Risk software application using a credit scoring model

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***Abstract*—** The purpose of this paper is to define a specific credit score model, based on the discriminant analysis in order to complete financial diagnoses on particular predefined classes. The model is built based on a set of observations for which the classes are known. The classes in this paper are made of companies with certain characteristics which reflect the creditworthiness of that entity.

Keywords — **c**redit scoring, discriminant analysis, dicriminant indicators, risk assessment, discriminant analysis algorithm

I. INTRODUCTION

THE available literature about credit scoring is mainly studying the evolution of financial indicators for a certain number of companies, which have failed or continued their activity during the analyzed period [1], [2], [3]. The failure as well as the success of the management structure is being assessed by a particular indicator known as cutting score, which is defined as a linear combination of a few main financial indicators.

The scoring models represent a way of identify, quantify and control the corporate risk of bankruptcy [4]. Their multidimensional character follows a financial diagnosis of the entity and allows a relevant ranking of the companies, considering some financial indicators which are integrated in a score function.

The obtained results cannot be extended from one class of companies to another, due to the fact that the construction of the cutting score indicator is based upon specific branches and do not have a wider consideration. The purpose of our analyses is to find a synthetic indicator that suits to a random number of companies, therefore to achieve a value of its own as a reference for the status of the analyzed company.

The discriminant analysis uses a collection of interval variables to predict a categorical variable that may be a dichotomy or have more than two values. The algorithm involves finding a linear combination of independent variables that creates the maximum difference between group membership in the categorical dependent variable.

The stepwise discriminate analysis is also available to determine the best combinations of predictor variables. At the moment there is no universal scoring model that could be used by all the financial institutions, due to the fact that each institution preserves its strategy in dealing with the customers [5].

Credit scoring plays a vital role in the economic growth by helping expand access to credit markets, lowering the price of credit and reducing delinquencies and defaults. The scoring model in this paper is based on the discriminant analysis and it is pointed in the usage of the bank, by creating a tool that corresponds to random companies analyzed simultaneously.

We assume we have a group of companies called G which is formed of two distinct subgroups G1 and G2, each representing one of the two possible states: running order and bankruptcy. These two possible states are defined by a number of g independent financial indicators which simultaneously influence the progress of the companies, in terms of decreasing or growth.

II. CREDIT SCORING FUNDAMENTALS

We assume that a random bank has access to information about its customers, regarding both the good payers (reimbursing loan without problems) and the bad payers (who had problems with repayment over time). This information may relate to age, salary, social status, job stability and other reimbursement problems of individuals and to financial statements of legal persons. In this paper there will be taken in consideration only two indicators, but the algorithm itself is expandable to as many variables a bank cares for analyze. End-to-end solutions enable the transforming of the operational risk management into a business opportunity, ensuring that operational risk management processes are effectively integrated into day-to- day business processes [6]. The solution enables the financial institution to proactively

Manuscript received September 27, 2011: Revised version received….
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identify its operational risk exposure on a real time basis and successfully manage the exposures, thereby reducing costs.

When a new customer is applying for a loan, the bank must decide whether to grant him or not the requested loan by applying a discrimination rule. As a result of this process, the applicant will receive a score which classifies the application in one of the existing categories (*e.g.* bad payers, good payers). The discrimination rule offers support for decision of granting or not granting a loan, by attending at the background of the applicant and providing the required risk assessment. A discriminant score represents a weighted linear combination of the discriminating variables, by creating an equation which minimizes the possibility of misclassifying cases into their respective groups or categories.

The purpose of the statistical analysis in the discriminant function analysis is to combine the variable scores in some way so that a single new composite variable, the discriminant score, is produced.

Credit scoring is the first formal approach to the problem of assessing the credit risk of a single debtor in a scientific and automated way, in direct response to the need of processing large volumes of applications for relatively small loans [7].
For the national economy, credit scoring helps smooth consumption during cyclical periods of unemployment and reduces the swings of the business cycle.

We assume we want to define a credit score model for a group G of 14 companies with different characteristics and distinct values for two basic financial metrics, liquidity and debt to equity. Therefore, we take in consideration the company's ability to pay off its short-terms debts obligations as well as the proportion of equity and debt the company is using to finance its assets.

