A COMPARISON STUDY OF RULE SPACE METHOD AND NEURAL NETWORK MODEL FOR LEARNING DIAGNOSIS AND IT'S AN APPLICATION

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1. Introduction

Both methods, Rule Space Method (RSM) and Neural Network Model (NNM) are techniques of statistical pattern recognition and classification approaches developed from different fields; one is for behavioral and the other is for neural sciences.

RSM is a technique of clustering examinees into one of the predetermined latent Knowledge States (KS) that are derived logically from an expert's hypotheses about how students learn. RSM uses the multivariate decision theory to classify individuals, and NNM that is considered as a nonlinear regression method uses the middle layer of the network structure as classification results. We have found that there two methods are similarities between the results from the two approaches, and moreover they have complementary characteristics when applied in practice.

In this paper, we discuss the comparisons of both approaches by focusing on the structure of the NNM and of KSs in the RSM. And we show an application result for a reasoning test.

2. Rule Space Method

RSM is a technique developed in the domain of the cognitive science. It starts from the use of an incidence matrix Q that characterizes the underlying cognitive processes and knowledge (Attribute) involved in each Item. It is a grasping method of each examinee's mastered/non-mastered learning level (Knowledge State, KS) from item response patterns, and a list of all the possible KSs can be generated algorithmically by applying Boolean Algebra to the incidence matrix Q. This method is fairly new but has lately started getting some attention because it is possible to provide diagnostic scoring reports for a large-scale assessment.

Up to now, the results of examinees' performance on a test are reported by total scores or scaled scores. However, if this technique is used in educational practices, it is possible to report which attributes each student mastered or non-mastered, in addition to his/her total scores. It is often true that the same total score may have several different KSs. By reporting detailed information of his/her KS, learning can be facilitated more effectively than just providing total scores only.

3. Feed-Forward Neural Network Model

In spite of that the mathematical formulization of the Feed-Forward NNM is simple, almost any nonlinear function can be approximated by selecting deferent numbers of middle layers and connections between neurons. When we apply this technique to existing data obtained from learning processes, we can use this model to search for the strategy of any joint intensity between units.

From a statistical point of view, NNM is a nonlinear regression model. In this paper Feed-Forward NNM is considered as a model-fitting procedure to estimate the optimum values of the parameters in the regression model.

This procedure is called parameter estimation in statistics, but is called a learning algorithm in NNM. One of the learning algorithms commonly used is Back Propagation (BP) that is a learning method by passing on errors to previous layers. BP is an adaptation of the steepest descent method to the NNM field. This method has a reducible faculty of the convergence to the local minimum point.

4. Science Reasoning Test

The Science Reasoning Test (SR-Test) is an entrance examination test that measures the student's interpretation, analysis, evaluation, reasoning, and problem-solving skills required in the natural sciences.

Since we got the ACT's (American College Testing, Inc.) cooperation, we used one open-form of their ACT Assessment tests for our experimentation. The test is based on units containing scientific information and a set of multiple choice questions about the scientific information. Calculators are not permitted to be used for the test. The scientific information for the test is provided in one of three types of formats.

The first format, data representation, presents graphic and tabular material similar to that found in science journals and texts. The questions associated with these format measure skills such as graph reading, interpretation of scatter plots, and interpretation of information presented in tables. The second format, research summaries, provides students with descriptions of one or more related experiments. The questions focus upon the design of experiments and interpretation of experimental results. The third format, conflicting viewpoints, presents students with expressions of several hypotheses or views that, being based on differing premises or on incomplete data, are inconsistent with one another. The questions focus upon the understanding, analysis, and comparison of alternative viewpoints or hypotheses.

The SR-Test questions require students to use scientific reasoning to answer the questions. The students are required to recognize and understand the basic features of, and concepts related to, the provided information; to critically examine the relationships between the information provided and the conclusions drawn or hypotheses developed; and to generalize from given information to gain new information, draw conclusions, or make predictions.

5. Numerical Examples

We applied the RSM to a data of fraction addition problems, and got a tree structure for the KS. We related RSM that derives the KS from an incidence matrix Q, to the Feed-Forward NNM. For that, we designed the network of the three-layer structure in which items were assigned to the input layer and Attributes were to the output layer. The KSs in the RSM were considered to correspond to the middle layers of NNM. We applied several numerical examples to the both methods, and found close similarities in their results although they were not identical.

