The Selection of Variables in the Models for Financial Condition Evaluation

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Abstract A quality of classification of studied phenomena, or objects depends on the selection of variables (features) and criteria of the assessment. The choice of financial ratios in the study of financial standing of companies is crucial. The article presents the proposal to apply measure of quality of selection to choose sub-optimal subsets of financial ratios that best describe the subject of the research, which is the company. The aim of this study is to present a solution that allows the selection of financial ratios with a very high cognitive value, enabling the building of integrated measures assess the financial condition of the company. The presented results show the process of selection of the five-elements subset from the set of 13 financial ratios.

Keywords Selection of information · Financial ratios · Optimization · Discriminatory models

1 Introduction

In the rapidly changing market economies continuous assessment of financial phenomena occurring in businesses, in particular continuous evaluation of their financial condition is expected. Proper evaluation of the processes occurring in the enterprise enables prediction of the financial situation of the company and taking pre-emptive action which could protect the company from bankruptcy.

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Enterprises can be described by certain characteristics, features that can be financial and non-financial indicators, ratios. The use of synthetic indicators in the assessment process allows the assessment of a company financial standing, this is integrated assessment. Of course, it is clear that not every financial indicator (feature) is equally important in the evaluation of companies, therefore is crucial in this respect to choose (select) financial indicators most valuable, useful and crucial from the point of view of the assessing enterprise.

Why some indicators are more often used than others? Various aspects effect the frequency of their use. One of them is the availability of data, for example not all companies are listed on the stock exchange, what means that mostly the market ratios of companies are not known, and therefore should be removed from the set of financial ratios [1].

Analysis of research by Hamrol [2], Hołda and Micherda [3] and Kowalak [4] shows that when choosing financial ratios authors have used different techniques for their selection. One technique is to use, for example correlation matrix. The second technique is to set yourself up as an expert in the selection of appropriate indicators. This technique was used by Altman, who was one of the first researchers to construct a discriminant model for company's financial condition evaluation. Another technique is guided by the literature. Currently, the authors are inspired by these indicators, which are often used to assess the insolvency of companies, something discussed in a number of publications. More information on the selection of features to build a synthetic index can be found in [5, 6].

The selection of features or choosing the indicators falls into an integrated assessment model can be based on different methods. In this paper it is proposed to use in this respect, quality measures of selection. These measures allow to evaluate the quality of selection, that is, in effect, to optimize the selection of a set of characteristics, which indirectly allows the selection of individual characteristics.

2 Quality Measures of Selection

We can evaluate feature quality selection by using selection measures which include evaluation, correctness and evaluating the level of adjustment carried out during the selection. This means that the quality measure selection directly do not select features. Using them is estimated already selected a set of features, which indirectly measure the quality of selection can be used to selections set of features. If the assessment of selected features will not be satisfactory, it is time once again select the features to build a synthetic indicator and to carry out their evaluation. However, given the very large number of possible combinations of features, evaluation of individual subsets is time-consuming [7]. In this paper we propose a method for selecting features for the construction of the synthetic index—integrated model of company's financial condition evaluation.

For example a company has specific characteristics (in the assessment of the financial condition it can be financial ratios) that describe the object. These characteristics are expressed by a sequence s of N variables $y_{1,}y_{2,\ldots,}y_N$. The larger the N, e.g. the number of features, more difficult to choose of financial indicators that can be used to build the synthetic indicator, which is more difficult to make a selection. You must use a suitably selected method which can measure quality characteristics. Based on measurements of the selected set of features of the object it can be classified to a specific class, for example in relation to evaluation the company's financial condition to two elements set of classes, which can be defined as: anticipating bankruptcy or continuation of activity. Classes can be described by $x_{1,}x_{2,\ldots,}x_L$, and their number can be determined by L [8, 9]. When you have a full probabilistic information $P(x_i)$—a priori probability of the classes and $f(y|x_i)$—conditional density probability distribution of the class, i = 1, 2, …, L), the classification to one of the designated classes refers to comparing the a posteriori conditional probabilities, $P(x_i|y)$, i = 1, 2, …, L.

In the literature you can find suggested various measures of quality of selection, a selection of these is presented in Table 1.

