Actionable predictive learning for insurance profit maximization

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Motivation

- **Predictive Modeling** is a core strategic capability of many top insurers (widely applied in marketing, underwriting, pricing, claims management, fraud detection, etc.)

- **Common goal of models**: to predict a response variable using a collection of **observable attributes** (e.g., Age, Yrs. Licensed, Gender, Territory, Claims and Conviction History, etc.)

Tons of literature on the above, but less attention has been paid to:

- In many important settings, the values of certain attributes can be proactively chosen at the discretion of a decision maker – called **actionable attributes or "treatments"**. For instance, we can choose:
  - Which policyholders should be contacted to prevent them from switching to an alternative insurer?
  - Which Auto insurance clients should be offered a Life policy?
  - By how much should we change the rates at policy renewal?

Motivation

- The values chosen for the actionable attributes have important **implications for the ultimate profitability of the insurance company**
- There is no "global" better action $\Rightarrow$ Relevant in the context of **treatment heterogeneity effects**
- The objective is NOT to predict a response variable with high accuracy (as in predictive modeling), but to select the **optimal action** or treatment for each client
- **Optimal personalized treatment** $\Rightarrow$ the one that maximizes the probability of a desirable outcome (e.g., Profits)
- Not addressed by traditional predictive modeling techniques (GLMs, CART, SVM, Neural Nets, etc.).

A toy example: The red/blue envelope problem

- Consider a Client Retention Program aimed to increase the overall retention rate of an insurance portfolio
- Treatment consists in a promotion sent either in a red or blue envelope

Table: Treatment impact on the client's renewal outcome

Client Type	Red envelope	Blue envelope
A	NOT renew	NOT renew
B	Renew	Renew
C	NOT renew	Renew
D	Renew	NOT Renew

- Clients 'A' and 'B' are indifferent to the color of the envelope
- The optimal personalized treatment is to send a Blue envelope to 'C' clients and a Red envelope to 'D' clients

Literature

- Literature is relatively scarce and mostly published recently
- **Personalized Medicine**: (Qian and Murphy, 2011; Zhao et al., 2012; Su et al., 2009)
- **Marketing**: (Jaskowski and Jaroszewicz, 2012; Radcliffe and Surry, 2011; Lo, 2002)
- **Economics**: Imai and Ratkovic (2013)
- **Insurance**: Personalized treatments in the context of Pricing, Client Retention and Cross-Selling

  Guelman, L. and Guillén, M. (2014). "A causal inference approach to measure price elasticity in automobile insurance". *Expert Systems with Applications* 41: 387–396.
  Guelman, L., et al. (2013). "Uplift random forests". Cybernetics & Systems, *forthcoming*.
  Guelman, L., et al. (2013). "Optimal personalized treatment rules for marketing interventions: A review of methods, a new proposal, and an insurance case study." *Submitted*.

The problem of selecting the optimal treatment is non-trivial...

- The **outcome of interest** – i.e., the optimal treatment – **is unknown** on a given training data set
- Each client can only be exposed to one treatment condition $\Rightarrow$ we can only observe the response under the exposed condition.
  The counterfactual response is never observed $\Rightarrow$ the “true” optimal treatment is not observed (Holland, 1986)
- A key distinction for building personalized treatment learning models is between **randomized experiments** and **observational data**.

Let's formalize the problem

- For now assume a controlled randomized experiment – i.e., clients are randomly assigned to two treatments, denoted by $A \in \{0, 1\}$
- Let $Y(a) \in \{0, 1\}$ denote a **binary potential response** of a client if assigned to treatment $A = a, \; a = \{0, 1\}$
- The **observed response** is $Y = AY(1) + (1 - A)Y(0)$
- Clients are characterized by a p-dimensional vector of baseline **predictors** $\mathbf{X} = (X_1, \ldots, X_p)^\top$
- Data consists of L i.i.d. realizations of $(Y, A, \mathbf{X}), \; \{(Y_\ell, A_\ell, \mathbf{X}_\ell), \; \ell = 1, \ldots, L\}$.

