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A Multicriteria Hierarchical Discrimination Approach for Credit Risk Problems

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Abstract

Recently, banks and credit institutions have shown an increased interest in developing and implementing credit-scoring systems for taking corporate and consumer credit granting decisions. The objective of such systems is to analyze the characteristics of each applicant (firm or individual) and support the decision making process regarding the acceptance or the rejection of the credit application. This paper addresses this problem through the use of a multicriteria classification technique, the M.H.DIS method (Multi-group Hierarchical DIScrimination). M.H.DIS is applied to real-world case studies regarding the assessment of corporate credit risk and the evaluation of credit card applications. The results obtained through the M.H.DIS method are compared to the results of three well-known statistical techniques, namely linear and quadratic discriminant analysis, as well as logit analysis.

Keywords: Credit risk assessment, credit card applications, multicriteria decision aid, classification.

1. Intoduction: The credit risk problem

In the competitive environment that has been modulated in the financial sector, each financial institution tries to expand its products. In spite of this effort, the allowance of credits towards firms and consumers constitutes the major source of income for

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the majority of financial institutions even today and at least in Greece. Thus, the efficient management of credit portfolios represents a significant component element of the developmental policy and the operation of every financial institution. In Greece, the problem of credit expansion and loan allowance has been a major issue not only due to its importance for the viability of the financial system, but also due to its effects on general features of the national economy (inflation control). Based on this framework, the Bank of Greece issued instructions to the financial institutions emphasizing the indispensability of direct development and application of credit risk control systems.

One major part of these credit risks derives from the loan process executed by firms and consumers. In these cases, credit risk refers to the risk that arises when a firm or consumer do not respond effectively to their loan obligations provided by a financial institution. The processing of credit risk evaluation and decision making relative to the loan process by firms and consumers, involves a trade-off between the following two elements:

1. The possible loss from the acceptance of financing of a firm/consumer, which finally does not respond to the obligations created from the financing (default risk).
2. The possible profit that derives from the financing of a firm/consumer, who cooperates perfectly with the financial institution that offers the financing.

The result of the analysis procedure of the existing trade-off between the above two elements, leads to the specification of the amount of credit that is ultimately granted.

Srinivasan and Kim (1987) point out that the problem of credit risk assessment and the decision making related to the financing of firms, present increased complexity which is incorporated in the three stage procedure, as proposed by the authors:

- Stage 1: Estimation of the present values of benefits and losses derived from granting credit over the financing period, based on the credit history of the applicant (firm or consumer).
- Stage 2: Combination of the above present values with the corresponding probabilities of default or non-default. This is done in order to calculate the expected net present value, stemming from credit granting.
- Stage 3: If the expected net present value is positive, then the credit is granted, otherwise it is rejected.

The implementation of the above procedure is based on the fact that consumer and corporate credit granting is a multiperiod problem, since the financial institution, which provides the financing, has the possibility of promoting its products towards the applicant (firm of consumer) with whom a cooperation has incurred. Thus, the probable benefits are not bounded only to the interest rates of the granted loan, but include the revenues that may come from the expansion of the cooperation between the financial institution and the applicant.

An important issue for the successful implementation and practical application of the above three-stage procedure, constitutes the estimation of default probability in stage 2. The confrontation of this problem on operational and practical levels is achieved through classification approaches. The use of classification techniques for the credit risk assessment aims to develop models which will assign the applicants (customers of firms) into categories, according to their credit risk level. Usually, two categories are used for this approach and they refer to: a) firms/consumers for whom the credit should be granted, and b) firms/consumers for whom the credit should be rejected. The gathering of the data required for the development of the appropriate credit risk model could be realized from the existing credit portfolio of the financial institution for which the development of model takes place. The development of such a credit risk assessment model provides significant advantages for each financial institution (Khalil et al., 2000):

