

Credit Scoring Model by Analytic Hierarchy Process (AHP)

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This paper proposes detailed steps in developing a credit scoring model based on a group analytic hierarchy process (AHP) to be used in the automated loan approval system. The information hierarchy is constructed from in-depth interviews and intensive workshops with loan approval experts consisting of 5 credit managers and 8 loan officers, who set the priorities of all components at each level of the information hierarchy using pair-wise comparison. The row geometric mean method (RGMM) is used to calculate relative priorities. The relative priorities are tested for their consistency and reviewed until consistent priorities of all components are derived. All consistent priorities from all experts are then aggregated by weighted geometric mean method (WGMM) and converted into credit scores using piecewise linear interpolation. The AHP credit scoring model is tested on actual 7,081 mortgage loan applications. The test results show that 47.6% of loan applications can be automated by sacrificing only 3.1% of decisions that are not consistent with the actual decisions.

Field of Research: Banking, Finance

1. Introduction

A credit scoring model is a key component of the automated loan approval system. There are several choices of credit scoring models, which can be divided into two main categories: parametric and non-parametric models. Parametric models include linear probability model, logit or probit model, discrimination analysis-based model, and neural networks while non-parametric models include mathematical programming, classification trees, nearest neighbour model, analytic hierarchy process (AHP) and expert systems.

There are several articles in the literature that try to compare these model choices. Srinivasan and Kim (1987) and Henley and Hand (1997) conclude that classification tree is the best method for a credit scoring model while Boyle et al. (1992) and Yobas, Crook and Ross (1997) conclude that linear regression is the best. However, Desai et al. (1997) argue that logistic regression is the best. Lovie and Lovie (1986) suggest that a large number of scorecards would be almost as good as each other as far as classification is concerned. This means that there can be significant changes in the weights around the optimal scorecard with little effect on its classification performance and it perhaps explains the relative similarity of the classification methods. This relative stability of classification accuracy to choice of method used has prompted experts to wonder if a scoring system is also relatively stable to choice of customer sample on which the system is built. The systems are very sensitive to differences in the population that make up the scorecard. The regression approaches, both linear and logistic, have all the underpinning of statistical theory. Thus, one can perform statistical tests to see whether the scores of an attribute are

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Saardchom

significant and, hence, whether that attribute should really be in the scorecard. This allows one to drop unimportant characteristics and arrive at lean, mean and robust scorecards.

Linear programming deals very easily with constraints that lenders might impose on the scorecard. For example, they may want to bias the product towards younger customers and so require the score for being under 25 to be greater than the score for being over 65. Regression approaches find it almost impossible to incorporate such requirements. One of the other advantages of linear programming is that it is easy to score problems with hundreds of thousands of characteristics so splitting characteristics into many binary attributes causes no computational difficulties, whereas statistical analysis of such data sets with large number of variables can cause computational problems.

The methods that form groups like classification trees and neural networks have the advantage that they automatically deal with interactions between characteristics, whereas for linear methods, these interactions have to be identified beforehand and appropriate complex characteristics defined.

Among all of these modelling choices, only the AHP and expert system models do not require historical data of applicants' characteristics in the model developing process. Therefore, both methods can be adopted by banks that do not have enough historical data to develop a credit scoring model. An expert system is particularly applicable when the decision maker makes decisions that are multiple and sequential or parallel and where the problem is ill-defined because of the multiplicity of decisions that can be made. Relatively few examples of an expert system used for credit scoring have been published and because the details of such system are usually proprietary, none that have been published give exact details.

Although logistic regression has been widely used for scorecard development, some types of loan cannot rely only on a statistical modelling procedure. Unlike the more automated and more frequent credit granting decisions for credit card, medium and long-term bank loans require a much deeper and more time-consuming analysis, in which qualitative expert judgments concerning performance attractiveness of the application play a very important role. A modelling procedure based on a group analytic hierarchy process (AHP) is well suited to address these issues because it allows the consideration of such qualitative expert judgments and makes the complex decision making possible by allowing for qualitative measures to derive the scale of priorities. Therefore, the AHP model is able to combine expert judgments concerning the performance attractiveness of the application and convert such combined judgment into credit scores.

The objective of this paper is to provide detailed steps of how an expert system such as analytic hierarchy process can be used to derive an effective credit scoring model. This paper is also different from other past published papers in that it provides the accuracy test comparing the model decisions with actual decisions. Therefore, the paper provides not only the methodology which is a better alternative for the type of bank loans that require qualitative expert judgments concerning performance attractiveness of the application, but also suggests an accuracy test that can better improve the effectiveness of the credit scoring model decisions.

