Retail Credit Risk Modeling Assignment

Xinyi (Cynthia) Shen, 1005778428
xinyi.shen@mail.utoronto.ca

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1. ***SB Loans Inc. conducted validation of the Adjudication Score. You need to write a report and interpret the results:***

% of Population	# Non-Defaulted	# Defaulted
10%	195	1
20%	196	0
30%	185	11
40%	173	23
50%	156	40
60%	194	2
70%	188	8
80%	194	2
90%	196	0
100%	186	9
Total	**1863**	**96**

a. ***Calculate KS Statistic. What do you think about the model performance for this model based on KS Statistic?***

% of Population	# Non-Defaulted	# Defaulted	Distribution of Non-Defaulted (%)	Distribution of Defaulted (%)	Cumulative Distribution of Non-Defaulted (%)	Cumulative Distribution of Defaulted (%)	KS
10%	195	1	10.5%	1.0%	10.5%	1.0%	9.4%
20%	196	0	10.5%	0.0%	21.0%	1.0%	19.9%
30%	185	11	9.9%	11.5%	30.9%	12.5%	18.4%
40%	173	23	9.3%	24.0%	40.2%	36.5%	3.7%
50%	156	40	8.4%	41.7%	48.6%	78.1%	29.5%
60%	194	2	10.4%	2.1%	59.0%	80.2%	21.2%
70%	188	8	10.1%	8.3%	69.1%	88.5%	19.5%
80%	194	2	10.4%	2.1%	79.5%	90.6%	11.1%
90%	196	0	10.5%	0.0%	90.0%	90.6%	0.6%
100%	186	9	10.0%	9.4%	100.0%	100.0%	0.0%
Total	**1863**	**96**	**Maximum KS**				**29.5%**

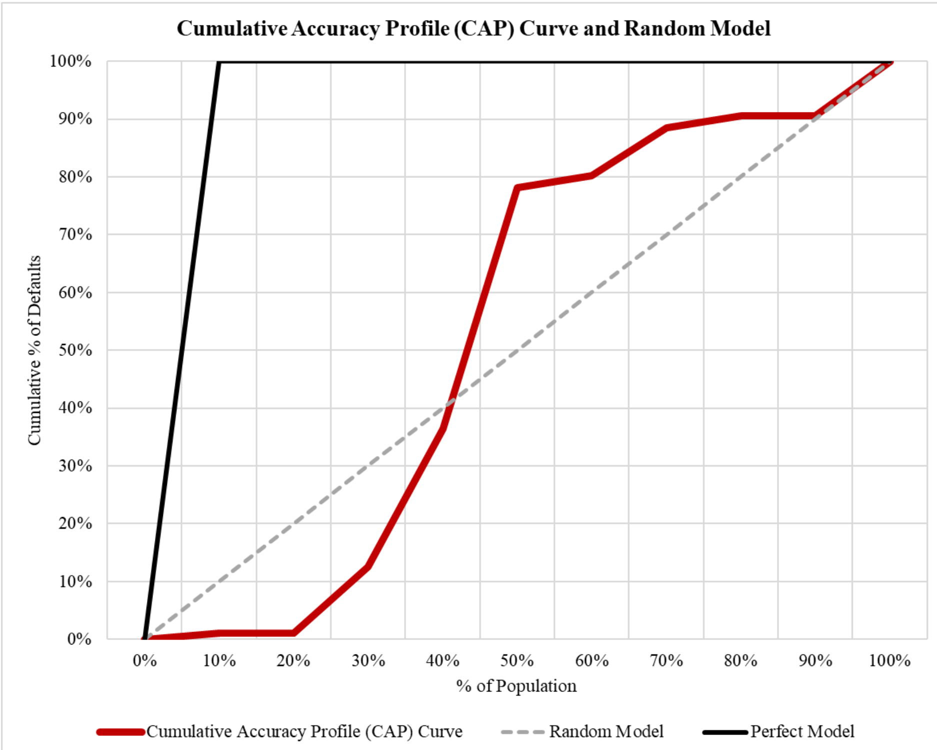
The KS Statistic is $KS = \sup|F_D(p) - F_{ND}(p)| = 29.5\%$,

where

- $F_D(p)$ is the cumulative distribution of defaults by % of population
- $F_{ND}(p)$ is the cumulative distribution of non-defaults by % of population.

A low KS statistic of 29.55% indicates moderate to poor discriminatory power in classifying non-defaults and defaults.

b. Use the data above to plot a Cumulative Accuracy Profile Curve and Random Model.



c. What do you think about the model performance for this model based on the chart created in (b)?

