Building a Robot Judge: Data Science for Decision-Making

6. Machine Learning and Causal Inference

Group Discussion: Real-World Algorithmic Rating System

- partner up into groups of 2-4.
- Flip a coin (or equivalent):
  - heads: `bit.ly/UK-visas` (Visa Algorithm)
  - tails: `bit.ly/UK-exams` (Grading Algorithm)
- Assignment (10 minutes):
  - 2 minutes: one student should summarize/describe the ML decision system described in the article.
  - 6 minutes: brainstorm at least 2 ways the system could be improved.
  - write down your answers and post them in Moodle.

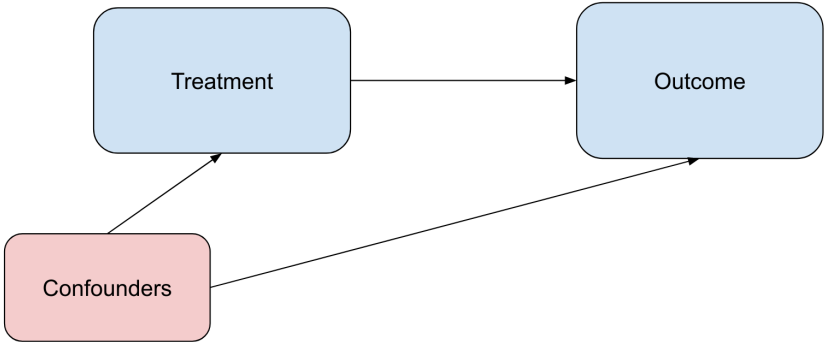
Learning Objectives

1. **Implement and evaluate machine learning pipelines.**
2. **Implement and evaluate causal inference designs.**
3. Understand how (not) to use data science tools (ML and CI) to support expert decision-making.

Today: What is gained with adding together 1+2?

Outline

Observed Confounders



- Recap from Week 2:
  - If the treated group and comparison group differ only by a set of observable characteristics, we can "control" or "adjust" for these variables to obtain causal estimates.

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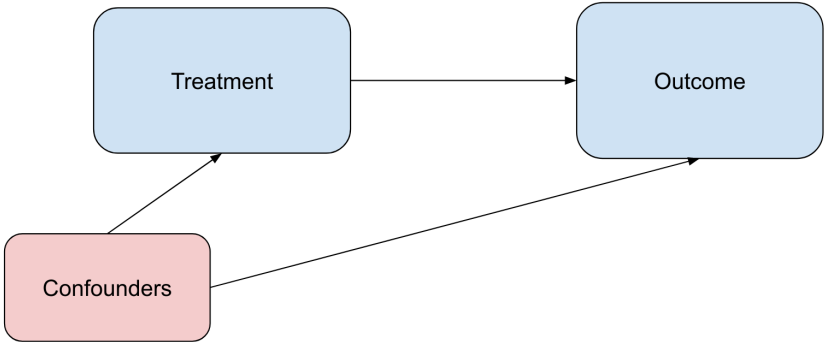

- Recap from Week 2:
  - If the treated group and comparison group differ only by a set of observable characteristics, we can "control" or "adjust" for these variables to obtain causal estimates.
- **Matching** is an alternative causal inference approach:
  - for each "treated" unit, find a matched "control" observation to compare to
  - (as opposed to including all observations in the dataset and adding covariates)

Matching

- Match each treated observation $i \in \{1, ..., n\}$, with Y_i, to a control observation i', with $Y_{i'}$. Then the treatment effect $\hat{\rho}$ is

$$\hat{\rho} = \frac{1}{n} \sum_{i}^{n} (Y_i - Y_{i'})$$

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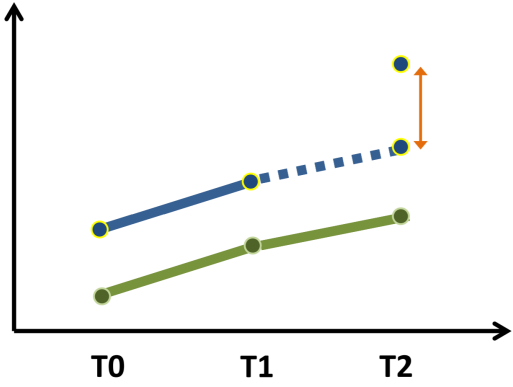
- Matching approaches:
  - Match treatment and control obs from the same group (e.g. same canton, court, classroom)
  - Compute distance measures based on covariates and match treatment observation to closest control observation.
  - Run k-means clustering on observed characteristics and match based on cluster assignment.
- can match a treatment observation to multiple control observations; can do a weighted average match based on proximity, etc.

