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AI foundations of the international business planning and the AI consciousness model

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Abstract:

With the continuous development of data mining instruments we acquire increasingly accurate and deep knowledge regarding the processes and network correlations related to business planning that can be considered one of the cornerstones of the world of business. During data mining activity patterns can be derived that provide assistance in the analysis of basic correlations. The most widely accepted analysis methods are hybrid data mining models and instruments, and within those neural networks that model the functioning of the human brain, which provide an avenue for the discovery and understanding of deeper correlations. By the application of data mining a consciousness model can be formulated, which evaluates and analyzes company movements, operations and decision making mechanisms. Data mining is one of the most important current paradigms of advanced business analyses and decision making instruments. It is a multidisciplinary approach that applies various techniques in the areas of statistics, machine learning and databases. One of the special branches of data mining inspects the correlations of financial balance sheets and reports as well as their derived indicators. In the case of this method, data mining provides the identification of data patterns in an innovative and ultimately interpretable manner. Data mining makes it possible for organizations to identify the statistical correlations between performance indicators more easily. In connection with this, by using hybrid data mining instruments the conscious operation of a specific company unit can be defined. By mapping conscious operations research may get closer to the mapping of the Unified Field.

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1. Introduction

The information technology inspection of balance sheet analyses, reports and financial analyses commenced in the 1960s, the research of computer auditing standards started in the 1990s, primarily focusing on standards and specifications. (Zhang et al, 2011)
In the area of accounting intelligent applications have been used for over three decades (Baldwin, 2006) and for the purpose of the utilization of data mining one of the first business disciplines was the discovery of complexity and system risks. Numerous research projects were conducted in connection with the accounting applications of data mining, however the majority of them focused on a specific field of accounting or data mining technique. (Coakley and Brown 2000; Yang, 2006; Calderon and Cheh 2002; Wang, 2010; Ngai, 2011). Here data mining represented the application of algorithms and extracting derivative patterns originating from data, which allowed the automatic discovery of implicit patterns and knowledge from large amounts of data. (Jiawei and Kamber, 2006) Data mining assists organizations in focusing on the most important information and knowledge available in their existing databases. The most significant data mining techniques are artificial neural networks, event based argumentation, genetic algorithms, decision trees, association rules, regression, self-organization maps, the K nearest neighbor search as well as the Bayes and fuzzy analyses. (Amania and Fadlalla, 2017). According to Dattilo et al, (2000) in the area of data mining neural networks and clustering are independently applicable techniques. However, a single data mining technique is insufficient to extract all the knowledge from a specific dataset. Therefore, hybrid data mining approaches, which support a specific data mining process in a combined manner, are the recommended, accepted and most frequently used techniques. By combining various classification methods, such as decision tree induction and clustering, sufficient and intuitive data descriptions can be created. (Dattilo et al, 2000)

All of these data mining techniques serve a special purpose, problem or business need. Various dedicated summary studies have been published regarding the application of data mining and financial as well as accounting applications. The large summary works classify, compare and summarize various data mining methods, algorithms and performance measurements, thus the works by Yang (2006), Wang (2010), Ngai et al, (2011). At the same time, other larger summary works analyze financial data mining through neural programming methods: Coakley and Brown (2000), Calderon and Cheh(2002).

2. Literature Review

The authors, Dattilo et al, (2000) for the analysis of balance sheet data created the system named DMTool by the combined application of various data mining and classification techniques (Dattilo et al, 2000). The architecture and main functional viewpoints of their system were expanded to the entirety of the classification and data description process of Italian company balance sheets. This model provides an integrated environment for data management and classification as well as for the analysis of the results. It fundamentally applies clustering and decision tree induction algorithms. (Dattilo et al, 2000) According to another method, a parallel simulation program was constructed for a single company, based on the logic of a balance sheet. The basic purpose of the work by Zhang et al, (2011) was the discovery of the cross section of balance sheet audit problems arising in the system audits of large corporate groups. The filtering out of unusual data and data analysis were performed according to the rules of correlation analysis, with the application of combined data mining methods and statistical models. (Zhang et al, 2011). The research was conducted by the simultaneous simulation of over 500 companies. The risk factor elements filtered out based on the result: invested assets, current construction, other liabilities, claim and stock accounting items and invoices (Zhang et al, 2011). The parallel simulation VBA based system was formulated so after the submission of company reports the system automatically generates a new balance sheet and report, as well as determines the risks. It displayed the discrepancies according the fetch logic, based on the comparison of maximum and minimum values in the original and the generated report, applying the methods of regression analysis in various processes. (Zhang et al, 2011)

