MS&E 228: Discussion and FAQ

Vasilis Syrgkanis

MS&E, Stanford

Michael Riad Bendok 2d

We have learned dozens methods to approach prediction and inference. If you were given a problem related to prediction/ and or inference and had 2 hours to report your findings, how would you begin ? What steps would you take to get from dataset to findings? I know this is an abstract question but maybe you can give an example from your time @ Microsoft. Would be awesome to come out of this class with a structured way to approach problems from scratch

3 Reply Edit Delete ···

Svea Drekshagen 23h

I would also be very interested in this question!

Reply Edit Delete ···

Dhananjay Balakrishnan 21h

yeah, this would be super nice. through the course of the class, we have seen quite a wide variety of methods and modelling assumptions; given a real-world problem, would be nice to know what the steps to do would be and also potential challenges/bottlenecks commonly faced in these tasks.

Reply Edit Delete ···

Y

Yikai Cao 18h

Throughout the course, we learned a lot of different causal inference methods and assumptions. In practice, when encountering a real-world causal inference problem for the first time, what's your personal workflow? Are there specific steps, diagnostic checks, or guidelines you always follow to decide which method to apply? If you could share any practical tips from your own experience, that would be great!

Reply Edit Delete •••

Y

Yao Xu 18h

I'm curious and unsure about when it is better to use double machine learning/plr or doubly robust learning/irm in practice. Since DR methods have much more robust properties, does it mean we should always use it in practice? Maybe one concern against DR would be higher variance as we observed in the psets? We have implemented both DML and DR in the homeworks with the same identification assumptions and binary treatments, but I didn't completely understand when it is better to use which models. Would you recommend using both LinearDRLearner and LinearDML to estimate the ATE when dealing with a binary treatment and the need for confidence intervals?

Reply Edit Delete ···

Max Schuessler 2d

Could we go through a summary of all the different settings/methods we have seen in class and make a tree-like map? I have seen a professor do this for an introductory class to ML in which she summarized in which settings which ML models work particularly well. To do this, she started off by splitting into regression versus classification first etc, then discussed settings such as high "p (predictors) low n (observations)" and the role of regularization. Perhaps something similar would be possible for causal inference and ML specifically, starting off with RCT versus non-RCT setting and then making branches going downstream. I think this could be incredibly helpful as a future reference.

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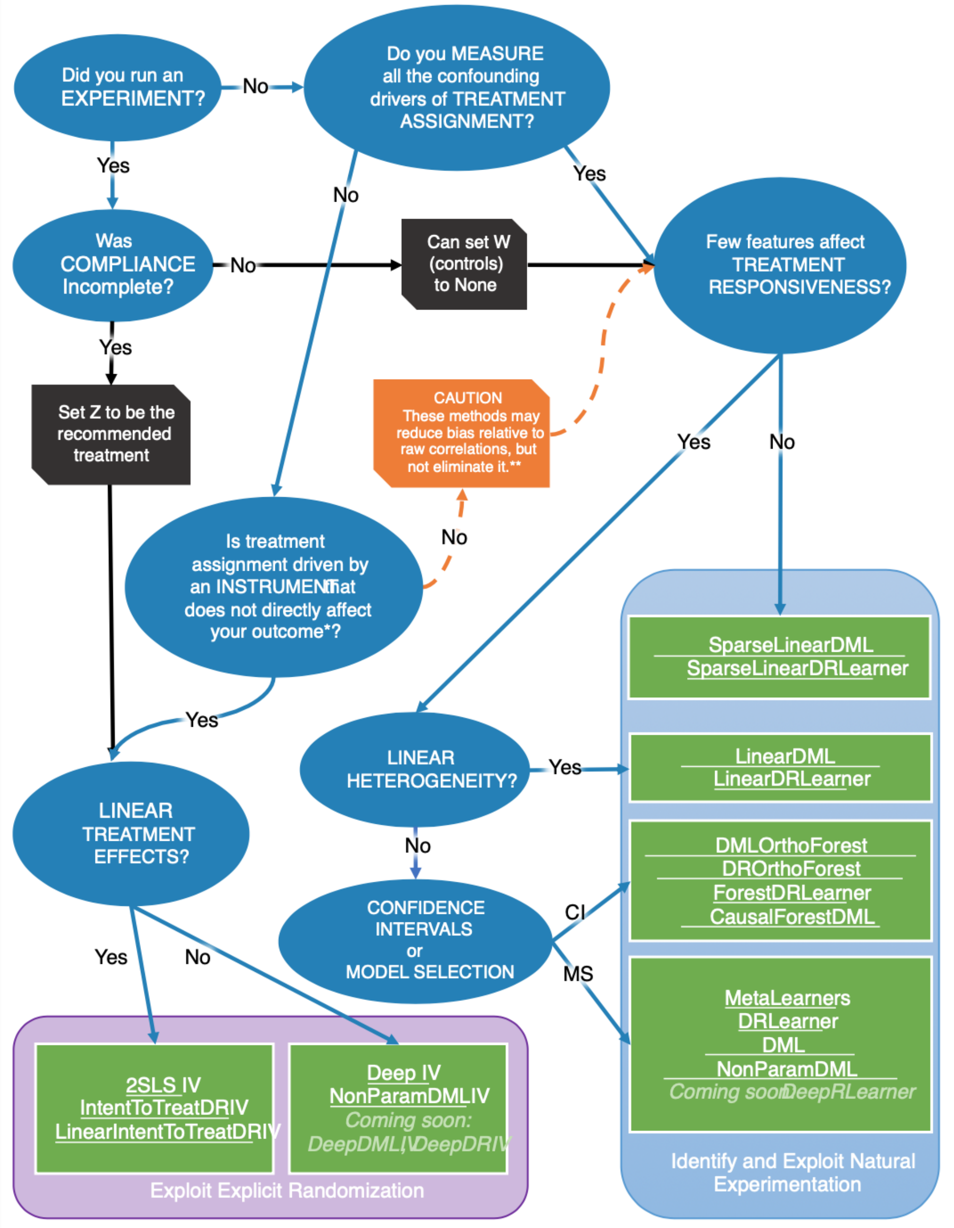
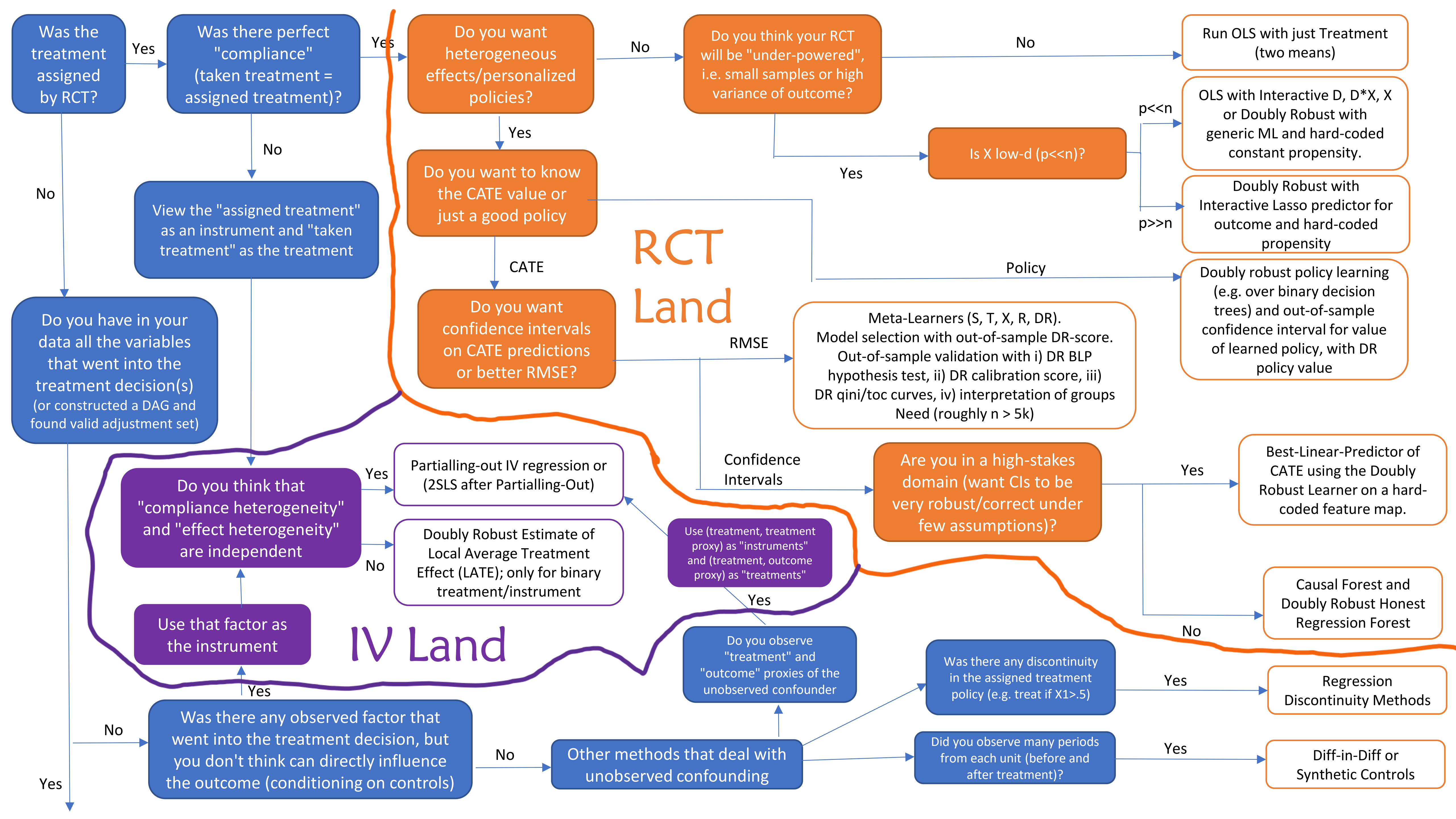
Daniel Jenson 2d

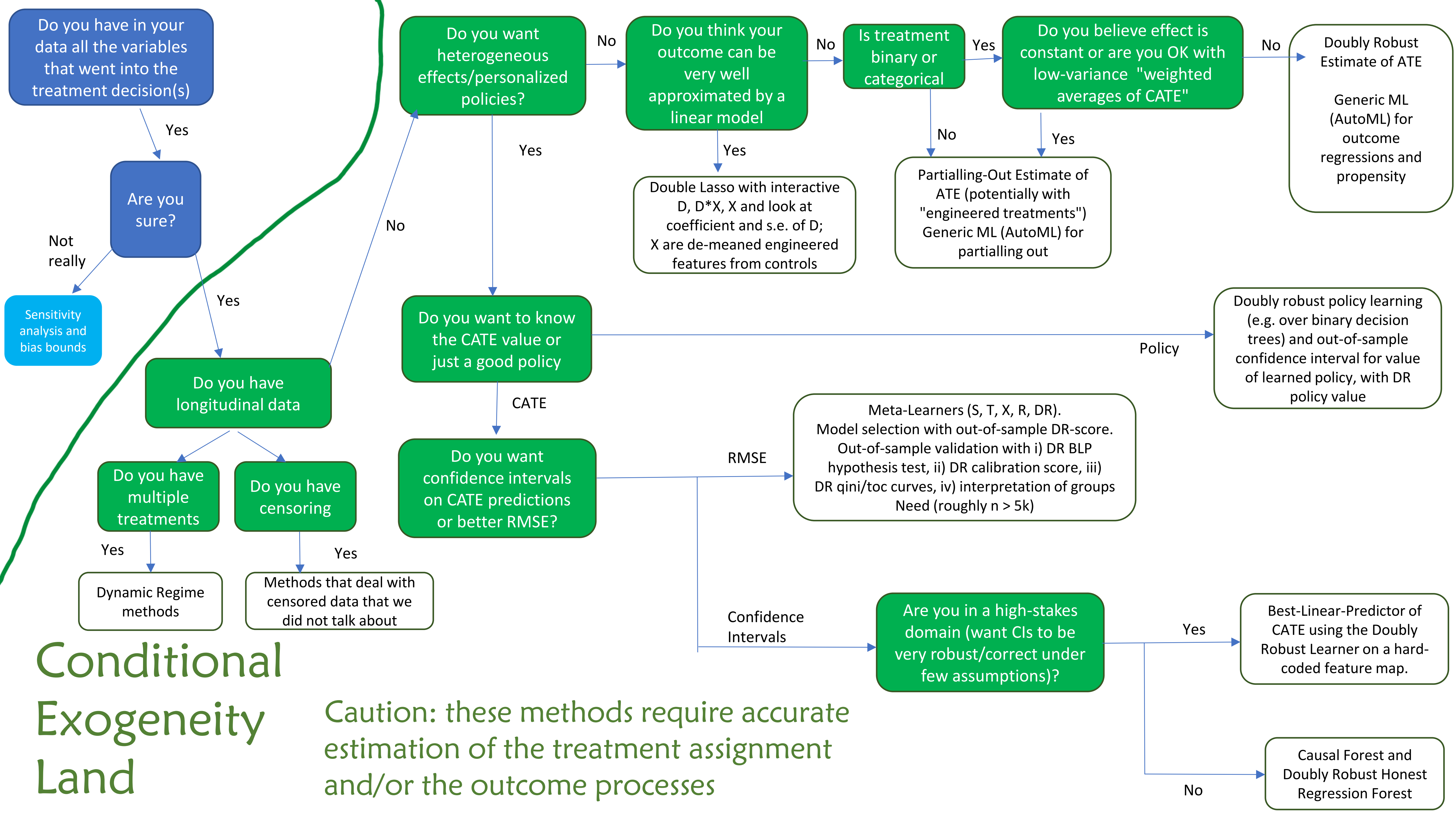
Can we build a mind map of the techniques we've used?

3 Reply Edit Delete •••

Library Flow Chart




Was the treatment assigned by RCT?
Yes
No
Was there perfect "compliance" (taken treatment = assigned treatment)?
Yes
No
View the "assigned treatment" as an instrument and "taken treatment" as the treatment
Do you want heterogeneous effects/personalized policies?
No
Yes
Do you think your RCT will be "under-powered", i.e. small samples or high variance of outcome?
No
Yes
Run OLS with just Treatment (two means)
Is X low-d (p<<n)?
p<<n
p>>n
OLS with Interactive D, D*X, X or Doubly Robust with generic ML and hard-coded constant propensity.
Doubly Robust with Interactive Lasso predictor for outcome and hard-coded propensity
Do you want to know the CATE value or just a good policy
CATE
Policy
Doubly robust policy learning (e.g. over binary decision trees) and out-of-sample confidence interval for value of learned policy, with DR policy value
RCT Land
Do you want confidence intervals on CATE predictions or better RMSE?
RMSE
Meta-Learners (S, T, X, R, DR). Model selection with out-of-sample DR-score. Out-of-sample validation with i) DR BLP hypothesis test, ii) DR calibration score, iii) DR qini/toc curves, iv) interpretation of groups Need (roughly n > 5k)
Confidence Intervals
Are you in a high-stakes domain (want CIs to be very robust/correct under few assumptions)?
Yes
Best-Linear-Predictor of CATE using the Doubly Robust Learner on a hard-coded feature map.
No
Causal Forest and Doubly Robust Honest Regression Forest
Do you have in your data all the variables that went into the treatment decision(s) (or constructed a DAG and found valid adjustment set)
Yes
No
Do you think that "compliance heterogeneity" and "effect heterogeneity" are independent
Yes
Partialling-out IV regression or (2SLS after Partialling-Out)
No
Doubly Robust Estimate of Local Average Treatment Effect (LATE); only for binary treatment/instrument
Use that factor as the instrument
IV Land
Use (treatment, treatment proxy) as "instruments" and (treatment, outcome proxy) as "treatments"
Yes
Do you observe "treatment" and "outcome" proxies of the unobserved confounder
Was there any observed factor that went into the treatment decision, but you don't think can directly influence the outcome (conditioning on controls)
Yes
No
Other methods that deal with unobserved confounding
Was there any discontinuity in the assigned treatment policy (e.g. treat if X1>.5)
Yes
Regression Discontinuity Methods
Did you observe many periods from each unit (before and after treatment)?
Yes
Diff-in-Diff or Synthetic Controls


Do you have in your data all the variables that went into the treatment decision(s)
Yes
Are you sure?
Not really
Sensitivity analysis and bias bounds
Yes
Do you have longitudinal data
Do you have multiple treatments
Yes
Dynamic Regime methods
Do you have censoring
Yes
Methods that deal with censored data that we did not talk about
No
Do you want heterogeneous effects/personalized policies?
No
Do you think your outcome can be very well approximated by a linear model
Yes
Double Lasso with interactive D, D*X, X and look at coefficient and s.e. of D; X are de-meaned engineered features from controls
No
Is treatment binary or categorical
No
Yes
Do you believe effect is constant or are you OK with low-variance "weighted averages of CATE"
Yes
Partialling-Out Estimate of ATE (potentially with "engineered treatments") Generic ML (AutoML) for partialling out
No
Doubly Robust Estimate of ATE
Generic ML (AutoML) for outcome regressions and propensity
Yes
Do you want to know the CATE value or just a good policy
Policy
Doubly robust policy learning (e.g. over binary decision trees) and out-of-sample confidence interval for value of learned policy, with DR policy value
CATE
Do you want confidence intervals on CATE predictions or better RMSE?
RMSE
Meta-Learners (S, T, X, R, DR). Model selection with out-of-sample DR-score. Out-of-sample validation with i) DR BLP hypothesis test, ii) DR calibration score, iii) DR qini/toc curves, iv) interpretation of groups Need (roughly n > 5k)
Confidence Intervals
Are you in a high-stakes domain (want CIs to be very robust/correct under few assumptions)?
Yes
Best-Linear-Predictor of CATE using the Doubly Robust Learner on a hard-coded feature map.
No
Causal Forest and Doubly Robust Honest Regression Forest
Conditional Exogeneity Land
Caution: these methods require accurate estimation of the treatment assignment and/or the outcome processes

N

Nick Monozon 23h

We've seen that causal inference approaches can leverage ML methods like random forests and neural networks. How do we balance the tradeoff between using complex models for better predictive performance and maintaining interpretability for causal conclusions? In what scenarios can we justify sacrificing some interpretability for performance while still ensuring actionable causal insights?

