Effective Methods for Measuring and Evaluating the Success of Newly Implemented Pricing Strategies

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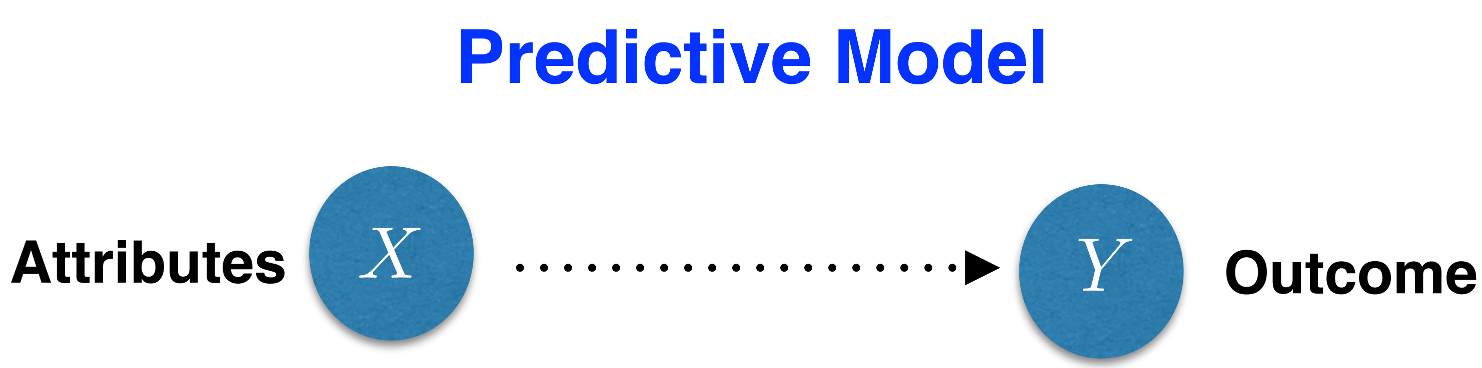
Agenda

- From Predictive to Causal Modeling.
- Causal Modeling with Experimental Data.
- Causal Modeling with Observational Data.
- Example: P&C Economic Price-Optimization.

From Predictive to Causal Modeling

Predictive Modeling has been established as a core strategic capability for many top insurers.

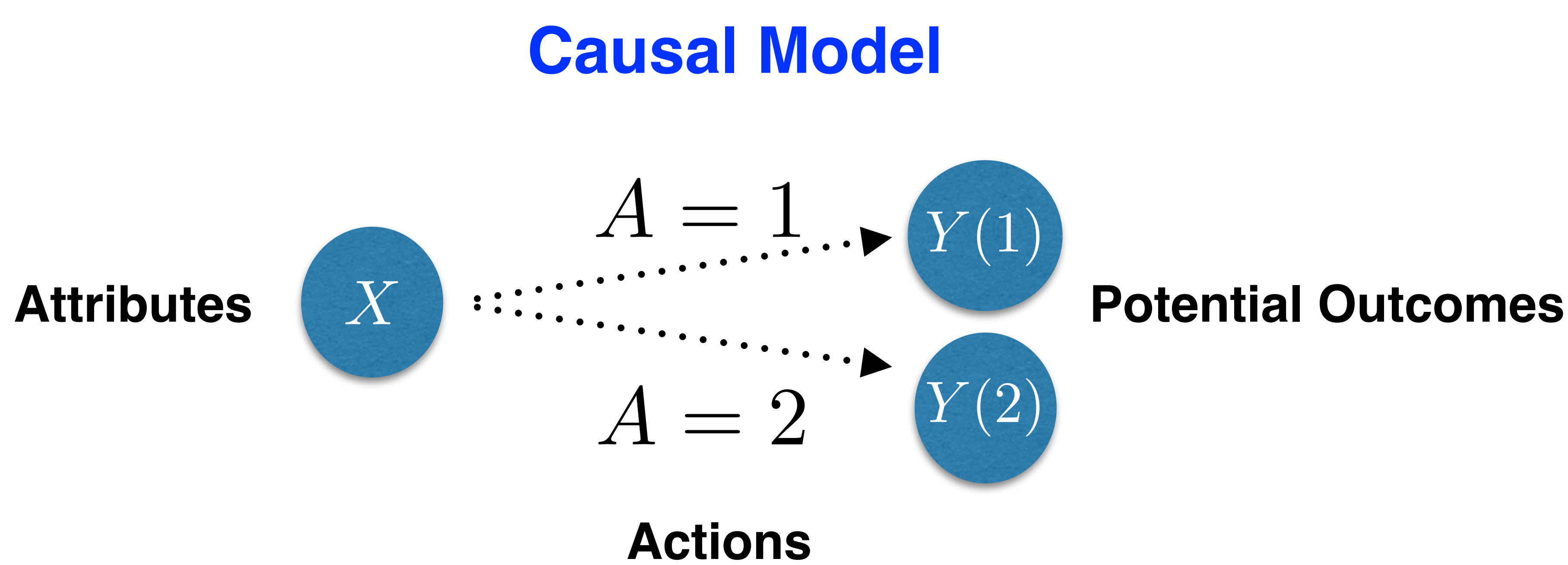
Goal: to predict an outcome variable using a collection of attributes under **"business as usual" conditions**.