We define the financial indicators that are taken in consideration for applying the algorithm, as it follows:

$$\text{Dept of equity} = \frac{\text{Total liabilities}}{\text{Shareholders Equity}} \tag{1}$$

$$\text{Liquidity} = \frac{\text{Liquid assets}}{\text{Short Term Debts}} \tag{2}$$

If this was to increase earnings by a greater amount than the debt cost (interest), then the shareholders benefit as more earnings are being spread among the same amount of shareholders. However, the cost of this debt financing may outweigh the return that the company generates on the debt through investment and business activities and become too much for the company to handle [4].

The aim of the analysis is to determine whether these variables will discriminate between those entities who are bankrupted and those who are not.

A high debt/equity ratio generally means that a company has been aggressive in financing its growth with debt, which can result in volatile earnings as a result of the additional interest expense. A higher value of the liquidity ratio denotes a larger margin of safety that the company possesses to cover short-term debts [8].

The discriminant analysis algorithm is presented is presented in what follows.

When there is a case that requires a solution based on the discrimination problem, then it is automatically indicated a categorical type of variable as a reply. These variables place individuals literally into categories, and cannot be quantified in a meaningful way.

It is assumed that the data (for the variables) represent a sample from a multivariate normal distribution [9]. There can be examined whether or not variables are normally distributed with histograms of frequency distributions. However, note that violations of the normality assumption are usually not fatal, meaning, that the resultant significance tests etc. are still trustworthy [7]. There can be used specific tests for normality in addition to graphs.

In stepwise discriminant function analysis, a model of discrimination is built step-by-step. Specifically, at each step all variables are reviewed and evaluated to determine which one will contribute most to the discrimination between groups [7]. That variable will then be included in the model, and the process starts again, including the determination of a linear equation that predicts the coverage of the studied case.

One can also step backwards; in that case all variables are included in the model and then, at each step, the variable that contributes least to the prediction of group membership is eliminated. Thus, as the result of a successful discriminant function analysis, one would only keep the "important" variables in the model, that is, those variables that contribute the most to the discrimination between groups [7].

Stepwise discriminate analysis, is an attempt to find the best set of predictors, often being used in an exploratory situation to identify those variables from among a larger number that might be used later in a more rigorous theoretically driven study. Discriminant function analysis assumes the same task as multiple linear regression by predicting an accomplishment.

We assume that the categorical variable defines a number of q available categories, so the sample of n entities (14 companies in our study) will be grouped in a number of q categories based on specific characteristics.

A categorical variable is one that has two or more categories, without intrinsic ordering to the categories. For example, gender is a categorical variable having two categories (male and female) and there is no intrinsic ordering to the categories, as well as the employed or the unemployed status. Whether a person represents a credit risk or not is also a categorical variable and again, there is no agreed way to order these from highest to lowest. A purely categorical variable is one that simply allows assigning categories but cannot automatically order the variables.

At the end of the discriminant function analysis process, each group has a normal distribution of discriminant scores. The degree of overlap between the discriminant score distributions can then be used as a measure of the success of the algorithm.

For a better representation, we note the vector of the indicators above with $x = (x_1, x_2, ..., x_g)$. Furthermore, by applying the same mechanism we can establish a vector of indicators for each of the subgroups G1 and G2 as it follows: $x_1 = (x_{11}, x_{21}, ..., x_{g1})$, $x_2 = (x_{12}, x_{22}, ..., x_{g2})$.

Standardizing the variables ensures that scale differences between the variables are eliminated. When all variables are standardized, absolute weights are used to rank variables in terms of their discriminating power. The largest weight is associated with the most powerful discriminating variable, ones with large weights being those which contribute mostly to differentiate the groups.

The descriptive technique successively identifies the linear combination of attributes known as canonical discriminant functions which contribute maximally to group separation.

The first step in analyzing multivariate data is computing the mean vector and the variance-covariance matrix for each subgroup and than for the entire group. The mean and the variance-covariance matrix are denoted by symbols μ respectively β as following:

(μ_1, β_1) defines vector x_1,

(μ_2, β_2) defines vector x_2 and

$(\mu_1, \mu_2, \beta_1, \beta_2)$ defines vector x .

Step1. The matrix $X(n \times p)$ is defined by a number of *n* entities and *g* measured variables, both mentioned above. This matrix can be interpreted either line by line which case the interpretation leads to relevant data about the *n* entities, or column by column regarding information about the *g* measured variables.