1. It introduces a common basis for the evaluation of customers who request financing from a financial institution. The credit applications are, usually, evaluated at a peripheral level and not at a central one, particularly in cases where the amount of the credit is limited. The practical implementation of a credit risk assessment model allows the use of a common evaluation system, thus reducing the peremptoriness and subjectivity that often characterize individual credit analysts.
2. It constitutes a useful guide for the definition of the amount of the credit that could be granted (Srinivasan and Kim, 1987).
3. It reduces the time and cost of the evaluation procedure, which could be restricted to applicants of high credit risk. Further analysis of the credit applications of these customers can be realized thoroughly from the specialized credit analysts, at a central level.
4. It facilitates management and monitoring of the whole credit portfolio of the financial institution.

The above four points justify the wide spread of credit risk assessment systems. At the research level, there has been a wide use of statistical approaches up to today. An analytical presentation of the relevant applications is outlined in the book of Altman et al. (1981). However, there has been a spread of alternative approaches such as machine learning and expert systems [Cronan et al. (1991), Tessmer (1997), Matsatsinis et al. (1997)], decision support systems [Srinivasan and Ruparel (1990), Duchessi and Belardo (1987), Zopounidis et al. (1996), Zopounidis and Doumpos (2000a)], genetic algorithms and neural networks (Fritz and Hosemann, 2000), multicriteria analysis [Bergeron et al. (1996), Zopounidis and Doumpos (1998), Jablonsky (1993), Lee et al. (1995), Khalil et al. (2000)], e.t.c.

The purpose of this paper is the presentation of the application of an innovative multicriteria approach in the development of credit risk assessment models for corporate and consumer credit granting. The basic features of the proposed hierarchical discrimination procedure (method M.H.DIS) are outlined in the section 2. Section 3 describes the application of the method in the credit risk assessment for corporate and consumer credit granting (evaluation of credit cards applications). The obtained results are compared to linear and quadratic discriminant analysis as well as to logit analysis. Finally, section 4 summarizes the main findings of this research and proposes some future research directions.

2. The Multi–Group Hierarchical Discrimination Method

The development of credit risk assessment models in this case study is performed through the M.H.DIS method. The general scheme of the procedure used to develop the credit risk assessment model through the M.H.DIS method is illustrated in Figure 1. Initially, a reference set A consisting of n firms a_1, a_2, ..., a_n, classified into q ordered classes $C_1 \hbar C_2 \hbar \ldots \hbar C_q$ (C_1 is preferred to C_2, C_2 is preferred to C_3, etc.) is used for model development (i.e., training sample). The firms are described (evaluated) along a set of m evaluation criteria $\underline{x} = \{x_1, x_2, \ldots, x_m\}$. The evaluation of a firm a on criterion x_i is denoted as x_{ia}. The set of criteria may include both criteria of increasing and decreasing preference. In the former case, higher values of the criteria are preferred, while in the latter case, lower values are preferred.

The development of the classification model is performed so as to respect the pre-specified classification, as much as possible. In this regard, the developed model should be able to reproduce (as accurately as possible) the classification of firms considered in the training sample. Once this is achieved, the classification model can be used for extrapolation purposes involving the classification of any new firm not included in the training sample. This is a common model development procedure that is widely used in statistics and econometrics (e.g., in discriminant, logit and probit analysis), as well as in other MCDA preference disaggregation approaches too. Such regressionbased techniques are used for model development in the UTA method (Jaquete-Lagrèze and Siskos, 1982) for ranking problems, in the UTADIS method (a variant of the UTA method for sorting problems; Jacquet-Lagrèze, 1995; Zopounidis and Doumpos, 1999), as well as in the context of the ELECTRE-TRI method (Mousseau and Slowinski, 1998), a well-known outranking relations approach for addressing classification problems (Yu, 1992).