From Predictive to Causal Modeling

Causal Modeling goes a step further relative to predictive modeling.

Goal: to predict an outcome under **changing conditions** — e.g., induced by alternative actions or "treatments".



Key Questions Faced by Decision Makers

Question	Estimand
Does the action affect the outcome?	**Average Treatment Effect (ATE)**
Does the action affect the outcome differently for different customer types?	**Subgroup Treatment Effect (STE)**
What is the impact of the action at the individual customer-level?	**Individual Treatment Effect (ITE)**

The **ITE** is an *unobserved* quantity, as a customer can never be observed simultaneously under more than one action — this is known as the **“fundamental problem of causal inference”**.

Causal Modeling with Experimental Data

- **Randomization**: the "gold standard" for scientific research.

  1. Randomly sample subjects from the population.

  2. Randomly assign subjects to treatment and control conditions.

  3. Estimate the ATE:

$$\text{ATE} = E[Y|\text{Action 1}] - E[Y|\text{Action 2}]$$

- As the sample size grows, the client attributes **X** will tend to be "balanced" between treatment and control groups — subjects become **"exchangeable"**.

- Even in an experimental setup, much can go wrong which requires statistical correction (Rubin, 2003).

Example: Price-Elasticity Estimation

- **Objective:** Estimate the impact of alternative rate increases on the portfolio's renewal rate.
- **Rate increase plays the role of the treatment** (e.g., 5% vs. 10%), and the response represents the **renewal outcome** (Y/N).
- Under randomized assignment of policyholders to rate changes, the **ATE (price-elasticity here)** can be computed straightforwardly.

Rate Change	+5%	+10%
N (policies)	10,000	10,000
Retained policies	9,200	8,700
Retention Rate	**92%**	**87%**

→ ATE = 87% - 92% = (5%)

Experimentation: Challenges and Threats

- Most insurance data come from “business as usual” conditions:
    - High costs associated with experimentation.
    - Legal and/or regulatory constraints.
    - Violation to ethical standards.
    - Lack of planning.
- In the absence of randomization, subjects are no longer exchangeable and thus direct comparisons can be misleading (Rosenbaum and Rubin, 1983).
- Assume the following extreme scenario (“**X**” indicates NO available data):

Rate Change	+5%	+10%
Age < 25 yrs	✓	✓
Age >= 25 yrs	✓	X

>= 25 yr old clients exposed to a 5% rate increase do not have a counterfactual under the 10% rate change group.

Regression-based Estimation: What Can Go Wrong?

- Need to adjust any difference in the outcome for differences in the client attributes under alternative treatments.

