Strategyproof Decision-Making in Panel Data Settings and Beyond

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In panel data settings, one observes repeated, noisy, measurements of a collection of units over a period of time, during which the units undergo different interventions. For example, units can be individuals, companies, or geographic locations, and interventions can represent discounts, health therapies, or tax regulations. This is a ubiquitous way to collect data, and, as a result, the analysis of panel data has a long history in econometrics and statistics. A common goal in the literature is to analyze how a principal (e.g., business platform, regulatory agency) can do “counterfactual inference”, i.e., estimate what will happen to a unit if it undergoes a variety of possible interventions. The ultimate goal of such counterfactual inference is to enable data-driven decision-making, where one does not just estimate statistical parameters of interest, but actually uses data to make better decisions. In medical domains, for example, the goal typically is not just estimating health outcomes for patients under different health therapies, but also a policy that selects appropriate therapies for new patients. However, the leap from counterfactual inference to data-driven decision-making comes with additional challenges: namely, when units know that they will be assigned disparate interventions based on their reported data, they have incentives to strategize with their reports. Such strategic interactions in panel data settings are observed in practice. For example, Caro et al. [4] observe that Zara store managers strategically misreported store inventory information to higher-ups in order to maximize sales at their local branch.

Consider an e-commerce platform that wishes to give one of several possible discounts to a new user to maximize some metric of interest, e.g. engagement levels. In this example time-steps are days/weeks/months, units are users, and outcomes are engagement levels. Suppose the company uses historical data to build a model that estimates the “counterfactual” trajectory of engagement levels of a new user under different discount policies, based on their observed trajectory of engagement levels thus far. If a user knew this were the case, then they have a clear incentive to strategically modify their engagement levels to receive a larger discount. Such strategic manipulations in response to data-driven decision-making have been observed in other domains such as lending [6] and search engine optimization [5]. In this paper, we focus on strategyproof intervention policies, i.e., policies that assign the utility-maximizing treatment to the units despite them strategically altering their data. Concretely, we answer two questions:

**Q1:** Is it possible to design intervention policies that are robust to strategic modification of data by units to receive a more favorable intervention? We call such policies strategyproof.

**Q2:** Can we leverage the structure typically present in panel data to derive computationally-efficient algorithms for learning strategyproof intervention policies?

Towards answering both questions, we build upon the framework for counterfactual inference with panel data called *synthetic interventions* [3], which itself is a generalization of the canonical framework of *synthetic control* [1, 2]. In both settings, there is a notion of a “pre-intervention” time period when all units are under control (i.e., no intervention), followed by a “post-intervention” time period, when each unit undergoes exactly one of many possible interventions (including control). Synthetic control methods can be used to estimate the counterfactual outcome if a unit did not undergo an intervention, i.e., remained under control. Given its simplicity, synthetic control has become a ubiquitous technique in econometrics to estimate counterfactuals under control in high-stakes domains including e-commerce, healthcare, and policy evaluation. Synthetic interventions is a generalization which allows one to estimate counterfactual outcomes not just under control, but also under intervention. Despite being a relatively new development, the synthetic interventions framework has been used by several companies across therapeutics, ride-sharing, and e-commerce, to estimate the best

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1 Another motivating example is the incentives of store managers in inventory management, as discussed in Caro et al. [4]. Here, time-steps are days/weeks/months, units are different products at a given store, outcomes are (reported) inventory levels, and interventions are different levels of discount.
intervention for a given unit. Given the growing popularity of the synthetic control and synthetic interventions frameworks in high-stakes decision-making, an issue that will likely arise is the strategic manipulation of observed outcomes by units. In particular, just as in the e-commerce example, units have an incentive to manipulate their pre-intervention outcomes in order to get a more favorable intervention during the post-intervention period. Indeed, if such strategic manipulations are not taken into account, we establish that the synthetic interventions estimator can perform poorly. The goal of the principal in such strategic settings is to assign the “correct” intervention to each unit—the intervention which maximizes some objective function such as total user engagement—during the post-intervention period, despite possible strategic manipulations to the unit’s pre-treatment behavior. As we observe, this can be thought of as designing a mechanism for strategyproof multi-class classification with panel data. Although many of our results apply more broadly to strategyproof multi-class classification, we focus on panel data (and in particular the setup of synthetic control and synthetic interventions) due to its ubiquity and for concreteness.

