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FACULTY WORKING PAPER NO. 1456

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Michael J. Shaw
James A. Gentry

College of Commerce and Business Administration
Bureau of Economic and Business Research
University of Illinois, Urbana-Champaign

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June 1988

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Michael J. Shaw, Assistant Professor
Department of Business Administration

James A. Gentry, Professor
Department of Finance

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ABSTRACT

This paper describes a knowledge-based artificial intelligence (AI) system called MARBLE that evaluates the riskiness of business loan applicants. MARBLE is an acronym for a decision support system (DSS) for managing and recommending business loan evaluation. A unique feature of MARBLE is that it has the capacity to learn; this is achieved by equipping MARBLE with an inductive inference engine that complements its deductive problem solver. The paper explains the AI system that uses inference rules to simulate the thought process of a lending officer when evaluating a loan request. The inductive learning approach and the learning logic of MARBLE are described and, additionally, there is an illustration of the system's operation in the loan evaluation process. The paper concludes with an empirical study of a MARBLE application.

USING AN ARTIFICIAL INTELLIGENCE SYSTEM TO EVALUATE BUSINESS LOANS[1]

Commercial banks are a primary source of credit for companies that do not have easy access to capital markets. In general, when comparing the risk characteristics of companies seeking bank credit to companies that have access to the capital markets, the risk characteristics of the former are greater than the latter. Determining which loan applicant should be extended credit, as well as the amount of credit, are major decisions that confront commercial bank lending officers, credit analysts and loan committees. These decision makers must assess the financial health of an applicant, which requires analysis of both quantitative and qualitative information concerning the outlook for the company. Managing this information can provide a competitive advantage. However, the highest payoff comes from a lending expert using the information which, in turn, produces the best possible results to the customer and the bank. The purpose of an expert system that evaluates loan applicants is to reduce the time devoted to the analysis and improve the quality of the evaluation, which would produce substantive benefits to commercial banks using the system, Leonard-Barton and Sriokia [27] and Sheil [40].[2]

This paper describes an ongoing research effort that develops a knowledge-based decision-support system (DSS) Stohr [42] for evaluating commercial loan applicants.[3] The system, referred to as MARBLE, managing and recommending business loan evaluation, is a knowledge-based DSS that uses 80 decision rules for evaluating commercial loans. MARBLE is an artificial intelligence (AI) system that mimics the lending judgment of experienced loan officers and was constructed in collaboration with several commercial banks.[4]

MARBLE utilizes an expert-system design and is equipped with an inductive learning capability.[5] Learning is an important feature of an intelligent system and reflects the process of improving performance by changing knowledge or control. There are two aspects in decision-support tasks where learning comes into play. First, learning decision rules for the knowledge base, which involves the knowledge-acquisition process and second, refining existing rules by observing prior problem-solving experience, commonly called the knowledge refinement process. The knowledge base is a repository of domain knowledge that is stored in a computer system [25].[6] To achieve these learning functions, MARBLE is equipped with an inductive inference engine that complements the deductive problem solver. The inference engine is that part of a knowledge-based system that controls the problem solving process. The inference engine processes knowledge in the knowledge base and thereby develops new conclusions [44].

The primary objective of the paper is to present an AI system that evaluates the riskiness of commercial loan applicants. The more specific objectives are to explain an AI system that mimics the thought process of a lending officer when evaluating a loan request; to explain the rules used in the loan evaluation process; to discuss the inductive learning approach used in MARBLE; to explain the underlying learning logic of the system and to illustrate its operation in the loan evaluation process; and finally to present an empirical study of a MARBLE application.

Loan Evaluation

When evaluating a commercial-loan application, loan officers, credit analysts, and loan review committees combine financial projections with qualitative information. The loan-granting decision is based on the analysis of a firm's historical and pro forma financial information and on the interpretation of qualitative information concerning its product markets and industry characteristics, plus the overall performance of management. Academic models of the loan-evaluation process have been based on regression analysis, Orgler [35], polytomous probit analysis, Dietrich and Kaplan [16], or recursive partitioning, Marais et. al., [28]. Haslem and Longbrake [23] and Dietrich and Kaplan [16] point out statistical analysis with linear models cannot capture the subjective judgments that are pervasive in the lending decision. The approach used by MARBLE is akin to the heuristic method employed by Cohen, Gilmore, and Singer [11], which simulates the decision process of loan officers. However, Anderson [2] indicates rules are an effective model of the decision-making process, therefore, MARBLE employs production rules as the basic knowledge representation. Furthermore, inductive learning is applied to enhance MARBLE's performance by automatically acquiring decision rules for loan classification.

Newell [33] uses two types of models to describe the learning process. First, the connectionist model describes the learning process in terms of activation patterns defined over nodes in a highly interconnected network. Second, the production-system model describes the learning process as symbol manipulation in a rule based system. MARBLE learning is achieved in a rule-augmenting system.

The evaluation of a loan application is based on information presented in financial statements plus qualitative information such as the quality of management, the ability to repay the loan, and the availability of collateral. Frequently the qualitative information is of greater value in the lending decision than the financial statement analysis. Exhibit 1 presents the decision-making process for evaluating business loans. The evaluation of a firm's credit worthiness is a score that weighs each of the characteristics presented in Exhibit 1. When the credit risk score is calculated, the risk classification of the applicant is established by comparing it to an objectively determined standard.

If the loan is approved, the bank establishes the terms of the loan with the customer in order to assure repayment. The final phase of the process involves organizing all the data and information used in the decision process and storing it in the loan documentation file. This file is the basis for future performance reviews.

