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Qualitative Modelling of Credit Scoring: A Case Study in Banking

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Abstract

Several modelling procedures have been suggested in the literature that aim to help credit granting decisions. Most of these utilize statistical, operational research and artificial intelligence techniques to identify patterns among past applications, in order to enable a more well-informed assessment of risk as well as the automation of credit scoring. For some types of loans, we find that the modelling procedure must permit the consideration of qualitative expert judgements concerning the performance attractiveness of the applications. In this paper, we describe in detail the various steps taken to build such a model in the context of the banking sector, using the MACBETH *interactive approach. The model addresses the scoring of medium and long term loans to firms, to enable the multicriteria assignment of each application to a category which may range from rejection to acceptance with different spreads.*

Keywords: Multicriteria assignment; credit scoring; banking; MACBETH.

1. Introduction

Credit granting is a common and important practice for both non-financial as well as financial institutions. To the former, credit is an instrument that helps the sale of its products and services; to

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the latter, it is, itself, a core product to be sold. In both cases, the definition of a credit policy plus the management of the subsequent relations with individual or corporate customers constitute a key element within modern financial management, one which is closely connected to commercial and marketing strategies.

Several models have been developed in order to assist decision-makers in their evaluation of the risk involved with credit operations. Most of these models try to automate, as much as possible, the informal judgments and investigations made by analysts, synthesizing in a numerical score the assessment of each customer's creditworthiness. They are generically called credit-scoring models, although some authors, like Thomas (2000), prefer to distinguish between credit-scoring models (if they are referred to new applications) and behavioural-scoring models (if addressed to existing customers). The second set of models use relatively more information, concerning the repayment and ordering history of customers, and claim to be able to help answering questions such as: shall the credit limit change according to a periodic re-evaluation process? What marketing actions shall be directed to the customers? If the customer starts to fall behind in his repayments, what actions must be taken?

Thomas (2000) makes an extensive survey of classification techniques used in credit and behavioural scoring models to discern between different risk classes. They include multiple-discriminant analysis and the related linear, logistic and probit regressions, classification trees, linear programming, genetic algorithms, expert systems, and nearest neighbour methods. Although not included in Thomas' survey, Rough Sets Theory (Pawlak, 1991; Slowinski and Zopounidis, 1995) and Multicriteria Decision Analysis (MCDA) can also be applied to support credit granting and, in general, to risk assessment and financial management problems (*cf.* Zopounidis, 1999). For example, an interesting proposal is the Multi-Group Hierarchical DIScrimination (M.H.DIS) method (Doumpos and Zopounidis, 2001), which develops a piecewise linear discrimination instead of a pure linear discrimination as in the traditional multiple-discriminant analysis.

Regardless of the technique adopted, a common procedure is followed to distinguish between what are seemingly good and bad loans. A sample of past loans is selected, which includes both successful and defaulted cases, and variables with predictive power regarding success/default are identified with the support of a specific classification technique (typically applied to data included in the application forms and the financial statements of the applicants). A formulation involving (weighting) the variables that better "separate the creditworthy sheep from the impecunious goat" (Brealey and Myers, 2000) is searched for, enabling the classification and subsequent placement of any new application into its appropriate category: either acceptance or refusal of the credit operation. Sometimes it is necessary to separate applications into more than two groups, classifying them into different risk classes. This will be the case when classes correspond to different credit limits or, in the case of bank loans, different interest rates corresponding to different spreads.

The case studied in this paper corresponds to this last situation. It addresses the analysis of medium and long-term bank loans to firms. These types of loans require a much deeper and more time-consuming analysis than other more frequent (and obviously more automated) issues such as the analysis of credit card holders or trade and consumer credit. In particular, this case includes, simultaneously, the consideration of the creditworthiness of a company (frequently, already a client of the bank) and the evaluation of a new application (usually an investment project) in terms of its profitability and financial structure. Moreover, it involves several evaluation aspects – such as the expertise of the management team or the credibility of the assumptions underlying the estimated cash flows – for which it is impossible to find performance indicators that directly describe and measure them. A multicriteria value model (Belton, 1999) is particularly well suited to address these issues, namely if its construction allows the consideration of qualitative value judgements, as in the MACBETH approach (Measuring Attractiveness by a Categorical Based Evaluation Technique – *cf.* Bana e Costa and Vansnick, 1997 and 1999).

