

Post-Regularization Inference for Dynamic Nonparanormal Graphical Models

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Abstract

We propose a novel class of dynamic nonparanormal graphical models, which allows us to model high dimensional heavy-tailed systems and the evolution of their latent network structures. Under this model we develop statistical tests for presence of edges both locally at a fixed index value and globally over a range of values. The tests are developed for a high-dimensional regime, are robust to model selection mistakes and do not require commonly assumed minimum signal strength.

The testing procedures are based on a high dimensional, debiasing-free moment estimator, which uses a novel kernel smoothed Kendall's tau correlation matrix as an input statistic. The estimator consistently estimates the latent inverse Pearson correlation matrix uniformly in both index variable and kernel bandwidth. Its rate of convergence is shown to be minimax optimal. Thorough numerical simulations and an application to a neural imaging dataset support the usefulness of our method.

(Joint work with Junwei Lu and Han Liu.)