The Organization of MARBLE

Production rules, Davis [12], are the basic form of knowledge representation in MARBLE. Rules are categorized by the appropriate context-types for which they are invoked. For example, some rules deal with profitability, some with repayment, and still others deal with loan evaluation. To capture fully the decision rules used in business loan evaluation, MARBLE currently uses ten different context-types in its knowledge base:

LOAN: The loan application;

EVALUATION: An evaluation of a new customer relationship;

FEASIBLE: A feasibility appraisal;

RECOMMEND: Detailed recommendations;

CREDIT: The credit-worthiness of the firm in relation to the proposed loan;

UTILIZATION: An indication of the extent that the customer will use the bank;

RETURN: An evaluation of the expected profitability to the bank of a customer relationship;

PROFITABILITY: The expected cash flow and/or profitability of the firm;

REPAYMENT: The ability to repay the loan; and

COLLATERAL: The evaluation of collateral.

During the consultation session context types are developed and arranged hierarchically as a context tree in the data structure. The context tree structures the knowledge base domain in MARBLE which, in turn, allows the system to separate large amounts of information into logical units. Each context solves one part of the lending problem and provides important information needed to solve the total loan evaluation problem. The current version of MARBLE is implemented in the Personal Consultant Plus, an expert system shell developed and marketed by Texas Instruments.

The problem solver in MARBLE is a production system which links the decision maker's problem environment with appropriate models, data, and decision rules residing in the DSS, Elam and Henderson [20], Stohr [41]. Based on the problem solving theory established by Newell and Simon [34], the decision-support tasks in MARBLE are information processing activities that result in a plan of action for evaluating the loan applicant. As shown in Exhibit 2 the problem solver embedded in the Consultation Module utilizes information from the knowledge-base, static database, dynamic database and a model base, Bonczek, et al., [4], Dolk and Konsynski [17], Dutta and Basu [11]. In MARBLE, the model-base contains program modules for financial analysis, mathematical programming routines, forecasting, and regression algorithms. The static database typically contains historical financial data and qualitative information concerning the company applying for a loan, e.g., an evaluation of management performance, outside credit ratings, if available, and an analysis of the firm's financial data. As illustrated by the consultation process shown in Appendix 1, this piece of procedural knowledge, represented by Rule 073, can be invoked as part of the process in evaluating a given loan application. Some sample rules used in MARBLE are shown in Appendix 2.

Appendix 1 shows an example of the consultation process with MARBLE. To make a loan granting decision, MARBLE begins by asking a sequence of questions relevant to the particular loan application. The input answers to these questions are used as new pieces of evidence which in turn, trigger new rules to be executed, and thereby generate or update hypotheses about the plausible conclusion. The inference process continues until enough evidence has been collected to support one of the hypotheses. The supportive information is used to reach a conclusion and/or a recommendation to either accept or reject the loan. As shown in the example, the user does not have to answer all the questions. That is, special designated keys can be used for situations such as querying the system about why a particular question is asked (F7) or, how the value for the parameter is determined (F8). In addition, if the user cannot answer a question, he can use the function key F4 to skip it.

As shown in Appendix 2, MARBLE follows the rule representation format used in the original MYCIN system, Buchanan and Shortliffe [9]. For example, a typical rule can be as follows:

IF: 1) the type of the company is manufacturing, and
2) the major-market of the company is Asia, and
3) the major-product of the company is machine-tool;
THEN: there is strong suggested evidence (0.8) that the profitability of the company is low.

The above is represented in MARBLE as:

```
PREMISE:  ($ AND (SAME CNTXT TYPE MANUFACTURING)
                 (SAME CNTXT MARKET ASIA)
                 (SAME CNTXT PRODUCT MACHINE-TOOL)

 ACTION:  (CONCLUDE CNTXT PROFIT LOW TALLY 0.8).
```

In the rule representation, CNTXT denotes the data object, i.e., context, corresponding to the applying company. SAME is a function comparing the equivalence between two values for the object. TALLY represents the confidence level of the preconditions, i.e., the premise, and 0.8 denotes the confidence level of this particular rule. The latter two parameters are usually referred to as <u>certainty factors</u>.

The inference process in an expert system such as MARBLE is essentially a process of collecting evidences for competing hypotheses until one of the hypotheses is strong enough to be the plausible conclusion. In this vein, a rule can be viewed as

IF: evidence e_i is observed,

THEN: hypothesis h_j can be concluded with probability x.

This piece of knowledge can be represented as $P(h_j|e_i) = x$, which is the conditional probability that the hypothesis is h_j in light of evidence e_i. Expert systems, such as MARBLE, seek to find a set of evidence that allows $P(h_j|e)$ to exceed some threshold for one of the possible hypotheses. For MARBLE, this resulting hypothesis is the recommended granting decision, together with the probability that the loan will be repaid.

Certainty factors provide MARBLE with the capability to handle probabilistic statements in the rules. MARBLE also has an embedded mechanism for gathering evidence for and against a hypothesis when two or more relevant rules are executed. The same mechanism is used in the MYCIN system and is described in detail in Buchanan and Shortliffe [9, p. 233].

In addition to acquiring knowledge through the common knowledge engineering process, i.e., the process of interviewing experienced loan officers and incorporating their knowledge in production rules, MARBLE also employs <u>inductive learning</u> to derive decision rules from training examples, Shaw [39]. A training example consists of two parts: (1) a data case which is basically a set of attributes, each with an assigned value and (2) a classification decision made previously on the data case by an experienced loan officer. Both positive and negative examples are used as input for the inductive learning module. When the learning involves multiple concepts, then the examples for a particular concept are the positive examples for that concept and the examples for any other concept are negative examples. As shown in Exhibit 3, the Knowledge Acquisition and Learning Module also refines some of the rules used by observing the performance trace. Currently this knowledge-refinement process is performed interactively in a fashion similar to program debugging. Eventually this process will also be mechanized using the incremental learning method, Dietterich et. al., [15]. This paper will focus on the inductive learning aspect.

