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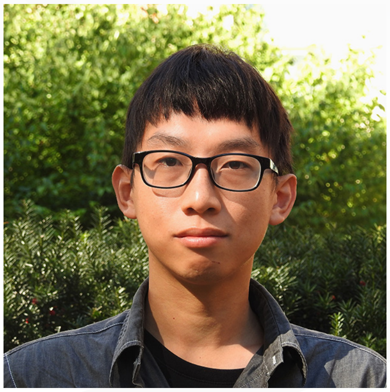
DISSERTATION PRESENTATION AND DEFENSE

Stochastic and Online Learning with Applications to Machine Learning and Statistics

WHEN
July 12, 2021
2:00 PM, CDT

WHERE
Via ZOOM
ZOOM information will be provided in the email announcement for this seminar.



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There is no doubt that big data are rapidly expanding nowadays in all fields like science and engineering domains. While the potential of massive data is considerable, in many scenarios of employing machine learning and statistic algorithms to imaging recognizing, natural language processing, and genetic studies, practitioners face many challenges, including high-dimensional data (the feature size is much large than the sample size), over-fitting, discrimination, and hidden confounding. Those problems impose additional difficulties due to over-parameterization, ill-conditioning, non-convex objectives and constraints, and limited power of computation and data storage. Therefore, fully exploiting data's value requires novel learning techniques. In this talk, I will present three projects in stochastic and online learning with applications to modern machine learning models and statistical methodologies. First, the theorems of accelerated first-order methods on strongly convex objective functions with the growth condition are derived. The growth condition, which is more realistic but rarely addressed in the literature, states the variance of the stochastic gradients can be dominated by a multiplicative part and an additive part. We show that there exists a trade-off between the convergence rate and robustness for multiplicative noise. Next, the no-regret analysis of online learning for non-linear models is considered. We establish an error control for biased stochastic gradient descent, which leads to a no-regret analysis for the circumstance where we only receive a non-convex approximation of a convex loss function. These results can be applied to a game-theoretical framework for building neural network classifiers with fairness constraints. Finally, canonical correlation analysis with low-rank constraints is studied. We prove algorithmic and statistical properties of two-dimensional canonical correlation analysis under mild conditions of the data generating process and further develop the error bound of using first-order stochastic methods, an effective initialization scheme, and a deflation procedure for extracting multiple canonical components. We believe that our works contribute not only to cutting-edge research in the field of optimization but also to complex and large-scale data analysis.

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