According to professional literature analyses, the characteristic of data mining instruments is 82% predictive, 11% descriptive and 7% prescriptive. The analysis of literature shows that neural networks are the most broadly applied technique. They were used by almost half (47%) of all applications. This level of dominance by neural networks may originate from the nature of neural networks, as general problem solving techniques, which are applied in all data mining types and tasks as well as business problems. Regression represented 20% of all applications. Ranked after it with 14% were decision trees, while support vector machines and genetic algorithms were used by 11% of applications. Other less broadly applied techniques include: self-organization maps, the K nearest neighbor search, discriminant analysis association rules, event based argumentation and clustering. Financial and accounting applications primarily inspected financial performance and analysis. One of the earliest applications of data mining in this area is the work of Callen et al, (1996), in which a neural network model was constructed for the forecasting of quarterly accounting revenues. This work compared neural networks with linear time series forecasting models, and described that linear time series forecasting models produced better quarterly revenue forecasts, then an artificial neural network model. The *replicability* of the experiment conducted by Callen et al, (1996) was difficult because of the absence of an accurate definition of the neural network model. (Callen, 1996)

3. Findings and discussion

The model is divided into 3 basic interfaces. The first interface is the data request interface. This is where the data is entered for the evaluation. The basic feature of the data request interface is that the data is entered in 10 year periods. Any different data entry results in a non-conscious company condition by the evaluation. After data entry the data are transferred into the evaluation module, which appears on a separate hidden interface, this is the second interface, the model's "artificial intelligence" (hereinafter referred to as: MMI). The MMI evaluates the correlations in the data. The evaluation module channels the data into 3 evaluation ranges: (i) non-conscious company behavior, (ii) slightly conscious company behavior, and (iii) conscious company behavior. The third interface appears separately as the result. The evaluation module first arranges the entered data into an order of consciousness, then evaluates it in a text, and secondarily supports the evaluation numerically. The system of conditions serving as the basis for the MMI model are comprised of (i) the abstractions and parameters of the conclusions of theoretical professional literature (ii) the results of the Orbis system test and (iii) the correlations discovered by me. I have already detailed the basics of the first two elements in Figures 3-4. I furthermore data visualized the innovational quality definition used by the Orbis system. For the visual segmentation of the data I used 3 types of software. Power BI Desktop, Tableau 10.4, and the QlikSilk program. From the aspect of displaying the data Power BI Desktop was proven to be the most useful, thus I used the visualizations displayed by it.

I used this form of the data for testing, for both type of datasets.

Equation 1. Aggregate of innovation data

$$|B|=\begin{bmatrix} \begin{Vmatrix} V_1 & j_1 \\ I_1 & k_1 \end{Vmatrix} & \begin{Vmatrix} V_1 & j_2 \\ I_1 & k_2 \end{Vmatrix} & \begin{Vmatrix} V_1 & j_3 \\ I_1 & k_3 \end{Vmatrix} & & \begin{Vmatrix} V_1 & j_m \\ I_1 & k_m \end{Vmatrix} \\ \begin{Vmatrix} V_2 & j_1 \\ I_2 & k_1 \end{Vmatrix} & \begin{Vmatrix} V_2 & j_2 \\ I_2 & k_2 \end{Vmatrix} & \begin{Vmatrix} V_2 & j_3 \\ I_2 & k_3 \end{Vmatrix} & \cdots & \begin{Vmatrix} V_2 & j_m \\ I_2 & k_m \end{Vmatrix} \\ \begin{Vmatrix} V_3 & j_1 \\ I_3 & k_1 \end{Vmatrix} & \begin{Vmatrix} V_3 & j_2 \\ I_3 & k_2 \end{Vmatrix} & \begin{Vmatrix} V_3 & j_3 \\ I_3 & k_3 \end{Vmatrix} & & \begin{Vmatrix} V_3 & j_m \\ I_3 & k_m \end{Vmatrix} \\ & \vdots & & \ddots & \vdots \\ \begin{Vmatrix} V_m & j_1 \\ I_m & k_1 \end{Vmatrix} & \begin{Vmatrix} V_m & j_2 \\ I_m & k_2 \end{Vmatrix} & \begin{Vmatrix} V_m & j_3 \\ I_m & k_3 \end{Vmatrix} & \cdots & \begin{Vmatrix} V_m & j_m \\ I_m & k_m \end{Vmatrix} \end{bmatrix}$$

where:

$|B|$ Innovation indicators dataset

$V_{(i)}$ International company (1-1000)

$I_{(i)}$ Quality variable (1-21)

$j(i)$ Annual value of the quality variable (1-10)

