CHAPTER
18

Advanced Models: Scoring Systems[1]

LEARNING OBJECTIVES *The material in this chapter prepares students to:*

- Understand the value and prevalence of scoring systems.
- Complete a score card.
- Create a scoring system.
- Understand on an intuitive level which mathematical techniques can assist in scoring systems.

If you ever applied for a car loan, your application was probably "scored" by your bank or your car dealer's financial group. Home mortgage applications, infant health evaluation, customer call lists, and much more all rely on fairly recently developed methods known as "scoring systems."

Scoring systems are used in a variety of industries for a variety of purposes, including the following:

- Attracting customers
- Selecting which customers to take when too many want your service
- Allocation of resources (employee time) among customers
- Data reduction

Why haven't you heard much about these systems? It will become clear, in this chapter, why these systems are rarely discussed by corporations and are almost always considered as extremely confidential. Well-designed scoring systems can cut costs and make your decision making much more consistent.

History of Scoring

The earliest scoring systems were developed in 1941 by David Durand for use by finance houses. A few more applications were reported through the 1960s, but the

1. This chapter is adapted from Metters, R. (2000). Models for Customer Selection. In Fitzsimmons and Fitzsimmons (eds.), *New Service Development*. Sage Publications, Thousand Oaks, CA. Reprinted by permission of Sage Publications, Inc.

use of scoring systems was not widespread and the few that were created were strictly used in the credit scoring arena. Customer solicitation and resource allocation scoring came later. In those early days, some people believed that "it is unlikely that credit scoring systems will be become widely adopted . . . [and] will be relegated to the academic world" (Harter, 1974).

The 1970s, however, saw an explosion of the use of scoring, especially credit scoring. Three factors converged to increase their use: advances in computing ability; the explosion of credit card use, which required a cheaper method of loan approval than for existing loans; and the passage of the Equal Credit Opportunity Act (ECOA) and Regulation B. The ECOA and Reg B prohibited discrimination in granting credit. Further, a legal case of discrimination could be shown statistically; that is, an individual did not have to show that a specific loan officer at a bank personally discriminated against him or her. Instead, showing statistically that a bank rejected the loan applications of a disproportionate number of minorities made a prima facie case of discrimination. The regulations stated that a defense for these charges is to make loans through a "statistically sound, empirically based" system of granting credit—or credit scoring. Scoring is now so widespread in retail banking and finance houses for approval for credit cards and auto loans that it would be unusual to find a U.S. retail bank that does not use scoring for this purpose.

Today creating scoring systems is a significant service business in itself. An acknowledged market leader in the field is The Fair, Isaac Companies in San Rafael, California, but the list would also include the European firms George Wilkinson Associates, Scorex Ltd. and CCN Systems. Some corporations, such as Merrill Lynch and GECC, however, developed their systems internally, as did several large commercial banks.

Scoring in Use Today

Many large corporations depend heavily on cold-call sales by their associates to generate new business. New stockbrokers, for example, must pick up the phone to identify new clients. The key question, of course, is whom to call. Lists of individuals identified by net worth or income are not available, but brokers clearly should only call potentially profitable customers who can afford to buy large amounts of financial products. As the characters in a movie about salesmen, *Glengarry Glen Ross*, would say, "It's the leads. The whole thing is the leads."

Merrill Lynch's solution was to get the leads by developing a scoring system. Their system infers customer profitability by comparing demographic data of potential customers with demographics from its current customer base. Merrill Lynch uses this procedure to develop the calling lists for their brokers (Labe, 1994).

In similar applications, direct mail and telephone solicitation companies that use customer selection, or scoring models, report a 50% reduction in acquisition costs while facing only a small reduction in customer response. Specifically, the direct mail marketer Fingerhut mails about 340 million catalogs per year to 7 million customers, which means that some customers would get up to 120 catalogs per year. Applying scoring methods cut their revenue a small portion, but cut mailing costs significantly, increasing profitability by $3.5 million a year (Campbell et al., 2001).

When Durand (1941) began his work, loan officers used their considerable judgment acquired over many years to evaluate a customer's loan application and decide whether to underwrite the loan. Today, most banks select loan recipients by assigning points to demographic characteristics. A clerk adds up the points and a

SERVICE OPERATIONS MANAGEMENT PRACTICES

Scoring Systems Change an Industry

In the "old days," banks were the natural place to get a home mortgage. An applicant filled out a lengthy application and waited a month or more to find out whether she was approved. It was thought that the individual expertise of knowledgeable lenders was necessary to evaluate credit risks.

Now, credit scoring is prevalent in the process. Instead of requiring human judgment for loan approval, information is typed into a computer and a proprietary scoring system used nationwide accesses credit reports and gives the applicant a numerical score. These scores—called *automated underwriting* in the industry—offer such a reliable measure of credit risk that knowledgeable bankers are no longer necessary. The reliability of credit scoring led to large-scale selling of home loans; that is, someone who brought in the customer for a loan could sell that loan to another investor, based largely on the credit score. Making loans no longer requires a vault full of cash.

