A DSS for Bank Credit Evaluation under Risk

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Abstract

The loan and credit function is the heart of banking, under the ever-changing market conditions. The lack of general loan review system in many banks and the lack of precise methods for measuring credit risk are two important reasons why a decision support system is necessary. This paper presents a model-based decision system with a model action table, a model base and a dynamic process system that triggers appropriate rules to select models to use upon different market signals. In the model base, we suggest models performing judgmental analysis to help a senior bank manager in loan processing that involves customer creditability evaluation and risks appraisal. The proposed processing system simulates the dynamic decision process of an experienced human bank loan officer. With the dynamic processing using the current market information, every possible outcome and its risk analysis can be obtained.

Keywords : DSS, Credit Evaluation, Blackboard System, Multi-criteria Decision Making, Model-based reasoning.

1 Introduction

Decision-making problems in loan evaluation and its risk appraisal are one of the most important and difficult tasks in credit management by banks and other financial institutions. A bank lends to many types of borrowers for varying periods, on many bases and for a variety of reasons. Loans therefore will vary in liquidity and risk, and assessing involves making judgement based on uncertain data. As one of the ill-structured problems decribed by Newell and Simon [18], it is too complex to be processed by conventional methods. In most cases, the examination of the loan application is based on an intuitive and empirical approach. The quality of the outcome often depends on the experience of the analyst, his perspicacity and overall impression of the firm applicant, his perception of the sector in which the firm operates and his knowledge of the bank's loan policy.

According to [29] the most common methods used are those of "Credit Scoring Model" [5,9,19] based on discriminant analysis to calculate a total score that ranks the applicant's credit rating and represents the degree of risk. To obtain a total score, first, points are assigned depending on the answer given to each item in the application form. Next the loan officer assigns weights to some financial ratios which they consider as significant. The total points for an application are then compared to some critical level which are determined from the senior manager's experience, and the loan is approved or rejected according to whether the score of the application is above or below this preassigned "cut off" point. In the absence of a rigorous theoretical framework, this is a sensible procedure [5]. In certain enhanced system, some statistics technology is added. For examples, a multivariate regression analysis may derive the credit-scoring models; a markov chain process may provide the basis for calculating the potential loss of a customer loan portfolio.

In recent years, some expert systems or knowledge-based systems were developed in this area [8,13,17,20,33]. In these systems, the user is asked questions about the applicant and its environment that generally require yes-or-no answers or one of three possible estimates:strong,average, and weak. The loan officer makes many subjective judgements as to the applicant's relative strength in the various areas. There is no strict formular that can be followed in arriving at the final loan decision, just as there isn't any well-defined problem descriptive method to describe the domain knowledge. When asked to explain the decision-making process in business organization, a loan officer usually says that executives exercise "judgement" and that this judgement is largely a function of experience, intuition and insight. So the human element, as it relates to both the loan officer and the applicant, plays a key role in the analysis of all the pertinent facts. With the development of AI, neural network is used to solve classification decision problem such as credit evaluation, prediction of bankruptcy of firms [1,14,31]. However it must find the correct algorithms for the neural network [21], and needs many samples to train the net. Research results indicated that the composition of the training set was a significant determinant of the neural network's predictive accuracy [26,27]. Under ever-changing market conditions, training sets can't express well the volatility of market rates. Too often, researchers "test" the usefulness of a statistical procedure by analyzing its results on the same set of data employed in developing the procedure. Since anyone sample may not be entirely representative of the population, there is a danger that samples estimated from the original sample may not be appropriate for the overall population. The study presented in this paper attempts to fill the gap between research and practicce, by providing comprehensive and integrated decision support system with dynamic processing using the current market signals. Section 2 gives some suggested models that can be used in this system and section 3 describes each component of the system in more details. Finally, a summary and an example is presented in section 4 to illustrate the use of the suggested models with the proposed system.