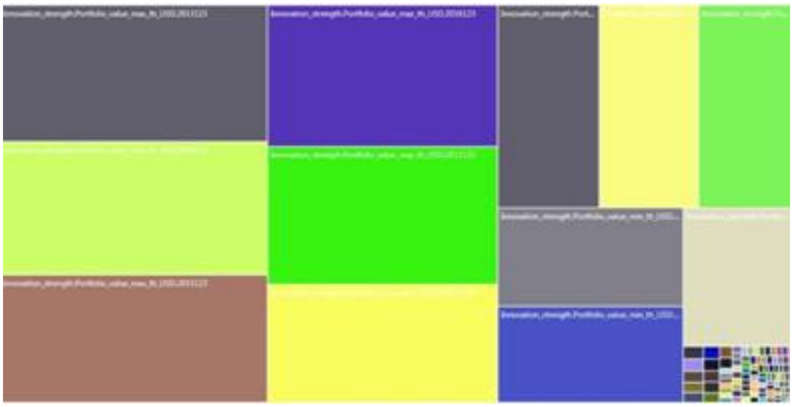
$k(i)$ Quarterly value of the quality variable (1-10)

Source: Own source. Own editing.

As the result of the test I received the following results:

From the aspect of data related to information technology companies:

Figure 1. K-centroid cluster data visualization of Infoalldt's innovation indicators.



Source: Own source. Own editing.

Figure 2. K-centroid cluster data visualization of Infoalldt's innovation indicators.

Source: Own source. Own editing.

and as applicable to mixed companies:

Figure 3. K-centroid cluster data visualization of NAICS2012 innovation indicators.

Source: Own source. Own editing.

Figure 4. K-centroid cluster data visualization of NAICS2012 innovation indicators.

Source: Own source. Own editing.

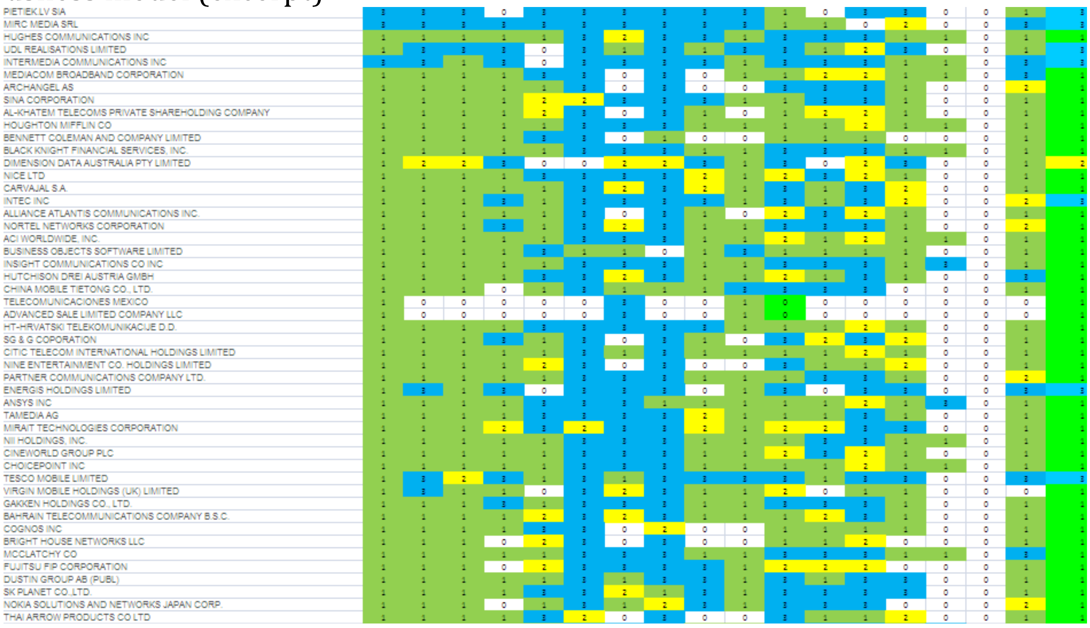
From the aspect of both, the data visualization of K-centroid clustering primarily displayed the Innovation strength-Portfolio value max. For this reason I integrated this value into the consciousness model, as the element showing innovation and defining quality. I divided the datasets originating from the Orbis system according to the above equation, into derived and non-derived as well as annual and quarterly datasets. A factored all data and subjected them to principal component analysis, then I clustered them.

