Learning Semiparametric Gaussian Copula Graphical Models

Graphical models have been widely used to explore conditional dependencies of high-dimensional data. It is common to assume that data are independently and identically generated from a specified Markov random field. However, in real-world applications, observations are often non-Gaussian and time-varying, which has a significant effect on statistical estimation and inference. In this talk, we consider learning semiparametric Gaussian copula graphical models to retain graphical interpretability without requiring the restricted Gaussian assumption. Theoretical properties are established under the high-dimensional setting, and numerical properties are also demonstrated. Our work extends the methodology and applicability of high-dimensional graphical models.

.Refreshments will be served after the seminar in 1181 Comstock Hall.