The Deployment of Data Mining into Operational Business Processes

Rok Rupnik and Jurij Jaklič
University of Ljubljana
Slovenia

1. Introduction

Data mining is progressively used in information systems as a technology to support decision making on the tactical level, as well as to enable decision activities within operational business processes. In general there are three categories of business decision making approaches: (1) decision making based on precisely defined business rules, (2) analytical decision making based on the analysis of information and (3) decision making based on intuition. In many cases there are all three categories used at a time. Business rule based decision making is typical for operational business processes, whereas other two are typical for managerial processes.
Data mining is predominantly used to support analytical decision making, which is typically based on models acquired from a huge quantities of data and therefore makes possible to acquire patterns and knowledge. Based on before introduced discussion one could assume that data mining can be used only in managerial processes. But, there are also operational business processes that require analytical decision activities, e.g. loan approval and classifying the set of customers for promotional mailings. Through data mining methods we can acquire patterns and rules, which can be used as business rules in operational processes. Thus, rules acquired through data mining methods can be used in operational business processes instead of or to support analytical decision activities. Data mining models should in such cases be acquired and used on a daily basis.
Some recent technology achievements, such as JDM API (Java Data Mining Application Interface), enable the possibility to develop application systems which utilize data mining methods and as such do not demand expertise in data mining technology for business users. Through JDM API we can develop transactional application systems or any other application systems which create and use data mining models. It means that application systems which use JDM API can be used to support operational business process with the possibility to utilize business rules acquired through data mining methods.
CRISP-DM 1.0 as the most used data mining methodology introduces four tasks within the deployment phase: plan deployment, plan monitoring and maintenance, produce final report and review project. None of those tasks provides detailed directions for the deployment of data mining models into business processes. The indicator that CRISP-DM 1.0 lacks such detailed directions mentioned is the fact that the CRISP-DM methodology update efforts intend to fulfill the following aim: "Integration and deployment of results with operational systems such as call centers and Web sites".

Source: Data Mining and Knowledge Discovery in Real Life Applications, Book edited by: Julio Ponce and Adem Karahoca,
ISBN 978-3-902613-53-0, pp. 438, February 2009, I-Tech, Vienna, Austria

The deployment of data mining is in fact the deployment of an information technology into business processes. It is therefore recommended to use the same general principles as at deployment of new technologies into business processes. It is true that data mining is in business processes used only in those steps where analytical decisions are needed. In spite of this, when data mining is deployed into business process it should at least to some extent be renovated. It should be renovated because the decision making process is changed and as a consequence it can affect other parts of a business process.
The challenge of deployment of the use of data mining in business processes also encompasses the roles granted to various actors within business process. In the early stages of data mining tools the vendors often emphasized that in the future their tools will be so simple that managers will be able to use them without any assistance. As we know the reality was quite different and often interdisciplinary teams (data mining experts, database experts, experts of statistics) were needed for data mining projects.
As evident from the discussion above, the classical data mining methodologies have to be extended for the cases where data mining is deployed in operational business processes. A proposal of such a methodological framework is presented in this chapter. The next section provides some background material on which the proposed methodology is based. Afterwards the proposal is presented in the form of a process model and described into more details. A case study is used to show an example of how a process can and has to be redesigned when deploying data mining. Besides, the case study serves to evaluate the previously proposed approach. At the end of the chapter, some general conclusions and lessons that can be learned from the case study are given.

2. Background

In this section we briefly introduce areas that are important for the mission of the paper.

2.1 Data mining

Data mining is the process of analyzing data in order to discover implicit, but potentially useful information and uncover previously unknown patterns and relationships hidden in data (Witten & Frank, 2005). In the last decade, the digital revolution has provided relatively inexpensive and available means to collect and store the data. The increase in data volume causes greater difficulties in extracting useful information for decision support. Traditional manual data analysis has become insufficient, and methods for efficient computer-based analysis indispensable. From this need, a new interdisciplinary field of data mining was born. Data mining encompasses statistical, pattern recognition, and machine learning tools to support the analysis of data and discovery of principles that lie within the data.
The data mining learning problems can be roughly categorized as either *supervised* or *unsupervised*. In supervised learning, the goal is to predict the value of an outcome based on a number of input measures; in unsupervised learning, there is no outcome measure, and the goal is to describe associations and patterns among a set of input measures (Rupnik et al., 2007).
Potential buyers classification naturally fits in supervised learning problems. Finding interesting subgroups of potential buyers and generally interesting associations among attributes requires using unsupervised learning techniques, such as association rules and clustering.

2.2 CRISP-DM process model

A data mining process model defines the approach for the use of data mining, i.e. phases, activities and tasks that have to be performed. Data mining represents a rather complex and specialized field. A generic and standardized approach is needed for the use of data mining in order to help organizations use the data mining.

CRISP-DM (CRoss-Industry Standard Process for Data Mining) is a non-proprietary, documented and freely available data mining process model. It was developed by the industry leaders and the collaboration of experienced data mining users, data mining software tool providers and data mining service providers. CRISP-DM is an industry-, tool-, and application-neutral model created in 1996 (Shearer, 2000). Special Interest Group (CRISP-DM SIG) was formed in order to further develop and refine CRISP-DM process model to service the data mining community well. CRISP-DM version 1.0 was presented in 2000 and it is being accepted by business users (Shearer, 2000).

CRISP-DM process model breaks down the life cycle of data mining project into the following six phases which all include a variety of tasks (Shearer, 2000; Rupnik et al., 2007):

- **Business understanding**: focuses on understanding the project objectives form business perspective and transforming it into a data mining problem (domain) definition. At the end of the phase the project plan is produced.
- **Data understanding**: starts with an initial data collection and proceeds with activities in order to get familiar with data, to discover first insights into the data and to identify data quality problems.
- **Data preparation**: covers all activities to construct the final data set from the initial raw data including selection of data, cleaning of data, the construction of data, the integration of data and the formatting of data.
- **Modelling**: covers the creation of various data mining models. The phase starts with the selection of data mining methods, proceeds with the creation of data mining models and finishes with the assessment of models. Some data mining methods have specific requirements on the form of data and to step back to data preparation phase is often necessary.
- **Evaluation**: evaluates the data mining models created in the modeling phase. The aim of model evaluation is to confirm that the models are of high quality to achieve the business objectives.
- **Deployment**: covers the activities to organize knowledge gained through data mining models and present it in a way users can use it within decision making.

