Integrated Analytics—The Next Generation in Automated Underwriting

By June Quah and Jinnah Cox

We are experiencing the most rapid evolution our industry has ever seen. Incremental innovation has been underway for the last 10 to 15 years, but currently, the pace of change is truly frenetic. Today, we are competing with not only peer companies, but also start-ups, third-party solution providers and others from outside the life insurance industry, who recognize the potential to disrupt the industry we know so well.

Data is essential to advancing change. When fluids are removed from underwriting, optimizing the use of the remaining available information to manage the additional mortality from misclassified cases while achieving high straight-through processing (STP) rates is key. A data-driven approach using predictive underwriting models is the next phase in our evolution. Enabling high STP rates with objective decision-making to best manage the extra mortality risk from the streamlined process requires analytics to be competitive and ensure accuracy. No longer is pricing fluidless business using MIB, MVR and prescription drug histories enough. Predictive analytics is the new normal and allows more risks not only to be triaged, but also to assist carriers in a more refined stratification of the risks.

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The following case study walks through the steps of a predictive modeling exercise to illustrate one way to use analytics to streamline the underwriting paradigm.

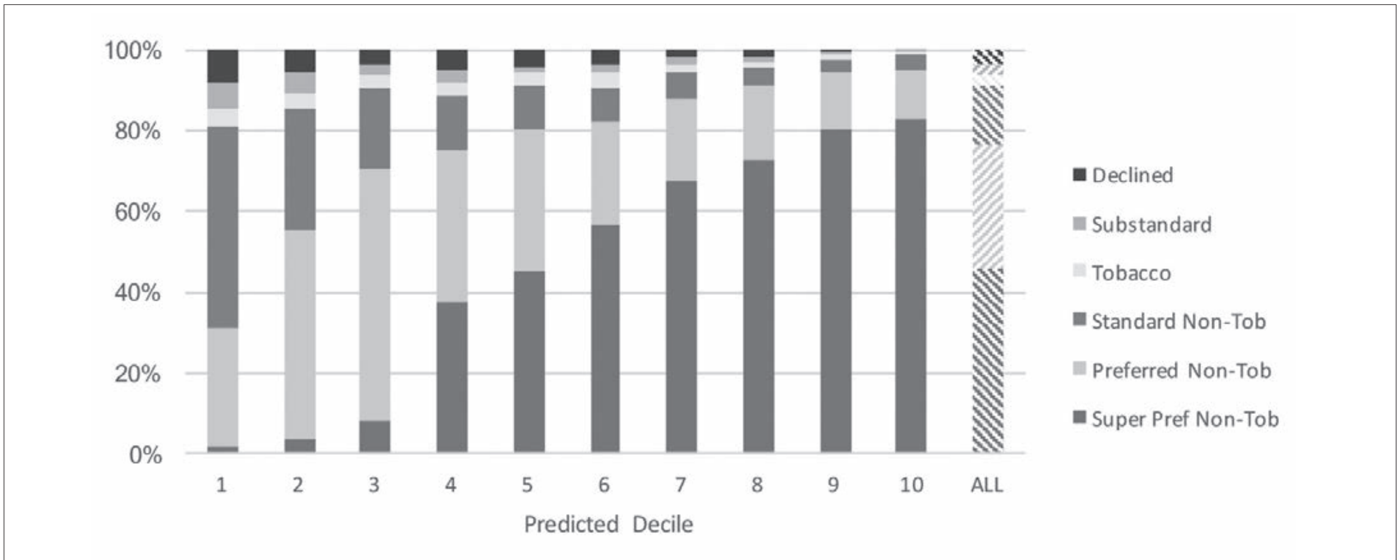
STEP 1: DEFINE THE PROCESS

The key objective for an automated underwriting analytic model is to meet a target straight-through processing rate with a limited impact on mortality. To accomplish this, the model must reliably predict risk class. In this case study, this was accomplished by developing a custom predictive underwriting triage model using historical data. The goal of this model was to accurately assign a subset of cases to an underwriting risk class without requiring medical exams, fluid testing or an attending physician statement (APS), but instead relying on other available data.