These two factors combined to change the industry of home mortgages. Now, mortgage brokers, who are not bank employees but who qualify prospective homeowners for mortgages for a living, are becoming the dominant force in the industry. According to a UBS Warburg analyst, traditional banks are becoming "a shrinking and increasingly irrelevant" part of the industry.

Source: Barta (2001).

loan is made if the point score exceeds a predetermined amount. Replacing or augmenting judgmental loan underwriting based on experience with customer selection by scoring reduced bad loan ratios by one-third. Banks could also cut costs through replacing higher-priced loan officers with lower-cost clerks. A third benefit comes from decisions that are more consistent. Under the traditional system—usually called a judgmental system because it relies on human judgment—an applicant can be turned down by one lender and accepted by another within the same bank.

The use of scoring models, instead of a more judgmental system, allowed GE Capital Corporation (GECC) to allocate resources more effectively. GECC faces the daunting task of collecting $1 billion of delinquent consumer loans each year. In order of decreasing expense to GECC, it can collect on a loan by initiating legal procedures, having a collector personally call, have a computer call the customer with a taped telephone message, send the customer a letter indicating he is delinquent, or do nothing and let the regular billing process inform the customer he did not make a payment. Scoring models allow GECC to target the appropriate method to a customer based on a computerized analysis of the customers' payment behavior. The scoring model allowed GECC to reduce loan losses by 9%, reduce costs of collection, and increase customer goodwill (Makuch et al., 1992).

These models are designed to replace individual expert judgment with a cheaper and more reliable method. Even when a score augments rather than replaces individual judgment, it is still useful in reducing the amount of communication and data needed.

An APGAR score was probably your first personal encounter with a scoring system. Every time an infant is born, one of the first tasks of hospital personnel is to determine its APGAR score. The APGAR score is helpful in describing a general level of health at a given moment by mentioning a single number rather than a long list of vital signs and movements of fingers and toes.

The use of scoring systems is widespread today. In Table 18.1 you can see the diverse use of scoring systems in industry. Although the creation of scoring models is itself a significant service industry, the nature of the scoring process lends itself to use in service firms rather than in manufacturing organizations. Scoring is most efficient and effective when evaluating large numbers of potential customers where statistical analysis can benefit from large sample sizes. The users of scoring systems,

TABLE 18.1: *Partial List of Industries that Use Scoring*

- Auto Insurance
  - Customer acceptance
- Brokerages
  - Customer solicitation
- Education
  - Nonneed (merit) based scholarships in colleges
  - Improving "yield" (percentage of admitted students who choose to enroll)
- Health Care
  - APGAR (score for infant health)
  - APACHE (score for emergency medicine)
  - Craniofacial Index (predicts sleep apnea)
- Mass Mail/Telemarketing and Retailers
  - Target market identification (e.g., high incomes)
  - Selecting solicitation targets (response rate prediction)
- Merchant Banks
  - Corporate bankruptcy prediction
- Parole Boards
  - Paroling prisoners
- Retail Banks and Finance Houses (e.g., Household Finance Corp.)
  - Loan approval for
    - credit cards
    - auto loans
    - home loans
    - small business loans
  - Solicitation for products (e.g., pre-approved loans)
  - Credit limit settings and extensions
  - Prediction of credit usage
  - Prediction of customer retention
  - Collection of bad debts
- Tax Collection
  - IRS income tax audits
- Utility Companies
  - Credit line establishment
  - Length of service provision

Source: Adapted from Metters (2000), Models for Customer Selection, in Fitzsimmons and Fitzsimmons (eds.), *New Service Development*. Sage Publications, Thousand Oaks, CA, p. 293.

therefore, tend to be service firms with individuals as customers, rather than manufacturers whose customers are other companies.

Scoring Methodologies and Implementation

Building a scoring system is simple in theory, but can be capricious and complex to implement. The five basic steps to building one are as follows:

1. Divide customers into two groups: "good" and "bad."
2. Determine risk score cut-off level.
3. Identify the variables associated with good/bad results.
4. Develop a numerical scorecard.
5. Score your customers.

Each of these steps is described in the following subsections.

Separating "Good" and "Bad" Customers

Because of the managerial decisions involved—often "accept" or "reject"—the outcomes of current customers (or "dependent variable") is usually either 0 or 1. For example, in scoring for credit acceptance, the two groups of data are those customers who paid off a loan and those who defaulted on a loan. The decision to make on prospective customers is accept or reject, or 0 or 1. Two categories are the most common number in practice, but more than two are possible with some techniques.

Numerical Risk Score

Step 2 also involves breaking current customer data into two categories. A profitability level is associated with each group, and an acceptable risk level is established. For example, consider a retailer planning a direct mail campaign. Combining mailing, printing, and other costs, we might assign a loss of \$0.45 for a piece of mail that lands in the trash and an average profit of \$20 for a direct mail customer who responds. If mail is sent to 100 potential customers that all have a 1% chance of responding, the profitability of the mailing will be 99 × (–\$0.45) + 1 × \$20 = –\$24.55, or a net loss. However, if mail is sent to 100 potential customers that all have a 3% chance of responding, the profitability of the mailing will be 97 × (–\$0.45) + 3 × \$20 = \$16.35, or a net profit. The equation which brings profits and losses into balance can be derived algebraically by considering the following rule: Approve a mailing until

$$\text{Expected Profit} = \text{Expected Loss from marginal account.}$$

Working through the algebra (not included here), we derive the following relationship: Probability threshold = loss from a bad account/(loss from a bad account + gain from a good account). Or, in this case 2.2% = 0.45/(0.45 + 20).

