Complexity analysis of Bayesian learning of high-dimensional DAG models

Quan Zhou and Hyunwoong Chang

Abstract

We consider MCMC methods for learning equivalence classes of sparse Gaussian DAG models when $p = e^{o(n)}$. The main contribution of this work is a rapid mixing result for a random walk Metropolis-Hastings algorithm, which we prove using a canonical path method. It reveals that the complexity of Bayesian learning of sparse equivalence classes grows only polynomially in $n$ and $p$, under some common high-dimensional assumptions. Further, a series of high-dimensional consistency results is obtained by the path method, including the strong selection consistency of an empirical Bayes model for structure learning and the consistency of a greedy local search on the restricted search space. Under the assumption of equal error variance, we can further prove the rapid mixing and strong selection consistency of Gaussian DAG learning.