The CreditRiskMonitor Payment Score

Camilo Gomez, Ph.D.   Sr. V.P. Quantitative Analysis   3/2/2012

The objective of the CreditRiskMonitor Payment Score is to provide subscribers with a predictive score, helping them to identify customers at risk of severe delinquency.

The intent of this model is to:

1. Provide a tool specifically designed for subscribers who contribute Trade A/R information.
2. Optimize the model to work within each subscriber's Trade data, without other inputs.
3. Model at the customer business entity level, separately, without corporate rollup.
4. Define "severely delinquent account" as an account showing, in the 90+ days past due category, an amount equal to or greater than 10% of the *average total balance* of the account.
5. Present the Payment Score on a 1—10 scale (where "1" is most risky) indicating an ordinal ranking of risk (because computing a fixed probability of "severe delinquency" is not feasible).

Using the *average total balance* (over the past 6 months) in the definition above, instead of the *current total balance*, provides a better sense of proportion in our analysis. We find that many accounts that become delinquent do so with a very small fraction of the "original" balance still owing. It is common for these delinquent accounts to show most of the amount still owing as delinquent. While clearly "delinquent," we choose not to label an account as "severely delinquent" for purposes of our model, when the "still owing" amount delinquent is a very small fraction of the "normal" balances over the past 6 months. For example, suppose an account carries total balances due averaging $10,000 for many months, while paying on time. Assume that one invoice for $200 begins to age, first 1-30 past due, then 30-60 past due, and eventually 90+ past due, while the remainder of the balance is paid in full. We would choose not to call this account "severely delinquent," even when it shows 100% of the $200 amount still owing in the 90+ category. In this example, we would say that the $200 still owing is too small fraction of the average balance to label this account "severely delinquent." This is why, for purposes of building a model to predict "severe delinquency," we choose to label only those accounts showing an amount, in the 90+ days past due category, that is 10% or more of the *average total balance* over the past 6 months.

The score is a relative score, an ordinal ranking of risk, where "1" is most risky and "10" is least risky. This means that a "1" is riskier than a "2", a "2" riskier than a "3", and so on, within context of a client's Trade A/R accounts. With the available data, we can't calculate a value for the specific probability of severe delinquency with sufficient certainty. The sample sizes are too small, and an "absolute risk" measure should probably be driven by a model that uses more data than just a single client's Trade A/R payment file.

Data

- The data used to develop the PaymentScore model was from aged trial balance data from 2008 through 2011, contributed to the CreditRiskMonitor Trade A/R database. This is the same data we use to produce Trade Payment reports.
- For each trade provider, accounts that are matched by CRMZ to the same counterparty were aggregated.
- The aggregated aged trial balance was adjusted for any credit balance present.

Data Segmentation

For model development, the data was segmented into two groups: a "Training/Testing" data set and a "Validation" data set. The Training/Testing data set was used to actually build the model. The Validation set, all data not used previously, was to test model performance. (In model development this "out-of-sample" testing is an important step to insure the model delivers generally applicable results.)

Dataset	Sample Size
Training/Testing	1,634,418
Validation	1,279,417

Input variables

The purpose of the CreditRiskMonitor Payment Score is to supply our trade contributors with a tool that mines their receivables portfolio for accounts with such high risk patterns. Keeping the focus on data from each trade provider, the model uses past information on payment patterns, delinquencies, and account specific data.

Our research has shown that the majority of high risk trade accounts exhibit payment patterns indicative of the future likelihood of "severe delinquency".
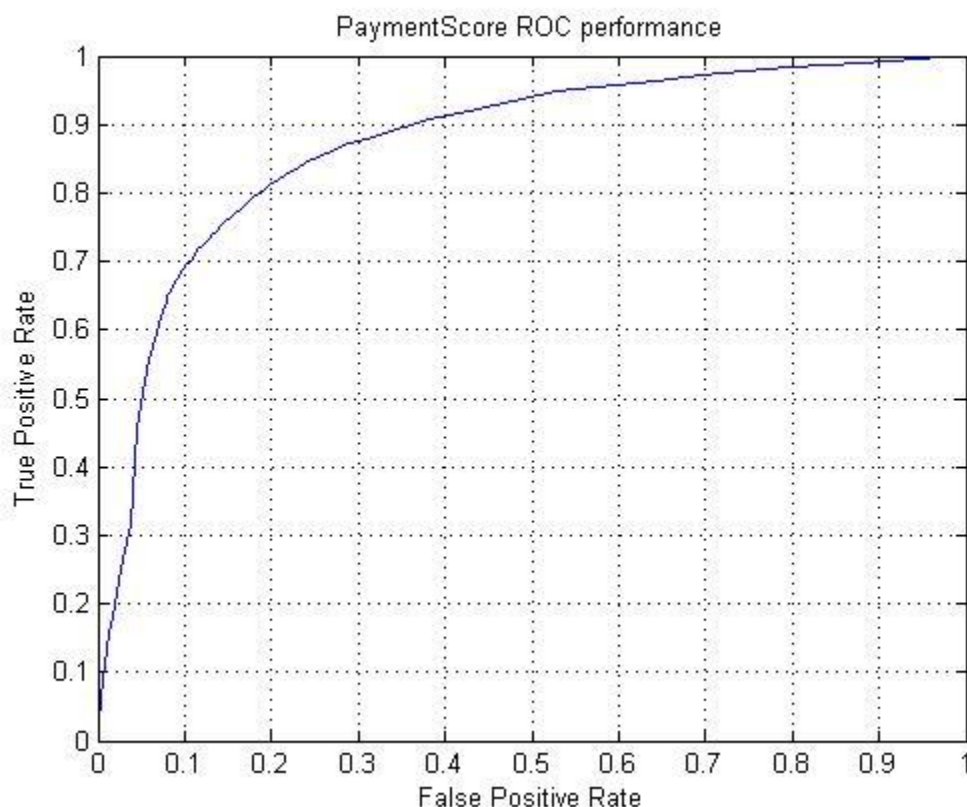
Model training and validation