Inductive Learning for Acquiring Decision Rules

Inductive learning can be defined as the process of inferring the description of a class from the description of individual objects of the class. The training examples are given in the form of cases and described by a vector of attribute values. Each class can be viewed as a concept which is described by a rule determined by inductive learning. If an input data case satisfies the conditions of this rule, then it represents the given concept. A concept is a symbolic description expressed in some description language that is true when applied to a data case describing the concept correctly and false otherwise. For example, a recognition rule for the concept "class IA firm" might be:

> "A firm whose asset exceeds $1,000,000.00, total debt is less than $250,000.00, and whose annual growth rate is more than 10%."

Using first-order predicate calculus (FOPC), Vere [43], as the knowledge representation, the same concept can be represented by a conjunction of attribute descriptions:

$$\text{customer } (t) \,\&\, (\text{asset } (t) > 1{,}000{,}000) \,\&\, (\text{total-debt } (t) < \$250{,}000) \,\&\, (\text{AGR}(t) > 0.10) \rightarrow (\text{class } (t) = \text{'IA'})$$

An alternative way to represent such a concept is to use the variable-valued logic (VL) proposed by Michalski [29] [30]. The aforementioned concept recognition rule can be represented by the VL formalism as follows:

$$[\text{assets} > \$1{,}000{,}000]\ \&\ [\text{total-debt} < \$250{,}000]\ \&$$
$$[\text{AGR} > 0.10] \rightarrow [\text{class} : \text{'IA'}].$$

An instance that satisfies the concept definition is called a positive example of that concept, whereas an instance that does not satisfy the concept definition is called a negative example of that concept. A <u>generalization</u> of an example is a concept definition which describes a set containing that example. For a set of training examples, the <u>generalization process</u> identifies the common features of these examples and formulates a concept definition describing these features. Thus, inductive learning can be viewed as a process of repetitively generalizing the descriptions observed from examples until the inductive concept definition is found. This resulting concept must be consistent with all the examples.

The input to an inductive learning algorithm consists of three parts: (1) a set of positive and negative examples, (2) generalization rules and other transformation rules, and (3) the criteria for a successful inference. Each training example has two components: first, a data case consisting of a set of attributes, each with an assigned value; the second component, on the other hand, is a classification decision made by a domain expert according to the given data case. The output generated by this inductive learning algorithm is a set of decision rules consisting of inductive concept definition for each of the classes. Learning programs falling into this category include AQ, Michalski [29], PLS, Rendell [38], and ID3, Quinlan [37]. These programs are sometimes referred to as "similarity based" methods, as opposed to explanation-based methods (Mitchell et al., [32]).

We can use the AQ program in Michalski [29] as an example to illustrate the process of rule learning. Suppose that the data shown in Exhibit 4 are part of a set of credit rating data serving as training examples for learning the concept for risk classification. The data set contains historical and pro forma financial information belonging to nine companies, each with an assigned risk class. Let's suppose that companies A, B, and C are known to be in Class I; companies D, E, and F are in Class IA; and companies G, H, and I are in Class II.

Two types of generalization rules are used in the learning process: domain specific rules and domain independent rules. An example of the domain specific rules used is

[Account-type = commission] V [Account-type = fees]-->
[Account-type = other-businesses].

This rule indicates that [Account-type = other business] is a generalization for either [Account-type = commission] or [Account-type = fees]. In addition, there is a set of domain independent rules for generalization. Michalski [29] listed various generalization rules of this type, such as the closing-interval rule and the dropping-condition rule, Michalski [29, p. 106].

The induction criteria used for this example are (1) to cover all the of positive examples, while not covering any of the negative examples, and (2) to include the least number of attributes in the concept definitions.

The AQ inductive learning algorithm is then applied to the set of example data, resulting in the following three inductive rules corresponding to the concept definition for the three classes:

1. [avg-inventory $\geq$ \$7,000] & [net-worth $\geq$ \$47,000] --> [class = I].
2. [\$37,000 $\leq$ net-worth $\leq$ \$48,000] & [inventory > \$8,000] --> [class = IA].
3. [F1 = H,A] & [total-debt $\geq$ \$26,000] --> [class = II].

The resulting three decision rules generated can then be used as decision rules for risk classification. These classification rules cover all the positive examples, but none of the negative examples. These two induction criteria are referred to as (1) the completeness and (2) the consistency conditions in Michalki [29].

Incorporating Inductive Learning in MARBLE

We shall use loan evaluation as an example to illustrate the application of inductive learning in MARBLE. The objective is to determine the risk classification of commercial bank loans. In order to describe the default risk of a given commercial loan, we assume a bank uses a five-category classification scheme, Dietrich and Kaplan [6]. Here, for the ease of illustration, only three classes, represented by I, IA, II, are actually used in the set of training examples. There are a total of nine training examples shown: customers A, B, C for class I; D, E, F for class IA; and G, H, I for class II.

An initial set of attributes using historical and pro forma financial information are included in each input data instance as training examples. As shown in Exhibit 5, this set of attributes includes nominal, linear, and structured attributes. In the more traditional data analysis techniques, such as regression or discriminant analysis, only linear and nominal attributes can be considered. The ability to process structural information constitutes one of the advantages of symbolic processing, as characterized by most AI programs, over numerical calculation as characterized by statistical analysis. The domain of each structured attribute usually can be represented by a hierarchy of attribute values, corresponding to a generalization tree. The two structured attributes used in this example are customer status and account type.