2 Some suggested models

In present day, financial market relies on global dissemination of price-sensitive information, traders' ability to communicate instantly, and the availability of powerful PC and sophisticated analytical software at dealer's fingertips. The money, bond, and equities markets are often grouped together under the term Capital markets. These markets bring together on the one hand those who wish to raise funds and who are willing to pay for the use of those funds, on the other hand investors who seek a return on the capital they have available to invest, and financial institutions who mediate between the two. Therefore market information is a barometer which reflects each organization's financial situation such as operational state, profit and loss conditions, and competition circumstances, yet it is most often the one overlooked. Few executives use information effectively on their jobs; many of them rely on intuition as a basis for decision [17]. In our system we propose to use market signals: interest rate, tax rate, exchange rate and the rate of gross profit, to perform quantitative analysis to help loan officer to make decisions.

In the business environment, quick response to ever-changing market information is important to make correct decisions. In building models, we have emphasized not only formulating the domain expert's experiences but also simulating the entire decision making process. So the final result usually emerges after having taken into account all the interdependencies among the various characteristics and components. Unlike the previous studies [17] where systems can be classified as passive forms of decision support, they do what the users explicitly direct them to do. For example, they answer what-if kinds of questions such as those presented in Table 1 to make decision.

If loan-type = business and business-type = existing and secured = yes and loan-size = between and target-market = acceptable then screening = applicable
If reason = long-term-sales-growth and annual-sales-growth = yes then purpose = acceptable
Question(loan-size) = *Is the amount of the loan under 250,000, between 250,000 and 2.5 million or over 2.5 million?(under / between / over)*
Question (reason) = *As a result of your investigation of the loan applicant, what have you determined to be the purpose of the loan? (long-term-sales-growth/shot-term-sales-growth/accounts-receivable/fixed-assets /cash-management/ one-time)*

table 1

Using current market signal for model process is an important advantage of the proposed evaluation system.
In the following suggested models, we assume that Government policies are stable, so that their effect on taxes, interest rate and numerous costs such as environmental and health and safety expenditures is insignificant.

Let

ρ: rate of return on stockholder's equity, N: original assets;

F: newly increased debts, i: risk-free interest rate;

γ: tax rate, W: earnings before interest and tax;

ω: the gross profit rate, M: turnover;

A:debt-total assets ratio; $\overline{A}$: the average value of A in same business;

Some of these are related :

$$\omega = \frac{W}{N+F} \tag{1}$$

$$\text{debt rate} \quad \delta = \frac{F}{N} \times 100\% \tag{2}$$

$$\text{debt-total assets ratio} \quad A = \frac{F}{F+N} \times 100\% \tag{3}$$

Obviously $0 \leq A < 1$

[**Analysis I**]: model (ρ) , reference [7] gives the details derivation.

$$\rho = (1-\gamma)(1+\delta)\omega - \omega_M \delta (1-\gamma), \text{ where } \omega_M = i,$$

and

$$\rho = (1-\gamma)(1+\delta)\omega - (1-\gamma)\omega_M \delta, \text{ where } \omega_M = \frac{i}{1-\gamma}.$$

Substituting the formula $A = \frac{F}{N+F}$, and $\delta = \frac{F}{N}$ into the above we can obtain

$$\rho = \frac{1-\gamma}{1-A}[\omega - \omega_M A]. \tag{4}$$

[**Analysis II**]: Bankruptcy Model– model($\varphi(\lambda)$).

Risk is thought of as an uncertainty regarding the rate of return from an investment [25]. The larger the range of possible returns, the more uncertain the investor is of the actual return, and therefore, the greater the risk.

No one can ever maintain $\hat{\omega} > \omega_M$, because of the keen competition in the market. Thus, once the market quotation turned sharply to be $\hat{\omega} < \omega_M$, there is a probability of the firm's bankruptcy within a short time.

According to [2], the past rate of return on almost any stock conforms closely to a normal distribution. Under this assumption, we let $\lambda = -\frac{\hat{\rho}}{\sigma(\hat{\rho})}$. That is

$$\lambda = -\frac{\hat{\omega} - A\omega_M}{\sigma(\hat{\omega})}. \tag{5}$$

and compute risk as

$$\varphi(\lambda) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\lambda} e^{-\frac{t^2}{2}} dt \tag{6}$$

To obtain an estimate of a company's operational situation , we

(1) compute the value of λ : $\lambda = -\frac{\hat{\omega} - A\omega_M}{\sigma(\hat{\omega})}$;

(2) calculate the value of $\varphi(\lambda) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\lambda} e^{-\frac{t^2}{2}} dt$;

(3) when $A = 0$, $\lambda = -\frac{\hat{\omega}}{\sigma(\hat{\omega})}$;

(4) we draw a curve to show the trend of risk increment under the current market situation. For a given value of ΔF (debt), we obtain a A then we can compute its corresponding $\varphi(\lambda)$ and get a series of value of $A - \varphi(\lambda)$. See figure 1.