The mass mailer, therefore, doesn't want to waste money mailing to those who won't respond, but will send mail to anyone with a 2.2% or greater chance of responding.

The mass mailer, therefore, would like to find some assessment of the "odds" of responding and send mailings to homes only with larger odds than 2.2%.

Variables Associated with Good/Bad Results

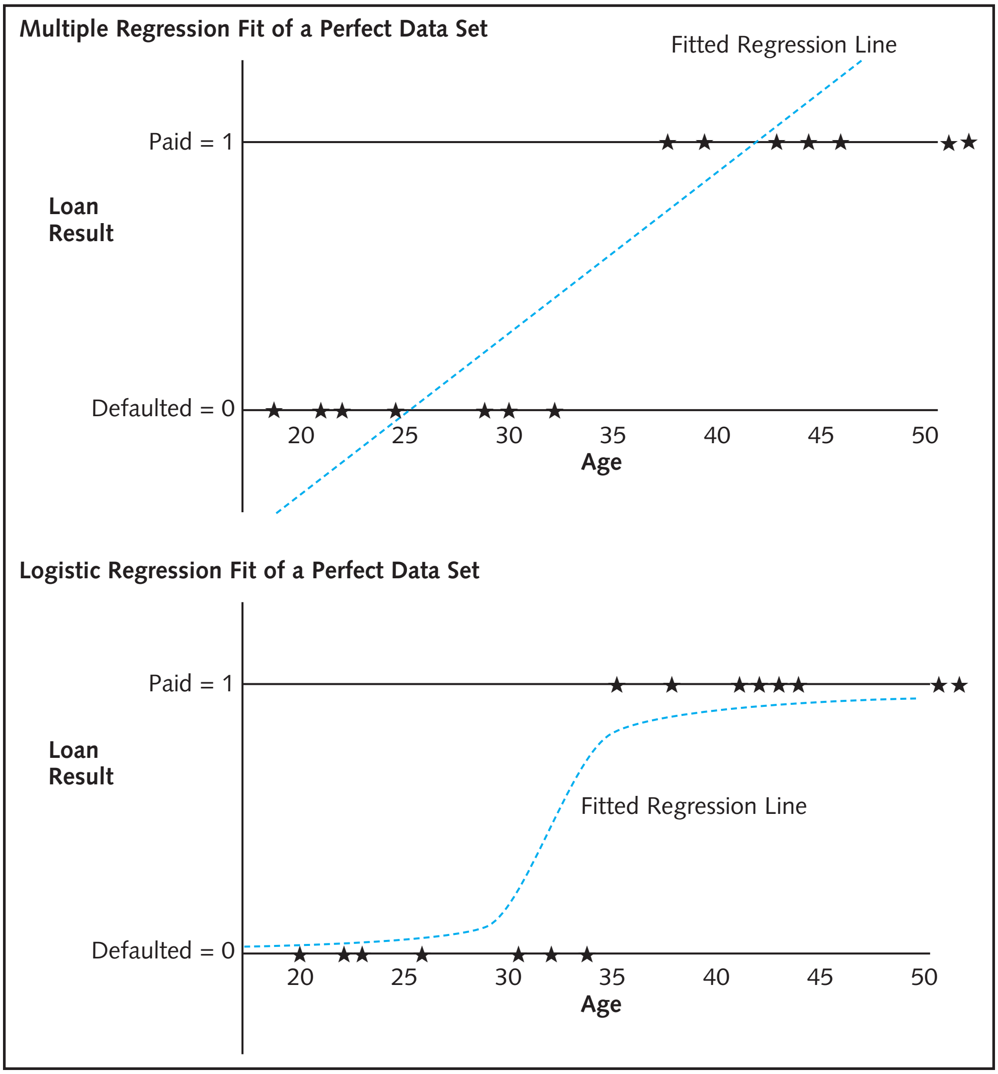
Clearly, we would like some method to assess the odds of a response for each potential customer. The general idea of scoring is to generate those odds by establishing statistical relationships based on a company's own customer base. That is, extrapolate the known outcomes of the company's current customers to demographic information of potential customers.

The difficult task is to assess the odds of customers who have conflicting demographic information. For example, a company may realize that their best customers are 35- to 50-year-old married female homeowners with incomes between $35,000 and $50,000. But given a choice of a 30-year-old married female homeowner with a $30,000 income and a 40-year-old single female renter with an income of $45,000, who should be chosen? Scoring models assign specific points to each demographic characteristic that make such trade-offs easy to see.

Developing a Numerical Scorecard

Unfortunately, the most widely practiced statistical technique, multiple regression, is insufficient for this task. Consider the "perfect" data set in Figure 18.1. Everyone under 35 years of age defaulted on loans and all those over 35 years paid their loans.

