Heterogeneous Treatment Effects and Optimal Targeting Policy Evaluation

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Main Objectives

We introduce an approach to evaluate the profit of any targeting policy using only a single randomized sample and propose a new estimation method called the *treatment effect projection*.

- Our approach allows us to compare arbitrarily many different targeting policies without incurring the cost of an equal number of large-scale field experiments.
- Our approach predicts the total profit of a policy based on the usable observations where the proposed and realized targeting assignments agree. It employs inverse probability weighting to account for the rate at which observations are not usable.

We consider an empirical application with randomized catalog mailing data.

- We provide a comparison of optimal targeting policies constructed from the estimated incremental effect of targeting. The estimation methods combine ideas from causal inference and machine learning literatures.
- We evaluate the predicted profits based on a new estimation method, the *treatment effect projection*.

Framework

We consider the following setup.

- A company interacts with a population of customers that are indexed by i.
- Each customer i receives a treatment, $W_i \in \{0,1\}$.
- $Y_i(0)$ and $Y_i(1)$ are the potential outcomes corresponding to either treatment, and we observe only one potential outcome for each customer.
- We observe a potentially high-dimensional vector of features for each customer, $X_i \in \mathbb{X}$.

We define the (potential) profit contribution depending on the targeting status as

$$\pi_i(W_i) = \begin{cases} mY_i(0) & \text{if } W_i = 0, \\ mY_i(1) - c & \text{if } W_i = 1. \end{cases}$$

where m is the profit margin and c is the cost of the targeting effort. $\pi_i(W_i)$ is the profit that accrues from customer i given targeting status $W_i \in \{0,1\}$.

A targeting policy is defined as $d : \mathbb{X} \to \{0,1\}$. We want to evaluate the expected profit from any d conditional of the customer features $(X_i) = (X_i)_{i=1}^N$.

$$\mathbb{E}[\Pi(d)|X_1,\ldots,X_N] = \sum_{i=1}^{N} \mathbb{E}\left[(1-d(X_i))\cdot\pi_i(0) + d(X_i)\cdot\pi_i(1)|X_i\right]$$

An optimal policy d^* will maximize $E[\Pi(d,(X_i))]$ for each individual customer. The optimal policy will only target a customer if and only if

$$E[\pi_i(1)|X_i] > E[\pi_i(0)|X_i] \Leftrightarrow m\tau(x) > c$$

for $\tau(x) \equiv E[Y_i(1) - Y_i(0)|X_i = x]$, which is the causal effect for customers with identical features $X_i = x$.

We assume unconfoundedness, overlap, and SUTVA to ensure our $\tau(x)$ is properly identified. However, identification is a property of infinite population and we want to evaluate the sampling properties of different estimators. Specifically, we make the distinction of indirect and direct estimation methods.

- **Indirect** methods for $\tau(x)$ are based on the outcome regression function

$$\mu(x,w) = E[Y|X = x, W = w]$$

  and estimate the CATE by $\hat{\tau}(x) = \hat{\mu}(x,1) - \hat{\mu}(x,0)$.
- **Direct** methods are directly trained to predict $\tau(x)$.

Targeting Policy Evaluation

To evaluate any targeting policy d in a randomized sample, we propose an inverse probability-weighted profit estimator

$$\hat{\Pi}(d,(X_i)) = \sum_{i=1}^{N}\left(\frac{1-W_i}{1-e(X_i)}(1-d(X_i))\cdot\pi_i(0) + \frac{W_i}{e(X_i)}d(X_i)\cdot\pi_i(1)\right)$$

where $e(X_i)$ is our propensity score. $\hat{\Pi}(d,(X_i))$ is an unbiased estimator for the expected profits $E[\Pi(d,(X_i))]$.

