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The Relationship between the Transparency in Provision of Financial Data and the Change in Investors' Expectations

Leonidas Sakalauskas[1], Zivile Kalsyte[2], Ingrida Vaiciulyte[1], Irmantas Kupciunas[2]

[1]*Vilnius University*
Akademijos str. 4, LT-08663, Vilnius, Lithuania
E-mail. sakal@ktl.mii.lt, ingrida_vaiciulyte@yahoo.com

[2]*Kaunas University of Technology*
Studentu str. 50, LT-51367, Kaunas, Lithuania
E-mail. kalsyte@yahoo.com, irmkupc@ktu.lt

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The purpose of the work is to establish a relationship between the enterprise's practice of providing financial data and the investors' opinion about the enterprise as well as to predict whether the enterprise will be inclined to cheat while providing its financial data in the future. To reflect the investors' opinion about an enterprise, the parameters of skew t-distribution and stable distribution calculated from stock data (close and volume) have been used. The obtained preference area, the parameters (calculated from close and volume stock price data) of the distributions and the indicators representing the present have been employed as Random Forest inputs in predicting the direction of the change in future Accounting & Governance Risk (AGR) rating, which defines the change in the risk of provision of financial data, i.e., whether the risk will increase or decrease. As it has been revealed by the selection of features, stable distribution parameters better reflect the amplitude of the change in stock prices, while the investors' preference area, drawn on the basis of skew t-distribution parameters, has reflected the discrepancy between the investors' expectations and the enterprise's actual value. The same most important selected features have been found to be equally well applicable in describing enterprises characterised by the tendency for AGR rating to rise as well as those characterised by the tendency for AGR rating to drop, or describing both those groups of enterprises collectively.

Keywords: *Random Forests, stable distribution, skew t-distribution, prediction, AGR rating, data analysis, Mathematical models.*

Introduction

When deciding whether to buy or sell the stock of a concrete enterprise, investors quite often base their decision on the financial statements of that enterprise. They hope that the financial accountability will fully reflect the results of the activity of the enterprise. However, not all enterprises are inclined to provide the data about their activity in a transparent manner. Cases of fraud are quite frequent. Therefore, investors often have difficulties in forming a correct picture of the activity of a certain enterprise. There are cases where investors overrate or underrate the stock of an enterprise only as a result of the fact that innaccurate data about the activity of the certain enterprise was provided for them. Therefore, it is very important to assess the AGR rating for an enterprise, which reflects the transparency of the presentation of financial data. If an enterprise is not inclined to cheat in presenting its financial data, one can make the assumption that it will be easier for investors to form an accurate opinion about the activity of that enterprise: there will be a lower probability that the stock will be overrated or underrated. Thus, it is possible to make the assumption that the stability of the opinion formed by investors about an enterprise is reflected in the change of stock prices and that it depends on whether an enterprise presents its financial data transparently. In order to reflect the transparency of financial data, AGR (accounting and governace risk) rating has been chosen.

The proprietary Accounting & Governance Risk (AGR) rating is a measure of corporate integrity based on forensic accounting and corporate governance metrics as well as an indicator of aggressive corporate behavior, which can put stakeholders at risk. The AGR score is based on a quantitative model that weights specific accounting and governance metrics derived from corporate reporting. The score ranges from 0 to 100, with lower scores indicating higher risk (EON, 2010; Price *et al.*, 2011; Spellman & Watson, 2009).

The investors' opinion about the change in the enterprise's results is described by the parameters of two distributions (stable and skew t-distributions) that are calculated on the basis of stock price data (Close and Volume). These distributions have been chosen because of the fact that stock price distributions are characterised by asymmetry and a heavy tail (Nolan, 2007). The parameters of skew t-distribution have been used for drawing an area of investors' preference.

Mean of distributions points to the prevailing investor expectations from the point of view of the enterprise, i.e. whether the majority of investors assess the activity of the enterprise and its prospects positively or negatively. Tails of distributions indicate the instability of the investors' opinions about the enterprise's results and its prospects. This may be related to an incorrect provision of the enterprise's results, which is reflected by the AGR rating.