FIGURE 18.1: *Fitting Categorical Data*



The results of standard regression appear in the first drawing, where the traditional straight line minimizing mean squared error is depicted. The numerical result of a regression on these data is the equation $Y = -0.87 + 0.04 \times \text{age}$. An Excel file with this equation is on the Student CD. This regression yields the odds of a 20-year-old paying back a loan to be negative (–0.07) and the odds of a 50-year-old to be far greater than 100% (1.13). Neither of these results makes sense in our general understanding of probabilities.

Access your Student CD now for an Excel file of this equation.

Mathematical techniques useful in scoring include discriminant analysis, decision trees, and, less commonly, logistic regression, integer programming, and neural networks.[2] For a visual example of how these techniques work, the trend line for logistic regression is shown on the second graph of Figure 18.1. Instead of fitting a straight line to data, logistic regression fits the function:

$$\text{score} = \ln[\text{odds}/(1 - \text{odds})] \tag{18.1}$$

Using the logarithm (ln) function sets bounds on the score at 0 and 1. Using some algebra on equation (18.1),

$$\text{odds} = e^{\text{score}}/(e^{\text{score}} + 1) \tag{18.2}$$

where $e \cong 2.718$.

This calculation gives an analyst more realistic results. For example, for the perfect data represented in Figure 18.1, the curve hugs the data nearly precisely. The fitted function is $\text{score} = -376.092 + 10.901 \times \text{age}$. An SPSS file with this equation is on the Student CD. So, a 34-year-old has a 0.4% chance of a good account, a $34\frac{1}{2}$-year-old a 49.8% chance, and a 35-year-old has a 99.6% chance of being a good account.

Access your Student CD now for an SPSS file of this equation.

At a greater level of complexity, some models in practice are "nested." First an analysis is performed on the data set as a whole. Then a subset of the data close to the cutoff value is analyzed again. The reason for this second level of analysis is that the variable values for cases in either extreme may distort the scores of the marginal cases.

The way in which a scoring system is implemented affects the method of data analysis. In some firms, a score is calculated directly from a computer system without any human intervention. In others, however, a score is calculated manually using a physical score card like the one depicted in Figure 18.2.

Assume the monetary relationship between good and bad accounts were such that a probability of a good account needed to be 90% for approval. Then the cutoff score of $\ln[.9/(1 - .9)] = 2.20$ would be appropriate. In the example of Figure 18.2, the fitted equation uses application data such as home ownership and age. The actual score card used by the clerk mimics the fitted equation by starting each applicant with 80 points (the constant for the fitted equation) and assigning points for each characteristic, such as adding 50 points for those age 56 or older and subtracting 20 points for those between 26 and 35 years. Those who score more than 220 points are approved.

Note that the point scores within a category are additive, not multiplicative. For example, a 56-year-old and a 75-year-old both get 50 points because they are in the same category: age $\geq$ 56. The reason for an additive score card is its simplicity: A clerk merely checks boxes and adds a column of numbers. The implication for an additive card on the modeling process is that each of the *independent* variables must

2. See Rosenberg and Gleit (1994) for a detailed review of the mathematics behind these techniques in the context of credit scoring.

FIGURE 18.2: *Score Card Fitted by Logistic Regression*

Required Odds of a Good Customer: 90%

Cutoff score for logistic regression: Ln [0.9/(1 – 0.9)] = 2.20

Fitted equation

.80 + 1.30 Own Home	– .05 Other	
+ .85 S + C w/bank	– .05 Checking	
+ .50 (56 + yrs. old)	+ .15 (36–55)	– .20 (<25)
+ .33 Retired	+ .25 Manager	– .26 Laborer
+ .53 (10 + yrs. job)	+ .25 (5–10 yrs.)	

For convenience, multiply all values by 100.

Everyone starts with 80 points.*

Residence	Own home + 130		Other –5
Bank Accounts	Savings and checking with bank + 85		Checking only –5
Age	56+ years + 50	36–55 years + 15	26–35 years – 20
Work	Retired + 33	Manager + 25	Laborer – 26
Time on Job	10 years or more + 53	5–10 years on job + 25	

Accept if score greater than 220.

*Score in blue for a renter (–5), with savings and checking with the bank (+ 85), 62 years old (+ 50), and retired (+ 33). Everyone starts with 80 points so the total point score is 243.

also be coded as (0,1); that is, each explanatory variable must be transformed by segmentation. For example, one continuous variable such as income could be transformed into three variables such as income less than \$40,000, income between \$40,000 and \$80,000, and income greater than \$80,000, each with a 0 or 1 as data, as in Table 18.2. This segmentation creates some modeling difficulties, however, because no general rules guide for the number of segments or for the location of segment borders (should it be age ≥ 56 or age ≥ 57?). Finding the best break points and

TABLE 18.2: *Variable Parsing in an Additive Scorecard: Example of an Income Variable*

Actual Variable Value	Variables Used in Scorecard 0 to 25	26 to 80	81 and above
20	1	0	0
33	0	1	0
110	0	0	1
19	1	0	0
55	0	1	0
86	0	0	1
147	0	0	1

the proper number of categories is an art as well as a science. In general, though, an easy way to determine whether one break point is better than another is whether the overall fit of the model is improved.