We also consider the expected profit from targeting the top ϕ percent of customers. For estimation method s, $\mathcal{I}_s(\phi)$ includes the ϕ customers with the largest predicted CATE. The expected profit of method s is larger than that of method s' for targeting the top ϕ if and only if method s is better at sorting customers according to the CATE.

$$\sum_{i\in\mathcal{I}_s(\phi)} \tau(X_i) > \sum_{i\in\mathcal{I}_{s'}(\phi)} \tau(X_i)$$

If method s provides better sorting than method s' for any ϕ, then $\mathbb{E}[\Pi_s(\phi,(X_i))]$ will attain a larger maximum than $\mathbb{E}[\Pi_{s'}(\phi,(X_i))]$ (for interior optimum).

Treatment Effect Projection

Causal KNN Regression

We define the causal KNN regression estimator as

$$\hat{\tau}_K(x) = \frac{1}{K}\sum_{i\in N_K(x,1)} Y_i - \frac{1}{K}\sum_{i\in N_K(x,0)} Y_i$$

where $N_K(x,w)$ are the K nearest neighbors with treatment status w. We do not observe the individual treatment effect so we tune K to the transformed outcome, which is defined as

$$Y_i^* = \frac{W_i - e(X_i)}{e(X_i)(1-e(X_i))}Y_i.$$

Y_i^* is observed for a known propensity score, and under unconfoundedness it is an unbiased estimator of the CATE. We choose K to be the value that minimizes the transformed outcome loss, $E[(Y_i^* - \hat{\tau}_K(X_i))^2|X_i]$.

Treatment effect projection (TEP)

We then project $\hat{\tau}_K(X_i)$ from the causal KNN regression onto features X_i. The projection step can be done with any regression method and allows for regularization.

Empirical Application

In our application, we estimate heterogeneous treatment effects and evaluate optimal targeting policies using catalog mailing data.

- We have randomized samples of catalog mailings in 2015 and 2016.
- For both samples, the targeting probability is $\frac{2}{3}$ and there are 472 features.
- There are 293 thousand observations in the 2015 data and 148 thousand observations in the 2016 data.

