Machine Learning for Economists and Business Analysts

Optimal Policy Learning

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Reference

Cagala, Rincke, Glogowsky, Strittmatter (2021): "Optimal Targeting in Fundraising: A Machine Learning Approach", download.

Overview

Motivation: Fundraising Example

CATE-Based Approach

Optimal Targeting Approach

Empirical Results

What are Policy Rules?

- Policy rules determine the allocation of treatments to individuals based on observable covariates.
- Policy rules are often labelled assignment rules, individualized treatment rules (ITR), personalized treatment rules, etc.

$\Rightarrow$ Policy rules can potentially improve the allocation of limited resources.

Scope of Applications

Targeted allocation of publicly sponsored programs:

- Assignment of unemployed to training programs.
- Preventive medical counselling (e.g. midwife or nutritionist).

$\Rightarrow$ Increase the effectiveness of publicly sponsored programs.

Targeted campaigns to foster public opinions/behavior:

- Get-out-the-vote campaigns.
- Information campaigns for organ donations.
- Marketing of charitable organisations.

$\Rightarrow$ Reduce the costs of the campaign.
$\Rightarrow$ Improve the desired response to the campaign.

Fundraising Expenditures

- Charities spend between 5% and 25% on fundraising (Andreoni and Payne, 2011).
- Money spend on fundraising cannot be used to finance the actual charitable activity.
- Donors are averse to charities with high overhead costs (Tinkelman and Mankaney, 2005, Gneezy et al., 2014).

$\Rightarrow$ Efficient fundraising is crucial for charities!

Optimal Targeting

- Many different fundraising instruments have been proposed (e.g. matching grants, gifts).
- Due to heterogeneity in donors preferences (e.g., altruism, warm-glow), the effects of any fundraising instrument are likely to be heterogeneous across individuals.
- Optimal targeting exploits this effect heterogeneity with the purpose to maximise the net donations (= donations - costs).
- Feasible allocation rules for fundraising instruments are based on observable characteristics that proxy heterogeneous preferences.

Field Experiment with Gifts

- Field experiment with small unconditional gifts (Dürrer's flower postcards) accompanied by a solicitation letter ($N \approx 20'000$).

- Individuals in the randomly selected treatment group received a mailer with the gift and solicitation letter.
- Individuals in the randomly selected control group received the solicitation letter, but not the gift.

Potential Effects of Gifts

- In theory, gifts work through social preferences by triggering a reciprocal reaction (Benabou and Tirole, 2006, Dufenberg and Kirchsteiger, 2004) .
- In line with this theory, Falk (2007) finds positive effects of gifts on donations.
- In contrast, Landry et al. (2010) and Yin et al. (2020) find that gifts can backfire and lower donations.
- Alpizar et al. (2008) find that gifts do not raise donations sufficiently high to justify the additional costs.
- Survey evidence suggests that 2/3 of donors do not want to receive gifts (Cygnus Applied Research, 2011).

$\Rightarrow$ Gifts appear to be a context with interesting heterogeneity!

Overview

Notation

- Treatment variable D_i (for $i = 1, ..., N$):

$$D_i = \begin{cases} 1 & \text{when a gift was sent, and} \\ -1 & \text{otherwise.} \end{cases}$$

- Potential outcomes:
  - $Y_i(1)$: Potential donations in response to the mailer with a fundraising gift.
  - $Y_i(-1)$: Potential donations in response to the mailer without a fundraising gift.
- Stable unit treatment value assumption (SUTVA):

$$Y_i = Y_i(-1) + \frac{1 + D_i}{2} \left(Y_i(1) - Y_i(-1) \right).$$

Treatment Effects

- Individual causal effects:

$$\delta_i = Y_i(1) - Y_i(-1)$$

- Average treatment effect (ATE):

$$\delta = E[\delta_i] = E[Y_i(1) - Y_i(-1)]$$

- Conditional average treatment effect (CATE):

$$\delta(x) = E[\delta_i | X_i = x] = E[Y_i(1) - Y_i(-1) | X_i = x]$$

Fundamental Identification Problem

Individual Causal Effects:

$$\delta_i = Y_i(1) - Y_i(-1).$$

Optimal Policy Rule:

$$\pi_i^* = 1\{\delta_i > 0\} - 1\{\delta_i \leq 0\}.$$

- Mailer with gift if $\delta_i > 0$.
- Mailer without gift if $\delta_i \leq 0$.

