What is the best information and/or risk analysis methodology to use for your credit and collection evaluation needs?
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INTRODUCTION

Historically, the majority of business credit decisions made by credit departments are based on data purchased from one of the major credit bureaus, i.e., Dun & Bradstreet (D&B), Equifax, Graydon or Experian. These companies provide various types of generic credit reports and associated services where the information contained comes from a relatively small number of data providers, approximately 6,000 of the 20 million companies operating in the US, for US-based credit bureaus together with various forms of public record data such as liens, judgments and published financial statements. Additionally, information may be provided by trade associations and of course the company’s own operating experience with their customers. Generic scores, credit bureau reports and data can be used either as a stand-alone evaluator or as a component of a judgmental-based model.

However, companies are now reconsidering this technique and are instead adopting statistical modeling (or a hybrid of statistical with the bureau data). The nature of the data provided by the credit bureau assumes that every company looking at the data has the same risk, because the risk measurement provided is the same for everybody.

The Supermarket Scenario: Why Bureau Data Does Not Tell the Most Accurate Story...

Ongoing risk analysis is vital, it drives credit limits, it helps prevent bad debt expense, and ultimately it should drive cash flow through collections prioritization. The use of bureau data for ongoing analysis is expensive, and even worse; it is not as accurate as statistical models for existing account management.

Let’s take for example, a supermarket. The supermarket may stock over 5,000 items, maybe over 50,000… and they may choose to pay its biggest, most important suppliers on a timely basis to maintain good relationships with them, while delaying payment to their smaller, less important suppliers. Hence, they would not be applying the same payment behavior to all of their suppliers, as some are being paid on time, while others are being paid late. So, if you were evaluating the risk of this supermarket in order to adjust a credit line or to prioritize collections – how would you do that? If you bought credit bureau data you would see how they pay the world as an aggregate; the value would be the same, even if the supermarket’s vendor payment activity varies significantly from one supplier to the next.

While it is understandable that a company may rely on bureau data when it is evaluating new customers, for ongoing risk measurement for the use in collections prioritization, the bureau data is not as accurate as the actual payment experience between the supplier and the buyer.

In this instance, a company that uses only credit bureau data to consider whether to extend credit to this supermarket will only see a flat value, and will not know whether the supermarket will pay them on time with their biggest suppliers, or late with their smaller suppliers.

Something else to consider with respect to credit bureau data is how many of your customers are represented in the bureau’s database. In most instances, you will see about 60% - 80% of your customers in the bureau database. However, if you develop a model using your own internal data, every company you do business with will be represented. The more data you collect over time, the more accurate you can be when determining the inherent risk in your portfolio.

If a statistical process is not utilized the decisions could potentially be inaccurate; the major flaw is that the bureau data does not take into consideration the specific risk of doing business with a specific customer, which is the major strength of statistical-based models.
With this said, there are situations where using a generic credit score or report from a credit bureau may make more economic sense over the use of a statistical model. Understanding this difference can translate to less bad debt expense and increased cash flow.

In this paper we discuss various situations and point out what credit information and/or risk analysis methodology is the most appropriate for a given situation and why. Before we proceed, however, let’s point out the main differences between judgmental and statistical models.

**JUDGMENTAL-BASED VERSUS STATISTICAL-BASED MODELS**

1. If you put 10 credit managers/financial directors in a room and had them agree on the most important factors for evaluating a company’s credit -and then asked them to assign model weights to the factors they consider important, they would come up with 10 different models. The factor weights would be based upon each individual’s past experience and judgment, and there is no way for anyone to know which model is best.

   In a statistical-based system, once the factors to be included in the model have been determined by various statistical tests, the weights are assigned by the statistical software used for model development. There will be one best-fitting model.

2. If the judgmental model is not performing well, it is extremely difficult to determine which factor(s) and weight(s) need to be adjusted. In a statistical-based system, it is a straightforward process to determine which variables are causing the problem in order to adjust the model.

   Over time, every model will need some fine tuning. With a judgmental-based system this may require redoing the entire modeling process.

3. Judgmental systems are not easy to build. You must answer questions like: How many and which variables should I use? What should the variable weights be? What should be my cut-off point between a good risk and a bad risk, etc.? Once the model is built, there will be no way of knowing how effective it is because there is not a standard procedure for evaluating it.

   Alternatively, due to the availability of sophisticated software and experienced statistical analysts at a statistical modeling firm, a statistical-based model can be developed in far less time than a judgmental model if the necessary history is available.

