

# The 14th International Conference on Numerical Optimization and Numerical Linear Algebra

August 15-18, 2023

TAIYUAN, SHANXI, CHINA

http://lsec.cc.ac.cn/~icnonla23

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**Information for Participants** 

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## Information for Participants

Conference Information

Hotel:	Jinci Hotel Taiyuan
	山西晋祠宾馆
Address:	No.669 Jinci Scenic Area, Jinyuan Qu, Taiyuan, Shanxi
	太原市晋源区晋祠风景名胜旅游区 669 号
Venue:	Huanghe Hall, Conference Center
	会议中心黄河厅

### Arrival

By air: the distance between Taiyuan Wusu International Airport and the conference hotel is about 23 km. It will cost you about 40 RMB (5.79 USD c.a.) to take a taxi. For the invited speakers, you will be picked up at the airport if you have sent your arrival information to the organizing committee.

By train: there is about 23 km from Taiyuannan railway station to the conference hotel. The taxi fare is about 38 RMB (5.5 USD c.a.)

### On-site Registration

On-site registration will take place at the **ground floor lobby**, **building 9, Jinci Hotel, Taiyuan** on **August 14** from **09:00** to **21:00**.

You can also register at any other time during the conference, but please contact Ms. Ying Liu in advance.

### Currency

Chinese currency is RMB. The current rate is about 7.15 RMB for 1 US dollar. The exchange of foreign currency can be done at the airport or the banks in Taiyuan. Please keep the receipt of the exchange so that you can change back to your own currency if you have RMB left before you leave China. Please notice that some additional processing fee will be charged if you exchange currency in China.

### Contact Information

If you need any help, please feel free to contact

• Ms. Ying Liu: +86-138-1080-6086

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# The 14th International Conference on Numerical Optimization and Numerical Linear Algebra

### AUGUST 15-18, 2023

## TAIYUAN, SHANXI, CHINA

### **Conference Schedule**

### August 15, Tuesday

08:30-09:00 Opening Ceremony

08:30-08:45 Welcome Address 08:45-09:00 Group Photo

09:00-10:25 Invited Talks V1

Chair: Ya-xiang Yuan

09:00-09:40 Zhi-Quan Luo, Converge or Diverge? A Story of Adam09:45-10:25 Yurii Nesterov, New Perspectives for Higher-Order Methods in Convex Optimization

10:25-10:45 Break

10:45-12:10 Invited Talks V2

#### Chair: Yu-Hong Dai

- 10:40-11:25 Thorsten Koch, Current Progress in MILP and QUBO Solving
- 11:30-12:10 Houduo Qi, Sparse SVM with Hard-Margin Loss: Newton-Augmented Lagrangian Method in Reduced Dimensions

12:15-14:00 Lunch

#### 14:30-15:30 Contributed Talks C1

#### Chair: Ya-Feng Liu

- 14:30-14:50 Zai Yang, SMART Spectral Analysis of Signals
- 14:50-15:10 Zheyu Wu, A Negative  $\ell_1$  Penalty Approach for One-Bit Precoding
- 15:10-15:30 Kaimin Wang, Resource Allocation for Reconfigurable Intelligent Surface Aided Broadcast Channels

#### 15:30-15:50 Break

## 15:50-17:10 Contributed Talks C2

#### Chair: Junjie Ma

- 15:50-16:10 Qingna Li, A Fast Smoothing Newton Method for Bilevel Hyperparameter Optimization for SVC with Logistic Loss
- 16:10-16:30 Shuyu Dong, Learning Large Causal Structures from Inverse Covariance Matrix via Matrix Decomposition
- 16:30-16:50 Yukuan Hu, Sampling-Based Approaches for Multimarginal Optimal Transport Problems with Coulomb Cost
- **16:50-17:10 Weiyi Shao**, On the Complexity of a Stochastic Levenberg-Marquardt Method

#### 17:30 Dinner

### August 16, Wednesday

09:00-10:25 Invited Talks V3

#### Chair: Yanfei Wang

- **09:00-09:40 Gang Bao**, Some New Directions in Computational Inverse Problems
- 09:45-10:25 Weiguo Gao, Solving Eigenvalue Problems in Quantum Many-Body Systems and Data Science

#### 10:25-10:45 Break

10:45-12:10 Invited Talks V4

Chair: Zaiwen Wen

- 10:45-11:25 Wen Li, Multi-linear PageRank: Theory and Algorithms
- 11:30-12:10 Tomohiro Sogabe, Numerical Algorithms for Computing Singular Values of a Generalized Tensor Sum

