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Consumer Credit Analysis

by Lawrence C. Galitz

The last twenty years has seen a revolution in consumer credit, with more and more people borrowing on an increasing scale. The explosion in demand for consumer credit could probably not have been met successfully without the development of better and more efficient techniques for handling a key decision. This decision - whether or not to lend money to a prospective borrower - underpins all credit operations. The well-being of a credit institution, and ultimately its survival, depends on the ability to make this fundamental lending decision correctly.

This article reviews the development and use of *credit scoring schemes,* the analytical tool that has been developed to deal with a large number of consumer credit applications quickly and cheaply. Without the advent of credit scoring schemes, it is unlikely that credit cards, revolving credit arrangements, and easy personal loans would be possible at the rates currently charged.

The article starts with a brief history of the evolution of credit scoring schemes, and then goes on to explain how schemes are set up and managed. A critique of their advantages and disadvantages follows, and the article concludes with some comments on the operations of these schemes, particularly in the light of current consumer protection legislation in the UK and the US.

Development of Credit Scoring Schemes

The most modern credit schemes are the highly sophisticated products of many years' statistical and mathematical analysis. However, the original idea for credit scoring came from more humble beginnings. In the first acknowledged article on the application of statistical techniques to consumer credit analysis, Durand (4) observed that borrowers with certain personal characteristics were more prone to default on their obligations than other borrowers not possessing that characteristic. For example, people in the US having a telephone are less likely to default than those without one.

This elementary idea was first transformed into the "risk index" technique, succinctly described by Smith (10). With the risk index technique, a list of personal characteristics is made, and for each one a separate "bad account probability" is computed using Bayes' theorem. This bad account probability is the probability of a borrower being bad given that he possesses that particular characteristic. To assess an applicant for a loan, his characteristics are noted, the bad account probabilities are looked up, and are summed to give an overall risk index. The higher the risk index, the more likely the applicant is to default, and a cut-off index level can be assigned, above which the risk is deemed to be too great.

The risk index technique was a considerable advance over earlier methods, but suffered from a fundamental drawback. When deriving the risk index for a loan applicant, the separate bad account probabilities are simply summed without regard to any possible interactions that may be present. In real life, the characteristics of individuals display complicated inter-relationships, and sub-optimal lending decisions will result if these are taken into account.

As an example, consider a lender faced with an applicant who is single, has only been two months in his present job, has moved house four times in the past three years, and changed his employer twice in the same period. Should the lender extend credit? With just the information presented here it is impossible to know whether the applicant is a drifter or a high-flyer, and a key characteristic missing is the applicant's type of job. If we are now told that the applicant is a seismologist working for an oil exploration company, we would feel somewhat differently about his creditworthiness than if he were a delivery driver.

The risk index technique, however, would simply aggregate the bad account probabilities for each of the applicant's characteristics. In most simple schemes, the adverse figures for characteristics like "single", "time in present address", and "time with present employers" would probably outweigh the good figure for "type of job - seismologist", and the applicant would be denied credit.

This drawback is typical of the univariate statistical technique, where variables - here, borrower characteristics - are considered singly. In order to cope with the multiple relationships that exist between variables, a multivariate statistical technique is necessary. During the 1950s, pioneering work was being carried out by applied statisticians to perfect a statistical technique called Multivariate Discriminant Analysis (MDA).

MDA can be used in applications where the population under analysis falls into a number of discrete, distinct and mutually exclusive groups. The independent variables associated with each observation can be analysed using MDA, and a set of formulae produced. With these formulae, a new observation can be classified into the particular group it most resembles.

A number of workers in the finance field, notably Myers and Forgy (6), saw the application of MDA to consumer credit. In this application there would be just two mutally exclusive groups: the group of good borrowers and the group of bad borrowers. The independent variables would be measurable personal characteristics of applicants, and the MDA technique would assign each new applicant into the group he or she most resembled. If the applicant were assigned to the good group, credit would be extended; if he or she were assigned to the bad group, then credit would be denied.

