IMB 467

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RETAIL CREDIT SCORING FOR AUTO FINANCE LTD.

Ajay V, the CEO of Auto Finance, was in office on a Saturday trying to come to grips with the default history of his customers. Auto Finance Ltd.* was a part of one of India's large conglomerates. The conglomerate was a major player in the two-wheeler business in India. Many of the people buying two-wheelers belonged to the lower middle class of India and did not have access to enough capital to buy the two-wheelers outright – typically costing between twenty-five to hundred thousand Indian Rupees (at the time of the setting of this case i.e., January 2007, 1 USD ~ 50 INR). For this reason, Auto Finance used to extend loans, typically on a fixed interest rate for 3-5 years, to enable cash-strapped customers to buy the vehicles. The loan facility enabled the two-wheeler division to reach out to a section of consumers that had hitherto not been able to purchase two-wheelers. However, the increased penetration was being achieved at a cost as there were a significant number of people defaulting on their loans. He wondered if there was a pattern in the defaulters.

One of the staff in his IT team had created a small tabular representation of the percentage of defaulters according to various categories (**Exhibit 1**) for the historic customers. Overall, around 71% of customers had delayed their repayments. There were some patterns in the data – male customers were better than female, default rates fell with age, income, and education. However, the number of customers was also very small in some of the categories – although post-graduates defaulted far less than others, only 4% of his customers were post-graduates. Although, he wanted to secure the best customers, he did not want to end up having too few of them either. Things became more complex as he considered combinations of categories. Trends could be seen; the default rate among customers between 30 and 40 years and having a post graduate degree was much more than customers with a post-graduate degree belonging to other age groups. Similarly, while business customers were slightly better than professional (salaried) customers, the pattern seemed to be opposite when looking at it among female customers. He understood things would be even more complex when he considered groups of three categories. He was reminded of statistical approaches that he had studied in his undergraduate days; concepts such as correlations between variables and multiple regression models that related outcomes of interest to sets of explanatory variables.

Ajay understood that discerning patterns required a more formal statistical approach. He knew there were methods for analyzing historical data to gain insights into the likelihood of a potential customer defaulting on a loan. Such credit scoring approaches could be used to identify the least risky ones from a pool of potential customers. He had read about this in a number of business journals and knew that he could provide more loans using a formal credit scoring approach. Scoring approaches could lead to reduction in overall delay and bad loans and directly improve his bottom line. He could also take credit granting decisions almost instantaneously and thus deal with large numbers of potential consumers quickly. Auto Finance was processing a 100 credit applications every day. Ajay estimated that profits would increase by INR 50,000 a day if applicants could be screened using a model that reduced default rate to 60%. In the long run, he could consider pricing his credit offerings based risk and make customized credit offers. Scoring models could also be used in conjunction with other information to design cross-selling programs. In general, an information-based strategy could improve immediate profitability and could lead to accumulation of knowledge of consumers. Such knowledge could well be a resource with the potential to provide his firm with a sustainable competitive advantage. Thus, he was convinced that adopting a scoring approach for credit granting decisions was the need of the hour. However, neither he nor anyone in his team had the experience of developing and implementing a scoring approach to credit granting decisions. He was discussing this with one of his friends who mentioned that analytical modeling of consumer behavior was one of the current focus areas in management research. Ajay decided to seek guidance from an academic consultant and contacted a professor at a leading business school in India.

Srinivas Prakhya, Professor of Marketing, and Sujoy Roychowdhury, prepared this case for class discussion. This case is not intended to serve as an endorsement, source of primary data, or to show effective or inefficient handling of decision or business processes.

CREDIT SCORING

Across the world today, people increasingly need to borrow or avail of credit to fulfill the financial needs of their upcoming purchases/requirements. The word "credit" is derived from the Latin term *credo* meaning "trust in" or "rely on". In arriving at the credit granting decision, the credit provider considers the tradeoff between the interest income and the possibility of the borrower defaulting. It is then imperative upon the borrower to establish trust in the minds of the lender that she has the ability and willingness to pay back the loan.

