Department of Applied Mathematics, The Hong Kong Polytechnic University

Workshop on Applied Mathematics + AI

17–19 December 2025

Co-organizers:

Preface

Welcome to the Workshop on Applied Mathematics + AI, jointly organized by Department of Applied Mathematics (AMA), CAS AMSS–PolyU Joint Laboratory of Applied Mathematics, CITIC-PolyU Interdisciplinary Mathematical Digital AI Joint Laboratory and PolyU-Huawei Mathematical Optimization Innovation Laboratory.

Applied Mathematics + Artificial Intelligence (AI) has experienced rapid and significant advancements in recent years. The aim of this workshop is to bring together applied mathematicians from academic institutions and engineers from industry to present and discuss the latest developments in this dynamic field. By fostering collaboration between applied mathematicians and engineers, the workshop will promote interdisciplinary exchange and provide a valuable opportunity for young researchers to learn about the current state-of-the-art in applied mathematics + AI.

The workshop gratefully acknowledges the patronage of The Hong Kong Polytechnic University, as well as the financial support provided by AMA and the three joint laboratories.

We sincerely hope that this workshop will enhance international collaboration between applied mathematicians and provide an opportunity for young researchers to learn the current state of the art in scientific computing.

Finally, we hope all participants have a fruitful workshop in The Hong Kong Polytechnic University and wish all overseas participants an enjoyable stay in Hong Kong.

Acknowledgements

We are very grateful for the support and contributions to the Workshop on Applied Mathematics + AI, as given by:

The Hong Kong Polytechnic University (PolyU)

Department of Applied Mathematics, PolyU

CAS AMSS-PolyU Joint Laboratory of Applied Mathematics (JLab)

CITIC-PolyU Interdisciplinary Mathematical Digital AI Joint Laboratory (AIJLab)

PolyU-Huawei Mathematical Optimization Innovation Laboratory (MOILab)

We would also like to thank the staff members in the Department of Applied Mathematics who have worked together in handling the various arrangements related to the workshop. Their assistance has been indispensable.

Organizing Committees

- Defeng Sun (co-Chair)
- Xiaojun Chen (co-Chair)
- Ting Kei Pong
- Houduo Qi
- Zhonghua Qiao
- Xiaoqi Yang
- Yancheng Yuan
- Wei Liu
- Guan Wang

Websites

CAS AMSS-PolyU Joint Laboratory of Applied Mathematics

CITIC-PolyU Interdisciplinary Mathematical Digital AI Joint Laboratory

PolyU-Huawei Mathematical Optimization Innovation Laboratory

Workshop Highlights

Venue

The workshop will be held at room N003 on the PolyU campus. Please refer to the campus map. Please note that smoking is not allowed on the PolyU campus.

On-campus Internet Access

NetID: gstama
Password: Polyu4ever
SSID: PolyUWLAN
Ref: https://polyu.hk/JfnRM

Detailed Schedule

17 December 2025 (Wednesday)

Time	Talk Title	Speaker	Chair
10:00 – 10:30	Tea Reception		
10:30 – 11:30	RiNNAL+: a Riemannian ALM Solver for SDP-RLT Relaxations of Mixed-Binary Quadratic Programs	Kim-Chuan Toh (National University of Singapore)	Defeng Sun
12:00 – 14:00	Lunch at U. Green		
Forum of Young Researchers in Mathematical Optimization			
14:00 – 14:30	Alternating Proximal Algorithm for Nonsmooth Saddle Point Problems with Group Penalties	Wei Bian (Harbin Institute of Technology)	TK Pong
14:30 – 15:00	Accelerating RLHF Training with Reward Variance Increase	Yancheng Yuan (PolyU)	Hailin Sun
15:00 – 15:30	Non-convergence Analysis of Randomized Direct Search	Zaikun Zhang (Sun Yat-sen University)	Wei Liu
15:30 – 16:00	Tea break		
16:00 – 16:30	Adaptive directional decomposition methods for nonconvex constrained optimization	Xiao Wang (Sun Yat-sen University)	Wei Bian
16:30 – 17:00	Solutions of Two-stage Stochastic Minimax Problems	Hailin Sun (Nanjing Normal University)	Zaikun Zhang
17:00 – 17:30	Damped Proximal Augmented Lagrangian Method for weakly-Convex Problems with Convex Constraints	Wei Liu (PolyU)	Xiao Wang
18:00 – 20:00	Dinner at Choi Fook Royal Banquet (Fortune Metropolis) (彩福皇宴置富都會)		