$\Rightarrow$ **Infeasible to identify and estimate individual causal effects!**

CATE Based Approaches

Conditional Average Treatment Effects (CATEs):

$$\delta(x) = E[\delta_i | X_i = x] = E[Y_i(1) - Y_i(-1) | X_i = x]$$

X_i contains exogenous pre-treatment covariates/features/attributes that are potentially responsible for effect heterogeneity.

Conventional Practice: Test based approach

$$\hat{\pi}_i = \hat{\pi}(X_i) = \begin{cases} 1 & \text{if } \hat{\delta}(X_i) \text{ significant positive,} \\ -1 & \text{otherwise.} \end{cases}$$

- Fixes the probability of type I errors (mistakenly rejecting the null).
- Unnecessarily many type II errors (mistakenly assuming the null).

$\Rightarrow$ Imbalance between type I and II errors.

Empirical Success Rule (Manski, 2004)

Empirical Success Rule:

$$\hat{\pi}_i = \hat{\pi}(X_i) = \begin{cases} 1 & \text{if } \hat{\delta}(X_i) > 0, \\ -1 & \text{if } \hat{\delta}(X_i) \leq 0. \end{cases}$$

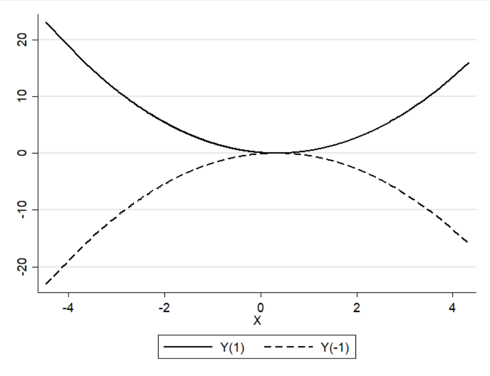
- Mailer with gift if $\hat{\delta}(X_i) > 0$.
- Mailer without gift if $\hat{\delta}(X_i) \leq 0$.

Caveats:

- The selection of a policy rule is a classification problem.
- CATEs estimators are not targeted at this classification problem.

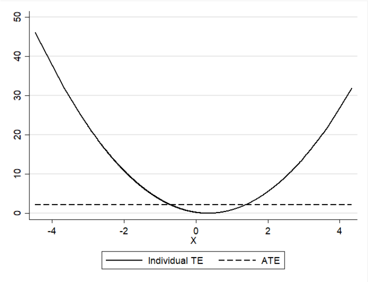
Simple Example

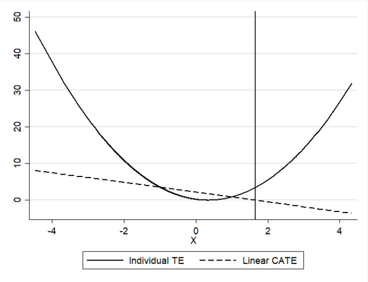
- $X \sim N(0, 1)$
- $Y(1) = (X - 1/3)^2$
- $Y(-1) = -(X - 1/3)^2$



Reference: Qian and Murphy (2011)

CATEs Not Suited for Policy Rules





- Treating everybody is optimal
- ATEs find optimal policy rule ($MSE_{ATE} \approx 9.4$), even though linear prediction of CATEs approximate the individual treatment effects better ($MSE_{ATE} > MSE_{CATE} \approx 7.8$)

Overview

Targeting Rule

- A targeting rule $\pi(x) \in \{-1, 1\}$ allocates the gift to potential donors based on the observable characteristics X_i.
  - Individuals with $\pi(X_i) = 1$ receive the mailer with the gift and
  - individuals with $\pi(X_i) = -1$ receive the mailer without the gift.