The major characteristic of the M.H.DIS method during the development of credit risk assessment models as opposed to other discrimination methods, is that it employs a hierarchical procedure in classifying the firms into predefined classes. In particular, the discrimination procedure employed in M.H.DIS proceeds progressively in the classification of firms, starting from class C_1 (lowest risk group). In the first stage, the firms found to belong to class C_1 (correctly or incorrectly) are excluded from further consideration. The objective of the second stage is to identify the firms that belong to class C_2. Once again, all the firms which belong to this class (correctly or incorrectly) are excluded from further consideration, and the same procedure continues until all firms are classified into the predefined classes. The number of stages in this hierarchical discrimination procedure is q-1 (where q is the number of classes).

The estimation of additive utility functions in M.H.DIS is accomplished through mathematical programming techniques. Two linear programs and a mixed-integer one are used in MHDIS to estimate optimally the utility functions for the classification of the alternative activities. The term "optimal classification" refers to the number of wrong misclassifications that are realized through the developed additive utility functions, as well as through the classification clarity (avoidance of classification decisions that could be defined as limited correct). For the performance of these two goals, a linear programming problem (LP1) is solved in order to minimize the overall misclassification error, measured as the total number of violations of the classification rules, that are presented in Figure 1, in each stage of the hierarchical classification approach. Then, a mixed-integer linear programming for the minimization of the number of wrong classifications, raised from the solution of LP1, is solved, by keeping all the correct classifications. Finally, a second linear programming (LP2) is solved in order to maximize the "clarity" of the classification achieved from the solution of LP2. An analytical presentation of this method and the mathematical programming formulations that are used, is outlined in the paper of Zopounidis and Doumpos (2000b).

3. Case studies

Two applications of the M.H.DIS method for the credit risk assessment in the cases of corporate and consumer credit granting are presented in this section. In each application, the results of MHDIS method are compared to the corresponding results of well-known statistical classification techniques.

3.1. Case study 1: Corporate credit risk assessment

The first application examines a sample of 39 firms obtained from the credit portfolio of ETEVA (a Greek industrial development bank), aiming at the development of a corporate credit risk assessment model. This model is developed to distinguish three classes of firms:

1. The firms of low credit risk, which can be financed without any hesitation from a financial institution (class C_1).
2. The firms of medium credit risk, for which the decision relative to the approval or not of their financing should be subject to further investigation (class C_2).
3. The firms of high credit risk that should not be financed (class C_3).

From the 39 firms examined, 20 of them belong to the first category, 10 to the second and 9 to the third. The credit risk assessment of firms and their incorporation into the above categories is based on the 12 criteria, as presented in Table 1.

It is obvious that the credit risk assessment in this application is not only based on the financial features of firms (financial indices g_1–g_6). Moreover, significant qualitative factors (criteria g_7–g_{12}) that have direct influence on the financial behavior of firms and their relation to the market, are also taken into account. The significance of this qualitative information has been pointed out from various financial researchers for the comprehensive examination of corporate credit risk (Zopounidis, 1987; Dimitras et al., 1996). This issue is of increased interest in the present application and the conclusions that are obtained.

The limited sample of firms in the present application poses a major problem in testing the true performance of the credit risk assessment model that can be developed through the M.H.DIS method. To overcome this problem a Jackknife procedure is employed to obtain an unbiased estimate of the classification error rate of the credit risk assessment model. This procedure is performed as follows: Initially, the sample of firms is divided, in a random way, into two sub-samples consisting of 36 and 3 firms, respectively. The first sub-sample is used as a reference set for the development of a credit risk assessment model. This model is, then, applied to the three firms (one from each class) included in the second sub-sample (holdout sample) to test its generalizing ability. This experiment is performed 150 times. In each replication a different credit risk assessment model is developed and tested. After all replications are perform an unbiased estimate of the classification error rate for the credit risk assessment models developed through the M.H.DIS method is obtained (McLachlan, 1992; Kahya and Theodossiou, 1999; Doumpos et al., 2000). Furthermore, this experiment facilitates the extraction of useful conclusions regarding the robustness of the different credit risk models, developed in each replication of the Jackknife procedure.

