Inference for Low-Rank Models
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Abstract:
This paper studies the inference problem of linear models whose parameter of interest is a high-dimensional matrix that can be well approximated by low-rank matrices. We focus on a class of “spiked low-rank matrices”, which satisfies: (1) its rank grows slowly compared to its dimensions, (2) the nonzero singular values diverge to infinity, and (3) the singular eigenvectors are coherent (i.e., nearly evenly spread on their entries). We show that this model covers a broad class of models of latent-variables, and nests with the matrix completion problem as a special case. While the nuclear-norm regression has been a standard for estimating low-rank matrices, it is biased and not sufficient for inference. We propose a new “rotation-debiasing” method for inference about product-parameters, which takes advantage of the fact that the low-rank matrix can be written as a product of left and right eigenvectors. We show that estimating product-parameters iteratively can remove the shrinkage bias of the nuclear-norm penalization, and produce an asymptotically normal estimator based on this method.