Understanding the Portfolio Defense SAVANT Credit Scoring Model

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Introduction

This document is designed to provide CU*Answers clients with a bit of background and supporting materials explaining how the SAVANT Scoring Model from our partner, Portfolio Defense, was set up and implemented to give you the 247 Lender Auto Decision Model.

FAQ Answers from Portfolio Defense

Q: What is the SAVANT Scoring Solution?

A: SAVANT is a set of expert scoring models designed for a variety of different lending portfolios. Using commonly available credit bureau, deal, and application information, you will be able to generate a predictive credit score that will permit you to evaluate the credit quality of your applicants. The great advantage of these tools is that you do not need your own data to develop them - they can be developed and deployed quickly. Further, they can allow you to more confidently expand your lending business into new geographic regions or new products where you do not have previous experience.

SAVANT models offer a proprietary method of setting cutoffs and estimating risk quantitatively. This permits you to use the model and create cutoff strategies with greater confidence, since you will know in advance that the model(s) rank-order the risk of your applicants, and you will have an idea of relative quality (odds estimates) at different score ranges.

Q: How are the models developed?

A: The statisticians at Portfolio Defense have over 30 years of detailed experience in the development of a great variety of different types of models, in every possible lending area. They have worked on literally hundreds of projects and developed thousands of scoring models for a great variety of clients, and with many different sources and types of data.

This experience permits us to know the types of variables that are most commonly predictive for different lending products and regions. We also have a pooled database of existing empirical data that we use to examine predictive variables and weight patterns for these different products and regions, as we develop each SAVANT model.

Each model is specifically designed to meet your unique needs. We use a questionnaire to learn about those needs, and design the model or models for each client. These are not "off the shelf" models that may grow stale, being unchanged for months or years, and they are not models that are sold to each

and every client, year after year. After all, how can you expect superior performance, or a competitive advantage, if you are using the same generic tools as your competition?

Q: How are SAVANT models used?

A: These models are designed to "rank-order" your applicants. This means that high scoring applicants represent better payment risk (or lower probability of delinquency and charge off) than lower scoring applicants. For example, if you select a "cut-off score", where you choose a score and accept all applicants at and above that score, you can be assured of accepting the higher quality applicants. If you set a cut-off score where 40% of your applicants would pass the score (a 40% acceptance rate) for example, you can be assured of accepting the highest quality 40% of your applicant population.

There are many business situations that call for the SAVANT Scoring Solution. If you do not currently have sufficient data with which to develop custom empirical models; if you are starting to offer new lending products or moving into a new geographic area; if you have not yet budgeted for an empirical development; or if you are new to scoring, and want an interim solution that you can use to establish your risk management procedures, automate models, and train your staff on credit scoring, SAVANT may be just what you need.

Q: How do I design a cut-off strategy with SAVANT?

A: The key issue is that these types of models are different from custom, "empirical" scorecards. Those models are based upon the actual observed performance of your lending customers with your products. And those types of models have an observed "odds-to-score" relationship, where you can choose a cutoff score and have specific performance estimates associated with that score.

However, you are using an expert or pooled model precisely because you do not have the data necessary for a custom empirical model development. This means that choosing a cutoff score is a more complex decision.

Our standard approach is to work with each client (in this case, CU*Answers) to analyze a recent applicant sample to give you a more quantitative measure of credit quality. Portfolio Defense has a proprietary methodology that allows you to have greater statistical confidence in measuring applicant risk at different SAVANT score levels, and thus use the models more effectively.

Q: How can I be certain that these models will fit into my lending operation?

A: The successful implementation of any risk model, no matter what the source, requires that it work in harmony with your existing credit policies and underwriting guidelines. Further, the use of credit scoring within your institution may be a significant change to your current operational procedures.

This section contains the steps that CU*Answers went through when it configured the SAVANT scoring model with Portfolio Defense to develop the final 247 Lender product used by our clients. **The charts included are not samples but rather show the results of our analysis of <u>actual</u> data sampled from the combined loan portfolios our client credit unions.**

Model Validation

An important regulatory requirement, as well as a good business practice, is the periodic validation of your credit scoring models. What this means is that, because you are using a scoring model to make credit risk decisions, you need to measure the performance of the model, or the ability of that model and the resulting score to separate between Good and Bad performing accounts.

There are several different ways to accomplish this. They depend upon the type of data that you have available and when it is available, and we will describe each of these in detail. One type of validation is a pre-installation validation, which can be performed if you already have some booked accounts with payment performance, and you will also need their credit bureau and application data from the time of application, as well as the ability to run this data through your systems and generate a Savant-based score (the score you want to validate). It is not always possible to have this data, for example if you are using the score for a new product, region or population.

