SELECTED BUSINESS INTELLIGENCE METHODS FOR DECISION-MAKING SUPPORT IN A FINANCE INSTITUTION

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Abstract: *This article deals with decision-making support methods' implementation in a medium size financial company with international operations. The objective of this article is to show the abilities of these methods to precise decision-making of management. At the beginning of this article there is briefly described the existing situation in this business sector in Central Europe. After that part Business Intelligence methods are described as well as the reasons while these methods have been introduced in small and medium enterprises. These methods are dependent on data, on acquisition of data and on validation of this data. Pre-processed data can be used for standard reporting. Utilization of this type of reporting is described on two examples in this article. These examples show dependences between exchange rate volatility and a specific period of the year. Then follows a demonstration of client classification - firstly on historical data from years 2010 to 2013 utilizing a cluster analysis. New clients have then been provisionally allocated to already designed groups thanks to the above-mentioned description of clusters. When the external environment changed, due to primarily the Czech National Bank interventions, it has been essential to design better classification methods for new clients. These methods are described in this article and results of these classification methods are compared.*

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JEL Classification: *C15, D89, O16.*

Introduction

Utilization of decision-making support methods has been, for a long period of time, the domain of primarily large companies. Currently these methods are becoming to be a regular tool for management by means of interlinking individual information systems and thanks to a larger offer of robust solutions targeted also at small and medium enterprises. During and after the economic crises of years 2008 - 2011 it was essential to more strictly control costs and to concentrate more on higher value added activities because of reduced margins arising due to lower demand. This pressure was visible across the entire economy while some companies were hit harder and some companies were hit less. In the framework of the banking sector some banks had to ask state bodies for support while some other banks went bankrupt. In the Czech Republic (CR) this crisis demonstrated itself by increased competition in acquisition of new clients, both from the business and the private sectors (e.g. saving cooperatives or banking subjects).

Finance sector has been at the same time influenced by financial regulation. Since January 1, 2011 in the European Union, new institutional order for regulation and supervision has been introduced under the name European System of Financial Supervision.

This system includes European Systemic Risk Board, three sector regulation European Supervisory Authorities and supervisory bodies in the individual European Union states. The individual organizations organize stress tests for subjects under their supervision. Regulatory elements are linked to these stress tests – primarily requirements for capital adequacy, risk diversification including diversification of bonds portfolio and so on. Another regulatory element is the introduction of a sector tax imposed on financial institutions. From among the Central European countries this applies primarily to Hungary where reduction of this tax has been recently announced. On the other hand this tax has been newly introduced in Poland (Balthazar, 2006), (Deloitte, 2015), (Slovik, Cournède, 2011).

The decision-making manner in any private company differs not only on the basis of the company size, or based on e.g. the size of its decision-making and support bodies, but also based on the company‘s sector orientation and on the branch in which it operates. A production company observes primarily input prices, supplies in stock and fulfilment of forecasted sales margins. Trading companies strive to understand trends and customers' needs, to set prices in relation to competition and to run marketing campaigns (Sekerka, 2002). For support to decision-making it is possible to use methods that are stated for instance in Business Intelligence (BI) (Grochowski, 1981) pyramid where on the base level is regular reporting (charts and graphs), then follows selective reporting, Dashboards and Ad Hoc analyses; then follow advanced analyses (classification and prediction) and on the top there is modelling (What-If scenarios and sensitivity analysis).

The objective of this article is to show the abilities and possibilities of a standard daily reporting and of BI. Standard reporting, on a daily basis, provides a basic overview of performance of an electronic money institution (EMI). Advanced BI analyses allow for categorization of existing clients and of new clients in the EMI.

1 Problem formulation

Fundamental attributes that have been utilized for observing EMIs are: volume of exchanged money a_1 and profits from this exchange a_2 (hereinafter the Volume and the Profit). Further the attributes Number of transactions a_3 and the Average profit per transaction a_4 have been employed. All of this is primarily observed from the position of clients and time- an individual client, a region, a state, a day, a week, a month, a quarter of a year and a year. The data have been calculated since January 1, 2010. The EMI analysis model is stated in Fig. 1.