Even though CRISP-DM recognizes that creation of the model is generally not the end of the project and introduces fours tasks within the deployment phase, it lacks more detailed directions for the deployment of the data mining results into an operational business process, which requires implementation of a repeatable data mining process (Chung & Gray, 1999).

2.3 Business processes and business process renovation

Throughout the last twenty years business process orientation gained importance in business community. There are several definitions of business processes. One of the widely used is the one by Davenport and Short (1990) that defines a business process as a set of logically related tasks performed to achieve a defined business outcome. Generally, there are two groups of generic business processes: operational and management processes.

Information is vital to all business processes that make up an organization's operations and management (Chaffey & Wood, 2005), therefore it should not be a surprise, that business process renovation research demonstrated the critical role of information technology in business process renovation (Broadbent et al., 1999). Nowadays information technology (IT) offers very good solutions for implementing business process renovation. The contributions of IT in business process renovation could be categorized in two different ways (Chang, 2000). Firstly, IT contributes heavily as a facilitator to the process of renovation. Secondly, IT contributes in the reengineering process as an enabler to master the new process in the most effective way (Davenport and Short, 1990). However, IT should be the enabler, but not the initiator of business process renovation projects.

In addition to IT, business process renovation requires consideration of organizational and managerial issues, such as cross-functional integration, stakeholder involvement, leadership qualities, and employee motivation. According to (Chaffey & Wood, 2005) the high failure rates for information systems projects are often a consequence of managers' neglect of how users will react to new ways of working.

3. The use of data mining in operational business processes

The use of data mining in business processes is increasing, but has still not reached the level appropriate to the potential benefits of its use. The literature review reveals that it is used mainly for the purposes of decision support (Rupnik et al., 2007). There are only few examples introducing daily use of data mining in business processes (Kohavi & Provost, 2001; Feelders et al., 2000; Chung & Gray, 1999). We can say that data mining is predominantly used to support decision making on a tactical level in decision processes and business processes.

What about the use of data mining to support business processes on operational level, i.e. operational business processes? We believe that the use of data mining in operational business processes represents a potential in cases where decisions can be operationalized based on stable models representing rules, in this case data mining models.

3.1 Related work

As mentioned before there is not much research done in the area of the use of data mining in operational business processes. There are also some papers discussing the use of data mining in business processes in general and they also represent important basis for our research.

Chung and Gray (Chung & Gray, 1999) argue that there is a lot of research done in the areas of data mining model creation, but there is a lack of research done in the area of the use of data mining models in operational business processes.

Kohavi and Provost (2001) argue that it is important to enable the use of data mining in business processes through automated solutions. They discuss the importance of the ease of integration of data mining in business processes. In their paper they discuss the integration of data mining in business processes as the consequence of the need to incorporate background knowledge in business processes. They state that deploying automated solutions to previously manual processes can be a rife with pitfalls. Authors also argue that one must deal with social issues when deploying automated solutions to previously manual processes.

Feelders et al. (2000) discuss the use of data mining in business processes with the emphasis on the integration of data mining models and solutions into existing application systems within information systems. Authors argue that it is essential that the results of data mining are used to support operational business processes like direct mailing for the selection of potential customers.
Gray (2005) discusses data mining as an option of knowledge sharing within the enterprise. Through the integration of data mining in operational business processes, knowledge sharing is not only present in business processes on a tactical level, but also on operational level.

3.2 Prior work

One of the motivations for our research presented in this chapter was also our prior work. We developed a data mining process model and appropriate data mining based decision support system to support decision processes in the telecommunication company (Rupnik et al., 2007). In our research we explored the use of data mining application systems approach of the use of data mining. In data mining application systems approach the data mining is not used in ad-hoc projects, but through data mining based decision support systems. Our aim was to define how business users can use data mining models to facilitate decision making where data mining experts create data mining models and business users use them.
One of the responds of the company that we got through the deployment of the system was the estimation that the use of data mining would also bring value added in operational level business processes.

3.3 The potentials of the use of data mining in operational business processes

We define operational business process as business process on operational level and they are significantly more structured than managerial processes. Although they are executed on an operational level, there are in many cases also decision-making components present in those processes. The decision-making components and the level of their use in operational business processes can be analyzed on classification of business rules and procedures (Raghu & Vinze, 2007) (Figure 1).

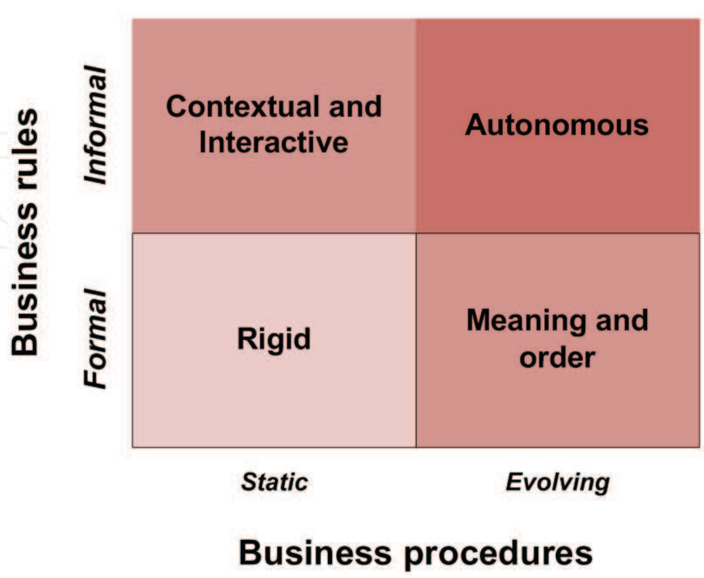

Fig. 1. Classification of decision-making components through business rules and business procedures

Operational business processes are typically based on rather formal business rules and static business procedures (Raghu & Vinze, 2007). We could say that the majority of operational business processes are *rigid* in their decision-making structure, i.e. they have rigid decision-making structure. Formal business rules leave no room for alternative interpretations, which means that those processes practically do not include analytical decision-making components. It is obvious that there is no room for the use of data mining in rigid decision making structures.

