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Transform Your Business With Predictive Analytics

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Are you and your peers thinking about predictive analytics and artificial intelligence? You are in good company if you are—as companies, regulators and professional groups—are all paying close attention! For example, we now see "chief analytics officers," an American Academy of Actuaries monograph and the Iowa Insurance Division as a founding partner of the Global Insurance Symposium. Why all the interest? Well, predictive analytics and artificial intelligence are some of the most transformative events in the history of our industry. The revolution has already begun, and predictive analytics and artificial intelligence are reshaping how we do business. Early adopters are poised to achieve major strategic advantages.

Why is predictive analytics important to our industry? The short answer is that predictive analytics can help us (1) improve the dynamics of our business and (2) reduce variability in financial statements. A slightly longer answer is that predictive analytics can enable us to better understand the complex causal relationships that affect the performance of our business. This increased understanding can happen in real time, thereby enabling the exponential strategic advantages that come with real-time influence over the business. In other words, we have the predictive insights in time to act on them. We no longer need to be reactive with our strategy and tactics. Thanks to predictive analytics, we can be proactive!

Before elaborating on this, we insert a word of caution, a quote from the 1970s by the famous statistician George E. P. Box: "All models are wrong, but some are useful." The models used in predictive analytics are no exception. Our aim in this article is to demonstrate the utility of predictive analytics models to our industry and how this utility can be maximized.

We start by showing the value of data with a real-life example. We go back to the 1930s—before the age of computers—so that we can focus on the data itself. One of the major accomplishments of Assistant District Attorney Eunice Hunton Carter was to effectively and efficiently use the data available to her to build a massive prostitution racketeering case against Lucky Luciano, a major organized crime boss. This case was successfully prosecuted, leading to the conviction, imprisonment and deportation of Luciano, the most successful prosecution of organized crime up to that time! Carter was not a data scientist, but she did collect huge amounts of data on prostitution—primarily from people visiting her office—and used the data to clearly demonstrate that organized crime controlled prostitution in New York City and that Luciano was the boss. Data is powerful!

Fast-forward to the 21st century. Most of us have used Amazon to make online purchases. While on the Amazon site, we will be told, "You might also like … ," "Recommended for you … ," or "Customers who bought this item also bought … ." How many times are we amazed that they are recommending exactly the product we need? Clearly, Amazon has effectively mined its data troves and used data science to identify what its customers are likely to need.

Let us look at how our industry compares with those like Amazon that are making effective use of predictive modeling and analytics. For example, I own a life insurance policy from one of the largest life insurers, and automobile and homeowners insurance from one of the largest property and casualty (P&C) writers. My life insurer has never recommended that I buy any product. The closest they have come is to send me a list of all the products they offer and suggest that I spend time discussing my needs with the producer. The P&C insurer (who also sells some life insurance) has done a bit more. Every few years, they recommend that I buy $100,000 of life insurance. But this is hardly personalized! What will it take for our industry to catch up to Amazon?

Now before we go on, we do acknowledge that the health space is using predictive analytics for items such as case finding for medical management programs and the identification of high-cost or high-risk health care patients. Life insurers are also using predictive analytics—at least in certain instances, such as with accelerated (or automated) underwriting and post-level term lapsation and premium setting. However, in other instances, where predictive analytics are used effectively in other industries (e.g., sales & retention), it would appear that many of us are not making as much use of predictive analytics as we could.

Perhaps we draw the conclusion that the experts have looked at it and determined that predictive analytics is unable to help our industry beyond its current uses. Well, when we examine the facts, we see that this is simply not true. For example, suppose

that Company A has poor lapse experience and wants to determine what it can do to improve its persistency. They can call everyone who lapses, find out their issues and try to convince them to reinstate. But, at best, this would be expensive and after the fact. They could call in-force policyholders instead before lapsation happens, but it would be hit or miss on whether they were calling customers at risk; hence, an expensive proposition with dubious results. Worse yet, some policyholders who otherwise would not have lapsed may get the idea from these calls to lapse their policies. Perhaps this partly explains why retention programs are not always given the highest priority by insurers. We are left with the question, "Is there something to do?" Can predictive analytics help Company A improve its retention?

