# Two Classification Methods of Individuals for Educational Data and an Application

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**Abstract**

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 developed in the domain of educational statistics. 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) from item response patterns. RSM uses multivariate decision theory to classify individuals, and NNM, considered as a nonlinear regression method, uses the middle layer of the network structure as classification results. We have found some similarities and differences between the results from the two approaches, and moreover both methods have supplemental characteristics to each other when applied to the practice.

In this paper, we compare both approaches by focusing on the structures of NNM and on knowledge States in RSM. Finally, we show an application result of RSM for a reasoning test in Japan.

**Keywords:** Rule Space Method, Neural Network Model, Educational Statistics, Cognitive Science.

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# 1 Introduction

A Neural Network model was proposed for the purpose of modeling the information processing in a person's brain in the 1940s. Neurons (nerve cell elements) are considered as the minimum composition unit of cerebral functions that can entangle in a complicated and organic manner. The model shows that all the logical reasoning can be described in a finite size of the number of neurons and connections [2]. The model enables us to express acquisition of new knowledge from learned examples in the past, therefore it can be used to help to solve one of the weaknesses in constructing an AI (Artificial Intelligence) system. It is known that expressing knowledge acquisition in an AI system is extremely difficult.

On the other hand, the Rule Space Method (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. The method can be considered as a statistical testing technique of the expert's hypotheses. These hypotheses are expressed by an item-attribute matrix (incidence matrix) $Q$ where attributes are representing underlying knowledge and cognitive processing skills required in answering problems [1]. A Knowledge State consists of attributes of the type mastered/non-mastered, and a list of all the possible Knowledge States 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 [3]. We have found that there 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 Neural Network Model (NNM) and of Knowledge States in the RSM. We show an application result for a reasoning test.

# 2 Rule Space Method

RSM is a technique developed in the domain of educational statistics [7]. 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. 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 did not master, in addition to his/her total scores. It is often true that several different Knowledge States may arise from the same total score. By reporting detailed information of his/her Knowledge State, learning can be facilitated more effectively than by just providing total scores.

# 3 Feed-Forward Neural Network Model

In spite of that the mathematical formulation of the Feed-Forward NNM is simple. Almost any nonlinear function can be approximated by selecting different 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 a 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 [4].

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 convergence to the local minimum point.

# 4 Science Reasoning Test

The Science Reasoning Test (SR Test) is an entrance examination that measures the student's interpretation, analysis, evaluation, reasoning, and problem-solving skills required in the natural sciences [5].

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

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

# 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, and requires experts' intense cooperation. The experts identify attributes involved in each item and express them in an

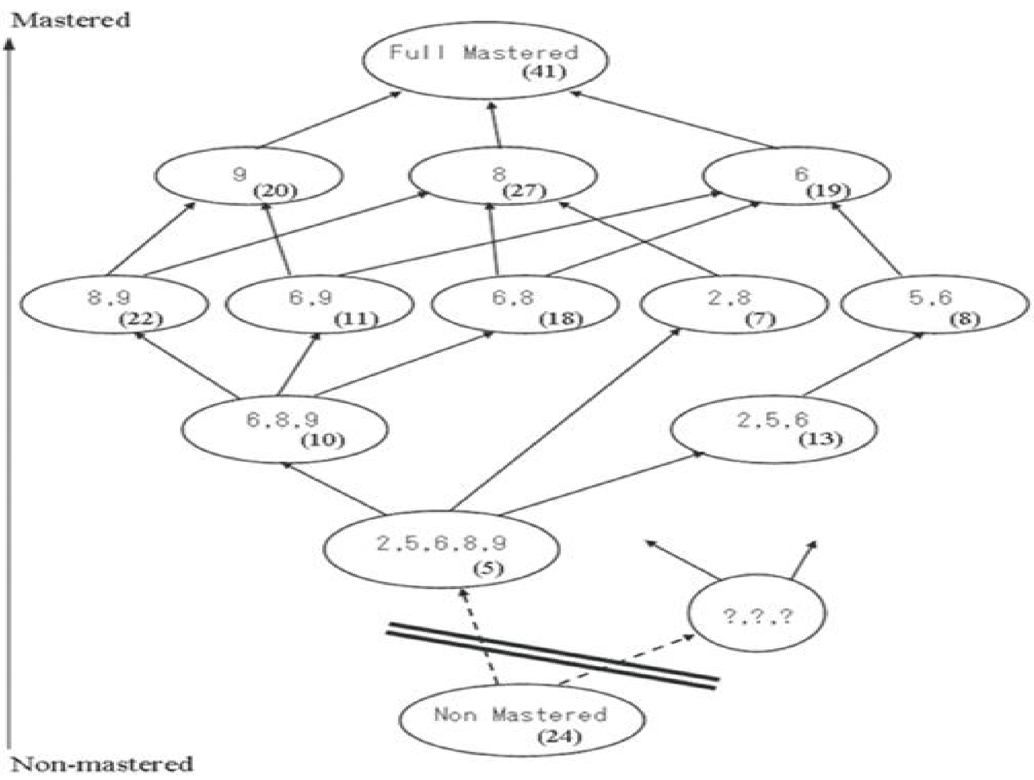


Figure 1: A tree representation of Knowledge States for the SR-Test data

incidence matrix $Q$. Multiple solution strategies for each item need to be investigated. 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 the 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 get useful results to apply these methods for the SR-Test data and our real examination data.

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