Consumer credit scoring in most guises is thus an application of the statistical technique MDA. In practice, schemes are dressed up and enhanced to suit the particular application, and are not simply the raw results taken straight from a computerised statistical analysis. Before moving on to study the principles underlying credit scoring, Fig. 1 provides a graphic illustration of the need for a multivariate analysis. The illustration is deliberately contrived to make its point, but nevertheless demonstrates the underlying principles of MDA.

The first two graphs plot the values of two characteristics, A and B, for ten labelled borrowers, five of whom are good (shown as "*"), the remaining five being bad (shown as "0").Taken separately, neither of the two characteristics is useful as a univariate predictor of creditworthiness, because good and bad borrowers are interspersed. The third graph plots both variables together, and immediately it can be seen that a diagonal line can be drawn which separates nearly all the good applicants from the bad ones. By plotting both variables simultaneously, a multivariate technique is being employed, and this now makes maximal use of the predictive powers of the observed variables.

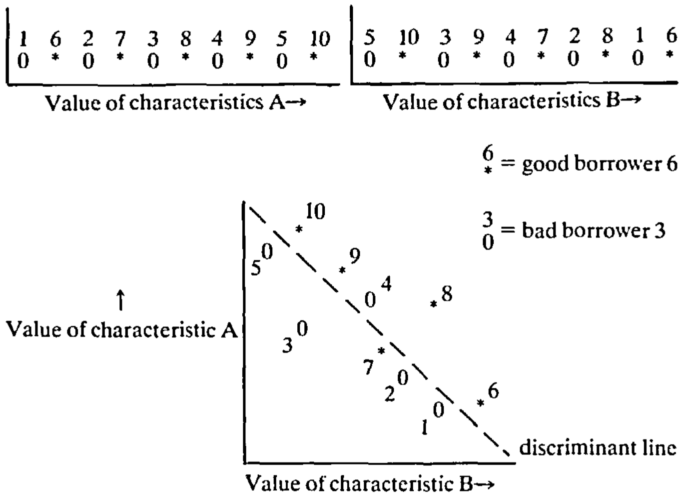

Fig. 1 The need to use multivariate statistics

When two independent variables are being used, the linear MDA technique can be illustrated clearly as the positioning of a straight line on the two-dimensional plot of observations so as to give maximal separation of the two groups. We can still picture this with three variables as the positioning of a plane in a three-dimensional spatial plot of the observations. Extension of the MDA technique to four and more variables is no different conceptually, and is the optimal positioning of an $(n-1)$ dimensional hyperplane in n-dimensional space to give maximal separation of the two groups. (If there were more than two groups, g-1 hyperplanes would be used to separate g groups.)

Principles and Assumptions

Consumer credit has two features that render it especially suitable for a systematic approach to the credit granting decision:

i) Consumer credit is characterised by a large number of relatively small value loans. Although margins are much higher than with commercial credit, the total profit from each loan is insufficient to justify a large expenditure on credit risk appraisal.

ii) There are a limited number of borrower characteristics that are relevant to the lending decision, and these are readily amenable to analysis. This contrasts with the problems of assessing the creditworthiness of companies, where there is a wide range of diverse characteristics, differing from company to company, all of which could conceivably be relevant to the lending decision.

Since there is a limited set of relevant information that can be gleaned from a new applicant, it seems logical to suppose that there is an objective way to assemble this information to distinguish optimally between potentially good and bad borrowers. The aim of a credit scoring scheme is to provide a lending institution with a system that is a satisfactory compromise between a theoretically "perfect" system, and one that is conveniently workable in practice.

Although there are several assumptions necessary from a statistical viewpoint (these are discussed later), there are just two key assumptions behind the use of credit scoring schemes from the financial and methodological viewpoint. They are:

i) The propensity of a borrower to repay a loan can be determined by measuring a number of personal and financial characteristics belonging to the borrower.

ii) The characteristics of a borrower remain stable over time. Measuring the borrower's characteristics *prior* to granting the loan will therefore give a reliable indication of his ability to repay *during* the course of the loan.

Traditional methods of consumer credit appraisal, while differing in their precise details, have in general all attempted to measure the "5C's" of credit: character, capacity, capital, collateral and conditions. The first three are probably the most important, for they measure the *willingness* to repay, and the *ability* to repay. (The final two deal with security for the lender in the case of default, and any special conditions that apply to the particular borrower or loan.)