18 December 2025 (Thursday) – Distinguished Lecture and Lab Sessions

Time	Talk Title	Speaker	Chair
08:30-9:00	Welcome Reception 歡迎		
09:00 – 09:30	Opening 開幕式	Ya-xiang Yuan (CAS, AMSS) 袁亞湘 (中國科學院數學與系統科學研究院研究員，中國科學院院士，中國科學技術協會副主席) Jun Wu (CITIC) 吳軍 (中信國際電訊行政總裁) Bo Bai (Huawei) 白鉑 (華為公司 2012 實驗室中央研究院理論部部長) Defeng Sun (PolyU) 孫德鋒 (香港理工大學講座教授, 應用數學系系主任)	Xiaojun Chen 陳小君
09:30 – 10:15	Introduction of • CAS AMSS-PolyU JLab • CITIC-PolyU AI JLab • PolyU-Huawei Lab 實驗室介紹： • 中國科學院數學與系統科學研究院－香港理工大學應用數學聯合實驗室 • 香港理工大學-中信集團人工智能數智創新聯合實驗室 • 香港理工大學一華為數學優化創新實驗室	Xin Liu (CAS, AMSS) 劉歆 (中國科學院數學與系統科學研究院研究員) Dongdong Zhan (CITIC) 詹東東 (中信香港人工智能科創中心助理主任) Jie Sun (Huawei) 孫傑 (華為 2012 實驗室香港理論研究部技術專家)	Xiaojun Chen 陳小君
10:15 – 10:45	Tea Break 茶歇		

Time	Talk Title	Speaker	Chair
10:45 – 11:45	Mathematical Foundations of Artificial Intelligence	Ya-xiang Yuan (CAS, AMSS) 袁亞湘 (中國科學院數學與系統科學研究院研究員，中國科學院院士，中國科學技術協會副主席)	Defeng Sun 孫德鋒
12:00 – 14:00	Lunch at Hotel ICON 午餐：唯港薈		
14:00 – 14:30	中信銀行「人工智能發展情況匯報」	Zhiming Chen (CITIC) 陳志明 (中信銀行信息技術管理部處長)	Guan Wang 王冠
14:30 – 15:00	中信重工「人工智能應用實踐情況分享」	Lei Yang (CITIC) 楊磊 (中信重工信息技術中心主任)	Guan Wang 王冠
15:00 – 15:30	中信戴卡「“人工智慧+” 探索與實踐」	Wei Niu (CITIC) 牛巍 (中信戴卡數字製造部部長)	Guan Wang 王冠
15:30 – 16:00	Tea Break 茶歇		
16:00 – 16:30	Forget BIT, It is All about TOKEN: Towards the First Principle for Understanding LLMs	Bo Bai (Huawei) 白鉑 (華為公司 2012 實驗室中央研究院理論部部長)	Yancheng Yuan 袁雁城
16:30 – 17:00	Rethink Algorithms as Dynamical Systems: An Optimal Control Formulation of Computational Complexity	Jie Sun (Huawei) 孫傑(華為 2012 實驗室香港理論研究部技術專家)	Yancheng Yuan 袁雁城
17:00 – 17:30	From Classical Solvers to Hardware-Empowered Solvers, with Applications from Communication Systems to Large Language Models	Fan Zhang (Huawei) 張帆 (華為 2012 實驗室香港理論研究部團隊經理)	Yancheng Yuan 袁雁城
18:00 – 20:00	Dinner at Ju Yin House 晚宴：聚賢樓		