[**Analysis III**] Strategy model for a company in competition

The analysis of the competitive situation provides indications of how well a company can do under competition, its financial position in relation to further competitive market requirement. A company (j) holds a competitive edge over her competitor (K), if the bankruptcy risk of the company (j) is less than that of the competitor (K), that is $\varphi(\lambda_j) < \varphi(\lambda_K)$.

In order to make $\varphi(\lambda_j) < \varphi(\lambda_K)$, we must have

$$\lambda_j < \lambda_K$$

that is,

$$-\frac{\hat{\omega}_j - A_j\omega_{Mj}}{\sigma(\hat{\omega}_j)} \leq -\frac{\hat{\omega}_K - A_K\omega_{MK}}{\sigma(\hat{\omega}_K)}.$$

Solving, we have

$$A_j \leq \frac{1}{\omega_{Mj}}\left[\hat{\omega}_j - \frac{\sigma(\hat{\omega}_j)}{\sigma(\hat{\omega}_K)}(\hat{\omega}_K - A_K\omega_{MK})\right]. \tag{7}$$

In particular, if the marketing conditions are the same and management experence is also similar between the two competitors, then we may simplify the above formula to obtain

$$A_j < A_K.$$

Therefore, in keen competition, the (j) should take a lower A than the competitor K in order to make $\varphi(\lambda_j) < \varphi(\lambda_K)$.

[**Analysis IV**] Model (F_j) for credit limit calculation.

According to [analysis III], the system can calculate the maximum amount of approved loan if one wants to apply for the loan.
The system takes the applicant's relative business as its competitor, and

(1) calculate the average $\overline{A}$

$$\overline{A} = \frac{1}{\sum_{k=1}^{n} a_k}[\sum_{k=1}^{n} a_k \cdot A_k] \tag{8}$$

where a is weight, $a_1 = \frac{F_1}{\sum_{k=1}^{n} F_k}, \ldots, a_n = \frac{F_n}{\sum_{k=1}^{n} F_k}$.
(2) compute the average value of the gross profit rate $(\overline{\omega})$.

$$\overline{\omega} = \frac{1}{\sum_{k=1}^{n} b_k} \cdot \sum_{k=1}^{n}[b_k\omega_k] \tag{9}$$

where b is weight, $b_1 = \frac{M_1}{\sum_{k=1}^{n} M_k}, \ldots, b_n = \frac{M_n}{\sum_{k=1}^{n} M_k}$; and M: turnover.

(3) evaluate a general standard deviation of operation performance ($\overline{\sigma}$).

$$\overline{\sigma} = \frac{1}{\sum_{k=1}^{n} c_k} \cdot [\sum_{k=1}^{n} [c_k \sigma(\hat{\omega}_k)] \tag{10}$$

where c is weight, in this case, $c_1 = b_1, \ldots, c_n = b_n$. But it can be assigned to other value according to different situation.

(4) calculate the credit limit F_j.

Since

$$\frac{F_j}{N_j + F_j} = A_j = \frac{1}{\omega_M j}[\hat{\omega}_j - \frac{\sigma(\hat{\omega}_j)}{\overline{\sigma}}(\overline{\omega} - \overline{A} \cdot \omega_M)]$$

therefore

$$F_j = \frac{N_j[\hat{\omega}_j - \frac{\sigma(\hat{\omega}_j)}{\overline{\sigma}}(\overline{\omega} - \overline{A}\omega_M)]}{\omega_M j - \hat{\omega}_j + \frac{\sigma(\hat{\omega}_j)}{\overline{\sigma}}(\overline{\omega} - \overline{A}\omega_M)} \tag{11}$$

Other models available in the model base include the following :

- Model $[\sigma(\hat{\omega})]$: Evaluate the firm's reputation.These models may use the information gathered on the applicant company's overall management character to evaluate the firm's reputation in her business field.
- Model (payback) : Check the ability of repayment on maturity.
- Model ($\hat{\omega}$): Compute the expected value of gross profit rate in enterprise.
- Model (Growth rate): Assesses the applicant's working capital situation , growth rate and expected profitability.
- Model(λ,ω_M): Evaluate the stability of business operation in terms of the applicant's marketing capabilities , operational characteristic and trends.