Table 2 summarizes the results concerning the influence of the examined evaluation criteria on the classification of firms in the three aforementioned categories. In this table, U1 denotes the utility function that characterizes the firms of low credit risk (class C1), while U~1 represents the utility function that characterizes the firms of medium and high credit risk (classes C2 and C3). U2 and U~2 represent the two additive utility functions developed for the distinction among the firms of low credit risk (class C2) and the firms of high credit risk (class C3).

The results of Table 2 indicate that the most significant factors that distinguish the firms of low credit risk from the remaining firms are their quality of management (g_7), as well as their profitability, as it is presented in the financial ratios earnings before interest and taxes/total assets (g_1) and net profits/net worth (g_2). On the other hand, the distinction among the firms of medium credit risk and the firms of high credit risk in the models developed through the method MHDIS, is based mainly on the financial features of firms and especially on the ratio total debt/cash flow (g_4), general and administrative expenses/sales (g_6) and net profits/net worth (g_2). The firms' market niche/position (g_8) and the special competitive advantages they have (g_{11}) constitute the most significant qualitative criteria in this distinction. The above ascertainments emphasize the increased significance that the examination of qualitative criteria has on credit risk evaluation of firms, a point which has already been noted in other research studies (Zopounidis, 1987; Dimitras et al., 1996).

Table 3 summarizes the classification results which were obtained during over all 150 replications of the Jackknife procedure, not only in the reference set but in the holdout sample as well. In general, the results obtained in the holdout sample, indicate that the classification of low credit risk firms through the additive utility functions developed from the M.H.DIS method, is accomplished with a significantly higher accuracy as compared to the classification of firms of other classes (C_2 or C_3). Thus, the adoption of such a credit risk assessment system presents limited probability of rejecting the credit application to a low risk firm (rejecting credit to a low risk firm has an opportunity cost for the financial institution). It should also be noted that the case of misclassifying a high credit risk firm into the class of a low credit risk firm never appears in the 150 repetitions of the Jackknife procedure. So, the probability of granting credit to a high firm is also limited (this case might lead to capital loss). In total, the average accuracy of the credit risk models developed through M.H.DIS to the holdout sample is 75.11%. This constitutes an unbiased assessment of the efficiency of the specified approach to corporate credit risk assessment in this application.

In the credit risk assessment area, there has been a wide implementation of various statistical classification techniques. Financial researchers often use the linear discriminant analysis and the logit analysis for the development of credit risk models. This is done in order to assign the firms into predefined categories relative to the risk level that they entail. A comprehensive review of the implementation of these techniques in the credit risk area and the relevant field of business failure prediction is provided in the books of Altman et al. (1981) and Zopounidis and Dimitras (1998), as well as in the study of Dimitras et al. (1996).

Besides the M.H.DIS method in the present application the linear discriminant analysis and the logit analysis are also used. The purpose for using these two methods is to investigate the relative efficiency of the proposed multicriteria approach as opposed to the "traditional" techniques that are widely used for the development of credit risk assessment models. The results of this comparison present the potentials of the M.H.DIS method in providing more reliable assessments as compared to the existing methodologies used both on an operational and practical level.

The results of the application of the two examined statistical techniques in the total of 150 replications of the Jackknife procedure are summarized in Table 4.

Comparing the results of the above table with the corresponding results of the M.H.DIS method, it is ascertained that in the reference set the average accuracy percentage of the proposed multicriteria methodology surpasses the linear discriminant analysis. In comparison with the logit analysis there is no difference (both techniques, logit analysis and M.H.DIS, classify correctly all the firms). This suggests that both the logit analysis and the M.H.DIS method have higher fitting ability in the data used during model development (reference set). This result is expected, since both techniques lead to the development of non-linear classification models, whereas linear discriminant analysis develops linear models.