Banks are complex organizations in which the process of granting credit to clients usually involves different levels of internal responsibility. In our specific case, the demand made by a firm for a medium or long term loan is firstly assessed by the account manager or a member of the Commercial Department of the bank. This analyst then prepares a technical report and a recommendation to be submitted to the decision-maker, who can be a branch, regional manager, or even a member of the Board of Directors, depending on the characteristics of the operation and the amount of money involved.

Our intervention began with several meetings with some of the bank officers involved in the process. It was understood that the general goal was to build a standardized procedure for analysing credit applications, leading subsequently to their assignment to one of three categories of recommended action. Namely: to reject credit granting, to accept it but impose a major spread corresponding to a higher risk, or to accept it with a minor spread (lower risk case). As shown in the scheme of fig. 1, the assignment is based upon evaluation criteria that reflect the key aspects identified during the interviews (see section 2).

The rest of the paper is organized as follows. In section 3 we discuss the type of evaluation model to be adopted; in section 4 we focus our attention on the criteria aggregation process; section 5 is dedicated to the assignment procedure; and, finally some conclusions are stated in section 6.

2. Specifying criteria for evaluating medium and long term loan applications

The aspects taken into account by the bank in the analysis of medium and long term loan applications vastly exceed the mere consideration of profitability and solvency of the investment project. Clearly, unprofitable projects (NPV<0) or projects implicating dangerous levels of debt ratio are rejected *a priori*, without the need for any further analysis; however, the assessment of the credibility of the assumptions underlying the expected project's cash flows requires a much broader analysis from the bank's point of view. Furthermore, the financial resources of credit institutions are limited, which brings to light the need to consider the commercial aspects of any application.

Accordingly, three major areas of concern arose from the interviewing process with the bank officers: *Commercial interest* of the bank pursued by way of the credit operation (component 1); *client's business profile* in terms of the firm's strength within its business area and consequently its credibility (component 2); and, *financial performance* of the firm both before and after the investment (component 3). For each of these three key components of analysis, a structuring workshop was organized to discuss the criteria upon which the attractiveness of credit applications should be evaluated (see table 1). For example, it turned out that the commercial interest (component 1) involved three types of concerns: the concern with the *prospects for future operations* (criterion 1.1); the *global risk* (concern 1.2) of the particular loan under analysis, inferred from the specific *industry's risk* (criterion 1.2.1) and the guarantee and term of the operation (respectively, criterion 1.2.2-*secured loan* and criterion 1.2.3-*loan maturity*); and, finally, the *client's account history* (concern 1.3) characterised by the *age of the account* (criterion 1.3.1) and the past behaviour of the applicant in terms of honouring, on time, payment compromises (criterion 1.3.2-*previous slow payments*).

Table 1 also includes, in front of each criterion, the indicator chosen by the bank experts in each area as a descriptor of performance with respect to that criterion. This will, in the future, permit the analysts of a credit application to assign to it a level of each descriptor, thereby defining the performances-profile of the application.

3. Discussing the type of evaluation model

Our interviewers were also asked to identify two reference levels of intrinsic value in each descriptor, operationalising the idea of a "good" performance and a "neutral" performance (that is, neither attractive nor repulsive). As an example, for criterion 3.1.2-*leverage*, it was established that a firm whose equity ratio equalled the respective industry's ratio had a "neutral" leverage performance while an equity ratio that exceeded the industry's ratio by 50% would be considered a "good" performance.