Saardchom

This paper focuses on the detailed steps of how the group AHP can be applied to credit scoring model development for mortgage loans. The paper is structured as follows: Section 2 describes the fundamental concept of the AHP. Section 3 explains how the credit scoring model by AHP is applied to the automated loan approval system. Section 4 shows the information hierarchy used for developing the credit scoring model by AHP. Section 5 presents the AHP credit scoring model results. The AHP model from section 5 is tested on actual mortgage loan applications and compared with the actual decisions in section 6 to show effectiveness of the AHP model when implemented in the automated loan approval system. Finally, section 7 discusses the conclusions.

2. Analytic Hierarchy Process (AHP)

The analytic hierarchy process (AHP) was introduced by Thomas L. Saaty (1980). It is a structured process for organizing and analyzing complex decisions. The AHP model is based on the principle that when we make a decision on a given matter, we consider a lot of information and factors, which can be represented as an information hierarchy. The most important step in the AHP is arranging a problem in a hierarchical structure. The decision makers have to decompose their decision problem into a hierarchy of more easily comprehended sub-problems, each of which can then be independently analyzed. Therefore, building this model requires the involvement of experts who define the mapping most suited to the problem. We are interested in how elements at the lowest level affect the top-level factor. Since this impact varies across factors, we need to define their weight or their priority, which are derived by a pair-wise comparison of these elements. The decision makers can use their judgments to compare the elements' relative importance. The key element of the AHP is that human judgments, not only the underlying information, can be used to perform the evaluations.

The AHP has been widely developed and has become one of the most commonly applied multi-criteria decision-making techniques. Its applications include personal or business decisions, public policy decisions, planning economic policies, determining consumer preference, estimating the economy's impact on sales, selecting portfolios, finding conflict resolution, benefit/cost decisions, resource allocation, military decisions, and many more. Carlos A. Bana e Costa, Luis Antunes Barroso, and Joao Oliveira Soares (2002) developed a qualitative credit scoring model for business loans based on similar concepts of the AHP.

The AHP framework also provides a measure for consistency of the decision maker when eliciting the judgment. The group version of AHP is applied when the analysis requires an aggregation of individual qualitative judgments (AIJ) and the aggregation of individual priorities (AIP).

2.1 AHP: Priorities Setting

At each level of the hierarchy, the relationships between the elements are established by comparing the elements in pairs. A pair-wise comparison can be done by forming a matrix to set priorities. The comparison starts from the top of the hierarchy to select the criterion

Saardchom

and then each pair of elements in the level below is compared. These judgments will then be transformed to the scale of 1 to 9 that represent the relative importance of one element over the other with respect to the property. The scale of 1 to 9 has the following qualitative meaning.

- 1: Equal importance of both elements.
- 3: Weak importance of one element over the other.
- 5: Much more important of one element over the other.
- 7: Very much more important of one element over the other.
- 9: Absolute importance of one element over the other.
- 2, 4, 6, 8: Intermediate values between two adjacent judgments.

If item i has one of the preceding numbers assigned to it when compared with item j , then j has the reciprocal value when compared with i . We should always compare the first element of a pair (the element in the left-hand column of the matrix) with the second (the element in the row on top).

2.2 AHP: Synthesis

Overall priorities can be made through synthesizing or pooling together the judgment made in the pair-wise comparisons. That is, the weighting and adding are needed to come up with a single number to indicate the priority of each element. With this establishment, we can represent the relative impact of the elements of a given level on each element of the next higher level. These pair-wise comparisons are repeated for all elements in each level. We can get the result of a vector of priority, of a relative importance, or of the elements with respect to each property. Then, we need to weigh each vector by the priority of its property to derive the net priority weights for the bottom level. If the number of elements to be ranked is n , then the number of judgment needed is $(n \cdot n - n)/2$.

The calculation of such priorities (weights) can be done by two methods: the eigenvector method (EVM) and the row geometric mean method (RGMM)

2.3 AHP: Eigenvector Method (EVM)

This prioritization procedure was introduced by Saaty (1977, 1980)

Let C_1, C_2, \dots, C_n be n elements to be compared, a_{ij} be the relative weight (or priority) of C_i with respect to C_j , and $A = (a_{ij})$ be an $n \times n$ square matrix, in which $a_{ij} = 1/a_{ji}$ for $i \neq j$, and $a_{ii} = 1$ for all i . A is consistent if $a_{ik} = a_{ij} a_{jk}$

Let ω be an eigenvector ($n \times 1$) and λ_{\max} be an eigenvalue.

$$A\omega = \lambda_{\max}\omega$$

Perfect consistency is difficult to achieve for the decisions based on human judgments. Human judgments typically change according to circumstances, new experiences, the

Saardchom

season or the time of the day. The measurement of the overall consistency under the AHP is called a consistency ratio.