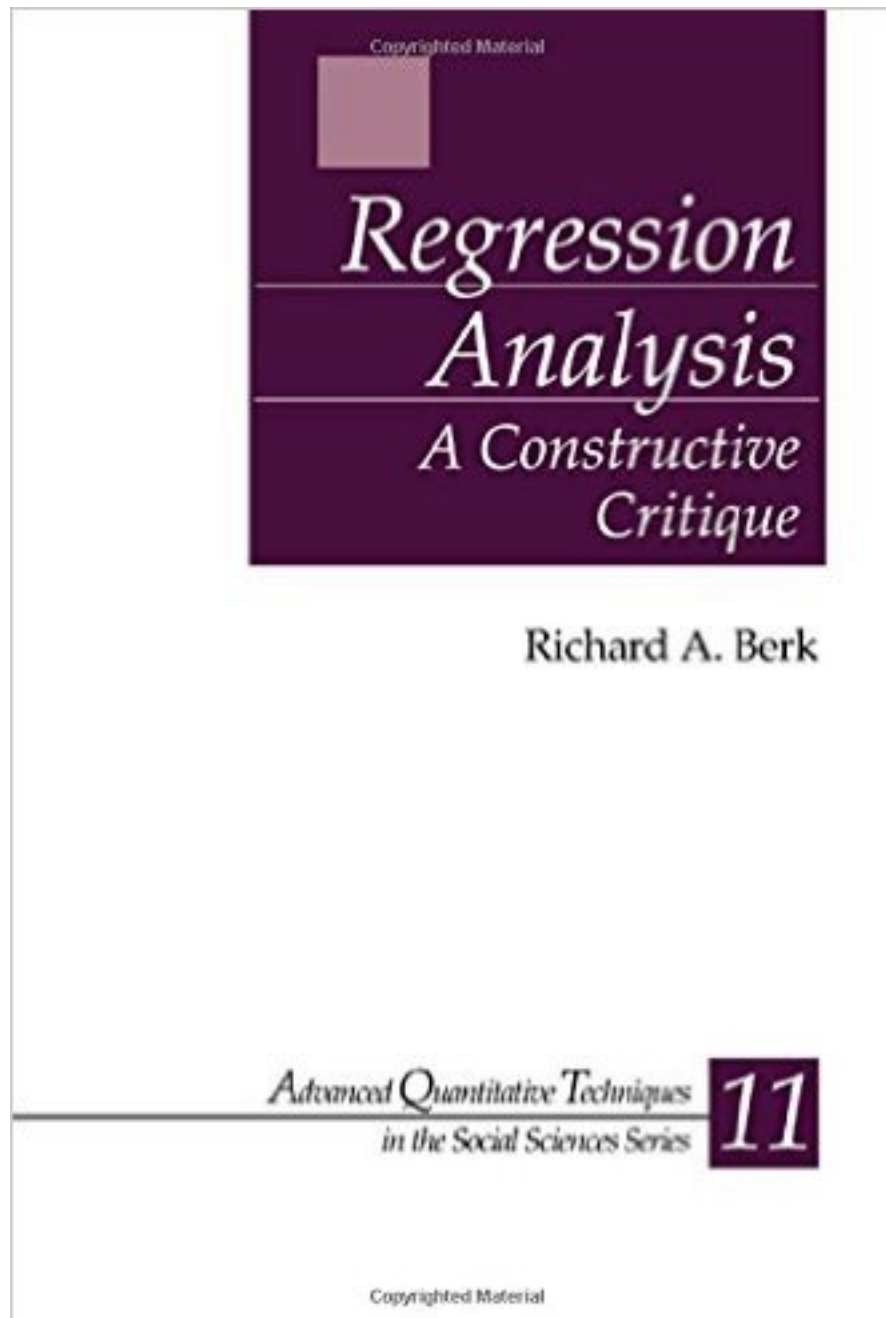
- The **standard regression approach** estimates:

$$Y = \alpha + \tau A + \beta X + \epsilon$$

where the slope τ of the treatment indicator is an estimator of the average treatment effect.

- In the absence of experimental data, **the standard regression approach is unreliable** (Berk, 2004):
    - **Regression-based methods mask non-overlap problems**, and they extrapolate inferences in regions of the predictors where certain treatment haven't been observed.
    - The **problem is worse with a large number of predictors**, as we cannot easily see non-overlap problems.
    - **Standard statistical software can be deceptive:** no warnings about potential non-overlap issues.

More about various strains of regression abuse…



Causal Inference with Observational Data

- An **observational study** attempts to draw inferences about the effect of treatments in the absence of experimental data (a.k.a. observational data).

- Rosenbaum and Rubin (1983) proposed **propensity score matching** as a method to remove the bias in the estimation of treatment effects from observational data.