The objective of Exhibit 6 is to illustrate that firm specific risk or creditworthiness increases as financial and nonfinancial characteristics of a company deteriorate. Chen and Shimerda [10] and Pinches, Eubank, Mingo and Caruthers [36] have shown there are seven factors that describe the financial health of a firm. Using these seven factors it is possible to describe fundamental differences between financially strong and weak companies, e.g.,

Factor	Types of Companies: Low Risk	High Risk
Return on Investment	high	low
Capital Turnover	high	low
Financial Leverage	low	high
Short-term Liquidity	high	low
Cash Position	high	low
Inventory Turnover	high	low
Receivable Turnover	high	low

The low risk companies are described as having small variability in each factor and as having low leverage and high return on investment, capital turnover, short-term liquidity, cash position, inventory receivable and turnover, and vice versa for high risk companies. When analyzing companies or industries the rankings associated with the factors are arranged in a continuum from high to low. Determining the rating of a firm for each of the seven characteristics is the basis for arriving at a comprehensive score for a firm.

The training example in Exhibit 4 reflects a loan officer's rating system that takes into account these seven factors used in analyzing a firm's financial health or risk class. Companies A, B and C are examples of firms with low risk characteristics. Companies D, E and F are examples of firms with mid-level risk characteristics, and companies G, H and I illustrate firms with higher risk characteristics.

An Empirical Study Using MARBLE

To test the performance of the inductive inference method for rule learning in the domain of loan risk analysis, we used MARBLE to analyze real-world data. Loan risk classification and the classification of a bankrupt firm are based on accounting information. This empirical study uses financial data for predicting bankruptcy. The task for the inductive inference engine is to perform concept learning about the characteristics of bankrupt firms. The learned rules based on such data are used as part of the risk analysis in MARBLE.

To identify the relevant attributes for learning the characteristics (concepts) of bankrupt firms, we adopted in the training examples the cash-based funds flow components which include funds from operations (NOFF), working capital (NWCFF), financing (NFFFF), fixed coverage expenses (FCE), capital expenditures (NIFF), dividends (DIV), and other asset and liability flows (NOTHER).

The ratio of these components to the total net flow (TNF) form the first seven attributes of each example. The eighth attribute is a scale measure, calculated by total net flows/total assets (TNF/TA). Thus, each training example consists of the following eight attributes (1) NOFF/TNF, (2) NWCFF/TNF, (3) NOTHER/TNF, (4) NFFF/TNF, (5) FCE/TNF, (6) NIFF/TNF, (7) DIV/TNF, and (8) TNF/TA.

The data are obtained from the bankruptcy study reported in Gentry, et. al., [21]. The Standard and Poor's Compustat 1981 Industrial Annual Research File of companies, and the Compustat Industrial Files were used to determine companies that failed during the period 1970-81. Balance sheet and income statement information for the failed companies was used to determine the funds flow components. There were a total of 29 companies of which the complete financial statement information for the year before the failure date was available. These companies are used as positive examples. Furthermore, each of the 29 failed companies was matched with a nonfailed company in the same industry, based on asset size and sales for the fiscal year before bankruptcy. The same set of financial data are provided for each of these nonfailed companies, which serve as negative examples of the concept. The objective of the analysis is to determine whether the inductive inference engine can effectively discriminate between failed and nonfailed companies by the financial data one year before failure. The rule learning program is written in PASCAL on VAX 11/780.

The set of training examples are the funds flow components of the failed and nonfailed firms. To test the predictive accuracy of the rules generated by the inductive inference algorithm, we used half of the sample for rule learning and the remainder of the sample for rule testing. The selection of training examples out of the set of data is based on a degree of representativeness of each data case. The training examples are companies with widely divergent characteristics.

The result of using the learned rules to test against the holdout sample is shown in Exhibit 6, which shows that the learned rules are quite effective in predicting and classifying. Since the inductive learning algorithm is both consistent and complete, the original positive and negative examples can be classified with perfect accuracy. Exhibit 3 shows that the learned rules can classify 29 failed firms and 29 nonfailed firms with 86.2 percent accuracy, which compares favorably with 83.3 percent accuracy resulting from the logit model reported in Gentry, et. al. The rules generated by inductive learning thus provide a valid decision aid for determining whether a firm has the characteristics of bankrupt firms.

Conclusions

We have presented an expert system that mimics the thought process of a lending officer at a commercial bank. The MARBLE system is user friendly and is based on rules widely accepted by commercial lending officers. The objectives of MARBLE are to help lending officers, credit analysts and loan review committees to improve the evaluation of loan applicants and to learn how expert systems operate. Based on the knowledge base and the information provided on the loan applicant, MARBLE synthesizes the information and estimates the probability that the loan will be repaid. Knowing that the probability estimate reflects the judgments of lending experts, management can use it to assist in the lending decision.

The MARBLE system has the capability of learning as it acquires new information. Examples were used to show the value of inductive inference in the knowledge acquisition process. Because decision rules can be generated and refined with new observations, the incorporation of the inductive learning component enables MARBLE to be adaptive in evaluating loan applicants. This type of learning capability makes it possible to build an intelligent DSS. An empirical study shows encouraging results for incorporating inductive learning in MARBLE for loan evaluation.

FOOTNOTES

[1]We are indebted to Linda Rinner of the Northern Trust Bank, Richard Watts of First Wachovia, Inc., and Harold Merrill of Arthur Andersen & Co. for their helpful suggestions during the development of MARBLE. Thanks are also due to Texas Instruments for providing the Lisp machine and Personal Consultant Plus, which we used to develop the MARBLE system reported in this paper. The financial support from the Herbert V. Prochnow Foundation for this research is gratefully acknowledged.