Most of the measures are specific to 2 class problems only while the measure C_k can be used when L ≥ 2 is present. Presenting a way of measures of the quality of the selection in the selection of indicators to build a synthetic index a measure C_k is used which distinguishes itself from other measures of specific properties.

Table 1 Quality measures of information selection

L.p.	Name of measure	Formula	
1.	Shannon	$H = \mathbf{E}\left\{-\sum_{l=1}^{L} P(x_i\|y)\log P(x_l\|y)\right\}$	(1)
2.	Vajda	$h = \mathbf{E}\left\{\sum_{l=1}^{L} P(x_i\|y)[1 - P(x_l\|y)]\right\}$	(2)
3.	Bayes	$B = \mathbf{E}\left\{\sum_{l=1}^{L} [P(x_i\|y)]^2\right\}$	(3)
4.	C_k	$C_k = E\left\{\frac{1}{L}\sum_{l=1}^{L} P^k(x_i\|y)\right\}^{1/k} \quad k = 2, 3\ldots$	(4)
5.	Bhattacharrya	$q = \mathbf{E}[P(x_1\|y)P(x_2\|y)]^{1/2}$	(5)
6.	Sammon	$S' = \mathbf{E}[\min_x\{P(x_1\|y), P(x_2\|y)\}]$	(6)
7.	Kołmogorov	$K = \mathbf{E}\|P(x_1\|y) - P(x_2\|y)\|$	(7)
8.	GM of Kolmogorov	$K_\alpha = \mathbf{E}\|P(x_1\|y) - P(x_2\|y)\|^\alpha 0 < \alpha < \infty$	(8)
9.	Ito (k = 0, 1, 2 …)	$Q_k = \frac{1}{2} - \frac{1}{2}\mathbf{E}\left\{[P(x_1\|y) - P(x_2\|y)]^{\frac{2(k+1)}{2k+1}}\right\}$	(9)
10.	Mahalanobis	$D = (\mu_1 - \mu_2)^T\left(\sum_1 + \sum_2\right)^{-1}(\mu_1 - \mu_2)$	(10)

Source [15]

2.1 Measure C_k

The measure C_k can be used when L ≥ 2, so this measure allows the assessment of the quality of the selected subset of features from the established accuracy and for any number of classes [10–12]. A measure is given by:

$$C_k(\underline{X}|\underline{Y}) = \sum_{Y} P(y)\left[\frac{1}{L}\sum_{i=1}^{L} P^k(x_i|y)\right]^{1/k} = \underset{Y}{E}\left[\frac{1}{L}\sum_{i=1}^{L} P^k(x_i|y)\right]^{1/k} \tag{11}$$

where

k	any number of natural, k ≥ 2,
L	number of classes, L ≥ 2,
$\underset{Y}{E}$	averaging operator on the set of all possible Y,
$P^k(x_i\|y)$	a posteriori conditional probability of the object belonging to one of the specified classes,
$\underline{X}$	random variable representing the class x_i,
$\underline{Y}$	random variable representing the object y.

3 The Synthetic Index—Discriminant Analysis Method

Discriminant models are most often used for construction of the synthetic index assessing the financial condition of the company which classify companies to two classes: bankrupt and not bankrupt or good and bad financial condition.

The literature suggests several methods of selection features (indicators) to build discriminant models. The authors are of the opinion that the use of quality measures of selection may allow for the creation of a new method of supporting the construction of successful discriminant models.

From the 60s of XX Century the researchers have built such models. Models of financial ratios presented in the literature are based on different and differing quantities of elements within these combinations [3, 4, 13, 14]. Table 2 shows the number of financial indicators used in the most popular models of discrimination (on the basis of the 47 examined models).

Analyzing the number of financial indicators used in the discriminating model (Table 2) can be seen that the number is from 3 to 12 indices. However, typically the number of indicators used in the construction of the model is from 4 to 6. The main question that should be asked at this point is how the authors of each model choose this number and the financial ratios. It is worth noting that some of the financial indicators are more often used in the models than others.

