Estimating High-dimensional Matrices: Information-Theoretic Limits and Computational Barriers

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Abstract: Statistical inference of large matrices arises frequently in the analysis of massive datasets such as covariance estimation, principle component analysis, clustering, etc. In this talk I introduce an information-theoretic machinery for studying estimation of high-dimensional matrices, which yields tight non-asymptotic minimax rates for a large collection of loss functions in a variety of problems. Based on the convex geometry of finite-dimensional Banach spaces, the minimax rates of oracle (unconstrained) Gaussian denoising problem is determined for all unitarily invariant norms. This result is then extended to denoising with submatrix sparsity (biclustering), where the excess risk depends on the sparsity constraints in a completely different manner. In the final part of the talk, I will give an example where attaining the minimax rate is provably hard in a complexity-theoretic sense. This observation reveals that there can exist a significant gap between the statistical fundamental limit and what can be achieved by computationally efficient procedures. This talk is based on joint work with Zongming Ma (Penn).