When decision-making structure is evolving in business procedures and still has formal business rules, then it is considered as being oriented towards *meaning and order*. Rules remain formal in order to ensure exact equity in the process. The procedures that implement the rules are evolving over time to allow some flexibility in the interpretation of rules. The evolving of decision-making structure is as a result achieved through innovativeness of flexibility in the interpretation of rules in business procedures. As higher level of decision-making structure is achieved through flexibility in the interpretation of rules there is no room for data mining to enhance business rules through lessons learned on past episodes.

Contextual and interactive decision-making structures are governed by effective representation of informal business rules. For this kind of knowledge-making structure is important to store and retrieve lessons learned from decision-making episodes from the past. This enables business rules to become more informal and adapted to patterns and acquired by data mining models. Through the use of knowledge acquired in the past highly formal business procedures can be better executed. The role of data mining for contextual and interactive decision-making structures is rather clear. The use of data mining enables the transformation of knowledge-making structure from rigid to contextual and interactive.

Autonomous decision-making structure is evolving in business procedures and is informal in business rules. Decision-making structures of this kind support and enable knowledge sharing, storing of knowledge and knowledge retrieval. Interactivity among decision makers both within and outside of process domain has positive effect on autonomous decision-making structures. Further positive effect is the possibility to retrieve knowledge related to solutions and procedures applied to similar decision problems from within and outside the problem domain. Data mining can as technology for acquiring of knowledge and knowledge retrieval in this case also contribute to the transformation to achieve autonomous decision-making structure.

3.4 The methodology of the implementation of data mining into operational business processes

Based on approaches to BI implementations (e.g. Moss & Atre, 2003; Williams & Williams, 2007), on a methodological framework to business process renovation and IS development (Kovačič & Bosilj-Vukšič, 2005), and according to our experience with the implementation of data mining in analytical business process we propose a methodology of the implementation of data mining into operational business processes. The main elements of the proposal are:

- business case assessment,
- DM readiness assessment,
- business process renovation, and
- CRISP-DM as the methodology used for DM itself.

The methodology has three phases where each of them has several activities. We describe the methodology, its phases and activities through subchapters.

3.4.1 First phase: exploratory data mining

This purpose of this phase is to evaluate the readiness of operational business process and people involved in it for the implementation of data mining in their operational business process. Beside that the first phase also defines the business value of the use of data mining in the process and evaluates risks and opportunities (Figure 2).