Table 2 Number of indicators in selected discriminant models

Name of the model	Number of ratios in the model
Beatge, Legault, Gebhardt, Prusak2, Prusak3	3
Koh and Killough, Springate, Taffler, Quick test, INE PAN7, Janek and Żuchowski, Gajdka and Stos2, Prusak1, Prusak4, Hamrol and Czajka & Piechocki, Gabrusiewicz, Hadasik1, Hadasik4, Wierzba	4
Bednarski, Altman, Weinrich, Ko, Robertson, INE PAN6, Gajdka and Stos1, Hołda, Appenzeller and Szarzec2	5
Beaver, Tamari, Edminster, Weibl, Mączyńska, Appenzeller and Szarzec1, Hadasik3	6
Altman and Haldeman & Narayanan; INE PAN5, Hadasik2, Hadasik5	7
Weinrich, INE PAN4	8
Fulmer, INE PAN3	9
Beerman	10
INE PAN2	11
INE PAN1	12

Source own work

4 The Use of Measure for Selection of Indicators—Study

The main purpose of the study is to select the best combination of 5 indicators from the 13 marked by Y1, Y2,…, Y13 financial indicators which are the best combination for building discriminant models. This selection is aimed at the choice of indicators that best describe the company's financial condition, classified as: poor financial condition (the expected bankruptcy), good financial condition.

The study used financial ratios of the largest companies listed on the Warsaw Stock Exchange, with the exception of companies in the financial sector, because they have a specific balance—so the number of examined companies is limited to 13 companies. For each company the value of individual indicators was calculated, and the research period covers three years (see Tables 4, 5 and 6).

In the study of the use measure C_k, the following assumptions are made:

- number of classes L = 2,
- a priori probability: $P(x_1) = 0.75, P(x_2) = 0.25$ calculated on the basis of a sample as the ratio of the number of companies with good financial condition to the total number of enterprises and accordingly, the ratio of the number of companies with poor financial condition to the total number of enterprises,
- parameter k = 2, a priori probability density functions are normal.

Conditional probability $P(x_i|y)$ can be calculated by Bayes formula [11, 16] for two classes:

$$P(x_i|y) = \frac{P(x_1) * f(y|x_1)}{P(x_1) * f(y|x_1) + P(x_2) * f(y|x_2)} \tag{12}$$

where

$P(x_1), P(x_2)$	a priori probability for class 1 and 2,
$f(y\|x_1)$	the conditional probability distribution density of the class 1,
$f(y\|x_2)$	the conditional probability distribution density of the class 2.

Assuming statistical independence of the characteristics of a normal distribution

$$f(y|x_1) = \prod_{i=1}^{5} \frac{1}{\sqrt{2\pi\sigma_{i1}^2}} \exp\left[\frac{-(y_i - \overline{y_{i1}})^2}{2\sigma_{i1}^2}\right] \tag{13}$$

σ_{i1}^2 standard deviation of the ith feature in the first class,
$\overline{x_{i1}}$ average of the ith feature in the first class.

$$f(y|x_2) = \prod_{i=1}^{5} \frac{1}{\sqrt{2\pi\sigma_{i2}^2}} \exp\left[\frac{-(y_i - \overline{y_{i2}})^2}{2\sigma_{i2}^2}\right] \tag{14}$$

σ_{i2}^2 standard deviation of the ith feature in the second class,
$\overline{x_{i2}}$ average of the ith feature in the second class.

Based on a sample descriptive statistics were calculated that will allow the calculation of the probability distribution density. Table 3 shows the designated interval (evaluation), the mean and the variance range for each features.

The assessment ratio was determined based on the average (13 indicators of 13 companies), whereas the mean and variance is based on the assessment interval.

Then the value of each indicator for the selected companies was calculated. The indicators calculated for the individual companies are shown in Tables 4, 5 and 6.

In Table 4, there are negative values of some indicators of companies: TPSA, CEZ, and GTC. Values below zero few indicators of CEZ, TPSA is due to a negative working capital. By contrast, negative index values GTC affect operating loss and net loss.

In Table 5, there are also the negative values of some indicators of companies: TPSA, CEZ, LOTOS, PGE, PKNORLEN and POLIMEXMS. At the value below zero few indicators TPSA, CEZ, PGE and POLIMEXMS influenced negative working capital. In contrast ratios non-positive LOTOS and PKNORLEN were caused by the negative value for both working capital and loss.

