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Theoretical Principles and Methods for Rating Softwares

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1. Structuring Aspects of Rating

The topic of "rating" gained many new facets in the last few years. Consequently, before upfront engagement with this topic, a deferral of the examined aspects is necessary. According to Serfing, among others (1996, S. 632), rating simply describes a method of bringing "The rated objects regarding a certain target in an ordered rank". Based on this general definition rating comes into use in many different areas of daily life; so that restaurants, high-schools, shares or companies get labeled with a rating-judgement. Special attention is to be taken on the matter — in this case it is the reliability and hence, the credit-worthiness of a subject. This describes the ability of a debtor to meet his payment obligations in the future. If the empirical importance of the (partial) retrieval of problematic credits gets disregarded, the probability of default comes into focus.

For the next step, the objects of investigation and the areas of evaluation, have to restricted. Shall the populations of private persons, emitters of bond issues, and companies be examined one at a time? Who shall be the user of this software? Banks, the companies themselves or advisors?

Clearly, it is in the interest of banks to measure the risk of default for their portfolio, in order to help regulate them. However, for this it is not enough, like one might assume, to simply get a decent result for the whole group, in which for some companies show exceptionally good results and some exceptionally bad; even as a good average result is achieved. This is due to a problem of adverse selection, because of dependency on the interests from rating results, to the same effect as Basel II. Through this the bank is put before following problems: How do I keep

good risks, which are categorized as bad risks from my bank, inside my portfolio? And how do I manage bad risks, which are categorized as good risks, from my bank? Also contracts with cost-sharing arrangements don't help to solve this dilemma — a common procedure to bypass or temper this problem—since in instances of insolvency the effect of cost-sharing arrangements doesn't apply. Especially fierce competition from banks regarding the attainment of a good client-base sets an automatism into play, that along with house-bank connections and customer relation programs, can be limited. Therewith it is clear, that every rating software has to focus on the PD of individuals (private persons or companies).

These individuals can be considered as a addressee for ratings, and therefore as a potential user of the rating software. Primarily it is capital-providers by their choice of capital location. This applies in the same way to capital-providers as well as bonded capital-providers. The enterpriser intersects the rating only in the second instance, namely when he wants to change the consequences faced from rating, for example if he wants to reach a lower bonded capital interest. Then again, if this is the case, the enterpriser does not only associate himself with the rating result, but also in how it came to this result. With this, he then is located in the area of rating advisory, a natural gateway to the company advisers, which are also using rating software clients. So the capital-providers demand investigations into the quality of the rating and less-urgently into the knowledge of the intern structure of rating. They are satisfied with a "black box". The enterpriser on the other hand shows less interest in the quality of the rating, but instead would like to have very detailed knowledge of the "black box".

This "black-box-rating-method" can very easily be described in abstract terms. Information is collected and afterwards get compressed into a rating-judgement. The rating judgement can be expressed as a letter-combination (AAA to CCC) and therefore as a relative classification, as a score or as a chance of insolvency. As a general rule, the first two kinds of rating-judgement aligns a class for the chance of insolvency. Formally this means, that a rating technology represents a function of the multitude of used information within rating-judgement, namely: Information multitude$\geqslant$rating-judgement.

Therefore, the question appears automatically after the relevant information is inputted. In economic estimations, should only influence-proven quantities be considered or do also those from a company's influencable quantities have to be included in the rating-method? This simple question is not to be answered in a simple manner. For instance, if a rating-method consists of 50 data-sets and if two identical data-sets emerge, besides those between different companies, then this leads inevitably to the same result appearing. For example, if the existence of a risk management system is not included in the information, then this results in inaccuracy of the rating method. If the chance of insolvency in a company gets through a risk management system reduced from 5% to 2%, because the severe risks will be recognized on one side and on the other side it is possible to counter-act, in this case the classification failure would be a healthy 3%.

The arrangement of reason and effect must be handled with utmost care. It is generally known, that the insolvency quota may vary after the volume of sales exceeds the magnitude of classes (see Leibbrand, 2001) and many economic estimations of the chances of insolvency approve this quadratic correlation. In this the magnitude is measured partly in sales volume and partly in employment figures. Small companies normally don't have the size to accommodate insolvency, in this case one retreats from the market (and pays off the debts). Big companies have a far lower chance of insolvency. This is due to better management and leading systems up to better diversification. If the company size is included in employment data, than it would be possible for a company, that because of sales volume problems, gets into a state of urgency, to boost short—term rating through the hiring of new personnel (and through this possibly of an extension of credit). Such occurrences are contrary to reason, and should be excluded from the rating methods. Namely the optimal employment data, in which it is crucial to gather exact figures, and an objective approach should reflect this.

So if the information relevant to the rating-method is known, its quality is of importance. Is it a raw estimation? How accurate is it? Is the estimation undistorted, meaning is it well-centred? If the information is very vague, no rating-method will produce detailed information towards the chance of insolvency that can be extracted. While the quality of the rating-method definitely also consists of a theoretical component, the precision of the processed information is a purely empirical question. For instance, the expression management quality is richly diffuse. Though, the established measuring specification can be refined further. Banks have also found, also because of this, that in rating-methods, IE binary questions (yes/no) have definitely proven themselves effective. With these questions one certainly only covers a small part of the total information multitude, however no further insecurity occurs in data collection.