Fundamental statistical parameters have been worked out for the given attributes. Large range is primarily with the Volume and the Profit. The values of the attributes have Poisson Distribution of probability. Then correlation coefficients have been calculated. These are illustrated in Tab. 1. From the correlation coefficients it issues that the Volume, the Profit and the Number of transactions are heavily dependent quantities. To replace these parameters by a single attribute is possible when observing one single client where the Volume and the Profit are linked by the set client's margin and thus the correlation coefficient approaches the value 1. With larger groups of clients' observation it is not possible to replace the parameters by a single parameter without loss of significant data (Šoltés, 2008).

In Tab. 2 there are stated values that illustrate uneven distribution of revenues. If we arrange clients, in descending order, based on the parameters Volume and Profit from the largest clients to the smallest clients then the first three columns show a relative number of clients who generate the given percentage of turnover, of profits respectively. Next columns then show how big part of the volume, the profit respectively, is realized by individual by frequency arranged groups of clients.

Fig. 1: Model of EMI analysis

Problem formulation, data collection and analysis
- Real data (2010, 2011, … , 2015)
- Set of attributes
  - Basic attributes
    - $\{ a_1, a_2, a_3$ and $a_4 \}$
- Data analysis
  - Elementary statistic parameters
  - Correlation analysis
  - Frequency analysis etc.

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Selected methods of BI
- Reporting
  - Average volumes per day
- Classification long time series
  - Data matrix for attributes $\{ a_1, a_2, a_3$ and $a_4 \}$
  - Clustering method/s
  - Cluster description for import and export groups
    - $\{ c_1, c_2, \ldots, c_{10} \}$
- Classification short time series
  - Data matrix for new 21 attributes
  - Methods (decision trees, artificial neural networks, logistic regression)

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Evaluation and analysis of "type of clients"

Source: Authors

A cluster analysis has been used for analysis of clients (profitable and non-profitable). The input data were the values of attributes a_1, a_2, a_3 and a_4 for years from 2010 to 2013. "New" clients' analysis done on the basis of defined clusters according to annual data is not sufficiently dynamic and does not take into consideration any shorter-term periods.

Tab. 1: Correlation coefficients for basic attributes

Attribute	**Attribute**		
	Volume total	Profits total	Number of transactions
Volume total	1		
Profits total	0.8267	1	
Number of transactions	0.7043	0.7387	1
Average profit per transaction	0.1877	0.2162	-0.0269

Source: Authors

Tab. 2: Frequency sorted groups of clients (in percent)

Volume of turnover or profits in %	Number of clients in % for		Volume of clients in %	Sum of percentage		Percentages per group	
	turnover	profits		turnover	profits	turnover	profits
10	0.18	0.39	10	63.98	59.45	63.98	59.45
20	0.72	1.19	20	79.83	77.08	15.86	17.63
30	1.66	2.42	30	88.17	86.53	8.34	9.46
40	3.13	4.22	40	93.07	92.11	4.90	5.58
50	5.29	6.78	50	96.04	95.53	2.97	3.41
60	8.04	10.23	60	97.86	97.59	1.82	2.06
70	12.98	15.12	70	98.97	98.82	1.11	1.23
80	20.15	22.55	80	99.61	99.54	0.63	0.72
90	33.17	35.61	90	99.91	99.90	0.31	0.35
100	100	100	100	100	100	0.09	0.10