- Expected net donations (= expected donations - costs of gift),

$$P(\pi(X_i)) = E\left[Y_i(\pi(X_i)) - \frac{1 + \pi(X_i)}{2} c\right],$$

where $Y_i(\pi(X_i))$ is the donation amount of individual i under the policy rule $\pi(X_i)$ and c are the variable costs of the gift.

Benchmarks

- Everybody receives the gift:
  - $\pi_1 = 1$
  - Expected net donations: $P(\pi_1) = E[Y_i(1)] - c$

- Nobody receives the gift:
  - $\pi_{-1} = -1$
  - Expected net donations: $P(\pi_{-1}) = E[Y_i(-1)]$

- 50/50 randomization:
  - Expected net donations:
    $$\begin{aligned} P(\pi_R) &= 1/2 \cdot (P(\pi_1) + P(\pi_{-1})) \\ &= 1/2 \cdot (E[Y_i(1) + Y_i(-1)] - c) \end{aligned}$$

Value Added of Targeting Rule

- Compared to the benchmark that everybody receives the gift:

$$Q_1(\pi(X_i)) = P(\pi(X_i)) - P(\pi_1) = E\left[\frac{\pi(X_i) - 1}{2}(\delta_i - c)\right].$$

- Compared to the benchmark that nobody receives the gift:

$$Q_{-1}(\pi(X_i)) = P(\pi(X_i)) - P(\pi_{-1}) = E\left[\frac{1 + \pi(X_i)}{2}(\delta_i - c)\right].$$

- Compared to the benchmark of 50/50 randomization:

$$Q_R(\pi(X_i)) = P(\pi(X_i)) - P(\pi_R) = \frac{1}{2}E\left[\pi(X_i)(\delta_i - c)\right].$$

Identifying Assumptions

- SUTVA
- Stratified randomisation with regard to observable characteristics Z_i:
  - CIA: $(Y_i(1), Y_i(-1)) \perp\!\!\!\perp D_i | Z_i = z$
  - Propensity score: $p(z, x) = Pr(D_i = 1 | Z_i = z, X_i = x) = Pr(D_i = 1 | Z_i = z) = p(z)$
  - Common support: $0 < p(z) < 1$
- Z_i are confounders that are relevant for identification.
- X_i are potentially relevant for effect heterogeneity.
- Z_i and X_i are not necessarily equivalent, but they may overlap.

Augmented Inverse Probability Weighting (AIPW)

- δ_i is an important ingredient for the estimation of targeting rules, but is unobservable in the data.
- Idea is to replace δ_i with an approximation score Γ_i.
- AIPW is one possible approximation score (Robins et al, 1994, Chernozhukov et al., 2018).
- The estimated AIPW score is $\hat{\Gamma}_i = \hat{\Gamma}_i(1) - \hat{\Gamma}_i(-1)$, with

$$\hat{\Gamma}_i(1) = \hat{\mu}_1(Z_i) + \frac{1+D_i}{2} \cdot \frac{Y_i - \hat{\mu}_1(Z_i)}{\hat{p}(Z_i)} \text{ and}$$
$$\hat{\Gamma}_i(-1) = \hat{\mu}_{-1}(Z_i) - \frac{D_i-1}{2} \cdot \frac{Y_i - \hat{\mu}_{-1}(Z_i)}{1-\hat{p}(Z_i)},$$

  where $\hat{\mu}_d(z) = \hat{E}[Y_i(d)|Z_i = z] = \hat{E}[Y_i|D_i = d, Z_i = z]$ and $\hat{p}(z) = \widehat{Pr}(D_i = 1|Z_i = z)$.
- You can think of AIPW as an IPW estimator with a small sample bias adjustment.