[2]Syntelligence has an expert system called Loan Advisor that evaluates loan applicants. It is being used on an experimental basis by First Wachovia, Inc., and the Wells Fargo Bank. BancA Corporation has developed Power 1 as a loan tracking and evaluation system that is being used on an experimental basis of Citibank, Mellon Bank and the Canadian Imperial Bank of Commerce. Loan evaluation and advisor expert systems are also being developed by several international banks, e.g., three French banks, Caisse d'Epargne, Caisse d'Epargne Ecrueil and Bangue de Bretagne, the Cera Spaarbank in Belgium, Union Bank, Credit Swisse and Bank Cantonale Vaudoise in Switzerland; possibly the Dresdnen Bank in Germany and Dai-ichi Kanygo Bank in Japan, [22]. Also see [18] for an AI application for commercial loan analysis.

[3]There are numerous other finance related applications that utilize expert systems. Examples of companies involved in finance related expert systems are: American Express, Applied Expert Systems, Inc., Arthur Andersen & Co., Bank of America, Chase Manhattan Bank, Chemical Bank, Citibank, Co-Gen-Sys, Continental Bank, First National Bank of Chicago, John Hancock Insurance Company, Merrill Lynch, Metropolitan Insurance Company, Palladean Expert Systems, Price Waterhouse, Sears, Shearson and Travelers Insurance Company.

[4]The expert's knowledge provides the key to expert performance, while knowledge representation and inference schemes provide the mechanism for its use [25, p. 7].

[5]Hayes-Roth, et al., [25, pp. 13-15] provide a description of types of expert system, e.g., interpretation, prediction, diagnosis, design, planning, monitoring, debugging, repair, instruction and control. Several of these generic categories of knowledge engineering applications have a special relevance to financial management problems.

[6]The power of an expert system derives from the knowledge it possesses, not from the particular formalisms and inference schemes it employs [25, p. 6].

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Appendix 1.

An Example of MARBLE's Question-Answering Mode
The following is the MARBLE system which reflects a part of the loan evaluation decision support system.

(1) "Who is the customer applying for LOAN-1?"
**ASEM INC.
{** indicated the user input.}

(2) "Is the customer a present customer?"
**YES

(3) "Is extensive credit checking needed on this customer?"
**YES

(4) "What is the rating of management performance?"
**F7
{F7 is a function key of showing WHY this question is needed.}

The rating of management quality is needed to determine the firm's credit-worthiness in relation to a particular loan application

RULE073
If 1) 1) the rating of management performance is HIGH, and
2) the outside credit rating of the firm is HIGH, and
3) credit rating based on the bank's financial analysis of the applicant's statements is HIGH, or
2) 1) a rating of management performance is HIGH, and
2) the outside credit rating of the firm is HIGH, and
3) credit rating based on the bank's financial analysis of the applicant's statements is AVERAGE, or
3) 1) a rating of management performance is HIGH, and
2) the outside rating of the firm is GOOD, and
3) credit rating based on the bank's financial analysis of the applicant's statements is HIGH, or
4) 1) a rating of management performance is AVERAGE, and
2) the outside rating of the firm is HIGH, and
3) credit rating based on the bank's financial analysis of applicant's statements is HIGH.
then 1) it is definite (100%) that the credit-worthiness is high.
2) it is definite (100%) that the extensive credit check is finished, and
3) inform the user of this decision.

{the user can input the value with some degree of certainty}
**HIGH
**8

(5) "What is the outside credit rating of the firm?"
**F8

{F8 is a HOW function key. The user is able to see how the value of previous parameters have been determined.}

HOW did the system determine the value of

MANAGEMENT-PERFORMANCE OF LOAN-1
CUSTOMER-STATUS OF LOAN-1
CUSTOMER-NAME OF LOAN-1

{If the user chooses management-performance, the following appears:}
MANAGEMENT-PERFORMANCE was determined to be HIGH with certainty 80% by user input.

****HIGH**

(6) What is the type of loan?
****TERM**

(7) What is the firm's 3-year average net profits?
****90,000,000**

(8) What is the firm's trend in net profits?
<u>F4**</u>
{F4 is the function key indicating that the answer is unknown}

(9) What is the industry median ratio of pretax profits to total tangible assets divided by prime rate of interest?
****2**

(10) What is the firm's ratio of pretax profits to total tangible assets divided by prime rate of interest?
****2**

(11) What is the firm's percentile in industry ratio of net profits to tangible net worth?
****0.8**

(12) What is the firm's percentile in industry inventory turnover ratio?
<u>F4**</u>

(13) What is the firm's percentile in industry: net profits?
<u>F4**</u>

(14) If the firm's percentile ratio of pretax profits to total tangible assets exceed prime rate, answer the ratio, otherwise press F4.
<u>F4**</u>

(15) What is the industry median trend in net profits?
****0.2**

(16) What is the ratio of cash to total current liabilities?
****0.2**

(17) What is the percentile value of the firm´s ratio of inventories to current assets?
**0.2

(18) What is the percentile value of the firm´s current ratio?
**0.8

(19) What is the proposed loan amount?
**10,000,000

(20) What is the legal loan limit?
**120,000,000

(21) What is the maximum loan limit determined by either the firm´s average deposits during the past year or during the past three years?
*100,000,000

(22) What is the ratio of proposed loan to firm´s total assets?
**0.34

(23) What is the purpose of the loan?
**PLANT AND EQUIPMENT

(24) What is the proposed maturity of the loan?
**4

(25) Is the firm in a fully secured basis?
**NO

(26) THE LOAN IS GRANTED WITH CERTAINTY FACTOR = 72%

Appendix 2

RULE077 [PROFITABILITYRULES]