Source: Authors

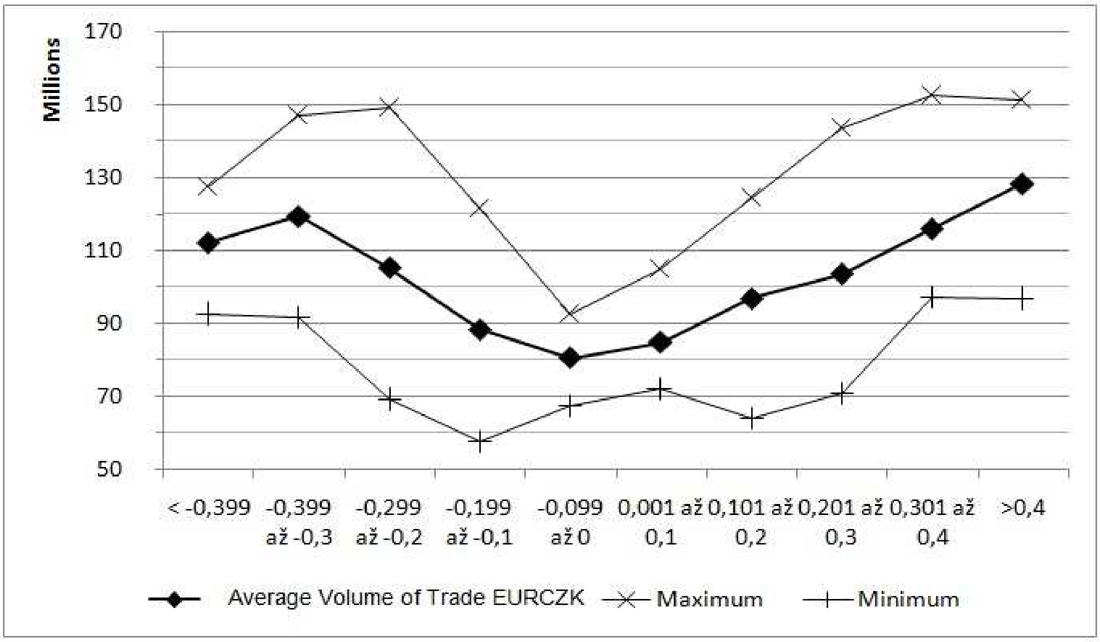
- Aggregated output attribute „a creditworthy client“ is defined based on 6 indicators: Volume for the first 6 and 12 months from signature of the Framework Agreement (FA); profit for the first 6 and 12 months from FA signature; number of transactions for the first 6 and 12 months from FA signature
- Input classification attributes (21 attributes) that are defined in the following way: Volume indicators (7 attributes) – the total volume for the first 3 months after FA signature, the volume of the first to the sixth transaction of the client, profit indicators (7 attributes) – the total profit for the first three month after the FA signature, the time period between the FA signature and the first trade stated in days, the time period between six consequent transactions stated in days. All input attributes have the character of the Poisson distribution of probability.

2 Reporting methods

Regular reporting is the basis for decision-making. Basic reporting cannot only summarize fundamental indicators of an entity, but it can also be helpful in the evaluation of these indicators. Its introduction is very cheap. In majority of cases MS Excel program is successfully used, or free open source is used – office packet software LibreOffice is available free of charge. In case more employees are supposed to work with the information in the reporting then it is useful to create a unified Dashboard that shows all key indicators at one place. Basic forms are on the Internet. From these examples it is possible to create, by means of a simple adjustment, unique decision-making reports (Excel Dashboards, 2016a), (Excel Dashboards, 2016b). The daily profit report is such an example. It is one of the key indicators for any company and it is a part of other further activities such as is for instance planning of costs. Top management, or possibly managers directly responsible for sales, are evaluated based on this indicator. This indicator influences also a number of other factors. In a payment institution one of such factors is exchange rate fluctuation. After very good results achieved for a couple of days consequent to the Czech National

Bank (CNB) interventions (the CNB introduced them in November 2013) drop of profits came about on a currency pair EUR-CZK. For this reason the Ad Hoc analysis has been executed, the results of this analysis are demonstrated in Fig. 2. The Left side shows the volume of exchanged finance of clients in one day and the bottom line shows the Exchange rate fluctuation on the specific day on the currency pair Euro-Czech Crown in crowns (Czech National Bank, 2013).

Fig. 2: Average volume of trades on the currency pair EUR/CZK according to exchange rate development

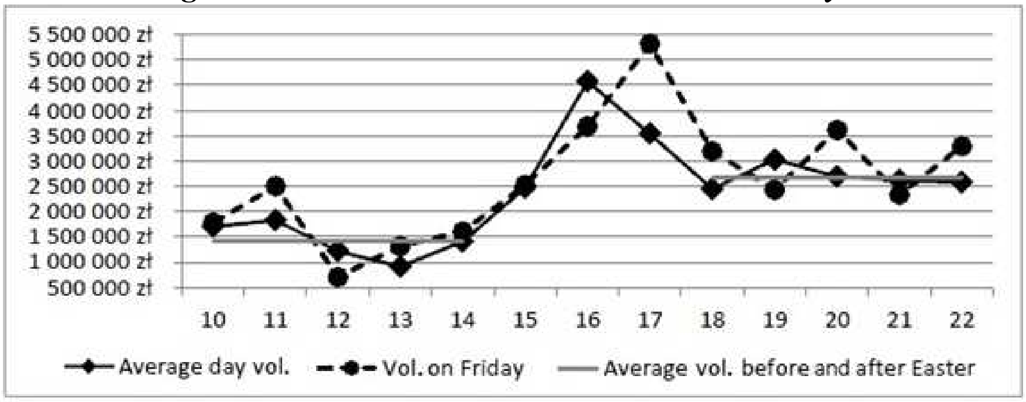


Source: (Mezera, Křupka, 2016)