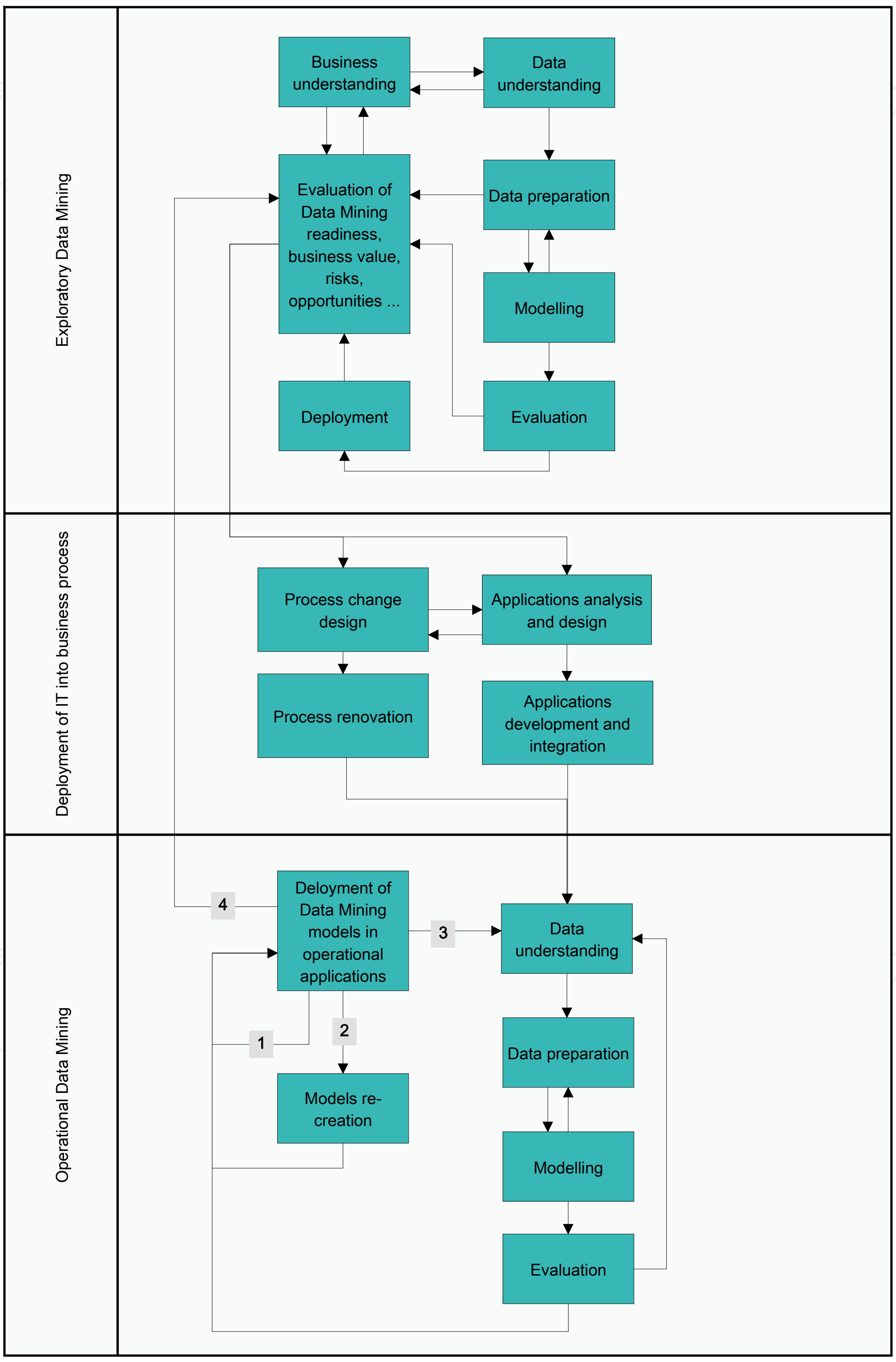

Fig. 2. The methodology of implementation of data mining into operational business processes

The process model of the first phase includes the CRIPS-DM process model activities and the evaluation activity, which justifies and confirms (or declines) the implementation of data mining into operational business process. Through CRISP-DM the problem domain is first explored and transformed to a problem definition suitable for data mining implementation through *business understanding* activity. After that the data needed for modeling is defined and prepared through *data understanding* and *data preparation* activities. Data mining models are then created, evaluated and deployed through the following activities: *modeling*, *evaluation* and *deployment*.

It is important to note that the aim of methodology is to implement data mining for daily use, not for ad-hoc use. As a result *data preparation* activity tends to automate data preparation to the highest possible stage and implement it as daily procedure which is executed automatically during night or on demand at any time.

The final activity is *Evaluation of DM readiness, business value, risks and opportunities*. This is core activity of the first phase which carries out the mission of the first phase: it evaluates the readiness of operational business process and people involved in it for the implementation of data mining in their operational business process. Beside that it also defines the business value of the use of data mining in the process, evaluates risks and opportunities. If the evaluation gives positive results, then the second phase is initiated.

3.4.2 Second phase: deployment of data mining into operational business process

This phase is in responsible for deployment of data mining in operational business process (Figure 2). For successful implementation of data mining there are two key activities which must be executed more or less simultaneously: *process change design* and *applications analysis and design*. The aim of the former is to define and design the changes that happen in operational business process in order that the use of data mining brings added value. The aim of the latter is to make analysis and design of the application that will use data mining and must be developed. There is not only new application that must be developed, there are also existing applications that must be adapted to the use of data mining models and changes in operational business process. Both activities are very dependent on each other. For example, the application must provide the functionalities suitable for changes designed in activity *process change design*. After the activity *applications analysis and design* is finished the development of application is initiated through activity *applications development and integration*. The aim of this activity is not only to develop application, but also to integrate it into information systems of the company.

When the activity *process change design* is finished the activity *process renovation* is initiated. The aim of this activity is to renovate the operational business process according to the changes defined and designed in previous activity.

3.4.3 Third phase: operational data mining

The last phase supports the daily use of data mining in operational business process. The first step of the phase is the re-execution of activity *data understanding*. This activity was already executed in the first phase. But, since between first and the third phase there can be quite a time difference, the activity is re-executed in order to adapt to the possible changes of the databases. After this activity the daily use of data mining through one or more applications is enabled. The activities that are performed daily have symbols in blue color (Figure 2).

Activity *data preparation* is responsible for daily creation of data sets that represents input for *modeling*. Data sets are either created automatically during night or by demand by business users. Modeling and evaluation are executed by the use of application developed in the second phase. The core activity for daily use of data mining in the operational business process is *deployment of data mining models in operational applications*. In this activity data mining models are used in various applications by business users. According to the experience of the use of data mining models the following scenarios are possible (Figure 2):

1. Business users do not notice any disadvantages in data mining models or effects of their use. In this case activity *deployment of data mining models in operational applications* is re-executed daily.
2. Business users notice some disadvantages in data mining models or disadvantages in effects of their use. If they know that there were no such changes done in the databases that represent sources for data preparation, then the activity *models re-creation* is invoked. This way the data mining models are re-created and they reflect the last changes in the contents of source databases.
3. Business users notice some disadvantages in data mining models or disadvantages in effects of their use. If they know that there were recent changes in the databases that represent sources for data preparation, then the activity *data understanding* is invoked. The aim of the re-invoking is to detect the effect of recent changes in the source databases and to find out if there are any changes necessary in the area of data preparation. After the activity *data preparation* is finished activities of *modeling* and *deployment* can be executed, i.e. the daily use of data mining models can go on.
4. Business users notice some disadvantages in data mining models or disadvantages in effects of their use. It can also happen that they know that there are changes happening in the company that affect the domain of operational business process and its mission. In this case the activity *Evaluation of DM readiness, business value, risks and opportunities* is re-executed in order to evaluate (and re-define) the use of data mining in the operational business process.

4. The use of data mining to support direct marketing – case study

In this section we present an example of data mining deployment into operational business process called *direct marketing*. We also discuss the renovation of the process needed to successfully deploy data mining.

The case study analyses the direct marketing process in a Slovenian publishing company (Publisher), which has published over 20,000 titles in print run approximately 100 millions in the last 60 years. Sales department, which is responsible for direct marketing sales, is a part of the Marketing and Sales unit. Sales through direct sales channels represent approximately 80 % of all sales in the last couple of years. There are several direct sales channels use: telemarketing, direct mail, email marketing, direct selling. Current practice shows that the target groups for different sales channels almost don't overlap. For example, elderly customers prefer telemarketing, which is mostly not preferred by other customer segments. This case study is limited to direct mailing (via snail mail), yet one could expect similar findings for other direct sales channels.