Another problem that is not to be underestimated lies in the subjectivity of the information. The controller of the company has access to all whole history records and the personnel responsible for ownership-distribution, which are both needed for sales-volume prognosis. With this he can make a good prognosis— albeit, still afflicted with a large amount of insecurity. He assumes that in the centre he is able to predict accurately, but that (smaller) deviations, up or down, are definitely possible. Does he go with this prognosis to the banker though? What conclusion can a banker reach from a sales-volume prognosis? Therein lies another important problem. The controller (and also the banker) knows that credit becomes cheaper with a more optimistic sales—volume prognosis. So how can the banker ascertain if the prognosis is not too optimistic? The answer is: he cannot. There is no way that the controller can prove internal information. In the long term the problem can be solved through reputation. Although it would be better to make the credit dearer or easier afterwards, depending on, whether or not the results are exceeded or not reached at all, as a kind of activated guarantee for the company.

Another example is the risk management system. In a company the manager is aware of all the risks, more-so than others. Nevertheless from the view of a capital provider (bank) he doesn't differ from a company manager, that doesn't know any of his risks. Paradoxically even a company with a barely-used, but well-documented risk management system is rated higher by the capital-provider. Even for a company, that flawlessly optimizes the company's value, this conflict with the rating-optimization increases the likelihood of insolvency.

Generally, two users of rating software can be identified, on the one side the (bonded—) capital providers and on the other side the companies (As well as their advisers, respectively). Thereby the work of the capital-provider has the following focus:

(1) Build up of a rating method utilizing the observable and non-observable and therefore strategically, from the perspective of the company, distort information,

(2) Calibration of the rating-method with statistical methods using empirical data to determine actual insolvencies,

(3) Ultimately, the chance of insolvency of single companies is of interest.

Next to the usual insecurity of this estimation, the biggest insecurity comes through the inaccurate measurement methods and the strategic distortion of company data.

The enterpriser, who wants to be able to influence his rating, is approached by several tasks:

(1) Evaluation of the rating-method from the capital provider,

(2) Identification of influence-able variables, in order to influence the information that is to be used in the rating method,

(3) Creation of unbiased and refined information (company planning and so on),

(4) Establishing a credibility for the information passed on to the capital provider.

The insecurity on one hand derives from the estimation of the rating-method and on the other hand from the effects on the success data.

2. Rating as a Prognosis of the Boundaries of Density Functions

Each rating finally represents the estimation of the boundary probabilities for two overlapping density functions, namely the probability density function for excessive indebtedness and liquidation. For these estimations the usual quality criterions apply for the estimator, special attention hereby is to be put on the in-distortion and the low variety. The aim is a optimally-precise prediction of the chance for insolvency. The estimation itself depends each time on an information status. This means that, for the estimation plans, for example company strategies, —risks, management quality, account processing, age of the machines and so on. The aim is the identification of the prognosis failure of a certain quantile of an allocative function.

It gets even more difficult if perennial chances for insolvency are to be drawn. Because of the long—term prognosis horizon, the whole density function for liquidation, and as the case may be, existing capital, has to be used effectively for the quality-judgement of a rating. Since the chance of insolvency changes in the second year, if , in the case of survival, the first years profit or cash flow has been incorrectly assessed. If two different rating-methods are to be compared it always requests the comparison of density functions over the edges of a liquidity and as the case may be own capital density function. The choice of a measurement for this is initially arbitrary. So, for instance, for a measurement benchmark only the chance

of insolvency through excessive indebtedness and liquidity could be used, or other characteristic figures of the density function can be chosen (1 or 2 moment), or a discretionary norm. For the choice of single criterions the weighting is arbitrary.

The minimal requirements for the description of a non-degenerated density function lies in the allegation of the expectation value and the variety. This means a rating has at least to calculate the existing capital and the liquidity-expected value and the distribution. Therefore only a prediction for any derivation in the chance for insolvency from a company plan model with explicit modulation of the risks (fluctuations) is the correct procedure (see paragraph 1. 2. 3.). Nevertheless the empirically-graspable prognosis quality can be far worse than in other methods, which are only based on middle values, because of unreliable data collection. The question is only to be answered empirically, after several years with more than one hundred insolvencies on a foundation of solid data. So it is that a good, calibrated finance rating can definitely deliver better results than the theoretically clean procedure of unrefined company planning, since it suffers immensely from the response quality to research into risk.

3. Rating Via Unrefined Company Planning

3.1 Description of a Typical Rating Method of This Category

Within the scope of a Saxon Ministry of Economics commissioned research project, which conducted the Institute for Practical Economic Research and Economic Advise (IAWW) together with the TU(Technical University) Dresden as well as the advisory association WIMA GmbH, RMCE RiskCon GmbH, as well as the FutureValue Group AG, for the first time in the determination of a rating for about 150 Saxon companies, a simulation model as a stan-dalone rating system has been introduced that:

(1) Can directly reduce the chance of insolvency from the simulation and therewith

(2) Can make rating-prognosis possible.