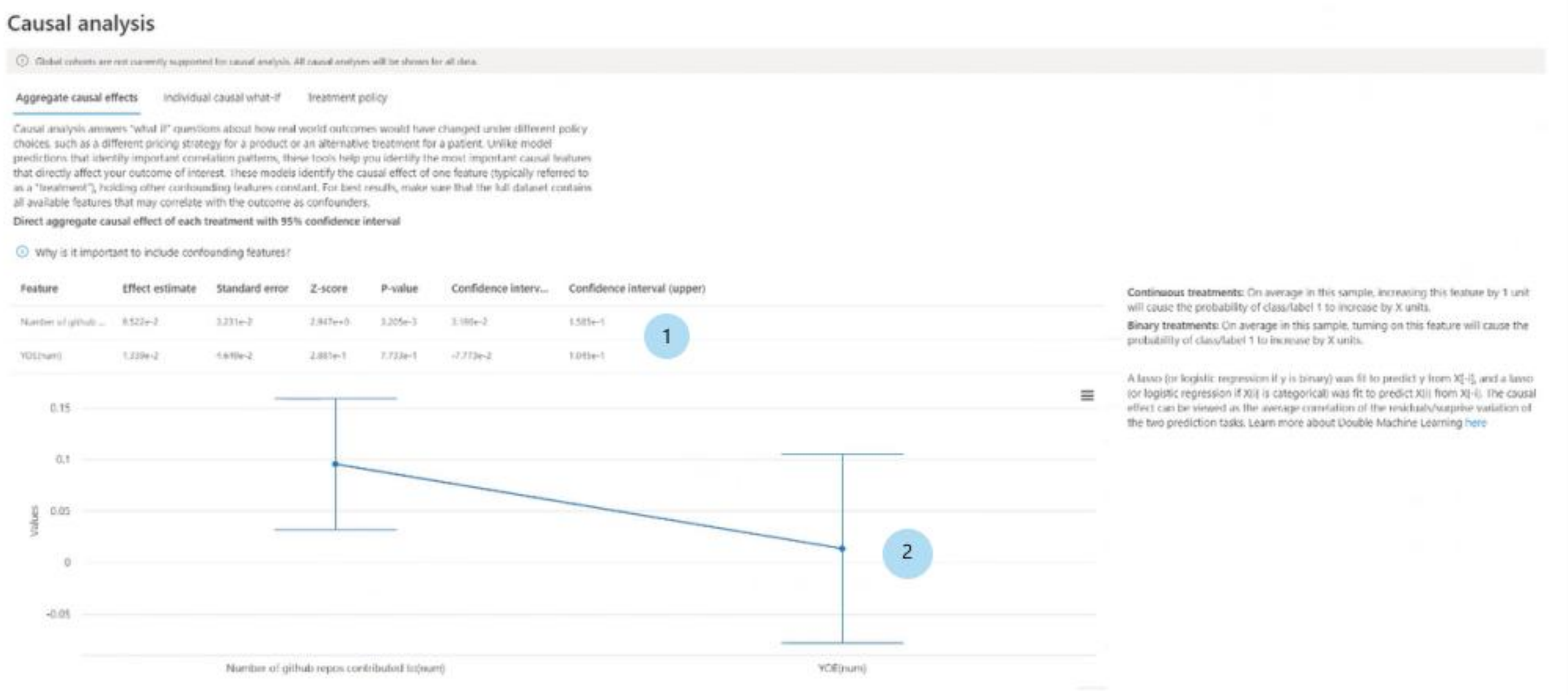
Reply Edit Delete •••

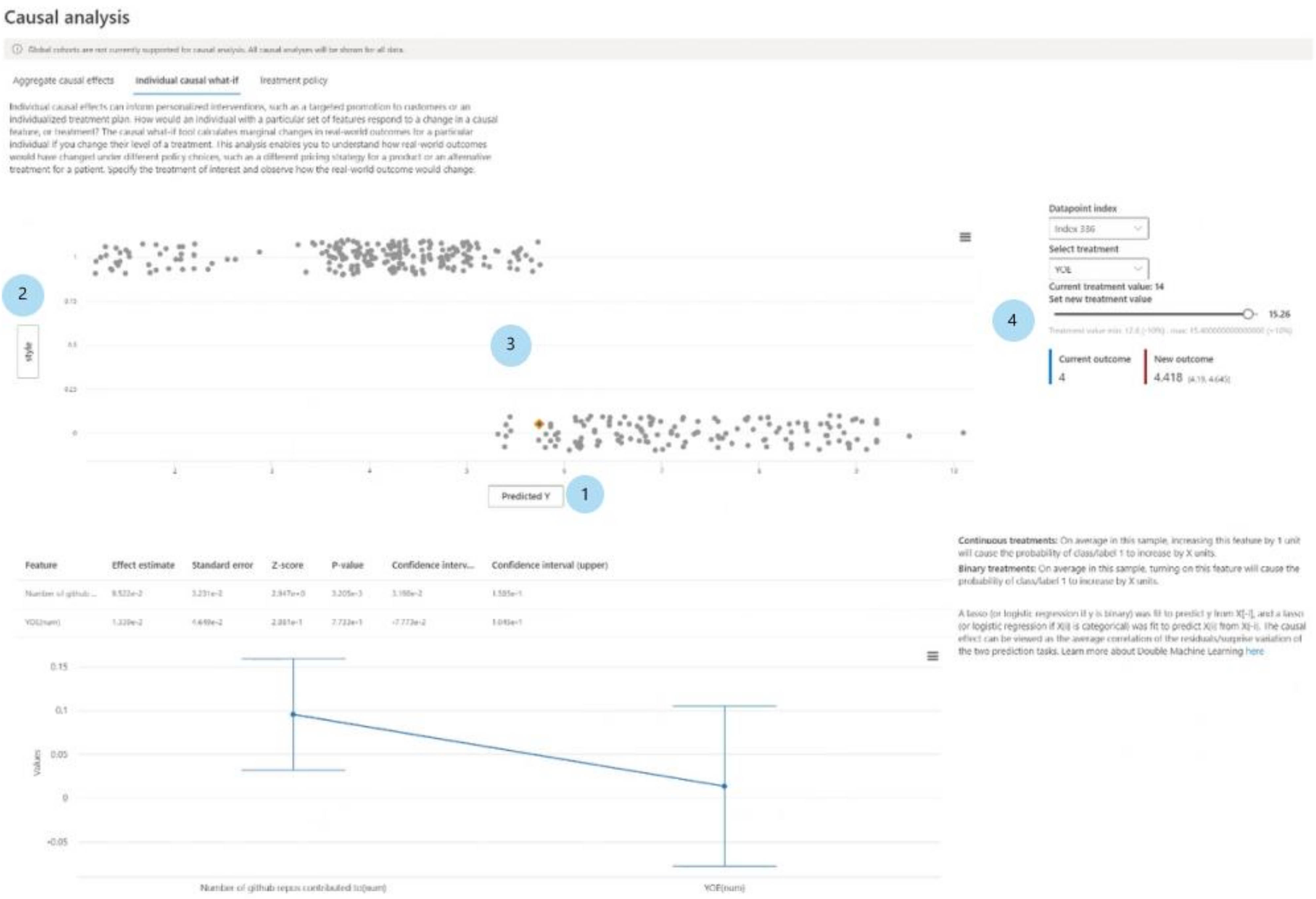
- When ML is used as a nuisance estimator, it does not really hurt the interpretability of the target quantity.
- The causal effect is identified as a function of a set of predictive models; interpretability of these models is less important, since you only care about the effect
- In fact, what you really want to know from these auxiliary models is: “did you manage to squeeze out all that is predictable” (e.g. out-of-sample R^2).
- So, compare causalML approach with approach that uses OLS for all prediction problems and present R^2 for each of these problems when using OLS vs when using more complex ML. If larger, that’s a good high-level argument

- When ML is used for the target causal quantity (e.g. heterogeneous causal effects), then ML is more problematic for interpretability
- But you can use all the interpretability tools that have been developed in ML, e.g. distilling into trees, SHAP values
- Out-of-sample validation metrics (e.g. qini curve, calibration plots) of ML-based CATE models vs linear models is a way to justify the more complex model

Azure Responsible AI Dashboard

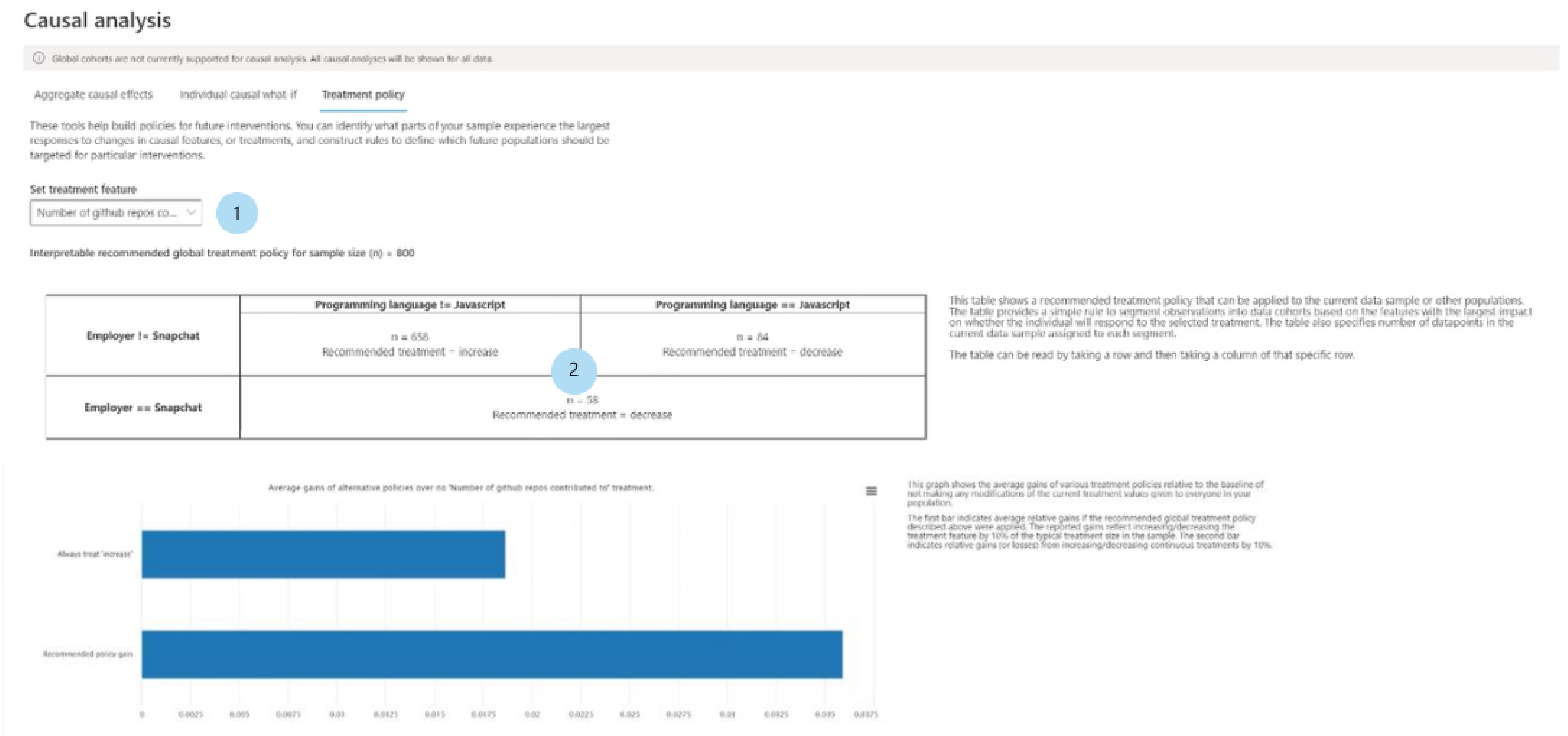
[Use the Responsible AI dashboard in Azure Machine Learning studio - Azure Machine Learning | Microsoft Learn]()




Causal analysis
Global cohorts are not currently supported for causal analysis. All causal analyses will be shown for all data.
Aggregate causal effects
Individual causal what-if
Treatment policy
Individual causal effects can inform personalized interventions, such as a targeted promotion to customers or an individualized treatment plan. How would an individual with a particular set of features respond to a change in a causal feature, or treatment? The causal what-if tool calculates marginal changes in real-world outcomes for a particular individual if you change their level of a treatment. This analysis enables you to understand how real-world outcomes would have changed under different policy choices, such as a different pricing strategy for a product or an alternative treatment for a patient. Specify the treatment of interest and observe how the real-world outcome would change.
2
style
3
Predicted Y
1
Datapoint index
Index 336
Select treatment
YOE
Current treatment value: 14
Set new treatment value
4
15.26
Current outcome
4
New outcome
4.418
Feature
Effect estimate
Standard error
Z-score
P-value
Confidence interv...
Confidence interval (upper)
0.15
0.1
0.05
0
-0.05
Values
Number of github repos contributed to(num)
YOE(num)
Continuous treatments: On average in this sample, increasing this feature by 1 unit will cause the probability of class/label 1 to increase by X units.
Binary treatments: On average in this sample, turning on this feature will cause the probability of class/label 1 to increase by X units.
A lasso (or logistic regression if y is binary) was fit to predict y from X[-i], and a lasso (or logistic regression if X[i] is categorical) was fit to predict X[i] from X[-i]. The causal effect can be viewed as the average correlation of the residuals/surprise variation of the two prediction tasks. Learn more about Double Machine Learning here

Azure Responsible AI Dashboard

[Use the Responsible AI dashboard in Azure Machine Learning studio - Azure Machine Learning | Microsoft Learn]



Azure Responsible AI Dashboard

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Thomas Sarda 22h

I was wondering if you could go over validation with synthetic data once again. In particular, are there assumptions in the way we generate the synthetic data that could make us too confident in the validation if they are violated, or does it always work ?

Reply Edit Delete •••

Clemence Marie Mottez 21h

I would be interested in this too!

Reply Edit Delete •••

- Performing well on semi-synthetic validation is a minimal check
- One should not take it for granted that if it works on semi-synthetic validation it worked well on the real data, but not working well on semi-synthetic is worrisome

- Semi-synthetic models do run the risk of being a bit simpler than the original data generating process and hence slightly easier to “succeed”

Ivan Aleksandar Veselinov Mavrov 20h

Can we discuss what our takeaway from Neyman orthogonality should be?
What were the implications of Neyman orthogonality on the statistical error of the estimate?
The term came up everywhere and it almost sounded as if it had magical properties that solve any identification problem.