The reference levels "good" and "neutral" make it possible to objectify the notion of intrinsic attractiveness of each application, assigning it to one of the following categories:

- *unattractive application (reject)*, if it is less attractive than a neutral fictitious application;
- *attractive application (major risk, accept with major spread)*, if it is at least as attractive as a neutral fictitious application, but less attractive than a fictitious good application;
- *very attractive application (minor risk, accept with minor spread)*, if it is at least as attractive as a fictitious good application.

The assignment of an application to a category is trivial if only one criterion is present (in which case it suffices to compare the performance of the applicant with the reference levels), but, as each component involves several criteria, some performances may be worst that neutral while others are between neutral and good or even better than good. Therefore, a formal assignment to categories requires some form of aggregation of the performances in the various criteria. To select which type of aggregation procedure should be used, the key question to ask the bank was if a credit application with a performance worst than neutral in a given aspect should be immediately rejected, or if the bank allowed this weakness to be compensated by a better than neutral performance(s) in a different aspect(s). It was also pointed out that this principle of compensation is behind any assignment procedure based on the additive calculation of an overall score. This issue motivated an interesting discussion among our interlocutors, in which pros and cons of a simple additive aggregation arose. All participants agreed that compensation is a reasonable hypothesis between unattractive and attractive performances on criteria within a component. Consequently, it was decided to build three separate additive aggregation models, one for each component.

If only one group of criteria (component) was present, applications with a component score resulting from the additive model smaller (respectively, higher) than the component score of a fictitious application "neutral all-over" would be considered attractive (respectively, unattractive). However, the bank officers decided that the same type of compensatory aggregation should be valid among the three components solely for applications with attractive *financial performance* (component 3). In other words, an application found to be unattractive in component 3 would be rejected independently of its attractiveness in the two other components.

It is worthwhile to mention that, in case the compensation hypothesis was not validated, a different multicriteria aggregation procedure could be adopted, for instance based on outranking concepts – like ELECTRE A mentioned in (Roy, 1990, p. 173), BANKADVISOR described in (Brans and Mareschal, 1990), or the application of ELECTRE TRI developed in (Bergeron *et al.*, 1997).

4. Building an additive aggregation model in each component using MACBETH

4.1. Developing value functions

The next phase was to build an evaluation model that enabled the measurement of the attractiveness of a credit application in terms of each evaluation component. Value functions were constructed for each criterion and weights were assessed for the criteria of each group. This was done with the support of the MACBETH software.

The value functions were developed from the bank officers' answers to the MACBETH questioning procedure. Consider, for example, criterion 3.1.2–*leverage* (before investment), whose descriptor was defined (see table 1) as the ratio between (firm's equity / firm's assets) and (industry's average equity / industry's average assets). A few reference levels were selected first: 0 (worst level: any non-positive ratio value is equally unattractive since, technically, it corresponds to bankruptcy), 0.5, 1 (neutral level), 1.5 (good level), 2 and 2.5 (best level: any ratio value greater or equal to 2.5 was considered, indifferently, very attractive). The bank officers were then asked to judge, qualitatively, the difference in attractiveness between each two of those references levels by choosing one of the MACBETH semantic categories: very weak, weak, moderate, strong, very strong, or extreme. Each time a judgement was formulated, the MACBETH software automatically tested its consistency with all the judgements previously formulated and pointed out eventual situations of inconsistency. The final consistent matrix of judgements is shown in Fig. 2, which also displays the numerical scale proposed by MACBETH to reconcile all of the qualitative judgements (note that the scores 0 and 100 were arbitrarily assigned to neutral and good, respectively). A discussion of the MACBETH scale was subsequently launched, based on the visual comparison of the magnitude of judgements (scale intervals). For some criteria the discussion led to adjustments of numerical values (within the limits indicated by MACBETH to prevent the relationship between the judgments to be violated). Finally, for each criterion, a piecewise linear value function could be defined, enabling the translation of performances into value scores.