The conclusions which were reached from the comparison of the M.H.DIS method with the examined statistical methods concerning the results of the holdout sample are particular significant. As it was already mentioned, these results constitute an unbiased estimate of the probability to obtain incorrect estimates concerning the credit risk of firms. According to the average accuracy of the methods applied in the holdout sample, the predominance of the multicriteria M.H.DIS method as opposed to the logit analysis and the discriminant analysis is evident. The average accuracy of the M.H.DIS method into the 150 repetitions of Jackknife procedure is 75.11% (Table 3), while the corresponding accuracies for the statistical techniques are 72.67% for the linear discriminant analysis and 70.89% for the logit analysis.

These results imply that the M.H.DIS method is able to meet the corporate credit risk assessment problem with higher efficiency as opposed to other methodologies, that have been already used at the operational and practical levels. Thus, the proposed methodology could be used instead of the existing techniques in order to realize more reliable assessments concerning the credit risk assessment level.

3.2 Case study 2: Evaluation of credit card applications

This second application examines the problem of evaluating credit card applications. The credit cards constitute one of the most important means of consumer borrowing from financial institutions. Their widespread use at a global level, during the last decades, has been a major income source for the financial institutions, by increasing simultaneously the risk that emerges from the financing of insolvent customers.

This finding implies that the credit risk assessment systems are not required only in the case of the corporate credit granting. They, also, present increased significance in the case of consumer credit granting and especially in the case of credit cards.

Based on the above observations the present application involves the development of an evaluation system for credit card applications in order to estimate the associated level of credit risk. For this purpose, the M.H.DIS method was applied in a sample of 67 credit card applications, that were submitted to the National Bank of Greece during the period May-June 2000. The credit officers of the bank classified these applications into two categories: the approved and the rejected applications. According to this classification that was realized from the bank, 34 applications were included to the group of approved applications and 33 to the group of rejected ones. The data considered in this application includes all the information that the applicants provide when submitting their application (personal information are not considered). Besides the above data, there has been no other information from the bank relative to the criteria that were used during the evaluation. The criteria on which the applications assessment was realized, are presented in Table 5 (a more detailed analysis of the modeling and the significance of the examined criteria is provided in the study of Papadimitriou, 2000).

It is obvious, that there are qualitative (g_2, g_3, g_7, g_8, g_9) and quantitative criteria with a limited number of discrete levels (g_1, g_4, g_5). The only criterion that is actually quantitative is the personal income (g_6) of each applicant. Many of these criteria have been underlined as significant in consumer credit granting as well as in evaluating credit card applications. An analytical review of these two areas and the influence of qualitative criteria on the decision making process, are presented in the studies of Capon (1982), Carter and Catlett (1987), Tessmer (1997).

The methodology that is followed during the application of the M.H.DIS method is similar to the one used in the corporate credit risk assessment problem discussed in the previous sub-section. Since the sample in this application is larger than the one used in corporate credit risk assessment, the number of replications realized during the Jackknife procedure is increased to 250.

Table 6 presents some statistics on the significance of the criteria. U_1 represents the utility function that characterizes the category of approved applications, while $U_{\sim 1}$ represents the utility function of the category of rejected applications. According to the results of the M.H.DIS method, the major element that characterizes both types of applications is the age of the applicants (g_1), followed by their family situation (g_3). On the contrary, the years of employment of the applicant with the same employee (g_4), the existence or not of cooperation with the bank (g_7), as well as the opinion of the branch where the applications are submitted (g_9) do not seem to affect the decision regarding the approval or rejection of the application.

The classification results of the M.H.DIS method are presented in Table 7. These results indicate that the method has high efficiency in the correct classification of applications belonging in the reference set, since the average accuracy during the realization of 250 repetitions, is 95.36%. On the other hand, the average accuracy of the holdout sample is significantly lower as opposed to the one of the reference set. This fact implies the difficulty to explain the decisions taken by the bank in approving/rejecting the credit card applications. Generally, the classification results obtained for the approved applications are much better than those of the rejected applications.

