Arbeitsbericht Nr. 16/2001
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New Issues in Credit Scoring Application
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1 Introduction

With the continuous development and changing in the credit industry, credit products play a more and more important role in the economy. Economic globalization and newly emerging service channels like Internet provide possibilities for the customers to seek and choose their creditors without regional and time limitations. Because of this trend, creditor must now be ready, willing and able to extend credit to business in other countries around the world. The credit granting institutions are therefore facing a more drastic worldwide competition. The increased demand and increased competition resulting from new economic environment offer new opportunities but also put forward new demands on credit granting institutions. They pursue urgently cost savings and efficiencies. This has led institutions to expend the role of technology in their credit management process.

As the volume of credits increases, the volume of insolvent credits presents an increasing trend too. In German, the number of insolvencies filed by companies in 2000 increased by 6.6% from 26476 (the number in 1999) to 28235, and in 2001 the number continued to increase at an even higher rate to by 14.3% to 32278. The number of consumer insolvencies was relatively low in 1999 because a settlement out of court has to be attempted before a bankruptcy petition can be filed. In 2000, however, that number already tripled to a total of about 10,500 cases. In the first half of 2001, the number climbed by another 50% to 6,807 cases (cf. DeSt02). Both financial institutions and regulation institutions pay much more attention to the increasing credit and the risks associated with it. Financial institutions need to invest considerable resources to develop efficient and sophisticated tools to evaluate and control credit risks.

Credit scoring model technology can supply the basic part of a decision support system that generates effective credit decisions to serve the new requirements. The credit scoring models involve the techniques that are called today the techniques of data mining. Classification methods are the most commonly used data mining techniques that are applied in the domain of credit scoring to predict the risk level of credit takers. Statistical and machine learning methods, such as linear and logistic regression, linear programming, and decision trees, neural networks, etc. have been used for developing credit scoring systems.

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1 As a result of the entry into force of the new Insolvency Law on 1 January 1999, the comparability of the data with those for previous years is limited. In particular the establishment of a simplified insolvency procedure enabling private individuals to free themselves of their debts through insolvency proceedings made the total number of insolvencies rise. The data on insolvencies filed by companies are almost comparable (cf. DeSt02).
This paper introduces background knowledge of credit scoring. Its origins, development, and current problems are reviewed. The emphasis is not the scoring techniques but the application issues.

Chapter 2 covers the definition of credit scoring. Meanwhile, its relationship with credit rating is discussed. It is introduced in chapter 3 that facing new economic environment how the application areas of scoring methods are expanded. The promotions of the application of credit scoring and its application limitations are also discussed. After that we go deep into some application issues faced by credit scoring model builders in Chapter 4: what information is considered in scoring models, how the sample for scoring models is selected. Summarization and conclusions are given finally.
2 Definition of credit scoring

2.1 Deductive and empirical credit scoring

There are two kinds of credit evaluations during the credit process in banks and other credit granting institutions. One is to make decisions on new credit applications, the other is to supervise the existing credit takers. The credit granting institutions will not give credit to everybody who asks for it. They must assess the risk level of a new applicant, and decides whether credits will be granted. After a credit is granted, it is supervised during the life of the credit. A credit granting institution wants to evaluate the credit standing of its credit takers, in order to early detect who could be defaulter in the future.

In both situations (screening credit request and evaluating the performance of existing debtors), the probability that a credit will become default during the life of the credit will be estimated and the credit customers will be classified into different risk levels according to the estimated default probabilities. This process is also known as risk assessment or credit classification.

Credit scoring method is used as one of risk assessment methods. The original meaning in "credit scoring" is that a score is assigned to each credit customer. The score is used as an indication of the risk level of the credit customers. By comparing the score with a cut-off-score, which is the division point between "risk" and "non-risk" customers, the customers are divided into two classes.

According to the way in which the scores are obtained, credit scoring methods can be divided into deductive credit scoring and empirical credit scoring (cf. Müll96, P. 50):

A deductive credit scoring system awards points (weights) to particular relevant attributes of the credit customers. The weighted value of attributes are aggregated (usually added) to a total score. The relevant attributes and their weights are determined by the credit decision makers based on their experiences. The classification of the customers is consistent and objective according to the scores, but the scores are often based on the subjective experiences. Therefore, a deductive scoring system is only quasi-objective (cf. Krus99, P. 3). Although deductive scoring systems are still being utilized by some credit grantors today (cf. SiDe89, P. 455-458), they are losing the effectiveness due to their inherent shortcomings².

Empirical credit scoring system is implemented with various scoring models techniques. The selection of the relevant attributes and the calculation of the scores are based on the past

² Some shortcomings of deductive credit scoring are summarized by Keyzlar/Wagner (cf. KeWa96, P. 25-29).
credit data with the help of some scoring algorithms. Credit scoring in this paper denotes always empirical credit scoring\(^3\).

The fundament of empirical credit scoring can be formally described as follows:

Suppose we have information related to the creditworthiness of a customer in the form as follows:

Independent variables: \(X_i, i=1,\ldots, k\), which are also known as predictors.

We assign a dependent variable to the customer, which is the measure of the default probability of this customer:

Dependent variable: \(Y\).

In other words, credit scoring is the process to give a value to \(Y\) according to \(X\) for every customer.

\(Y\) is made empirically by scoring models, which are also called scorecards or classifiers. A creditor selects a random sample of its past debtors and analyzes it by building scoring models to identify characteristics that relate to creditworthiness. Comparing to past debtors with similar profiles whose credit performances are known, scoring models can predict the future performances of current customers.

The basic empirical credit scoring process can be described as two steps (cf. Figure 2.1/1):

Step 1: Model building

Step 2: Model using: predicting

The input data are historical data on \(n\) credit customers with known risk classes. The input data is in the form of:

1. Independent variables: \(X_{ij}, i=1,\ldots, n; j=1,\ldots, k\).
2. Dependent variable: \(Y_i, i=1,\ldots, n\).

\(X_{ij}\) is the value of the \(j\)\(^{th}\) predictor of the \(i\)\(^{th}\) customer. \(Y_i\) is the known risk level of the \(i\)\(^{th}\) customer, which may have two values (e.g. default and non-default) or multiple values (e.g. current, delinquent, bankruptcy, and charge-off four risk levels).

Scoring model is generated from the input data through various approaches and is applied to new customers to predict their unknown value of dependent variable \(Y\). A credit decision is taken based on this prediction of \(Y\). The prediction can either be the risk classes with two or

\(^3\) The term of "credit scoring" are not used uniformly in the literature. For example, "credit scoring" is used only for deductive scoring methods and are discussed distinctly from the new model approaches such as neural networks (cf. Krus99, P.67). In this paper, credit scoring techniques denote all of the empirical scoring methods, including traditional statistical methods as well as new methods in machine learning, and neural networks areas; the application area of credit scoring covers both private customers and business customers.
Definition of credit scoring

multiple categorical values or a continuous score (e.g. from 0 to 100 percent, which represents the probabilities to become default). If Y has continuous values, a credit decision is made by comparing the value of Y with a suitable threshold.

