

CBRNets: Regularizing neural networks to learn continuously-valued treatment effects from observational data

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We investigate the problem of individual treatment effect (ITE) estimation for treatments with a continuously-valued dosages, i.e., individual dose responses. Such settings are prevalent in a variety of domains, from healthcare to business, economics, and beyond.

As a problem of causal inference, the individual dose response must usually be estimated from observational data. Being subject to dosage selection bias, that is, that the observed dosages are dependent on the characteristics of an observation, learning from such data is challenging. Preceding studies have found that traditional machine learning approaches fail to generalize the dose response under dosage selection bias. Established causal machine learning approaches, such as SCIGAN, DRNets and VCNets attempt to solve those limitations. We add to this family of methods by proposing CBRNets, a novel causal machine learning approach for the estimation of dose responses. CBRNet leverages the heterogeneity of training observations to build balanced latent representations of the data to find unbiased estimates of individual dose responses.

In our work, we discuss the benefits of our method over established methods, and discuss potential use cases in business decision making and operations research. We validate the potential of CBRNets on a set of semi-synthetic experiments.