The inconsistency is captured by a single number, $\lambda_{\max} - n$, which reflects the deviations of all a_{ij} from the estimated ratio of priorities ω_i / ω_j . If $\lambda_{\max} = n$, A is a consistent matrix. If $\lambda_{\max} > n$, a consistency index (C.I.) can be calculated as

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

The larger CI means greater inconsistency. Saaty (1980) proposed the use of a normalized measure, the Consistency Ratio (CR), to provide the inconsistency measure that is independent of the order of the matrix, n.

$$\text{Consistency Ratio (CR)} = \frac{CI}{RI(n)}$$

The random CI, called RI(n), is the expected value over a large number of positive reciprocal matrices of order n, whose entries are randomly chosen in the set of values $\{1/9, \dots, 1, \dots, 9\}$

$$RI(n) = E[CI(n)]$$

The consistency ratio gives a measure of where the judgments in pairwise comparison matrix lie between totally consistent and totally random. When CR = 1, then $CI = E[CI(n)] = RI(n)$ and the judgments are totally random, meaning low precision. High values of CR reflect even more inconsistency and thus we are interested in values of CR as low as possible.

Saaty (1980) proposed a rule of thumb for the CR which is a 10% threshold. Thus, the hypothesis to be tested in the process of building the credit scoring model is as follows:

$$H_0: CR < 10\%$$

If the hypothesis is rejected, when CR is greater than 10%, the most inconsistency judgments are modified and a new ω is derived to improve the consistency.

2.4 AHP: Row Geometric Mean Method (RGMM)

There are several other prioritization procedures, among which is the Row Geometric Mean Method (RGMM). The use of RGMM has significantly increased due to its psychological and mathematical properties. When the prioritization procedure is not the EVM, the aforementioned CI is no longer appropriate and new consistency measures are required. Priorities under RGMM are given by

Saardchom

$$\omega_i = \left(\prod_{j=1}^n a_{ij} \right)^{1/n}$$

Crawford and Williams (1985) suggest that the estimator of the variance of the perturbations can be used as a measure of the consistency, where the lower the value, the better the consistency of the judgments.

$$s^2 = S / df = \frac{2 \sum_{i < j} (\log a_{ij} - \log \omega_i / \omega_j)^2}{(n-1)(n-2)}$$

The degrees of freedom are the differences between the judgments included $n(n-1)/2$ and the estimated parameters $(n-1)$

$$n(n-1)/2 - (n-1) = (n-1)(n/2 - 1) = (n-1)(n-2)/2$$

The smaller the s^2 , the shorter the distance between the judgments a_{ij} and the ratios ω_i / ω_j and the smaller the variance of perturbation will be and the better will be the fit between the judgments and the priority vector ω .

A measure of consistency proposed by Crawford and William (1985) is given by

$$GCI = \frac{2}{(n-1)(n-2)} \sum_{i < j} \log^2 e_{ij}$$

where the error terms are $e_{ij} = a_{ij} \omega_j / \omega_i$. GCI can be seen as an average of the squared difference between the log of the errors and the log of unity.

$$GCI = \frac{2}{(n-1)(n-2)} \sum_{i < j} (\log e_{ij} - \log 1)^2$$

Aguaron and Moreno-Jimenez (2003) follow the proposal of Crawford and Williams without entering into the analysis of the validity of the CR as a consistency measure in AHP. They proposed the threshold called Geometric Consistency Index (GCI). GCI can be normalized in a way analogous to that carried out with Saaty's consistency ratio by dividing the value that measures the log quadratic distance between the errors e_{ij} and unity (s^2) by its expected value.

The expected value of s^2 is a constant: if the judgments of a pair-wise comparison matrix follow independent, reciprocal and identical distributions, the mean of the GCI is given by

$$E[GCI] = \text{Var}(\log a_{ij})$$

Saardchom

Theoretical relation between the GCI and the CR is given by

$$GCI = \frac{2n}{n-2} CI + o(\epsilon^3)$$

where $\epsilon = \max_y \{|\log e_{ij}|\}$ and $e_{ij} = a_{ij} \omega_j / \omega_i$.

Recall that $CR = CI / RI(n)$; thus,

$$\begin{aligned} GCI &= \frac{2n}{n-2} CR * RI(n) + o(\epsilon^3) \\ &= k(n)CR + o(\epsilon^3), \text{ where } k(n) = \frac{2n}{n-2} RI(n) \end{aligned}$$

This $k(n)$ shows the relationship between CR and GCI, where $RI(n) = E[CI(n)]$. The $k(n)$ results of simulation of 100,000 matrices for each order (n) are shown in Table 1.