The challenge lies in the fact that the ability and willingness to pay can only be an assessment by the lender at the time of borrowing – the lender would never know for certain if the borrower will actually pay or not. There is strong information asymmetry between the two parties. This may lead to a poor selection of people eligible for credit – because if good people are not given credit, then the lender will lose possible interest income (an opportunity cost); on the other hand, if credit is extended to people who then do not pay back, the lender has his principal at risk. Economists term this error of wrong selection as adverse selection. The costs of the two possible errors in decision may not be equal. There is also the potential of the borrower changing his behavior after agreeing to a repayment contract which the lender cannot enforce perfectly– an instance of what economists' term as moral hazard. To alleviate these problems, banks and other lending institutions try to avail of information about the customers' ability and willingness to pay (creditworthiness). They try to use this information to reduce the information asymmetry and gain competitive advantage by improving the odds of making the correct choice.

Traditional lending was based on the underwriters' judgmental assessment of prospective borrowers according to the 5Cs of credit: - *character* (of the applicant), *capacity* (to borrow), *capital*, *collateral,* and *conditions* (external factors). These assessments were based on the underwriter's experience and were thus essentially subjective decisions. In many instances such as credit card and credit for durable purchases, the number of loans is large and the value of each loan is small. In such high volume and low value credit operations, subjectively assessing each instance is not efficient. Credit scoring has transformed this into a transactional process where the customers' data is fed into statistical models to arrive at the creditworthiness.

Scoring refers to the use of mathematical techniques which can be used to rank order customers according to some real or perceived qualities so as to discriminate between them and ensure that the decision of extending credit is objective and leads to the best aggregate outcome. The objective of any credit scoring system is to attach a single value to every customer which indicates the desirability of the customer. Scores are usually represented as numbers or grades. It is the objective of credit scoring techniques to identify for all customers in one segment (say business/retail, retail home loans/auto loans/personal loans), unique and consistent scores for comparison and ordering.

Credit scoring was first used[1] in the 1960s to determine whether people applying for credit would repay the debt and was initially used only to identify accept/reject decisions. However in recent years, this has been extended to the complete management of credit (also called ***CRMC – Credit Risk Management Cycle***) and includes the measurement of the 4Rs of credit viz. risk, response, revenue, and retention. Raymond[1] summarizes the four areas of CRMC very succinctly in **Table 1**.

[1] Raymond A, 2007, *The Credit Scoring Toolkit,* Oxford University Press.

Table 1

Aspects of Consumer Behavior

Risk	Credit	Will he pay?
	Fraud	Will he cheat?
	Insurance	Will he claim?
Response	Response	Will he buy?
	Cross-sell	Will he buy others?
Retention	Churn	Will he use me and leave?
	Attrition	Will he leave?
Revenue	Utilization	Will he use it?
	Profit	Will it be worth it?

Credit scoring involves building a model of creditworthiness using historical data and policies. The model is used to arrive at an assessment of risk which may be enhanced with judgmental decision if required. Rules are then developed which can be used for accept/reject decisions as well as for designing the credit offering (pricing (interest rates), collection type (direct debit/pre-paid check, etc.), and collateral requirements).

There are multiple advantages which can be obtained if a bank or lending institution uses credit scoring models. The most obvious is the increase in aggregate accuracy resulting from using a model for assessment of risk to identify creditworthy individuals from a large pool of prospective customers. Also, the speed, consistency, objectivity, and responsiveness of the decision-making process are increased. Additionally, the reach of the lending institution is increased as the rules can be used by branch networks or electronic channels and operating costs are reduced if volumes are high and economies of scale are achieved.

The credit scoring approach however is not without problems. Development of a good database can be a challenging task and model development requires unique skills. Sustained effort may be required to manage the change in the organization’s decision making approach. One serious concern with respect to credit scoring is that the process is backward looking and assumes that the future will be similar to the past. Models have to be rebuilt if there are any structural changes.