Credit scoring schemes emulate this process by asking a series of questions that will eventually build up a profile of the borrower, this profile being aimed specifically at measuring these two concepts of willingness to repay, and ability to repay.

Most of the questions on a typical loan application form deal with the concept of *stability*. Questions like:

- length of time at current address?
- length of time with current employer?
- marital status?
- number of dependants?
- type of job?
- any other loan commitments, either currently or in the past?

all give an indication of the applicant's stability. The assumption here is that a stable borrower with some (but not too many) commitments is unlikely to default on the loan. Stability is therefore implicitly assumed to be a surrogate for willingness to repay.

Other questions address themselves to ability to repay:

- present salary?
- regular monthly outgoings?
- number of dependants?
- net disposable income?
- type of job?

although not all lenders ask this kind of question, surprisingly enough.

Already, one can see that the two concepts of willingness and ability to repay are interlinked, with some of the questions applying to both. This emphasises once again the need to adopt a total approach in gauging the creditworthiness of a prospective borrower.

Practical credit scoring schemes go a long way towards building a profile of the prospective borrower, even though the operation of schemes in practice seems deceptively simple. In practice, a standard form would be filled in by the applicant, and this is submitted for credit assessment. Every response made by the applicant is then given a numerical score obtained from a master table giving scores for each of the possible answers to each question. The applicant's total score is obtained by adding all the separate scores, and is compared to a cut-off score. If the applicant's score is above the cut-off, the loan is granted (subject to a status check to ensure that the applicant is who he says he is); if the score is below the cut-off, the loan is declined. Some schemes have two cut-off levels defining three regions: definite acceptance subject only to status check, referral for further manual assessment, and definite rejection.

Despite the simple working of such a system, a well constructed scheme can work well in distinguishing between good and bad risks, and can indeed take into account the complex inter-relationships between different characteristics of each applicant. The next few sections explain exactly how a credit scoring scheme is established and maintained.

Establishing a Credit Scoring Scheme

There are several distinct stages involved in establishing a credit scoring scheme. These are as follows:

i) Gather data. All objective credit scoring schemes are based on data from previous loan applicants. To create a scheme from scratch, the first step is to gather data from past loan applicants, about whom the outcome of the loan - good or bad - is known. This usually means extracting 5,000 to 10,000 cases from the files of the credit institution covering the past few years' experience. There must be a sufficient number of cases to ensure that the scheme produced is reliable, in the statistical sense; at the same time, the cases must be reasonably up to date to ensure that social and demographic changes to the population do not render the sample out of date.

Each case extracted from the files must be assigned to one of the two groups - good or bad. In practice, of course, there will be many loans which do not fall neatly into these two categories, but show various degrees of default. One solution is to classify all loans displaying any problems as bad, recognising that any loan requiring special attention is going to increase operational costs. Another solution is to create three or more groups labelled "good", "outright default", and "problematical". A third, and popular solution, is to classify all loans according to their ultimate profitability, taking all administrative and bad debt costs into account. All loans yielding a positive return, no matter how small, are labelled as good, while those making any loss are labelled as bad.

ii) Once the sample of data is collected, the sample is sub-divided into two portions, an "active" and a "hold-out" group. The reason for this is very important. If the variability of a statistical formula is tested on the same data that was used to derive the formula, the measured goodness of fit will be spuriously high when compared with its performance on other data. The accepted technique is to derive the statistical formula on one portion of the original data, the active sample, and to test it on a second portion of the data, the hold-out sample, which the system has not encountered before. The goodness of fit derived using this method is a better indicator of the performance of the formula when subjected to field data.

iii) Using the active sample, the data is processed by computer using either a standard discriminant analysis package, or one that has been tailored for the credit scoring application. In performing the analysis, the computer will first isolate, usually one by one, the variables that are the best predictors of creditworthiness. It will then produce the set of weights that take into account the relative importance of the variable, and the kind of units in which that variable is expressed.