Reply Edit Delete •••

- Neyman orthogonality is simply a signal of more robust estimation
- The main thing it implies is: if your nuisance ML models have an error of ϵ then for an estimation method that is no Neyman orthogonal, you should expect the error in your causal model/quantity to be of $O(\epsilon)$, while for a Neyman orthogonal method you should expect the error to be $O\left(\epsilon^2\right)$
- If $\epsilon^2 = o\left(\sqrt{n}\right)$ and your target causal model is parametric (or a parameter), then the error in the nuisances is not of first-order importance in the error for the target causal quantity and hence asymptotically the causal estimate behaves as if you had the correct nuisance models
- This then leads to easy to implement confidence interval construction
- There is no magic: you still need quite accurate nuisance models, i.e. $\epsilon = o(1)$ for error improvement and $\epsilon \sim n^{-1/4}$ for confidence intervals

B

Bocheng Dai 20h

In real-world industry applications, what are the main use cases of causal inference in fields like finance, healthcare, and technology? What are the future trends in this area? What key challenges is current research aiming to address? Additionally, what are the most commonly used causal inference methods or models in the industry today, and why are they preferred?

Reply Edit Delete •••

A

Anna Vdovina 20h

This is probably not a very well-formulated question but I would be curious to know more about which topics/questions/methods are currently "hot" in the industry and which ones you predict will become more prominent in the near future. Causal inference, in general, is a very broad field, which parts of it do you think are more relevant for academic research and which are more well-suited for exploring in the industry? For example, is theoretical research valued in the industry at all?

♡ 1 Reply Edit Delete •••

A

Annie Zhu 20h

In class and in problem sets, we have seen examples of the causal inference techniques applied to real world datasets. I was wondering if there were any other specific applications of the methods learned in this class that you found particularly interesting or insightful?

Reply Edit Delete •••

Causal AI for Sustainability

Our lab works on understanding causal factors of vulnerability of a region to natural hazards, with the aim of informing appropriate policy interventions.

Causal AI for Healthcare

Our lab works on topics such as detecting implicit biases in medical decisions, understanding the causal effects of latent treatment dimensions from observational patient treamtent trajectories and evaluation of policy changes in Kidney Exchange systems.

Causal AI for Operations

Our lab works on data-driven pricing, customer segmentation, return-on-investment and the impact of GenAI at work.

Causal AI for Digital Experiments

Our lab works on developing data analytic tools for experimentation in digital platforms, such as estimation of heterogeneous effects from large scale A/B tests and recommendation A/B tests.

https://causal-machine-learning.github.io/kdd2021-tutorial/
https://drive.google.com/file/d/1QJJUCo4LH5kGQP3kaJlG1RdhjhaJWp-5/view

https://docs.google.com/presentation/d/1FvRtis2fm4c2R7XmRKWMTtZaZjUObW1fGxpNmapmjKI/edit#slide=id.ge6ef5be800_0_478

https://drive.google.com/file/d/1yyIu_3epIVXbwzJj658Iv4vxHGjtPh8n/view

https://drive.google.com/file/d/1FEKXFHHATntHjsEymXnEw6GAiUGMm8sG/view

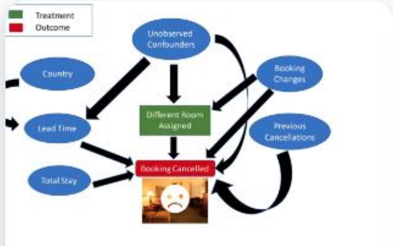
Overview

EconML is a Python package that applies the power of machine learning techniques to estimate individualized causal responses from observational or experimental data. The suite of estimation methods provided in EconML represents the latest advances in causal machine learning. By incorporating individual machine learning steps into interpretable causal models, these methods improve the reliability of what-if predictions and make causal analysis quicker and easier for a broad set of users.

EconML is open source software developed by the ALICE team at Microsoft Research.

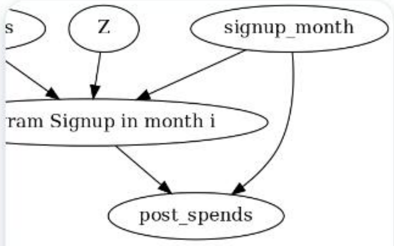
Flexible **Unified** **Familiar Interface**

Case Studies



Hotel Booking Cancellations

Beyond predictive models: The causal story behind hotel booking cancellations.



Effect of Customer Loyalty Programs

Estimating the effect of a member rewards program.

Optimizing Article Headlines

Introducing the do-sampler for causal inference.

Effects of Home Visits on Infant Health (IHDP)

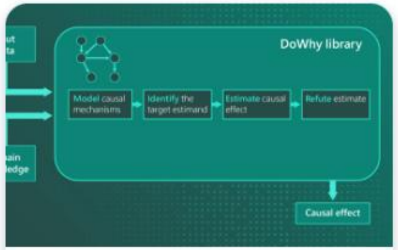
Understanding the question of why.

See more case studies →

News

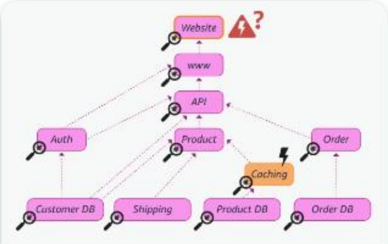
National Association for Business Economics Conference

Causal inference at scale presented at NABE.



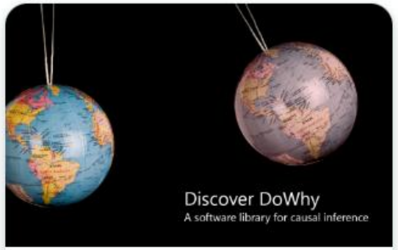
DoWhy evolves to independent PyWhy model to help causal inference grow

Identifying causal effects is an integral part of scientific inquiry. It helps us understand everything from



AWS contributes novel causal machine learning algorithms to DoWhy Python library

New features go beyond conventional effect estimation by attributing events to individual components of complex



Announcing DoWhy, a software library for causal inference

For decades, causal inference methods have found wide applicability in the social and biomedical sciences. As computing systems start latest

Search docs

About Causal ML

`Causal ML` is a Python package that provides a suite of uplift modeling and causal inference methods using machine learning algorithms based on recent research. It provides a standard interface that allows user to estimate the **Conditional Average Treatment Effect** (CATE) or **Individual Treatment Effect** (ITE) from experimental or observational data. Essentially, it estimates the causal impact of intervention **T** on outcome **Y** for users with observed features **X**, without strong assumptions on the model form.

Uber

Booking.com

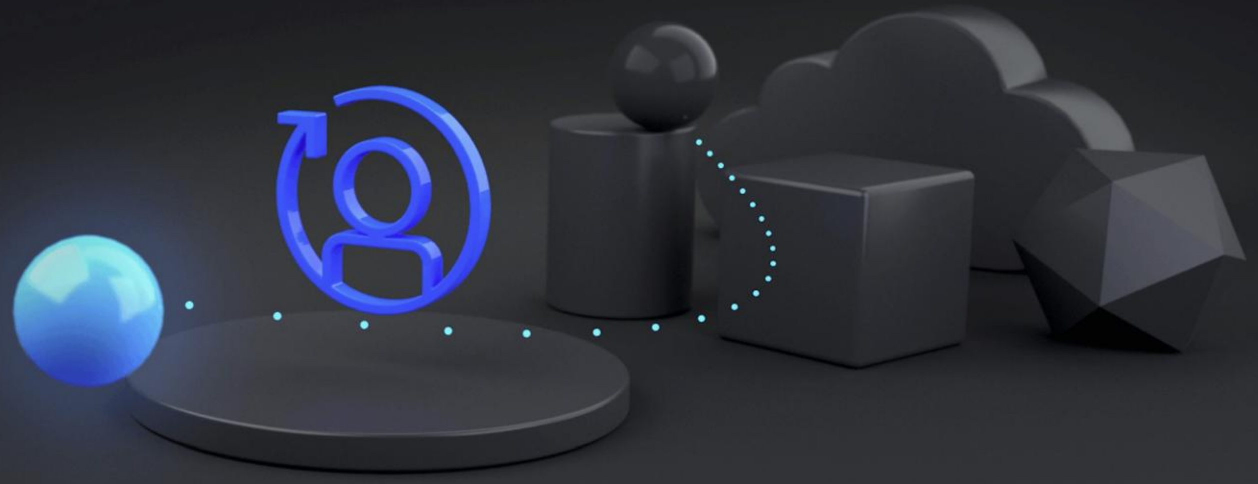
UpliftML

UpliftML is a Python package for scalable unconstrained and constrained uplift modeling from experimental data. To accommodate working with big data, the package uses PySpark and H2O models as base learners for the uplift models. Evaluation functions expect a PySpark dataframe as input.

Personalizer

Deliver personalized, relevant experiences for each of your users.

Try Personalizer free | Create a pay-as-you-go account



Create optimized user experiences

Boost conversion and engagement, and add real-time relevance to product recommendations, with reinforcement learning–based capabilities available only through Azure. Select hero content, optimize layouts, and personalize offers with two API calls. Use Personalizer, part of Azure Cognitive Services, as a standalone personalization solution or to complement existing ranking engines—with no machine learning expertise required.

Chat with sales

AWS Machine Learning Blog

Power contextual bandits using continual learning with Amazon SageMaker RL

by Saurabh Gupta, Anna Luo, Bharathan Balaji, Siddhartha Agarwal, Vineet Khare, and Yijie Zhuang | on 29 AUG 2019 | in Amazon SageMaker, Artificial Intelligence | Permalink | Comments | Share

Resources

Getting Started
What's New

Google Cloud

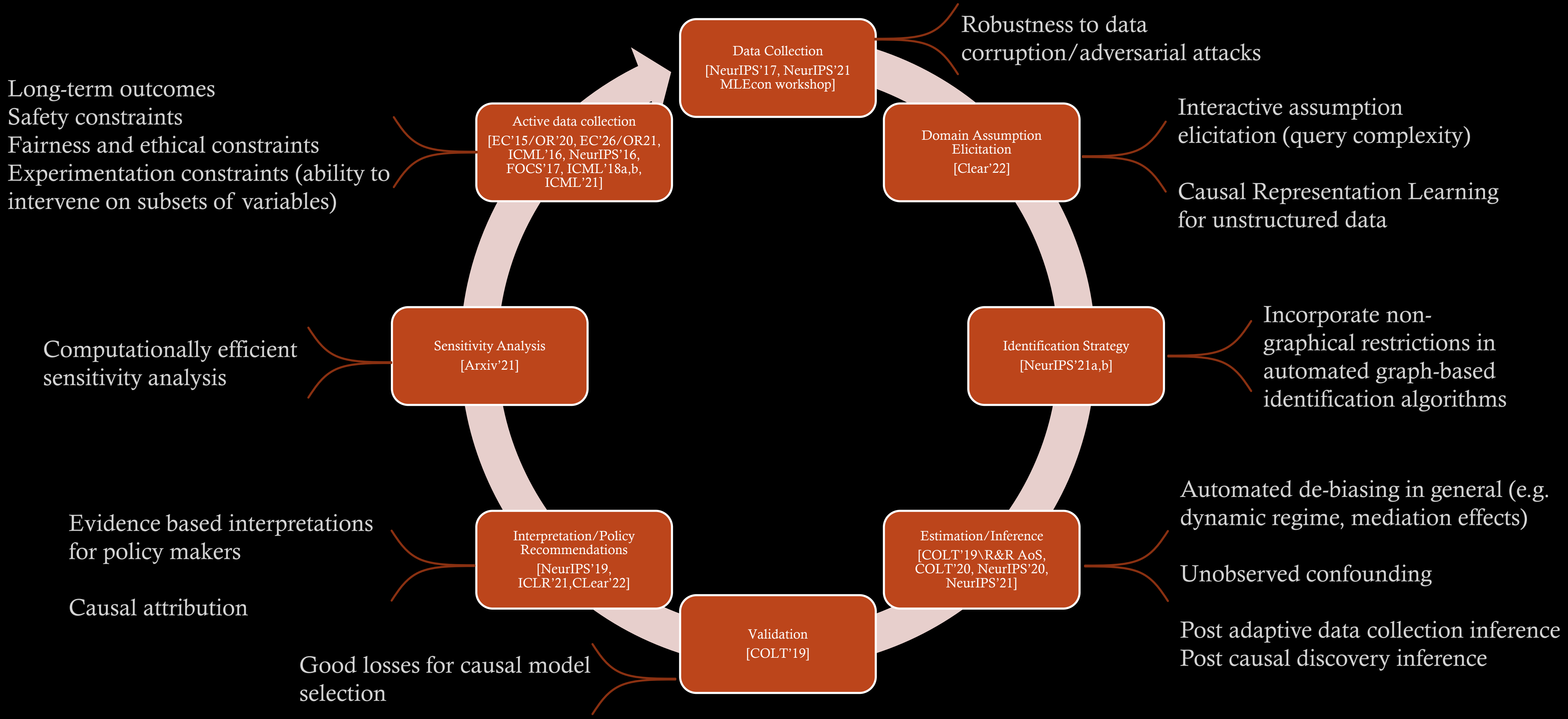
AI & Machine Learning

Online shopping gets more personal with Recommendations AI

July 22, 2020

IKEA Retail (Ingka Group) has increased global average order value for eCommerce by 2% with Recommendations AI

Many Research Challenges



- https://github.com/causaltext/causal-text-papers

Adapting Text Embeddings for Causal Inference

Victor Veitch*   Dhanya Sridhar*   David M. Blei

Department of Statistics and Department of Computer Science
Columbia University

bedding methods. We illustrate the methods by answering the two motivating questions—the effect of a theorem on paper acceptance and the effect of a gender label on post popularity. Code and data available at github.com/vveitch/causal-text-embeddings-tf2.

Table of Contents

https://insitro.com/

A Flexible Approach for Predictive Biomarker Discovery

Preprint

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$$\mathbb{E}\left[\left(\tilde{Y} - \theta'\tilde{W}\right)\tilde{Z}\right]$$

Michael Rutherford James 20h

In homework 6, assignment 3c we were asked to find the covariance matrix using the general theorem of moment restrictions:

If moment is Neyman orthogonal and RMSE of $\hat{g}$ is $o_p(n^{-1/4})$, plus regularity conditions

$$\sqrt{n}\,(\hat{\theta} - \theta_0) \to N\left(0, J_0^{-1}\Sigma(J_0^{-1})^{\top}\right)$$

where $J_0 := \nabla_\theta M(\theta_0, g_0)$ and $\Sigma := E\left[m(Z;\theta_0,g_0)\, m(Z;\theta_0,g_0)^{\top}\right]$

I had thought I understood this, but when actually implementing it with multiple moment restrictions, I realized I was confused about the actual implementation of finding the covariance matrix. I would find it helpful if we could go through a quick example of this or just see the solution to this problem.

Reply Edit Delete ···

Abdulaziz Abdulrahman S Alharbi 19h

In this class, we assumed that the causal graph structure was already known. However, in real-world scenarios without access to domain experts, how feasible is it to rely solely on structure learning algorithms to infer the DAG from observational data? If these approaches are viable, what practical guidelines and key considerations should we keep in mind when using them?

Reply Edit Delete •••

A

Arnav Gangal 19h

This is related to some of the other questions folks have asked, but how do we robustly evaluate the strengths and weaknesses of different causal inference methods when the ground truth is unknown? Asking because the validation criteria for causality feels a lot more nebulous and case-by-case than conventional ML. Is there any systematic approach that you've found helpful to weigh up competing considerations like the strength of the necessary assumptions or the interpretability?

Reply Edit Delete •••

- Stability and calibration
- Using a small experimental sample to validate
- Using multiple observational datasets and separately estimating, with agreement

GoTo:

- Doubly robust ATE estimate for binary and Partialling out estimate for categorical (first with just Lasso models on expanded features and then with generic AutoML)
- Meta learners for CATE with out-of-sample doubly robust based evaluation (calibration, hypothesis tests)

Tingjun Lin 18h

Say you have RCT data (n=2000) and want to do causal inference with it. You want to sharpen the confidence interval as much as possible for treatment effect estimates for both ATE and CATE, what would the procedures be like. Will you do something different if n=500 and n=1000?

In social science, If the reviewer of a journal says that, you should just run a linear regression and treat DML as a robustness check in the appendix, how would you respond?

Reply Edit Delete ···

Janet Caroline Malzahn 13h

+1 for the questions on how to justify using newer methods in academia. It seems like there are rewards for creating new methods, but relatively little appetite for applied work that uses the super cutting edge because people/referees are unfamiliar with it. How do you think we do you recommend justifying the use of new tools in the context of social science academia?

Reply Edit Delete •••

Yupeng Chen 15h

One challenge I've been thinking about is how to communicate and justify the choice of a specific method to stakeholders who may not be familiar with causal inference. If you're working with a decision-maker (e.g., a policymaker, business executive, or clinician) who is skeptical of the assumptions behind a method like DML or DR, how would you explain why it is preferable to a more traditional method like linear regression? Are there particular intuitive explanations or diagnostics that you have found useful in practice for shifting the culture towards using causal ML estimates?