12:15-14:00 Lunch

### 14:30-15:30 Contributed Talks C3 Chair: Jinyan Fan

- 14:30-14:50 Chunfeng Cui, Dual Number Matrices with Nonnegative Standard Parts and Dual Markov Chain
- 14:50-15:10 Lei Wang, Decentralized Optimization over the Stiefel Manifold by an Approximate Augmented Lagrangian Function
- 15:10-15:30 Yuhai Zhang, An Overlap-Based Branching Scheme for Covering Location Problems

#### 15:30-15:50 Break

## 15:50-17:10 Contributed Talks C4

### Chair: Bin Gao

- 15:50-16:10 Zi Xu, Primal Dual Alternating Proximal Gradient Algorithms for Nonsmooth Nonconvex Minimax Problems with Coupled Linear Constraints
- 16:10-16:30 Xiaoyu Wang, Generalized Polyak Step Size for First Order Optimization with Momentum
- 16:30-16:50 Nachuan Xiao, Convergence Guarantees for Stochastic Subgradient Methods in Nonsmooth Nonconvex Optimization
- 16:50-17:10 Jiayuan Wu, Convergence Analysis of an Adaptively Regularized Natural Gradient Method
- 17:30 Dinner

### August 17, Thursday

### 09:00-10:25 Invited Talks V5 Chair: Xin Liu

- **09:00-09:40** Lin Xiao, A Gauss-Newton Method for Minimizing Nonnegative Smooth Functions
- 09:45-10:25 Geovani N. Grapiglia, Recent Result on Nonmonotone Line-Search Methods

#### 10:25-10:45 Break

10:45-11:25 Invited Talks V6

### Chair: Thorsten Koch

10:45-11:25 Wenbao Ai, On the Tightness of an SDP Relaxation for Homogeneous QCQP with Three Real or Four Complex Constraints

### 11:30-12:10 Contributed Talks C5 Chair: Xinwei Liu

- 11:30-11:50 Tom M. Ragonneau, COBYQA: A Derivative-Free Trust-Region SQP Method for Nonlinearly Constrained Optimization
- 11:50-12:10 Pengcheng Xie, A New Model-Based DFO Method Using an Improved Under-Determined Model

12:15-14:00 Lunch

### 14:30-15:30 Contributed Talks C6 Chair: Zaikun Zhang

- 14:30-14:50 Ming Yan, Optimal Gradient Tracking for Decentralized Optimization
- 14:50-15:10 Kun Yuan, Unbiased Compression Saves Communication in Distributed Optimization: When and How Much?
- 15:10-15:30 Shi Pu, Distributed Stochastic Gradient Methods over Networks

15:30-15:50 Closing Ceremony

17:30 Dinner

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## Free Discussion

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# Part I

Invited Talks

### On the Tightness of an SDP Relaxation for Homogeneous QCQP with Three Real or Four Complex Constraints

#### Wenbao Ai

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In this talk, we consider the problem of minimizing a general homogeneous quadratic function, subject to three real or four complex homogeneous quadratic inequality or equality constraints. For this problem, we present firstly a sufficient and necessary test condition to detect whether its typical semidefinite programming (SDP) relaxation is tight or not. This test condition is easily verifiable, and is based on only an optimal solution pair of the SDP relaxation and its dual. When the tightness is confirmed, a global optimal solution of the original problem is found simultaneously in polynomial-time. Furthermore, as an application of the test condition, S-lemma and Yuan's lemma are generalized to three real and four complex quadratic forms first under certain exact conditions, which improves some classical results in literature.

### Some New Directions in Computational Inverse Problems

Gang Bao

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Inverse problems are concerned with determining model parameters from the observed data, which have played an important role in diverse application areas. A well-known representative inverse problem is electrical impedance tomography (EIT), also known as Calderón's problem, which determines the electrical conductivity from the voltage to current map on the boundary. The EIT problem arises in many practical applications, such as medical imaging and nondestructive testing. However, the problem is known to be severely ill-posed, in particular, small perturbations in the measured data may lead to large errors in the reconstructions. Stable numerical solution of the EIT problem remains a big challenge in computational inverse problems. In this talk, the speaker will discuss some new directions for solving inverse problems. Of particular interest are recursive linearization methods based on multiple frequency data, deep learning methods, and optimal transportation approaches. These methods are shown to be suitable for solving severely ill-posed problems. Numerical results will be presented to validate the effectiveness and feasibility of the methods.