The CAP curve deviates to some degree from the random model, so the model performs somewhat better than the random model, but it does not achieve a steep rise indicative of high predictive power like the perfect model. The shape where the CAP curve deviates from the random model accounts for a moderate to small proportion of the shape surrounded by the perfect model, suggesting that the model has moderate to poor discriminatory power in differentiating defaults and non-defaults.

d. Are your results consistent with your conclusions in questions b and c? Please explain.

Yes, the results in questions b and c for the analyses of the KS Statistic and CAP curve are consistent, both suggesting that the model has moderate to poor discriminatory power in differentiating defaults and non-defaults.

The KS statistic quantitatively suggests moderate to poor performance. The KS statistic of 29.5% is on the lower end of the spectrum for a model with strong discriminatory power. In credit risk modeling, a KS statistic above 40% is generally preferred, indicating that a model can effectively distinguish between defaults and non-defaults. A KS value of around 30% suggests moderate to poor discriminatory power.

The CAP curve plot confirms this assessment visually. The CAP curve does not come close to the perfect model, which would sharply rise to capture a high percentage of defaults within the first few population segments. The CAP curve's moderate deviation from the random model suggests that the model has some predictive capability, but it does not have high predictive power. This aligns with the KS statistic result, reinforcing that the model has only moderate to poor discriminatory power.

2. *SB Loan Inc. adjudicates customers using the scorecard in Table 2.*

Table 2

Variable	Bin	Score	WOE	Default	Population
Intercept		515			
Amortization	Amortization < 72	7	0.18	9%	70%
	72 <= Amortization	0	-0.2	12%	30%
Month Since Last Delinquency	Month Since Last Delinquency <4	0	-2	44%	10%
	4 <= Month Since Last Delinquency	9	0.02	10%	70%
	Missing	14	1.05	4%	20%
Utilization	Utilization < 73	23	1.36	3%	55%
	73 <= Utilization < 93	25	0.74	4%	25%
	93 <= Utilization < 100	13	0.12	9%	10%
	100 <= Utilization < 103 or Missing	7	-0.6	17%	7%
	103 <= Utilization	0	-1.5	33%	3%
Deposit Balance	Deposit Balance < 50	0	-0.9	22%	15%
	50 <= Deposit Balance< 750 or Missing	8	0.02	10%	40%
	750 <= Deposit Balance < 20,000	19	1.42	3%	35%
	20,000 <= Deposit Balance	37	3.6	0%	10%
Number of Inquiries	Number of Inquiries < 4 or Missing	19	0.63	6%	55%
	4 <= Number of Inquiries <7	14	0.09	9%	30%
	7 <= Number of Inquiries < 11	6	-0.7	18%	10%
	11 < Number of Inquiries	0	-1.3	29%	5%
Current Delinquency	Current Delinquency < 1	29	0.96	4%	85%
	1 <= Current Delinquency < 2	7	-0.6	17%	10%
	2 <= Current Delinquency <3	0	-2.1	48%	5%

