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A survey of personalized treatment models for pricing strategies in insurance

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HIGHLIGHTS

- Models of personalized treatment learning are useful for pricing and marketing.
- A summary of those models is presented for estimating changes in the customer value.
- Insurers can adjust price to reduce short-term benefits.
- Insurers can focus on most profitable customers and do efficient cross-selling.
- The causal conditional inference tree method improves cross-selling rates.

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ABSTRACT

We consider a model for price calculations based on three components: a fair premium; price loadings reflecting general expenses and solvency requirements; and profit. The first two components are typically evaluated on a yearly basis, while the third is viewed from a longer perspective. When considering the value of customers over a period of several years, and examining policy renewals and cross-selling in relation to price adjustments, many insurers may prefer to reduce their short-term benefits so as to focus on their most profitable customers and the long-term value. We show how models of personalized treatment learning can be used to select the policy holders that should be targeted in a company's marketing strategies. An empirical application of the causal conditional inference tree method illustrates how best to implement a personalized cross-sell marketing campaign in this framework.

1. Introduction

Actuarial science in nonlife insurance deals with the problem of pricing by calculating the fair premium each customer should pay for an insurance contract. Nevertheless, the final price offered to the customer is also markedly influenced by the specific conditions prevailing in the insurance market and by each company's commercial strategy over time. Examples of such strategies can be readily consulted in the literature: for example, De Kok (2003) argues that a company offering a new product has marketing instruments that can influence market growth until a specific target market share has been reached for the new product. Additionally, at a given moment in time, a company observing an increase in customer lapses could offer its policies at a reduced rate so as to attract new customers and avoid losing its market share; alternatively, it might offer a multi-product discount to existing customers when buying additional insurance products from the same insurer. Nevertheless, the insurer must be careful when implementing such actions, as they will have a direct impact on the company's level of risk and solvency. In this context, predictive purchasing models can provide some orientation to the company as to which action should be adopted in each situation, but the particular nature of the insurance business has yet to be properly examined and discussed in the marketing literature. A number of recent papers have focused primarily on the reactions of those holding insurance to price changes, but none of them presents a comprehensive framework for addressing the problem of pricing, renewal and cross-selling (Donnelly et al., 2013; Kaishev et al., 2013; Guillén et al., 2011, 2012; Thuring et al., 2012).

Pricing products is an aspect of the activity of an insurance company that, on top of fair premium calculation, seeks to satisfy many fundamental objectives: to avoid the lapses of its profitable customers (retention), to attract new customers away from its

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competitors (market share growth), and to sell more policies to existing customers in the portfolio (cross-selling). The bonus-malus system, which is at the core of a posteriori ratemaking, is sometimes used as part of an overall strategy aimed at retaining good customers, as has been evidenced by Pitrebois et al. (2003), where "good" customers can be defined as being equivalent to profitable customers, i.e. those for whom observed losses over the years are lower than expected.

Customer retention and marketing interventions are generally expensive and if unsuccessful, they may represent a loss for the insurance company. In this sense, the presence of marketing costs in insurance has been noted in the literature (Broeders et al., 2011; Faust et al., 2012). The success of a campaign depends on a number of factors, but perhaps the most important is the way target customers are selected. For instance, it is clear that not all customers will respond in the same way to a specific price increase. Additionally, the expected profit generated by the customer as a result of a policy renewal or a new policy underwriting also needs to be taken into consideration.

Evidence of the losses that accrue when targeting the wrong policy holder for a marketing intervention can also be found in several articles. Thuring et al. (2012) are able to identify policy holders who have up to 64% more claims than a priori expected in a new insurance policy which might have been wrongly offered to them by the insurer. In a similar context, Kaishev et al. (2013) analyze the magnitude of that loss and report that it might be attributable to just a few policy holders in the portfolio. Finally, Guillén et al. (2011) identify policy holders that were negatively impacted by a retention program, i.e., they present a higher probability of canceling their policy after being targeted by a retention program. In all these cases, the insurance company could have avoided the loss suffered if they had correctly selected the customers to be contacted for a marketing action.