### Solving Eigenvalue Problems in Quantum Many-Body Systems and Data Science

#### Weiguo Gao

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This talk presents our collaborative work on the development of algorithms for solving various eigenvalue problems found in physical sciences and data science. We introduce a novel orthogonalization-free method accompanied by two specific algorithms designed to tackle extreme eigenvalue problems. Additionally, we propose the linearization method as a solution for eigenvalue-dependent nonlinear eigenvalue problems and discuss the convergence of eigenvector-dependent nonlinear methods. Furthermore, we explore the potential of applying reinforcement learning algorithms to address large-scale k-sparse eigenvalue problems. Through experimental demonstrations, we showcase the efficiency of these newly developed algorithms.

### **Recent Result on Nonmonotone Line-Search Methods**

Geovani N. Grapiglia

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Nonmonotone line-search methods form an important class of iterative methods for smooth unconstrained optimization. In this talk, we present a general framework that includes most of existing nonmonotone methods as particular cases. Under mild assumptions, worst-case complexity results are established. The generality of our results allow more freedom for the development of new algorithms with convergence guarantees. Exploiting this flexibility, we design new nonmonotone methods tailored to problems with many non-global local minimizers. Adaptations of our general method in the context of nonlinear equations and nonsmooth convex optimization will also be discussed.

### Current Progress in MILP and QUBO Solving

Thorsten Koch

Institut für Mathematik Technische Universität Berlin Berlin, Germany Applied Algorithmic Intelligence Methods Department Zuse Institute Berlin Berlin, Germany Email: koch@zib.de

It is regularly claimed that quantum computers will bring breakthrough progress in solving challenging combinatorial optimization problems relevant in practice. In particular, Quadratic Unconstraint Binary Optimization (QUBO) problems are said to be the model of choice for use in (adiabatic) quantum systems during the NISQ era. Even the first commercial quantum-based systems are advertised to solve such problems. QUBO is an interesting way of modeling combinatorial optimization problems. Theoretically, any Mixed Integer Program can be converted into a QUBO. In practice, however, there are some caveats. We review the state of QUBO solving on digital computers and give insights regarding current benchmark instances and modeling. Any Integer Linear and Quadratic Program can be reformulated as a QUBO and vice-versa. In many cases, the fastest way to solve QUBOs is to solve them as Integer Linear Programs. We report on a study investigating the progress made in LP and MILP solver performance during the last two decades by comparing the solver software from the beginning of the millennium with the current codes. On average, we found out that the total speed-up for solving LP/MILP was about 180 and 1,000 times, respectively. However, these numbers have a very high variance, and they considerably underestimate the progress made on the algorithmic side: many problem instances can nowadays be solved within seconds, which the old codes cannot solve within any reasonable time. We will report on how we measure performance and why it is challenging to compute one reasonable number. Finally, taking the results into perspective, we get an idea of how much Quantum Computers need to get faster to challenge digital computers to solve combinatorial optimization problems.

### Multi-linear PageRank: Theory and Algorithms

Wen Li

School of Mathematical Sciences South China Normal University Guangzhou, China Email: liwen@scnu.edu.cn

Multi-linear PageRank is a generalization of PageRank, which can be applied to Data clustering, Hypergraph partitioning etc. In this talk we focus on theoretical analysis and numerical algorithms for solving multi-linear PageRank in recent years. Numerical examples are given to illustrate the efficiency of the proposed algorithms.

### Converge or Diverge? A Story of Adam

Zhi-Quan Luo

School of Science and Engineering The Chinese University of Hong Kong, Shenzhen Shenzhen, China Email: luozq@cuhk.edu.cn

Adam is one of the most popular algorithms in deep learning, used in lots of applications including ChatGPT. Despite the popularity, the theoretical properties of Adam were largely unknown, and how to tune Adam was not clear. Reddi et al. (2018) pointed out the divergence issue of Adam, and since then many variants of Adam were proposed. However, vanilla Adam remains exceptionally popular and it works well in practice. Why is there a gap between theory and practice? We point out there is a mismatch between the settings of theory and practice: Reddi et al. (2018) pick the problem after picking the hyperparameters of Adam, i.e.,  $(\beta_1, \beta_2)$ ; while practical applications often fix the problem first and then tune  $(\beta_1, \beta_2)$ . We conjecture for the latter practical setting, i.e. allowing tuning hyperparameters, Adam can converge. In this talk, we present our recent findings that confirm this conjecture. More specifically, we show that when the 2nd-order momentum parameter  $\beta_2$  is large enough and 1st-order momentum parameter  $\beta_1 < \sqrt{\beta_2} < 1$ , Adam converges. In general, Adam converges to the neighborhood of critical points; and under an extra condition (strong growth condition), Adam converges to critical points. These results lead to suggestions on how to tune Adam hyperparameters, which are confirmed by empirical experiments.