4. Judgmental models are rarely, if ever, validated. After a judgmental model is prepared for use, the developers typically do not go back in time and say, “if we had this model six months ago how well would it have predicted the next six months?” In a statistical-based system there is always an element that validates the output before using it. It’s the validation process that tells you how good your model is and helps you determine whether it’s adequate for your needs.

5. Most importantly, judgmental systems cannot quantify risk. They are essentially ranking systems where the company with the highest score is considered the lowest risk. But, the score can’t tell you the probability or odds that a given company will pay its bill within any particular time period. Statistical-based systems do this as a matter of course. It is this property of statistical-based models that allow them to be the basis for optimum allocation of credit and collection personnel.

The next section will look at some typical credit and collection operational requirements and discuss which model is best suited to address certain specific needs.
NEW APPLICANT CREDIT RISK EVALUATION

One of the best uses of generic scores and credit bureau data is to help you review new applicants for credit. The bureaus have reports that are specifically designed to help you review new applicants. In most cases, you will likely only provide a small line of credit to a new account until you have been doing business with them for a significant period of time and are happy with their payment pattern. Then you'll have to protect yourself against the possibility of the account's overall credit deterioration, over time, which often translates to purchasing more credit bureau information in the future.

Essentially, deciding what type of credit evaluation to use with new applicants is a function of the volume of new applicants. The following depicts a set of guidelines often adopted by best practices companies:

» Low number of applicants – less than 50 a month and low dollars: Use bureau credit reports or scores.

» Low number of applicants – less than 50 a month and high dollars: Use bureau credit reports supplemented by financial statements and trade/bank references.

» Medium number of applicants – between 50 and 500 a month: Use a judgmental rules-based system and financial statement data, if high dollars. Additionally, generic scores and bureau reports can be used to supplement and/or verify your decision.

» High number of applicants – over 500 a month: Use a custom statistical-based credit score enhanced with bureau data that is designed for evaluating new accounts.

A custom statistical-based model for new applicants is typically only relevant if you have a significant volume of new business each month, this is estimated at greater than 500 new accounts. You will have to purchase historical credit bureau data for your new applicant model because you don’t have any experience with the new customer, but the statistical-based model can help you set a more applicable credit line for the new customer and, therefore, may account for some additional business when compared to the lower credit line a bureau generic model will support.

Additionally, you’ll save substantial money on future credit bureau data purchases because you will only buy the data that is required to produce the model’s scores. Also, if you are using a statistical-based new account model, you will most likely have a statistical-based model in place for evaluating existing accounts, and once you have been doing business with the new applicant for a few months you’ll be able to use your existing account model to evaluate the customer, and will not need additional credit bureau data. Your own data can be used to evaluate the future risk of that account.
EXISTING ACCOUNT CREDIT AND COLLECTION RISK EVALUATION

For evaluating a request for additional credit or determining the collectability of a past due account for an existing customer, statistical-based models are being adopted quickly - over the use of the more traditional judgmental-based models. The only caveat is that these companies must have a sufficient number of accounts as well as the required data to build the model. Typically, a portfolio of at least 1,500 accounts and eighteen to twenty-four months of accounts receivable data is required for an effective model. If you don’t meet these criteria, a judgmental-based model together with credit bureau data will have to suffice. So, as noted before, the volume of the accounts that need to be evaluated is the major driver of what methodology to use.

» Low number of existing customers and low dollars: Use bureau credit reports or scores supplemented by an analysis of customer payment patterns, i.e., do they pay on a timely basis and what is the frequency of arrears?

» Low number of existing customers and high dollars: Use bureau credit reports or scores supplemented by an analysis of customer payment patterns and periodic requests for financial statements and bank references.

» Over 1,500 accounts: Companies with over 1,500 accounts will likely benefit from statistical scoring (or a hybrid of statistical with bureau data) versus using bureau data alone. The statistical system that uses only internal data is typically the most effective for optimal allocation of collection resources. When these companies can use the model output to drive collections prioritization, there is typically a sharp improvement in collections effectiveness.

USING A STATISTICAL-BASED MODEL

Companies can use statistical-based models that are created using trade experience data over a period of time and are then calibrated to a specific portfolio. In this scenario, the models are always validated before application. Validation allows you to know just how well the model has performed historically and likely will perform once it is put into production. In comparison, judgmental-based models are rarely, if ever, validated. Statistical models are most often used to evaluate ongoing risk in the portfolio in order to drive collections prioritization.