A simulation allows the company to forecast sales volume, costs and other influential factors that would appear on balance sheets, for a project-leader through a planning period of over five years in consideration of the interrogated risks. With the help of simulation-based calculation methods, one can receive an allocation for the balance sheet profit and of the liquidity of the company, whereby the chance of insolvency-through excessive indebtedness or liquidity-over a period of five years can be directly determined. Then a rating-note or a rating-grade rank can be aligned to the subject, in such a way that the probability of failure can be determined. The initial point of derivation for this rating is the description of the probability of insolvency. The cause of insolvency is self-evident in the following situations:

(1) An excessive indebtedness, meaning the figure of (economic) capital is smaller than zero, and

(2) Liquidation, meaning that the payment obligations are no longer covered through liquid funds and an agreement for short-term credit is made

In order to be able to determine the probability for excessive indebtedness, the allocation function of the owned capital has to be determined in each period. This result defines the capital acquired over a period of time from the capital acquired in the previous period, plus the changes of the surplus saved capital and of the deposits and withdrawals, as well as of the retained balance sheet profits, whereupon an alternation of capital—similar funds such as bonds and bindings against allied companies or associations or deposits of informal associates are not included in the planning period. Then with yearly records and analysis of acquired capital, a probability of a non—positive capital can be determined, which precisely matches the cause for insolvency: "excessive indebtedness". But since, as an general rule within companies no excessive documentation of indebtedness exists, as there is concentration on the vital assets, excessive indebtedness occurs. If the companies have hidden reserves in a larger amount , the PD will be estimated too high. If on the other hand high derivative company values, through acquisition, are in the balance sheet, it is possible that the PD can be underestimated. The situation of liquidity occurs for a company, if its payments—out exceed the payments-in plus liquid funds plus not yet exhausted credit lines. But before this situation occurs, the company still has several adaptabilities. Especially investments that can be delayed or even be abandoned. Through down—sizing or short term work from personnel, a state of liquidity can also be salvaged.

Main components (regarding the company model, that was the basis of such planning) are the calculation of profit— and the calculated estimate of loss as well as the budgeted balance sheet (see Fig. 1). The interest applies for the allocation function of capital as well as for liquidation. For the fore—mentioned indicators of

profit are modeled according to the formula "profit, is sales volume minus expenses", this means in one hand, sales volume process and on the other hand costs process and its details must be described.

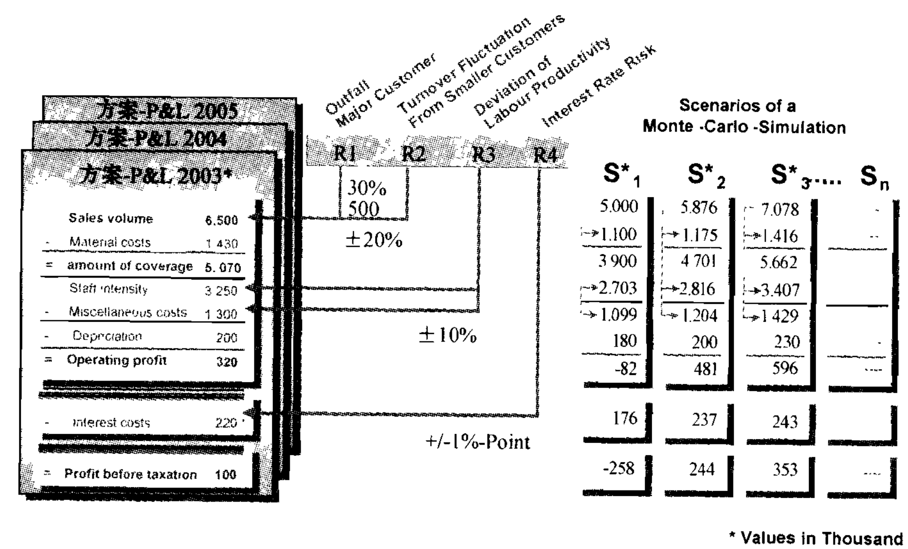

Fig. 1 Randomly-determined company model

In determining the probability of insolvency for the period of middle-termed company planning, the company is seen through randomly determined processes, means and affin-linear dependency's on the sales volume (detailed specifications are found in Leibbrand, 2002 and 2004, as well as Gleissner and Leibbrand, 2004a and 2004b). As randomly-defined processes establish the sales volume, the material recovered paper utilization rate, the personnel costs and the interest rates could be modelled, whereby the fore-mentioned processes make the base variation possible and therewith the calculation of the insolvency probability. As a means for discovery, the attitude towards investing, the personnel adjustment, the distribution politics and the setting of a credit line would be appropriate. Affin-linear dependencies of different balance sheet— and P&L—positions of the sales volume define the penetrating power of turnover fluctuations on the acquired capital and liquidity. Risks that exists within the company like machine failure or miscalculations are considered as separate stochastic processes.