Predictive analytics can supply us with important information that can lead to retention of a policy that otherwise would have lapsed. For example, predictive analytics—without human intervention—has demonstrated that some data, such as the premium payment date (previously thought of by many as important only for administrative purposes), can be significant determinants of lapsation risk. Lower- and middle-income customers who pay their premiums shortly after they receive their paychecks, when they have sufficient funds in their checking accounts, are more likely to keep their policies in force. Those customers whose premium due dates fall a longer time after they receive their paychecks—by which time they may have spent their most recent paycheck—are more likely to lapse. Armed with this knowledge and other discoveries generated by predictive analytics, insurers and producers can know which policyholders to call and when as well as why these customers are at high risk. The machine makes these connections by itself without anyone needing to know them beforehand. Clearly, predictive analytics can be used to improve policyholder retention. As Sir Francis Bacon said in 1597, "Knowledge is power."

Using predictive analytics for retention is particularly powerful, as the model can be extended to related-use cases. For example, once a predictive model is set up to improve retention, it can be further developed to provide more accurate financials with lower variability. Below, we explore how to achieve this by strengthening the assumption-setting process for lapsation.

One big issue in building lapse rate assumptions is the combination of experience from different economic or interest rate environments. For mortality, we routinely combine experience of five years and assume that the year with a particularly harsh winter and a flu epidemic is offset by the year with a particularly mild winter. On the other hand, this is much more difficult for lapses, due to the many different combinations of interest rate environments we can have and the fact that they do not necessarily average out. How do we use predictive analytics to effectively combine lapse experience of periods in close proximity to each other that have different interest rate environments?

One fundamental aspect of predictive analytics is feature engineering. Feature engineering uses domain knowledge of the use case (e.g., the setting of lapse assumptions) to create variables that make the algorithms work. Feature engineering, which can be different for every problem, would tell us to select variables that incorporate the magnitude of interest rates and recent changes in interest rates—and possibly others. Naturally, we would select additional variables that may impact lapsation—based on our knowledge of the business—to include in the model. The model would then identify the appropriate policyholder segments by which to analyze the lapse experience as well as tell us what this experience is for each segment. It goes without saying that we could instruct the model to consider only segments with sufficient credibility.

Based on this, the predictive analytics model would use the selected variables to identify the impact that the interest rate environment (as well as other factors) has on lapses, and the model could effectively identify a base lapse rate vector (or matrix, as the case may be) that is independent of the rate environment. We produce more refined policyholder segments that have been newly identified and are using more data and extended study periods to set credible lapse rate assumptions with lower variability. The lapse assumptions are more accurate than those produced previously, and financial models and results will have lower variability. Clearly, predictive analytics can provide critical support to improve lapse rate assumptions and policyholder retention. Whether this support has strong incremental effects or **exponential** strategic advantages depends on the insurer's implementation. To achieve exponential strategic advantages, the insurer would automate the predictive analytics. The automation would enable expeditious analysis of additional potentially predictive factors that arise from time to time as well as real-time learnings on the impact of behavioral, economic, market and other environmental changes. The insurer can then be proactive—on an ongoing basis—and not reactive in improving policyholder retention and understanding its emerging lapse experience.

Returning to the sales process, let us think about how much valuable information we collect that we do not use. For example, when a policyholder notifies us of a change in address, do we treat it purely as an administrative matter or do we analyze it to see whether the move suggests changed economic or family circumstances and, hence, a need for increased coverage? Do we effectively target our products to customers or prospects who have had life change events? Do we do this in real time? Do we recognize the value in Amazon's "People like you bought …" and its applicability to our industry? Given that many people simply do not buy what a needs analysis says they should buy, perhaps we can start by letting people know how much coverage others in similar circumstances have. This may not solve the entire gap in life insurance coverage, but it is a message that resonates with customers, as Amazon has demonstrated, and it would be a door opener for us to get in and talk to the customers and prospects about their needs. This would be good for business and good for society!

We in the insurance industry have built our businesses by collecting and effectively analyzing huge volumes of data. Let us continue to innovate and use the new tools now available to us. We can effectively revitalize—and, indeed, revolutionize—our businesses using predictive analytics. Exponential strategic advantages are ours for the taking! ■

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