Reply Edit Delete •••

14 October 2019

The Royal Swedish Academy of Sciences has decided to award the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2019 to

Abhijit Banerjee
Massachusetts Institute of Technology, Cambridge, USA

Esther Duflo
Massachusetts Institute of Technology, Cambridge, USA

Michael Kremer
Harvard University, Cambridge, USA

"for their experimental approach to alleviating global poverty"

Their research is helping us fight poverty

The research conducted by this year's Laureates has considerably improved our ability to fight global poverty. In just two decades, their new experiment-based approach has transformed development economics, which is now a flourishing field of research.

11 October 2021

The Royal Swedish Academy of Sciences has decided to award the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2021

with one half to

David Card
University of California, Berkeley, USA

"for his empirical contributions to labour economics"

and the other half jointly to

Joshua D. Angrist
Massachusetts Institute of Technology, Cambridge, USA

Guido W. Imbens
Stanford University, USA

"for their methodological contributions to the analysis of causal relationships"

Natural experiments help answer important questions for society

This year's Laureates – David Card, Joshua Angrist and Guido Imbens – have provided us with new insights about the labour market and shown what conclusions about cause and effect can be drawn from natural experiments. Their approach has spread to other fields and revolutionised empirical research.

GENERIC MACHINE LEARNING INFERENCE ON HETEROGENOUS TREATMENT EFFECTS IN RANDOMIZED EXPERIMENTS, WITH AN APPLICATION TO IMMUNIZATION IN INDIA

VICTOR CHERNOZHUKOV, MERT DEMIRER, ESTHER DUFLO, AND IVÁN FERNÁNDEZ-VAL

ABSTRACT. We propose strategies to estimate and make inference on key features of heterogeneous effects in randomized experiments. These key features include *best linear predictors of the effects* using machine learning proxies, *average effects sorted by impact groups*, and *average characteristics of most and least impacted units*. The approach is valid in high dimensional settings, where the effects are proxied (but not necessarily consistently estimated) by predictive and causal machine learning methods. We post-process these proxies into estimates of the key features. Our approach is generic, it can be used in conjunction with penalized methods, neural networks, random forests, boosted trees, and ensemble methods, both predictive and causal. Estimation and inference are based on repeated data splitting to avoid overfitting and achieve validity. We use quantile aggregation of the results across many potential splits, in particular taking medians of p-values and medians and other quantiles of confidence intervals. We show that quantile aggregation lowers estimation risks over a single split procedure, and establish its principal inferential properties. Finally, our analysis reveals ways to build provably better machine learning proxies through causal learning: we can use the objective functions that we develop to construct the best linear predictors of the effects, to obtain better machine learning proxies in the initial step. We illustrate the use of both inferential tools and causal learners with a randomized field experiment that evaluates a combination of nudges to stimulate demand for immunization in India.

- First, ML analogues of what you would run OLS for, are not changing the identification argument
- In fact, the ML analogues are simply always “dropping” assumptions
- For instance, identification by conditioning is the assumption you are invoking to identify an effect
- Whether you run OLS to estimate it or ML, it does not change the identification argument
- It does though drop the linearity assumption on the conditional expectations
- So, from that perspective it is not bad to view it as a robustness check
- If the ML method got substantially larger R^2 than OLS, then a good argument to run the ML variant.

- One reason why the class was structured the way it was, so that we start from what people have been doing for a while (OLS) and then build on top
- Example:
  - "CausalML Denier": I am estimating an effect of D on Y controlling for X
  - "CausalML Advocate": Oh so, really what you are estimating is the correlation of the part of D that is not linearly predictable from X, with the part of Y that is not linearly predictable from X.
  - "CausalML Denier": Really?
  - "CausalML Advocate": Yes, there is this famous FWL theorem that shows that OLS is equivalent to this
  - "CausalML Denier": Good to know.
  - "CausalML Advocate": By the way, why wouldn't you also want to remove from Y or D the parts that can be predictable from X in a non-linear manners? Don't you run the risk that this remnant parts are leaving some implicit unobserved confounding on the table?
  - "CausalML Denier": Hm, good idea, I should be doing that, but how?
  - "CausalML Advocate": Let's talk about DoubleML…

- Example:
  - “CausalML Denier”: I ran an RCT and constructed an interactive OLS model to learn effect heterogeneity
  - “CausalML Advocate”: Interesting! How well does your heterogeneous effect model prioritize into treatment?
  - “CausalML Denier”: Hm…how do I judge that?
  - “CausalML Advocate”: Well, there’s these cool AUC and QINI curves that tell you exactly that and can help you decide how well your effect model is for stratification
  - “CausalML Denier”: Good to know.
  - “CausalML Advocate”: By the way, what if effect differs only if some people are low-income and old? Did you include interactions in your OLS?
  - “CausalML Denier”: Hm, good idea, but if I start doing that the number of variables will explode and OLS is very unstable
  - “CausalML Advocate”: Let’s talk about Meta-learners and Causal/Doubly Robust Forests… You can automatically segment the population. Then you can also check if the complex model did better than your original OLS using the AUC curve. If it does better you can also un-pack what the model discovered by coarsely visualizing the model as a decision tree, or by using methods for feature importance for generic ML

- Example:
  - “CausalML Denier”: Once I condition on demographic information X, proximity to college Z is a great instrument, to estimate the effect of college D on income Y
  - “CausalML Advocate”: Fantastic! How will you estimate this on data?
  - “CausalML Denier”: I’ll run 2SLS, with “treatments” (D,X) and instruments (Z,X)
  - “CausalML Advocate”: Interesting, does that estimate the average effect among compliers?
  - “CausalML Denier”: I think so. That’s what I know is happening when we don’t have X. Isn’t it the case with X too?
  - “CausalML Advocate”: Not really. When you have X’s the analogue of the LATE is the ratio of the (average effect Z->Y) / (average effect Z->D)
  - “CausalML Denier”: Exactly, and this is what implicitly is estimated in the two OLS stages of 2SLS
  - “CausalML Advocate”: Hm… not really. This only the case if Y is a linear function of Z and D is a linear function of Z… More generally, this analogy breaks
  - “CausalML Denier”: but then what should I do?
  - “CausalML Advocate”: Let’s talk about DoubleML for IVs….

- Other strategies to convince “non-believers: run out-of-sample diagnostics on your causal ML model that are based on OLS or simple summary statistics!
- Example: BLP using ML-CATE predictions as features
- Example: Calibration
- Example: Group average effects for groups defined based on ML-CATE
- Example: Interactive OLS regression where the ML-CATE is one of the features you use to interact
- Similarly, instead of doubleML, you could train a model to predict the outcome from X, train a model to predict the treatment from X, then use the predictions of these models as extra features you are controlling for in an OLS regression. This is double ML in-disguise. And you can pitch it as: I’m only using ML for clever feature engineering and then just running your favorite OLS regression ☺

Winter 2023 Questions

Roberto Lobato Lopez 2d

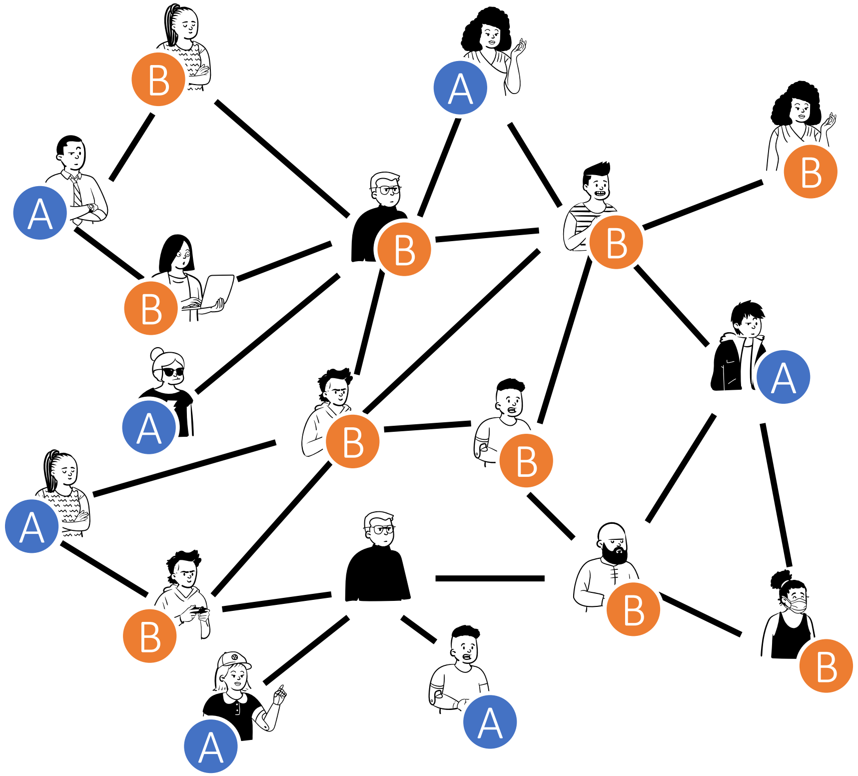
I would like to know the intuition of what to do when we have don't have Stable Unit Value Assumptions or we have Spill over efffects. For example, in networks.

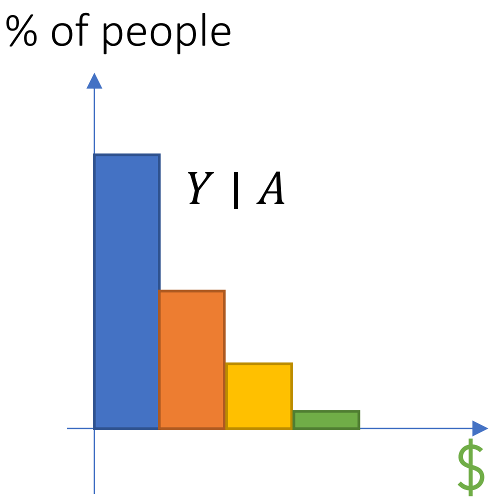
Reply Edit Delete •••

Interference

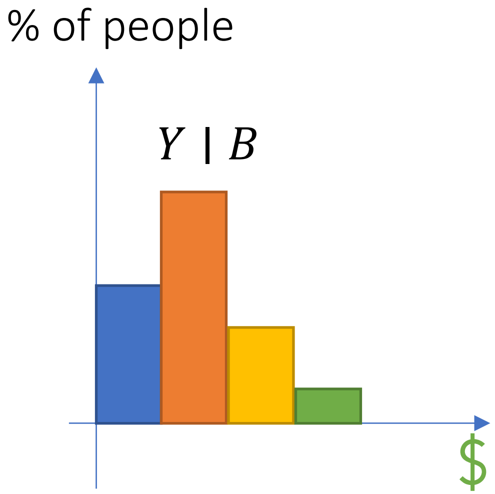
- Social Network interference
- Equilibrium effects
- Stateful systems and time effects

Social Network Interference



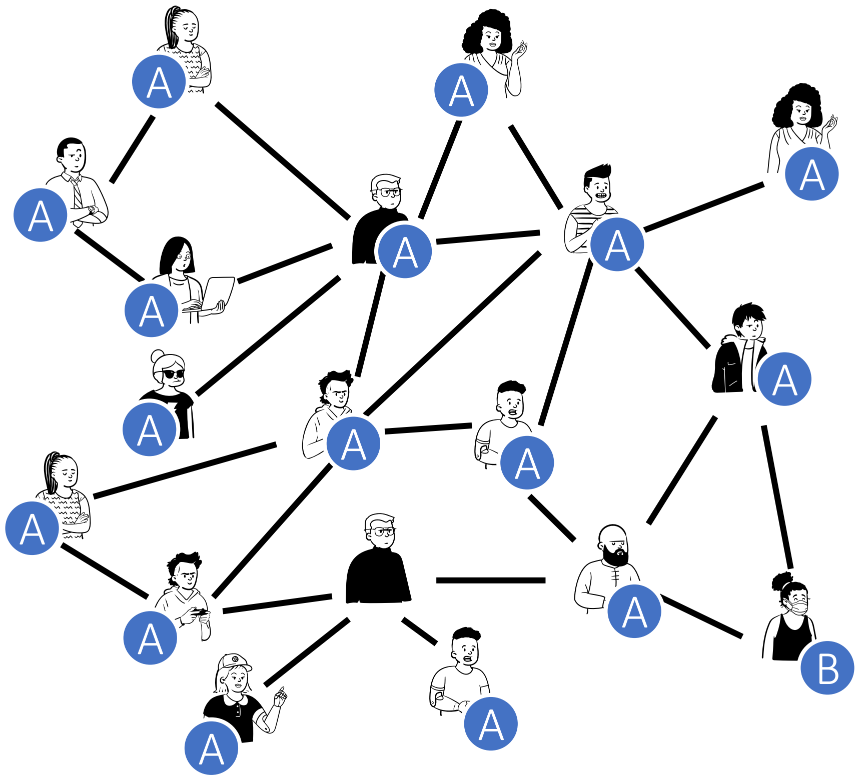


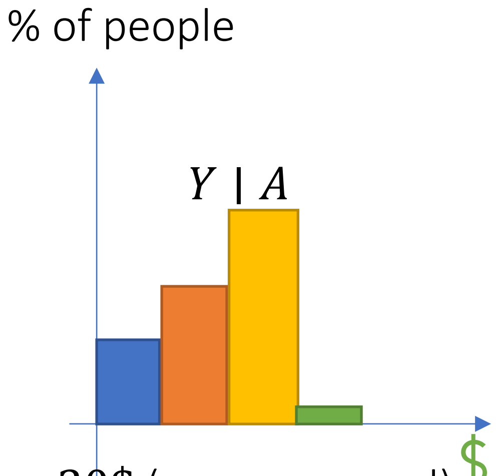
$\mu_A = 10\$$ (average spend)



$\mu_B = 20\$$ (average spend)

Counterfactual world





$\mu_A = 30\$$ (average spend)

Image Source: https://www.leadpages.com/blog/ab-testing-split-testing/

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Big challenges call for big solutions. Tune in to #OHOP21 on 9 November to hear thinkers, doers and leaders discuss the global response to climate change. Watch the event, get inspired and discover how we can take action ➡️ingka.com/one-home-one-p... #AssembleABetterFuture #COP26

Source: @IKEA

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The moment is now. Climate action can't wait any longer. Join global thinkers, doers & leaders at #OHOP21 on 9 Nov – where they'll discuss the need for urgent change & action to help create a better future. Learn more: ingka.com/one-home-one-p... #COP26 #AssembleABetterFuture