19 December 2025 (Friday) – Invited Talks

Time	Activity / Talk Title	Speaker	Chair
09:30 – 10:30	Offline Policy Learning with Weight Clipping and Heaviside Composite Optimization	Jong-Shi Pang (University of Southern California)	Xiaojun Chen
10:30 – 11:00	Tea break		
11:00 – 12:00	Martingale Deep Neural Networks for Stochastic Optimal Controls	Wei Cai (Southern Methodist University)	Zhonghua Qiao
12:00 – 14:00	Lunch at Ju Yin House		
Forum of Young Researchers in Mathematical Optimization			
14:00 – 15:00	Enhancing Distributional Robustness in Principal Component Analysis by Wasserstein Distances	Xin Liu (CAS, AMSS)	Houdou Qi
15:00 – 15:30	Tea Break		
15:30 – 16:00	An MILP-Based Solution Scheme for Factored Markov Decision Processes	Man-Chung Yue (The University of Hong Kong)	Hailin Sun
16:00 – 16:30	Alternating minimization for square root principal component pursuit	Yangjing Zhang (CAS AMSS)	Yancheng Yuan
16:30 – 17:00	ripALM: A Relative-type Inexact Proximal Augmented Lagrangian Method	Lei Yang (Sun Yat-sen University)	TK Pong

Talk Titles and Abstracts

Invited Talks

Kim-Chuan Toh (NUS)
Title: RiNNAL+: a Riemannian ALM Solver for SDP-RLT Relaxations of Mixed-Binary Quadratic Programs
Abstract: Doubly nonnegative (DNN) relaxation usually provides a tight lower bound for a mixed-binary quadratic program (MBQP). However, solving DNN problems is challenging because: (1) the problem size is $\Omega((n+l)^2)$ for an MBQP with n variables and l inequality constraints, and (2) the rank of optimal solutions cannot be estimated a priori due to the absence of theoretical bounds. In this work, we propose RiNNAL+, a Riemannian augmented Lagrangian method (ALM) for solving DNN problems. We prove that the DNN relaxation of an MBQP, with matrix dimension $n+l+1$, is equivalent to the SDP-RLT relaxation (based on the reformulation-linearization technique) with a smaller matrix dimension $n+1$. In addition, we develop a hybrid method that alternates between two phases to solve the ALM subproblems. In phase one, we apply low-rank matrix factorization and random perturbation to transform the feasible region into a lower-dimensional manifold so that we can use the Riemannian gradient descent method. In phase two, we apply a single projected gradient step to update the rank of the underlying variable and escape from spurious local minima arising in the first phase if necessary. To reduce the computation cost of the projected gradient step, we develop pre-processing and warm-start techniques for acceleration. Unlike traditional rank-adaptive methods that require extensive parameter tuning, our hybrid method requires minimal tuning. Extensive experiments confirm the efficiency and robustness of RiNNAL+ in solving various classes of large-scale DNN problems.

Ya-xiang Yuan (Chinese Academy of Sciences)
Title: Mathematical Foundations of Artificial Intelligence
Abstract: This report briefly presents the key findings from the joint advisory project "Mathematical Foundations of Artificial Intelligence" conducted by the Academic Divisions of the Chinese Academy of Sciences and the National Natural Science Foundation of China. Beginning with diverse definitions of artificial intelligence, the report provides a description of its essence, discusses the foundational models, theoretical frameworks, and algorithmic underpinnings of AI, and briefly addresses the opportunities and challenges that artificial intelligence presents to the field of mathematics.

Jong-Shi Pang (University of Southern California)
Title: Offline Policy Learning with Weight Clipping and Heaviside Composite Optimization
Abstract: Offline policy learning (OPL) is a technique that uses historical data to learn an optimal personalized decision rule with the goal of maximizing the overall reward for a given population. In the standard estimate-then-optimize framework, reweighting-based methods (e.g., inverse propensity weighting or doubly robust estimators) are widely used to produce unbiased estimates of policy values. However, when the propensity scores of some treatments are small, these reweighting-based methods suffer from high variance in policy value estimation, which may mislead the learning algorithm into selecting a suboptimal policy.