The profit has been influenced by long-term stagnation of the exchange rate. Its development cannot be forecasted with reliability and that is why only the long-term expected development has been included in the plan. However, the evaluation of profit and potential changes in the plan are done with the knowledge of this quantity. It is, jointly with other factors as seasonal and weekly cycles, holidays and similar, the substantive part of the reporting (Gormley, Meade, 2007), (Hinderer, Waldmann, 2001), (Mezera, Křupka, 2015).

The influence of public holidays and seasonal cycles is visible in Fig. 3. There on the left axis is visible the volume of exchanged zlotys by Polish clients and on the bottom axis there are stated weeks from the first half of year 2014. Weeks 10 to 14 illustrate low economic activity that is typical for the first quarter of the year. Then comes Easter Holidays – on this holiday exchange offices need a large volume of zlotys because Polish nationals working abroad travel to Poland (they work primarily in Great Britain, Ireland and Germany). After Easter holidays economic activities in Poland increase because an agriculture season starts. In other Central European states there is not so prominent seasonal element. Despite that the first quarter of the year is the still low activity period of the entire year (Andersen, et al., 2003), (Kiymaz, Berument, 2003).

Fig. 3: PLN sales in EMI around Easter holidays2014



Source: (Mezera, Křupka, 2015)

3 Advanced analyses

Advanced analyses deal with the detection of so far undetected interlinks or they should determine the rate in which an output parameter is influenced by individual input parameters. When doing a classification we strive to assign an element, based on the information we have already, to a group of similar elements. Based on the group (into which the element have been assigned) we can later deduce its future behaviour (Pal, Shiu, 2004). With prediction we strive to estimate the volume of the input parameter that is in majority cases solved by regression methods. It is possible also to use different methods such as artificial neural networks (Kvasnička, et al., 1997, p. 98), decision trees, logistic regression, and similar. In the framework of these analyses it is essential to find valid parameters that in fact really influence the outputs. With a growing size of the company there usually also growths the number of these parameters and by that, at the same time, the volume of data that is possible to process. There are two possible approaches for this large volume of data. The first approach is the decomposition of large units into smaller units and consequently solving the smaller units. This is less demanding regarding capacities and all capabilities of statistics and of BI can be used for this task. The second approach is to work with big data where big data it means terabytes or petabytes size (Jemal, Faiz, 2015). The advantage here is that any hidden connections can be detected that cannot be detected at data decomposition. On top of that standard BI methodology can be used "Cross Industry Standard Process for Data Mining", commonly known by the acronym CRISP-DM. The disadvantage is high demands on company technical and human capacities. That is why a number of such services, also in large companies, are outsourced. The results of such analysis are then used in standard reports or in decomposed observations (Calegari, Ciucci, 2010).

The first step toward analysis of clients by means of clustering was normalization and standardization of data. As it has been mentioned above data had, prior to the normalization, Poisson distribution of probability. The normalization was done by means of logarithmic functions. Then standardization of data followed. Then it was already possible to sort out data into groups. The number of these groups was not possible to estimate. That is why Kohonen's maps (the neural network that utilizes learning without a teacher) were used for the determination of the number. By using these maps the number of groups was set at 10 (Kvasnička, et al., 1997). K-means method was used as the clustering method. This method sorted out data into ten groups. With a detailed view on the individual groups clients were sorted out into two large groups-to exporters (sellers of foreign currency) and to importers (sellers of domestic currency). Their character and business opportunities define the difference between these two groups. The importers are usually trading companies. They purchase in the time when they have little goods for sale left available. They must exchange currency also in the time periods when the exchange rate is less favourable for them. Further they have a dramatically higher number of transactions than the exporters. For this reason they are more sensitive to fees related to currency exchange and sending of money (that means the type of a price list). At the same time they strive to keep the margin low. However, due to lower Volumes their negotiation power is less strong.