4.2. Weighting the criteria and the components

In order to measure the attractiveness of the applications in each component, its scores on the respective criteria must be aggregated. For this purpose, as explained in section 3, an additive value model was used (which requires that the criteria within each component be additively independent, a hypothesis considered acceptable in our case – for details, see von Winterfeldt and Edwards, 1986). Let $v_j(a)$ (j = 1, ..., n_c) be the value scores of application a in the n_c criteria of component C (= 1, 2, or 3). The component score $V_c(a)$ of a will be given by the general expression

$$V_c(a) = \sum_{j=1}^{n_c} w_j . v_j(a) \text{ with } \sum_{j=1}^{n_c} w_j = 1 \text{ and } w_j > 0 \text{ and } \begin{cases} v_j(good_j) = 100 \\ v_j(neutral_j) = 0 \end{cases} \quad (1)$$

in which the parameters w_j are *scaling factors* of the value scales v_j (j = 1, ..., n_c) – commonly known as “weighting coefficients” or relative “weights” – that allow to harmonise value units in the different criteria.

We pointed out to the bank officers that the weights in the additive model could not be assessed by directly comparing criteria in terms of “intrinsic relative importance”, a mistake common to several popular weighting procedures (Keeney, 1992, pp. 147–148 calls it *the most common critical mistake*). The weights of the criteria were assessed with reference to the performance ranges between $good_j$ and $neutral_j$ (j = 1, ..., n_c), based on MACBETH judgements. We will illustrate the weighting procedure for component 1–*Commercial interest*, which integrates six criteria (1.1, 1.2.1, 1.2.2, 1.2.3, 1.3.1, and 1.3.2 – see table 1 and fig. 3). First, the bank officers were asked to consider six fictitious applications, each one "good" on one single criterion and "neutral" on all five of the others (of course, all of these applications are more attractive than an application "neutral all-over"). Then, they were asked to rank these fictitious applications in terms of overall attractiveness for credit granting and to judge qualitatively the differences of attractiveness between them. The judgements are shown in the matrix of fig. 3 along with a bar chart of the weights proposed by MACBETH. The discussion of the MACBETH weights gave rise to adjustments within the intervals of possible variation (exhibited in fig. 3 for criterion 1.2.3), leading to the final weights shown in the top right corner of fig. 3. A similar process was followed in weighting the criteria within each of the other two components.

The component scores $V_1(a)$, $V_2(a)$ and $V_3(a)$ of an application a can then be calculated by the additive model (1). Note that $V_c = 0$ for an application with "neutral" performances in all the criteria of component C (C = 1 to 3), and $V_c = 100$ for an application with "good" performances in all the criteria of component C (C = 1 to 3).

A final weighting was made involving judgements among the three groups of criteria. In this case the MACBETH procedure was used to compare three fictitious applications, each one "good" in all the criteria within one component and "neutral" in all the other criteria. The weights achieved for components 1, 2 and 3 were 0.35, 0.45 and 0.20, respectively. The overall score $V(a)$ of an application a is then given by $0.35V_1(a)+0.45V_2(a)+0.20V_3(a)$. Note that $V(a) = 0$ for the reference application "neutral all-over" and $V(a) = 100$ for the reference application "good all-over". Finally, remember from section 3 that $V(a)$ as a sense only if a is an application with *attractive financial performance* (component 3), i.e., for which $V_3(a) \geq 0$.

5. Assignment to categories

The performance of an application a in each criterion j, its scores $v_j(a)$ given by the value-functions, its component scores

$V_1(a)$, $V_2(a)$ and $V_3(a)$ given by the additive model (1), and its overall score $V(a)$, constitute the information system for the assignment of a to one risk category. Additionally, the following basic assignment rules were defined with the bank officers, operationalising what has been stated in section 3:

Rule i. If $V_3(a) < 0$, a is rejected.
Rule ii. If $V_3(a) \geq 0$ and $V(a) < 0$, a is rejected.
Rule iii. If $V_3(a) \geq 0$ and $0 \leq V(a) < 100$, a is accepted with major spread.
Rule iv. If $V_3(a) \geq 0$ and $V(a) \geq 100$, a is accepted with minor spread.