STEP 2: SELECT THE DATA

Application data (e.g., age, gender, and self-reported height and weight), tele-interview information, and third-party underwriting data (e.g., MVR, Rx and MIB) were available for each case. The actual final underwriting decision and risk class were also available. For our target issue age and

Figure 1
Distribution of Actual UW Class by Predicted Decile Test Data



face amount range, there were two years of applications with complete underwriting data. The data was able to be directly downloaded from the underwriting system, which saved the company significant time and resources.

STEP 3: DETERMINE PREDICTORS OF MORTALITY

While there were several hundred inputs into the model, about 100 were found to be predictors of underwriting risk class. These ~100 predictors included obvious things—such as gender and age, and not-as-obvious things, such as marital status and reason for weight loss.

While third-party data, such as credit-based mortality scores, is increasingly being used to predict and manage mortality, it has limited value in predicting medically-based underwriting classes. Generally, a starting point is evaluating these commercially-available tools, but also building a predictive model for underwriting triage. Thus, these tools can and should be used in tandem. In our case study, no commercially-available risk classifier was used as a predictor in the model, but rather, the score was used as an initial qualification criteria to help mitigate mortality risk.

STEP 4: BUILD THE MODEL

A multi-class classification model was used with the following categories as the target outcome: Best non-tobacco (NT), Second Best NT, Residual Standard NT, and Refer To Underwriter (UW) (tobacco, substandard, and declines).

The statistical/data mining software R was used to develop the predictive model. The final model is a multinomial logistic model, chosen due to its simplicity, transparency, interpretability and ease of implementation. Alternative models such as the lasso regularized generalized linear regression and gradient boosting were tested with comparable results.

STEP 5: VALIDATE THE MODEL

Using stratified random sampling, 70 percent of the available data was selected to train the predictive models, and the remaining 30 percent was set aside for later use to validate the models. Validating the predictive model on data that was not used to build the model is a crucial step in any analytic project. It gives us confidence that the predictive model will perform well on new cases.

One visual way to determine how well a model is fitting your data is to look at the decile analysis. A decile chart groups the data into 10 equal buckets, ranked according to the probability of a certain outcome. Here, the outcome is the probability of being the best risk, where the likelihood is very low, decile 1, and very high, decile 10. In reviewing a decile chart, you want to see the proportions for the various risk classes exhibiting a "staircase effect," with the best risk class representing the majority of the higher deciles and being insignificant in the lower deciles. The decile chart that follows (Figure 1) on the 30 percent of holdout test data shows that the model can accurately segment underwriting classes, as deciles 7 to 10 have a much higher proportion of Best NT cases.

Thus, our model seems to be meeting our goal to accurately assign risks to underwriting classes.

Figure 2
Model Predicted Probabilities

Case	Target Outcome: Actual UW Class	Best NT	Second Best NT	Resid Std NT	RUW	Class with Max Probability	Predicted UW Class Assignment using confidence thresholds
Case 1	Best NT	94%	5%	1%	0%	Best NT	Best NT
Case 2	Declined	2%	44%	30%	24%	Second Best NT	RUW
Case 3	Second Best NT	8%	73%	14%	5%	Second Best NT	Second Best NT
Case 4	Declined	70%	12%	11%	7%	Best NT	Best NT
Case 5	Residual Std NT	55%	8%	35%	2%	Best NT	Residual Std NT

STEP 6: EXTRACT OUTPUT FROM THE MODEL

The predictive model produces as output the predicted probabilities of each target underwriting class for any given case. Figure 2 illustrates some examples of the model output. For example, Case 1 is predicted to have a 94 percent probability of being Best NT. A simple assignment method would be to assign the class with the highest predicted probability as the predicted class. For Case 1, that is the Best NT class. However, there are cases where the highest predicted probability is not as high, indicating that there is less confidence in assigning a case to that class. For example, Case 2's highest predicted probability is the Second Best NT class at 44 percent, but it also has a 30 percent probability of being Residual Standard NT and a 24 percent probability of being Refer To UW. These probabilities indicate that there is less confidence in assigning a class to Case 2.