Each entity of the *n* entities of the analyzed sample corresponds to a line in the matrix, meaning a vector containing a number of *g* elements (variables or indicators) will be written as it follows: $x_i = (x_{i1}, x_{i2}, ..., x_{ig})$.

Each variable of the *g* variables of the analyzed sample corresponds to a column in the matrix, meaning a vector containing a number of *n* entities will be written as it follows:

$$x_j^n = (x_{1j}, x_{2j}, ..., x_{nj}) .$$

Step2. We define the vector *m* by its coordinates known as centroid, containing each mean of the *g* variables as it follows: $m = (m_1, m_2, ..., m_g)$.

The group centroid is the mean value of the discriminant score for a given category of the dependent variable. There are as many centroids as there are groups or categories. The cut-off represents the mean of the two centroids.

Step3. We define vector s as the vector of the standard deviations as it follows:
$s = (s_1, s_2, ..., s_g)$.

Discriminant analysis forecasts a group membership which demands a briefly examination of the significantly differences between groups on each of the independent variables, by using group means.

Step4. We define the estimated variance- covariance matrix for the *g* number of variables.

The basic assumption of the Discriminant analysis is that the variance-co-variance matrices are equivalent meaning that do not differ between groups formed by the dependent.

Step5. We define the vector containing each mean of the variables connected with the *q* number of categories. This particular vector is called the centroid of the category and for a random category called *c*, it can be written as it follows:
$m^c = (m_1^c, m_2^c, ..., m_g^c)$.

Step6. We define the covariance matrix of the *g* variables. By projecting the coordinates $(x_{k1}, x_{k2}, ..., x_{kp})$ of a random *k* entity on the axe Δ with coordinate $u = (u_1, u_2, ..., u_g)$ it is obtained the following value:

$$c_k = x_{k1} \times u_1 + x_{k2} \times u_2 + ... + x_{kg} \times u_g \tag{3}$$

The value of c_k is called the score of the axe and represents the distance between the projection of entity *k* and the centroid of the vector *m* [7].

The synthetic indicator we want to obtain is usually expressed by a linear combination of the *g* indicators as the score mentioned above. The synthetic indicator will be compared to the value of z_c called cutting score which has the same architecture of the score itself, but it has to be predefined for the analyzed sample of entities.

The purpose of a discriminant technique is to find the axe Δ for which the discrimination of the projection is maxim.

The classification of the *n* entities upon the discriminant function is possible by referring to equation (1). Hence, we will obtain the values c^1, c^2 as projections of the centroids of the two categories on the axe. Therefore, the cutting score of the entities on the axe is defined as it follows:

$$c_{cs} = \frac{\eta_1 \times c^1 + \eta_2 \times c^2}{\eta_1 + \eta_2} \tag{4}$$

A random entity which achieves a score c_k has two possibilities regarding its position to the cutting score c_{cs}, respectively above it or beyond it. Each option classifies the entity in one of the two mentioned categories.

The success rate of discrimination is defined by the formula:

$$r_s = \frac{\eta_{11} + \eta_{22}}{\eta_1 + \eta_2} \tag{5}$$

We have noted the spread of the entities in the class (group/subgroup) with the symbol η .

Initial group	Number of entities in the initial group	Group after classification	
		1	2
1	η_1	η_{11}	η_{12}
2	η_2	η_{21}	η_{22}

Table 1. Success rate of discrimination

A similar process of classification for two categories with the same distribution would lead to a success rate of discrimination of 50%. Therefore, the value difference between r_s and 50% is considered an indicator for the quality of the discrimination.

It is assumed that the variance/covariance matrices of variables are homogeneous across groups. Minor deviations are not that important; however, before accepting final conclusions for an important study it is probably a good idea to review the within-groups variances and correlation matrices. When in doubt, it is recommended to try re-running the analyses excluding one or two groups that are of less interest [7].

III. Applied scoring architecture

In this paper we will present a computer application that follows the algorithm mentioned above, using the Visual Basic programming environment.

The proper functioning of a financial institution is represented by the informational system based on a viable architecture that ensures quick and secured access to information.