a. *Does this scorecard make sense? Describe why or why not.*

Variable	Bin	Score Points	WOE	Default Rate	Population %	# Defaulted	# Non-Defaulted	Distribution of Defaulted	Distribution of Non-Defaulted	WOE	IV	Predictive Power
Intercept		515										
Amortization	Amortization < 72	7	0.18	9%	70%	6%	63.70%	63.64%	70.70%	0.1052	0.0074	
	72 <= Amortization	0	-0.2	12%	30%	4%	26.40%	36.36%	29.30%	-0.2160	0.0153	
Total					100%	10%	90%	100%	100%		0.0227	Weak
Month Since Last Delinquency	Month Since Last Delinquency <4	0	-2	44%	10%	4%	5.60%	36.07%	6.38%	-1.7325	0.5143	
	4 <= Month Since Last Delinquency	9	0.02	10%	70%	7%	63.00%	57.38%	71.75%	0.2236	0.0321	
	Missing	14	1.05	4%	20%	1%	19.20%	6.56%	21.87%	1.2044	0.1844	
Total					100%	12%	88%	100%	100%		0.7309	Strong
Utilization	Utilization < 73	23	1.36	3%	55%	2%	53.35%	28.80%	56.59%	0.6757	0.1878	
	73 <= Utilization < 93	25	0.74	4%	25%	1%	24.00%	17.45%	25.46%	0.3776	0.0302	
	93 <= Utilization < 100	13	0.12	9%	10%	1%	9.10%	15.71%	9.65%	-0.4868	0.0295	
	100 <= Utilization < 103 or Missing	7	-0.6	17%	7%	1%	5.81%	20.77%	6.16%	-1.2148	0.1774	
	103 <= Utilization	0	-1.5	33%	3%	1%	2.01%	17.28%	2.13%	-2.0923	0.3169	
Total					100%	6%	94%	100%	100%		0.7418	Strong
Deposit Balance	Deposit Balance < 50	0	-0.9	22%	15%	3%	11.70%	39.52%	12.77%	-1.1300	0.3023	
	50 <= Deposit Balance< 750 or Missing	8	0.02	10%	40%	4%	36.00%	47.90%	39.28%	-0.1985	0.0171	
	750 <= Deposit Balance < 20,000	19	1.42	3%	35%	1%	33.95%	12.57%	37.04%	1.0804	0.2644	
	20,000 <= Deposit Balance	37	3.6	0.0001%	10%	0%	10.00%	0.00%	10.91%	11.4198	1.2460	
Total					100%	8%	92%	100%	100%		1.8298	Strong
Number of Inquiries	Number of Inquiries < 4 or Missing	19	0.63	6%	55%	3%	51.70%	35.68%	56.97%	0.4681	0.0997	
	4 <= Number of Inquiries <7	14	0.09	9%	30%	3%	27.30%	29.19%	30.08%	0.0302	0.0003	
	7 <= Number of Inquiries < 11	6	-0.7	18%	10%	2%	8.20%	19.46%	9.04%	-0.7671	0.0800	
	11 < Number of Inquiries	0	-1.3	29%	5%	1%	3.55%	15.68%	3.91%	-1.3881	0.1633	
Total					100%	9%	91%	100%	100%		0.3432	Strong
Current Delinquency	Current Delinquency < 1	29	0.96	4%	85%	3%	81.60%	45.33%	88.22%	0.6657	0.2855	
	1 <= Current Delinquency < 2	7	-0.6	17%	10%	2%	8.30%	22.67%	8.97%	-0.9267	0.1269	
	2 <= Current Delinquency <3	0	-2.1	48%	5%	2%	2.60%	32.00%	2.81%	-2.4323	0.7100	
Total					100%	8%	93%	100%	100%		1.1223	Strong

First, we calculate the distribution of defaulted and non-defaulted according to the given population percentage and default rate. Then, we calculate the WOE and IV for each category variable to decide whether this scorecard needs regrouping. Note that there is a 0% default rate, which could lead to a divide by zero error, so we smooth this error by assigning a very small value of 0.0001% to this default rate.

Then, we look at some possible regrouping ideas. Note that the IV value for the amortization group is greater than 0.02 but less than 0.1, which indicates a weak predictive power. Thus, the amortization group may be removed. Also, there is a small IV value of 0.0003 for the "4 <= Number of Inquiries <7" bin, which indicates that this bin can be merged with the "7 <= Number of Inquiries < 11" bin to improve the predictive power for number of inquiries. After regrouping, we get the following table:

Variable	Bin	WOE	Distribution of Defaulted (PD)
Month Since Last Delinquency	Month Since Last Delinquency <4	-1.7325	36.0656%
	4 <= Month Since Last Delinquency	0.2236	57.3770%
	Missing	1.2044	6.5574%
Utilization	Utilization < 73	0.6757	28.7958%
	73 <= Utilization < 93	0.3776	17.4520%
	93 <= Utilization < 100	-0.4868	15.7068%
	100 <= Utilization < 103 or Missing	-1.2148	20.7679%
	103 <= Utilization	-2.0923	17.2775%
Deposit Balance	Deposit Balance < 50	-1.1300	39.5209%
	50 <= Deposit Balance< 750 or Missing	-0.1985	47.9041%
	750 <= Deposit Balance < 20,000	1.0804	12.5748%
	20,000 <= Deposit Balance	11.4198	0.0001%
Number of Inquiries	Number of Inquiries < 4 or Missing	0.7544	27.6151%
	4 <= Number of Inquiries < 11	-0.4808	60.2510%
	11 < Number of Inquiries	-1.1018	12.1339%
Current Delinquency	Current Delinquency < 1	0.6657	45.3333%
	1 <= Current Delinquency < 2	-0.9267	22.6667%
	2 <= Current Delinquency <3	-2.4323	32.0000%

To get a new scorecard after regrouping, we need to fit a logistic regression to get coefficients of each category variable so that we can multiply coefficients by WOEs to arrive at the new score calculation. However, it seems that we have not provided the necessary data to fit the logistic regression or a predefined scale table to calculate new scores.

Therefore, we need to consider another way to understand this question.

Another reasonable understanding:

When it comes to Utilization, this scorecard does not make sense since lower utilization should have higher score points and higher utilization should have lower score points since utilization is total credit used divided by total credit limit. However, when Utilization < 73, the score points is 25; when 73 ≤ Utilization ≤ 93, the score points are 25.

b. How can you improve this scorecard? Explain how and show a new scorecard.