Source: @IKEA

Image source: https://blog.hootsuite.com/social-media-ab-testing/

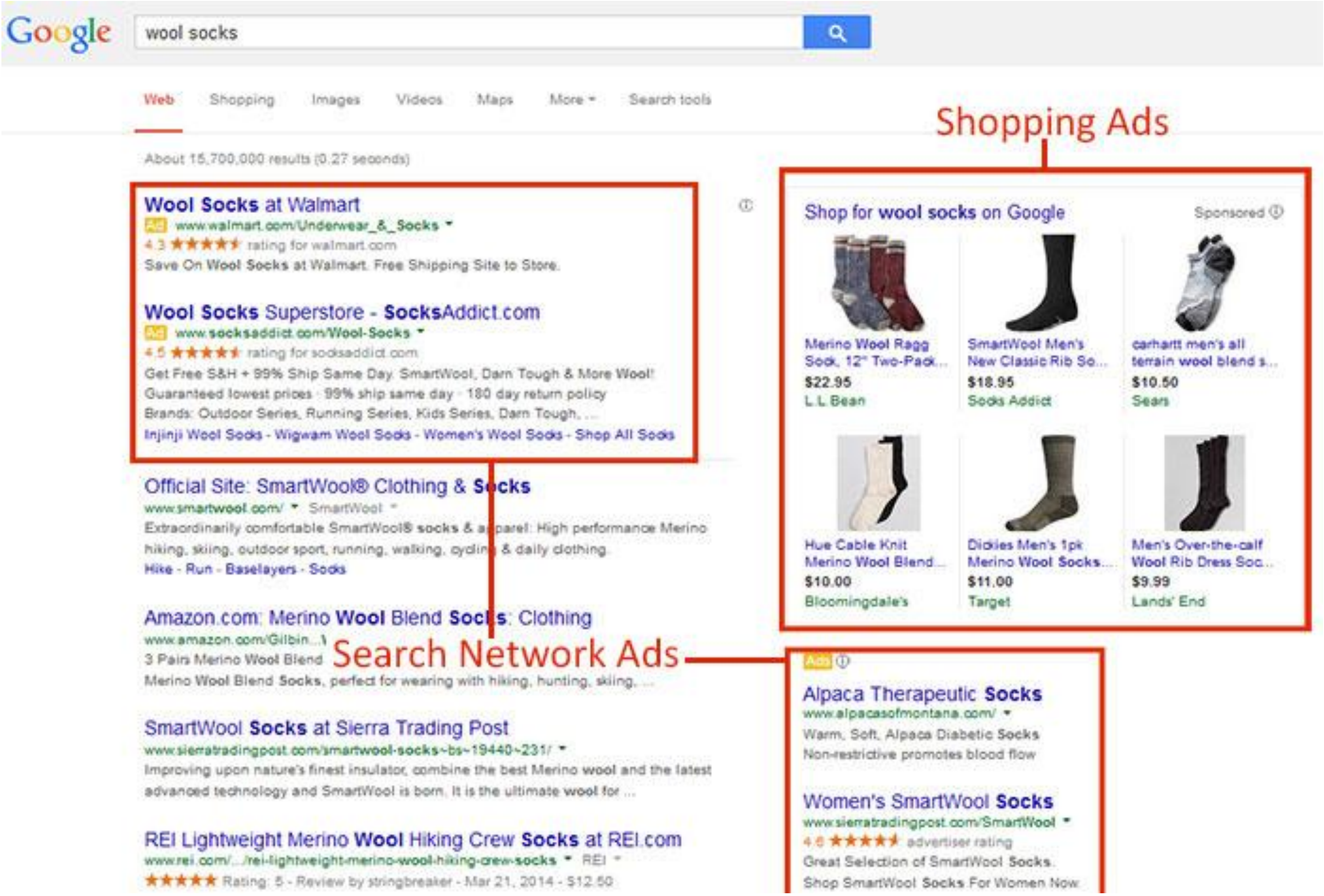
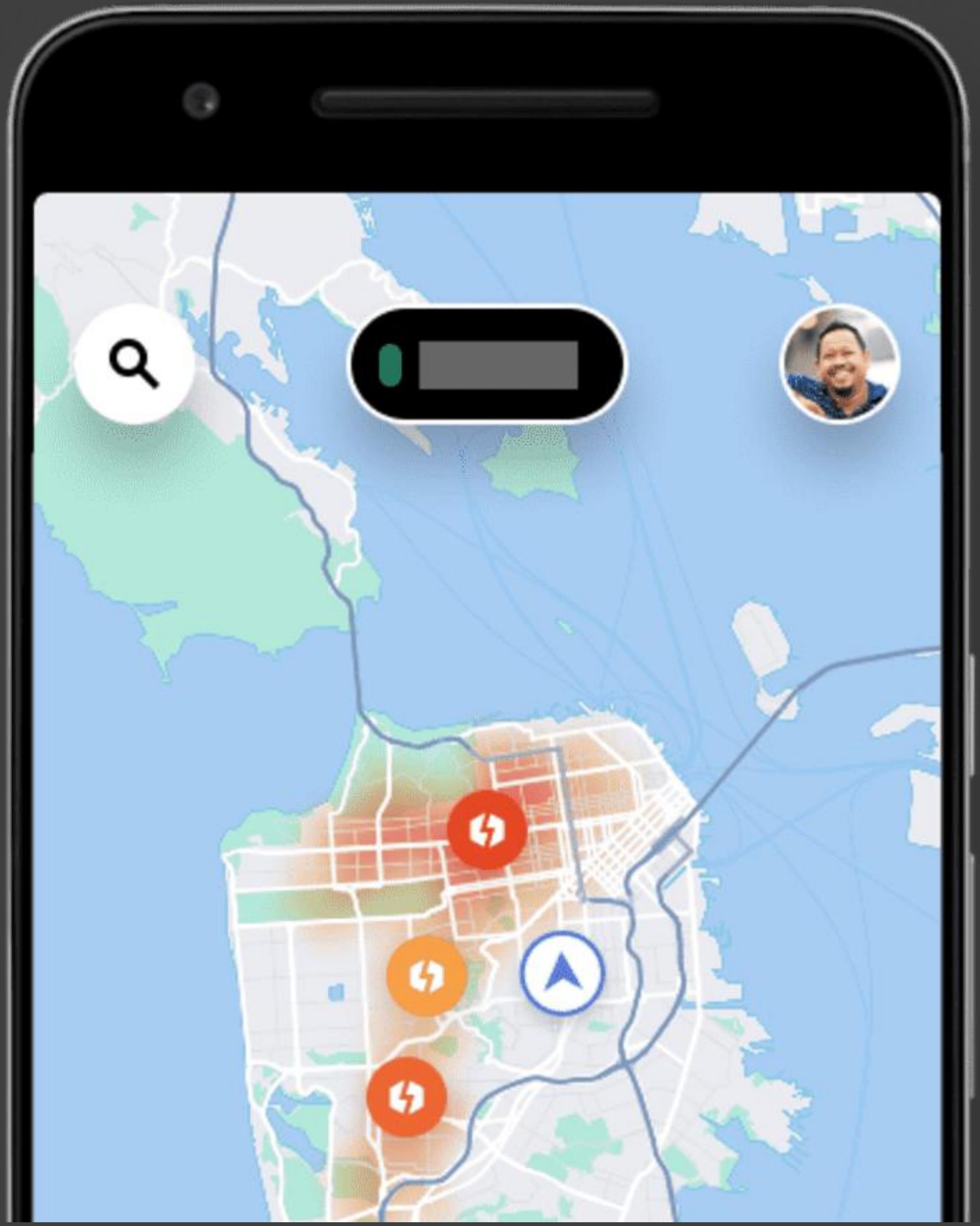


Image source: https://googleadsstrategy.com/google-adwords-search-network-vs-display-network/



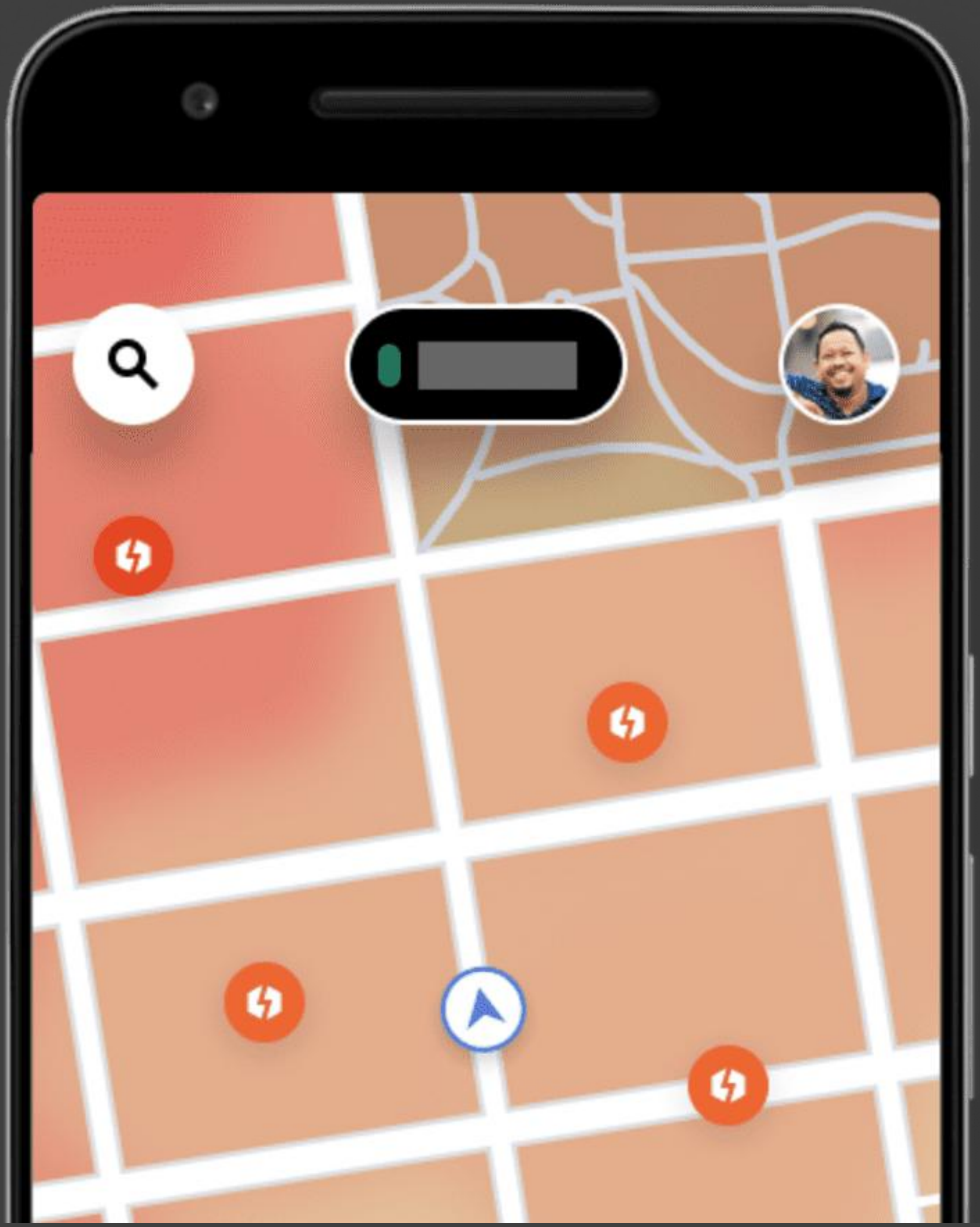
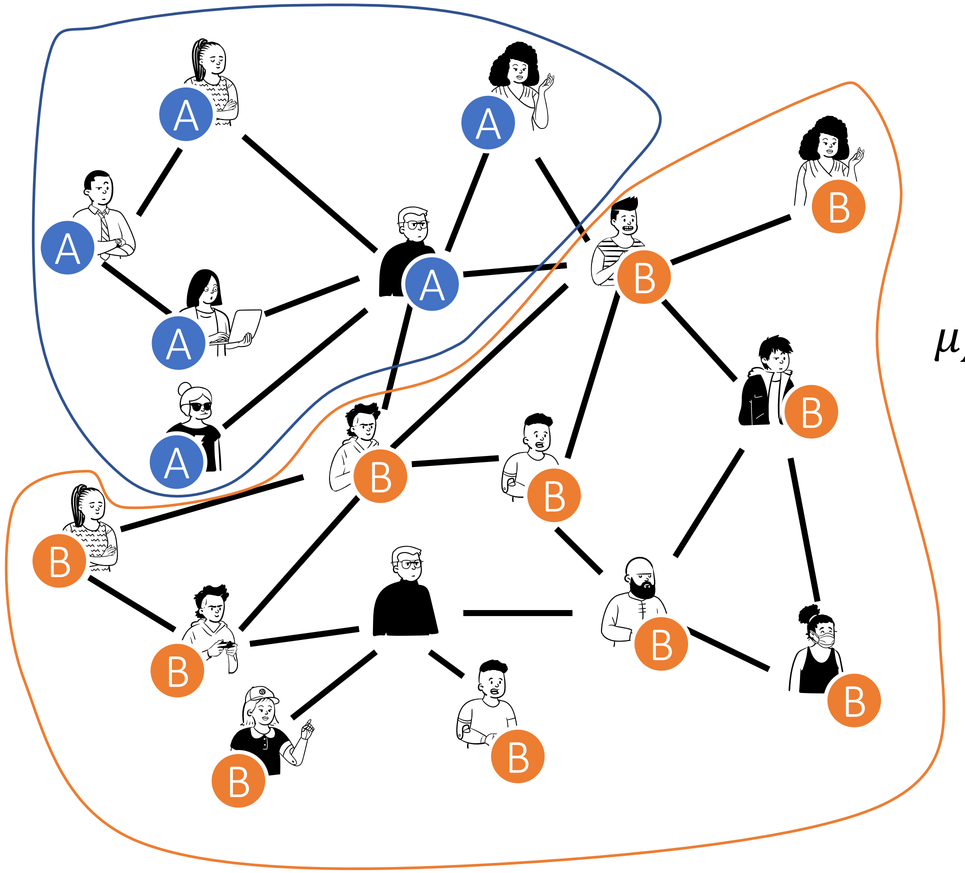
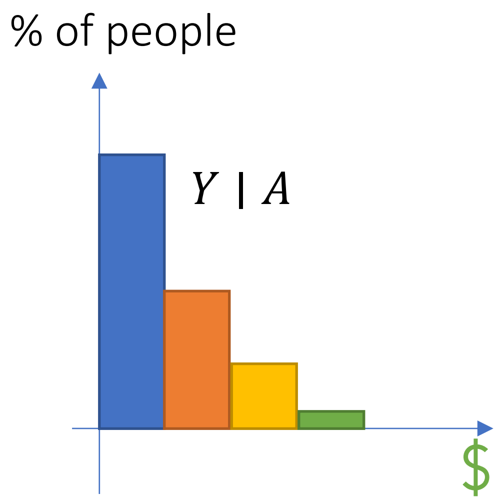


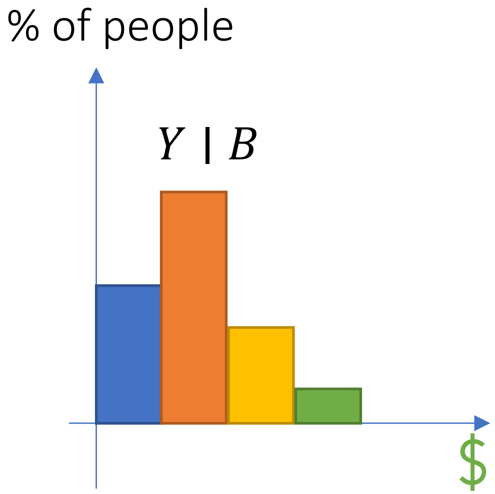
Image source: https://www.uber.com/us/en/drive/driver-app/how-surge-works/

Approach: Clustering





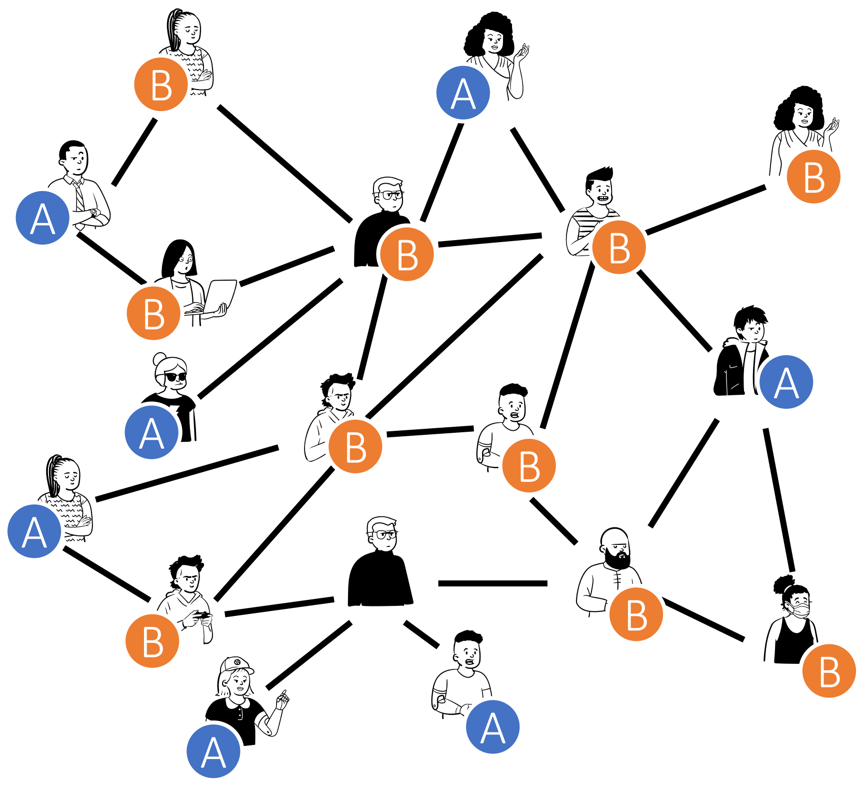
$\mu_A = 10\$$ (average spend)

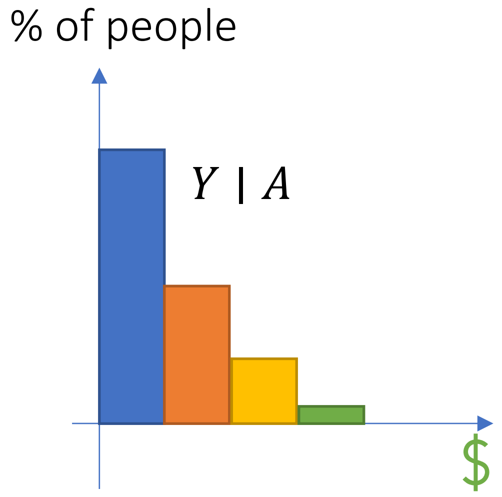


$\mu_B = 20\$$ (average spend)