Differences-in-Differences



- use all untreated units as comparison groups for the treated units.
- Two-way fixed-effects regression:

$$Y_{jt} = \alpha_j + \alpha_t + \gamma D_{jt} + \varepsilon_{jt}$$

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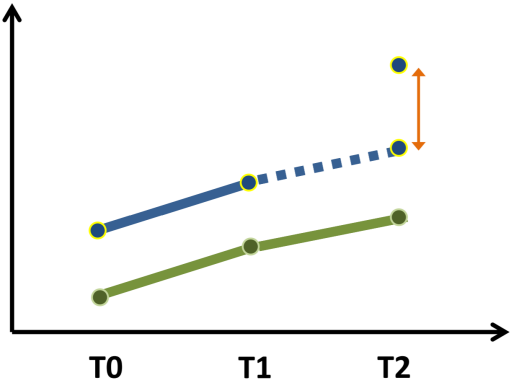

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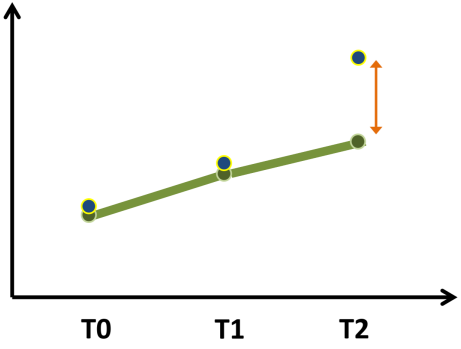
Matched Differences-in-Differences



- for each treated unit j, search over comparison group and find most similar unit j'. Then estimate

$$Y_{jt} - Y_{j't} = \alpha + \gamma \mathrm{D}_{jt} + \varepsilon_{jt}$$

  - can match on covariates
  - can match on probability of treatment at the same time as j.
  - try to find j' with similar pre-trend

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$$Y = \alpha + \rho D + X'\beta + \epsilon$$

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- then $\hat{\rho} = \frac{1}{n}\sum_i^n (Y_i - Y_{i'})$ is causally identified.
- Rather than matching, can also adjust for $\hat{D}(X)$ in the regression:

$$Y = \alpha + \rho D + \beta_D \hat{D}(X) + \epsilon$$

  - in practice, can include fixed effects for small bins of $\hat{D}(X)$. then all individuals are compared to other individuals with a similar propensity score.

Note: while PSM (adjusting for $\hat{D}(X)$) is sufficient to get unbiased $\hat{\rho}$ if X contains all confounders, including X as well in the regression might still shrink standard errors.

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The following is also sufficient to identify a causal effect:

- Learn an outcome regression $\hat{Y}(X)$, a cross-validated prediction of the outcome based on the observed confounders.
  - e.g., elastic net, xgboost regressor.
- If the prediction model $\hat{Y}(X)$ correctly learns the influence of all confounders on the outcome, then the regression

$$Y = \alpha + \rho D + \beta_Y \hat{Y}(X) + \epsilon$$

provides causal estimates.

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  - propensity score matching to learn $\hat{D}(X)$
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- Then:
  - only one of the models ($\hat{D}(X)$ or $\hat{Y}(X)$) has to be correct for $\hat{\rho}$ to be causally identified.

Outline

Synthetic Control

- with matched differences-in-differences, we matched each treated unit to a single similar control unit.
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- **synthetic control**: construct a synthetic "match" from a weighted average of other individuals (based on covariates).
- Statistically comparable to fixed effects or matching, but **powered up with ML.**

Example: Tobacco Laws in CA

In 1988, California passed anti-tobacco legislation (Proposition 99)

- Increased tax by \$0.25/pack
- Extra tax revenues earmarked to health budget
- Funded anti-smoking campaigns
- Clean-air signs in closed spaces