When a consumer applies for credit or extension of financial services, lenders can use credit scores to make faster, more consistent decisions. In addition,

credit scores can be combined with decision-making technologies that can be programmed with pre-established rules and score "cut-off " levels to

automate the decision-making process, thereby eliminating much of the risk of human error and subjectivity. The financial institutions need to save a significant amount of time and financial resources by accessing a comprehensive scenario to help capital planning and capital computation [10].

The versatility of the computing platforms provides agility to control risk yet accelerate projects development. A greater range of strategic information initiatives takes place by filling functionality around data quality, data services and business based on Service-oriented architecture. Service-oriented architecture (SOA) is a flexible set of design principles used during the phases of systems development and integration in computing. A system based on a SOA will package functionality as a suite of interoperable services that can be used within multiple, separate systems from several business domains [7].

Managers are seeking complete, integrated model solutions that are able to determine and improve the company's cash flow by use of accurate and detailed analysis.

The challenge for all banks is not only to create a centre of excellence with established international standards of communication, but also to reconstruct and automate their business processes to maximize efficiency.

Scorecards that rate an applicant's suitability do not always reflect the much more needed and crucial data, such as information that may also be industry-specific.

Specific types of credit scores can be used to rate businesses and financial institutions and predict such factors as financial stability, solvency and risk of liquidation. In addition to speed and convenience, scoring makes credit cheaper, which means lower costs and greater access for consumers due to time savings and automation of the process itself.

Credit scores enable lenders to better predict risk, which reduces the guarantee a lender needs to charge to cover its potential losses. In conjunction with this and the increased competition, credit scores have dramatically increased consumer choice and credit card interest rates have plummeted.

The IT systems that currently support each service require review and extension. The technology used must be future-proofed to suit integration of existing and future development platforms, without meaning core system replacement. Within a bank's legacy systems reside vital components of the organization's competitive edge, the mission-critical processes and systems that form the heart of the enterprise [8]. They may require rationalization, documentation and better understanding, for the benefit of extracting more value – but nevertheless they exist, and have been bought and paid for, and have proven reliability; processing billions of transactions per day across the globe. Core services should be individually identifiable and re-usable, such that systems development is far easier and quicker. In this way construction and maintenance costs are significantly reduced [11]. Service Oriented Architecture SOA is a key technology concept to achieve this level of re-use and avoids the extreme cost and risk of complete systems replacement.

S.O.A is one of the first steps in addressing the necessity to modernize business capability using technology as opposed to making the capability fit within the constraints of technology [7].

Models that are used to predict a customer's ability to pay its bills are called predictive scoring models and they are used whether for offering a new loan or for extending credit on an existing account.

Models that are used to predict if existing customers are likely candidates to pay or to extend their possible delinquency in paying are called risk scoring models. Models that predict whether a customer is a candidate for bankruptcy are called default scoring models.

These scoring models improve profitability by increasing the level of automation. Credit analyst's intervention is reduced on routine transactions by developing credit strategies to automatically approve low risk accounts. This allows credit analysts to focus their efforts on more difficult, higher risk applicants. The software looks to increase approval rates and/or decrease delinquency rates. It allows for improved efficiency, productivity and turnaround time by increasing automation and allowing the credit staff to make credit decisions more quickly and effectively. The decrease in credit decision turnaround time often can improve the overall application-booked rate [12]. It also produces a higher quality, lower-risk portfolio by identifying low, medium and high risk applicants. This in turn gives an effective credit strategy and a more profitable portfolio.

These models give credit managers a basis for their further decisions; however, they do not represent the final word. A combination of these models can be devised or credit departments can create their own scorecards based on the variables they are looking for. The final choice must augment credit risk management by providing both application and behavioural scores, supported by a configurable workflow [13].

The purpose of this paper is to create a specific solution, by identifying key factors that are used to make credit decisions. The sources of data are identified and a database is being set up on its own or by linking other databases. The basis of the credit scoring system is a statistical program that compares any performance against entities with similar profiles. The model must be based on real data and statistics, so that it helps the user treat the applicants objectively.

A software platform designed for credit management expert soft ware system, integrates company policies, procedures and objectives to provide intelligent support for day-to-day decisions. It exchanges information with in-house systems and outside information sources, also interacting with the sales and marketing departments and revealing detailed reports and analysis.

