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MARBLE: A Decision-Support System for Business Loan Evaluation

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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Michael J. Shaw, Assistant Professor
Department of Business Administration

James A. Gentry, Professor
Department of Finance

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ABSTRACT

This paper develops an artificial intelligence system for evaluating the risk characteristics of a company applying for a commercial loan. The system is called MARBLE which is an acronym for a decision support system (DSS) for managing and recommending business loan evaluation. Utilizing a knowledge based environment that has the capacity to learn, MARBLE is equipped with an inductive inference engine that is complementary to the inductive problem solver. The paper provides an overview of the business loan application process and the structure of MARBLE's production rules that are used in the loan evaluation process. The learning logic of MARBLE is developed 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.

Although there are many types of bank loans, commercial banks are a primary source of credit for companies that do not have easy access to capital markets. In general, the risk characteristics of companies seeking bank credit are greater than companies needing credit in the capital markets. Thus, determining which business loan applicant should be extended credit and how much credit are major decisions for commercial bank lending officers and credit analysts. Assessing the financial health of a company requires careful analysis of both quantitative financial statement information as well as qualitative information concerning the outlook for the company.[17] Having the necessary information, the correct credit analysis model, and the ability to interpret the information correctly is a task of bank lending staff. A knowledge-based expert system with features such as explanation ability, heuristic inference, reasoning with uncertainty and structured representation of knowledge is an invaluable tool in the loan decision-making process.

Recent research efforts have used the methodology of knowledge-based expert system to design decision-support systems (DSSs).[16,19,39] A system that stresses decision-support and integrates various decision-support functions in the knowledge-based environment is referred to as a knowledge-based DSS.

This paper describes an ongoing research effort to develop a knowledge-based decision-support system that specializes in financial decision support for commercial banks. The system, referred to as MARBLE (a decision-support system for managing and recommending business loan evaluation), is a knowledge-based DSS that uses 80 decision rules for evaluating commercial loans. The MARBLE system was designed to use the lending judgment of experienced loan officers. It was constructed in collaboration with a commercial bank in Chicago.

In addition to the common expert-system design, MARBLE is also equipped with the learning capability. Learning is an important feature of any intelligent system. There are two aspects in decision-support tasks where learning comes into play: (1) learning decision rules for the knowledge base, i.e., the knowledge-acquisition process and (2) refining existing rules by observing prior problem-solving experience, i.e., the knowledge refinement process. To achieve these learning functions, MARBLE must be equipped with an inductive inference engine that is complementary to the deductive problem solver. Thus, an important design issue concerns the inductive inference technique for rule learning and knowledge acquisition.

There are practical incentives to introduce inductive learning into MARBLE. First, an important part of the DSS contains decision rules used by experienced loan officers, but we observe that it is not easy to acquire knowledge from loan officers in the form of rules. Second, there may not be an expert in evaluating business loans because the evaluation is highly judgmental. We observed it is often difficult to achieve a consensus among loan officers on the best set of rules to use. Third, even when the decision rules have been determined and employed, MARBLE needs a means to refine the rules continuously. These problems can be resolved by incorporating an inductive-learning component in the knowledge-based DSS.

The objectives of the paper are to develop MARBLE and show it employs production rules that represent the basic knowledge of a bank lending system; to present an overview of the business loan application process; to develop MARBLE as an integrated problem-solving model structured around the business loan decision making process; to provide the structure of MARBLE's production rules used in the loan evaluation process; 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.

Business Loan Evaluation

Typically, the evaluation of a business-loan application is a subjective decision process made independently by loan officers and credit analysts. 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, and the overall performance of management. The loan-evaluation decision is traditionally analyzed by statistical linear models, such as regression analysis,[31] or polytomous probit analysis,[21] or recursive partitioning.[24] As pointed out by Haslem and Longbrake[20] and Dietrich and Kaplan,[21] statistical analysis with linear models cannot capture the subjective judgments and the qualitative evaluation so important in the lending decision. In essence, the approach used by MARBLE is akin to the heuristic simulation method employed by Cohen, Gilmore, and Singer,[10] which simulates the decision process of loan officers. MARBLE, however, employs production rules as the basic knowledge representation, which has been pointed out as an effective model of the human decision-making process.[2] In addition, the knowledge-based expert technology enables MARBLE to be equipped with uncertainty reasoning, explanation, and incremental refinement capabilities. As will be shown, inductive learning can be applied to enhance MARBLE's performance further by automatically acquiring decision rules for loan classification. There are two schools in the development of mental models for describing learning processes: (1) the connectionist model, which describes mental processes in terms of activation patterns defined over nodes in a highly interconnected network; and (2) the production-system model, which describes mental processes as symbol manipulation in a production system.[2,29] The method we use for incorporating learning in MARBLE is the second approach in which learning is achieved by rule-augmenting.

