Causal Segmentation Analysis with Machine Learning in Large-Scale Digital Experiments

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Why Segment A Population?

- Netflix has 200M+ (and growing) users, constituting a diversity of potential population segments.
- Better understanding this eclectic user-base helps us to
    - improve treatment schedule allocation in A/B experiments,
    - understand and prioritize fairness of treatment impacts,
    - assess differential impacts of proposed product alterations.
- Causal inference provides a *formal* language for discovering and evaluating segments through their treatment effects.

Defining Treatment Effect Heterogeneity

- For a given A/B test or quasi-experiment, we assume data on each of the n units may be expressed $O = (W, A, Y)$, where
  - W: baseline (e.g., region, device type, viewing history),
  - $A \in \{0, 1\}$: treatment assignment (i.e., A vs. B arm),
  - Y: the outcome of interest (e.g., viewing hours).
- Among W, we choose a set of segmentation variables $V \subset W$, whose realizations correspond to user segments of interest.
- The conditional average treatment effect (CATE) evaluates the treatment effect *within a stratum* $v \in V$. The CATE is

$$\text{CATE}(v) = \mathbb{E}[\, \underbrace{\mathbb{E}(Y \mid A = 1, W) - \mathbb{E}(Y \mid A = 0, W)}_{\text{counterfactual mean difference of A=1 vs. A=0}} \mid V = v]$$

Doubly Robust Estimation of Treatment Effect Heterogeneity

- Utilize **doubly robust** estimators of the CATE (Luedtke and van der Laan 2017, VanderWeele et al. 2019).
    - Accurate (i.e., consistent) estimate even when one of the two nuisance quantities is modeled poorly.
    - Efficient (minimal variance) estimate when both well-modeled.
- Ensemble **machine learning** (e.g., van der Laan et al. 2007) for flexible estimation of nuisance quantities.
- **Cross-fitting** (Bickel et al. 1993, Zheng and van der Laan 2011) to identify "should-treat" segments while *preserving inference* for effect measures estimated with machine learning.

Detecting Segments Benefiting from Treatment

- Goal: identify segments T benefiting from treatment, where T are a subset of strata $v \in V$.
- Absolute benefit, defined as $T = \{v : \text{CATE}(v) > \theta\}$ for a given user-specified cutoff $\theta \in \mathbb{R}^+$.
- Relative benefit (subject to cost or side-effects), in which only strata benefiting from treatment ($T \subseteq \{v : \text{CATE}(v) > 0\}$) are subjected to a constraint like $\sum_{v \in T} \text{cost}(v) p(V) \leq \text{budget}$.
- Assign treatment based on CATE point estimates or through hypothesis testing $H_0 : \text{CATE}(v) \leq \theta, H_1 : \text{CATE}(v) > \theta$.

Population Effects of Dynamically Treating Segments

- Dynamic rule: assign treatment only to segments T benefiting from treatment in terms of CATE, i.e., $A = d(V) = \mathbb{I}(v \in T)$.
- Use doubly robust estimators of heterogeneous treatment or optimal treatment effects (HTE, OTE).
- OTE: $\psi_{\text{OTE}} = \mathbb{E}[\mathbb{E}(Y \mid A = d(V), W) - \mathbb{E}(Y \mid A = 1, W)]$, compare dynamic treatment to “treat-all” strategy.
- HTE: ψ_{HTE} compares treatment effects of “should-treat” ($V \in T$) and “should-not-treat” ($V \notin T$) segments.
- Both OTE and HTE characterize the efficacy of the *learned* dynamic rule, informing how interventions should be deployed.

The `sherlock` R Package

- Free and open source data science tool implementing our causal segment discovery framework.
- Supports both causal segment detection and population effect estimation of segment-specific dynamic treatment rules.
- Out-of-the-box machine learning via `sl3` (Coyle et al. 2021) and cross-validation via `origami` (Coyle and Hejazi 2018).
- Available at `https://github.com/Netflix/sherlock`, with plans in place for a release on the CRAN repository.

Illustration in a Quasi-Experimental Study

num_devices	is_p2plus	is_newmarket	baseline_ltv	baseline_viewing	treatment	outcome_viewing
3	0	1	0.539	0.000	1	0.406
2	1	1	1.328	1.637	0	2.328
3	1	0	0.000	0.000	1	3.400
2	1	0	1.027	0.000	0	1.934
2	1	1	0.000	0.000	0	1.376
3	0	1	0.000	1.401	0	2.683

Measurements on six random units from a *synthetic* dataset.

- Baseline covariates (W): account's number of devices, whether a newly enrolled member, being in a new market region, lifetime value of account, account's baseline viewing hours.

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num_devices	**is_p2plus**	is_newmarket	baseline_ltv	baseline_viewing	treatment	outcome_viewing
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2	1	1	0.000	0.000	0	1.376
3	0	1	0.000	1.401	0	2.683

Measurements on six random units from a *synthetic* dataset.

- Segmentation variables ($V \subset W$): account's number of devices (num_devices), whether a newly enrolled member (is_p2plus).

Illustration in a Quasi-Experimental Study

num_devices	is_p2plus	is_newmarket	baseline_ltv	baseline_viewing	**treatment**	outcome_viewing
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Measurements on six random units from a *synthetic* dataset.

- Treatment (A, non-randomized): a new user interface.

Illustration in a Quasi-Experimental Study

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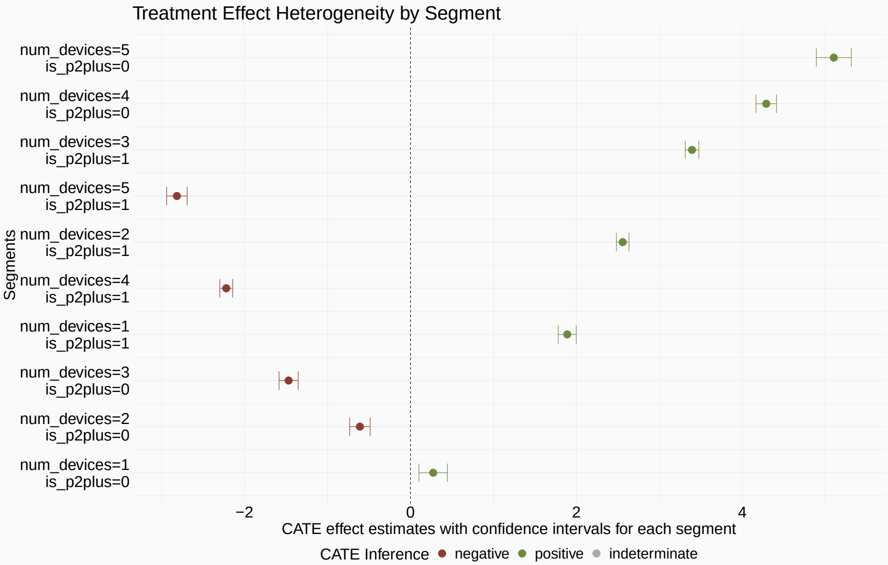
Measurements on six random units from a *synthetic* dataset.

- Outcome (Y): metric of account's viewing hours.

Treatment Heterogeneity Across Segments



https://github.com/Netflix/sherlock

Thank you!

https://nimahejazi.org

https://twitter.com/nshejazi

https://github.com/nhejazi

https://arxiv.org/abs/2111.01223

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