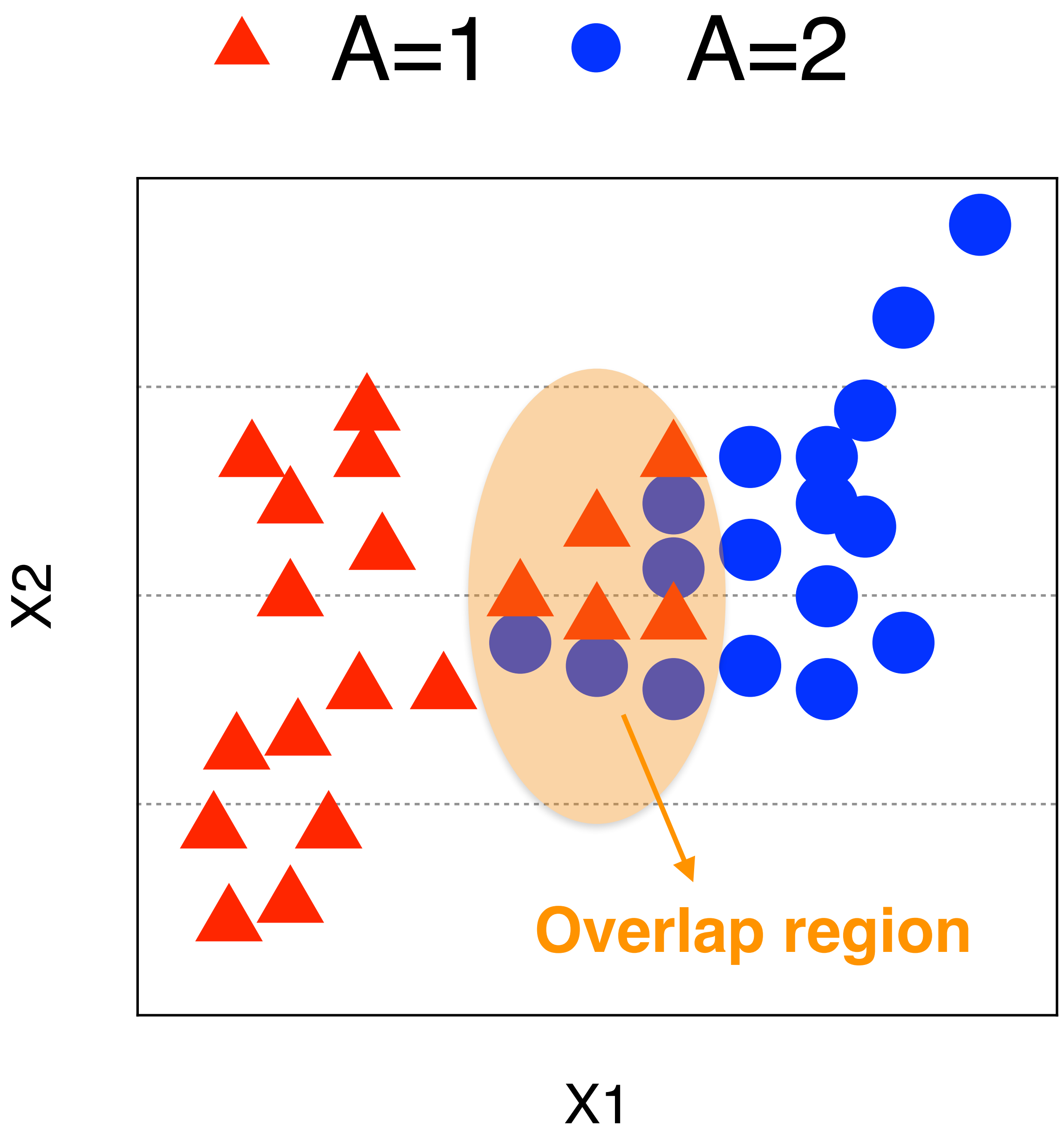
- These methods have become increasingly popular in a wide variety of fields (from economics to medicine).

- **Key concept:** Under certain data conditions, we can approximate a randomized experiment from observational data.

Key Data Conditions: **Common Support**

Common support (a.k.a. overlap) requires that similar customers were exposed to different actions.

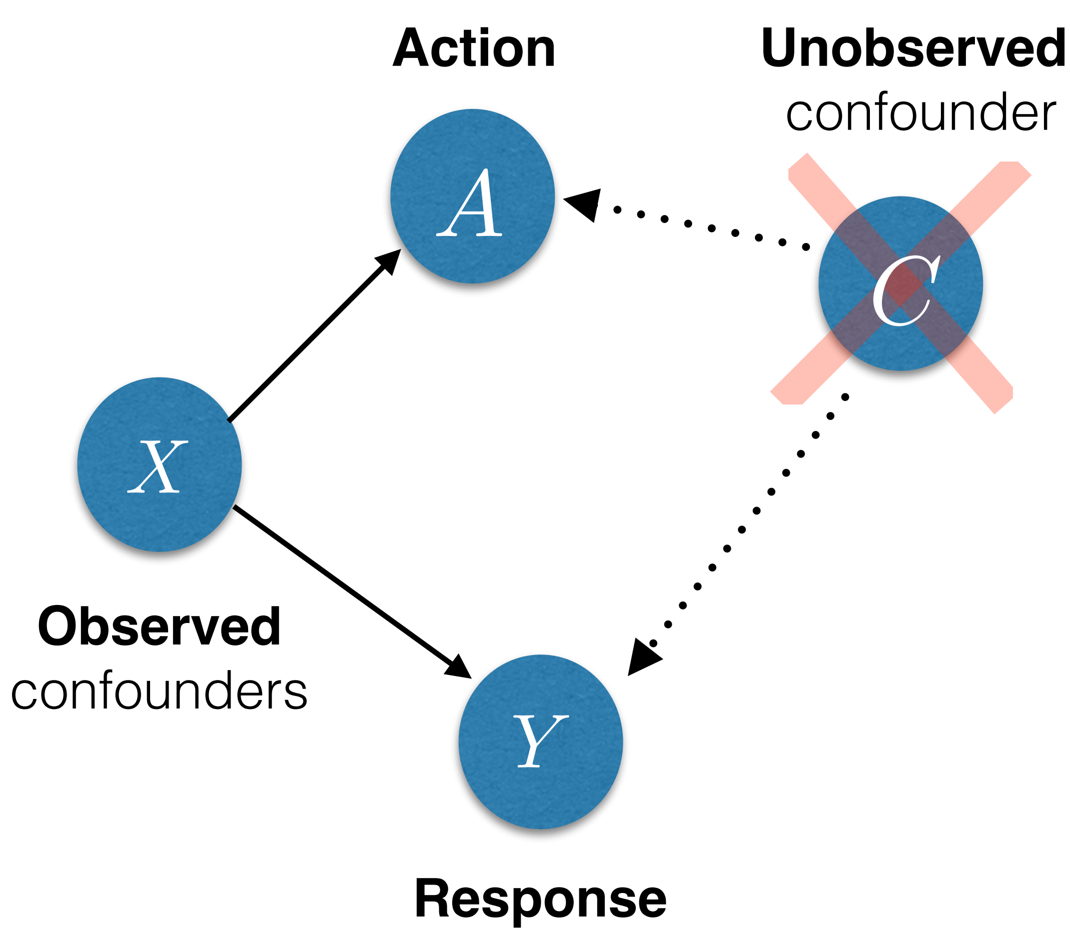
Figure: Distribution of customers colored by action.



