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Learning Robust Risk Scores from Observational Data under Unobserved Confounders

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We consider the problem of learning, from observational data, a logistic regression model to predict the risk of an adverse outcome under no treatment. These problems arise routinely in public health and the social sciences, e.g., to help prioritize individuals for scarce resources or services. The vast majority of the literature on the topic assumes unconfoundedness, i.e., no unobserved confounders affect both treatment assignments and outcomes. However, this assumption often fails to hold in practice. In this research, we propose a logistic regression-based risk prediction model that is robust to potential unobserved confounders. Our approach constructs uncertainty sets for inverse propensity weights, inspired by sensitivity analysis in causal inference and Wasserstein distributionally robust optimization. We demonstrate the effectiveness of our approach on a set of synthetic data and semi-synthetic data, showing that our robust approach achieves better performance compared to the baseline non-robust approaches. We also conduct a case study on scarce housing resource allocation to people experiencing homelessness, based on the real data from LA County Homeless Management Information System.

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