The product of the analysis is a formula of the kind illustrated below:

$$
\begin{aligned}
S = \; & a_{11}V_{11} + a_{12}V_{12} + a_{13}V_{13} + \ldots \; a_{1m}V_{1m} \\
& + a_{21}V_{21} + a_{22}V_{22} + a_{23}V_{23} + \ldots + a_{2n}V_{2n} \\
& + a_{31}V_{31} + a_{32}V_{32} + a_{33}V_{33} + \ldots + a_{30}V_{30} \\
& + \ldots \\
& + a_{k1}V_{k1} + a_{k2}V_{k2} + a_{k3}V_{k3} + \ldots + a_{kz}V_{kz}
\end{aligned}
$$

where S is the applicant's total score

a_{ij} is the weighting given the j'th possible response to question i

V_{ij} is the standard value of the j'th possible response to question i (usually assigned the value unity)

k is the total number of questions on the form

m,n,o.. are the total number of possible responses to questions 1,2,3.. respectively

For operational convenience, the collection of a's are combined in a master credit score table like the one illustrated in Table 1. This shows, for example that a23 is 12, meaning that an applicant giving the third response as his answer to question 2 would get 12 points towards his total score.

iv) The product of the third phase is the preliminary table of credit scores. The efficacy of this can now be tested on the hold-out sample. If the scheme proves satisfactory by correctly classifying an acceptable number of applicants from the hold-out sample, the next step can be followed. Otherwise a careful analysis must be made to see why the scheme has failed. Often, failure at this stage can stem from application forms that provide insufficient information about the applicant. Occasionally, the type of market and applicant may simply be unsuitable for automated credit assessment, and this would be expected in lending schemes intended for people at either extreme of the financial spectrum.

v) Once the scoring scheme has been developed and verified, a cut-off score (or scores) must be chosen. The precise positioning of this depends on the number of factors which include: profit margin on good loans, efficiency of collection efforts on bad loans, volume of business, fixed costs, and accounting and tax conventions.

Table 2 shows how a cut-off score can be derived from management accounting information that is produced as a by-product of stages (iii) and (iv). The optimal cut-off is the one producing maximum profits, taking into account the relative volume of good and bad applicants in every credit score band, and the relative profit of good loans compared with bad ones.

An alternative method of deriving information is via a graphical analysis of the data as shown in Fig. 2. Fig. 2a shows the profile of scores for both good and bad applicants. Fig. 2b shows the volume of applicants accepted as a funcion of cut-off score; the lower the cut-off, the higher the number of acceptees. Fig. 2c graphs the profits from accepting good applicants together with the losses from accepting bad ones. Fig.

Table 1: Example of a set of fictitious credit scores

Q1 In which part of the country do you live?

RESPONSE	SCORE
Wales	5
Scotland	4
Northern Counties	5
Midlands	3
South East	0
South West	1
London	3

Q2 How long have you been working in your present job?

RESPONSE	SCORE
under six months	6
6-12 months	20
1-2 years	12
2-3 years	8
3-4 years	5
4-5 years	4
5-10 years	3
10-15 years	1
more than 15 years	0

Q3 What is your occupational status?

RESPONSE	SCORE
self-employed	19
unskilled	31
semi-skilled	22
skilled	16
supervisory	14
clerical	7
administrative	3
technical	7
professional	6
other	6
unpaid	13

Q4 What is your age?

RESPONSE	SCORE
under 25	17
25-30	18
30-35	21
35-40	23
40-45	24
45-50	18
50-55	15
55-60	6
60-65	0
over 65	8

Source: Batt and Fowkes (1972)