On the contrary, exporters sell goods and receive foreign currency. In case they have at the same time also sales on the domestic market then they utilize so called natural hedging toward Exchange rate fluctuations in such way that they pay out wages and salaries and taxes in the domestic currency while they pay for loans, energy fees and inter-company invoices in foreign currencies (usually in EURs). Thanks to that strategy, they do not exchange money so often and with regard to the size of such companies volumes are also relatively small and not so frequent. It is done usually once or twice in a quarter of a year. As an example of such company we can state company BRAVO Isolit located in Jablonné nad Orlicí. Also with those companies that have more than 90% of revenues from abroad (for instance – piano producer Petrof) it can be observed that they exchange foreign currency less frequently then the importers. In this case it happens about two or three times in a month. With regard to the fact that these companies do not send out foreign currency but only receive it, such companies are not burdened by the fees related to such transfers and thereby they are not so sensitive to these fees. At the same time they have time space available to wait for better exchange rates. When the market is volatile these companies welcome the option to monitor the exchange rate by means of an order. When the market reaches the pre-defined values they already quickly confirm the deal. When the market is less volatile (the current state on the currency pair EUR/CZK) then, thanks to the volumes they have, the negotiation position of the exporters is strong and they can push for and achieve reduction of the margin (Baillie, Bollerslev, 1991), (Baillie, Bollerslev, 2002), (Melvin, Yin, 2000).

The average values for the individual clusters are in Tab. 3. The difference between the first and the second clusters' volumes is given by the fact that the first cluster includes also exchange offices that have a high volume and a high number of transactions. That is why the difference in both the Turnover and the Profit is so high. These first two clusters illustrate The Most Important Clients (13.8%), whose participation in the entire company volume is 78.73% (Mezera, Křupka, 2014).

Smaller clients create the following four clusters. Here we can see how similar these clusters are in both the Volume and the Profit but how dissimilar they are in the Number of transactions and consequently by the Profit per transaction (profit/transaction). This fully corresponds to the above-described behaviour of the importers and the exporters.

Tab. 3: Average values of the basic attributes in the individual clusters

Cluster	Type of group	Turnover volume total (in CZE)	Profit volume total (in CZE)	Number of transactions	Average of profit per transaction
c_1	Import	52 427 378	148 156	272.06	550.70
c_2	Export	34 836 204	81 686	68.55	1 188.70
c_3	Import	8 257 069	28 148	94.46	299.20

c_4	Export	9 024 410	20 901	23.61	887.90
c_5	Import	2 216 415	7 316	32.80	220.50
c_6	Export	3 777 535	7 549	7.21	1 041.10
c_7	Import	698 142	1 993	12.24	164.70
c_8	Export	978 580	1 931	3.13	612.40
c_9	Not defined	194 181	472	3.48	135.00
c_{10}	Not defined	32 836	82	3.18	25.40

Source: Authors

The seventh and the eighth clusters are created by so called threshold clients. The company does not realize any loss on these clients, but neither these clients contribute to any major profits of the company. Firstly these clients should be reference clients (e.g. natural entities with any relations to some significant firms). Or they are natural business entities that are just on the start of their business activities and it is good to offer to them some good conditions since they can become more important clients in the future.

The ninth and the tenth clusters are those clients for which the differentiation to exporters or importers is not significant. Both clusters represent one-time clients or clients whose importance for the company is very limited. Such clients are utilized only in regions where there is low brand recognition and thus these clients can become reference clients for such regions.

This sorting out of clients into clusters according to their significance has helped EMI to correctly set price-lists. Further it is of major importance for marketing actions and for exchange offers and orders. For a long period of time the average profit per transaction was used for classification of new clients with no client history.

In the middle of the year 2014 it was clear that the existing status of sorting of new clients into clusters only by means of the Average profit per transaction could not be used any longer due to increased error levels. In that period the exchange rate was stabilized due to the CNB intervention measures above the limit of 27CZK/Euro. Thanks to this it was easier for clients to be knowledgeable/to understand the offered exchange rates. This situation increased pressure in order to lower margins and to lower the profit per transaction. This is the reason why it became essential to divide new clients to profitable and non-profitable clients based on another data from the first three months after contract signature. This classification is done after one-year time have elapsed from contract signature. The estimate is thus very complex. A number of factors enter into the business relation and these factors cannot be easily quantified – for instance competition offers, production failure, exchange rate disadvantageous for the client, and similar issues. However it is essential to try to do this because of margin settings, price list and agent compensations. In year 2015 the payment institution found out by means of an analysis that the share of non-profitable clients that were classified as profitable is among individuals (IN) bigger that among legal entities (LE) or among entrepreneurs / freelancers (EN). On the other hand with the LE group a high rate of errors in the existing classification has been identified. 2385 clients have been tested, out of that 743 IN and 1292 LE. According to standard statistical methods (comparison of the median value, median and other parameters according to individual attributes) classification parameters have been changed. Thanks to that the quality of the output (profitable and non-profitable) has improved by more than 10% (see Tab. 4). Consequently also other possibilities for classification improvement have been researched into. In Tab. 4there are stated three most successful algorithms: the Top Down Induction of Decision Trees (TDTID) – C5 algorithm, the neural network – Multi Layer Perceptron (MLP) and logistics regression. The above-stated classification algorithms have shifted the quality of the classification again by about 10% (with IN over 87%). The results stated here are for a test group comprising 30% clients (223 IN and 388 LE).