As such, confidence threshold rules were incorporated so that when the predicted probabilities fall below specific thresholds, the case is referred to underwriter instead of being assigned a predicted class.

We tested many combinations of threshold rules, varying the predicted probabilities from several classes. By definition, there is a trade-off for the number of accurately predicted versus misclassified cases and the number of cases automated versus referred to underwriter as the threshold varies. The thresholds were calibrated to maximize the number of automated cases, targeting our desired straight-through rate while managing the extra mortality to be in the target range.

STEP 7: COMPARE PREDICTED CLASS OUTCOME TO FULLY-UNDERWRITTEN DECISION

Comparing the predicted risk class to the actual fully-underwritten risk class yields valuable insight. This can either confirm that we are satisfied with the model outcome, or shed light on areas the model is missing. In our case study, this comparison showed that the model accurately predicted ~90 percent of the cases where Best NT was the actual fully-underwritten decision. Again, this confirms that the model is meeting its goal for fitting risk class.

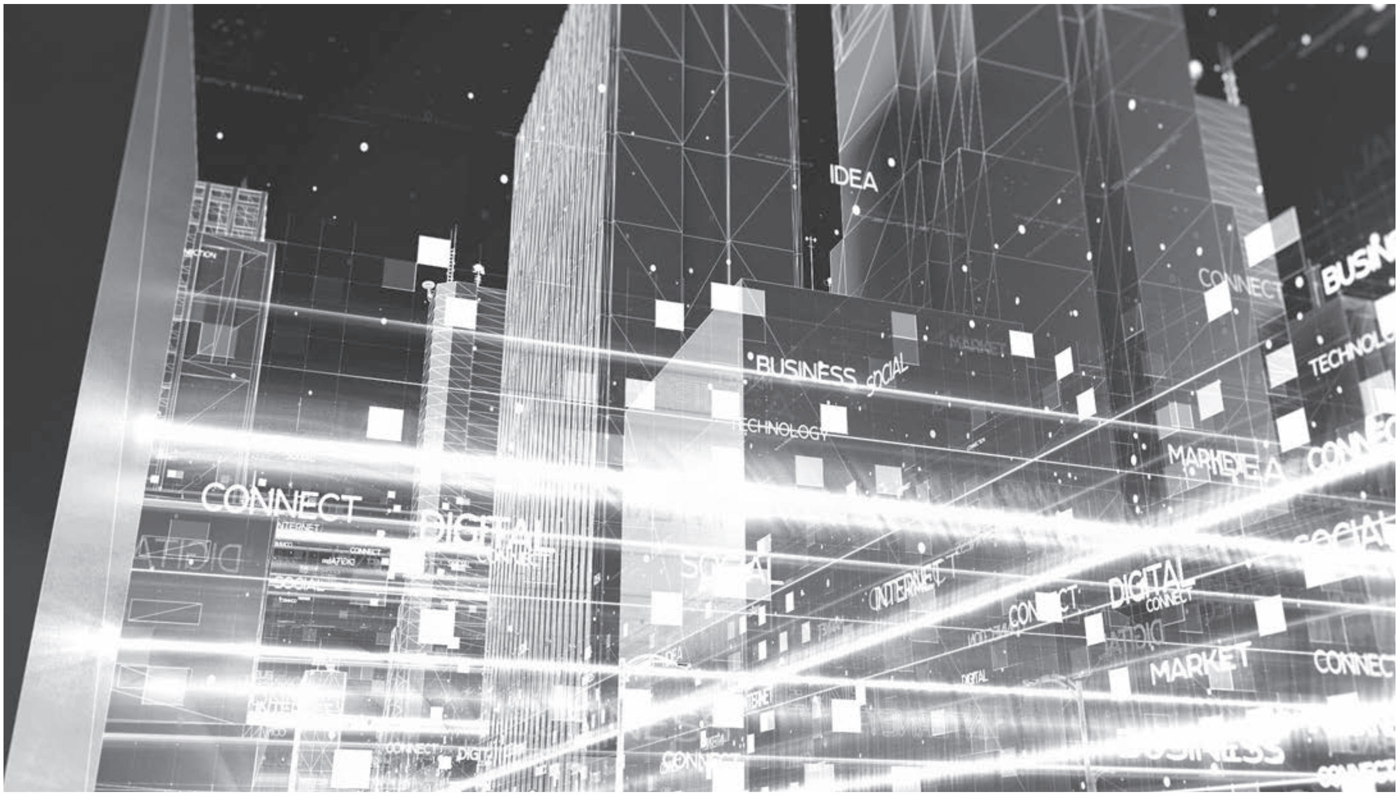
Class misclassification, resulting in additional mortality, occurs when the predictive model assigns a better underwriting class compared to what would have been determined using traditional medical underwriting. The misclassification occurs as the predictive model is developed using a subset of the most predictive underwriting data (~100 predictors) and not the complete underwriting information available for full underwriting.

