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Causal Machine Learning for Evaluating the Effectiveness of Business Strategies

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Abstract

Firms adopt strategies selectively: those that adopt a new pricing model, a digital channel or a sustainability programme differ systematically from those that do not, so a comparison of adopters with non-adopters confounds the strategy's effect with the characteristics that drove adoption. This paper examines how causal machine learning can recover strategy effects from observational data and, beyond the average, identify which firms benefit most. A simulation harness generates 6,000 firms in which adoption depends on size, prior growth and digital maturity, outcomes depend nonlinearly on the same variables, and the true treatment effect is heterogeneous, averaging 1.69 outcome units. Five estimators are compared: the naive adopter–non-adopter difference, covariate-adjusted regression, double/debiased machine learning (DML), and T- and X-learner meta-algorithms for conditional average treatment effects (CATE). The naive difference overstates the effect almost threefold (4.85), whereas DML (1.74), the X-learner (1.72) and adjusted regression (1.72) recover it closely. The X-learner recovers firm-level effects with a correlation of 0.96 to the truth, and a targeting policy that adopts the strategy only where its estimated effect exceeds its cost achieves 98% of the oracle policy's value, against 67% for uniform adoption. The paper sets out a workflow for strategy evaluation that moves from identification assumptions through estimation to policy learning, and discusses the organisational conditions under which the required assumptions are credible.

Keywords: causal inference; double machine learning; heterogeneous treatment effects; meta-learners; strategy evaluation; policy learning

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Introduction

Strategy research and practice both ask whether a given strategy works. The question is causal: what would the outcome have been had the firm not adopted the strategy? Because firms choose their strategies, observational comparisons answer a different question, namely how adopters differ from non-adopters, and the two answers coincide only when adoption is as good as random. The resource-based view [1] makes the problem acute: firms adopt strategies that fit their resources, and those resources also affect outcomes directly.

Classical remedies include regression adjustment, matching and propensity-score methods [2], [3]. They require that the analyst specify the adjustment correctly, and they deliver an average effect that may hide substantial heterogeneity. Causal machine learning extends these tools in two directions. Double/debiased machine learning (DML) uses flexible learners to estimate the nuisance functions, namely the outcome and adoption models, while retaining valid inference for the effect of interest [4]. Meta-learners and causal forests estimate conditional average treatment effects (CATEs) that vary with firm characteristics [5], [6], which turns evaluation into a basis for targeting: the strategy should be pursued where its estimated effect exceeds its cost [7].

This paper demonstrates the approach in a controlled setting in which the true effects are known. It asks how badly naive comparisons mislead under realistic selection, how accurately DML and meta-learners recover average and heterogeneous effects, and how much value a CATE-based targeting policy captures relative to uniform adoption. It then proposes a workflow for applying these methods to strategy evaluation in practice.

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BACKGROUND

The evaluation problem

Let $W_i \in \{0, 1\}$ indicate adoption, Y_i the outcome and $\mathbf{X}_i$ a vector of pre-adoption characteristics. The individual effect $\tau_i = Y_i(1) - Y_i(0)$ is never observed, since only one potential outcome is realised. Under unconfoundedness, adoption is independent of potential outcomes given $\mathbf{X}$, and the average effect is identified by adjusting for $\mathbf{X}$ [3], [8]. The credibility of unconfoundedness depends on whether the drivers of adoption are observed, which is why the first step of any strategy evaluation is to document how adoption decisions were made.

Double/debiased machine learning

DML [4] estimates the effect in a partially linear model, $Y = \tau W + m(\mathbf{X}) + \varepsilon$, by residualising both Y and W on $\mathbf{X}$ with flexible learners and regressing the residuals on each other. Cross-fitting, in which nuisance functions are estimated on one fold and residuals computed on another, removes the bias that flexible learners would otherwise induce. The resulting estimator is root-N consistent under mild conditions on nuisance estimation quality.

Heterogeneous effects

Meta-learners [5] combine standard supervised learners to estimate CATEs. The T-learner fits separate outcome models for adopters and non-adopters and takes their difference. The X-learner refines this by imputing each unit's counterfactual from the other group's model, fitting models to the imputed effects, and weighting them by the propensity score; it performs well when the groups are unbalanced. Causal forests [6] estimate CATEs directly with honest tree splitting. A CATE estimate supports policy learning: adopt where $\tau(\mathbf{X})$ exceeds cost [7].