Accept/Solicit/Apply Resources to Customers over the Set Score

Use of credit scoring scorecards is straightforward. Those who score above the predetermined score pass this test and those who don't either are declined credit or some type of exception analysis is required by a lender to move an application forward.

Other types of scorecards, however, can proceed differently. Thus far the examples shown focused on scoring demographic factors, such as age and zip code. Another important and related technique is called *behavioral scoring* and relates to the performance of a customer within a system. The most common example of behavioral scoring is in the collection of delinquent loans. Earlier, we gave an example from GECC, but the practice is becoming fairly common.

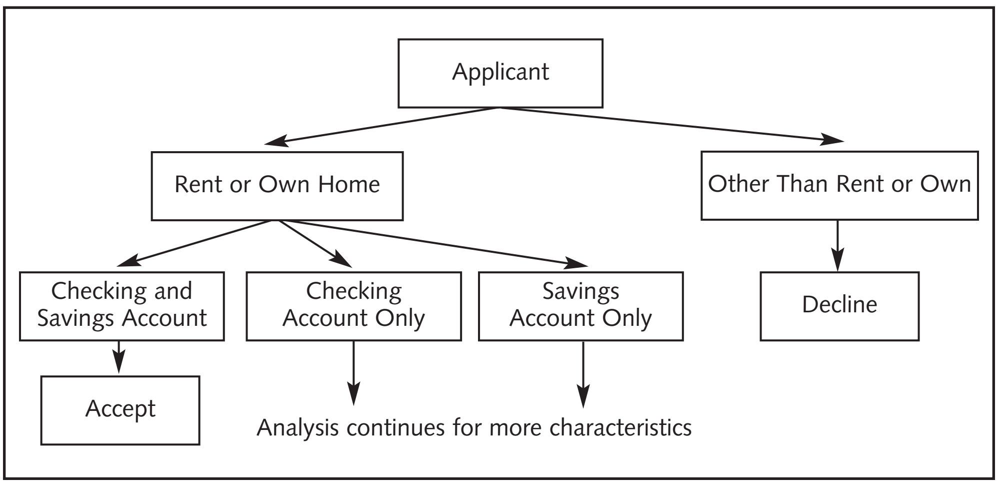
As related earlier, a number of approaches are available for collecting on a delinquent loan. Prior to using a scoring system, many companies used a standard practice of sending a letter first, then a telephone call at a designated interval. A scoring system, however, scores behavior such as how recently the debtor made a payment, how much was paid, the percentage of minimum payments made, previous history of missed payments, and other factors to determine a method to minimize the combined costs of collection and bad debt.

Figure 18.3 illustrates another type of score card often seen in practice. This type of card stems from the decision tree or recursive partitioning approach. Operationally, the applicant's demographic characteristics are followed down the tree until either an acceptance or rejection ends a branch.

Problems with Scoring Systems

Scoring systems clearly mark an improvement over judgmental systems in both fairness and cost, but they are not a panacea. Problems with scoring systems can be divided into two categories: methodology problems and implementation problems.

FIGURE 18.3: *Decision Tree Example of a Score Card*



Methodological Problems

The "good" versus "bad" account may make intuitive sense for a Yes or No decision, but from a managerial standpoint this coding neglects the underlying differentials in customer profitability. In the context of line-of-credit approval, for example, one account can lose $100,000 and another only $10, yet they are all coded 0. Conversely, a line-of-credit that is never used (and, therefore, does not generate revenue) and a highly profitable line of credit are both coded 1. An ideal system would take profitability into account, rather than just a simple Yes or No. The odds of defaulting or paying off are different from the odds of being a very profitable or unprofitable customer. One can imagine a more complex scoring system that does not merely make Yes or No decisions, but gives everyone credit with a corresponding interest rate that reflects his or her risk and profitability.

Scoring systems also suffer from "screening bias." As stated by Rosenberg and Gleit (1994, p. 596): "The best credit system would grant credit to every applicant during some time period to gain credit information for the entire population." Unfortunately, many scoring systems rely on the currently installed customer base. If some groups are systematically excluded prior to implementing a scoring system, therefore, the system contains no data by which to judge them.

A third methodological problem focuses on the life of a scoring system. Any scoring system is only valid for as long as the customer base remains the same. Entering or targeting new markets or changes in mores or economic conditions may render a scoring system useless. A general rule of thumb is that a scoring system needs to be recalibrated every three to five years.

Myers and Forgy's (1963) research provides a good example of the shelf-life problem. They found that the presence of a telephone in a household was an indicator of someone who would pay debts. In their study, 8% of households did not have a telephone, and those households were an astounding 10 times more likely to default than households with a telephone. Today, only an extremely small number of U.S. citizens do not have telephones, which means the telephone criterion should no longer apply. Yet, in the mid-1980s some banks still awarded score card points for the presence of a phone number on an application.

Implementation Problems

Scoring systems face some criticism for how they are used and because employees and shrewd customers can subvert them if they are not implemented properly.