It must not be presumed that credit scoring has only helped the lenders and that the borrowers are worse off. Since the approach is relatively easier to scale up, borrowers have more access to credit. With increased adoption of this approach by competitors in the industry, the consumer benefits from lower rates and more choice. There is also increased access to unsecured credit, that is, credit without any collateral. On the flip side, there are concerns about privacy since lenders have access to a large amount of data on the borrowers. Further, customers face the possibility of getting blacklisted if they have had a poor credit history. Additionally, credit scoring models are mostly correlational and do not try to identify causes and thus individual borrowers who are denied credit because their profile is similar to other borrowers with poor credit history even though they themselves may have both the ability and willingness to pay may feel discriminated.

CREDIT SCORING – WHAT LIES BENEATH?

Ajay had called the professor to his office for a discussion with his top management. He wanted to understand from him what they needed to do to be able to use credit scoring models for the business. The professor had some expertise in quantitative methods and models of consumer behavior. He tried to explain the underlying principles with minimum recourse to equations and statistical formulae. He explained:

> In credit repayments, there are two fundamental traits which are important – willingness to pay and ability to pay. Though they sound very similar, they are distinct in that an individual’s willingness to pay is likely to be an enduring aspect of character while ability to pay could vary

based on situational constraints. Unfortunately, standard credit scoring models do not do a great deal in trying to differentiate between the two. Yet, much can be done by considering the two together and asking what personal characteristics could be correlated with willingness and ability to pay. It is important to note that willingness and ability to pay are not observable. Consumer behavior is often influenced by such unobservable or latent variables. For example, attitude and motivation are unobservable but are important determinants of outcomes such as choice of brand, occupation, etc. In some contexts, the latent variable could be related to observable consumer characteristics; for example, willingness and ability to repay could be related to income, wealth, occupation, etc. and these relationships can be specified in a model of repayment behavior. Also, there could be some observable events that are manifest when the latent variable crosses some threshold. In the context of credit scoring, this event is one of default.

He then wrote on the whiteboard:

$$y^* \leq y_0^*\text{, then we have a default } Y = 1$$

Here, y^* is the latent variable for willingness and ability to pay. If the willingness and ability to pay is less than some threshold then the person will default otherwise he will pay. It can be shown formally that identifying the threshold value does not matter – which is a good thing as it is impossible to measure in our context – we don't even have any unit to measure the willingness and ability to pay!!!

Ajay interjected:

It would be very useful to consider separately the aspects of willingness and ability to pay. I may consider extending credit to someone with a lower ability to pay but I will not do so for one who has a low willingness to pay.

The professor replied:

Well, that separation would no doubt be useful. It would be more challenging to develop a scoring approach that explicitly separates these two aspects of repayment behavior and we can work on that later. For now, let us focus on standard credit scoring models – as they will indeed give you a lot of insight into the decision-making process. What data do you have?

Manish, who headed the Credit Management division said:

Well, we have a database of about 29,000 customers who were fixed tenure loans. Of these, about 20,000 of them have been late in their monthly repayments at least once (**Exhibit 1**). For each of them, we have several demographic details as well as the total number of days of delay in payments.

The professor said:

Excellent, we will split the data into two halves and try to estimate using one the probability that a person with a certain profile will default and use that model to see how well it works on the other set. Effectively, the objective of any credit scoring technique is to build a model that provides an estimate the probability of default for a given profile. The probability of default for new customers can be assessed using the above model. You then can use the same to decide if it will be suitable to extend credit to the customer. I understand from Ajay's brief that your typical loan interest rate is 12%. So. if you extend credit to a customer, you stand to gain 12% of the principal if the customer is good; and lose some or your entire principal if the customer is bad. On the other hand, if you do not give credit to a customer you end up not losing your principal if he were bad; and an opportunity loss of 12% if he were good. We can use this information on gains and losses to identify the probability of default at which it is most appropriate to classify customers as good and bad.

"So we use linear regression to find the probability of default?" asked Alok, a recent management graduate.