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

Insert Figure 1 Here

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.

Integrated Problem Solving in MARBLE

A DSS is usually linked to an external database and a model base[1,4,38] that is characterized by a large amount of data and program modules. The problem solver of MARBLE can be viewed as a production system[29,12] where production rules are used to represent (1) procedural knowledge, (2) decision heuristics, and (3) model abstraction. Procedural knowledge is the knowledge about the essential steps of making a given decision, which is mostly related to information collection. For example, in evaluating a company's credit-worthiness, the supporting information includes the performance measurement of the management, the outside credit rating of the firm, if available, and credit analysis of the firm's financial data. This piece of procedural knowledge is shown as Rule 073 in Appendix 1. Because the decision heuristics are rules of thumb used by loan officers that are inherently judgmental, this class of rules requires considerably more effort to obtain and refine. The rules generated by inductive learning belong to this category. The third type of rules is used to represent the model knowledge available for decision support; these rules indicate the application requirements of each model and the precedence relations between models.

With these different types of decision-support knowledge, the problem solver serves as a bridge that links the decision maker's problem environment with the appropriate models, data, and decision rules residing in the DSS. An example of the consultation session performed by the problem solver interacting with the user is shown in Appendix 1.

The basic inference mechanism for accomplishing decision support tasks in a knowledge-based DSS, such as MARBLE, is based on the problem-solving theory established by Newell and Simon,[30] which treats problem solving as a process of search through state space. A problem is defined by an initial state, a desirable goal state, a set of operators that transforms one state into another, and a set of constraints that an acceptable solution must meet. Problem-solving under this theory involves the selection of an appropriate sequence of operators that will succeed in transforming an initial state into a goal state through a series of steps. For decision-support tasks, the steps selected in the process are primarily information processing activities that result in a plan of action. Problem solving utilizes information from the knowledge-base, external database, dynamic database (sometimes referred to as blackboard), and a model base.[4,14,15] In the case of MARBLE, the model-base can contain program modules for financial analysis, mathematical programming routines, forecasting, simulation, or regression algorithms. The external database typically contains the historical loan data and financial information of companies applying for loans. Therefore, special care must be taken to handle the interface between the system's knowledge-base, model base, and database.[14,37]

The Organization of MARBLE

In MARBLE, production rules are the basic form of knowledge representation. 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. The grammar of the rules, described by the BNF formalism, is shown in Table 1. Some sample rules used in MARBLE are shown in Appendix 2.

To capture fully the decision rules used in business loan evaluation, MARBLE currently uses nine 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.

The context-types instantiated during the consultation session are arranged hierarchically in a data structure termed the context tree, as shown in Figure 2. The current version of MARBLE is implemented in the TI Personal Consultant.

Insert Figure 2 Here

The context tree helps to structure a knowledge base domain in MARBLE by allowing the designer to separate a large amount of information into logical units. Each context can solve one part of the total problem and provide important information needed to solve the problem as a whole.

Inductive Learning

The ability to learn has long been recognized as an essential feature of any intelligent system. Dietterich, et al.[13] categorizes learning methods into four areas based on their behavioral characteristics: rote learning, learning by being told, learning from examples, and learning by analogy. Most existing knowledge-based systems use "learning by being told" for acquiring problem-solving knowledge. That is, the system acquires its domain knowledge from experienced decision makers in the field, e.g., experienced loan officers in the case of MARBLE, and transform the knowledge into the representation form in the knowledge-base.

Inductive learning can be defined as the process of inferring the description of a class from the description of individual objects of the class. Training examples are given in the form of instances and described by a vector of attribute values. Each class can be viewed as a concept which is described by a concept recognition rule as a result of inductive learning. If an input data instance satisfies 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 positive instance and FALSE when applied to a negative instance of the concept.[4] 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) as the knowledge representation, the above concept can be represented by well-formed-formulas (WFFs).[5,40] For example the same concept can be represented by a conjunction of attribute descriptions:

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

An alternative way to represent such a concept is to use the variable-valued logic (VL) proposed by Michalski.[25] The VL language is an extended form of if-then rules where many-valued logic is involved. The premise section of each rule is a conjunction of multivalued attribute variables and each attribute is enclosed by a bracket with its corresponding values. A <u>selector</u> relates an attribute to a value or a disjunction of values. For example, [type-of-firm = manufacturing v steel] is a selector which assigns two disjunctive values to an attribute. The conjunction of such selectors forms a <u>complex</u>. The aforementioned concept recognition rule can be represented by the VL formalism as follows:

[assets > $1,000,000][total-debt < $250,000]

[AGR > 0.10] → [class : 'A'].