Fairness

Despite the fact that credit scoring systems arose partly to equalize access to credit, some minorities feel that scoring systems lock them out of obtaining credit. The Federal Reserve says the data agree with them, but industry disputes that finding. It is believed that minority applicants face a higher hurdle, because of the manual override procedure at many banks. It is alleged that most banks allow a lender to ask for an exception to an insufficient score for marginal customers, but some feel that those exceptions strongly favor nonminority customers.

As another example, many universities are concerned about their "yield," or the percentage of students who are accepted by the school who eventually enroll. University rating organizations like *U.S. News & World Report* use the yield statistic to rank schools, so a better yield may increase a school's ranking. Firms like Noel-Levitz and George Dehne & Associates create scoring systems for schools to improve their yield. For many schools, however, increasing yield means turning down excellent students and admitting inferior ones. A student with a 1600 SAT score, a 4.0 GPA, and who is captain of the basketball team may be denied admission to a school, because the school's yield model indicates that such a student would be unlikely to enroll. Denying that student admission increases both the yield rate and rejection rate, both measures that are used to rate universities.

Impersonal Decision Making

By their nature, scoring systems are impersonal, which can lead both to comic errors and customer irritation. In a celebrated case, a Federal Reserve governor with a spotless credit record was denied a Toys "R" Us credit card, because the scoring system negatively weighted a large number of recent inquiries on his credit report. Scoring cannot evaluate factors such as political ramifications and extenuating circumstances effectively. Consequently, some manual review often is desirable.

Face Validity

Scoring systems often find patterns in the data that appear nonsensical or are difficult to explain. For example, auto insurance companies sometimes base the decision to insure motorists on their credit records, rather than on their driving records.

Misuse/Nonuse of Scoring Cards

When implementing scoring systems care must be taken with both employees and potential customers. If scoring system parameters become public knowledge, potential customers can "game" a system. It became known, for example, that Johns Hopkins University was less likely to offer students scholarships if they came to an on-campus interview. Scoring systems revealed that if students were interested enough to go to an on-campus interview, a scholarship, instead of a loan, would not be further inducement to enroll, whereas a scholarship changed the enrollment probabilities more drastically for students who showed less initial interest.

Consider, also, that banks never check certain information provided by credit card applicants, yet it contributes to a score. If potential customers discovered that, they could inflate their scores.

Employees can help applicants increase their scores by "guiding" them through an application process. If the incentives for employees are based on the number of accepted applications that they generate, employees have a stake in making their clients look as good as possible.

A solution to these problems is to hide the scorecard from employees and customers. For example, the national U.S. scoring system for mortgage loan approval is a proprietary system of the system developer, The Fair, Isaac Companies. Mortgage brokers are unaware of the point totals given to specific customer attributes, thereby making it difficult for mortgage brokers to take unfair advantage of the system. Similarly, the IRS has steadfastly refused to divulge the algorithm that decides which tax returns get audited.

Scoring also has human resource implications. Employees often see scoring systems as a denigration of their experience and talent and a threat to their jobs. The idea that their years of experience can be replaced by a score card is not generally embraced enthusiastically. Consequently, when first replacing or augmenting a judgmental system with a scoring system, efforts must not focus on employee reduction. To do so would invite subtle sabotage through incorrect scoring or to a more open refusal to use the system.

Summary

Scoring techniques are applied in a wide variety of industries and for a number of different functional uses, including customer selection, customer solicitation, and resource allocation among customers. The construction of scoring systems is a service industry in itself, and because of the nature of the techniques, they are much more useful to service providers than to manufacturers.

The use of scoring systems is likely to increase. A large drawback to their use in the past was the need to collect data, which meant entering data from customer files manually into a computer system. Today, most customer data is held electronically, so the costs of implementing scoring systems continue to decline. Further, as scoring contributes more to financial successes, those companies that do not use scoring systems will be at a considerable competitive disadvantage. Although scoring systems do suffer from some methodological problems, proper implementation of a well-designed scoring system can contribute to building and maintaining a successful business.

Review Questions

1. Give some examples of industries that could or do currently use scoring systems and discuss how this practice impacts their business profitability, their strategic focus, and their costs.
2. What are some ethical considerations in using scoring systems?
3. Name some industries that should be particularly sensitive to charges of discrimination in the use of scoring systems. Discuss ways to lessen these occurrences and strategies for coping with such charges.
4. Why can't standard regression models be used for many scoring models?

Problems

18.1. Based on the following information, decide whether the applicant scores sufficiently to receive an account.

- Average profit for a successful account is \$500
- Average loss for an unsuccessful account is \$4,500
- A fitted equation is as follows

$$0.75 + 0.82\,(25 < \text{age} < 45) + 1.10\,(\text{age} > 45)$$
$$-0.35(\text{time on job} < 2 \text{ years}) + 1.22(\text{time on job} > 5 \text{ years})$$

Applicant: 37 years old, 7 years at the current job

Determine the applicant score and the appropriate cutoff point.

