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PROXIMAL CAUSAL INFERENCE FOR MODIFIED TREATMENT POLICIES

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The proximal causal inference framework enables the identification and estimation of causal effects in the presence of unmeasured confounding by leveraging two disjoint sets of observed strong proxies: negative control treatments and negative control outcomes. In the point exposure setting, this framework has primarily been applied to estimands comparing counterfactual outcomes under a static fixed intervention or, possibly randomized, regime that depends on baseline covariates. For continuous exposures, alternative hypothetical scenarios can enrich our understanding of causal effects, such as those where each individual receives their observed treatment dose modified in a pre-specified manner - commonly referred to as modified treatment regimes. In this talk, I will discuss current work where we extend the proximal causal inference framework to identify and estimate the mean outcome under a modified treatment regime, addressing this gap in the literature. We propose a flexible strategy that does not rely on the assumption that all confounders have been measured - unlike existing estimators - and leverages modern debiased machine learning techniques using non-parametric estimators of nuisance functions to avoid restrictive parametric assumptions. Our methodology was motivated by immunobridging studies of COVID-19 vaccines aimed at identifying correlates of protection, where the individual's underlying immune capacity is an important unmeasured confounder. We demonstrate its applicability using data from such a study and evaluate its finite-sample performance through simulation studies.

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