The development of models and methods for multiple graph data is of critical importance both in statistical network theory and across application domains, including neuroscience, biology, and the social sciences. Although single-graph inference is a well-studied problem, multiple network analysis still possesses many open questions, in part because of the challenges inherent in appropriately modeling graph heterogeneity and yet retaining sufficient model simplicity.

In this talk, we present a model that describes a collection of networks with a shared latent structure on the vertices but potentially different individual connectivity patterns. The model is both flexible enough to meaningfully account for important individual differences, and tractable to allow for accurate and scalable inference. In particular, a joint spectral embedding of adjacency matrices leads to simultaneous consistent estimation and asymptotic normality of underlying parameters for each graph. We show how the methodology can be used for subsequent inference tasks, including graph hypothesis testing, multilayer community detection, and dimensionality reduction, and apply it to a dataset of brain networks, showing a meaningful determination of heterogeneity across scans of different subjects. We also discuss further problems in multiple network analysis, including inference for time series of graphs, network classification, and graph matching.