KEEP the Best

How insurers can use predictive analytics to improve profitability.

by Bob Meyer and Wade Bontrager

It is commonly understood that it costs more to acquire a new customer than it does to keep an existing one. Equally important, however, is that certain existing customers may be substantially more profitable than others.

Ideally, insurers should aim to increase retention rates for their most profitable customers and reduce retention of those least profitable. However, when insurers look at profitability at the customer level, they often focus on customers who have had high loss ratios in the past.

When they attempt to segment customers, they use highly summarized approaches without the granularity necessary to drive real-time business decisions.

Few insurers take a comprehensive view of the interactions at play between retention and profitability, and even fewer fully use predictive analytics to proactively improve the quality of their business over time.

Predictive analytics enables insurers to carry out a real-time, granular approach to managing their businesses by helping them, through a scoring process, to understand how groups of customers, and even individual customers, contribute to or erode profitability. Once customers have been scored based on profitability and retention, insurers can execute tailored strategies that enable them to optimize position in the marketplace.

Such strategies could include preferred customer service, flexible payment plans, retention discounts or cross-sales initiatives. Furthermore, quotes developed on potential new business can be scored instantly, thereby maximizing and accelerating the return on the investment made in acquiring the new business.

Limits to Traditional Approaches

A major limitation in traditional approaches to analyzing customer profitability is that they tend to look at data in a univariate manner—that is, one slice of the cake at a time. After the first slice is reviewed and placed back into the cake, another slice of the cake is made, perhaps including a portion of the first slice. These univariate analyses proceed variable by variable, looking for profitability differences in one field of data at a time—for example, examining premium size, then tenure, then geographic area.

In addition to being slow, by the time the slicing and dicing is done, segments under review are so small as to be virtually meaningless. Completing the cake analogy, you end up with a plateful of crumbs.

Univariate analyses can be a blunt instrument for detecting profitability

Key Points

- **The Situation:** Certain existing customers may be substantially more profitable than others.
- **The Problem:** Few insurers take a comprehensive view of the interactions at play between retention and profitability.
- **The Solution:** Predictive analytics can be used to identify which customers contribute to or erode profitability.

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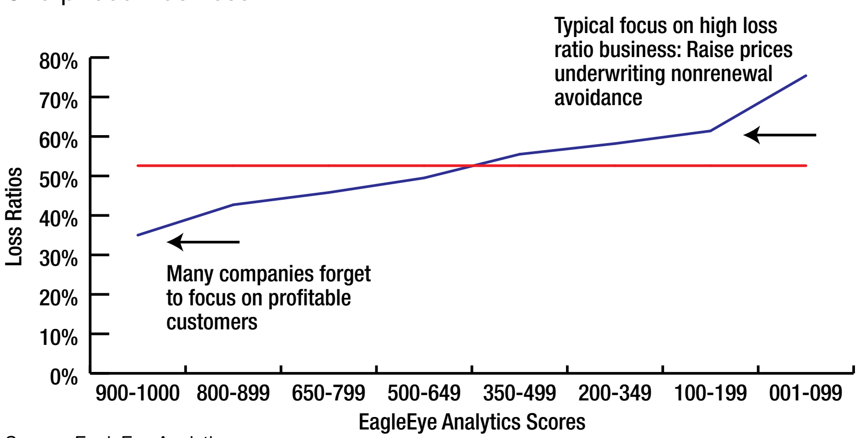
Figure 1

The Power of Analyzing Profitability and Retention Simultaneously

Personal Auto Portfolio: Predictive Analytics Identifies Under- and Overpriced Business



Source: EagleEye Analytics

variance. The factors most predictive of differences in long-term profitability invariably include a simultaneous review of multiple variables and are not discoverable when examining variables individually. Other techniques generate segments of varying profitability described by several variables. The problem with this approach is that these simple descriptions are not granular enough to discriminate between customers in the same segment that have vastly different profit margins. The use of predictive analytics methods, driven by sophisticated machine-learning techniques, enables insurers to quickly and easily build models that predict profitability and retention levels, generating very specific scores for each policy.

Traditional analyses are myopic in other ways, too. For one thing, lines of business are frequently siloed and analyzed separately. Even if data is shared among teams, it may not be analyzed collectively. This is important because profitability in one line may be either directly or indirectly related to profitability in another. In addition, profitability and retention might be analyzed separately—yet analyzing them together is one of the most potent approaches for optimizing profits.

