STATISTICS SEMINAR

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Thursday, September 22, 2016
Dickens Hall, Room 207, 4:00-5:00 pm
Refreshments: Dickens 108, 3:30-4:00 pm

Efficient Augmentation and Relaxation Learning for Treatment Regimes using Observational Data

Individualized treatment rules aim to identify if, when, which, and to whom treatment should be applied. A globally aging population, rising healthcare costs, and increased access to patient-level data have created an urgent need for high-quality estimators of individualized treatment rules from observational data. A recent and promising line of research for estimating individualized treatment regimes is to recast the problem of estimating an optimal treatment rule as a weighted misclassification problem. Here, we consider a class of estimators for optimal treatment rules that are analogous to convex large-margin classifiers. The proposed class applies to observational data and is doubly-robust in the sense that correct specification of either a propensity or outcome model lead to consistent estimation of the optimal individualized treatment rule. Moreover, our estimator attains the semiparametric efficiency bound when both models are correct. We derive rates of convergence for the pro- posed estimators and use these rates to characterize the bias-variance trade-off for estimating individualized treatment regimes with classification-based methods. Simulated experiments informed by these results demonstrate that it is possible to construct new estimators within the proposed framework that significantly outperform existing methods. We illustrate the proposed methods using data from a labor training example and a study of inflammatory bowel syndrome.