Network Interference and Effect Modification

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Abstract: While most of causal inference studies typically disregard interference between units, it's important to recognize that agents often interact through social, physical, or virtual connections, and the effect of the intervention can propagate from one unit to other connected individuals in the network. In this work, we propose an innovative machine learning algorithm called Network Causal Tree (NCT), which combines a tree-based methodology with a Horvitz-Thompson estimator to assess the heterogeneity of treatment and spillover effects with respect to individual and network characteristics, in the presence of clustered network interference. Using NCT, we examine the heterogeneous effects of information sessions on the adoption of a new insurance policy in rural China.

Keywords: causal inference, interference, networks.

1 Introduction

According Cox (1958), *inteference* occurs when the treatment assignment of one unit affects the outcome of other units. In the context of policy interventions, interference can arise from many types of interactions, such as social, physical, or virtual connections. The standard Rubin Causal Model for causal inference studies (Rubin, 1986) assumes no interference. However, when interference is likely to occur but is ignored, it introduces bias into the estimates (Forastiere *et al.* , 2021). Furthermore, understanding spillover effects is crucial for measuring the overall impact of an intervention and enhancing the efficiency of treatment assignment mechanisms. As a result, recent research has developed innovative methodologies to address interference.(see, e.g., Sobel, 2006; Rosenbaum, 2007). In parallel to this field of research on interference, researchers have developed machine learning algorithms to assess the heterogeneity of treatment effects with respect to individual characteristics (Athey &

Imbens, 2016). The intuition behind these algorithms is that sub-populations are partitioned by iteratively separating those groups whose estimated average treatment effect deviates the most.

In this study, we present a cutting-edge integration of the aforementioned two topics in the field of causal inference through the introduction of a novel machine learning algorithm, named *Network Causal Tree* (NCT), that investigates the heterogeneity of both treatment and spillover effects with respect to individual, neighborhood and network characteristics, in randomized settings. NCT works in the presence of *clustered network interference*, where agents belong to separate clusters and spillover mechanisms occur only within clusters, according to the links of a cluster-specific network. Conditional effects are estimated by using an extended version of the Horvitz-Thompson estimator (Aronow & Samii, 2017) to allow for clustered network interference. We showcase the NCT methodology to assess the effect of intensive training sessions to promote the uptake of a new weather insurance policy for rice farmers living in villages of rural China (Cai *et al.* , 2015). In this setting, interference is likely to arise, since treated households may share what they have learned with the interfering untreated households.

2 Methods

2.1 Clustered Network Interference

We examine a sample $\mathcal{V}$ consisting of N units distributed across K distinct clusters. Each cluster is represented by the indicator $k \in \mathcal{K} = [1,\dots,K]$, and within each cluster k, units are identified by the index $i = 1,\dots,n_k$.. These units interact within a clustered network structure $\boldsymbol{G}$, where units belonging to the same cluster may share connections, while connections between different clusters are absent. Essentially, $\boldsymbol{G}$ can be seen as a collection of K separate subgraphs, denoted as G_k. The assignment of units to the intervention is random, and we use the binary variable $W_{ik} \in 0,1$ to represent the treatment assigned to unit i in cluster k. The observed outcome for each unit is indicated by Y_{ik}. Additionally, for each unit ik, we have access to a set of individual or network characteristics denoted as $\mathbf{X}_{ik}$.

To define the potential outcomes (Rubin, 1986), we have to rely on some assumptions on the interference mechanism. Here, we assume that *Clustered Network Interference* (CNI) takes place. Under CNI i) the spillover mechanism is confined to units within the same cluster, and ii) an individual's outcome is influenced by the treatment status of units directly connected to her/him based on the cluster-specific network. Potential outcomes are indexed with respect to the individual intervention W_{ik} and to the neighborhood treatment G_{ik}, which represents a numerical synthesis of the treatment assignment vector of the neighbors: $Y_{ik}(W_{ik}, G_{ik})$. Here, the variable G_{ik} represents a binary network exposure based on a threshold function applied to the number of treated neighbors: G_{ik} equals 1 if the unit ik has at least one treated neighbor, 0 otherwise. We outline four estimands of interest $\tau_{(w,g;w',g')}$, two treatment effects and two spillover effects, where treatment (spillvoer) effects are defined by comparing average potential outcomes under different levels of the individual (neighborhood) treatment status, while keeping as fixed the level of the neighborhood (individual) treatment.

2.2 The Network Causal Tree algorithm

The NCT algorithm is designed to detect and estimate heterogeneous treatment and spillover effects in randomized settings, under CNI. NCT is also able to discover the heterogeneity with respect to more than one estimand simultaneously. NCT takes as inputs the observed data $\{W_{ik}, Y_{ik}, \mathbf{X}_{ik}\}_{ik \in \mathcal{V}}$, the global network $\boldsymbol{G}$, the experimental design and a vector of weights $\omega(w, g; w', g')$ ruling the extent of which estimands contribute to the criterion function, while it returns as output a partition Π of the covariate space, together with point estimates and standard errors of the conditional average causal effects:

The algorithm provides three main steps. In the first step, NCT randomly splits clusters in two sets - the discovery set and the estimation set. In the second step, using the discovery set, NCT sprouts a tree according to the in-sample splitting function and stops when a stopping criterion is met (reached maximum depth, insufficient sample size in the leafs). In the third step, NCT computes the estimated effects and the corresponding standard errors, in all the partitions identified at the first step.

3 Empirical results

Data include 4,586 households living in specific villages of rural China and provide information on the friendship networks connecting households in the same village. Some households are randomly assigned to receive intensive information sessions on a new weather insurance policy, while the remaining households receive *simple* sessions. Households who have at least one treated household in their neighborhood are assumed to receive an indirect exposure to the intervention. The outcome indicates whether the household decides to take

up the insurance policy. The heterogeneity of treatment and spillover effects is evaluated with respect to variables that refer either to characteristics of the household (production area, size) or to characteristics the of the household's owner (sex, age, level of education, risk aversion, perceived probability of disaster, trust in the government).
Results suggest that the most important heterogeneity drivers of the treatment effect are the production area, the risk aversion and the trust in the government. Spillover effects are not statistically significant.

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