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SPEAKER TITLES/ABSTRACT

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"The EAS Approach for Graphical Selection Consistency in Vector Autoregression Models"

As evidenced by various recent and significant papers within the frequentist literature, along with numerous applications in macroeconomics, genomics, and neuroscience, there has been substantial interest to understand the theoretical estimation properties of high-dimensional vector autoregression (VAR) models. To date, however, while Bayesian VAR models have been developed and explored empirically (primarily in the econometrics literature) there exist very few theoretical investigations of the repeated sampling properties for Bayesian VAR models in the literature. Despite this fact, Bayesian methodology can surely offer important contributions to the high-dimensional VAR model literature, beyond what could be developed in a frequentist framework. One notable such contribution is the construction of posterior distributions over the set of all relative model probabilities. This framework of posterior inference has been widely exploited over the last decade in the high-dimensional linear regression literature, and we anticipate it will see comparable success for high-dimensional VAR models in the near future. In this direction, we construct methodology via the ε-$admissible$ subsets (EAS) approach for posterior-like inference of relative model probabilities over all sets of active/inactive components of the VAR transition matrix. We provide a mathematical proof of $strong$ graphical selection consistency for the EAS approach for stable VAR(1) models, and demonstrate numerically that it is an effective strategy in high-dimensional settings. The EAS methodology is an entirely new perspective on model selection which was originally developed to effectively account for linear dependencies among subsets of covariates in the high-dimensional linear regression setting.