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Agent-based Decision Support System using Case-based Reasoning

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Abstract: The paper describes decision support system for modelling, organize, and simulation of continuous, as well as discrete event systems. Models, control methods, and tools are in database specified by their attributes. Each attribute's weight is initially estimated according to importance and classification power of a given feature. Automatic learning of attributes weights uses the answers of the users after simulation provided by the system to increase the quality of case-based reasoning.

Keywords: Decision support system, Case-based reasoning, Case-based learning,

I. Introduction

A formal model is a representation of a system within a defined mathematical framework. A good model captures the key characteristics of the system under study so that the system can be better understood and better decisions can be made about it. Because the model is merely an abstract representation of the actual system, it is always an approximation to and simplification of reality. But the mathematical analysis of a good model can be very effective at investigating the properties of the system and forecasting or simulating system behaviour. In a sensitivity analysis, the consequences of changes to one or more parameters of the model are ascertained by comparing before and after analyses. Hence, sensitivity analyses provide answers to what-if questions about the system. As mentioned in the previous section, a formal model or set of models can be used to examine a physical, societal, or hybrid system. A DSS is an easy-to-use computer package that encodes modelling and analytical capabilities for one or more formal models. The DSS permits practitioners and researchers to create, revise, and analyze a model to support decisions; of course, the model is only a representation, so the DSS cannot provide exact answers that indicate how the system will function or what should be done to improve it.

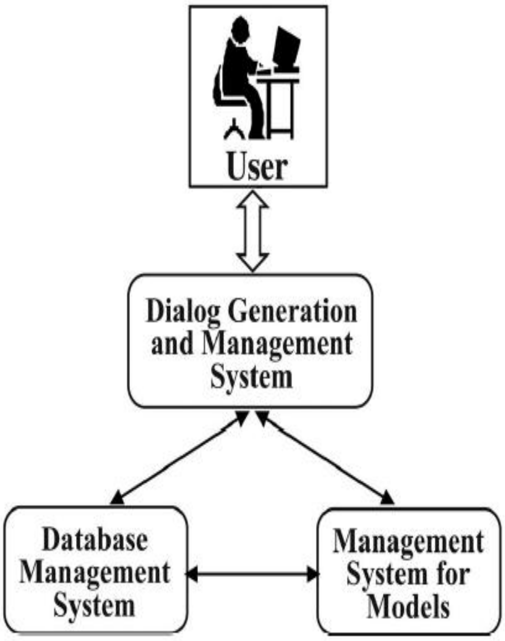

Fig. 1. Main components of a DSS

DSS technologies constitute one of the most important components of the field of information technology (IT), which includes the development and application of computer software and hardware. A Decision Support Systems Engineering, the main components of a DSS are a database management system, a model management system, and a dialog generation and management system. Fig. 1 depicts the interaction of a user or decision maker with a DSS that is designed to improve the decision-making process. The database management system must handle data both internal and external to the user's organization. A collection of data structures and operations that may be applied to these structures is required to handle data ranging from quantitative statistical data, such as water quality measurements, to qualitative knowledge about a situation, such as how environmentally responsible a corporation has been in the past. The management system for models, shown on the right in Fig. 1, is composed of a set of models that may be employed to describe common decision situations that confront a user or organization. This model base may include both societal and physical systems models from which the user can select. Models of hydrological processes, for example, are usually part of the set of physical systems models used in addressing water resources problems. After calibrating the models by using information obtained from the database or directly from the user, analyses can be carried out, followed by interpreting results and sensitivity analyses. The dialog generation and management system allows the user to interact with the DSS in a convenient and meaningful manner. It handles input regarding the user's needs with respect to the decision problem under study and furnishes appropriate output to support decisions. At each stage, the dialog system prompts the user to choose courses of action from a menu of options that may be shown as buttons, highlighted textual displays, or icons. Feedback to a request from the user is usually immediate, and information is often displayed graphically using informative colour combinations.

II. Agent-based Decision Support System

In knowledge engineering, agents offer the flexibility to integrate many different categories of processing within a single system. Agent definitions range from descriptions based on a functional analysis of how agents are used in technology to far more ranging expositions based on different interpretations of the role and objectives of artificial intelligence and cognitive science. Artificial intelligence is a very diverse field and agents are used as metaphors for work in many areas.
Multi-agent systems are appropriate for domains that are naturally distributed and require automated reasoning [4]. Agents should perform the following capabilities to some degree:

- Planning or reacting to achieve goals,
- Modeling the environment to properly react to situations,
- Sensing and acting,
- Inter-agent coordination,
- Conflict resolution (coordination is a continuous process, conflict resolution is event-driven, triggered by conflict detection).