Image Source: https://www.leadpages.com/blog/ab-testing-split-testing/

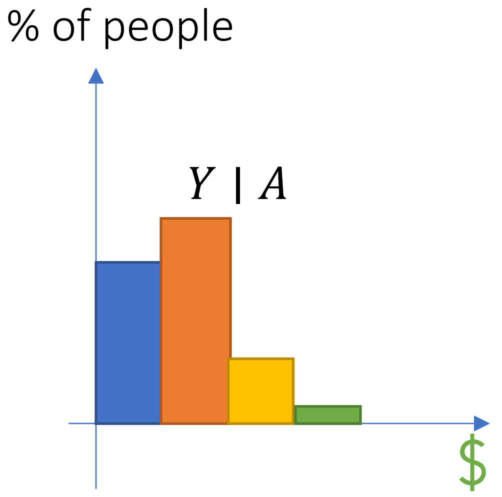
Approach: Structural Bias Correction





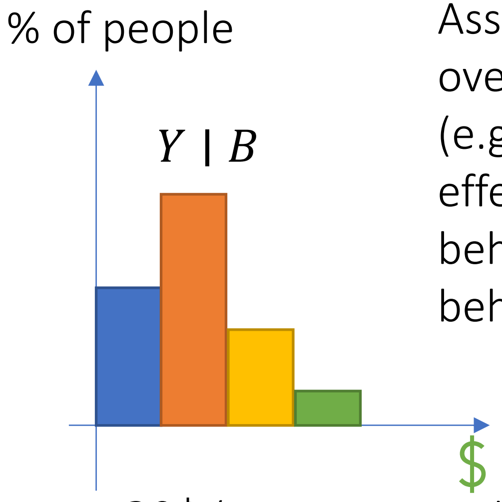
$\mu_A = 10\$$ (average spend)

Correct Spill-Over Bias

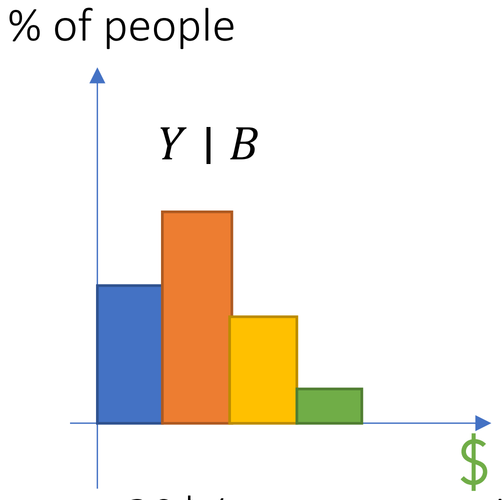


$\mu_A = 10\$$ (average spend)

Use Network Information + Assumptions on how spill-overs change outcome (e.g. additive homophily effects, market equilibrium behavior, Nash equilibrium behavior)



$\mu_B = 20\$$ (average spend)



$\mu_B = 20\$$ (average spend)

Image Source: https://www.leadpages.com/blog/ab-testing-split-testing/

Yifan Shen 2d

Can we briefly talk about some real-life examples of survival analysis in longitudinal studies and how can apply what we have learnt in class to it?

♡ 2 Reply Edit Delete •••

Survival Data

- If your outcome is survival then you need to adjust for censoring
- Easiest way to combine with what we've learned
  - Focus on un-censored samples
  - De-bias the "selection" by dividing the observed outcomes by the probability that censoring doesn't happen by the time of the observation $\Pr(C > t \mid X)$
  - Can be estimated via reduction to many classification problems or via CDF estimators (Nelson-Aalen estimator; Survival Forests)
  - Then apply all that we learned on these "transformed outcomes"
- More tailored:
  - Estimation of Heterogeneous Effects with Survival Outcomes
  - Meta Learners for Survival Data R-package

Survival Analysis and CATE

- Xu et al. "The Systolic Blood Pressure Intervention Trial (SPRINT) is a multicenter RCT that evaluated the effectiveness of an intensive blood pressure (BP) treatment goal (systolic BP < 120 mm Hg) as compared to the standard BP goal (< 140 mm Hg) on reducing risks of cardiovascular disease (CVD). SPRINT recruited 9,361 participants and found that the intensive treatment reduced the risk of fatal and nonfatal CVD and all-cause mortality for patients at high risk of CVD events [Wright et al., 2015]."

Roberto Lobato Lopez 2d

I would love to see some examples of RCT gone wrong. Like when researchers just assumed that because they could leverage enough datapoints, naive A/B testing was enough.

♡ 2 Reply Edit Delete •••

Modern Challenges of A/B tests

- Interference
- Long range objectives
- Multiple exposures over time
- Non-compliance

Roberto Lobato Lopez 2d

I have seem some examples of synthetic controls (mainly in finance) that are constructed by weighting "similar" subjects. I'm a little bit skeptic on them. Any comments?

Reply Edit Delete •••

Synthetic A/B Testing using Synthetic Interventions

Anish Agarwal, Devavrat Shah, and Dennis Shen*

Abstract

Suppose there are N units and D interventions. We aim to learn the average potential outcome associated with every unit-intervention pair, i.e., $N \times D$ causal parameters. While running $N \times D$ experiments is conceivable, it can be expensive or infeasible. This work introduces an experiment design, *synthetic A/B testing*, and the *synthetic interventions* (SI) estimator to recover all $N \times D$ causal parameters while observing each unit under at most two interventions, independent of D. Under a novel tensor factor model for potential outcomes across units, measurements, and interventions, we establish the identification of each parameter. Further, we show the SI estimator is finite-sample consistent and asymptotically normal. Collectively, these also lead to novel results for panel data settings, particularly for synthetic controls. We empirically validate our experiment design using real e-commerce data from a large-scale A/B test.

Riley Juenemann 2d

Are there application domains where causal inference is not (often) used that you think could really benefit from incorporating some of these techniques?

Reply Edit Delete •••

Operations Management and business decision making (non-digital)

Allex Desronvil 2d

Thank you -- two questions: (1) I was wondering if it would be possible to talk about good rules-of-thumb in selecting/pursuing a causal inference strategy and (2) I was wondering if you could offer some good directions to start with diff-in-diff, please.

Reply Edit Delete •••

Diff-in-Diff requires observing two periods from each unit Y1, Y2

Y1 pre-treatment Y2 post-treatment

Assumes conditional exogeneity on time-difference in potential outcomes (aka parallel trends)

$Y1(0) - Y2(0)$ independent of D given X => We can estimate $E[Y1(0) - Y2(0) \mid D=1]$ (identification by conditioning)

We then observe

$E[Y2(1) - Y2(0) \mid D=1] = E[Y2(1) - Y1(0) + Y1(0) - Y2(0) \mid D=1] = E[Y2 - Y1 \mid D=1] - E[Y2(0) - Y1(0) \mid D=1]$

Equivalent to Average Treatment effect on the treated (ATT)! Can deploy doubly robust estimate for ATT.

What's Trending in Difference-in-Differences?
A Synthesis of the Recent Econometrics Literature*

Jonathan Roth† Pedro H. C. Sant'Anna‡ Alyssa Bilinski§
John Poe¶

December 26, 2022

Structural Nested Mean Models Under Parallel Trends Assumptions

Zach Shahn[1,2], Oliver Dukes[3], David Richardson[4], Eric Tchetgen Tchetgen[3], and James Robins[5]

[1]CUNY School of Public Health, New York, NY, USA
[2]IBM Research, Yorktown Heights, NY, USA
[3]University of Pennsylvania, Philadelphia, PA, USA
[4]University of California Irvine, Irvine, CA, USA
[5]Harvard TH Chan School of Public Health, Boston, MA, USA

John Kohler 2d

Sometimes in econometrics, we transform our outcome variables in order to give special meaning to our parameter estimates (for example, taking the log of Y and X to calculate elasticities). Is machine learning capable of flexibly capturing these sorts of transformations in the output space? (we have only discussed input space transformation so far) Is there any connection to class material or is this a completely separate question of interpretation rather than estimation?

Reply Edit Delete •••

Log-like? Identified ATEs defined with zero-valued outcomes are (arbitrarily) scale-dependent*

Jiafeng Chen
Harvard Business School
Department of Economics, Harvard University

Jonathan Roth
Department of Economics, Brown University

February 1, 2023

Abstract

Economists frequently estimate average treatment effects (ATEs) for transformations of the outcome that are well-defined at zero but behave like $\log(y)$ when y is large (e.g., $\log(1+y)$, $\operatorname{arcsinh}(y)$). We show that these ATEs depend arbitrarily on the units of the outcome, and thus cannot be interpreted as percentage effects. Moreover, we prove that when the outcome can equal zero, there is no parameter of the form $E_P[g(Y(1), Y(0))]$ that is point-identified and unit-invariant. We discuss sensible alternative target parameters for settings with zero-valued outcomes that relax at least one of these requirements.

John Kohler 2d

Tell us about your career so far! Would love to hear about your experience at Microsoft Research, your decision to come to Stanford, and any career advice you have for causal inference in industry

♡ 2 Reply Edit Delete •••

- EECS (04-09) (Athens, Greece)
- Cornell CS PhD (09-14): Theoretical Computer Science; Algorithmic Game Theory
- Microsoft Research NYC Postdoc (14-16): Machine Learning theory, Online Learning Theory
- Microsoft Research New England (16-22) (Researcher; Principal Researcher): Causal Machine Learning, Econometrics; The ALICE Project and EconML
- Stanford MS&E (22-)

The ALICE project

(Automated Learning and Intelligence for Causation and Economics)

- Research + Industry Problems + Software Development
- New application domains for causal inference, lead to novel CausalML methodologies
  - Recommendation A/B tests at TripAdvisor ⇒ ML heterogeneous effects with instruments
  - Long-term Return-on-Investment (ROI) at Microsoft ⇒ Dynamic effects + surrogates in high dimensions
  - Personalized pricing and heterogeneous demand ⇒ Statistical learning for heterogeneous causal effects

Major research challenges addressed by my work

- High-dimensionality of data and valid inference [ICML'18a, COLT'20, NeurIPS'21, CLeaR'22, Arxiv'21a,b,c]
- Unobserved confounding [NeurIPS'19, NeurIPS'20]
- Dynamic aspects of decision making [NeurIPS'15 (best paper), ICML'16, NeurIPS'16, FOCS'17 & JACM'20, EC'15 & OR'20, ICML'18b,c, ICML'21, NeurIPS'21a,b]
- Personalized effects and policies [ICML'19, NeurIPS'19, **COLT'19 (best paper) & R&R Annals of Stats**, CLeaR'22]

Contributions to statistical learning theory, high-dimensional statistics, semi-parametric and non-parametric inference theory, optimization theory, online learning theory

The MSR ALICE Project

Automated Learning and Intelligence for Causation and Economics

- **Research.** Advance methodological research in econometrics and ML
- **Impact.** Apply Econ + ML methods to industry and societal problems
- **Software.** Develop software tools that reduce barriers to entry

EconML is a Python package that applies the power of machine learning techniques to estimate individualized causal responses from observational or experimental data.

Flexible model forms avoid strong assumptions and can estimate personalized responses to treatment

Unified API brings together all the latest advances in causal machine learning and econometrics

Familiar Interface built on standard Python packages make causal analysis quicker and easier for a broad set of users

The ALICE project

downloads 704k | Starred 1.9k | downloads/month 88k

EconML

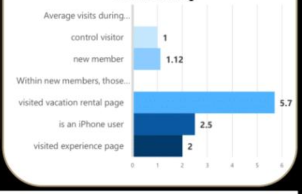
- Research + Industry Problems + Software Development
- New application domains for causal inference, lead to novel CausalML methodologies
  - Recommendation A/B tests at TripAdvisor ⇒ ML heterogeneous effects with instruments
  - Long-term Return-on-Investment (ROI) at Microsoft ⇒ Dynamic effects + surrogates in high dimensions
  - Personalized pricing and heterogeneous demand ⇒ Statistical learning for heterogeneous causal effects
- Making CausalML methods accessible with the EconML library

Microsoft Walmart Electrolux

"Developing a deep understanding of our travelers so we can create truly relevant experiences is at the core of what we do at TripAdvisor. Our partnership with Microsoft Research has allowed us to unlock critical insights that inform how to improve those experiences in a 1:1 manner."

—Matthew Dacey, Vice President Membership and Growth at TripAdvisor

Heterogeneous Effect of Membership



Using Non-Linear Models to Study Aerosol-Cloud Interactions in the Southeast Pacific

Machine Learning-Aided Causal Inference Framework for Environmental Data Analysis: A COVID-19 Case Study

The Role of "Live" in Livestreaming Markets: Evidence Using Orthogonal Random Forest

Youth well-being predicts later academic success

When a Voice Assistant Asks for Feedback: An Empirical Study on Customer Experience with A/B Testing and Causal Inference Methods

Empirical Estimates on Hand Manipulation are Recoverable: A Step Towards Individualized and Explainable Robotic Support in Everyday Activities

Causal Inference and COVID-19 Nursing Home Patients: Identifying Factors That Reduced Mortality Risk

A World of Causal Inference with EconML by Microsoft Research

微软EconML简介：基于机器学习的Heterogeneous Treatment Effects估计

EconML with R in the Tidyverse

Example Usage with Multiple Continuous Treatment, Multiple Outcome Observational Data

Zillow · Humana · Grab · Google

Data Scientist

Microsoft Introduces New Resources & Tools To Help Implement AI Responsibly

EconML/CausalML KDD 2021 Tutorial

Causal Inference and Machine Learning in Practice with EconML and CausalML: Industrial Use Cases at Microsoft, Yuwei Wu 1d

Can we go over more examples of policy optimization based on heterogeneous treatment effects?

Reply Edit Delete •••

Amod Hegde 20h

Can you tell us how the Causal + ML combo has impacted the field of causal inference? Has this led to an increase in the adoption of causal inference in the industry? Does this open up new interesting application domains for causal inference which weren't accessible before?

Reply Edit Delete •••

https://causal-machine-learning.github.io/kdd2021-tutorial/
https://drive.google.com/file/d/1QJJUCo4LH5kGQP3kaJlG1RdhjhaJWp-5/view

https://docs.google.com/presentation/d/1FvRtis2fm4c2R7XmRKWMTtZaZjUObW1fGxpNmapmjKI/edit#slide=id.ge6ef5be800_0_478

https://drive.google.com/file/d/1yyIu_3epIVXbwzJj658Iv4vxHGjtPh8n/view

https://drive.google.com/file/d/1FEKXFHHATntHjsEymXnEw6GAiUGMm8sG/view

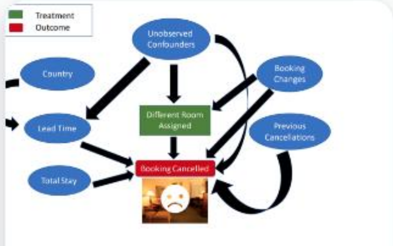
Overview

EconML is a Python package that applies the power of machine learning techniques to estimate individualized causal responses from observational or experimental data. The suite of estimation methods provided in EconML represents the latest advances in causal machine learning. By incorporating individual machine learning steps into interpretable causal models, these methods improve the reliability of what-if predictions and make causal analysis quicker and easier for a broad set of users.

EconML is open source software developed by the ALICE team at Microsoft Research.

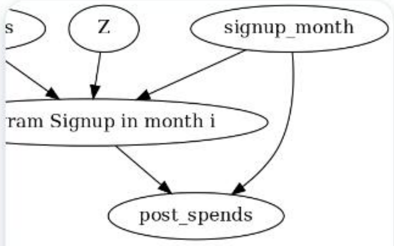
Flexible | **Unified** | **Familiar Interface**

Case Studies



Hotel Booking Cancellations

Beyond predictive models: The causal story behind hotel booking cancellations.



Effect of Customer Loyalty Programs

Estimating the effect of a member rewards program.

Optimizing Article Headlines

Introducing the do-sampler for causal inference.

Effects of Home Visits on Infant Health (IHDP)

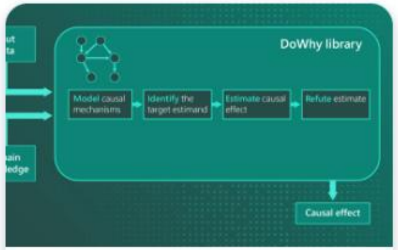
Understanding the question of why.

