More Accurate Risk Scoring using Predictive Modeling

How Predictive Modeling Trumps Traditional Risk Scorecards to Deliver a Competitive Edge

Abstract

Predictive modeling methods, based on machine learning algorithms that optimize model accuracy, have revolutionized industries from manufacturing to marketing and sales. However, in the financial industry, credit risk scores are still often built using traditional statistical models: Decisions about credit worthiness are made using scorecards that add factors such as savings, age and income to determine a final credit score.

With today's advanced analytics tools, there's no reason for financial organizations to miss out on the benefits of modern predictive modeling algorithms. This paper explains how your organization can use predictive modeling to build better credit risk models and scorecards, without sacrificing the critical benefits of traditional scorecards, and thereby become more competitive in the complex financial services domain.

Introduction

Traditional scorecards for evaluating credit risk

To make decisions about credit worthiness, many financial organizations use traditional scorecards that add factors such as savings, age and income to determine a final credit score. Figure 1 shows a sample credit risk scorecard. The most important columns are the first, second and last ones:

- The first column lists the predictor variables (such as Value of Savings and Amount of Credit).
- The second column shows the specific interval boundaries or categories for categorical predictors. For example, Value of Savings includes the ranges "< 140" and "140–700."
- The last column shows the credit score factor to be used for applicants who fall into the respective interval. For example, the third row shows that if an applicant has a Value of Savings between 140 and 700, a score value of 95 is added to the total credit score. If Amount of Credit is between 6,600 and 10,000, a score of 86 is added, and so on.

Variable	Value/Range	WoE	Estimate	Wald stat.	p value	Scoring	Rounded scoring
Value of Savings	no savings	-27.136	-0.47421	9.14308	-0.78158	69.218	69
Value of Savings	<140	-13.955	0.050230			84.350	84
Value of Savings	140-700	76.214	0.42398	5.15610	0.05802	95.134	95
Value of Savings	700-1400	76.214	0.42398	5.15610	0.05802	95.134	95
Value of Savings	>1400	76.214	0.42398	5.15610	0.05802	95.134	95
Value of Savings	Neutral value	-	-			78.426	78
Amount of Credit	(-inf;6600>	15.197	0.85632	21.20606	0.49185	107.609	108
Amount of Credit	(6600;10000>	-33.108	0.095280			85.650	86
Amount of Credit	(10000;inf)	-72.951	-0.95160	14.94535	-1.43405	55.443	55
Amount of Credit	Neutral value	-	-			100.265	100
Purpose of Credit	other	-35.920	-0.42493	4.41124	-0.82146	70.640	71
Purpose of Credit	new car	77.384	1.27399	12.66513	0.57236	119.660	120
Purpose of Credit	furniture	41.006	0.19345	0.83184	-0.22227	88.482	88
Purpose of Credit	repair	-60.614	-0.96806	6.77839	-1.69683	54.968	55
Purpose of Credit	retraining	-23.052	0.02663	0.00851	-0.53924	83.669	84
Purpose of Credit	used car	-10.286	-0.101080			79.984	80
Purpose of Credit	television	-10.286	-0.101080			79.984	80
Purpose of Credit	household appliances	-10.286	-0.101080			79.984	80
Purpose of Credit	vacation	-10.286	-0.101080			79.984	80
Purpose of Credit	business	-10.286	-0.101080			79.984	80
Purpose of Credit	Neutral value	-	-			84.389	84
Payment of Previous Credits	paid back	73.374	0.88965	23.21711	0.52777	108.570	109
Payment of Previous Credits	hesistant	-123.407	-0.99876	20.11074	-1.43528	54.082	54
Payment of Previous Credits	problematic running ac...	-123.407	-0.99876	20.11074	-1.43528	54.082	54
Payment of Previous Credits	no previous credits	-8.787	0.109110			86.049	86
Payment of Previous Credits	no problems with curren...	-8.787	0.109110			86.049	86
Payment of Previous Credits	Neutral value	-	-			89.630	90
Installment in % of Available Income	> 35	25.131	0.23697	1.06216	-0.21369	89.738	90
Installment in % of Available Income	25-35	15.547	0.28106	1.91049	-0.11748	91.010	91
Installment in % of Available Income	15- 25	6.454	-0.05284	0.06128	-0.47117	81.376	81
Installment in % of Available Income	< 15	-15.730	-0.465190			69.478	69
Installment in % of Available Income	Neutral value	-	-			78.970	79
Balance of Current Account	no running account	-81.810	-0.73755	24.93609	-1.02703	61.619	62

Figure 1. A sample traditional scorecard for computing credit scores

To make decisions about credit worthiness, many financial organizations use traditional scorecards that add factors such as savings, age and income to determine a final credit score.