- Estimates of treatment effects are only reliable within the overlap region.
- Outside the overlap region, causal effect estimates involves risky extrapolation.

Key Data Conditions: **Unconfoundedness**

Unconfoundedness requires that historic actions were entirely based on the observed attributes **X**.



- Confounders are variables associated with both the treatment and the outcome.
- Unobserved confounders will bias treatment effect estimates (omitted variable bias).
- Unconfoundedness is untestable and irreversible by statistical methods.

Propensity Score

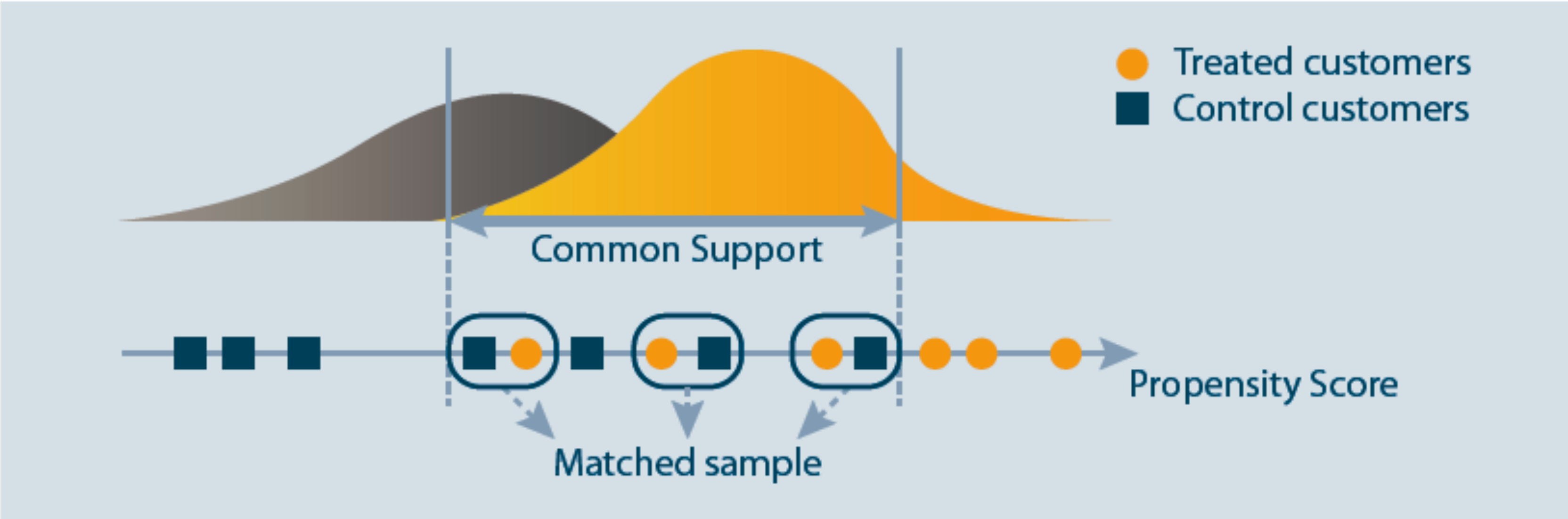
- In randomized experiments, subjects are assign to actions using some sort of **random mechanism**.
- In the absence of randomization (and assuming the key data conditions hold) subjects are assigned to actions on the basis of their attributes **X**.
- To approximate a randomized design from observational data **we need to understand the assignment mechanism**.
- This is answered by the **Propensity Score,** which is defined as the conditional probability of assignment to treatment given the attributes:

$$\pi(X) = \text{Prob}(A = 1|X).$$

Matching on the Propensity Score

- **Goal of matching**: Achieve balance on attributes between subjects exposed to different treatments.

- **The key idea:** Pair subjects that differ in the treatment they received, but have **approximately the same probability** of being assigned to the same treatment — i.e., the same propensity score.



Propensity Score — Balancing Property

What allows us to pair (match) subjects based ONLY on the propensity score?

Balancing Property

If we match subjects on the propensity score, the **distribution of attributes X** will be similar between treatment and control groups in the matched sample.

