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An Adjusted Decision Support System through Data Mining and Multiple Criteria Decision Making

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Abstract

Decision Support Systems (DSS) is a specific class of computerized information system that support business and organizational decision making activities. In the other hand, Data Mining (DM) extends the possibilities for decision support by discovering patterns and relationships hidden in the data and therefore enabling an inductive approach to data analysis. Also, Multiple Criteria Decision Making (MCDM) is concerned with structuring and solving decision and planning problems involving multiple criteria. In this paper an approach is introduced to integrate the DSS with DM and MCDM methods. It causes to synergy of DSS, through getting more options to analysis, using expert's information, and improving evaluation process.

Keywords: Decision Support Systems; Data Mining; Multiple Criteria Decision Making

1. Introduction

Since the early 1970s, scholars in the areas of management information systems (MIS) and decision support systems (DSSs) have recognized the important roles of computer-based information systems which play an important role in supporting managers in their semi-structured or unstructured decision making activities [1].

There are three fundamental components of DSSs; database management system (DBMS) which serves as a data bank for the DSS. The second component is Model-based management system (MBMS). The role of MBMS is analogous to that of a DBMS and, finally the method of dialog generation and management system (DGMS) [2, 3]. Considering the data generation in most application fields and also the availability of database technology, lots

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of data is being collected and warehoused which is the preliminary need of a DSS. Therefore to achieve an efficient DSS, the vital need is to discover useful and reliable information from these databases as second step.

Since 1990, the most important tool to knowledge discovery from large database has been Data Mining (DM). It is a process of semi-automatically analyzing large databases to find valid, novel, useful and understandable patterns. DM has enjoyed great popularity in recent years, with advances in both research and commercialization [4, 5]. In addition, DM has paid attention to modeling as much as preprocessing and cleaning data to gain best results [6, 7].

The use of DM to facilitate decision support enables new approaches to problem solving by discovering patterns and relationships hidden in data and therefore enabling an inductive approach to DSS. In addition, the decision to collaborate DM and DSS is also based on the fact that the traditional use of DM through its software tools does not bring it closer to business users due to the complexity of DM tools. The tools are very complex and needs expertise in DM technology. In the other words, understanding the DM algorithms and parameters for implementing in a large data set is a great task [8, 9].

In the integrating approach, knowledge is automatically extracted from a large amount of row data by employing DM technologies, structured and transformed into appropriate forms, and finally retrieved by a hybrid reasoning engine in order to provide DS for decision makings in special situations. The table 1 is briefly presented some related work in DMDSS area:

Table1. The scheme of DMDSS study

Application	Author
Integrating DM and DS through computational intelligence [10, 11]	Delisle, et al.
Develop DMDSS on Oracle platform [12, 13]	Rupnik, et al.
Describe some applications of DMDSS in public health care [14]	Lavrac, et al.
Present a multi-perspective of integration in an IDSS framework [15]	Liu, et al.
Provide a system-wide profile of patient-specific pathology requests and extract knowledge through DM with Kohonen's self-organizing maps [16]	Zhuang, et al.
Propose the use DT algorithms to classify the diseases [17]	Kumar, et al.
Present multi-agent via DSS, DM and case based reasoning [18]	Srinivasan, et al.

Moreover, during the past 40 years, the Multiple Criteria Decision Making (MCDM) methods have made remarkable progress and have been developed into a mature discipline. In general, multiple criteria problems can be divided into two categories: multiple criteria alternative problems and multiple criteria optimization problems [19, 20]. Recently, researchers have tried to apply these methods in different areas especially in Data Mining [21-23].

The goal of this paper is to adjust the DSS framework concentrating on these requirements. The proposed integrated approach consists of forth major components: data management, data mining, validation and user interface.

The paper is organized as follows. Section 2 presents the decision support systems, data mining and multiple criteria decision making methods which are used as the main technologies. Section 3 proposed the adjusted approach in details. The paper ends with concluding remarks in section 4.

2. Methodology

In this section, the applied methods used in our approach such as, decision support systems, data mining and multiple criteria decision making are briefly described.