Typically, a final credit decision is returned with the final credit score. This decision is made by comparing the credit score to specified cutoff values. Each applicant whose score fails to meet the cutoff can be provided with specific reasons for the rejection.

Building a traditional scorecard

The process of building a credit scorecard usually follows three steps:

1. Data preparation and predictor coding
2. Model building using logistic regression
3. Deploying predictive models and using the scorecard to assess credit worthiness

For technical details on how to do this in Dell Statistica, see the Dell Statistica Electronic Statistics Textbook, "Statistical Applications of Credit Scoring."

Benefits of traditional scorecards

Traditional scorecards have several benefits that explain their popularity:

- Final credit scores are the simple sum of individual factors determined by placing applicants into specific categories. It is easy to see what specific factors were most beneficial for a favorable credit decision and which were detrimental and led to rejection of a credit application.
- Because the basic statistical model is linear, it is easy to understand the behavior of the credit risk model. That is, in most cases, you can derive simple summaries, such as "the higher the education of an applicant, the lower the credit default risk."

Predictive modeling approaches

Given that traditional scorecards are easy to build, use and understand, why are some progressive financial institutions using other, perhaps more complex, approaches to credit scoring? The answer is simple: Predictive modeling methods often deliver more accurate predictions of risk than traditional scorecards. With more accurate predictions of risk, more credit can be extended to more applicants, while maintaining or even reducing the overall default rate. Thus, predictive models can increase profits.

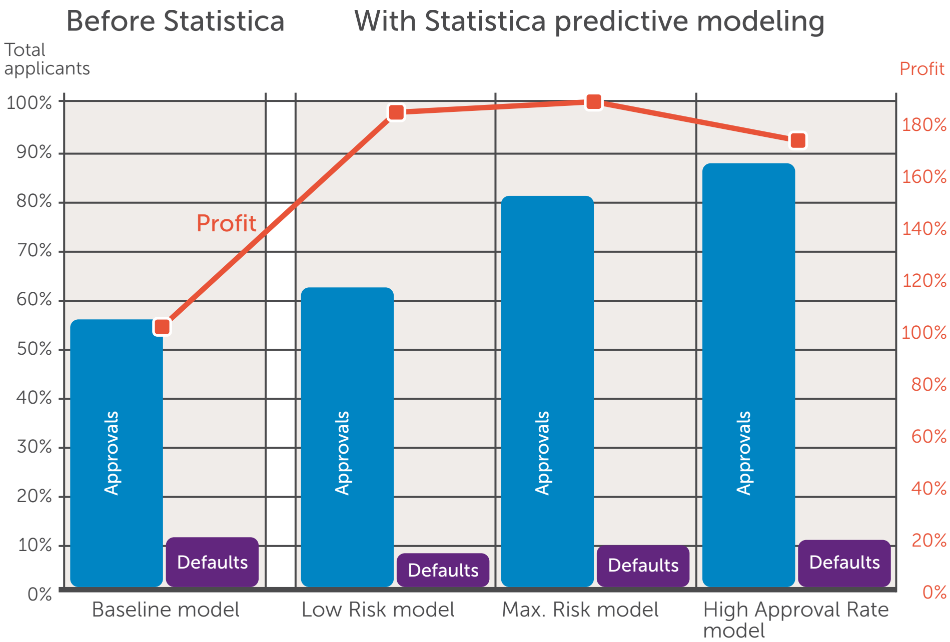

Figure 2. Statistica's predictive modeling delivers significantly more profit than a traditional scorecard.

Case study: How more accurate scorecards increased profitability for a real customer

For example, moving from a traditional model to predictive modeling significantly improved accuracy and increased profits for a large Statistica customer, as illustrated in Figure 2.