3 Characteristics of the proposed system

The basic components of the proposed system are presented in figure 2.

The system consists of a processing system, a model action table, a model base, a decision action table and a data base. The processing system is a controller. It directly interacts with the user to obtain input data and interacts with the model action table, the model base and the decision action table to generate a decision or suggestion. The model action table is a set of rules which indicate the problem domain knowledge for model execution. It is implemented as part of the processing system. The model base is a collection of problem-solving models designed by the domain expert, such as those presented in section 2. The decision action table consists of decision rules which also are domain knowledge. When activated, they give advices and decisions. The loan analysis process begins when a loan application is received. The system requires the user to input the amount of expected loan, the applicant firm's attributes and some financial data such as current debts, current assets and earnings before interest and tax. Based on information about the firm applicant,the processing system can select some choices and present to the user, and examines the various rules for performing model selection and calculation, and gives some suggestions such as the maximum amount of the request loan under the limited risk if the application is approved. The communication between the user and the system continues until a satisfactory solution is found. Figure 3 gives an example flow chart for performing the loan evaluation and analysis.

Figure 4 illustrates the controling flow of the processing system.

We describe the system components in more details in the following section.

3.1 Model Index Card

Every model in the model base has a Model Index Card, as shown in Table 2

Model index card

Model name	:	Identifying each model
Function	:	functionalities description
Assumption	:	on what condition it will be used
Parameters	:	variables used in model
Model Confidence	:	satisfactory of using the model
Model reference	:	reference to a mathematics model in model base

table 2

Each Model Index Card (MIC) has a model name and a number of slots. Slots accept value of various types, namely, numerical, logical and symbolic. The last slot in MIC is a model reference which corresponds to the problem solver in the model base.

Three examples of MIC are shown in the following:

Model name	:	model ($\hat{\omega}$)
Function	:	compute the expected value of gross profit rate in firm
Assumption	:	any change in gross profit rate
Parameters	:	M , sales record per month
Model Confidence	:	0.85
Model reference	:	@ [$\hat{\omega}$]

table 3

Model name	:	model (ρ)
Function	:	compute firm applicant's liabilities effect
Assumption	:	loan request
Parameters	:	ω, A, δ, γ, i
Model Confidence	:	0.9
Model reference	:	@ [ρ]

table 4

Model name	:	bankruptcy model
Function	:	calculate the applicant's credit risk for every credit loan
Assumption	:	ω follows a normal distribution
Parameters	:	$\hat{\omega}$, i, A, $\sigma(\hat{\omega})$
Model Confidence	:	0.8
Model reference	:	@BANKRUPT 1

table 5

3.2 Applicant Report Card

The processing system builds an Applicant Report Card (ARC)for each applicant. ARC is just like a list which is used to store criteria and their assessed value from the models. As can be seen from the example in table 6.

Name	criteria varable	model	result
company J	risk	@Bankrupt 1	0.1586
	growth rate	@Growth	increase
	credit reputation	@[$\sigma(\hat{\omega})$]	average
	$\hat{\omega}$	@[$\hat{\omega}$]	yes
	solvency	@[payback]	average
	loan period		short
	interest rate	i	0.125
	debt-total assets ratio	A	0.2
	original assets	N	100
	request loan	F_{new}	300
	debt	F	100

table 6

The criteria are determined by the problem domain and its environmental information.

3.3 Model Action Table

The Model Action Table is a set of rules, table 7 containing such an example.