Augmented Inverse Probability Weighting (AIPW)

- AIPW identifies ATEs $\delta = E[\Gamma_i]$ and CATEs $\delta(x) = E[\Gamma_i | X_i = x]$.
- Chernozhukov et al. (2018) show that the ATE estimator

$$\hat{\delta} = \frac{1}{N} \sum_{i=1}^{N} \hat{\Gamma}_i$$

  is $\sqrt{N}$-consistent and semi-parametrically efficient (if the nuisance parameter converge sufficiently fast).
- In contrast to OLS, AIPW allows for fully flexible heterogeneous effects.

Estimation of the Optimal Targeting Rule

- Athey and Wager (2019) propose to maximise the sample analog of $Q_R(\pi(X_i))$

$$\pi^* = \text{argmax}_\pi \left\{ \frac{1}{2N} \sum_{i=1}^{N} \pi(X_i)(\hat{\Gamma}_i - c) \right\},$$

  where the unobservable individual causal effect δ_i is replaced with the AIPW score $\hat{\Gamma}_i$.

- This equivalent to the weighted classification estimator

$$\pi^* = \text{argmax}_\pi \left\{ \frac{1}{2N} \sum_{i=1}^{N} \pi(X_i) sign(\hat{\Gamma}_i - c)|\hat{\Gamma}_i - c| \right\},$$

  (Beygelzimer and Langford, 2009, Zadrozny, 2003).

Value Added of Machine Learning

- We could estimate π^* with a weighted Logit estimator (or any other weighted classification estimator).
- Then we would have to select the characteristics X_i manually.
- There is a bias-variance trade-off:
  - If we include too few characteristics, we might overlook important heterogeneity.
  - If we include too many characteristics, we overfit the model which may leads to bad out-of-sample accuracy.
- Machine learning algorithms can balance the bias-variance trade-off in a data driven way.
- We consider decision trees, which can include non-linear and interaction terms without pre-coding.
- In the main specifications, we use the optimal policy trees of Zhou et al. (2019).

Classification Methods

- **Classification Trees**
  - In contrast to regression trees, classification trees use different performance measures
  - These measures are targeted to minimise the impurity (instead of the regression fit)
  - Entropy or Gini index
- **Logistic LASSO**
- **Classification Forest**
- **Support Vector Machines**

Out-of-Sample Off-Policy Evaluation

- Once we have obtained π^*, we can estimate

$$\hat{P}(\pi^*(X_i)) = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\Gamma}_i(\pi^*(X_i)) - \frac{1+\pi^*(X_i)}{2}c\right),$$

$$\hat{Q}_1(\pi^*(X_i)) = \frac{1}{N}\sum_{i=1}^{N}\frac{\pi^*(X_i)-1}{2}\left(\hat{\Gamma}_i - c\right),$$

$$\hat{Q}_{-1}(\pi^*(X_i)) = \frac{1}{N}\sum_{i=1}^{N}\frac{1+\pi^*(X_i)}{2}\left(\hat{\Gamma}_i - c\right), \text{ and}$$

$$\hat{Q}_R(\pi^*(X_i)) = \frac{1}{2N}\sum_{i=1}^{N}\pi^*(X_i)\left(\hat{\Gamma}_i - c\right).$$

- These estimators are consistent and semi-parametrically efficient (Chernozhukov et al., 2018).
- We apply a cross-fitting procedure to assess the targeting rule out-of-sample.

Overview

Experimental Data

- Field experiment in cooperation with a fundraiser operating within the structure of the Catholic church in an urban area in Germany in 2014.
- All experimental participants received a letter with information about the fundraiser's cause (maintaining clergy houses, parish centers, and churches) and a donation request.
- A randomly selected treatment group additionally received a small unconditional gift.
- Attached to the letter is a bank transfer form pre-filled with the fundraiser's bank account information and the recipient's name.
- Donations are made exclusively via bank transfer, and the fundraiser does not provide any information about individual donations to the church parishes.

Heterogeneity Variables

- **Socio-economic characteristics:**
  Gender, age, marital status, years residency.
- **Donation history:**
  Number of previous donation, total previous donations, maximum previous donations, yearly donations of the previous 5 years.
- **Geo-spatial information of home address:**
  Number of restaurants, supermarkets, medical facilities, cultural facilities, and churches in the proximity (300 meters radius), distance to city hall, main station, main church, and airport, travel distance to main station, elevation.