(Note that the LHS of the rule is a conjunction of selectors.)

The process of inductive inference is itself a problem-solving process where solutions, the inductive concept descriptions, can be obtained through searching.[23,33,34] Concept descriptions are derived through a sequence of transformations to generate the goal descriptions. The states are defined by the possible symbolic concept description, structured in a search space called the hypothesis space. Based on this paradigm, the inductive inference system consists of these components: (1) the hypothesis space which organizes all the concept descriptions by a partial ordering; (2) the class of transformation rules being considered, such as the generalization rules; (3) the set of training examples; and (4) the criteria for a successful inference, such as the simplicity of hypothesis generated, goodness of fit, completeness, and consistency.[3]

Generalization is essential for making inductive inference. If a concept description Q is more general than the concept description P, then the transformation of P to Q is called generalization. P is said to be more general than Q if and only if there are more instances covered by P than by Q. Based on the concept of generalization, inductive inference can be viewed as a process of generalizing the initial descriptions as observed from examples and intermediate concept-descriptions until the inductive concept-descriptions consistent with all the examples are found. Thus, the generalization relations between concept-descriptions provide the basic structure to guide the search in inductive inference. This generalization relation can be accounted for in inductive inference by ordering concept-descriptions according to their degree of generality/specificity and by using transforming rules to achieve generalization.

The input to the MARBLE's inductive learning component 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. The resulting output is a set of decision rules consisting of inductive concept description for each of the classes. The inference process used in MARBLE for inductive learning is based on the star methodology developed by Michalski,[25,27] in which negative examples are used in the learning process to constrain the search space for the inductive concept descriptions. In other words, the inductive learning algorithm uses negative examples to ensure that the learning process would only search through those descriptions consistent with positive examples and not covered by negative examples.

Incorporating Inductive Learning in MARBLE

We shall use the 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 on a given commercial loan, a bank usually would use a five-category classification scheme.[21] 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 Figure 3, 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 shown in Figure 4. The tree structure will be used to apply appropriate generalization rules in the induction process, as will be illustrated in (ii) below.

(i) Training examples.

After choosing the relevant attributes, a set of data descriptions $\{e_k^i\}$, i = 1, 2, 3, and the corresponding class $\{K_i\}$. (K_i = I, K_2 = IA, K_3 = II) are used as training examples. This set of training examples is displayed in Figure 5.

The objective of Figure 5 is to illustrate that firm specific risk or creditworthiness increases as financial and nonfinancial characteristics of a company deteriorate. Chen and Shimerda[9] and Pinches, Eubank, Mingo and Caruthers[32] 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	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 comprehensive score for a firm.

The training example in Figure 5 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.

Insert Figures 3, 4 and 5 Here

(ii) Generalization rules.

The domain-specific knowledge, represented by the generalization trees in Figure 4, can be specified in VL language by the following generalization rules:

R1:

[past-account-eval = one-year]V[past-account-eval = two-year]V

[past-account-eval = three-year] --> [past-account-eval = present];

R2:

[account-type = commission]V[account-type = fees]

--> [account-type = other-businesses].

In addition, there are a set of generalization rules, independent of the application, that can be applied in the inductive inference process. Michalski[25] comprehensively surveyed various types of generalization rules for transforming and generalizing descriptions. The inductive inference process employed requires the application of generalization rules based on the attributes' generalization tree and based on such rules as the closing-interval rule and the dropping-condition rule.[36]

(iii) Induction criterion

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

(iv) The inference process and the rules learned

The inductive rules generated by the learning algorithm for describing the three classes of input are as follows:

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 are then stored in MARBLE, using the rule format described in Table 1. These classification rules covered 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.

<u>Empirical Study on a MARBLE Application</u>

To test the performance of the inductive inference method for rule learning in the domain of loan evaluation and risk analysis, we have conducted an empirical study using real-world data. Loan risk classification and the classification of a bankrupt firm are based on accounting information. Because loan information is held by banks and considered private, we have used public financial information to classify the risk of bankruptcy. This 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.