If 1) firm´s 3-year average net profits is greater than 0, and
2) industry median ratio of pretax profits to total tangible assets divided by prime rate of interest is greater than or equal to 1, and
3) firm´s ratio of pretax profits to total tangible assets divided by prime rate of interest is greater than or equal to 1, and
4) firm´s percentile in industry ratio of pretax profits to total tangible assets is greater than or equal to .75, and
5) firm;s percentile in industry ratio of net profits to tangible net worth is greater than or equal to .75, and
6) firm´s percentile in industry inventory turnover rate is greater than or equal to .5,

Then the firm´s profitability rating is HIGH.

```
PREMISE:  ($AND (GREATERP* (VAL1 CNTXT P1) 0)
                (GREATEQ* (VAL1 CNTXT R1) 1)
                (GREATEQ* (VAL1 CNTXT R2) 1)
                (GREATEQ* (VAL1 CNTXT R3) .75)
                (GREATEQ* (VAL1 CNTXT R4) .75)
                (GREATEQ* (VAL1 CNTXT R5) .5))
ACTION:   (DO-ALL
                (CONCLUDE CNTXT PROFITABILITY-RATING HIGH TALLY 1000))
```

RULE020 [EVALUATIONRULES]

If 1) The credit-worthiness measure, S1, is known, and
2) the indication of the extent to which a customer relationship with the firm, S2, will build the bank is known, and
3) the evaluation of expected profitability to the bank of a customer relationship with the firm, S3, is known, and
4) the weight which the bank´s management gives to the credit-worthiness S1 is known, and
5) the weight which the bank´s management gives to build the bank S2 is known, and
6) the weight which the bank´s management gives to the profitability S3 is known,

Then the final evaluation score is [[[S1 times the weight which the bank´s management gives to the credit-worthiness S1] plus [the indication of the extent to which a customer relationship with the firm will build the bank times the weight which the bank´s management gives to build the bank S2]] plus [the evaluation of expected profitability to the bank of a customer relationship with the firm times the weight which the bank´s management gives to the profitability S3]].

```
PREMISE:  ($AND (KNOWN CNTXT S1)  (KNOWN CNTXT S2)
              (KNOWN CNTXT S3) (KNOWN CNTXT W1)
              (KNOWN CNTXT W2) (KNOWN CNTXT W3))
```

```
ACTION:  (DO-ALL
            (CONCLUDE CNTXT FINAL-EVAL-SCORE
              (PLUS
                (PLUS
                  (TIMES (VAL1 CNTXT S1)  (VAL1 CNTXT W1))
                  (TIMES (VAL1 CNTXT S2)  (VAL1 CNTXT W2)))
                (TIMES (VAL1 CNTXT S3) (VAL1 CNTXT W3)))
            TALLY 1000))
```