Sales marketing processes are currently supported by the *Libris* application, which is in use for more than 30 years. There are several problems with the *Libris* as not all the direct marketing activities are adequately supported. The main drawback is that each data

processing for selecting prospective buyers from the *Libris* database requires several hours. Therefore queries are run during nights. Consequently, running times for lists of potential customers are very long.
In the current (As-Is) direct marketing process (Figure 3) a product manager first defines a target group for the book that is to be marketed. There are several possible ways or criteria to define the group:

- Through demographic data (gender, age, city) and other characteristics of customer that have bought similar titles in the past are analyzed. *Demographs* and *geographs* are used for this type of analysis (Robertson, 2005).
- Based on the characteristics of "similar books". Product manager creates the list of those books according to his experience, i.e. his business knowledge. The *Libris* application enables several ways for selecting "similar titles", e.g. using the book classification.
- By the use of the RFM (Recency, Frequency, Monetary) method. Each customer that has bought at least one title in the last 5 years has a 3 digit RFM code.

The product manager then fills a paper form with the selected characteristic of the target group. As we can see, the selection criteria are defined using a combination of data that is derived from the entire history of sales and from the knowledge, intuition and experience of product managers. It is obvious that data analysis and business knowledge are very important for direct marketing process, what makes this process rather knowledge intensive.
At this point of the process the IT staff is drawn in the process. The product manager sends them the request for preparing the prospective buyers list that includes the above mentioned paper form with the selection criteria. In most cases the attributes that are used for defining the criteria are standard and predefined. In these cases the IT staff enter the criteria in the *Libris* and the list is created over the night.
There are some cases when the product manager wants to use complex criteria or additional attributes, besides the standard ones. In such situations a preliminary data processing is done in the earlier phase, at the time of criteria definition. This even prolongs the time required for preparing the prospective buyers list. Preferably, the IT staff that is involved in preparing the list should have quite a great deal of business knowledge, too. For example, they have to understand whether the result makes sense if there are X customers on the list. At the moment, there is only one such person (IT staff member – analyst) employed with the Publisher, therefore he is the critical element in the process. This is one of the reasons for which the Publisher has started to consider using modern information technology and data analytical methods in the direct marketing processes.
When the prospective buyers list is prepared, it is reviewed by the product manager and the criteria are modified if necessary. If so, the data processing has to be repeated the next night. When the final list is prepared in the required form, it is forwarded to the printing office by the product manager for printing and personalization of the marketing materials. Responses of the customers are recorded in the database, which enables analysis of the response and the creation of data mining models to improve future campaigns.
An important role of IT staff can be observed from the above description and the model (Figure 3) of the direct marketing process. However, IT staff contributes little to the process value added, as they act mostly as data stewards. Besides, the average process cycle time is rather long due to the night processing. And, as mentioned, each requirement for the mailing list change increases this time for a least one day. Consequently, flexibility and possibility for on-line analyses is diminished.

