

Inference for Differential Networks in a High-dimensional Setting

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Abstract

In this expository talk, we discuss statistical inference in a high-dimensional setting. After presenting the general framework, we present a recent line of work on estimating differential networks. First, we consider a Gaussian setting and show how to directly learn the difference between the graph structures. A debiasing procedure will be presented for construction of an asymptotically normal estimator of the difference. Unlike the existing approaches for differential network inference that require sparsity of individual precision matrices from both groups, we only require sparsity of the precision matrix difference. This allows for applications in cases where individual networks are not sparse, such as networks that contain hub nodes, but the differential network is sparse. We discuss the methods' theoretical properties, evaluate its performance in numerical studies and highlight directions for future research. Next, we discuss a methodology for performing valid statistical inference for difference between parameters of generak Markov network in a high-dimensional setting based on the regularized Kullback-Leibler Importance Estimation Procedure that allows us to directly learn the parameters of the differential network, without requiring for separate or joint estimation of the individual Markov network parameters. We prove that our estimator is regular and its distribution can be well approximated by a normal under wide range of data generating processes and, in particular, is not sensitive to model selection mistakes. Furthermore, we develop a new testing procedure for equality of Markov networks, which is based on a max-type statistics. A valid bootstrap procedure is developed that approximates quantiles of the test statistics.