Learning an individualized dose rule (IDR) in personalized medicine is a challenging statistical problem. Existing methods for estimating the optimal IDR often suffer from the curse of dimensionality, especially when the IDR is learned nonparametrically using machine learning approaches. We propose a dimension reduction framework by exploiting that the IDR can be represented by a nonparametric function which relies only on a few linear combinations of the original covariates, leading to a more parsimonious model. To achieve this, we consider two approaches, a direct learning approach that yields the IDR as commonly desired in personalized medicine, and a pseudo-direct learning approach that focuses more on learning the dimension reduction space. Under regularity assumptions, we provide the convergence rate for the semiparametric estimators and Fisher consistency properties for the corresponding value function. In both approaches, we use an orthogonality constrained optimization approach on the Stiefel manifold to solve the dimension reduction space. Performances are evaluated through simulation studies and a warfarin pharmacogenetic study.

Refreshments will be served following the seminar in 1181 Comstock Hall.