Thanks to this significant improvement profits have increased (less profitable clients have less friendly tariffs and margins, more profitable clients have relevant trading conditions and are less prone to switch to competition) and costs have become optimized (optimization of the reward system)

Tab. 4: Comparison of classification methods

Method	Classification of LE client	Classification of IN client
	correct / incorrect (in %)	correct/incorrect (in %)
Original classification	62.71 / 37.29	66.03 / 33.97
Statistical methods	73.54 / 26.46	76.31 / 23.68
TDIDT – C5	81.76 / 18.24	87.15 / 12.85
MLP	83.65 / 16.35	87.25 / 12.75
Logistic regression	79.25 / 20.75	86.85 / 13.15

Source: (Mezera, Křupka, 2016)

Decomposition thus not only reduces demands on capacities of companies in comparison with utilization of Big data, but at the same time, it is a way how to improve individual decision-making processes and to increase efficiency especially in those cases where this efficiency is managed according to the behaviour of very different groups of the researched objects. Utilization of similar principles is possible also for e.g. tax administration – it also deals with different groups of tax payers (IN, EN and LE).

Conclusion

In this article standard decision making processes in the EMI have been introduced. In the introduction the financial sector has been described as well as its changes in recent years. Primarily new regulatory measures imposed in order to prevent the recurrence of the financial crisis have been mentioned. Due to the CNB interventions companies (primarily banks and EMIs), which are operating in the currency exchange sector, had to react to this situation adequately. One of the approaches used to tackle this situation was the introduction of BI. The BI was utilized primarily in two areas. One area was the daily reporting and the related observation of the key parameters of a company. Another area was the approach to new and existing clients, that means customer relationship management (CRM) optimization. Both of these areas have been illustrated on examples.

The first case illustrates a simple utilization of reporting for review of an undertaking's financial results. Exchange fluctuations cannot be predicted for a longer period of time. Despite that they significantly influence business parameters including, for instance, meeting profit goals. Thereby it is important to monitor their development and when it is necessary to adjust company's evaluation or company's business plan respectively because the difference between the lowest and the highest average value is more than 60%.

The classification of clients for the objective of better CRM in EMI was started even before the CNB interventions. Clients were assigned to clusters by clustering methods (Kohonens' maps and K-means method). This sorting showed big differences in behaviour between the group Importers and the group Exporters. Each of these groups was then divided into four groups according to the volume of exchanged money. Other clients are too small and next division does not make any sense. The discovered knowledge about clusters was used, for a certain period of time, also for the classification of new clients. This changed after the interventions when it became important to make this classification more precise.

Data from the time period three months after contract signature had to be used. The original situation with error rate from 33% (IN clients) to 38% (LE clients) has been improved by means of statistical modelling methods. New classification criteria have led to accuracy improved by 10%. More advanced methods (TDIDT, NNs, LR) increase the accuracy again by 10% and have been utilized for setting trading parameters (margin, price list) for the period after three months of contract signature. This arrangement is fully in the payment institution's competence and as such it does not have to be totally unambiguous and it may change. In this way savings in costs have been achieved by means of optimization of bonuses for agents as well as increased profits per clients have been achieved – for those clients that otherwise used to be little profitable or even represented loss for the company.

Both of the executed analyses show how the BI methods are employed in the EMI. The illustrated differences in profit fulfilment in the first case and the improved quality of classification in the second case are a clear evidence that BI provides a very strong support for decision-making and it prevents hasty and inaccurate decisions. In the future association rules can be used for the classification of clients, too (Kašparová, Pilc, 2016).

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