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Building Successful Scoring Models

By Vincent Bordes

Scorecards are commonly used by DCAs and lenders on top of classic segmentation to enhance cash collections. The adoption of scoring techniques in the collections arena was often slower than in the application or customer management functions, but the use of these models has become standard practice. Used correctly they can provide powerful tools for understanding and predicting debtor behaviour, which in turn allows better strategy setting and increased returns.

With the debt collection environment having changed dramatically recently, many collections teams are taking the opportunity to review or rebuild their analytical tools to more accurately reflect the current climate. With this in mind we take the opportunity to discuss some of the issues and considerations that arise in the development of collections scoring models.

Model Development Issues

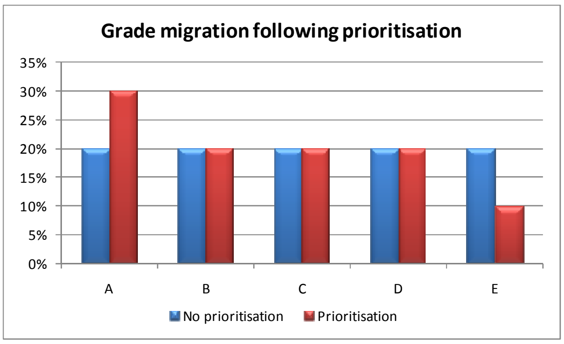
The standard scoring tools developed for use in collections operations usually take the form of propensity-to-pay models. External solutions such as the generic scores provided by the credit bureau are also often of this type. Developed using techniques such as standard logistic regression, the aim is to discriminate between debtors in terms of their likelihood to make a payment.

This modeling approach contains two inherent issues:

1. The quality of a debtor should be assessed by the total amount of debt he or she is able to repay as opposed to the propensity to make a payment
2. This technique assumes no operational impedance, i.e. that all debtors are treated in the same way within the collections process and that collections techniques and strategies are the same across all debtors

These two issues are both fundamental. The first one may result in the model performance being sub-optimal, in that it is not really predicting the outcome that is required for the business. The second will generate bias and incorrect correlations between debtor characteristics and performance, as the operational drivers of observed performance are not being captured. For instance, a debtor with a high value debt may out-perform a debtor with a low value debt simply because they are subject to a more stringent collections strategy.

Let's consider a simple example to illustrate this second issue further. Assume that a consistent collections strategy with no prioritisation is applied to a portfolio of debtors. These debtors are then split into 5 equal sized groups in terms of payment performance, with grade A being those most likely to pay and grade E being the least likely. The blue bars in the figure below reflect the mix of debtors by grade and therefore the overall quality of the portfolio.



Now, assume customers in Grade E are prioritised so that tougher collections techniques are applied to them. Payment performance improves and half of the debtors in grade E make payments. When re-developing the scorecard, the debtor performance distribution will appear to be shown by the red bars in the figure shown here, with far more 'good' performers. However, the migrated debtors are only in grade A because different processes were applied to them. If the new score is developed with no particular care to these accounts, they will no longer receive prioritised treatment and will probably migrate back to Grade E, making the scorecard appear 'faulty' or inaccurate.

Countering the Problems

Euristix have observed a wide variety of approaches used by collections teams to deal with the issues discussed above, ranging from the simplistic to the sophisticated. Some of these are outlined below:

Ignore the problem – As simplistic as it may sound, this is the approach chosen by many modeling teams. Often this is not a conscious decision to ignore an issue, but the model development methodologies applied to the problem may implicitly assume a homogeneity of collection treatments across the development population.

The underlying assumption is that the same strategies are applied to debtors and that it is consistent over time or that debtors are randomly allocated to collection strategies. In many cases this could indeed be true, as a significant number of DCAs and collections operations do not apply different strategies to debtors. However, this leads to a fundamental contradiction in that the main purpose of the scorecard development is to design segment level based strategies that will themselves bias the results of the scorecard in the future!

Retain a random sample – The concept here is a simple one: keep a significant proportion of the debtor base free of prioritisation and tailored collection strategy. Then this base can be used as the model development population to create unbiased statistical models to apply to the entire debtor base. The issue of course is the potential for lost value on the unprioritised debtor group, who are not being subjected to the most optimal and debtor-specific strategies being applied on the remainder of the book.

Model value not propensity – It is possible to take account of the complexity or prioritisation of previously applied collections strategy by including cost information within the models. The idea is to model the true value of the debtor by including not just the cash recovered from the debtors' payments, but also the cost associated with the collections activities undertaken. This is a conceptually very appealing approach, but the difficulty arises from the requirement to have accurate cost information held at a debtor level within the data warehouse.

Champion/challenger – Using champion/challenger methodology to deploy any new collections scheme, whether it be a new scorecard or a revised legal strategy, is a good way to understand the precise impact of any given change. Analysing the different performance between the champion and challenger groups will help avoid any unwelcome surprises and also make it easier to unpick the effects of strategy on performance for future modeling.   This is in many ways a more advanced version of the random sample retention discussed above, with the advantage that all debtors can be moved to the preferred scheme once the impact has been quantified.

Segmenting the debtor database - To optimise the benefit of the collections models within the business, it is key to segment your debtor base prior to the build of any models. Developing a scorecard across all your debtors will undoubtedly be sub-optimal - the scorecard will be completely biased as existing payers will appear to be so good that payment history will dominate the model. Although the scorecard will show a high level of performance from a statistical perspective, it will be no use to the business. Indeed, the main ranking given by the scorecard will be driven by historical payments and it will not be possible to discriminate the debtors which do not yet have behavioural information.

A better approach consists of separating the development sample into sub-segments with similar behaviours. One example partitioning of the debtors could be 'Debtors on payment plans', 'New debtors', 'Existing non-plan debtors with a recent payment' and 'Existing non-plan debtors with no recent payment'. Building multiple scorecards will obviously increase the amount of analytical work, but will provide the best tool to actually derive value from the resulting model result. This approach will help to ensure that proper discrimination is obtained, even between debtors who have had similar payment behaviour historically.

Outcome definition – As for any other scorecard development, the choice of the outcome is critical. Commonly collections teams develop logistic regression models with a binary outcome, simply because these are the most familiar model type. First introduced for underwriting decisions, with a dichotomous 'good/bad' outcome, these models have become ubiquitous in the financial services sector. The binary outcome approach may work in collections, but preliminary analysis should be undertaken to understand the distribution of a value-based outcome, such as the profitability per pound of face value. Only then can a sensible and value-optimising outcome be chosen and the most relevant modelling technique selected, whether it be a regression technique or something else entirely.

Achieving the Best Results

As always there is no magic solution to guarantee optimum results, but it is important to realise that the (re-)development of collection scoring models provides an opportunity to implement the correct techniques and discipline for your business. Each of the tools and techniques described above has their place and the key is to select the right combination of methodologies, segmentation and governance to provide the right tool for a given collection operation. A simple approach might well be the most suitable, but there may also be real benefit from introducing a scorecard segmentation or a different outcome measure. Understanding this and making an informed choice will ensure that the analytical effort will reap actual rewards rather than adding another layer of unnecessary complexity.

If you would like more information about the article above or wish to discuss how Euristix could help you in this area, then please contact Vincent Bordes, vincent.bordes@euristix.com