In this paper, we systematically develop a novel OPL algorithm based on a weight-clipping estimator that truncates small propensity scores and is shown to optimally balance the bias-variance trade-off. We address the policy optimization challenges induced by the resulting bilevel and discontinuous objective, when the policy class is restricted to linear mappings, by reformulating the problem as a Heaviside composite optimization problem, which provides a rigorous framework for computation. The reformulated policy optimization problem is efficiently solved by the progressive integer programming method. To provide theoretical guarantee for the proposed algorithm, we establish a suboptimality upper bound that relates the mean squared error of (worst-case) policy estimation to the generalization error in policy learning. This analysis highlights the necessity of balancing the bias-variance trade-off, as achieved by the proposed weight-clipping estimator.

Wei Cai (Southern Methodist University)
Title: Martingale Deep Neural Networks for Stochastic Optimal Controls
Abstract: In this talk, we will present a highly parallel and derivative-free martingale neural network method, based on the probability theory of Varadhan's martingale formulation of PDEs, to solve Hamilton-Jacobi-Bellman (HJB) equations arising from stochastic optimal control problems (SOCPs), as well as general quasilinear parabolic partial differential equations (PDEs). In both cases, the PDEs are reformulated into a martingale problem such that loss functions will not require the computation of the gradient or Hessian matrix of the PDE solution, and can be computed in parallel in both time and spatial domains. Moreover, the martingale conditions for the PDEs are enforced using a Galerkin method realized with adversarial learning techniques, eliminating the need for direct computation of the conditional expectations associated with the martingale property. For SOCPs, a derivative-free implementation of the maximum principle for optimal controls is also introduced. The numerical results demonstrate the effectiveness and efficiency of the proposed method, which is capable of solving HJB and quasilinear parabolic PDEs accurately and fast in dimensions as high as 10,000.

Xin Liu (AMSS)

Title: Enhancing Distributional robustness in principal Component Analysis by Wasserstein Distances

Abstract: We consider the distributionally robust optimization (DRO) model of principal component analysis (PCA) to account for uncertainty in the underlying probability distribution. The resulting formulation leads to a nonsmooth constrained min-max optimization problem, where the ambiguity set captures the distributional uncertainty by the type-2 Wasserstein distance. We prove that the inner maximization problem admits a closed-form optimal value. This explicit characterization equivalently reformulates the original DRO model into a minimization problem on the Stiefel manifold with intricate nonsmooth terms, a challenging formulation beyond the reach of existing algorithms. To address this issue, we devise an efficient smoothing manifold proximal gradient algorithm. Our analysis establishes Riemannian gradient consistency and global convergence of our algorithm to a stationary point of the nonsmooth minimization problem. We also provide the iteration complexity $O(\epsilon{-}3)$ of our algorithm to achieve an ϵ-approximate stationary point. Finally, numerical experiments are conducted to validate the effectiveness and scalability of our algorithm, as well as to highlight the necessity and rationality of adopting the DRO model for PCA.

Huawei's Talks

Bo Bai

Title: Forget BIT, It is All about TOKEN: Towards the First Principle for Understanding LLMs

Abstract: In recent years, LLMs has developed rapidly and has begun to play an important role in many fields. However, there is little research on the principles behind large models. In fact, the lack of understanding of the theory of large models also limits the application of this technology in many key scenarios. In this report, we try to establish a semantic information theory framework to understand the principles of large models from the core concept of TOKEN in the era of large models and learn from Shannon's ideas and methodologies. The main contents of the report include vector representation and compression of semantics, probabilistic modeling of large models, parameterized memory and semantic information flow of large models. We hope that these attempts will inspire researchers to focus on the new information theory for the AI era and to make original achievements in the semantic information theory for large models.

