UC RIVERSIDE
UNIVERSITY OF CALIFORNIA

STATISTICS DEPARTMENT SEMINAR

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Professor
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Olmsted Hall 420
May 28th 2019
3:45-4:45pm
Reception in Olmsted 1331
at 3:15 P.M.
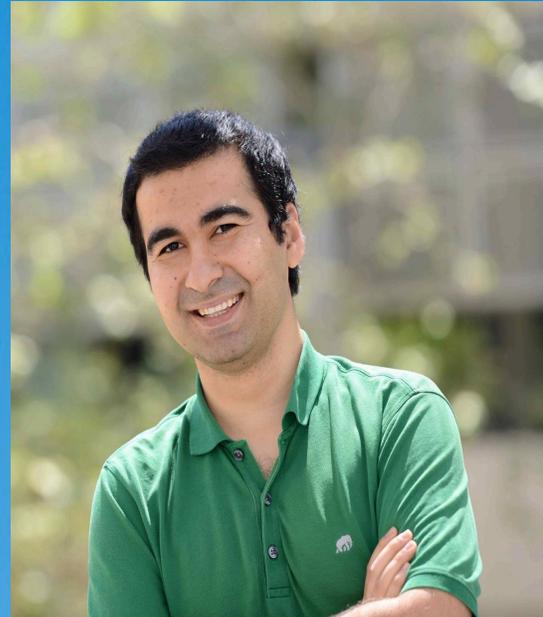
"**Overparameterization without overfitting: from compressed sensing to deep learning**"

Abstract

Modern machine learning algorithms are often trained in the overparameterized regime where the number of parameters in the model exceeds the size of the training dataset. Despite overparameterization, these algorithms surprisingly avoid overfitting to the training data. In this talk I will present theoretical results demystifying this success by focusing on two class of problems.

In the first class of problems we avoid overfitting by using a model prior, such as sparsity, to narrow down the search space of the algorithm by using a proper regularization. For these problems, we introduce a general framework to quantify the benefit of prior knowledge in terms of problem geometry. This leads to a remarkably accurate characterization of the algorithmic behavior including estimation error, rate of convergence, and sample complexity.

The second class of problems typically arise in deep learning and require no explicit regularization during training. While neural networks have the capacity to overfit any dataset including noise, somewhat paradoxically, they continue to predict well on unseen test data. Towards explaining this phenomena, we show that, neural networks trained by the gradient descent algorithm (1) are provably robust to noise/corruption on a constant fraction of the labels and (2) provably generalize to test data despite overparametrization.

Biography

Samet Oymak is an assistant professor in the Department of Electrical and Computer Engineering, at the University of California, Riverside. He received his MS and PhD degrees from California Institute of Technology; where he was awarded the Wilts Prize for the best thesis in Electrical Engineering. Before joining UCR, he spent time at Google and financial industry, and prior to that he was a fellow at the Simons Institute and a postdoctoral scholar at UC Berkeley. His research explores the mathematical foundations of data science and machine learning by using tools from optimization and statistics. His active research topics include non-convex optimization, reinforcement learning, deep learning theory, and high-dimensional statistics.