2.1. Decision Support Systems

Decision support systems are new computerized applications that act as a support system for supporting the organizational and business decision makers in the activities going on in their business and other industries. Accordingly, the great system that is effective can compile the most important information from documents, business models, and raw data and even help solving problems and making useful decisions. Decision support systems are typically used for strategic and tactical decisions faced by upper-level management with a reasonably low frequency and high potential consequences in which the time taken for thinking through and modeling the problem pays generously in the long run [1-3]. There are three fundamental components of DSSs [2, 24]:

- Database management system (DBMS). A DBMS serves as a data bank for the DSS. It stores large quantities of data that are relevant to the class of problems for which the DSS has been designed and provides logical data structures with which the users interact.
- Model-base management system (MBMS). The role of MBMS is analogous to that of a DBMS. Its primary function is providing independence between specific models that are used in a DSS from the applications that use them.
- Dialog generation and management system (DGMS). The main product of an interaction of DGMS with a DSS is insight. As their users are often managers who are not computer-trained, DSSs need to be equipped with intuitive and easy-to-use interfaces.

While a variety of DSSs exists, the above three components can be found in many DSS architectures and play a prominent role in their structure. Typical application areas of DSSs are management and planning in business, health care, military, and all areas in which management will encounter complex decision situations.

2.2. Data Mining

Generally, Data Mining (DM) is the process of analyzing data from different perspectives and summarizing it into useful information. It will find patterns in data which are interesting and valid [4, 5]. Numerous DM algorithms exist, including the predictive DM algorithms, which result in classifiers that can be used for prediction and classification, and descriptive data mining algorithm that serve other purposes like finding of associations, clusters, etc. The area has recently gained much attention of every application fields like industry, economics, medicine, CRM, trade, etc, due to the existence of large collections of data in different formats, and the increasing need of data analysis and comprehension.

2.3. Multiple Criteria Decision Making

Multiple criteria decision making is a sub-discipline of operations research that explicitly considers multiple criteria in decision-making environments. MCDM is concerned with structuring and solving decision and planning problems involving multiple criteria. In general, multiple criteria problems can be divided into two categories: multiple criteria alternative problems (MADM) and multiple criteria optimization problems (MODM).

Typically, there is not a unique optimal solution for such problems and it is necessary to use decision maker's preferences to differentiate between solutions.

3. Integrated Framework

As it is mentioned, to improve the efficiency of DSS and DM operations, an integrated method is introduced to integrate DSS with DM [8-18]. Also, to increase the effectiveness of this approach, another scientific method, MCDM, is used. Figure 1 shows the deployment diagram of DSS through described methods which presents much useful, reliable and powerful decision.

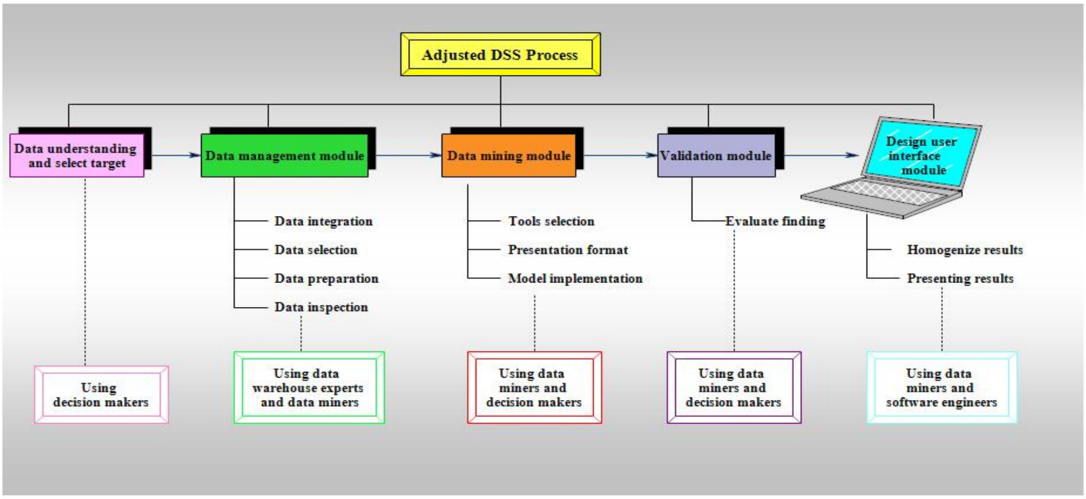

Figure1. The deployment diagram of DSS

Therefore, the proposed DSS includes the following steps:

1. Data understanding and select target
2. Data integration
3. Data selection
4. Data preparation
5. Data inspection
6. Tools selection
7. Presentation format
8. Model implementation
9. Evaluate finding
10. Homogenize results
11. Presenting results

At the first step one should understand the project objectives and requirements from a business perspective, and then convert this knowledge into a decision making problem definition and a preliminary plan design to achieve the objectives. Also, one should get familiar with the data, to identify data quality problems, to discover first insights into the data, or to detect interesting subsets to form hypotheses about hidden information.