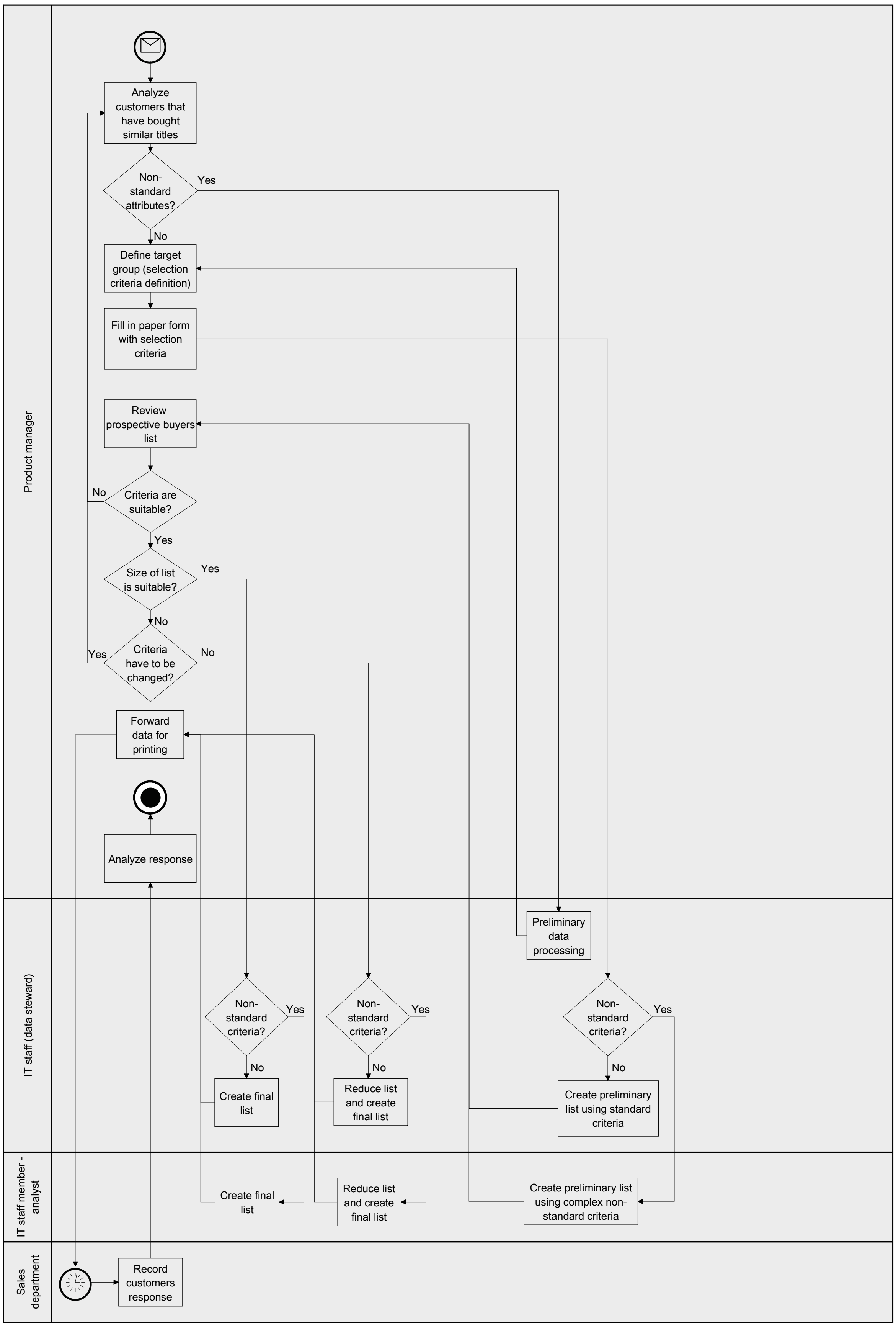

Fig. 3. The AS-IS direct marketing process model

Therefore, an analytical application is under deployment. It is expected to offer a possibility for autonomous analyses to the business users, such as product managers and other sales staff. They will be able to create and analyze prospective buyers lists, to pivot data cubes, to query the data, to perform *what-if* analyses, to define their own filtering criteria, etc. As already noted, the analytical activities in the process are knowledge intensive, thus it is reasonable to expect that there is a vast potential for the use of data mining. Publisher is already considering to implement data mining, in the first phase for determining prospective buyers and for predicting response to marketing campaigns, i.e. to support direct marketing process.

At the moment, all purchases are recorded in the Publisher's database. Besides that, they want to record each contact and communication with customers in the future. This will enable to upgrade from the purchase analysis to the customers analysis.

The TO-BE process model can be easily mapped to the methodological framework, shown on Figure 4. The labels 1, 2, and 3 match to the corresponding labels in the figure that shows the methodological framework.

4.1 TO-BE direct marketing process

The use of Data mining will enable new ways for customer segmentation and discovering customer groups for marketing campaigns. The standard attribute set will not be the only way for segmentation any more, the segmentation on various attributes will be enabled. Publisher is aware that deployment of data mining would require a renovation of the direct marketing process, including changes in the employee roles and responsibilities. After all, the latter is the reason for consideration to deploy new information technologies. As with other information technologies, the data mining is an enabler for business process renovation on one side, however it also requires process changes on the other side.

Step-by step changes of the direct marketing process are planned; first the analytical application will be deployed and later on the data mining application will be launched. Accordingly, the transition is expected to be smoother, particularly the changes related to the changing of roles. In the first phase the product managers will autonomously query and analyze the database. They will learn more about the database content and in this way they will get ready for the data mining, where the knowledge and understanding of the database content is one of the key success factors. As it can be learned from the direct marketing experiences, around 50 % of the success is in good understanding of the data. Only in the second phase, the data mining models for generating the prospective buyers list will be used inside the analytical application. An integration of both systems is planned.

The TO-BE process (Figure 4) shows the direct marketing process flow after the analytical application and data mining will be deployed. Significant differences can be noticed when the AS-IS and TO-BE processes are compared:

- A significant shift in the workload of the IT staff toward the business users can be noticed. The number of activities preformed by the IT staff is minimized, and moreover they are not involved in each marketing campaign. They have to acquire the appropriate level of new knowledge in the data mining, as they are mostly involved in building new models and re-creating of models. They are also involved in the designing of problem definitions together with business users, integration of models into the direct marketing application and into the analytical application, etc. Thus, the IT staff will have the role of a Data Mining model constructor.