Many insurers also do not incorporate data sources from outside the organization, even though external data can be a rich source of predictive power and a vehicle for impactful actions. Finally, and perhaps most importantly, insurers today are still reacting to trends found in past data—after claims have been reported, reserved for and paid. Predictive analytics focuses on predicting the profit or loss potential of customers before a financial loss or nonrenewal occurs.

Predicting Profitability

Because the very essence of predictive analytics is to make use of the granular aspects of an insurer's data, it is better able to produce more consistently accurate findings more quickly than traditional analytical methods. Instead of telling a machine-learning-based predictive analytics engine which specific variables to focus on when building models, a user will ask the engine to make a specific prediction.

For example, the prediction could be, "Which customers are most profitable over a given period?" The engine then analyzes the data set across all variables to cluster customers based on their consistent profitability performance over time. The results are not based on variables chosen a priori by the analyst, and may even be counterintuitive.

In insurance, putting the same retention effort toward every customer is not a winning strategy.

This is why modern predictive analytics works so well: It detects hidden patterns of correlation that can be used to predict future outcomes, free from the biases of the modeler. The data used in a predictive model can include standard insurer data, but it can also use external information ranging from census data to consumer preferences to weather conditions. These open up vast areas of potential for segmenting customers and predicting which ones will contribute most to the bottom line.

Predictive analytics can use data across business lines to examine correlations among different types of policies. If an analysis uncovers a segment of customers that is more profitable when holding both auto and homeowners policies, strategies can be deployed to encourage that segment to purchase both.

The key strength of predictive analytics is that once customer segments have been identified, the results of the analysis can be used to make predictions about future behavior—not just for those customers, but also for any existing or future customers. Applying the predictors can support the development of precise sales territories, targeted marketing campaigns, effective pricing and retention strategies for the most-profitable customer segments.

That last point is particularly important. In insurance, putting the same retention effort toward every customer is not a winning strategy. Adverse selection affects every book of business and accelerates over time if actions are not taken. By definition, highly profitable customers are always at a higher level of risk for attrition. Not only can predictive analytics identify these customers, but it also can suggest strategies that are likely to improve the odds of retaining them.

Similarly, predictive analytics enables the identification of underperforming customers who have high historical retention rates. The results will likely point to ways to mitigate some of the risks brought on by retaining these accounts, such as re-underwriting, inspections and premium audits. Targeting specific segments with programs designed to address both their profitability and retention profile is a highly effective way to increase profits.

How It Works

To see how predictive analytics can improve profitability, take the example of XYZ Insurance Co. The ability of XYZ to predict accurately which customers will renew their coverages over the long term is important to profitability as a whole. However, what XYZ really wants to know is which customers are most likely to be profitable over the long term and what actions they might take to attract and retain those customers.

The reverse is also true. Profitability can be improved through a plan to shed or limit the renewal of policies on poorly performing segments.

XYZ uses predictive analytics to analyze its customer data, which is appended with demographic and geographic data to increase the richness of the analysis. The company built custom scoring models that predicted both the profitability and the retention of every policy in the portfolio.

The analysis identified a significant

group of customers that is both highly profitable and shows relatively poor retention (see Figure 2).

Increasing renewal rates for this segment of business could significantly improve overall profitability, so a targeted retention program is initiated to that end. Retaining more of the customers within the red box in Figure 2 would improve profitability of this portfolio significantly.

On the other hand, XYZ has identified a segment of customers that has both a high loss ratio and high retention. The company takes action to reduce the number of renewals in this segment. While it is a relatively small segment of the overall portfolio, this is a low-cost step that can have a real impact on profits over the long term. Demographic characteristics of this segment are identified and new business of this type can be purposely avoided, as shown in Figure 3.

By more appropriately analyzing its data, XYZ can now apply a predictive profitability score to customers. Because of this capability, the company can identify adverse trends in one to two quarters instead of one to two years, as would be the case when using traditional backward-looking analytic approaches. XYZ is now in position to reduce its combined ratio significantly and may achieve this by not raising rates at all.