Table 1: $k(n)$ Simulation Results

N	RI(n)	k(n)
3	0.525	3.147
4	0.882	3.526
5	1.115	3.717
6	1.252	3.755
7	1.341	3.755
8	1.404	3.744
9	1.452	3.733
10	1.484	3.709
11	1.513	3.698
12	1.535	3.685
13	1.555	3.674
14	1.570	3.663
15	1.583	3.646
16	1.595	3.646

If the judgment matrices are close to consistency (small errors), then the two measures, CR and GCI are proportional. In general, the behaviour of the two measures is similar for the different values of n . For low values of Saaty's CR, the relationship between CR and GCI is linear. This relationship is particularly significant when CR is below 0.1. As the range increases, the slopes estimated through regression decrease due to the small concavity of the relation. With this relationship, Aguaron and Jimenez (2003) proposed the thresholds, shown in Table 2, for GCI corresponding with Saaty's CR:

Saardchom

Table 2: CR and GCI

CR	0.01	0.05	0.1	0.15
GCI (n=3)	0.0314	0.1573	0.3147	0.4720
GCI (n=4)	0.0352	0.1763	0.3526	0.5289
GCI (n>4)	~0.037	~0.185	~0.37	~0.555

The interpretation of the GCI used for RGMM is analogous to the CR used with the EVM proposed by Saaty. When the values of the GCI is greater than the corresponding threshold, the most inconsistent judgment (that with larger e_{ij}) has to be modified in the sense of approximating a_{ij} to ω_i/ω_j . Recall that $e_{ij} = a_{ij}\omega_j/\omega_i$, which is the error obtained when the ratio ω_i/ω_j is approximated by a_{ij} .

2.5 AHP: Group Version

An aggregation of individual decisions can be done either by aggregation of Individual Judgment (AIJ) or aggregation of individual priorities (AIP). There is no requirement on the minimum number of judgment or minimum number of priorities. As a result, the author suggests that the process should incorporate as many decision makers as possible. In the following sections, the author gathers information hierarchy and pair-wise comparison matrices from all 5 credit managers and 8 loan officers who can grant mortgage loans at this bank.

An aggregation procedure of either AIJ or AIP can be carried out by weighted geometric mean method (WGMM). Saaty (1980) and Aczel and Saaty (1983) argue that the WGMM is the only separable synthesizing function that satisfies the unanimity, the homogeneity and the reciprocal properties.

Let $A^{[k]} = (a_{ij}^{[k]})$ be the judgment matrix provided by the k^{th} decision maker when comparing n elements ($i, j = 1, \dots, n$) with $\omega^{[k]} = (\omega_1^{[k]}, \omega_2^{[k]}, \dots, \omega_n^{[k]})$ being its priority vector

where $\omega_i^{[k]} > 0$ and $\sum_{i=1}^n \omega_i^{[k]} = 1$, and β_k being the weight of the k^{th} decision maker, $k = 1, 2,$

\dots, m in the group where $\beta_k > 0$ and $\sum_{k=1}^m \beta_k = 1$. If all decision makers are equally weighted,

then $\beta_k = \frac{1}{m}$ for all k .

Group judgment matrix can be represented by

$$A^G = (a_{ij}^G) \text{ with } a_{ij}^G = \prod_{k=1}^m (a_{ij}^{[k]})^{\beta_k}$$

Saardchom

Group priority vector can be shown as

$$\omega^G = (\omega_y^G) \text{ with } \omega_y^G = \prod_{k=1}^m (\omega_y^{[k]})^{\beta_k}$$

From the individual judgment matrices, $A^{[k]} = (a_y^{[k]})$, $k = 1, 2, \dots, m$, an aggregating individual judgment (AIJ) can be done by obtaining $A^G = (a_y^G)$ with $a_y^G = \prod_{k=1}^m (a_y^{[k]})^{\beta_k}$ from the individual judgment matrices $A^{[k]} = (a_y^{[k]})$ by using WGMM. Then, using the RGMM to derive the group priority vector, ω^G . On the other hand, an aggregating Individual Priority (AIP) can be achieved by obtaining the individual priority vectors, $\omega^{[k]} = (\omega_1^{[k]}, \omega_2^{[k]}, \dots, \omega_c^{[k]})$ for each decision maker using the RGMM, then deriving the group priorities $\omega^G = (\omega_y^G)$ with $\omega_y^G = \prod_{k=1}^m (\omega_y^{[k]})^{\beta_k}$ using the WGMM.