At the execution of the simulation in one run, for example, (see scenario S_1

from Fig. 1) it is assumed that in "The Company" that the greatest client drops out (which is why the sales volume in Fig. 1 drops from the estimated value of 6.500 TEuro to 5.00 TEuro), a major order gets miscalculated (the other expenses rise from 20% of the sales volume to 22%) and personnel expenses rise (the personnel expenses rise from 50% of the sales volume to 54%). The accumulation of these unfortunate circumstances leads to an annual loss of 258 TEuro. But if-like assumed-only an acquired capital the volume of 150 TEuro is at hand, this loss can not be absorbed, so that insolvency on the basis of excessive indebtedness comes into existence. In another scenario, in which the sales volume rises by 9%, the material-recovered paper utilisation rate stays constant, at constant wages productivity growth can be reached (scenario S_3 in Fig. 2), the company reaches an annual surplus in the volume of 353 TEuro before taxes and at a tax rate of 44% 198 TEuro after taxes, thus an extraordinarily good result. 10.000 simulation runs stated that the frequency diagram from the upcoming Fig. 2(354 simulation results can not be displayed, since they are located outside of the area from −230TE and +250TE).

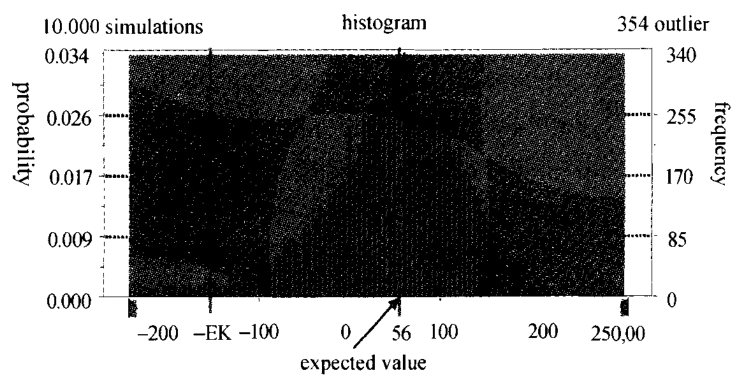

Fig. 2 Simulation result of the randomly defined company planning for the annual surplus

The determination of rating through randomly defined company planning has a crucial theoretical advantage compared to the traditional rating-systems; that fluctuations of the income level are modelled and that it is solely aimed towards the future. Theoretically over time the randomly-defined company planning model is the optimal path, which although requires careful consideration, can prove itself as worthwhile, if for example it becomes laborious, complex or even impossible for a credit institution to receive the relevant information.

3.2 Judgement

Through increased simulations, the probability of insolvency can be user-defined, approached delicately, and without information being given directly at a desk. Whether or not the calculated probability of insolvency matches the actual, depends on two set screws. On the one hand on the quality of the company model and on the other hand on the quality of the assumed stochastic processes.

From the saxon-rating-project it is known that the modelling of the company has a crucial influence on the probability of insolvency. If, for instance, an German enterprises the accelerated depreciation remains unconsidered, the probabilities of insolvency will be displayed as far too high. It is also easy to understand the modelling-sensitivity for the effect of a sales-collapse on the annual surplus. If for example no personnel are dismissed at a sales-volume calibration, than as a general rule insolvency has already occurred.

The second big lever on the rating-result comes from the modelling of the stochastic processes and their correlation structure. For instance, are the expenses for products and the staff members positively correlated? How high is the risk of a flood water damage? Also here the Saxon-rating-process showed that on the part of the enterpriser, the risk situation is not adequately evaluated(see also Leibbrand, 2004).

But since the prognosis of insolvency probability depends mainly on the use of randomly defined processes, the end quality comparison for finance ratings-that is for the short-term-is not at all impressive. However it seems to be desirable, that the companies start to think in density functions, so that the responsible individuals within the companies become more able to observe the randomly-defined processes more precisely. This is particularly helpful, in order to show for example, the consequences of alternative strategies and planning in rating-prognosis, and to make a contribution to crisis prevention in this way. Prognosis for insolvency probabilities through stochastic simulation are then incredibly meaningful, when for a company (for instance because of great structural changes, growth or distinctive coincidental effects through historical annual closing data.) occurring risks for last annual closings are not representative of the future.

4. Empirical Statistic Models

The starting point for the development of a rating-method of this category is an empirical data base, which includes for each therein contained credit exposure and the ownership of multiple properties, as well as their solvency status. With the help of statistical methods it is possible to determine an objective selection and weighting of bonity factors. In the following, the three most common representatives of empirical-statistic models are described.

4.1 Description of the Typical Rating-methods of This Category

In the (linear multi-variable) discriminant allocation, the objects of the database are first assigned to exactly one of two overlapping-free subsets A and B, on the basis of observeable properties ("A: dropped out" and B: not dropped out). Between these subsets lies the to be determined discriminant function D, a weighted (a_i) linear combination of from each other independent coefficient K_i.

$$D=a_0+a_1 \cdot K_1+a_2 \cdot K_2+\cdots+a_n \cdot K_n$$

The first difficulty is the determination of a "good" analytical structure, meaning one that in the the occurrence of poorly-allocated subjects is minimized, as is the choice of properties. These firstly have to be for business management purposes, meaningful, informative, and convincing; and with this have to be selective. Furthermore they have to be quantifiable and normally distributed with equal variance − covariance matrixes. For a high-selectivity the alteration of two properties should overlap as little as possible, meaning that the middle values of the alteration should be as far apart from each other as possible and the variance sum should be as small as possible (compare with Fig. 3). Through the request for quantifiability, qualitative properties are removed. Through appropriate scaling methods however the necessary prerequisites can be fulfilled (for instance see Eigermann, 2001).