It identifies trends and opportunities within specific markets and establishes and maintains control and operating standards. The main objective must be to combine credit scoring with speed, accuracy and consistency. The features must include tools that generate tabular and graphical reports.

The predictive scoring models are using advanced statistical technique and attributes condensed into a single number indicating the likelihood that a company will become severely delinquent in payment over the next 12 months. These scores indicate the firm's willingness to pay in a timely manner, the higher the score the lower the risk of delinquency.

Analyzing delinquencies and defaults can highlight specific variables in the program that might be modified to screen out particularly bad risks and enhance program profitability.

The performance patterns by credit score and loan-to-value ratio are very similar for borrowers at all income levels. These must be configured with complex rules for optimization of risk mitigants which enables to take maximum advantage of credit risk mitigants in form of reduced requirement of capital [14].

The strategy of cost reduction by avoiding unnecessary risks represents an opportunity of the financial sector to compete and maintain profitability.

A credit scoring based software is natively integrated with modules that are supporting a comprehensive process of identification, assessment, mitigating, monitoring and reporting of operational risk [15].

In Figure 1 we present the main form of the application that collects data and transforms it into relevant information for further decisions.

The user introduces the name of the company or any kind of information that particularly defines the analyzed entity, as well as the necessary financial fields from the customer's application. These fields are represented by the total of liabilities, the shareholders equity, the liquid assets and the short term debts. When introduced, the application automatically determines the two indicators that we take in consideration, respectively debt to equity and the liquidity of the company.

The user has the possibility of analyzing one or more companies, each time by clicking the Append to Sample button. This will send all the data that has been introduced so far into a vector called Initial Sample Data.

The user has the possibility to save, as well as to erase data from the sample. However, at this moment the Initial Sample Data vector is not fully completed, unless the user clicks on Evaluate Primary Status button first. By clicking this button, the application does a primary classification in one of the subgroups, G1-Bankruptcy or C2- Running order, following a pattern that is usually used in basic credit scoring models.

By analyzing the first indicator Debt To Equity, we can observe that healthy companies achieve small values for the mean variable, to the opposite of the bankrupted companies that achieve big values for the same variable (Figure 2). This automatically leads to a certain level of this indicator, called α, that will be able to classify another performance (of a different company) by comparison to itself.

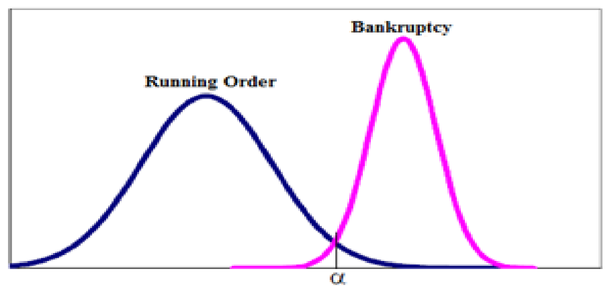

Fig. 1. Repartition of the first indicator

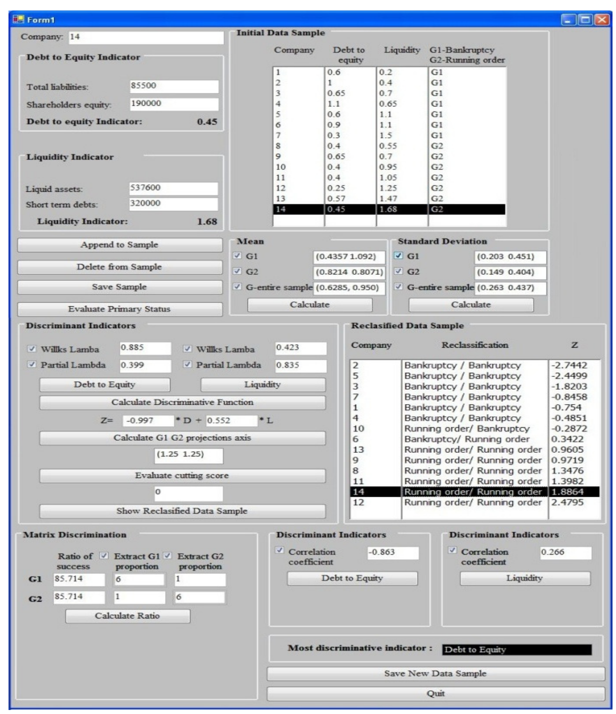

Fig.2. Main Form of the application

There is also an uncertainty area, which means that if a company has a calculated indicator belonging to this area, it is unlikely to decide whether this company is healthy of not.