### New Perspectives for Higher-Order Methods in Convex Optimization

Yurii Nesterov

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In the recent years, the most important developments in Optimization were related to clarification of abilities of the higher-order methods. These schemes have potentially much higher rate of convergence as compared to the lower-order methods. However, the possibility of their implementation in the form of practically efficient algorithms was questionable during decades. In this talk, we discuss different possibilities for advancing in this direction, which avoid all standard fears on tensor methods (memory requirements, complexity of computing the tensor components, etc.). Moreover, in this way we get the new second-order methods with memory, which converge provably faster than the conventional upper limits provided by the Complexity Theory.

### Sparse SVM with Hard-Margin Loss: Newton-Augmented Lagrangian Method in Reduced Dimensions

#### Houduo Qi

Department of Applied Mathematics The Hong Kong Polytechnic University Hong Kong, China Email: houduo.qi@polyu.edu.hk

The hard margin loss function has been at the core of the support vector machine (SVM) research from the very beginning due to its generalization capability. On the other hand, the cardinality constraint has been widely used for feature selection, leading to sparse solutions. This paper studies the sparse SVM with the hard-margin loss that integrates the virtues of both worlds. However, SSVM-HM is one of the most challenging models to solve. In this paper, we cast the problem as a composite optimization with the cardinality constraint. We characterize its local minimizers in terms of P-stationarity that well captures the combinatorial structure of the problem. We then propose an inexact proximal augmented Lagrangian method (iPAL). The different parts of the inexactness measurements from the P-stationarity are controlled on different scales in a way that the generated sequence converges both globally and at a linear rate. This matches the best convergence theory for composite optimization. To make iPAL practically efficient, we propose a gradient-Newton method in a subspace for the iPAL subproblem. This is accomplished by detecting active samples and features with the help of the proximal operator of the hard margin loss and the projection of cardinality constraint. Extensive numerical results on both simulated and real datasets demonstrate that the proposed method is fast, produces sparse solution of high accuracy, and can lead to effective reduction on active samples and features when compared with several leading solvers. This is a joint work with Prof XIU Naihua and Zhang Penghe.

### Numerical Algorithms for Computing Singular Values of a Generalized Tensor Sum

Tomohiro Sogabe

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We consider computing singular values of the following generalized tensor sum:

$$T := I_n \otimes I_m \otimes A + I_n \otimes B \otimes I_\ell + C \otimes I_m \otimes I_\ell \in \mathbb{R}^{\ell m n \times \ell m n},\tag{1}$$

where  $A \in \mathbb{R}^{\ell \times \ell}$ ,  $B \in \mathbb{R}^{m \times m}$ ,  $C \in \mathbb{R}^{n \times n}$ ,  $I_m$  is the  $m \times m$  identify matrix, and the symbol " $\otimes$ " denotes the Kronecker product (tensor product).

The generalized tensor sum (1) arises in a discretization of partial differential equations such as the stationary convection-diffusion equation and the Helmholtz equation. Utilizing the tensor structure, computing the eigenvalues is a relatively easy task, i.e., the eigenvalues can be written as a simple function of the eigenvalues of much smaller matrices A, B, and C, reducing the possibly huge eigenvalue problem to three small eigenvalue problems. On the other hand, computing singular values of (1) may not have such a relation, leading to the requirement of (memory-efficient) numerical algorithms.

We have been working on (memory-efficient and cost-efficient) numerical algorithms for some singular values of the generalized tensor sum (1). For the extremal singular values, the Lanczos bidiagonalization method over a tensor space was proposed in [1]. It was, however, experimentally found that the convergence to the minimum singular value tended to be slow. This motivated us to develop the invert Lanczos bidiagonalization method over tensor space for computing the smallest singular value [2]. Further, the shiftand-invert Lanczos bidiagonalization method over tensor space was proposed for computing an arbitrary singular value in [3]. In this talk, these studies are explained in a unified manner based on the review paper [4]. For the shift-and-invert Lanczos bidiagonalization method over tensor space, Krylov subspace methods (see, e.g., [5]) play an important role in efficiently computing singular values.