The second difficulty alludes to the determination of weighting. Hereby, like in all statistical methods, the quality and the scale of the empirical data base is of crucial importance. This applies especially to the data base containing omitted credits.

Also at the regression method, the dependency of a binary variable y ($y=0$: solvent, $y=1$: insolvent) shall be modelled from other independent variable, X. Required is a directive, $p = P(y=0: X_1, \cdots, X_n)$ for the determination of the probability p, with which Y at given parameter volume (he says: at given occurrence or the properties) $X_1, \cdots, X_n$, is given the value 0. A prerequisite is, that the value range of the to−be determined function P lies between 0 and 1.

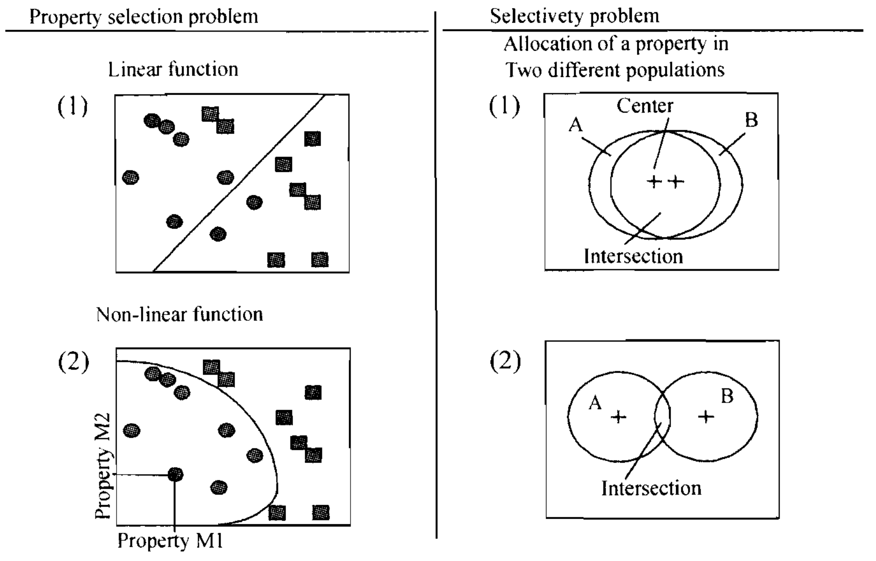

Fig. 3 Property selection problem and selectivity problem

The so-called logistic regression is widespread, in which for the function P the following approach is chosen, which shows an s-shaped progression of the function (compare Fig. 4):

$$p=P(Y=0:X_1, \cdots, X_n)=\frac{e^Z}{1+e^Z}=\frac{1}{1+e^{-Z}}$$

$$\text{mit } Z=b_0+b_1 \cdot X_1+b_2 \cdot X_2+\cdots+b_n \cdot X_n$$

For the estimation of the coefficients b_i, a maximum-likelihood-function is used.

Since at the logistic regression there is no bondage to the scaling of the incoming variables, qualitative properties can be processed more directly. In order to do so, however, for each occurrence of a qualitative property a so called dummy-variable has to be introduced, which can only take on the values 0 ("occurrence fulfilled") and 1 ("occurrence-not-fulfilled").

Another representative of empirical statistical methods is displayed by neural nets. Hereby it is a matter of adaptive computer programs, which on a technical level, resemble the human brain. The basic modules of a neural net are, in accor-

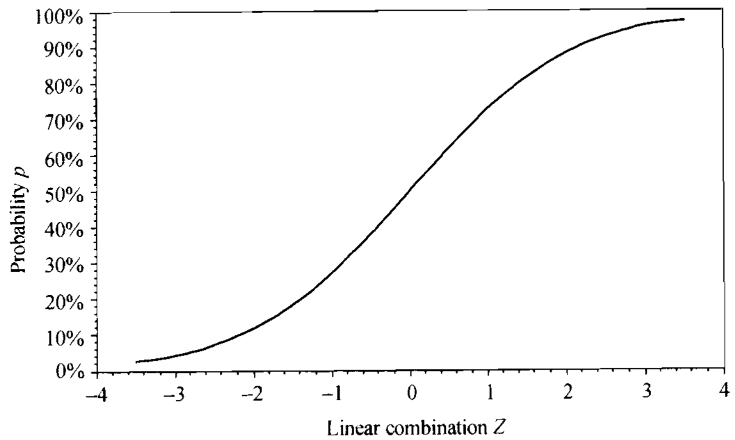

Fig. 4 logistic regression: progression of the model function

dance to the biological arch-type, so-called neurons (nerve cells), which, when made of multiple layers, are linked together and build an adaptive network. Hereby special importance lies in the contact points between two neurons, the synapses-since through them, the experience, meaning knowledge, in form of weight is stored. Typically an artificial neuron network nowadays consists of several hundred neurons, that are arranged in layers (input—, hidden—, and output foundations. compare Fig. 5).