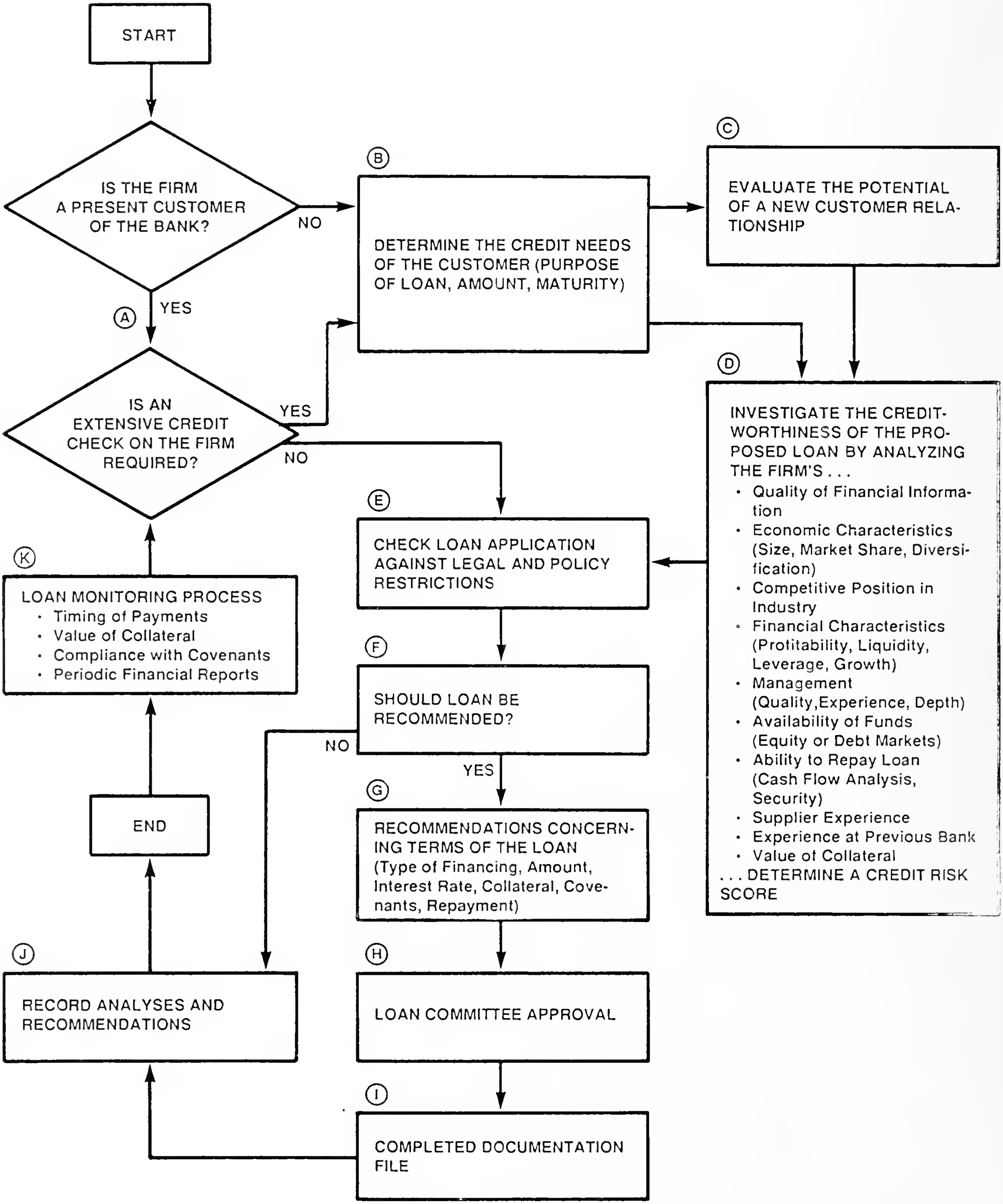

Exhibit 1 Business Loan Decision Making Process

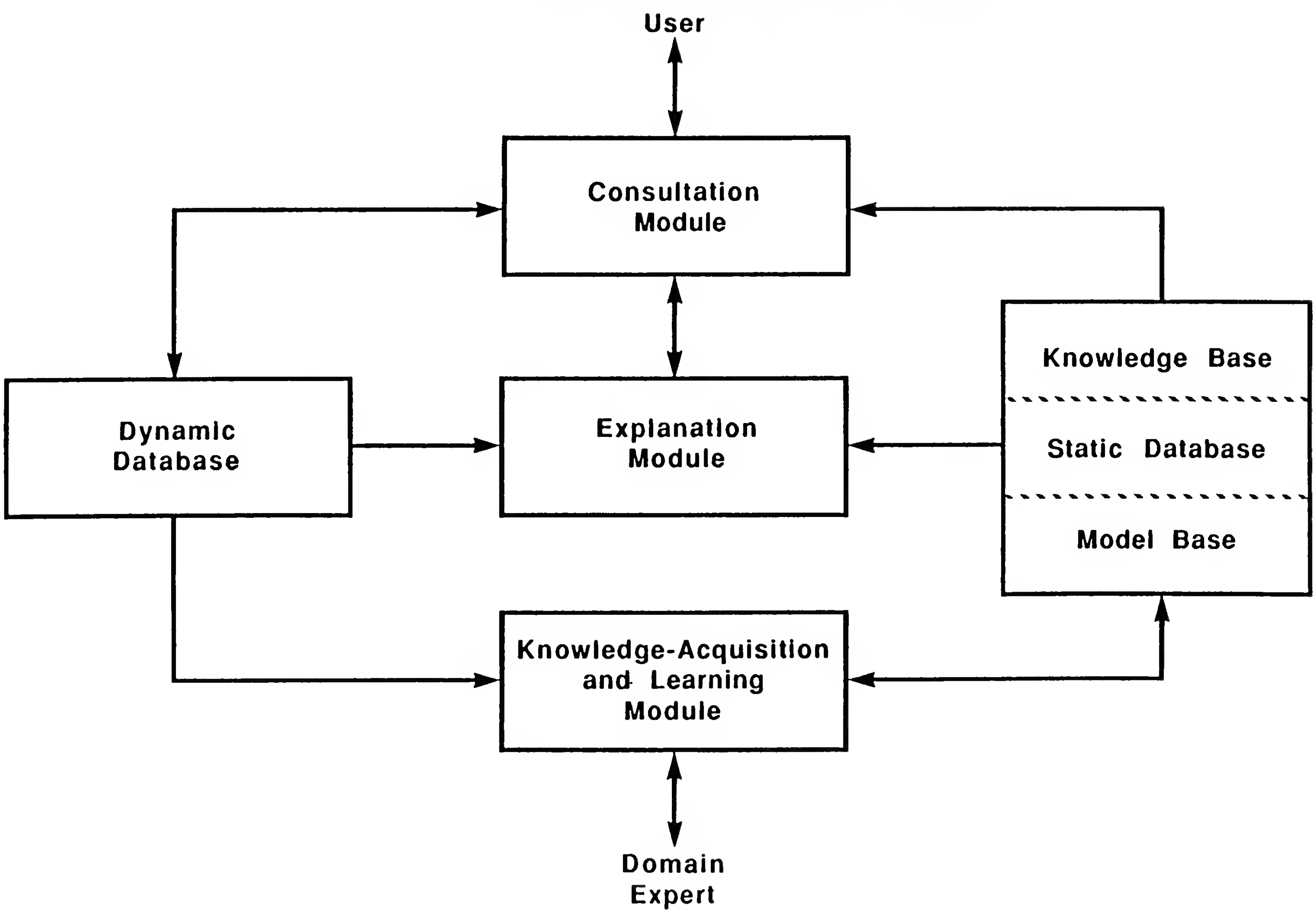

EXHIBIT 2 The Organization of MARBLE

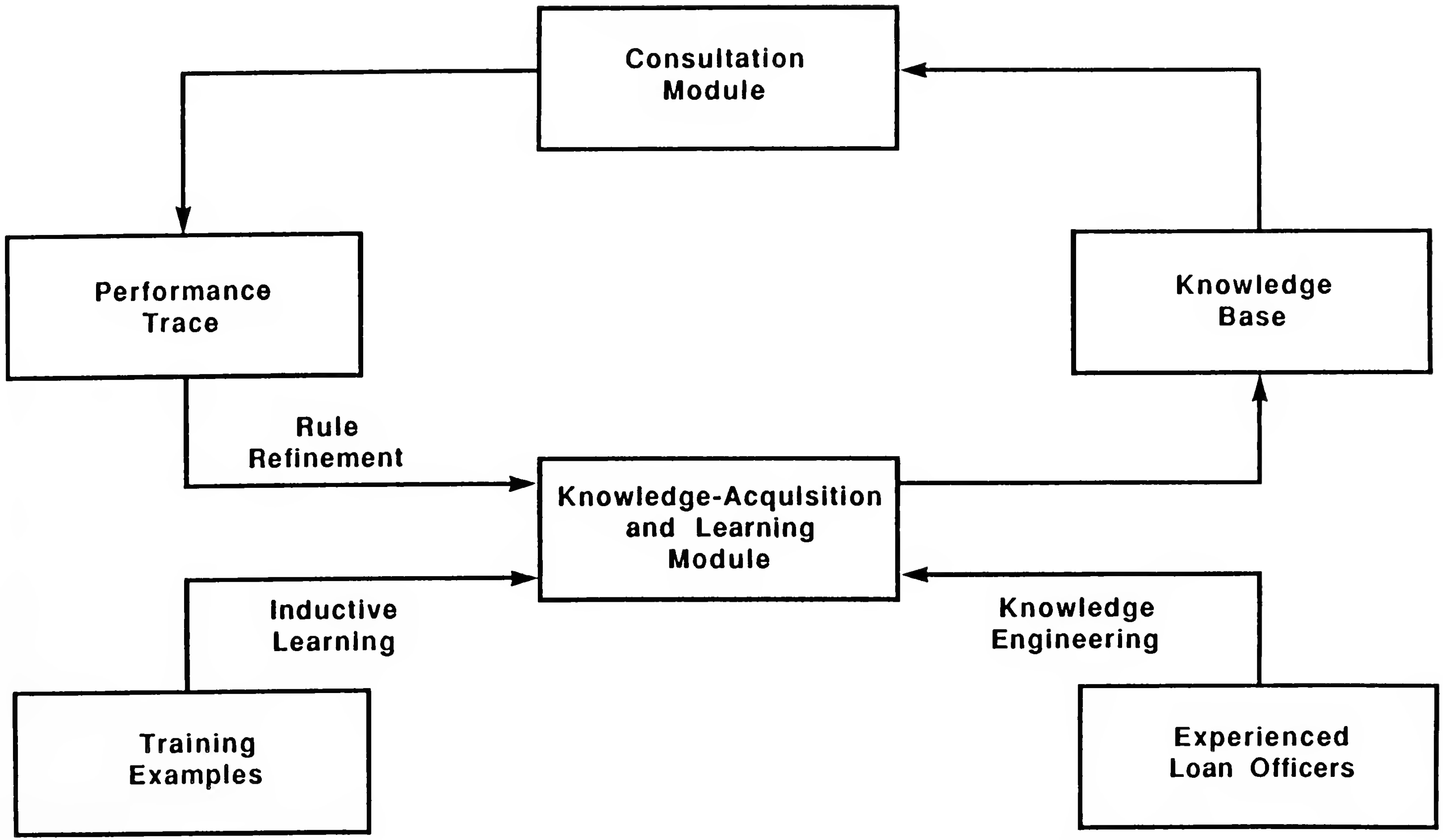

EXHIBIT 3 Interactions Between the Knowledge-Acquisition and Learning Module and the Rest of the MARBLE Environment

Classification	I			IA			II		
Company Code	A	B	C	D	E	F	G	H	I
Mgmt-rating	H	H	H	A	H	A	A	M	A
Credit-rating	H	H	A	A	A	A	M	A	A
Current assets	57	39	43	42	38	52	45	37	46
Net-worth	57	55	49	37	46	40	38	29	36
Total-debt	23	17	20	19	28	25	36	27	35
Funds	9	8	7	8	9	6	-9	7	5
Cash	4	3	5	6	4	5	6	6	5
Cur. liability	39	28	47	55	39	45	57	53	57
Inventory	21	15	18	12	14	11	7	13	14
Avg-inventory	9	14	11	6	6	5	3	5	6
Avg-profits	12	15	13	8	9	9	9	9	-0.8
Past-acc-eval	1Y	2Y	3Y	2Y	1Y	1Y	3Y	2Y	NA
Cust-status	C	C	N	C	C	N	N	C	C
Account-type	C	E	D	D	T	E	E	T	T

Legend: H=High, A=Average, M=Medium
C=Current, N=New
C=Commission, E=Employee-trade, D=Deposits, T=Trust-funds

EXHIBIT 4 Data of 9 Customers
(all figures in $1,000)

Name	Description	Type
Mgmt-rating	the rating of management performance	nominal domain={high,average marginal,reject}
Credit-rating	the outside credit rating	nominal domain={high,average marginal,reject}