To design a multi-agent system for a given problem, the designer has to understand how should agent and AI techniques be applied to the domain, what competencies agents need, and which techniques implement those competencies. Thus, multi-agent system design consists of
(1) Dividing resources and domain responsibilities among agents,
(2) Determining which core competencies satisfy which domain responsibilities, and
(3) Selecting techniques to satisfy each core
competency. According to distributed domain-specific responsibilities agent-based systems may be heterogeneous, with each agent responsible for a different set of goals or homogeneous, where agents share the same goals. Agents in the proposed system work according to simple workflow that is specified by user in terms of required support. Decision support systems are used by people who are skilled in their jobs and who need to be supported rather than replaced by a computer system. The broadest definition states that decision support system is an interactive computer-based system or subsystem intended to help decision makers use communications technologies, data, documents, knowledge and/or models to identify and solve problems, complete decision process tasks, and make decisions. Five specific decision support system types include [7]:

- Communications-driven DSS,
- Data-driven DSS,
- Document-driven DSS,
- Knowledge-driven DSS,
- Model-driven DSS.

III. Case-based Reasoning

Case-Based Reasoning (CBR) [4] is a method of solving a current problem by analogizing the solution to previous similar problems. A CBR system draws its knowledge from a reasonably large set of cases contained in the case library of past problems rather than only from a set of rules. It solves new problems by adapting solutions that were used to solve new problems. Instead of relying solely on general knowledge of a problem domain, or making associations along generalized relationships between problem descriptors and conclusions, the CBR approach collects information about previous cases, and then retrieves this information for similar cases. By adopting this approach, it is able to utilize the specific knowledge of previously experienced, actual situations. Subsequently, the previous solutions may be adapted so that they more closely match the current problem and situation. Thus, such a reasoning method is very suitable for decision making in construction bidding—a complex, dynamically changing, and highly unstructured problem domain. This paper presents a case-based reasoning decision support system (CBR-DSS) that assists contractors in solving mark up estimation problem. The CRR-DSS uses successful cases of previous completed projects to derive solution to new project mark up estimation problem. The principle of the CBR-DSS is to analogy new project with previous projects.

3.1 Application of CBR

Since case-based reasoning has been put forward, researches in this area increases a lot. After continuous development, case-based reasoning had been applied in both academic and commercial fields till 1990's. and now, the fields where CBR can be used become more and more, such as, application of CBR in industrial process.

CBR can be used to make diagnosis in different area, such as commercial and industrial area. And also it is possible to make the best decision according to a good case-based system. What is more, in order to get a better design, CBR system provides some useful successful experience, which may contribute greatly to part of the design. On the other hand, the application most commonly seen is to apply CBR to commercial field, to do decision making or to do assessment and so on. However, the wide application of CBR does not mean that CBR can be used everywhere. It is necessary to make sure some conditions are satisfied, for example, case base is available and the assumption should be valid that similarity in problems can indicate that the solutions are similar, and so on.

Despite that CBR can be useful in many ways, CBR usually work together with other methods to get a desired purpose. Article [1] introduces an improved case-based reasoning. As the large number

Despite that CBR can be useful in many ways, CBR usually work together with other methods to get a desired purpose. Article introduces an improved case-based reasoning. As the large number of attributes in Case-based reasoning system (CBR) brings a huge information redundancy which reduces the matching and retrieval efficiency, a novel reduction method based on Water-Filling is proposed in [1] to remove those unnecessary attributes. A hierarchical memetic algorithm was proposed in [10] for combined feature selection and similarity modelling in case-based reasoning. And also Chun Guang Chang put forward another way to reduce the size of cases, and applied it to solve the practical dynamic scheduling problem of some iron and steel works. Rough set based reduction technique for case attributes is studied to improve the efficiency of case retrieval.

IV. Reasoning in Decision Support System

A described agent-based decision support system consists of:

(1) database of modelling and control methods and tools,
(2) case base of models created and simulated in past,
(3) knowledge base of the control theory domain,
(4) Web-portal enabling to specify user requirements, to display results of reasoning, and to connect a provider of a selected tool.

In the system, there are three possibilities of reasoning:

- Classical database querying: Models, control methods and tools are searched in database according to user specified requirements and given context.
- Case-based reasoning: Whenever no model or control method matches exactly the user requirements, the model forms and control methods are reasoned from similar cases.
- List of similar cases to the user specifications and requirements: If the user requires support in a form of accomplished similar case, similar cases with references to a tool where simulation can be done are provided (useful for e-learning purposes).

Attributes used in questionnaires to systems specification are weighted by real number 0 - 1. Each attribute's weight is initially estimated according to importance and classification power of a given feature.

V. Learning Algorithm

After considering many aspects, a novel case-based approach is proposed to get the unsolved real value output. Two main steps for this new algorithm are as follows: at first, K nearest neighbour regression algorithm is used to add one more attribute to the original cases, that is, the coefficients of the linear line. Secondly, a new unknown input attribute x0 remains to be solved. After searching for some useful cases which already add the coefficient as an input attribute, the output of the new problem can be calculated in a very easy and time-saving way.

- **Off-line Calculation Method**

K nearest neighbour algorithm together with regression is applied in the off-line calculation stage. By using KNN regression, the coefficients for the linear line can be calculated, which is an important step in this proposed case-based approach.