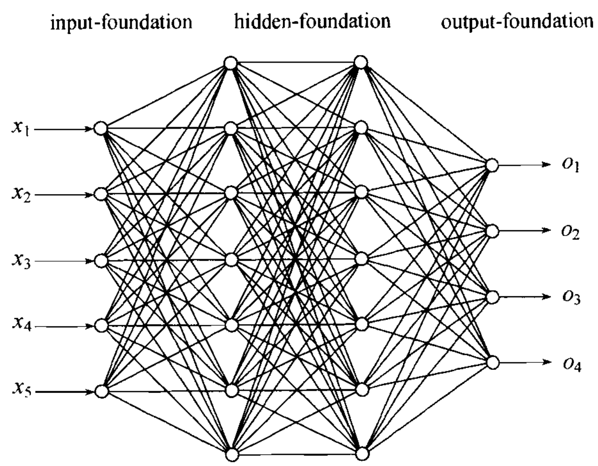

Fig. 5 Neural network (error-backpropagation-network)

Fig. 6 shows the functioning of an artificial neuron j. From the up-streamed neurons incoming information y_i, and within the synopsis saved weights w_{ij}, in one

first step the weighted sum x_j is being processed (gebildet). Subsequently, the compressed value x_j gets transformed through a non-linear process to a value, which in the final step gets passed on to all down streamed neurons. A possible transformation is the logic function

$$y_j = 1/(1+\exp(-x_j)).$$

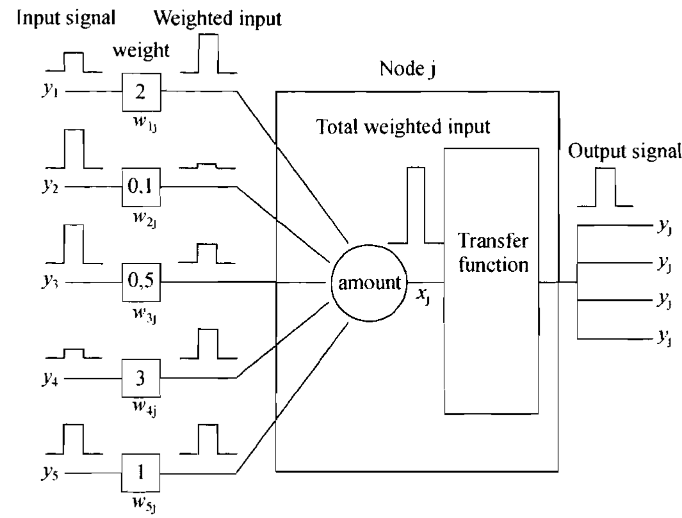

Fig. 6 Functioning of an artificial neuron

Neural networks are non-classical computer programmes in a sense, as their decisions are based within the existing scope of the programming specified: "if—then—else" instruction. Instead, they learn themselves, meaning that they independently extract the causal structure from given data and with it build up a knowledge—base. During the training, the network successively optimizes its synapses weights with the help of the presented incoming information, from which is known, if they are "good" or "bad". The aim within this phase of knowledge adoption is to carry out weight adjustments to be result-oriented, in order to optimize the decision frequency step by step, meaning the selectivity between "good" and "bad" cases. Mathematically this process can be described, for example through an inverse gradient in a multidimensional failure (mountain row) The aim is to reach the global minimum.

When compared to the previously described methods, neural networks possess no restrictions concerning property variables. A great advantage of neural networks also lies in their ability to still provide useful results, even with missing information or having obtained partly-falsified incoming data. Furthermore in the case of an adaption, neural networks do not need to be entirely programmed anew, but simply trained again from its starting point.

4.2 Judgement

The judgement described in section 4.1 on the basis of empirical – statistic models can and should occur from two different angles of view, that for single users and addressents of a rating are of different importance. So next to the pure selectivity of the methods also their traceability should be questioned. It appears, that in the three mentioned methods not both requests can be optimally fulfilled at the same time.

Essential property characteristics of linear-multi-variant discriminatory-analysis is their innate linearity. With this goes a great restriction concerning the determination of an ideal, separate, function. On the other hand, this precise linearity assures an accurate measure of transparency in accordance to the meaning and importance of the single properties being rated. This way single coefficients can be directly interpreted through financial means and possible economic difficulties can easily be identified. For a relative comparison of the meaning and importance of the single properties, all properties and coefficients should be normalised like in the following:

$$\widetilde{K}_i = \frac{K_i}{\sigma^2} \quad \text{and} \quad \bar{a}_i = a_i \cdot \sigma^2$$

with σ = standard aberration of the property.

In contrast to the analytical grouping method, results acquired through logistic regression in general, were scattered and robust. Investigating transparency, however demands making cut backs. In fact, also at this stage, with the usage of the function coefficient bi the resulting function p can be checked in regards to economic incongruancies, but the importance of single criteria can only comprehended difficulty. The reason for this is the non-linear graph of the function, which results in showing that the influence of single variables is not constant, but that it changes depending on the X-values.

Neuronal networks posses, when given a sufficient foundation of background training data, the highest selectivity of the three methods introduced in this section. For the user, however, they present themselves as a "Black Box", since all information is merely stored within the synapses inside of the system. The results, determined through a neuronal network are either impossible, or very nearly impossible to use to investigate into plausibility.