Apart from the M.H.DIS method, three statistical classification techniques are also applied on the examined data related to the evaluation of credit card applications. Besides the linear discriminant analysis and the logit analysis, that were also used in the previous application, the quadratic discriminant analysis is also considered in this application (it was not used in the corporate credit risk assessment problem due to the existence of high correlations among the evaluation criteria). The results of these methods are summarized in Table 8.

The comparison of M.H.DIS results (Table 7) with the corresponding results of the other three statistical techniques implies the comparatively higher efficiency with which the evaluation of credit card applications could be addressed through the proposed multicriteria approach. More specifically, the average classification accuracy of the M.H.DIS method is higher than the corresponding accuracy of the other three statistical techniques, not only in the reference set, but in the holdout sample as well. The M.H.DIS method is the only method which presents an overall classification accuracy higher than 60% in the holdout sample. The significant difference between the M.H.DIS method and the three statistical approaches, with regard to their ability in correctly classifying the rejected applications, should also be pointed out. In particular the average classification accuracy for the rejected applications (class C_2) of the three statistical techniques range from 48.80% (linear discriminant analysis) to 56.80% (logit analysis), while the corresponding average accuracy of the M.H.DIS method is 60.40% (Table 7). In general, when considering an application as "approved", while it should have been rejected, constitutes a major component element of credit risk. This finding, in combination with the higher overall accuracy of the M.H.DIS method, constitutes significant implications for the effectiveness of the method as a tool to develop a powerful credit card assessment system.

4. Conclusions and future directions

This paper examined the contribution of an innovative methodology to address problems related to the credit risk assessment of corporate entities and individual consumers. The proposed methodology is based on the use of the multicriteria method M.H.DIS for the development of classification models that can be used in decision making regarding credit granting. The implementation of this method in two real-world problems indicated that its use in the daily practice of financial institutions could contribute to the attainment of more accurate assessments relative to the credit risk of firms and consumers, as opposed to the corresponding assessments obtained with existing statistical approaches.

The practical implementation of this method requires the development of an integrated decision support system for supporting corporate and consumer financing decisions. Such a system could cover the daily requirements of each financial institution, by allowing the direct evaluation of each credit granting application, with objectivity and coherence. Moreover, such a system could contribute to the optimal management of the existing credit portfolio of the financial institution by allowing the comprehensive monitoring and control of the loans already granted. In this way, a major part of risks, in which each financial institution is exposed, could be avoided.

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Table 1: *Corporate credit risk evaluation criteria (Source: Slowinski and Zopounidis, 1995)*

g_1:	Earnings before interest and taxes/Total Assets
g_2:	Net Income/Net Worth
g_3:	Total Debt/Total Assets
g_4:	Total Debt/Cash flow
g_5:	Interest expenses/Sales
g_6:	General and administrative expenses/Sales
g_7:	Quality of management
g_8:	Market niche/position
g_9:	Technical equipment
g_{10}:	Organization-Staff
g_{11}:	Special competitive advantages
g_{12}:	Market trend

Table 2: *Statistics on the significance of credit risk evaluation criteria (150 repetitions)*

	Average weight				**Number of repetitions with weight ≥10%**			
	U_1	U_{-1}	U_2	U_{-2}	U_1	U_{-1}	U_2	U_{-2}
g_1	14.48%	44.75%	1.17%	4.02%	81	119	3	22
	(0.125)	(0.245)	(0.035)	(0.092)				
g_2	26.28%	7.99%	14.98%	10.37%	131	30	87	64
	(0.125)	(0.104)	(0.133)	(0.123)				
g_3	4.90%	2.35%	8.78%	7.08%	28	17	57	44
	(0.071)	(0.042)	(0.111)	(0.097)				
g_4	1.53%	1.88%	26.13%	22.12%	5	9	129	119
	(0.034)	(0.044)	(0.135)	(0.150)				
g_5	6.11%	3.30%	6.67%	6.16%	56	17	39	42