Jie Sun

Title：Rethink Algorithms as Dynamical Systems: An Optimal Control Formulation of Computational Complexity

Abstract：Computational complexity is a fundamental measure of algorithms. Yet, existing metrics such as operations counts (e.g., FLOPs) - rooted in the Turing machine abstraction - neglect key factors including algebraic structure, data locality and hardware heterogeneity. Consequently, these metrics often fail to predict the vast performance differences of algorithms running on modern computing platforms (e.g., CPU/NPU). Here we propose a control-theoretical framework that treats algorithms as controlled dynamical systems. By unifying concepts from dynamical systems and optimal control theory, we view an ``optimal algorithm" not merely as one with the fewest steps, but as a minimal-action geodesic trajectory in an operator space. This new formulation explicitly accounts for the cumulative effect of structured operators (such as matrix-vector computations) and naturally measures the ``energy cost" of computation, bridging the gap between theoretical operation counts and physical realization.

Fan Zhang

Title： From Classical Solvers to Hardware-Empowered Solvers, with Applications from Communication Systems to Large Language Models

Abstract: This talk first shares the latest results in traditional large-scale optimization and highlights its practical value via cases like optimizing data networks for efficient information transmission and refining optical communication networks to boost signal stability and bandwidth utilization. It then turns to the AI era, where the surge in computational resources (e.g., GPUs, NPUs) drives optimization solver performance. This improves efficiency, may reshape the industry, and addresses challenges of hardware-empowered optimization solvers such as hardware-tailored optimization methods, parallel strategies for distributed environments, and solutions for billion-variable applications like power system unit commitment. Additionally, this talk will also explore mathematical optimization's untapped potential in LLMs, noting it offers a more systematic approach than heuristic methods to solve pain points like training resource allocation and inference acceleration issues.

Forum of Young Researchers in Mathematical Optimization

Wei Bian (Harbin Insitutte of Technology)

Title: Alternating Proximal Algorithm for Nonsmooth Saddle Point Problems with Group Penalties

Abstract: In this talk, we bring forward a class of min-max problems (SP) with element and group indicator functions, which is capable of representing several different feature information of the variables. We consider this model with a Lipschitz continuous convex-concave coupling function and bound box constraints on the two variables. First, we build up a continuous relaxation model (CSP) of it with equivalence on the saddle points. Further, by strengthening the optimality conditions for these two problems, we define the notions of the strong local saddle points of (SP) and the target directional (td)-stationary points of (CSP), which are also one-to-one correspondence. Second, when the coupling function in (SP) is smooth, we propose two types of algorithms, one is the Proximal Gradient Descent-Ascent (APGDA) algorithm, and the other is the Alternating Proximal Gradient Descent-Ascent (APGDA) algorithm. Both of two algorithms own the subsequence convergence to the strong local saddle points of (SP), and convergence rate estimations on the gradient information and a predefined gap function values. Finally, the smoothing method is introduced to solve the case with a nonsmooth coupling function, and the convergence analysis of the proposed corresponding algorithms are also established.

Zaikun Zhang (Sun Yat-sen University)
Title: Non-convergence Analysis of Randomized Direct Search
Abstract: Direct search is a popular method in derivative-free optimization. Randomized direct search has attracted increasing attention in recent years due to both its practical success and theoretical appeal. It is proved to converge under certain conditions at the same global rate as its deterministic counterpart, but the cost per iteration is much lower, leading to significant advantages in practice. However, a fundamental question has been lacking a systematic theoretical investigation: when will randomized direct search fail to converge? We answer this question by establishing the non-convergence theory of randomized direct search. We prove that randomized direct search fails to converge if the searching set is probabilistic ascent. Our theory does not only deepen our understanding of the behavior of the algorithm, but also clarifies the limit of reducing the cost per iteration by randomization, and hence provides guidance for practical implementations of randomized direct search. This is a joint work with Cunxin Huang, a Ph.D. student funded by the Hong Kong Ph.D. Fellowship Scheme.

