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クラスルームにおける暗黙的知識の解読と説明

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あらまし
ニューラルネットワークは、サブシンボリックであり暗黙的な知識を学習する。その結果から解を判断することはできるが、人間にはこの判断が分かり難いものである。特に、クラスルームでの教授・学習活動においては暗黙的知識はあまり役に立たない。人間が通常用いている知識はシンボリックな知識であるからである。例えば、経済学や地理学といった科目では授業において多量の資料を扱う場合がある。人間にとってこれらの資料の意義や意味は理解しやすいものではない。このような資料を何らかのパターンによって表現した場合、ニューラルネットワークは、それらに対する反応を効果的に学習ことが可能である。クラスルームにおいて、学生がこれらの資料を読みこなしと説明することができるようにするために、教授者はサブシンボリックな表現からシンボリックな表現へと変換するためのツールを必要とする。我々はこのようなツールをルール抽出アルゴリズムを用いて実装することを試みる。本稿では、ニューラルネットワークからルールを抽出する環境の開発に関して詳述し、その上で開発環境の評価結果を示す。

Reading and Explaining Implicit Knowledge in a Classroom

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Abstract

Neural Networks train on knowledge that is sub-symbolic and implicit. They can take decisions, but these decisions are not transparent for humans. Especially in a classroom environment, there is little use for implicit knowledge. The knowledge teacher and pupils deal with is mostly explicit, i.e., symbolic. There are subjects, though, like Economy, Geography, a.o., which deal with large amounts of data, whose behaviour is less obvious to the human eye. These data and the responses to different patterns are very suitable to train on neural networks. In order to read and explain these data in a classroom, the teacher needs a translator from the sub-symbolic language into the symbolic one. These translators are the so-called Rule Extraction Algorithms. In this paper we discuss and show a development of an environment of rule extraction from neural networks, which has application in the classroom. We also test the developed environment and show the results.

1 Introduction

The work that we are presenting here has resulted from tests and developments achieved in a doctor-thesis [Cristea 99c]. This thesis started the basis for a Japanese-Romanian cooperation Project entitled "Neural Network Knowledge Eliciting". The research on this project is being continued at the Laboratory of Artificial Intelligence and Knowledge Engineering, The Graduate School of Information Systems, University of Electro-Communications, in collaboration with the Laboratory of Digital Signal Processing, Politehnica University Bucharest.

The aim of this work is to build a new additional type of classroom tool, that can read the information from a Neural Network (NN) based tool. Such NN tools were used in the past, too, but not so very often, due to their hidden nature of "back-box" structure. Students need to understand what is going on, and the teacher has to be able to give explanations. Therefore, sub-symbolic NN knowledge is not useful. The new research direction of rule extraction opens new possibilities for a somehow stagnant NN research, and also can provide new useful tools for many domains, including Education.

As the design and first construction steps of this Rule Extraction environment for teaching was explained in past papers [Cristea et al. 99b], we will just concentrate here one some new aspects and tests of the work.

The remainder of this paper is structured as follows. Firstly, we are going to introduce the system that we are gradually building. The third section presents a validity testing procedure that we developed for the current stage of the system. In the following section, the results according to the designed validity testing are shown. In the last section, conclusions are drawn.

2 The system

The system consists of three basic modules: the *Neural Network Engine* module, the *Rule Extraction* module and the *User Interface* module. The first module has the role of training on the provided time series data, learning the dependencies that appear in this data. The second module is based on a collection of REX tools and has the role to transform the knowledge stored in the neural network into rules. The last module is responsible for the interaction with the end-user, in this case, the teacher preparing for his/her class. More details about the system design and construction can be found in [Cristea et al. 98, 99b]. [Cristea et al. 98] also presents a case study of how a teacher can benefit from adding new knowledge from the field (practical knowledge) in the form of rules extracted from neural networks, to his/her presentation in front of the students, presentation which traditionally is based only on domain knowledge (theory).

3 Validity testing procedure

The system proposed is difficult to evaluate, out of many reasons. First of all, there are no benchmarks in this specific domain, as the proposed system is a pioneer in this line of research. Secondly, the previously defined quality criteria are qualitative and not quantitative, and also highly subjective, so their measurement is difficult.

