Random matrix theory aids statistical inference in high dimensions

This talk is on bootstrapping spectral statistics in high dimensions. Spectral statistics play a central role in many multivariate testing problems. It is therefore of interest to approximate the distribution of functions of the eigenvalues of sample covariance matrices. Although bootstrap methods are an established approach to approximating the laws of spectral statistics in low-dimensional problems, these methods are relatively unexplored in the high-dimensional setting.

The aim of this talk is to focus on linear spectral statistics (LSS) as a class of "prototype statistics" for developing a new bootstrap method in the high-dimensional setting. In essence, the method originates from the parametric bootstrap, and is motivated by the notion that, in high dimensions, it is difficult to obtain a non-parametric approximation to the full data-generating distribution.

From a practical standpoint, the method is easy to use, and allows the user to circumvent the difficulties of complex asymptotic formulas for LSS. In addition to proving the consistency of the proposed method, I will discuss encouraging empirical results in a variety of settings. Lastly, and perhaps most interestingly, simulations indicate that the method can be applied successfully to statistics outside the class of LSS, such as the largest sample eigenvalue and others.