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Modeling Covariate Transition for Efficient Estimation of Longitudinal Treatment Effects in Randomized Experiments

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Code Paper Website

Motivation

- **Regression-adjustment** methods are useful for variance reduction in randomized experiments, but standard methods mainly use pre-treatment covariates and estimate a single average effect
- It is important to capture insights into the temporal evolution of treatment effects (e.g., immediate, delayed, or persistent effects)
- Post-treatment histories are key covariates, but naive conditioning may change the causal estimand

Problem Setup

Our work focuses on longitudinal randomized experiments under static regimes

$$\{(\bar{X}_{i,T}, \bar{W}_{i,T}, \bar{Y}_{i,T})\}_{i=1}^{n} \overset{\text{i.i.d.}}{\sim} P_{\bar{Z}_T}$$

- $Y_t \in \mathcal{Y}_t \subseteq \mathbb{R}$: Outcome at time t
- $W_t \in \mathcal{W}_t$: Treatment assignment at time t
- $X_t \in \mathcal{X}_t \subseteq \mathbb{R}^d$: Covariates at time t

Goal of this work

Estimate the time-varying effects $\{\mathrm{ATE}(t)\}_{t=1}^{T}$ not just a single cumulative effect, where

$$\mathrm{ATE}(t) = \mu_{\bar{w}_t}(t) - \mu_{\bar{w}'_t}(t), \quad \mu_{\bar{w}_t}(t) = \mathbb{E}[Y_t(\bar{w}_t)].$$

The empirical estimator is unbiased and consistent,

$$\hat{\mu}^{emp}_{\bar{w}_t}(t) := \frac{1}{n_{\bar{w}_t}} \sum_{i:\bar{W}_{i,t}=\bar{w}_t} Y_{i,t},$$

- Since predictive histories can improve its precision, we utilize the following mean regression

$$m^{(t)}_{\bar{w}_t}(\bar{h}_t) = \mathbb{E}[Y_t(\bar{w}_t) \,|\, \bar{H}_t(\bar{w}_{t-1}) = \bar{h}_t]$$

- Challenges: it receives post-treatment histories

Methodology

To represent the dynamic trajectories in the historical data, we utilize the **transition kernels**

Measure Factorization via Transition Kernels

$$P^{\bar{w}_{t-1}}_{\bar{H}_t}(d\bar{h}_t) = P_{H_1}(dh_1) \prod_{\tau=1}^{t-1} p^{(\tau)}_{\bar{w}_\tau}(dh_{\tau+1} \,|\, \bar{h}_\tau).$$

Forward-Integrated Regression

$$\Gamma^{(\tau)}_{\bar{w}_t}(\bar{h}_\tau) = \int_{\mathcal{H}_{\tau+1}} \Gamma^{(\tau+1)}_{\bar{w}_t}(\bar{h}_{\tau+1}) p^{(\tau)}_{\bar{w}_\tau}(dh_{\tau+1} \,|\, \bar{h}_\tau), \quad \Gamma^{(t)}_{\bar{w}_t}(\bar{h}_t) = m^{(t)}_{\bar{w}_t}(\bar{h}_t).$$

Our estimator can capture temporal dynamics while avoiding post-treatment bias thanks to transition kernels

Dynamic Regression-Adjusted Estimator

$$\hat{\mu}^{dy\text{-}adj}_{\bar{w}_t}(t) = \frac{1}{n_{\bar{w}_t}} \sum_{i:\bar{W}_{i,t}=\bar{w}_t} \left(Y_{i,t} - \hat{\Gamma}^{(t)}_{\bar{w}_t}(\bar{H}_{i,t})\right) + \frac{1}{n}\sum_{i=1}^{n} \hat{A}^{(t)}_{\bar{w}_t}(\bar{H}_{i,t}) + \frac{1}{n}\sum_{i=1}^{n} \hat{\Gamma}^{(1)}_{\bar{w}_t}(X_{i,1}),$$