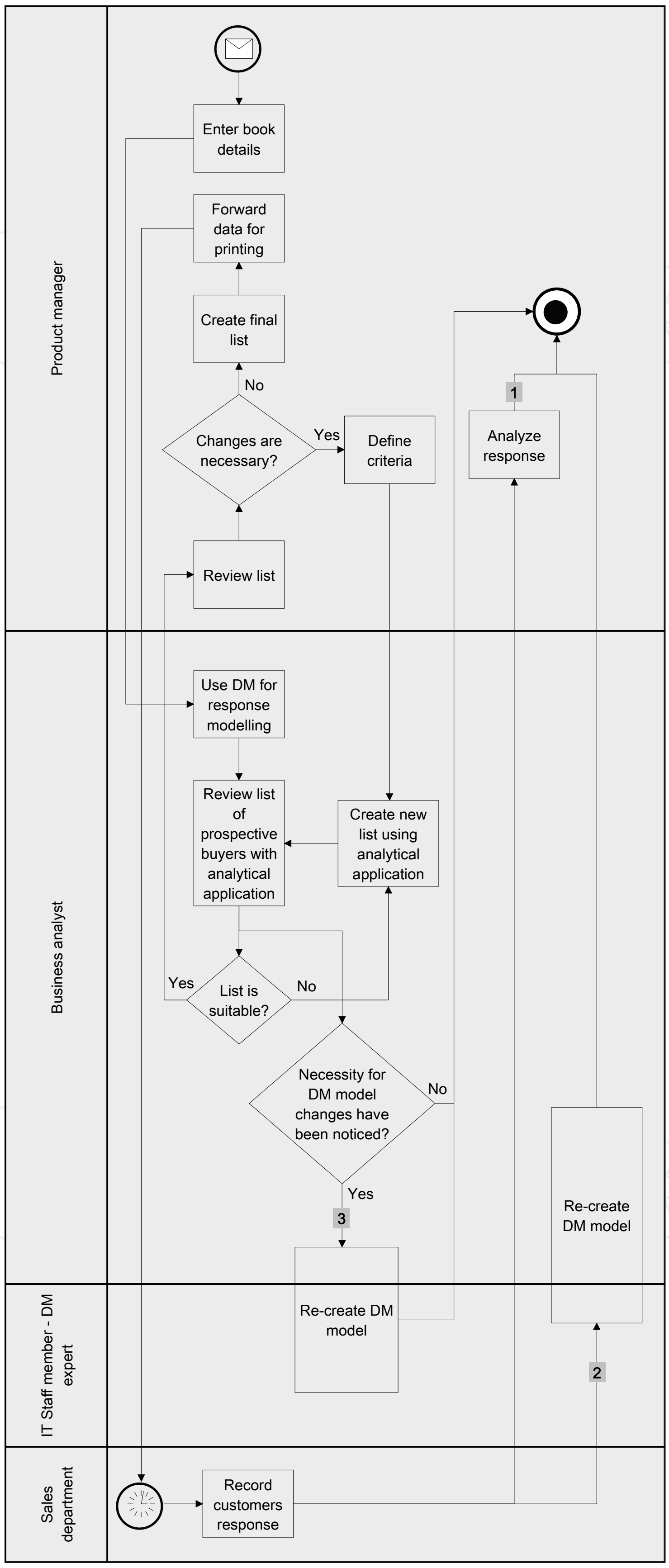

Fig. 4. The TO-BE process model – after the data mining deployment

- It can not be expected that the product managers will be able to do all the additional analyses by themselves, therefore a new role appears on the business users' side: business analyst. Despite this is a business user, an advanced level of information technology knowledge is desired for such a person.
- Analytical activities are much more emphasized and the number of activities with the low added value is decreased. Moreover, the data mining supports the analytical activities.
- An increased number of possible iterations (see the closed loops in the process model) as the consequence of the increased interactivity can be noticed. This enables greater flexibility during the preparation of the prospective buyers list.

5. Lessons learned

According to the methodology presented (Figure 2) we have already finished the first phase and the part of the second phase which covers process renovation. The data mining models acquired in the first phase and test instance of direct mailing process gave positive results.

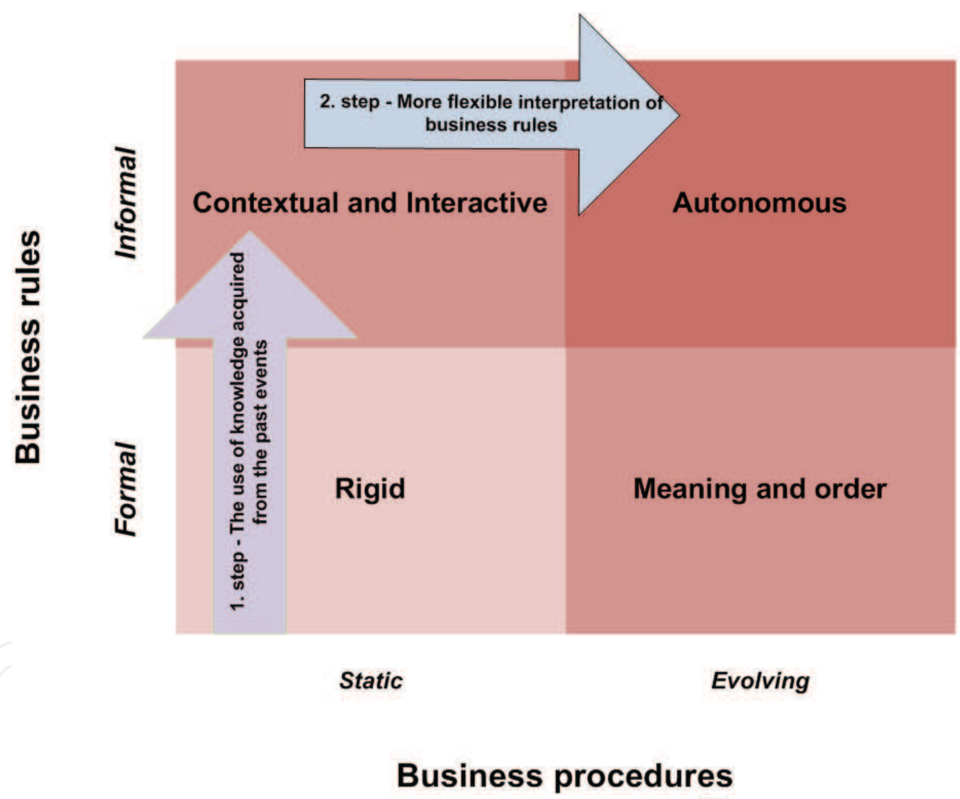

Fig. 5. Horizontal and vertical shift to higher level of decision-making structures

It has become clear that business process renovating and deploying automated solutions is not an easy task. Business users in general agree with the need to deploy data mining into direct marketing process. But, there is a little resistance felt and we know that the third phase will be not an easy task at all.

We believe that through our methodology there will be two shifts to a higher level of decision-making structures (Figure 5). The first step, the vertical shift from formal business rules to informal business rules will be achieved through the use of data mining, i.e. through knowledge acquired through decision-making episodes and patterns from the past.

According to our estimation this will be reached after about one year of use of data mining in the renovated process. The second step, the horizontal shift from static business procedures to evolving business procedures can be achieved through more flexible interpretation of business rules. We believe that for the successful implementation of data mining in operational business processes first the vertical shift must be achieved (Figure 5). After reaching the stage of *contextual and interactive* decision-making structures the advances in interpretation of business rules, also those acquired through data mining models, enable the shift to *autonomous* decision-making structure. We believe that the Publisher, for which we did the research introduced, must reach *autonomous* decision-making structure within their operational business processes. In our opinion successful sales oriented companies must reach autonomous decision-making structure in order to be successful and more agile than their competition (Raghu & Vinze, 2007).
The advances in interpretation of data mining models can be achieved after some time when the company reaches higher level of maturity of the use of data mining. Data mining models with their rules represent the basis to acquire business rules (Figure 6). As the maturity of the use of data mining in the company grows, the business users develop business rules through the evolution of data mining models.

