Hybrid Expert System

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Abstract: - This article deals with hybrid expert system that has knowledge base realized through a hierarchical structure of artificial neural networks (NN). The decision tree is built by C4.5 algorithm at first. In the next step the nods of the tree are replaced by NN. They are trained to split the data in the same way as the nods. So the problem is separated into partial sub-problems that are solved by individual NN. At the end an expert is requested to change the structure of particular NN according to his knowledge and experiences. Each NN solves a partial sub-problem what decreases demands upon the capability of an expert and accelerates the time needed to harmonize the knowledge base. Unlike the traditional expert system, the output of this architecture is not classification, however we receive a list of hypotheses evaluated by certain value of the hypothesis trust.

Key-Words: - expert system, connectionist expert system, knowledge base, neural network, decision tree

1 Introduction

Expert systems (ES) are knowledge-based systems that provide expertise similar to that of experts in restricted application area. Expert system is a program that can provide expertise for solving problems in defined application area in the same way the experts do [1].

The biggest problem, at diagnostic expert systems working with rules, is production of knowledge base, as its harmonizing can take even months. Yet this technique is common with most expert systems nowadays. In certain cases we can see an expert unable to define his knowledge and skills through rules. Actually, human expert does not usually use formal logic in each situation; he rather compares the current case to its similar model and tries to solve it in a similar way. This way we can be inspired by real thinking of an expert, whose brain works with neural network data parallel and accordingly to models previously stored in his memory. This leads to the idea of hybrid expert systems using artificial neural networks and rules represented by decision tree together [2,3].

2 Explicit vs. Implicit Expert System

At ordinary explicit expert systems working with rules, the biggest problem is time-consuming production and harmonizing of knowledge base. On the other hand, possibility of inference algorithm explanation is an advantage. At system with implicit realization, knowledge base production is faster, but it is bought out by inability to find out the reasoning for computed decisions. It is also impossible to assure the correct function for all possible combinations on the expert system inputs.

From the knowledge base dimension point of view, we practically are not restricted by the amount of rules at the explicit representation. Those systems are able to solve even very extensive and complicated tasks. At the implicit realization, we are nowadays restricted to minor tasks, as it is impossible to teach vast neural networks. That way implicit realization is more suitable for limited problem area solutions.

Considering knowledge acquiring and editing, a knowledge engineer and expert on the given field are regularly being consulted at rules systems. They form rules and test results together. Apart from this, knowledge is stored in training set when neural networks are used. This set consists of example inferences and an expert is not necessary for its production. Training set should contain enough patterns sufficient to cover the solved area. This method is therefore more suitable to solve problems with lack of rules and accessible set of inferences [4].

At present, it is advantageous to combine both methods. When we know the rules, we use ordinary approach; when we do not know exact procedures the expert uses but we have enough of the experimental data about his behavior, we use neural networks.

3 Hybrid Expert System

Hybrid expert systems [5,6,7] are intended for simplification and acceleration of the harmonizing process by the combination of explicit and implicit

expert systems. They profit from qualities of both approaches. Usually the neural networks preprocess some data in hybrid systems [8,5] or create an independent modular part of the complete decision process [9,10,11,12].

3.1 Knowledge Base Representation

Knowledge of an expert is expressed in knowledge base. Production and harmonizing this knowledge base are usually pursued by discussion of an expert and knowledge engineer over the problematic field. When using ordinary (explicit) knowledge representation approach, the base is formed by symbolic formulas.

Our hybrid expert system is based on connected neural networks hierarchy. The produced decision tree, whose nodes are replaced by neural networks, then represents factual knowledge base [13]. Feed-forward layered perceptron networks determined with the help of Backpropagation [14] algorithm are implemented in the system. Neural network has three layers (input, hidden and output layer) and the number of neurons in hidden layer is variable. The queries are associated into groups that solve one neural network. So the problem is separated into partial sub-problems, that we are able to cover with training patterns in high quality and this way acquire very good results with full use of neural network's generalization.

Inputs of neural networks represent replies to nods' queries. The inputs may be of two kinds:

- discrete – e.g. replies of the type yes/do not know/no; little, much; etc.
- continuous – replies in the number representation.

By the replies to individual queries are set the neural network inputs that are represented by the values in the <0-1> range.