In the empirical study, we apply the inductive inference algorithm to the problem of bankruptcy prediction. To identify the relevant attributes for learning the characteristics (concepts) of bankrupt firms, we adopted the cash-based funds flow components[18] which include funds from operations (NOFF), working capital (NWCFF), financial

(NFFFF), fixed coverage expenses (FCE), capital expenditures (NIFF), dividends (DIV), and other asset and liability flows (NOA&LF).

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) NOA&LF/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 conducted by Gentry, et al.[18] 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 available. The rule learning program is written in PASCAL on PDP 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 use the holdout sample technique and use half of the sample for rule learning; the rules are then tested on the remainder of the sample. The selection of training examples out of the set of data is based on a degree of representativeness of each data case. Based on the "outstanding representatives" method,[26] the training examples are selected so that they are most distant from each other and, therefore, are the most representative examples. The beam search version of the inductive inference algorithm is used with beam-width = 10.

The result of using the learned rules to test against the holdout sample is shown in Table 2, 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. Accordingly, Table 3 shows the learned rules classify the whole set of data cases, 29 failed firms and 29 nonfailed firms, with 86.2% accuracy, compared with 83.3% accuracy resulting from the logit model used in Gentry, et al.,[18] the rules generated by inductive learning appear to provide a valid decision aid for determining whether a firm has the characteristics of bankrupt firms.

Summary

The knowledge-based expert system is an effective tool for decision support because of features such as explanation ability, heuristic inference, reasoning with uncertainty, and capabilities for incremental refinement. We have extended the knowledge-based decision support systems by adding an inductive learning method. It helps automate the knowledge-acquisition process and generate decision rules.

By using examples in the MARBLE domain, we have shown the utility of inductive inference to knowledge acquisition and to enhancing the problem-solving capability of DSSs. Since decision rules can be generated and refined through new observations. The incorporation of the inductive learning component enables MARBLE to be adaptive in its problem-solving process. This type of learning capability would be essential in the effort of building an intelligent DSS. The empirical study shows encouraging results for incorporating inductive learning in MARBLE for loan evaluation.

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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 the 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 the
         applicant's statements is HIGH.
then  1) it is definite (100%) that the credit-worthiness is high.
      2) it is definite (100%) that 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 an UNKNOWN function key.}