Pre-installation Validation

In this first case, let us assume that you have this information. The first thing you will need to do is select a group of booked accounts that you consider Good and Bad, based upon their payment performance. Typically a Good would be someone that, had you know how they were going to perform in the future, you would have wanted their business; a Bad is someone that, had you known their future performance, you would have not wanted to approve their application. You can often find Goods, by just taking a random sample of accounts that are Current; Bads can be selected from accounts in Collection, recent charge-offs, repossessions, foreclosures, etc. Select about 300 of these, in each group, along with their original application information. Using that original application information, you then generate what their Savant score would have been, at the time of their application; thus ending up with a set of 300 Good performers, 300 Bad performs, and their individual scores. With this information, you can produce a score distribution, tabulating the Goods and Bads, which score at and above each cutoff score, and it might look something like Figure 1 below. This type of analysis can be performed on data that you currently have in your archives, or you can start using the Savant score, and perform the test after accounts have matured or seasoned.

Figure 1: Good/Bad Odds
Using Data Sampled from CU*Answers Client Loan Portfolios

Savant Score	Actual Goods	Cumulative Goods	Cumulative Good Percent	Actual Bads	Cumulative Bads	Cumulative Bad Percent	Good/Bad Odds
<140	130	485	100.00%	64	213	100%	7.58
140-149	16	355	73.20%	11	149	70%	32.27
150-159	18	339	69.90%	10	138	65%	33.90
160-169	8	321	66.19%	7	128	60%	45.86
170-179	18	313	64.54%	7	121	57%	44.71
180-189	20	295	60.82%	5	114	54%	59.00
190-199	14	275	56.70%	9	109	51%	30.56
200-209	13	261	53.81%	13	100	47%	20.08
210-219	20	248	51.13%	10	87	41%	24.80
220-229	17	228	47.01%	11	77	36%	20.73
230-239	17	211	43.51%	13	66	31%	16.23
240-249	15	194	40.00%	9	53	25%	21.56
250-259	19	179	36.91%	7	44	21%	25.57
260-269	15	160	32.99%	7	37	17%	22.86
270-279	13	145	29.90%	7	30	14%	20.71
280-289	15	132	27.22%	6	23	11%	22.00
290-299	20	117	24.12%	3	17	8%	39.00
300-309	9	97	20.00%	2	14	7%	48.50
310-319	22	88	18.14%	4	12	6%	22.00
320-329	15	66	13.61%	3	8	4%	22.00
330-339	15	51	10.52%	3	5	2%	17.00
340-349	17	36	7.42%	1	2	1%	36.00
350+	19	19	3.92%	1	1	0%	19.00
Total Counts	485	4,615		213	1,548		

The way to produce this type of table is to start off with the scores of each account, and tabulate them with say, 10 point ranges. Then total the Goods and Bads, so that you have the number of Goods and Bads that score at and above that cutoff score (such as 170 and above, 180 and above, etc.). Then determine the percentage of all Goods and Bads that cored at or above each cutoff score range.

You can then calculate the Good/Bad Odds by dividing the Actual Goods within a cell by the Bads, and observe the relationship between Odds and Score. If there is a positively sloping relationship between Odds versus Score (say, if you plotted out the points), or if Odds increase as Score increases in this example, then a model or score can be said to empirically validate.

Figure 2: Difference Between Cumulative % Goods/Bads
Using Data Sampled from CU*Answers Client Loan Portfolios

Savant Score	Actual Goods	Cumulative Goods	Cumulative Good Percent	Actual Bads	Cumulative Bads	Cumulative Bad Percent	Difference Between Cumulative % Goods/Bads
<140	130	485	100.00%	64	213	100%	0.00%
140-149	16	355	73.20%	11	149	70%	3.24%
150-159	18	339	69.90%	10	138	65%	5.11%
160-169	8	321	66.19%	7	128	60%	6.09%
170-179	18	313	64.54%	7	121	57%	7.73%
180-189	20	295	60.82%	5	114	54%	7.30%
190-199	14	275	56.70%	9	109	51%	5.53%
200-209	13	261	53.81%	13	100	47%	6.87%
210-219	20	248	51.13%	10	87	41%	10.29%
220-229	17	228	47.01%	11	77	36%	10.86%
230-239	17	211	43.51%	13	66	31%	12.52%
240-249	15	194	40.00%	9	53	25%	15.12%
250-259	19	19	3.92%	7	44	21%	-16.74% max KS
260-269	15	15	3.09%	7	37	17%	-14.28%
270-279	13	13	2.68%	7	30	14%	-11.40%
280-289	15	15	3.09%	6	23	11%	-7.71%
290-299	20	20	4.12%	3	17	57%	-52.54%
300-309	9	9	1.86%	2	14	7%	-4.72%
310-319	22	22	4.54%	4	12	6%	-1.10%
320-329	15	15	3.09%	3	8	4%	-0.66%
330-339	15	15	3.09%	3	5	2%	0.75%
340-349	17	17	3.51%	1	2	1%	2.57%
350+	19	19	3.92%	1	1	0%	3.45%
Total Counts	485	3,704		213	1,548		

To create Figure 2, we have focused only on the cumulative percentages and have now added a column to our previous table which focuses on the differences between the cumulative Goods and Bad Percentages. You find the point where they have the greatest difference; this is the KS (Kolmogorov-Smirnov) statistic, and it is a measure of a model's predictive power (it can range from a minimum of 1 to a maximum of 99). When you run your data through, generate the score, produce the score distribution, and calculate the KS statistic, you will have not only validated the power of the Savant score, but you will have a comparative measure of that predictive power, which can be compared to other models or scores.