The rationality of empirical scoring model is that the risk level of a new credit customer can be predicted based on the similar credit customers in the past, whose subsequent results have been known.

![Figure 2.1/1: The process of empirical credit scoring](image)

The process of empirical credit scoring is essentially a classification decision\(^4\). The task of classification decision simply refers to the process of assigning things into one of multiple categories or classes based on their properties. To make this classification decision, classification models are constructed inductively by generalizing from numerous recorded prior specific examples, i.e., by discovering and analyzing patterns found in prior solved cases (cf. Quin93, P. 1). The models then can be used to decide the class membership of an unknown case.

The problem of classification in this sense has been studied extensively by the statisticians as well as the database and artificial intelligence communities. In statistics the classification problem is sometimes called the prediction problem, and in the field of machine learning it is often called supervised concept learning (cf. WeKu91, P. 4), since it adjusts the parameters of learning model according to the known value of output, i.e., the learning process is guided by the provided examples. It is distinguished from unsupervised learning or clustering in which the classes are inferred from the data\(^5\).

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\(^4\) The problem of classification in the context of a quantitative class label is referred to as the regression modeling problem (cf. AgYu99, P. 19). For simplicity and unity, in this paper we term all modeling techniques as classification techniques.

\(^5\) The construction of a classification model from a set of data for which the true classes are known has also been variously termed as pattern recognition, discrimination. Other authors, especially those in the community of machine learning, have referred to these techniques as inductive learning, empirical learning, or case-based reasoning (cf. Mich94, P. 1).
2.2 Credit scoring and credit rating

Credit rating method is addressed also to credit risk management, which classifies credit risks into grades. In order to make a clear-cut definition of what credit scoring means in this paper, credit rating is introduced and compared with credit scoring. In the following, two kinds of credit rating are discussed: Ratings published by public credit agencies and established by internal rating systems of credit granting institutions (cf. Table 2.2/1).

<table>
<thead>
<tr>
<th></th>
<th>Credit scoring</th>
<th>Credit rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producers</td>
<td>credit granting institution, vendors of scoring model</td>
<td>Internal rating system</td>
</tr>
<tr>
<td>Objects of evaluation</td>
<td>consumer credit and small business credit within institutions</td>
<td>business loans and institutional loans within institutions</td>
</tr>
<tr>
<td>Outcomes</td>
<td>scores or classes</td>
<td>number of grades (different across institutions)</td>
</tr>
<tr>
<td>Users</td>
<td>institution itself</td>
<td>institution itself, supervisor</td>
</tr>
<tr>
<td>Main purposes</td>
<td>routine credit decisions</td>
<td>credit risk management and control</td>
</tr>
<tr>
<td>Methods</td>
<td>empirical models</td>
<td>experts’ judgment, models</td>
</tr>
<tr>
<td>Objective or subjective</td>
<td>mainly objective</td>
<td>half objective, half subjective</td>
</tr>
</tbody>
</table>

Table 2.2/1: Differences of credit scoring and credit rating

1. Producers of ratings/scores and objects of evaluations:
   - Credit scoring models may be built by the credit granting institutions themselves or provided by commercial scoring model vendors. No matter in which way, scoring models are used by the institutions to their credit products, which usually are consumer credits or small business credits, such as credit cards issued by a credit card company, credit insurance provided by an insurance company. These credit products are often offered on a large scale and every credit may concern relative small amount of money.
   - Internal rating systems of banks or other credit granting institutions typically produce ratings only for their own business and institutional loans, not for consumer loans or other assets (cf. TrCa98, P. 897).
   - Credit rating agencies produce many kinds of ratings. The objects of the rating given by international credit agencies may include: the better-known companies worldwide; sovereigns and sub-national entities, bonds of all types, various government
obligations, commercial paper and medium-term notes, and asset-backed securities and other issues. (cf. Chor00, P. 39).

2. Outcomes and Usage

- Credit scoring is often used by a credit granting institution for routine credit decision making, such as screening credit applications by reaching a two choices decision: 'approval' or 'rejection', routinely reviewing the exiting debtors to predict the possible future defaulters.

- Ratings established by an internal rating system are the summary indicator of the risk for individual credit exposures. Credit rating systems rate each individual credit exposure into one of some grades (the number of grades varies across institutions), each of which is associated with a degree of risk of loss due to borrower's failing to pay as promised (cf. Basel00, P. 2). Although ratings provide reference to assist credit decision making, it is usually not used only for routine decision making, but also for other various purposes in the credit risk management and control, such as portfolio monitoring and management reporting, analysis of the adequacy of loan loss reserves or capital, profitability and loan pricing analysis, and as inputs to formal portfolio risk management models (cf. TrCa98, P. 897).

- Each independent rating agency has its own scale of grades and follows its own system, but the grades of these ratings converge towards a common frame of reference (cf. Table 2.2/2).

The independent credit ratings given by rating agencies play an important role in the financial market, since they can give independent opinion to the increasing number of worldwide entities to be rated which involve new and diverse cultural and accounting criteria with which financial institutions are not necessarily familiar. They establish a common language allowing everybody in business, industry and finance using the same frame of reference (cf. Chor00, P. 37). Their ratings are used by lenders, investors and regulators to exercise vigilance and to fine-tune their opinions.

- The ratings published by credit agencies, include the credit information contained in their report are also useful information resources for scoring models. Banks also refer themselves to public ratings when establishing their own internal rating systems.
### Table 2.2/2: Long-term senior debt rating by Moody's, S&P and Fitch IBCA (cf. Chor00, P. 43, cf. Putn01, P. 1111)