#### References

- [1] A. Ohashi, T. Sogabe, On computing maximum/minimum singular values of a generalized tensor sum, Electron. Trans. Numer. Anal., 43 (2015), pp. 244-254.
- [2] A. Ohashi, T. Sogabe, On computing the minimum singular value of a tensor sum, Special Matrices, 7 (2019), pp. 95-106.

- [3] A. Ohashi, T. Sogabe, Numerical algorithms for computing an arbitrary singular value of a tensor sum, Axioms 10 (2021), 211. (14pp.)
- [4] A. Ohashi, T. Sogabe, Recent development for computing singular values of a generalized tensor sum, J. Adv. Simul. Sci. Eng. (JASSE), 9 (2022), pp. 136-149. (Invited paper)
- [5] T. Sogabe, Krylov Subspace Methods for Linear Systems Principles of Algorithms, Springer Series in Computational Mathematics, Springer, 2023.

### A Gauss-Newton Method for Minimizing Nonnegative Smooth Functions

#### Lin Xiao

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We consider the problem of minimizing the average of a large number of smooth but possibly non-convex functions. For machine learning applications, each of the loss functions has the extra property of being non-negative and thus can be written as the composition of the square and its real-valued square root. With such a seemingly trivial reformulation, we can apply the Gauss-Newton method, or the Levenberg-Marquardt method by adding a quadratic regularization. We show that the resulting algorithm is highly adaptive and can automatically warm up and decay the effective step size while tracking the loss landscape. We provide convergence analysis of this method in convex, non-convex and stochastic settings. Both the convergence rates and empirical evaluations compare favorably to the classical (stochastic) gradient method. This is joint work with Antonio Orvieto from ETH Zurich.

# Part II

**Contributed Talks** 

### Dual Number Matrices with Nonnegative Standard Parts and Dual Markov Chain

Chunfeng Cui

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We propose a dual Markov chain model to accommodate probabilities as well as perturbation, or error bounds, or variances, in the Markov chain process. This motivates us to extend the Perron-Frobenius theory to dual number matrices with primitive and irreducible nonnegative standard parts. We show that such a dual number matrix always has a positive dual number eigenvalue with a positive dual number eigenvector. The standard part of this positive dual number eigenvalue is larger than or equal to the modulus of the standard part of any other eigenvalue of this dual number matrix. We present an explicit formula to compute the dual part of this positive dual number eigenvalue. The Collatz minimax theorem also holds here. The results are nontrivial as even a positive dual number matrix may have no eigenvalue at all. An algorithm based upon the Collatz minimax theorem is constructed. The convergence of the algorithm is studied. We give an upper bound on the distance of stationary states between the dual Markov chain and the perturbed Markov chain. Numerical results on both synthetic examples and dual Markov chain including some real world examples are reported.

This talk is based on the joint work with Prof. Liqun Qi.

### Learning Large Causal Structures from Inverse Covariance Matrix via Matrix Decomposition

#### Shuyu Dong

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Learning causal structures from observational data is a fundamental yet highly complex problem when the number of variables is large. In this paper, we start from linear structural equation models (SEMs) and investigate ways of learning causal structures from the inverse covariance matrix. The proposed method, called O-ICID (for Independencepreserving Decomposition from Oracle Inverse Covariance matrix), is based on continuous optimization of a type of matrix decomposition that preserves the nonzero patterns of the inverse covariance matrix. We show that O-ICID provides an efficient way for identifying the true directed acyclic graph (DAG) under the knowledge of noise variances. With weaker prior information, the proposed method gives directed graph solutions that are useful for making more refined causal discovery. The proposed method enjoys a low complexity when the true DAG has bounded node degrees, as reflected by its time efficiency in experiments in comparison with state-of-the-art algorithms.