	(0.066)	(0.061)	(0.092)	(0.084)				
g_6	9.27%	10.11%	20.09%	22.07%	49	32	127	135
	(0.117)	(0.126)	(0.087)	(0.072)				
g_7	33.66%	27.84%	1.62%	3.68%	150	150	10	26
	(0.100)	(0.072)	(0.048)	(0.072)				
g_8	0.08%	0.08%	7.70%	11.62%	–	–	49	72
	(0.000)	(0.000)	(0.102)	(0.113)				
g_9	0.07%	0.07%	3.19%	1.62%	–	–	22	12
	(0.000)	(0.000)	(0.073)	(0.054)				
g_{10}	0.10%	0.10%	0.07%	0.07%	–	–	–	–
	(0.000)	(0.000)	(0.000)	(0.000)				
g_{11}	0.07%	0.07%	9.54%	11.14%	–	–	62	77
	(0.000)	(0.000)	(0.114)	(0.111)				
g_{12}	3.45%	1.48%	0.05%	0.05%	24	10	–	–
	(0.076)	(0.046)	(0.000)	(0.000)				

Parentheses include the standard deviation

Table 3: *Average classification accuracy of the M.H.DIS method in corporate credit risk assessment (150 repetitions)*

Credit risk classes	Reference Set	Holding Sample
C_1	100%	99.33%

	(0.000)	(0.081)
C_2	100%	60.00%
	(0.000)	(0.490)
C_3	100%	66.00%
	(0.000)	(0.474)
Overall accuracy	100%	75.11%
	(0.000)	(0.232)

Parentheses include the standard deviation of accuracy rates.
Comparison with the statistical approaches

Table 4: *Average classification accuracy of the statistical techniques in corporate credit risk assessment (150 iterations)*

Credit risk classes	**Linear discriminant analysis**		**Logic analysis**	
	Reference Set	Holding Sample	Reference Set	Holding Sample
C_1	100.00%	89.33%	100.00%	93.33%
	(0.000)	(0.309)	(0.000)	(0.249)
C_2	92.96%	64.00%	100.00%	52.00%
	(0.054)	(0.480)	(0.000)	(0.500)
C_3	99.00%	64.67%	100.00%	67.33%
	(0.034)	(0.478)	(0.000)	(0.469)
Overall Accuracy	97.32%	72.67%	100.00%	70.89%
	(0.019)	(0.261)	(0.000)	(0.253)

Parentheses include the standard deviation of the accuracy rates.

Table 5: *Evaluation criteria for the assessment of credit card applications*

g_1:	Age
g_2:	Family situation
g_3:	Occupation
g_4:	Number of years to same employee

g_5: Number of years to present address
g_6: Personal income
g_7: Cooperation with the bank
g_8: Deposit account for automatic repayment
g_9: Opinion of the branch

Table 6: *Statistics on the significance of evaluation criteria in assessing credit card applications (250 replications)*

	U_1			U_{-1}		
	Mean	**Standard deviation**	**Number of replications with weight ≥0%**	**Mean**	**Standard deviation**	**Number of replications with weight ≥10%**
g_1	28.94%	0.101	235	21.87%	0.099	228
g_2	11.38%	0.082	155	10.62%	0.081	141
g_3	14.12%	0.078	176	14.57%	0.075	185
g_4	2.80%	0.021	1	3.50%	0.026	5
g_5	12.13%	0.071	142	14.27%	0.071	177
g_6	9.85%	0.053	101	11.87%	0.061	137
g_7	1.27%	0.029	8	4.81%	0.066	77
g_8	12.85%	0.105	154	12.67%	0.103	159
g_9	6.66%	0.063	102	5.84%	0.062	93

Table 7: *Average classification accuracy of the M.H.DIS method in assessing credit card applications (250 replications)*

Credit card application classes	**Reference set**	**Holdout sample**
C_1	99.66%	64.00%
	(0.012)	(0.480)
C_2	91.06%	60.40%
	(0.017)	(0.489)
Overall accuracy	95.36%	62.20%
	(0.045)	(0.485)

Parentheses include the standard deviation of the accuracy rates.