Model Action Table	
Condition	**Action**
result(X) = $\varrho(X)$ and result (Y) = $\varrho(Y)$	C

table 7

An action rule takes one of the following form: 1)**IF** X is A **THEN** call model ..., 2) **IF** X is A AND/OR Y is B **THEN** call model ..., etc. where X and Y are models or variables respectively ; A and B are values or logical values respectively. Such rules cannot be executed by an ordinary inference engine, however [24,4,12,6] especially the blackboard system often used in distributed AI system [3,10] propose some solutions when there is a procedure involved in the inference schemes. Three examples of action rule in the above model action table are shown in table 8.

Model Action Table	
Condition	**Action**
model(λ,ω_M) returns 'increase' and model(Growth) returns 'increase'	model(payback)
model($\hat{\omega}$) returns 'yes' and model(ρ) returns 'increase'	model($\sigma[\hat{\omega}]$)
model($\sigma[\hat{\omega}]$) returns 'good' and borrow is 'true'	model(F_j)

table 8

The first row (rule) indicates that

IF applicant's stability is increasing and Growth rate is increasing

THEN call model(payback).

It is possible that some model's output would signal the processing system to proceed to another model. For example, when many firms want to apply loan, these firm's market trends would signal the system to execute some models, and models' outcome would in turn signal the system to calculate credit limits.

3.4 Decision Action Table

The decision action table (DAT), as shown in table 9, specifies the decision or suggestion according to the different criteria. It is used by the processing system together with the ARC to determine the final decision or suggestions.

Decision Action Table	
Condition	**decision and suggestion**
if (debt + request) - 5*N = 0	deny
if $risk < 0.1$ and credit reputation is 'high' and solvency is 'high minus'	approve(amount=request loan)
if $risk < 0.1$ and credit reputation is 'average' and solvency is 'high minus' and loan term is 'short'	approve(amount=request loan)
if $risk < 0.1$ and credit reputation is 'average' and solvency is 'high minus' and loan period is 'long'	approve(amount=F_j)
if $0.1 < risk < 0.15$ and credit reputation is 'average' and solvency is 'average'	approve(amount=F_j)

table 9

3.5 Data base

In order to perform a reliable and complete study of a firm, the consecutive basic financial statements (historic records) for every company must be available in the data base. Apart from these financial data, the system has its own market information resources.The data in database subsystem thus include internal data sources (Finance, Marketing, Production and Personal data) and external data.

Internal data come from the bank's transaction processing system, the bank's general ledger accounting system and its own census data.

External data may include industry data, marketing research data, government regulations, tax rate schedules, interest rate, exchange rate,or national economic data. These data might come from the government, trade associations, marketing research firms, econometric forecasting firms and its own efforts in collecting external data. In many case, these data are provided by computerized online services.

3.6 Processing System

The processing system, PS, is the heart of the proposed DSS and has direct control over all the constituents of the system. In a typical application,it starts by processing an initial set of computation to determine the value of all the necessary parameters. The controling flow of the processing system then proceeds as follows:

1. select a suitable model action rule from the MAT.

2. invoke the model contained in the particular MIC refered to in the rule.

3. after the model is executed, the result will be put in the Applicant Report Card (ARC) if the result is one of the criteria.

4. repeat 1-3 untill all criteria variables have been given values.

The processing system then applies the decision rule from DAT to analyse the information in the ARC and gives the decision or suggestions.

4 summary and example

With our model-based reasoning system, we attempt to match human problem-solving behavior to some predefined models. We propose to organize the knowledge about the domain problem, its relation with respect to the models of solution, and the relations among the models into different sets such as MAT,DAT ant ARC. These knowledge sets are not similarly structured and each requires different handling by the processing system. In fact, what we have proposed resembles a blackboard system [6,10] in the following ways:

1. The models in our system correspond directly to the "knowlege sources"in blackboard systems. Our models can be independently executed like knowledge sources as long as model assumptions are satisfied and input values are defined.

2. The model action table is the database maintained by the blackboard sysem to keep track of which knowledge source to consider for activation. In our case, of course, the knowledge source refers to a particular model. Each rule in the model action table expresses directly the triggering condition of a knowledge source.

3. The decision action table and applicant record card are another two databases maintained by the blackboard system to keep track of the decision criteria to apply to the applicant for evaluation.