<table>
<thead>
<tr>
<th>S&amp;P and Fitch IBCA</th>
<th>Moody's</th>
<th>Credit message</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>Aaa</td>
<td>Very high quality</td>
</tr>
<tr>
<td>AA+</td>
<td>Aa1</td>
<td></td>
</tr>
<tr>
<td>AA</td>
<td>Aa2</td>
<td>High quality</td>
</tr>
<tr>
<td>AA-</td>
<td>Aa3</td>
<td></td>
</tr>
<tr>
<td>A+</td>
<td>A1</td>
<td>Good payment ability</td>
</tr>
<tr>
<td>A</td>
<td>A2</td>
<td></td>
</tr>
<tr>
<td>A-</td>
<td>A3</td>
<td></td>
</tr>
<tr>
<td>BBB+</td>
<td>Baa1</td>
<td>Adequate payment ability</td>
</tr>
<tr>
<td>BBB</td>
<td>Baa2</td>
<td></td>
</tr>
<tr>
<td>BBB-</td>
<td>Baa3</td>
<td></td>
</tr>
<tr>
<td>BB+</td>
<td>Ba1</td>
<td>Uncertainty in payment ability</td>
</tr>
<tr>
<td>BB</td>
<td>Ba2</td>
<td></td>
</tr>
<tr>
<td>BB-</td>
<td>Ba3</td>
<td></td>
</tr>
<tr>
<td>B+</td>
<td>B1</td>
<td>Higher risk investing</td>
</tr>
<tr>
<td>B</td>
<td>B2</td>
<td></td>
</tr>
<tr>
<td>B-</td>
<td>B3</td>
<td></td>
</tr>
<tr>
<td>CCC+</td>
<td>Caa1</td>
<td>Vulnerability to default</td>
</tr>
<tr>
<td>CCC</td>
<td>Caa2</td>
<td></td>
</tr>
<tr>
<td>CCC-</td>
<td>Caa3</td>
<td></td>
</tr>
<tr>
<td>CC</td>
<td>Ca-C</td>
<td>Bankruptcy likelihood or other major shortcoming</td>
</tr>
<tr>
<td>C</td>
<td></td>
<td></td>
</tr>
<tr>
<td>D*</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Fitch IBCA further distinguishes between DDD, DD and D.

3. **Approach**

- Credit scores can be deductively established, but more effective methods are empirical models (cf. Chapter 2.1). Scoring models can be built by credit grantors themselves. But many companies produce scoring models as products. Their clients cover from banks, insurance companies and other credit institutions like credit cards companies to other industries like telecommunications, etc. Some model vendors are listed in Table 2.2/3.:
<table>
<thead>
<tr>
<th>Companies’ name</th>
<th>Main clients area</th>
<th>Specific solutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASA (cf. ASA01)</td>
<td></td>
<td>Real-time scoring and segmenting, Clustering and predictive modeling, Credit risk assessment.</td>
</tr>
<tr>
<td>Austin Logistics (cf. AuLo01)</td>
<td>Consumer credit industry.</td>
<td>Collection process.</td>
</tr>
<tr>
<td>Experian (cf. Expe01)</td>
<td>Financial services, Insurance, Retail, Telecommunications, Electric utility, E-commerce.</td>
<td>Various scorecards: Application scoring, Behavior scoring, Response scoring, Collection scoring, etc.</td>
</tr>
<tr>
<td>HNC (cf. HNC01)</td>
<td>Financial services, Insurance, Telecommunications, etc.</td>
<td>Bankruptcy prediction, Fraud detection, etc.</td>
</tr>
<tr>
<td>Magnify (cf. Magn01)</td>
<td>Insurance, Direct/e-marketing, Government.</td>
<td>Predicting delinquency, Fraud detection, Increased profitability, etc.</td>
</tr>
<tr>
<td>The modeling Agency (cf. Mode01)</td>
<td></td>
<td>Credit card monitoring, Collection decision supporting.</td>
</tr>
<tr>
<td>Scorex (cf. Scor01)</td>
<td>Banking and finance, Retail, Mail order, Mortgage lending, Utilities, Telecommunications, Insurance.</td>
<td>Scorecard: Credit scoring, Behavior scoring, Response / marketing scoring, Churn / attrition scoring.</td>
</tr>
</tbody>
</table>

Table 2.2/3: Commercial vendors of scoring models

These companies provide specific solutions or general model strategies. The clients can either buy the general scoring model products from them or built their own customized in-house scoring models supported by these companies’ consulting services.

- The processes of establishing internal credit rating are not same across banks. In a study of banks’ internal rating systems by the Basel committee in spring 1999, three main categories of rating processes are identified: Statistical-based processes, constrained expert judgement-based processes, and expert judgement-based processes. These categories can be viewed as different points along a continuum.
Definition of credit scoring

defined by the degree of reliance on quantitative techniques, on the one hand, and reliance on the personal experience and expertise of loan and credit officers, on the other hand. According to this study, it appears that objective models play a more prominent role in small corporate lending than for middle market or large corporate (cf. Figure 2.2/1). Only small number of banks surveyed reported that ratings are assigned using only quantitative tools. Most of others rely in different degrees on the subjective judgment of experts. Models or specified objective analysis provide a 'baseline' that can be adjusted little or more by raters (cf. Basel00, P. 17-19).

Figure 2.2/1: Categories of rating processes in banks' internal rating system

- Public credit agencies assign ratings based on experts' judgment as well as credit risk models. In fact, many credit agencies provide credit risk models as product to banks and financial institutions. Various risk management models play more important role than before. Although they are no substitute for sound judgment and they are not supposed to be used for any and every product or market situation, without the assistance of computers and models, rating agencies are neither able to easily track changes in default risk, nor to do so in a timely fashion (cf. Chor00, P.122). However, the process of rating by credit agencies depends significantly on the analyst's background and experience. While certain tools can help, human efforts represent the largest part of the job (cf. Chor00, P.108).

The models used for credit ratings based on two main approaches: structural approach and empirical approach. Structural approach is based on modeling the underlying dynamics of interest rates and firm characteristics and deriving the default/bankruptcy probability based on these dynamics. The examples of models based on structural approach are shown in Table 2.2/4. In empirical approach the relationship of default and characteristics of firms is learned from data (cf. Atiy01, P. 929).
Table 2.2/4: Examples of credit risk models based on structural approach (cf. Atiy01, P. 932)

Example of model products for corporate rating based on empirical approach is Moody's Public Firm Risk Model, which use neural networks as the main technology (cf. MoodPu00, P. 12).

Traditionally, credit scoring and rating distinct with each other clearly, they have their respective major application area. But the boundary between them is being blurred as currently both have been developed and borrowed some characters from another (cf. Figure 2.2/2). The overlapped area in Figure 2.2/2 means:

First, application areas: In corporate credit analysis, scoring models are also used as an assistant tool to analyze quantitative features like financial ratios of a corporate.

Second, used techniques: Banks and rating agencies also utilize empirical scoring models as one of its quantitative tools to establish rating systems.