All of this discussion of score validation is interesting, but it assumes that you have the Goods and Bads with which to test and evaluate the power of the score or model. What if that is not the case? How would you be able to estimate the value of a new Savant score, if you did not have any empirical performance data? We have a proprietary method which allows you to make use of generic Credit Bureau scores and the Odds that are associated with those scores, and use as a surrogate to measure demonstrate that the Savant model will rank-order Goods and Bads, and will have an Odds to Score relationship which validates. This example is discussed in our next section, where we talk about using a sample of recent applicants.

Recent Applicant Analysis

In this example, we do not have any performance data or booked accounts. Most consultants would tell you that there is no way that you could evaluate the model or try to build your confidence in it. What you do have available is a random sample of some recent applicants (you can perform this test by running applications through your system, either using the Savant score to make decisions, to gather this data for a period and continue your existing underwriting practices; either way is fine).

You want your applicant sample to be unbiased. That means that you don't want to choose applicants from too short a time period, or from a period which is not typical of your business (you have either unusually poor quality applicants, or unusually good applicants, for example). When you have this random sample, you total all of the applicants which fall within a Savant score range, or cell, say 10 points. It would be good to have sufficient numbers, 1000 would be good.

For each applicant you also have a generic CB score value (Beacon, Empirica, or Experian-Fair, Isaac scores are examples of these, but others are also acceptable). It would be best to user only one type of score, and not to mix different types of CB scores together in this experiment.

You calculate an average CB score value within each cell, and repeat for a number of cells (probably 10 or more cells would be good, breaking the applicant volumes into 10% ranges or so). You now have a different average CB score for each cell. Then, you would look up the projected Odds that are estimated for the CB scores (your consumer credit reporting bureau should make these "Odds Charts" available to you - use the performance definitions that are most meaningful to your business, 60+, 90+ etc.). You can enter the Odds into your table for each average CB score, and observe the Odds projections that you have. Looking at the relationship of Odds to Score, as before, shows us that this Savant score rank-orders Goods from Bads, and has a positive relationships.

Figure 3: Credit Bureau Score Odds
*Using Data Sampled from CU*Answers Client Loan Portfolios*

TransUnion

Savant Score	Total Applicant Counts	Average Cell CB Score	CB Score Odds
<140	522	479	1.1
140-149	37	589	4.1
150-159	50	606	4.8
160-169	52	619	4.8
170-179	46	628	7
180-189	63	626	7
190-199	60	636	7
200-209	59	648	9.7
210-219	52	658	9.7
220-229	58	655	9.7
230-239	58	680	14
240-249	55	686	21.3
250-259	83	689	21.3
260-269	92	699	21.3
270-279	85	715	31.3
280-289	75	713	31.3
290-299	69	735	52.7
300-309	72	742	93.2
310-319	101	756	93.2
320-329	88	776	161.3
330-339	81	777	161.3
340-349	64	783	283.6
350+	80	794	283.6
Total Counts	2,002		

Equifax

Savant Score	Total Applicant Counts	Average Cell CB Score	CB Score Odds
<140	220	560	3.3
140-149	26	583	4.3
150-159	26	596	4.3
160-169	31	613	5.6
170-179	24	616	5.6
180-189	17	647	10.2
190-199	28	641	10.2
200-209	26	645	10.2
210-219	15	653	10.2
220-229	25	661	15.2
230-239	36	670	15.2
240-249	33	686	22.6
250-259	33	697	22.6
260-269	30	703	35.8
270-279	36	714	35.8
280-289	26	727	54.5
290-299	36	743	89.2
300-309	33	754	89.2
310-319	28	769	151.3
320-329	46	788	264.1
330-339	40	790	264.1
340-349	13	786	264.1
350+	20	797	264.1
Total Counts	848		

Setting Initial Score Cutoffs or Credit Tiers

Now that you have performed some type of pre-installation validation, it is helpful to create a process where we can set a cutoff score (or in some cases establish credit or risk tiers). You will want to consider a number of different factors. What credit quality are you seeking in your booked accounts? One way to answer this question is to determine your minimum acceptable credit standards, or what is the relative quality of the worst applicant that you would be willing to put on your books. This can be measured by Good/Bad Odds, or the proportion of Goods and Bads within a given group. For example, 10:1 Odds means that out of 11 total applicants, 10 will pay at an acceptable level, while one will become seriously delinquent or worse.