Barzilai and Golany (1994) prove that using the RGMM, AIJ and AIP provide the same priorities, which can be easily proved as shown below.

$$\begin{aligned} \omega_i^G(AIJ) &= \left(\prod_{j=1}^n a_{ij}^G \right)^{1/n} = \left(\prod_{j=1}^n \prod_{k=1}^m (a_{ij}^{[k]})^{\beta_k} \right)^{1/n} \\ &= \prod_{k=1}^m \left(\left[\prod_{j=1}^n (a_{ij}^{[k]}) \right]^{1/n} \right)^{\beta_k} \\ &= \prod_{k=1}^m (\omega_i^{[k]})^{\beta_k} \\ &= \omega_i^G(AIP) \end{aligned}$$

However, this result is not true for EVM. The two approaches present the same order of complexity for their respective algorithms. However, it is usual in practice to start with checking whether each individual judgment is consistent. This means that the $A^{[k]}$, $\omega^{[k]}$, and GCI^k are known in advance, so it might be simpler and more efficient to work with the AIP approach which requires only $o(mn)$ operations than with the AIJ approaches which requires $o(mn^2)$ operations. Again, if the individual judgments are of acceptable inconsistency, the group judgments are also of acceptable inconsistency.

Xu (2000) suggests that the EVM should be used as the prioritization procedure and the WGMM as the aggregation procedure. If the decision makers have an acceptable inconsistency when eliciting the judgments, then so has the group. Escobar, Aguaron, and

Saardchom

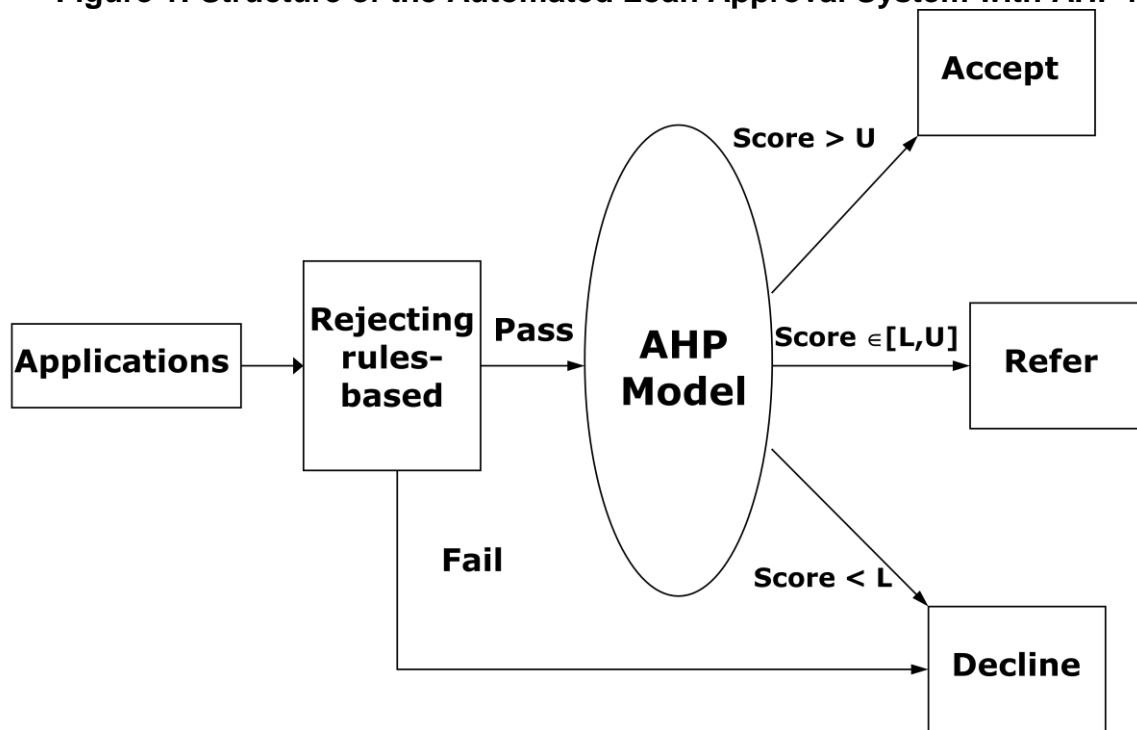
Jimenez (2004) prove that when using the RGMM as the prioritization procedure and the WGMM as the aggregation procedure, the inconsistency of the group is smaller than the largest individual inconsistency. In other words, the group inconsistency is at least as good as the worst individual inconsistency for both aggregation approaches (AIJ and AIP).