### Sampling-Based Approaches for Multimarginal Optimal Transport Problems with Coulomb Cost

#### Yukuan Hu

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The multimarginal optimal transport problem with Coulomb cost arises in quantum physics and is vital in understanding strongly correlated quantum systems. Its intrinsic curse of dimensionality can be overcome with a Monge-like ansatz. A nonconvex quadratic programming then emerges after employing discretization and  $\ell_1$  penalty. To globally solve this nonconvex problem, we adopt a grid refinements-based framework, in which a local solver is heavily invoked and hence significantly determines the overall efficiency. The block structure of this nonconvex problem suggests taking block coordinate descent-type methods as the local solvers, while the existing ones can get seriously afflicted with the poor scalability induced by the associated sparse-dense matrix multiplications. In this work, borrowing the tools from optimal transport, we develop novel methods that favor highly scalable schemes for subproblems and are completely free of the full matrix multiplications after introducing entrywise sampling. Convergence and asymptotic properties are built on the theory of random matrices. The numerical results on several typical physical systems corroborate the effectiveness and better scalability of our approach, which also allows the first visualization for the approximate optimal transport maps between electrons in threedimensional contexts.

### A Fast Smoothing Newton Method for Bilevel Hyperparameter Optimization for SVC with Logistic Loss

#### Qingna Li

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SVC with logistic loss has excellent theoretical properties in classification problems where the label values are not continuous. In this paper, we reformulate the hyperparameter selection problem for support vector classification with logistic loss as a bilevel optimization problem in which the upper-level problem and the lower-level problem are both based on logistic loss. The resulting bilevel optimization model is converted to a single-level nonlinear programming (NLP) problem based on the KKT condition of lowerlevel problem. Such nonlinear programming contains a set of nonlinear equality constraints and a simple lower bound constraint. To solve such NLP, we apply a smoothing Newton method to solve the KKT system, which contains one pair of complementarity constraints. We show that the smoothing Newton method has a superlinear convergence rate. Extensive numerical results verify the efficiency of the proposed approach. In particular, compared with other methods, our algorithm can achieve competitive results while consuming less time than other methods.

### Distributed Stochastic Gradient Methods over Networks

#### Shi Pu

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In this talk, we discuss several distributed stochastic gradient methods that enjoy the so-called asymptotic network independence property, which is achieved whenever a distributed method executed over a network of n nodes asymptotically converges to the desirable solution at a comparable rate to a centralized method with the same computational power as the entire network; it is as if the network is not even there! In particular, we discuss how to design algorithms to improve the transient times for achieving the network independent convergence rates and how to save communication costs through compression. We also introduce some new results on distributed random reshuffling (RR) methods.

### COBYQA: A Derivative-Free Trust-Region SQP Method for Nonlinearly Constrained Optimization

#### Tom M. Ragonneau

Department of Applied Mathematics The Hong Kong Polytechnic University Hong Kong, China Email: tom.ragonneau@polyu.edu.hk

This talk introduces COBYQA, a derivative-free trust-region SQP method for general nonlinear optimization problems. The method builds the trust-region quadratic models using Powell's derivative-free symmetric Broyden update. An essential feature of COBYQA is that it always respects bound constraints, if any. COBYQA is competitive with NEWUOA and BOBYQA while being able to handle more general problems. On linearly constrained problems, COBYQA outperforms LINCOA if the problems contain bound constraints that cannot be violated. Most importantly, COBYQA outperforms COBYLA on all types of problems, regardless of whether bound constraints (if any) can be violated.

COBYQA is implemented in Python and is publicly available at https://www.cobyqa.com. This is joint work with Zaikun Zhang.

### On the Complexity of a Stochastic Levenberg-Marquardt Method

#### Weiyi Shao

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In this report, we introduce a stochastic Levenberg-Marquardt algorithm for nonlinear least squares problems. We study the global complexity of the algorithm and give an upper bound of the expected iteration number to get an approximate solution at which the gradient norm of the objective function is less than a given tolerance.

### Resource Allocation for Reconfigurable Intelligent Surface Aided Broadcast Channels

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For the reconfigurable intelligent surface (RIS) aided broadcast channel, the weighted sum rate maximization model is considered, where the precoding vectors and the RIS matrix with discrete phase shifts are jointly optimized. Two approximation schemes with and without power allocation are proposed. First, the approximation scheme with power allocation is proposed. The highly nonconvex optimization problem is approximated through maximum ratio transmission, zero forcing and Courant penalty function techniques. And the water filling method works for power allocation and admission control. The other approximation is the weighted signal-to-interference-plus-noise ratio maximization, where the power allocation is prefixed in the corresponding algorithm. For both approximation schemes, the simplified optimization problems are solved by the projected gradient method, where the discrete variables are updated in closed form formula. Simulation results show that the proposed schemes as well as algorithms achieve higher sum rate with lower computational cost compared to the state of the art method.