And we applied the RSM to a data of SR-Test of 286 Japanese students. The number of attributes and items are 12 and 18, respectively. Figure 1 is the tree representation of the KSs that shows the examinee's mastered/non-mastered learning level. In this figure, each circle is the KS, and the numbers in the circle are the IDs of non-mastered attribute. Or the number in the parenthesis is the number of examinee classified in this KS. We can find the fact that the main solving attribute IDs are 6, 8 and 9, and secondary attribute are 2 and 5. The total examinee classified in these KSs is 225, which is about 80% of all. The main streams to reach the full mastered state are three KSs of left-hand side in the third layer from the top.

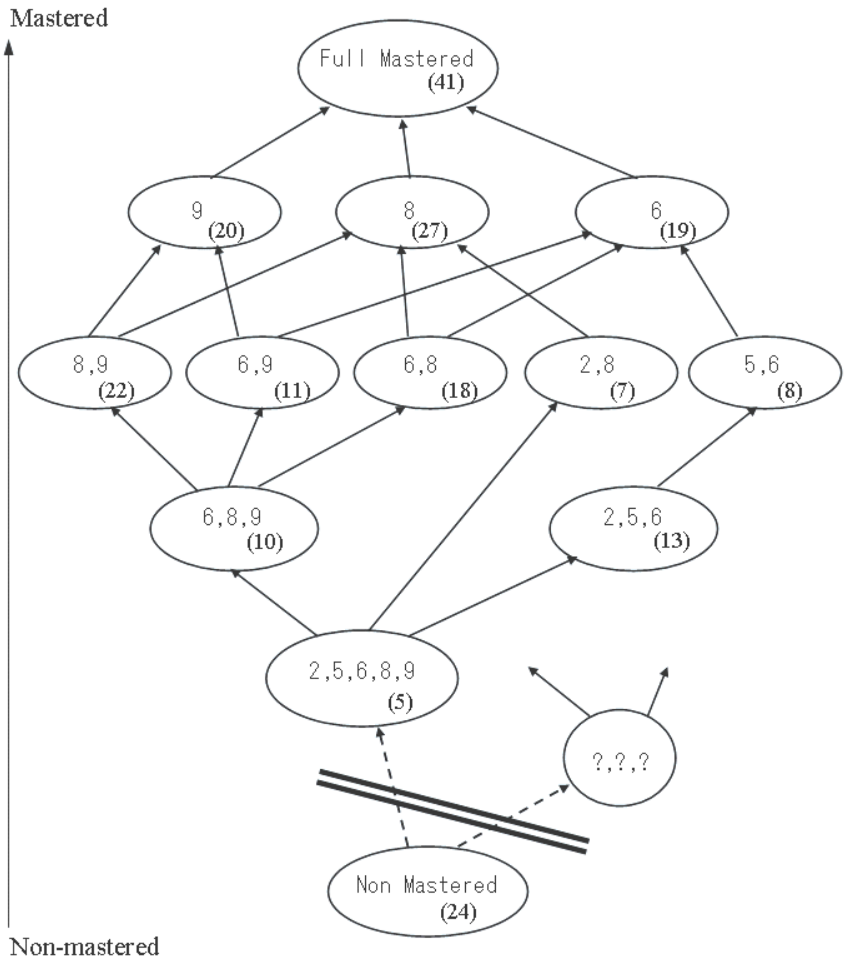

Figure 1. A tree representation of Knowledge States for the SR-Test data

6. Discussion and Conclusions

We investigated the relationship between the characteristics of the middle layer of NNM and the Knowledge States in the RSM, and discussed their similarities and usefulness at the weaknesses existing in the RSM.

It is well known that the composition of an incidence matrix Q in the RSM is a very laborious task, requires experts' intense cooperation. The experts identify attributes involved in each item and express them in an incidence matrix Q. It needs to investigate multiple numbers of solution strategies for each item. This is extremely hard work. If an examinee's mastering level (cluster) is known to some extent from past experiences, it is also possible to construct a network in which these clusters are assigned to the output layer of NNM. The middle layer drawn from this model is expected to correspond to Attributes. It may be possible to use this result for replacing a task analysis required in making an incidence matrix Q in RSM.

We plan to clarify the difference and similarities of the two models with numerical examples, or will apply to this problem the technique of the deep learning in the AI fields.

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