Trick. The Organizing Committee includes Edward Baker, Hari Natarajan and Tallys Yunes. Further details will gradually appear on the conference web site at `http://www.bus.miami.edu/events/ios2012/index.html`.

Previous editions of the conference were at San Antonio (2006), Atlanta (2008) and Gainesville (2010). Some of you may know/remember that the School of Business Administration at the University of Miami hosted the wonderful Mixed-Integer Programming meeting, MIP 2006. Anyone who was at that meeting knows that it is a delightful venue – especially in February.