14:00-14:50, Dec. 12th, 2015
Session (4)

Learning causal networks via additive faithfulness

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Abstract

In this work we introduce a statistical model, called additively faithful directed acyclic graph (AFDAG), for causal learning from observational data. Our approach is based on additive conditional independence (ACI), a recently proposed three-way statistical relation that shares many similarities with conditional independence. However, the nonparametric characterization of ACI does not involve multivariate kernel, so is distinct from conditional independence. Due to this special feature, AFDAG enjoys the flexibility of a nonparametric estimator but avoids the curse of dimensionality when handling high-dimensional networks. We develop an estimator for AFDAG based on a linear operator that characterizes ACI, and propose a modified PC-algorithm to implement the estimating procedures efficiently, so that their complexity is determined by the number of edges rather than the dimension of the network. We also establish the consistency and convergence rates of our estimator. Through simulation studies we show that our method outperforms existing methods when commonly assumed conditions such as Gaussian or Gaussian copula distributions do not hold. Finally, the usefulness of AFDAG formulation is demonstrated through its application to a proteomics data set.

(This is a joint work with Tianqi Liu (Yale), Bing Li (Penn State), and Hongyu Zhao (Yale).)

Key words: Additive conditional independence, additive reproducing kernel Hilbert space, directed acyclic graph, global Markov property, normalized additive conditional covariance operator, PC-algorithm.