See more case studies →

News

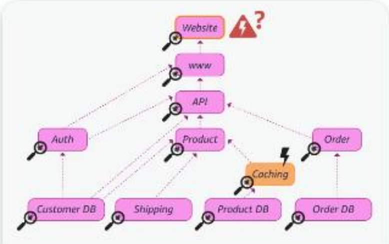
National Association for Business Economics Conference

Causal inference at scale presented at NABE.



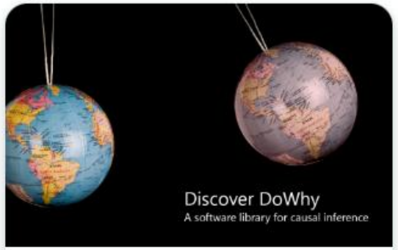
DoWhy evolves to independent PyWhy model to help causal inference grow

Identifying causal effects is an integral part of scientific inquiry. It helps us understand everything from



AWS contributes novel causal machine learning algorithms to DoWhy Python library

New features go beyond conventional effect estimation by attributing events to individual components of complex



Announcing DoWhy, a software library for causal inference

For decades, causal inference methods have found wide applicability in the social and biomedical sciences. As computing systems start latest

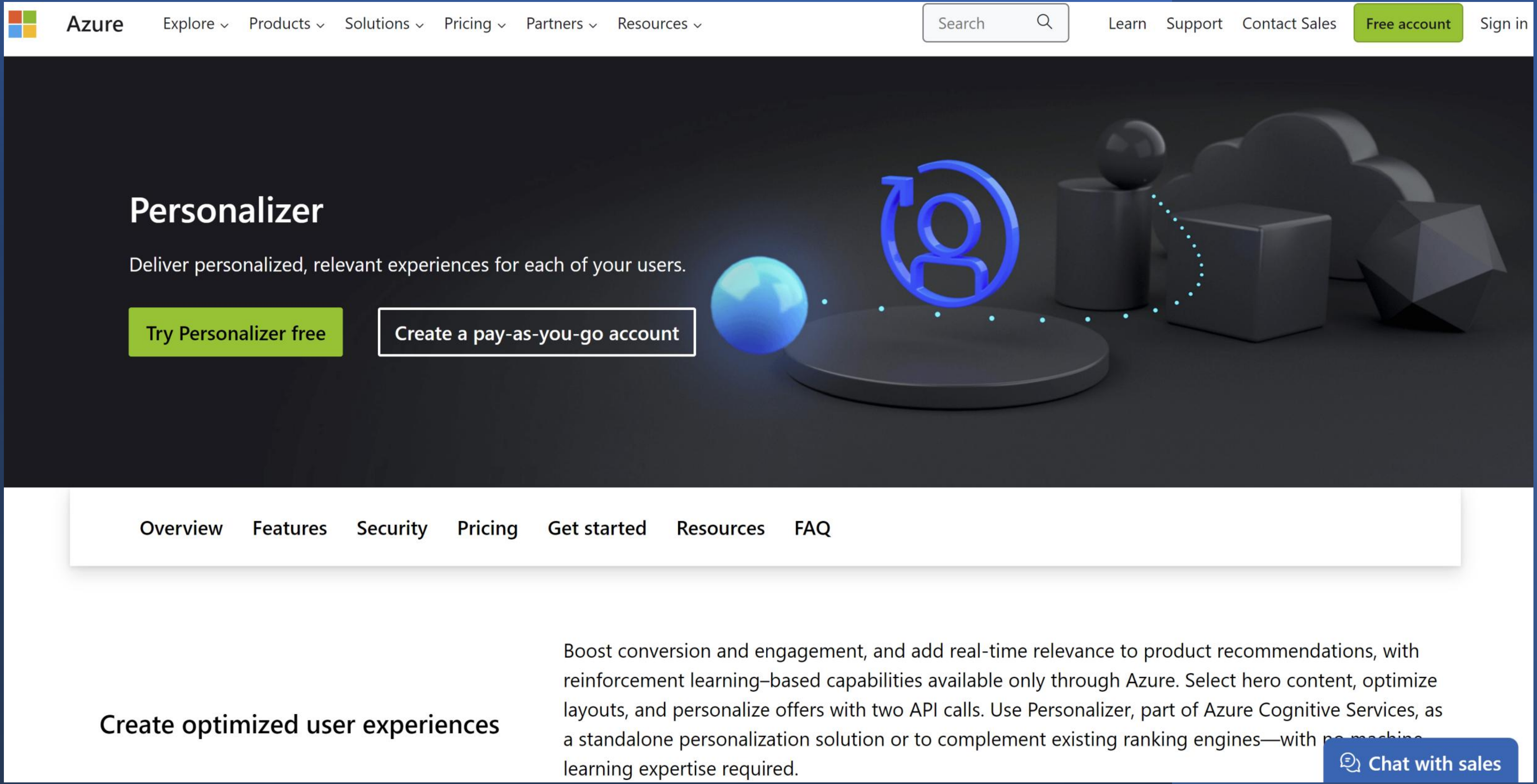
Search docs

About Causal ML

`Causal ML` is a Python package that provides a suite of uplift modeling and causal inference methods using machine learning algorithms based on recent research. It provides a standard interface that allows user to estimate the **Conditional Average Treatment Effect** (CATE) or **Individual Treatment Effect** (ITE) from experimental or observational data. Essentially, it estimates the causal impact of intervention **T** on outcome **Y** for users with observed features **X**, without strong assumptions on the model form.

Uber

UpliftML is a Python package for scalable unconstrained and constrained uplift modeling from experimental data. To accommodate working with big data, the package uses PySpark and H2O models as base learners for the uplift models. Evaluation functions expect a PySpark dataframe as input.


Azure
Explore
Products
Solutions
Pricing
Partners
Resources
Search
Learn
Support
Contact Sales
Free account
Sign in
Personalizer
Deliver personalized, relevant experiences for each of your users.
Try Personalizer free
Create a pay-as-you-go account
Overview
Features
Security
Pricing
Get started
Resources
FAQ
Create optimized user experiences
Boost conversion and engagement, and add real-time relevance to product recommendations, with reinforcement learning–based capabilities available only through Azure. Select hero content, optimize layouts, and personalize offers with two API calls. Use Personalizer, part of Azure Cognitive Services, as a standalone personalization solution or to complement existing ranking engines—with
learning expertise required.
Chat with sales

AWS Machine Learning Blog

Power contextual bandits using continual learning with Amazon SageMaker RL

by Saurabh Gupta, Anna Luo, Bharathan Balaji, Siddhartha Agarwal, Vineet Khare, and Yijie Zhuang | on 29 AUG 2019 | in Amazon SageMaker, Artificial Intelligence | Permalink | Comments | Share

Resources

Getting Started
What's New

Google Cloud

AI & Machine Learning

Online shopping gets more personal with Recommendations AI

July 22, 2020

IKEA Retail (Ingka Group) has increased global average order value for eCommerce by 2% with Recommendations AI

Yasu Yoshida 1d

I would like to know more about the frontiers of current research and the challenges you are trying to solve with your current research.

♡ Reply Edit Delete •••

Cecile Bourbonnais 13h

Are there specific emerging areas of research in causal inference right now that are most exciting to you, especially given recent technological advances? Or fields outside of medicine/econ that historically have not relied on causal inference as much, but that you feel should or are starting to?

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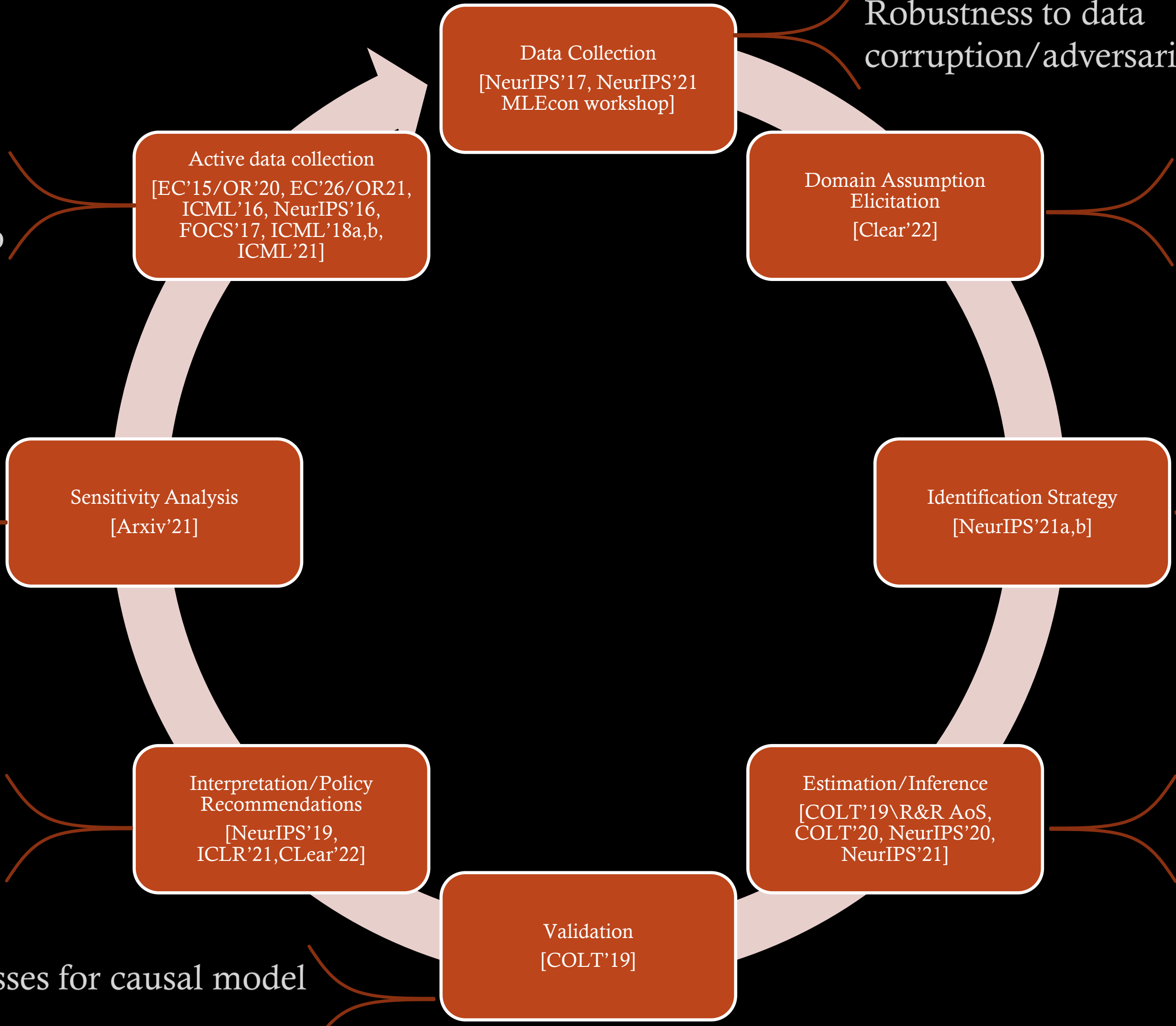
Many Research Challenges



Robustness to data corruption/adversarial attacks

Interactive assumption elicitation (query complexity)

Causal Representation Learning for unstructured data

Incorporate non-graphical restrictions in automated graph-based identification algorithms

Automated de-biasing in general (e.g. dynamic regime, mediation effects)

Unobserved confounding

Post adaptive data collection inference
Post causal discovery inference

Good losses for causal model selection

Evidence based interpretations for policy makers

Causal attribution

Computationally efficient sensitivity analysis

Long-term outcomes
Safety constraints
Fairness and ethical constraints
Experimentation constraints (ability to intervene on subsets of variables)

◈ https://github.com/causaltext/causal-text-papers

Adapting Text Embeddings for Causal Inference

Victor Veitch* Dhanya Sridhar* David M. Blei

Department of Statistics and Department of Computer Science
Columbia University

bedding methods. We illustrate the methods by answering the two motivating questions—the effect of a theorem on paper acceptance and the effect of a gender label on post popularity. Code and data available at github.com/vveitch/causal-text-embeddings-tf2.

Table of Contents

Max Schuessler 23h

Have you seen any of those methods being applied to -omics analyses in biology? I heard that in biostatistics, researchers traditionally use modelling to understand causal effects of a specific biomarker. What are the differences between modelling and the approaches we discussed in class in terms of their application?

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https://insitro.com/

A FLEXIBLE APPROACH FOR PREDICTIVE BIOMARKER DISCOVERY

PREPRINT

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Daniel Jenson 22h

I've been going through some of the earlier proofs and I'm still not sure what we mean when we say 'partial out X and D from 1' so that you get $\tilde{1}$. In my mind, X=(1, W), so if you have 1 ~ D + X, this is equivalent to 1 ~ D + 1 + W, in which case it will assign the coefficient 1 to the bias term in X and ignore D and W?

Reply Edit Delete •••

$$V_{11} = \frac{\mathrm{E}\epsilon^2 \tilde{D}^2}{(\mathrm{E}\tilde{D}^2)^2}.$$

Applying the same theory for β_1 (the intercept coefficient), yields[20]

$$\sqrt{n}(\hat{\beta}_1 - \beta_1) \approx \sqrt{n}\frac{\mathbb{E}_n \epsilon \tilde{1}}{\mathbb{E}_n \tilde{1}^2} \overset{a}{\sim} N(0, V_{22}),$$

20: To explain the derivation, note that by partialling out D and W (recall that $X = (1, W)$) from 1 and Y, we obtain

$$\tilde{Y} = \beta_1 \tilde{1} + \epsilon; \quad \tilde{1} := (1 - D).$$

The projection of 1 on D and W is given by D since D is binary and we've assumed $\mathrm{E}W = 0$.

where $\tilde{1} := (1 - D)$ is the residual after partialling out D and $\boxed{X}$ from 1 and

Typo! Should have been W

$$V_{22} = \frac{\mathrm{E}\epsilon^2 \tilde{1}^2}{(\mathrm{E}\tilde{1}^2)^2}.$$

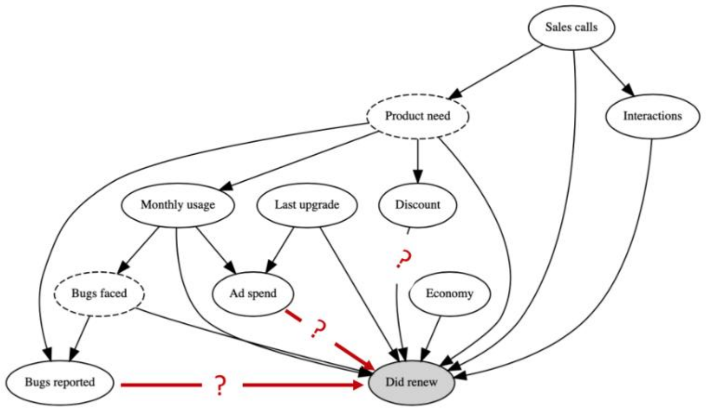
Louis Gautier 21h

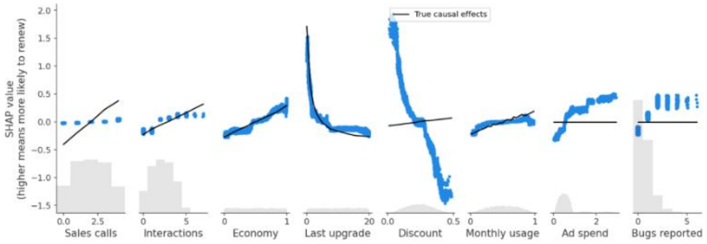
Could you please go back over the motivation slides from the very first lecture (the example on building a model that predicts whether a customer will renew their product subscription) and explain how you got the true causal effect graphs on slide 17? It would be very useful to see how to use the tools of the course to tackle this problem.

Reply Edit Delete •••

Require domain knowledge

of the high-level mechanisms that underlie the data collection process





https://towardsdatascience.com/be-careful-when-interpreting-predictive-models-in-search-of-causal-insights-e68626e664b6

Partialling Out DoubleML

Mike Van Ness 20h

Even though causal inference seems to be a large area of research and practice in Economics, I struggle to understand how causal inference is used in an economic setting, likely because of my lack of any knowledge of Economics. From my viewpoint, it seems that economics in the real world is so complex that it would be impossible to ever successfully do identification because there would always very likely be unobserved confounding. Can you explain a few simple problems in economics where causal inference is useful?