Prioritizing Collections
The purpose of a collection scoring model is to allow you to determine which accounts are GOOD and which are BAD. Once this is determined, you can optimize the allocation of your collection resources by having them concentrate on the accounts that are most likely to become problems and not on accounts that will eventually pay. The validation quantifies just how well the model has achieved its purpose.

Validating the Model
Additionally, validation can provide a comparison between models and let you know whether one model is superior to another in a fair test. In the following example, we are going to compare three models to each other. One developed only from the company’s internal data while the others are two different types of generic credit bureau scores. The purpose of this type of comparison is to determine whether a company’s own data is sufficiently predictive for credit analysis and, therefore, allows the company to avoid the cost of credit bureau data.
RISK-BASED COLLECTIONS

Statistical-based scoring quantifies specific risk probabilities on your accounts. And it is that capability that most separates it from credit bureau generic scores or in-house judgmental-based scoring. The scores produced as the product of statistical-based scoring essentially provide a measure of the risk that a given customer will pay their bill on a timely basis. The standard output from a statistical-based scoring system includes not only a credit score but also the probability that the account will go bad i.e. Probability of Bad (PBAD) within a specified period from the scoring date, usually six months, and an estimate of the cash value of the account that is at risk, i.e., Cash at Risk (CAR). These values, when properly applied, will aid you in allocating collection resources to specific accounts such that the return on investment (ROI) from collection operations will be maximized.

Prioritizing Collections: Using Statistical Modeling to Build a Work Queue

To understand how statistical modeling drives collections, let’s look at a typical situation that a company can find itself in and see how this additional information can be applied. Collection resources are limited and every overdue account cannot be directly addressed by a collector so a decision needs to be made as to which accounts to call directly and which ones to handle by a less expensive method – say by a dunning notice of some type.

Let’s assume that you only have the resources available to make one call and there are two accounts in question. Account AAA owes $50,000 and has a Probability of Bad (PBAD) of 10%, i.e., has only a 10% chance of going bad within six months and their CAR is $5,000 (PBAD times AR value). Account BBB owes $20,000 and has a PBAD of 50% so their CAR is $10,000. Who do you call?

From a risk-based collections standpoint you call Account BBB. And from both a statistical-based as well as a common sense based position, here’s why. Account AAA is a relatively good risk, a PBAD of 10% indicates a lower risk account and the chances are that the account will pay in due course and may resent a collection call which could upset otherwise good customer relations. Additionally, they represent only about 50% (100 times 5,000/10,000) of the risk that Account BBB represents. In other words, a call to Account BBB gets you about 200% more bang for your collection dollar than a call to Account AAA. Account BBB has a PBAD of 50% and is a very high risk account. Accounts in this class should be monitored very closely and called as soon as they are one-day late.

In this situation, the action implied by risk-based collections is the opposite of what a historical collection decision would be which would be to call Account AAA, the higher value account, because you would not know that Account BBB actually represents significantly more risk.
THE VALIDATION PROCEDURE

During the validation process, a company’s historical data is put through a specific statistical-based model. The results of the analysis are then compared to the present-day, actual data. Were the predictions accurate? This validates the statistical-based model that you built and also allows you to better understand what you can expect if the model is implemented at your company. It should be noted, that this type of information is rarely, if ever, available prior to implementing a judgmental-based model.

SAMPLE VALIDATION OUTPUT

A significant amount of data is produced as a byproduct of the development of a statistical-based model. However, for the purposes of this discussion, we will focus on the following outputs and the information they provide that allows personnel to be more efficiently allocated:

1. Net30Score - This is the account’s credit score on a scale of 0.01 to 100, with 0.01 being the worst score and 100 being the best

2. Probability of Bad (PBAD) - The probability that a customer will go bad within 6 months, or another predetermined period, from the date of score

3. Risk Class - Used as the basis for applying collection strategies

4. Cash At Risk (CAR) - The cash value of a customer’s account that is at risk, computed by multiplying the Probability of Bad by the outstanding A/R balance

Comparing Statistical Models with Bureau Data

The following chart is one way to show the results of a validation analysis. The scored accounts are rank-ordered from greatest risk to least risk and distributed into deciles which essentially show how well the models were able to segregate the BAD from the GOOD accounts. Here, the results of models from different sources are compared to each other, thereby providing the information necessary to determine which type of model is best for your application.
In the above chart, the results of two different generic bureau scores are compared to Net30Score. As can be observed, in the first and highest risk decile, Net30Score is far superior to either score in differentiating GOOD from BAD accounts which, after all, is the basic underlying purpose of commercial credit scoring. Specifically, when applied to the same account population, Net30Score captured 47.8% of the future BADs through the first decile compared to Bureau Score 1’s 22.7%, and Bureau Score 2’s 16.0%, improvements of 110.6% and 198.1% respectively. And, given that Net30Score is developed using only your own data, it will be able to score more accounts than the bureau reports, its predictive capability will be significantly better, and it will not require spending money on generic bureau data.