In order to validate the model, a sample of eighteen applications (a_1 to a_{18}) was selected: a_1 to a_9 had been previously refused by the bank, the other nine had been accepted – a_{10} to a_{12} with major spread (a_{10} to a_{12}) and a_{13} to a_{18} with minor spread. The component scores and overall scores of these 18 applications were computed (see fig. 4).

One can observe that the first eight applications, previously rejected by the bank, have $V_3(a) < 0$. There is no other application with $V_3(a) < 0$. This validates assignment *rule i*. It is also interesting to point out that *rule ii*, by itself, would not be enough to justify the rejection of those 8 applications since the overall scores of applications a_7 and a_8 are positive. Moreover, the rejection of a_9 is justified by *rule ii* because $V(a_9) < 0$.

The only discrepancies between the previous bank decisions and the model are the different assignments of applications a_{10} and a_{13}. According to *rule ii*, a_{10} would be rejected, while the bank had (holistically) decided to accept it with major spread; note that a_{10} is attractive on component 3 ($0 < V_3(a_{10}) < 100$) but unattractive on components 1 and 2 ($V_1(a_{10}) < 0$ and $V_2(a_{10}) < 0$). On the other hand, according to *rule iii*, a_{13} would be accepted with major spread; note that a_{13} is very attractive on component 3 ($V_3(a_{13}) > 100$) but only attractive on both components 1 and 2 ($0 < V_1(a_{13}) < 100$ and $0 < V_2(a_{13}) < 100$).

A possible justification for both discrepancies could be either that the weight assigned to component 3 (0.20) is underestimated in the model, or that the bank's experts who analysed a_{10} and a_{13} had implicitly over-weighted the *financial performances* . A sensitivity analysis (see fig. 5) on the weight of component 3 (keeping constant the proportion between the weights of the two other components) was performed using the software PROBE (*Preference Robustness Evaluation* – *cf*. CISED Consultores, 1998). As shown in fig. 5, the model would accept application a_{10} for a weight of component 3 at least equal to 0.365, an increase considered very high by the bank officers. The case of a_{13} is even worst (0.7 at least). It was also noted that these values are both greater than 1/3, therefore implying a different ranking of the weights of the three components. At the end of the discussion, our interlocutors concluded that there was an implicit over-weighting of component 3 in the previous analyses of a_{10} and a_{13} and decided to keep the weights unchanged.

A final remark must be made concerning a possible expansion of the assignment model in order to include more risk classes: for instance, to distinguish a top category for projects with almost null risk (assigning to it a *prime rate*). This would require a larger sample of past loans including a significant number of top projects. Then, the analysis of the scores of these applications could be used to establish a numerical threshold separating such top category. One could also establish the threshold(s) by adopting a procedure based on the definition of reference profiles, as the one described in (Bana e Costa and Oliveira, 2001).

6. Conclusion

Credit scoring models play an increasingly important role in modern financial management. Their implementation can increase the efficiency and accuracy of credit granting. In particular, they may bring a decrease in the risk premium required by financial institutions, leading to cheaper credit. Unfortunately, the literature on bank credit is scarce due to the traditional confidentiality that surrounds this sector. This was the first motivating factor for describing an applied study on this matter. It showed that there is a large number of aspects to be considered in the appraisal of medium and long term loan applications, which include not only the usual financial ratios, but also the commercial interest of the operation and the client's profile.

The second motivating factor stems from the desire for a consistent judgemental approach. The bulk of the recent literature on this subject (*cf.* Lewis, 1992) relies on the idea of using classification techniques for extracting patterns from past data in order to assess the creditworthiness of the applicants. While this can be a fruitful investigation, aiding to validate the choice of the relevant criteria, it hardly accommodates the complex nature of some of the aspects and value functions reported in this paper. Our judgemental-based modelling procedure, however, handles these problems in a systematic way by using the MACBETH approach to construct a model that evaluates the attractiveness of credit applications. Furthermore, its interactive nature fosters a learning attitude throughout the model building process.