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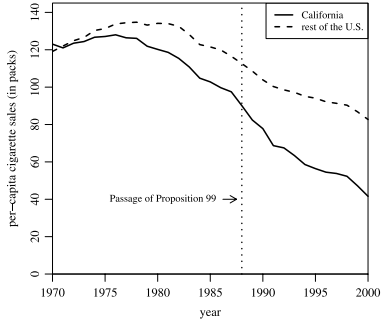
pd.read_stata("http://fmwww.bc.edu/repec/bocode/s/synth_smoking.dta")
```

Trends in cigarette sales: Parallel trends fails



Source: Abadie, Diamond and Hainmueller (2010)

Rest of US is not a good comparison group for California

- Trends start diverging in 1970s, before the reform
- Parallel trends assumption fails $\Rightarrow$ Cannot apply diff-in-diff

Synthetic Control Setup

- *Dataset:*
  - $j = 1, ..., J$ *units,* $t = 1, 2, ..., T$ *periods.*
  - Outcome Y_{jt} (e.g. cigarette sales)
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- Control group:
  - Remaining units (other states) are potential controls ("donor pool")
- Objective:
  - find combination of untreated units that best approximates treated unit

Formalization

- Define weights ω_j where $\sum_j \omega_j = 1$.

$$\text{Synthetic Control Treatment Effect} = \Delta Y_t = \underbrace{Y_{1t}}_{\text{treated}} - \underbrace{\sum_j \omega_j^* Y_{jt}}_{\text{synthetic}}$$

i.e., the outcome in the treated group, minus a weighted average of the outcomes in the control group (donor pool).

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- Let $x_{j1}, ..., x_{jk}, ..., x_{jm}$ be the set of observed characteristics for matching (e.g. population, employment rate, income tax rate).
- Synthetic control weights ω_j^* chosen to minimize

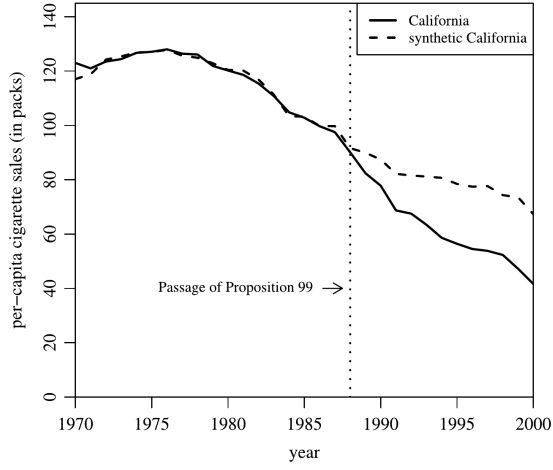
$$\sum_k \nu_k \left(\underbrace{x_{1k}}_{\text{treated}} - \underbrace{\omega_j x_{jk}}_{\text{synthetic}} \right)^2$$

  - ν_k = weight on k-th variable, chosen to minimize pre-reform MSE for ΔY_t, that is, to match on pre-trends.

Synthetic California

Table 2. State weights in the synthetic California

State	Weight	State	Weight
Alabama	0	Montana	0.199
Alaska	–	Nebraska	0
Arizona	–	Nevada	0.234
Arkansas	0	New Hampshire	0
Colorado	0.164	New Jersey	–
Connecticut	0.069	New Mexico	0
Delaware	0	New York	–
District of Columbia	–	North Carolina	0
Florida	–	North Dakota	0
Georgia	0	Ohio	0
Hawaii	–	Oklahoma	0
Idaho	0	Oregon	–
Illinois	0	Pennsylvania	0
Indiana	0	Rhode Island	0
Iowa	0	South Carolina	0
Kansas	0	South Dakota	0
Kentucky	0	Tennessee	0
Louisiana	0	Texas	0
Maine	0	Utah	0.334
Maryland	–	Vermont	0
Massachusetts	–	Virginia	0
Michigan	–	Washington	–
Minnesota	0	West Virginia	0
Mississippi	0	Wisconsin	0
Missouri	0	Wyoming	0



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Inference

- Synthetic control does not give standard errors. Instead, use bootstrap approach:
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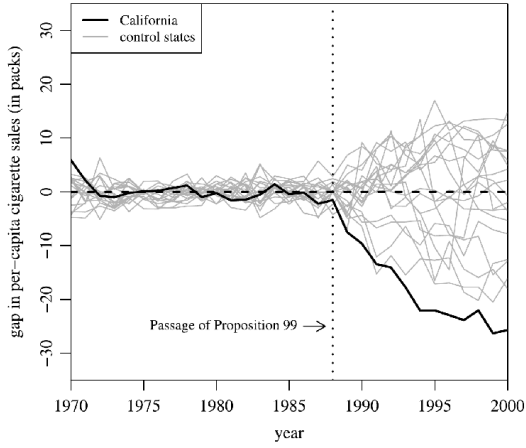

Application 2: Effect of Reunification on West Germany GDP

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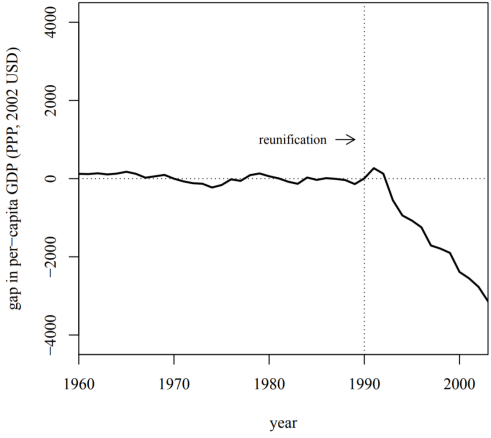
Country	Weight	Country	Weight
Australia	0	Netherlands	0.11
Austria	0.47	New Zealand	0.11
Belgium	0	Norway	0
Canada	0	Portugal	0
Denmark	0	Spain	0
France	0	Sweden	0
Greece	0	Switzerland	0
Ireland	0	United Kingdom	0.17
Italy	0	United States	0
Japan	0		0.14



Summary: Synthetic Control

Advantages:

1. Works with a single treated unit.
2. Makes explicit the contribution of each comparison unit to the synthetic control
3. Quantitative and qualitative ways to analyze similarities and differences of treatment and synthetic control
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Limitations:

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- see Goldin, Nyarko, and Young (2023) for a generalization of this approach using time series neural nets.

Outline

What if we have more control covariates than observations?

- the OLS estimator requires that the predictor matrix be full rank.