Another way to show the results is to distribute the accounts into risk classes, thereby providing a starting point for the allocation of collection resources.

In this instance, the Extreme Risk Class has a BAD rate almost 34 times higher than the Very Low Risk Class. This tells you that dollar for dollar you will get more productivity from your collection personnel if they concentrate on the higher risk classes where, on average, 18.1% of the accounts represent 66.7% of the accounts most likely to go BAD. (For additional discussion see following section on Risk-Based Collections)

Another advantage of statistical-based scoring is that you can use the model’s output to help determine the total amount of the A/R portfolio that is at risk, i.e., will be paid in greater than 90 days or not at all.
To estimate Cash at Risk (CAR) we use the PBAD, or the probability that the customer will go BAD for each account, and multiply it by the A/R dollar value of that account and then total those products within each risk class. Then summing the CAR for each risk class produces the portfolio CAR.

Here, 17.3% of the scored accounts represent 67.2% of the CAR, again demonstrating the model’s ability to segregate GOOD from BAD accounts and providing the ability to more efficiently allocate collection personnel, as well as the basis for a more accurate estimate of the reserve for bad debts. You may note that all of the accounts were not scored. This is because they were either already labeled BAD, there was insufficient history to evaluate them or they were very high value and it was decided to review them manually.

### Analysis of Net30Score Output

**Average Number of Accounts per Month in Validation Sample - 7,921**

<table>
<thead>
<tr>
<th>RISK CLASS</th>
<th>SCORE RANGE</th>
<th>AVERAGE NUMBER OF ACCOUNTS IN RISK CLASS</th>
<th>PERCENT OF ACCOUNTS IN RISK CLASS</th>
<th>CUMULATIVE ACCOUNTS THROUGH RISK CLASS</th>
<th>AVERAGE NUMBER OF BAD* ACCOUNTS IN RISK CLASS</th>
<th>BAD* RATE IN RISK CLASS</th>
<th>CUMULATIVE PERCENT BAD* THROUGH RISK CLASS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme</td>
<td>≤ 23.79</td>
<td>271</td>
<td>3.4%</td>
<td>3.4%</td>
<td>165</td>
<td>60.8%</td>
<td>24.6%</td>
</tr>
<tr>
<td>Very High</td>
<td>23.8 to 40.77</td>
<td>304</td>
<td>3.8%</td>
<td>7.3%</td>
<td>112</td>
<td>36.9%</td>
<td>41.3%</td>
</tr>
<tr>
<td>High</td>
<td>40.78 to 54.94</td>
<td>861</td>
<td>10.9%</td>
<td>18.1%</td>
<td>170</td>
<td>19.8%</td>
<td>66.7%</td>
</tr>
<tr>
<td>Moderate</td>
<td>54.95 to 61.29</td>
<td>952</td>
<td>12.0%</td>
<td>30.2%</td>
<td>85</td>
<td>8.9%</td>
<td>79.3%</td>
</tr>
<tr>
<td>Low</td>
<td>61.3 to 75.75</td>
<td>1,143</td>
<td>14.4%</td>
<td>44.6%</td>
<td>58</td>
<td>5.1%</td>
<td>88.0%</td>
</tr>
<tr>
<td>Very Low</td>
<td>&gt; 75.75</td>
<td>4,390</td>
<td>55.4%</td>
<td>100.0%</td>
<td>80</td>
<td>1.8%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

*See Bad definition on Validation Data Characteristics slide. Any account not BAD is considered GOOD.