The same analysis on the second indicator Liquidity reveals that healthy companies achieve big values for the mean variable, to the opposite of the bankrupted companies that achieve small values for the same variable (Figure3). There is also an uncertainty are for this second indicator called β, meaning for a value in this nearby, it is unlikely to decide whether this company is healthy of not.

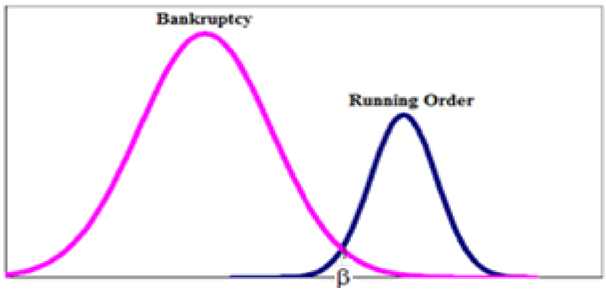

Fig. 3. Repartition of the second indicator

We have described a possible one-dimensional analysis, taking each of the indicators and compare the companies behaviour related to it. Thus this analysis is not sufficient, because of the fact that the indicators and their behaviour have not been simultaneous analyzed, which the application will further proceed [16].

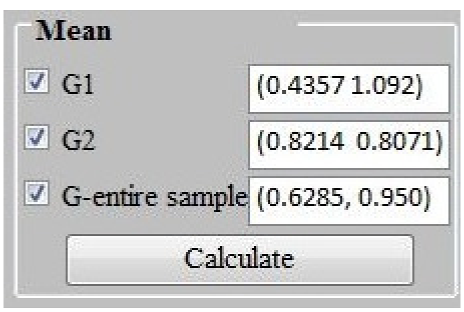

Fig. 4.Calculating the mean

Step1. In order to continue the algorithm, the application determines the specific mean for each subgroup as well as for the entire group, by clicking the Calculate button in the group called Mean.

When selecting one or more options in the group Mean, the application transforms data in the Initial Data Sample vector and displays it into each corresponding textbox.

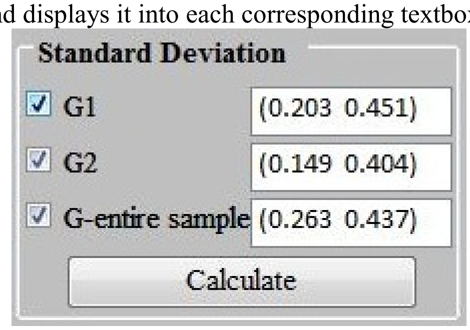

Fig. 5. Calculating the standard deviation

The algorithm has calculated the mean for each subgroup, respectively *mG2* = (0.4357, 1.092) and m*G1* = (0.8214, 0.8071), as well as for the entire group: *m* = (0.6285, 0.950)

Step2. In order to continue the algorithm, the application determines the specific mean for each subgroup as well as for the entire group, by clicking the Calculate button in the group called Standard Deviation.

When selecting one or more options in the group Standard Deviation, the application transforms data in the Initial Data Sample vector and displays it into each corresponding textbox.

The algorithm determines the standard deviation for each subgroup, respectively *sG2* = (0.149, 0.404) and *sG1* = (0.203, 0.451), as well as for the entire group *s* = (0.263, 0.437).

Step3. The algorithm determines the variance-covariance matrix for the subgroups

$W_{G1G2} = \begin{pmatrix} 0.0273 & 0.0168 \\ 0.0168 & 0.1575 \end{pmatrix}$ and for the entire group $W = \begin{pmatrix} 0.0645 & -0.0107 \\ -0.0107 & 0.1779 \end{pmatrix}$.