Third, the considered factors: The credit rating of a corporate should consider a wide scope of quantitative and qualitative information, some of them were thought not easy to be quantified and analyzed only by experts. The new challenge of scoring model techniques is how to incorporate more qualitative information. For example, some techniques based on fuzzy set and rough set theories have been attempted to solve this problem.
Definition of credit scoring

Credit Scoring  Credit Rating

Possible application areas
Consumer credit  Corporate credit

Used Techniques
Empirical models  subjective analysis by experts

Considered Factors
Narrow  Wide

Figure 2.2/2: Blurring boundary of credit scoring and credit rating
3 The expanding application range of credit scoring

Before scoring models appeared, credit analysts had made credit decisions (such as whether to grant loans) based on their judgments. Whether or not scoring models can produce more accurate classification than subjective judgments has been discussed since scoring models were first used in practice. Despite many criticisms, the applications of credit scoring techniques are widely spread. The application area of credit scoring has spread from consumer credit to business credit; the business objectives of credit scoring have extended from credit application stage to pre-application stage and performance stage. These two directions of extending will be explained in the following two sections.

3.1 Application areas

Credit scoring as a method of credit evaluation has been used in practice for more than 50 years. The first consultancy using scoring methods was formed in San Francisco by Bill Fair and Earl Isaac in the early 1950s (cf. Thom00, P. 151). The first success of the application of credit scoring is in the area of credit cards. After that banks started using scoring for their other products like personal loan, auto loan, home loan, while in the last few years scoring has been used for small business loans. The application of scoring techniques is not restricted to banks and insurance companies, but also in similar decision making problems in other sectors, such as the telecommunications, retailers, and mail order firms (cf. Figure 3.1/1).

Empirical credit scoring has been accepted as the classic methods by many credit institutions for consumer credit. Since early 1990s, credit scoring has become the dominant method for assessing grants of many kinds of consumer loan. Loan decisions are made without the intervention or involvement of individual loan officers (cf. Eise96, P. 271). The first usage of credit scoring systems in Germany was in the area of private customers in mail order firms in 1975. Its widespread was not as rapid as in US and UK. However, the applications have been extended to bank areas especially for credit card and installment credit (cf. Müll96, P. 50).

In making consumer credit decisions the empirical scoring methods are not only the only way of handling the large number of transactions, but it seems that they produce more accurate classifications than subjective judgmental assessments by human experts (cf. RoGl94, P. 608; HaHe97, P. 530-531). Although there are many unsolved problems about credit
scoring⁶, empiricism has shown that scoring systems are very robust in most actual lending situations (cf. Thom00, P. 155; John92).

But the application of empirical scoring models in the area of business credit is still not widespread. Of all the areas of bank lending, business credit was one that many believed was too complex to be potentially amenable to scoring. Business credits were thought to be too heterogeneous, and documentation is not standardized within institutions --- let alone across institutions. Finally, the risks tend to be more varied and complex (cf. Eise96, P. 273).

An approach for banks to assess credit risk in business loan is to produce an internal credit rating, which takes into account various quantitative as well as subjective factors through a rating system. One of the criticisms of this approach is that the subjective aspect of the prediction makes it difficult to make consistent estimates. Some banks, especially smaller ones, use the ratings issued by the standard credit rating agencies. The problem with these ratings is that they tend to be reactive rather than predictive (for the agencies to change a rating of a debt, they usually wait until they have a considerably high confidence/evidence to support their decision) (cf. Atiy01, P. 929).

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⁶ Some problems in applying discriminant analysis for credit scoring were presented by RoGl94 (cf. RoGl94, P. 593-596). Some of limitations of empirical credit scoring will be discussed later in this paper (cf. chapter 3.4).
There is a need, therefore, to develop quantitative prediction models that can serve as tools to deriving probability of default. Empirical approach is one of the approaches that predict the risk of default/bankruptcy for business loan. The research in empirical approach model building for business credit was usually not termed as credit scoring, but as bankruptcy prediction or business failure classification (cf. AlNa97, P. 1). But the used model techniques are the same as in the credit scoring model building for consumer credit. One of the pioneers researching empirical approach is Altman, who used classical multivariate discriminant analysis with five financial ratios to build the famous Z-score-model (cf. Altm93, P.186; Hart98, P. 162).

Since business credit decisions often involve various and complex factors, not like scoring models for consumer credit decision, the bankruptcy prediction models have been traditionally used as a quantitative tool to help credit experts to analyze the credit risk of firms rather than an automatic decision making system.

In USA, empirical models have begun to be applied to screen business loan applications in the middle 1990s in USA, since banks begun to recognize that lending some amount of money on a credit card to the owner of a one-man business and lending the same amount of money to his firm is a similar sort of decision (cf. Thom00, P. 163). So Credit scoring techniques has begun to be applied to screen small business loan applications (cf. Eise96, P. 272; Akha01, P. 3). Small business loan are often offered in larger scale. Scoring models can cope with large number of credit cases efficiently.

In Germany, the empirical models have been successfully applied to the business credit area, especially the models of the balance sheet analysis using financial ratios. The large available data come from the public credit agencies are used as another data resource that has been used by credit granting institutions to build their internal scoring models for their business credit products.

### 3.2 Business objectives

Scoring models that predict the future behavior of new applicants and existing debtors are called 'applicant scoring' and 'behavior scoring' respectively. Scoring techniques were firstly used for the determination of the granting of a credit. In 1994, Rosenberg/Gleit concluded according to two survey papers in 1983 that the applicant scoring was widespread because of the fine definition of the accept/reject decision for a new applicant, while application of scoring techniques for other decisions were much less studied because other decisions are not easy to formulate (cf. RoGl94, P. 590).

However, the application of scoring models has nowadays come to cover a wider range of objectives. The original idea of estimating the risk of defaulting has been augmented by scorecards at other aspects of the credit risk management: at the pre-application stage, at
the application stage or once the customer has actually been accepted, at the performance stage (cf. Lund92, P. 95) (cf. Figure 3.2/1).

![Figure 3.2/1: Expanding of scoring models’ application to different stages](image)

Scoring models with different objectives has been developed (cf. Eise96, P. 271; Scor01; RoGl94, P. 589-590). They can be generalized into four categories as listed below:

1. **Marketing aspect:**

   **Purposes:**
   - Identify credit-worthy customers most likely to respond to promotional activity in order to reduce the cost of customer acquisition and minimize customer dissatisfaction.
   - Predict the likelihood of losing valuable customers and enables organizations to formulate effective customer retention strategy.

   **Examples:**
   - Response scoring: The scoring models that estimate how likely a consumer would respond to a direct mailing of a new product.
   - Retention/attrition scoring: The scoring models that predict how likely a consumer would keep using the product after the introductory offer period is over or change to another lender.

2. **Application aspect:**

   **Purposes:**
   - Decide whether or not to extend credit, and how much credit to extend. Forecast the future behavior of a new credit applicant by predicting loan-default or poor-repayment behaviors at the time the credit is granted.