### Cash at Risk (CAR) Accounts

<table>
<thead>
<tr>
<th>RISK CLASS</th>
<th>SCORE RANGE</th>
<th>EXPECTED BAD* RATE IN RISK CLASS</th>
<th>NUMBER OF ACCOUNTS IN RISK CLASS</th>
<th>% SCORED ACCOUNTS IN RISK CLASS</th>
<th>CUM % SCORED ACCOUNTS THRU RISK CLASS</th>
<th>A/R IN RISK CLASS</th>
<th>% A/R IN RISK CLASS</th>
<th>CAR IN RISK CLASS</th>
<th>% CAR IN RISK CLASS</th>
<th>CUM % SCORED CAR THRU RISK CLASS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme</td>
<td>≤ 23.79</td>
<td>61.7%</td>
<td>239</td>
<td>3.0%</td>
<td>3.0%</td>
<td>1,637,124</td>
<td>3.3%</td>
<td>969,504</td>
<td>23.8%</td>
<td>23.8%</td>
</tr>
<tr>
<td>Very High</td>
<td>23.8 to 40.77</td>
<td>38.4%</td>
<td>279</td>
<td>5.5%</td>
<td>6.5%</td>
<td>1,811,388</td>
<td>3.6%</td>
<td>713,257</td>
<td>17.5%</td>
<td>41.3%</td>
</tr>
<tr>
<td>High</td>
<td>40.78 to 54.94</td>
<td>20.1%</td>
<td>862</td>
<td>10.8%</td>
<td>17.3%</td>
<td>5,413,036</td>
<td>10.8%</td>
<td>1,055,421</td>
<td>25.9%</td>
<td>67.2%</td>
</tr>
<tr>
<td>Moderate</td>
<td>54.95 to 61.29</td>
<td>8.8%</td>
<td>984</td>
<td>12.3%</td>
<td>29.6%</td>
<td>6,839,572</td>
<td>13.7%</td>
<td>616,739</td>
<td>15.1%</td>
<td>82.4%</td>
</tr>
<tr>
<td>Low</td>
<td>61.3 to 75.75</td>
<td>4.4%</td>
<td>1,111</td>
<td>13.9%</td>
<td>43.4%</td>
<td>8,963,302</td>
<td>17.9%</td>
<td>472,019</td>
<td>11.6%</td>
<td>94.0%</td>
</tr>
<tr>
<td>Very Low</td>
<td>&gt; 75.75</td>
<td>2.0%</td>
<td>4,525</td>
<td>56.6%</td>
<td>100.0%</td>
<td>9,873,175</td>
<td>19.8%</td>
<td>245,258</td>
<td>6.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Total Scored Accounts</td>
<td>8.2%</td>
<td>8,000</td>
<td>100.0%</td>
<td>34,537,597</td>
<td>69.2%</td>
<td>4,072,199</td>
<td>100.0%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Percentage of Scored A/R Portfolio at Risk 11.8%

| BAD at Score | 999 | 100.0% | 752 | 6,214,848 | 12.4% | 6,214,848 |
| Too Thin to Score | 998 | - | 363 | 700,781 | 1.4% | - |
| Other | 997 | - | 7 | 8,482,643 | 17.0% | - |
| Total Non-Scored Accounts | 1,122 | 15,398,273 | 30.8% | 6,214,848 |
| Total All Accounts | 9,122 | $49,935,870 | 100.0% | $10,287,047 |

Percentage of Total A/R Portfolio at Risk 20.6%
CONCLUSION

Several factors need to be considered when deciding whether to use generic scores, credit bureau reports and data or a judgmental-based model enhanced with credit bureau data, versus a statistical-based model:

For New Credit Applicants:
» Up to 50 new accounts per month – use generic credit bureau reports and depending on the amount of credit required supplement with financial statements and bank references. Additionally, be very conservative in the amount of credit extended until you have some operating history with the account.

» Between 50 and 500 new accounts per month – use judgmental/rules-based system supplemented with generic scores, bureau data and financial statement and bank references depending on the amount of credit requested.

» Greater than 500 new accounts per month – consider developing a statistical-based new account model together with a statistical-based credit line application. This could be cost-justified due to the ability to better determine an applicable credit line which may provide additional revenue opportunities.

For Existing Customers:
» If your portfolio contains less than 1,500 accounts, it is unlikely that there will be enough data to develop a robust statistical-based model. Use a judgmental-based model enhanced with credit bureau data.

» If your portfolio contains more than 1,500 accounts, a statistical-based model is justified and will provide all of the benefits previously discussed – essentially the ability to optimally allocate credit and collection personnel and a myriad of other information that will improve operational efficiency.

The critical characteristic that separates statistical models from judgmental models is their ability to quantify risk. This capability, more than any other, is what makes statistical-based models such a powerful tool for the credit and collection function.

By knowing and using the probability of the occurrence of specific credit and collection events, it is possible to optimize the allocation of the resources available in a given credit and collection environment, thereby developing strategies that mitigate the possibility of negative results, while simultaneously increasing the credit lines of low risk accounts and providing the opportunity for additional revenues.
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