♡ 1 Reply Edit Delete •••

14 October 2019

The Royal Swedish Academy of Sciences has decided to award the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2019 to

Abhijit Banerjee
Massachusetts Institute of Technology, Cambridge, USA

Esther Duflo
Massachusetts Institute of Technology, Cambridge, USA

Michael Kremer
Harvard University, Cambridge, USA

"for their experimental approach to alleviating global poverty"

Their research is helping us fight poverty

The research conducted by this year's Laureates has considerably improved our ability to fight global poverty. In just two decades, their new experiment-based approach has transformed development economics, which is now a flourishing field of research.

11 October 2021

The Royal Swedish Academy of Sciences has decided to award the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2021

with one half to

David Card
University of California, Berkeley, USA

"for his empirical contributions to labour economics"

and the other half jointly to

Joshua D. Angrist
Massachusetts Institute of Technology, Cambridge, USA

Guido W. Imbens
Stanford University, USA

"for their methodological contributions to the analysis of causal relationships"

Natural experiments help answer important questions for society

This year's Laureates – David Card, Joshua Angrist and Guido Imbens – have provided us with new insights about the labour market and shown what conclusions about cause and effect can be drawn from natural experiments. Their approach has spread to other fields and revolutionised empirical research.

GENERIC MACHINE LEARNING INFERENCE ON HETEROGENOUS TREATMENT EFFECTS IN RANDOMIZED EXPERIMENTS, WITH AN APPLICATION TO IMMUNIZATION IN INDIA

VICTOR CHERNOZHUKOV, MERT DEMIRER, ESTHER DUFLO, AND IVÁN FERNÁNDEZ-VAL

ABSTRACT. We propose strategies to estimate and make inference on key features of heterogeneous effects in randomized experiments. These key features include *best linear predictors of the effects* using machine learning proxies, *average effects sorted by impact groups*, and *average characteristics of most and least impacted units*. The approach is valid in high dimensional settings, where the effects are proxied (but not necessarily consistently estimated) by predictive and causal machine learning methods. We post-process these proxies into estimates of the key features. Our approach is generic, it can be used in conjunction with penalized methods, neural networks, random forests, boosted trees, and ensemble methods, both predictive and causal. Estimation and inference are based on repeated data splitting to avoid overfitting and achieve validity. We use quantile aggregation of the results across many potential splits, in particular taking medians of p-values and medians and other quantiles of confidence intervals. We show that quantile aggregation lowers estimation risks over a single split procedure, and establish its principal inferential properties. Finally, our analysis reveals ways to build provably better machine learning proxies through causal learning: we can use the objective functions that we develop to construct the best linear predictors of the effects, to obtain better machine learning proxies in the initial step. We illustrate the use of both inferential tools and causal learners with a randomized field experiment that evaluates a combination of nudges to stimulate demand for immunization in India.

Causal Inference in Economics

- Beyond RCTs, methods that handle unobserved confounding are much more credible and more frequently used

- Instrumental Variables (demand, labor, education)
- Difference in Difference
- Regression Discontinuity
- Synthetic Controls (country level program evaluation)

Journal of Political Economy

Lead Editor: Magne Mogstad
Editors: John Asker, Andrew Atkeson, Mark Bils, Leonardo Bursztyn, Melissa Dell, Rachel Griffith, Emir Kamenica, Greg Kaplan, John List, Lance Lochner, Esteban Rossi-Hansberg, Azeem Shaikh

As education levels rise, we expect earnings and therefore the returns to be affected in a few ways. First, more educated workers are more productive and earn higher wages. Second, educated workers may reside in regions where there are fewer educated workers, making them relatively more valuable in the labor market. But if large numbers of people receive additional education, there is also a GE effect in the labor market: an increase in the abundance of high-skill labor puts downward pressure on the earnings skill premium. Yet as more skilled workers join the labor force, skill-biased capital may be adopted by firms in these regions, raising the premium. Indeed, as workers switch to more productive skill groups, overall output may increase, to the benefit of all workers. I estimate all of these components of the GE effects to better quantify the distributional impacts and the changes in labor market benefits.

The policy I study was India's flagship education scheme in the 1990s and early 2000s, the District Primary Education Program (DPEP), which expanded public schooling in half the country by targeting low-literacy regions. At that time, it was the largest program for primary education in the

Under the allocation rule, districts that had a female literacy rate below the national average were more likely to receive the program. I compare regions on either side of the cutoff to estimate causal impacts. The RD allows me to tackle biases that arise when estimating the individual returns to

Journal of Political Economy

Personalized Pricing and Consumer Welfare

Jean-Pierre Dubé and Sanjog Misra

PDF | PDF PLUS | Abstract | Full Text | Supplemental Material

Abstract

We study the welfare implications of personalized pricing implemented with machine learning. We use data from a randomized controlled pricing field experiment to construct personalized prices and validate these in the field. We find that unexercised market power increases profit by 55%. Personalization improves expected profits by an additional 19% and by 86% relative to the nonoptimized price. While total consumer surplus declines under personalized pricing, over 60% of consumers benefit from personalization. Under some inequity-averse welfare functions, consumer welfare may even increase. Simulations reveal a nonmonotonic relationship between the granularity of data and consumer surplus under personalization.

Journal of Political Economy

Lead Editor: Magne Mogstad
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Vertical Contracts with Endogenous Product Selection: An Empirical Analysis of Vendor Allowance Contracts

Sylvia Hristakeva

PDF PDF PLUS Abstract Full Text Supplemental Material

Abstract

Producers frequently provide retailers with financial incentives to secure product distribution. These payments often take the form of vendor allowances: lump-sum transfers to retailers that do not directly depend on quantity sold. I introduce an estimation strategy that uses observed product selections to inform unobserved allowances. I use retailers' replacement threats, which may allow them to capture both vendor transfers and lower wholesale prices. A counterfactual restricts firms to contract on only wholesale prices. Results show that vendor allowances may have not only (negative) product distortion effects but also (potentially positive) pricing effects.

The estimation methodology addresses retail price endogeneity by employing cost shifters as instrumental variables. I create a distance measure to capture transportation costs from each producer's manufacturing facility to each market. I locate yogurt plants in the United States that were used during the sample period. Appendix C summarizes the collected geographic distance information. To calculate a proxy for transportation costs between plants and each market, I combine these geographic distances with gas prices obtained from the US Energy Information Administration.

Hailong Chen 19h

What are the most common mistakes people do in causal inference practice?

1 Reply Edit Delete •••

- Believing that if you blindly control for a gazillion of features you have addressed unobserved confounding

- Trying to extra heterogeneity from very few samples

- Blindly using recent causal ml techniques as if it was a predictive problem without understanding anything about the data

- Believing that if you use machine learning to control, you fixed your unobserved confounding problem

Megan Li 19h

Are there any causal inference techniques that are widely used but you believe should be deprecated? If so, why?

♡ 1 Reply Edit Delete •••

Why Propensity Scores Should Not Be Used for Matching*

Gary King† Richard Nielsen‡

November 10, 2018

Abstract

We show that propensity score matching (PSM), an enormously popular method of preprocessing data for causal inference, often accomplishes the opposite of its intended goal — thus increasing imbalance, inefficiency, model dependence, and bias. The weakness of PSM comes from its attempts to approximate a completely randomized experiment, rather than, as with other matching methods, a more efficient fully blocked randomized experiment. PSM is thus uniquely blind to the often large portion of imbalance that can be eliminated by approximating full blocking with other matching methods. Moreover, in data balanced enough to approximate complete randomization, either to begin with or after pruning some observations, PSM approximates random matching which, we show, increases imbalance even relative to the original data. Although these results suggest researchers replace PSM with one of the other available matching methods, propensity scores have other productive uses.

Zhuoyang Liu 14h

In SEM, suppose we have

$$Y = \alpha D + \beta^T W + \epsilon$$

Can we write down the following:

$$Y(1) = \alpha + \beta^T W + \epsilon_1$$

and

$$Y(0) = \beta^T W + \epsilon_0$$

If yes, are

$$\epsilon_1$$

and

$$\epsilon_0$$

the same? (so that

$$Y(1) - Y(0) = \alpha \; a.s.$$

).

Reply Edit Delete •••

Yes, if you assume such a linear SEM this is the implicit assumption on the potential outcomes! (quite restrictive indeed)

Can be relaxed if we only assume that the epsilon is un-correlated with all the other variables, not just independent. Then that implicitly allows for epsilon to depend on treatment d, but should always be mean zero

Junting Duan 14h

I'd love to know some popular topics in current research in causal inference.

I also have two technical questions: 1.In Lecture 5, we learned that single Lasso is not Neyman orthogonal and it might omit some strong predictors for the treatment. Could you intuitively explain why omit strong predictors for the treatment is a problem for estimating the treatment effect? 2. For the second plot on P29 Lecture 14, how do we derive the confidence bounds for ATE?

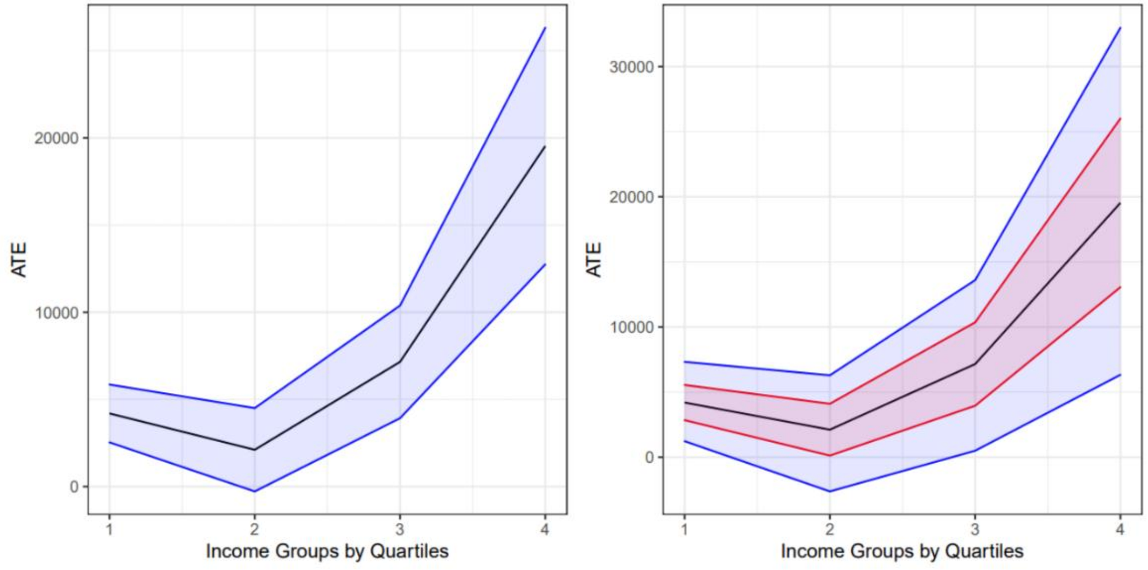
Thanks a lot!

Reply Edit Delete •••

- If you have a strong predictor of the treatment that was omitted by the single lasso due to regularization (as other factors were much stronger for the outcome), it is as if you did not control for that variable. This yields strong confounding bias.

LONG STORY SHORT: OMITTED VARIABLE BIAS IN CAUSAL MACHINE LEARNING

V. CHERNOZHUKOV, C. CINELLI, W.K. NEWEY, A. SHARMA, V. SYRGKANIS



(a) Estimates under no confounding. **(b)** Bounds under posited confounding.

Note: Estimate (black), bounds (red), and confidence bounds (blue) for the ATE. Confounding scenario: $\rho^2 = 1$; $C_Y^2 \approx 0.04$; $C_D^2 \approx 0.031$. Significance level of 5%.

$$\theta_s = \mathrm{E}[m(W^s, g_s) + (Y - g_s)\alpha_s],$$

)18d, 2021a). This representation is Neyman c
which is a key property required for DML. An

$$\mathrm{E}(Y - g_s)^2 =: \sigma_s^2,$$

gonal with respect to g_s. The final component
wing formulation:

$$\mathrm{E}\alpha_s^2 = 2\mathrm{E}m(W^s, \alpha_s) - \mathrm{E}\alpha_s^2 =: \nu_s^2,$$

estimators are defined as

$$\widehat{\theta}_s := \mathrm{DML}(\psi_\theta); \quad \widehat{\sigma}_s^2 := \mathrm{DML}(\psi_{\sigma^2}); \quad \widehat{\nu}_s^2 := \mathrm{DML}(\psi_{\nu^2});$$

$$\psi_\theta(Z;\theta,g,\alpha) := m(W^s,g) + (Y - g(W^s))\alpha(W^s) - \theta;$$
$$\psi_{\sigma^2}(Z;\sigma^2,g) := (Y - g(W^s))^2 - \sigma^2;$$
$$\psi_{\nu^2}(Z;\nu^2,\alpha) := (2m(W^s,\alpha) - \alpha^2) - \nu^2.$$

$$\varphi_\pm^o(Z) = \psi_\theta^o(Z) \pm \frac{|\rho|}{2}\frac{C_g C_\alpha}{S}(\sigma_s^2\psi_{\nu^2}^o(Z) + \nu_s^2\psi_{\sigma^2}^o(Z)).$$

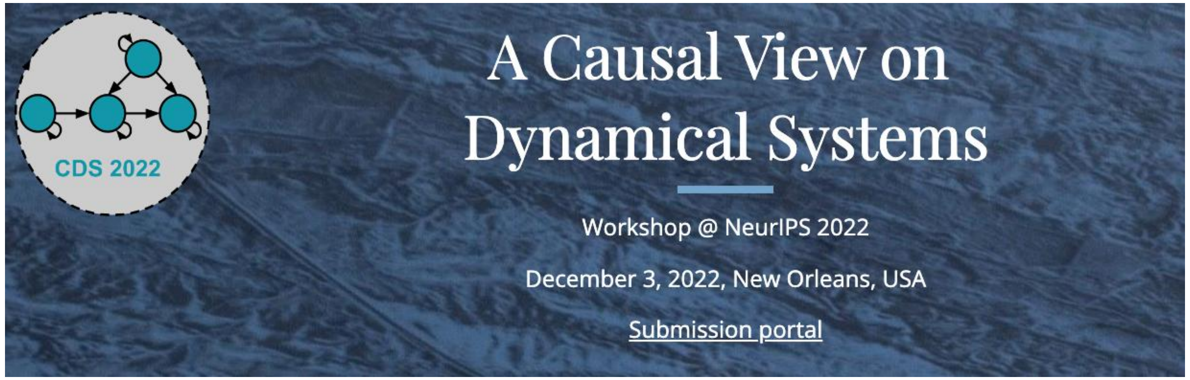
confidence bound

$$[\ell, u] = \left[\widehat{\theta}_- - \Phi^{-1}(1-a)\sqrt{\frac{\mathrm{E}\varphi_-^{o2}}{n}},\ \widehat{\theta}_+ + \Phi^{-1}(1-a)\sqrt{\frac{\mathrm{E}\varphi_+^{o2}}{n}}\right]$$

Soumya Koppaka 11h

How can we improve our ability to identify and estimate causal effects in complex and dynamic systems? Because in many real world settings, there exist multiple correlated covariates, and feedback loops, some of which may be dynamic and difficult to measure.

♡ Reply Edit Delete •••



https://sites.google.com/view/caudyn2022

http://networks.ece.mcgill.ca/sites/default/files/A%20Tutorial%20on%20Causal%20Inference%20in%20Dynamical%20Systems.pdf

Shannon Marie Meyer 4h

Sorry this one is late - do you have any favorite exploratory data analysis methods for the setting of high-D causal inference? It can be easy to get lost in the details when starting on a project... (though maybe our best tools are the current literature and DAGs)

Reply Edit Delete •••

- Double lasso for ATE (for continuous treatments); Doubly Robust (for categorical)

- Double lasso with feature interactions for quickly seeing if there is heterogeneity

- Generic meta learners with out of sample doubly robust validation for more flexible heterogeneity

David Troxell 1h

Since there is no way to validate the causal estimates we obtain given observational data (as discussed in lecture), are there any other ways besides confidence intervals to quantify the uncertainty of our estimate? For example, can full/split conformal inference provide some insight as to the stability of our modeling process (as opposed to the estimate itself)?

Another question I have is: after obtaining a DAG and identifying a valid adjustment set, is there a go-to process you usually follow in what to do next? Since we have discussed so many models/options I'm a bit confused on a good practical first step to do after identifying a valid adjustment set.

Reply Edit Delete •••

- Stability and calibration
- Using a small experimental sample to validate
- Using multiple observational datasets and separately estimating, with agreement
- Conformal inference cannot target expected effects, only individual (random effects) and typically will yield very large intervals

GoTo:

- Doubly robust ATE estimate for binary and Partialling out estimate for categorical (first with just Lasso models on expanded features and then with generic AutoML)
- Meta learners for CATE with out-of-sample doubly robust based evaluation (calibration, hypothesis tests)