Thus, the history of AGR rating reflects the practice of presenting enterprise's financial data (financial statements). If in the past an enterprise was presenting its data incorrectly, then one may expect that it will continue doing so in the future. The parameters of distributions calculated from stock data reflect the change in investors' opinions. The purpose of the work is to establish a relationship between an enterprise's practice of providing financial data and the investors' opinion about the enterprise. When an enterprise provides its financial data in a non-transparent manner, investors are deprived of a possibility of building up an accurate picture about the enterprise's financial situation and its prospects. Meanwhile, where expectations do not match reality, trust in the particular enterprise is lost. The loss of trust can initiate the drop in enterprise's stock price (Ramnath *et al.*, 2008).

By means of the selection of the most important features, it has been sought to discover which parameters of the distributions have the greatest impact on the prediction of the direction of the future change in AGR. An attempt has also been made to make it clear as to the use of which parameters of the distributions permits the best representation of the expectations held by investors in respect of a certain enterprise: i.e. whether the enterprise is overrated or underrated. As a result, the foregoing has contributed to a greater accuracy of the model and a better depiction of the nature of the process at issue.

Random Forests

Random Forests consist of an ensemble of separate decision trees. Each decision tree is trained by separating at random from the training sample a certain part (two thirds) of the data, while the rest of the data (Out of Bag (OOB) data) is used for testing. An error of the tested part of the data decreases while increasing the number of decision trees (Archer & Kimes, 2008; Breiman, 2001; Chan & Paelinckx, 2008; Genuer *et al.*, 2010; Hapfelmeier & Ulm, 2013; Liu *et al.*, 2013).

The Random Forests model accommodates information as the practice of financial data presentation; financial results are reflected in the investors' expectations in the background of the financial crisis.

The importance of the features (input data, which is discussed in greater detail in the section "Methodology") is measured by using the OOB data. The selected features depend on the amount of the data falling into OOB. Therefore, while selecting the most important features, 7 different amounts of the data falling into OOB were taken. If the number of features is marked as N, then the number of the features falling into OOB was selected as follows: $\sqrt{N}-2$, $\sqrt{N}-1$, $\sqrt{N}$, $\sqrt{N}+1$, $\sqrt{N}+2$.

The mean of importance of the features was calculated for the OOB data. By employing the backward elimination of features, each 5 % of the least important features were removed until there would remain only 1 feature. It was sought to find out under which set of features the Out of Bag error was lowest. Such features were considered to be the most important ones (Guyon, 2008; Kalsyte *et al.*, 2013).

Stable Distribution

The authors start from the Close and Volume empirical data analysis, by estimating the mean, variance, skewness and asymmetry (Spall, 2003; Avramov *et al.*, 2009). Then, they fit data series to the normal and α-stable distributions (Nikias & Shao, 1995).

Following the well-known definition (Breiman, 2001), a random vector X has stable distribution and denotes $X \overset{d}{=} S_\alpha(\sigma,\beta,\mu)$, here S_α is the probability density function, if X has a characteristic function (2) of the form:

$$\phi(t)=\begin{cases}\exp\left\{-\sigma^\alpha\cdot|t|^\alpha\cdot\left(1-i\beta\,\mathrm{sgn}(t)\tan(\frac{\pi\alpha}{2})\right)+i\mu t\right\}, & \text{if } \alpha\neq 1\\ \exp\left\{-\sigma\cdot|t|\cdot\left(1+i\beta\,\mathrm{sgn}(t)\frac{2}{\pi}\cdot\log|t|\right)+i\mu t\right\}, & \text{if } \alpha=1\end{cases} \quad (1)$$

Each stable distribution is described by 4 parameters: the first one and most important is the stability index $\alpha\in(0;2]$, which is essential when characterizing financial data. The others, respectively are: skewness $\beta\in[-1,1]$, a position $\mu\in\mathbf{R}$, the parameter of scale $\sigma>0$.

The probability density function of α-stable distribution is:

$$p(x)=\frac{1}{2\pi}\int_{-\infty}^{+\infty}\phi(t)\cdot\exp(-ixt)dt \quad (2)$$

In the general case, this function (2) cannot be expressed in closed form. The infinite polynomial expressions of the density function are well known, but it is not very useful for Maximal Likelihood Estimation (MLE) because of the error estimation in the tails, the difficulties with truncating the infinite series, and so on (Owen, 2002). The authors use an integral expression of the PDF in standard parameterization and Zolotarev-type formula (Kabasinskas *et al.*, 2012). The p^{th} moment of any random variable X exists $E|X|^p=\int_0^\infty P(|X|^p>y)dy$ and is finite only if $0<p<\alpha$. Otherwise, it does not exist. So, if α parameter of some series is less than 2 it is understood that the variance does not exist, and if it is less than 1, the mean cannot be used as a positional characteristic of such variable.