  - in particular, collinear predictors will break OLS
- with clustered standard errors, have to have more clusters than predictors.
- $\rightarrow$ Machine learning can help.

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  - X is a high-dimensional set of predictors – some are confounders, most are not.
  - we will use **lasso** to select which predictors to include in our OLS regression.

Selecting Controls with Double Lasso (2)

- Data prep:
  - drop from X any potential mediators and colliders.
  - add interactions and transformations, e.g. $x_4 x_5$, x_5^2.
  - standardize each variable in X to variance one

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- Data prep:
  - drop from X any potential mediators and colliders.
  - add interactions and transformations, e.g. $x_4 x_5$, x_5^2.
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- Train two lasso models, $Y \sim \text{Lasso}(X)$ and $D \sim \text{Lasso}(X)$:
  1. use CV grid search across the whole dataset to select best penalties λ_Y and λ_D.
  2. Run both lasso models with whole dataset, get subsets of non-zero predictors, X_Y and X_D
- Construct $X_{YD} = X_Y \cup X_D$, the union of the lasso-selected covariates.

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- Then regress

$$Y = \rho D + X'_{YD}\beta + \epsilon$$

  - Belloni et al (2014): If the model is approximately sparse. the estimate for $\hat{\rho}$ is consistent and efficiently estimated.

What if $g(\cdot)$ is not linear?

- Lasso assumes that $g(X)$ is linear in X.
  - we somewhat relaxed that assumption by adding interactions and quadratic transformations.
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- Lasso assumes that $g(X)$ is linear in X.
  - we somewhat relaxed that assumption by adding interactions and quadratic transformations.
  - but how do we know what interactions/transformations to add?
- Can use a non-linear model, e.g. xgboost, to approximate and adjust for $g(X)$.
  $\rightarrow$ Double Machine Learning / Doubly Robust Estimation (Chernozhukov et al 2018)

Double ML: Setup

$$Y = \rho D + g(X) + \epsilon$$

- low-dimensional treatment D, high-dimensional set of (observed) confounders X.
  - OLS regression without adjusting for confounders will be biased for $\hat{\rho}$
  - can we just include them in the regression as linear covariates?
    - will not adjust correctly due to potential non-linearities.
    - will probably fail to converge due to high dimensionality / collinearity / overfitting

Double ML method

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Cross-Fitting: Split into samples A and B, 50% of data each, to prevent overfitting:

- Fit (1) and (2) on sample A, then predict (3) and regress (4) on sample B, to estimate $\hat{\rho}_A$
- vice versa: fit (1)/(2) on sample B, and predict/regress (3)/(4) on sample A, to learn a second estimate for $\hat{\rho}_B$.
- average them to get a more efficient estimator:$\hat{\rho}^* = \frac{1}{2}(\hat{\rho}_A + \hat{\rho}_B)$.

Video Presentation: “The Gender Pay Gap Revisited with Big Data”

Outline

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- Treatments don't affect every individual equally.
  - for example, effect of sleep on productivity might depend on age of the worker.

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  - for example, effect of sleep on productivity might depend on age of the worker.
- The simplest way to estimate these is to interact treatment with another covariate (the "**moderator**"):

$$Y_i = \rho_1 D_i + \rho_2 \text{Age}_i + \rho_3 D_i \text{Age}_i + \epsilon_i$$

  - here, ρ_3 summarizes heterogeneous impact by age: $\frac{\partial Y_i}{\partial D_i} = \rho_1 + \rho_3 \text{Age}_i$