With these problems in mind, we tried to combine qualitative rating with quantitative statistics, and developed a method to evaluate the system in an easy and rapid way. The method used was the questionnaire method, so often used in educational software design. To examine the validity of the system, an experiment, with domain experts was preferable. As the perspective users are educators and teachers from everywhere, this questionnaire was made available on the Internet, and the address is: *http://www.ai.is.uec.ac.jp/u/alex/TESTS/questionnaire.html*

Teachers, instructors and people involved in the educational process from many countries were invited to fill in this questionnaire. The contents was as follows. The first page to access was an explanatory page, that stated the problem and the desired goals. The next page to be accessed was the first example case, consisting of a pair of a [graphical display of a time series] and of [the rules that were extracted from it]. The following four pages were similar, only displaying different time series. The last page was the questionnaire. Pointers back to the explanation page and the example page were also provided, for easy access.

The method used for evaluation was the questionnaire method. The input for the experts were time-series charts and the respective rules extracted by the REX system. The output expected from the experts were the answers to a questionnaire. The evaluation of the answers was based on 3 main observations:

1. evaluation of the personal profile of the expert (for determining the degree of expertise)
2. evaluation (EV) of SSKEE by expert
3. EV of expert's opinion on REX research in education (pointing the right way or not)

2. and 3. were averaged and biased with 1.

The exact computation of the evaluation scores determined from the answers to the questionnaire is shown in the following. The answers to the questions were evaluated in 0, 0.25, 0.5, 1, which correspond to the answers 'Yes', 'A little', 'Almost not at all', 'No'. The computed values are: Personal Adequateness (PA), Computer Skills (CS), Overall PA (OPA), opinion of the expert about the use of products of such research, In Favour of Progr.(FP), the amount in which the built system seems to have reached the set Goal(RG), and an Overall(OV) evaluation of the system. These values are then expressed in percentage. Here are the exact formulas (q$<$ *number* $>$ is referring to question number $<$ *number* $>$):

PA = (1/5) * (q12+q14+q15+q16+q27)
CS = q11
OPA = (1/2) * (PA + CS); if (OPA ¡ 0.5) stop
FP = (1/8) * (q5+q6+q7+q8+q9+q10+q12+q18)
RG = (1/3) * (q2+q3+q4)
OV = [(1/2) * (PA+CS)] * (FP+RG)

4 Results

The overall reply was very much (87%) in favour of the system, and of such systems generally speaking (over 75%). The information gathering system was made to automatically reject subjects which presented a low personal adequateness to judge upon the system (based on their computer skills and other factors). The replies of such subjects were not recorded by the system. The accepted specialists showed an overall personal adequateness of over 87%. Biased with the personal adequateness of the questioned subjects, the system was evaluated at a percentage of over 70% overall performance, specialist acceptance and usefulness. All these data can be seen in figure 1. The thicker line represents the movement of the average, the thinner are individual ones. There is an ongoing refinement of the system according to suggestions of specialists. Therefore, the presented results are preliminary, and the interested specialists are invited to check our www address presented above.

5 Conclusions

We developed an integrated environment to serve as an assistant in the educational process. We explained that a NN engine can store sub-symbolic knowledge and a rule extraction module can transform it into symbolic knowledge, in order to provide useful information and assistance during the teaching process, which can deal only with symbolic knowledge.

We also showed the difficulties in evaluating such a system and how we tried to bypass them by using experts.

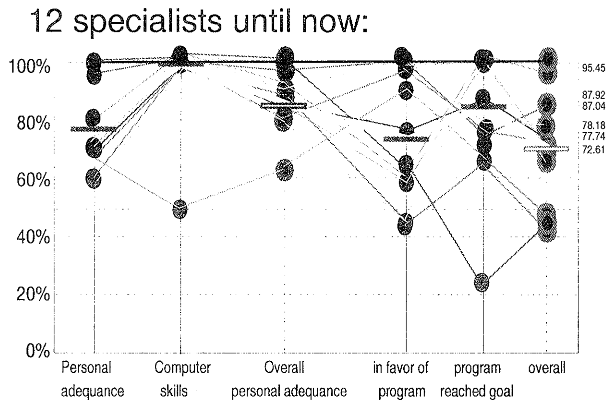

図 1: Preliminary results

From the response of the questioned experts, such a system seems to be required, so we believe that further developments should be pursued.

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