As mentioned earlier, for construction of the integrated model 5 characteristics of the company have been used most often. Therefore, it was decided to test the combination of 5-five features that will provide the best outcome C_k measure.

Table 3 Compilation of descriptive statistics for features and for first and second class

Class 1					Class 2				
Feature	Rating		Average	Deviation	Feature	Rating		Average	Deviation
y1	1.2	2	1.6	0.4	y1	1.19	0.49	0.84	0.35
y2	0.7	1.2	0.95	0.25	y2	0.69	0.3	0.495	0.195
y3	0.1	0.6	0.35	0.25	y3	0.61	1	0.805	0.195
y4	0.1	0.3	0.2	0.1	y4	0.09	0	0.045	0.045
y5	0.1	0.2	0.15	0.05	y5	0.21	0.5	0.355	0.145
y6	0.06	0.12	0.09	0.03	y6	0.059	−0.015	0.022	0.037
y7	0.4	0.7	0.55	0.15	y7	0.39	0.1	0.245	0.145
y8	0.1	0.2	0.15	0.05	y8	0.09	−0.2	−0.055	0.145
y9	0.045	0.1	0.0725	0.0275	y9	0.044	−0.015	0.0145	0.0295
y10	0.1	0.2	0.15	0.05	y10	0.21	0.6	0.405	0.195
y11	0.25	0.5	0.375	0.125	y11	0.24	0.1	0.17	0.07
y12	0.2	0.3	0.25	0.05	y12	0.19	−0.2	−0.005	0.195
y13	0.1	0.3	0.2	0.1	y13	0.09	0	0.045	0.045

Source own work

Table 4 Summary of indicators for the investigated companies in 2009

WIG 20[a]	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
y1	0.6	4.3	0.9	1.1	2.8	2.2	2.1	1.6	2.1	1.0	1.4	1.3	1.9
y2	0.3	0.5	0.3	1.6	0.1	0.8	1.0	0.6	0.4	0.8	1.4	1.9	0.4
y3	0.5	0.2	0.6	0.6	0.6	0.5	0.6	0.6	0.3	0.3	0.6	0.4	0.7
y4	0.2	0.4	0.2	0.6	−0.1	0.3	0.1	0.1	0.5	0.2	0.0	0.7	0.1
y5	0.0	0.0	0.0	0.1	1.6	0.2	0.2	0.1	0.1	0.1	0.2	0.1	0.0
y6	0.0	0.1	0.1	0.4	−0.1	0.2	0.0	0.1	0.1	0.0	0.0	0	0.1
y7	0.1	0.8	0.4	0.4	0.4	0.7	0.4	0.4	0.7	0.7	0.4	0.1	0.3
y8	−0.1	0.1	−0.0	0.0	0.1	0.2	0.2	0.3	0.1	0.0	0.1	0.3	0.1
y9	0.1	0.1	0.1	0.3	−0.1	0.2	0.1	0.1	0.1	0.0	0.0	0.1	0.1
y10	0.4	0.3	0.4	0.1	0.3	0.1	0.1	0.7	0.1	0.2	0.1	0.1	0.2
y11	0.3	0.7	0.3	0.4	0.4	0.6	0.4	0.4	0.4	0.5	0.4	0.2	0.1
y12	−0.1	0.1	−0.0	0.1	0.2	0.3	0.3	1.2	0.2	0.0	0.2	0.1	0.2
y13	0.3	0.2	0.3	0.3	0.2	0.6	0.3	0.1	0.2	0.0	0.6	0.2	0.2

Source own work

X1 TPSA, *X2* ASSECOPOL, *X3* CEZ, *X4* CYFRPLSAT, *X5* GTC, *X6* KGHM, *X7* LOTOS, *X8* PBG, *X9* PGE, *X10* PGNIG, *X11* PKNORLEN, *X12* POLIMEXMS, *X13* TVN

The number of possible combinations of features $\binom{13}{5}$ amounting to 1287 is quite significant. In order to test such a large combination a computer program has been used to find all the combinations and a choice of five characteristics for which measure C_k adopted greatest value.