Table Two: Numerical Derivation of Optimal Cut-Off Score

Interval Statistics						Cumulative Statistics							
Score Interval	%age Goods	%age Bads	Good Count	Bad Count	Odds	Score Limit	%age Goods Accepted	%age Bads Accepted	Good Count	Bad Count	Profit from Goods	Losses from Bads	Total Profit
<60	7.0	31.5	633	295	2.1	0	100.0	100.0	9063	937	45315	93700	(48385)
60- 69	4.1	12.6	371	118	3.1	> 60	93.0	68.5	8430	642	42150	64200	(22050)
70- 79	5.6	12.3	511	115	4.4	> 70	88.9	55.9	8059	524	40295	52400	(12105)
80- 89	8.2	10.9	744	102	7.3	> 80	83.3	43.6	7548	409	37740	40900	(3160)
90- 99	10.7	9.9	968	93	10.4	> 90	75.1	32.7	6804	307	34020	30700	3320
100-109	11.1	7.0	1002	66	15.2	> 100	64.4	22.8	5836	214	29180	21400	7780
110-119	11.9	5.5	1079	52	20.7	> 110	53.3	15.8	4834	148	24170	14800	9370
120-129	11.3	4.3	1027	40	25.7	> 120	41.4	10.3	3755	96	18775	9600	9175
130-139	9.9	2.7	901	25	36.0	> 130	30.1	6.0	2728	56	13640	5600	8040
140-149	6.2	1.4	560	13	43.1	> 140	20.2	3.3	1827	31	9135	3100	6035
150-159	5.7	1.0	511	9	56.8	> 150	14.0	1.9	1267	18	6335	1800	4535
160-169	3.3	0.4	300	4	75.0	> 160	8.3	0.9	756	9	3780	900	2880
>170	5.0	0.5	456	5	91.2	> 170	0.5	0.5	456	5	2280	500	1780

[Optimal cut-off point under this scheme is 115 points]

Source: Figures extracted from H.J.M. Roy & E.M. Lewis, "Credit Scoring as a Management Tool", *Consumer Credit Leader,* November, 1981.

2d combines the two graphs of Fig. 2c to show the aggregate profit from the credit operation, again as a function of the cut-off score. This has a peak at the position of maximum profits, and this coincides with the optimal cut-off score.