Let's formalize the problem

- At the most granular level, the personalized treatment effect is a comparison between $Y(1)$ and $Y(0)$ on the same client. Usually,

$$Y_\ell(1) - Y_\ell(0) \; \forall \; \ell = \{1, \dots, L\}$$

- But as discussed above, this is an unobserved quantity
- In practice, the best we can do is to estimate the personalized treatment effect by conditioning on clients with profile $\mathbf{X} = \mathbf{x}$
- Thus, we define the *personalized treatment effect* (PTE) by

$$\begin{aligned}\tau(\mathbf{x}) &= E[Y_\ell(1) - Y_\ell(0) | \mathbf{X}_\ell = \mathbf{x}] \\ &= E[Y_\ell | \mathbf{X}_\ell = \mathbf{x}, A_\ell = 1] - E[Y_\ell | \mathbf{X}_\ell = \mathbf{x}, A_\ell = 0].\end{aligned}$$

The two-model approach to PTE estimation

1. Estimate $E[Y|\mathbf{X}, A = 1]$ using the treated clients only
2. Estimate $E[Y|\mathbf{X}, A = 0]$ using the control clients only
3. An estimate of the PTE for a client with predictors $\mathbf{X}_\ell = \mathbf{x}$ is

$$\hat{\tau}(\mathbf{x}) = (\hat{Y}_\ell|\mathbf{X} = \mathbf{x}_\ell, A_\ell = 1) - (\hat{Y}_\ell|\mathbf{X} = \mathbf{x}_\ell, A_\ell = 0).$$

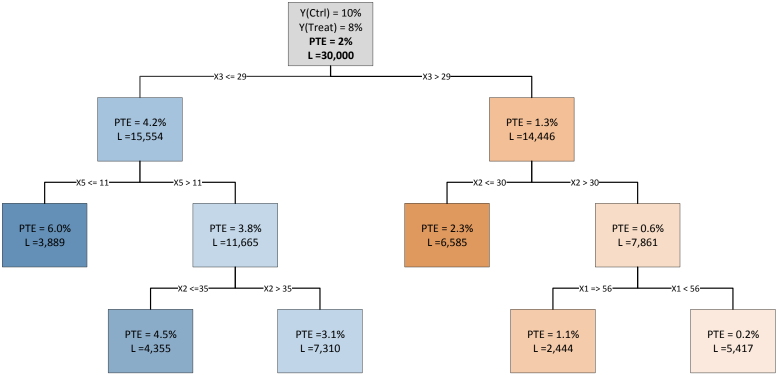
Pros:

- Any conventional statistical or algorithmic binary classification method may serve to fit the models.

Cons:

- Models developed to predict the wrong target!
  - The method emphasize the prediction accuracy on the response, not the accuracy in estimating the **change in the response caused by the treatment**
  - Relevant predictors for Y are usually different from relevant PTE predictors

Causal Conditional Inference Tree



Y(Treat) = Attrition rate on treated clients
Y(Ctrl) = Attrition rate on control clients
PTE = Personalized treatment effect: Y(Ctrl) - Y(Treat)
L = Number of clients

Causal Conditional Inference Tree - Pseudocode

Algorithm 1 Causal conditional inference tree

```
for each terminal node do
    Test the global null hypothesis H_0 of no interaction effect between
    the treatment A and any of the p predictors at a level of significance
    α based on a permutation test (Strasser and Weber, 1999)
    if the null hypothesis H_0 cannot be rejected then
        Stop
    else
        Select the j*th predictor X_{j*} with the strongest interaction effect
        (i.e., the one with the smallest adjusted P value)
        Choose a partition Ω* of the covariate X_{j*} in two disjoint sets
        M ⊂ X_{j*} and X_{j*} \ M based on the G^2(Ω) split criterion
    end if
end for
```

$$G^2(\Omega) = \frac{(L-4)\{\overbrace{(\bar{Y}_{n_L}(1) - \bar{Y}_{n_L}(0))}^{\text{Left Node}} - \overbrace{(\bar{Y}_{n_R}(1) - \bar{Y}_{n_R}(0))}^{\text{Right Node}}\}^2}{\hat{\sigma}^2\{1/L_{n_L}(1) + 1/L_{n_L}(0) + 1/L_{n_R}(1) + 1/L_{n_R}(0)\}}$$

R implementation: The **uplift** package in CRAN

The highlights:

- Implements various functions for training personalized treatment learning models (a.k.a., uplift)
- Currently 5 estimation methods are implemented
  - Causal conditional inference forests (`ccif`)
  - Uplift random forests (`upliftRF`)
  - Modified covariate method (`tian_transf`)
  - Modified outcome method (`rvtu`)
  - Uplift k-nearest neighbor (`upliftKNN`)
- Exploratory Data Analysis (EDA) tools designed for PTE models
- Functions for evaluating performance of PTE models
- Profiling results of PTE models
- PTE Monte Carlo simuations
- Package in continuous development