Table 5 Summary of indicators for the investigated companies in 2008

WIG20	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
y1	0.3	1.3	0.8	1.4	2.6	2.7	2.3	1.5	0.9	1.5	0.8	0.9	2.6
y2	0.4	0.5	0.3	1.5	0.0	0.8	1.6	0.7	0.4	0.8	1.7	1.3	0.5
y3	0.5	0.3	0.6	0.6	0.6	0.3	0.5	0.6	0.4	0.3	0.6	0.7	0.6
y4	0.0	0.2	0.2	0.6	0.1	0.9	−0.1	0.1	0.3	0.1	−0.0	0.1	0.3
y5	0.0	0.0	0.0	0.1	3.3	0.1	0.2	0.0	0.1	0.1	0.1	0.1	0.0
y6	0.1	0.1	0.1	0.4	0.1	0.2	−0.1	0.1	0.1	0.0	−0.0	0.1	0.2
y7	0.5	0.7	0.4	0.4	0.5	0.7	0.5	0.3	0.6	0.7	0.4	0.3	0.4
y8	−0.2	0.1	−0.1	0.2	0.2	0.3	0.2	0.2	−0.2	0.1	−0.1	−0.1	0.2
y9	0.0	0.1	0.1	0.4	0.1	0.2	−0.1	0.1	0.6	0.0	−0.1	0.0	0.0
y10	0.1	0.3	0.3	0.1	0.7	0.1	0.1	0.7	0.1	0.2	0.1	0.3	0.2
y11	0.3	0.7	0.2	0.4	0.5	0.6	0.5	0.3	0.3	0.5	0.4	0.3	0.4
y12	−0.2	0.1	−0.1	0.7	0.2	0.4	0.4	0.7	−0.0	0.1	−0.1	−0.2	0.3
y13	0.3	0.1	0.4	0.4	0.3	0.6	0.4	0.1	0.1	0.0	0.3	0.0	0.2

Source own work

Table 6 Summary of indicators for the investigated companies in 2007

WIG20	X1	X2	X3	X5	X6	X7	X8	X9	X10	X11	X12	X13
y1	0.3	1.5	0.9	3.7	3.5	2.2	1.3	1.3	1.8	1.6	1.5	1.9
y2	0.4	0.4	0.5	0.0	1.0	1.6	0.6	0.5	0.6	1.4	1.3	0.6
y3	0.5	0.4	0.5	0.5	0.3	0.3	0.7	0.4	0.3	0.5	0.6	0.5
y4	0.3	0.1	1.6	0.3	1.2	0.4	0.1	0.5	0.3	0.2	0.1	0.2
y5	0.0	0.0	0.1	2.7	0.1	0.2	0.0	0.0	0.1	0.2	0.1	0.0
y6	0.1	0.1	0.1	0.2	0.3	0.1	0.1	0.1	0.0	0.1	0.1	0.2
y7	0.5	0.7	0.5	0.5	0.7	0.7	0.3	0.7	0.7	0.5	0.4	0.5
y8	−0.3	0.1	−0.0	0.3	0.4	0.3	0.2	0.0	0.1	0.2	0.2	0.1
y9	0.0	0.1	0.1	0.1	0.3	0.1	0.1	0.1	0.0	0.1	0.0	0.1
y10	0.1	0.4	0.1	0.4	0.1	0.1	0.8	0.1	0.2	0.1	0.4	0.2
y11	0.4	0.6	0.3	0.5	0.6	0.7	0.3	0.3	0.5	0.5	0.4	0.5
y12	−0.3	0.1	−0.0	0.4	0.7	0.7	0.6	0.0	0.1	0.3	0.6	0.1
y13	0.4	0.0	0.5	0.4	0.6	0.5	0.1	0.1	0.4	0.4	0.1	0.3

Source own work

Studies have shown that a very large number of combinations of indicators gives the highest value $P(x_1|y) = 1$, $C_k = 0.375$. Therefore, the results have been rounded to ten decimal places. Statement contained in Table 7 shows the number of possible combinations for the companies in the coming years, for which the value of measure C_k was the highest.