18.2. Based on the following information, decide whether this person should be the target of a telephone solicitation.

- Average profit for a successful call is \$50
- Average loss for an unsuccessful call is \$1
- A fitted equation is as follows

$$-0.15 + 0.28(25 < \text{age} < 45) + 0.10(\text{age} > 45)$$
$$-0.35(\text{time on job} < 2 \text{ years}) + 0.22(\text{time on job} > 5 \text{ years})$$

Applicant: 37 years old, 7 years at the current job

Determine the applicant score and the appropriate cutoff point.

TABLE 18.5: *Data for Problem 18.5*

Observation	Age	Good (1), Bad (0)
1	25	1
2	31	1
3	34	0
4	37	1
5	45	1
6	46	1
7	49	1
8	52	0
9	53	0
10	55	1
11	59	0
12	63	0
13	66	0
14	70	0

18.3. What are the odds of a customer being a good one if the output score from a logistic regression model is 1.55? Use equation (18.2).

18.4. What are the odds of a customer being a good one if the output score from a logistic regression model is 0.89? Use equation (18.2).

Access your Student CD now for data for Problem 18.5.

18.5. For the data in Table 18.5, find the relationship of age to being a "good" account by traditional linear regression and by logistic regression. What is the probability of a 26-year-old being a good account measured by traditional regression and by logistic regression?

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CASE STUDY

MBA Savings and Loan[3]

It was a Friday afternoon in late April when the officers' meeting of the Goizueta Business School Savings and Loan officially convened. In attendance were the two outgoing second-year officers, Julee Carucci and Jim King II, and the two incoming first-year officers, Nancy Toland and Leonard Beren.

"If we're going to expand over to Divinity and Law, our manual processes are going to be too much work. We're going to need more efficient systems," said Julee. "We can start with the loan approval process. Poring over loan applications is time consuming, but worse than the time is the aggravation. People take it so personally when they're turned down. Anyway, we have enough data now to use a scoring system for loan approval. With a scoring system we can shift the credit approval responsibility away from the loan officer."

"Agreed," noted Jim. "A scoring system would also cut out a lot of training time every year for the outgoing lenders. Nothing against you two first-years, but I certainly don't have a lot of enthusiasm for training right now."

The MBA Lending Program

In 2000 a supplemental loan program was established for the MBAs. Unlike loan funds set up for education expenses, this program loaned money for nontraditional student needs such as vacations, moving expenses, and furniture purchases. The program was initiated by the dean as an auxiliary student service. The dean believed it provided another way to improve the relationship between the school and its students. The original funding was derived from the school endowment. Loans could be made for up to $5,000. Repayment terms varied from three months to three years, depending on circumstances. The program was intended to be profitable, with the proceeds retained by the student association.

The program was administered each year by two second-year students who were elected by their classmates the year prior. These students had the responsibility of credit approval, setting interest rates and payment schedules, payment processing, and bad debt collection.

By 2003 the MBA lending program had become an accepted institution. More than 700 loans were made, and the program showed a small profit. Due to the program success, the program would be expanded to lend monies to students in the nearby schools of law and divinity in the next academic year. It was expected that demand would be as strong in those schools as in Goizueta.

3. *Source:* The subject of this case is fictitious. Data for the cases is contained on the CD that accompanies this text.

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Credit Approval

Students applied for loans in a fashion similar to that of bank loans. A formal application was submitted (Table 18.3) and the application was reviewed by both officers. A credit report was also obtained for each potential borrower (Figure 18.4). The application was sent to the admissions office for comparison to admissions data, but the rest of the information provided by the applicant was accepted at face value and with no attempt at corroboration.

Both officers had to agree on granting the loan for credit to be extended. Approximately 80% of the students who applied received credit. For about 85% of the applications both lenders agree on acceptance or rejection. "Most applications are fairly clear," said Jim. "There are obvious good risks and bad risks." Of the remaining 15%, after lengthy debate, about half were eventually accepted.

"The ones we turn down seem to react in three ways," said Julee. "About half seem to get mad about it. Occasionally there are heated words, but usually it's more of a seething look they get. Some folks just sort of withdraw. They feel like a credit denial is a scarlet letter or something. Then there are those who shrug it off, probably because they never expected to get it in the first place. We do get some outlandish requests." The MBA lending program officers replaced the Operations Management professors as the favorite target at the annual dunk tank.

The methods used for credit approval were a combination of experience, lessons learned from the past officers, and hunches. At base, though, Julee and Jim differed in their views on credit approval. Julee felt that character, more than financial status,

TABLE 18.3: *Credit Application Information*

Demographic Data	Financial Data
Name	Annual salary at last job
Social security number	Checking account number
Date of birth	Savings account number
Current address	Total indebtedness
Home phone	Other credit accounts
Previous address	
Time at last address	
Nearest relative	
Previous employer ("none" if coming directly from undergraduate institution)	
Time on last job ("none" if coming directly from undergraduate institution)	
Undergraduate institution	
GPA at undergraduate institution	