This graph, which is based on actual data, shows the enormous impact that a high-quality, accurate model of credit risk can have on the bottom line:

- Using the Baseline model, approving approximately 55 percent of applications for credit resulted in eventual credit defaults of just over 10 percent.
- The right side of the figure shows the results of using a powerful ensemble predictive model built with Statistica and three different cutoff values for credit approval. Using this more accurate predictive model, the customer was able to approve more credit — almost 85 percent of all applicants in the High Approval Rate model — while either decreasing or maintaining the Baseline default rate.

The effect on the profitability is dramatic: over 80 percent greater profit resulted for all cutoff values considered using the predictive models. In short, the more accurately a creditor can predict the risk of credit default, the more selective that creditor can be in extending credit only to those who will pay back the money with all interest as agreed.

For additional Statistica customer success stories, please visit statsoft.com/Resources/Customers/Success-Stories.

Building accurate risk models

Of course, to deliver this value, the predictive model must be accurate. Building accurate risk models requires using algorithms that can find and approximate any systematic relationships between predictor variables and credit default risk, regardless of factors such as whether the relationships are nonlinear or highly interactive (for example, whether different models should be applied to different age groups). Such algorithms are called "general approximators"

Using the more accurate predictive model, one Statistica customer was able to approve more credit — almost 85 percent of all applicants in the High Approval Rate model — while either decreasing or maintaining the Baseline default rate.

Replacing traditional scorecards with advanced predictive modeling tools can yield significant and rapid return on investment.

because they can approximate any relationship, no matter how complex, and leverage those relationships to make more accurate predictions.

Voting models and "boosting"

The algorithms that have proven to be very successful and that are refined in the Statistica platform are those applying voting (averaging) of predictions from different tree models, or by "boosting" those models. Boosting is the process of applying a learning algorithm repeatedly to the poorly predicted observations in a training sample to represent correctly all homogeneous subgroups, including groups of difficult-to-predict applicants and outliers.

The details of effective predictive modeling algorithms may be complex. However, adding advanced analytics to existing scorecards with easy-to-use software that includes data mining recipes and templates will streamline the process and yield a high return on investment (ROI).

The dreaded "black box" and how to open it

A common concern about predictive modeling techniques is that these models are "black boxes" that make it nearly impossible to gain insights into the reasons for specific predictions or the general mechanisms and relationships that drive the key outcomes, such as credit default.

Good solutions are available to address this concern, and all of them are easily implemented with Statistica. Two approaches are:

- What-if (scenario) analysis — For every prediction made through a black-box predictive model, the computer can run comprehensive what-if analyses to evaluate what the credit default probability prediction would have been if different values had been observed for each predictor variable. For example, if an applicant is 18 years old and credit is denied, the computer can quickly evaluate what the credit decision would have been if the applicant had been 20 years old or 30 years old.

  Applying this basic approach systematically to every prediction or group of predictions will provide detailed insights into the inner workings of even the most complex models, and into the specific predictors and their interactions that are responsible for a specific credit decision.
- Two-stage modeling — Another approach is to use the predictions of the most accurate black-box model as a starting point, and drill down into the model to identify the specific interactions and predictor bins that were important in driving the risk prediction (for example, using what-if scenarios or the various standard results around predictor importance available in Statistica). With that knowledge, you can build better and more comprehensive common scorecards that include the relevant predictor interactions, pre-scoring segmentation of homogeneous groups of applicants, specific binning solutions and so on.

Deploying predictive models

Risk models derived via predictive modeling tools are best deployed in an automated scoring solution. Typically, these solutions will manage the entire modeling lifecycle, from model development, model management, to single-click deployment for real-time or batch scoring with version control and audit logs for regulatory compliance.

Conclusion

Replacing traditional scorecards with advanced predictive modeling tools can yield significant and rapid ROI. Statistica includes a variety of powerful algorithms, such as boosted trees, tree-nets (or random forests) and automatic neural network ensembles, that have proven their effectiveness with real-world customers. Moreover, Statistica is easy to use, delivers comprehensive model lifecycle management and integrates easily with business rules and logic. By adopting predicting modeling, your organization can realize the revenue benefits associated with more accurate risk prediction and become more competitive in the complex financial services domain.

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