Table 7 shows that in most cases you can not select a single best combination of indicators to assess the company, except for TPSA, PBG, PGNiG and POLIMEXMS. Therefore, the next selection of search results is a compilation of the

Table 7 Summarizes the best combination of five indicators

Year	X1	X2	X3	X4	…	X8	X9	X10	X11	X12	X13
2009	22	1026	23	763		1	495	1	495	1	239
2008	1	231	270	735		1	104	1	124	1	347
2007	168	126	809	–		1	495	654	540	1	239

Source own work

Table 8 Sets of the optimal combination in a given year

Year	Number of combinations	The frequency of events
2009	2	9
2008	9	8
2007	3	10

Source own work

most common set combinations. The nominated sets aim to reduce the number of available combinations of features (see Table 8).

Analysis Table 8 shows that is possible to find two the best sets of combinations in 2009. However, in 2008 there are 9, and in 2007 there are 3. These sets significantly reduced the number of the best combinations for a given year. However, when we analyze all three years can be clear that only two combinations most frequently occur in this period (see Table 9).

In Table 9 it can be seen that there were selected two optimal combinations of indicators: Y1; Y3, Y7, Y11, Y13 and Y1, Y4, Y9, Y11, Y13. These combinations make up the majority of debt ratios, profitability and liquidity. The target is to select the best combination, which makes it necessary to carry out further studies.

The next step to obtain the optimal combination is to use reduction. Thanks to its use the number of possible combinations will be reduced. For the reduction will be applied mathematical operations: each result will be raised to the tenth power. Tables 10 and 11 summarizes the best combination after the reductions.

Table 9 Summary of a set of the most common sub-optimal combination of financial ratios selected through the application of measures of quality of selection C_k for the period of three years (2007–2009)

The best combinations	Sum
Y1—current assets/current liabilities Y3—total liabilities/total assets Y7—equity/total assets Y11—(equity − share capital)/total assets Y13—retained earnings/total assets	26
Y1—current assets/current liabilities Y4—(net profit + depreciation)/total liabilities Y9—net profit/total assets Y11—(equity − share capital)/total assets Y13—retained earnings/total assets	26

Source own work

Table 10 Set of the best combinations of indicators—after the reduction

Year	X1	X2	X3	X4	…	X8	X9	X10	X11	X12	X13
2009	1	793	4	621		1	495	1	495	1	27
2008	1	23	130	638		1	65	1	47	1	62
2007	94	4	736	–		1	495	392	495	1	28

Source own work

Table 11 The set of the most frequently occurring combinations of the year—after reduction

Year	Number of combinations	Frequency of occurring
2009	2	7
2008	21	5
2007	17	9

Source own work

Table 12 The set of the mostly occurring combinations of the all 3 years

The best combination	Sum
Y1—current assets/current liabilities Y2—revenues from sales/total assets Y4—net profit + depreciation/total liabilities Y11—(equity − share capital)/total assets Y13—retained earnings/total assets	21

Source own work

Analysis of all three years showed that can distinguish only one best combination of indices (see Table 12).

Optimal combination from the point of view of quality selection measure create both liquidity ratios, turnover, debt and profitability.

5 Summary

The analyze of 47 discriminant models allowed to demonstrate that the most common to the construction of the synthetic index is used an average of 5 characteristics (features, ratios) to evaluate of company's financial condition. In the article the 13 features that were chosen are the most commonly used in discriminant models tested (a minimum of 5 times). These features are: debt ratios (4 indicators), liquidity ratios, profitability and turnover ratio (3 ratios). Of these 13 features one should choose the combination of the five characteristics by which the highest level of measurement is obtained. There were selected five features guided by the frequency of the number of indicators used to build discriminant models. There was checked every possible combination of the features for choice 5 from 13 features, it means 1287 combinations.

Efforts were made to find as small as possible combination of the best features, which caused that had to be done further research. In further studies we used reduction. The aim of the reduction was to reduce a number of features through mathematical operation: each outcome measure was elevated to the tenth power. Also in this case the number of the best combination was too large for the presentation of results, although in some cases the number of best combinations was reduced. Like the previously there were used sets of best combinations. Only by analysis of three years there was selected one best combination of: y1, y2, y4, y11, y13 (total occurrences in the set is 21).

The use of the quality selection measure did not immediately clear results, which was why different kinds of reductions were use, in order to determine the best combination. Determining 5 from 13 features can be debatable. Analysis of literature showed that for the construction the most common models four, five and six indicators were used. This situation proves that the combination of four or six indicators could prove to be a better combination.

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