Descriptive Statistics

	Mean	Std. Dev.	Skew.	Kurt.	Min.	Max.
	(1)	(2)	(3)	(4	(5)	(6)
			Warm list			
1st year after the experiment:						
Donation amount (in Euro)	16.02	30.38	4.70	39.05	0	450
Donation dummy	0.49				0	1
1st and 2nd year after the experiment:						
Donation amount (in Euro)	30.48	53.19	4.96	49.23	0	900
Donation dummy	0.57				0	1
			Cold list			
1st year after the experiment:						
Donation amount (in Euro)	0.18	3.00	38.39	2'049.4	0	200
Donation dummy	0.009				0	1
1st and 2nd year after the experiment:						
Donation amount (in Euro)	0.43	4.85	23.12	779.6	0	240
Donation dummy	0.017				0	1

Descriptive Statistics

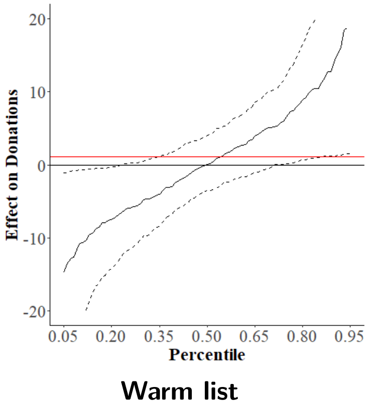
	Warm-list		Cold-list	
	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)
Socio-economic characteristics				
Female dummy	0.53		0.50	
Single dummy	0.50		0.64	
Widowed dummy	0.05		0.02	
Age (in years)	68.51	18.30	48.40	19.32
Duration residency in urban area (in years)	7.43	1.67	5.97	2.82
Donation history before the experiment				
Number of donations previous 8 years	3.97	2.83	0	
Max. donations previous 8 years (in Euro)	36.02	42.90	0	
Total donations previous 8 years (in Euro)	125.9	176.0	0	
Donations 1 year ago (in Euro)	20.59	35.27	0	
Donations 2 years ago (in Euro)	17.23	29.29	0	
Donations 3 years ago (in Euro)	15.95	27.51	0	
Donations 4 years ago (in Euro)	15.82	27.59	0	
Donations 5 years ago (in Euro)	15.25	28.24	0	
Geo-spatial information about home address				
Elevation (in meters)	317.1	10.46	316.1	10.32
In 300 meters proximity:				
Number of restaurants	7.98	10.14	10.33	11.61
Number of supermarkets	1.08	1.36	1.29	1.50
Number of medical facilities	9.59	12.72	10.72	13.13
Number of cultural facilities	0.11	0.51	0.14	0.53
Number of churches	1.01	1.48	1.18	1.53
Distance to main station (in km)	3.25	2.11	2.86	2.02
Distance to city hall (in km)	3.11	2.00	2.79	1.88
Distance to main church (in km)	3.14	2.03	2.79	1.93
Distance to airport (in km)	5.46	1.75	5.55	1.64
Travel time to main station (in minutes)	17.81	9.20	16.13	8.66
Observations	2,354		17,425	

Average Effects

	Warm list (1)	Cold list (4)
ATE	1.22	0.19*
	(1.15)	(0.10)
ATE - costs	0.06	-0.97***
	(1.15)	(0.10)
Strata controls	Yes	Yes
Observations	2'354	17'425

Notes: The outcome variable is donation amount (in Euro) during the first year after the gift was sent.

Effect Heterogeneity



Notes: Figure is based on the sorted effects model of Chernozhukov, FernÃ¡ndez-Val, and Luo (2018).