Current-assets	the amount of current assets, calculated from the pro forma balance sheet	linear
Net-worth	the amount of net worth	linear
Total-debt	the amount of total debt	
Funds	the funds for debt service	linear
Cash	the amount of cash	linear
Current-liabilities	the amount of current liabilities	linear
Current-inventory	the amount of current inventory	linear
Average-inventory	the amount of three-year average inventory	linear
Avg-profits	three-year average of net profits	linear
Past-account-evaluation	the evaluation of past account	structured
Customer-status	the applicant's status with the bank	nominal domain={current,new}
Account-type	the applicant's account type either in this bank or from other banks	structured

EXHIBIT 5 Relevant Attributes for Credit Rating

	Total Number of Testing Cases	Number of Correct Prediction	Percentage Correct
Failed Firms (Positive Examples)	15	11	73.3%
Nonfailed Firms (Negative Examples)	15	11	73.3%

EXHIBIT 6 The Prediction Accuracy of the Inductive Inference Algorithm Using Holdout Sample

	Total Number of Testing Cases	Number of Correct Prediction	Percentage Correct
Failed Firms (Positive Examples)	29	25	86.2%
Nonfailed Firms (Negative Examples)	29	25	86.2%

EXHIBIT 7 The Classification Accuracy of the Inductive Inference Algorithm Using the Whole Sample