### Decentralized Optimization over the Stiefel Manifold by an Approximate Augmented Lagrangian Function

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In this talk, we focus on the decentralized optimization problem over the Stiefel manifold, which is defined on a connected network of *d* agents. The objective is an average of *d* local functions, and each function is privately held by an agent and encodes its data. The agents can only communicate with their neighbors in a collaborative effort to solve this problem. In existing methods, multiple rounds of communications are required to guarantee the convergence, giving rise to high communication costs. In contrast, this talk proposes a decentralized algorithm, called DESTINY, which only invokes a single round of communications per iteration. DESTINY combines gradient tracking techniques with a novel approximate augmented Lagrangian function. The global convergence to stationary points is rigorously established. Comprehensive numerical experiments demonstrate that DESTINY has a strong potential to deliver a cutting-edge performance in solving a variety of testing problems.

### Generalized Polyak Step Size for First Order Optimization with Momentum

#### Xiaoyu Wang

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In machine learning applications, it is well known that carefully designed learning rate (step size) schedules can significantly improve the convergence of commonly used first-order optimization algorithms. Therefore how to set step size adaptively becomes an important research question. A popular and effective method is the Polyak step size, which sets step size adaptively for gradient descent or stochastic gradient descent without the need to estimate the smoothness parameter of the objective function. However, there has not been a principled way to generalize the Polyak step size for algorithms with momentum accelerations. This paper presents a general framework to set the learning rate adaptively for first-order optimization methods with momentum, motivated by the derivation of Polyak step size. It is shown that the resulting techniques are much less sensitive to the choice of momentum parameter and may avoid the oscillation of the heavy-ball method on ill-conditioned problems. These adaptive step sizes are further extended to the stochastic settings, which are attractive choices for stochastic gradient descent with momentum. Our methods are demonstrated to be more effective for stochastic gradient methods than prior adaptive step size algorithms in large-scale machine learning tasks.

### Convergence Analysis of an Adaptively Regularized Natural Gradient Method

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We study the convergence properties of the natural gradient methods. By reviewing the mathematical condition for the equivalence between the Fisher information matrix and the generalized Gauss-Newton matrix, as well as the comparisons on the computation and storage, we reveal the popularity of the natural gradient method. To ensure the global convergence, an adaptively regularized natural gradient method is proposed. By requiring sufficient probabilistic accurate estimations on both the function and the gradient evaluations, we establish the almost sure convergence. In the local convergence, we employ the local error bound condition and show the convergence rate can be quadratic by adding mild assumptions on the stochastic estimates of gradients and Fisher information matrices.

### A Negative $\ell_1$ Penalty Approach for One-Bit Precoding

Zheyu Wu

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One-bit precoding is a popular problem in 5G wireless communications. Mathematically, the problem can be formulated as an optimization problem with piece-wise linear objective and discrete one-bit constraint. This talk will introduce a negative  $\ell_1$  penalty approach for solving the problem. Specifically, the approach is based on an exact negative  $\ell_1$ penalty model, which penalizes the one-bit constraint into the objective with a negative  $\ell_1$ norm term. To solve the penalty model, we further transform it into an equivalent min-max problem and propose an efficient alternating proximal/projection gradient descent ascent (APGDA) algorithm. The APGDA algorithm enjoys low per-iteration complexity and is guaranteed to converge to a stationary point of the min-max problem. Numerical results show the superiority of the negative  $\ell_1$  penalty approach over the existing approaches.

### Convergence Guarantees for Stochastic Subgradient Methods in Nonsmooth Nonconvex Optimization

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In this paper, we investigate the convergence properties of the stochastic gradient descent (SGD) method and its variants, especially in training neural networks built from nonsmooth activation functions. We develop a novel framework that assigns different timescales to stepsizes for updating the momentum terms and variables, respectively. Under mild conditions, we prove the global convergence of our proposed framework in both single-timescale and two-timescale cases. We show that our proposed framework encompasses a wide range of well-known SGD-variant methods, including heavy-ball SGD, SignSGD, Lion, and normalized SGD. Furthermore, when the objective function adopts a finite-sum formulation, we prove the convergence properties for these SGD-variant methods based on our proposed framework. In particular, we prove that these SGD-variant methods find the Clarke stationary points of the objective function with randomly chosen stepsizes and initial points under mild assumptions. Preliminary numerical experiments demonstrate the high efficiency of our analyzed SGD-variant methods.

