Statistical Inference for Optimal Transport via Density Estimation

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Abstract

The optimal transport problem has received a surge of interest as a methodological tool for statistical applications. This has led to a recent flurry of research on statistical inference for objects arising from the optimal transport framework. In particular, a large body of work has derived sufficient conditions under which the empirical plugin estimator of the Wasserstein distance admits a non-degenerate limiting distribution centered at its population counterpart. These conditions typically constrain the complexity of the underlying ground spaces. In this talk, I will take a different perspective, and discuss plugin estimators of the 2-Wasserstein distance based on density estimation. Such estimators provide a rather different set of assumptions under which one can perform efficient inference. Indeed, we show that our plugin estimators enjoy a central limit theorem with desirable centering whenever the underlying distributions admit sufficiently smooth densities. We further show that a bias-corrected analogue of our estimators obeys the same asymptotics so long as the underlying densities lie in a sufficiently small, but possibly nonsmooth, function class. Moving beyond the Wasserstein distance, I will also discuss our ongoing work on performing inference for optimal transport maps. In this context, we show that the fitted optimal transport map between density estimators obeys a pointwise central limit theorem under appropriate conditions.

This talk is based on joint work with Sivaraman Balakrishnan, Jonathan Niles-Weed, and Larry Wasserman.