To facilitate the operations, the above steps have classified into four modules. The detailed explanation of each module and its steps are given in the following sections.

3.1. Data Management Module

This module contains the following steps:

- Data integration
- Data selection
- Data preparation
- Data inspection

An advantage of combination of DSS and DM is using the information given by the experts, managers and other decision makers in addition to available database. This information is more than determining the purposes and fields of study, and contains some expert information about decision making areas that can be in quantity, quality and text type's data [28]. Then in second step, these data should be integrated with row available database by data warehousing experts.

The next step is data selection to achieve the goals. It is a subset of integrated database that should be classified. The descriptive statistical methods, conjunction tables and clustering techniques can be used for this purpose.

Data preparation includes all required activities for constructing the final data set (the data that will be fed into the modeling tool). Tasks include table, case, and attribute selection as well as transformation and cleaning of data for modeling tools which usually will be implemented by descriptive statistical methods and statistical graphs.

At the last step of this module, data inspection is implied to evaluate prepared data for analysis. As mentioned above, the data management module is very important to reach the consistent and constructive results because of garbage in, garbage out.

3.2. Data Mining Module

The main goal of data mining module is to help decision makers to understand characteristics of different situations and predict future events by analyzing available information via a collection of DM functions. The data management module provides fundamental supports for DM and other DS applications. The related steps of this module are:

- Tools selection
- Presentation format
- Model implementation

The data understanding and target selection together with data inspection are major guides for DM tools selection. DM uses methods, algorithms, and techniques from a variety of disciplines to extract useful knowledge from large amounts of data in order to support decision making [4, 5]. DM functionalities can be broadly divided into class characterization and discrimination, mining frequent patterns and association rules, classification and prediction, and cluster analysis [25-27]. Meanwhile to increase efficiency, it is common to apply combination of DM tools and MCDM methods.

In addition to these usual tasks, the decision makers can use the MCDM methods to rank and prioritize the group of options, and optimize multi-objectives. Peng et al. [23] have proposed an incident information management framework that has consisted in the three major components: data integration, DM and MCDM. The third module has utilized MCDM methods to assess the current situation, find the satisfactory solutions, and take appropriate responses in a timely manner.

Mosavi [21] has introduced the classification task of DM as an effective option for identifying the most effective variables of the MCDM systems. Also, in his article, different areas of MCDM including MODM, visualization and decision making have appeared which are very popular and supportive in dealing with engineering optimization problems.

Authors have suggested a combination approach to choose patterns from association rules mining through ANP (submitted in research area). They have employed ANP and experts opinions to ranking influenced attributes and given a suggestion for threshold of confidence.

Then in next step, the Presentation format have tried to discuss about what kinds of outputs utilize by managers and final users especially in graphical formats or any simple types. Finally, Model implementation starts DM process which contains classification, clustering, prediction, and association rules mining.

3.3. Evaluation Module

The objective purpose of this module is to evaluate the implementation of DM. Actually it is necessary to assess the performance of mining models against real data. Also, according to DM goals which is extracting novel, hidden and interesting information from row data, it may obtains seductive results or produces too many rules which confuses the decision makers.

There are many approaches for assessing the quality and characteristics of a DM model such as: [4, 5]

- Using various measures of statistical validity such as; MSE, root MSE, R^2, adjusted R^2, AIC, scatter diagram, etc. to evaluate the data or the model.
- Separate the data into training and testing sets to test the accuracy of predictions; the most popular method is cross validation [29].
- Experts' evaluation of the results of DM implementation to determine whether the discovered patterns have a logical meaning in the targeted scenario.

All of these methods are useful in validation and they are used iteratively to create, test, and refine models to answer a specific problem, as there is not a single comprehensive rule to evaluate the goodness of a model or sufficiency of the data.