4. The blackboardsystem works by responding to any event that makes a change to the blackboard. In our case, the event corresponds either to an intervention by the end-user,possibly as and when he receives a new market signal, or to a completion of a model execution which refreshes some values on the blackboard.

5. Our processing system carries out the control mechanism as exercised by the control component in the blackboard system. It chooses a course of action on the basis of the state of the blackboard. It is expected that the control mechanism would follow different techniques in processing the different databases on the blackboard, viz, the MAT, DAT and the ARC.

We would emphasize that the separation of these knowledge sets (corresponding to the databases on the blackboard) allows them to be maintained by different levels of users. Thus, end-user can be expected to modify criteria in the ARC and DAT. Modelers can be relied to improve on models in the MAT and the model base. It is then easy to see how such a DSS system can be adaped to apply in other problem domain [32]. We conclude with an example to further explain the working of the proposed system on the loan review problem. Figure 3 gives a flow chart of bank credit evaluation process.

The system is started with the arrival of a company's loan application. After some financial data such as current debts, current assets and earnings before interest, request loan and loan period have been entered, the processing system makes an initial set of computation to instantiate values of parameters such as ω, A and δ in table 3 and 4. The processing system then choose action rules from MAT to call MIC of the model ($\hat{\omega}$) and MIC of the model (λ,ω_M) to run the corresponding models. According to table 8, model ($\hat{\omega}$)'s output would signal the processing system to choose another action rule to call model($\sigma(\hat{\omega})$),and so on. All the results will be put into each applicant's ARC respectively, and the decision action table will be used on each applicant's ARC by the processing system to give decision (See table 3,4,5,6,8 and 9). From table 6 and table 9, processing system gives a final decision : approve (amount = F_j). { The computation goes as following: $\hat{\omega}_j = 15\%$, $\sigma(\overline{\omega}) = 15\%$, $\overline{A} = 0.3$, $A_j \leq \frac{1}{12.5\%}[15\% - \frac{10\%}{15\%}(15\% - 12.5\% \cdot 0.3)] = 60\%$, that is $F_j \leq 60\%(N_j + F_j)$, we have $F_j = 1.5N_j$ (F_j —- the maximum amount of the request loan for compamy j)}.

5 Conclusions

Loan and credit are the heart of banking. Under the ever-changing market conditions, the lack of general loan review system and the precise methods for measuring credit risk in many banks are two important reasons why such a decision support system is necessary.

Current market signal-driven analysis process and simulating the problem solving processing of an experienced expert are important characteristic of this system where we modeled the knowledge for applying analytical techniques to ill-structured problems. The processing system simulates the dynamic decision process of an experienced human bank loan officer. It incorporates all essential information and selects action rules to run appropriate models during the analysis process. The data and criteria it used come from its own information resource, enabling the system to have unbiased and objective view to every company. In the computation of risk in the models we proposed, we use the variance concept much quoted in finance literature [16]. The proposed system processes many data from financial statements,and supplies (1) a degree of overall risk derived from the granting of loan, (2) suggestions on the maximum amount of approved loan, (3) competition strategy for company. The integration of processes from the data to the readily feasible model ensures a smooth information flow within processes. As a consequence, the total quality of the system can be improved. The system can also be used in company for providing the decision advice to manager when the company wants to apply credit from financial institutes. We have likened our approach to a blackboard system where the blackboard is more organised with more structured contents. We shall continue to examine the different control mechnisms that are required to process these different contents and to interface with the models in the model base. The emphasis will be on the flexibility to be provided in the different technological levels for the decision support system, namely, the modeling by the domain expert, the support of the modeling toolsmith, and the final decision making.