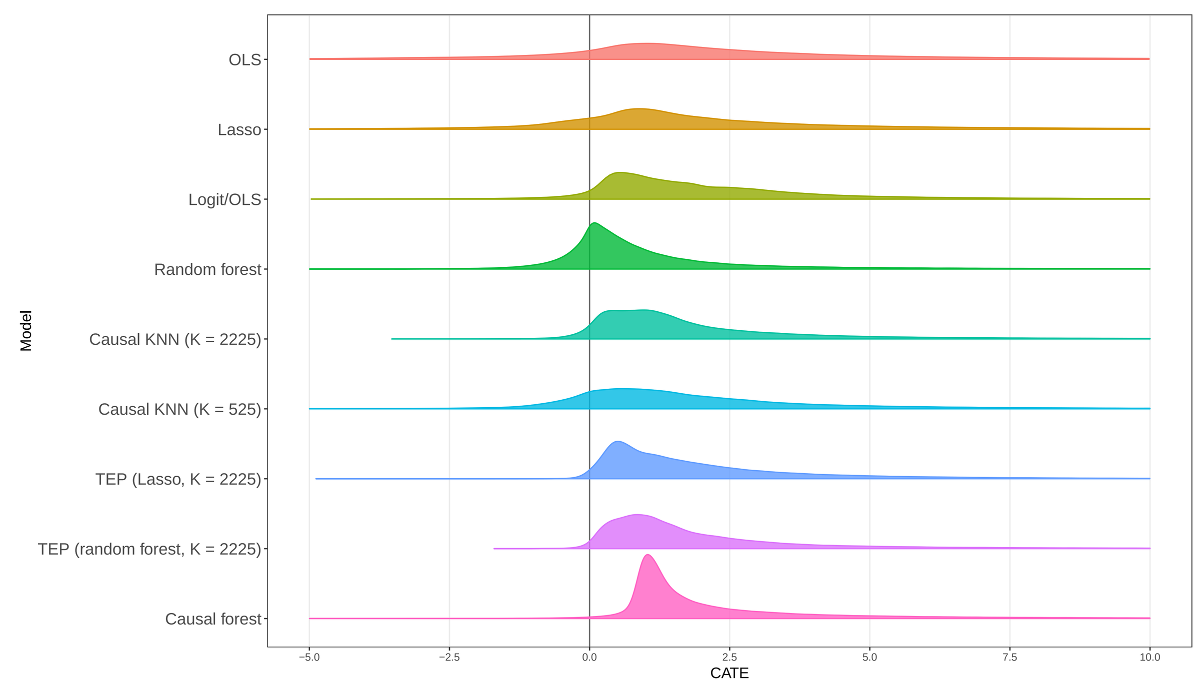

Figure 1: Predicted CATE (2015)

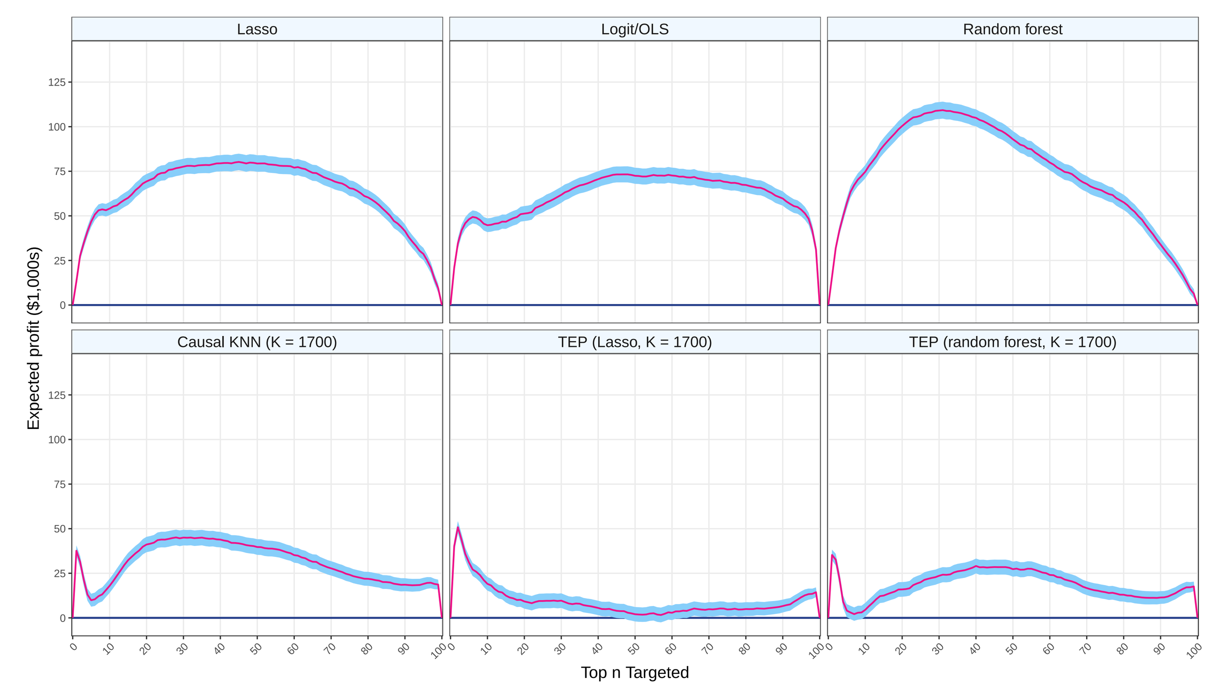

Figure 2: Expected profit: Causal forest vs. other methods

Conclusions

- Our approach allows researchers to evaluate the profits of an arbitrary amount of targeting policies given a single randomized sample.
- Estimation methods trained to directly predict the incremental effect of targeting yield larger profits and superior targeting policies than those of indirect methods that predict the incremental effect through outcome regression.
- In our empirical application, our proposed treatment effect projection estimation method performs as well as the recently introduced causal forest in Wager and Athey (2017).

References

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[2] Stefan Wager and Susan Athey. Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*, 2017.

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