The first contribution of our work is a general framework for decision-making in the presence of strategic agents in the panel data setting. In our setting, a principal originally observes historical data from pre- and post- intervention outcomes of \( n \) units. Each of these units \( i \in \{1, \ldots, n\} \) is randomly assigned an intervention \( d_i \) as in an A/B test (i.e., a randomized control trial), so they do not have incentive to strategize with their pre-intervention outcomes. After observing this historical data, the principal commits to an intervention policy \( \pi \), which uses a unit’s pre-intervention outcomes to assign its intervention during the post-intervention period. Then \( m \) new units arrive and strategically modify their pre-treatment outcomes; units are allowed to move in a ball of radius \( \delta \) around their true pre-intervention outcomes, but they are not further constrained. We call this behavior best-responding. Finally, the principal observes the altered pre-intervention outcomes, assigns interventions according to policy \( \pi \), and collects the post-intervention rewards. The goal of the principal in this setting is to deploy a policy \( \pi \) that is strategyproof, i.e., assigns the utility-maximizing intervention to each unit, despite the fact that they may have strategically modified their pre-intervention outcomes. We call this utility-maximizing intervention the unit’s type.

Given that units know the principal’s policy \( \pi \) and they are allowed to best respond anywhere within \( \delta \) of their true pre-intervention outcome, it may seem like \( Q1 \) has a negative answer. However, we derive the necessary and sufficient conditions for a strategyproof intervention policy to exist. In order to obtain this full characterization, we translate out the principal’s problem of assigning interventions to the dual space (i.e., the space of the units’ actions), and derive properties that units of the same type must share.

Our next contribution is to specialize our characterization of strategyproof intervention policies to the setting where unit outcomes at each round are determined by a latent factor model. Under a latent factor model, unit outcomes under different interventions are linearly dependent on a unit latent factor (i.e., their type), as well as a latent vector that is time- and intervention-specific. In this specification, the rewards of the principal are linear in their (expected) pre-intervention outcomes, which implies the units are linearly separable based on their type. We show that our necessary and sufficient condition for a strategyproof intervention policy to exist is always satisfied when there are two interventions, but it is in general not satisfied for three or more interventions. The intuition for both results is that in order for an intervention policy to be strategyproof under the latent factor model, the principal has to shift the decision boundaries by some amount in order to account for the fact that units are able to strategize. When the number of interventions is more than two, it may be the case that there are units of different types whose pre-intervention outcomes are “close enough” to each other such that no movement of the boundary can prevent all units from fooling the principal. Importantly, we show that assigning three or more interventions in a panel data setting with strategic agents can be interpreted as an instance of strategic multiclass classification, a natural generalization of the well-studied strategic (binary) classification problem to the multiclass setting. As such, our impossibility result for strategyproof intervention policies translates to an impossibility result for strategyproof classification with three or more classes. To the best of our knowledge, we are the first to both draw this connection, and discuss strategic multiclass classification altogether.

Having characterized strategyproof intervention policies under a latent factor model, we shift our focus to \( Q2 \). For the case of two interventions, we provide an algorithm for learning a strategyproof intervention policy from historical data. The analysis relies on two steps: First, we upper-bounds the difference between the reward of the learned policy and that of the optimal policy by the estimation error on the rewards of the test units. Second, we leverage bounds for estimation from the “error-in-variables” regression literature to derive end-to-end finite sample guarantees. We show that under relatively minor algebraic assumptions, our intervention policy is asymptotically optimal in the limit of infinite data. Next, we provide analogous finite sample guarantees for the setting with an arbitrary number of treatments—under an additional assumption on the difference in rewards between the optimal and next-best intervention for each type of unit.

Finally, we complement our theoretical results with experiments based on panel data from product sales at several stores over the course of 18 months. We find the data is well-approximated by a latent factor model, and that our intervention policy outperforms a baseline policy which does not take strategic interactions into consideration—even when the algorithm’s estimate of \( \delta \) (the unit effort budget) is misspecified. The full version of the paper may be found at https://arxiv.org/pdf/2211.14236.pdf.

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