   **Example:**
   - Applicant scoring: The scoring models that estimate how likely a new applicant of credit will become default.

3. **Performance aspect:**

   **Purpose:**
Predict the future payment behavior of the existing debtors in order to isolate problem ones, to which more attention and assistance can be devoted, thereby reducing the likelihood that these debtors will become problem.

Example:

Behavior scoring: Scoring models that evaluate the risk levels of existing debtors.

4. Bad debt management:

Purpose:

Select optimal collections policies in order to minimize the cost of administering collections or maximizing the amount recovered from the delinquents' account.

Example:

Scoring models for collection decisions: Scoring models that decide when actions should be taken on the accounts of delinquents and which of several alternative collection techniques might be more appropriate and successful.

As demonstrated above, in the competitive market of today, credit scoring is no longer a simple matter of obtaining a prediction of creditworthiness to determine whether to accept or reject a given individual. In fact, in the present environment, the overall objective of credit scoring is to be able to attract quality credit applicants who can subsequently be retained and controlled while maintaining an overall profitable portfolio. The predictions to be produced and the decisions to be made have to be more complicated (cf. Lund92, P. 95). Credit scoring is traditionally used to rank the customer by default risks but now it can be used to rank customers by the probabilities of their other actions.

Another major change in the last few years is that credit lenders wish to change from minimizing the risk of a consumer defaulting to maximizing the profit a consumer brings them. Moving to profit scoring implies many challenges. For example, it is required to define the 'profitable' and 'non-profitable' customers. Since profits are affected by many factors and many decisions, such as acceptance decisions, credit limitation decisions, default recovery decisions, marketing decisions, and pricing decisions. One needs all the transactions' and accounts' information in order to calculate the profitability of the customers. Some of the relevant data may be not available or not easily accessible. Further more, the definition of 'profitable' customers is not a straightforward problem when some other factors are considered, such as 1). what is a reasonable time horizon to consider profit, 2). profit is a function of economic conditions, 3). should one consider the profit on each product in isolation or look at the profit over all possible products. Thomas explained a number of implementation problems encountered in making this change to profit scoring and some approaches that have been tried by researchers (cf. Thom00, P. 165-167).
Table 3.2/1 shows that various types of scoring models mentioned above are used in the three stages of overall credit management process.

<table>
<thead>
<tr>
<th>Stages</th>
<th>Types of scoring</th>
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<tbody>
<tr>
<td>Pre-application</td>
<td>Response scoring</td>
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<tr>
<td>Application stage</td>
<td>Applicant scoring</td>
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<tr>
<td>Performance stage</td>
<td>Behavior scoring</td>
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<tr>
<td></td>
<td>Retention/attrition scoring</td>
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<tr>
<td></td>
<td>Scoring for collection decision</td>
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</tbody>
</table>

*Table 3.2/1: Various types of scoring models in three stages*

### 3.3 New promotions on credit scoring techniques

Impersonal nature of the process may be still the main suspicion that prevents adoption of empirical scoring models. The experienced personal judgment was thought to be more reliable for credit decisions. Whether or not empirical scoring models are more accurate than the experienced personal judgment has not been widely validated. However, accurate prediction is not the only thing which must be taken into account in current economic environment of credit industry. Increased competition, pressuring margins and decreasing customer satisfaction have placed modern scoring model techniques at the forefront of priorities for credit services. Today, advanced scoring model techniques play a necessary role in helping credit decision making. This necessity can be recognized in the following aspects:

1. **Online credit channel**

   The new lending channel requires instant credit decisions. New services solutions in financial institutions coherently deliver financial services over multi-channel like branch, call center, internet and mobile communication for the customers. Banks and other financial service organizations are realizing that their Internet channel means adding more demand on their services. The challenge to the decision-makers behind all of these channels is how to best serve and protect the customer. In a complete, end-to-end, robust Internet lending solution, they must make consistent and intelligent real time decisions on their large quantity of online credit applications.

2. **Supervision requirement**

   According to the recently published 'The New Basel Capital Accord', banking supervisors have moved towards accepting the internal-ratings based approach as a basis for the
The expanding application range of credit scoring

determination of adequate capital reserves for credit risks. This will generate significant advantages for those credit institutions that have sound internal rating-system.

Credit scoring models are used by some banks in their internal rating system, although the relative role of models varied widely across these banks (cf. Basel00, P. 17-18; Tuns01, P. 28). Credit scoring addresses the Probabilities of Default (PD), which is one of the loss characteristics\(^7\). It can solve only the part of the rating system. But it is an important part, since it is the key to an internal rating system that being able to show to regulators that the internal risk grades are powerful, calibrated to default probabilities, and empirically validated (cf. MoodEu01, P. 3).

Furthermore, new conditions are also provided for the development of scoring models. The large available data come from both the public credit information companies and the data warehouse of credit granting institutions has enabled researchers to investigate the use of these data (cf. Eise96, P. 273). The advent of data mining techniques mean that the technical problems of analyzing such vast amounts of data are being addressed (cf. Thom00, P. 165) (cf. Figure 3.3/1).

All these requirements and conditions have jointly served to prompt serious attempts to develop scoring models both for consumer credit and for business credit. Credit scoring, a

\(^7\) Other loss characteristics are the facility's loss given default (LGD), the level of exposure at default (EAD), the credit's expected loss (EL) and unexpected loss (UL) (cf. Basel00, P. 9).
The expanding application range of credit scoring technique that can support quick, objective, accurate, consistent credit decisions, can be expected to be widely used. The standardization and the automatization of credit decision that is already realized to some extent in the section of private customers will be also extended to business customers in the future.

3.4 The application limitations of empirical scoring models

The advantages of using scoring methods have been proved by many banks and credit institutions (cf. Dink95, P. 51):

- Effective decision process provides high predictive accuracy to support the credit decision making.
- Objective decision process prevents the effect of personal attitude.
- Automatic decision process reduces the time and cost to deal with mass credit cases.
- Efficient decision process allows credit experts to concentrate on the individual difficult and important credit cases.

However, there are some limitations that inhere in the empirical scoring methods:

- Some models are not transparent, they cannot be understood by persons explicitly. Whether the scoring models are reasonable is often suspicious. This limitation prevents its applications on the credits with large amount of money whose default behaviors have significant negative influence. Explanations need to be made on the important decisions associated with them.

- Some model techniques are good at handling quantitative features, but qualitative features can not be appropriately explained. For example, discriminant analysis can produce the relationship between financial ratios and default risks, but the management quality, the technical Know-how, the position on the market may not be analyzed quantitatively (cf. Baet94, P. 1). Only through experienced experts can judgements be made.