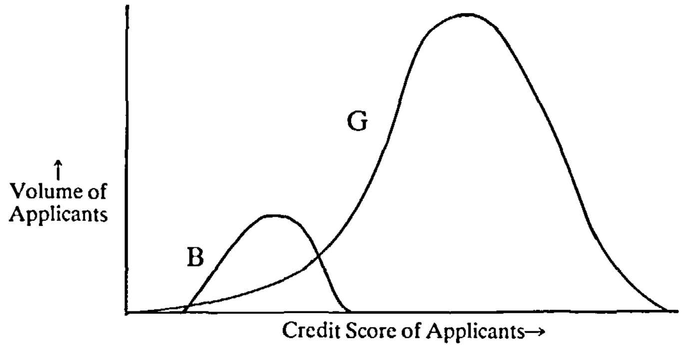

Fig. 2a Quality profile of applicants

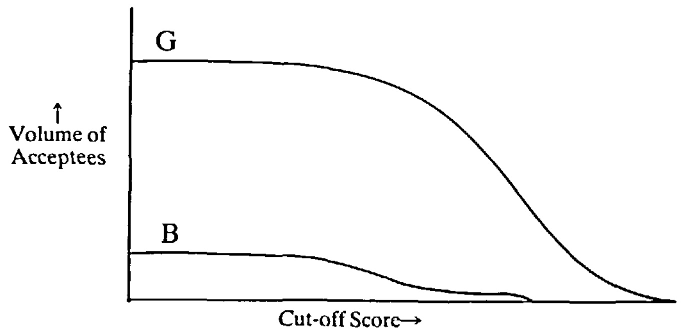

Fig. 2b Cumulative quality profile of business accepted

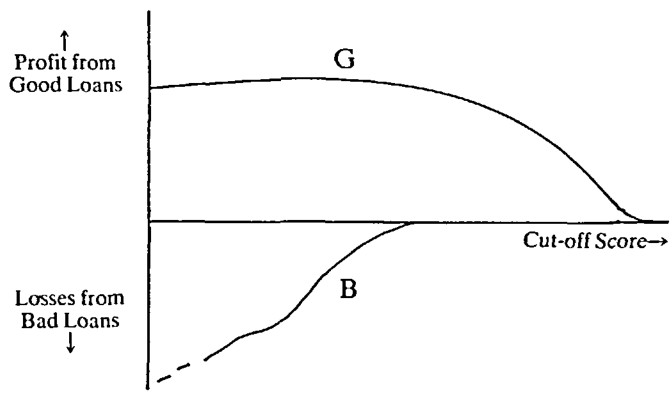

Fig. 2c Profits and losses from business accepted

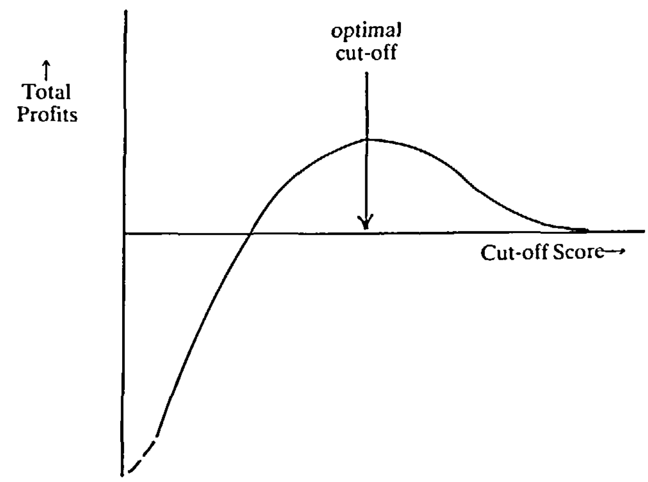

Fig. 2d Total profits from business accepted

vi) Once the optimal cut-off score has been determined, the scheme is ready for field trials, and can be operated alongside traditional methods of credit risk appraisal until the scheme has proved its worth. The automated credit scoring scheme can then replace the older method.

Alternative accounts of the processes involved in setting up a credit scoring system are given in Batt and Fowkes (1), Griffiths (5) and Roy (8).

Managing the Credit Scoring Scheme

Once the credit scoring scheme is in operation, maintenance is comparatively straightforward, and is far less of a task than setting the scheme up in the first place. There are two main features of operation that need attention periodically.

The first check is to ensure that the predictive ability of the scheme is not deteriorating. If the scheme accepts too many applicants who turn out to be bad, then losses will mount. Not immediately obvious are the profits foregone if the scheme rejects too many applicants who would have turned out good, and this is less easy to measure.

The next periodic check is to ensure that the aggregate profile of applicants being handled by the scheme is essentially the same as that used to develop the scheme in the first place. If it is found that there are substantial differences, the reasons need to be investigated and the scheme updated if necessary. This is because nearly all credit scoring schemes are "tuned" to suit a specific kind of loan and a particular kind of applicant; they will not perform optimally if either is changed.

If either of these checks reveals that the scheme requires attention, it can be updated using the data accumulated while the scheme is running. Frequently, this will already be held on computer, and it is therefore less onerous a procedure to revise the scheme that is the case when having to extract data manually from handwritten files.

Credit Scoring Schemes in Practice

Credit scoring has become very widespread in the US and UK as a result of several forces. First, the community of borrowers has become more mobile than in the past, and it is no longer the case that a bank manager or lending officer has a life-long personal knowledge of applicants for credit. Second, this lack of personal contact is compounded by the increasing tendency of credit institutions to centralise their operations remote from the bulk of their customers. Frequently the only contact between lender and borrower is by post. Third, the spiralling cost of labour and the decreasing cost of computerisation has led to a shift from manual to automated procedures in order to cut costs. This is especially necessary in a competitive environment where the lender offering the lowest rates is more likely to gain an increased market share.

Credit scoring can thus be seen at all levels of credit granting. At its simplest, it is now used frequently for small loans from bank and finance house branches. Instead of the manager being involved personally in every small loan, a clerk can now help the applicant fill the form, score it, and grant or deny credit depending upon the applicant's total score.Only unusual or borderline cases need be referred to the manager, who can therefore make more efficient use of his time. At the other extreme, the credit granting process can be automated in its entirety. This is seen with large national credit card companies, where application form details are keyed directly into the computer, which scores the form, and either issues a credit card or a standard rejection letter automatically. One advantage of virtually complete automation is the fact that the credit scoring formulae are held internally by the machine, and are not generally available to staff. A potential security hazard is thus obviated.