A cross-sell example: Auto ⇒ Property Insurance

- A randomized experiment with a cross-sell binary "treatment"

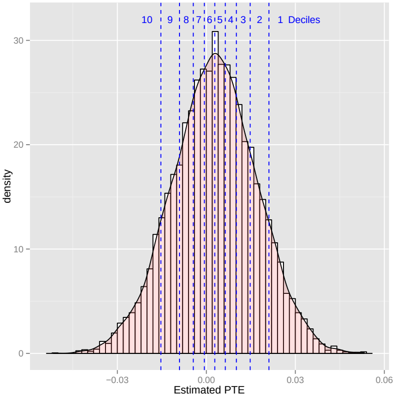
Table: Cross-sell rates by group

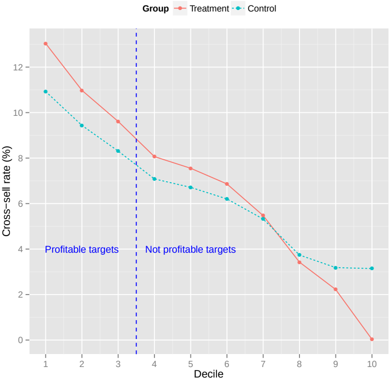
	Treatment	Control
Purchased Home policy = N	30,184	3,322
Purchased Home policy = Y	789	75
Cross-sell rate	2.55%	2.21%

- The average treatment effect is **0.34%** (2.55% - 2.21%), which is not statistically significant (P value $= 0.23$)

- Can we identify a subgroup of clients for which the treatment was effective? If so, target those clients in the future.

A cross-sell example: Auto ⇒ Property





Ratemaking and personalized treatment learning

- Consider the existing portfolio of an insurer where the premium $P_{\ell t}$ charged to policyholder $\ell = \{1, \ldots, L\}$ in year t is given by

$$P_{\ell t} = \hat{LC}_{\ell t} + E_{\ell t} + A_{\ell t}$$

  where

  $\hat{LC}_{\ell t} =$ Expected loss cost
  $E_{\ell t} =$ Expenses
  $A_{\ell t} =$ Profit loading

- **Loss cost** estimation has seen an enormous advance with predictive modeling
- **Profits** have remained obscure and rather forgotten.

Ratemaking and personalized treatment learning

- We can think of A_ℓ as an actionable attribute or "treatment" which can take values on a continuous scale
- The problem is to select the **optimal personalized treatment**: *the one that maximizes the overall profitability of the insurance portfolio* $(\sum_{\ell=1}^{L} P_{\ell t} - \hat{LC}_{\ell t} - E_{\ell t})$
- Assuming $\hat{LC}_\ell$ and E_ℓ are exogenous, **then selecting the optimal** $A_\ell \Rightarrow$ **selecting the optimal** P_ℓ
- The impact of a change in P_ℓ on the overall profitability of the portfolio is a-priori uncertain as a big enough P_ℓ will make a policyholder more likely to switch to an alternative insurer
- This requires understanding the precise impact of a change in P_ℓ on the probability of renewal for each policyholder ℓ – i.e., the **price elasticity**

Price Elasticity as a missing data problem

- *Price elasticity involves a comparison of the potential renewal outcomes for alternative rate changes (the "treatments") defined on the same policyholder*
- Due to the **fundamental problem of personalized treatment learning models** $\Rightarrow$ each policyholder can only be exposed to one rate change value, so only one of the potential renewal outcomes is an observed outcome. *The counterfactual outcomes are never observed*.
- One way to think about the **counterfactual outcomes** is that their values are **"missing"** and therefore they should be multiply inputed to represent their uncertainty.

Price Elasticity as a missing data problem

- To simplify, let's bin the rate change into five ordered values $A = \{1 < \ldots < 5\}$ and assume a 1-year horizon
- 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 $A = a;\ a = \{1 < \ldots < 5\}$
- Dots indicate counterfactual outcomes, which are missing
- The price elasticity estimation problem $\equiv$ the problem of filling in the missing values in the client-by-rate change table with reliable estimates.