The professor replied:

> Well, you can, but strictly speaking you are modeling the probability of default and a linear model may well give you probabilities which are more than one or less than zero. Also, a linear regression would give you a linear probability model – the probability of default increases linearly with increase in independent variables. The basic linear regression model assumes that the expected value of a dependent variable conditional on independent variables is a weighted linear combination of the independent variables.
>
> $$y = bx + \epsilon,$$
>
> that is, the dependent variable y is expressed as a weighted (b is a row vector of weights) combination of independent variables (x is a column vector of independent variables) and a random error ε. In this context, y takes a value of 1 (default) or 0 (no default). In this accept/reject scenario, you can take a linear regression approach and interpret positive b coefficients as increasing the probability of default and negative ones as decreasing the probability of default. However, this will not work if you wish to make a multi-class classification, for e.g., good, OK, and bad customers. Even in the instance where the dependent variable is binary and the objective is to model the probabilities associated with these values, the linear regression approach is flawed since it can predict values outside the (0, 1) range. There are other technical reasons as to why the linear regression approach is not appropriate. You would need to tweak the model so that you can be sure your dependent variable always lies between 0 and 1 so that you can interpret the results clearly – a logistic regression would be more appropriate. There is also the possibility of using other techniques which do not attempt to find regression models – such techniques are called non-parametric models and examples are classification trees and neural networks. Their objective is identical – can we find some method of identifying new customers as good and bad or good/poor/bad as the instance may be?

Alok asked:

> How will the model change if we use three classes – good, OK, and bad customers as the intermediate class could help us in extending credit with differential interest rates? We can classify people who delayed till 90 days as OK customers because finally they did pay the amount on following up. Currently, we identify those with repayment overdue by 90 days and give their accounts to some bad debt collection firms at a sizeable discount, as it does not make financial sense to continue following up on the customer. Effectively on our P&L statement, we mark it as a bad-debt loss. Maybe, we could consider individuals whose cumulative delay is between 90 and 120 days and consider offering them the loan at a higher interest rate. We would surely not want to offer credit to those who are likely to delay repayment by more than 120 days.

Explained the professor:

> Well, the logistic regression model can only be used in a two-class classification model.
>
> However, there are models which are very similar to logistic regression – we should however use them with caution. One possible model is the ordered logit, which assumes that the same linear relationship between the explanatory variables and the latent variable holds in the three (in our case, but more generally k) classes. This assumption needs to be tested before the model can be used. If this assumption is found to be valid, the model can be used to identify individuals who are likely to belong to the OK or marginal class.

Continued the professor:

> However, it is possible that such an assumption may not be valid. Whether such an assumption is valid can be tested after estimating the parameters of the model. If it is not valid, we must choose a different model, called the multinomial logit, which again is similar to the logistic regression. Such a model inherently says that the characteristics of people in the three (in our case) classes are

> different. This model assumes that the odds of being in one class as against another are independent of anything in other classes and this assumption also needs to be tested in a similar way after the model estimation.

"What's your recommendation, Professor? Which model should we choose?" asked Ajay.

Opined the professor:

> I would say that we first concentrate on the two-class model – not only is it easier but it can also provide a lot of insight into the credit default story. Once that is firmed up and is in place in production you may decide to fine tune the model with a three-class classification using an ordered logit representation. If that is not appropriate, we will need to look at the multinomial logit representation.

BUILDING THE MODEL

At the next meeting, Ajay decided that Alok would work with the professor to identify and build a model which could recommend whether credit should be extended to a prospective customer or not. This would then be used by the sales team and also into the credit management teams to ensure a relatively less risky portfolio of customers that would increase profitability for Auto Finance Ltd.