Skew t-Distribution

In general, skew t-distribution is represented by a multivariate skew-normal distribution with the covariance matrix, depending on the parameter distributed according to the inverse-gamma distribution. According to this representation, the density of skew t-distribution as well as the likelihood function is expressed through multivariate integrals that are convenient to be estimated by the maximum likelihood method (Cabral *et al.*, 2008).

There are examples where skew t-distribution is applied in biological research, localization of infectious agents or the prediction of the actual statistical properties of financial markets in statistical literature and so on (Azzalini & Capitanio, 2003; Azzalini & Genton, 2008; Cabral *et al.,* 2008; Kim & Mallick, 2003; Panagiotelis & Smith, 2008).

It will be demonstrated that skew t-distribution reflects the difference between the investors' expectations and results, since in this distribution data is described by the Gaussian distribution with a random vector of mean and random variance. The skew t-variable is denoted by $ST(\mu,\Sigma,\Theta,b,\eta)$. A multivariate skew t-distribution defines a random vector X that is distributed as a multivariate Gaussian vector:

$$f(x,a,t,\Sigma)=(t/\pi)^{\frac{d}{2}}\cdot|\Sigma|^{-\frac{1}{2}}\cdot e^{-t\cdot(x-a)^{T}\cdot\Sigma^{-1}\cdot(x-a)},\Sigma\geq 0, \quad (3)$$

where the mean vector a, in its turn, is distributed as a multivariate Gaussian $N(\mu,\Theta/2t),\Theta\geq 0$ in the cone $\eta\cdot(a-\mu)\geq 0,\eta\subset R^{d}$, where d is the dimension, and the random variable t follows from the Gamma distribution:

$$f_1(t,b)=\frac{t^{\frac{b}{2}-1}}{\Gamma(b/2)}\cdot e^{-t}. \quad (4)$$

By definition, d-dimensional skew t-distributed variable X has the density as follows:

$$p(x,\mu,\Theta,\Sigma,b,\eta)=2\cdot\int_{0}^{\infty}\int_{\eta\cdot(a-\mu)\geq 0} f(x,a,t,\Sigma)\cdot f(a,\mu,t,\Theta)\cdot f_1(t,b)dadt=$$
$$=\int_{0}^{\infty}\int_{\eta\cdot(a-\mu)\geq 0}\frac{2}{\pi^{d}\cdot|\Sigma|^{\frac{1}{2}}\cdot|\Theta|^{\frac{1}{2}}\cdot\Gamma\left(\frac{b}{2}\right)}\cdot t^{\frac{b}{2}+d-1}\times$$
$$\times e^{-t\cdot\left((x-a)^{T}\cdot\Sigma^{-1}\cdot(x-a)+(a-\mu)^{T}\cdot\Theta^{-1}\cdot(a-\mu)+1\right)}dadt, \quad (5)$$

where $\Sigma\geq 0,\Theta\geq 0$ are the full rank $d\times d$ matrices. The equation of integration area $\eta\cdot(a-\mu)\geq 0,\eta\subset R^{d}$ defines an area of investors' expectations, which may be represented graphically (Fig. 2).

The estimation of parameters μ,Σ,Θ,b,η will be examined by following the maximum likelihood approach (Vaiciulyte and Sakalauskas, 2011). The log-likelihood function can be expressed as

$$L(\mu,\Sigma,\Theta,b,\eta)=-\sum_{i=1}^{K}\ln(p(X^{i},\mu,\Sigma,\Theta,b,\eta))\rightarrow\min_{\mu,\Sigma,\Theta,b,\eta} \quad (6)$$

The optimality conditions in this problem are derived by taking and setting the first derivatives with respect to parameters to be estimated as equal to zero (Sakalauskas & Vaiciulyte, 2012).

But, first, the transformation of the data is carried out: the mean of the sample is subtracted from the data and divided by variance. The present case requires centering and scaling in order to ease the running of the minimization program (otherwise the program would have to optimize according to the parameters of a very different scale). After having cantered and scaled the data and having solved the minimization task, the initial scales are resumed, i.e., the data is decentered and descaled backwards.