- The features that embodied by an empirical model often reflect the historical information about a risk. This analysis often lacks the perspective consideration, which is very important for business credits. For example, the most commonly used information in scoring models is the data in financial statements, which are history-oriented because they are often published several months later (cf. Baet94, P. 1). Other important future-oriented information, such like the trend of the market and the future economic situations, might be estimated by experts or other analysis tools. Their estimations have been seldom included in empirical scoring models. Therefore, the prognoses of empirical scoring models can not guarantee the exact performance of a credit taker. In practice,
most insolvent events are caused by the factors that come out after the credit is granted (cf. Füse01, P.52).

These pros and cons of scoring models focus on one point: Can individual analysis of experts be substituted by empirical models? Experts are good at analyzing unstructured information and more flexible in adapting to the varying conditions. Models have the ability to handle large number cases efficiently and consistently.

Due to these pros and cons of scoring models, the usage of empirical scoring models should be careful and should be used differently for different kind of credits.

- Consumer credit and small business credit:

  The decisions on these types of credit have been made by credit scoring system automatically. These credits are often granted to large number of credit applicants and often with small amount of money. Moreover, these credits have approximate homogeneous profile (Hofm90, P. 942). For these credit products, the advantage of empirical scoring models can be best demonstrated. However, even if for these credit products, human interventions on credit decisions are also necessary with individual difficult and important cases.

- Large and middle business credit:

  For the business credit with larger amount of money, the credit decision is important and some associated information is not easily analyzed by models, so as to the extensive and individual analysis about the quantitative and qualitative credit information can not be substituted. However, although credit decisions can not be made only depending on empirical models, models are often used as useful tools that assist experienced credit analysts to make their subjective judgments, especially used effectively for analyzing the quantitative factors such as the financial data from balance sheets.
4 Application issues in credit scoring

4.1 Information for credit scoring

Scoring systems utilize information relating to the traditional 5Cs of credit: (1) character (the willingness to repay debt), (2) capacity (the financial ability to repay debt), (3-4) capital and collateral (possessions or equities from which payment might be made), and (5) conditions (reflecting the general economic environment, or special conditions applying to the borrower or the type of credit) (cf. RoGl94, P. 590).

For different kinds of credits different credit information is needed to assess their risks.

For consumer credit and private customers, the data are relative homogenous and easily obtained. Some examples of the predictors that are used usually are:

<table>
<thead>
<tr>
<th>Information resources</th>
<th>Application Forms</th>
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<tbody>
<tr>
<td>Public credit information companies</td>
<td></td>
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</table>

Information categories and examples:

<table>
<thead>
<tr>
<th>Information categories and examples</th>
<th>Application Forms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic personal information</td>
<td>Age, Sex, etc.</td>
</tr>
<tr>
<td>Family information</td>
<td>Marriage status, Number of children, etc.</td>
</tr>
<tr>
<td>Residential information</td>
<td>Status, Number of years at the current address, etc.</td>
</tr>
<tr>
<td>Employment status</td>
<td>Occupation, Number of years in current occupation, etc.</td>
</tr>
<tr>
<td>Financial status</td>
<td>Salary, other assets and expenses, etc.</td>
</tr>
<tr>
<td>Security information</td>
<td>Form and value of securities, etc.</td>
</tr>
<tr>
<td>Information on credit bureau reports</td>
<td>Past payment history, Number of inquiries for information on the applicant, etc.</td>
</tr>
</tbody>
</table>

*Table 4.1/1: Information for consumer credit scoring*

Generally, this information includes both the details in applicant's application form and the information held by credit information agencies. In many organizations a mass of information of previous customers and their subsequent performance are saved that serve as the main source of information to construct credit scoring models.

For business credit customers, the data are more complicated and involve a large variety of information, which include basic information as well as bank information, financial
information, trade payments histories, and even information concerning management quality (cf. Table 4.1/2).

The basic information can be obtained from the business reports provided by public credit information companies. These reports can be obtained with low information fee and can be received online. Business reports contain basic information such as addresses, legal forms, dates of foundation as well as information about earnings, profits, paying morals and overall business situation of the risks (cf. HeSc99, P. 5). The credit applications come from not only local area, but also from many regions that may be new to the credit officers. The credit officers are always lacking in the experiences that used to judge the creditworthiness of an international credit application. Credit information agencies play an important part in the information gathering process of any credit institutions. Because of their efforts, accurate and timely credit decisions can now be made within minutes instead of hours or days.

<table>
<thead>
<tr>
<th>Information resources</th>
<th>Application Forms.</th>
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<tbody>
<tr>
<td></td>
<td>Public credit information companies.</td>
</tr>
<tr>
<td></td>
<td>Banks.</td>
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<tr>
<td></td>
<td>Financial Market.</td>
</tr>
<tr>
<td></td>
<td>Government statistic reports.</td>
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<td></td>
<td>etc.</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Information categories</th>
<th>Basic information.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Payments histories.</td>
</tr>
<tr>
<td></td>
<td>Information of securities.</td>
</tr>
<tr>
<td></td>
<td>Personal credit information of firms' owners.</td>
</tr>
<tr>
<td></td>
<td>Financial information of firms (e.g. financial statement, income statement, and cash flow statement).</td>
</tr>
<tr>
<td></td>
<td>Information from bank (e.g. bank report).</td>
</tr>
<tr>
<td></td>
<td>Industry sector information.</td>
</tr>
<tr>
<td></td>
<td>Indicators of stock price of the firms.</td>
</tr>
<tr>
<td></td>
<td>Indicators of economic conditions.</td>
</tr>
<tr>
<td></td>
<td>etc.</td>
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</table>

Table 4.1/2: Information for business credit scoring

Other information, that thought to be important predictors of the payment performance of small business loans, is the information on owners or principals of the firm (cf. Eise96, P.
The personal credit history of small business owners is highly predictive of the loan repayment prospects of their business (cf. Akha01, P. 3). The personal information can be derived from credit agencies that provide personal credit information.

Financial information is also used to construct corporate scoring models. Important financial information comes from financial statement, income statement and cash flow statement. Many academic research developed bankruptcy models depending mainly on ratios measuring corporate financial strength.

Information that reflects the economic situation of the industrial sector has also been considered in scoring models. For example, share of companies with bad debts in an industrial sector, share of bankrupt companies in an industrial sector. It seems obvious to expect that the greater these two numbers, the more risky is the industry and consequently the higher is the credit risk of a company in this industry (cf. Lait99, P. 102).

Other information that may have significant effect on the probability of default is economic condition indicators (cf. Thom00, P. 164), or indicators extracted from the stock price of the firm (cf. Atiy01, P. 932).

New changing in credit industry may result in changing of the important predictors of credit risk. Incorporating more predictive independent variables into credit scoring is therefore an important advance. The information that should be considered will not be restricted as listed in Table 4.1/2.