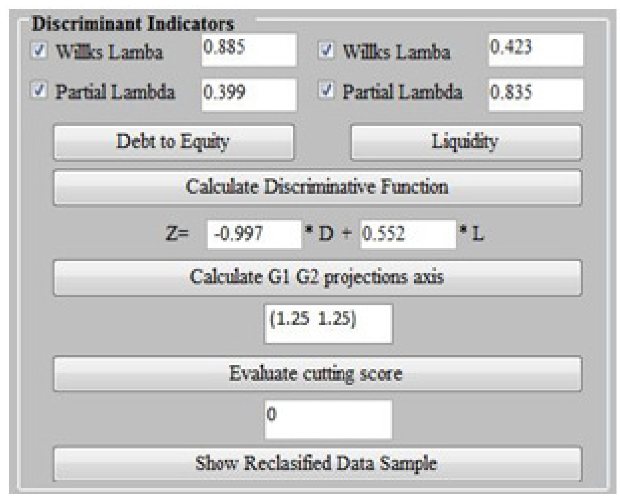

Fig. 6. Discriminant indicators

The algorithm determines as well as the correlation matrix for the subgroups $\mathrm{V}_{\mathrm{G1G2}} = \begin{pmatrix} 1 & 0.256 \\ 0.256 & 1 \end{pmatrix}$ and for the entire group $\mathrm{V} = \begin{pmatrix} 1 & -0.100 \\ -0.100 & 1 \end{pmatrix}$.

Step4. In order to continue the algorithm, the application has to calculate the Willks Lambda and the Partial Lambda for each of the two indicators taken into consideration. Wilks Lambda indicates the significance of the discriminant function, providing the proportion of total variability not explained. The value of the main diagonal elements proportionally leads on the success of the discriminant ratio.

Step5. The application will determine the standard discriminant after the Lambda functions have been established, as following:

$$z = -0.997 * D + 0.552 * L \qquad (6)$$

Reclassified Data Sample

Company	Reclassification	Z
2	Bankruptcy / Bankruptcy	-2.7442
5	Bankruptcy / Bankruptcy	-2.4499
3	Bankruptcy / Bankruptcy	-1.8203
7	Bankruptcy / Bankruptcy	-0.8458
1	Bankruptcy / Bankruptcy	-0.754
4	Bankruptcy / Bankruptcy	-0.4851
10	Running order/ Bankruptcy	-0.2872
6	Bankruptcy/ Running order	0.3422
13	Running order/ Running order	0.9605
9	Running order/ Running order	0.9719
8	Running order/ Running order	1.3476
11	Running order/ Running order	1.3982
14	Running order/ Running order	1.8864
12	Running order/ Running order	2.4795

Fig. 7. Reclassified Data Sample

The centroids of the subgroups G1-Banktrupcy and G2-Running order are projected on the axe Δ, using the coordinates (1.25, 1.25), which the application reveals after the user click on the Calculate G1, G2 projection axis button. Therefore, the application establishes the value of $z_c = 0$ the cutting score in current analysis.

The user has now the possibility of reclassifying the Initial Data Sample, which is basically one of the most important aspects of our scoring model, because it minimizes risk by offering a more accurate view upon the current analyze.

Step6. We want to determine the class of an observation based on a set of variables known as predictors or input variables. These discriminant functions are used to predict the class of a new observation with unknown class.

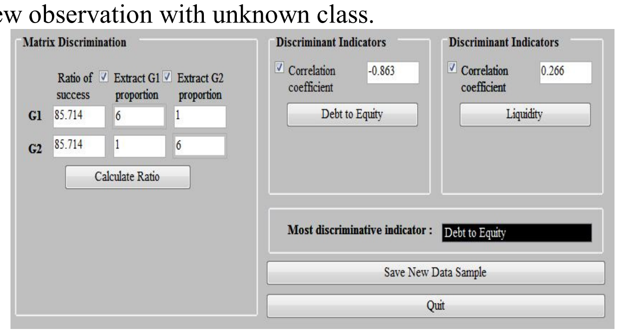

Fig. 8. Discriminant Indicators

Figure 5 presents the ascending scorings of the companies that resulted after the applying the discriminant function (6). The algorithm analyzes the value of the most discriminative indicator which turns to be debt to equity indicator, due to its highest value for the F-statistic. The F-statistic represents the ratio between the spread of the class (subgroups G1-Bankruptcy and G2- Running order) and the spread inside the class.

Several techniques have been used in the construction of credit scoring models; the most common techniques used are traditional statistical methods. It is a request that dynamic workflow enables a faster adaptation to customer acquisition, credit decision management and administrative automation, credit assessment, decisioning, pricing, portfolio management and internal ratings that addresses a bank's need for a comprehensive and standardized credit approval processes.