Conditional Treatment Effects

- Consider the more general model

$$Y = \underbrace{\rho(X)}_{\text{CTE}} D + g(X) + \epsilon$$

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  - the causal effect $\rho(X)$ is a function of X.
  - this is the conditional treatment effect (CTE) – that is, the effect conditional on X.
- Can learn flexible representation of $\hat{\rho}(X)$ using machine learning.

T-Learner Method

- Residualize Y on the fixed effects and controls to get rid of $g(X)$:

$$Y = \rho(X)D + \epsilon$$

  - if D is randomly assigned (e.g. RCT), this is not necessary.
  - Recall: the average (non-conditional) treatment effect is obtainable by OLS: $\hat{\rho}_{OLS} = \frac{\text{Cov}(Y,D)}{\text{Var}(D)}$.

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$$Y = \rho(X)D + \epsilon$$

  - if D is randomly assigned (e.g. RCT), this is not necessary.
  - Recall: the average (non-conditional) treatment effect is obtainable by OLS: $\hat{\rho}_{OLS} = \frac{\text{Cov}(Y,D)}{\text{Var}(D)}$.

T-Learner Method:

- Using any machine learning method (e.g. xgboost):
  - Learn $\mu_0(X) = \mathbb{E}(Y|X, D = 0)$
  - Learn $\mu_1(X) = \mathbb{E}(Y|X, D = 1)$
- Tune parameters in whole dataset using cross-validation.
- The conditional treatment effect estimate is $\hat{\rho}(X) = \mu_1(X) - \mu_0(X)$.

Other CTE estimators

- There are many such estimators.
  - See Knaus, Lechner, and Strittmatter (2020).
- T-learner is easiest to explain, but it is not the preferred estimator.
- Causal Forests should be the default model used
  - CausalForestDML in econml package.
  - See econml package documentation for extensive background and explanation.

Cagala et al 2021, Optimal Targeting in Fundraising: Setting

Figure 1: The gift consisting of the three folded cards and envelopes

Notes: The gifts consisted of three different folded cards showing flower motifs from paintings of Albrecht Dürer plus three envelopes.

- charity field experiment: 2345 warm-list donors, 17,425 cold-list donors
  - treament group (got a gift): 1180 warm-list, 2283 cold-list

The gifts work

Table 2: Average treatment effects of the gift on donations

	Warm list			Cold list		
	OLS	OLS	AIPW	OLS	OLS	AIPW
	(1)	(2)	(3)	(4)	(5)	(6)
A. Average treatment effects	1.24	1.21	1.22	0.19***	0.19***	0.19*
	(1.25)	(1.16)	(1.15)	(0.07)	(0.07)	(0.10)
B. Average treatment effects net of costs	0.08	0.05	0.06	-0.97***	-0.97***	-0.97***
	(1.25)	(1.16)	(1.15)	(0.07)	(0.07)	(0.10)
Strata controls	No	Yes	Yes	No	Yes	Yes

Notes: This table shows the estimated ATEs of the gift treatment on donations. The first set of estimates uses the amount donated in the first year after the gift as an outcome variable (euro). The second set of estimates additionally subtracts the gift's cost from the donation amount. We report results for the following specifications: unconditional OLS (Columns 1 and 4), OLS with strata control variables (Columns 2 and 5), and AIPW (Columns 3 and 6). Because the AIPW model allows for heterogeneous treatment effects, this model represents our preferred specification. Standard errors are in parenthesis. ***/**/* indicate statistical significance at the 1%/5%/10% level.

Conditional Treatment Effects and Targeting

Cagala et al 2021

- data on donor characteristics X:
  - demographics, donor history
  - detailed info on neighborhood from Google Maps API, collected using the mailing address.

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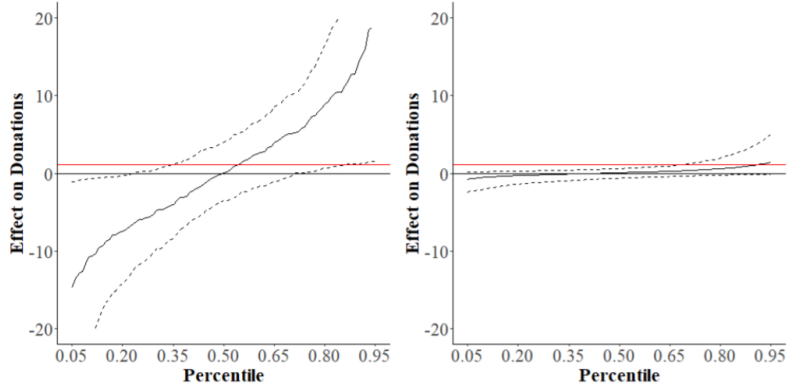
  - detailed info on neighborhood from Google Maps API, collected using the mailing address.
- for each treatment group $D =$ gift or no gift, train a machine learning model on characteristics X to predict donations $\hat{Y}(X|D)$.