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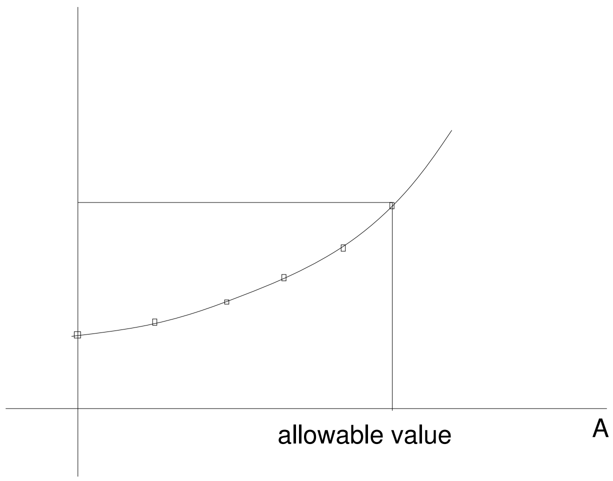

Figure 1

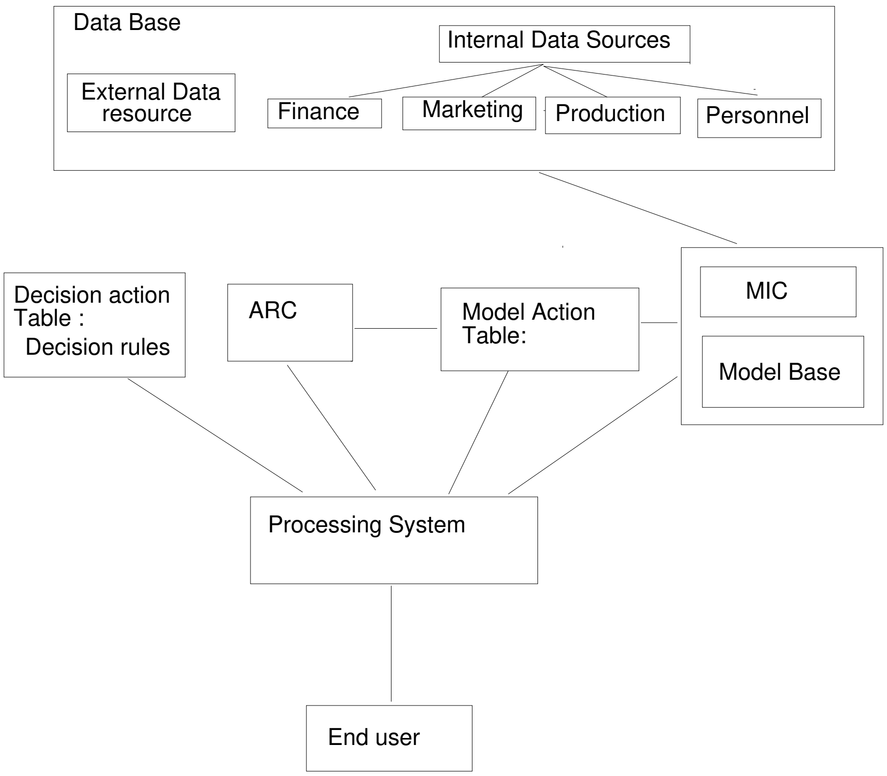

Figure 2

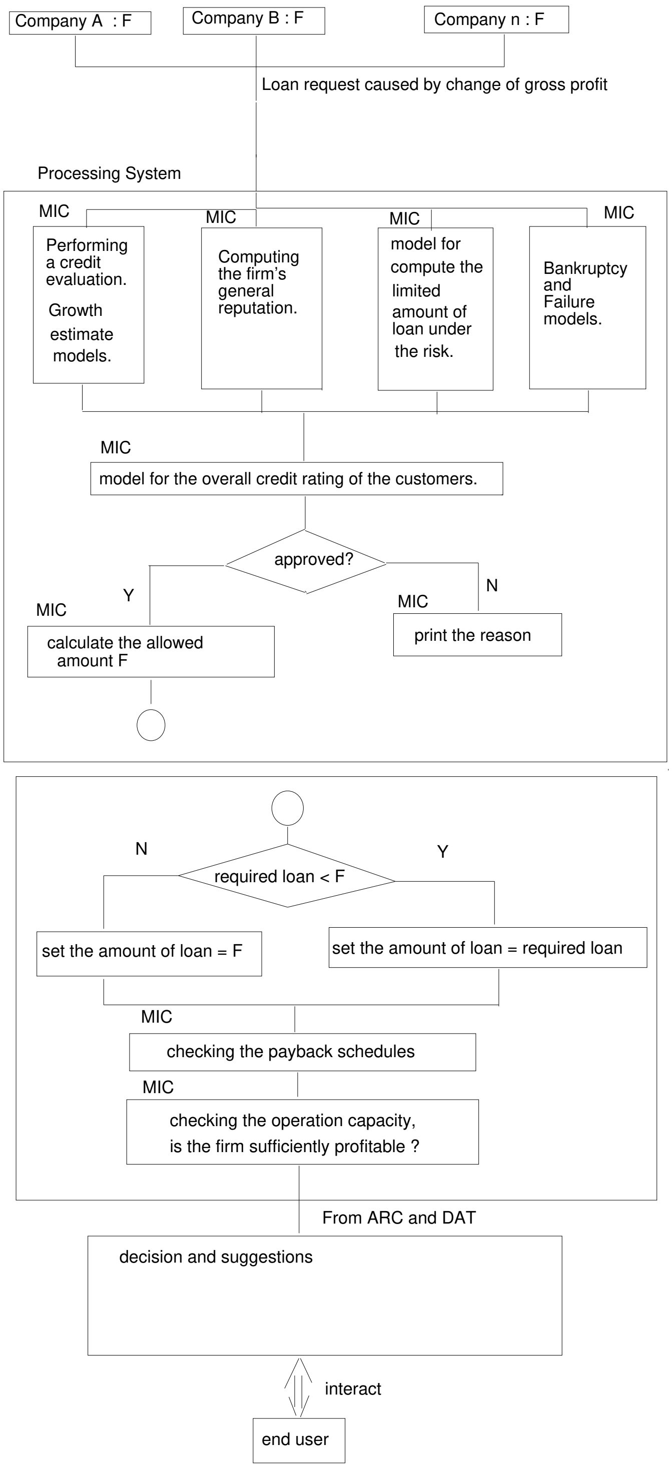

Figure 3 : overall flow chart of evaluation

