Online Graph Topology Learning from Matrix-valued Time Series

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Résumé

This work is concerned with the statistical analysis of matrix-valued time series. These are data collected over a network of sensors (typically a set of spatial locations), recording, over time, observations of multiple measurements. From such data, we propose to learn, in an online fashion, a graph that captures two aspects of dependency: one describing the sparse spatial relationship between sensors, and the other characterizing the measurements' relationship. To this end, we introduce a novel multivariate autoregressive model to infer the graph topology encoded in the coefficient matrix which captures the sparse Granger causality dependency structure present in such matrix-valued time series. We decompose the graph by imposing a Kronecker sum structure on the coefficient matrix. We develop two online approaches to learn the graph in a recursive way. The first one uses Wald test for the projected OLS estimation, where we derive the asymptotic distribution for the estimator. For the second one, we propose a novel Lasso-type optimization problem. We rely on homotopy algorithms to derive updating rules for estimating the coefficient matrix. Furthermore, we provide an adaptive tuning procedure for the regularization parameter. Numerical experiments using both synthetic and real data, are performed to support the effectiveness of the proposed learning approaches.

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