CASE STUDY

FIGURE 18.4: *Credit Report*

______________________________ ______________________________
Applicant Name Spouse Name

______________________________ ______________________________
Present Address Years at address

______________________________ ______________________________
Previous Address Years at address

______________________________ ______________________________
Social Security Number Spouse Social Security Number

____
Employer Position Hire Date

_______/_____________________ $ _____________________
Verified/Date Income

____
Spouse Employer Position Hire Date

_______/_____________________ $ _____________________
Verified/Date Income

Public Records: ☐ None Learned ☐ See Below

Court records checked for judgments, foreclosures, tax liens, and bankruptcies through:

☐ Direct Search/Repositories ☐ Repositories

Trade Name Account Number	Opened/ Updated	High Credit	Balance Owing	Terms	Mths. Rev.	Past Due	Account Status 30/ 60/ 90
Bank of America I139272	06/97 03/02	5000	00	—	48	00	Rev 00/000/00

Inquiries: no inquiries in the past 90 days

CODES:

Acct. Desg.:	Account Designation of I for Individual or J for Joint.
Opened/Updated:	Date account opened and date latest information posted to account.
High Credit:	Credit limit for revolving debt or initial loan amount for installment loans. "R-1" indicates loan type and worst payment. "R" indicates a revolving loan versus I for installment. "1" indicates that there has never been a late payment. "2" would indicate a previous 30-day late payment, etc.
Terms:	Number of months on an installment loan.
Mths. Rev.:	Number of months account has been reported to credit bureau.
Past Due:	Current past due status.
Account Status:	Total number of times account has been 30, 60, 90 days late.
Inquiries:	Number of times account has been checked recently. An indicator of other credit being applied for simultaneously.

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was a better guarantee of loan repayment. She balanced the information on the credit application with a personal judgment of the applicant's integrity. Jim, however, relied solely on the information contained in the credit application.

Both were somewhat critical of the other's selection criteria. "Jim is always muttering, 'If we would lend only to Harvard grads we wouldn't have any collection problems.' He went to Harvard himself and he's got a real hang-up about where someone went for undergrad," said Julee as she rolled her eyes. "That's not just me, that's a few years of experience talking," replied Jim. "The folks who taught us told us that the people who went to the better schools tended to pay up. Besides, you seem to have a fondness for people with high undergrad GPAs."

The amount of credit extended was not always a fixed amount. Applicants were encouraged to make one application for a total credit limit rather than apply many times for specific funds. The amount of credit limit given was more a source of contention than the approval process. Both Julee and Jim accorded a higher limit to those applicants they felt were better risks. Due to their difference in perceived risk between applicants they rarely agreed initially on a total credit limit.

Bad Debt Collection

A nagging problem of the MBA lending program was bad debts. Approximately 10% of the borrowers did not repay the entire amount of their loan and another 10% repaid only after litigation was started. It was estimated that a successful account contributed an average of $200 to the MBA association, but a bad account cost an average of $700. Because debt collection was carried out by the officers, the methods of collection varied significantly depending on the particular officer. Julee and Jim each handled half the accounts.

Julee believed that early and vigorous actions deterred bad debts. If a borrower was 10 days late with a payment, Julee sent a strongly worded letter to the borrower. If the delinquency persisted another week, she telephoned to remind the borrower. If the borrower continued to be a month late and was still in school, a large red poster was placed high on the wall above the student mailboxes with the word "Deadbeat" and the offender's name in 200 point type. For borrowers not still in school, Julee would advise relatives and employers of the payment delinquency. Julee would continue to contact the borrower by phone and letter up to 180 days delinquency. At this point the loan was declared in default and, on principal, Julee would instigate legal proceedings to recover the loan no matter the amount in default. For borrowers still in school and more than a few months late, she was known to greet them in the hall as "the defendant."

Jim found the collection part of the job distasteful and his style differed considerably from Julee's. He would send out a written "reminder" notice for someone a

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TABLE 18.4: *Variables for Data Collection*

Variable	Description
AGE	Age in years
SALARY	Annual pay at last job
T_JOB	Time on last job in years
U_G	B.A. at most competitive school = 1; competitive school = 2; less competitive = 3 (school ratings according to Barron's)
GPA	GPA at undergraduate school
SAVE	Presence of savings account (0,1) variable
CR_NONE	No credit on file: 1, otherwise: 0
CR_GOOD	No worse than three 60-day lates on credit report (0,1) variable
CR_BAD	Worse than one 90-day late on credit report (0,1) variable

month or two months late. Once every few months he would dedicate the afternoon to calling borrowers more than a few months late.

Although Jim found Julee's methods uncivilized, her default rate was the lowest the program had seen in its five year history: 13% compared to Jim's 22%.

Credit Approval Training

Despite Jim's reluctance, a credit approval training session was scheduled for a few days later. The same five completed applications (data on disk) that Julee and Jim had been taught from the prior year were brought along. Further, Jim brought along the data on 500 past borrowers to help Nancy and Leonard start the credit scoring process. (Variables collected are described in Table 18.4. Data are on the accompanying CD in both Excel and SPSS format.)

Access your Student CD now for data in Excel worksheet form.

Questions:

1. Create a scorecard derived from the data on disk, score each of the five test applicants, and designate whether to accept or reject.
2. Is the MBA lending program a good idea?
3. How should credit limits be established?
4. How should bad debts be collected? How do various collection methods correspond to the overall strategic issues of running a school?