Abstract

Quantitative Gaussian approximation bounds are important to obtain finite-sample, non-asymptotic inferential guarantees for various statistical problems. In this talk, I will discuss recent results on deriving such bounds for a class of stabilizing statistics. Examples of such statistics include $k$-nearest neighbor based entropy estimators, random forest predictors, and matching based Average Treatment Effect (ATE) estimators. The central challenge in these problems is to handle the delicate dependency structure arising in such statistics. We handle this by introducing and utilizing various geometric notions of stabilization, which we combine with Malliavin-Stein's method to establish our results. These notions of stabilization are quite universal in characterizing the local dependencies, and thus provides a powerful tool for obtaining Gaussian approximation bounds for many statistical applications, including the aforementioned ones.