Yancheng Yuan (PolyU)
Title: Accelerating RLHF Training with Reward Variance Increase
Abstract: Reinforcement learning from human feedback (RLHF) is an essential technique for ensuring that large language models (LLMs) are aligned with human values and preferences during the post-training phase. As an effective RLHF approach, group relative policy optimization (GRPO) has demonstrated success in many LLM-based applications. However, efficient GRPO-based RLHF training remains a challenge. Recent studies reveal that a higher reward variance of the initial policy model leads to faster RLHF training. Inspired by this finding, we propose a practical reward adjustment model to accelerate RLHF training by provably increasing the reward variance and preserving the relative preferences and reward expectation. Our reward adjustment method inherently poses a nonconvex optimization problem, which is NP-hard to solve in general. To overcome the computational challenges, we design a novel $O(n \log n)$ algorithm to find a global solution of the nonconvex reward adjustment model by explicitly characterizing the extreme points of the feasible set. As an important application, we naturally integrate this reward adjustment model into the GRPO algorithm, leading to a more efficient GRPO with reward variance increase (GRPOVI) algorithm for RLHF training. Experiment results demonstrate that the GRPOVI algorithm can significantly improve the RLHF training efficiency compared to the original GRPO algorithm.

Xiao Wang (Sun Yat-sen University)
Title: Adaptive directional decomposition methods for nonconvex constrained optimization
Abstract: In this paper, we study nonconvex constrained optimization problems with both equality and inequality constraints, covering deterministic and stochastic settings. We propose a novel first-order algorithm framework that employs a decomposition strategy to balance objective reduction and constraint satisfaction, together with adaptive update of stepsizes and merit parameters. Under certain conditions, the proposed adaptive directional decomposition methods attain an iteration complexity of order $O(\varepsilon^{-2})$ for finding an ε-KKT point in the deterministic setting. In the stochastic setting, we further develop stochastic variants of approaches and analyze their theoretical properties by leveraging the perturbation theory. We establish the high-probability oracle complexity to find an ε-KKT point of order $\tilde{E}(\varepsilon^{-4}, \varepsilon^{-6})$ (resp. $\tilde{E}(\varepsilon^{-3}, \varepsilon^{-5})$) for gradient and constraint evaluations, in the absence (resp. presence) of sample-wise smoothness. To the best of our knowledge, the obtained complexity bounds are comparable to, or improve upon, the state-of-the-art results in the literature.

Hailin Sun (Nanjing Normal University)
Title: Solutions of Two-stage Stochastic Minimax Problems
Abstract: This paper introduces a class of two-stage stochastic minimax problems where the first-stage objective function is nonconvex-concave while the second-stage objective function is strongly convex-concave. We establish properties of the second-stage minimax value function and solution functions, and characterize the existence and relationships among saddle points, minimax points, and KKT points. We apply the sample average approximation (SAA) to the class of two-stage stochastic minimax problems and prove the convergence of the KKT points as the sample size tends to infinity. An inexact parallel proximal gradient descent ascent algorithm is proposed to solve this class of problems with the SAA. Numerical experiments demonstrate the effectiveness of the proposed algorithm and validate the convergence properties of the SAA approach. This is a joint work with Professor Xiaojun Chen.