3. Applications to Mortgage Loan Approval Process

Before the financial crisis in 1997, the automated loan approval system and credit scoring model were rather new concepts in Thailand. The impact of the 1997 financial crisis pressured every bank in Thailand to improve their credit approval process by centralizing the loan approval decisions. Without the automated loan approval system, the centralized loan decision is almost impossible given the overwhelming number of loan applications.

The author worked with one large commercial bank in Thailand in a pilot project to improve its mortgage loan approval process with three main objectives: 1) to shorten the approval time by a combination of rules-based system and credit scores; 2) to implement a rejecting rules-based system; and 3) to develop a credit scoring model. Due to the lack of data to build a statistical credit scoring model, the credit scoring using the AHP was introduced. Figure 1 shows the structure of the proposed automated loan approval process.

Figure 1: Structure of the Automated Loan Approval System with AHP Model



The rejecting rules-based is implemented to rule out the applications with certain characteristics that would be automatically declined by the bank's credit policy without having to calculate the credit scores. For example, ages of applicants at loan maturity must not exceed 60 years old for salary applicants and 65 years old for self-employed applicants. The bank can also set up a rule automatically to reject applicants in the credit

Saardchom

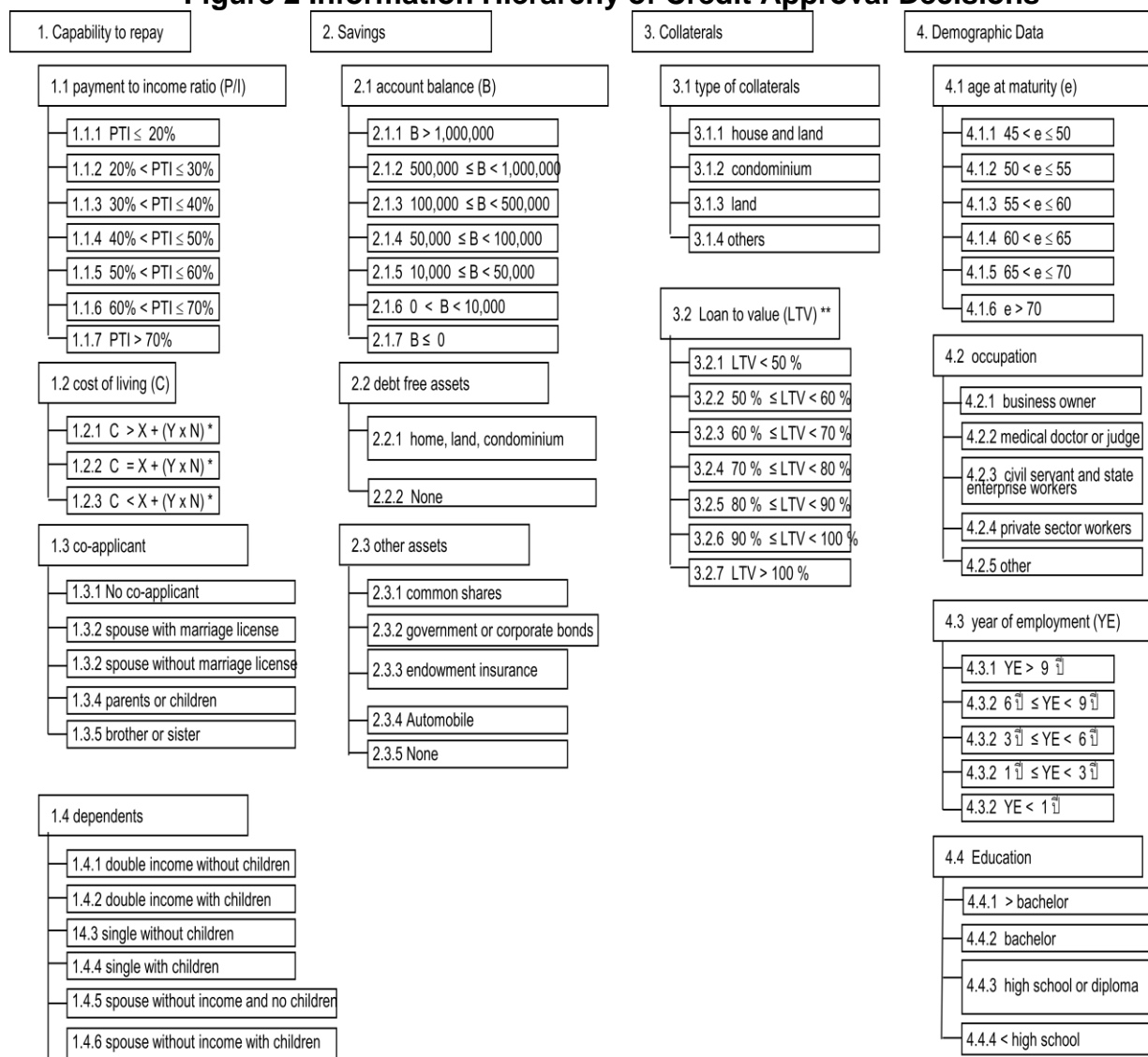
black list. Only the applications that pass the rejecting rules-based will be calculated credit scores by the AHP model. Credit scores are used to classify applicants into three groups: automatically accept group (credit score is larger than the upper threshold), automatically decline group (credit score is lower than the lower threshold), and a refer group (credit score is between the lower and upper thresholds.) This refer group is manually reviewed by a loan officer.