Optimal cross-selling involves experience rating or other ways of incorporating historical knowledge of the customer. It also involves a good underlying pricing model. Finally, it involves a good model for the probability of a sale. The *personalized treatment learning* framework discussed in this paper can incorporate all these components simultaneously. However, experimental data are required for that purpose. That is, the assignment of policy holders to the cross-sell marketing action must be performed using a chance procedure. On the contrary, if policy holders are exposed to the action based on some underlying non-random mechanism, the personalized treatment learning formulation is not directly applicable.

In this paper we present a summary of alternative methods formulated in the context of personalized treatment learning and we describe them in the framework of a model that considers the price of a policy as the sum of three components, namely fair premium, loadings and profits, where profits are related to the value of the customer. We show the implementation of causal conditional inference trees in a real insurance dataset to identify policy holders who should be targeted by a cross-sell campaign. This new method identifies the customers who are likely to be more positively influenced by a marketing effort and who will generate positive expected profits for the insurance company. The paper is organized as follows. In Section 2, the model describing the price charged to a policy holder and the value generated by a strategic action are presented. In Section 3, models for personalized treatment learning are described. An empirical application of personalized treatment methods in cross-selling in insurance is presented in Section 4 and Section 5 concludes.

2. Model

We assume that the price $P^*_{\ell t}$ charged to policy holder $\ell = \{1, \ldots, L\}$ for a given contract in year $t = \{1, \ldots, T\}$ is the sum of three components:

1. a fair premium ($LC_{\ell t}$), resulting from an evaluation of the policy holder's risk characteristics, that is, an estimation of expected loss claims;
2. a price loading ($SR_{\ell t}$), capturing solvency requirements, managerial efficiency or caution; and, finally,
3. profits $B_{\ell t}$, reflecting a minimum level of return to the company's shareholders or to the insurance company's owner.

The fair premium is readily calculated via predictive modeling combined with loss models. Price loadings and profits are not so straightforward, because they need to be viewed from a broader perspective. Part of the explanation might lie in the fact that solvency requirements and strategic actions are designed at the macro level, and as such involve the whole portfolio and not just each individual policy. As a result, price loadings have been studied to some extent in the context of regulatory capital, management science and marketing. Unfortunately, contributions in management science and marketing rarely address insurance applications; moreover, they are generally concerned with consumer preferences, that is, with demand as opposed to supply.

A major drawback when addressing the three components of price is the lack of a common time horizon. The fair premium calculation is usually performed on a one-year basis, as are solvency regulations. Yet, managers and shareholders may prefer a longer perspective and request a multi-year evaluation of risk. However, if a period of several years is considered, then policy renewal has to be taken into account as do a number of other questions. Many insurers, in fact, appear to prefer to reduce their profits a little in order to raise renewal rates, since overall company profits may in fact rise higher than the level obtained when customers are lost, especially if good customers (those for whom observed losses over the years are below expectations) opt to move to a rival company.[1] Here, we define renewal $D_{\ell t}$ as a binary variable which equals 1 if policy holder ℓ renews his policy in year t, and 0 otherwise. In the multi-period setting, renewal ($D_{\ell t}$) and price ($P^*_{\ell t}$) are mutually dependent. In fact, it is intuitive that if the price increases many policy holders will abandon the company, but if the price falls then renewal is more likely than lapsing.

The interaction between price and renewal has been studied previously by Guelman and Guillén (2014), the authors concluding that price elasticity is not constant throughout the portfolio. Here, in addition, we argue that dependence between renewals and price adjustments is not stable over time, because the relationship may depend on external factors such as the prices offered by competitors in the insurance market.

The customer value is important when evaluating lapses. Typically, only renewal rates are reported; however it might be preferable to report the "retained value". Instead of looking at lapse rates, managers might consider the value of the customers that have lapsed and compare this to the value of those who have stayed.

We assume that there are L policy holders in a portfolio and that they may hold more than one policy. We indicate each type of insurance product by j, where $j = 1, \ldots, K$ and K is the total number of possible insurance products. The company can control prices, so let us call $A_{\ell jt}$ the price change to be offered to policy holder ℓ in year t for policy j before renewal. We then estimate the expected change in the customer value due to this potential price change.

[1] Note that it has been argued that some optimal pricing techniques may imply that insurance policies are sold below the fair premium prices. This could be critical for the insurance company. Instead, we only consider a reduction of profits as we argue that pricing below actuarial fairness should be penalized by regulators.