### 4.2 The time horizon of the sample

When constructing a scoring model, the historical data for each individual customer are used in a sample. The sample is taken from the available portfolios of customers. At the application time, the information of a customer is collected, after the granting of the credit, the performance of the customer is recorded during the effective period of the credit contract. The sample for building a scoring model must be selected from a time horizon.

In the case of applicant scoring (cf. Figure 4.2/1-a), at the application time (point A), the data known about the customers are gathered. After a fixed period (outcome period), say 18 months, at point B, the payment behavior about the customers over this period are collected and defined into classes (e.g. into 'default' and 'non-default'). The data known at A are characteristics of the applicants and used as the independent variables; the payment behaviors known at B are performances of the customers and used as the dependent variable.

For behavior scoring, that predicts how the existing accounts will perform, the credit information that happened after the credit granting should also be included. Extra information
in behavior scoring models compared with applicant scoring is gathered in such a way (see Figure 4.2/1-b): Picking some time as the observation point (A). The time preceding this --- say the previous 12 months --- is the performance period. New variables that describe what happened in the performance period are added. The information known at point A (original variables and new variables) is used as independent variables. A period of time following the observation point A (say following 12 months, ending at point B) is 'outcome period'. At point B, the customer's behavior is assessed based on the performance over 'outcome period' and used as the dependent variable (cf. Thom00, P. 161).

![Diagram of the sample horizon](image)

*Figure 4.2/1: Time horizon of the sample*

The two parts of sample (independent and dependent variables) are selected at different points of time. The values of independent variables or predictors are known at point A, while the values of the dependent variable or risk classes are known at point B. The time between A and B is 'outcome period'. It is a question how to choose the suitable time horizon for 'outcome period'.

The normal time horizon for consumer applicant scoring is twelve to eighteen months (cf. Thom00, P. 153): analysis shows that the default rate as a function of the time the customer has been contracted with the organization builds up initially and it is only after twelve months or so (longer usually for loans) that it starts to stabilize. Thus any shorter a horizon is underestimating the bad rate and not reflecting in full the types of characteristics that predict default. A time horizon of more than two years leaves the system open to population drift in that the distribution of the characteristics of a population change over time, and so the population sampled may be significantly different from that the scoring system will be used on.
The choice of time horizon is even more critical for behavior scoring (cf. Thom00, P.161). The 'outcome period' for the behavior scoring is the time of credit scoring forecast. Behavior scoring uses cross-sectional data, i.e. the state of the customers at the end of performance period and at the end of outcome period. In this way it is trying to develop a longitudinal forecasting system. Suppose a behavior scoring model is built on a sample with 12 months 'outcome period', then this model can be used to forecast whether a current risk will become problematic within future 12 months. This time horizon for consumer behavior scoring practically used are from six months to two years (cf. Jost98, P. 140).

The samples selected for corporate bankruptcy prediction require a longer time horizon than consumer credit. There exist models that are designed to predict bankruptcy three-years-ahead or five-years-ahead. One way of sample collection that assures a forecast time horizon is usually used: a number of bankrupt firms are selected and complemented by a number of healthy firms that cover the same time horizon. Then the data about these firms a period of time before their bankruptcy are collected. If the data three years before the bankruptcy events are used in the model building, the model can predict the bankruptcy three-years-ahead (see Figure 4.2/2-a).

However, the time horizon of the sample is not always so rigorous in practice due to the lack of bankrupt cases. In order to get more samples of bankrupt firms, some model builders took a mixed sample (cf. Utho97, P. 202; Atiy01, P. 932). For example, the data of bankrupt firms
used by Uthoff cover the period spanning 4 month to 54 months before the bankruptcy events (see Figure 4.2/2-b).

4.3 Reject inference

There is an unavoidable problem in selecting the sample for building an applicant scoring model. Ideally, the scoring model should base on the population of all people who apply for a credit, which is said through-the-door population by the credit scoring practitioners. A reliable sample should be drawn randomly from this population, so that every case, no matter they are accepted or rejected, has the same chance of being in the sample. But actually, the data saved in the systems of most credit institutions contains only data on the customers to whom a credit has been given, who were classified as good risks possibly by an earlier scorecard. This produces a bias in the sample.

The scoring model based on this biased sample has a serious problem: There are usually sound reasons for rejecting any applicants and so it is believable that the rejects have a higher default rate than those who were previously accepted. If the scoring system based only on the accepted customers, then the obvious characteristics leading to delinquency or bankruptcy in the group of the rejected applicants can never have the opportunity to be proved and considered in the scoring model. Feelders, et al. (cf. Feel95, P. 107) gave a simple example that make this problem more understandable: Suppose that having the value 'no' for binary variable A has such a negative impact on the credit decision that it can not be compensated by favorable values for other variables. In that case all accepted customers have the value 'yes' for variable A. This means that there is no association between A and whether or not someone defaults in the database. However, in the population of applicants there probably is a very strong association.

The credit institution may have the application form details on those customers it rejected for credit but no knowledge of how they would have performed.

To solve this problem, the idea of 'reject inference' has been suggested and used by many in the consumer credit industry. It is the process of deducing how a rejected applicant case would have behaved had it been granted the credit: the performance classification will be assigned to rejected cases. The data is then included in the scoring model development process. The accounts with known classification are to be augmented, in order to obtain a complete picture of the population applying for credit.

The scoring model that inferred the information of the rejected applicants should theoretically be better than one built only on those accepted credit. Several methods of reject inference have been proposed (cf. HaHe94). However, the effectiveness of these methods is still being disputed. Hand and Henley have discussed the various methods of reject inference and conclude that reliable reject inference is impossible. The particular claims of the
improvements that have been achieved by reject inference are based on either chance or additional information such as correct assumption, or other ad hoc adjustment (cf. HaHe93, P. 55).

Other alternative solution is to accept every applicant or some of the applicants that would normally be rejected for a short of time and use them as the sample aiming to build improved scoring models. This would be an expensive solution that might not be adopted by the most organizations (cf. Thom00, P. 150; HaHe97, P. 538).