The Data

The financial data of the enterprises under examination comprises the period from 2007 to 2009. That is the period of the economic recession, starting by the end of 2007. The year of 2008 was characterised by particularly pronounced problems of liquidity, while towards the end of 2009 the economic hardship assumed a different character. As the enterprise's financial situation changes on the year basis, the data of a different year for the same enterprise has been considered as the data of a new enterprise. This permitted to increase the amount of data by a factor of three.

The enterprises whose stock data have been used for the experiments belong to the following sectors: Diagnostic Substances; Drug Manufactures, Major; Drug Manufactures, Other; Health Care Plans; Hospitals; Medical Instruments and Supplies; Medical Laboratories and Research; Medical Appliances and Equipment; Specialized Health Services; Biotechnology in the US healthcare industry.

Methodology

1) Stable distribution is defined by the following parameters: alpha (characteristic exponent), beta (skewness), gamma (scale) and delta (location). Stable distribution parameters are calculated from stock price data – Close (4 parameters) and Volume (4 parameters): $x_j^{stbl}, j=1,...8$, j here and below is an index for features (Belovas *et al.,* 2006);

2) skew t-distribution is defined by the following parameters:

μ – mean vector,

Σ,Θ – covariance matrices,

b – the extinction degree,

η – scalar, enabling to establish the area of preferences (priorities).

Skew t-distribution parameters are calculated from stock price data – Close (5 parameters) and Volume (5 parameters): $x_j^{skw}, j=1,...10$. The means of the said both samples, standard deviations and integration area are also calculated;

3) additional parameters describing the present-day situation: AGR rating and stock-defining parameters – Close and Volume: $x_j^{o}, j=1,...3$;

4) Random Forests classification model is created, which permits to predict the direction of the future change in AGR y_j^{AGR} (AGR rating will rise, drop or remain unchanged). The model employs the following input parameters: $x_j^{M_3}=\{x_j^{sbl},x_j^{skw},x_j^{o}\}$.

Experiments

It is aimed at finding out as to which features had the greatest impact on predicting the future AGR class (AGR will rise or drop). The features with a negative impact are removed. The analysis of errors is given in Table 1.

The marked squares in the table show the numbers of correct predictions. The line Output_1 gives the number of Class_1 predictions (that AGR rating shows the tendency to drop in the future). As it is indicated in the first column of the table, the number of correct Class_1 predictions was 113, while the number of inaccurate ones was 30.

Table 1

Confusion matrix

Performance metric Acc (both classes): 83,204 % (322/387)			
	Target_1	Target_2	Acc (%)
Output_1	113	30	76,351
Output_2	35	209	87,448

The line Output _2 indicates the number of Class_2 predictions (that AGR rating shows the tendency to rise in the future). As it is indicated in the table, in this case there were 209 correct predictions and 35 inaccurate ones. The column Acc shows that the overall accuracy of both classes of the model reaches 83,20 percent. Class_1 accuracy was estimated to be 76,35 percent, while Class_2 accuracy was 87,44 percent.

The features that are most important in predicting the direction of the change in AGR can be specified as follows (Fig. 1): Class_1 are the most important features for enterprises characterised by the tendency for the future AGR to rise, Class_2 – the most important features for enterprises characterised by the tendency for the future AGR to fall, while Class_3 includes features that are most important for the both types of the said enterprises.

The following denotations are used:

AGR (current), Close (current), Volume (current) – parameters representing the current situation: AGR rating, Close and Volume data, respectively;

Alpha1, Beta1, Gamma1, Delta1 – stable distribution parameters calculated from Close data;

Alpha2, Beta2, Gamma2, Delta2 – stable distribution parameters calculated from Volume data;

Miu1 – the mean of skew t-distribution Close data;

Miu2 – the mean of skew t-distribution Volume data;

$$\mu = \begin{pmatrix} Miu1 \\ Miu2 \end{pmatrix} = \begin{pmatrix} \text{Close\_mean} \\ \text{Volume\_mean} \end{pmatrix}$$

Sigma1 – Σ parameter of Close data;

Sigma2 – skew t-distribution covariance of Σ matrix of Close and Volume data;