Out-of-Sample Results for the Warm List

	Share Treated	Net Donations	Optimal Targeting Rule vs. Everybody	Nobody	Random
	(1)	(2)	(3)	(4)	(5)
	Panel A: Results for Target Variable				
Net Donation Amount	0.334	17.61***	2.141***	2.199***	2.170***
(1st year)		(0.971)	(0.817)	(0.813)	(0.575)
	Panel B: Second Order Effects				
Net Donation Amount		32.94***	2.328*	3.753***	3.040***
(1st and 2nd year)		(1.661)	(1.405)	(1.412)	(0.995)
Donation Probability		0.503***	0.007	0.025**	0.016*
(1st year)		(0.013)	(0.013)	(0.010)	(0.008)
Donation Probability		0.582***	0.001	0.017*	0.009
(1st and 2nd year)		(0.013)	(0.013)	(0.009)	(0.008)

Notes: Donation amounts are measured in Euro. Standard errors are in parentheses.

⇒ 14% increase in donations during 1st year.

Out-of-Sample Results for the Cold List

	Share Treated	Net Donations	Optimal Targeting vs. Everybody	Nobody	Random
	(1)	(2)	(3)	(4)	(5)
Panel A: Results for Target Variable					
Net Donation Amount	0.014	0.15***	0.97***	-0.005	0.48***
(1st year)		(0.02)	(0.10)	(0.012)	(0.05)
Panel B: Second Order Effects					
Net Donation Amount		0.44***	0.96***	0.04	0.50***
(1st and 2nd year)		(0.07)	(0.13)	(0.06)	(0.07)
Donation Probability		0.009***	-0.007***	0.001	-0.003**
(1st year)		(0.001)	(0.003)	(0.001)	(0.001)
Donation Probability		0.017***	-0.006*	0.001	-0.003
(1st and 2nd year)		(0.001)	(0.003)	(0.001)	(0.002)

Notes: Donation amounts are measured in Euro. Standard errors are in parentheses.

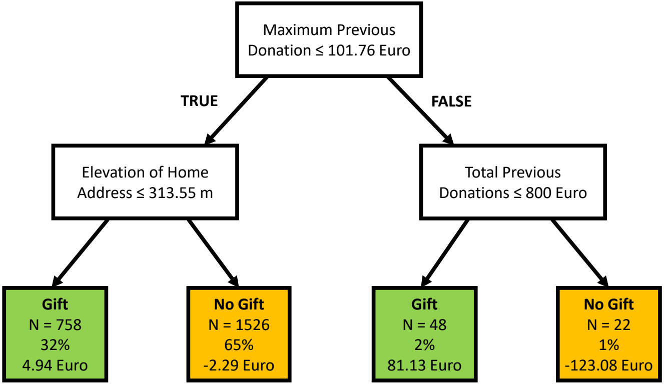
Characteristics of Net Donors in the Warm List

	Individuals targeted by the algorithm				Std.
	Yes		No		Diff.
	Mean	Std. Dev.	Mean	Std. Dev.	
	(1)	(2)	(3)	(4)	(5)
Socio-economic characteristics					
Female dummy	0.507		0.539		6.459
Single dummy	0.503		0.496		1.464
Widowed dummy	0.050		0.052		0.974
Age (in years)	68.08	18.23	68.72	18.34	3.488
Duration residency (in years)	7.423	1.690	7.439	1.659	0.951
Donation history before the experiment					
Num. donations prev. 8 years	4.097	2.827	3.900	2.829	6.934
Max. don. prev. 8 years (in Euro)	39.94	44.61	34.05	41.89	13.63
Total don. prev. 8 years (in Euro)	130.98	150.69	123.39	187.39	4.460
Donations 1 year ago (in Euro)	22.69	36.49	19.53	34.60	8.891
Donations 2 years ago (in Euro)	17.91	30.30	16.89	28.77	3.466
Donations 3 years ago (in Euro)	16.61	27.49	15.62	27.52	3.593
Donations 4 years ago (in Euro)	16.71	28.33	15.37	27.21	4.813
Donations 5 years ago (in Euro)	15.69	24.48	15.03	29.96	2.410
geospatial information about home address					
Elevation (in meters)	308.66	6.266	321.38	9.524	157.80
In 300 meters proximity:					
Number of restaurants	10.86	13.30	6.528	7.711	39.88
Number of supermarkets	1.062	1.371	1.086	1.362	1.748
Number of medical facilities	10.17	13.95	9.298	12.041	6.703
Number of cultural facilities	0.240	0.796	0.050	0.241	32.27
Number of churches	1.166	1.515	0.934	1.460	15.60
Distance to main station (in km)	3.247	2.521	3.245	1.867	0.053
Distance to city hall (in km)	2.927	2.237	3.196	1.856	13.11
Distance to main church (in km)	2.986	2.365	3.218	1.836	10.99
Distance to airport (in km)	5.427	1.236	5.483	1.960	3.408
Travel time to main station (in min.)	18.42	11.79	17.50	7.560	9.371
Observations	787		1'567		

