香港浸會大學理學院
HKBU Faculty of Science

DEPARTMENT OF COMPUTER SCIENCE

PhD Degree Oral Presentation

PhD Candidate:	Mr Jian LOU
Date	23 August 2018 (Thursday)
Time:	2:30 pm - 4:30 pm (35 mins presentation and 15 mins Q & A)
Venue:	RRS732, Sir Run Run Shaw Building, HSH Campus

“Study on Efficient Sparse and Low-rank Optimization and Its Applications”

Abstract

Sparse and low-rank models have been becoming fundamental machine learning tools and have wide applications in areas including computer vision, data mining, bioinformatics and so on. It is of vital importance, yet of great difficulty, to develop efficient optimization algorithms for solving these models, especially under practical design considerations of computational, communicational and privacy restrictions for ever-growing larger scale problems. This thesis proposes a set of new algorithms to improve the efficiency of the sparse and low-rank models optimization.

First, facing a large number of data samples during training of empirical risk minimization (ERM) with structured sparse regularization, the gradient computation part of the optimization can be computationally expensive and becomes the bottleneck. Therefore, I propose two gradient efficient optimization algorithms to reduce the total or per-iteration computational cost of the gradient evaluation step, which are new variants of the widely used generalized conditional gradient (GCG) method and incremental proximal gradient (PG) method, correspondingly.

Furthermore, the large data dimension (e.g. the large frame size of high-resolution image and video data) can lead to high per-iteration computational complexity, thus results into poor-scalability of the optimization algorithm from practical perspective. In particular, in spectral k-support norm regularized robust low-rank matrix and tensor optimization, traditional proximal map based alternating direction method of multipliers (ADMM) requires to evaluate a super-linear complexity subproblem in each iteration. I propose a set of per-iteration computational efficient alternatives to reduce the cost to linear and nearly linear with respect to the input data dimension for matrix and tensor case, correspondingly.

In addition, since machine learning datasets often contain sensitive individual information, privacy-preserving becomes more and more important during sparse optimization. I provide two differentially private optimization algorithms under two common large-scale machine learning computing contexts, i.e., distributed and streaming optimization, correspondingly. For the distributed setting, I develop a new algorithm with 1) guaranteed strict differential privacy requirement, 2) nearly optimal utility and 3) reduced uplink communication complexity, for a nearly unexplored context with features partitioned among different parties under privacy restriction. For the streaming setting, I propose to improve the utility of the private algorithm by trading the privacy of distant input instances, under the differential privacy restriction.

***** ALL INTERESTED ARE WELCOME *****