4. Information Hierarchy

The author interviewed 5 credit managers and 8 loan officers of the bank to gather information on their credit approval decisions, after which the proposed information hierarchy was presented to all of them for their approval. The credit managers and loan officers had undergone a productive debate and reached an agreement for the information hierarchy shown in Figure 2.

Saardchom

Figure 2 Information Hierarchy of Credit Approval Decisions



At the top level of the hierarchy, there are four criteria used for credit approval decisions. These include capability to repay, the applicants' level of savings, the collateral used to back the loan and the applicants' demographic data. Under capability to repay, there are four factors to be considered: payment to net income ratio, cost of living, information of the co-applicant and the number of dependents incurred costs to the loan applicants. The cost of living is calculated based on the assumption that each applicant living in Bangkok bears the cost of living of 8,000 baht per month, while those living outside Bangkok bears a smaller amount of 5,000 baht per month. For each dependent living in Bangkok incurs the additional cost of 2,000 baht per month to the applicant, and 1,500 baht per month for independent living outside Bangkok. For the applicants' saving level, information on bank account balance, real estate property and other assets are considered. The collateral is considered by its type and its value relative to the applied loan amount. The loan-to-value (LTV) is calculated as the ratio of loan amount to collateral appraisal value. Demographic

Saardchom

data of the applicants to be considered include age, education, employment and education. There is no gender discrimination in the credit approval decision. The lowest level of the hierarchy contains the range of possible values of the mentioned higher-level factors.

5. AHP Model Result

Based on the methodology in section 2 and information hierarchy in section 4, we created matrices of possible values for each element at each hierarchy level to be evaluated and given priorities of 1 to 9, using a pair-wise comparison, by each credit manager and loan officer. An example of a pair-wise comparison matrix is shown in Table 3. Given the information hierarchy in a previous section, there are 14 pair-wise comparison matrices evaluated by 5 credit managers and 8 loan officers.

Table 3: Example of a Pairwise Comparison

	Capability	Saving	Collateral	Demographic
Capability	1	1/4	3	4
Saving	4	1	4	5
Collateral	1/3	1/4	1	4
Demographic	1/4	1/5	1/4	1

Following Escobar, Aguaron, and Jimenez (2004), the priorities (or weights) of each element in the hierarchy are calculated by row geometric mean method (RGMM). Using RGMM, the priority matrix in Table 1 can be converted to a vector of relative weights shown in Table 4.

Table 4: Vector of Relative Priorities Based on RGMM

Criteria	Relative Priorities
Capability	0.2437
Saving	0.5537
Collateral	0.1407
Demographic	0.0619
Total	1.0000

Each of these relative priorities vectors was tested for its consistency by comparing its CGI with an acceptable level in Table 2. When a CGI was larger than its acceptable level, a

Saardchom

pair-wise comparison matrix was reviewed by that particular credit manager or loan officer until we reached a vector of relative priorities with an acceptable CGI. Then, all consistent individual priorities were aggregated by the weighted geometric mean method (WGMM).

At the lowest level of the information hierarchy, credit managers and loan officers defined the value where each component is considered bad and neutral so that we could arbitrarily assign the score of 0 and 100 for each component, respectively. Then, the piece-wise linear interpolation was applied to transform these weights into credit scores. The credit scores of each criterion could be calculated by summing the multiplication of the value scores of each component and the weight of such component.

6. AHP Model and Automated Loan Approval System

The credit scores derived from section 5 were tested on a sample of mortgage loan applications in 2010. There were 7,081 applications, 3,800 of which were approved applications and 3,281 of which were rejected applications. The credit score distribution is shown in Figure 3. Given this score distribution, the upper and lower cut-off scores were chosen to classify loan applications into automatically approved, automatically rejected and refer groups. The upper and lower cut-off scores were 675 and 475. That means an application with a credit score larger than 675 and lower than 475 will be automatically approved and automatically rejected, respectively. An application with a credit score between 475 to 675 will be reviewed manually by loan officers and credit managers.