(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?^T
**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) Waht 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))
```

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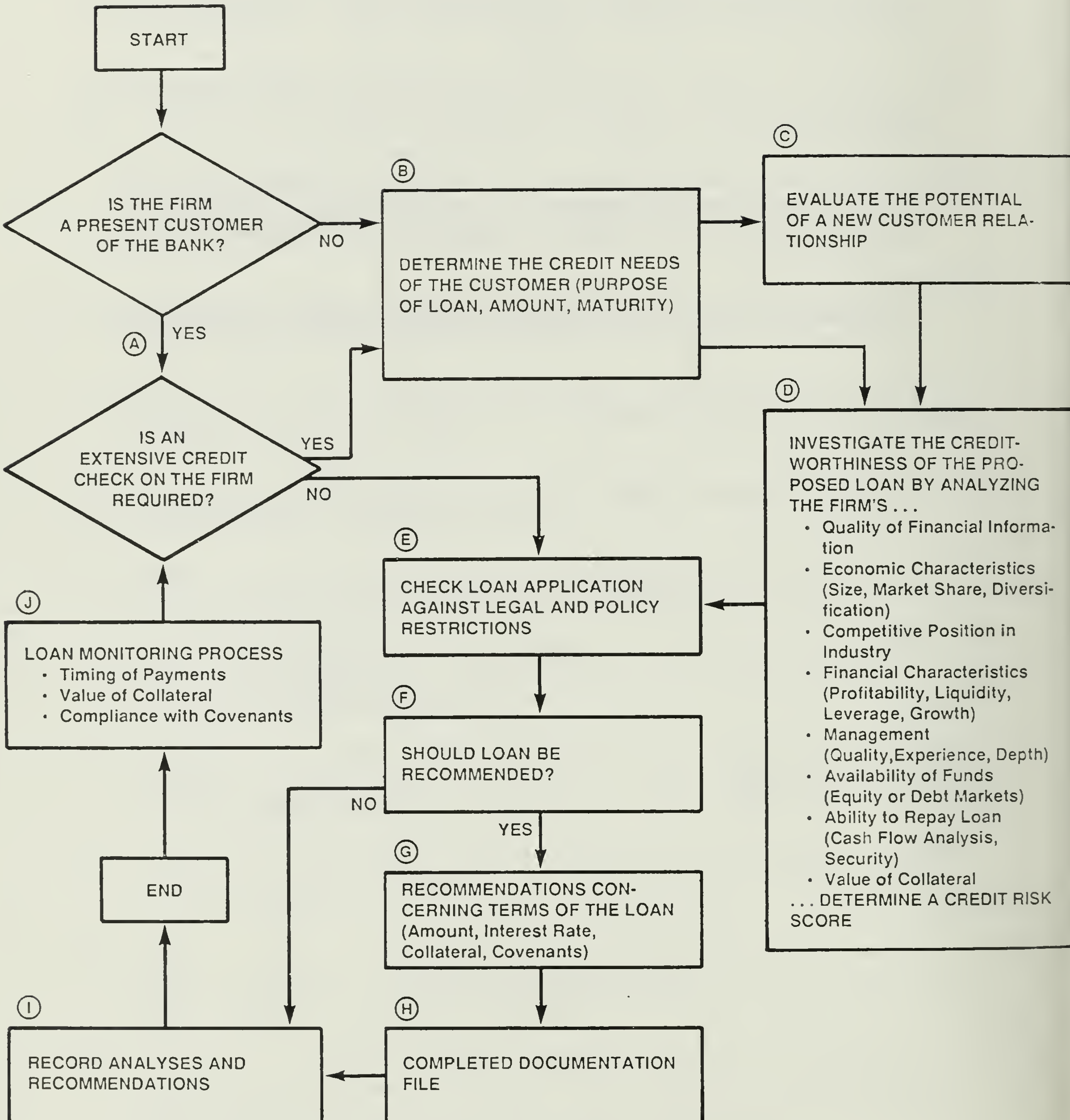


Figure 1 Business Loan Decision Making Process

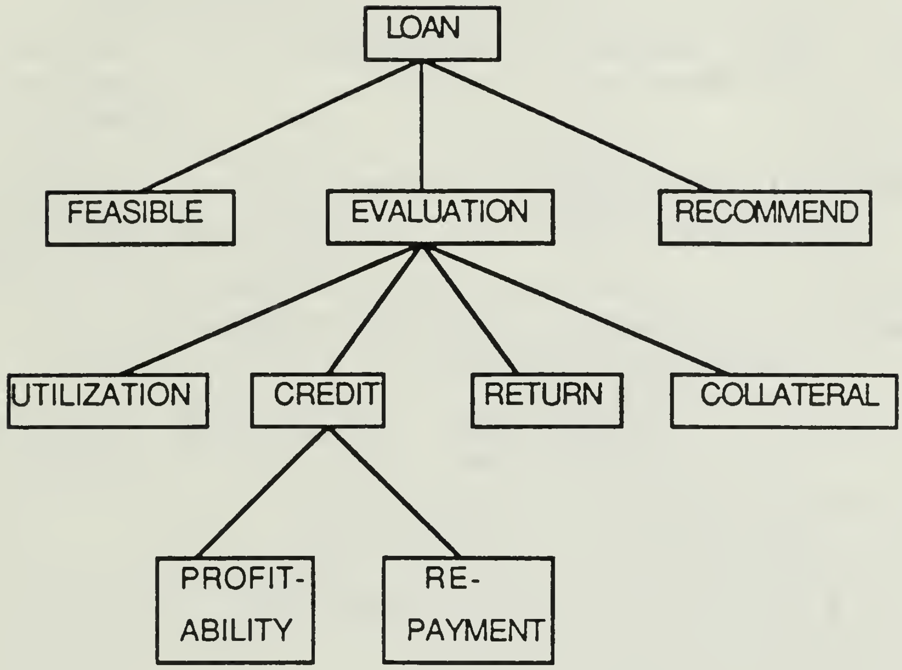
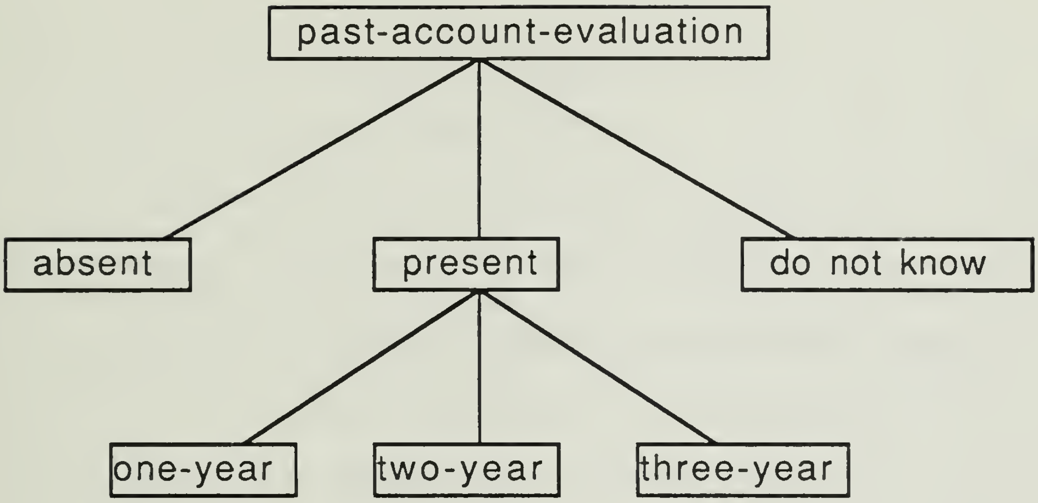


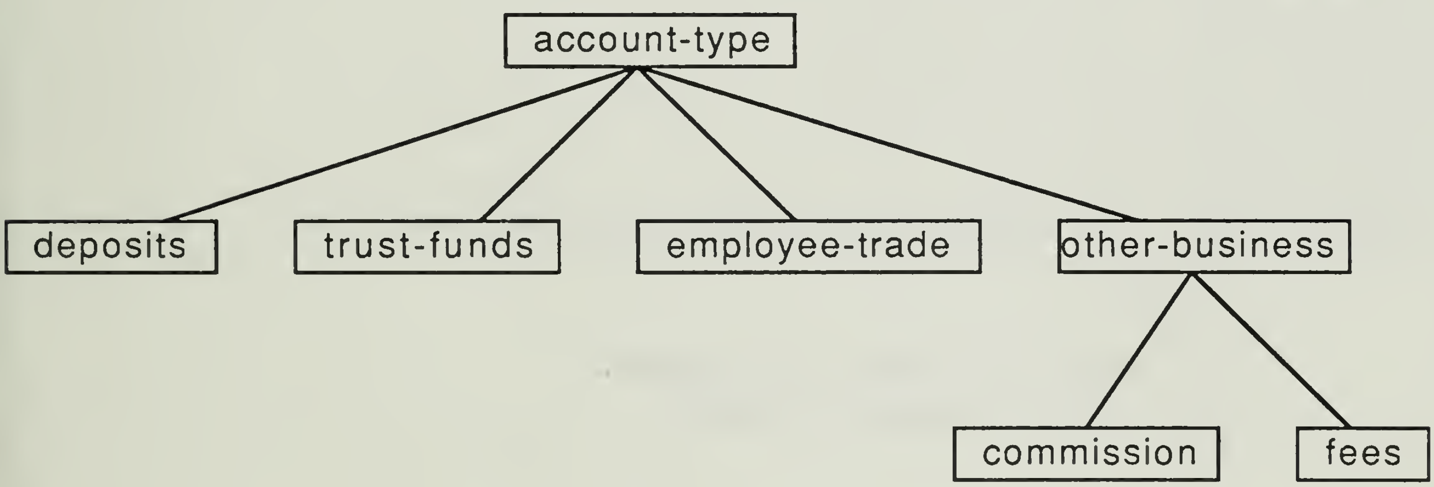
Figure 2 Organization of the Context-Types

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

Figure 3 Relevant Attributes for Credit Rating



(a)



(b)

Figure 4 Two Examples of Structured Attributes

	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

Figure 5 Data of 9 Customers
(all figures in $1,000)

```
      <rule> :: = <premise> <action>

   <premise> :: = ($AND <condition> ... <condition>)

 <condition> :: = ((<func1> <context> <parameter>) |

                  ((<func2> <context> <parameter> <value>) |

                  ($OR <condition> .. <condition>)

    <action> :: = <conclusion> | <actfunc> |

                  (DO-ALL <conclusion> ... <conclusion>) |

                  (DO-ALL <actfunc> <actfunc> <actfunc>)

<conclusion> :: = ((<confunc> <context> <parameter> <value> TALLY <cf>))
```

Table 1 The Format of Rules Used in MARBLE

	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%

Table 2 The Prediction Accuracy of the Inductive Learning Procedure Using Holdout Example

	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%

Table 3 The Classification Accuracy of the Inductive Learning Procedure Using the Whole Example