Credit scoring can also be applied in a wider sphere. At least one national mail order company in the UK has used credit scoring as a central part of its operation. New agents are scored in the usual way, but the novel part of the scheme is the process of scoring every agent every day, building in factors like size and frequency of new orders, and speed of payment. The system thus maintains a profile of every agent that is always completely up-to-date.

Advantages and Disadvantages of Credit Scoring Schemes

Adoption of credit scoring confers a great many advantages upon the user and, to a lesser extent, the consumer. Credit scoring is, however, not without its disadvantages. This section explores the balance between the benefits and drawbacks of credit scoring.

a) Advantages

These include the following:

i) Applicants can be assessed very quickly, and can therefore receive prompt answers to their credit applications.

ii) The credit scoring system is objective, being based solely upon past data on credit applicants and the outcome of their loans; subjective judgement and individual lending officer's biases are not part of the scheme.

iii) The system provides an optimal trade-off between acceptance of good and bad applicants at the cut-off point. At this point, the extra profit from accepting good applicants is just offset by the extra losses from accepting bad applicants; profit is maximised because marginal costs equal marginal revenues.

iv) The system provides more quantitative controls for management. If the credit institution wishes to improve the overall quality of borrower, or wishes to reduce the volume of loans for a period, it need only increase the cut-off score. Quantitative data is available from the system that will advise beforehand the precise level of new cut-off score to achieve the desired level of borrower quality or lending volume.

v) The scheme can be operated by staff with a far lower level of training than would be necessary for manual credit assessment; more experienced staff can concentrate on special or marginal applications.

vi) For a national lender, the scheme can provide information on the credit quality of broad geographic regions; advertising can be targetted more selectively.

b) Disadvantages

These include the following:

i) Credit scoring schemes cannot be started in a vacuum; they need a source of past experience in order to develop a new scheme. Similarly an existing credit scoring scheme cannot handle totally new circumstances immediately, but must wait until experience on the outcome of loans granted under the new circumstances filters through.

ii) There is a *pre-screening bias*. This arises because reliable credit scoring schemes can only be developed from data where the outcome of the loan is known. Thus, it can only work with cases where the credit institution had lent in the past, and which have already gone through the institution's existing credit scoring system. The first scoring developed is therefore technically invalid, because it is based on a stream of applicants who have already been screened, but it is intended to deal with the "through-the-door" population of applicants. Even when experience accumulates, the system will never know what would have happened to rejected applicants had they been extended credit. The implicit assumption is that these applicants would have defaulted, but there is never any confirmation of this. The credit scoring system works with imperfect information, and can therefore never be perfect.

Some commerical specialists in the design of credit scoring systems have developed a process of "augmentation" which attempts to fill in the missing information. While this is better than ignoring the pre-screening bias, it can never compensate for information which is simply not available.

iii) The applicant's score is derived from present and past borrower characteristics, and therefore relies on the past being a reliable indicator of the future. Few schemes, if any, attempt to project a borrower's creditworthiness into the future.

iv) The system cannot suggest new questions to ask applicants which may be more useful than the existing ones; it can only process the information that it is provided with.

v) The statistical assumptions underlying the use of MDA include:
- the population groups are mutually exclusive, exhaustive and defined
- all variables are drawn from a multivariate normal population
- the dispersion matrices of different groups are identical

In practice, *ex ante* creditworthiness is not a question of simply good or bad, black or white, but is a continuous variable. *Ex post* creditworthiness can be compartmentalised into profitable and not-profitable, but this is not a fundamental distinction, depending as it does on many factors other than the intrinsic creditworthiness of the borrower. For this reason, a statistical technique other than MDA may be more appropriate. The other two assumptions do not apply either, mainly as a result of using many nominal and zero-one variables instead of cardinal variables.

vi) Credit scoring usually treat all those with similar characteristics identically. Renting a home is invariably considered less creditworthy than owning a home, but some occupations (for example, the police, or a lighthouse keeper) provide rented accomodation as part of the job. Few schemes are able to couple characteristics to this level of detail, and would treat all tenants alike.