A large number of candidate variables were selected and created, including account specific data and statistics describing particular payment patterns. Using the Training/Testing dataset, a subset of the candidate variables was selected based on their ability to predict severe delinquency. Once the subset of variables was identified, the Training/Testing dataset was used to build a model giving the relative likelihood that an account would experience severe delinquency in the subsequent 12 months. As noted above, the model's output is a score from 1 (worst) to 10 (best) indicating the propensity for an account to become severely delinquent. Since the model is intended to be used on an individual trade provider's portfolio of receivables, the absolute risk can vary from portfolio to portfolio, however the relative risk between accounts in the same portfolio is maintained. In other words an account with a score of 10 is less risky than one with 9, which is less risky than one with 8, ...

The model's performance was validated using the Validation dataset. For this Validation dataset the average incidence of delinquency ran at 11.6% overall. An account with a score of 10 had a delinquency

incidence of 1.5%, about 1/8 as risky as the average account. An account with a score of 1 had an incidence of delinquency of 66%, about 6 times as risky as the average. So, we can say the CreditRiskMonitor Payment Score is effective at discriminating between accounts with a low risk of severe delinquency from those with a high risk of delinquency.

Another way of evaluating the effectiveness of the model is by using what is known as an ROC curve. The graph below shows the result for the model using the Validation dataset. Because delinquent accounts are a small fraction of the total population, a way to understand this graph is to imagine all accounts ranked by risk score along the x-axis, with the worst scores being on the left. This curve is a property of the model and it says, for example, that the lowest 10% of scores capture roughly 70% of delinquent accounts. We think this degree of effectiveness will make the CreditRiskMonitor Payment Score a practical tool for many of our subscribers, to help them take different actions with their accounts presenting different risks.

The stability of the model's score is an important factor in supporting decisions. A volatile score is impractical and difficult to use, even if it is statistically accurate. Scores in the mid range (4 – 7) had a standard deviation of 2 score points and those on the extremes of the scale had a standard deviation of less than 1 score point over a 6 month period of time. This implies that accounts with a score of 9 or 10 tended to stay in that range over a 6 month period of time, similarly accounts scored 1 or 2 also tended to stay in this high risk region over a similar period. We can say that the Payment Score shows good stability.

The scoring model was found to operate effectively with a minimum of three months of aging reports. Longer time histories will yield higher degrees of accuracy. So, when using the score, subscribers should keep in mind that it will not be applicable to accounts with less than three months of history.

Summary and conclusion

The CreditRiskMonitor PaymentScore has, in this first iteration, been designed:

- For use by Trade Contributors.
- To be based solely on each Trade Contributor's own data.
- The PaymentScore estimates the risk that each customer will, in the next 12 months, become "severely delinquent".
  - Where "severely delinquent" means that the aggregate 90+ days past due category of account balance aging will show an amount that is equal to or greater than 10% of the average total monthly balance during the past 6 months.

In this white paper, we have not revealed the input variables or the model details, because we intend for the Payment Score to remain proprietary. However, we have explained in detail the approach taken in this modeling analysis, the types of variable categories identified and used, and the general structure of the model. We have discussed some important attributes of Trade Payment data, which any modeling analysis must take into account. We have also discussed the accuracy of the model in identifying high risk accounts (illustrated by the ROC curve) and showed that it does a good job estimating the risk of future severe delinquency.

We anticipate that the Payment Score, as made available to Trade Contributors in this iteration of the model, will be useful to Contributors in a number of ways. We expect it will prove useful to those who already run their own payment scores, as a second point of view identifying relationships requiring extra attention. For those lacking an in-house scoring capability, the score may be useful (for example) in prioritizing accounts for specific collections treatments.

We plan to improve the Payment Score in the months to come, and welcome your comments and suggestions as we work to make this score more predictive and useful.