where $\hat{A}^{(t)}_{\bar{w}_t}$ is correction term for transition innovations

Theory

Summary of Theoretical Results

Under suitable assumptions,

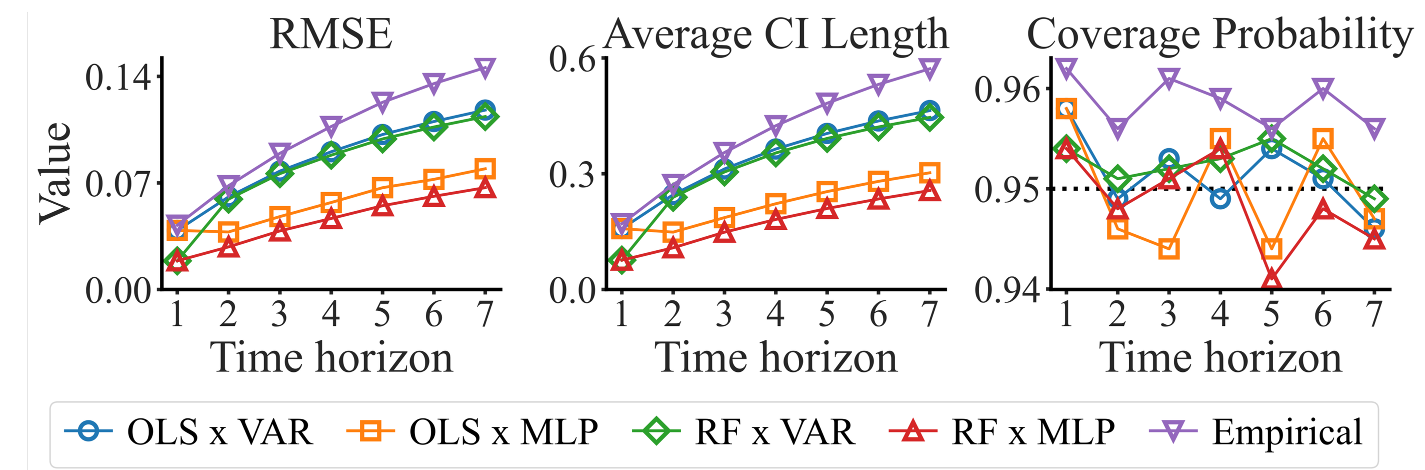
- Neyman orthogonality with cross-fitting gives valid statistical inference
- Our estimator satisfies $\sqrt{n}(\hat{\theta}_t - \theta_t) \rightsquigarrow \mathcal{N}(0, \Sigma_t)$, and attains the semiparametric efficiency bound Σ_t
- Oracle dynamic adjustment is asymptotically no worse than the empirical estimator

Simulation Study

Synthetic datasets are generated according to

$$Y_{i,t} = g(X_{i,t}, Y_{i,t-1}) + \tau(t) W_{i,t} + \varepsilon_{i,t},$$
$$dX_{i,t} = Q \cdot f(Q^\top X_{i,t}, Y_{i,t-1}, W_{i,t})dt + \sigma_X dB_t,$$

- (1) nonlinearity, (2) irrelevant covariates, (3) influences from past treatments, and (4) time-varying effects

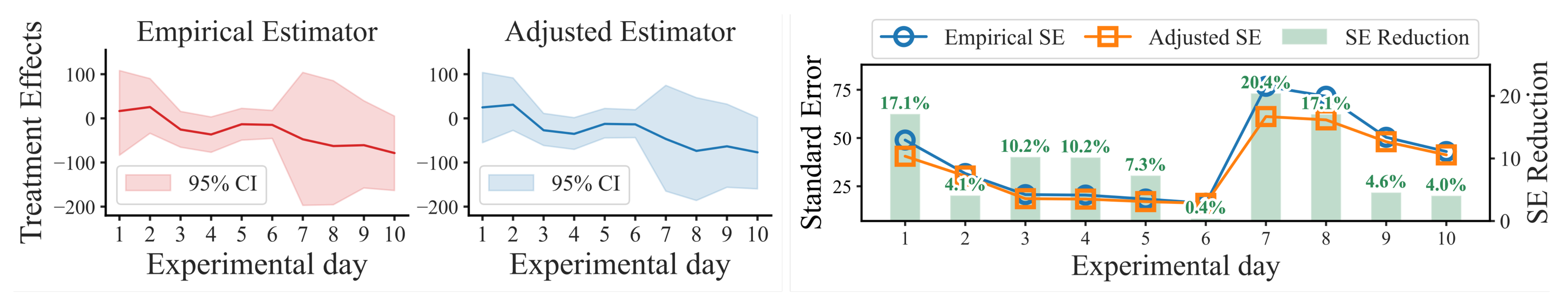


- Our estimator achieves improvements in both RMSE and CI length compared to empirical baseline, while maintaining the nominal coverage probability
- While linear adjustment moderately enhances precision, a nonlinear one achieves further improvements

Application to Real-World Datasets

Our framework is applied to A/B test data from a large-scale streaming platform to evaluate its practicality

- 10-day A/B test for up-next content recommendations
- Outcome: daily viewing time of a target series
- Control group: user interaction based recommendations
- Treatment group: recommendations based on content-level similarity from item features



(a) Estimated longitudinal treatment effects (b) Standard errors and reduction rates over time

- Standard errors are reduced by about 0.4-20.4%

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