Wei Liu (PolyU)
Title: Damped Proximal Augmented Lagrangian Method for weakly-Convex Problems with Convex Constraints
Abstract: We present a damped proximal augmented Lagrangian method (DPALM) for solving problems with a weakly-convex objective and convex linear/non-linear constraints. Instead of taking a full stepsize, DPALM adopts a (possibly) damped dual stepsize. We show that DPALM can produce a (near) ε-KKT point within $O(\varepsilon^{-2})$ outer iterations if each DPALM subproblem is solved to a proper accuracy. In addition, we establish overall oracle complexity (i.e., total number of evaluations of function values and (sub)gradients) of DPALM when the objective is either a regularized smooth function or in a regularized compositional form. For the former case, DPALM achieves a complexity of $O(\varepsilon^{-2.5})$ to produce an ε-KKT point by applying an accelerated proximal gradient (APG) method to each DPALM subproblem 1 . For the latter case, the complexity of DPALM is $O(\varepsilon^{-3})$ to produce a near ε-KKT point by using an APG method to solve a Moreau-envelope smoothed version of each subproblem. Our outer iteration complexity and the overall complexity either generalize existing best ones from unconstrained or linear-constrained problems to convex-constrained ones, or improve over the best-known results on solving the same-structured problems. Furthermore, numerical experiments on linearly/quadratically constrained non-convex quadratic programs and linear constrained robust nonlinear least squares are conducted to demonstrate the empirical efficiency of the proposed DPALM over several state-of-the-art methods and a specialized solver.

Man-Chung Yue (The University of Hong Kong)
Title: An MILP-Based Solution Scheme for Factored Markov Decision Processes
Abstract: Factored Markov decision processes (MDPs) are a prominent paradigm within the artificial intelligence community for modeling and solving large-scale MDPs whose rewards and dynamics decompose into smaller, loosely interacting components. Through the use of dynamic Bayesian networks and context-specific independence, factored MDPs can achieve an exponential reduction in the state space of an MDP and thus scale to problem sizes that are beyond the reach of classical MDP algorithms. However, factored MDPs are typically solved using custom-designed algorithms that can require meticulous implementations and considerable fine-tuning. In this paper, we propose a mathematical programming approach to solving factored MDPs. In contrast to existing solution schemes, our approach leverages off-the-shelf solvers, which allows for a streamlined implementation and maintenance; it effectively capitalizes on the factored structure present in both state and action spaces; and it readily extends to the largely unexplored class of robust factored MDPs, whose transition kernels are only known to reside in a pre-specified ambiguity set. Our numerical experiments demonstrate the potential of our approach.

Yangjing Zhang (Chinese Academy of Sciences)
Title: Alternating minimization for square root principal component pursuit
Abstract: Recently, the square root principal component pursuit (SRPCP) model has garnered significant research interest. It is shown in the literature that the SRPCP model guarantees robust matrix recovery with a universal, constant penalty parameter. While its statistical advantages are well-documented, the computational aspects from an optimization perspective remain largely unexplored. In this paper, we focus on developing efficient optimization algorithms for solving the SRPCP problem. Specifically, we propose a tuning-free alternating minimization (AltMin) algorithm, where each iteration involves subproblems enjoying closed-form optimal solutions. Additionally, we introduce techniques based on the variational formulation of the nuclear norm and Burer-Monteiro decomposition to further accelerate the AltMin method. Extensive numerical experiments confirm the efficiency and robustness of our algorithms.

Lei Yang (Sun Yat-sen University)
Title: ripALM: A Relative-type Inexact Proximal Augmented Lagrangian Method
Abstract: Inexact proximal augmented Lagrangian methods (pALMs) are particularly appealing for tackling convex constrained optimization problems because of their elegant convergence properties and strong practical performance. To solve the associated pALM subproblems, efficient methods such as accelerated methods or Newton-type methods are essential. Consequently, the effectiveness of the inexact pALM hinges on the error criteria used to control the inexactness when solving these subproblems. However, existing inexact pALMs either rely on absolute-type error criteria (which may complicate implementation by necessitating the pre-specification of an infinite sequence of error tolerance parameters) or require an additional correction step to guarantee convergence when using relative-type error criteria (which can potentially degrade the practical performance of pALM). To address these deficiencies, this work proposes ripALM, a relative-type inexact pALM, for constrained convex optimization. This method can simplify practical implementation while preserving the appealing convergence properties of the classical absolute-type inexact pALM. Numerical results demonstrate the competitive efficiency of ripALM compared to existing state-of-the-art methods. As our model encompasses a wide range of application problems, the proposed ripALM offers broad applicability and has the potential to serve as a basic optimization toolbox.