It may seem that this list of disadvantages condemns the use of credit scoring schemes. However, the first three points apply equally well to traditional systems, and the fourth is relatively minor. The fifth point can be countered by saying that, while not satisfying the strict assumptions underlying the MDA technique, credit scoring schemes developed using the MDA technique work well enough in practice, and so they may as well be used.

The combined effect of the various advantages of credit scoring schemes lowers the cost of running the credit operation, and ensures a more efficient allocation of credit resources to creditworthy applicants. The total cost of providing consumer credit is therefore lower and this benefits society as a whole. Credit scoring schemes do sometimes slip up, as the example in (vi) above shows, and this can deny credit to an otherwise creditworthy applicant. To cope with this, all schemes allow for careful manual reassessment of an application where the prospective borrower complains. This is probably more effective than traditional schemes where the prospective borrower has already been assessed manually when his application is first considered.

On balance, credit scoring schemes provide substantial benefits for lender and borrower alike, and it is therefore not surprising to see why they have become so widespread over the past two decades.

Credit Scoring and Discrimination

On both sides of the Atlantic, we have witnessed the growth of the consumer lobby, and the introduction of successive waves of consumer protection legislation. In the US it is now illegal to discriminate on the grounds of sex, colour, race, religion, marital status or receipt of public assistance benefits(2). Some of these are banned outright (sex and marital status), while the remainder may be used if they can be shown to be "demonstrably and statistically sound". In the UK, discrimination on the grounds of race, religion, colour or sex is now banned by statute.

This creates problems for lenders because the very nature of their task is discrimination - in this context the ability to discriminate between potentially good and potentially bad lending risks. However, this does not imply discrimination in the pejorative sense. It is simply not in the interests of a lender to discriminate on irrational or irrelevant grounds because such action would result in the loss of profits. It only makes sense for the lender to discriminate on the basis of known facts and relevant criteria. The lender can achieve his objective if he lends to all applicants who are creditworthy, and denies credit to all those who are not.

Creditworthiness is not a quality that can be measured like other personal characteristics such as height and weight; it can only be measured indirectly using surrogates. The problem arises when surrogates like marital status, which can be demonstrated to have a high statistical correlation with creditworthiness, are banned from use. The ability of the lender to make sound decisions is then impaired. In this example, loans will be extended to a higher proportion of non-married people (single, separated, widowed or divorced) than would otherwise be liked, and the incidence of bad debts will probably increase. Equally well, some married people on the borderline of creditworthiness, who would otherwise be granted credit with the help of the positive attribute of marriage, may now be denied credit. In both cases, credit resources are not being channelled optimally and society as well as individuals lose out.

Discrimination in lending is a complex subject because it appears in many guises. The example above shows what happens when anti-discrimination legislation is passed to prevent the selection of individuals on the basis of certain criteria. The intention of this legislation is to prevent the different treatment of individuals who are basically similar except for differences in some seemingly irrelevant characteristic like marital status. Unfortulately, where these criteria are, in fact, relevant measures of creditworthiness, some borrowers unjustly lose out. Discrimination also can occur when individuals are treated similarly because they have seemingly identical characteristics when, in fact, they require different treatment. An example using the ownership/tenancy characteristics was mentioned earlier in this article; the problem also appears when considering lending to women. How is the lender to distinguish between the "career" woman and the one who plans shortly to leave her job and raise a family? The whole subject of discrimination is an involved one, and we can only raise a few points within the scope of this article. The topics are discussed further in the articles by Brandel(2), Chandler and Ewert(3), Peterson(7), and in chapter six of Russell's book(9).

The use of credit scoring does highlight some difficult and thorny social problems, but it has not created problems that did not exist before.

Credit Scoring and the Future

Despite the problems that credit schemes have encountered during their brief history, they have now established themselves as a successful and practical operations research technique applied to finance. As people become more sophisticated in the management of their personal finances, they will make increasing use of credit, probably on a more selective basis. Credit rating systems will grow in importance, and will more accurately reflect individual's true creditworthiness, perhaps on a daily or even a realtime basis. There are, of course, dangers involved when computer-based systems contain large amounts of personal data. However, the benefits and convenience that will accrue through their use, as already demonstrated by international credit cards and on-line cash dispensers today, should more than outweigh the potential drawbacks.

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