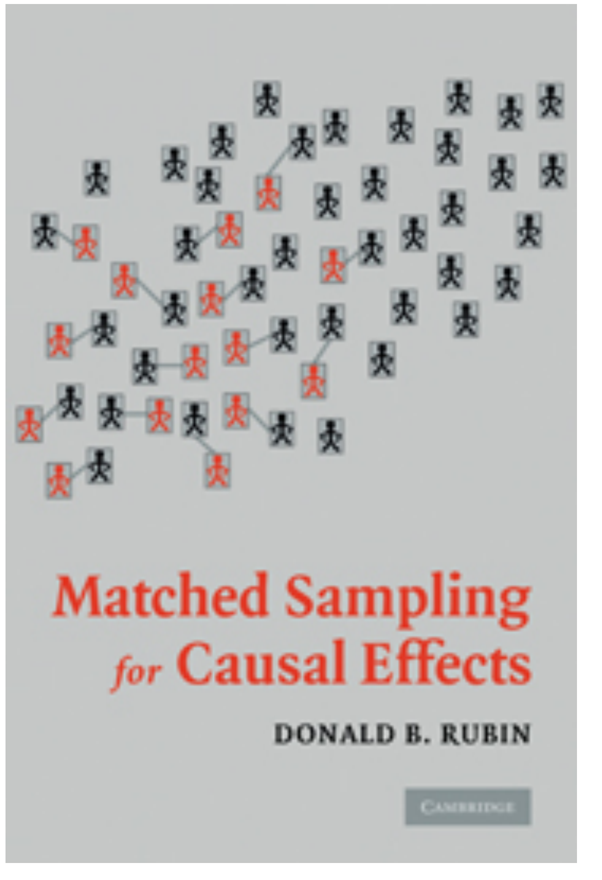
More on Matching…

Matching algorithms have many variants. There are 3 key choices:

1. The **definition of distance** between two subjects in terms of their attributes.

2. The choice of the **algorithm** used to form the matched pairs and make the distance "small" (**greedy vs. optimal matching**).

3. The **structure of the match** — i.e., the number of treated and control subjects that should be included in each match set.



Example

Propensity Score Matching for P&C Economic Price Optimization.

The Problem

1. Estimate the probability of policy renewal for each client under alternative rate changes (price-elasticity).

2. Used the estimates derived in 1 to determine the "optimal" rate change for each client.

Optimal *is defined as the set of rate changes (one for each client) that maximizes the company's profitability function subject to a desired overall (portfolio-level) retention rate.*

Data Challenges

- No access to experimental data from which to estimate the impact of alternative rating actions.
- Clients were historically exposed to rating actions based on:
    - A pricing modeling exercise.
    - Regulatory constraints.
    - Competitive analysis.
    - General business objectives.

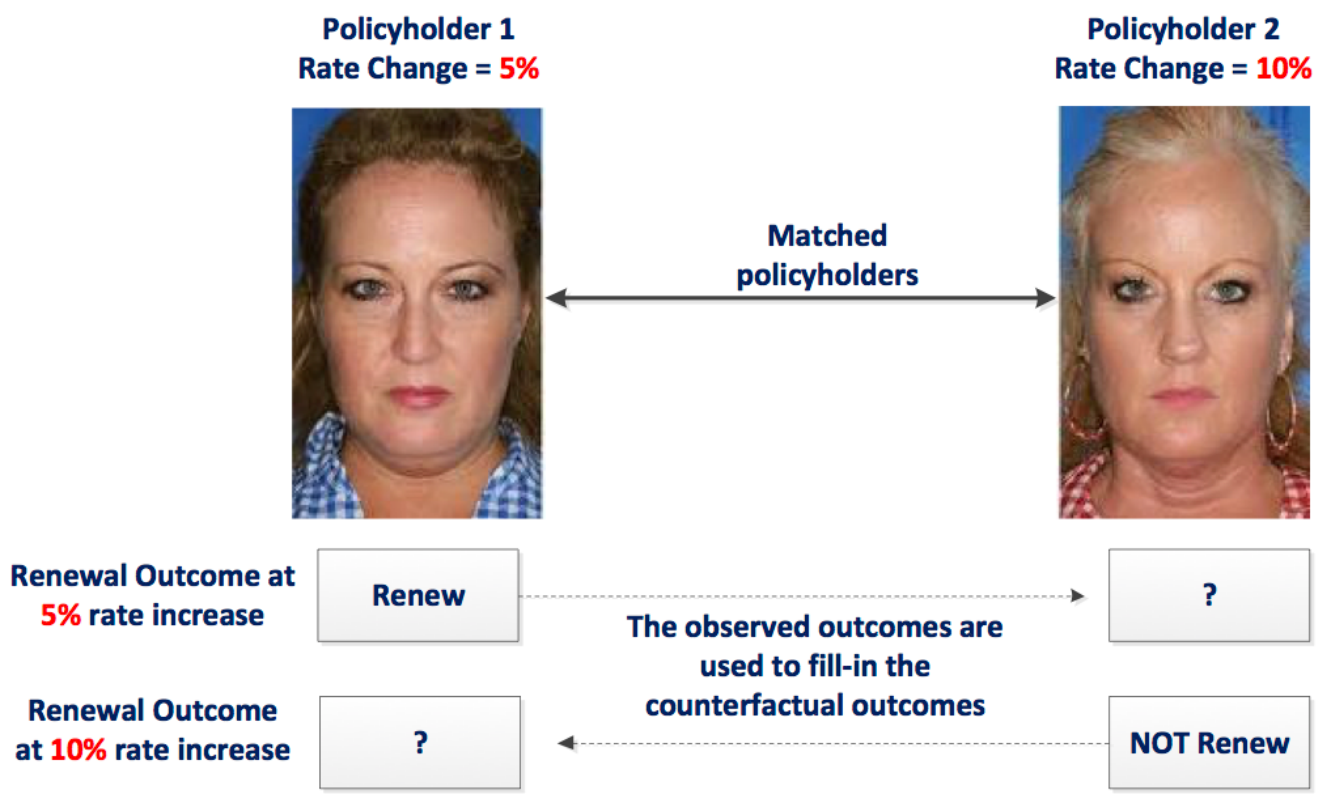
The starting point: Client-by-rate change table