Sigma3 – Σ parameter of Volume data;

$$\Sigma = \begin{pmatrix} Sigma\,1 \\ Sigma\,2 \\ Sigma\,3 \end{pmatrix} = \begin{pmatrix} \text{cov}_{\Sigma}(\text{Close, Close}) \\ \text{cov}_{\Sigma}(\text{Close, Volume}) \\ \text{cov}_{\Sigma}(\text{Volume, Volume}) \end{pmatrix}$$

Teta1 – theta parameter of Close data;

Teta2 – skew t-distribution covariance of Θ matrix of Close and Volume data;

Teta3 – theta parameter of Volume data;

$$\Theta = \begin{pmatrix} Teta\,1 \\ Teta\,2 \\ Teta\,3 \end{pmatrix} = \begin{pmatrix} \text{cov}_{\Theta}(\text{Close, Close}) \\ \text{cov}_{\Theta}(\text{Close, Volume}) \\ \text{cov}_{\Theta}(\text{Volume, Volume}) \end{pmatrix}$$

b – skew t-distribution extinction degree;

Eta – skew t-distribution scalar, which permits to establish the preference area, or, in other words, the angle between axis Ox and tangent of the line $\eta \cdot (a - \mu)$;

Close (mean) – mean of the Close data sample;

Volume (mean) – mean of the Volume data sample;

Close_std – square deviation of Close data;

Volume_std – square deviation of Volume data;

Region – the integration area parameter, representing the customers' preference area, which is calculated as follows:

$$\text{Region} = Miu\,2 - Volume(mean) + Eta \cdot \frac{Miu\,1 - Close(mean)}{Close\_std}.$$

As it is indicated by Figure. 1, the same features are equally well applicable in describing enterprises characterised by the tendency for AGR rating to rise as well as those characterised by the tendency for AGR rating to drop.

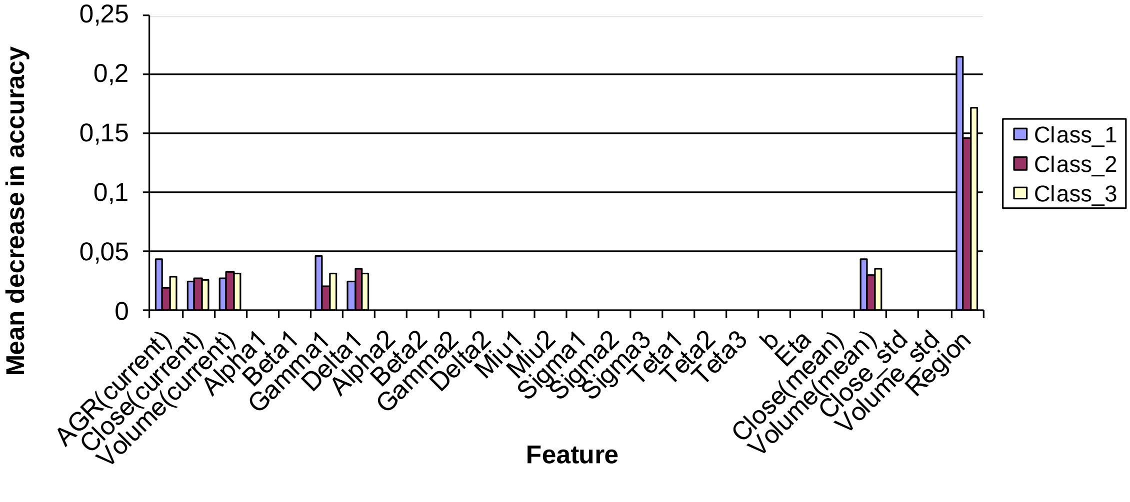

Figure 1. The results of investigation for the definition of most important features

The parameters of skew t-distribution were calculated for two groups of data vectors:

1) Close and AGR;
2) Volume and AGR.

On the basis of the said parameters, the preference area, defining investors' expectations, was drawn. The preference area is defined by a semi plane, comprising a line and an area with arrows drawn at it. As it is indicated by Figure 2, the determining of the preference area in the first case was influenced by Close and AGR, while in the second case – only by Volume (AGR had no impact).

Hence, investors' expectations, which are reflected in stock price (Close), depend on transparency of provision of financial data, which in turn is reflected by AGR rating. The preference area is drawn separately for both cases. It was examined how the preference area had been changing in 2007, 2008 and 2009. Diagrams (Figure 2) show that with the course of time investors' expectations (preference areas) were subject to marginal change. Consequently, one may draw a conclusion that in the given cases the economic crisis had no impact on investors' expectations.