- Optimal targeting rule is (roughly) ranking by $\hat{Y}$ and giving treatment to those for which

$$\hat{Y}(X|1) - c > \hat{Y}(X|0)$$

where c is the cost of the gift.

Effects are Heterogeneous

Figure 2: Sorted effects



(a) Warm list

(b) Cold list

Notes: This figure shows the heterogeneity of the effect of the gift on the donation amount. To that end, it sorts the estimated conditional average treatment effects by size and plots the size of the treatment effect in euro (vertical axis) against the percentiles of the effect size (horizontal axis). The red horizontal line represents the cost of the gift (1.16 euro). The solid line depicts the sorted effects. We report results between the 5 and 95 percentiles. The dashed lines report uniformly valid 95% confidence intervals, which build on a multiplier bootstrap and 500 replications.

Table 3: Out-of-sample performance of targeting rule in the warm list

	Expected outcome value under optimal targeting	Optimal targeting vs. benchmarks all-gift	no-gift	random-gift
	(1)	(2)	(3)	(4)
Panel A: Share of individuals that should receive the gift				
A1. Share treated 0.33				
Panel B: Results for primary outcome variable				
B1. Net donation amount (1st year)	17.61*** (0.97)	2.14*** (0.82)	2.20*** (0.81)	2.17*** (0.58)
Panel C: Results for secondary outcome variables				
C1. Donation probability (1st year)	0.503*** (0.013)	0.007 (0.013)	0.025** (0.010)	0.016* (0.008)
C2. Net donation amount (1st and 2nd year)	32.94*** (1.66)	2.33* (1.41)	3.75*** (1.41)	3.04*** (0.10)
C3. Donation probability (1st and 2nd year)	0.582*** (0.013)	0.001 (0.013)	0.017* (0.009)	0.009 (0.008)

Notes: This table documents the out-of-sample performance of our estimated optimal targeting rule, focusing on the warm list. The goal of optimal targeting is to maximize donations, net of costs. Panel A reports the share of individuals that, according to the rule, should receive the gift. Panel B reports the expected consequences of our rule for net donations as our main outcome. Panel C, instead, focuses on secondary outcomes. The columns can be interpreted as follows. Column 1 reports the expected value of the outcomes under optimal targeting. For example, we expect that, under optimal targeting, the donations, net of costs, would be 17.61 euro. Columns 2–4 show how optimal targeting changes the outcomes relative to three benchmark scenarios: everybody receives the gift (Column 2), no one receives the gift (Column 3), and the gift is randomly assigned to half of the sample (Column 4). Methodologically, the optimal targeting rules are estimated with Exact Policy-Learning Trees and a search depth of two (Zhou *et al.*, 2018). Donations are measured in euro. Standard errors are in parentheses. ***/**/* indicate statistical significance at the 1%/5%/10% level.

This week's assignment

Two parts:

1. Complete a jupyter notebook on matching / double ML / heterogenous treatment effects.

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Two parts:

1. Complete a jupyter notebook on matching / double ML / heterogenous treatment effects.
2. Peer review of response essays:
   - You will be randomly assigned two anonymized essays from one of your classmates.
   - Write one paragraph (5-10 sentences) about each essay, providing constructive feedback/suggestions. Identify at least one strength of the essay, and one area for improvement.
   - Follow the rubric on the homework assignments page.

Activity: Brainstorming about Moderators

Revisit your customized causal graph:

- Add a new "bubble" with the header "Moderators", and list some potential variables/characteristics that you expect to have a larger or smaller treatment effect.