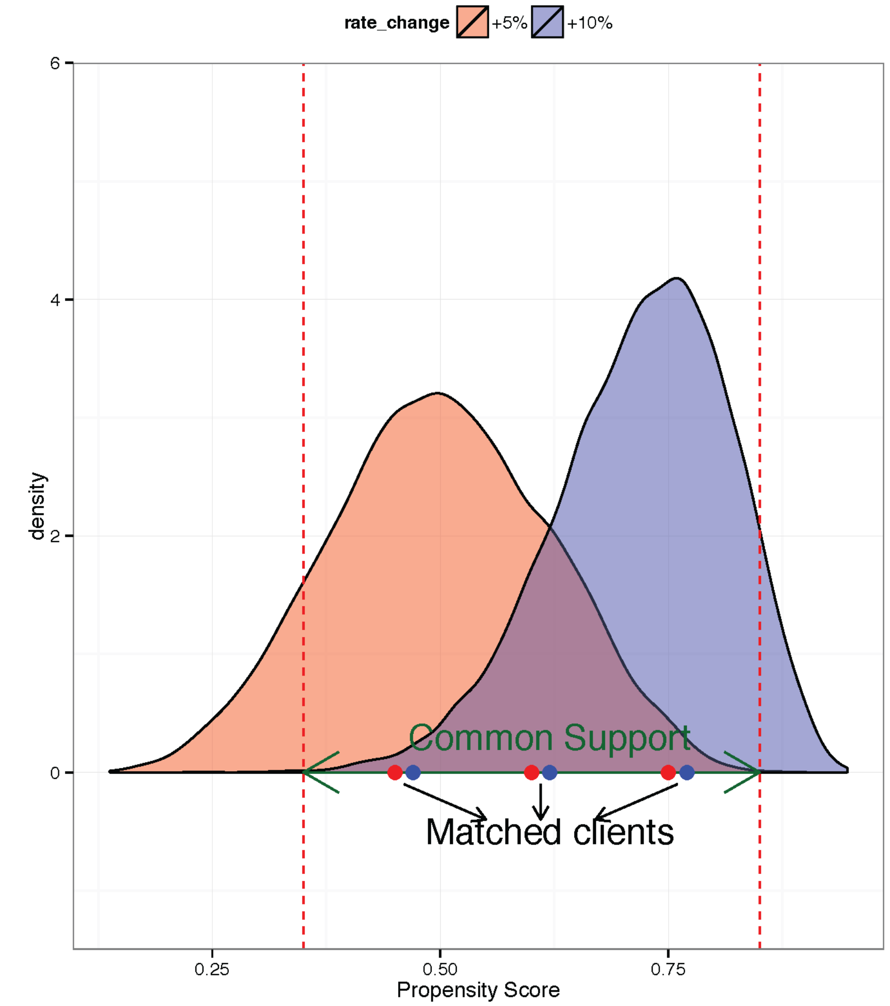
- The entries $r_{\ell a}$ below denote the observed renewal outcome $\in \{0,1\}$ of policyholder $\ell = \{1, \ldots, L\}$ when exposed to rate change level $A = a$.
- To simplify, the rate change is binned into five ordered values $A = \{1 < \ldots < 5\}$.
- Dots indicate counterfactual renewal outcomes, which are unobserved.
- The price elasticity estimation problem is equivalent to the problem of filling in the missing values in the client-by-rate change table with reliable estimates.