A third way is to obtain information on rejected applicants from other credit suppliers who did grant them credit (cf. HaHe97, P. 538). However, there is no relevant literature discussing its practical effect on the scoring models.

\[\text{Goods} \quad \text{Bads} \]
\[\text{Total population} \quad \text{Non-applicants} \quad \text{Applicants} \]
\[\text{Goods} \quad \text{Bads} \]
\[\text{Rejects} \quad \text{Accepts} \]
\[\text{Goods} \quad \text{Bads} \]

\[\text{Goods} \quad \text{Bads} \]
\[\text{Total population} \]
\[\text{Applicants} \quad \text{Accepts} \]

\[\text{Figure 4.3/1: The biased sample for applicant scoring}\]

The problem of bias sample is highlighted by some researchers (cf. RoGl94, P. 596) (see Figure 4.3/1). The criticism argued that the scoring systems produce an unreliable loan policy, because people who never applied for a credit, as well as people who are rejected for credit, are not considered in developing systems to separate good risks from bad ones. Even if the likely behaviors of the rejected customers are inferred, there are still many potential customers who never make an application for credit. Their information and behavior can
never be included in a scoring model. Since the scoring system is developed from a sample of people given credit, it is not unbiased when applied to people seeking credit.

It is should be remarked that this problem happens only on the scoring models for screening credit applicants (applicant scoring). The consumer credit industry pays especially more attention to the problem. For the behavior scoring, which is used for the current existing debtors, the sample can be taken from the same population without bias. Therefore, the problem is always ignored for corporate bankruptcy prediction models, which can be thought as behavior scoring models.

4.4 The identification of the risk classes

Credit scoring makes it possible for creditors to segment customers into classes that are likely to show different delinquent or bankrupt rates and identify the factors responsible for the delinquency or bankruptcy. The first thing that is needed to do in developing a scoring model is to get a sample of credit takers whose performance are known, that means how they have actually performed. The performance of the risks during the time horizon 'outcome period' is used to define their risk classes (cf. Chapter 4.2). Identification of risk classes is actually the problem of definition of 'risk concept'. The accurate definition of risk classes is decisive for the applicability of the scoring models.

In most scoring model systems the performances of the risks are typically split into two categories: Good and Bad. For business credit scoring models, the examples of "bad" definition are bankruptcy filing by a company, bond default, bank loan default, etc. (cf. AlNa97, P. 3). Some measures used typically for consumer credit scoring models are number of months of missed payment, amount over the overdraft limit, current-account turnover, or functions of these and other variables (cf. KeHa99, P. 331).

At first thought it seems that the collected cases may have definite classes, for example, the bankrupt and non-bankrupt firms. But in fact, the definition of 'good' and 'bad' risks varies and depends on what is the aim of the scoring system and on the inclination of the researcher or on other special conditions. For example, the "bad" firms are defined as those that resulted in final credit loss to the bank or wherever a temporal delay occurred (cf. Baet88, P.183).

The implication of the 'Good' and 'Bad' definition is that a positive decision will be made to the good risks, a negative decision to bad risks. For example, in an applicant scoring model, the decision maker defined the risks that have missed 90 days of payments can be thought as bad risks. That means, if he knew that a risk miss 90 days of payments, he would not grant the credit to him. In some sense, the definition of what is meant by a 'good' customer is the subjective judgment criterion of the credit decision maker (cf. Mcco99, P. 21) and may be
changed with economic and commercial factors. For example, in a more cautious credit decision, the "good" customers is those have never been missed in payments.

The definition of risk classes can also be more or less stringent for behavior scoring, which depends on the purpose of the scoring model. As an example, in an installment loan (cf. Figure 4.4/1), suppose risk level is measured by the number of consecutive missed repayments: $R_1$ is one times missed repayment; $R_2$ is three consecutive missed repayments. When the scoring model aims to identify the most dangerous customers in order to take some actions to them to prevent the expected loss, the definition of good risks should be less stringent --- smaller than $R_2$, i.e., good risks are those who have missed repayments consecutively for less than three times. When the aim is to identify the customers that are so good that do not need any manual work of credit analysts, the definition of good risks may be more stringent --- smaller than $R_1$, i.e., the risks that have never missed in repayments is considered 'good'.

![Figure 4.4/1: More and less stringent risk classes' definitions](image)

A practice which has been common in the consumer credit industry is to divide the cases into three classes of risk (good, bad and indeterminate), but use only the 'good' and 'bad' two classes to train the scoring models, and then models are used to classify new applicants as either good or bad risks. For example, 'good' risks might be those borrowers who have never missed in payment, 'bad' risks might be those who have missed for three or more consecutive repayments and 'indeterminate' might be those who have missed either for one or for two consecutive repayments (cf. Figure 4.4/2).
This practice arose because 'good' and 'bad' are ambiguous concepts. The aim of scoring models is to decide whether or not the consumer will yield a profit. Those customers defined as 'good' might definitely yield a profit, those defined as 'bad' might definitely not be profitable and the indeterminates might or might not be profitable --- depending on such unpredictable factors as economic changes over the term of the loan. The standard method then seeks to construct a rule which separates the definitely profitable from the definitely unprofitable (cf. HaHe97, P. 525).

Sometimes, there are not available past cases with known payment behaviors. It is a common problem in practice that the available cases with actual classes are not enough for model building, especially for the newly established system for which old customers’ data do not exist (cf. Heno83, P. 158). In this situation, one alternative solution is the manual classification. The credit customers are evaluated by experts and classified into different risk levels (cf. Krah98, P. 109). Although the trained models with these cases do not strictly conform to the assumption of predictive scoring models, this kind of solution can be realized in practice when cases with true classes are not available.

Two classes definition of risk levels is typical in the credit scoring literature. Two risk classes definition makes it easy to measure the relationship between predict variables and the performance. Moreover, it facilitates the measure of the goodness of the prediction. However, multiple risk classes can also be accomplished by some advanced scoring models like neural networks, decision trees. For example, risks can be divided into current, delinquent, bankruptcy and charge-off four classes (cf. Jost98, P. 140).
Summary and conclusion

Empirical credit scoring as a technique that has its traditional statistical background is in this paper looked as the classification problem of data mining.

Restricted originally in the reject/accept decisions on consumer credits, the applications of scoring methods have come to cover the area of business credit and other stages of credit decisions such like marketing, performance aspects and bad debt management.

Despite many limitations of empirical scoring models their applications have a wider prospect due to the new requirements from the changing environment of the credit industry. The large volume of available credit data are organized and established by credit institutions and public information agencies. The new model techniques are developed by statisticians and machine learning researchers. Both sides together provide the conditions for the building of effective scoring models.

Although automatic scoring models cannot substitute completely the personal analysis in some credit areas, they can support the credit decision in a more objective, consistent, and efficient way.

Many application issues of credit scoring methods are reviewed in this paper, from the necessary information included in the scoring models to the various sampling problems.

From this paper we can conclude that credit scoring is a complex decision process. In fact, due to this complexity, the process of credit scoring is not standardized. Credit scoring has always been based on a pragmatic approach: many techniques are applied on it to find the effective models. The effectiveness of a model can be validated only in practice. A solution can not be suitable for everywhere, only for specific circumstances.
Literature