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Table 1: *Value tree resuming the three components' concerns and criteria (and respective descriptors of performance) for evaluating medium and long term loan applications.*

1 Commercial interest
- 1.1 Prospects for future operations (number of bank transactions expected to take place with the client over the next 3 years)
- 1.2 Global risk concerns
  - 1.2.1 Industry's risk (bank rating of the risk of the client's business area)
  - 1.2.2 Secured loan (ratio between the monetary value of the secured loan and loan amount)
  - 1.2.3 Loan maturity (number of years until the complete payment of the principal)
- 1.3 Client's account history
  - 1.3.1 Age of the account (number of years since the opening of client's account)
  - 1.3.2 Previous slow payments (number of client's slow payments over the last 3 years)
  - 1.3.3 Client's business profile

2 Client's business profile
- 2.1 Top managers' experience
  - 2.1.1 Experience in business administration (average number of years experienced in senior management activities by top managers of the firm)

- 2.1.2 Experience in the industry (average number of years experienced in the industry by top managers of the firm)
- 2.2 Market strength of the firm
  - 2.2.1 Market share (ratio between firm and industry annual sales)
  - 2.2.2 Relationships with suppliers (ratio between the average payment period of the firm and of the industry)
- 2.3 Revenues control
  - 2.3.1 New versus lost clients of the firm (ratio between the number of new clients and the number of clients lost, over the last year)
  - 2.3.2 Doubtful accounts (ratio between the allowance for doubtful accounts and accounts receivable)
  - 2.3.3 Average collection period (ratio between the average collection period of the firm and of the industry)
- 2.4 Costs control
  - 2.4.1 Cost of goods sold and supplies expense (6-levels constructed scale representing the evolution over the last 3 years of the trend of the ratio 'costs of goods sold and supplies expense / sales')
  - 2.4.2 Personnel costs (6-levels constructed scale representing the evolution over the last 3 years of the trend of the ratio 'personnel costs / value added')

3 Financial performance

- 3.1 Client's financial performance before the investment (b-i)
  - 3.1.1 Profitability (ratio between 'b-i firm's cash flow / b-i firm's sales' and 'industry's average cash flow / industry's average sales')
  - 3.1.2 Leverage (ratio between 'b-i firm's equity / b-i firm's assets' and 'industry's average equity / industry's average assets')
  - 3.1.3 Interest burden (ratio between 'b-i firm's interest expenses / b-i firm's cash flow' and 'industry's average interest expenses / industry's average cash flow')
  - 3.1.4 Liquidity (b-i firm's current ratio over industry's average current ratio)
  - 3.1.5 Preferential creditors (ratio between tax and social security debts and total liabilities)
- 3.2 Client's financial performance after the investment (a-i)
  - 3.2.1 Project's profitability (profitability index)
  - 3.2.2 Profitability variation (ratio between 'a-i firm's cash flow / a-i firm's sales' and 'b-i firm's cash flow / b-i firm's sales')
  - 3.2.3 Leverage variation (ratio between 'a-i firm's equity / a-i firm's assets' and 'b-i firm's equity / b-i firm's assets')
  - 3.2.4 Interest burden variation (ratio between 'a-i firm's interest expenses / a-i firm's cash flow' and 'b-i firm's interest expenses / b-i firm's cash flow')