In this study, the implementation of all procedures is recommended to synergy. In fact, it is not only using statistical measures and cross validation but also using indirect knowledge and opinions of experts is also essential. The common scientific method which is used for evaluation is MCDM and there are many discourses about application of MCDM in evaluation options. The following table briefly presents the recent study in this area:

Table2. The employment of MCDM in evaluation process

Application	Author
Evaluate classification algorithms in financial risk management [30]	Peng, et al., 2011
Present a framework by data mining, and MCDM methods in incident information management [23]	Peng, et al., 2011
Extend the linear programming to MCDM problems with the interval-valued intuitionist fuzzy information [31]	Chen, et al., 2012
Group decision making process for insurance company selection problem with extended VIKOR method under fuzzy environment [32]	Yücenur, et al., 2012

Kaliszewski et al. [33] have presented an approach to interactive MCDM based on preference driven Evolutionary Multi-objective Optimization with controllable accuracy. The approach relies on formulae for lower and upper bounds on coordinates of the outcome of an arbitrary efficient variant corresponding to preference information expressed by the Decision Maker.

Li et al. [34] have proposed a multiple kernels multi-criteria programming approach based on evolution strategy (ES-MK-MCP) for credit decision making. They have introduced a linear combination of kernel functions to enhance the interpretability of credit classification models, and propose an alternative to optimize the parameters based on the evolution strategy.

Campanella and Ribeiro [35] have assumed the classic MCDM model that, when taking a decision, the decision maker has defined a fixed set of criteria and is presented with a clear picture of all available alternatives. The task has then reduced to computing the score of each alternative, thus producing a ranking, and choosing the one that maximizes this value.

Hence, regarding to collaborating DSS, in this study it is proposed to apply combination approach for validation process. For more consideration the following illustration is presented:

If the main goal of analysis is classification, there are different alternatives; logistic regression, decision trees, neural network, support vector machine, Bayesian network, etc. all of these methods could be employed and then prioritize them by MCDA methods, then via available assessment criteria such as overall accuracy, precision, true positive rate, true negative rate, etc [23] one can evaluate the results.

Meanwhile the multi-objective optimization methods could also be used. When decision makers present a utilization function or goals of their organization through mathematical formulation they would be studied by MODM methods. In these cases, the objective of DM module is extracting patterns that evaluation measures of them are based on the minimization of deviations or the maximization of utility functions from the priorities of decision makers.

Moreover, the decision makers could employ the MCDA methods in ordinary measures cases for assessment phase. For example, typical financial measures are usually used in bankruptcy prediction models.

3.4. Design User Interface Module

The user interface is one of the main modules of DSS optimizing and it has a remarkable role to fulfill the cooperation of data warehousing experts, data miners, subject experts and decision makers. Also, it could fill the space between data miners and business users [36]. In the design field of human–system interaction, the goals of interaction between a human and a system are to obtain effective operation, control the system, and get the necessary feedback from the system. Examples of this broad concept of user interfaces include the interactive aspects of computer operating systems, hand tools, heavy machinery operator controls, and process controls.

A user interface is the discipline by which people (users) interact with a system in which includes hardware (physical) and software (logical) components.

Generally, the goal of human-system interaction engineering is to produce a user interface which makes it easy, efficient, and enjoyable to operate a system in the way which produces the desired result. This generally means that the operator needs to provide minimal input to achieve the desired output, and also that the system minimizes undesired outputs to the human [37]. Therefore, two main tasks in this module are homogenized and presenting results based on decision makers' needs and their knowledge.

4. Conclusions

Nowadays, decision makers invariably need to use decision support technology in order to tackle complex decision making problems. In this area, data mining has an important role to extract valuable information. Also, the successful application of data mining technology requires that one possess specific DM decision-making skills. For instance, the effective application of a data mining process is littered with many difficult and technical decisions (i.e. data cleansing, feature transformations, algorithms, parameters, evaluation, etc.).

Consequently, the use of data mining and decision support methods, including novel visualization methods, can lead to better performance in decision making, improve the effectiveness of developed solutions and enables tackling of new types of problems that have not been addressed before. On the other hand, the MCDM method deals with the vast area of decision making; choosing the best option among various alternatives, and optimization of goal among multi-objective situations. Therefore, the decision support systems (DSS), data mining (DM) and multiple criteria decision making (MCDM) are complementary methods for decision making process, and they have also a strong link with expert systems.

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