Table: **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}

A key additional complexity

- **Reliable estimates of effects attributable to treatments require experimental data** (i.e., coming from randomized experiments)
- This means that for reliable price elasticity estimation, data must come from a randomized assignment of policyholders to rate change levels
- **This condition rarely holds in practice**: rate changes are mostly derived from a pricing modeling exercise $\Rightarrow$ rate change is a deterministic function of the policyholder's observed risk characteristics
- Thus, we end up with **observational data** – i.e., not derived from experimentation
- **Policyholders exposed to different rate change levels are not directly comparable**.

But...what is the problem?

- **The standard approach**: model the policyholder's lapse outcome as a function of the rate change and the policyholder's covariates
- The **key assumption**: the inclusion of those covariates adjust for the exposure correlations between price elasticity and other explanatory variables
- **Problem:** non-overlapping supports of X between policyholders exposed to different rate change levels
- **As an extreme example**: Assume policyholder's Age is associated with the lapse outcome

Age	Rate Change	
	5%	10%
$<$ 25 yrs.	✓	✓
$\geq$ 25 yrs.	✓	NA

  - "✓" indicates whether historical data is available
  - Clients $\geq$ 25 yrs. exposed to a 5% rate change don't have a good comparison in the 10% rate change group

But...what is the problem?

- Regression analysis masks this fact and assumes that the estimated price elasticity model is good for all policyholders (even for those never observed under a specific rate change)
- In real data sets, extreme examples such as the above are rare, but **non-overlap situations are common**
- **Non-overlap** refers to the extent to which the distribution of the key renewal/lapse predictors differ across policyholders historically exposed to different rate change levels
- The problem is even worse with a **large number of predictors**, as groups may differ in a multivariate direction and so non-overlap problems are more difficult to detect

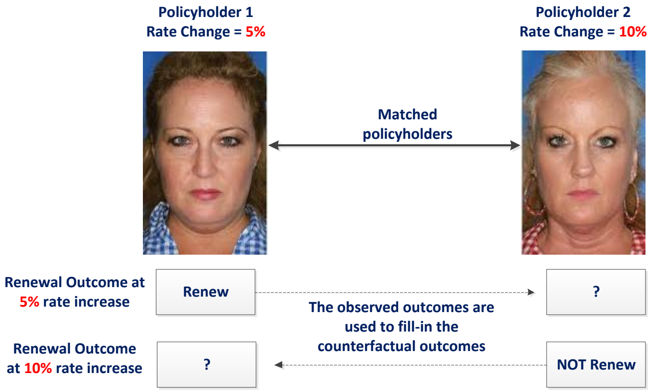
Propensity scores and Matching algorithms

Some good news...

- Under certain data conditions (Rosenbaum and Rubin, 1983):
  - We can construct a randomized-type of experiment from observational data $\Rightarrow$ helpful for determining **price elasticity at the portfolio level**
  - It's possible to infer the "missing" counterfactual renewal outcomes (and thus fill-in the missing values in the client-by-rate change table) $\Rightarrow$ helpful for determining **price elasticity at the individual policyholder level**
- The key concepts are **propensity scores** (Rosenbaum and Rubin, 1983) and **matching algorithms** (Gu and Rosenbaum, 1993)

Matching: conceptual framework

- Let's say in the training data we have 2 policyholders which are very similar in terms of their relevant lapse predictors **X** – i.e., about the same age, driving record, living in the same neighbourhood, etc.
- But, they have been exposed to different rate change levels – e.g., 5% and 10% (enough historical data may allow us to find such pair)



Matching algorithms

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

1. The **definition of distance** between two policyholders in terms of their characteristics
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)

In Guelman and Guillén (2014), we used **optimal pair matching**
$\Rightarrow$ equivalent to finding a flow of minimum cost in a certain network (a standard combinatorial optimization problem)

Propensity scores

- Even with a moderate number of predictors, exact matches on $\mathbf{X}$ are not feasible $\Rightarrow$ propensity scores come into play
- Given a binary treatment $A \in \{0, 1\}$, the **propensity score** is the conditional probability of assignment to treatment 1 given $\mathbf{X}$,

$$\pi(\mathbf{X}_\ell) = P(A_\ell = 1 | \mathbf{X}_\ell)$$

- In a randomized experiment, $\pi(\mathbf{X}_\ell) = 1/2 \ \ \forall \ \mathbf{X}_\ell$
- In an observational study, the propensity score can be estimated (e.g., logistic regression)
- With more than two treatments, we could (i) consider all possible treatment dichotomies or (ii) build a multinomial response model.