We can improve this scorecard by swapping the current score points for Utilization < 73 and for 73 ≤ Utilization < 93. A new scorecard is

Variable	Bin	Score Points	WOE	Default Rate
Intercept		515		
Amortization	Amortization < 72	7	0.1800	9%
	72 ≤ Amortization	0	-0.1700	12%
Month Since Last Delinquency	Month Since Last Delinquency < 4	0	-1.9600	44%
	4 ≤ Month Since Last Delinquency	9	0.0200	10%
	Missing	14	1.0500	4%
Utilization	Utilization < 73	25	1.3600	3%
	73 ≤ Utilization < 93	23	0.7400	4%
	93 ≤ Utilization < 100	13	0.1200	9%
	100 ≤ Utilization < 103 or Missing	7	-0.6200	17%
	103 ≤ Utilization	0	-1.4700	33%
Deposit Balance	Deposit Balance < 50	0	-0.9300	22%
	50 ≤ Deposit Balance< 750 or Missing	8	0.0200	10%
	750 ≤ Deposit Balance < 20,000	19	1.4200	3%
	20,000 ≤ Deposit Balance	37	3.6000	0%
Number of Inquiries	Number of Inquiries < 4 or Missing	19	0.6300	6%
	4 ≤ Number of Inquiries < 7	14	0.0900	9%
	7 ≤ Number of Inquiries < 11	6	-0.6800	18%
	11 ≤ Number of Inquiries	0	-1.2700	29%
Current Delinquency	Current Delinquency < 1	29	0.9600	4%
	1 <= Current Delinquency < 2	7	-0.6200	17%
	2 <= Current Delinquency < 3	0	-2.0900	48%

c. ***A customer came to apply for a seven-year installment loan on October 31, 2024. Yesterday, they applied for credit at a different bank. Although they paid all of their credit recently, they forgot to pay one credit card in January 2024. The customer currently has two credit cards: one with a $5,000 limit and $4,000 balance, and a second with a limit of $7,000 and a balance of $6,500. Last month they had $500 in their savings account with SB Loan Inc., but they recently deposited a $2,000 check to that account after getting a new job. Calculate a score for the customer using the scorecard that you created in (b).***

The base score points should be the intercept, 515.

The number of months left on the customer's existing loan is $7 \times 12 = 84 > 72$. The corresponding score points to add should be 0.

The customer's last delinquency happened in January 2024, and the time that they came to apply for a loan was October 31, 2024. Thus, it has been greater than 4 months since last delinquency. The corresponding score points to add should be 9.

The customer's utilization is $\frac{Total\ Credit\ Used}{Total\ Credit\ Limit} = \frac{\$4{,}000+\$6{,}500}{\$5{,}000+\$6{,}500} = 87.5\%$, so $73 \leqslant$ Utilization < 93. The corresponding score points to add should be 23.

The customer's deposit balance is $\$500 + \$2{,}000 = \$2{,}500$, so 750 ≤ Deposit Balance < 20,000. The corresponding score points to add should be 19.

The customer recently applied for a new credit card at a different bank, applied for a seven-year installment loan, and has two credit cards, so the total number of inquiries is 4. The corresponding score points to add should be 14.

The customer paid all of their credit recently, so the Current Delinquency < 1. The corresponding score points to add should be 29.

Therefore, the score for the customer using the new score card is $515 + 0 + 9 + 23 + 19 + 14 + 29 = 609$.

Note: In this approach, we take the installment loan the customer is applying into account, which is a stricter way since we can see how many scores the customer will have after the customer holds the new loan.

d. Do you think this customer will be approved for credit? Provide a rational for your answer.

The maximum possible score points should be 646, and 609 is a little far from the maximum score points; therefore, it may be considered as poor credit performance. However, if SB Loan Inc. considers a score of 609 as acceptable for loan approval (above their minimum threshold), the customer is likely to be approved.

e. What is the probability that this customer will default in the next 12 months given that the score is scaled in the following way: Odds of 40:1 (non-defaulted: defaulted) at 740 points, with odds doubling every 20 points? Please show all the calculations.

The difference between score points is $740 - 609 = 131$.

The number of 20-point intervals fit into the 131-point difference is $131 \div 20 = 6.55$.

The adjusted odds for a score of 609 is $40 \times \left(\frac{1}{2}\right)^{6.55} = 0.4269$.

To calculate the probability of default, we have

$$\begin{aligned} \frac{1 - PD}{PD} &= 0.4269 \\ \frac{1}{PD} &= 1.4269 \\ PD &= 1 \div 1.4269 \\ &= 70.0826\% \end{aligned}$$