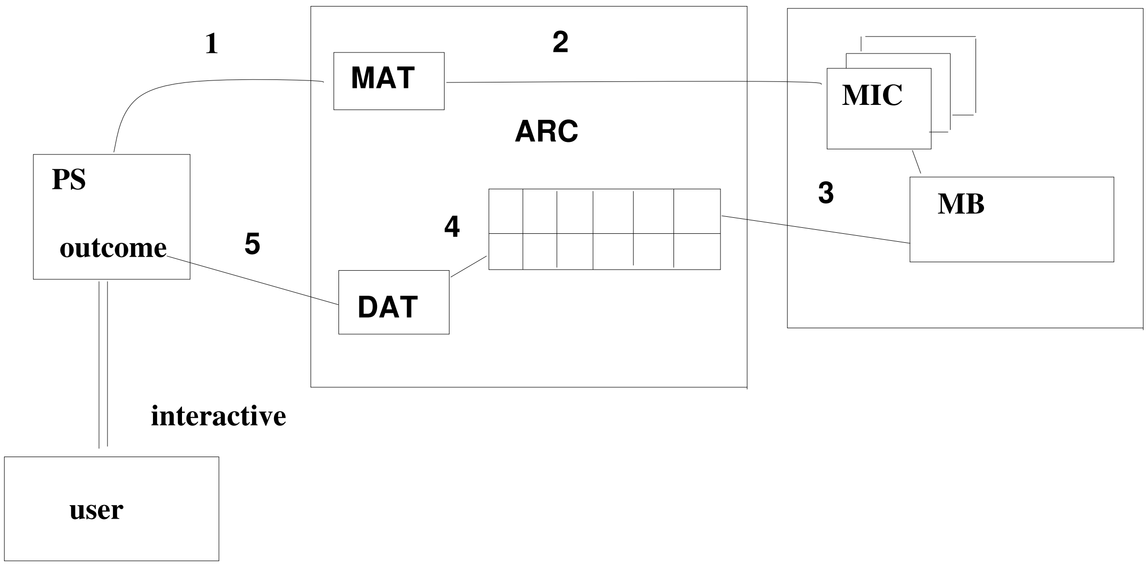

Figure 1: Here PS: processing system, MAT: model action Table, MIC: model index card, ARC: applicant report card, MB: model base, DAT: decision action Table, Outcome : the final result

Figure 4