Propensity scores - Balancing Property

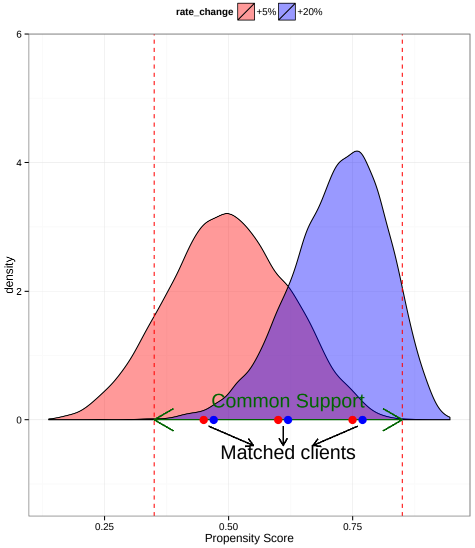
- An important property of the propensity score allows us to **match only on the propensity score**

- The **Balancing Property**: Treatment A and the observed covariates $\mathbf{X}$ are conditionally independent given the propensity score $\pi(\mathbf{X})$,

$$A \perp \mathbf{X} | \pi(\mathbf{X})$$

i.e., conditional on the propensity score $\pi(\mathbf{X})$, the distribution of $\mathbf{X}$ is similar for A=1 and A=0.

Propensity score for 20% vs. 5% rate change dichotomy



Filling the Client-by-Rate change table

1. *Replace the actual renewal outcomes with probability estimates*

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	.	.	.	.	$\hat{r}_{L5}$

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	$\hat{r}_{L1}$	$\hat{r}_{L2}$	$\hat{r}_{L3}$	$\hat{r}_{L4}$	$\hat{r}_{L5}$

Filling the Client-by-Rate change table

3. *Develop a "global model" of the response.*
   - Develop a global model $\hat{\hat{r}}_{\ell t}(\mathbf{x}_\ell)$, obtained by fitting the estimates $\hat{r}_{\ell t}$ of the observed responses, plus the estimates of a subset of the counterfactual responses on the vector of observed characteristics $\mathbf{x}_\ell$ and rate change level $a = \{1 < \ldots < 5\}$
   - This model allows us to predict the renewal outcome for each rate change $A = a$ and value of $\mathbf{X}$.

Table: **Client-by-Rate change table filled with "global" renewal probability estimates**

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	$\hat{\hat{r}}_{L1}$	$\hat{\hat{r}}_{L2}$	$\hat{\hat{r}}_{L3}$	$\hat{\hat{r}}_{L4}$	$\hat{\hat{r}}_{L5}$

Economic price optimization

- The proposed framework to fill-in the counterfactual renewal outcomes with probability estimates allows us to **more efficiently solve the Economic Price Optimization problem**

- **The problem**: which rate change should we expose each policyholder to maximize the overall expected profit of the portfolio subject to a fixed overall retention rate?

- Recall that: An **Optimal personalized treatment** is the one that maximizes the probability of a desirable outcome (treatment $\equiv$ rate change and the outcome $\equiv$ profits)

The optimization problem: An integer program

Maximize an expected profit function

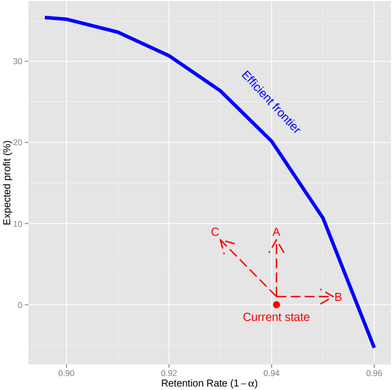
$$\underset{Z_{\ell a} \forall \ell \forall a}{\text{Max}} \sum_{\forall \ell} \sum_{\forall a} Z_{\ell a} \left[P_{\ell}(1 + RC_a)(1 - \hat{LR}_{\ell a})(1 - \hat{\hat{r}}_{\ell a}) \right]$$

subject to a retention constraint

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

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

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



Wrapping up

- We introduced the concept of predictive learning with actionable attributes (in the context of marketing and pricing intervention activities)
- The values chosen for these attributes have important implications for the ultimate profitability of the insurer
- Off-the-shelf predictive modeling algorithms can generally not be used to tackle learning with actionable attributes
- The nature of the data is key: experimental vs. observational (experimental data is more common in marketing than in pricing interventions)
- Discussed methods and tools useful for each data context.

Your turn...