1. K Nearest Neighbour Algorithm

K Nearest Neighbour (KNN) algorithm is a classification and prediction method used widely in pattern recognition and data mining, and it is a supervised machine learning method. It is also one of the basic technologies in the field of data mining. It has been proved to be very effective in many fields, but the researches on KNN algorithm applying for real-valued output are rare relatively.

Given a set of training samples:

$$S = \{(x_i, y_i) \mid i = 1, 2, \cdots, m, (x_i, y_i) \in R^p \times R\}$$

Where xi and yi respectively represent input attribute and output, and they are both real values. Given a sample x0 to be predicted, KNN is used to predict its associated real-valued output y_0.

The traditional KNN regression algorithm mainly includes two steps: Firstly, associated output values of K nearest training samples, which have the shortest distance with x0 , are selected by KNN in S , denoted as Y={ y_1, y_2,… y_k}. Secondly, the average value of Y is used as the predicted value of y_0, that $y0 = \frac{1}{K}\sum_{i=1}^{K} Yi$ An obvious improvement is that the weighted average value of Y is used to be the predictive value of y0, that is, $Y_0=\sum_{i=1}^{K} WiYi \ / \sum_{i=1}^{K} Wi$ where the distance weight w_i is inversely proportional to distance, and the associated algorithm is called distance-weighted KNN. Studies have shown that KNN regression algorithm achieves relatively better effects in some practical applications. However a new way is proposed to get the output y_0, which is corresponding to the input attribute x_0.The first step is the same with the traditional KNN algorithm. Euclidean distance shown below in equation 1is applied to act as the similarity metric.

$$\text{Distance}=\sqrt{(X10-X1i)^\wedge 2+(X20-X2i)^\wedge 2+\cdots(Xn0-Xni)^\wedge 2} \qquad \text{(equation 1)}$$

Where x is a n-dimension variable, (x_{10}, x_{20} ,……, x_{n0}) is the input attribute of the unsolved problem, and (x_{i1}, x_{i2} , …, x_{ni}) is the existing case. By calculating all the Euclidean distance between the unsolved problem $x_0$and the known cases in the dataset, the specified K nearest neighbours can be obtained. On the other hand, the second step is regression essentially, but some more work has to be done before applying regression, that is, the following case adaptation part.

VI. Case Adaptation

The major difficulty in case-based reasoning system is the adaptation from retrieved case. Most of the design problems have to be adapted manually due to the complexity of the adaptation processes. The approach to make case adaptation varies much. The adaptation patterns are the combinations of process parameters, which would affect the final outcome of a product. A particular process pattern when observed in a process suggests a good or bad effect in the final product unlike the traditional adaptation rules, which suggest the amount of change to be made to the final solution.
In this paper, from the K neighbours relative to be the nearest to the unsolved input attributex0.it is possible to find a method to get the output of this input x0. This kind of method can be used to get the average value of these neighbours or something else. However, in this paper, case adaptation is conducted to get more accurate information with these limited neighbours. That is, get the incremental value between two different neighbours. In this way, the useful size of data is increased to Ck2. thus more accurate information are given by using these limited useful neighbours.

$$X_{new} = \sum_{i=1}^{K} \sum_{j=i+1}^{K}(Xi - Xj) \qquad \text{(equation 2)}$$

$$Y_{new} = \sum_{i=1}^{K} \sum_{j=i+1}^{K}(Yi - Yj) \qquad \text{(equation 3)}$$

In the equations above, Xnew and Ynew are vectors to store the adapted cases. And xi and yi is the obtained cases by using K nearest neighbor algorithm.

- **On-line Calculation Method**

After the off-line work has been done, an updated dataset is achieved. Every time a new problem arrives, instead of large calculation of the K nearest neighbour regression method mentioned above, the output value can be calculated in a very simple way with the help of the coefficient attribute. Obviously, this way to deal with CBR system is much less time-consuming.
On the other hand, it is necessary to understand the reason for the validity and reliance of this new input attribute. Let us consider two situations: the first situation is applying K nearest neighbour regression method and calculating everything on-line when a new problem comes; the second situation can be the approach we put forward in this article, making some off-line calculation and then get the on-line results. In the first situation, the new problem is the test case and all the data in the original dataset are the training data when conducting KNN regression. And coefficients for the linear line will be calculated and used to get the output value. However, in the second situation, one of the data in the original dataset acts as the test case, and all the others are training data. As it can be seen, the only difference between these two situations when calculating the coefficient attribute is that there is just one case less in the training data in the second situation compared with the first situation. Usually, if one case is eliminated from a dataset, which has a pretty large amount of data, there will not be big difference to the desired results.
To make the output value more accurate, a specified number of neighbours for the unsolved problem can be found. It is better to take the average value of all the output of these neighbours.

VII. Conclusions

Decision support system for control theory domain has been described. The database of the system contains methods and tools for modelling and control synthesis as well as a set of complete models of systems specified by their attributes. Each attribute's weight is initially estimated according to importance and classification power of a given feature. Automatic learning of attributes weights uses the answers of the users to increase the quality of case-based reasoning.

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