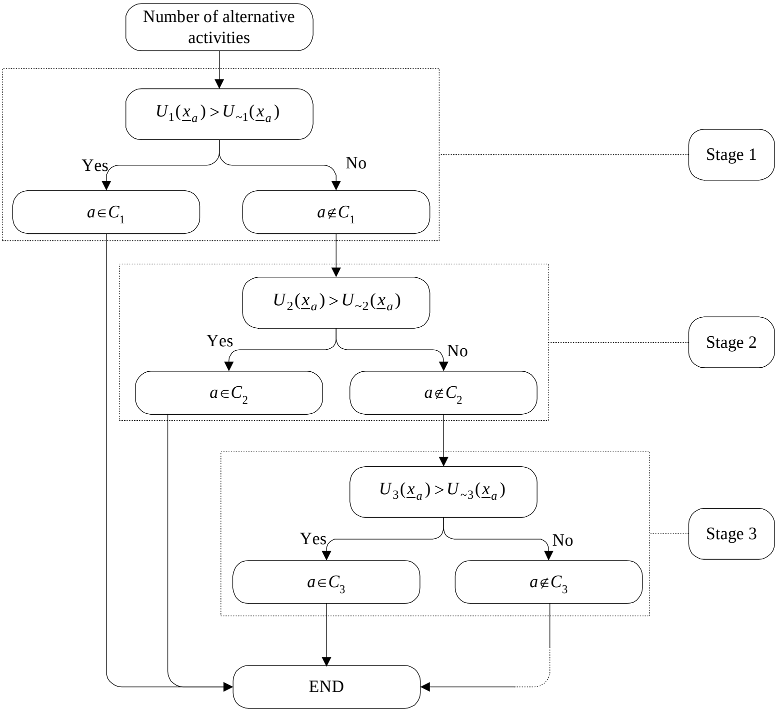
Comparison with statistical approaches

Table 8: *Average classification accuracy of the statistical techniques in assessing credit card applications (250 replications)*

	Reference set			Holdout sample		
Credit card application classes	**LDA**	**QDA**	**LA**	**LDA**	**QDA**	**LA**
C_1	82.26% (0.030)	91.58% (0.023)	70.88% (0.026)	67.20% (0.469)	66.80% (0.471)	57.60% (0.494)
C_2	72.34% (0.036)	69.64% (0.046)	63.13% (0.034)	48.80% (0.500)	51.60% (0.500)	56.80% (0.495)
Overall accuracy	77.30% (0.060)	80.61% (0.116)	67.00% (0.049)	58.00% (0.494)	59.20% (0.491)	57.20% (0.495)

Parentheses include the standard deviation of the accuracy rates.
LDA=Linear Discriminant Analysis, QDA=Quadratic Discriminant Analysis, LA=Logit Analysis.

Figure 1: *The hierarchical discrimination process in the M.H.DIS method (Source: Zopounidis and Doumpos, 2000b)*



Number of alternative activities
$U_1(\underline{x}_a) > U_{\sim 1}(\underline{x}_a)$
Yes
No
$a \in C_1$
$a \notin C_1$
Stage 1
$U_2(\underline{x}_a) > U_{\sim 2}(\underline{x}_a)$
Yes
No
$a \in C_2$
$a \notin C_2$
Stage 2
$U_3(\underline{x}_a) > U_{\sim 3}(\underline{x}_a)$
Yes
No
$a \in C_3$
$a \notin C_3$
Stage 3
END