Table 1: **Client-by-Rate change table**

	Rate Change Level				
Client	Level 1	Level 2	Level 3	Level 4	Level 5
1	.	r_{12}	.	.	.
2	.	.	r_{23}	.	.
3	r_{31}	.	.	.	.
4	.	.	.	r_{44}	.
5	.	r_{52}	.	.	.
6	.	.	.	.	r_{65}
...	...	...	...	...	...
L	.	.	.	.	r_{L5}

Propensity Score Matching





- “**Clone policyholders**”: similar in terms of the relevant lapse predictors — i.e., about the same age, driving record, live in the same neighbourhood, etc.
- But exposed to different rate change levels.

- **Propensity score**: Probability of assignment to a 10% relative to a 5% rate increase.
- Distribution of propensity score is shown for each rate change group.
- Clients are matched only in the common support (overlap) region.

Filling the client-by-rate change table

Step 1: Replace the actual renewal outcomes with probability estimates: estimate $E[r_{\ell a}|X, A]$.

Client	Rate Change Level				
	Level 1	Level 2	Level 3	Level 4	Level 5
1	.	$\hat{r}_{12}$	.	.	.
2	.	.	$\hat{r}_{23}$	.	.
3	$\hat{r}_{31}$	.	.	.	.
...	...	...	...	...	...
L	.	.	.	.	$\hat{r}_{L5}$

Step 2: Infer the counterfactual renewal outcomes from the matched pairs (as far as the overlap situation permits).

Client	Rate Change Level				
	Level 1	Level 2	Level 3	Level 4	Level 5
1	$\hat{r}_{11}$	$\hat{r}_{12}$	$\hat{r}_{13}$	$\hat{r}_{14}$	$\hat{r}_{15}$
2	$\hat{r}_{21}$	$\hat{r}_{22}$	$\hat{r}_{23}$	$\hat{r}_{24}$	.
3	$\hat{r}_{31}$	.	.	.	.
...	...	...	...	...	...
L	$\hat{r}_{L1}$	$\hat{r}_{L2}$	$\hat{r}_{L3}$	$\hat{r}_{L4}$	$\hat{r}_{L5}$

Step 3: Develop a "global model" of the response: fit the observed + counterfactual renewal estimates on X and A.

Client	Rate Change Level				
	Level 1	Level 2	Level 3	Level 4	Level 5
1	$\hat{\hat{r}}_{11}$	$\hat{\hat{r}}_{12}$	$\hat{\hat{r}}_{13}$	$\hat{\hat{r}}_{14}$	$\hat{\hat{r}}_{15}$
2	$\hat{\hat{r}}_{21}$	$\hat{\hat{r}}_{22}$	$\hat{\hat{r}}_{23}$	$\hat{\hat{r}}_{24}$	$\hat{\hat{r}}_{25}$
3	$\hat{\hat{r}}_{31}$	$\hat{\hat{r}}_{32}$	$\hat{\hat{r}}_{33}$	$\hat{\hat{r}}_{34}$	$\hat{\hat{r}}_{35}$
...	...	...	...	...	...
L	$\hat{\hat{r}}_{L1}$	$\hat{\hat{r}}_{L2}$	$\hat{\hat{r}}_{L3}$	$\hat{\hat{r}}_{L4}$	$\hat{\hat{r}}_{L5}$

Price Optimization

Key Ideas

- Given the estimated renewal probability values, we can efficiently solve the price optimization problem.
- Find the rate change level for each client that maximizes the firm's profit function subject to portfolio-level retention constraints.
- The profit function considers: current premium, expected losses, and predicted renewal probabilities at the client-level.

The Integer Program

Maximize Profit

$$\underset{Z_{\ell a} \forall \ell \forall a}{\text{Max}} \sum_{\forall \ell} \sum_{\forall a} Z_{\ell a} \left[P_\ell (1 + RC_a)(1 - \hat{LR}_{\ell a})(1 - \hat{\hat{r}}_{\ell a}) \right]$$

Subject to retention constrains

$$\sum_{\forall a} Z_{\ell a} = 1 \quad \forall \ell$$

$$Z_{\ell a} \in \{0, 1\}$$

$$\sum_{\forall \ell} \sum_{a} Z_{\ell a} \hat{\hat{r}}_{\ell a} / L \leq \alpha .$$

Check-out our paper for more details…

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A causal inference approach to measure price elasticity in Automobile Insurance

CrossMark

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Key Takeaways

- Causal modeling is a more appropriate framework than predictive modeling when the objective is to assess the impact of alternative actions.
- When possible, planning a randomized experimental controlled design is the best approach to draw conclusions from the effect of alternative actions.
- As most insurance databases are derived from "business as usual conditions", inferences about treatment effects require special modeling considerations.
- Under certain data conditions, propensity score matching can be used to remove the bias in the estimation of treatment effects from observational data.
- At the very least, a visual display showing the common support region between subjects exposed to alternative actions can be useful to illustrate the extent of overlap.