5. Expertsystems

5.1 Description of the Typical Rating-Methods of This Category

Expertsystems are software solutions, which aim to simulate the problem-solving ability of the human brain. They form an area in the field of research of artificial intelligence, often referred to as "knowledge-based systems".

The creation of an expertsystem takes three stages. In the first step, the acquisition, knowledge gets gathered and comprehended. Thereby, the knowledge can be available for the experts in the form of numbers, data, facts and rules as well as "diffuse" experiences. The representation of the knowledge, meaning the display and storing of information as a knowledge base, forms the second step and is carried out through If-Then rules, so called production rules. The last step forms the inference, meaning the deductive conjunction of the If-Then rules in order to determine a problem solution. This happens through hardware or software, with which it is possible to operate on the knowledge base.

A special case of expertsystems is formed by fuzzy-logic-systems, which allow it, to diffusely interpret data, meaning to free oneself from the classical two-valued logic. Fuzzy-logic makes it possible, with the help of affiliation grades, to describe a person as "0% non-credit worthy", "80% credit-worthy" and "30% very-credit-worthy" and still not to allocate them pure binary to one of the two classes "non-credit worthy" and credit-worthy.

The starting point of the fuzzy theory is the definition of "diffuse" multitudes, so called fuzzy-sets, which also allow the partial affiliation of an element to a multitude. The grade of the affiliation to a fuzzy-set is described through an affiliation function μ. As a basic rule, for the affiliation grade that appears as, a triangle, trapeze-shaped, bell – shaped (normal curve of distribution) or a graph of function with s – shaped flanks is chosen.

Next to the fuzzy-sets, the linguistic variables represent the second essential development in the concept of the fuzzy-logic. These don't take on numerical values, but linguistic descriptions like "good", "middle" and "bad". Behind each of these variables stands a fuzzy-set. In Fig. 7 the linguistic variable "owned capital contingent" is displayed with the attributes "low", "middle" and "high" and the associated fuzzy-sets. While an owned capital contingent of 26% in a binary system would have to be described either as "low" or "high", the fuzzy-theory makes it possible to describe the it as "to 22% low", "to 61% middle" and "to 0% high".

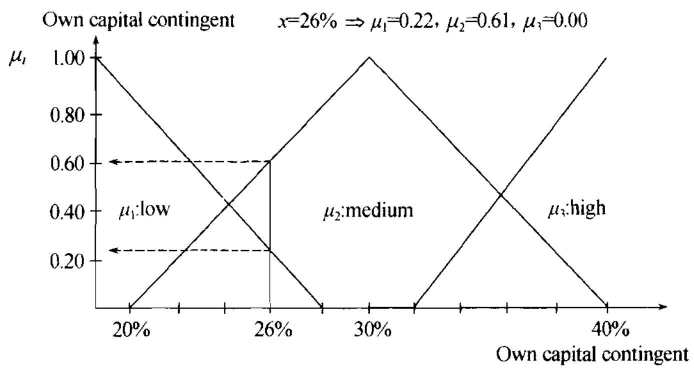

Fig. 7 the linguistic variable, ,owned capital contingent

The knowledge of a fuzzy logic system is gathered in the knowledge base and is available there in form of If-Then-rules, which are based on the experiences of credit experts. Possible rules that are saved for availability in the knowledge basis are:

• If the owned capital is "high" and the staff intensity is "low", then the company is "slightly" insecure.

• If the owned capital is "middle" and the staff intensity "middle", then the company is "moderately" insecure.

• If the own capital is "low" and the staff intensity "high", then the company is "highly" insecure.

Fig. 8 shows the schematic build up of a fuzzy logic system. At first in the scope of fuzzy-fication the owned quantities are transformed into affiliation grades according to linguistic variables. Subsequently, inference of fuzzy-logic takes over the computer-controlled interpretation of the If-Then-rules, which are stored in the knowledge base. The results inferred from such logic is again a linguistic variable, which in the last step gets transformed in a clear, precise judgement through an information refining process.

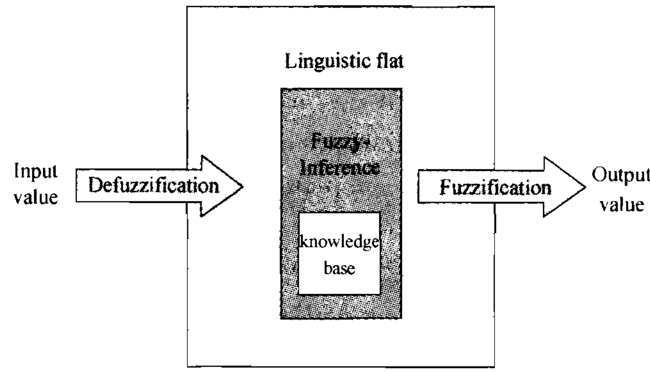

Fig. 8 schematic build of a fuzzy logic system

5.2 Judgement

The quantity of an empirical-statistic model crucially depends on the data-base that has been used for development. The stability of an expert system, in contrast, is solely based on the quality of knowledge from the experts and their appropriate representation. Therefore the prerequisite is, that the principle of the underlying problems is understood exactly. This determines the limits of data-based reliability. Furthermore, expert systems produce results that are more determinate in regards to missing information units.

