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Title: Equivalence Principles for Nonlinear Random Matrices: A Closer Look

Abstract: In recent years, several novel random matrix ensembles have emerged in the fields of machine learning and signal processing. The spectral properties of these matrices have been shown in numerous studies to be instrumental in addressing critical issues such as the training and generalization performance of neural networks, and the fundamental limits of high-dimensional signal recovery. Consequently, there is an increasing interest in accurately understanding the spectral and other asymptotic properties of these matrices. Differing from their classical counterparts, these new random matrices often bear a greater degree of structure, a result of nonlinear transformations. This combination of structure and nonlinearity presents substantial technical challenges when attempting to apply existing tools from random matrix theory to these new ensembles.

In this presentation, I will discuss several closely related equivalence principles that establish an asymptotic equivalence between a variety of nonlinear random matrices and certain linear random matrix ensembles, which are comparatively easier to analyze. Furthermore, I will demonstrate how these equivalence principles can be employed to characterize the performance of kernel methods and random feature models across different scaling regimes.

Joint work with Hong Hu and Horng-Tzer Yau