IV. CONCLUSIONS

To assess credit risk, lenders gather information on a range of factors, including the current and past financial circumstances of the prospective borrower and the nature and value of the property serving as
loan collateral. The objective of credit scoring is to help credit providers quantify and manage the financial risk involved in providing credit so that they can make better lending decisions quickly and more objectively [17]. Credit scores also help to reduce discrimination because credit scoring models provide an objective analysis of a consumer's creditworthiness. This enables credit providers to focus on only information that relates to credit risk and avoid the personal subjectivity of a credit analyst or an underwriter [4].

The discriminant analysis represents an effective method for multivariate data analysis, often being use to extract relevant information from large and heterogeneous amounts of data. As a technique for classifying a set of observations into predefined classes, the discriminant analysis highlights their similarities and differences between them, creating an important advantage in describing the variability of a data set. Therefore, the method reduces the number of dimensions, without a significant loss of information. Probably the most common application of discriminant function analysis is to include many measures in the study, in order to determine the ones that discriminate between groups [7].

The purpose of the discriminant function analysis is related to the examination of the differences between groups on the basis of the features of the studied cases. It is then determined the weight of each feature in the group separation process.

Predictive discriminant function analysis refers to the possibility of assigning new cases to groups, also by using the scores of one entity on the predictor variables to predict the category to which the individual belongs.

The loan processing has rapidly increased in speed due to scoring systems. Rather than perform lengthy credit investigation, creditors and other lenders are able to access credit scores to determine credit risks [10]. Due to the nature of its business, risk management is inherent to financial industry. In banking there is an ever present risk of payment default, fraud, theft, identity theft, and operational risk connected with internal procedures and processes [18].

Consumers also benefit from increased competition as a result of credit scoring. Credit scores make it possible for lenders to prescreen and qualify applicants cost-effectively, thereby facilitating more efficient competition among lenders. Credit scoring models have enabled the development of the sub-prime lending industry where sub-prime consumers have poor credit records and fall short of credit acceptance and risk [19].

The most common use of credit scores is in making credit decisions for loan applications. In addition to decisions on personal loan applications, financial institutions now make use of credit scores to help set credit limits, manage existing accounts, and forecast the profitability of consumers and customers.

Traditionally, the banking system focuses on IT development in Back Office regarding operational aspects and production. The next stage attends the compliance with local and international laws and regulations in the industry such as anti-money-laundry. After this stage there are taken in consideration aspects of customer management systems and distribution, meaning the Front Office. These represent major opportunities of growth, because the first attracts customers and the second helps their effective management, by providing differentiation in the market.

Credit scoring has several benefits for the economy as a whole, by increasing access to consumer credit and reducing credit costs. It helps consumers smooth consumption between periods of high and low income, as well as promoting economic expansion and protecting against recession by reducing liquidity restraints.

This product identifies potential areas of risk and opportunity rules-based analysis which in turn produces written commentaries and system generated reports. Comparisons can be made to portfolios, peer groups or industry standards. It also provides a comprehensive, enterprise-wide credit management solution in which the credit professional has day-to-day operational, analytical and consultative tools [20].

The product analyzes financial statement ratios and trends, textual expert commentary, customer comparisons to portfolio peer groups, a forecasting template and complete credit score results. This in turn provides better visibility and communication regarding customer accounts. It also acknowledges calculated risks associated with the entire credit portfolio due to consistent application of credit policy.

Service orientation represents a construction method rather than a technology, being applied particularly to one system when it needs to offer functions to other systems [3].

When it comes to finding a credit scoring package, credit managers seek models that will enhance their business and help them to make a thorough decision.

Credit risk management systems follow a modular approach and allow banks to calculate capital requirement from the simplest approach to the advanced ones. It makes business sense for an industry that recognizes the importance of exploiting competitive advantage through technology to consider an approach that allows them to identify, upgrade and re-use existing legacy assets, while also taking advantage of new technologies.

In recent years, new techniques have been increasingly used to construct credit scoring models. One of the major problems that can arise when constructing a credit scoring model is that the model may be built using a biased sample of consumers and customers who have been granted credit.

Applying service orientation is a way of improving the business flexibility and agility required by the competitive environment, providing an ensemble that is meaningful to the business and hides the technical components.

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