### A New Model-Based DFO Method Using an Improved Under-Determined Model

Pengcheng Xie

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Derivative-free optimization is widely seen in many real applications. One important class of derivative-free optimization algorithms is trust-region algorithms based on quadratic models given by under-determined interpolation. We propose a new derivativefree trust-region method by introducing an improved under-determined quadratic interpolation model. This talk will contain the theoretical motivation, computational details, quadratic model's implementation-friendly formula, and related numerical results.

### Primal Dual Alternating Proximal Gradient Algorithms for Nonsmooth Nonconvex Minimax Problems with Coupled Linear Constraints

Zi Xu

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Nonconvex minimax problems have attracted wide attention in machine learning, signal processing and many other fields in recent years. In this paper, we propose a primal dual alternating proximal gradient (PDAPG) algorithm and a primal dual proximal gradient (PDPG-L) algorithm for solving nonsmooth nonconvex-(strongly) concave and nonconvexlinear minimax problems with coupled linear constraints, respectively. The iteration complexity of the two algorithms are proved to be  $O(\epsilon^{-2})$  (resp.  $O(\epsilon^{-4})$ ) under nonconvexstrongly concave (resp. nonconvex-concave) setting and  $O(\epsilon^{-3})$  under nonconvex-linear setting to reach an  $\epsilon$ -stationary point, respectively. To our knowledge, they are the first two algorithms with iteration complexity guarantee for solving the nonconvex minimax problems with coupled linear constraints.

### Optimal Gradient Tracking for Decentralized Optimization

#### Ming Yan

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In this talk, I will focus on solving the decentralized optimization problem of minimizing the sum of objective functions over a multi-agent network. The agents are embedded in an undirected graph where they can only send/receive information directly to/from their immediate neighbors. Assuming smooth and strongly convex objective functions, we propose a single-loop decentralized gradient-type method, named Optimal Gradient Tracking (OGT), that achieves the optimal gradient computation complexity and the optimal communication complexity simultaneously. Its development involves two building blocks that are also of independent interest.

### **SMART** Spectral Analysis of Signals

Zai Yang

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Spectral analysis of signals is a core component of modern information techniques. The rapid developments of radar sensing and wireless communications have advanced its research from fast Fourier transform (FFT) in the 1960s, to maximum-likelihood and subspace methods emerging in the 1980s, and then to sparse and compressed sensing methods of this century. In this talk, we present our latest progress on this topic by solving the highly nonconvex maximum-likelihood optimization problem with a Structured MAtric Recovery Technique (SMART). SMART is inspired by our high-dimensional extension of the Carathéodory-Fejér Theorem (1911) that also forms the basis of the previous subspace and infinite-dimensional compressed sensing methods.

### Unbiased Compression Saves Communication in Distributed Optimization: When and How Much?

Kun Yuan

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Communication compression is a common technique in distributed optimization that can alleviate communication overhead by transmitting compressed gradients and model parameters. However, compression can introduce information distortion, which slows down convergence and incurs more communication rounds to achieve desired solutions. Given the trade-off between lower per-round communication costs and additional rounds of communication, it is unclear whether communication compression reduces the total communication cost. This talk explores the conditions under which unbiased compression, a widely used form of compression, can reduce the total communication cost, as well as the extent to which it can do so. To this end, we present the first theoretical formulation for characterizing the total communication cost in distributed optimization with communication compression. We demonstrate that unbiased compression alone does not necessarily save the total communication cost, but this outcome can be achieved if the compressors used by all workers are further assumed independent. We establish lower bounds on the communication rounds required by algorithms using independent unbiased compressors to minimize smooth convex functions, and show that these lower bounds are tight by refining the analysis for ADIANA. Our results reveal that using independent unbiased compression can reduce the total communication cost by a factor of up to  $\min\{n,\kappa\}$ , where n is the number of workers and  $\kappa$  is the condition number of the functions being minimized. These theoretical findings are supported by experimental results.

### An Overlap-Based Branching Scheme for Covering Location Problems

#### Yuhai Zhang

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In the branch-and-bound algorithm, the variable branching step creates two subproblems obtained by restricting the range of a variable. One weakness of the branch-and-bound algorithm for solving covering location problems is that the feasible sets of the two generated subproblems may have some intersection part (called overlap). In this talk, we introduce a new branching scheme for solving covering location problems to overcome this weakness. Our branching strategy attempts to remove the overlap in the branch-andbound tree and guide the selection of branching variables. Numerical results demonstrate the effectiveness of the proposed branching scheme.

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# The organizing committee wishes you a pleasant stay in Taiyuan!



Taiyuan, Shanxi, China