Characteristics of Net Donors in the Cold List

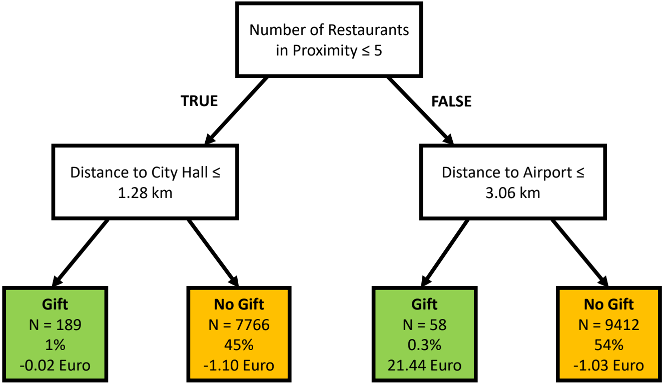
	Individuals targeted by the algorithm				Std.
	Yes		No		Diff.
	Mean	Std. Dev.	Mean	Std. Dev.	
	(1)	(2)	(3)	(4)	(5)
Socio-economic characteristics					
Female dummy	0.558		0.503		11.04
Single dummy	0.713		0.642		15.24
Widowed dummy	0.024		0.017		4.518
Age (in years)	47.58	21.00	48.41	19.30	4.132
Duration residency (in years)	5.677	2.964	5.973	2.818	10.22
geospatial information about home address					
Elevation (in meters)	313.47	8.183	316.15	10.34	28.71
In 300 meters proximity:					
Number of restaurants	5.482	3.524	10.40	11.67	57.08
Number of supermarkets	0.888	1.122	1.296	1.502	30.77
Number of medical facilities	13.73	10.20	10.68	13.17	25.89
Number of cultural facilities	0.040	0.196	0.146	0.532	26.43
Number of churches	1.100	1.017	1.177	1.538	5.957
Distance to main station (in km)	1.995	0.890	2.874	2.028	56.14
Distance to city hall (in km)	1.364	0.645	2.816	1.885	103.02
Distance to main church (in km)	1.588	0.743	2.803	1.932	83.03
Distance to airport (in km)	4.143	1.038	5.567	1.642	103.68
Travel time to main station (in min.)	12.50	6.312	16.18	8.680	48.45
Observations	251		17'174		

Exact Policy Tree Warm List



Note: Figure based on the optimal policy tree of Zhou et al. (2019) and Sverdrup et al. (2020)

Exact Policy Tree Cold List



Note: Figure based on the optimal policy tree of Zhou et al. (2019) and Sverdrup et al. (2020)