The modeling approach also can be extended to finding new customers that will have attractive profitability and retention characteristics. This requires a two-stage analysis, which starts with an approximate model using generally available data to decide where to prospect and then uses the richer data in the application for a more precise model for quoting and underwriting.

First, the carrier's historical data is used to create a model that uses generally available data to identify neighborhoods likely to contain the highest proportions of the target customers down to the ZIP+4 level. The company can create a targeted sales program in these neighborhoods. Additionally, the carrier could run a sales contest with its agents to draw in more of the targeted prospects.

As the campaign generates new applications with additional data, this information is used to predict the loss ratio and retention rate of the application in real time for underwriting purposes. Applications are processed using exception-based underwriting; high scores are accepted, poor scores rejected and intermediate scores are routed for additional underwriting action.

Taken as a whole, these strategies have the potential to improve XYZ's bottom line significantly. Based on the analysis depicted in Figures 2 and 3, XYZ took the corresponding two actions that enabled the company to improve profitability by $1.5 million on its $125 million auto book.

Identifying Hidden Patterns

Insurers today are used to relying on past performance as an indicator of future results—with all the problems that particular approach entails.

Predictive analytics uses intelligent algorithms and machine-learning technology to identify hidden patterns in the data that are highly predictive of both customer profitability and customer retention.

This methodology enables insurers to identify customer segments that are most likely to be profitable over a given period. And not just current customers, but future customers as well.

This has powerful implications for marketing, pricing, underwriting and service-level management and perhaps most importantly, the ability to take action to retain good customers before they leave, rather than to spend a large multiple to replace them with new business.

Best of all, thanks to advances in computing power and the ability to leverage analytics in the cloud, predictive analytics is within reach of even smaller insurers.

In other words, there's no excuse to stick to the rear-view mirror when attempting to improve insurer profitability. BR

Figure 2

High-profit, low-retention customer segment in red

Loss Ratio	Retention 98.5%	97.7%	96.7%	95.8%	94.5%	91.5%	87.3%	80.8%	Exposure Total
35.0%	3.0%	1.6%	1.8%	0.9%	0.4%	0.1%	0.4%	0.5%	9%
42.7%	3.6%	2.2%	1.8%	0.8%	0.7%	0.3%	0.7%	0.6%	11%
45.8%	2.0%	3.0%	3.5%	2.4%	1.6%	1.1%	1.2%	0.5%	15%
49.5%	0.7%	2.0%	3.6%	3.4%	2.6%	1.9%	1.2%	0.6%	16%
55.5%	0.3%	1.0%	2.6%	3.4%	3.7%	2.7%	1.5%	0.7%	16%
58.2%	0.0%	0.4%	1.5%	2.7%	3.6%	4.2%	2.0%	0.8%	15%
61.4%	0.0%	0.1%	0.5%	1.4%	2.0%	2.9%	2.0%	1.0%	10%
75.4%	0.0%	0.0%	0.1%	0.7%	1.2%	2.7%	1.5%	2.0%	8%
Exposure Total	10%	10%	15%	16%	16%	16%	11%	7%	100%

Source: EagleEye Analytics

Figure 3

Low-profit, high-retention customer segment in red

Loss Ratio	Retention 98.5%	97.7%	96.7%	95.8%	94.5%	91.5%	87.3%	80.8%	Exposure Total
35.0%	3.0%	1.6%	1.8%	0.9%	0.4%	0.1%	0.4%	0.5%	9%
42.7%	3.6%	2.2%	1.8%	0.8%	0.7%	0.3%	0.7%	0.6%	11%
45.8%	2.0%	3.0%	3.5%	2.4%	1.6%	1.1%	1.2%	0.5%	15%
49.5%	0.7%	2.0%	3.6%	3.4%	2.6%	1.9%	1.2%	0.6%	16%
55.5%	0.3%	1.0%	2.6%	3.4%	3.7%	2.7%	1.5%	0.7%	16%
58.2%	0.0%	0.4%	1.5%	2.7%	3.6%	4.2%	2.0%	0.8%	15%
61.4%	0.0%	0.1%	0.5%	1.4%	2.0%	2.9%	2.0%	1.0%	10%
75.4%	0.0%	0.0%	0.1%	0.7%	1.2%	2.7%	1.5%	2.0%	8%
Exposure Total	10%	10%	15%	16%	16%	16%	11%	7%	100%

Source: EagleEye Analytics