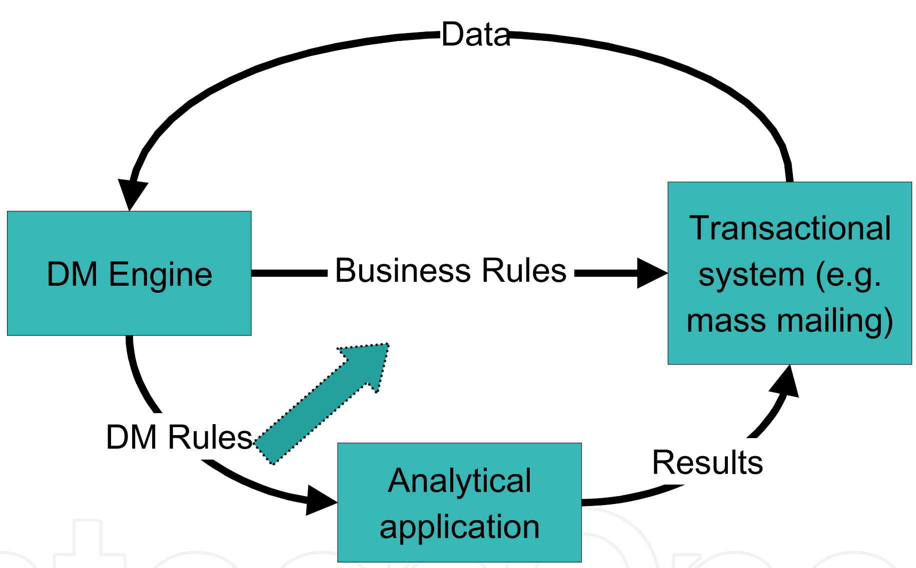

Fig. 6. From data mining rules to business rules

5.1 Future work

We are already plan activities for our future work. Our contribution delivered so far is methodology of deployment of data mining in operational business processes and direct mailing process renovation. When the third phase starts we will monitor the efficiency of our TO-BE process model. We will do monitoring together with product managers and executives responsible for marketing and sales. Based on monitoring we intend to do modifications in TO-BE process model when it will be needed. We also intend to do modifications in our data mining deployment methodology when there will be any indications requiring it. In our future work we see big potentials in defining criteria for selecting/determining scenario within activity *deployment of data mining models in operational applications* (Figure 2; section 3.4.3).

6. References

Broadbent, M.; Weill, P. & St.Clair, D. (1999). The implications of information technology infrastructure for business process redesign. *MIS Quarterly*, Vol. 23, No 2, 159-182, ISSN 0276-7783

Chaffey, D. & Wood, S. (2005). *Business Information Management: Improving Performance Using Information Systems*, Prentice Hall, ISBN 0-273-68655-0, Essex

Chang, S. L. (2000). Information technology in business processes. *Business Process Management Journal*, Vol. 6, No. 3, 224–237, ISSN 1463-7154

Chung, H.M. & Gray, P. (1999). Special Section: Data mining. *Journal of management information systems*, Vol. 16, No. 1, 11-16, ISSN 0724-1222

Davenport, T.H. & Short, J.E. (1990). The new industrial engineering: information technology and business process redesign. *Sloan Management Review*, Vol. 31, No. 4, 11-27, ISSN 0019-848X

Feelders, A.; Daniels, H. & Holsheimer, M. (2000). Methodological and practical aspects of data mining. *Information&Management*, Vol. 37, No. 5, 271-281, ISSN 0378-7206

Gray, P. (2005). New thinking about the enterprise. *Information systems management*, Vol. 11, No. 1, 91-95, ISSN 1058-0530

Kohavi, R. & Provost, F. (2001). Applications of data mining to electronic commerce. *Data mining and knowledge discovery*, Vol. 5, No. 5, ISSN 1384-5810

Kovačič, A. & Bosilj-Vukšić, V. (2005). *Business process management* (In Slovene). GV založba, ISBN 86-7061-390-5, Ljubljana

Moss, L. T. & Atre, S. (2003). *Business Intelligence Roadmap: The Complete Project Lifecycle for Decision-Support Applications*. Addison-Wesley Professional, ISBN 0-201-78420-3, Boston

Raghu, T.S. & Vinze, A. (2007). A business process context for knowledge management. *Decision support systems*, Vol. 43, No. 3, 1061-1079, ISSN 0167-9236

Robertson, S.P. (2005). Voter-centered design: toward a voter decision support system. *ACM transactions on computer-human interaction*, Vol. 12, No. 2, 263-292, ISSN 1073-0516

Rupnik, R.; Kukar, M., & Krisper, M. (2007). Integrating data mining and decision support though data mining based decision support system. *Journal of computer information systems*, Vol. 47, No. 3, 89-104, ISSN 0887-4417

Shearer, C. (2000). The CRISP-DM model: the new blueprint for data mining. *Journal for data warehousing*, Vol. 5, No. 4, 13-22, ISSN 1548-3924

Williams, S., & Williams, N. (2007). *The Profit Impact of Business Intelligence*. Morgan Kaufmann, ISBN 978-0-12-372499-1, San Francisco

Witten, I.H., & Frank, E. (2005). *Data Mining: Practical Machine Learning Tools and Techniques*, Morgan-Kaufmann, New York, USA

Data Mining and Knowledge Discovery in Real Life Applications

Edited by Julio Ponce and Adem Karahoca

ISBN 978-3-902613-53-0
Hard cover, 436 pages
Publisher I-Tech Education and Publishing
Published online 01, January, 2009
Published in print edition January, 2009

This book presents four different ways of theoretical and practical advances and applications of data mining in different promising areas like Industrialist, Biological, and Social. Twenty six chapters cover different special topics with proposed novel ideas. Each chapter gives an overview of the subjects and some of the chapters have cases with offered data mining solutions. We hope that this book will be a useful aid in showing a right way for the students, researchers and practitioners in their studies.