Relevant Data Sources Warm List

Share Treated (1)	Net Donations (2)	Targeting Rule vs. Everybody (3)	Nobody (4)	Random (5)	All Data Sources (6)
Socio-Economic Characteristics					
0.55	15.71***	0.24	0.29	0.27	-1.91**
	(0.79)	(0.86)	(0.77)	(0.58)	(0.89)
Donation History					
0.12	17.20***	1.73**	1.79**	1.76***	-0.41
	(0.97)	(0.82)	(0.81)	(0.58)	(0.55)
Geo-Spatial Information					
0.49	17.40***	1.93**	1.98**	1.95***	-0.22
	(0.91)	(0.84)	(0.79)	(0.58)	(0.61)
Socio-Economic Characteristics and Donation History					
0.11	17.05***	1.58*	1.64**	1.61***	-0.56
	(0.96)	(0.84)	(0.79)	(0.58)	(0.56)
Socio-Economic Characteristics and Geo-Spatial Information					
0.48	16.97***	1.50*	1.55*	1.53***	-0.64
	(0.89)	(0.84)	(0.80)	(0.58)	(0.62)
Donation History and Geo-Spatial Information					
0.33	17.61***	2.14***	2.20***	2.17***	0
	(0.97)	(0.82)	(0.81)	(0.58)	

Notes: Donation amounts are measured in Euro. Standard errors are in parentheses.

Relevant Data Sources Cold List

Share Treated	Net Donations	Targeting Rule vs. Everybody	Nobody	Random	All Data Sources
(1)	(2)	(3)	(4)	(5)	(6)
Socio-Economic Characteristics					
0.015	0.14***	0.96***	-0.014**	0.47***	-0.01
	(0.02)	(0.10)	(0.007)	(0.05)	(0.014)
Geo-Spatial Information					
0.014	0.15***	0.97***	-0.005	0.48***	0
	(0.02)	(0.10)	(0.012)	(0.05)	

Notes: Donation amounts are measured in Euro. Standard errors are in parentheses.

Alternative Estimators Warm List

	Share Treated	Net Donations	Optimal Targeting vs. Everybody	Nobody
	(1)	(2)	(3)	(4)
Logit				
Baseline model	0.47	16.19***	0.72	0.78
		(0.90)	(0.81)	(0.82)
Flexible model	0.43	15.45***	-0.02	0.04
		(0.80)	(0.91)	(0.71)
Logit-Lasso	0.83	15.86***	0.39	0.45
		(0.91)	(0.62)	(0.98)
Exact policy learning tree				
depth = 1	0.39	15.05***	-0.42	-0.36
		(0.77)	(0.98)	(0.61)
depth = 3	0.34	15.49***	0.02	0.08
		(0.88)	(0.87)	(0.76)
CART				
depth =2	0.11	16.10***	0.63	0.68
		(0.94)	(0.93)	(0.69)
Cross-validated depth	0.33	17.40***	1.93**	1.98**
		(0.96)	(0.83)	(0.80)
Classification forest	0.42	15.88***	0.41	0.47
		(0.83)	(0.89)	(0.73)

Notes: Donation amounts are measured in Euro. Standard errors are in parentheses.

Alternative Estimators Cold List

	Share Treated	Net Donations	Optimal Targeting vs. Everybody	Nobody
	(1)	(2)	(3)	(4)
Logit				
Baseline model	0.047	0.15***	0.96***	-0.01
		(0.04)	(0.10)	(0.03)
Flexible model	0.058	0.11***	0.93***	-0.05*
		(0.03)	(0.10)	(0.03)
Logit-Lasso	0.0003	0.16***	0.97***	-0.002
		(0.02)	(0.10)	(0.001)
Exact policy learning tree				
depth = 1	0.07	0.06***	0.87***	-0.10***
		(0.02)	(0.10)	(0.01)
CART				
depth =2	0.042	0.10***	0.92***	-0.06***
		(0.02)	(0.10)	(0.02)
Cross-validated depth	0.0006	0.16***	0.97***	-0.001**
		(0.02)	(0.10)	(0.0003)
Classification forest	0.001	0.15***	0.97***	-0.005
		(0.02)	(0.10)	(0.003)

Notes: Donation amounts are measured in Euro. Standard errors are in parentheses.

Ethical Concerns

- Statistical discrimination even if we omit critical variable (e.g., gender, migration, etc.)
- Examples: hiring decisions, flight prices, program assignments
- More or less than discrimination than humans?
- Targeting rules also have the potential to reduce discrimination, but it has to be used appropriately
- Current scandals: Cambridge Analytica, Amazons' unethical hiring algorithm