I primarily took into consideration the elements defining the specific factor, and I primarily filtered the data that were contained 100 percent in every element set. I separately highlighted those elements that I considered defining, which I primarily used in the consciousness model. Both from the aspect of information technology companies and mixed companies, the following 3 elements became elements that can be primarily involved in the model: Operating revenue (Turnover), Shareholders funds, Total assets. In the non-derived portion, the independent factor elements or their parts in at least 75 %: Cash flow, Shareholders funds per employee, Profit per employee, Total assets per employee, Operating revenue per employee, Working capital per employee, Number of employees Year.
The factors of the derived values and their components are 40 in the case of both company types. The Figure shows. I indicated the elements in the same factor group with yellow color, which were contained 100 percent in every factor. Defining elements in the case of derived indicators: a Profit margin, EBITDA margin, Gross margin, P/L for period net income. In the derived portion, the independent factor elements or their parts in at least 75 %: ROE using P/L before tax, Net assets turnover Quarter, Solvency ratio (Asset based), ROCE using net income, ROA using net income. I determined the factors extracted from the Orbis system relative to the 1,000 element number, which I considered internal values within the model. The consciousness boundary values described in theoretical professional literature are mostly identical with the results of my analyses. The conclusions in theoretical professional literature have been proven by empirical studies. The important consciousness boundary values, which occur in both datasets: number of employees, gross profit margin, revenue values, liquidity, solvency.

4. Conclusions

The consciousness model indicates the specific partial results with colors and pattern. Thus, the color blue is non-conscious, yellow is slightly conscious, and green is conscious in its features. The summary result is indicated in the last line of the model. Summarizing all of these, in the comparison of annual data, from the aspect of Infoalldt, the number of non-conscious companies is 238, that of slightly conscious companies is 1, that of non-conscious companies is 701. From the aspect of NAICS2012, also in the comparison of annual data, 495 companies carry the pattern a conscious company based on the model, the 120 companies the pattern of slightly conscious, and 385 companies the pattern of non-conscious .

Figure 5. Result patterns of annual data of innovative companies generated by the consciousness model (excerpt).



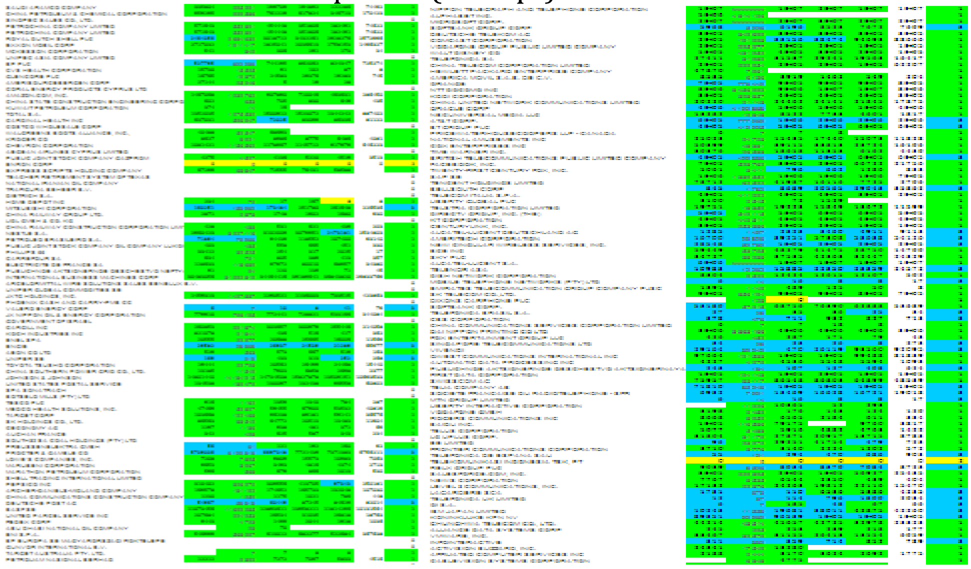
Source: Own source. Own editing.

The two distinguishable patterns in groups, consciousness is an important factor in in the case of the model results of information technology companies as well as mixed companies, which is shown by the similar pattern.

Figure 6. Result patterns of annual data of mixed companies generated by the consciousness model (excerpt).

Source: Own source. Own editing.

Figure 7. The innovation element's pattern in the annual data of the consciousness model of NAICS2012 and Infoalldt companies (excerpt)



Source: Own source. Own editing.

Figure 8. The innovation element's pattern in the quarterly data of the consciousness model of NAICS2012 and Infoalldt companies (excerpt).

Source: Own source. Own editing.

The research area related to this range of topic is unlimited, in which the primary goal is joining and mapping the Unified Field, by the use of which we can understand more than just the fundamental system of economics. The even more accurate functioning of the model can be facilitated by the application of neural networks assisting *deep learning*, thereby according the basic principles they become adaptable for other independent data systems. The system can be further refined by program elements applying artificial intelligence.

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