Figure 3: Score Distribution by Actual Loan Approval Decisions

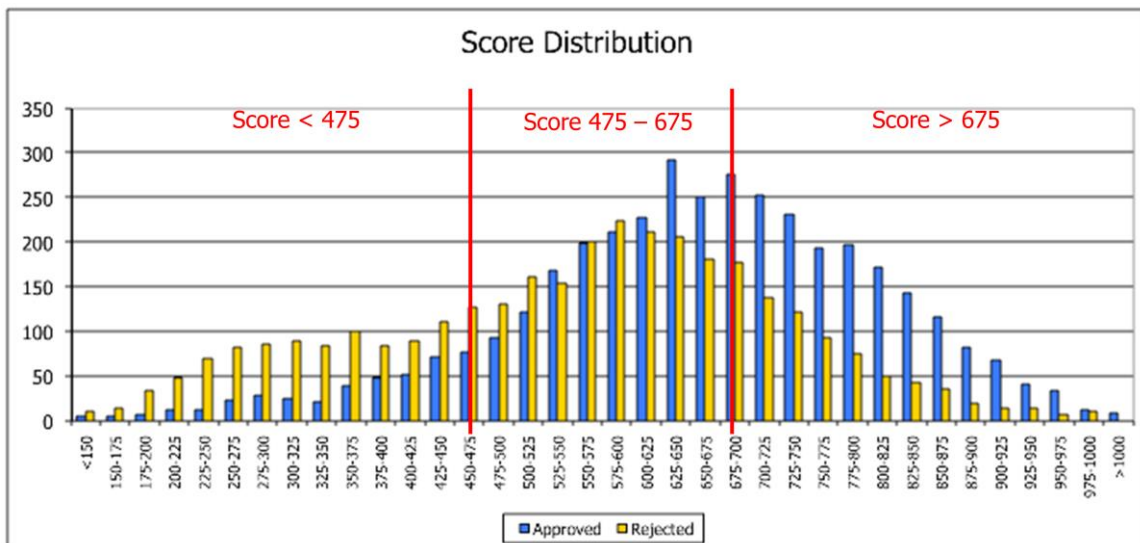


Table 5 shows the number and percentages of loan applicants by score range and by actual loan approval decisions. It indicates that the chosen upper and lower cut-off scores resulted in an automatically approved group of 19.4% and an automatically rejected group of 28.2%. The upper and lower cut-off score produced the automated decisions which were not consistent with the actual manual decisions by only 1.4% and 1.7%, respectively.

Saardchom

Thus, the automated approval loan system with the chosen cut-off scores can automate the loan approval decisions by the total of 47.6% with only 3.1% of inconsistent decisions.

Table 5: Actual Loan Approval Decisions by Score Range

Score	Number			Percentage		
	Approved	Rejected	Total	Approved	Rejected	Total
<475	121	1254	1375	1.7%	17.7%	19.4%
475-675	1785	1925	3710	25.2%	27.2%	52.4%
>675	1894	102	1996	26.7%	1.4%	28.2%
Total	3800	3281	7081	53.7%	46.3%	100.0%

7. Conclusions

This paper explains the detailed steps of how the AHP could be applied to the credit scoring model and implemented in the automated loan approval system. The AHP is a valuable decision making technique when there is a problem of data availability for developing a credit scoring model. In addition, the AHP credit scoring model is an appropriate technique for the type of loan that requires complex analysis.

Under a pilot project to improve the mortgage loan approval process of a commercial bank in Thailand, the expert judgments were gathered to create an information hierarchy. Using the pair-wise comparison, the experts set priorities for each component of information hierarchy. The relative priority vector was calculated based on RGMM. Each relative priority vector was tested for its consistency and revised until all consistent priorities were derived. Then, all consistent priorities were aggregated by WGMM and converted to credit scores by piece-wise linear interpolation.

The credit scoring model by the AHP was tested on 7,081 applications, 3,800 of which were approved applications and 3,281 of which were rejected applications. With the chosen upper and lower cut-off scores, the automated loan approval system could automate the loan approval decisions by almost half (47.6%) with only 3.1% of automated decisions that are not consistent with actual decisions made by the experts.

Although the AHP has the strengths in its ability to rank choices in the order of their effectiveness and to detect inconsistent judgment, it only works because the matrices are all of the same mathematical form—a positive reciprocal matrix. If the scale of 1 to 9 is changed to other scales, the numbers in the end result may be changed.

Saardchom

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