For the effective development of fuzzy-logic-systems, complex development tools are indispensable. The main problem is the comparatively high calculating effort, since in the calculation of single part conclusions and of the end result one has to work with fuzzy-logic sets. Hereby, as a basic rule fuzzy-logic sets should be displayed tabularly, so that along with the size of tables, the accuracy of a calculation as well as the underlying calculation time appears in succession. Furthermore, criteria for the quality rating and for stability verification are missing.

Which one of the methods exhibited in this article are to be preferred by the department of drop-out probability, and therefore the rating for a specific rating software solution cannot be answered through a blanket assumption. The different methods have-as shown-specific advantages and disadvantages. Finance reference-number-based rating on the basis of discriminate analysis or neural networks can both form, especially in the short-term, a very good prognosis of drop-out probability. The simulation-based methods, in contrast, have certain distinct advantages-because of structural changes in the company's historical annual balance sheet data.

which is troublesome, and middle-to-long termed prognoses (prognosis of drop out probability) seem to be suggestive. Another advantage of the simulation-based methods is to be seen in the fact that they can also be used to simulate the consequences of changes of in company strategies and company planning or of risk management (for example of insurance solutions) with the emphasis on the consequences towards drop-out probability. In this respect, methods of these kinds are precisely appropriate, if rating strategies are being developed and optimal possible courses of action are being searched for by the company in question. Because of the different strengths of each single method, it is naturally imaginable to connect different quantitative methods with each other-A technique that has actually been chosen in a couple of rating-software systems.

References

[1] Eigermann, J., 2001, Quantitative Credit–Ratingverfahren in der Praxis, Finanz Betrieb 10/2001, S. 521–529

[2] Füser, K., 2001, Intelligentes Scoring und Rating, Gabler, Wiesbaden, 2001

[3] Füser, K.; Gleißner, W., 2005, Rating Lexikon, München

[4] Gleißner, W.; Leibbrand, F., 2004a, Der neue Ratingansatz, Bankmagazin, 03/2004, 38–39

[5] Gleißner, W.; Leibbrand, F., 2004b, Indikatives Rating und Unternehmensplanung als Grundlage für eine Ratingstrategie, in Achleitner, A. –K.; Everling, O. (Hrsg), Handbuch Ratingpraxis, Gabler, Wiesbaden, 369–411

[6] Gleißner, W. (2004): Value–Based Corporate Risk Management, in: Frenkel, M. /Hommel, U. /Rudolf, M. (Hrsg.) Risk Management. Challenge and Opportunity, 2004, S. 479–494

[7] Leibbrand, F., 2001, Unternehmensgründungen und insolvenzen, in Blum, U.; Leibbrand, F., (Hrsg.), Entrepreneurship und Unternehmertum Denkstrukturen für eine neue Zeit, Gabler, Wiesbaden, 57–109

[8] Leibbrand, F., 2002, Die Ermittlung der Insolvenzwahrscheinlichkeit mittels stochastischer Unternehmensplanung, Working Paper, mimeo

[9] Leibbrand, F., 2004, Klassifikation von Unternehmertum als grobe Richtschnur für das Existenzgründerrating, in Achleitner, A. –K.; Everling, O. (Hrsg), Existenzgründerrating, Gabler, Wiesbaden, 439–458

[10] Oesterreichische Nationalbank und Finanzaufsicht FMA, 2004, Ratingmodelle und –validierung, Leitfadenreihe zum Kreditrisiko, www. fma. gv. at, 2004

[11] Serfling, K.; Badack, E.; Jeiter, V., 1996, Möglichkeiten und Grenzen des Credit Rating, in Büschgen, H.; Everling, O. (Hrsg.), Handbuch Rating, Wiesbaden, 629–655

Developments in Credit Agency Regulation

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1. Introduction

The recent subprime mortgage crisis once more reveals the decisive role credit rating agencies play in the financial markets. Despite the skepticisms arising from earlier scandals such as Enron, regulatory bodies worldwide have largely pursued a wait-and-see approach, hoping for a voluntary self-commitment of credit rating agencies to consistently adopt the IOSCO Code of Conduct. However, the international dimension of the current crisis seems to require internationally coordinated action to restore integrity of and confidence in the rating industry.

This paper gives an overview over developments in credit agency regulation since the 1930s. Chapter 2 focuses on supranational activities, activities in the U. S. and in Europe. Although the discussion has largely shifted to this international level, chapter 3 puts a focus on activities in Germany, as it is the origin of some of the first initiatives to develop standards for credit rating agencies.

2. International and Supranational Activities

2.1 U.S. Securities and Exchange Commission (SEC)

Already since the 1930s depression ratings have been incorporated into government regulation of the United States. As a result of the sharp decline in credit quality the U. S. Office of the Comptroller of the Currency (OCC) prohibited banks from holding bonds not rated at least BBB by S&P's and Moody's in 1936. As roughly half of the listed bonds were rated below BBB at the time, both bond busi-