STEP 8: CONSIDER MORTALITY COSTS AND PROGRAM BENEFITS

While mortality experience is not yet available, we can estimate the extra mortality for automated business by comparing the present value of death benefits for each risk combination between fully underwritten and the risk class predicted by the model.

Without fluid-testing, medical exams and APS, there will be some loss of information from potential misrepresentation of health status and undiagnosed adverse medical conditions. In addition, we expect there will be some increased mortality from the sentinel effect—the self-selection of unhealthy applicants to apply for coverage when testing is not done. This should be considered when setting the mortality expectation for this program.

However, there are also significant expense savings that should also be reflected in your pricing, including the elimination of fluid tests and exams and less time spent underwriting each case. It also enables appropriate underwriting focus and allows underwriters to focus their time on complex cases. There is also the potential to realize higher take-up and cross-sell rates. These expense savings and benefits can in many cases counteract the additional mortality expected from these programs.



STEP 9: INTEGRATE THE MODEL INTO THE UNDERWRITING SYSTEM

A predictive model has limited effectiveness if it cannot be fully integrated into your existing underwriting platform. In this case, the predictive model solution was able to be fully integrated into the underwriting engine. An automated solution was developed to capture the inputs to the models, perform the calculations, and make the predictive assignment available to the underwriter within the platform. A qualifying case that is not referred to underwriter can be issued with a risk class within minutes of full applicant information being received.

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STEP 10: MONITOR RESULTS

The performance of the program should be carefully monitored and reviewed. Post-issue audits, such as ordering APS or medical records on a subset (e.g., 10 percent) of approved streamlined applications, helps to monitor and understand any material applicant misrepresentations and deviation of the model performance from expected.

Best practice for monitoring programs include reports to track and understand the before and after distribution of cases across various attributes and distribution channels. Other items to track include third-party hit rates, placement rates, and straight-through processing rates. This helps to better understand any changes in customer behavior and the impact of those changes on the underwriting decision and resulting mortality experience. For example, comparing self-reported weight data over time may reveal that applicants are understating their weight as they are now aware that not all cases require full underwriting.

Any modification to the underlying underwriting philosophy and rules engine should also be closely examined to ensure alignment with the predictive model. Continued monitoring and feedback will guide the ongoing and future refinements to the predictive model.

CONCLUSION

With start-up activity well underway in Silicon Valley and innovation hubs around the globe, our evolution will likely continue at this rapid pace. Pure data is only part of the equation. Other advances, such as Electronic Health Records, wearable devices, wellness programs, and verbal and facial analytics, are rapidly emerging as new areas that will likely impact streamlined underwriting. Data analytics is, and will continue to be, the key in reaching that elusive balance between the convenience of fluidless underwriting and accurate risk classification. This paper highlighted an Underwriting Triage predictive model, which is only one of several available predictive model types that can deliver value in filling information gaps left by removing underwriting requirements, accurately placing risk and streamlining the process to enhance the customer experience. ■

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