3.2.5 Liquidity variation (a-i firm's current ratio over b-i firm's current ratio)

Figure 1. *General overview of the model*

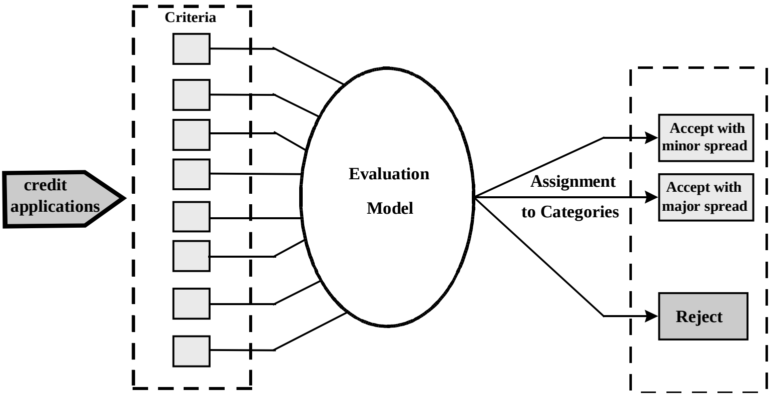
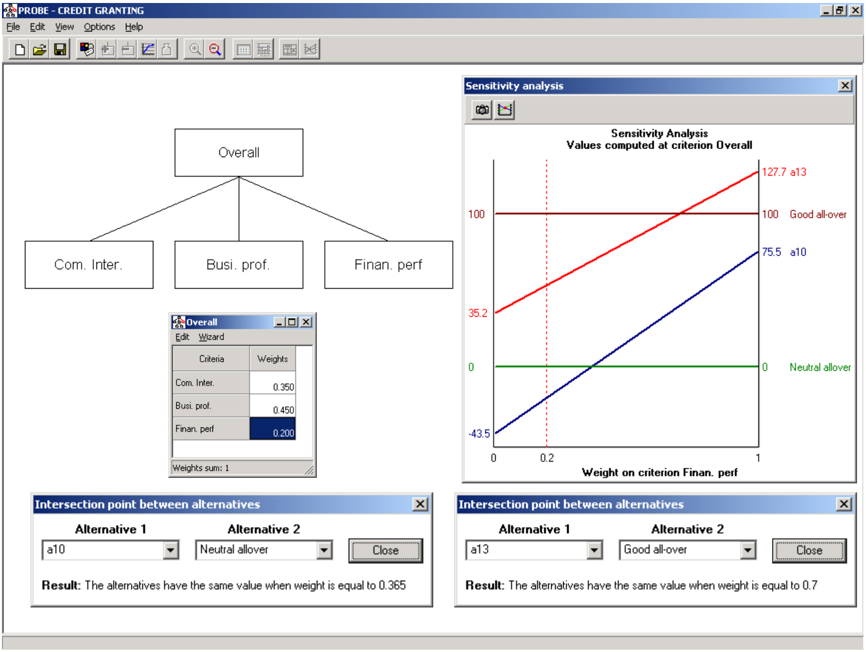


Figure 2. *Criterion 3.1.2-leverage: Matrix of qualitative judgements, macbeth scale and piecewise linear value function. (Note that unattractive performances, i.e. worst than neutral, have negative scores.)*

Figure 3. *Weighting criteria of component 1.*

Figure 4. *Component scores and overall scores of the 18 applications in the sample. (Despite the fact that overall scores of applications with negative scores on component 3 (V3(a) < 0) are substantively meaningless, nevertheless the calculations were made for validation purposes.)*

Figure 5. Sensitivity analysis on the weight of component 3.


PROBE - CREDIT GRANTING
File Edit View Options Help
Overall
Com. Inter.
Busi. prof.
Finan. perf
Overall
Edit Wizard
Criteria Weights
Com. Inter. 0.350
Busi. prof. 0.450
Finan. perf 0.200
Weights sum: 1
Sensitivity analysis
Sensitivity Analysis
Values computed at criterion Overall
127.7 a13
100 Good all-over
75.5 a10
0 Neutral allover
100
35.2
0
-43.5
0
0.2
1
Weight on criterion Finan. perf
Intersection point between alternatives
Alternative 1
Alternative 2
a10
Neutral allover
Close
Result: The alternatives have the same value when weight is equal to 0.365
Intersection point between alternatives
Alternative 1
Alternative 2
a13
Good all-over
Close
Result: The alternatives have the same value when weight is equal to 0.7