Outputs of the neural networks represent individual hypothesis. The hypothesis may also be of two kinds:

- resulting – point directly to the result,
- partial – point to another node.

On the basis of partial hypotheses two following neural networks are solved and they are mutually interconnected. Resulting hypotheses of the system are not connected to any input. Both partial and resulting hypotheses may occur more times in knowledge base.

Interconnection of single neural networks may be done in two ways (Fig.1). The first way is by means of preceding neural network output and following neural network input. This way we also set the reply to the query in the following network. The second and main way is interconnection when output from preceding network sets probability of solution of succeeding neural network. It means all the outputs of succeeding network are adjusted (multiplied) according to this probability. If the network probability is insignificant in the eyes of expert, network is not solved any more and system does not pass through this branch any longer.

By this approach we acquire a decision tree, in which, based on solution of one partial problem, one or more following problems are solved with defined probability.

When knowledge base is created, several important principles have to be hold. It is not possible to join one output to more inputs and, vice versa, more outputs cannot be attached to one input. It applies also to input for probability of network solution. Next condition is that each query may be set only once, which means that it cannot occur more times in the decision tree. It is necessary because of parallel decision tree passing.

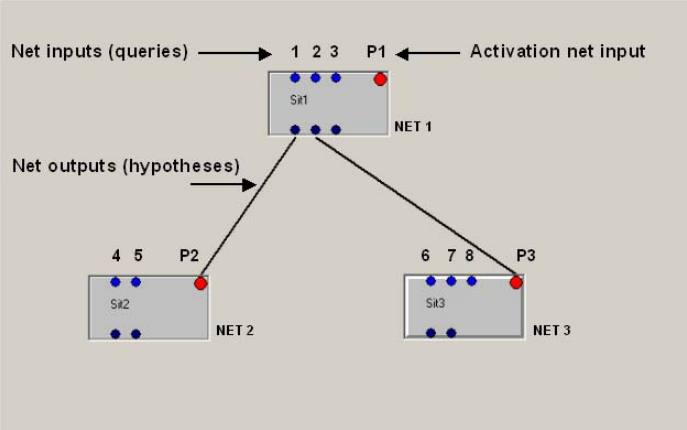

Fig.1 Structure of hybrid expert system

3.2 Inference Mechanism

Inference mechanism of hybrid expert systems determines the way the system makes queries during consultation. At first a net without any input value from another network is found. This net is consulted and the calculated values are stored. Subsequently is performed calculation of the networks that have connections from preceding network on their inputs. For our example (see Fig.1) is chosen Network 1 at first, then queries 1, 2, and 3 are set, calculation of the hypotheses h1, h2, h3 is made, and we continue with Network 2. Queries 4 and 5 are set, and hypotheses h4 and h5 values are calculated.

Before Network 2 consultation beginning, activation input p2 may occur as it determines the weight this net would be consulted. When the h1 hypothesis value is lower then the requested value determined for Network 2, the network is not solved at all.

3.3 Building the New Expert System

The new hybrid expert system is based on the NexS [13]. Its building consists of four steps.

1st step

Modification of the data obtained from the expert. It is necessary to transform the data format for the purposes of the decision tree algorithm.

2nd step

Tree building. We used the C4.5 algorithm [14] which is able to use both discrete logical values and continuous numerical values as attributes for branch evaluation. It is able to process missing values and noisy data, and it even has implemented a method to prune the trees, that evaluates errors in branches and then specifies which branches are not to be included in the final tree.

3rd step

Replacing the tree nods with the neural networks. Neural networks replace the nods. The nets are trained to split the data in the same way as the nods.

4th step

Harmonizing of the knowledge base. This is the only step that requests the presence of an expert who can modify the tree topology and change the structure of the nods consisting of neural networks.

4 Conclusion

Hybrid expert system with automatic knowledge base decision tree formation was developed. Neural networks improve the ability of decision trees in classification. The node representation based on neural networks hierarchy splits the state space into areas by multivariate function approximations. Classification improvement is then apparent mainly in areas of state space where we are approaching a boundary between two different classes. The architecture of this system accelerates the harmonizing process and decreases demands on the capability of an expert.

Unlike the decision trees, our hybrid expert system does not serve a classification as result, but only one hypothesis. Nevertheless we receive a list of hypotheses evaluated by certain value of the hypothesis trust.

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