Exhibit 1

Summary statistics for default rates by some categories

VARIABLE	CLASS	% POPULATION	% DEFAULTER
OVERALL	-	100	71.18
GENDER	MALE	92.33	65.52
	FEMALE	7.67	71.65
PROFESSION	PROFESSIONAL	85.16	71.37
	BUSINESS	14.84	70.07
EDUCATION	HS	23.18	73.95
	UNDERGRADUATE	72.79	70.88
	POST-GRADUATE	4.04	60.58
AGE	30 or LESS	32.12	72.55
	30-40	36.16	72.51
	40+	31.72	68.28
INCOME	LESS THAN 5000 INR	24.48	76.79
	BETWEEN 5000 and 8000 INR	29.01	71.69
	GREATER THAN 8000 INR	46.51	67.91
INCOME & EDUCATION	HS - LESS THAN 5000 INR	7.30	79.16
	HS - BETWEEN 5000 and 8000 INR	9.05	74.15
	HS - GREATER THAN 8000 INR	6.83	69.60
	UG - LESS THAN 5000 INR	16.58	76.12
	UG - BETWEEN 5000 and 8000 INR	21.24	71.24
	UG - GREATER THAN 8000 INR	34.96	68.18
	PG - LESS THAN 5000 INR	0.59	66.47
	PG - BETWEEN 5000 and 8000 INR	0.94	63.97
	PG - GREATER THAN 8000 INR	2.51	57.93
AGE (in years) & EDUCATION	HS - 30 OR LESS	7.06	76.42
	HS - 30-40	8.70	74.47
	HS - 40+	7.42	70.99
	UG - 30 OR LESS	23.66	72.24
	UG – 30-40	26.03	72.28
	UG - 40+	23.10	67.92
	PG - 30 OR LESS	1.41	58.23
	PG - 30-40	1.42	64.72
	PG - 40+	1.21	58.45
GENDER & PROFESSION	MALE, PROFESSIONAL	78.10	71.85
	MALE, BUSINESS	14.23	70.53
	FEMALE, PROFESSIONAL	7.05	59.32
	FEMALE, BUSINESS	0.61	66.06

Note:
% POPULATION indicates the number of customers in that class w.r.t. total number of customers, for e.g., 92.33% of customers is male.
% DEFAULTER indicates the percentage of defaulters in the class in question, for e.g., 71.65% of female customers are defaulters.

Exhibit 2

Metadata of columns for Exhibit 1

Column Name	Description	Comments
Agmt No	Agreement Number	
Contract Status	Contract Status	
Start_Date	Contract_Start_Date	
AGE	AGE of Borrower	
NOOFDEPE	No. of dependents	
MTHINCTH	Monthly Income in Thousands INR	
SALDATFR	When does the person receive salary?	If salary date fraction is 1, then person is receiving salary on 31st and will be paying the EMI on the same date. On the other hand, if they receive their salary on 15th of the month, salary date fraction is 0.5.
TENORYR	Tenor in Years	
DWNPMFR	Fraction of loan in down payment	
PROFBUS	Business = 1 Professional = 0	
QUALHSC	Flag to denote if highest qualification is HSC.	HSC is the 10 + 2 examination.
QUAL_PG	Flag to denote if highest qualification is post-graduation	Thus, undergraduates have both the QUALHSC and QUAL_PG columns as 0.
SEXCODE	Male = 1, Female = 0	
FULLPDC	Flag is set to 1 if the person has given post-dated checks in full	
FRICODE	Flag is set to 1 if the person owns a refrigerator	
WASHCODE	Flag is set to 1 if the person owns a washing machine	
Region	The region	Valid values are (not all may be on the data): AP1 (Andhra Pradesh Region 1) AP2 (Andhra Pradesh Region 2) Chennai KA1 (Karnataka Region 1) KA2 (Karnataka Region 2) KE2 (Kerala Region 2) TN1 (Tamil Nadu Region 1) TN2 (Tamil Nadu Region 2) Vellore (Vellore)

(Exhibit 2 Contd.)

Branch	Denotes the branch Auto Finance where loan is approved	Valid values are (not all may be on the data): Bangalore Chennai Coimbatore Ernakulam Kumbakonam Madurai Pondy Salem Tiruchy Tirunelveli Tirupathi Vellore Vijayawada Vizag
Defaulter Flag	1 if customer has delayed even once, 0 otherwise	
Defaulter Type	Flag to perform 3 class classification. 0: Never delayed (Good customer) 1: At least one delay. but always paid before 90 days (OK customer) 2: At least one delay (customer did not pay even after 90 days)	