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Making Predictive Analytics Our Own

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Over the past few years, many quantitative roles in insurance companies have been filled by data scientists, economists and other near-professions rather than actuaries. In my area of practice, health care, the focus of these roles has been to produce studies that determine whether a recommendation to reduce costs or increase quality, such as a disease management program or an employee wellness program, is effective or not. With health care at 17 percent of the GDP, well-controlled, reliable statistical studies provide critical insights and background information for clinicians and business leaders alike. As an actuary, I regularly review every study I can get my hands on as a starting point for pricing a new product or for evaluating the impact that a change in technology may have on future health care costs. While I find these studies to be a useful starting point, most of them are just too specific, too complicated and too dated to use directly in my work. Instead, I devise something that is simple to apply and easy to explain. Of course, I caveat my work, describe the risks, monitor the results and update as needed.

Each time I go through this process, I ask myself the question "Is there any way to apply the power of predictive analytics in this process?" I have concluded that the answer to this question is yes and that the result will be the next generation of predictive analytics. But what do we need to know or learn to make this happen? Here are some examples.

Monitoring Experience. As actuaries, we routinely monitor experience for almost all our work, especially repeatable tasks like pricing and reserving. The most difficult part of that work is often deciding what to do once the results are tallied: Should we lower the rates? Should we raise the reserves? What happens if we wait for more data? The big fear for every actuary, of course, is that we will take some kind of action based on recent experience, only to find out later that the original projection was correct all along. If the original projection was based on a statistical model, then we can answer the question, "What are the chances I would see these results if my original projection is correct?" The answer to that question can provide valuable guidance in the decision-making process.

If a simple linear regression analysis was used for the original projection, the math is easy. We can use the variance of the residuals to calculate the probabilities. Of course, as the projection gets more complicated, so does the probability calculations.

Pricing Risk. We have all studied risk analysis as part of the exam process. In most cases, the underlying theory is based on the assumption that we have a single distribution that defines the "total risk" and all the risk-related calculations are based on that distribution. In reality, the hardest part of what we do is to determine the total risk. As a health actuary, determining the trend is almost always the key pricing assumption. A health actuary will have a real problem if pricing is based on the assumption that the average health care costs will increase by 5 percent next year only to find out later that they increased by 10 percent. Given this sensitivity to trends, the questions I am asked most often include:

- If we add a 1 percent margin to our best estimate, what are the chances we will lose money anyway?
- If we cut rates by 2 percent in order to be competitive, then how much can we expect to lose?
- How comfortable are you really with your best estimate?
- What are the chances we will lose more than $1 million?

To answer these questions, we really need to think of risk in two components: A pricing risk and a random variation risk. The random variation risk is the risk associated with fluctuations if the overall pricing assumptions were exactly right. If a projection is based on a simple linear regression, then the random variation risk is the risk as calculated using the variance of the residuals. Suppose, for example, that an insurer used a simple linear regression to determine that their best estimate of claims costs was $1,000 per life with a standard deviation of $50. To be conservative, they added a $50 provision for adverse deviation for a total of $1,050. The expected gain is the margin, $50. But, since the margin and the standard deviation are the same, then the probability of a loss is about 16 percent. Is this sufficient to meet the concerns of the insurer or is it too conservative for marketing purposes?

The pricing risk is the risk, or opportunity, that happens if the overall claims are missed either intentionally or not intentionally. In the prior example, suppose the original projection was wrong and the true best estimate is $1,030, then the expected net gain is now only $20, but the probability of losing money has gone up to 35 percent. Is this safe enough? Too conservative? And what is the probability of missing the trend by 3 percent anyway? In this case, the pricing risk for the scenario is $30, the value of the miss. The overall impact of this scenario is $30 x the probability of a $30 miss. If a simple linear regression is used, then that probability can be determined using the variance of the slope estimator. The total pricing risk is the sum of the pricing risk over all scenarios.

Admittedly, the examples above are simple and lead to an obvious question: Why do we need to do this when in all likelihood the chances of a 3 percent understatement are the same as a 3 percent overstatement and it will eventually come down to the best estimate scenario anyway? So, even if the pricing scenarios are symmetrical, which is a big if, the underlying risk may or may not be symmetrical, especially if there is any type of reinsurance or policy limits involved.

Behavioral Economics. Actuaries have been talking about the impact of consumer behavior on experience for some time now. Historically, the emphasis has been mostly on avoiding anti-selection, but more recently there has been more and more discussion on the impact of consumer behavior on insurance products. Life actuaries, for example, are looking at ways to use information about whether or not a prospect goes to the doctor regularly as an underwriting tool. Health actuaries often look at the effectiveness of using financial and other incentives in encouraging consumers to participate in well programs and other efforts to reduce cost or increase quality.

Well-controlled studies are key to measuring the impact of consumer behavior on past experience. The major question is, however, "How can we design a new program or product to get the optimal impact?" This is where behavioral finance comes in. Behavioral economics is a relatively new field that looks at the effects that psychological, social and emotional factors have on how consumers make financial decisions. This concept has been popularized in books like "Nudge" and "Predictably Irrational." One of the major take-aways from this field is that consumers tend to be somewhat irrational and are often influenced by the way alternatives are presented. Understanding this concept more fully can have a major impact on product development, especially if products can be designed in a way that reduces anti-selection.

Currently, most of the quantitative work in this field has been based on theoretical experiments: Is a consumer more likely to trade a sure $100,000 for a 10 percent chance for $1,000,000? If you give someone a free candy bar, will they give it away for free or charge for it? Although these experiments are fun and somewhat useful to an actuary, they do not reflect how consumers will react in a real situation where the health and financial security of their family may be at stake. Since actuaries have access to a considerable amount of data and a keen knowledge of the underlying business context, actuaries are in a unique position to capitalize on this as an area for personal growth and the growth for the profession.

So, can actuaries really make predictive analytics their own? Of course we can. Many actuaries are already using the techniques described above in their work. We can expect these actuaries to begin sharing their work and their findings more and more through the SOA continuing education and research infrastructure. ■

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