METHODOLOGY

Strategy adoption and outcome process

The harness simulates N = 6,000 firms with four pre-adoption characteristics: standardised size, prior growth, market conditions and digital maturity. Adoption follows a logistic propensity that rises with size, prior growth and digital maturity, so that adopters are larger, faster-growing and more digitally mature than non-adopters. The outcome is

$$Y = 3\,size + 2\,growth + 1.5\sin(market) + 0.5\,digital^2 + W \cdot \tau(\mathbf{X}) + \varepsilon,\ \varepsilon \sim \mathrm{N}(0, 1.5^2), \quad (1)$$

$$\tau(\mathbf{X}) = 2.0 + 1.5\,digital - 1.0 \cdot \mathbb{1}[size < -0.5], \quad (2)$$

so that the outcome depends nonlinearly on the characteristics and the strategy's effect is larger for digitally mature firms and smaller for small firms. The true average treatment effect (ATE) is 1.692. Unconfoundedness holds by construction because all drivers of adoption are among the characteristics.

Estimators

Five estimators are compared. The naive estimator is the difference in mean outcomes between adopters and non-adopters. Adjusted regression regresses Y on W and the four characteristics linearly. DML uses gradient boosting for both nuisance functions with five-fold cross-fitting. The T-learner fits gradient-boosting outcome models separately by adoption status. The X-learner follows the procedure of [5] with gradient-boosting models and a gradient-boosting propensity model. All models use scikit-learn [9] with default hyperparameters.

Evaluation

ATE estimators are compared with the true ATE. CATE estimators are evaluated by root-mean-square error against the true $\tau(\mathbf{X})$ and by the correlation between estimated and true effects. Policy value is assessed under an adoption cost of 1.0 unit: the value of a policy is the mean over firms of $(\tau(\mathbf{X}) - 1.0)$ for firms the policy selects, compared across uniform adoption, the X-learner policy that adopts where $\hat{\tau}(\mathbf{X}) > 1.0$, and the oracle policy that adopts where $\tau(\mathbf{X}) > 1.0$.

RESULTS

Average effects

Table 1 reports the ATE estimates. The naive comparison yields 4.848, nearly three times the true value of 1.692, because adopters are larger and faster-growing firms whose outcomes would have been higher regardless. Adjusted regression (1.720), DML (1.738) and the X-learner (1.722) all recover the true effect within 0.05, and the T-learner (1.845) is within 0.16. Linear adjustment performs well here because the confounders enter the outcome mainly linearly; DML's advantage is that it does not rely on that fact, and it would retain its accuracy if the nonlinear terms were larger. Figure 1 (left) displays the estimates.

Table 1: Average treatment effect estimates against the true value (synthetic firms, N = 6,000)

Estimator	*Estimated ATE*	*Deviation from true ATE (1.692)*
Naive difference in means	4.848	+3.156
Covariate-adjusted regression	1.720	+0.028
Double/debiased ML (partially linear)	1.738	+0.046
T-learner (mean CATE)	1.845	+0.153
X-learner (mean CATE)	1.722	+0.030

Heterogeneous effects

The X-learner recovers firm-level effects with an RMSE of 0.419 against a true effect standard deviation of roughly 1.5, and a correlation of 0.964 with the truth (Figure 1, right). The T-learner's RMSE is 0.716; its separate outcome models each have to learn the full nonlinear outcome surface from one group, and the difference of two noisy surfaces is noisier still. The X-learner's imputation step and propensity weighting reduce this noise, which is the mechanism that gives it the advantage in unbalanced samples [5].

Policy value

Table 2 reports the value of three adoption policies under a cost of 1.0. Uniform adoption yields 0.692 per firm, because many firms have effects below cost. The oracle policy, which adopts only where the true effect exceeds cost, yields 1.032. The X-learner policy yields 1.013, which is 98% of the oracle's value and 46% more than uniform adoption. The heterogeneity that the naive analysis ignores, and that the ATE averages away, is therefore where most of the strategy's economic value is created.