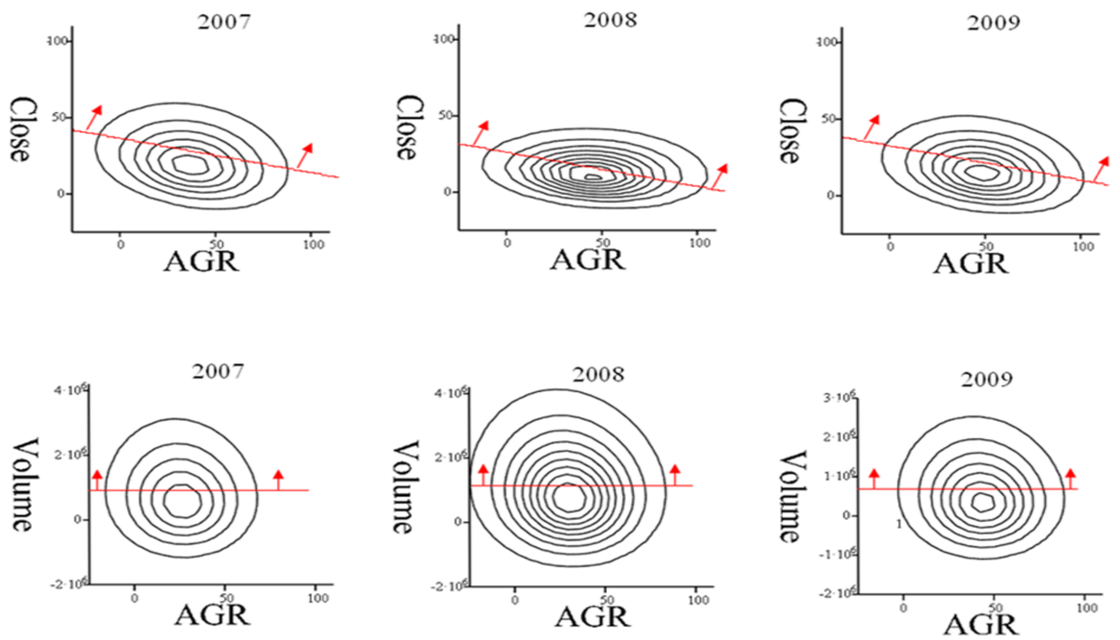

Figure 2. Customers' preference area

Conclusions

When an enterprise is confronted with difficulties and incurs losses as a result of wrong decision-making, more often than not attempts are made to conceal these facts from the investors. In this way, it is sought to avoid drops in stock prices. Thus, investors are deceived and prevented from building an accurate picture of the enterprise's activity. In particular, a large number of such cases may be expected during a financial crisis. Therefore, the research focused on the period of 2007–2009.

In this paper, a relationship between the enterprise's financial data and the investors' opinion about the enterprise preventing stock price is established using mathematical models. The possibilities of using of predictive methods for application modelling construction is estimated, and reflecting the results of the activity of the enterprise financial accountability regarding information asymmetry concept. Skew t-distribution is used to examine the change of investors' preference area in 2007, 2008 and 2009. It was sought to predict the direction of the change in the Accounting and Governance Risk (AGR) rating (AGR will rise, or drop).

Using parameters of distributions and indicators representing the present employed as Random Forest inputs in predicting the direction of the change in future AGR is relevant regarding possibility to find the optimal solution for multi-objective decisions.

1. Using the skew t-distribution confirms the claim that AGR is related to stock price and volume fluctuations.
2. Experiments showed that with the course of time investors' preference areas were subject to marginal change. Consequently, one may draw a conclusion that in the given cases the economic crisis had no impact on investors' expectations.
3. Investors' expectations, which are reflected in stock price (Close), depended on transparency of provision of financial data, which in turn is reflected by AGR rating.
4. During the selection of the most important features, it has emerged that the parameters representing the current situation (AGR rating, Close and Volume data) are of great significance. Consequently, if an enterprise is currently inclined to provide its financial data in a non-transparent manner, it is quite probable that it will continue doing so in the future as well.

5. In the model the parameter reflecting the investors' preference area has been found to have the greatest impact.
6. The same features are applicable for describing enterprises characterised by the tendency for AGR to rise as well as those characterised by the tendency for AGR to fall.

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