Table 2: Mean net value per firm of three adoption policies (adoption cost 1.0)

Policy	*Mean net value per firm*	*Share of oracle value*
Adopt everywhere	0.692	67%
Adopt where X-learner CATE > cost	1.013	98%
Oracle (adopt where true effect > cost)	1.032	100%

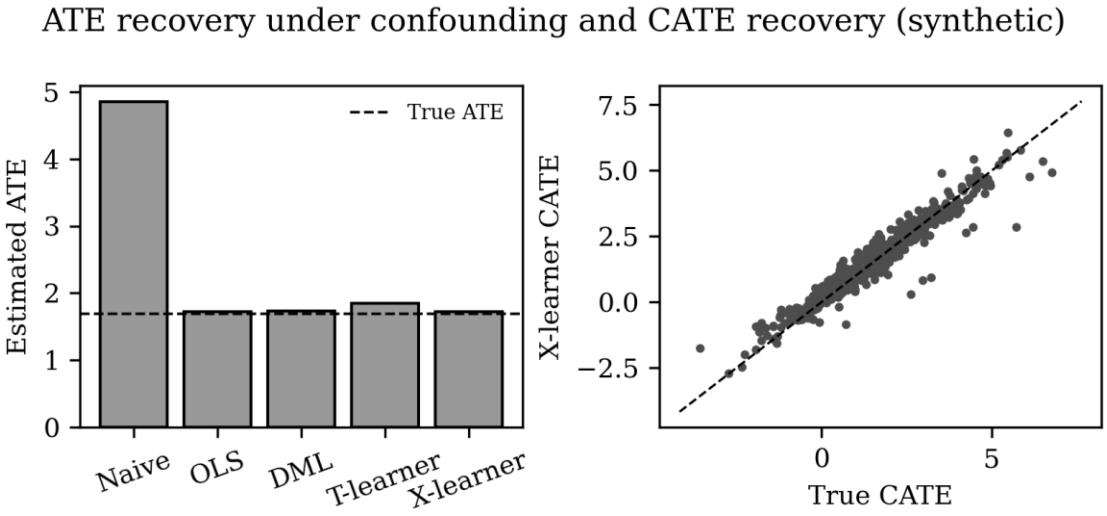


Figure 1: Left: ATE estimates by estimator against the true ATE. Right: X-learner CATE estimates against true firm-level effects for 600 randomly selected firms.

A Workflow for Strategy Evaluation

The results suggest a five-step workflow.

Step 1, identification. Document the adoption process and list the variables that influenced it. If important drivers are unobserved, unconfoundedness fails and the methods below will inherit the naive estimator's bias in attenuated form; instrumental variables, difference-in-differences or staggered-adoption designs should be considered instead.

Step 2, overlap. Check that adopters and non-adopters overlap on the characteristics; estimate

propensity scores and trim regions where one group is absent. Without overlap no method can estimate effects for those firms.

Step 3, average effect. Estimate the ATE with DML, using flexible nuisance learners and cross-fitting, and compare with adjusted regression as a specification check. Large disagreement signals nonlinearity that the regression misses.

Step 4, heterogeneity. Estimate CATEs with an X-learner or causal forest, and validate them out of sample, for instance by checking that firms ranked in the top CATE quartile show larger adjusted effects than those in the bottom quartile.

Step 5, policy. Translate CATEs into an adoption rule that compares estimated effect with cost, estimate the policy's value relative to uniform adoption, and, where possible, confirm with a pilot in which the rule is applied to some units and not others.

Discussion

Unconfoundedness is a strong assumption, and in the simulation it held by construction. Strategies adopted in response to private information, such as a manager's expectation of a demand shift, violate it. Sensitivity analysis, which asks how strong an unobserved confounder would have to be to overturn a conclusion, should accompany every observational evaluation, and natural experiments should be exploited where they exist.

Limitations

The harness satisfies unconfoundedness and overlap by design, uses default learners, and specifies a treatment-effect function that depends on two of the four characteristics in simple forms. Effects are static, whereas real strategies unfold over time and interact with competitors' responses. Confidence intervals for the DML and CATE estimates were not computed. All numbers are simulation outputs and are not estimates of any actual strategy's effectiveness.

Conclusion

In a controlled simulation with realistic selection into strategy adoption, a naive adopter–non-adopter comparison overstated the strategy's effect nearly threefold, while double/debiased machine learning and the X-learner recovered the average effect within three percent and the X-learner recovered firm-level effects with a correlation of 0.96. A targeting policy based on estimated heterogeneous effects captured 98% of the value available to an oracle, compared with 67% for uniform adoption. Causal machine learning thus offers strategy researchers and practitioners a route from biased association to credible estimates of average and heterogeneous effects, and from evaluation to targeting, provided that the identification assumptions are examined with care.

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